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RESOLUTION, RECOMMENDATION, AND EXPLANATION IN RICHLY STRUCTURED SOCIAL NETWORKS

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Abstract

Resolution, Recommendation, and Explanation in Richly Structured Social Networks

by

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There is an ever-increasing amount of richly-structured data from online social media. Making effective use of such data for recommendations and decisions requires methods capable of extracting knowledge both from the content as well as the structure of such networks. Utilizing richly-structured networks derived from real-world data involves three major challenges that I address in this dissertation: 1) matching multiple references that correspond to the same entity (a problem known as entity resolution), 2) exploiting the heterogeneous nature of the data to provide accurate recommendations, and, given the complexity and heterogeneity of the data, 3) explaining the recommendations to users. My goal in this work is to address these challenges and improve both accuracy and user experience for resolution and recommendation over richly-structured social data.

In the first part of this work, I introduce a collective approach for the problem of entity resolution in familial networks that can incorporate statistical signals, relational information, logical constraints, and predictions from other algorithms. Moreover, the method is capable of using training data to learn the weight of different similarity scores and relational features. In experiments on real-world data, I show the importance of supporting mutual exclusion and different types of transitive relational rules that can model the complex familial relationships. Furthermore, I show the performance improvements in the ER task of the collective model compared to state-of-the-art models that use relational features but lack the ability to perform collective reasoning.

In the second part of this work, I present a general-purpose, extensible hybrid recommender system that can incorporate and reason over a wide range of social data sources. Such sources include multiple user-user and item-item similarity measures, content, and social information. Additionally, the framework automatically learns to balance these different information signals when making predictions. I experimentally evaluate my approach on two popular recommendation datasets, showing that the proposed framework can effectively combine multiple information types for improved performance, and can significantly outperform existing state-of-the-art approaches.

In the third part of this work, I show how to generate personalized, hybrid explanations from the output of a hybrid recommender system. Next, I conduct two large crowd-sourced user studies to explore different ways explanations can be presented to the users: a non-personalized and a personalized. In the first, non-personalized study, I evaluate explanations for hybrid algorithms in a variety of textual and visual formats. I find that people do not have a specific preference among different versions of textual formats. At the same time, my analysis indicates that among a variety of visualization formats people prefer Venn diagrams. In the second, personalized study, I ask users to evaluate the persuasiveness of different explanation styles and find that users prefer item-based and content-based styles over socio-based explanations. I also study whether the number of the explanation styles can affect the persuasiveness of the explanation. My analysis indicates that users lose interest after showing them three to four different explanation styles. Finally, I experiment with a variety of formats that hybrid explanations can be presented to the users, such as textual or visual, and find that textual explanations are perceived as most persuasive.

I formulate the problems of entity resolution, recommendation, and explanation as inference in a graphical model. To create my models and reason over the graphs, I build upon a statistical relational learning framework called probabilistic soft logic. My models, which allow for scalable, collective inference, show an improved performance over state-of-the-art methods by leveraging richly-structured data, i.e., relational features (such as user similarities), complex relationships (such as mutual exclusion), a variety of similarity measures, as well as other heterogenous data sources (such as predictions from other algorithms).

To the two men of my life, Alex and Lampros

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Chapter 1

Introduction

As the amount of recorded digital information increases, there is a growing need for efficient and timely methods for performing knowledge discovery and enabling informed decisions. A multitude of heterognenous data networks today are continuously capturing online information around relationships and interactions between users, such as: social networks (e.g., Facebook, Twitter), media-sharing networks (e.g., YouTube, Flickr), media-consumption networks (e.g., Netflix, iTunes), information-sharing networks (e.g., Yelp), genealogical and historical networks (e.g., Ancestry.com), or networks of physical objects (Internet of Things).

Given the enormous size of data present in such networks and their heterogeneous nature, the task of proactively extracting knowledge through queries in order to make decisions is not straightforward. Getting familiar with the intricacies of each network, how to query and what to look for, requires significant time investment from a user's perspective. On the other hand, from the users point of view, receiving relevant, interesting, and explainable *recommendations* in an on-demand fashion, is a more effective and efficient approach as they do not need to worry about how to best interact with each network.

Although there is a large body of work on recommender systems in general

[100], providing recommendations over heterogenous data networks is a relatively new area. In the traditional recommender system setting, the item recommendations presented to users are generated by leveraging the ratings that users have provided in the past. This data is also known as the user-item recommendation matrix. On the other hand, in the case of heterogenous data networks, we can leverage information from a variety of sources. For example, the same users in two different networks may interact with an item (e.g., Facebook and Twitter accounts accessing a news site), a user may interact with the same item on two or more heterogeneous networks (e.g., a user purchased items on Amazon and ciao.co.uk), or we can have a combination of several heterogeneous networks of users and items.

In order to address the problem of recommendations over heterogenous richly-structured data neworks, I addressed three major challenges. First, I created a modeling framework based on probabilistic soft logic [4] for performing entity resolution and identifying coreferent items across heterogenous networks. Second, I designed and implemented an efficient and effective recommendation approach that can leverage the heterogeneity of the data to provide recommendations to users that are of higher accuracy compared to current state-of-the-art approaches. Third, I created a generic algorithm that explains the output of the recommendations and the reasoning behind it to users.

The task of model-building in domains with rich structure has been extensively studied in the fields of probabilistic programming [45] and statistical relational learning (SRL) [43], which provide programming language interfaces for encoding knowledge and specifying models. Probabilistic programs are useful for encoding graphical models that reason with graph-structured probabilistic dependencies. Graphical models are a natural fit for the problems of entity resolution and recommendation given that both problem spaces can be represented as a graph.

In this work, I use a modeling language called probabilistic soft logic (PSL) [4]. PSL provides a general declarative framework for combining statistical signals (such as attribute similarities), relational information (such as relationship overlap), logical contraints (such as transitivity and bijection), as well as information from any additional sources (such as the predictions of other algorithms). PSL supports collective inference, i.e., decisions are made jointly, rather than independently, which has been shown to improve performance in a variety of tasks, such as classification or prediction. Another advantage of PSL, is that models are defined by providing a set of first-order logical rules and, as a result, explanations of PSL's output can be generated by translating these first-order logical rules to natural language phrases. Finally, the models defined by PSL programs, called hinge-loss Markov random fields (HL-MRFs), are amenable to efficient and scalable inference, which is crucial not only in the entity resolution and recommender systems context but also, and most importantly, in the context of large-scale heterogenous data networks.

1.1 Contributions

In this dissertation, I show how entity resolution, recommendation, and explanation are important components of modern decision making systems and how they mix and relate together. Both resolution and recommendation can benefit from richly structured information; however, it is not straightforward how to construct these models. In this dissertation I show that an approach that can combine relational and collective relational signals and can synthesize signals from multiple sources outperforms state-of-the-art. Although we can generally create models of high accuracy for resolution and recommendation, these models are often difficult to interpret. To this end, I show how to integrate the rich models with a personalized explanation approach and perform user studies to identify which explanation components users find most persuasive. Overall, I showed how to build both accurate and explainable models.

In the following, I provide a more detailed discussion of the contributions of this disseration around the challenges of resolution, recommendation, and explanation.

Challenge 1: Effective entity resolution in richly-structured social networks. The first challenge is to determine which “entities” (for example, a user or an item) are the same across two or more networks. For example, given the Facebook and Twitter graphs, it is important to know that a given Facebook user is the same with another Twitter user, in order to use this user’s information and preferences effectively in the recommendation step. This problem is known as entity resolution (ER) and has been addressed in the context of databases [22], where typically the entities appear within the same network with limited or no relational information. The advent of heterogenous networks has brought additional, richly-structured relational data that we can leverage to improve entity resolution. Indeed, previous works [9, 30, 104] exploit relational information to improve the accuracy of the entity resolution task. However, much of the prior work in relational entity resolution has incorporated only one, or a handful, of relational types, has limited entity resolution to one or two networks, or has been hampered by scalability concerns.

Contribution: In this dissertation, I provide a collective model using PSL that addresses the ER problem in the context of richly-structured social networks with a large number of relationship types. The approach is scalable and can be applied to resolving entities over an arbitrary number of networks. Furthermore, the model is able to support mutual exclusions constraints (e.g., a user from one network can be matched to at most one other user from another network) as well as different types of transitive relational rules that can model complex relationships, in a scalable way. An additional contribution of the approach is that it automatically learns to balance different information signals (such as attributes and relations) when resolving the entities. I motivate the need of the approach with an application for resolving mentions in healthcare records and, specifically, resolving entities in familial networks. In experiments on real-world data, I show the importance of supporting mutual exclusion and different types of transitive relational rules that can model the complex familial relationships. Furthermore, I show the performance improvements in the ER task of the collective model compared to state-of-the-art models that use relational features but lack the ability to perform collective reasoning. Additionally, I present how to apply the model of the familial networks to the recommender system setting and, more specifically, in the case of identifying the same items (e.g., products) across sets of items.

In the case of richly-structured familial social networks, we are given multiple partial representations of a family tree, from the perspective of different family members. The task is to reconstruct a family tree from these multiple, noisy, partial views. This is a challenging task mainly because attribute and relationship data is frequently incomplete, unreliable, and insufficient. For example, two distinct individuals (e.g., a grandparent and his grandchild) may share the same name across different generations which makes it difficult to discern that they are indeed two different entities and should be treated as such. Similarly, individuals may change their last name after marriage, which makes it difficult to infer that two references with very different last names correspond to the same entity. To address these challenges, I built an entity resolution model using PSL that can discern the same entities across multiple partial representations of an underlying family tree [66, 67, 68]. The entity resolution framework incorporates statistical signals (such as name similarity), relational information (such as sibling overlap), logical constraints (such as transitivity and bijective matching), and predictions from other algorithms (such as logistic regression and support vector machines). My findings show that: i) name similarities are not enough, since the performance of different models when using only this piece of information is relatively low, ii) attribute similarities, such as age, greatly improve performance when combined with name similarities, iii) relational similarities significantly improve the performance of the model in settings with low noise, iv) collective relational similarities significantly improve the performance of the entity resolution task in settings with high noise, and v) incorporating predictions from other algorithms always improves performance. Additionally, through experiments on real-world data, I show that my models significantly outperform state-of-the-art models that use relational features but lack the ability to perform collective reasoning.

Connecting my work on entity resolution and recommender systems, I perform ER over the set of items that are candidates for recommending by extending the model for entity resolution in familial networks. Identifying the coreferent items allows for making the user-item matrix more dense. The user-item matrix is a data structure that is inherent in most recommender algorithms and increasing its density typically leads to more accurate recommendations. In addition to improved accuracy, finding the coreferent items also allows for addressing an additional problem inherent in the area of recommender systems: the cold-start problem. More specifically, inferring that a newly-added item is coreferent with an existing already-rated item enables us to recommend the new item without the need for ratings from users. However, entity resolution in the recommender systems scenario (e.g., products) is a very challenging task, since it is not clear when two items should be merged or not. For example, two cameras varying in their color may appear twice on a web site, but may correspond to the exact same model. In this case, it is unclear whether those two products should be resolved, because some users may not be interested in the color of the camera but only in the technical specifications, while others may consider the color more important than the technical specifications. For the first group of users, the two cameras are the same product, so merging them would be beneficial since it will increase the density of the the user-item matrix. On the other hand, for the second group of users merging the two products is not a good decision.

Challenge 2: Leverage the richly-structured data to improve recommendation accuracy. The majority of recommendation algorithms [63] are basically designed to use the information provided by the user-item recommendation matrix and do not usually leverage the richly-structured data when generating recommendations. However, the rich structure of the data has great potential of improving recommendation algorithm performance since it captures rich interactions between users and items. Indeed, previous work on hybrid recommender systems, which use a combination of signals such as social connections, item attributes, and user behavior, demonstrate improved recommendation accuracy [2, 13, 27]. However, existing hybrid recommender systems are not generic. Instead, they are typically designed for a specific problem domain, such as movie recommendations. As a result, they have a limited ability for generalizing to other settings or making use of additional, external information.

Contribution: In this dissertation, I created a hybrid recommender model using PSL, called HyPER (HYbrid Probabilistic Extensible Recommender) [65] that is general-purpose, extensible, can use arbitrary data modalities, and delivers state-of-the-art performance. HyPER incorporates and reasons over a wide range of information sources, such as multiple user-user and item-item similarity measures, content, and social information. At the same time, HyPER automatically learns how to balance the signals coming from these sources when making predictions. The modeling approach is flexible, problem-agnostic, and easily extensible to new data sources. Through extensive experimental evaluation on two benchmark recommendation datasets, I show that HyPER can greatly improve accuracy by combining multiple information types and signficantly outperforms existing state-of-the-art approaches. In order to get additional impactful insights for my approach, I built smaller HyPER models with each information type individually (e.g., a model that uses only one user similarity measure) as well as more complicated HyPER models that combine the smaller hybrid models that use a given type of information (e.g., a model using all available user similarity measures). I show that: i) the performance of different user and item-based collaborative filtering models varies based on the different similarity measures used, with models using distances computed in the latent space typically performing the best, ii) the model that combines all similarity measures performs better than the sub-models that use only one similarity measure, iii) both content and friendship information help performance, and the model that combines both content and social information matches and often surpasses the performance of the best individual model, iv) a HyPER ensemble that combines the input from popular state-of-the-art recommender algorithms without using any additional information (e.g., content of the items) performs better than the individual baselines, v) comparisons between the full HyPER model which uses all the available information signals and different sub-models using only one type of information (e.g., only user-based collaborative filtering) shows that the full model performs the best, indicating that HyPER can successfully combine and balance the different information sources in order to improve performance.

Challenge 3: Improve user experience and persuasiveness by explaining the output of complex recommender systems. Although the performance of recommender systems has significantly improved using hybrid methods like HyPER, most systems operate as black boxes, i.e., they do not explain to users *why* a recommendation was provided. Since users have a need for meaningful recommendations [79], recent work [52, 10, 107, 116, 20] studies how to provide explanations. Typically, explanations from a single recommendation algorithm come in a single style. For example, a content-based recommender system will generate only content-based explanations. However, for hybrid recommenders that combine several data sources such as ratings, social network relations, or demographic information, users expect *hybrid explanations* that combine all relevant sources of information and present explanations of more than one styles. Such explanations are both effective [90] and desirable by the users [11].

Contribution: In this dissertation, I presented an approach for explaining the recommendations generated by a hybrid recommender engine. More specifically, the approach utilizes the output of the HyPER model to provide hybrid explanations, i.e., explanations combining more than one styles (e.g., content-based together with social-based). I also provide a list of explanation variables that can alter how explanations are presented. For example, we can vary the textual and visual format, the explanation styles, as well as the volume of the explanations. Another contribution of this dissertation is the insights collected from two large-scale user studies on hybrid explanations. These insights can serve as a guideline for the recommender system research community around how different explanation variables can impact the subjective persuasiveness and user experience of recommendations. In summary, I show that: i) rule-based explanations perform poorly, ii) there is no statistically significant difference between different variations of textual formats, iii) textual explanations are ideal when compared to simple visualization formats such as cluster dendrograms, iv) among a variety of visual formats, people prefer Venn diagrams, v) people prefer item-centric over user-centric explanations, and vi) people prefer to see at most three to four explanations per recommendation.

1.2 Structure of Disseration

This dissertation is structured as follows:

Chapter 2 provides a brief primer on PSL, the statistical relational learning framework that is used in this dissertation for performing effective entity resolution and providing accurace and explainable recommendations. The discussion that follows, elaborates on the features of the three main areas of this dissertation (resolution, recommendation, and explanation) that necessitate the choice of PSL. The chapter concludes by providing some simple examples illustrating how PSL can be applied to each one of these areas.

Chapter 3 formally defines the problem of entity resolution in richly-structured social networks, such as familial networks. The main body of this chapter explains how to develop a scalable entity resolution framework that incorporates attributes, relational information, logical constraints, as well as predictions from other baseline algorithms, in a collective PSL model. The evaluation section of this chapter presents the results from extensive experiments on two real-world datasets (patient data from the National Institutes of Health and Wikidata). The results demonstrate that the approach outperforms state-of-the-art methods while scaling gracefully with the problem size. The chapter continues by providing a detailed analysis of the features most useful for relational entity resolution in richly structured social networks, thus providing readers with practical advice on how to perform relational entity resolution in other scenarios. The chapter concludes by explaining how the work in entity resolution in familial networks can be applied for the task of entity resolution for products in the recommender systems setting. This work is published in Kouki et at. [66, 67, 68].

Chapter 4 models the recommendation problem as a bipartite graph, where users and items are vertices, and ratings are edges between users and items. The chapter continues by explaining how to build a PSL model that augments the graph to construct a probabilistic graphical model with additional edges encoding similarity information, predicted ratings, content, social information, and metadata. The graph-based PSL model which is called HyPER (HYbrid Probabilistic Extensible Recommender) can additionally encode additional sources of information and outputs of other recommendation algorithms in a similar way, i.e., in the form of additional links or nodes. Additionally, the solution can learn how to balance the different input signals. A key contribution of the framework is that it is flexible, problem-agnostic, and easily extensible. Finally, HyPER is evaluated on two rich datasets from the local business and music recommendation domains (Yelp and last.fm) and is compared to state-of-the-art recommendation approaches. The experiments show that HyPER can effectively combine multiple information sources to improve recommendations, resulting in significantly improved performance over existing methods in both datasets. The contributions on hybrid recommender systems were published in Kouki et al. [65].

Chapter 5 extends HyPER to produce real-time recommendations while incorporating a variety of information sources. The chapter discusses how to generate customized explanations in real time by leveraging the output of HyPER. The approach supports several different explanation styles, including user-based, item-based, content, social, and item popularity. Using Amazon Mechanical Turk (AMT), two large user-studies are conducted to evaluate the generation of explanations: one personalized and one non-personalized. In the first study, several dimensions for designing explanation interfaces are first identified and then evaluated in terms of user experience in a variety of text and visual, graph-based formats. One of the key findings is that among a variety of visual interfaces, users prefer Venn diagrams. In the second study, recommendations and explanations are personalized to each user by taking into account this user's previous history, preferences, and social connections. Different explanation styles are evaluated (e.g., user-based, item-based), finding that users prefer item-based and content-based styles. When varying the number of the explanation styles shown, the basic outcome is that users' pay attention only for up to three or four different explanation styles and then they lose interest. Finally, a variety of presentation formats (such as textual or visual) are evaluated in terms of persuasiveness. The conclusion is that textual explanations are perceived as the most persuasive. A first version of the work in explanations for hybrid recommender systems is featured in Kouki et al. [69] and a full version is in preparation [70].

Chapter 6 concludes this dissertation by summarizing the basic findings and discussing the importance of the results and contributions in the areas of entity resolution, recommender systems, and explanations.

Chapter 2

Background in Probabilistic Soft Logic

In this dissertation, we cast the problems of entity resolution and rating prediction as inference in a graphical model. To reason over the graph we use a statistical relational learning framework, called probabilistic soft logic (PSL) [4]. PSL is an open source machine learning framework[1] for developing probabilistic models. To perform entity resolution, we use PSL to define a probability distribution over the entities. To perform rating prediction, we use PSL to define a probability distribution over the ratings. PSL uses a first-order logical syntax to define a graphical model. In contrast to other approaches, PSL uses continuous random variables in the $[0, 1]$ unit interval and specifies factors using convex functions, allowing tractable and efficient inference. PSL has been successfully applied in a various domains, such as cyberbullying [111], stance predictions in online forums [105], fairness in relational domains [40], energy disaggregation [112], product alignment [33], bioinformatics [28], causal structure discovery [29], and knowledge graph identification [95].

[1]`http://psl.linqs.org`

PSL defines a Markov random field associated with a conditional probability density function over random variables $\mathbf{Y}$ conditioned on evidence $\mathbf{X}$,

$$P(\mathbf{Y}|\mathbf{X}) \propto \exp\Big(-\sum_{j=1}^{m} w_j \phi_j(\mathbf{Y}, \mathbf{X})\Big) \ , \tag{2.1}$$

where ϕ_j is a convex potential function and w_j is an associated weight which determines the importance of ϕ_j in the model. The potential ϕ_j takes the form of a *hinge-loss*:

$$\phi_j(\mathbf{Y}, \mathbf{X}) = (max\{0, \ell_j(\mathbf{X}, \mathbf{Y})\})^{p_j} \ . \tag{2.2}$$

Here, ℓ_j is a linear function of $\mathbf{X}$ and $\mathbf{Y}$, and $p_j \in \{1, 2\}$ optionally squares the potential, resulting in a *squared-loss*. The resulting probability distribution is log-concave in $\mathbf{Y}$, so we can solve maximum a posteriori (MAP) inference exactly via convex optimization to find the optimal $\mathbf{Y}$. We use the alternating direction method of multipliers (ADMM) approach of Bach et al. [4] to perform this optimization efficiently and in parallel. The convex formulation of PSL is the key to efficient, scalable inference in models with many complex interdependencies.

PSL derives the objective function by translating logical rules specifying dependencies between variables and evidence into hinge-loss functions. PSL achieves this translation by using the *Lukasiewicz* norm and co-norm to provide a relaxation of Boolean logical connectives [4]:

$$\begin{aligned} p \wedge q &= \max(0, p + q - 1) \\ p \vee q &= \min(1, p + q) \\ \neg p &= 1 - p \ . \end{aligned}$$

Bach et al. [4] provide a detailed description of PSL operators.

2.1 Balancing information sources and signals using PSL

An important task of any prediction algorithm that operates in richly-structured social networks (such as entity resolution or hybrid recommender systems) is to trade off and balance the different information sources or signals according to their informativeness. Each of the first-order rules that we introduce using PSL, corresponds to a different information source or signal, and is associated with a non-negative weight w_j in Equation 2.1. These weights determine the relative importance of the information sources, corresponding to the extent to which the corresponding hinge function ϕ_j alters the probability of the data under Equation 2.1, with higher weight w_j corresponding to a greater importance of information source j. For each rule we learn a weight using Bach et al. [4]'s approximate maximum likelihood weight learning algorithm for templated HL-MRFs. The algorithm approximates a gradient step in the conditional likelihood,

$$\frac{\partial logP(\mathbf{Y}|\mathbf{X})}{\partial w_j} = \mathbb{E}_w[\phi_j(\mathbf{Y},\mathbf{X})] - \phi_j(\mathbf{Y},\mathbf{X}) \ , \tag{2.3}$$

by replacing the intractable expectation with the MAP solution based on w, which can be rapidly solved using ADMM.

We use the above weight learning mechanism to learn the importance of different (1) information signals in the domain of entity resolution and (2) information sources in the domain of recommender systems. Our comprehensive experiments demonstrate that using this mechanism, we can learn to appropriately balance many information sources and signals, resulting in improved performance over previous state-of-the-art approaches on various richly-structured social networks.

2.2 PSL for Entity Resolution

In the entity resolution setting we are given multiple partial representations of an underlying network. Each representation consists of a number of users (or items) called mentions. The challenge is to find the coreferent mentions, i.e., which users (or items) match or which users (or items) correspond to the same entity. Several features of this problem necessitate the choice of PSL: (1) entity resolution in richly-structured social networks is inherently collective, requiring constraints such as transitivity and bijection; (2) the multitude of relationship types require an expressive modeling language; (3) similarities between mention attributes take continuous values; (4) potential matches scale polynomially with mentions, requiring a scalable solution. PSL provides collective inference, expressive relational models defined over continuously-valued evidence, and formulates inference as a scalable convex optimization.

To illustrate PSL in an entity resolution context, the following rule encodes that mentions (users in this case) with similar names and the same gender might be the same person:

$$\textsc{SimName}(\mathtt{m}_1, \mathtt{m}_2) \wedge \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\ , \tag{2.4}$$

where $\textsc{SimName}(\mathtt{m}_1, \mathtt{m}_2)$ is a continuous observed atom taken from the string similarity between the names of $\mathtt{m}_1$ and $\mathtt{m}_2$, $\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2)$ is a binary observed atom that takes its value from the logical comparison $\mathtt{m}_1$.gender = $\mathtt{m}_2$.gender and $\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$ is a continuous value to be inferred, which encodes the probability that the mentions $\mathtt{m}_1$ and $\mathtt{m}_2$ are the same person. If this rule was instantiated with the assignments $\mathtt{m}_1$=`John Smith`, $\mathtt{m}_2$=`J Smith` the resulting hinge-loss potential function would have the form:

$$\begin{aligned}&\max(0, \textsc{SimName}(\texttt{John Smith}, \texttt{J Smith})\\&+ \textsc{eqGender}(\texttt{John Smith}, \texttt{J Smith})\\&- \textsc{Same}(\texttt{John Smith}, \texttt{J Smith}) - 1)\ .\end{aligned}$$

We present the PSL model for entity resolution in richly-structured social networks in Chapter 3.

2.3 PSL for Recommender Systems

PSL is especially well-suited to collaborative filtering based recommendation graphs as it can accomodate the growing need for flexible recommender systems that can incorporate richly structured data sources to improve recommendations. In particular, we choose to use PSL in the recommender systems domain, for the following reasons: (1) the multitude of different information sources available (e.g., social connections, similarities between items, and similarities between users) require an expressive modeling language; (2) the need for flexibility and extensibility require a general problem-agnostic framework that will be able to fuse information from currently unspecified additional information types and similarity measures; (3) speed is of paramount importance which requires a scalable solution; (4) the framework should provide a mechanism that automatically learns to appropriately balance all available information sources.

To illustrate PSL in a movie recommendation context, the following rule encodes that users tend to rate movies of their preferred genres highly:

$$\textsc{LikesGenre}(\texttt{u}, \texttt{g}) \wedge \textsc{IsGenre}(\texttt{m}, \texttt{g}) \Rightarrow \textsc{Rating}(\texttt{u}, \texttt{m})\ ,$$

where $\textsc{LikesGenre}(\texttt{u}, \texttt{g})$ is a binary observed predicate, $\textsc{IsGenre}(\texttt{m}, \texttt{g})$ is a continuous observed predicate in the interval $[0, 1]$ capturing the affinity of the movie to the genre, and $\textsc{Rating}(\texttt{u}, \texttt{m})$ is a continuous variable to be inferred, which encodes the star rating as a number between 0 and 1, with higher values corresponding to higher star ratings. For example, we could instantiate $\texttt{u} = \texttt{Jim}$, $\texttt{g} = \texttt{classics}$ and $\texttt{m} = \texttt{Casablanca}$. This instantiation results in a hinge-loss potential function in the HL-MRF,

$$\begin{aligned}\max(&\textsc{LikesGenre}(\texttt{Jim}, \texttt{classics})\\ &+ \textsc{IsGenre}(\texttt{Casablanca}, \texttt{classics})\\ &- \textsc{Rating}(\texttt{Jim}, \texttt{Casablanca}) - 1, 0)\ .\end{aligned}$$

We present the PSL model for recommender systems in richly-structured social networks in Chapter 4.

2.3.1 PSL for Explanations

Most of the recommender systems that are able to provide state-of-the-art accuracy by exploiting the rich structure of the data and the multitude of different information sources, operate as black boxes, i.e., it is not possible to explain the reasoning behind the recommendation proposed to a user. As a result, providing recommendations using these frameworks is a very challenging task. PSL is a bright exception: the models are defined by a set of first-order logical rules. The process of generating explanations is as easy as implementing a parser that translates these first-order logical rules to natural language explanations. In what follows, we describe a simple example, where we can use PSL to generate explanations in a recommender systems setting.

To implement user-based collaborative filtering recommendations, the following rule is included in the PSL model:

$$\textsc{SimilarUsers}(u_1, u_2) \wedge \textsc{Likes}(u_1, i) \Rightarrow \ \textsc{Likes}(u_2, i)\ . \tag{2.5}$$

In addition to the user-based collaborative filtering rule above, the PSL model also includes item-based collaborative filtering rules with mean-centering priors, as well as rules for social-based recommendations using friendships, and content-based rules for using item attributes. The model's rules are specified as an abstract model and are used to define a probabilistic graphical model. Next, a process known as *grounding* is used to combine the model with data and instantiate a set of propositions. For example, given a dataset with user ratings and a social network, user similarities, item similarities, social relationships, and item attributes are generated as evidence. Together, these ground rules are used by PSL to define a probabilistic graphical model which ranks unseen user-item pairs.

Running inference in the model generates recommendations captured by the LIKES predicate. After inference is complete, we select the top k items for each user. Then, for each of the top $\textsc{Likes}(u, i)$, we produce associated groundings used during the inference process. For example, in a restaurant recommendation setting, suppose that $Mary$'s top recommended restaurant is $Crudo$ (i.e., the predicted value of the unobserved variable $\textsc{Likes}(Mary, Crudo)$ has the highest value among all other predicted values). While inferring the value of $\textsc{Likes}(Mary, Crudo)$, the model generated the following *ground* rules:

$$\begin{aligned}
\textsc{Friends}(Mary, Cindy) \wedge \textsc{Likes}(Cindy, Crudo) &\Rightarrow \textsc{Likes}(Mary, Crudo)\\
\textsc{Peruvian}(Limon, Crudo) \wedge \textsc{Likes}(Mary, Limon) &\Rightarrow \textsc{Likes}(Mary, Crudo)\\
\textsc{SimilarUsers}(Mary, John) \wedge \textsc{Likes}(John, Crudo) &\Rightarrow \textsc{Likes}(Mary, Crudo)\\
\textsc{SimilarItems}(Crudo, LaMar) \wedge \textsc{Likes}(Mary, LaMar) &\Rightarrow \textsc{Likes}(Mary, Crudo)
\end{aligned}$$

To provide explanations, we just need to implement a parser that transforms the above ground rules to natural language. The output of a parser for this particular example would be:

We recommend *Crudo* because:

- Your friend Cindy likes Crudo

- You like Peruvian restaurants, like Crudo
- Users with similar tastes as you like Crudo
- People who like LaMar, also like Crudo and you like LaMar

In what follows, we present our work on entity resolution, recommender systems, and explanations in richly-structured social networks using PSL.

Chapter 3

Entity Resolution in Richly Structured Social Networks

Entity resolution, the problem of identifying, matching, and merging references corresponding to the same entity within a dataset, is a widespread challenge in many domains. Here, we consider the problem of entity resolution in familial networks, which is an essential component in applications such as social network analysis [50], medical studies [72], family health tracking and electronic healthcare records [51], genealogy studies [34, 73] and areal administrative records, such as censuses [117]. Familial networks contain a rich set of relationships between entities with a well-defined structure, which differentiates this problem setting from general relational domains such as citation networks that contain a fairly restricted set of relationship types.

As a concrete example of entity resolution in familial networks, consider the healthcare records for several patients from a single family. Each patient supplies a family medical history, identifying the relationship to an individual and their symptoms. One patient may report that his 15-year old son suffers from high blood sugar, while another patient from the same family may report that her 16-

year old son suffers from type 1 diabetes. Assembling a complete medical history for this family requires determining whether the two patients have the same son and are married.

In this setting, a subset of family members independently provide a report of their familial relationships. This process yields several ego-centric views of *a portion* of a familial network, i.e., persons in the family together with their relationships. Our goal is to infer the entire familial network by identifying the people that are the same across these ego-centric views. For example, in Figure 3.1 we show two partial trees for one family. In the left tree, the patient "Jose Perez" reported his family tree and mentioned that his 15-year old son, also named "Jose Perez," has high blood sugar. In the right tree, the patient "Anabel Perez" reported her family tree and mentioned that her 16-year old son suffers from type 1 diabetes. In order to assemble a complete medical history for this family we need to infer which references refer to the same person. For our example trees we present in Figure 3.2 the resolved entities indicated by the same colors. For example, "Ana Maria Perez" from the left tree is the same person with "Anabel Perez" from the right tree. Our ultimate goal is to reconstruct the underlying family tree, which in our example is shown in Figure 3.3.

Typical approaches to performing entity resolution use attributes characterizing a reference (e.g., name, occupation, age) to compute different statistical signals that capture similarity, such as string matching for names and numeric distance for age [117]. However, relying only on attribute similarity to perform entity resolution in familial networks is problematic since these networks present unique challenges: attribute data is frequently incomplete, unreliable, and/or insufficient. Participants providing accounts of their family frequently forget to include family members or incorrectly report attributes, such as ages of family members. In

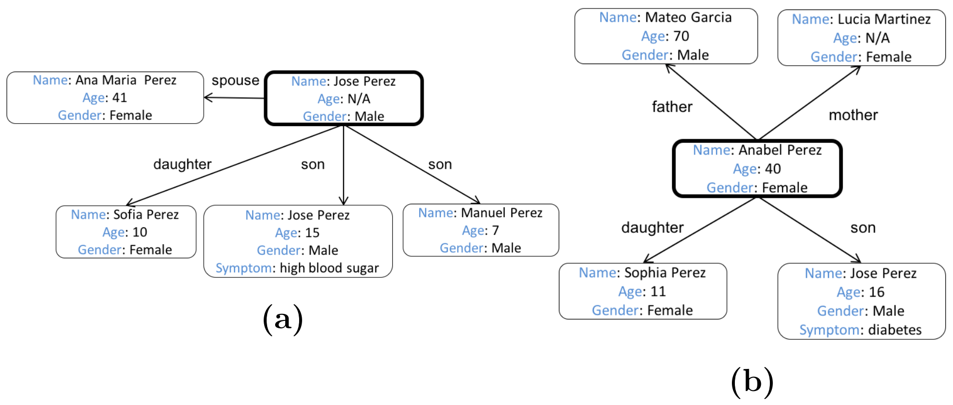


Figure 3.1: Two familial ego-centric trees for family F. Bold black borders indicate the root of the tree, i.e., the root of tree (a) is "Jose Perez" and the root of tree (b) is "Anabel Perez".

