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Narreme: Tools for Telling Tales with Participatory Sensing Data

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Narreme:
Tools for Telling Tales with Participatory Sensing Data

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Computer Science

by

Vidyut Samanta

2012

Abstract of the Dissertation

Narreme: Tools for Telling Tales with Participatory Sensing Data

by

Vidyut Samanta

Doctor of Philosophy in Computer Science

University of California, Los Angeles, 2012

Professor Deborah Estrin, Chair

The proliferation of sensors in consumer mobile phones has made them a powerful data collection platform. We have become more interested in collecting data to document and learn about our own lives, our relationships with the community, and the environment we live in. However, current research is mostly focused on analysis of quantitative data, and a lot of important information that can be extracted from qualitative data such as images and text annotations is being ignored. The focus of this dissertation was to research and build techniques based on narratology to help users analyze and make sense of the qualitative data they have collected and to communicate the information and knowledge they extract from the data though narratives. More specifically, our main contribution was in the creation and evaluation of two techniques that were fundamental to narration tools: clustering and conflict discovery. We used these techniques to build the Narreme toolset that enables user-assisted creation of compelling narratives with participatory sensing data. The toolset consists of three tools: (a) Narreme clustering tool which helps a user organize her thoughts and identify supporting qualitative data consisting of images and text for her narratives, (b) Narreme conflict discovery tool helps the user better understand where conflict could be introduced in her narratives, and, (c) Narreme video editing tool which is used to create a video slideshow narrative and adjust the order based on a narrative tension curve. We evaluated the effectiveness of our techniques and toolset through user studies.

The dissertation of Vidyut Samanta is approved.

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University of California, Los Angeles

2012

To my grandfather,

who was a master storyteller

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Publications

Katie Shilton, Vids Samanta, Deborah Estrin *Telling Traces: Learning from Data through Participatory Sensing*, in progress for IEEE Computing, 2012

Mat Laibowitz, Vids Samanta, Syed Reza Ali, Ronald Azuma. *Chamber of Mirrors: A Socially-Activated Game Exploits Pervasive Technology.* IEEE Pervasive Computing, 2012.

Vids Samanta. *Using Clock Skew Fingerprints to Increase the Cost of Spoofing on Participatory Sensing Devices.* UCLA CSD Technical Report # 110011, 2011.

Jason Wither, Rebecca Allen, Vids Samanta, Juha Hemanus, Yun-Ta Tsai, Ronald Azuma, Will Carter, Rachel Hinman, Thommen Korah. *The Westwood Experience: Connecting Story to Locations Via Mixed Reality.* IEEE International Symposium on Mixed and Augmented Reality 2010, Arts, Media and Humanities Proceedings, 2010.

Sasank Reddy, Vids Samanta, Jeff Burke, Deborah Estrin, Mark Hansen, Mani B Srivastava, *MobiSense–Mobile Network Services for Coordinated Participatory Sensing,* Proceedings of the 9th International Symposium on Autonomous Decentralized Systems, 2009.

Jeffrey Goldman, Katie Shilton, Jeff Burke, Deborah Estrin, Mark Hansen, Nithya Ramanathan, Sasank Reddy, Vids Samanta, Mani Srivastava, and Ruth West. *Participatory Sensing: A citizen-powered approach to illuminating the patterns*

that shape our world. Washington, DC: Woodrow Wilson International Center for Scholars, 2009.

Katie Shilton, N. Ramanthan, Vids Samanta, Jeff Burke, Deborah Estrin, Mark Hansen, Mani Srivastava. *Participatory Design of Urban Sensing Networks: Strengths and Challenges,* Participatory Design Conference, Bloomington, Indiana, Sept. 30 Oct 4, 2008.

Vidyut Samanta, Chase Laurelle Knowles, Jeff Burke, Fabian Wagmister, Deborah Estrin, *Metropolitan Wi-Fi Research Network in the Communities of the Los Angeles State Historic Park*, The Journal of Community Informatics, Vol. 4 No. 1, Special Issue: Wireless Networking for Communities, Citizens and the Public Interest, 2008.

Vidyut Samanta, Jason Ryder, Sona Chaudhuri, Jeff Burke, Deborah Estrin, Fabian Wagmister. *UCLA/Cisco Metropolitan Wi-Fi Research Network,* IEEE LANMAN Workshop, 2007.

Xiaoqiao Meng, Petros Zerfos, Vidyut Samanta, Starsky H.Y. Wong, Songwu Lu, *Analysis of the Reliability of a Nationwide Short Message Service* IEEE INFOCOM, 2007.

Petros Zerfos, Xiaoqiao Meng, Vidyut Samanta, Songwu Lu, *A Study of the Short Message Service of a Nationwide Cellular Carrier* Internet Measurement Conference, 2006.

Heemin Park, Jonathan Friedman, Pablo Gutierrez, Vidyut Samanta, Jeff Burke, Mani B. Srivastava. *Illumimote: Multi-Modal and High Fidelity Light Sensor*

Module for Wireless Sensor Networks, IEEE Sensors Journal, 2006.

Heemin Park, Jonathan Friedman, Pablo Gutierrez, Vids Samanta, Jeff Burke, Mani B Srivastava, *Illumimote: A High Performance Light Sensor Module for Wireless Sensor Networks,* in the 43rd DAC/ISSCC Student Design Contest, 2nd place, 2006.

Vidyut Samanta, Ricardo Oliveira, Advait Dixit, Parixit Aghera, Petros Zerfos, Songwu Lu, *Impact of Video Encoding Parameters on Dynamic Video Transcoding.* IEEE Communication Systems Software and Middleware, 2006.

Vidyut Samanta, *A Study of Mobile Messaging Services.* Master‘s Thesis, 2005.

"[Narrative] is, I believe, one of the principal ways in which we absorb knowledge."

— Toni Morrison

CHAPTER 1

Introduction

Humans have an inherent ability to identify relationships between people in our community, objects that surround us, the environment we live in, and events that take place in our lives. These relationships enable us to create a cohesive narrative around these things, giving them an overall meaning. We use these narratives as a means of recollecting, communicating, and passing on knowledge.

With the proliferation of sensors in mobile devices, we have become interested in documenting and learning more about our own lives, our relationships with the community and the environment we live in [GWW04, Pen04, EP06]. Recently there has also been growing excitement in using mobile phones to capture data about people, objects and events in our lives. However, as the volume of data being captured increases, analyzing this data and sense-making (especially for qualitative data) is becoming a challenge. The focus of this work is to develop techniques and design algorithms to build a user-assisted authoring system to create meaningful narratives from such data.

We believe these narratives will help in two ways: (a) for sense-making for oneself, by understanding and giving meaning to the data, and creating relationships in the data as part of the narrative building process, and, (b) as a way to communicate to others what one has learned by using the narrative as a structure for storytelling.

The notion of using narratives for sense-making and communicating meaning this way is by no means a new concept. In cognitive science, narratives have been used for making sense of one's experiences and as a resource for structuring and understanding one's environment [Her11a, Abo10, BSN08, Rya03]. Narratives have also played a major role in HCI research [Lau90, Lau91, Mul03]. There have also been studies of narratives as a tool for navigating and sense-making in computer-mediated environments [Rya06, Rya01].

The term *narrative* has slightly varying definitions depending on the context of usage. Based on the definition of narrative in [Dic12] and [Oxf10], we define it for our purposes as: a specific organization of content (events, experiences, etc.) used to communicate an overarching set of goals and ideas. We would also like to point out that narrative and story are sometimes used as synonyms. However, story is usually defined with the main purpose of entertainment for example, in [Oxf10] it is defined as "an account of imaginary or real people and events told for entertainment".

1.1 Participatory Sensing

Burke et al. [BEH06] introduces the idea of *Participatory Sensing* where mobile phones are used as an enabler for participatory research through *campaigns* to collect data for a specific purpose using local knowledge. For example, members from a community can participate in a data collection campaign for which they can use their phones to snap, tag, and upload photos of community events, perform volunteer assessments of the pedestrian or bike-friendliness of neighborhoods, or to improve the ease of reporting environmental threats.

Participatory sensing can take many forms, from personal investigation (also referred to as life-logging, self-quantifying, or self-surveillance) to coordinated research with many participants. For example, Your Flowing Data [Yau12] is a project that asks individuals to send short messages recording data points (e.g., weight, exercise accomplished, mood, or food eaten) throughout the day. The project provides users with visualizations to explore patterns and learn from their data. Individuals interested in tracking things that interest them can create collections of these things using services like Kullect [Kul11] and Pinterest[Pin12]. Interested enthusiasts involved in self-tracking often share their experiences and results at blogs like The Quantified Self [qua12]. Individual tracking projects are supported by software such as PACO, the Personal Analytics Companion [Pac12]. Some of these services also enable coordinated group participation and sharing. Creating a group board on Pinterest or a group collection on Kullect and can be used as a simple coordinated research platform.

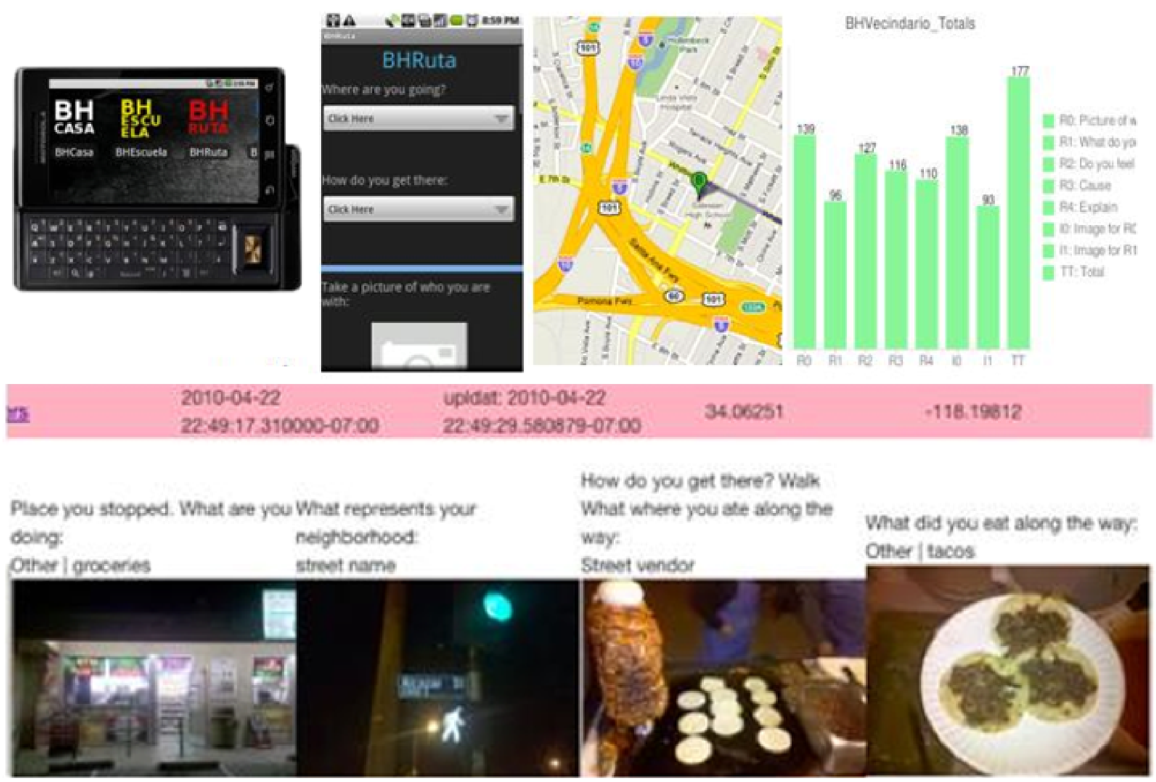


Figure 1.1: Building a Healthy Boyle Heights Campaign. Shows a data collection program running on an android smartphone, location traces visualized on a map, survey answers aggregated in a bar chart and a gallery of annotated images that were collected

Ohmage[RAF12] is a formalized effort in building a participatory sensing platform that can be used by individuals and coordinated research groups with many participants. It is a mobile-to-web platform that records, analyzes, and visualizes data from both prompted experience samples entered by the user as well as continuous streams of data passively collected from sensors or applications onboard the mobile device.