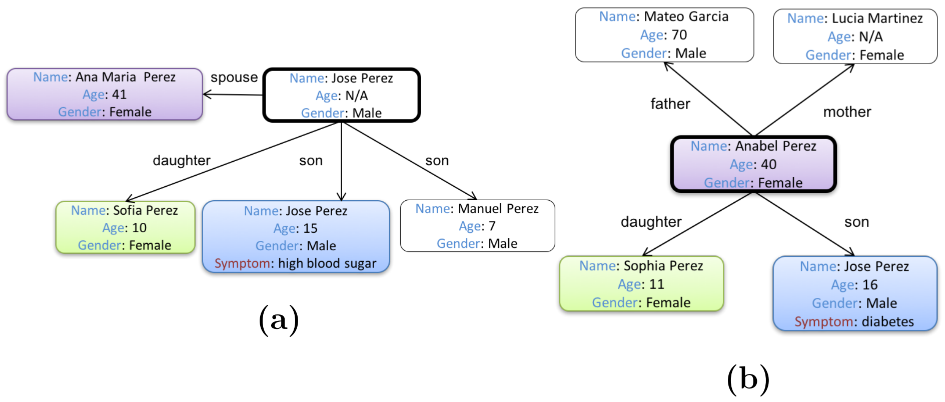


Figure 3.2: The two familial ego-centric trees for family F with resolved entities. Persons in same color represent same entities, e.g., "Ana Maria Perez" from tree (a) and "Anabel Perez" in tree (b) are co-referent. White means that the persons were not matched across the trees.

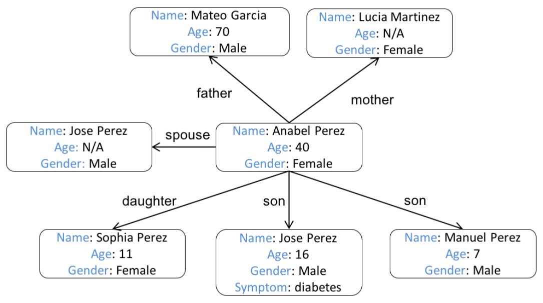


Figure 3.3: The aggregated family tree for family F.

other cases, they refer to the names using alternate forms. For example, consider the two ego-centric trees of Figure 3.1. The left tree contains one individual with the name "Ana Maria Perez" (age 41) and the right one an individual with the name "Anabel Perez" (age 40). In this case, using name and age similarity only, we may possibly determine that these persons are not co-referent, since their ages do not match and the names vary substantially. Furthermore, even when participants provide complete and accurate attribute information, this information may be insufficient for entity resolution in familial networks. In the same figure, the left tree contains two individuals of the name "Jose Perez", while the right tree contains only one individual "Jose Perez." Here, since we have a perfect match for names for these three individuals, we cannot reach a conclusion which of the two individuals of the left tree named after "Jose Perez" match the individual "Jose Perez" from the right tree. Additionally using age similarity would help in the decision, however, this information is missing for one person. In both cases, the performance of traditional approaches that rely on attribute similarities suffers in the setting of familial trees.

In this scenario, there is a clear benefit from exploiting *relational information* in the familial networks. Approaches incorporating relational similarities [9, 30, 58] frequently outperform those relying on attribute-based similarities alone. *Collective* approaches [104] where related resolution decisions are made jointly, rather than independently, showed improved entity resolution performance, albeit with the tradeoff of increased time complexity. General approaches to collective entity resolution have been proposed [94], but these are generally appropriate for one or two networks and do not handle many of the unique challenges of familial networks. Accordingly, much of the prior work in collective, relational entity resolution has incorporated only one, or a handful, of relational types, has limited entity resolution to one or two networks, or has been hampered by scalability concerns.

In contrast to previous approaches, we develop a scalable approach for collective relational entity resolution across multiple networks with multiple relationship types. Our approach is capable of using incomplete and unreliable data in concert with the rich multi-relational structure found in familial networks. Additionally, our model can also incorporate input from other algorithms when such information is available. We view the problem of entity resolution in familial networks as a collective classification problem and propose a model that can incorporate statistical signals, relational information, logical constraints, and predictions from other algorithms. Our model is able to collectively reason about entities across networks using these signals, resulting in improved accuracy. To build our model, we use probabilistic soft logic (PSL) which was described in detail in Chapter 2. We reiterate that PSL is especially well-suited to entity resolution tasks due to its ability to unify attributes, relations, constraints such as bijection and transitivity, and predictions from other models, into a single model.

The remainder of this Chapter is structured as follows. In Section 3.2 we formally define the problem of entity resolution for familial networks . In Section 3.1 we provide a survey of related approaches to relational entity resolution. In Section 3.3 we introduce a process of *normalization* that enables the use of relational features for entity resolution in familial networks. In Section 3.4 we develop a scalable entity resolution framework that effectively combines attributes, relational information, logical constraints, and predictions from other baseline algorithms. In Section 3.5 we perform extensive evaluation on two real-world datasets, from real patient data from the National Institutes of Health and Wikidata, demonstrating that our approach beats state-of-the-art methods while maintaining scalability as problems grow. More specifically: (i) we provide a detailed analysis of which features are most useful for relational entity resolution, providing advice for practitioners (Section 3.5.3) and (ii) we experimentally evaluate the state-of-the art approaches against our method, comparing performance based on similarity functions (Section 3.5.4), noise level (Section 3.5.5), and number of output pairs (Section 3.5.6). Finally, in Section 3.7 we highlight several potential applications for our method and promising extensions to our approach.

3.1 Related Work

There is a large body of prior work in the general area of entity resolution [22]. In this work we propose a collective approach that makes extensive use of relational data. In the following we review collective relational entity resolution approches which according to [96] can be either iterative or purely-collective.

For the iterative collective classification case, [9] propose a method based on greedy clustering over the relationships. This work considers only one single relation type, while we consider several types. [30] propose another iterative approach which combines contextual information with similarity metrics across attributes. In our approach, we perform both reference and relation enrichment, by applying inversion and imputation. Finally, [58] propose an approach for the reference disambiguation problem where the entities are already known. In our case, we do not know the entities beforehand.

In the case of purely collective approaches, [3] propose the Dedupalog framework for collective entity resolution with both soft and hard constraints. Users define a program with hard and soft rules and the approach produces a clustering such that no hard constraints are violated and the number of violated soft constraints is minimized. Dedupalog is well-suited for datasets having the need to satisfy several matching restrictions. In our case, we have several soft rules with a smaller number of constraints. In another approach, [25] design a conditional random field model incorporating relationship dependencies and propose an algorithm that jointly performs entity resolution over the model. In this work too, the number of relationship types considered is small. Finally, [104] propose a generalization of the Fellegi-Sunter model [36] that combines first-order logic and Markov random fields to perform collective classification. The proposed Markov Logic Networks (MLNs) operate on undirected graphical models using a first-order logic as their template language, similar to PSL. However, the predicates take only boolean values, while in PSL the predicates take soft truth values in the range $[0, 1]$. Soft truth values are more appropriate in the entity resolution problem setting for two reasons: first, they can better capture notion of similarity (such as name similarity) and second, the predictions can be interpreted as probabilities (in the range $[0, 1]$) which is convenient when applying the matching restrictions algorithm (as we will see this algorithm requires as input a ranked list). Finally, extensive experiments from the related work [5, 4] have shown that HL-MRFs can achieve improved performance in much less time compared to MLNs. As HL-MRFs are faster and their output is directly usable from a matching restriction approach that is needed in our scenario, we do not compare our approach to MLNs.

Overall, the purely collective approaches come with a high computational cost for performing probabilistic inference. As a result, they cannot scale to large datasets unless we use techniques that make the EM algorithm scalable [96]. Our approach uses PSL which as we will show, ensures scalable and exact inference by solving a convex optimization problem in parallel. Speed and scalability is of paramount importance in entity resolution and in particular when we run the prediction task collectively using transitivity and bijection rules.

Regarding the problem of entity resolution in familial networks, we recently proposed a first approach [66]. The problem setting is the same as in the current work, but the approach is non-collective using well-studied classifiers enhanced with features capturing relational similarity. In this work we propose a more sophisticated collective approach to the familial entity resolution problem.

Additionally, there are some works from the ontology alignment and knowledge graph identification domains that are close to our approach. [106] propose a probabilistic approach for ontology alignment. The tool accepts as input two ontologies and distinguishes the same relations, classes, and instances. As a result, the approach does not take into account transitivity and bijection constraints, which are key features in the familial networks in order both to provide a valid solution and to improve performance. In another approach, [94] use PSL to design a general mechanism for entity resolution in knowledge graphs, a setting with a similarly rich relational structure. Their work considers entity resolution within and between graphs and provides general templates for using attributes and relationships in non-collective and collective rules. However, as we will explain, familial networks have unique characteristics and constraints that differ substantially from knowledge graphs, and in particular they do not explicitly consider the problem of entity resolution across several subgraphs.

3.2 Problem Setting

We consider the problem setting where we are provided a set of ego-centric *reports* of a familial network. Each report is given from the perspective of a *participant* and consists of two types of information: family members and relationships. The participant identifies a collection of family members and provides personal information such as name, age, and gender for each person (including herself). The participant also reports their relationships to each family member, which we categorize as first-degree relationships (mother, father, sister, daughter, etc.) or second-degree relationships (grandfather, aunt, nephew, etc.). Our task is to align family members *across* reports in order to reconstruct a complete family tree. We refer to this task as *entity resolution in familial networks* and formally define the problem as follows:

Problem Definition. We assume there is an underlying family $\mathbf{F} = \langle \mathbf{A}, \mathbf{Q} \rangle$ which contains (unobserved) actors $\mathbf{A}$ and (unobserved) relationships $\mathbf{Q}$ amongst them. We define $\mathbf{A} = \{A_1, A_2, \ldots, A_m\}$ and $\mathbf{Q} = \{r_{t_a}(A_i, A_j), r_{t_a}(A_i, A_k),$ $r_{t_b}(A_k, A_l) \ldots r_{t_z}(A_k, A_m)\}$. Here $t_a, t_b, t_z \in \tau$ are different relationship types between individuals (e.g. son, daughter, father, aunt). Our goal is to recover $\mathbf{F}$ from a set of k participant reports, $\mathcal{R}$.

We define these reports as $\mathcal{R} = \{\mathbf{R}^1, \mathbf{R}^2, \ldots, \mathbf{R}^k\}$, where superscripts will henceforth denote the participant associated with the reported data. Each report, $\mathbf{R}^i = \langle p^i, \mathbf{M}^i, \mathbf{Q}^i \rangle$ is defined by the reporting participant, p^i, the set of family members mentioned in the report, $\mathbf{M}^i$, and the participant's relationships to each mention, $\mathbf{Q}^i$. We denote the mentions, $\mathbf{M}^i = \{p^i, m_1^i, \ldots, m_{l_i}^i\}$, where each of the l_i mentions includes (possibly erroneous) personal attributes and corresponds to a distinct, unknown actor in the family tree (note that the participant is a mention as well). We denote the relationships $\mathbf{Q}^i = \{r_{t_a}(p^i, m_x^i), \ldots, r_{t_b}(p^i, m_y^i)\}$, where $t_a, t_b \in \tau$ denote the types of relation, and m_x^i and m_y^i denote the mentioned family members with whom the participant p^i shares the relation types t_a and t_b respectively. A participant p^i can have an arbitrary number of relations of the same type (e.g. two daughters, three brothers, zero sisters). Our goal is to examine all the mentions (participants and non-participants) and perform a matching across reports to create sets of mentions that correspond to the same actor. The ultimate task is to construct the unified family $\mathbf{F}$ from the collection of matches.

Entity Resolution Task. A prevalent approach to entity resolution is to cast the problem as a *binary, supervised classification* task and use machine learning to label each pair of entities as matching or non-matching. In our specific problem setting, this corresponds to introducing a variable $\textsc{Same}(x, y)$ for each pair of entities x, y occurring in distinct participant reports. Formally, we define the variable $\textsc{Same}(m_x^i, m_y^j)$ for each pair of mentions in distinct reports, i.e., $\forall_{i \neq j} \forall_{m_x^i \in \mathbf{M}^i} \forall_{m_y^j \in \mathbf{M}^j}$. Our goal is to determine for each pair of mentions if they refer to the same actor.

In order to achieve this goal, we must learn a decision function that, given two mentions, determines if they are the same. Although the general problem of entity resolution is well-studied, we observe that a significant opportunity in this specific problem setting is the ability to leverage the familial relationships in each report to perform relational entity resolution. Unfortunately, the available reports, $\mathcal{R}$ are each provided from the perspective of a unique participant. This poses a problem since we require relational information for each *mention* in a report, not just for the reporting participant. As a concrete example, if one participant report mentions a son and another report mentions a brother, comparing these mentions from the perspectives of a parent and sibling, respectively, is complex. Instead, if relational features of the mention could be reinterpreted from a common perspective, the two mentions could be compared directly. We refer to the problem of recovering mention-specific relational features from participant reports as *relational normalization*, and present our algorithm in the next section.

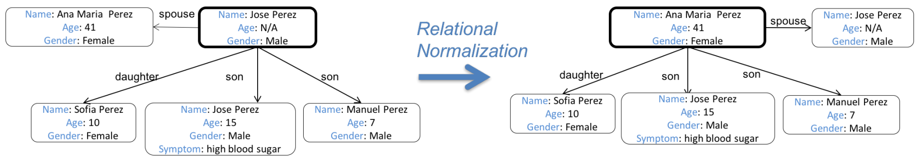


Figure 3.4: Left: the tree corresponding to a participant report provided by "Jose Perez". Right: the derived normalized tree from the perspective of "Ana Maria Perez".

3.3 Preprocessing via Relational Normalization

Since the relational information available in participant reports is unsuitable for entity resolution, we undertake the process of normalization to generate mention-specific relational information. To do so, we translate the relational information in a report $\mathbf{R}^i$ into an *ego-centric tree*, $\mathbf{T}^i_j$, for each mention m^i_j. Here the notation $\mathbf{T}^i_j$ indicates that the tree is constructed from the perspective of the j^{th} mention of the i^{th} report. We define $\mathbf{T}^i_j = \langle m^i_j, \mathbf{Q}^i_j \rangle$, where $\mathbf{Q}^i_j$ is a set of relationships. Constructing these trees consists of two steps: relationship inversion and relationship imputation.

Relationship Inversion: The first step in populating the ego-centric tree for m^i_j is to invert the relationships in $\mathbf{R}^i$ so that the first argument (subject) is m^i_j. More formally, for each relation type $t_j \in \tau$ such that $r_{t_j}(p^i, m^i_j)$, we introduce an inverse relationship $r_{t'_i}(m^i_j, p^i)$. In order to do so, we introduce a function $inverse(\tau, m^i_j, p^i) \rightarrow \tau$ which returns the appropriate inverse relationship for each relation type. Note that the inverse of a relation depends both on the mention and the participant, since in some cases mention attributes (e.g. father to daughter) or participant attributes (e.g. daughter to father) are used to determine the inverse.

Relationship Imputation: The next step in populating $\mathbf{T}^i_j$ is to impute relationships for m^i_j mediated through p^i. We define a function $impute(r_x(p^i, m^i_j),$

$r_y(p^i, m_k^i)) \rightarrow r_k(m_j^i, m_k^i)$. For example, given the relations $\{r_{father}(p^i, m_j^i),$ $r_{mother}(p^i, m_k^i)\}$ in $\mathbf{T}^i(p^i)$, then we impute the relations $r_{spouse}(m_j^i, m_k^i)$ in $\mathbf{T}_j^i$ as well as $r_{spouse}(m_k^i, m_j^i)$ in $\mathbf{T}_k^i$.

Figure 3.4 shows an example of the normalization process. We begin with the left tree centered on "Jose Perez" and after applying inversion and imputation we produce the right tree centered on "Ana Maria Perez". Following the same process we will produce three more trees centered on "Sofia Perez", "Manuel Perez", and "Jose Perez" (with age 15). Finally, we note that since initially we have relational information for just one person in each tree, then it will be impossible to use any relational information if we do not perform the normalization step.

3.4 Entity Resolution Model for Familial Networks

After recovering the mention-specific relational features from participant reports, our next step is to develop a model that is capable of collectively inferring mention equivalence using the attributes, diverse relational evidence, and logical constraints. We cast this entity resolution task as inference in a graphical model, and use the PSL framework, introduced in Chapter 2, to define a probability distribution over co-referent mentions. In what follows, we describe in detail our entity resolution model.

3.4.1 PSL Model for Entity Resolution

We define our model using rules similar to those in (2.4), allowing us to infer the Same relation between mentions. Each rule encodes graph-structured dependency relationships drawn from the familial network (e.g., if two mentions are co-referent then their mothers should also be co-referent) or conventional attribute-based similarities (e.g., if two mentions have similar first and last name then they are possibly co-referent). We present a set of representative rules for our model, but note that additional features (e.g., locational similarity, conditions from a medical history, or new relationships) can easily be incorporated into our model with additional rules.

Scoping the Rules

Familial datasets may consist of several mentions and reports. However, our goal is to match mentions from the same family that occur in distinct reports. Obviously, mentions that belong to different families could not be co-referent, so we should only compare mentions that belong to the same family. In order to restrict rules to such mentions, it is necessary to perform scoping on our logical rules. We define two predicates: BELONGSTOFAMILY (abbreviated $\mathrm{BF}(\mathtt{m}_x, \mathtt{F})$) and FROMREPORT (abbreviated $\mathrm{FR}(\mathtt{m}_i, \mathtt{R}_i)$). BF allows us to identify mentions from a particular family's reports, i.e., $\{m^i_x \in \mathbf{M}^i \text{ s.t. } \mathbf{R}^i \in \mathbf{F}\}$, while FR filters individuals from a particular participant report, i.e., $\{m^i_x \in \mathbf{M}^i\}$. In our matching, we wish to compare mentions from the same family but appearing in different participant reports. To this end, we introduce the following clause to our rules:

$$\mathrm{BF}(\mathtt{m}_1, \mathtt{F}) \wedge \mathrm{BF}(\mathtt{m}_2, \mathtt{F}) \wedge \mathrm{FR}(\mathtt{m}_1, \mathtt{R}_i) \wedge \mathrm{FR}(\mathtt{m}_2, \mathtt{R}_j) \wedge \mathtt{R}_i \neq \mathtt{R}_j$$

In the rest of our discussion below, we assume that this scoping clause is included but we omit replicating it in favor of brevity.

Name Similarity Rules

One of the most important mention attributes are mention names. Much of the prior research on entity resolution has focused on engineering similarity functions that can accurately capture patterns in name similarity. Two such popular similarity functions are the Levenshtein [81] and Jaro-Winkler [117]. The first is known to work well for common typographical errors, while the second is specifically designed to work well with names. We leverage mention names by introducing rules that capture the intuition that when two mentions have similar names then they are more likely to represent the same person. For example, when using the Jaro-Winkler function to compute the name similarities, we use the following rule:

$$\textsc{SimName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \ .$$

This rule reinforces an important aspect of PSL: atoms take truth values in the $[0, 1]$ interval, capturing the degree of certainty of the inference. In the above rule, high name similarity results in greater confidence that two mentions are the same. However, we also wish to penalize pairs of mentions with dissimilar names from matching, for which we introduce the rule using the logical not ($\neg$):

$$\neg\textsc{SimName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \ .$$

The above rules use a generic SimName similarity function. In fact, our model introduces several name similarities for first, last, and middle names as follows:

$$\begin{aligned}
&\textsc{SimFirstName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\textsc{SimMaidenName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\textsc{SimLastName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\neg\textsc{SimFirstName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\neg\textsc{SimMaidenName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\neg\textsc{SimLastName}_{JW}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \ .
\end{aligned}$$

In the above rules we use the Jaro-Winkler similarity function. In our basic model, we additionally introduce the same rules that compute similarities using the Levenshtein distance as well. Finally, we experiment with adding other popular similarity functions, i.e., Monge Elkan, Soundex, Jaro [117], and their combinations and discuss how different string similarity metrics affect performance in the experimental section.

Personal Information Similarity Rules

In addition to the name attributes of a mention, there are often additional attributes provided in reports that are useful for matching. For example, age is an important feature for entity resolution in family trees since it can help us discern between individuals having the same (or very similar) name but belonging to different generations. We introduce the following rules for age:

$$\begin{aligned} \textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow &\quad \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \\ \neg\textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow &\quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \ . \end{aligned} \tag{3.1}$$

The predicate $\textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2)$ takes values in the interval $[0, 1]$ and is computed as the ratio of the smallest over the largest value, i.e.:

$$\textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2) = \frac{\min\{\mathtt{m}_1.\text{age}, \mathtt{m}_2.\text{age}\}}{\max\{\mathtt{m}_1.\text{age}, \mathtt{m}_2.\text{age}\}} \ .$$

The above rules will work well when the age is known. However, in the familial networks setting that we are operating on it is often the case where personal information and usually the age is not known. For these cases, we can specifically ask from our model to take into account only cases where the personal information is known and ignore it when this is not available. To this end, we replace the rules in (3.1) with the following:

$$\textsc{KnownAge}(\mathtt{m}_1) \wedge \textsc{KnownAge}(\mathtt{m}_2) \wedge \textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$$

$$\textsc{KnownAge}(\mathtt{m}_1) \wedge \textsc{KnownAge}(\mathtt{m}_2) \wedge \neg\textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$$

In other words, using the scoping predicates $\textsc{KnownAge}(\mathtt{m}_1)$ and $\textsc{KnownAge}(\mathtt{m}_2)$ we can handle missing values in the PSL model, which is an important characteristic.

While attributes like age have influence in matching, other attributes cannot be reliably considered as evidence to matching but they are far more important in disallowing matches between the mentions. For example, simply having the same gender is not a good indicator that two mentions are co-referent. However, having a different gender is a strong evidence that two mentions are not co-referent. To this end, we also introduce rules that prevent mentions from matching when certain attributes differ:

$$\neg\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$$

$$\neg\textsc{eqLiving}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\ .$$

We note that the predicates $\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2)$ and $\textsc{eqLiving}(\mathtt{m}_1, \mathtt{m}_2)$ are binary-valued atoms.

Relational Similarity Rules

Although attribute similarities provide useful features for entity resolution, in problem settings such as familial networks, relational features are necessary for matching. Relational features can be introduced in a multitude of ways. One possibility is to incorporate purely structural features, such as the number and types of relationships for each mention. For example, given a mention with two sisters and three sons and a mention with three sisters and three sons, we could design a similarity function for these relations. However, practically this approach lacks discriminative power because there are often mentions that have similar relational structures (e.g., having a mother) that refer to different entities. To overcome the lack of discriminative power, we augment structural similarity with a matching process. For relationship types that are surjective, such as mother or father, the matching process is straightforward. We introduce a rule:

$$\textsc{SimMother}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \ ,$$

SimMother may have many possible definitions, ranging from an exact string match to a recursive similarity computation. In this subsection, we define SimMother as equal to the maximum of the Levenshtein and Jaro-Winkler similarities of the first names, and discuss a more sophisticated treatment in the next subsection. However, when a relationship type is multi-valued, such as sister or son, a more sophisticated matching of the target individuals is required. Given a relation type t and possibly co-referent mentions m_1^i, m_2^j, we find all entities $M_x = \{m_x^i : r_t(m_1^i, m_x^i) \in \mathbf{Q}_1^i\}$ and $M_y = \{m_y^j : r_t(m_2^j, m_y^j) \in \mathbf{Q}_2^j\}$. Now we must define a similarity for the sets M_x and M_y, which in turn will provide a similarity for m_1^i and m_2^j. The similarity function we use is:

$$\textsc{Sim}_t(\mathtt{m}_1, \mathtt{m}_2) = \frac{1}{|M_x|} \sum_{\mathtt{m}_x \in M_x} \max_{\mathtt{m}_y \in M_y} \textsc{SimName}(\mathtt{m}_x, \mathtt{m}_y) \ .$$

For each $\mathtt{m}_x$ (an individual with relation t to $\mathtt{m}_1$), this computation greedily chooses the best $\mathtt{m}_y$ (an individual with relation t to $\mathtt{m}_2$). In our computation, we assume (without loss of generality, assuming symmetry of the similarity function) that $|M_x| < |M_y|$. While many possible similarity functions can be used for SimName, we take the maximum of the Levenshtein and Jaro-Winkler similarities of the first names in our model.

Our main goal in introducing these relational similarities is to incorporate relational evidence that is compatible with simpler, baseline models. While more sophisticated than simple structural matches, these relational similarities are much less powerful than the transitive relational similarities supported by PSL, which we introduce in the next section.

Transitive Relational (Similarity) Rules

The rules that we have investigated so far can capture personal and relational similarities but they cannot identify similar persons in a collective way. To make this point clear, consider the following observation: when we have high confidence that two persons are the same, we also have a stronger evidence that their associated relatives, e.g., father, are also the same. We encode this intuition with rules of the following type:

$$\textsc{Rel}(\texttt{Father}, \texttt{m}_1, \texttt{m}_a) \wedge \textsc{Rel}(\texttt{Father}, \texttt{m}_2, \texttt{m}_b) \wedge \textsc{Same}(\texttt{m}_1, \texttt{m}_2) \Rightarrow \textsc{Same}(\texttt{m}_a, \texttt{m}_b) \ .$$

The rule above works well with surjective relationships, since each person can have only one (biological) father. When the cardinality is larger, e.g., sister, our model must avoid inferring that all sisters of two respective mentions are the same. In these cases we use additional evidence, i.e., name similarity, to select the appropriate sisters to match, as follows:

$$\begin{aligned} &\textsc{Rel}(\texttt{Sister}, \texttt{m}_1, \texttt{m}_a) \wedge \ \textsc{Rel}(\texttt{Sister}, \texttt{m}_2, \texttt{m}_b) \wedge \textsc{Same}(\texttt{m}_1, \texttt{m}_2) \wedge \textsc{SimName}(\texttt{m}_a, \texttt{m}_b) \\ &\Rightarrow \textsc{Same}(\texttt{m}_a, \texttt{m}_b) \ . \end{aligned}$$

Just as in the previous section, we compute SimName by using the maximum of the Jaro-Winkler and Levenshtein similarities for first names. For relationships that are one-to-one we can also introduce negative rules which express the intuition that two different persons should be connected to different persons given a specific relationship. For example, for a relationship such as spouse, we can use a rule such as:

$$\textsc{Rel}(\texttt{Spouse}, \texttt{m}_1, \texttt{m}_a) \land \textsc{Rel}(\texttt{Spouse}, \texttt{m}_2, \texttt{m}_b) \land \neg\textsc{Same}(\texttt{m}_1, \texttt{m}_2) \Rightarrow \neg\textsc{Same}(\texttt{m}_a, \texttt{m}_b) \ .$$

However, introducing similar rules for one-to-many relationships is inadvisable. To understand why, consider the case where two siblings do not match, yet they have the same mother, whose match confidence should remain unaffected.

Bijection and Transitivity Rules

Our entity resolution task has several natural constraints across reports. The first is bijection, namely that a mention m_x^i can match at most one mention, m_y^j from another report. According to the bijection rule, if mention m_a from report R_1 is matched to mention m_b from report R_2 then m_1 cannot be matched to any other mention from report R_2:

$$\textrm{FR}(\texttt{m}_a, \texttt{R}_1) \land \textrm{FR}(\texttt{m}_b, \texttt{R}_2) \land \textrm{FR}(\texttt{m}_c, \texttt{R}_2) \land \textsc{Same}(\texttt{m}_a, \texttt{m}_b) \Rightarrow \neg\textsc{Same}(\texttt{m}_a, \texttt{m}_c) \ .$$

Note that this bijection is *soft*, and does not guarantee a single, exclusive match for $\texttt{m}_a$, but rather attenuates the confidence in each possible match modulated by the evidence for the respective matches. A second natural constraint is transitivity, which requires that if m_a^i and m_y^j are the same, and mentions m_y^j and m_c^k are the same, then mentions m_a^i and m_c^k should also be the same. We capture this constraint as follows:

$$\textrm{FR}(\texttt{m}_a, \texttt{R}_1) \land \textrm{FR}(\texttt{m}_b, \texttt{R}_2) \land \textrm{FR}(\texttt{m}_c, \texttt{R}_3) \land \textsc{Same}(\texttt{m}_a, \texttt{m}_b) \land \textsc{Same}(\texttt{m}_b, \texttt{m}_c) \Rightarrow$$
$$\textsc{Same}(\texttt{m}_a, \texttt{m}_c) \ .$$

Prior Rule

Entity resolution is typically an imbalanced classification problem, meaning that most of the mention pairs are not co-referent. We can model our general belief that two mentions are likely not co-referent, using the prior rule:

$$\neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \ .$$

Rules to Leverage Existing Classification Algorithms

Every state-of-the-art classification algorithm has strengths and weaknesses which may depend on data-specific factors such as the degree of noise in the dataset. In this work, our goal is to provide a flexible framework that can be used to generate accurate entity resolution decisions for any data setting. To this end, we can also incorporate the predictions from different methods into our unified model. Using PSL as a meta-model has been successfully applied in recent work [92]. In our specific scenario of entity resolution, for example, the predictions from three popular classifiers (logistic regression (LR), support vector machines (SVMs), and logistic model trees (LMTs)) can be incorporated in the model via the following rules:

$$\begin{aligned}
&\textsc{Same}\text{LR}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\neg\textsc{Same}\text{LR}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\textsc{Same}\text{SVM}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\neg\textsc{Same}\text{SVM}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\textsc{Same}\text{LMT}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\\
&\neg\textsc{Same}\text{LMT}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \ .
\end{aligned}$$

Note that for each classifier we introduce two rules: 1) the direct rule which states that if a given classifier predicts that the mentions are co-referent then it is likely that they are indeed co-referent and 2) the reverse rule which states that if the classifier predicts that the mentions are not co-referent then it is likely that they are not co-referent. Additionally, using PSL we can introduce more complex rules that combine the predictions from the other algorithms. For example, if all three classifiers agree that a pair of mentions are co-referent then this is strong evidence that this pair of mentions are indeed co-referent. Similarly, if all three classifiers agree that the pair of mentions are not co-referent then this is strong evidence that they are not co-referent. We can model these ideas through the following rules:

$$\textsc{SameLR}(\mathtt{m}_1, \mathtt{m}_2) \wedge \textsc{SameSVMs}(\mathtt{m}_1, \mathtt{m}_2) \wedge \textsc{SameLMTs}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow$$
$$\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$$
$$\neg\textsc{SameLR}(\mathtt{m}_1, \mathtt{m}_2) \wedge \neg\textsc{SameSVMs}(\mathtt{m}_1, \mathtt{m}_2) \wedge \neg\textsc{SameLMTs}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow$$
$$\neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)\ .$$

Flexible Modeling

We reiterate that in this section we have only provided *representative* rules used in our PSL model for entity resolution. A full compendium of all rules used in our experiments is presented in Appendix 6.1. Moreover, a key feature of our model is the flexibility and the ease with which it can be extended to incorporate new features. For example, adding additional attributes, such as profession or location, is easy to accomplish following the patterns of Subsection 3.4.1. Incorporating additional relationships, such as cousins or friends is simply accomplished using the patterns in Subsections 3.4.1 and 3.4.1. Our goal has been to present a variety of patterns that are adaptable across different datasets and use cases.

3.4.2 Learning the PSL Model

Given the above model, we use observational evidence (similarity functions and relationships) and variables (potential matches) to define a set of ground rules. Each ground rule is translated into a hinge-loss potential function of the form (2.2) defining a Markov random field, as in (2.1) (Section 2.1). Then, given the observed values $\mathbf{X}$, our goal is to find the most probable assignment to the unobserved variables $\mathbf{Y}$ by performing joint inference over interdependent variables.

As we discussed in 2, each of the first-order rules introduced in the previous section is associated with a non-negative weight w_j in Equation 2.1. To learn the weights, we follow the process described in Section 2.1. Finally, since the output of the PSL model is a soft-truth value for each pair of mentions, to evaluate our matching we choose a threshold to make a binary match decision. We choose the optimal threshold on a held-out development set to maximize the F-measure score, and use this threshold when classifying data in the test set.

3.4.3 Satisfying Matching Restrictions

One of the key constraints in our model is a bijection constraint that requires that each mention can match at most one mention in another report. Since the bijection rule in PSL is *soft*, in some cases, we may get multiple matching mentions for a report. To enforce this restriction, we introduce a greedy 1:1 matching step. We use a simple algorithm that first sorts output matchings by the truth value of the $\textsc{Same}(m_x^i, m_y^j)$ predicate. Next, we iterate over this sorted list of mention pairs, choosing the highest ranked pair for an entity, (m_x^i, m_y^j). We then remove all other potential pairs, $\forall_{m_a^i, a \neq x}(m_a^i, m_y^j)$ and $\forall_{m_b^j, b \neq y}(m_x^i, m_b^j)$, from the matching. The full description can be found in Algorithm 1. This approach is simple to implement, efficient, and can potentially improve model performance, as we will

```
input : A set of mention pairs classified as MATCH together with the
        likelihood of the MATCH
output: A set of mention pairs satisfying the one-to-one matching restrictions
1 repeat
2     pick unmarked pair $\{a_i, a_j\}$ with highest MATCH likelihood;
3     output pair $\{a_i, a_j\}$ as MATCH;
4     mark pair $\{a_i, a_j\}$;
5     output all other pairs containing either $a_i$ or $a_j$ as NO MATCH;
6     mark all other pairs containing either $a_i$ or $a_j$;
7 until all pairs are marked;
```

Algorithm 1: Satisfying matching restrictions.

discuss in our experiments.

3.5 Experimental Validation

3.5.1 Datasets and Baselines

For our experimental evaluation we use two datasets, a clinical dataset provided by the National Institutes of Health (NIH) [44] and a public dataset crawled from the structured knowledge repository, Wikidata.[1] We provide summary statistics for both datasets in Table 3.1.

The NIH dataset was collected by interviewing 497 patients from 162 families and recording family medical histories. For each family, 3 or 4 patients were interviewed, and each interview yielded a corresponding ego-centric view of the family tree. Patients provided first and second degree relations, such as parents and grandparents. In total, the classification task requires determining co-reference for about $300,000$ pairs of mentions. The provided dataset was manually annotated by at least two coders, with differences reconciled by blind consensus. Only 1.6% of the potential pairs are co-referent, resulting in a severely imbalanced

[1]Code and data available at: `https://github.com/pkouki/icdm2017`.

Dataset	**NIH**	**Wikidata**
No. of families	162	419
No. of family trees	497	1,844
No. of mentions	12,111	8,553
No. of 1^{st} degree relationships	46,983	49,620
No. of 2^{nd} degree relationships	67,540	0
No. of pairs for comparison	300,547	174,601
% of co-referent pairs	1.6%	8.69%

Table 3.1: Datasets description

classification, which is common in entity resolution scenarios.

The Wikidata dataset was generated by crawling part of the Wikidata[2] knowledge base. More specifically, we generated a seed set of 419 well-known politicians or celebrities, e.g., "Barack Obama".[3] For each person in the seed set, we retrieved attributes from Wikidata including their full name (and common variants), age, gender, and living status. Wikidata provides familial data only for first-degree relationships, i.e., siblings, parents, children, and spouses. Using the available relationships, we also crawled Wikidata to acquire attributes and relationships for each listed relative. This process resulted in 419 families. For each family, we have a different number of family trees (ranging from 2 to 18) with $1,844$ family trees in total, and $175,000$ pairs of potentially co-referent mentions (8.7% of which are co-referent). Mentions in Wikidata are associated with unique identifiers, which we use as ground truth. In the next section, we describe how we add noise to this dataset to evaluate our method.

We compare our approach to state-of-the-art classifiers that are capable of providing the probability that a given pair of mentions is co-referent. Probability values are essential since they are the input to the greedy 1-1 matching restrictions algorithm. We compare our approach to the following classifiers: logistic regres-

[2]`https://www.wikidata.org/`
[3]`https://www.wikidata.org/wiki/Q76`

sion (LR), logistic model trees (LMTs), and support vector machines (SVMs). For LR we use a multinomial logistic regression model with a ridge estimator [18] using the implementation and improvements of Weka [38] with the default settings. For LMTs we use Weka's implementation [71] with the default settings. For SVMs we use Weka's LibSVM library [19], along with the functionality to estimate probabilities. To select the best SVM model we follow the process described by Hsu et al. [55]: we first find the kernel that performs best, which in our case was the radial basis function (RBF). We then perform a grid search to find the best values for C and γ parameters. The starting point for the grid search was the default values given by Weka, i.e., C=1 and γ=1/(number of attributes), and we continue the search with exponentially increasing/decreasing sequences of C and γ. However, unlike our model, none of these off-the-shelf classifiers can incorporate transitivity or bijection.

Finally, we note that we also experimented with off-the-shelf collective classifiers provided by Weka.[4] More specifically, we experimented with Chopper, TwoStageCollective, and YATSI [32]. Among those, YATSI performed the best. YATSI (Yet Another Two-Stage Classifier) is collective in the sense that the predicted label of a test instance will be influenced by the labels of related test instances. We experimented with different configurations of YATSI, such as varying the classification method used, varying the nearest neighbor approach, varying the number of the neighbors to consider, and varying the weighting factor. In our experiments, YATSI was not able to outperform the strongest baseline (which as we will show is LMTs), so, for clarity, we omit these results from our discussion below.

[4]Available at: `https://github.com/fracpete/collective-classification-weka-package`

3.5.2 Experimental Setup

We evaluate our entity resolution approach using the metrics of *precision*, *recall*, and *F-measure* for the positive (co-referent) class which are typical for entity resolution problems [22]. For all reported results we use 5-fold cross-validation, with distinct training, development, and test sets. Folds are generated by randomly assigning each of the 162 (NIH) and 419 (Wikidata) families to one of five partitions, yielding folds that contain the participant reports for approximately 32 (NIH) and 83 (Wikidata) familial networks.

The NIH dataset is collected in a real-world setting where information is naturally incomplete and erroneous, and attributes alone are insufficient to resolve the entities. However, the Wikidata resource is heavily curated and assumed to contain no noise. To simulate the noisy conditions of real-world datasets, we introduced additive Gaussian noise to the similarity scores. Noise was added to each similarity metric described in the previous section (e.g., first name Jaro-Winkler, age ratio). For the basic experiments presented in the next Section 3.5.3, results are reported for noise terms drawn from a $N(0, 0.16)$ distribution. In our full experiments (presented in Section 3.5.5) we consider varying levels of noise, finding higher noise correlated with lower performance.

In Section 3.4.1 we discussed that PSL can incorporate multiple similarities computed by different string similarity functions. For the basic experiments presented in the next Section 3.5.3, results are reported using the Levenshtein and Jaro-Winkler string similarity functions for PSL and the baselines. In our full experiments (presented in Section 3.5.5) we consider adding other string similarity functions.

In each experiment, for PSL, we use three folds for training the model weights, one fold for choosing a binary classification threshold, and one fold for evaluating model performance. To train the weights, we use PSL's default values for the two parameters: number of iterations (equal to 25) and step size (equal to 1). For SVMs, we use three folds for training the SVMs with the different values of C and γ, one fold for choosing the best C and γ combination, and one fold for evaluating model performance. For LR and LMTs we use three folds for training the models with the default parameter settings and one fold for evaluating the models. We train, validate, and evaluate using the same splits for all models. We report the average precision, recall, and F-measure together with the standard deviation across folds.

3.5.3 Performance of PSL and baselines

For our PSL model, we start with a simple feature set using only name similarities (see Subsection 3.4.1), transitivity and bijection soft constraints (see Subsection 3.4.1), and a prior (see Subsection 3.4.1). We progressively enhance the model by adding attribute similarities computed based on personal information, relational similarities, and transitive relationships. For each experiment we additionally report results when including predictions from the other baselines (described in Subsection 4.3.1). Finally, since our dataset poses the constraint that each person from one report can be matched with at most one person from another report, we consider only solutions that satisfy this constraint. To ensure that the output is a valid solution, we apply the greedy 1:1 matching restriction algorithm (see Subsection 3.4.3) on the output of the each model.

For each of the experiments we also ran baseline models that use the same information as the PSL models in the form of features. Unlike our models implemented within PSL, the models from the baseline classifiers do not support collective reasoning, i.e., applying transitivity and bijection is not possible in the baseline models. However, we are able to apply the greedy 1:1 matching restriction algorithm on the output of each of the classifiers for each of the experiments to ensure that we provide a valid solution. More specifically, we ran the following experiments:

Names: We ran two PSL models that use as features the first, middle, and last name similarities based on Levenshtein and Jaro-Winkler functions to compute string similarities. In the first model, PSL(N), we use rules only on name similarities, as discussed in Section 3.4.1. In the second model, PSL($N + pred$) we enhance PSL(N) by adding rules that incorporate the predictions from the other baseline models as described in Subsection 4.3.1. We also ran LR, LMTs, and SVMs models that use as features the first, middle, and last name similarities based on Levenshtein and Jaro-Winkler measures.

Names + Personal Info: We enhance **Names** by adding rules about personal information similarities, as discussed in Section 3.4.1. Again, for PSL we ran two models: PSL(P) which does not include predictions from the baselines and PSL($P + pred$) that does include predictions from the baselines. For the baselines, we add corresponding features for age similarity, gender, and living status. This is the most complex feature set that can be supported without using the normalization procedure we introduced in Section 3.3.

Names + Personal + Relational Info (1st degree): For this model and all subsequent models we perform normalization to enable the use of relational evidence for entity resolution. We present the performance of four PSL models. In the first model, PSL(R_1), we enhance PSL(P) by adding first degree relational similarity rules, as discussed in Section 3.4.1. First degree relationships are: mother, father, daughter, son, brother, sister, spouse. In the second model, PSL($R_1 + pred$) we extend PSL(R_1) by adding the predictions from the baselines. In the third model, PSL($R_1 TR_1$), we extend the PSL(R_1) by adding first-degree transitive relational rules, as discussed in Section 3.4.1. In the fourth model, PSL($R_1 TR_1 + pred$), we extend the PSL($R_1 TR_1$) by adding the predictions from the baselines. For the baselines, we extend the previous models by adding first-degree relational similarities as features. However, it is not possible to include features similar to the transitive relational rules in PSL, since these models do not support collective reasoning or inference across instances.

Names + Personal + Relational Info (1^{st} + 2^{nd} degree): As above, we evaluate the performance of four PSL models. In the first experiment,

PSL($R_{12} TR_1$), we enhance the model PSL($R_1 TR_1$) by adding second-degree relational similarity rules, as discussed in Section 3.4.1. Second degree relationships are: grandmother, grandfather, granddaughter, grandson, aunt, uncle, niece, nephew. In the second experiment, PSL($R_{12} TR_1$+$pred$), we enhance PSL($R_{12} TR_1$) by adding the predictions from the baselines. In the third experiment, PSL($R_{12} TR_{12}$), we enhance PSL($R_{12} TR_1$) by adding second-degree transitive relational similarity rules, as discussed in Section 3.4.1. In the fourth experiment, PSL($R_{12} TR_{12} + pred$), we enhance PSL($R_{12} TR_{12}$) by adding the predictions from the baselines. For the baselines, we add the second-degree relational similarities as features. Again, it is not possible to add features that capture the transitive relational similarity rules to the baselines. Since Wikidata dataset does not provide second degree relations, we do not report experimental results for this case.

Discussion

We present our results in Table 3.2 (NIH) and Table 3.3 (Wikidata). For each experiment, we denote with bold the best performance in terms of the F-measure.

		NIH		
Experiment	**Method**	**Precision(SD)**	**Recall(SD)**	**F-measure(SD)**
Names	LR	0.871 (0.025)	0.686 (0.028)	0.767 (0.022)
	SVMs	0.870 (0.022)	0.683 (0.027)	0.765 (0.020)
	LMTs	0.874 (0.020)	0.717 (0.027)	0.787 (0.022)
	PSL(N)	0.866 (0.021)	0.761 (0.028)	0.810 (0.023)*
	PSL($N + pred$)	0.873 (0.021)	0.764 (0.022)	**0.815** (0.019)
Names + Personal Info	LR	0.968 (0.010)	0.802 (0.035)	0.877 (0.024)
	SVMs	0.973 (0.008)	0.832 (0.025)	0.897 (0.017)
	LMTs	0.961 (0.012)	0.857 (0.020)	0.906 (0.016)
	PSL(P)	0.942 (0.014)	0.900 (0.022)	0.920 (0.015)*
	PSL($P + pred$)	0.949 (0.008)	0.895 (0.018)	**0.921** (0.013)*
Names + Personal + Relational Info (1st degree)	LR	0.970 (0.012)	0.802 (0.034)	0.878 (0.024)
	SVMs	0.983 (0.008)	0.835 (0.026)	0.903 (0.018)
	LMTs	0.961 (0.010)	0.859 (0.020)	0.907 (0.014)
	PSL(R_1)	0.943 (0.012)	0.881 (0.030)	0.910 (0.015)
	PSL($R_1 + pred$)	0.958 (0.009)	0.885 (0.017)	0.920 (0.013)*
	PSL(R_1TR_1)	0.964 (0.007)	0.937 (0.015)	0.951 (0.009)*
	PSL($R_1TR_1 + pred$)	0.966 (0.009)	0.939 (0.011)	**0.952** (0.010)*
Names + Personal + Relational Info (1st + 2nd degree)	LR	0.970 (0.012)	0.807 (0.051)	0.880 (0.032)
	SVMs	0.985 (0.006)	0.856 (0.029)	0.916 (0.019)
	LMTs	0.975 (0.008)	0.872 (0.016)	0.921 (0.011)
	PSL($R_{12}TR_1$)	0.964 (0.008)	0.935 (0.017)	0.949 (0.010)*
	PSL($R_{12}TR_1 + pred$)	0.970 (0.008)	0.943 (0.011)	**0.957** (0.009)*
	PSL($R_{12}TR_{12}$)	0.965 (0.008)	0.937 (0.015)	0.951 (0.009)*
	PSL($R_{12}TR_{12} + pred$)	0.969 (0.009)	0.943 (0.011)	0.956 (0.008)*

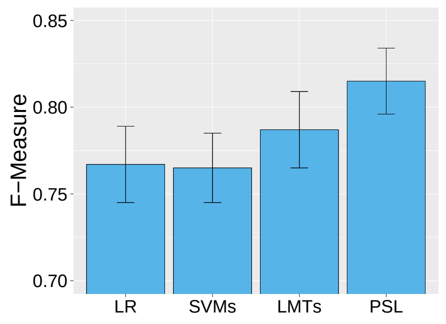
Table 3.2: Performance of PSL and baseline classifiers with varying types of rules/features for the NIH dataset. Numbers in parenthesis indicate standard deviations. Bold shows the best performance in terms of F-measure for each feature set. We denote by * statistical significance among the PSL model and the baselines at $\alpha = 0.05$ when using paired t-test.

		Wikidata		
Experiment	**Method**	**Precision(SD)**	**Recall(SD)**	**F-measure(SD)**
Names	LR	0.905 (0.015)	0.6598 (0.022)	0.720 (0.018)
	SVMs	0.941 (0.017)	0.607 (0.034)	0.738 (0.026)
	LMTs	0.926 (0.011)	0.660 (0.034)	0.770 (0.023)
	PSL(N)	0.868 (0.014)	0.754 (0.031)	0.806 (0.016)*
	PSL($N + pred$)	0.876 (0.017)	0.757 (0.031)	**0.811** (0.016)*
Names + Personal Info	LR	0.953 (0.015)	0.713 (0.032)	0.815 (0.022)
	SVMs	0.970 (0.011)	0.723 (0.034)	0.828 (0.023)
	LMTs	0.960 (0.014)	0.745 (0.037)	0.838 (0.022)
	PSL(P)	0.908 (0.026)	0.816 (0.042)	0.858 (0.016)*
	PSL($P + pred$)	0.928 (0.026)	0.839 (0.040)	**0.880** (0.017)*
Names + Personal + Relational Info (1st degree)	LR	0.962 (0.013)	0.756 (0.028)	0.846 (0.015)
	SVMs	0.975 (0.012)	0.776 (0.035)	0.864 (0.019)
	LMTs	0.967 (0.015)	0.785 (0.037)	0.866 (0.019)
	PSL(R_1)	0.914 (0.017)	0.866 (0.031)	0.889 (0.011)*
	PSL($R_1 + pred$)	0.934 (0.018)	0.900 (0.023)	0.916 (0.011)*
	PSL(R_1TR_1)	0.917 (0.018)	0.878 (0.016)	0.897 (0.007)*
	PSL($R_1TR_1 + pred$)	0.927 (0.018)	0.907 (0.019)	**0.917** (0.011)*

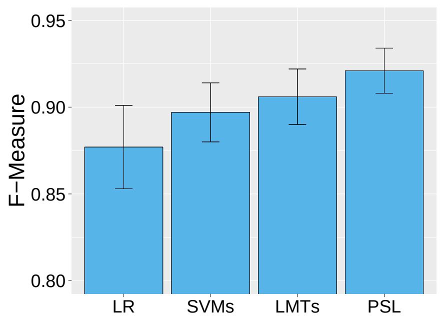
Table 3.3: Performance of PSL and baseline classifiers with varying types of rules/features for the Wikidata dataset. Numbers in parenthesis indicate standard deviations. Bold shows the best performance in terms of F-measure for each feature set. We denote by * statistical significance among the PSL model and the baselines at $\alpha = 0.05$ when using paired t-test.

We present the results for both our method and the baselines and only for the positive class (co-referent entities). Due to the imbalanced nature of the task, performance on non-matching entities is similar across all approaches, with precision varying from 99.6% to 99.9%, recall varying from 99.4% to 99.9%, and F-measure varying from 99.5% to 99.7% for the NIH dataset. For the Wikidata, precision varies from 98.7% to 99.8%, recall varies from 98.9% to 99.9%, and F-measure varies from 99.5% to 99.7%. Furthermore, to highlight the most interesting comparisons we introduce Figures 3.5, 3.6, and 3.7 as a complement for the complete tables. The plots in these figures show the F-measure when varying the classification method (i.e., baselines and PSL) or the amount of information used for the classification (e.g., use only names). Figures in blue are for NIH while figures in orange are for the Wikidata dataset. Next, we summarize some of our insights from the results of Tables 3.2 and 3.3. For the most interesting comparisons we additionally refer to Figures 3.5, 3.6, and 3.7.

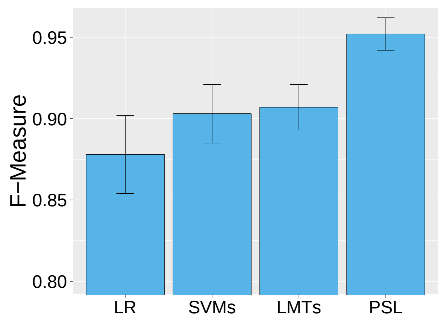
PSL models universally outperform baselines: In each experiment PSL outperforms all the baselines using the same feature set. PSL produces a statistically significant improvement in F-measure as measured by a paired t-test with $\alpha = 0.05$. Of the baselines, LMTs perform best in all experiments and will be used for illustrative comparison. When using name similarities only (**Names** models in Tables 3.2 and 3.3) PSL(N) outperforms LMTs by 2.3% and 3.6% (absolute value) for the NIH and the Wikidata dataset accordingly. When adding personal information similarities (**Names + Personal Info**), PSL(NR) outperforms LMTs by 1.4% and 2% for the NIH and the Wikidata accordingly. For the experiment **Names + Personal + Relational Info** 1^{st} **degree**, the PSL model that uses both relational and transitive relational similarity rules, PSL(R_1TR_1), outperforms LMTs by 4.4% for the NIH and 3.1% for the Wikidata. Finally, for



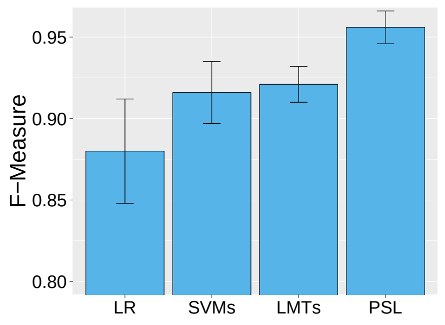
(a) Names



(b) Names + Personal Info



(c) Names + Personal + Relational Info (1st degree)



(d) Names + Personal + Relational Info (1st + 2nd degree)

Figure 3.5: NIH Dataset: Graphical representation of the performance (F-measure) of the baselines and the PSL models in different experimental setups. Standard deviations are shown around the top of each bar. For the PSL, we report the results for the models PSL($N + pred$), PSL($P + pred$), PSL($R_1 T R_1 + pred$), and PSL($R_{12} T R_{12} + pred$) respectively.

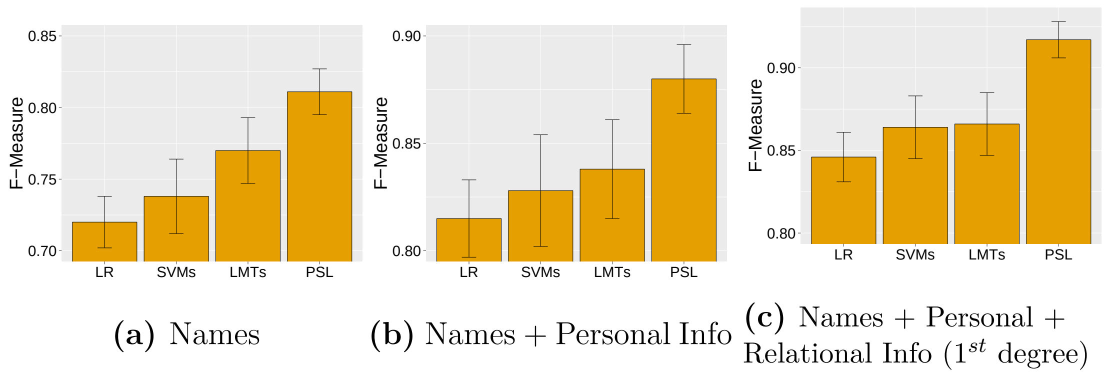


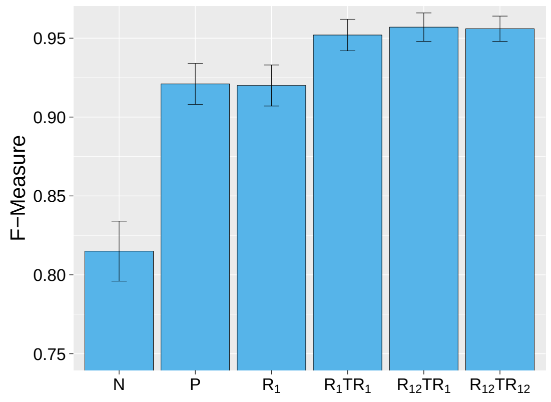
Figure 3.6: Wikidata Dataset: Graphical representation of the performance (F-measure) of the baselines and the PSL models in different experimental setups. Standard deviations are shown around the top of each bar. For the PSL, we report the results for the models PSL(N+$pred$), PSL(P+$pred$), and PSL(R_1TR_1+$pred$) respectively.

the NIH dataset, for the experiment that additionally uses relational similarities of second degree, the best PSL model, PSL($R_{12}TR_{12}$), outperforms LMTs by 3%. When incorporating the predictions from the baseline algorithms (LR, SVMs, and LMTs) we observe that the performance of the PSL models further increases. We graphically present the superiority (in terms of F-measure) of the PSL models when compared to the baselines in all different sets of experiments in Figures 3.5 and 3.6 for the NIH and the Wikidata datasets accordingly.

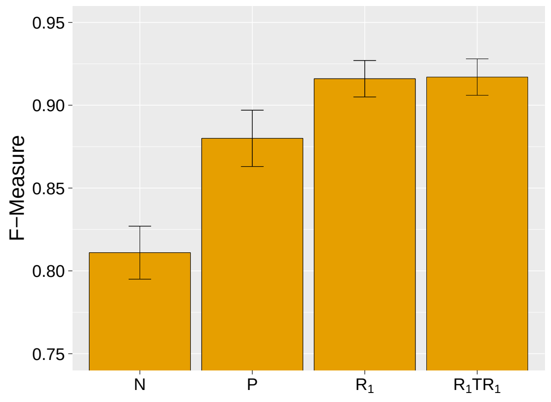
Name similarities are not enough: When we incorporate personal information similarities (**Names + Personal Info**) on top of the simple **Names** model that uses name similarities only, we get substantial improvements for the PSL model: 11% for the NIH and 5.2% for the Wikidata (absolute values) in F-measure. The improvement is evident in the graphs presented in Figure 3.7 when comparing columns N and P for both datasets. The same observation is also true for all baseline models. For the NIH dataset, the SVMs get the most benefit out of the addition of personal information with an increase of 13.2%. For the Wikidata dataset, LR gets the most benefit with an increase of 9.5% for the F-measure.

First-degree relationships help most in low noise scenarios: We found that reliable relational evidence improves performance, but noisy relationships can be detrimental. In the NIH dataset, incorporating first-degree relationships using the simple relational similarity function defined in Subsection 3.4.1 decreases performance slightly (1%) for the PSL model (also evident in Figure 3.7a when comparing columns P and R_1). For LR, SVMs and LMTs, F-measure increases slightly (0.1%, 0.6%, and 0.1% respectively). However, for the Wikidata, the addition of simple relational similarities increased F-measure by 3.1% for PSL(R_1) (this is shown is Figure 3.7b when comparing columns P and R_1). The same applies for the baseline models where we observe improvements of 2.8% for LMTs, 3.6% for SVMs, and 3.1% for LR. We believe that the difference in the effect of the simple relational features is due to the different noise in the two datasets. NIH is a real-world dataset with incomplete and unreliable information, while Wikidata is considered to contain no noise. As a result, we believe that both the baseline and PSL models are able to cope with the artificially introduced noise, while it is much more difficult to deal with real-world noisy data.

Collective relations yield substantial improvements: When we incorporate collective, transitive relational rules to the PSL(R_1) model resulting to the PSL(R_1TR_1) model – a key differentiator of our approach – we observe a 4.1% improvement in F-measure for the NIH dataset. This is also evident in Figure 3.7a when comparing columns R_1 and R_1TR_1. We note that this is a result of an increase of 5.1% for the recall and 2.1% for the precision. Adding collective rules allows decisions to be propagated between related pairs of mentions,



(a) NIH



(b) Wikidata

Figure 3.7: Graphical representation of the performance of PSL in terms of F-measure with varying types of rules for (a) the NIH and (b) the Wikidata datasets. Standard deviations are shown around the top of each bar. All reported results are from PSL models that use the predictions from other algorithms.

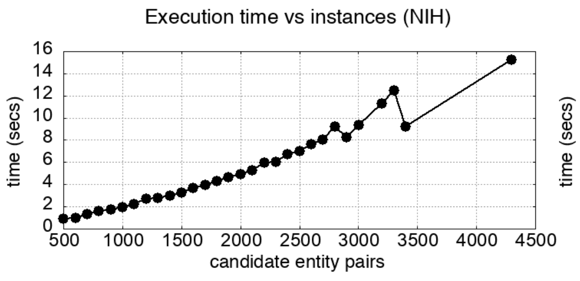
exploiting statistical signals across the familial network to improve recall. The Wikidata also benefits from collective relationships, but the 0.8% improvement in F-measure score is much smaller (for graphical illustration, there is no obvious improvement when comparing columns R_1 and R_1TR_1 of Figure 3.7b). For this cleaner dataset, we believe that simple relational similarity rules were informative enough to dampen the impact of transitive relational similarity rules. As a result, these rules are not as helpful as in the more noisy NIH dataset.

Second-degree similarities improve performance for the baselines: The addition of simple relational similarities from second degree relationships, such as those available in the NIH dataset, yield improvements in all baseline models. When adding second-degree relationships, we observe a pronounced increase in the F-measure for two baselines (1.6% for LMTs and 1.3% for SVMs), while LR has a small increase of 0.2%. For our approach, PSL($R_{12}TR_1$), slightly decreases the PSL(R_1TR_1) model (0.2% for F-measure), while the addition of second-degree transitive relational features (model PSL($R_{12}TR_{12}$)) improves slightly the performance by 0.2%.

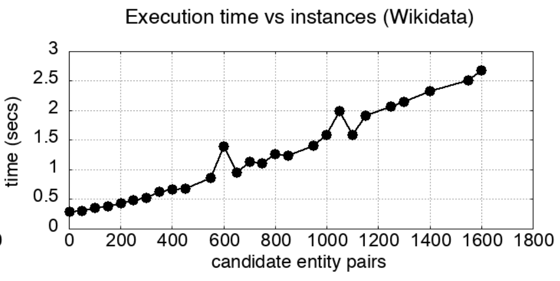
Predictions from other algorithms always improve performance: In all our experiments, we ran different versions of the PSL models that included or omitted the predictions from the baselines, i.e., LR, SVMs, LMTs (discussed in Subsection 4.3.1). We observe that the addition of the predictions of the other algorithms always increases the performance of the PSL models. More specifically, for the NIH dataset, the addition of the predictions from LR, SVMs, and LMTs slightly increases the F-measure of the PSL models. In particular, F-measure increases by 0.5% for the experiment **Names** and 0.1% for the experiment **Names + Personal Info**. Also, the experiment PSL($R_1 + pred$) improves the F-measure of the experiment PSL(R_1) by 1.0%, and the experiment PSL($R_1TR_1 + pred$) slightly improves the F-measure of the experiment PSL(R_1TR_1) by 0.1%. For the case of the experiment PSL($R_1 + pred$) we can see that its performance (F-measure=0.910) is very close to the performance of the baselines (e.g., the F-measure for the LMTs is 0.907). As a result, adding the baselines helps the PSL model to better distinguish the true positives and true negatives. However, in the case of the model PSL(R_1TR_1) we can see that there is a clear difference between the PSL model and the baselines, so for this experiment adding the predictions of those cannot improve at a bigger scale the performance of the PSL model. Last, for the experiment **Names + Personal + Relational Info (1st + 2nd degree)** we observe that adding the predictions from the other algorithms slightly increases the F-measure by 0.8% for the experiment PSL($R_{12}TR_1 + pred$) and 0.5% for the experiment PSL($R_{12}TR_{12} + pred$). In all cases, we observe that the increase in F-measure is the result of an increase in both the precision and the recall of the model (the only case that we observe a small decrease in the recall is the experiment **Names + Personal Info**). For the Wikidata dataset, we observe that the F-measure improves significantly in all experiments when adding the predictions from the baselines. This is a result of the increase of both the precision and the recall. More specifically, we observe the following increases for the F-measure: 0.5% for the experiment **Names**, 2.2% for the experiment **Names + Personal Info**, 2.7% and 2.0% for the two versions of the experiment **Names + Personal + Relational Info (**1^{st} **degree)**.

Precision-recall balance depends on the chosen threshold: As we discussed in Section 3.4.2 for the PSL model we choose the optimal threshold to maximize the F-measure score. This learned threshold achieves a precision-recall balance that favors recall at the expense of precision. For both datasets, our model's recall is significantly higher than all the baselines in all the experiments. However, since PSL outputs soft truth values, changing the threshold selection criteria in response to the application domain (e.g., prioritizing cleaner matches over coverage) can allow the model to emphasize precision over recall.

Matching restrictions always improves F-measure: We note that valid solutions in our entity resolution setting require that an entity matches at most one entity in another ego-centric network. To enforce this restriction, we apply a 1-1 matching algorithm on the raw output of all models (Section 3.4.3). Applying matching restrictions adjusts the precision-recall balance of all models. For both PSL and the baselines across both datasets, when applying the 1-1 matching restriction algorithm, we observe a sizable increase in precision and a marginal drop in recall. This pattern matches our expectations, since the algorithm removes predicted co-references (harming recall) but is expected to primarily remove false-positive pairs (helping precision). Overall, the application of the 1-1 matching



(a)



(b)

Figure 3.8: An analysis of the scalability of our system ((a) is for the NIH and (b) for the Wikidata). As the number of potentially co-referent entity pairs increases, the execution time of our model grows linearly for both datasets.

restrictions improves the F-measure for all algorithms and all datasets. Since the results before the 1-1 matching do not represent valid solutions and it is not straightforward to compare across algorithms we do not report them here.

PSL is scalable to the number of instances, based on empirical results: One motivation for choosing PSL to implement our entity resolution model was the need to scale to large datasets. To empirically validate the scalability of our approach, we vary the number of instances, consisting of pairs of candidate co-referent entities, and measure the execution time of inference. In Figure 3.8 we plot the average execution time relative to the number of candidate entity pairs. Our results indicate that our model scales almost linearly with respect to the number of comparisons. For the NIH dataset, we note one prominent outlier, for a family with limited relational evidence resulting in lower execution time. Conversely, for the Wikidata, we observe two spikes which are caused by families that contain relatively dense relational evidence compared to similar families. We finally note that we expect these scalability results to hold as the datasets get bigger since the execution time depends on the number of comparisons and the number of relations per family.

3.5.4 Effect of String Similarity Functions

In Section 3.4.1 we discussed that PSL can easily incorporate a variety of string similarity functions. In the basic experiments (Section 3.5.3) all models (PSL and baselines) used the Levensthein and Jaro-Winkler string similarity functions. In this section, we experiment with a wider set of string similarity functions and simple combinations of them in order to study how such different functions can affect performance. More specifically, for all the models (PSL and baselines) we ran the following experiments:

– **Levenshtein (*L*)**: We use first, middle, and last name similarities computed using the Levenshtein string similarity function only.

– **Jaro-Winkler** (***JW***): We add Jaro-Winkler similarities.

– **Monge-Elkan** (***ME***): We add Monge-Elkan similarities.

– **Soundex** (***S***): We add Soundex similarities.

– **Jaro** (***J***): We add Jaro similarities.

– $\boldsymbol{max(L, JW, ME, S, J)}$: We combine the string similarity functions by using the maximum value of all the similarity functions.

– $\boldsymbol{min(L, JW, ME, S, J)}$: We combine the string similarity functions by using the minimum value of all the similarity functions.