Figure 1.1 shows a community-based participatory sensing campaign that was conducted with the Building a Healthy Boyle Heights (BHBH) Collaborative using an early version of Ohmage.

The Ohmage mobile application was installed on android phones and was configured to enable the participants to gather data about the neighborhood, daily route, work, home and school environments. The application had five mini-surveys tailored for each topic, and asked people to collect pictures and add annotations in response to some of the survey questions. For example, Figure 1.2 shows the set of questions that were asked for the neighborhood survey. A total of 68 participants filled out 462 surveys during this campaign.

1.2 Need for Narratives to Make Sense of Data

After the campaign was completed, the data was analyzed with statistical tools such as R to produce useful charts and maps. Detailed results can be found in the report [AAB10]. However, we didn't have any tools to analyze the qualitative data from images and annotations.

Over 700 annotated images were collected and had a lot of interesting information that was not captured in the quantitative data. For example, high school students were asked to document interactions with teachers outside of class. The students were given phones with a survey that they could launch whenever they interacted with teachers outside class. The survey asked students to respond to the following questions: Where did the interaction take place? Which teacher?

BH Neighborhood Survey Questions
Take a picture of where you are now: *Toma una foto del lugar donde estas en este momento:*
Label picture: *Describa la foto*
Options Home Work, Friends House, Market, Other *Casa, trabajo, casa de un amigo, mercado, otro.*

Take a picture of what best represents what you do after school/work: *Toma una foto que mejor represente lo que haces después de la escuela o el trabajo*
Label picture: *Describe la foto*
Taking care of children, TV, Chores, Homework, Friends/neighbors, Errands, Sports/dance, Other: *Cuidar niños, ver TV, tareas domésticas, tareas escolares, encargos de amigos-vecinos, deportes/danza, otro.*

To what extent do you feel safe in your neighborhood at this moment?*: ¿Hasta qué punto te sientes seguro en tu vecindario en este momento?*
OPTIONS Very safe, Somewhat safe, Not safe: *muy seguro, seguro, inseguro*

Figure 1.2: Sample survey questions from the BHBH neighborhood campaign

How long did it last? Was this related to class? The survey also asked students to take a picture and add a comment about the interaction. The first four questions were easy to analyze using statistical tools such as R to produce basic visualizations like the chart on the left in Figure 1.3.

The images and annotations on the right give a different depth to the information. Such qualitative feedback can be very helpful in adding a new dimension to the quantitative measurements. It gives the measurements a larger context, and subtleties that are otherwise overlooked can be brought to the forefront. However, it is very difficult to build a system that can automatically interpret this kind of qualitative data, especially when there are multiple participants contributing data, with their own idiosyncrasies, which makes the data appear fragmented when looked at as a collective pool.

As humans, we are inherently able to find connections between disconnected and fragmented ideas and things [Moo11]. We use these connections to create a

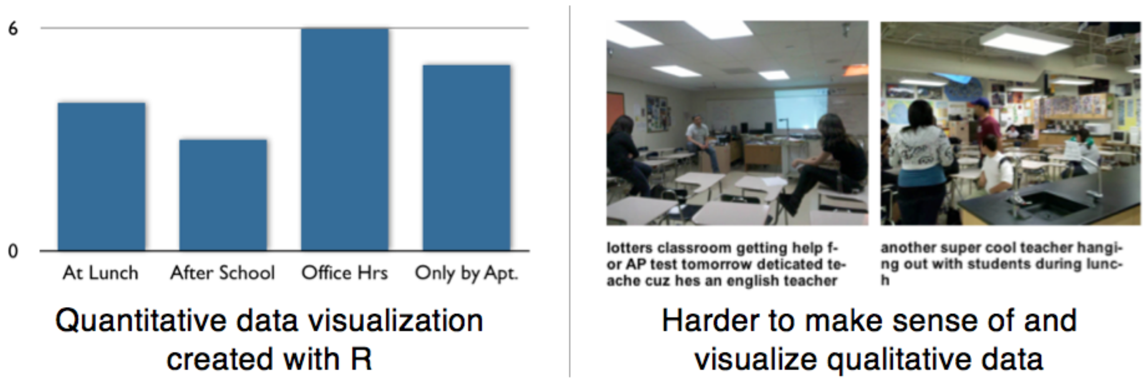


Figure 1.3: Comparison of qualitative and quantitative data from the BHBH campaign

cohesive narrative around these things, giving them an overall meaning [Wor04]. We use these narratives as a means of recollecting, communicating, and passing on knowledge. Hence, we believe that narratives can also be used to make sense of fragmented participatory sensing data.

Community members who participated in the BHBH campaign were asked about how participating in the campaign helped them personally. People talked about paying more attention to what represented their community and they wanted to be able to share their concerns and opinions with others who didn't know about their community. One participant responded: *"Many people don't know what Boyle Heights is like and this will be a chance to show them"*. They felt very proud that others would see photos of their community. But the pictures alone may not be able to communicate the views of the participants who collected them. Building a narrative with the photos would be a way to give more meaning to these pictures when presented to people outside the community, and an opportunity to include the thoughts of the participants.

Participants were interested in comparing their responses with others in the community to look for common concerns. For example, one participant said: *"My house needs a lot of repairs. I got to use the camera to document it and I want to* *see if other homes are as bad or worse than mine."*

Community members and leaders also expressed interest in having tools to view and analyze the data they collected. They requested tools that would be informative, easy to interpret, and engaging to view. The goal was to explain their perspective, and produce a platform to voice common concerns and share them with other community members.

1.3 Research Statement

Previous work in participatory sensing has focused on infrastructure needs for data collection [SRC07], [LEM08], [AST06], [Fro07], [Kul11], privacy and selective sharing of data [MHM10], recruitment of participants[Red10], activity classification [RBE08] [MRS09], analysis of collected data, and on individual mashups for visualization of collected data [CEN08], [RPH07]. However, there is a gap when it comes to understanding and communicating the overall meaning of qualitative data, especially for community-driven campaigns, such as the BHBH campaign. The focus of this dissertation is to fill this gap by developing techniques and tools that will allow users to build narratives with qualitative data as a way to better understand it and give it an overall meaning.

We realized that it is very difficult to build algorithms that could automatically create narratives from data, but it is inherent to humans. It can be a very tedious and labor-intensive task to sift though a large data set of hundreds of images and annotations. This realization led to the exploration of a toolset that we named *Narreme* tools. They would assist a user to interpret and make connections in the data and provide automated ways to group and filter data and create a narrative. The research contribution of this thesis is the development and evaluation of algorithms and software modules used to implement such a toolset.

We decided on a set of design principles for the Narreme tools based on the feedback from participants in the BHBH campaign:

- They should be easy to use by community members who were not domain experts and did not have formal training in statistical packages like R.
- They should provide a way to browse qualitative data such as images and free text and easily find common subjects in this data.
- They should provide users with a way to present their own interpretation of these subjects along with their emotional reaction to them.
- Outputs should be engaging and easily sharable and accessible to any audience.

In the next chapters, we will describe the Narreme tools and the techniques and algorithms used in building the tools. We will explain their working and usage in detail. We will also look at related work in the area. Finally, we will explain how we evaluated our tools and techniques though a user study with participants from Boyle Heights and Maywood who created narratives using our tools, and present the results of our user study.

1.4 Terminology

Earlier we defined *narrative*. In this dissertation, we also frequently talk about *conflict* and *tension* as they relate to narratives.

Conflict in literature has been defined as "the struggle within the story" [Sea12]. Conflict is the primary way to create tension, and thereby interest, in a narrative by adding doubt as to the outcome [Rob86].

Tension "is what keeps the reader reading, because they're wondering what's going to happen next" [Moo05]. It is what makes a narrative compelling to an audience. Tension in a narrative is built up by the conflicts faced by characters or objectives in a narrative.

1.5 Contributions

1. We created the Narreme Toolset for creating engaging narratives with participatory sensing data. The tools help a user identify connections in qualitative data, create groups of connected data, discover where to introduce narrative tension and produce a video slideshow that can be shared easily with any audience.

2. We created and evaluated two techniques that, we believe, are fundamental to narration tools: clustering and conflict discovery.

3. We performed a formal user study to evaluate the Narreme tools, the usability, and the effectiveness in creating narratives that were engaging to an audience.

4. During our user study we conducted three workshops with the Boyle Heights and Maywood communities in East Lost Angeles. This supported the goals of the community organization Union de Vicinos and fostered community building.

5. We did a survey of related work and provided a comprehensive summary of the area. We reviewed work in text-based clustering for our clustering tools. The design of our tools was based on ideas from Narratology and structure. We reviewed the works of different narratologists and provided details that influenced our design. We also used Natural Language Processing (NLP) algorithms for making sense of annotations and for sentiment analysis, and we describe related work in these fields.

6. The Narreme tools were built in a modular way so that they could be extended and may be used as a platform for evaluating relevant NLP algorithms.

CHAPTER 2

Background

In this chapter we present an overview of the participatory sensing system, and explain how our research and the Narreme tools enhances this system.

2.1 Participatory Sensing System

Participatory Sensing is a process whereby individuals and communities can use sensor-rich smart phones to collect, share, and organize information about personal and environmental factors that impact community health. Participatory sensing offers communities and individuals a method for making robust observations through directed data collection initiatives or campaigns. By harnessing common smart phone utilities such as internet access, camera, microphone, text input and positioning systems, communities can incorporate mobile sensing applications into everyday life activities. For example, participants can self-report observations during their daily commute, during a walk to get lunch, etc. Campaign organizers and researchers can then access that data in almost real-time, analyze collected observations, and use the data to gauge and determine specific needs within their neighborhood environments.

Campaign organizations can use the information they learn from community data campaigns, along with the processed data as strong evidence to advocate or make a case around a topic that they care about.