We note that for the PSL, we run the version PSL(N) and not the version PSL(N+*pred*), i.e., we do not use the predictions from the other models in our PSL model. We present the results in Table 3.4 for the NIH dataset. As we discussed, for the Wikidata dataset we introduced artificial noise to all the similarities so we focus on the NIH dataset to get a clear picture of the performance of the similarity functions. Here is a summary of the results from Table 3.4:

The performance of the models changes when the string similarity functions change: For PSL, the difference between the model that performs the

		NIH		
Method	**String Functions**	**Precision(SD)**	**Recall(SD)**	**F-measure(SD)**
PSL	Levenshtein (L)	0.850 (0.017)	0.757 (0.044)	0.801 (0.029)
	+ Jaro-Winkler (JW)	0.866 (0.021)	0.761 (0.028)	0.810 (0.023)
	+ Monge-Elkan (ME)	0.871 (0.025)	0.766 (0.035)	0.815 (0.028)
	+ Soundex (S)	0.866 (0.019)	0.765 (0.034)	0.812 (0.024)
	+ Jaro (J)	0.868 (0.029)	0.762 (0.035)	0.812 (0.031)
	$max(L, JW, ME, S, J)$	0.834 (0.025)	0.741 (0.027)	0.785 (0.024)
	$min(L, JW, ME, S, J)$	0.861 (0.019)	0.752 (0.025)	0.803 (0.021)
LMTs	Levenshtein (L)	0.874 (0.025)	0.699 (0.031)	0.776 (0.026)
	+ Jaro-Winkler (JW)	0.874 (0.002)	0.717 (0.027)	0.787 (0.022)
	+ Monge-Elkan (ME)	0.865 (0.026)	0.714 (0.031)	0.782 (0.027)
	+ Soundex (S)	0.862 (0.026)	0.715 (0.027)	0.782 (0.024)
	+ Jaro (J)	0.854 (0.028)	0.711 (0.028)	0.776 (0.024)
	$max(L, JW, ME, S, J)$	0.848 (0.028)	0.739 (0.032)	0.789 (0.029)
	$min(L, JW, ME, S, J)$	0.870 (0.026)	0.681 (0.037)	0.764 (0.030)
SVMs	Levenshtein (L)	0.870 (0.027)	0.716 (0.029)	0.785 (0.025)
	+ Jaro-Winkler (JW)	0.870 (0.022)	0.683 (0.027)	0.765 (0.020)
	+ Monge-Elkan (ME)	0.867 (0.020)	0.675 (0.043)	0.759 (0.033)
	+ Soundex (S)	0.870 (0.030)	0.68 (0.038)	0.763 (0.031)
	+ Jaro (J)	0.870 (0.023)	0.679 (0.027)	0.763 (0.023)
	$max(L, JW, ME, S, J)$	0.834 (0.035)	0.719 (0.033)	0.772 (0.033)
	$min(L, JW, ME, S, J)$	0.858 (0.021)	0.656 (0.038)	0.743 (0.030)
LR	Levenshtein (L)	0.871 (0.026)	0.689 (0.031)	0.769 (0.024)
	+ Jaro-Winkler (JW)	0.870 (0.022)	0.683 (0.027)	0.765 (0.020)
	+ Monge-Elkan (ME)	0.870 (0.024)	0.688 (0.026)	0.768 (0.021)
	+ Soundex (S)	0.872 (0.024)	0.694 (0.026)	0.772 (0.021)
	+ Jaro (J)	0.872 (0.023)	0.693 (0.027)	0.772 (0.021)
	$max(L, JW, ME, S, J)$	0.827 (0.027)	0.715 (0.033)	0.767 (0.030)
	$min(L, JW, ME, S, J)$	0.871 (0.024)	0.697 (0.029)	0.763 (0.023)

Table 3.4: Performance of PSL and baseline classifiers for the experiment that uses only name similarities with varying the string similarity functions used. Numbers in parenthesis indicate standard deviations. For all experiments apart from one ($max(L, JW, ME, S, J)$)PSL statistically significantly outperforms the baselines that use the same string similarity functions for the f-measure at $\alpha = 0.05$ when using paired t-test.

best and the model that performs the worst is 3% absolute value, for LMTs 2.5%, for SVMs 4.2%, and for LR 0.9%.

The setting of string similarity functions that performs best is different for each model: For PSL, the best model uses Levensthein, Jaro-Winkler, and Monge-Elkan. For LMTs, the best model uses the $min(L, JW, ME, S, J)$, for SVMs the best model uses the Levensthein, and for LR the best model uses Levensthein, Jaro-Winkler, Monge-Elkan, and Soundex.

PSL models outperform baselines: In each experiment, PSL outperforms all the baselines using the same string similarity functions. With one exception (for $max(L, JW, ME, S, J)$) PSL statistically significantly outperforms the baselines that use the same string similarity functions for the F-measure at $\alpha = 0.05$ when using paired t-test. For the experiment $max(L, JW, ME, S, J)$ LMTs outperform PSL (by 0.5% absolute value) but this difference is not considered statistically significant. For graphical illustration, Figure 3.9 shows the F-measure for the baselines and the PSL model for the setting that each model performed the best. For example, for PSL, we plot the F-measure when using Levensthein, Jaro-Winkler, and Monge-Elkan while for LMTs, we plot the F-measure when using the $min(L, JW, ME, S, J)$.

3.5.5 Effect of noise level

As we discussed, to simulate the noisy conditions of real-world datasets, we introduced additive Gaussian noise to all the similarity scores (names, personal information, relational information) of the Wikidata dataset drawn from a $N(0, 0.16)$ distribution. In this section, we experiment with varying the introduced noise. For all experiments, for all models (both PSL and baselines), we additionally ran experiments when introducing noise from the following distributions: $N(0, 0.01)$,

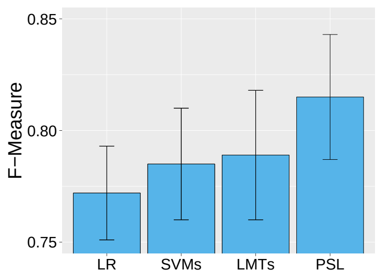


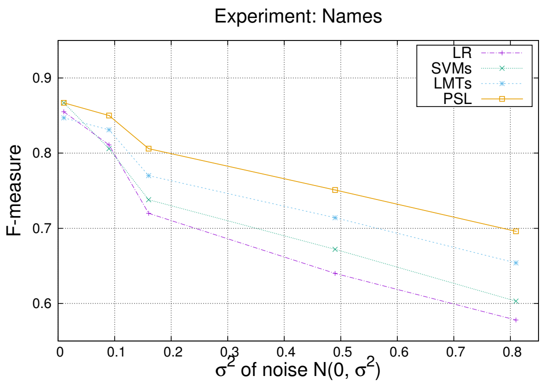
Figure 3.9: NIH Dataset: Graphical representation of the performance (F-measure) of the baselines and the PSL model for the combination of string similarities that each model performs the best. For the PSL, we plot the F-measure when using Levensthein, Jaro-Winkler, and Monge-Elkan. For LMTs, we report results when using the $min(L, JW, ME, S, J)$, for SVMs we report results when using the Levensthein, and for LR we report results when using Levensthein, Jaro-Winkler, Monge-Elkan, and Soundex. Standard deviations are shown around the top of each bar.

$N(0, 0.09)$, $N(0, 0.49)$, $N(0, 0.81)$. We present our results in Table 3.10 where we plot the average F-measure computed over 5 fold cross-validation with respect to the noise added to the similarities. For the experiments of the PSL we use the following versions: for the experiment **Names** we use the model PSL(N), for the experiment **Names + Personal Info** the model PSL(P), and for the experiment **Names + Personal + Relational Info (1st degree)** the model PSL(R_1TR_1). In other words, we do not include the predictions from the other baseline models - but we expect them to perform better than the ones we report here since all the experiments that include the predictions outperform the experiments that do not include the predictions for the Wikidata dataset (Table 3.3). As expected, when the noise increases then the F-measure decreases and this is true for all models. Another observation is that with very small amount of noise (drawn from $N(0, 0.01)$ or $N(0, 0.09)$ distributions) all the models perform similarly. However, when increasing the noise (drawn from $N(0, 0.16)$, $N(0, 0.49)$, or $N(0, 0.81)$ distributions) then the difference between the models becomes more pronounced.

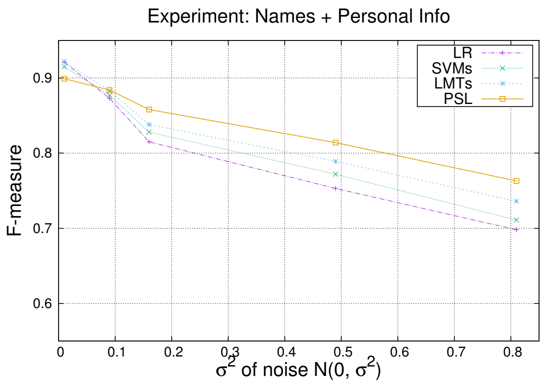
When noise is drawn from these distributions, PSL consistently performs the best for all experiments (**Names**, **Names + Personal Info**, **Names + Personal + Relational Info**). This difference is statistically significantly better at $\alpha = 0.05$ when using paired t-tests for all experiments. Among the baselines, LMTs perform the best, followed by SVMs, and finally LR.

3.5.6 Performance with varying number of predicted matches

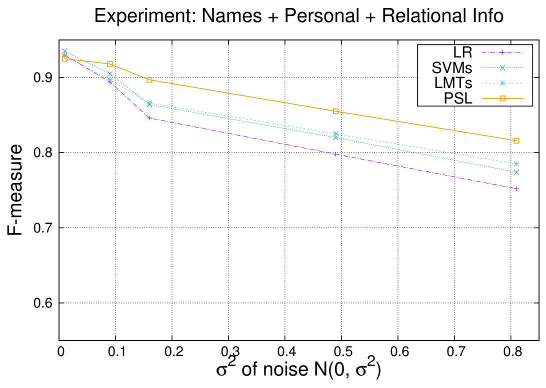
In this section, our goal is to study the performance of the PSL models and the baseline classifiers with respect to the threshold used for classifying the instances. As we discussed, PSL learns the threshold using a validation set. The baseline classifiers also use some internal threshold to determine whether each pair is co-referent. Since the learned thresholds are different for each model, it would be unfair to plot the F-measure with respect to the threshold to compare the methods. Similarly, precision-recall curves in this setting would not be informative: since the values of the thresholds are not related, it does not make sense to report that a method A is better than method B at a particular threshold. To overcome the above issues and make a fair comparison of the methods we follow the related work [49, 6, 82] and choose the threshold so that each method produces the same number of predicted matches (i.e., true positives and false positives). To this end, we compute the F-measure when varying the number of predicted matches for each algorithm. For each value of the predicted matches, we compute the precision as the ratio of the true positives over the true positives and false positives in the predicted matches, the recall as the ratio of the true positives over the true positives and false negatives in the predicted matches, and the F-measure as the weighted balance of the precision and recall. We present the results for the NIH dataset in Table 3.11 and for the Wikidata in Table 3.12. In all experiments, we



(a)

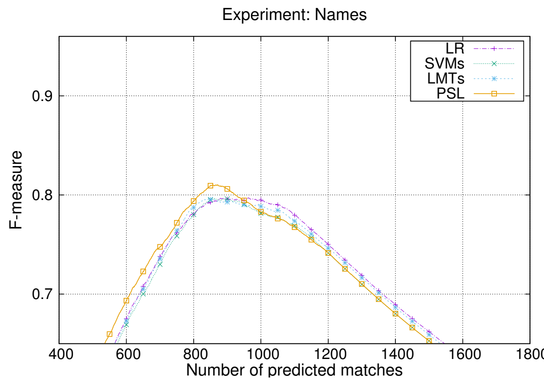


(b)

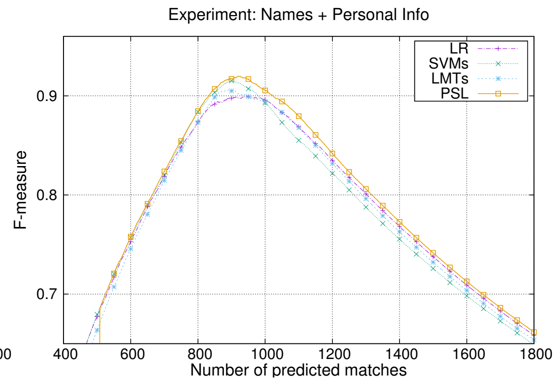


(c)

Figure 3.10: An analysis of the performance of the models (PSL and baselines) when varying the noise in the similarities for the Wikidata dataset (for the experiments (a) **Names**, (b) **Names + Personal Info**, (c) **Names + Personal + Relational Info (1^{st} degree)**). We report average F-measure scores from a 5-fold cross validation. As the noise increases, the F-measure decreases. For the minimum amount of noise all the models perform similarly. However, as the noise increases the difference in the performance becomes more evident.



(a)



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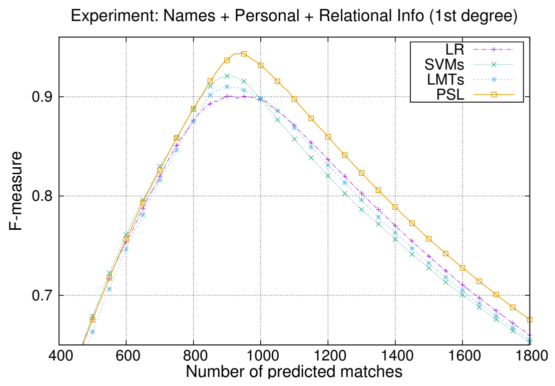

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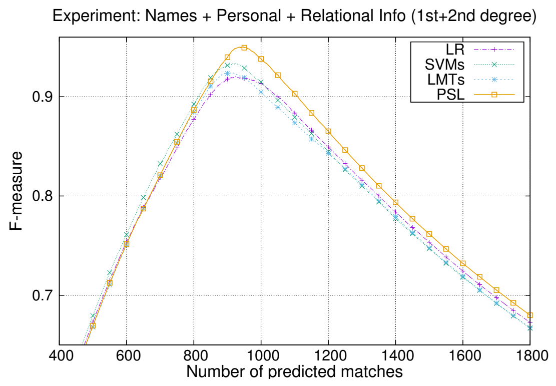
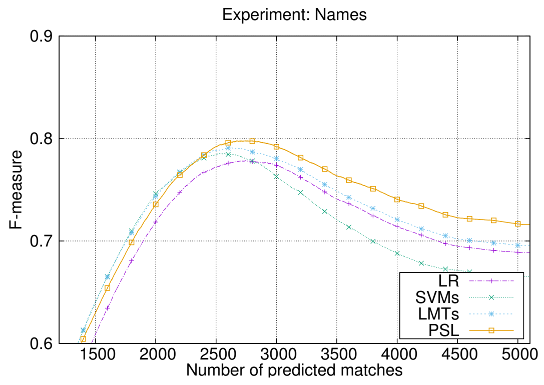
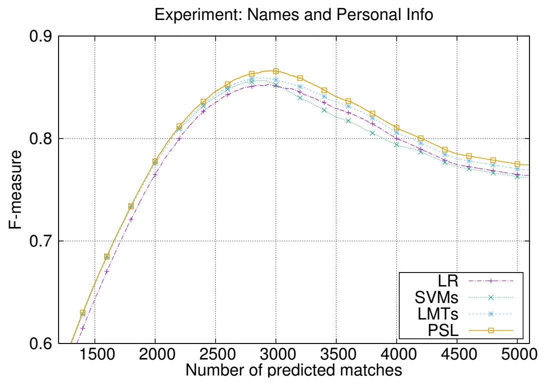


(d)

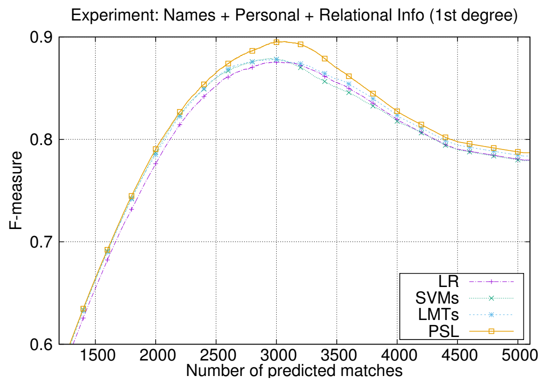
Figure 3.11: An analysis of the performance of the models (PSL and baselines) with respect to the number of the predicted matches for the NIH dataset (for the experiments (a) **Names**, (b) **Names + Personal Info**, (c) **Names + Personal + Relational Info (1^{st} degree)**, (d) **Names + Personal + Relational Info (1^{st}+2^{nd} degree)**). We report average F-measure scores from a 5-fold cross validation.



(a)



(b)



(c)

Figure 3.12: An analysis of the performance of the models (PSL and baselines) with respect to the number of the predicted matches for the Wikidata dataset (for the experiments (a) **Names**, (b) **Names + Personal Info**, (c) **Names + Personal + Relational Info (1st degree)**). We report average F-measure scores from a 5-fold cross validation.

report the results of the PSL models that include the predictions of the other classifiers. More specifically, we report the results of the models: PSL($N + pred$), PSL($P + pred$), PSL($R_1 T R_1 + pred$), and PSL($R_{12} T R_{12} + pred$) (only for the NIH dataset).

For the NIH dataset, for the experiment **Names**, we observe that PSL consistently outperforms all the baselines when the number of matches is smaller than 950. However, when the number of matches is larger than 1000 the performance of the PSL is lower than the baselines. For all the other experiments (**Names + Personal Info**, **Names + Personal + Relational Info (1^{st} degree)**, and **Names + Personal + Relational Info (1^{st} + 2^{nd} degree)**) all models perform similarly when the number of predicted matches is smaller than 800. When the number of predicted matches is larger than 800 we can see that the PSL models consistently outperform all the baselines. For the Wikidata dataset, for all the experiments we observe that all the models perform similarly for small number of matches (up to 2500). However, when the number of matches increases (i.e., larger than 2500) then we observe a clear win of the PSL models.

3.6 Other Applications: Recommender Systems

In this section, we show how we can apply our approach to the domain of recommender systems and, in particular, to the items of the user-item recommendation matrix. Identifying the coreferent items allows for increasing the density of the user-item matrix. In addition to improving accuracy, finding the coreferent items enables us to address an additional problem inherent to the area of recommender systems: the cold-start problem. More specifically, inferring that a newly-added item is coreferent with an existing already-rated item enables us to recommend the new item without the need for ratings from users.

Entity resolution in the recommender systems setting (e.g., products) is a very challenging task, since it is not straightforward whether two items should be merged. For example, two cameras varying in their color may appear twice on a web site, but may correspond to the exact same model. In this case, it is unclear whether those two products should be resolved, because some users may not be interested in the color of the camera but only in the technical specifications, while others may consider the color more important than the technical specifications. For the first group of users, the two cameras are the same product, so merging them would be beneficial since it will increase the density of the the user-item matrix. On the other hand, for the second group of users merging the two products may be a sub-optimal decision.

In this section, we describe how we can perform entity resolution for products with a focus on the cold-start problem. The basic idea is that we should resolve products with very similar characteristics (e.g., similar names, description, reviews) only if they have a very small number of ratings. Once those products acquire a sufficient number of ratings by users then we should treat them as separate products. The reasoning behind this approach can be explained best through an example: consider that there is a very succesfull camera (e.g., "Nikon D3400") with a large number of ratings and a new version becomes available (e.g., "Nikon D3500"). Both cameras are of the same brand and have very similar characteristics. When the new version of the camera becomes available for sale, it has no ratings, so merging it with the previous version of the camera can help provide some ratings. However, once the new version gets a sufficient number of ratings, then we can recommend the new camera based only on the ratings for this new version.

3.6.1 Problem Formulation for Entity Resolution in Recommender Systems

In a typical recommender system setting, there is a set of users $\mathcal{U} = \{u_1, u_2, ..., u_k\}$, a set of items $\mathcal{I} = \{i_1, i_2, ..., i_n\}$, and a set of observed ratings $\mathcal{R}$, i.e., recorded ratings from a subset of users $\mathcal{U}$ to a subset of items $\mathcal{I}$. Given the above, the task is to perform rating prediction, i.e., predict the values of a set of unobserved ratings $\mathcal{R}'$.

In our setting, we consider an entity resultion step that we need to perform before the recommender system problem. More specifically, the given set of items $\mathcal{I}$ oftentimes contains duplicates. We refer to this set as a set of *references* $\mathcal{I}$ where each reference has attributes $i.A_1$, $i.A_2$, $i.A_k$. The references correspond to a set of unknown entities $\mathcal{E} = \{e_m\}$ which is the set of unique items. The duplicate items that have been resolved map to the same entity in $\mathcal{E}$. We introduce the attribute $i.E$ to refer to the entity to which reference i corresponds to. The first part of the problem is to recover the hidden set of entities $\mathcal{E} = \{e_m\}$ and the entity labels $i.E$ for individual references given the observed attributes of the references. We note that the set of entities $\mathcal{E} = \{e_m\}$ should be regularly updated based on the available number of ratings for each item i. The second part of the problem is how to exploit the discovered entity set $\mathcal{E}$ in order to improve the rating prediction task.

3.6.2 Entity Resolution Task

To discover the hidden set of entities we extend the model of Section 3.4. We first introduce a latent variable $\textsc{SameLatent}(\mathtt{p}_1, \mathtt{p}_2)$ whose value represents the probability that two products are coreferent independent from the number of ratings. To compute the value of this latent variable, we start by introducing rules that can capture similar product names, similar product description, and similar price. These rules can be defined as follows.

$$\textsc{SimName}_{SIM}(\mathtt{p}_1, \mathtt{p}_2) \Rightarrow \textsc{SameLatent}(\mathtt{p}_1, \mathtt{p}_2)$$
$$\textsc{SimPrice}_{SIM}(\mathtt{p}_1, \mathtt{p}_2) \Rightarrow \textsc{SameLatent}(\mathtt{p}_1, \mathtt{p}_2)$$
$$\textsc{SimDescription}_{SIM}(\mathtt{p}_1, \mathtt{p}_2) \Rightarrow \textsc{SameLatent}(\mathtt{p}_1, \mathtt{p}_2)\ .$$

The notation is similar to the notation used in Section 3.4. To compute name, price, and description similarity we can use different similarity metrics SIM like in the case of entity resolution in familial networks.

Additionally, we can use simple relational information in order to disallow matches of different products. For example we can model the intuition that two products that belong to different categories (e.g., the movie "Twinlight" with the book "Twinlight") should not be merged as follows:

$$\neg\textsc{BelongToDifferentCategory}(\mathtt{p}_1, \mathtt{p}_2) \Rightarrow \neg\textsc{SameLatent}(\mathtt{p}_1, \mathtt{p}_2)\ .$$

Furthermore, we can use more complicated relational information when available. For example, big eCommerce websites such as `Amazon.com` provide parent-child relationships that can be further exploited. In `Amazon.com`, each parent-child relationship has three basic elements: the parent product, the child product, and the variation theme. A parent product is a non-buyable product used to relate child products. The Amazon catalog uses the parent product to establish relationships between the child products. For example, if two shirts have the same parent then they are related and are considered child products. The child product is an instance of the parent product. We can have many child products that are all related to one parent product. Each child varies in some way, for example, by size or by color. The variation theme defines how related products differ from each other. For example, in the "Clothing, Accessories and Luggage" category, child products can differ from each other by size or color. We can leverage the above relational information with a special care when using the variation theme. For example, for the category "Clothing, Accessories and Luggage" two products with different size should probably be considered as the same, however, this is not true for two products with different colors (for example, there may be a user that hates the black color but loves the purple color). To this end, we need first to define which variation themes allow for merging and which do not allow for merging. We can do this by introducing the predicate $\textsc{ImportantVariationalTheme}(\mathtt{t})$ which is true if the theme $\mathtt{t}$ is considered an important differentiator for two products (such as color) and false if the theme $\mathtt{t}$ is not considered an important differentiator for two products (such as size). We can introduce rules that capture the intuition that if two products belong to the same parent category and have different variational theme and the variation theme is considered as an important differentiator then the products should not be merged as follows:

$$\begin{aligned}\textsc{BelongToTheSameParent}(\mathtt{p}_1,\mathtt{p}_2) \wedge \textsc{ImportantVariationalTheme}(\mathtt{t})\\ \wedge\textsc{BelongsToVariationalTheme}(\mathtt{p}_1,\mathtt{t}_1)\wedge\\ \wedge\textsc{BelongsToVariationalTheme}(\mathtt{p}_2,\mathtt{t}_2) \wedge \mathtt{t}_1 \neq \mathtt{t}_2 \Rightarrow\\ \neg\textsc{SameLatent}(\mathtt{p}_1,\mathtt{p}_2)\ .\end{aligned}$$

Similarly, we can add the inverse rule that captures the intuition that if two products belong to the same parent category and have different variational theme and the variation theme is not considered as an important differentiator then the products should be merged as follows:

$$\begin{aligned}\textsc{BelongToTheSameParent}(\mathtt{p}_1,\mathtt{p}_2) \wedge \neg\textsc{ImportantVariationalTheme}(\mathtt{t})\\ \wedge\textsc{BelongsToVariationalTheme}(\mathtt{p}_1,\mathtt{t}_1)\wedge\\ \wedge\textsc{BelongsToVariationalTheme}(\mathtt{p}_2,\mathtt{t}_2) \wedge \mathtt{t}_1 \neq \mathtt{t}_2 \Rightarrow\\ \textsc{SameLatent}(\mathtt{p}_1,\mathtt{p}_2)\ .\end{aligned}$$

Additionally, we can introduce transitive relational rules that allow for collective classification. For example, for the case of complementary products, we can capture the intuition that if we have strong evidence that two products are the same, then their complementary products should also be the same when additional evidence is also available, e.g., if their names are similar. An example of complementary products can be a cell phone with its charger. If we have strong evidence that two cell phones belong to the same entity and their complementary products have very similar names then we can infer that the complementary products belong to the same entity. The following intuition can be captured by the following rule:

$$\begin{aligned}\textsc{ComplementaryProducts}(\mathtt{p}_1,\mathtt{p}_a) \wedge \textsc{ComplementaryProducts}(\mathtt{p}_2,\mathtt{p}_b)\wedge\\ \textsc{SameLatent}(\mathtt{p}_1,\mathtt{p}_2) \wedge \textsc{SimName}_{SIM}(\mathtt{p}_a,\mathtt{p}_b) \Rightarrow \textsc{SameLatent}(\mathtt{p}_a,\mathtt{p}_b)\ .\end{aligned}$$

Finally, to capture the fact that we want to merge products for the cases where the value of the latent variable $\textsc{SameLatent}(\mathtt{p}_1,\mathtt{p}_2)$ is high and at the same time one product has a sufficient number of ratings, while the other has limited ratings, we introduce the predicate $\textsc{ColdStartItem}(\mathtt{p}_1)$. This predicate is true if the product has a number of ratings below a threshold and false if the product has a number of ratings above a threshold. We introduce the following rule to merge an item that has limited number of ratings with an item that has a sufficient number of ratings:

$$\neg\textsc{ColdStartItem}(\mathtt{p}_1) \wedge \textsc{ColdStartItem}(\mathtt{p}_2) \wedge \textsc{SameLatent}(\mathtt{p}_1, \mathtt{p}_2) \Rightarrow \textsc{Same}(\mathtt{p}_1, \mathtt{p}_2)\ .$$

3.6.3 Rating Prediction Task

For the rating prediction task, instead of using the set of items $\mathcal{I}$ which may contain duplicate items, we propose to use the set of the resolved items $\mathcal{E}$ produced during the entity resolution task. So, for each item $i \in \mathcal{I}$ we will use the entity that corresponds to, i.e. $i.E$. As a result, the new set of items that will be given as input to the recommender system is $\mathcal{I}' = \{i_1.E, i_2.E, ..., i_n.E\}$. The set of users and observed ratings will stay the same.

3.7 Conclusions and Future Work

Entity resolution in familial networks poses several challenges, including heterogeneous relationships that introduce collective dependencies between decisions and inaccurate attribute values that undermine classical approaches. In this work, we propose a scalable collective approach based on probabilistic soft logic that leverages attribute similarities, relational information, logical constraints, and predictions from other algorithms. A key differentiator of our approach is the ability to support bijection and different types of transitive relational rules that can model the complex familial relationships. Moreover, our method is capable of using training data to learn the weight of different similarity scores and relational features, an important ingredient of relational entity resolution. In our experimental evaluation, we demonstrated that our framework can effectively combine different signals, resulting in improved performance over state-of-the-art approaches on two datasets. In our experimental evaluation, we also showed that, in most cases, our model outperforms the baselines for a varying set of similarity functions and for varying levels of noise. Additionally, the experimental evaluation showed that the PSL models outperform the baselines when we fix the number of predicted matches.

In this paper, we motivate the importance of our approach with an application for resolving mentions in healthcare records. We additionally showed how we can extend the proposed framework to the domain of recommender systems to resolve products. However, the problem of entity resolution in richly structured domains has many additional applications. In domains similar to healthcare, companies such as `ancestry.com`, `genealogy.com`, `familysearch.org`, and `23andMe.com` provide genealogical discovery services, which require a similar entity resolution process. In addition, our approach can be very beneficial to applications in social networks where linking user accounts across several social platforms in the presence of a diverse set of relationships (e.g., friends, followers, followees, family cycles, shared groups), ambiguous names, and collective constraints such as bijection and transitivity, can provide great performance gains and improved user experience as we discuss in the next section.

In future work, we plan to apply our approach to a broader set of problems and discuss general strategies for multirelational entity resolution. Additionally, we plan to explore structured output learning techniques [85] inside PSL. Such techniques can directly consider the matching constraints during the learning phase instead of post processing the classification results. We also plan to explore temporal relations, e.g. ex-wife, and more complex relationships, e.g. adopted child. Finally, in certain cases, we might inadvertently introduce inaccurate relations when following the approach of Section 3.3. To address this, we plan to expand our work to account for uncertainty in the relational normalization step by assuming a probability assigned to each populated relationship instead of the hard values that we currently assign.

Chapter 4

Recommendations in Richly Structured Social Networks

Recent work on hybrid recommender systems has shown that recommendation accuracy can be improved by combining multiple data modalities and modeling techniques within a single model [2, 26, 27, 75, 77]. Existing hybrid recommender systems are typically designed for a specific problem domain, such as movie recommendations, and are limited in their ability to generalize to other settings or make use of any further information. As our daily lives become increasingly digitally connected, the list of data sources available for recommendations continues to grow. There is a need for general-purpose, extensible frameworks that can make use of arbitrary data modalities to improve recommendation.

The challenge of custom model-building has been extensively studied in the fields of probabilistic programming [45] and statistical relational learning (SRL) [43], which provide programming language interfaces for encoding knowledge and specifying models. Probabilistic programs can be used to encode graphical models for reasoning with graph-structured probabilistic dependencies. Graphical models are a natural approach to recommendations given that the user-item rating matrix can be interpreted as a graph, with weighted edges between users and items corresponding to the respective ratings [27].

In modern recommendation contexts, a bipartite user-item graph is insufficient to represent all available information, such as user-user and item-item similarity, content, social information, and metadata. For example, neighborhood-based collaborative filtering techniques can be interpreted as predicting ratings based on an extension of the user-item graph with additional edges between pairs of similar users or similar items (Figure 4.1). We need a more general representation to reason over this richly structured information.

In this work, we propose a general hybrid recommender framework, called HyPER (HYbrid Probabilistic Extensible Recommender), which leverages the flexibility of probabilistic programming in order to build adaptable and extensible hybrid recommender systems which reason over complex data. In particular, we use probabilistic soft logic (PSL) which was described in detail in Chapter 2. We reiterate that PSL is especially well-suited to collaborative-filtering based recommendation graphs as it is able to fuse information from multiple sources and it was originally designed as a flexible framework for reasoning and combining similarities [12]. It provides a general declarative framework for combining entity similarities, attribute similarities, and information from additional sources including the predictions of other algorithms. As discussed, PSL allows for efficient and scalable inference, which is crucial in a recommendation context.

Our contributions include (1) a general and extensible hybrid recommender system with a probabilistic programming interface, (2) a method for learning how to balance the different input signals in the hybrid system, and (3) extensive experimental studies using several information sources which validate the performance of the proposed framework and highlight contribution of each source to the

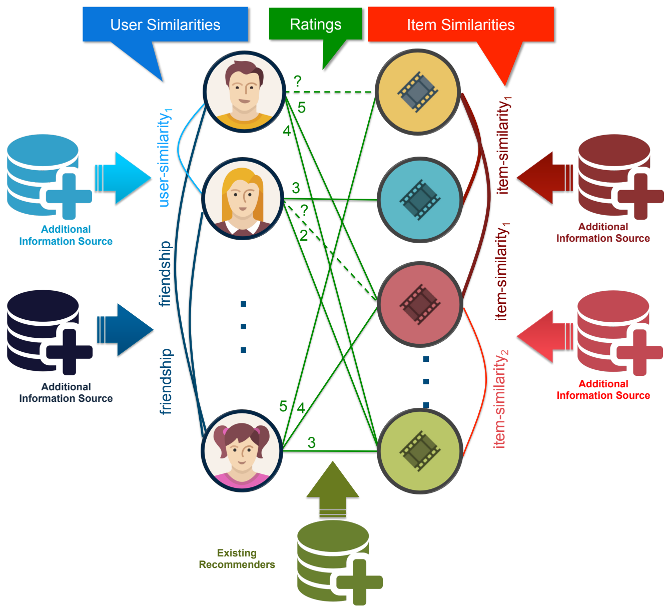


Figure 4.1: Example recommendation graph.

final prediction. To the best of our knowledge, our proposed HyPER framework is the first which provides a mechanism to extend the system by incorporating and reasoning over currently unspecified additional information types and similarity measures.

We evaluate our system on two rich datasets from the local business and music recommendation domains (Yelp and Last.fm) comparing our model to state-of-the-art recommendation approaches. Our results show that HyPER is able to effectively combine multiple information sources to improve recommendations, resulting in significantly improved performance over the competing methods in both datasets.

4.1 Background

Recommender systems play a significant role in many everyday decision-making processes which affect the quality of our lives, from the restaurant we have lunch at, to the hotel for our vacation, to the music we listen to. Traditional recommender systems primarily leverage underlying similarities between users and items in order to make predictions based on observed ratings. Content-based filtering (CB) approaches compute these similarities by using features extracted from content to build user profiles, which are compared with content features of items. While content-based approaches can recommend newly added items, they are limited by a lack of serendipity. The recommendations are limited to the user's known likes and do not generally include items out of the user's (recorded) comfort zone [76].

Collaborative filtering (CF) techniques address this by identifying similar users or items based on their rating patterns instead of content, using methods such as neighborhood-based approaches and matrix factorization models. However, collaborative filtering methods typically do not perform well in "cold-start" settings, where there are few ratings for a user or an item [64]. Moreover, pure rating-based collaborative filtering approaches cannot take advantage of data which may be available in addition to ratings.