Participatory sensing helps to encourage involvement of community members in understanding their neighborhoods strengths, needs, and activities by enabling them to collect data about what is important to them from their individual perspectives. It also encourages sharing and easy access and distribution of collected data though web based data management so that participants can access, analyze, and make their own observations about the data. This enables participants to understand the significance of their individual data sensing contributions at personal and community levels.

Participatory sensing is influenced by the fundamental principles of Community Based Participatory Research (CBPR), methodologies that integrate community members into research projects as co-investigators [CM08], [BA06]. By coordinating increasingly available devices, participatory sensing offers automation, scalability, and possibilities for real-time upload, processing and feedback. These features can augment traditional CBPR efforts such as participatory urban planning [Cor03], geographic information systems [ES06a], and Photovoice initiatives [Wan96].

Experience Sampling Method (ESM) asks participants to stop at certain times and capture data of their experience in situ and in real-time [CL87]. ESM includes self-report surveys, diary studies as well as Ecological Momentary Assessment (EMA). Researchers use this method because data is captured in the moment and so there is little need for participants to try and recall events. This quality of self-reporting (combined with minimal contact with the researchers) can raise the ecological validity of in situ observational studies.

The mobile phone application used in participatory sensing can be modeled on ESM and can run in the background, collecting information from sensors such as accelerometers and location sensors. Activity classification on these sensor streams can be used to determine when the user is performing a certain activity and the application can then prompt the user to capture their data based on the activity. For example, the activity classifier can detect when the user is bicycling and during the bicycle commute it can prompt the user to capture data about something related to their commute.

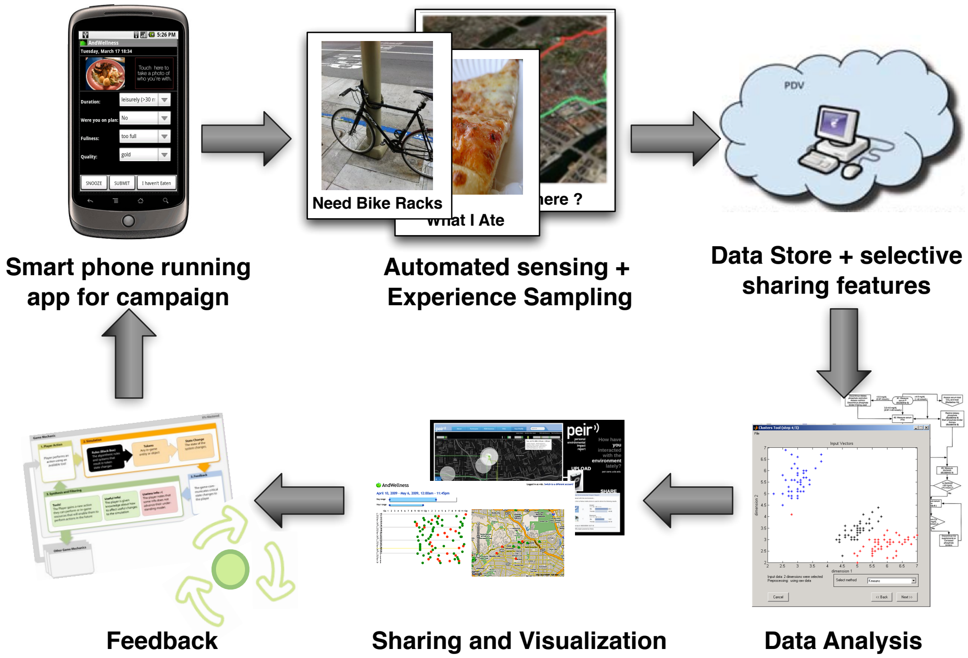


Figure 2.1: Participatory Sensing System Components

Figure 2.1 shows the Participatory Sensing system components. A custom application might be tailored to a campaign with EMS or an appliction like Ohmage [RAF12], Kullect [Kul11], MyExperience [Fro07], or Nokia Simple Context [Nok08] can be used to quickly deploy a campaign. Data is uploaded using the mobile phone's Internet connection to a database that has selective sharing rules that participants can set up beforehand. The database can be accessed by other systems and processes for further processing and mashed with external sources like Google maps, and can then be visualized and shared. The system might also have a feedback loop, which goes back to the phone application so participants can get instant feedback about data they captured after it is processed.

The focus of this dissertation was in the data processing, sharing and visualization part of the system described above. The Narreme clustering tool helps in the analysis of qualitative participatory sensing data. The conflict discovery and video editing tool help visualize the data. The final output video narrative helps in sharing and communicating the ideas expressed in the data.

CHAPTER 3

Narreme Tools

The Narreme toolset enable users to create engaging narratives with participatory sensing data. The main features of the tools are listed below :

- They are designed to be easily accessible using a web browser and they support both English and Spanish users.
- The tools put the user in control and assist in discovering a theme or a central topic for the user's narrative. The tools help the user find data to support this central theme and build a narrative around it. Our goal was not to create a completely automated system that churned out mechanical narratives but rather to focus on a user-assisted authoring system.
- The tools enable framing of the events and finding conflict and harmony[1]. Additionally, tension curves are used to order events. Tension in a narrative is traditionally used to keep the audience interested. A tension curve is a plot of tension over time for a story. Conflict increases tension and harmony reduces tension.
- The final output of the Narreme tools is a video slideshow narrative. This format makes it easy to share and distribute to a large audience.

The toolset consists of three tools that were designed to address the design principles we talked about in 1.3:

[1] Narratives are composed of a sequence of events. An event is something that happened in the narrative [Kea02]. In the case of narratives created from participatory sensing data we can think of an event as something temporal that can be expressed by a set of data elements.

1. Narreme Clustering Tool,

2. Narreme Conflict Discovery Tool, and,

3. Narreme Video Editing Tool

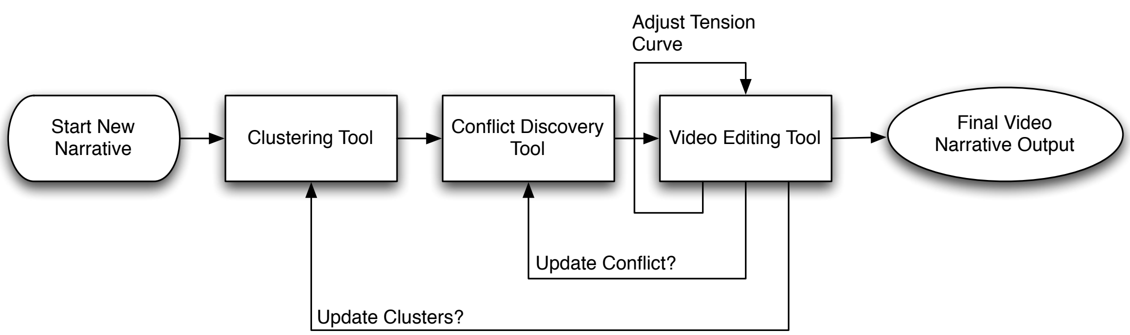


Figure 3.1: User Flow Diagram for Narreme Tools

Users are expected to move though the tools in a linear path when they start a new narrative, and then move back-and-forth between the tools to tweak their narratives (Figure 3.1 shows the user flow diagram).

1. Users start by creating an initial set of clusters in the Narreme Clustering Tool.

2. They decide what clusters are in conflict or harmony in the conflict discovery tool.

3. Users move on to the video editing tool to view an automatically-generated slide show video of the images in their clusters (in the order in which the user created them), along with a tension curve. The tension curve shows narrative tension over time for the narrative in the present form.

4. Users can adjust the ordering in the video editing tool itself, or move back-and-forth between tools to adjust conflict-harmony values and/or add and remove elements from their clusters, or even create new clusters. Changes

made by the user in any tool get reflected in the tension curve and they can view updated versions of their video in the editing tool. They can iterate over this process until they are happy with the final outcome.

Next, we present the user interface and usage details for each tool.

Figure 3.2: UI for the Narreme Clustering Tool

3.1 Narreme Clustering Tool

This tool helps users identify the main subjects they want to use in their story. It enables the user to filter though the raw data of annotated images and create groups containing images that support a common idea. Figure 3.2 shows a screen grab of this tool.

The UI consists of four components:

1. **Container for the raw dataset**: On the left side of the UI is a container for the entire dataset. It has three columns for images, annotations and

categories that can be specified during data collection. Data can be sorted or grouped using the pulldown menus on the tabs above each column. Figure 3.3 shows a detailed view of the filters, pulldown menu and the data grouped by category.

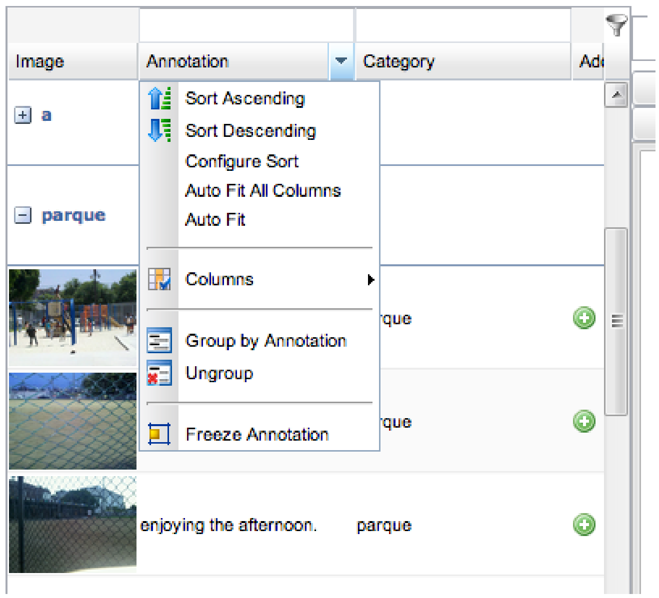


Figure 3.3: Detailed view of the raw data filters and grouping menu functions

2. **Canvas for creating, viewing and editing clusters**: The container in the center of the UI is for viewing, editing and creating clusters. Users can start by creating a cluster manually by adding images from the raw data container onto the canvas, or view or edit a saved cluster or a cluster from the automated suggestions. The annotation of individual images can be edited by clicking on the annotation under the image. Before saving a new cluster, a user needs to specify a title for the cluster in the Subject field above the canvas.

3. **Saved clusters**: When a user saves a cluster it appears in the saved clusters container which is at the top right portion of the UI.