To address these shortcomings, hybrid recommender systems (HRSs) were introduced, combining content-based and collaborative-filtering techniques (e.g. [2, 26, 27]). HRS techniques can improve performance over content-based and collaborative filtering methods alone, especially in the case where the ratings matrix is sparse [2]. However, existing HRSs have their own limitations. First, they are problem- and data-specific. Each HRS is typically motivated by a specific problem domain (e.g. movie recommendations) and the solution is fine-tuned to solve a specific problem with datasets of specific characteristics. Hence, HRSs typically cannot be generalized to different problem domains or input data, or be easily expanded to incorporate knowledge from richer datasets.

As the web has evolved into a participatory, user-driven platform, additional information is increasingly becoming available. Users form social networks, give verbal feedback on items via reviews, endorse or down-vote items or other users, form trust relationships, "check-in" at venues, and perform many other social actions that may potentially be leveraged to better understand users in order to improve recommendations. A flexible and extensible hybrid recommender system which can make use of this wealth of information is increasingly important.

The remainder of this Chapter is structured as follows. In Section 4.2, we place our system in the context of related work. In Section 4.3 we introduce HyPER, a general hybrid recommendation framework which is extensible and customizable using PSL. We systematically evaluate our framework in Section 4.4. Finally, we conclude with a discussion and future plans in Section 4.5.

4.2 Related Work

There is a large body of work on recommender systems; see Ricci et al. [100] for an overview. We focus our related work discussion on hybrid recommender systems, and particularly systems that can incorporate richly structured and social data as well as graphical modeling approaches. In Burke [13]'s taxonomy of hybrid recommender systems our work falls into the "feature augmentation" category.

Hybrid systems typically combine two or more approaches in order to provide better recommendations, usually content-based and collaborative filtering approaches [47, 37] or variations of collaborative filtering approaches [61]. Gunawardana and Meek [47] present a domain-agnostic hybrid approach for using content to improve item-item modeling. After the Netflix Prize competition, ensemble methods [57] have gained popularity. Factorization Machines [98] are a general matrix factorization method that can be applied to design hybrid factorization models. Recently, as user-generated content has become available, researchers have studied how to leverage information such as social relationships [75, 77], reviews [78, 74], tags [48], and feedback [103] to improve recommendations. Incorporating additional information for users and/or items is especially beneficial in cold-start settings [41]. Dooms [31] argues that a flexible recommendation system that automatically generates good hybrid models would be very valuable as information sources increase. Our model provides such flexibility, allowing for the combination of as many information sources as are available. Fakhraei et al. [35] use PSL to reason over multiple similarity measures for predicting drug-target interactions.

Chen at al. [21] learn the strength of ties between users based on multi-relational network information. The learned network is combined with item-based collaborative filtering to improve recommendation results. Burke et al. [14, 42] integrate different dimensions of data about users in a heterogeneous network by using metapaths to create multiple two-dimensional projections representing relationships between entities (e.g. users-tags) and then linearly combining these projections. Also using metapaths, Yu et al. [118] propose a global and a personalized recommendation model. In their approach, implicit feedback is incorporated into metapaths and latent features for users and items are generated using matrix factorization.

De Campos et al. [26] propose a probabilistic graphical modeling recommendation approach using Bayesian networks. Their approach combines individual predictions from content-based and user-based collaborative filtering components. Hoxha and Rettinger [54] also discuss a probabilistic graphical modeling representation, using Markov Logic Networks (MLNs) [101] to combine content with collaborative filtering. Both MLNs and HL-MRFs operate on undirected graphical models using a first-order logic as their template language, while Bayesian networks are directed. We chose HL-MRFs because they can represent ordered data such as ratings, and due to their scalability with parallel convex optimization for inference. Speed and scalability is of paramount importance in recommender systems and in particular when we run the prediction task collectively over multiple types of input data with a variety of similarity measures.

4.3 Proposed Solution

We propose HyPER, a general hybrid framework that combines multiple different sources of information and modeling techniques into a single unified model. HyPER offers the capability to extend the model by incorporating additional sources of information as they become available. Our approach begins by viewing the recommendation task as a bipartite graph, where users $\mathcal{U}$ and items $\mathcal{I}$ are the vertices, and ratings are edges between users and items [27]. Using PSL [4], a flexible statistical relational learning system with a probabilistic programming interface, this graph is then augmented to construct a probabilistic graphical model with additional edges to encode similarity information, predicted ratings, content and social information, and metadata. We then train the graphical model to learn the relative importance of the different information sources in the hybrid system, and make predictions for target ratings, using graphical model learning and collective inference techniques.

Figure 4.1 shows an overview of our modeling approach. In the figure, items and users are nodes, and green edges represent the ratings that users gave to items, with edge weights corresponding to the rating values. The goal is to predict the edge weights for unobserved edges, denoted as dashed lines. Neighborhood-based approaches find the k most similar users or similar items, and use their ratings to make these predictions. In our graph-based representation, we interpret these k-nearest neighbor relationships as k edges which are added to the graph. In Figure 4.1, blue edges encode user similarities and red edges correspond to item similarities.

We can further encode additional sources of information and outputs of other recommendation algorithms within this graph-based representation in a similar way, i.e. in the form of additional links or nodes. For instance, latent factor methods identify latent representations which can be used to augment the graph with weighted edges encoding predictions of user-item ratings based on the latent space. The latent representations can also be used to construct additional user-user and item-item edges by identifying similar users and similar items in the latent space. Content information and metadata, such as demographics and time information, can be incorporated in the graph representation by identifying further similarity links, or by adding nodes with attribute values, and edges to associate these values with users and items. Furthermore, social information from digital social media is inherently relational, and can readily be incorporated into a graph-based representation.

Having encoded all available information in the graph, the next step is to reason over this graph to predict unobserved user-item rating edges. We view the prediction task as inference in a graphical model, the structure of which is defined by our graph representation. We use the PSL framework, introduced in Chapter 2, to define a probability distribution over unobserved ratings. In the next section we describe in detail our unified recommender system modeling framework.

4.3.1 PSL Model for Hybrid Recommender Systems

The strengths of the HyPER framework include the ability to extensibly incorporate multiple sources of information in a unified hybrid recommendation model, as well as learning how to balance these signals from training data. HyPER models are specified using a collection of PSL rules which encode graph-structured dependency relationships between users, items, ratings, content and social information. Additionally, the model provides the flexibility to incorporate prior predictions, such as mean-centering predictors and the results of other recommendation algorithms. In what follows, we present the rules that define the HL-MRF model for the core of the HyPER framework. We emphasize that while this set of rules covers a breadth of input sources, the model can be readily extended to incorporate other sources of information such as time, implicit feedback, and social interactions, with the introduction of new PSL rules. Moreover, additional similarity measures and recommendation algorithms can straightforwardly be included with analogous rules.

User-based Collaborative Filtering

Motivated by the basic principles of the neighborhood-based approach, we can define PSL rules of this form:

$$\textsc{SimilarUsers}_{\textsc{sim}}(\mathtt{u}_1, \mathtt{u}_2) \wedge \textsc{Rating}(\mathtt{u}_1, \mathtt{i}) \Rightarrow \ \textsc{Rating}(\mathtt{u}_2, \mathtt{i}) \ .$$

This rule captures the intuition that similar users give similar ratings to the same items. The predicate $\textsc{Rating}(\mathtt{u}, \mathtt{i})$ takes a value in the interval $[0, 1]$ and represents the normalized value of the rating that a user $\mathtt{u}$ gave to an item $\mathtt{i}$, while $\textsc{SimilarUsers}_{\textsc{sim}}(\mathtt{u}_1, \mathtt{u}_2)$ is binary, with value 1 iff $\mathtt{u}_1$ is one of the k-nearest neighbors of $\mathtt{u}_2$. The similarities can be calculated with any similarity measure

$\textsc{sim}$, as we will describe in Section 4.3.1. The above rule represents a template for hinge functions which reduce the probability of predicted ratings as the difference between $\textsc{Rating}(\mathtt{u}_2, \mathtt{i})$ and $\textsc{Rating}(\mathtt{u}_1, \mathtt{i})$ increases, for users that are neighbors.

Item-based Collaborative Filtering

Similarly, we can define PSL rules to capture the intuition of item-based collaborative filtering methods, namely that similar items should have similar ratings from the same users:

$$\textsc{SimilarItems}_{\textsc{sim}}(\mathtt{i}_1, \mathtt{i}_2) \wedge \textsc{Rating}(\mathtt{u}, \mathtt{i}_1) \Rightarrow \quad \textsc{Rating}(\mathtt{u}, \mathtt{i}_2) \ .$$

The predicate $\textsc{SimilarItems}_{\textsc{sim}}(\mathtt{i}_1, \mathtt{i}_2)$ is binary, with value 1 iff $\mathtt{i}_1$ is one of the k-nearest neighbors of $\mathtt{i}_2$ (using similarity measure $\mathtt{sim}$), while $\textsc{Rating}(\mathtt{u}, \mathtt{i})$ represents the normalized value of the rating of user $\mathtt{u}$ to item $\mathtt{i}$, as discussed above.

Combining Collaborative Filtering Measures

By including both types of rules described in Sections 4.3.1 and 4.3.1 we can define an HL-MRF model that combines user-based and item-based techniques to predict ratings. There exist many measures available to compute similarities between entities for user-based and item-based methods, and these different measures capture different notions of similarity. For instance, in neighborhood-based approaches, vector-based similarity measures are broadly used, whereas in latent factor approaches other similarities, applicable to the low dimensional space, are preferred. While most existing recommender systems are designed to use a single similarity measure, HyPER allows for the simultaneous incorporation of multiple similarity measures, and can automatically adjust the importance of each based on training data.

In this instantiation of our HyPER framework we use the most popular similarity measures in the neighborhood-based recommendations literature [27]. More specifically, we apply Pearson's correlation and cosine similarity measures to calculate similarities between users and items; for the items we additionally apply the adjusted cosine similarity measure. To incorporate matrix-factorization collaborative filtering, and inspired by Hoff et al. [53], we compute similar users and items in the low-dimensional latent space using two popular distance measures in that space, namely, cosine and Euclidean. The user similarities are identified using the following rules:

$$\begin{aligned}
\textsc{SimilarUsers}_{\textsc{cosine}}(\mathtt{u}_1,\mathtt{u}_2) \wedge \textsc{Rating}(\mathtt{u}_1,\mathtt{i}) \Rightarrow & \quad \textsc{Rating}(\mathtt{u}_2,\mathtt{i}) \\
\textsc{SimilarUsers}_{\textsc{pearson}}(\mathtt{u}_1,\mathtt{u}_2) \wedge \textsc{Rating}(\mathtt{u}_1,\mathtt{i}) \Rightarrow & \quad \textsc{Rating}(\mathtt{u}_2,\mathtt{i}) \\
\textsc{SimilarUsers}_{\substack{\textsc{latent}\\\textsc{cosine}}}(\mathtt{u}_1,\mathtt{u}_2) \wedge \textsc{Rating}(\mathtt{u}_1,\mathtt{i}) \Rightarrow & \quad \textsc{Rating}(\mathtt{u}_2,\mathtt{i}) \\
\textsc{SimilarUsers}_{\substack{\textsc{latent}\\\textsc{euclidean}}}(\mathtt{u}_1,\mathtt{u}_2) \wedge \textsc{Rating}(\mathtt{u}_1,\mathtt{i}) \Rightarrow & \quad \textsc{Rating}(\mathtt{u}_2,\mathtt{i}) \ .
\end{aligned}$$

Analogous rules are introduced to identify similar items, but are omitted due to space limitations. As noted earlier, this initial set of similarity measures can be readily expanded by adding the corresponding rules, in the same form as above.

Mean-Centering Priors

Each individual user considered in a recommender system has her own biases in rating items (e.g. some users tend to be stricter than others). Moreover, each item's rating is influenced by its overall quality and popularity (e.g. a popular blockbuster may get higher ratings on average than a low-budget movie). To address such biases, a recommender system needs to incorporate a normalization mechanism, both per user, and per item. Using mean-centering normalization for neighborhood-based approaches, or including intercept terms in probabilistic latent factor models, addresses this issue and generally improves performance [27]. In our HyPER framework we encode this intuition with rules that encourage the ratings to be close to the average, per-user and per-item:

$$\begin{aligned} \textsc{AverageUserRating}(\texttt{u}) &\Rightarrow \quad \textsc{Rating}(\texttt{u},\texttt{i}) \\ \neg\textsc{AverageUserRating}(\texttt{u}) &\Rightarrow \neg\textsc{Rating}(\texttt{u},\texttt{i}) \end{aligned}$$

$$\begin{aligned} \textsc{AverageItemRating}(\texttt{i}) &\Rightarrow \quad \textsc{Rating}(\texttt{u},\texttt{i}) \\ \neg\textsc{AverageItemRating}(\texttt{i}) &\Rightarrow \neg\textsc{Rating}(\texttt{u},\texttt{i})\ . \end{aligned}$$

The predicate $\textsc{AverageUserRating}(\texttt{u})$ represents the average of the ratings over the set of items that user $\texttt{u}$ provided in the training set.
Similarly, $\textsc{AverageUserRating}(\texttt{i})$ represents the average of the user ratings an item $\texttt{i}$ has received. The pair of PSL rules per-user and per-item corresponds to a "V-shaped" function centered at the average rating, which penalizes the predicted rating for being different in either direction from this average.

In order to capture cases where we have no information about a user or an item, we use a general prior rating centered at the average value of all of the ratings in the system (i.e. the average over all items rated by all users). We encode this prior with the following rules:

$$\begin{aligned} \textsc{PriorRating} &\Rightarrow \ \ \textsc{Rating}(\texttt{u},\texttt{i}) \\ \neg\textsc{PriorRating} &\Rightarrow \neg\textsc{Rating}(\texttt{u},\texttt{i})\ . \end{aligned}$$

The real-valued predicate $\textsc{PriorRating}$ represents the average of all of the ratings.

Using Additional Sources of Information

Incorporating other sources of information pertaining to items, users, and their respective ratings to our framework is straightforward. In the present instantiation of our framework, we use the content of the items to find similar items:

$$\textsc{SimilarItems}_{\textsc{Content}}(\texttt{i}_1, \texttt{i}_2) \wedge \textsc{Rating}(\texttt{u}, \texttt{i}_1) \Rightarrow \ \textsc{Rating}(\texttt{u}, \texttt{i}_2)\ .$$

In this rule, the predicate $\textsc{SimilarItems}_{\textsc{Content}}(\texttt{i}_1, \texttt{i}_2)$ represents items that have similar content-based features (e.g. in the movie recommendation domain such features are the genre, actor, director, etc.), instead of similar ratings.

The HyPER framework can also incorporate social information, when this is available. For instance, in the present instantiation of the system, we leverage social network friendship links as follows:

$$\textsc{Friends}(\texttt{u}_1, \texttt{u}_2) \wedge \textsc{Rating}(\texttt{u}_1, \texttt{i}) \Rightarrow \ \textsc{Rating}(\texttt{u}_2, \texttt{i})\ .$$

Note that our framework is flexible and can incorporate many other sources of information that are available. For instance, we can leverage demographic information by computing similarity neighborhood relationships in demographic feature space and employing the rule:

$$\textsc{SimilarUsers}_{\textsc{Demo}}(\texttt{u}_1, \texttt{u}_2) \wedge \textsc{Rating}(\texttt{u}_1, \texttt{i}) \Rightarrow \ \textsc{Rating}(\texttt{u}_2, \texttt{i})\ .$$

Leveraging Existing Recommendation Algorithms

Every recommendation algorithm has strengths and weaknesses which may depend on data-specific factors such as the degree of sparsity or the shape of the data matrix. This imposes a big limitation in the recommendation process, as choosing one algorithm as the core of a recommender system limits its strength to a particular set of domains. In this work, our motivation is to provide a flexible framework that can be used as-is to generate accurate recommendations for any domain and data regime. Therefore, instead of selecting a single recommendation algorithm, we propose to incorporate the predictions from different methods into our unified model. These predictions are further augmented with any other available information, using the rules discussed above. For example, the predictions from matrix factorization (optimizing regularized squared error via stochastic gradient descent) (MF), Bayesian probabilistic matrix factorization (BPMF) [102], and item-based collaborative filtering can be incorporated in the model via the following rules:

$$\begin{aligned}
\textsc{Rating}_{\text{MF}}(\texttt{u},\texttt{i}) &\Rightarrow \ \textsc{Rating}(\texttt{u},\texttt{i}) \\
\neg\textsc{Rating}_{\text{MF}}(\texttt{u},\texttt{i}) &\Rightarrow \neg\textsc{Rating}(\texttt{u},\texttt{i}) \\[2ex]
\textsc{Rating}_{\text{BPMF}}(\texttt{u},\texttt{i}) &\Rightarrow \ \textsc{Rating}(\texttt{u},\texttt{i}) \\
\neg\textsc{Rating}_{\text{BPMF}}(\texttt{u},\texttt{i}) &\Rightarrow \neg\textsc{Rating}(\texttt{u},\texttt{i}) \\[2ex]
\textsc{Rating}_{\substack{\text{ITEM}\\\text{BASED}}}(\texttt{u},\texttt{i}) &\Rightarrow \ \textsc{Rating}(\texttt{u},\texttt{i}) \\
\neg\textsc{Rating}_{\substack{\text{ITEM}\\\text{BASED}}}(\texttt{u},\texttt{i}) &\Rightarrow \neg\textsc{Rating}(\texttt{u},\texttt{i}) \ .
\end{aligned}$$

Additional algorithms can be easily incorporated in a similar manner.

4.3.2 Learning the PSL Model

An important task of any hybrid recommender system is to trade off and balance the different information sources according to their informativeness for predicting ratings. Each of the first-order rules introduced above corresponds to a different information source in our hybrid model, and is associated with a non-negative weight w_j in Equation 2.1. We learn the weight of each rule following

Dataset	Yelp	Last.fm
No. of users	34,454	1,892
No. of items	3,605	17,632
No. of ratings	99,049	92,834
Content	514 business categories	9,719 artist tags
Social	81,512 friendships	12,717 friendships
Sparsity	99.92%	99.72%

Table 4.1: Dataset Description

		Yelp		Last.fm	
Model		RMSE (SD)	MAE (SD)	RMSE (SD)	MAE (SD)
Base models	Item-based	1.216 (0.004)	0.932 (0.001)	1.408 (0.010)	1.096 (0.008)
	MF	1.251 (0.006)	0.944 (0.005)	1.178 (0.003)	0.939 (0.003)
	BPMF	1.191 (0.003)	0.954 (0.003)	1.008 (0.005)	0.839 (0.004)
Hybrid models	Naive hybrid	1.179 (0.003)	0.925 (0.002)	1.067 (0.004)	0.857 (0.004)
	BPMF-SRIC	1.191 (0.004)	0.957 (0.004)	1.015 (0.004)	0.842 (0.004)
	HyPER	**1.173** (0.003)	**0.917** (0.002)	**1.001** (0.004)	**0.833** (0.004)

Table 4.2: Overall Performance of Different Recommender Systems on Yelp and Last.fm.

the process described in Section 2.1.

4.4 Results

In this section we evaluate our HyPER framework with comparison to state-of-the-art recommender algorithms. We report experimental results on two popular datasets for both the complete hybrid model and for each individual component of our hybrid models.[1]

4.4.1 Datasets and Evaluation Metrics

For our experimental evaluation we used the Yelp academic dataset and the Last.fm dataset.[2][3] Our goal with Yelp is to recommend local businesses to users

[1]Code is available at `https://github.com/pkouki/recsys2015`
[2]`https://www.yelp.com/academic_dataset`
[3]`http://grouplens.org/datasets/hetrec-2011/`

by predicting the missing ratings of businesses based on previous ratings. For our experiments, we used all businesses, users, and ratings from Scottsdale, Arizona, one of the largest cities in the dataset. Since we employ user and item similarities as well as social information, it makes sense to focus those relationships within the subgroup of the businesses of one physical location. Additionally, we used the categories of each business as content information and the explicit user friendships provided as social information. Yelp users give ratings from 1 to 5 stars, which we linearly scaled into the [0,1] range that PSL operates over for the purposes of our model.

For the Last.fm dataset our goal is to recommend artists to users. As Last.fm does not provide explicit user-artist ratings we leverage the number of times a user has listened to an artist to construct implicit ratings. We use a simple model-based approach, where the repeated-listen counts for each user across artists are modeled with a negative-binomial distribution. We used this distribution as it is appropriate for count data where the sample variance is greater than the sample mean, which is typically the case for Last.fm. For each user, we fit a negative binomial to their counts via maximum likelihood estimation, and we calculate the user's implicit rating for an artist as the cumulative distribution function (CDF) of the distribution, evaluated at the artist's count. This corresponds to the proportion of hypothetical artists that a user would listen to less than the given artist, under the model. The Last.fm dataset also includes tags on artists that we use for content-based information, as well as user friendship data that we use for social recommendation.

We deliberately selected two datasets with a similar total number of ratings but a different ratio of users to items. Different recommendation methods may perform better with more users than items or vice versa, and hybrid systems must account for this. We provide the summary statistics of the two datasets in Table 4.1.

To learn the appropriate balance between information sources for HyPER, i.e. to learn the weights of each rule in the model, we train using the approximate maximum likelihood method described in Section 4.3.2, with 20% of the training folds treated as the prediction target variables $\mathbf{Y}$. During testing, we performed MAP inference to make predictions using ADMM. We report the root mean squared error (RMSE) and the mean absolute error (MAE). We compute these metrics by performing 5-fold cross-validation and reporting the average cross-validated error.

4.4.2 Experimental Results

We report overall results with comparison to a selection of competing algorithms in Table 4.2, and show more detailed results for the individual components of our hybrid models in Tables 4.3 and 4.4. The following sections discuss these results.

Overall Performance Comparison

We study the performance of HyPER in comparison to several state-of-the-art models. We considered the following baselines:

- **Item-based:** The method in Equation 4.16 from [27], using Pearson's correlation with a mean-centering correction, as implemented in Graphlab.[4]
- **Matrix factorization (MF):** MF optimizing for regularized squared error using stochastic gradient descent [64], as implemented in Graphlab.

[4]`http://www.dato.com`

- **Bayesian probabilistic matrix factorization (BPMF):** The Bayesian variant of probabilistic matrix factorization, trained using Gibbs sampling [102].
- **Naive hybrid:** A simple hybrid approach where the predictions of the above models are averaged.
- **BPMF with social relations and items' content (BPMF-SRIC):** A hybrid model that extends BPMF with social and content information [75].

The performance of our model is statistically significantly better than the baselines at $\alpha = 0.05$ for both datasets and evaluation metrics when using paired t-test. We denote with bold the numbers that are statistically significantly better. These results confirm our initial intuition that by incorporating a wide variety of information sources and balancing them appropriately, the HyPER framework manages to perform very well with rich and diverse datasets. We explore HyPER components in more detail in the following section.

Performance per Information Type

For each type of information, we further evaluated our approach by building simple HyPER models with each rule individually, and comparing these to combined hybrid sub-models comprising all of the corresponding rules of that type. Each sub-model also included the corresponding mean-centering rules (e.g. the user-average rating rule for the user-based models). To balance the effect of each rule, we performed weight learning within each training fold to learn rule weights. We report the results for the Yelp dataset in Table 4.3 and for the last.fm dataset in Table 4.4. The results show that for each information type, the HyPER model which combines all of the corresponding components performs significantly better than each component, considered in isolation. We denote with bold the cases where the performance of each HyPER model is statistically significantly better than all the individual models in the same category at $\alpha = 0.05$ using paired t-test. The final HyPER model shown in the last line, which combines all of the available information into a single hybrid model, also performs statistically significantly better than all sub-models and baselines.

Mean-Centering Priors: We created simple HyPER models using only the average rating of each user, or the average rating of each item, or the average overall rating, as well as a combined model. In the case of Yelp, the item-average model had a lower error compared to the user average rule, while the opposite was true for Last.fm (Tables 4.3(a) and 4.4(a)). This may be because the ratio of users to items is different in the two datasets. The combined model performed better than the individual models in both datasets.

Neighborhood-Based Collaborative Filtering: We constructed individual models based on the similarities described in Section 4.3.1. The number of neighbors is typically set to between 20 and 50 in the literature [27], and so we used 50 neighbors for users/item in all experiments. We also employed a mean-centered approach by providing each of these models with the corresponding average-rating mean-centering rules (e.g. the average user-rating rule for user-based collaborative filtering). As in the previous experiment, user-based techniques perform poorly on Yelp, but have better performance on Last.fm (Tables 4.3(b), 4.4(b) and 4.3(c), 4.4(c)). The opposite is true for the item-based techniques, which perform poorly on Last.fm, but better on Yelp. The performance varied between the different similarity measures, with distances computed in the latent space usually performing the best individually. Again, the HyPER combination of all similarity measures improves performance.

	Model	RMSE (SD)	MAE (SD)
(a) Mean-centering	User average rating	2.313 (0.008)	1.656 (0.008)
	Item average rating	1.215 (0.003)	0.932 (0.001)
	Overall average rating	1.280 (0.005)	1.030 (0.004)
	HyPER (all mean-centering rules)	**1.199** (0.003)	0.952 (0.002)
(b) User-based	Similar users (Pearson)	2.313 (0.008)	1.656 (0.008)
	Similar users (cosine)	2.313 (0.008)	1.657 (0.008)
	Similar users (latent, cosine)	2.227 (0.007)	1.597 (0.007)
	Similar users (latent, Euclidean)	2.226 (0.009)	1.596 (0.008)
	HyPER (all user-based rules)	**2.194** (0.008)	**1.573** (0.008)
Item-based	Similar items (Pearson)	1.213 (0.004)	0.931 (0.002)
	Similar items (cosine)	1.211 (0.003)	0.928 (0.001)
	Similar items (adjusted cosine)	1.210 (0.004)	0.924 (0.002)
	Similar items (latent, cosine)	1.212 (0.003)	0.923 (0.001)
	Similar items (latent, Euclidean)	1.212 (0.003)	0.931 (0.001)
	HyPER (all item-based rules)	**1.208** (0.004)	0.923 (0.002)
(d) Content &Social	Similar items (content)	1.200 (0.003)	0.939 (0.002)
	Friends	1.199 (0.003)	0.932 (0.002)
	HyPER (content + social rules)	**1.195** (0.003)	**0.927** (0.002)
(e) Base models	Item-based	1.216 (0.004)	0.932 (0.001)
	MF	1.251 (0.006)	0.944 (0.005)
	BPMF	1.191 (0.003)	0.954 (0.003)
	HyPER (baseline rules)	**1.179** (0.003)	**0.926** (0.002)
	HyPER (all rules)	**1.173** (0.003)	**0.917** (0.002)

Table 4.3: Performance of HyPER sub-models on Yelp.

Additional Sources of Information: We constructed individual and hybrid models using friendship information, as well as content similarity between items based on the business category and the tags of artists for Yelp and Last.fm respectively. We used Jaccard similarity for both datasets. In each sub-model we also provided additional rules for mean centering using both average user and item ratings. Content and friendship information help performance in both datasets, and the model that combines both content and social information matched and often improved on the best individual models' performance (Tables 4.3(d) and 4.4(d)).

Leveraging Existing Algorithms: As discussed in section 4.3.1, our framework is able to combine predictions from a number of different models. In Tables 4.3(e) and 4.4 (e) we show the performance of three baseline recommenders, and in the fourth line we present the results of a HyPER ensemble which combines

	Model	RMSE (SD)	MAE (SD)
(a) Mean-centering	User average rating	1.043 (0.004)	0.873 (0.004)
	Item average rating	1.399 (0.009)	1.092 (0.008)
	Overall average rating	1.792 (0.004)	1.464 (0.004)
	HyPER (all mean-centering rules)	**1.032** (0.004)	**0.861** (0.004)
(b) User-based	Similar users (Pearson)	1.043 (0.004)	0.874 (0.004)
	Similar users (cosine)	1.043 (0.004)	0.873 (0.004)
	Similar users (latent, cosine)	1.025 (0.004)	0.862 (0.004)
	Similar users (latent, Euclidean)	1.025 (0.004)	0.863 (0.004)
	HyPER (all user-based rules)	1.025 (0.004)	**0.861** (0.004)
Item-based	Similar items (Pearson)	1.397 (0.008)	1.098 (0.006)
	Similar items (cosine)	1.396 (0.008)	1.100 (0.007)
	Similar items (adjusted cosine)	1.405 (0.008)	1.092 (0.007)
	Similar items (latent, cosine)	1.379 (0.009)	1.080 (0.008)
	Similar items (latent, Euclidean)	1.379 (0.008)	1.081 (0.008)
	HyPER (all item-based rules)	**1.362** (0.007)	**1.070** (0.006)
(d) Content &Social	Similar items (content)	1.029 (0.004)	0.867 (0.004)
	Friends	1.013 (0.004)	0.853 (0.004)
	HyPER (content + social rules)	1.013 (0.004)	**0.857** (0.004)
(e) Base models	Item-based	1.408 (0.010)	1.096 (0.008)
	MF	1.178 (0.003)	0.939 (0.003)
	BPMF	1.008 (0.005)	0.839 (0.004)
	HyPER (baseline rules)	**1.005** (0.005)	**0.836** (0.004)
	HyPER (all rules)	**1.001** (0.004)	**0.833** (0.004)

Table 4.4: Performance of HyPER sub-models on Last.fm.

the results of those recommenders, without any additional rules. The combined model performed better than the individual baselines.

Relative Importance of Information Sources: When performing weight learning (Section 4.3.2), the learned weights of the rules are indicative of the relative importance of the signals. For Last.fm, average user ratings had a high rule weight while average item ratings did not, while the reverse was true for Yelp, suggesting a difference in the importance of user judiciousness versus item popularity between the data sets. Item similarities had a high weight for Last.fm, while MF predictions had a high weight for Yelp. Negated rules, which decrease predicted ratings, were typically weighted lower than their non-negated counterparts. In general, the rules for BPMF predictions had high weights.

4.5 Conclusions and Future Work

In this Chapter we presented HyPER, a new hybrid recommender system which is flexible, problem-agnostic, and is easily extensible via a probabilistic programming interface. HyPER uses a hinge-loss MRF formulation, allowing scalable and accurate inference. Our comprehensive experiments demonstrate that HyPER can learn to appropriately balance many information sources, resulting in improved performance over previous state-of-the-art approaches on two benchmark datasets.

In our future work we plan to extend our model to account for knowledge coming from ontologies as well as temporal signals. Finally, the current evaluation shows that our model outperforms state-of-the-art algorithms for the rating prediction task. In the future, we would like to evaluate the performance of our model in the ranking task and compare it with state-of-the-art algorithms such as Bayesian Personalized Ranking [99].

Chapter 5

Explanations in Richly Structured Social Networks

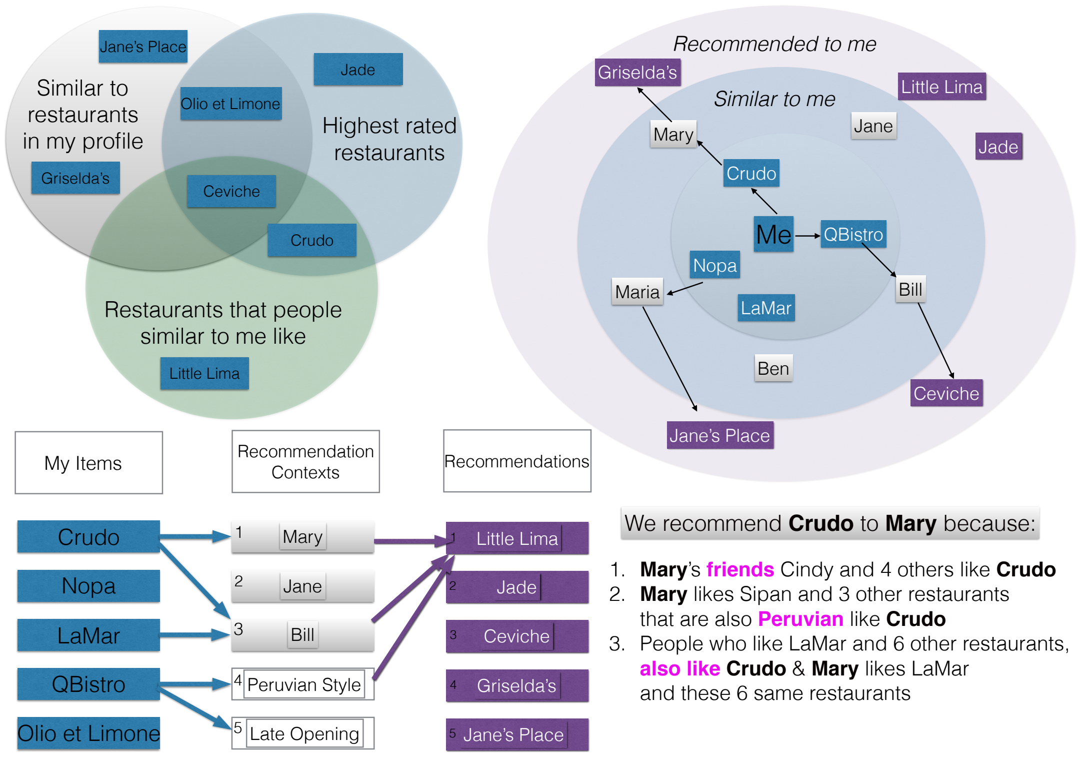
A driving force behind recent improvements in recommender systems are frameworks that combine information from diverse sources such as social connections, collaborative filtering (CF) approaches, and item metadata to provide better recommendations. These "hybrid" recommender systems have proven effective in making state-of-the-art recommendations, but their benefits have come at the cost of increased complexity and opacity. As recommendations have become central to combating information overload and shaping decisions, users increasingly demand convincing explanations to help them understand why particular recommendations are made [11, 86]. In this Chapter, we develop a framework for providing real-time, personalized explanations from hybrid recommenders and perform two real-world user studies to better understand which explanations and visualizations are the most convincing.

The majority of literature on explaining recommendations [52, 10, 107, 116, 20] has focused on studying explanations from non-hybrid (single-source) recommender systems. Typically, explanations from single-source recommenders come in a *single style*, e.g., a content-based recommender system produces content-based explanations. Existing work has explored user preferences for these single-style explanations [52, 10]. Visualization techniques for explaining recommendations include interfaces with concentric circles [87, 59], Venn diagrams [91], and pathways between columns [11], among many others. A recent survey [90] of different single-style explanation approaches has concluded that hybrid explanations, which combine multiple styles, such as user-based and item-based, are more effective than non-hybrid counterparts. Despite these findings, there has been no comprehensive study to determine the best methods for presenting recommendations while taking into account user preferences for hybrid explanations.

In this Chapter, we use the basic design principles described in Chapter 4 to build a music recommender system capable of incorporating any number of information sources. Then, we extend this system to provide explanations that vary in style, volume (i.e., number of explanation styles), and visualization format. Finally, we conduct two large user studies, a non-personalized and a personalized one. In the first, non-personalized study, users evaluate several different design approaches (e.g., textual, visual) for hybrid explanations. This general evaluation strategy can be used to study user preferences for different recommendation domains, such as career sites, music services, and navigational routes. To the best of our knowledge, this is the first study that adapts visualization techniques to hybrid recommenders and compares user preferences for hybrid explanations. We use the findings from the first study and perform a second personalized one, where we provide real users of a social media site personalized recommendations with hybrid explanations. Our goal is to understand how different variables (style, volume, format) impact the subjective persuasiveness of recommendations. Recent research [8] has indicated that there may be a relationship between a person's personality and the type of explanation that is most persuasive, so we also conduct an exploratory analysis for hybrid explanations. To the best of our knowledge, our work is the first comprehensive study of the effect of such variables on *personalized hybrid explanations*.

In more detail, in the first part of our work, we extend HyPER introduced in Chapter 4, to produce real-time recommendations while incorporating a variety of information sources. We build a real-time data collection system for acquiring a user's history, social connections, tags, and popularity statistics from a social media site. We use these signals to create a hybrid model similar to the model described in Chapter 4 that incorporates user-user and item-item similarities using CF, content, social, and popularity information. Next, we implement a parser that generates customized explanations from the output of the hybrid system in real time. We support several different explanation styles, including user-based, item-based, content, social, and item popularity. Table 5.1 shows an example of a recommendation along with the explanations generated by our framework.

In the second part of our work, we study the effect of different explanation presentation styles on user experience. To this end, we identify several dimensions for designing interfaces. We conduct a crowd-sourced user study ($N = 200$) using Amazon Mechanical Turk (AMT) where we show to the participants a set of different interfaces that provide recommendations along with hybrid explanations. This study answers several fundamental questions about designing hybrid explanations: 1) What visualization is best for hybrid explanations? 2) How should explanations be organized? 3) How much information should be in each explanation? 4) How detailed should each explanation be? Figure 5.1 presents a sample of different visualizations that we generated in order to understand user preferences for hybrid explanations. Among different visualizations we find that Venn



We recommend **Crudo** to **Mary** because:

1. **Mary**'s **friends** Cindy and 4 others like **Crudo**
2. **Mary** likes Sipan and 3 other restaurants that are also **Peruvian** like **Crudo**
3. People who like LaMar and 6 other restaurants, **also like Crudo** & **Mary** likes LaMar and these 6 same restaurants

Figure 5.1: A subset of visualizations presented in our user study of hybrid explanations.

diagrams outperform all other visual interfaces. Additionally, we find that users do not prefer a specific form of textual explanations, i.e., different presentations of textual explanations perform more or less the same.

In the third part of our work, we generate real-time recommendations along with personalized explanations for users of the last.fm music platform. We conduct a crowd-sourced user study ($N = 198$) using AMT, recruiting users with active last.fm accounts. During the study, we crawl each user's music preferences and run the hybrid model, producing real-time recommendations along with explanations. First, we ask users to subjectively evaluate the accuracy and novelty of recommendations (without providing any explanation) generated by our model and randomly selected items. This online evaluation demonstrates a 37% im-

Explanation Style	We recommend *U2* because:
(I) User-based	User *Aren* with whom you share similar tastes in artists listens to U2.
(II) Item-based	(a) People who listen to your profile item *AC/DC* also listen to U2. (b) Last.fm's data indicates that U2 is similar to *Coldplay* that is in your profile.
(III) Content	(a) U2 has similar tags as *Beatles* that is in your profile. (b) U2 is tagged with *rock* that is in your profile.
(IV) Social	Your friend *Cindy* likes U2.
(V) Item popularity	U2 is a very popular in the last.fm database with 3.5 million listeners and 94 million playcounts.

Table 5.1: An example of a hybrid explanation for a single artist (U2). Multiple styles are generated from the hybrid model, including two item-based and content-based sources. The first four styles are personalized, while the fifth one is non-personalized.

provement in accuracy over randomly generated recommendations. Next, we ask users to evaluate the persuasiveness of different explanation styles. We find that users prefer item-based and content-based styles. Inspired by Berkovsky et al. [8], we also consider the personality traits of users as a control variable. We find interesting patterns between explanation persuasiveness of particular styles and personality traits which we analyze in our results. Next, we study whether the volume of the explanation styles can affect the persuasiveness of the explanation. For example, is a user convinced when they are provided with three explanation styles but overwhelmed when the number of provided styles increases to six? Our analysis indicates that users lose interest after we show to them three to four different explanation styles. Finally, we experiment with a variety of formats that we can present hybrid explanations to the participants, such as textual or visual. We find that textual explanations are perceived as most persuasive.

The remainder of the Chapter is structured as follows. In Section 5.1 we discuss the related work. In Section 5.2 we describe our generic hybrid recommendation framework. For the purpose of this Chapter, we use the music domain as an example and specifically data and users from last.fm. Our framework uses the basic design principles described in Chapter 4. In Sections 5.3 and 5.4 we describe in detail the non-personalized and personalized user studies, the research questions, and our results. Finally, in Section 5.5 we report the basic conclusions and describe our future work plans.

5.1 Related Work

We organize our discussion of previous studies on explanations for recommender systems along three themes: i) work on single-style explanations, ii) work combining more than one explanation style and, iii) work surveying the state-of-the-art in explanations for decision support and recommender systems.

Single-Style Explanations. Herlocker et al. [52] show that certain explanation and presentation styles can increase a recommender system's effectiveness in convincing users to make a purchase. Bilgic and Mooney [10] compare single-style explanations that use content-based keywords, item-based CF, or prior rating history. Vig et al. [116] show that explanations using tags improve effectiveness. Tintarev and Masthoff [109] found that, despite improving user satisfaction, personalization can reduce the effectiveness of content-based explanations. Recently, Oramas et al. [89] built a music knowledge base and generated content-based natural language explanations. They found that the effectiveness of an explanation depends on the familiarity with recommender systems and the users' music education. PeerChooser [87] provides user-based CF explanations through an interactive graphical interface in the form of concentric circles. Berkovsky et al. [8] study the effect of three different explanation styles (item-based, average rating, and popularity-based) on user trust considering the users' personality traits as a control variable. Inspired by this work, we study whether varying the explanation style or volume changes the persuasiveness of explanations when controlling for different personality traits.

Hybrid Explanations. Most research on hybrid explanations focuses on proposing graphical interfaces to visualize the different explanation styles. TalkExplorer [115] combines content, tag, and social-based filtering techniques to provide an interactive interface in the form of clustermaps. SetFusion [91] builds on TalkExplorer and replaces clustermaps with Venn diagrams showing improved user experience. TasteWeights [11] builds an interactive hybrid recommender system that combines social, content, and expert information. The framework shows the reasoning behind the recommendations in the form of pathways among columns. Nguyen et al. [83] aim to reduce the noise in user ratings by proposing interfaces that support explanations in the form of tags, exemplars, and their combination. Symeonidis et al. [107] combine content-based filtering and rating history to generate natural language explanations which are all of the same type. Finally, Kouki et al. [69] manually generate hybrid explanations in a restaurant recommendation setting. The authors conduct a synthetic user study where participants evaluate non-personalized explanations that were manually produced. In this Chapter, we implement a hybrid recommender system which automatically generates recommendations together with explanations, building on a system called HyPER [65]. We use this system to generate personalized, real-time recommendations with explanations for active users of a music platform. In our personalized user study we analyze both the recommendation quality and the explanation persuasiveness by varying several different variables.

Surveys on Explanations. Nunes and Jannach [86] review the literature on explanations in decision-support systems. The authors distinguish variables such as the length of the explanation, its vocabulary, and the presentation of the explanation and conclude that additional studies are necessary to assess the impact of these variables. One of the goals of our work is to determine whether the explanation length and its presentation affect user satisfaction. Friedrich and Zanker [39] propose a taxonomy that categorizes different explainable recommender systems. The authors argue that future research should create new kinds of information, interaction, and presentation styles and also analyze how, and under what conditions, these will affect different explanation objectives. To this end, we offer seven different explanation styles and study their effect on persuasiveness when taking different variables into account.

To summarize, our work differs from prior art in the following ways:

- Several general user interfaces (GUIs) and visualizations have been proposed for recommendations, including concentric circles (PeerChooser [87, 59]), clustermaps (TalkExplorer [115]), Venn diagrams (SetFusion [91]), and paths among columns (TasteWeights [11, 60]). Extending these ideas, we focus on *hybrid explanations* and study user preferences across designs and interfaces.

- Existing work proposing explanations either does not involve a recommendation algorithm [8], or uses a baseline recommender [11, 89]. In our case, we show how to generate explanations from the HyPER recommender system that has showed improved performance over the state-of-the-art. Additionally, we evaluate the accuracy of our framework in an online setting over real data. Our work considers seven different explanation styles, while most of prior work considers up to three explanation styles. To the best of our knowledge, our personalized user study is the first one analyzing the effect of different personalized explanation styles, their volume, and format on persuasiveness. Finally, our personalized study is the first that considers the users' personality traits as a control variable.

5.2 Explainable Hybrid Recommender

In this section, we describe how we use the hybrid recommender system (HyPER) presented in Chapter 4 to generate explainable recommendations. We first describe how we use HyPER to implement a music recommender system (which we call HyPER-music) and then we discuss how we transform the model's probabilistic factors to explanations capturing the different recommender signal types.

5.2.1 Hybrid Music Recommender Model

As we saw, HyPER provides a generic and extensible recommendation framework with the ability to incorporate any other sources of information that are available in any custom dataset or application scenario. In this chapter, we focus on music recommendations. We use a subset of all the rules proposed in HyPER and, given its extensibility, we add several rules to leverage dataset-specific information available in our music dataset. We propose a hybrid music-recommender system, called HyPER-music, which consists of the following rules:

$$\textsc{SimUsers}_{CF}(u_1, u_2) \wedge \textsc{Listens}(u_1, a) \Rightarrow \textsc{Listens}(u_2, a) \tag{5.1}$$

$$\textsc{SimArtists}_{CF}(a_1, a_2) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2) \tag{5.2}$$

$$\textsc{SimArtists}_{last.fm}(a_1, a_2) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2) \tag{5.3}$$

$$\textsc{SimArtists}_{content}(a_1, a_2) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2) \tag{5.4}$$

$$\textsc{HasTag}(a_1, t) \wedge \textsc{HasTag}(a_2, t) \wedge \textsc{Listens}(u, a_1) \Rightarrow \textsc{Listens}(u, a_2) \tag{5.5}$$

$$\textsc{SimFriends}(u_1, u_2) \wedge \textsc{Listens}(u_1, a) \Rightarrow \textsc{Listens}(u_2, a) \tag{5.6}$$

$$\textsc{PopularArtist}(a) \Rightarrow \textsc{Listens}(u, a) \tag{5.7}$$

$$\neg\textsc{Listens}(u, a) \tag{5.8}$$

The logic behind the above rules is similar to the logic behind the rules described in Section 4.3. Specifically, rule 5.1 captures the intuition that similar users listen to similar artists. A predicate such as $\textsc{Listens}(u_2, a)$ takes values in the interval $[0, 1]$ and represents the probability that user u_2 will listen to artist a. Higher predicate values indicate higher probability that the given user will listen to the given artist. As before, predicate $\textsc{SimUsers}_{CF}(u_1, u_2)$ is binary, with value 1 iff u_1 is one of the k-nearest neighbors of u_2. We compute user similarities using CF information (indicated by the CF subscript). We compute similar users using the Jaccard and cosine similarities. We compute the Jaccard similarity using the set of artists a given user has listened to, and cosine similarity using vectors containing the number of times a user listened to each artist. As before, we use the 20 most similar neighbors. This limit applies to all similarities that we describe in the rest of this section.

Rule 5.2 captures the intuition that a user listens to similar artists. Artist similarity is computed using CF information by computing Jaccard similarity, i.e., which are the users that have listened to an artist. Rule 5.3 is similar to rule 5.2 with the difference that we use last.fm's artist similarity (described in Section

5.4.1). We don't know the exact formula for this similarity but it is a combination of CF and tag information. Rule 5.4 captures the intuition that users are likely to listen to artists with similar content. In this case, we compute content similarity using tags. More specifically, we compute the Jaccard similarity metric between two artists by using the shared tags of the artists. Rule 5.5 is a simpler version of rule 5.4 and captures the intuition that a user will likely listen to two artists sharing the same tag.

Rule 5.6 captures the intuition that friends with similar tastes listen to same artists. Rule 5.7 captures that intuition that a user will likely listen to a popular artist from the last.fm database. Rule 5.8 captures our general belief that a user will likely not listen to an artist. Again, we note that the model is very easy to extend to incorporate new information sources by adding additional first-order rules.

5.2.2 Generating Personalized Explanations

As discussed in Chapter 2, the rules used by any PSL model specify dependencies between variables and evidence. After encoding all available information, i.e., similarities and observed user-item likes, the next step is to use our model for predicting unobserved user-item likes. During grounding, the model is combined with data and set of propositions is instantiated. As described in detail in Section 4.3, the set of ground rules defines a probabilistic graphical model. Performing inference over this model generates predictions for unseen (i.e., unobserved) user-artist pairs, captured by the $\textsc{Listens}$ predicate. After the inference completes for a user u, we select the $\textsc{Listen}(u, a)$ that scored in the top k positions. For each of the top k $\textsc{Listens}(u, a)$, we use the groundings generated during inference to create personalized explanations of the following styles:

- **User-based**, with explanations similar to the example of Table 5.1(I) using the groundings of rule 5.1.
- **Item-based CF** and **item-based last.fm**, with explanations similar to Table Table5.1(II-a, II-b), using the groundings of rules 5.2 and 5.3 respectively.
- **Content-based Jaccard** and **content-based tags**, with explanations similar to Table 5.1(III-a, III-b) using the groundings of rules 5.4 and 5.5 respectively.
- **Social-based**, with explanations similar to Table 5.1(IV) using the groundings of rule 5.6.
- **Popularity-based**, with explanations similar to Table 5.1(V) using the groundings of rule 5.7.

As an example, let's assume that for user *Jen*, the predicted value of the unobserved variable $\textsc{Listens}(Jen, U2)$ has the highest value among all other predicted values and, during inference, the following ground rules associated with $\textsc{Listens}(Jen, U2)$ were generated:

$$\begin{aligned}
\textsc{SimUsers}_{CF}(Jen, Aren) \wedge \textsc{Listens}(Aren, U2) &\Rightarrow \textsc{Listens}(Jen, U2)\\
\textsc{SimArtists}_{CF}(U2, ACDC) \wedge \textsc{Listens}(Jen, ACDC) &\Rightarrow \textsc{Listens}(Jen, U2)\\
\textsc{SimArtists}_{last.fm}(U2, \mathit{Coldplay}) \wedge \textsc{Listens}(Jen, \mathit{Coldplay}) &\Rightarrow \textsc{Listens}(Jen, U2)\\
\textsc{SimArtists}_{content}(U2, \mathit{Beatles}) \wedge \textsc{Listens}(Jen, \mathit{Beatles}) &\Rightarrow \textsc{Listens}(Jen, U2)\\
\textsc{HasTag}(U2, \mathit{Rock}) \wedge \textsc{HasTag}(\mathit{Slayer}, \mathit{Rock}) \wedge \textsc{Listens}(Jen, \mathit{Slayer}) &\Rightarrow \textsc{Listens}(Jen, U2)\\
\textsc{SimFriends}(Jen, \mathit{Cindy}) \wedge \textsc{Listens}(\mathit{Cindy}, U2) &\Rightarrow \textsc{Listens}(Jen, U2)\\
\textsc{PopularArtist}(U2) &\Rightarrow \textsc{Listens}(Jen, U2)
\end{aligned}$$

In order to generate explanations from the ground rules, we develop a parser that takes as input the groundings and outputs sentences in natural language.

Explanation Style	We recommend *Crudo* because:
Social	Your friend Cindy likes Crudo
Content	You like Peruvian restaurants, like Crudo
User-based	Users with similar tastes as you like Crudo
Item-based	People who like LaMar, also like Crudo and you like LaMar
Item average rating	Crudo is highly rated
User average rating	You tend to give high ratings

Table 5.2: Example of an explanation for a restaurant recommendation.

Table 5.1 shows the natural language explanations generated by the ground rules shown in this specific example. Again, we highlight the fact that the HyPER model is easily extensible in new datasets and information sources. For example, we can define a similar model in a restaurant recommendation setting and provide explanations like the ones shown in Table 5.2. In the next section we describe the two user studies we conducted using the output of two different HyPER models. In the first, non-personalized study, we use the static output of a hypothetical HyPER model in a restaurant recommendation setting that is able to produce explanations like the ones shown in Table 5.2. In the second personalized study, we run in real-time the HyPER-music model and generate personalized recommendations along with explanations like the ones shown in Table 5.1.

5.3 First Study: Non-Personalized Hybrid Explanations

In this Section we describe the first non-personalized user study on hybrid explanations. More specifically, in Section 5.3.1 we identify several dimensions for designing explanation interfaces. In Section 5.3.2 we define the research questions we aim to answer with this study. In Section 5.3.3 we give an overview of the user study and in Section 5.3.4 we present the results which answer the research questions. Finally, in Section 5.3.5 we summarize our findings.

5.3.1 Presentation of Explanations

In this study, we assume that we are given the output of a hypothetical HyPER model in a restaurant recommendation setting, that produces explanations like the ones in Table 5.2. The next step is designing an interface to present these explanations to users. At a high level, the goal of any presentation style is to improve the user experience. We study the effect of different explanation presentation styles on user experience. To this end, we identify several dimensions for designing interfaces:

- **Presentation (Pres.)**: Natural language (Table 5.2), rule-based, or graphical visualizations.
- **Weighting (Wgt)**: Whether or not explanation weights are displayed. As we discussed, HyPER supports a weight learning mechanism that automatically learns to balance the different information signals (e.g. social, content) when making predictions.
- **Grouping (Group)**: Whether or not explanations are grouped by style. Each rule can have many groundings in a dataset. For example, do users prefer to be shown the explanation *"Mary's friend Cindy likes Crudo; Mary's friend Josh likes Crudo"* or grouping explanations, *"Mary's friends Cindy and Josh like Crudo."*?
- **Information Density (Dens.)**: Amount of information shown. Should explanations be high or low information? If there are many groundings for each of the template rules, do users like to be shown all the groundings

or do they get overwhelmed and prefer to be shown a small subset of the groundings?

- **Aggregation (Aggr.)**: Whether or not rules are aggregated in the grouping case. Do users prefer explanations of the type *"Mary's friends Cindy and 4 others like Crudo."* or *"Mary's friends Cindy, Josh, Rosie, George, Michael like Crudo."*?

- **Meta-explanations (Meta)**: Amount of high-level metadata in explanations (i.e., user similarity, item average rating, and user average rating). Do users prefer to see explanations that can be highly personalized or they see a value in explanations that are general and not so easy to personalize? We consider social, content, and item-based explanations easy to personalize and user, item popularity, and user average rating not easy to personalize.

- **Visualization (Visual)**: What is the best way to visualize hybrid explanations? Literature has proposed different ways to visualize explanations. We use these visualizations in a hybrid explanation setting and evaluate which one users prefer. In particular, we check the performance of concentric circles [87, 59], Venn diagrams [91], pathways among columns [11], and one new approach that is based on pathways among columns that additionally shows the reasoning behind each prediction. For Venn diagrams we used only 3 intersections which has been shown to work well in the previous literature [115].

In addition to the effect of different presentation styles on user experience, we also studied whether users have a specific preference over the *ranking* of the different explanation styles. For example, do users prefer to see social explanations before content-based ones?

Treat.	Pres.	Wgt	Group	Dens.	Aggr.	Meta
BASE	no exp.	no	no	NA	no	NA
AGGR	english	no	yes	low	yes	low
GROUP	english	no	yes	high	no	low
RULE	rule	no	no	low	no	high
WGT	english	yes	no	low	no	high
PLAIN	english	no	no	low	no	high
NO-GR	english	no	no	med	no	low
MED-IN	english	no	yes	med	no	low
LOW-IN	english	no	yes	low	no	low
		Visual Style				
COL	visual	COLumns + pathways				
CPR	visual	Columns + Pathways with Reasoning				
VENN	visual	VENN diagram				
CC	visual	Concentric Circles				

Table 5.3: Dimension values for each treatment for the different types of explanations tested.

5.3.2 Research Questions

The above dimensions help us define and answer the following four fundamental questions about recommendations and explanations coming from a hybrid system:

1. What visualization is best for hybrid explanations?
2. How should explanations be organized?
3. How much information should be in each explanation?
4. How detailed should each explanation be?

5.3.3 Study Design

In this section, we describe our study from the point of view of one participant. The study is divided in two phases. In the first phase, we ask the participant to fill in a pre-questionnaire (this is the same for all participants). In the second part of the study, we show a variety of mockups to the participants. We note that the mockups are non-personalized and they are the same for all participants.

First Phase: Pre-study Questionnaire

The title of the study was “PSLViz! A new way to explore recommendation” which was followed by a short description: “You are about to explore new ways to find interesting items!” Afterwards, we asked the participant a set of demographic questions (age range, gender, education level). We also asked users to indicate if they have issues with color blindness. Next, we asked the participants questions related to visualization familiarity (reported in lines 2-5 of Table 5.5). Responses were provided using a 7-point Likert scale from “Totally Disagree” to “Totally Agree”.

Second Phase: Main Study Questionnaire

In the second part of the study, interface mockups were shown to participants in random order. We ran a synthetic experiment where all users were shown the exact same mockups that were manually generated. Each mockup presented a hybrid explanation for a random user called *“Mary”* for the restaurant *“Crudo”*. For each mockup, we elicited answers for a set of user experience questions, corresponding to understandability, system satisfaction, and perceived persuasiveness (Table 5.5). Testing all possible subsets of dimensions was prohibitive, so we chose subsets that we judged as the most informative for explanation design. We evaluated explanations for a variety of textual and visual formats. We also included a baseline treatment (BASE) where we presented a recommendation item without any explanation. More specifically, we presented a total of 13 treatments to the participants, 9 text-based (Figures 5.2- 5.9) and 4 visual-based (Figures 5.10 - 5.13). The treatment without the explanation (BASE) was “We recommend that Mary likes Crudo”. Table 5.3 summarizes the dimension values for each treatment for the different types of explanations tested. Here is a more detailed description of the treatments:

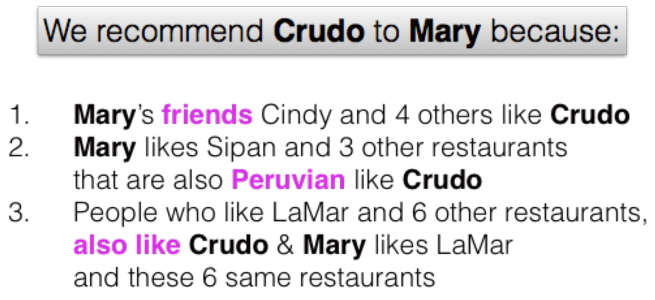
- Treatment AGGR, (Figure 5.2) presents explanations in text format, does not assign weights to explanations, groups different instantiations of the same rule in one explanation sentence (e.g., we show one explanation that includes friends), aggregates instances of the same rule in one explanation sentence (e.g., we aggregate the friends in a number (4) and does not refer to the name of each friend), the amount of information shown is low (e.g., we present the name of only one friend), and takes into account only user preferences (and does not include high-level explanations).

- Treatment GROUP (Figure 5.3) presents explanations in text format, does not assign weights to explanations, groups different instantiations of the same rule in one explanation sentence (e.g., we show one explanation that includes friends), does not aggregate instances of the same rule in one explanation sentence (e.g., all friends are listed by their names), the amount of information shown is high (e.g., we present 5 similar friends), and takes into account only user preferences.

- Treatment RULE (Figure 5.4) presents explanations in text, rule-based format, does not assign weights to explanations, does not group different instantiations of the same rule, does not aggregate instances of the same rule, the amount of information shown is low, and takes into account both user preferences and high-level metadata (e.g., user similarity).

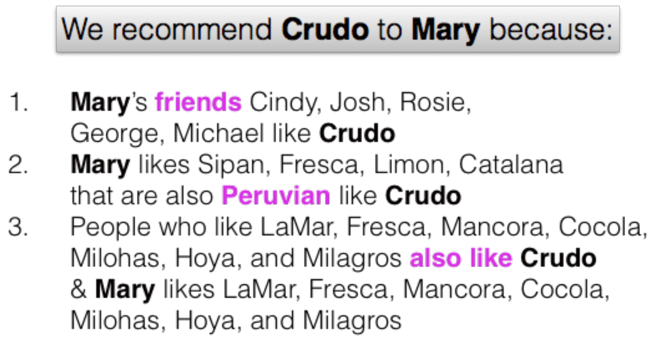
- Treatment WGT (Figure 5.5) presents explanations in text format, does assign weights to explanations, does not group different instantiations of the same rule, does not aggregate instances of the same rule, the amount of information shown is low, and takes into account both user preferences and high-level metadata.

- Treatment PLAIN (Figure 5.6) presents explanations in text format, does not assign weights to explanations, does not group different instantiations of the same rule, does not aggregate instances of the same rule, the amount of information shown is low, and takes into account both user preferences and high-level metadata.
- Treatment NO-GR (Figure 5.7) presents explanations in text format, does not assign weights to explanations, does not group different instantiations of the same rule, does not aggregate instances of the same rule, the amount of information shown is medium, and takes into account only user preferences.
- Treatment MED-IN (Figure 5.8) presents explanations in text format, does not assign weights to explanations, groups different instantiations of the same rule, does not aggregate instances of the same rule, the amount of information shown is medium, and takes into account only user preferences.
- Treatment LOW-IN (Figure 5.9) presents explanations in text format, does not assign weights to explanations, does groups different instantiations of the same rule, does not aggregate instances of the same rule, the amount of information shown is low, and takes into account only user preferences.
- Treatment COL (Figure 5.10) presents explanations in visual format, in the form of columns and pathways like TasteWeights [11].
- Treatment CPR (Figure 5.11) presents explanations in visual format, in the form of columns and pathways with reasoning.
- Treatment VENN (Figure 5.12) presents explanations in visual format, in the form of Venn diagrams like [91].


We recommend **Crudo** to **Mary** because:

1. **Mary**'s **friends** Cindy and 4 others like **Crudo**
2. **Mary** likes Sipan and 3 other restaurants that are also **Peruvian** like **Crudo**
3. People who like LaMar and 6 other restaurants, **also like Crudo** & **Mary** likes LaMar and these 6 same restaurants

Figure 5.2: Text: AGGR


We recommend **Crudo** to **Mary** because:

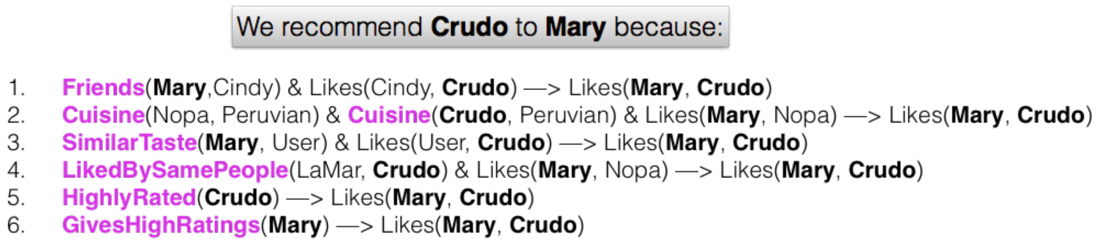
1. **Mary**'s **friends** Cindy, Josh, Rosie, George, Michael like **Crudo**
2. **Mary** likes Sipan, Fresca, Limon, Catalana that are also **Peruvian** like **Crudo**
3. People who like LaMar, Fresca, Mancora, Cocola, Milohas, Hoya, and Milagros **also like Crudo** & **Mary** likes LaMar, Fresca, Mancora, Cocola, Milohas, Hoya, and Milagros

Figure 5.3: Text: GROUP

- Treatment CC (Figure 5.13) presents explanations in visual format, in the form of concentric circles like [59, 87].

For each of the 13 treatments, we asked users to rate their agreement with a set of statements in a 7-point Likert scale (from Strongly Agree to Strongly Disagree). The set of statements are depicted in lines $7-11$ of Table 5.5.

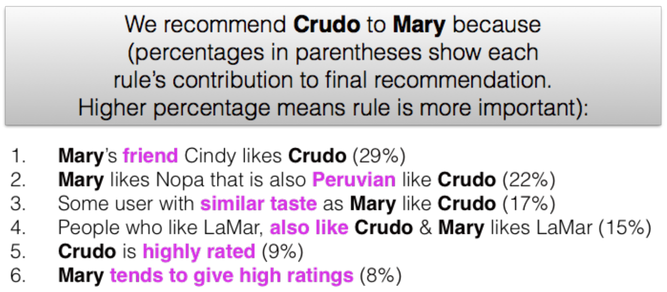
Since visual representations lacked context, we provided the participants with additional information. For the visual COL we gave this information: "In the visual, the first column shows people. The second column shows a set of contexts (e.g. people or features), and the third column a set of items. A recommendation is a set of arrows that connects these entities". Similarly, for the visual CPR we gave the information: "In the visual, the first column shows people. The second column shows a set of functions or "rules", and the third column a set of items. A



We recommend **Crudo** to **Mary** because:

1. **Friends**(**Mary**,Cindy) & Likes(Cindy, **Crudo**) —> Likes(**Mary**, **Crudo**)
2. **Cuisine**(Nopa, Peruvian) & **Cuisine**(**Crudo**, Peruvian) & Likes(**Mary**, Nopa) —> Likes(**Mary**, **Crudo**)
3. **SimilarTaste**(**Mary**, User) & Likes(User, **Crudo**) —> Likes(**Mary**, **Crudo**)
4. **LikedBySamePeople**(LaMar, **Crudo**) & Likes(**Mary**, Nopa) —> Likes(**Mary**, **Crudo**)
5. **HighlyRated**(**Crudo**) —> Likes(**Mary**, **Crudo**)
6. **GivesHighRatings**(**Mary**) —> Likes(**Mary**, **Crudo**)

Figure 5.4: Rules: RULE

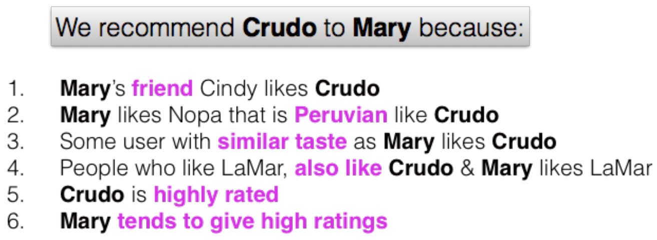


We recommend **Crudo** to **Mary** because (percentages in parentheses show each rule's contribution to final recommendation. Higher percentage means rule is more important):

1. **Mary**'s **friend** Cindy likes **Crudo** (29%)
2. **Mary** likes Nopa that is also **Peruvian** like **Crudo** (22%)
3. Some user with **similar taste** as **Mary** like **Crudo** (17%)
4. People who like LaMar, **also like** **Crudo** & **Mary** likes LaMar (15%)
5. **Crudo** is **highly rated** (9%)
6. **Mary** **tends to give high ratings** (8%)

Figure 5.5: Text: WGT

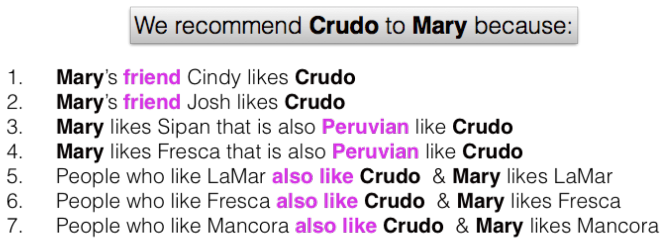
recommendation is a set of arrows that connects these entities. Here, green arrows represent the recommendation, and red arrows represent the reasoning, or explanation for that recommendation." Next, for the visual VENN we also provided the following explanation text: "The visual is a Venn diagram showing intersection between hybrid recommendation information sources. One is similar users, another is a set of popular items, and the other is a set of predictions from similar users. The recommendation common to all three sources is "Cheviche." Finally, for the visual CC we presented the additional explanation: "In the visual, concen-



We recommend **Crudo** to **Mary** because:

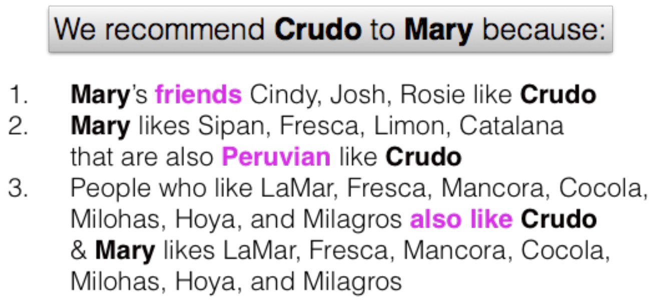
1. **Mary**'s **friend** Cindy likes **Crudo**
2. **Mary** likes Nopa that is **Peruvian** like **Crudo**
3. Some user with **similar taste** as **Mary** likes **Crudo**
4. People who like LaMar, **also like** **Crudo** & **Mary** likes LaMar
5. **Crudo** is **highly rated**
6. **Mary** **tends to give high ratings**

Figure 5.6: Text: PLAIN


We recommend **Crudo** to **Mary** because:

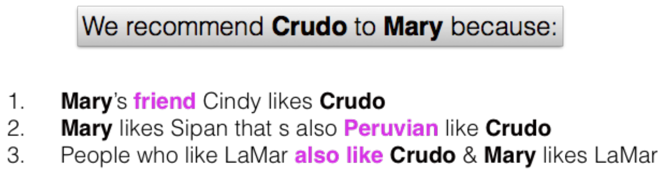
1. **Mary**'s **friend** Cindy likes **Crudo**
2. **Mary**'s **friend** Josh likes **Crudo**
3. **Mary** likes Sipan that is also **Peruvian** like **Crudo**
4. **Mary** likes Fresca that is also **Peruvian** like **Crudo**
5. People who like LaMar **also like** **Crudo** & **Mary** likes LaMar
6. People who like Fresca **also like** **Crudo** & **Mary** likes Fresca
7. People who like Mancora **also like** **Crudo** & **Mary** likes Mancora

Figure 5.7: Text: NO-GR


We recommend **Crudo** to **Mary** because:

1. **Mary**'s **friends** Cindy, Josh, Rosie like **Crudo**
2. **Mary** likes Sipan, Fresca, Limon, Catalana that are also **Peruvian** like **Crudo**
3. People who like LaMar, Fresca, Mancora, Cocola, Milohas, Hoya, and Milagros **also like** **Crudo** & **Mary** likes LaMar, Fresca, Mancora, Cocola, Milohas, Hoya, and Milagros

Figure 5.8: Text: MED-IN


We recommend **Crudo** to **Mary** because:

1. **Mary**'s **friend** Cindy likes **Crudo**
2. **Mary** likes Sipan that s also **Peruvian** like **Crudo**
3. People who like LaMar **also like** **Crudo** & **Mary** likes LaMar

Figure 5.9: Text: LOW-IN

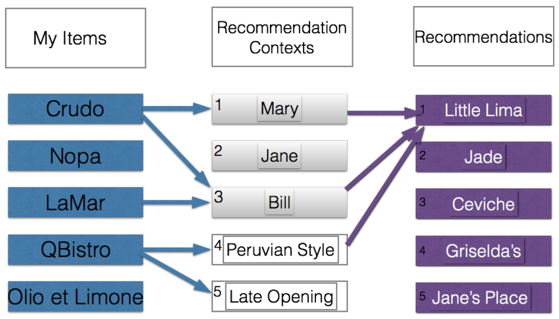


Figure 5.10: Visual: Columns and pathways (COL)

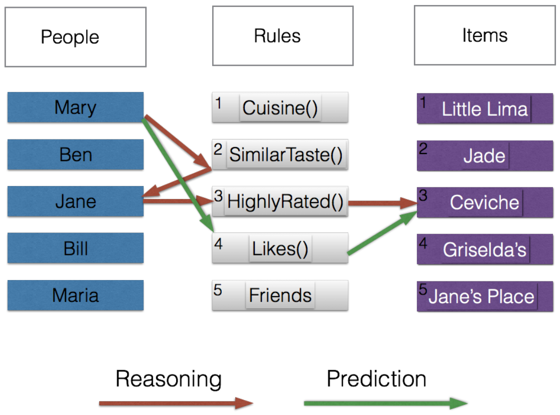


Figure 5.11: Visual: Columns and pathways with reasoning(CPR)

tric circles show one active user, receiving a recommendation, with layers around that user showing profile items (inner layer), similar users, and recommendations (outer layer)."