4. **Automated cluster suggestion**: The bottom right side of the UI contains a component for automated cluster suggestions (Figure 3.4

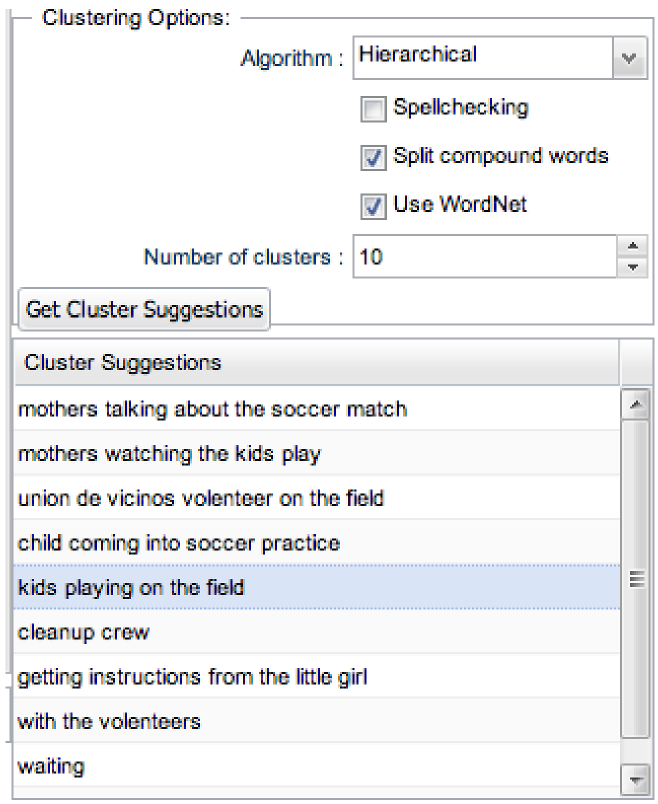


Figure 3.4: UI COMPONENT FOR AUTOMATED CLUSTER SUGGESTIONS

For most users, the expected behavior is to get the cluster suggestions using the default values in the options panels (which were decided based on results from an internal pilot study with high school students during a summer program. More about the pilot can be found in 4.2.1).

Users can trigger the automated clustering on the entire data set or on portions they have pre-filtered.

Advanced users can select different options, before running the automated clustering:

- Select from three different clustering algorithms; K-means clustering [Har79], Hierarchical clustering [HTF09], and Fuzzy C-means clustering [KRC12]

- Select number of clusters
- Select whether she wants to spellcheck data
- Select if she wants to split compound words
- Select if she wants to use the WordNet senses

The working of the options is described in 4.2.

The tool takes the data and pre-processes it using text analysis based on options selected and then runs the clustering algorithms on it. The tool then produces automated suggestions for clusters. A user can click on any suggestion and it opens up on the canvas. Then, the user can make changes to the cluster by adding or removing elements, or editing annotations of individual elements. Finally, the user can save it for their narrative.

3.2 Narreme Conflict Discovery Tool

Once the user has created the clusters and identified the subjects they want to use in their narrative using the Narreme clustering tool, they can use the Narreme Conflict Discovery tool to compare the emotions and sentiments they associated with each cluster to all of the clusters. Figure 3.5 shows the UI for this tool. The tool has a simple interface that displays all the clusters created by the user in pairs. A slider below each pair is used to describe whether the ideas in the clusters are in conflict or harmony with each other. We used Natural Language Processing (NLP) based text sentiment analysis [ES06b, TNK10] to set the initial position of the slider. Users can then move the slider to the position they think is appropriate. This helps the user as the initial position chosen by the automated sentiment analysis should be the same position the user would choose or close to it. In addition, it can also be used as a way to train and improve the sentiment analysis system when the user chooses a different position instead.

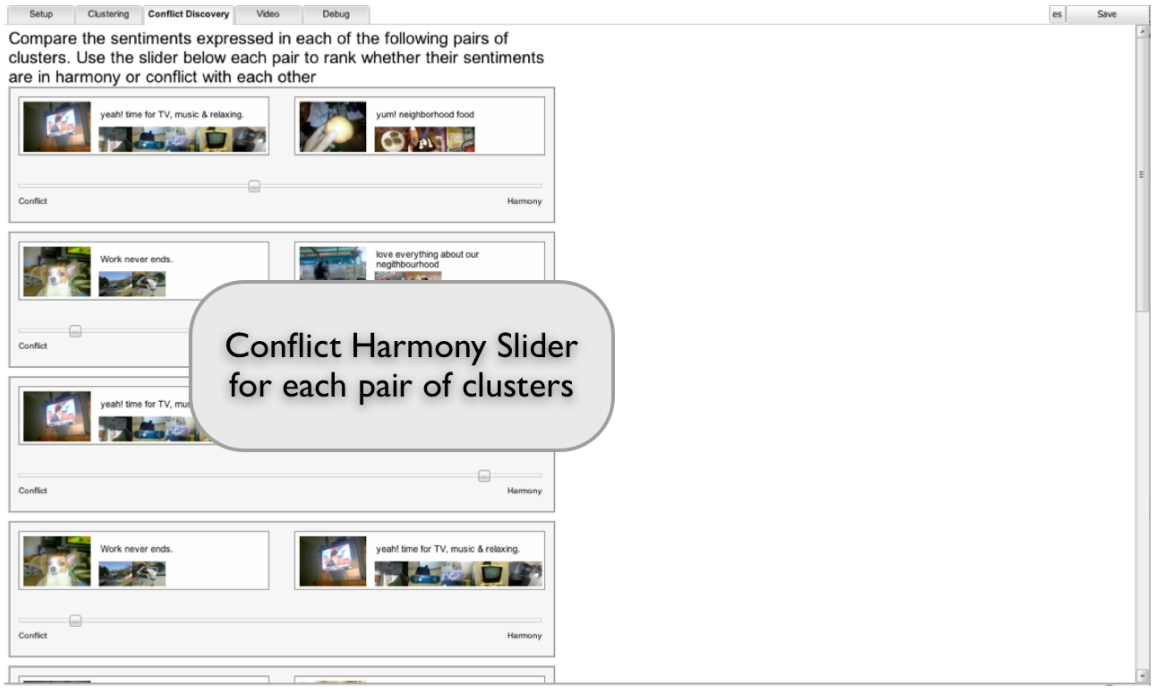


Figure 3.5: UI for Narreme Conflict Discovery Tool

3.3 Narreme Video Editing Tool

After assigning conflict-harmony values to every pair of clusters, this data, along with the images and annotations (as captions), is woven together automatically to create a video slide show, and made available to the user in the video editing tool. Figure 3.6 shows the interface of the editing tool.

The user can use the video-editing tool to then tweak the automatically generated narrative. She can view a narrative tension curve for the video and change the ordering to get different curves until they are satisfied with the outcome. She can also use manual editing functions to change the amount of time an image is displayed, change transitions, add new transitions, add special effects, and edit or add new title cards or captions.

This tool was built by extending MovieMasher [Mov12] which is an open source Extensible Flash (AS3) and PHP online video editor.

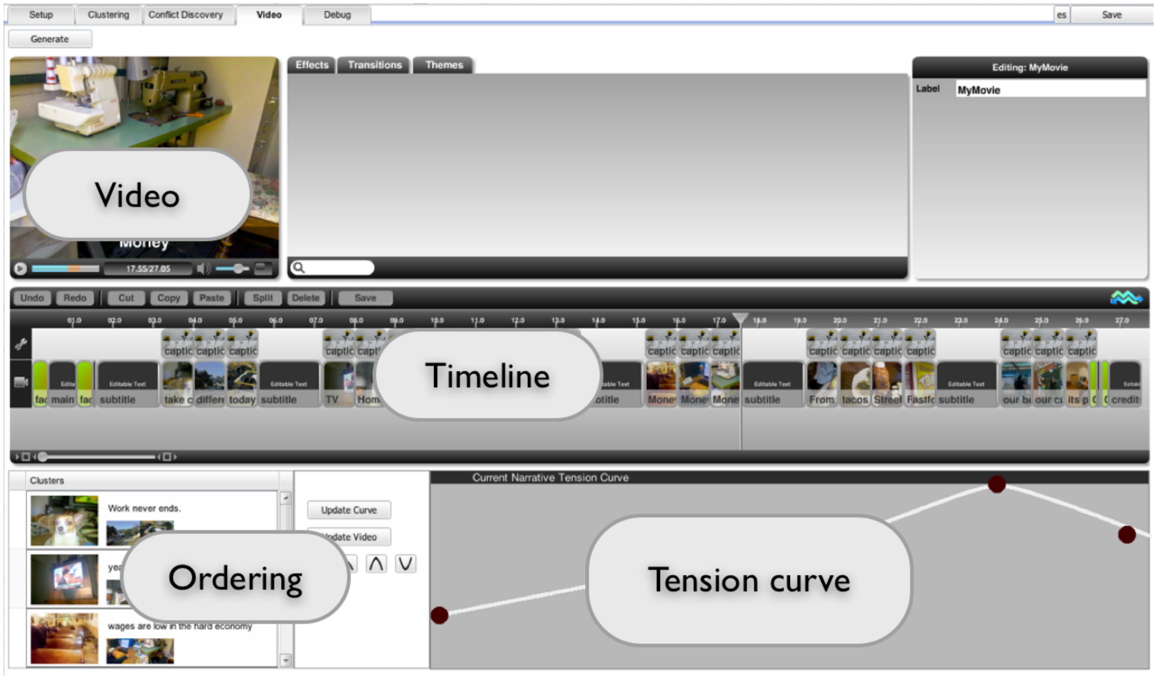


Figure 3.6: UI for Narreme Video Editing Tool

The UI has 5 main components:

1. **VideoWindow:** The top right is a window for previewing the video while editing.

2. **Timeline:** The mid-section of the UI is a timeline. Every image in each cluster is present on the timeline in the order in which they will appear in the video. Automatically generated title cards with the subject of each cluster are used to separate clusters.

3. **Ordering and Tension curve window:** The window at the bottom presents the narrative tension curve for the current ordering of the clusters. A user can change the tension curve, which will automatically reorder the images in the narrative to match the new curve and update the video window and timeline. The user can then play the new video and continue manipulating the tension curve to find the narrative ordering that is most

engaging.

4. **Options and Effects Panels:** The top middle and top right contain panels for tweaking options such as controlling how long an image should appear, changing text attributes, and advanced effects such as colorization of images.

CHAPTER 4

Techniques and Algorithms

In the previous chapter we described the Narreme toolset. In this chapter we discuss the algorithms and software modules used to implement the toolset, and our narrative-informed design choices.