Additionally, we we also studied whether users have a specific preference over the ranking of the different explanation styles. The description of the ranking question can be found in Table 5.4.

5.3.4 Results

In this section, we first describe the sample of participants of the study. Next, we describe our analysis. Finally, we discuss the basic findings of this study.

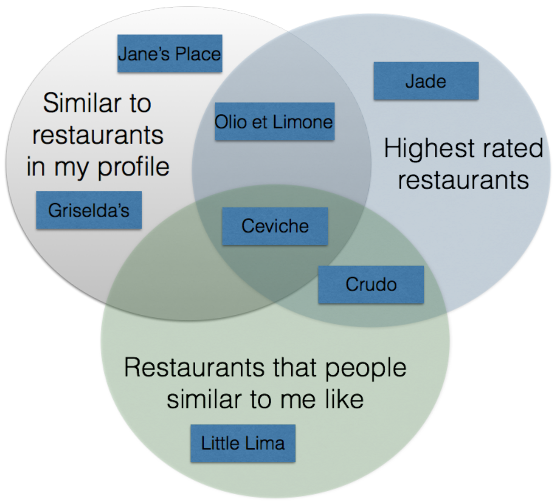

Jane's Place
Similar to restaurants in my profile
Olio et Limone
Jade
Highest rated restaurants
Griselda's
Ceviche
Crudo
Restaurants that people similar to me like
Little Lima

Figure 5.12: Visual: Venn diagrams (VENN)

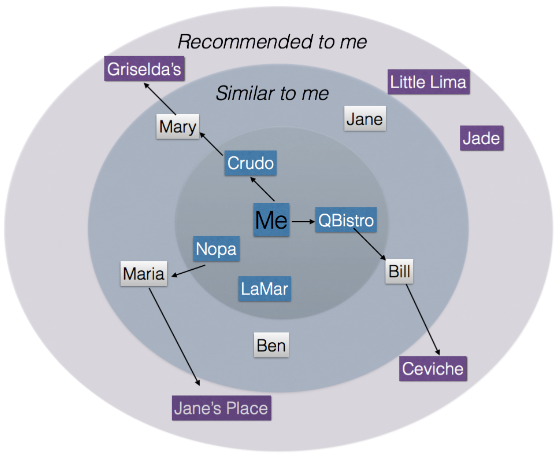


Figure 5.13: Visual: Concentric circles (CC)

Participants

We recruited 200 workers for the study and we required each of them to have a minimum of 50 previous successful HITS. All users completed the study (we filtered out all users that abandoned the study at some point). The design used in our study [88] has been shown to minimize effects of satisficing (e.g., tab-click behavior) in crowdsourced studies. The data was checked for satisficing users by checking input patterns and timings, however, none of the participants

Suppose Mary is recommended the restaurant "Crudo" by PSLViz. Below, is a list of possible explanations from the recommender system (assume all are correct). Please rank the following explanations with the one you prefer the most at the top.
1. Mary's friend Cindy likes Crudo.
2. Mary likes Nopa. Nopa and Crudo are Peruvian.
3. Some users with similar tastes to Mary like Crudo.
4. People who like La Mar also like Crudo, and Mary likes La Mar.
5. Crudo is highly rated.
6. Mary tends to give high ratings.

Table 5.4: The ranking question. We randomized the order different explanation styles were shown to avoid any order-related biases.

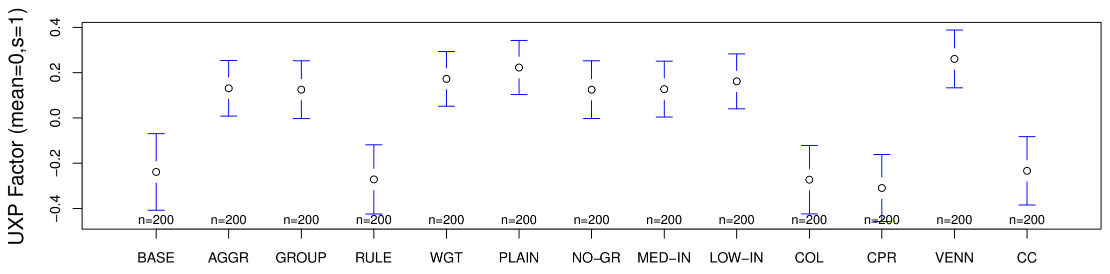


Figure 5.14: Mean UXP for each treatment. Errors bars are 95% confidence intervals. Treatment descriptions are given in Table 5.3.

showed indications of violating the assumptions of the study. Each participant was rewarded with \$0.5 as incentive. 95% of participants were between 18 and 50 years of age (with 5% being above 50) and 42% male and 58% female. Out of the 200 users, 15 reported to have issues with color blindness. For those users, we performed a separate analysis that is discussed later in this section. The data was checked for satisficing users by checking input patterns and timings, however, none of the participants showed indications of violating the assumptions of the study.

Analysis

Subjective metrics relating to recommender systems have shown to be strongly correlated (e.g., [93]), thus, confirmatory factor analysis was used to group the question items into a latent user experience variable to allow for simpler presentation of results and eliminate measurement error. A Cronbach's alpha [24] of 0.89 indicates good internal reliability of the constructed user experience (UXP) factor. Average variance extracted (AVE) was 0.64, indicating good convergent validity ($AVE > 0.5$).

Our experiment considered how participants' individual characteristics could affect user experience scores for each treatment. Analysis showed co-variance between visualization familiarity and user experience was less than 0.5, which indicates good discriminant validity between the constructs.

Visualization Familiarity (VF) ($\alpha = 0.85$, $AVE = 0.60$)	$\mathbf{R^2}$	**Est.**
I am familiar with data visualization.	0.54	0.96
I frequently tabulate data with computer software.	0.63	1.20
I have graphed a lot of data in the past.	0.81	1.38
I am an expert at data visualization.	0.57	1.21
User Experience (UXP) ($\alpha = 0.87$, $AVE = 0.64$)	$\mathbf{R^2}$	**Est.**
Understandability: The recommendation process is clear to me.	0.73	0.86
Satisfaction: I would enjoy using this system if it presented recommendations in this way.	0.68	0.82
Persuasiveness: The recommendation is convincing.	0.77	0.88

Table 5.5: The latent VF and UXP factors built on participant responses to subjective questions.

Figure 5.14 shows a plot of the mean user experience (factor loadings fixed to 1). To test for differences between the within-subjects treatments, we used structural equation modeling (SEM) [114], which can accommodate latent variables during significance testing, thus eliminating measurement error. We specified two factor models: the first with all within-subjects variables loaded onto a single fac-

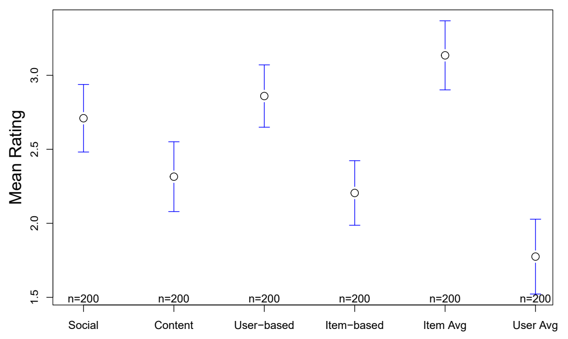


Figure 5.15: Means of participant ratings (1-6, with 6 being the highest preference) for the explanation style ranking task. Error bars are 95% confidence intervals.

Regression	β	**Std. Err**	**P(>|z|)**
BASE UXP ← VF	0.21	0.08	**
AGGR UXP ← VF	0.10	0.08	0.2
GROUP UXP ← VF	0.18	0.08	*
RULE UXP ← VF	0.41	0.09	***
WGT UXP ← VF	0.38	0.09	***
PLAIN UXP ← VF	0.28	0.08	**
NO-GR UXP ← VF	0.35	0.09	***
MED-IN UXP ← VF	0.32	0.09	***
LOW-IN UXP ← VF	0.24	0.08	**
COL UXP ← VF	0.57	0.09	***
CPR UXP ← VF	0.33	0.09	***
VEN UXP ← VF	0.39	0.09	***
CC UXP ← VF	0.29	0.08	***

Table 5.6: Regressions coefficients (β) in a SEM that examine the relationship between visualization familiarity and observed user experience for each treatment. UXP/VF are latent variables with $\mu = 0, \sigma = 1$, effect sizes (β) on UXP are measured as SD from the mean as VF changes. Significance levels for this table: *** $p < .001$, ** $p < .01$, * $p < .05$.

tor (null hypothesis: no differences between treatments); the second with a factor specified for each of the 13 treatments (hypothesis: treatments cause a change in UXP). The model with a factor specified for each treatment achieved better fit. We used the Akaike Information Criterion (AIC) to estimate the quality of each model (a lower AIC indicates better comparative fit) and achieved $AIC = 25838$ for the single factor model vs. $AIC = 22908$ for the model with a factor for each treatment. This result indicates that there exist differences in UXP between treatments and thus the null hypothesis is rejected.

Next, we performed post-hoc tests between each treatment using a Raykov change model [97] (this mimics the popular Tukey test [113] while still allowing the use of latent variables). In this method, one factor (treatment) is used as a baseline and a slope is calculated between it and another factor. The post-hoc test showed that the interface using Venn diagrams (VENN) was significantly better than all other visual treatments and the baseline ($p < 0.001$ for BASE, COL,CPR, and CC). VENN also performed significantly better than AGGR, GROUP, NO-GR, MED-IN, and LOW-IN ($\forall\ p < 0.05$). The RULE treatment performed significantly worse than the explanations in plain English, as well as VENN ($\forall\ p < 0.001$). All English treatments performed significantly better than the baseline BASE ($\forall\ p < 0.001$). There was no significant difference between any of the English treatments ($\forall\ p > 0.10$), however, the mean for PLAIN was the highest. Consequently, weights, information density, aggregation, and grouping were also non-significant ($\forall\ p > 0.10$).

Results from the ranking task are shown in Figure 5.15. For our analysis we converted the ranking into rating data, i.e., the item listed first was given a rating of 6 and the item ranked last received rating 1. Users showed the strongest preference for item average rating explanations, followed by user-based and social explanations. A repeated measures ANOVA revealed differences in rating between the explanation styles ($p < 0.001$). A Tukey post-hoc test showed no statistical difference between social, user-based, and item average rating explanations ($\forall\, p > 0.10$). However, social, user-based, and item average rating were significantly better than item-based and user average rating ($\forall\, p < 0.05$). User-based and item average rating were significantly better than content explanations (both $p < 0.05$).

Finally, we conducted analysis on the relationship between visualization familiarity and user experience. A SEM was built with visualization familiarity regressed onto user experience measurements for each treatment (Table 5.6). Results indicate that visualization familiarity predicts increased user experience in all treatments, except AGGR. The highest increase in user experience is seen in COL and RULE. Model fit: $N = 200$ with 174 free parameters, $RMSEA = 0.064$ ($CI : [0.058, 0.069]$), $TLI = 0.89, CFI = 0.90$ over null baseline model, $\chi^2(772) = 1397$ (indicate acceptable fit, however, note that overall model fit is not an indicator of whether effects exist between variables).

Answers to the Post-Study Questionnaire

At the end of the study, we asked users to give us any comments (in free text format) regarding the study. The most interesting comments can be found in Appendix 6.1.

5.3.5 Discussion

In this first user study, we presented an evaluation of different visualization approaches using hybrid explanations. The results support prior findings [39] that explanations improve the user experience of recommender systems.

More specifically, Venn diagrams outperform all other visual interfaces and five of seven English interfaces, but are difficult to adapt to more than three sources. Natural language approaches were preferable to rule groundings from HyPER. Our experiments did not show a statistically significant difference across dimensions such as weights, information density, aggregation, or grouping in these explanations. This suggests that most plain English explanations may perform more or less the same in recommendation settings. Our results indicated that social, user-based, and item average rating explanations were the preferred explanation styles by users. Furthermore, we have established a reliable scale, as evidenced by Cronbach's α, for visualization familiarity which might be used to tailor explanation styles to individual users.

Additionally, we discovered that color-blind users ($N = 14$) rated the RULE interface higher in terms of UXP than the rest of the sampled population, with marginal significance ($\beta = 0.15, p = 0.051$). The mockup for this interface used a fairly intense violet color which may have been difficult to read for all but the colorblind users. While the colorblind sample was not large enough to change the results of the study, it highlights the need to accommodate these types of users when evaluating UXP for recommender systems.

The mockups that we showed to users were manually produced and not generated by the HyPER system. As a result, the study was synthetic and did not support personalization. To analyze factors such as the quality of the recommendation and whether users agree and connect with the evidence, we conducted a personalized user study that we present in the next section.

5.4 Second Study: Personalized Hybrid Explanations

In this Section we describe the second personalized user study on hybrid explanations. More specifically, in Section 5.4.1 we describe the properties of the last.fm dataset. In Section 5.4.2 we define the research questions we aim to answer with this study. In Section 5.4.3 we give an overview of the user study and in Section 5.4.4 we present the results which answer the research questions. Finally, in Section 5.4.5 we summarize our findings.

5.4.1 Last.fm Dataset

In this Chapter, we use the domain of music to demonstrate our hybrid recommendation model and explanations. We use data from the last.fm website for two reasons: i) last.fm provides an API[1] offering convenient access to music data and ii) last.fm contains a wide range of information that can be exploited by our hybrid model: friendships among users, rating history for users, content information for artists (in the form of tags), and popular artists in the database. The Last.fm exposes two main API types, *Users* and *Artists*. The *User* API provides access to user demographic information (e.g. country of origin), user's top artists by listening frequency, and user's friends. The *Artist* API provides access to similar artists to a given artist based on both CF and tag information and the top user-provided tags for an artist. Last.fm also offers general top-chart methods returning information such as the k artists with the highest number of listeners or playcounts as well as the k tags appearing the highest number of times across last.fm's database. In order to integrate with last.fm's API we built a crawler

[1] `https://www.last.fm/api`

using pylast[2] that allows us to collect information for each user in our study in real time.

5.4.2 Research Questions

We structure our work around answering the following four fundamental questions about recommendations and explanations coming from a hybrid system:

1. **What is HyPER-music's performance for online recommendations?** The HyPER framework [65] has reported state-of-the-art performance for the rating task in an offline setting for two different datasets, i.e., business and music recommendation. In this question, our goal is to measure the accuracy of our modified version of the HyPER framework (HyPER-music) in an online setting. To this end, we compare HyPER-music to a recommender engine that recommends random artists from the last.fm dataset (i.e., without taking into account any previous user preferences on artists).

2. **How does explanation persuasiveness vary with different explanation styles?** An explanation from a hybrid recommender system usually contains several different styles, such as user-based and social-based. In this question, our goal is to study whether varying the different styles changes the persuasiveness of an explanation. Additionally, following on from prior work [110] showing that personality strongly correlates with user preferences, we study whether there is any difference in the preferred explanation style when we take the users' personality traits into account. Our hypothesis is that users with specific personal characteristics will be persuaded by different explanation styles. For example, an extrovert may be receptive

[2]`https://github.com/pylast/pylast`

to social style explanations, while an introvert may prefer item-based style explanations.

3. **What is the ideal volume (i.e., number) of explanation styles?** One pitfall in explanatory systems is information overload. In this question, we identify the inflection point in terms of volume, after which users lose interest. We vary the volume of different explanation styles presented to a user for each recommendation. Our hypothesis is that different volumes of explanation styles will result in different persuasiveness levels. Our goal is to determine the optimal number of explanation styles that balance information overload and persuasiveness. We additionally study whether there is any difference when we take the users' personality traits into account, i.e., does a user's personality indicate their preference in terms of explanation volume?

4. **How do explanation formats affect user experience?** Prior work on non-personalized explanations [69] showed that user experience is affected by the format of the explanations, i.e., users prefer simple visual formats over complex ones. Based on these results, in this work, we study the effect of textual and simple visual formats (Venn diagrams and cluster dendrograms) in personalized explanations. Our hypothesis is that different visual formats will result in different levels of user experience.

5.4.3 Study Design

In this section, we describe our study from the point of view of one participant [3]. The study is divided in two phases. In the first phase, we ask the participant to fill in a pre-questionnaire (this is the same for all participants). To improve efficiency in the study, while this step is in process, we crawl the music data for this

[3] We use the AMT platform to recruit active last.fm participants.

participant and run the HyPER-music model which generates recommendations with explanations. In the second part of the study, we show the personalized recommendations with explanations to the participant and ask a set of questions. We follow a methodology similar to Knijnenburg et al.'s [60]. We note that the questions are templates and are the same for all participants, while the recommended artists and the actual explanations are personalized to each participant.

Ease-of-Satisfaction ($\alpha = 0.89$)	$\mathbf{R^2}$	**Est.**
I think I will trust the artists recommendations given in this task.	0.68	0.93
I think I will be satisfied with the artists recommendations given in this task.	0.89	1.11
I think the artist recommendations in this task will be accurate.	0.67	1.01
Visualization Familiarity ($\alpha = 0.92$)	$\mathbf{R^2}$	**Est.**
I am competent when it comes to graphing and tabulating data.	0.75	1.44
I frequently tabulate data with computer software.	0.71	1.46
I have graphed a lot of data in the past.	0.78	1.52
I frequently analyze data visualizations.	0.68	1.46
Personality - I see myself as...	Trait	
Extroverted, enthusiastic. Reserved, quiet.	Extroversion	
Dependable, self-disciplined. Disorganized, careless.	Dependability	
Open to new experiences, complex. Conventional, uncreative.	Openness	
Calm, emotionally stable. Anxious, easily upset.	Neuroticism	
Sympathetic, warm. Critical, quarrelsome.	Agreeableness	

Table 5.7: Pre-study questions asked to the participants. Factors (ease-of-satisfaction and visualization familiarity) are determined by participant responses to subjective questions. R^2 reports the fit of the item to the factor. Est. is the estimated loading of the item to the factor. α is Cronbach's alpha (a measurement of reliability).

First Phase: Pre-study Questionnaire, Data Collection, and Generation of Recommendations and Explanations

In this first phase of the study, we inform the participant that, in order to participate, she needs to have a last.fm account with at least ten artists in her profile and at least five friends. We prompt participants that are interested in the study but do not have a last.fm account to follow detailed instructions on how to create an account and enrich their profile with the prerequisites. After the participant provides their last.fm id, we check that it meets the prerequisites. If it does, we ask the participant to answer the pre-questionnaire, otherwise we go back to informing the participant about the prerequisites and how to satisfy them.

In the pre-study questionnaire we ask the participant questions related to the ease-of-satisfaction in the field of music recommendations, as well as questions related to visualization familiarity. We additionally ask questions related to the five basic dimensions of personality, called the Big Five traits [110]. We adopt the questionnaire by Gosling et al. [46] which has the advantage that it is very brief and highly reliable. We report all the pre-study questions in the first column of Table 5.7. Responses are provided using a 7-point Likert scale from “Totally Disagree” to “Totally Agree”. During the time that the participant answers the pre-study questions, in the background, we sequentially perform the following tasks:

Crawl data: using the last.fm API methods described in Section 5.4.1, we crawl the top 20 artists for this participant’s profile. Next, for each of these artists, we crawl the top 20 tags and the top 20 most similar artists. For each similar artist, we crawl the top 20 tags. Next, we retrieve the top 20 friends of this participant along with their 20 most favorite artists.

Create candidate set: For the participant u of the study, we create a set of candidate artists $\mathbf{A} = \{a_1, a_2, \ldots, a_n\}$. For each artist $a \in \mathbf{A}$, we generate an unobserved predicate $\textsc{Listens}(u, a)$. Our HyPER-music model will make predictions for **all** the unobserved $\textsc{Listens}(u, a)$ predicates. Last.fm contains a large number of artists, with the typical property that a large number of users listen to a small number of artists (popular artists) and most of the artists have very few users that listen to them (long tail). Since the generation of recommendations should be performed very quickly, we need to apply some selection criteria in order to reduce the number of artists $a \in \mathbf{A}$.[4] At the same time, we want the recommended artists to be personalized to each participant's tastes. To this end, for each participant we create a personalized set of candidate artists $\mathbf{A}$ which consists of: (i) the 20 most similar artists (based on the last.fm similarity) in the participant's profile, (ii) the 20 top artists for each of this participant's friends, and (iii) the overall top 1000 artists in the last.fm database.

Compute similarities: we compute all the necessary similarities for the HyPER-music model to run for this participant. More specifically, we compute: (i) similarities between this participant and a subset of last.fm users (explained in detail below) that generate data for grounding Rule 5.1 from Section 5.2, (ii) similarities between the participant and his friends, generating data for Rule 5.6, and (iii) similarities between the artists in the candidate set and the artists in the last.fm database (both using CF and tag information). Similarities computed using CF information generate data for Rule 5.2 and similarities using tag information generate data for Rule 5.4. The similarities that generate data for Rule 5.3 are already computed by last.fm and we access them by calling the respective API method for each artist. We should finally note that, when computing the CF user and item similarities, the similarity computation is performed while the participant is

[4]This process is usually performed in ranking tasks [1].

completing the questionnaire and, as a result, this computation needs to be as fast as possible in order to not keep participants waiting while recommendations are computed. Since the computation of user-user similarities is a very expensive operation [84], for this study, we compute user and item similarities using CF information from a smaller subset of the last.fm dataset that we crawled containing 1475 users, 8672 artists, and 28639 user-artists pairs.

Run the HyPER-music model: In this step, we run the process of grounding the rules, where we combine the model described in Section 5.2 with the evidence and instantiate a set of propositions. Evidence consists of similarities computed in the previous step, users' rating history, social connections, tags, and popularity statistics. After grounding, we run inference in order to predict the probability that participant u will listen to artist a ($a \in \mathbf{A}$). In other words, we predict the values of the unobserved predicates $\textsc{Listens}(u, a)$. At the end of the inference step, we sort the predictions for the predicates $\textsc{Listens}(u, a)$ from highest to lowest predicted value and we pick the ones that scored the highest.

Organize the explanations: To organize the explanations we use the basic findings from a non personalized crowd-sourced study in hybrid explanations [69] and we group explanations of the same style together. For example, if there are three groundings of the rule 5.1 with similar users Aren, Sonia, and Mary, we group those into one single sentence: "User *Aren, Sonia, and Mary* with whom you share similar tastes in artists, likes U2". Since the number of groundings for each rule can be very large, it is not possible to show all the groundings of a rule. In this case, we use a threshold $k = 3$ and show at most 3 groundings of each rule. To select which k groundings to show, we pick the groundings that involve the highest similarity values. For example, if we have many groundings of the rule 5.1 we select the three users that have the highest similarity with the participant

u of the study.

Second Phase: Main Study Questionnaire

After generating the top k recommendations and organizing them, the next step is to present them to the participant. As discussed, we work towards answering questions related to 1) the accuracy and novelty of the recommended artists compared to recommendations that are generated randomly and 2) the participant preferences' toward different explanation styles, volume, and format. To this end, we show each participant three artists that were picked at random from the candidate set $\mathbf{A}$ and three artists that ranked in the top three positions after running the HyPER-music framework. For the three artists that are recommended by HyPER-music, we also ask the participants questions about the explanations provided. We organize the study around the four questions that we discussed in Section 5.4.2:

Task 1 (answers research question 1): We recommend three random artists to the participant, i.e., we select three artists from the candidate set $\mathbf{A}$ at random. For each artist, we show their official picture as well as the link to the artist's last.fm account, but do not provide an explanation for the recommendation. For each of the randomly recommended artists, we ask the participants to rate the accuracy and novelty of the recommendation using questions in Table 5.8 (under "Perceived Accuracy" and "Perceived Novelty"). We compare these responses to those for HyPER-music given later in the experiment. Formally, with this task we test the following hypothesis:

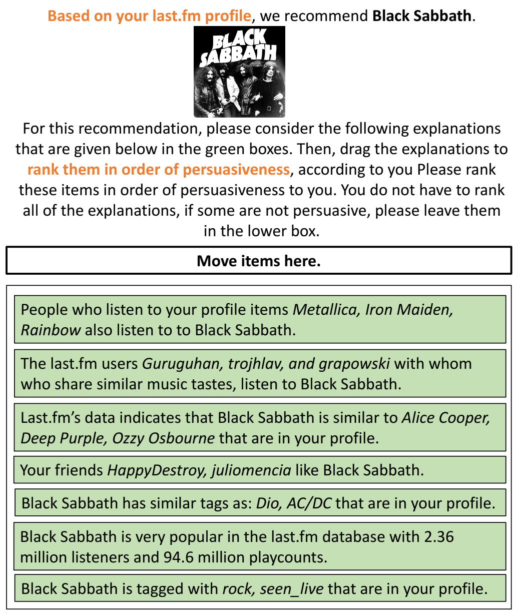
- H_1: Recommendations from HyPER-music are more accurate than random.

Task 2 (answers research question 2): We show the participant the artist that ranked in the top position of the HyPER-music model (along with a picture and the link but without any explanation) and ask the same questions related to perceived accuracy and novelty. Next, we show the same artist with only **one** explanation style (e.g., user-based) and ask for a 7-point Likert scale rating (from "Not Persuasive at all" to "Very Persuasive") to the question "How persuasive is this explanation?". Next, we show the exact same artist with a different explanation style (e.g., social) and ask for an answer to the same statement. We continue until we receive a response for all the explanation styles that were generated by the HyPER-music framework. To avoid any order-related biases, we randomize the presentation order of different explanation styles. Formally, with this task we test the following hypotheses:

- H_2: Explanation style predicts perceived persuasiveness.
- H_3: A person's personality predicts perceived persuasiveness.

Task 3 (answers research questions 3): We show the participant the artist that ranked in the second position of the HyPER-music model (along with a picture and the link but without any explanation) and ask the same questions related to perceived accuracy and novelty. Next, we show the participant all the explanation styles that were generated by the HyPER-music framework. We ask the participant to rank the explanation styles from the most to the least important in order of persuasiveness to them. We give the participant the option to rank only the styles that are interesting and omit the ones that are uninteresting. Again, we randomize the initial order of the styles. Figure 5.16 shows an example of the ranlking question. Formally, with this task we test the following hypotheses:

- H_4: People prefer to see the maximum number of explanation styles available.


Based on your last.fm profile, we recommend **Black Sabbath**.

For this recommendation, please consider the following explanations that are given below in the green boxes. Then, drag the explanations to rank them in order of persuasiveness, according to you Please rank these items in order of persuasiveness to you. You do not have to rank all of the explanations, if some are not persuasive, please leave them in the lower box.

Move items here.

People who listen to your profile items *Metallica, Iron Maiden, Rainbow* also listen to to Black Sabbath.

The last.fm users *Guruguhan, trojhlav, and grapowski* with whom who share similar music tastes, listen to Black Sabbath.

Last.fm's data indicates that Black Sabbath is similar to *Alice Cooper, Deep Purple, Ozzy Osbourne* that are in your profile.

Your friends *HappyDestroy, juliomencia* like Black Sabbath.

Black Sabbath has similar tags as: *Dio, AC/DC* that are in your profile.

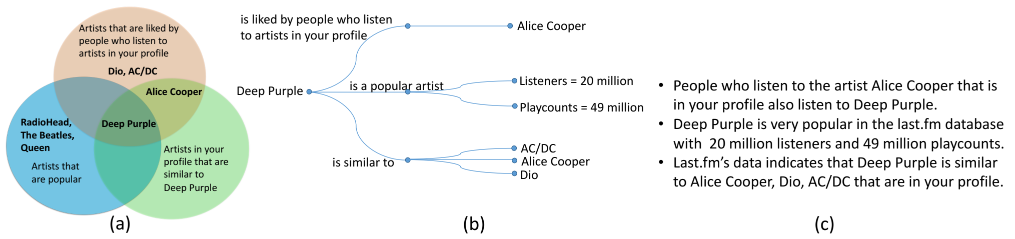
Black Sabbath is very popular in the last.fm database with 2.36 million listeners and 94.6 million playcounts.

Black Sabbath is tagged with *rock, seen_live* that are in your profile.

Figure 5.16: Example of the ranking question (**Task 3** of the study) for the recommended artist "Black Sabbath".

- H_5: A person's personality predicts their preferred volume of explanation styles.

Task 4 (answers research question 4): We show the participant the artist that ranked in the third position of the HyPER-music model (along with a picture and the link but without any explanation) and repeat the process with the perceived accuracy and novelty questions. Next, we present the same recommended artist


Artists that are liked by people who listen to artists in your profile
Dio, AC/DC
Alice Cooper
RadioHead, The Beatles, Queen
Deep Purple
Artists that are popular
Artists in your profile that are similar to Deep Purple
(a)
is liked by people who listen to artists in your profile
Alice Cooper
Deep Purple
is a popular artist
Listeners = 20 million
Playcounts = 49 million
is similar to
AC/DC
Alice Cooper
Dio
(b)
(c)

- People who listen to the artist Alice Cooper that is in your profile also listen to Deep Purple.
- Deep Purple is very popular in the last.fm database with 20 million listeners and 49 million playcounts.
- Last.fm's data indicates that Deep Purple is similar to Alice Cooper, Dio, AC/DC that are in your profile.

Figure 5.17: Example of the different explanation formats for the same recommended artist "Deep Purple" (Task 4 of the study). (a) Venn diagrams, (b) static cluster dendrograms, (c) textual. We also show intereactive cluster dendrogrmas which are the same as static (b) with the difference that the participant can interact with the blue bullets (open or close them).

with the same explanation styles using different formats (one textual and three visuals). For each format we ask the participant a 7-point Likert scale answer to the set of user experience (UXP) statements presented in Table 5.8 (under "Reception (UXP)"). To determine which visualizations to show, we use the results of the crowd-sourced, but non-personalized, study [69]. According to that, Venn diagrams significantly outperformed concentric circles and columns and pathways (with or without reasoning) which participants found too complicated. Based on this finding, we show the participants Venn diagrams and two very simple forms of pathways among columns, i.e., two cluster dendrograms, one static and one interactive. Figure 5.17 illustrates an example of the different formats shown to the same participant for the recommended artist "Deep Purple". For the cluster dendrograms we show only the static version. The difference between the two versions of the cluster dendrograms is that in the first case, we present all the visualization information at once and there is no option for interaction, while in the second case we hide some of the information and ask the participants to interact with the blue bullets (open or close them) of the diagram in order to reveal all the information available. We note that since Venn diagrams can accommodate three different styles, we restrict all the other visual and textual explanations to show only three styles. To select which three out of the seven offered styles to show, we choose the three styles reported to improve performance in prior work, i.e., user-based, item-based CF, and popularity-based. As before, we randomize the order that we show the different formats. Formally, with this task we test the following hypothesis:

- H_6: Explanation format predicts a person's reception (UXP) of an explanation.

Finally, in the middle of the study we ask the satisficing question: "Please answer "Somewhat not Persuasive" to this question". This question, which is the same for all participants, helps us to test for satisficing.

Perceived Accuracy ($\alpha = 0.96$)	R^2	*Est.*
The recommended artist represents my tastes.	0.86	1.05
This is an accurate recommendation	0.88	1.05
I like the recommended artist.	0.93	1.06
Perceived Novelty ($\alpha = 0.94$)	R^2	*Est.*
I have never listened to this artist before.	0.91	1.44
I am aware of the recommended artist.	0.74	1.19
The recommended artist is new to me.	0.91	1.45
Reception (UXP) ($\alpha = 0.93$)	R^2	*Est.*
(Confidence): This explanation makes me confident that I will like this artist.	0.73	1.04
(Transparency): This explanation makes the recommendation process clear to me.	0.71	1.06
(Satisfaction): I would enjoy using a recommendation system if it presented recommendations in this way.	0.79	1.17
(Persuasiveness): This explanation for the recommendation is convincing.	0.88	1.19

Table 5.8: Questions for the main study asked to the participants. Again, factors (perceived accuracy, perceived novelty, and UXP) are determined by participant responses to subjective questions. As before, we report R^2, Est., and Cronbach's alpha.

5.4.4 Results

In this section, we first describe the sample of participants of the study. Next, we report the factors created from the subjective questions along with statistics related to the fit. Next, we report the results of the study and hypotheses testing. Significance levels in this section are reported as follows: *** = $p < .001$, ** = $p < .01$, and * = $p < .05$. Finally, we discuss the basic findings of this study.

Participants

We collected 212 samples of within-subjects participant data using Amazon's Mechanical Turk. Overall, 92% of participants were between 18 and 50 years of age, and 60% were male. Each participant was rewarded with \$3 as incentive. Satisficing, the practice of gaming research studies, is a legitimate concern for any crowd-sourced platform [56]. We checked the data for satisficing participants by carefully examining input/timing patterns and checking the answer to the satisficing question. After filtering out participants that exhibited satisficing behavior, there were $N = 198$ samples for analysis.

Factor Fit

In Tables 5.7 and 5.8 we report with bold the factors that were confirmed from participant responses on the subjective questions. Next to each factor, we show a measurement of internal reliability (Cronbach's α [108]) for each dependent variable that was solicited via the questionnaires. All factors achieved good or excellent internal reliability. All factors achieved good discriminant validity using the Campbell & Fiske test [15]. To improve modeling of personality traits (which were not factored), we load a different latent variable on each response with a fixed value (1). Then, we free the variance of each response and fix the variance of the latent variable to the variance of the response.

Effectiveness of Hybrid Recommendations

As discussed, to validate the quality of the recommendations generated by the HyPER-music framework, for each recommended artist (throughout the study) we asked the participants questions related to perceived accuracy and novelty of the recommendation. We compared the predictions from HyPER-music with random

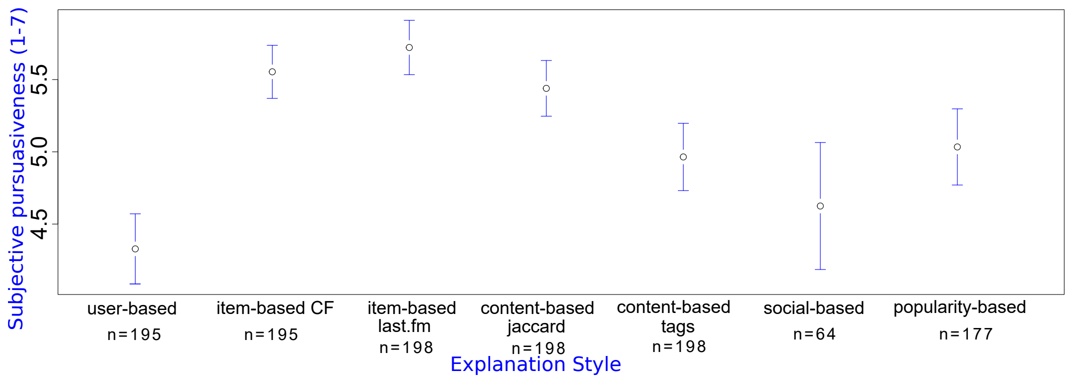


Figure 5.18: Mean subjective persuasiveness for each style of explanation, taken on a Likert Scale (1-7).

recommendations in terms of subjective accuracy using the questions reported on top of Table 5.8. For each of the three hybrid and random recommendations, we averaged together the subjective accuracy. The random recommendations resulted in a mean accuracy of 3.53 out of 7 and the hybrid recommendations resulted in a mean accuracy of 5.64 out of 7 (i.e., the improvement we get with HyPER-music is 37%). The best fitting item for perceived accuracy, "I like the recommended artist," was used in a repeated measures ANOVA (ANalysis Of VAriance), showing a significant effect ($B = -2.11 * **, S = 0.12$). Thus, we accept H_1, i.e., that recommendations from HyPER-music are more accurate than random. The improved accuracy provided by the hybrid recommendation is accompanied by a drop in novelty in comparison with random, with means 2.1 out of 7 and 5.5 out of 7, respectively ($p < 0.001, S = 0.15$).

Preferences for Explanation Styles

We used the questions asked in Task 2 of the study to test for differences in persuasiveness when showing different explanation styles. Figure 5.18 shows the mean subjective persuasiveness ("How persuasive is this explanation?") across each explanation style. A repeated-measures ANOVA showed a general difference between explanation styles ($F = 32.635, p < 0.0001$). Thus, we accept H_2, i.e., explanation style predicts perceived persuasiveness. A Tukey post-hoc test [113] showed significant improvements by item-based CF, content-based Jaccard, and item-based Last.fm styles over user-based ($\forall p < 0.001$), popularity-based ($\forall p < 0.025$), content-based tags ($\forall p < 0.001$), and social-based ($\forall p < 0.001$). No significant improvement was found for item-based Last.fm over item-based CF, or content-based Jaccard.

To test the significance of personality traits in the persuasiveness of an explanation, we conducted an exploratory structural equation modeling (SEM) [114] analysis. It is well known that people may change their ratings of items based on user experience or persuasive explanations [52], so we accounted for this effect by controlling for the accuracy/novelty of each recommendation and the participant's self-reported ease of satisfaction. Then, we tested for an effect of each of the ten personality traits on the seven different explanation styles by performing a regression between each. This resulted in a total of 70 hypotheses, so we controlled for multiplicity via the Benjamini-Hochberg procedure with $Q = 0.10$ [7], which is recommended for exploratory SEM analysis [23].

Figure 5.19 shows the results from the exploratory analysis. Of the ten personality traits, only four were shown to have a significant bearing on persuasiveness of the explanation (dependable, calm, anxious, critical). These four responses could be grouped into their larger personality traits: conscientiousness (dependable), neuroticism (anxious, calm), and agreeableness (critical). Conscientious participants reported being easier to satisfy. The participants seemed to be split in terms of neuroticism: calm participants tended to be more receptive of popularity-based explanations while anxious tended to be more receptive of item-based CF explanations. If the participant identified as dependable *and* calm or anxious *and* critical, the effects disappeared. As a result, we accept H_3, i.e., a person's personality predicts perceived persuasiveness. Finally, the effect sizes of perceived accuracy appeared to be double that of perceived novelty and any personality-based effect.

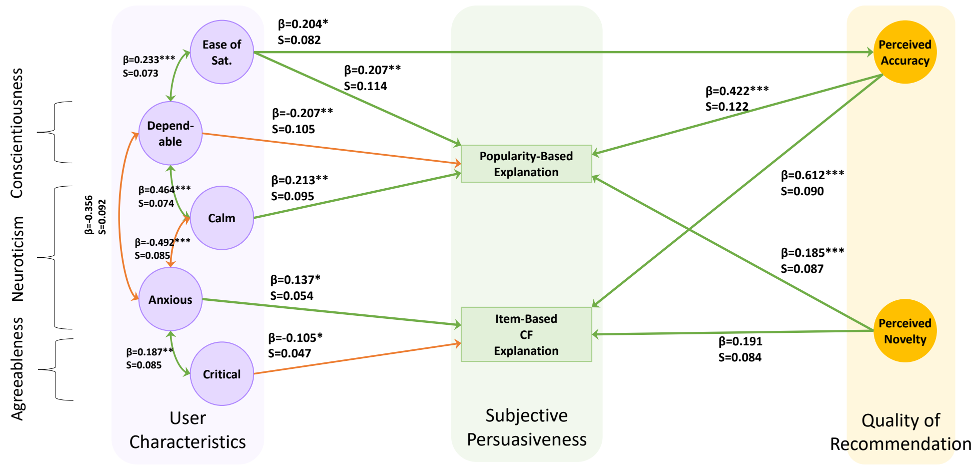


Figure 5.19: An SEM explaining the role of personality in persuasiveness of explanation. Unidirectional arrows indicate regression, bidirectional arrows indicate covariance; red arrows indicate a negative effect, green arrows indicate a positive effect; latent factors were scaled so β values indicate effect sizes in units of standard deviations. Standard error (S) is given. Model fit: $N = 177$ with 40 free parameters $= 4.5$ participants per free parameter, $RMSEA = 0.077$ $(CI : [0.060, 0.094])$, $TLI = 0.932, CFI > 0.948$ over null baseline model, $\chi^2(80) = 164.628$.

Preferred Volume of Explanation Styles

Next, we analyzed the orderings given by the participants in the ranking questions (Task 3 of the study). First, we noted that if the rankings are treated as ratings (1^{st} position = 7 points, 2^{nd} position = 6 points, etc.), each explanation style has the same relative score as shown in Figure 5.18 (this serves as a second level of validation for explanation preferences). Second, the mean number of explanation styles ranked was 2.61, however, we discovered that almost 40% of participants chose to leave all explanation styles in the bottom box without ranking them. When removing these participants, we found that the mean number of explanation styles was 4.32. To test H_4 (people prefer to see the maximum number of explanation styles available), we conducted a one-sample t-test to check if the mean of the sample was significantly different than 7, which was the maximum volume of available explanation styles. We found a significant difference ($t = -22.9, p < 0.001$), which remained significant when omitting participants who had not ranked any explanations ($t = -13.8, p < 0.001$). Thus we reject H_4, concluding that people lose interest after approximately three to four explanation styles. Finally, we tested whether or not personality predicted the volume of explanation styles ranked. We tested ten regressions (multiplicity control again with $Q = 0.10$) within an SEM which revealed that dependable people were likely to rank less ($\beta = -0.166*, S = 0.15$) and open people were likely to rank more ($\beta = 0.212**, S = 0.144$). Thus we accept H_5, i.e., a person's personality predicts their preferred volume of explanation styles.

Textual vs. Visual Formats

As discussed, in Task 4 of the study, for one artist we showed four different explanation formats (one textual and three visual) and asked participants to answer a set of UXP questions reported in Table 5.8. We plot the persuasiveness score, which reported the best R^2 value, for each visual/textual format in Figure 5.20. A repeated-measures ANOVA showed a difference between treatments ($F = 10.13, p < 0.001$). Therefore, we accept H_6, i.e., explanation format predicts a user's reception of an explanation. Specifically, text explanations were perceived as more persuasive than every visual format ($\forall p < 0.001$). To investigate further, we considered whether visualization familiarity predicted better reception of the visual formats. Four regressions were tested in an SEM when controlling for the accuracy of the recommendation and self-reported ease-of-satisfaction, showing that more familiarity with visualization predicted better reception of the Venn diagram ($\beta = 0.151*, S = 0.077$). Finally, our analysis does not show any statistically significant difference between the static and interactive version of the same visual format (cluster dendrograms).

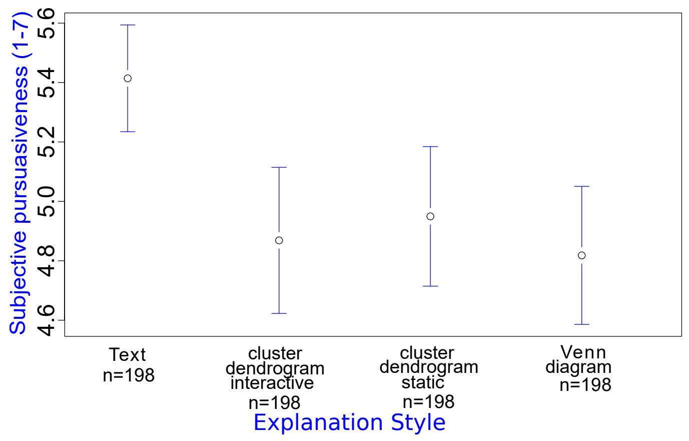


Figure 5.20: Mean subjective persuasiveness for each format of explanation, taken on a Likert Scale (1-7).

Answers to the Post-Study Questionnaire

At the end of the study, we asked users to give us any comments (in free text format) regarding the study. The most interesting comments can be found in Appendix 6.1.

5.4.5 Discussion

Here, we highlight the most important findings from the personalized user study.

People prefer content-centric but not socio-centric explanations. User-based and social-based explanations were rated as relatively less persuasive by the participants. Although the non-personalized popularity-based explanations were rated more favorably, they were still significantly less persuasive than the content-based explanations. Moreover, we discovered that calm participants (low neuroticism) preferred popularity-based explanations, while anxious participants (high neuroticism) preferred item-based CF explanations. Calm participants were also likely to be sympathetic and extroverted which may explain their higher receptiveness to popular items. Additionally, participants that identified as dependable did not have any preference for the popularity-based explanation, potentially suggesting they are less sensitive by popular opinion. Likewise, neurotic participants (who were also likely to be introverted and reserved), showed a slight preference for item-based CF explanations, which surface patterns of particular tastes shared with others.

People prefer to see at most three to four explanations. Our analysis of the varying volume of explanation styles indicates that a relatively large percentage of users prefer to see no explanation with a recommendation, a possible artifact of our experimental design. For the rest of the participants, we find that the average number of explanations they prefer is 4.32. We also discovered that open participants were persuaded by many explanations, while conscientious participants preferred fewer. We believe this due to the fact that open participants seek new experiences, while conscientious participants are turned off by clutter and disorganization. However, despite the significant effects, due to the correlation between those two traits and relatively low effect sizes, personalization of explanation volume may be unnecessary. A default of three to four explanations would be sufficient for most people. We recommend follow-up work specifically to target the role of neuroticism in explanation reception.

Textual explanations are ideal. Our analysis indicates that text explanations were perceived as more persuasive compared to three different visual formats.

When considering visualization familiarity as a control variable, we find that users with more familiarity in visualization are more receptive to the Venn diagrams. Despite this, our model did not predict that participants familiar with visualization would prefer the Venn diagram *over* the text explanations. As a result, we believe that textual explanations would likely satisfy nearly everyone. Finally, our analysis does not show any statistically significant difference between the static and interactive versions of the same visual format (cluster dendrograms).

5.5 Conclusion and Future Work

In this work, we proposed the HyPER-music recommender system which extends the HyPER model and generates music recommendations with a variety of explanation styles in real time. We conducted two user studies: i) a non-personalized study where we evaluated different visualization approaches using hybrid explanations, and ii) a personalized study where users evaluated the accuracy of recommendations and persuasiveness of different explanations under varying the styles, volume, and format.

In our future work, we plan to support a conversational recommender system that will use the observations from interactions with users and adjust the explanations based on their preferences. Additionally, we are interested in extending the HyPER framework to take into account the explanations during the process of generating the predictions. We want to study whether incorporating the explanations in the prediction process has any effect on the accuracy of the recommendations. Finally, we plan to focus on explanation design in scenarios where users have limited space or time for exploring the explanations.

Chapter 6

Conclusion

In this dissertation, I presented a collective probabilistic approach that is generalizable, scalable and can offer on-demand, accurate recommendations and explanations over richly-structured social networks. I organized my work around three core areas that are fundamendal for recommendations over richly-structured networks: 1) entity resolution that aims at aggregating different views of a heterogenous network, 2) a hybrid recommender that exploits the rich structure of social networks and can incorporate information coming from a variety of information sources, and 3) explanations of the complex reasoning behind the proposed recommendations to users.

In my work, I formulated the problems of entity resolution, recommendation, and explanation as inference in a graphical model. To create my models and reason over the graphs, I built upon a statistical relational learning framework called probabilistic soft logic. My models, which allow for scalable, collective inference, showed an improved performance over state-of-the-art methods by leveraging richly-structured data, i.e., relational features (such as user similarities), complex relationships (such as mutual exclusion), a variety of similarity measures, as well as other heterogenous data sources (such as predictions from other algorithms).

In the area of entity resolution, I implemented a collective classification approach based on PSL. My contributions include (1) a scalable entity resolution framework that effectively combines attributes, relational information, logical constraints, and predictions from other algorithms, (2) a method for learning how to balance the different similarity scores and relational features, (3) extensive experimental studies on two real-world datasets where it is demonstrated that the framework can effectively combine different signals, resulting in improved performance over state-of-the-art approaches on two datasets, and (4) a set of conclusions from the experimental evaluation that can be used by entity resolution practitioners. More specifically, the experimental studies showed that: i) name similarities are not enough for the task of entity resolution in relational domains, ii) the addition of attribute information results in a notable increase in the performance, iii) first-degree relationships help most in low noise scenarios, iv) collective relations yield substantial improvements, v) incorporating predictions from other algorithms always improves performance, vi) the performance of different entity resolution models changes when the string similarity functions change, while the setting of string similarity functions that performs best is different for each model.

In the area of hybrid recommendations, I implemented a hybrid recommender system called HyPER. My contributions include (1) a general and extensible hybrid recommender system with PSL, (2) a method for learning how to balance the different input signals in the hybrid system, and (3) extensive experimental studies on several information sources which validate the performance of the framework and highlight the contribution of each source to the final prediction. The HyPER framework is the first to provide a mechanism for incorporating and reasoning over additional information sources as they become available. Experimental evaluation of the approach on two popular recommendation datasets, showed that HyPER effectively combined multiple information types for improved performance and significantly outperformed existing state-of-the-art approaches.

In the area of explanations, I extend HyPER to provide hybrid personalized explanations. My contributions include (1) a method for generating hybrid explanations from a hybrid recommender system built in PSL, (2) a list of ways explanations can be presented such as varying the textual and visual formats, the explanation styles, as well as the volume of the explanations, and (3) two large crowd-sourced user studies (a personalized and a non-personalized) which generated a set of conclusions useful for designers of hybrid explanation interfaces. In particular, the key conclusions of the non-personalized study were that Venn diagrams outperformed all other visual interfaces, while natural language approaches were preferable to rule groundings from HyPER. The key conclusions of the second personalized study were the following: i) people prefer to see at most three to four explanations, ii) textual explanations are ideal, and iii) people prefer item-centric over user-centric explanations.

From a modeling perspective, all three areas of entity resolution, recommendation, and explanation present commonalities that I have leveraged in order to deliver improvements over the state-of-the-art. More specifically, my findings show that:

- Incorporating rules that can capture the relations of the richly-structured social networks always improves performance, especially when these rules allow for collective inference. In the case of entity resolution, I showed that simple relational rules (e.g., mother similarity) improved performance compared to models that did not use this piece of information for datasets with relatively low noise. However, for datasets with noisy relationships and attributes, simple relational rules slightly improved performance, while transitive relational rules (e.g., collective rules for mother relationship) that allowed for collective classification significantly boosted performance. For the case of recommender systems, relational rules that capture user and item similarities improved performance.

- Combining more than one similarity metrics improves performance. For the case of entity resolution, I showed that the model that combines rules that uses a variety of name similarity functions (i.e., Jaro-Winkler, Levenshtein, and Monge-Elkan) outperforms the models that use a subset of the above similarity measures. For the case of recommender systems, I showed that the model that uses the combination of all similarity measures improves performance compared to the models that use only one type of similarity measure. The above outcome is true for both the cases of user-based and item-based collaborative filtering.

- Incorporating predictions from other algorithms improves performance. For the case of entity resolution, incorporating predictions from simple classifiers that are not able for collective reasoning such as logistic regression and SVMs improved the performance of the entity resolution task. More importantly, adding the predictions from the baselines, significantly improves the precision of the proposed model, i.e., they help to better distinguish the true positives and true negatives. For the case of recommender systems, adding the predictions from simple collaborative filtering (such as user-based and item-based neighborhood methods) as well as more sophisticated matrix factorization methods (such as Bayesian probabilistic matrix factorization) always improves performance. An interesting note here is that, although some methods do not perform well in different settings (e.g., user-based methods do not perform well in settings where we have limited information for the users), adding those to the model does not hurt the performance of the model. This is due to the fact that the weight learning mechanism used in the model can learn this information from training data and, as a result, it can reduce the weights of these rules to the final prediction.

- Incorporating all the information available along with a mechanism that can learn the importance of each signal gives the best performance. For the entity resolution problem, we got the best performance for the setting that we used all the available information from the familial networks, i.e., names, attributes, relations, transitive relations, and predictions from other algorithms. For the recommender systems setting, combining ratings, content for items, item similarities, user similarities, and predictions from other algorithms reports the best performance. In both cases, I use the same weight learning mechanism provided by PSL which automatically learns to balance the different information signals when making predictions.

6.1 Future Directions

Although this work addressed the three core challenges in the areas of entity resolution, recommendation, and explanation, it has limitations in certain areas. For example, in the area of entity resolution, there is currently no public dataset that can be used for evaluating the problem of entity resolution in recommender systems. Additionally, in the area of recommender systems, temporal signals as well as using external knowledge bases can potentially provide additional performance improvements. In the area of explanations, the user studies conducted were for recommendations in low risk domains (restaurant and music). The results can be generalized for other low risk recommendation domains, such as movie recommendation. However, for high risk recommendation contexts, such as job recommendation, additional studies are needed to verify that these findings hold in these domains.

The work in this dissertation opens up the possibility for interesting extensions for resolution, recommendation, and explanation. In the area of entity resolution, a promising future direction is to expand the proposed approach to disambiguate users and items across different platforms. A problem of particular interest is linking user accounts across several social platforms (e.g., Facebook, Twitter) in the presence of a diverse set of relationships (e.g., friends, followers, followees, family cycles, shared groups), ambiguous attributes (e.g., names, age), and collective constraints (e.g., bijection and transitivity). The result of this task will be a single netwrok where all information from multiple networks will be aggregated and resolved. Leveraging this network is expected to provide even further improvements for recommender systems.

In the area of hybrid recommender systems in richly structured social networks, the HyPER model can be extended with temporal dynamics. User preferences change over time and, as a result, methods that model time-drifting in recommender systems outperform those that do not account for temporal dynamics [62]. Another interesting future direction is to extend the HyPER model to account for knowledge coming from external knowledge graphs, since this has been shown to improve recommendation accuracy [17]. Finally, researchers can exploit cross-domain recommendations [16] in order to further improve the accuracy of hybrid recommender systems. Cross-domain recommender systems exploit useful knowledge from one domain and apply it to enhance recommendations in another domain. Given the fact that richly structured social networks may include information about multiple domains, cross-domain recommendations may further improve the accuracy of a hybrid recommender system.

In the area of explanations in recommender systems, a promising future direction is to explore the idea of supporting a conversational recommender system that will use the observations from interactions with users to adjust the explanations. Another promising future direction is to extend the HyPER framework to take into account the explanations during the process of generating the predictions. Early related work [80] has shown positive results when explanations participate in the process of ranking the recommendations. Finally, the explanations presented in this disseration are in the context that users have no constraints in terms of time or storage space when exploring the recommendations and explanations. In the future, researchers may be interested in exploring explanations in other contexts, e.g., when users are interested in finding music in their cellphone and have limited time and/or screen space to explore the explanations.

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APPENDIX 1: PSL Model Rules

Name Similarity Rules

$\textsc{SimFirstName}_{JaroWinkler}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimMaidenName}_{JaroWinkler}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimLastName}_{JaroWinkler}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{SimFirstName}_{JaroWinkler}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{SimMaidenName}_{JaroWinkler}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{SimLastName}_{JaroWinkler}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimFirstName}_{Levenshtein}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimMaidenName}_{Levenshtein}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimLastName}_{Levenshtein}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{SimFirstName}_{Levenshtein}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{SimMaidenName}_{Levenshtein}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{SimLastName}_{Levenshtein}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

Personal Information Similarity Rules

$\textsc{KnownAge}(\mathtt{m}_1) \wedge \textsc{KnownAge}(\mathtt{m}_2) \wedge \textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{KnownAge}(\mathtt{m}_1) \wedge \textsc{KnownAge}(\mathtt{m}_2) \wedge \neg\textsc{SimAge}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{eqLiving}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \quad \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

Relational Similarity Rules of 1^{st} Degree

$\textsc{SimMother}(\mathtt{m}_a, \mathtt{m}_b) \wedge \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimFather}(\mathtt{m}_a, \mathtt{m}_b) \wedge \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimDaughter}(\mathtt{m}_a, \mathtt{m}_b) \wedge \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimSon}(\mathtt{m}_a, \mathtt{m}_b) \land \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimSister}(\mathtt{m}_a, \mathtt{m}_b) \land \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimBrother}(\mathtt{m}_a, \mathtt{m}_b) \land \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimSpouse}(\mathtt{m}_a, \mathtt{m}_b) \land \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

Relational Similarity Rules of 2^{nd} Degree

$\textsc{SimGrandMother}(\mathtt{m}_a, \mathtt{m}_b) \land \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimGrandFather}(\mathtt{m}_a, \mathtt{m}_b) \land \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimGrandDaughter}(\mathtt{m}_a, \mathtt{m}_b) \land \textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimGrandSon}(\mathtt{m}_a, \mathtt{m}_b) \land$

$\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimAunt}(\mathtt{m}_a, \mathtt{m}_b) \land$

$\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimUncle}(\mathtt{m}_a, \mathtt{m}_b) \land$

$\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimNiece}(\mathtt{m}_a, \mathtt{m}_b) \land$

$\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{SimNephew}(\mathtt{m}_a, \mathtt{m}_b) \land$

$\textsc{eqGender}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

Transitive Relational (Similarity) Rules of 1^{st} Degree

$\textsc{Rel}(\mathtt{Mother}, \mathtt{m}_1, \mathtt{m}_a) \land \textsc{Rel}(\mathtt{Mother}, \mathtt{m}_2, \mathtt{m}_b) \land \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \land \textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow$

$\textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Father}, \mathtt{m}_1, \mathtt{m}_a) \land \textsc{Rel}(\mathtt{Father}, \mathtt{m}_2, \mathtt{m}_b) \land \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \land \textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow$

$\textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Spouse}, \mathtt{m}_1, \mathtt{m}_a) \land \textsc{Rel}(\mathtt{Spouse}, \mathtt{m}_2, \mathtt{m}_b) \land \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \land \textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow$

$\textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Spouse}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Spouse}, \mathtt{m}_2, \mathtt{m}_b) \wedge \neg\textsc{Same}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \neg\textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Daughter}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Daughter}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Son}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Son}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Sister}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Sister}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Brother}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Brother}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

Transitive Relational (Similarity) Rules of 2^{nd} Degree

$\textsc{Rel}(\mathtt{GrandMother}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{GrandMother}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{GrandFather}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{GrandFather}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{GrandDaughter}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{GrandDaughter}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge$

$\textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge \textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{GrandSon}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{GrandSon}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Aunt}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Aunt}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Uncle}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Uncle}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Niece}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Niece}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

$\textsc{Rel}(\mathtt{Nephew}, \mathtt{m}_1, \mathtt{m}_a) \wedge \textsc{Rel}(\mathtt{Nephew}, \mathtt{m}_2, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2) \wedge\ \textsc{SimName}(\mathtt{m}_a, \mathtt{m}_b) \wedge$

$\textsc{eqGender}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b)$

Bijection and Transitivity Rules

$\mathrm{FR}(\mathtt{m}_a, \mathtt{R}_1) \wedge \mathrm{FR}(\mathtt{m}_b, \mathtt{R}_2) \wedge \mathrm{FR}(\mathtt{m}_c, \mathtt{R}_2) \wedge \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b) \Rightarrow \neg\textsc{Same}(\mathtt{m}_a, \mathtt{m}_c)$

$\mathrm{FR}(\mathtt{m}_a, \mathtt{R}_1) \wedge \mathrm{FR}(\mathtt{m}_b, \mathtt{R}_2) \wedge \mathrm{FR}(\mathtt{m}_c, \mathtt{R}_3) \wedge \textsc{Same}(\mathtt{m}_a, \mathtt{m}_b) \wedge \textsc{Same}(\mathtt{m}_b, \mathtt{m}_c) \Rightarrow \textsc{Same}(\mathtt{m}_a, \mathtt{m}_c)$

Rules to Leverage Existing Classification Algorithms

$\textsc{Same}\mathrm{LR}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{Same}\mathrm{LR}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{Same}\mathrm{SVM}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{Same}\mathrm{SVM}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{Same}\mathrm{LMT}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{Same}\mathrm{LMT}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\textsc{Same}\mathrm{LR}(\mathtt{m}_1, \mathtt{m}_2) \wedge \textsc{Same}\mathrm{SVM}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \wedge \textsc{Same}\mathrm{LMT}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

$\neg\textsc{Same}\mathrm{LR}(\mathtt{m}_1, \mathtt{m}_2) \wedge \neg\textsc{Same}\mathrm{SVM}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \wedge \neg\textsc{Same}\mathrm{LMT}\textsc{s}(\mathtt{m}_1, \mathtt{m}_2) \Rightarrow \neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

Prior Rule

$\neg\textsc{Same}(\mathtt{m}_1, \mathtt{m}_2)$

APPENDIX 2: User comments from the two user studies

Comments from the first non-personalized study

- *"I found the diagrams more difficult to understand than the texts, because that is not my background. "*
- *"Diagram based model is looking more complex ."*
- *"Those systems of recommendations are full of flaws, and especially regarding restaurants. Aside from the type of cuisine, there are too many other factors affecting my disliking or liking a restaurant."*
- *"The simpler presentations were better but all of them seemed labored and cluttered. The circular one was the most incomprehensible. Using these techniques would, for me, take all the pleasure out of anticipating the restaurant so there may be better uses for this type of analysis than restaurant choices."*
- *"I thought the different explainers were interesting. I've always been kind of curious as to who these recommender systems work under the surface."*
- *"I found the recommendation system to be interesting and nice."*
- *"I know more details gathered from this study. It is good experience to know the recommendation."*
- *"I would like to have this system very much."*
- *"I preferred the visualizations for recommendation systems."*
- *"The part where it pointed out mary gives high scores was kinda off putting."*
- *"The preference of friend is seen everywhere but friends could have different tastes."*

Comments from the second personalized study

- *"The recommendations where it branches out to other info and facts was my favorite. "*
- *"Generally, I would prefer more in depth explanations than simple ones."*

- *“Avoid venn diagrams.....they are never appealing.”*
- *“I think that it is a good platform to find music and people with the same taste in music.”*
- *“I liked when the categories like pop, rock or alternative are included in the recommendation. That would help with the choice to click on one.”*
- *“I don’t think the high volume of listening is a good factor since many artists that I like are not high profile big bands, for instance, Iron Butterfly, and 10 years After. These groups are not as popular as Led Zeppelin, but fit my music tastes.”*
- *“I think that the explanation tree is very unique and helpful.”*
- *“I liked the trees presentation - it looked good and was simple and made me feel involved in the decision-making process.”*
- *“I really like the diagrams. Especially the overlapping circles. The branching tree was good too. While I"m not sure I’ll use the service the idea for showing recommendations is great!”*
- *“I liked the Venn diagram best for this type of information! It was fairly unique.”*
- *“I might not be in the majority, but my tastes are very eclectic. As such, I feel that just because I listen to Band A and Band B doesn’t mean others will like both. Since my tastes aren’t well matched I’m less likely to be convinced when a platform says that “User A and myself both like Band A, and User A likes Band B, I’ll like Band B.””*
- *“I feel that the diagrams were overall better options to persuade people and myself of the music recommendations. It would be more persuasive if it used more comparisons, i.e this band is similar to these other 5 bands or people who liked this band also liked)”*
- *“I think that the recommendations were on point. It is especially important that people aren’t overwhelmed with information, and I think the simple graphs provide the best presentation to the end user.”*
- *“I thought the live recommendation system was pretty cool. I’d probably use a tool like that to find new music. I also didn’t experience any technical issues.”*
- *“I think there are probably characteristics of individual tracks/songs that people are attracted to which might vary less than variation within artist.”*

- *"I think the technology you use to recommend artists is very interesting and accurate!"*
- *"Seems there is too much algorithms and data analysis designed in recommending music and artists to users. Music is inherently a subjective thing so I'm not sure I think this is the best method."*
- *"I prefer text best rather than diagrams for recommendations."*
- *"The last option of recommendation system (tree with orange dots) was similar to the first, but I didn't like it as much because you had to click each dot to get the information, where it just presented to you quickly in the first option. The Venn diagram was pretty confusing. The text descriptions work, but don't carry the weight of having the graphical recommendations."*
- *"The tagged as data doesn't really work for me in this instance. "seen live" does nothing for me. I like the visual feedback though. "*