4.1 Software Architecture

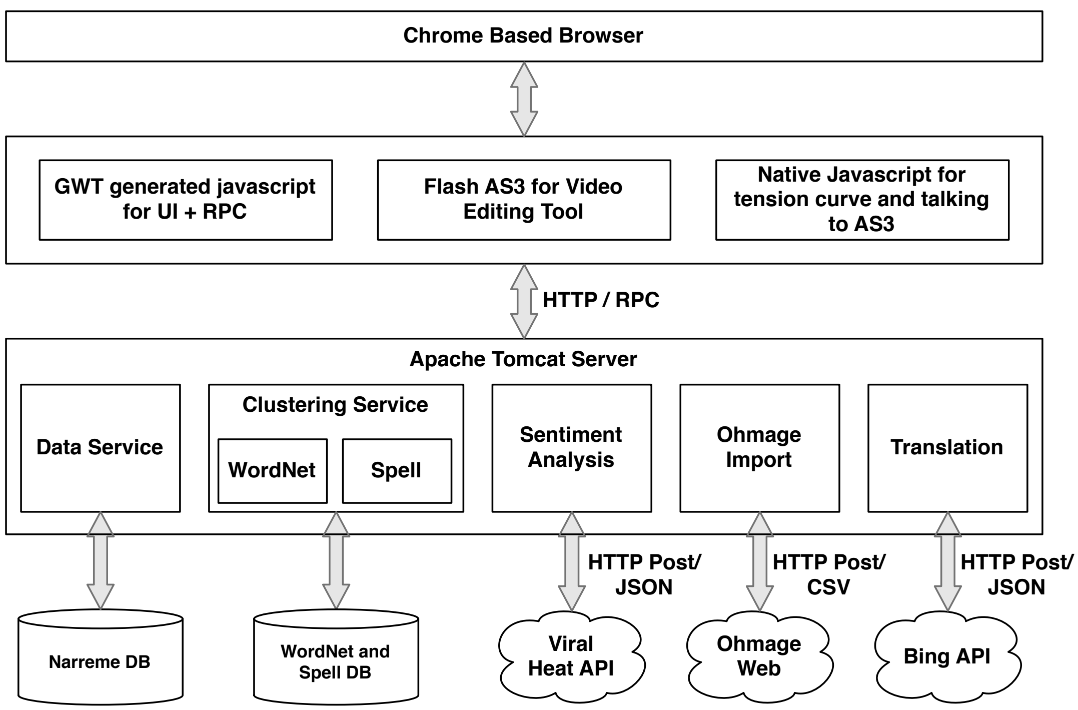


Figure 4.1: Narreme Architecture

Figure 4.1 shows the software architecture for the Narreme tools. We wanted to build the tools in a way that they could be easy to set up on any participant's computer without having any special dependencies and decided to use a browser-based solution. The bulk of our user interface is built using Google Web Toolkit (GWT), which is a development toolkit for building and optimizing complex browser-based applications [Dew08]. We also integrated an open-source Flash-based video editing API called MovieMasher [Mov12] into the application. This was done by implementing a native Javascript solution which interfaced GWT code with the MovieMasher Action Script.

Using GWT made it possible for any one to use our tools though a chrome-based web browser, and made it possible to implement complex processing on a server, which interfaced with the browser-based application thought RPC. GWT makes it possible to write the server and client code together in Java, which makes them tightly integrated. GWT generates javascript from the Java code for the client side user interface.

On the server side, Java code runs in Apache Tomcat. We designed and implemented the following software modules on the server side:

1. Data service module that managed all the data for our application. It is used to interface with a back-end SQLite database that contained the datasets and also handled user project data for loading and saving narratives created by users.

2. Clustering service, where we implemented our algorithm to preprocess user annotations using lexical techniques before running clustering algorithms on it in the R statistical computing language.

3. Spell-checking helper module using the Levenshtein spelling algorithm [MVM09] for getting spelling suggestions from a database of English language words to add spelling suggestions to user annotations for the clustering service.

4. Word sense disambiguation module that used the WordNet api [Mil95], [Fel98] and provided different word senses to add to user annotations for the clustering service.

5. Translation service for translating data between Spanish and English, which used the Bing translation engine.

6. Ohmage import service that got new data from a campaign running on Ohmage.

7. Sentiment analysis module for calculating sentiment scores for clusters. This used the Viral Heat sentiment analysis API [Vir12].

The architecture is easily extensible, and new software modules can be added to the server without much effort. For example, if someone wanted to try a different approach to clustering or sentiment analysis or use a different database, she or he can do this by extending the appropriate service.

4.2 Data Clustering

Previous work in data clustering of annotated images has focused on clustering very large data sets with millions of Flickr images based on user annotations [Naa07], [CKT06]. These systems learn from the many relationships that start emerging from a large number of elements and can do better clustering as the numbers increase. However, for our application we dealt with data sets that are comparatively very small (100-1000 images). Data elements in such small data sets by their nature are very idiosyncratic and relationships are not clear. This makes it a more challenging problem.

We developed a technique for data clustering smaller datasets of annotated images that uses algorithms to preprocess the annotations based on lexical techniques and relate them to the large WordNet database of word senses before running a clustering algorithm.

The clustering tool has three options that can be selected to run different linguistic and lexical analysis on the data before running a clustering algorithm.

1. The first option is spelling suggestions. When this option is selected all annotations are checked for spelling errors. A set of spelling suggestions for each misspelled word is added to the feature set for the annotation containing the misspelled word. The misspelled word is also left in the feature set. For example, if an annotation contained the misspelled word: **frend**, selecting this option would add **{friend, trend, ..}** to the new feature set.

2. The second option splits compound words. Compound words in linguistics are comprised of two or more stems. For example: **textbook = text + books**

   When this option is selected compound words are split into their stems and both the compound word and the stems are inserted into the feature set for the annotation. So for "textbook" the feature set would contain: **{textbook, text, book}**

3. The next option is for adding WordNet synsets to the feature set. WordNet is a lexicon of the English language that also captures the semantic relationships between words. It contains information about different senses of words and combines synonyms into structures called synsets. For example Figure 4.2 shows the senses for the word "sister".

   Most synsets are connected to other synsets through different semantic relationships:

   Hypernyms: Word X is a hypernym of Y if every Y is a kind of X.
   i.e. it is a **IS A** relationship.

e.g. collection is a hypernym of library.

Hyponym: The converse of a **hypernym.**

e.g. Surfing is a hyponum for Water Sport.

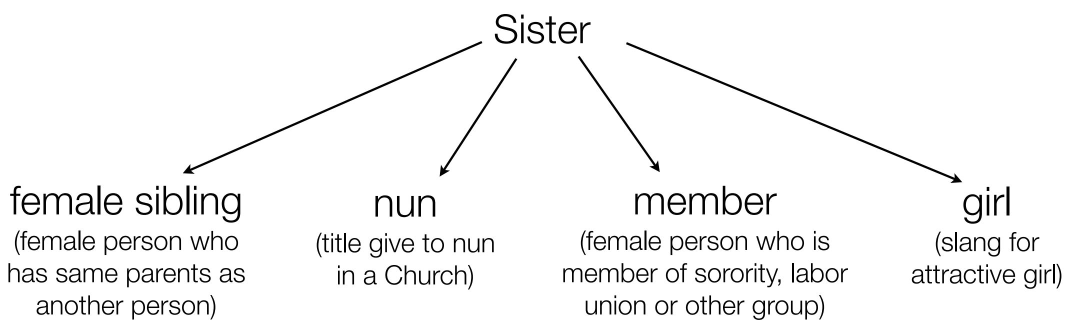


Figure 4.2: WordNet senses for the word "sister"

When the option is selected word Hypernyms are added to the feature set. This creates a hierarchical tree forming relationships between words.

4.2.1 Pilot Study and Results

We conducted a pilot study with fifteen high school students who were participating in a summer internship program at UCLA, to help test our clustering techniques. The students were learning about participatory sensing and ran a campaign on advertising around the UCLA campus.

We built a simple application that used our clustering techniques and allowed the students to cluster the data from their advertising campaign. Students were asked to select different preprocessing options and run the clustering. The application would display the clusters based on the options selected.

The students were then asked to look at each cluster and rank whether it made sense on a scale of 1-5. Where 1 meant they didn't agree the cluster made sense, and 5 meant it made perfect sense.

From the students' rankings, we calculated a mean score for each set of clustering options that could be selected. Table 4.1 and Figure 4.3 shows the results.

Preprocessing Techniques	**K-means**	**Hierarchical**	**Fuzzy c-means**
No Preprocessing	2.61	2.52	2.59
spell	2.20	2.00	2.50
split	2.80	2.55	2.54
wordnet	2.84	4.03	2.98
wordnet + spell	2.50	3.58	2.56
wordnet + split	2.83	4.03	2.95
word net + spell + split	1.50	3.56	2.60

Table 4.1: User-based rating of clustering techniques

From these results we can conclude that:

1. When there is no preprocessing all clustering algorithms perform about the same.

2. Spelling suggestions made clustering results worse in all cases, we saw 10% reduction in the ratings for hierarchical clustering, 8% and 2% in K-means and C-means respectively.

3. Compound word splitting improves results slightly. We saw a 4% improvement for K-means.

4. *On adding WordNet sense and hypernyms we see a remarkable improvement in clustering results. This is observed specially when using Hierarchical clustering where we see a 30.2% improvement.* This is because wordNet hypernyms help create a hierarchical structure which makes the hierarchical clustering perform well.

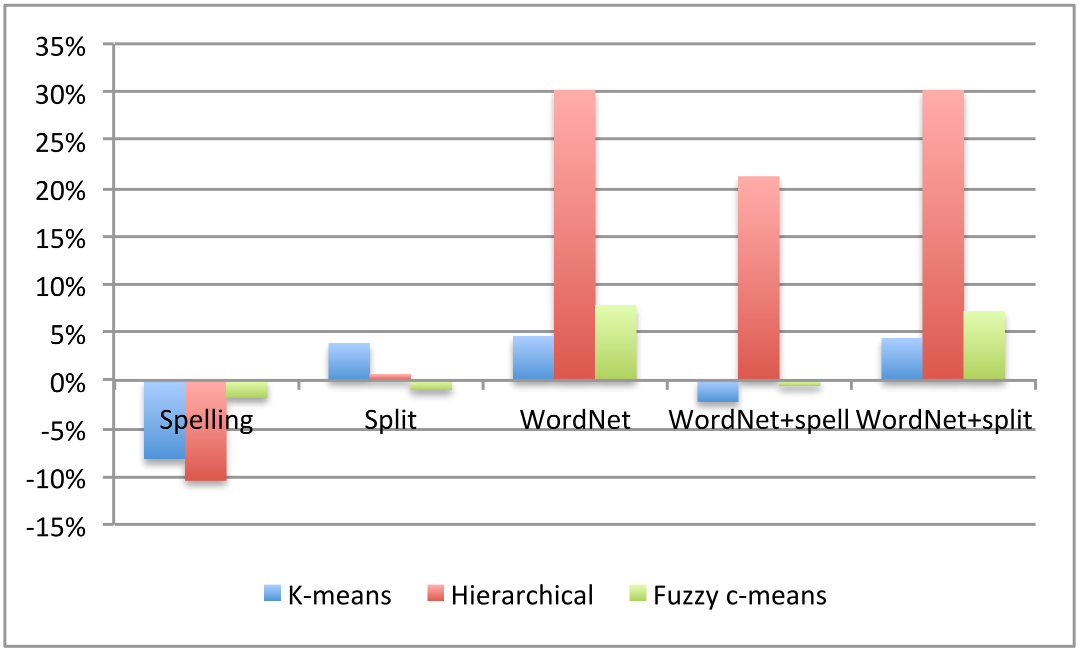


Figure 4.3: PERCENTAGE IMPROVEMENT IN RATING BASED ON CLUSTERING TECHNIQUES

These results are consistent with our early experimentation in B.3. In the early experiments, we evaluated clustering techniques by manually creating optimal clusters for a small dataset and compared results from different automated results to our manual clusters. (For details see Appendix B).

Based on these results we preconfigured the Narreme toolset so that by default it would preprocess data by splitting compound words, and, adding word senses and hypernyms from WordNet. Then, by default it would use the hierarchical clustering algorithm to create cluster suggestions from the dataset.

4.3 Similarities Between Narreme Tools and Writing Process Recommendations

The professional field of writing research and instruction is called *Writing Process*, and is also referred to as Composition Studies or Composition and Rhetoric. There has been a lot of work done in this field since the 1970s [Emi71, Mur72, Mat87, Ric83, De 84, BB84].

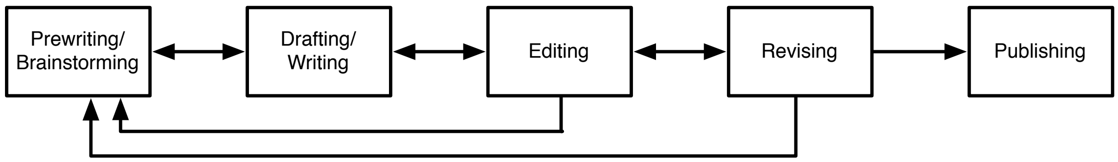


Figure 4.4: 5 STEP WRITING PROCESS

The writing process as it is taught in most high schools and university composition classes today, consists of 5 stages: (1) Prewriting or Brainstorming, (2) Drafting or Writing, (3) Editing, (4) Revising, and, (5) Publishing. Figure 4.4 shows how a writer goes through the steps. This flow is very similar to the flow we presented earlier in Figure 3.1 for the way a user would create a new narrative project using the Narreme tools.

The brainstorming phase in the writing process is where one generates a large number of ideas in no particular order. There are three different recommendations to approach this; free-writing, clustering or mapping or mind-mapping (this is the writing process technique called clustering, which has similarities to our clustering process which we discuss below), and outlining.

Freewriting is a process where a writer starts by getting her ideas down spontaneously without paying attention to spelling or grammar, and without looking back at what she has written until she is satisfied the she has written enough. Then, she goes back to elaborate on things that she thinks are important [Elb89]. Outlining as the name suggests, is technique of creating a hierarchical plan before writing.

Clustering or mapping as described by Rico [Ric86] is a visual technique where a writer starts by writing down the main subject and then jots down ideas around it. She then draws circles around each idea and connects them to the main idea, drawing color coded lines to connect related ideas (see example in Figure 4.5).

Rico claims that this process enhances creativity.

Figure 4.5: Example of Clustering in the Writing Process for the topic 'Clustering'

This kind of clustering, as a brainstorming process for writing, is very similar to how the Narreme Clustering tool helps a user in brainstorming for creating the video narratives. The tool allows a user to manually create clusters of images with a common main subject, but in addition also uses statistical clustering analysis to provide users with suggestions as an additional brainstorming tool. The clustering tool also allows the user to reorder the images within a cluster and connect related ideas by editing the annotations for individual images. This is like drawing the line between related ideas in the writing process.

In the writing process translating the maps from the brainstorming phase to ordered groups of ideas, and ordering the groups into a narrative is hard. In the Narreme tools we help the user order the clusters visually by using a tension cure. We will describe this in the next section.

The editing and revision phase of the writing process is where the author might change the order and review the document. This is similar to what the Narreme video editing tool allows the user to do.

4.4 Narrative Informed Design

Reuven Frank, a broadcast news pioneer and producer at NBC, once sent a memo to the crew of the NBC Documentary, The Tunnel that stated:

> *"Every news story should, without sacrifice of probity or responsibility, display the attributes of fiction, of drama. It should have structure and conflict, problem and denouement, rising and falling action, a beginning, a middle, and an end. These are not only the essentials of drama; they are the essentials of narrative."* [Mus04]

The significant point here is that elements of dramatic[1] and narrative structure are an important means in passing knowledge and keeping the audience engaged at the same time even for news and non-fictional documentary. Narratives are essential mechanisms to our education, entertainment, and social well-being [Kea02] and one of the principal ways in which we absorb knowledge [Pag01]. This inspired us to study and design our tools based on principles from Narratology. We particularly focused on narrative structure, and on the conflict to help build and resolve tension and help understand how to order events to have maximum impact on an audience.

[1] The word *drama* comes from a Greek word which means "action", and can be defined as a specific mode of a fictional story represented in performance (live theater) [Ela02]. It can also refer to a genre that is used by film and television industry, but in this dissertation when we refer to drama, or dramatic work and dramatic structure, we are referring to the former definition.

4.4.1 Conflict

Conflict is an essential part of narratives. It is the inherent incompatibility between two or more ideas. Conflict is the primary way to create tension and thereby interest in a narrative by adding doubt as to the outcome[Rob86]. In dramatic fiction, conflict usually arises between the ideas and objectives of a protagonist and an antagonist. It is harder to understand where conflict can arise in non-fictional and documentary style narratives.

4.4.1.1 Conflict Prediction using Sentiment Analysis

In order to better understand where conflict can be introduced in narratives created with participatory sensing data, we developed a technique to pairwise compare clusters of data based on the emotions each cluster hoped to evoke in an audience. Our technique is based on performing *sentiment analysis* on the subject of each cluster.

Sentiment analysis, also referred to as *opinion mining* is an application of natural language processing (NLP) and text analysis to identify sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, and events [Liu12]. Traditionally, most work in Sentiment analysis has focused on looking for sentiments expressed in larger pieces of text, such as reviews for a restaurant, or article, a news story, or blog postings [PLV02]. More recently there has been a focus on social media, which has led to analysis of much shorter texts. For example, performing sentiment analysis for micro-blogs such as twitter and comments in Facebook [BPM09] , [BCM11], [GBH10].

We used a sentiment analysis service from a social media analytics platform called Viral Heat [Vir12], which was optimized for performing sentiment analysis on shorter text. The service returns a predicted mood and probability for any

English text limited to 360 characters. To determine what clusters are in conflict we created a list of all the clusters used in a narrative and got the predicted mood and probability for each cluster. Then we pairwise compared all the predictions for all clusters and, if the predictions were opposing, we determined that there was conflict and used the probability to assign a value to this conflict. If the mood was similar, we determined there is harmony.

We built our conflict discovery tool based on using this technique. In the tool, we presented the user with the list of all the pairwise comparisons, and for each comparison had a slider between conflict and harmony. With this position we set our predicted conflict score. If a user agreed with the score she leave it in place to accepted it. Is she didn't agree with it she could move the slider to the position, which she felt was correct. In 6.5.3 we present a detailed evaluation of our conflict prediction technique through user studies.

4.4.2 Structure of Narratives

Narrative structure is the general framework or model that defines the order and method in which a narrative is presented to an audience. The analysis of narrative structure for dramatic works dates back to 335BC with Aristotle's Poetics [HA68]. Aristotle says "A whole is that which has a beginning, a middle, and an end" and must relate to one another as being either "necessary or probable" [ABF61]. This arguably is the origin of the western three act dramatic structure. In-fact, Hollywood screenwriter Syd Field established a three act paradigm for hollywood screenplays in *The ScreenWriter's Workbook* [Fie84] which is based on this model.

Later, in the 1860s, German playwright Freytag expanded Aristotle's structure to have 5 stages: (1) exposition or introduction, (2) rising action, (3) climax, (4) falling action, and (5) resolution or denouement [Mad08]. Figure 4.4.2 shows Freytag's pyramid diagram of these five stages that evolved into the broadly applicable structure in western society for narrative today [DSB12].

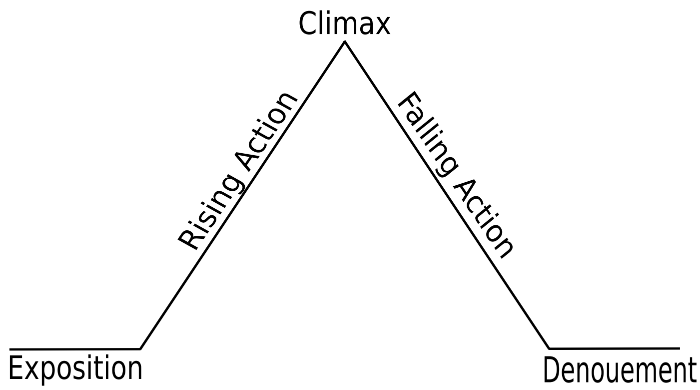


Figure 4.6: Freytag's Pyramid

In the 1920s, the notion of narrative structure saw renewed interest since Narratologists from the Russian Formalist School began to analyze it. They divided the composition of a story into the *fabula* and the *syuzhet* [GKS05]. Fabula is the story's theme, and subject matter, or all the knowledge and facts about the narrative world, and, *syuzhet* is the structure and ordering of events. This school was characterized by Viktor Shklovsky and Vladimir Propps work. Propp analyzed several Russian folk tales and identified common traits and themes within them. He broke down the structure of folk tales into a parametric model with 31 narrative units and created a formal symbol and function for each unit [Pro28].

Joseph Campbell's *The Hero's Journey* analyzes a basic structure of many narratives with archetypical Heroes [Cam03]. This structure follows an individual who leaves home to venture into the unknown on a quest. This individual is often the narrator or author. During the quest the individual is tested is tested by many hardship. Finally, the individual returns home triumphant and with a gift to help her community. Traditionally Nicaraguan stories use a similar structure know as the Robleto structure [DSB12]. The individual is the narrator in this structure and embarks on multiple short journeys before returning. There is a recurring statement that occurs after each journey that unites them.

Screenwriter Blake Snyder has developed a similar beat sheet analyzing the structure of hollywood feature films [Sny05] (Figure 4.7). From the figure we can see this is a detailed analysis of the 3-act structure which again can be linked back to Aristotle's plot with the beginning, middle and end.

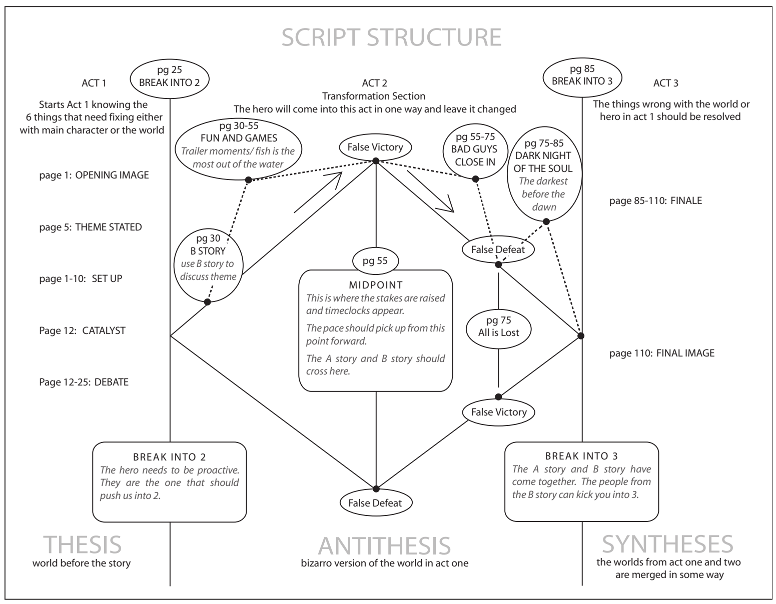


Figure 4.7: Blake Snyder's beat sheet

Michael Newman studied the structure of prime time television. He split the structure of episodic television into 3 levels. The micro level or beats are 2 minutes in length. They each have a defined beginning, middle and end. The next level is the episode and the macro level is large story arcs; a plot that expands over multiple episodes [New06].

The structure of news briefs and journalistic articles were described by Blundell in *The Art & Craft of Feature Writing* [Blu88]. These structures typically try to start with an *anecdotal lead*; a microcosm of a larger story that focuses on a character, followed by the *nut graft* where the details explicitly describing the value of the news story are presented.

4.4.2.1 Graphical Representation of Narrative Structure

Writers often use a tension curve (sometimes called a story curve, or plot arc) as a graphical representation tool for visualizing story structure [Hil11, McK97]. They can be mapped back to Aristotle's 3-act structure or modified representations of Freytag's pyramid for example, see Figure 4.8.

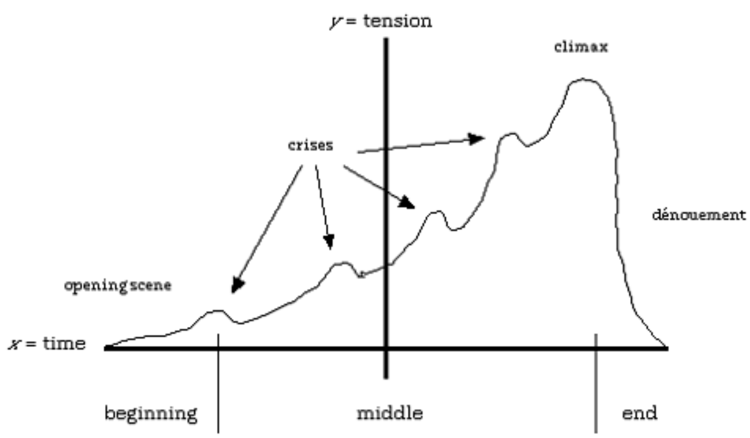


Figure 4.8: Tension curve for a standard 3-act narrative

These curves usually plot tension over time, and can be used to represent an overall story, or emotions internal to a character, or the emotions the audience experiences when they view the story. For example, Figure 4.9 shows a story arc drawn by Kurt Vonnegut for Cinderella describing what the audience experiences [Siv09]. He uses misery and ecstasy instead of tension on the y-axis. As we can expect some events to have more impact than others, but another important point to note is that the tension (or misery-ecstasy in this case) builds up on previous events. In this example, when Cinderella receives an invitation to go to the ball, the happiness begins to increase when the fairy godmother makes her clothes. It accumulates on the previous value and when she goes to the ball and dances with the prince it goes further up. Had the fairy godmother not made clothes before the ball, the ecstasy level of the audience at the point when the ball takes place would have been lower.

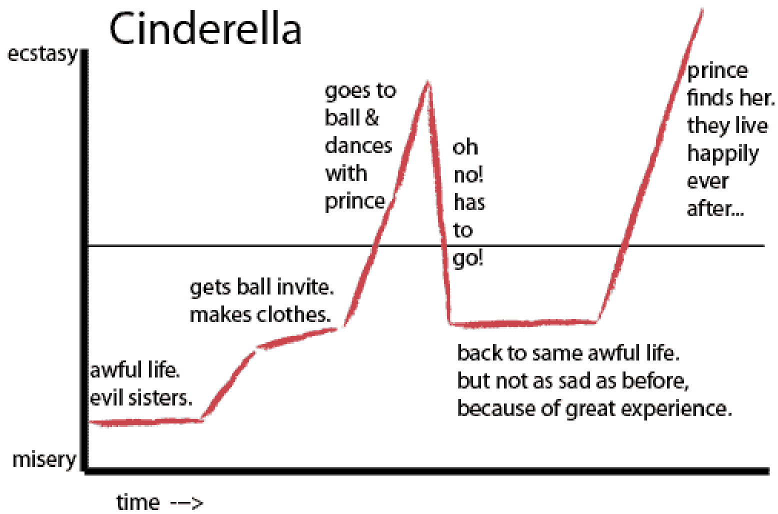


Figure 4.9: Kurt Vonnegut's narrative curve describing the audiences experience for Cinderella

4.4.2.2 Structure of Narratives Created with Narreme Tools

After reviewing this extensive work on story structure, we designed our tools so they could create a framework structure without making the author worry about the details of the structure.

This is accomplished by dividing the composition of a story just like the Russian Formalist School had done with *fabula* and *syuzhet*. In the Narreme tools, the clusters created by an author contain all the subject matter and can be thought of as the *fabula*, while the connections and ordering of events can be thought of as *syuzhet*. However, for the overall structure we found that Propp's model of structure was too limiting as it focused on folktales and was harder to generalize. So was Campbell's "Hero's journey".

We found it more useful to start with Aristotle's idea of having a definite beginning, middle and end and then building more details in-between. As we pointed out earlier, this structure is the basis the 3-act structure in western narratives. It has also been successful in the 2-minute short story arcs analyzed by Newman in the micro beat level of episodic television.

Structure in narratives created with the Narreme tools starts within clusters. Clusters force the user to distinguish between data and create groups that represent a single idea or event. We designed the Narreme tools such that they forced the user to create a minimum of three clusters to support any story. This ensures that there is a definite beginning, middle and end.

Further asking users to associate emotions for each cluster made the ideas or events expressed by each cluster more defined. The conflict discovery then helped understand how the different events could interact with each other and how they could transition from one event to another.

Finally, the tension curves in the video editing tool helped the user to visually see the structure of their final narratives and compare different ways to order events, for example, Figure 4.10 shows 4 different tension curves generated by the Narreme tools for the same narrative for different ways to order events.

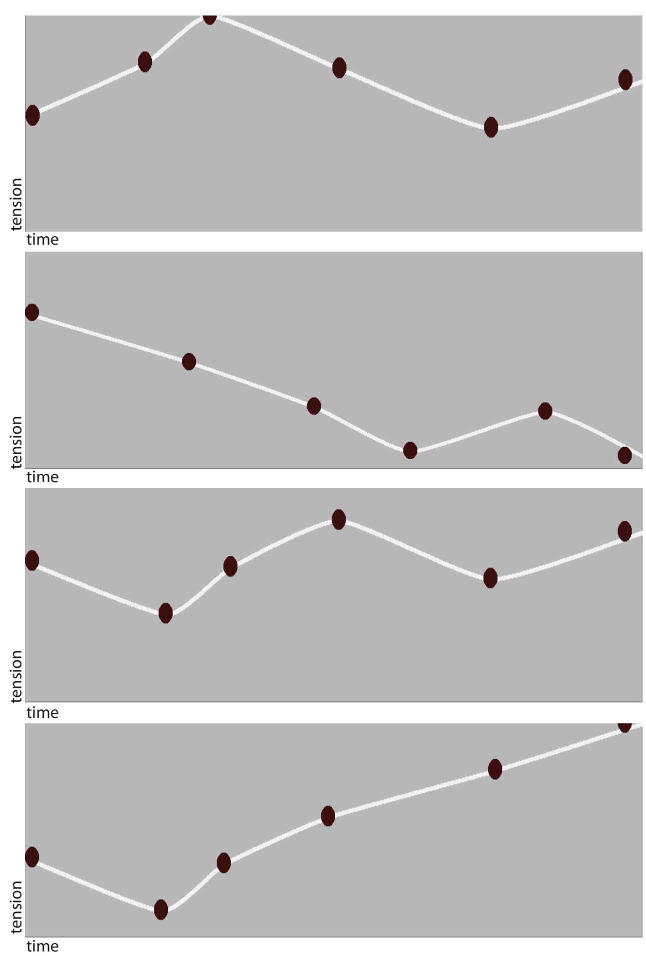


Figure 4.10: Tension curves generated by Narreme tools for 4 different orderings for the same narrative

CHAPTER 5

Related Work

The overall research presented in this dissertation does not have any direct precedent due to its unique application space and design space that combines the field of classification and knowledge extraction with narratology. In this chapter, we present related work in these two fields from which sub-components of this project have grown.

5.1 Classification and Knowledge Extraction

5.1.1 Data Clustering

There is a lot of work on clustering of textual data, to understand relationships between data and in turn provide better results for search engines, tag clouds, and image search. Begelman's work was one of the first to use clustering algorithms to improve the user experience of tagging services [Beg06]. It explores how clustering can be used to create more useful categories than the traditional rigid categories that are commonly used for grouping tags.

Yippy.com (originally Clusty) is a search engine that uses linguistic knowledge to create clustered search results[1]. It has an interesting feature called remix. When a user runs a search, along with the traditional search engine style results, this service provides a list of clustering categories for the results, and offers the remix option. If the user doesnt like the initial set of clusters, they can press the

[1]http://www.blogherald.com/2008/02/12/using-clusty-for-blog-content-and-research/

remix button, which will produce a new set of clusters for a *subtler set* of topics.

We talked about Namman's[Naa07], and Chakrabarti's [CKT06] work earlier, which focused on clustering very large data sets with millions of Flickr images based on user annotations. These systems learn from the many relationships that start emerging from a large number of elements and can do better clustering as the numbers increase. CGL [PLL10] is a robust community-guided learning system to improve mobile sensor classifiers using unreliable textual labels. However, they have a limited set of classes, which are known before hand.

NSTO [TJ05] is a text clustering process using a neural network. In this work, text is represented in string vectors rather than numerical vectors. The authors claim that representation of texts into numerical vectors leads to two main problems: sparse distribution and huge dimensionality of the feature vectors. A similar approach could be used to optimize the Narreme automated clustering process.

In [BBZ07] the authors develop a latent Dirichlet allocation with WordNet which helps in disambiguating word senses by learning the domains from the corpus in which each word is considered.

Specia [SM07], Schmitz [SHJ06], and Schutz [SB05] all focus on creating ontologies and folksonomies from text annotations or tags and use this to extract relations between the annotations or tags.

Recently, Karandikar [Kar10] developed a system for clustering short status messages from Twitter and Facebook using a topic model based approach, by using the topic distribution of each tweet. This could be used as an alternate approach in our clustering tool if we have a larger dataset in the future.

Gharib et. al [GFA08] use a similar approach to our clustering approach but for web documents. They use WordNet lexical categories and fuzzy c-means. Their results show that using WordNet lexical categories with a fuzzy c-means algorithm "achieves great performance optimizations" for web document clustering. We saw similar performance improvements with the participatory sensing data. However, our results show that in analyzing participatory sensing data, we saw better performance when we used WordNet lexical categories with the Hierarchical clustering algorithm than fuzzy c-means clustering algorithm.

There is also related work in the area of sense-making and summarization of life-logging data by clustering and finding relationships in the data. Gordon Bell's MyLifeBits [GBL06] presents how data from the sensors on SensCams [GWW04] can be used to find relationships between the images captured by the device.

5.1.2 Hypertext Authoring

In the 1960s, Nelson developed hypertext which toady has become the underlying structure of the World Wide Web. It is a way to create links between text displayed on a screen to other text or media. A reader could then access the linked text or media by clicking on the text that had the link [Nel65].

In the 1990s there was a lot of work on authoring systems for creating hypertext links in documents automatically and with assistance from users. These systems had to understand the semantic information contained in the documents so they could find where to create links. This is a similar problem to understanding how to link different annotations. For instance, Basili et al. [BGP94] used document structure and semantic information by means of natural language processing techniques to extract a set of keywords and then create links on these. This is similar to what we do in our pre-processing stage.

Another hypertext authoring system that is much closer to our approach of pre-processing annotations is a system that looked at hypertext authoring of newspaper articles [Gre97]. They created a lexical chain using WordNet, just like we implemented in our preprocessing stage before automated clustering.

We also looked at the work by Kurohashi et al. [KNS92] who created a hypertext dictionary for the field of information science. They used linguistic patterns from a encyclopedic dictionary in the field as well as a thesaurus for finding synonyms. We did not have any domain specific dictionary for the subject of community participatory campaigns so it was not possible for us to use a similar strategy. Although, one could envision that such a domain specific dictionary might be created over time with the usage data of the Narreme tools.

5.2 Narratology

Probably the closest directly related work is a project from MIT called the Spinner [Lai08]. This is a narrative informed system of ubiquitous camera and on-body wearable sensors [Lai10]. The project uses knowledge extraction to understand human behavior from on-body sensors data. This data was used with a narrative model to inform an editing system to cut and stitch videos collected by the ubiquitous camera network.

We described narrative structure in section 4.4.2 and talked about Aristotle [ABF61], Freytag [DSB12], Propp [Pro28], Campbell [Cam03], Snyder [Sny05], Field [Fie84] , Newman [New06], and Blundell [Blu88]. There is an AI storytelling system that was built on a Propanian model [FC02], and uses the structure from this model. However, as we explained earlier this was too restrictive for our needs and we found it more useful to start with Aristotle's idea of having a definite beginning, middle and end and then building more details in-between.

Chris Crawford's book on Interactive Storytelling [Cra04] is also another important reference in this area. The book is about strategies in interactive storytelling from game mechanics perspective, but the chapter on Data-Driven Strategies provides some useful insight in that can be used in creating narratives from data. In this chapter he describes a data-driven storytelling engine that uses a database, which holds two types of data 1) story components i.e. basic parts of the story, 2) connectivity data that describes how parts may connect with each other. He describes how the engine can assemble a story from this data in response to a user's input. Crawford leaves the connectivity system abstract but refers to Propp's work and Georges Patti's [Pol24] work in reducing basic story types into a set of thirty-six. This is also an import reference for story structure along with [Nob85]. In the Narreme authoring system we use a similar approach; we abstract the idea of story components in the clusters a user would create with our system. The connective data are the details in the descriptions that a user supplies that make the relationships within and between clusters.

It is interesting to look at the technology used for Faade [MS02, Art05], an interactive drama prototype. Particularly the drama manager that sequences dramatic beats in response to the history of a players interaction. This might be a useful extension to the Narreme tools if it can be used to suggest different directions a user could take while authoring a narrative based on history of previous narratives created with the tools.

Sans Soleil or Sunless [Mar83] is a French documentary/ travelogue directed by Chris Marker. The film has no real characters. A narrator reads out letters sent to her by a fictitious cameraman. This narration is juxtaposed with the images and video clips supposedly shot by the cameraman and this is used as the main mechanic to move the narrative forward and give the film overall meaning. Although the film is carefully curated it gives the appearance that it was assembled together from a database of images, video clips and letters. The style of this film is the closest to the kind of output the Narreme tool might can generate.

As we mentioned earlier, narratives have also been used in sense-making in cognitive science for making sense of one's experiences and as a resource for structuring and understanding one's environment and the world [Her11a, Abo10, BSN08, Rya03].

Though, even before the field of cognitive-science began looking at narrative as a tool for sense-making, it had been discussed in Artificial Intelligence by Schank and Abelson's [SA77] in 1977. Later, In *Tell Me a Story*, Schank looked closely at the way stories relate to our memory and understanding, and looked at ways to apply this " to build machines that have interesting stories to tell and procedures that enable them to tell these stories at the right time" [Sch90]. In 1998, Gordan [Gor99] looked at how knowledge of narrative structure, and sensor data can be used to browse information. More recently, Morgn [Mor06] created a system called LifeNet which uses narrative knowledge bases and common sense assertions to bootstrap learning algorithms for classifying and recognizing human activities from sensors. Also, the StoryNet project [WBS05] created a database of scripts that are used to search and predict subsequent elements of large collections of data. The techniques we developed and the Narreme tools differ from these Artificial Intelligence projects. We are not using narrative ideas to build completely automated algorithms to generate and make sense of data, but rather using the same techniques to help users search, explore and understand large datasets.

Although not directly related to our research, narratives have also played a major role in HCI research. For example, narratives are used to better understand the interaction of a user with a system, and as a means of communicating how a system works to a user [Lau90, Lau91, Mul03]. There have also been studies of narratives as a tool for navigating and sense-making in computer-mediated environments such as those that Marie-Laure Ryan talks about [Rya06, Rya01].

5.3 Related Tools for Narrative Creation with Data

Quill by Narrative Science [Nar12] is a system that generates narratives automatically from data. Like the Narreme tools, this system also separates story structure from subject matter, (which is referred to as "the facts", in this system). The system uses data analytics to extract facts from raw data. These facts are then interpreted by artificial intelligence techniques, which test the facts from different angles. Finally, a story is generated by adding structure and language to the interpreted facts.

Qwiki [Inc12] is a tool that initially focused on automatically creating video narratives from various websites like Wikipedia on different topics. It grabs images from webpages that were relevant to the topic and found blurbs of text which was converted to an audio track using text to speech. The focus of Qwki has since changed and a new set of tools are being tested which offer users a way to make interactive multimedia stories [Ste12]. At the time of this writing, we were not able to test and compare these new tools to the Narreme tools because it was being run as a private beta.

In [CKH07], Cho presents a tool to summarize a user daily life in cartoon form from mobile phone logs and data.

StoryTelling Machines is a tool that uses techniques from cognitive science and axiology to help users create "Micro-Movie" presentations [Stm12]. Their tool asks the user to fill out a guided questionnaire. The tool then rearranges and compiles the answers into a script, and stitches together a storyline and creates a micro-movie for the web.

SiftRiver [Her11b] is a platform that allows users to sift thought data from multiple real-time sources such as SMS, Tweets, RSS and email and organize the data by narrative themes. It provides a way to visualize the data using these themes in different output formats such as text, maps, timeline, graphs, charts, heatmaps and galleries of photos, video, and audio.

Rocco, Byrne and MIKE are three tools that have been used in sports story creation [ABT00]. They are used to create expressive natural language commentary for a sports game from the game's play-by-play data.

SCoReS [LBL12] is another tool related to sports stories. It is a sports commentary recommendation system that recommends brief stories to the commentator that are relevant to the sports game in progress. The commentator can tell these stories to the audience while the game is in progress to keep the audience engaged.

CHAPTER 6

Employing User Feedback

In this chapter we present an evaluation of the Narreme tools and our hypothesis on building narratives with participatory sensing data as a means to better understand and present qualitative data, and as a way to communicate information from the data in a way that is engaging to an audience.

We conducted a user study with thirty participants who each used the tools over the course of 4 weeks to create narratives to share with their community. We used their feedback to test and evaluate our tools and hypothesis.

We hoped to accomplish the following goals though this user study:

1. To evaluate the user interface, usability and performance of Narreme tools.
2. To determine if the tools are effective for users in finding the right data and discovering themes for their narratives.
3. To find out which aspects of the Narreme tool are most effective in helping the user create engaging stories.
    (a) Do the tools help a user in defining an overall structure for their narratives?
    (b) Do they help the user determine the internal details of their story, i.e. do the tools help in discovering how events and characters in their story interact with each other, and where they can introduce conflict and harmony?

(c) Does visualizing the overall story with a tension curve help the user organize events in their narratives?

4. To understand if there is a relationship between this genre of stories (short non-fiction) and certain types of tension curves that makes them more or less engaging to an audience.

6.1 Study Background

In Chapter 1, Section 1.1 we described the Building a Healthy Boyle Heights (BHBH) data collection campaign with mixed income participants from the Boyle Heights community where about 68 residents documented various conditions in and between work, school and home as they went about their daily routines. Participants in this project filled out mobile phone based surveys and collected 715 annotated images capturing people, places, events and other things in their community. However, we did not have tools to analyze the views expressed in the annotations and images at that time, and the project only focused on quantitative analysis of the collected data.

We realized that we had a rich dataset of qualitative data from the BHBH campaign. This prompted us to use this dataset in the evaluation of the Narreme tools. We decided that the best people to help with the evaluation would be participants from the same community so the data would be meaningful to them.

6.2 Study Participants

We approached the community organization Union de Vecinos at Boyle Heights and demonstrated our tools and described our project to them. We asked them if they would partner with us to do workshops on narrative creation using our tools with participants from their community.

They were excited about the tools and were interested in seeing what narratives community members would create with the existing data.They also felt it was necessary to allow for new data collection. They felt it would be a positive community development exercise where community members would participate in workshops together and learn from each other. They also said they had many adult community members who had little or no experience with using a computer and felt that this would be a good exercise for them to work on together with their children.

They did not want to limit the topics or ask the participants to think about any particular issues or document anything specific but were more interested in looking at what ideas community members might come up with on there own.

They also felt that it would be valuable to do a combined workshop with the Maywood community as well, which is close to Boyle Heights.

6.2.1 Recruitment

Union de Vecinos helped us recruit participants from both Boyle Heights and Maywood communities. We had four main criteria for recruiting participants for our study:

1. The participants had to be at least 14 years of age. This was mainly because we wanted a baseline of a minimum of elementary school education. (We had consents from parents or guardians of chilldren under 18).

2. We required that participants could read and write fluently in either English or Spanish or were bilingual.

3. The participants had to be members of either Boyle Heights or Maywood communities i.e. they lived, worked, and/or went to school in those communities.

4. We wanted participants who could commit to participating in three, 90-120 minute workshops over the course of a month and had some time for additional data collection using a mobile phone.

Outreach leaders and volunteers from Union de Vicinos helped identify members of the community based on these criteria and reached out to them to participate in our workshop . Most of these were also active participants in community events .

6.2.2 Participant Demographics

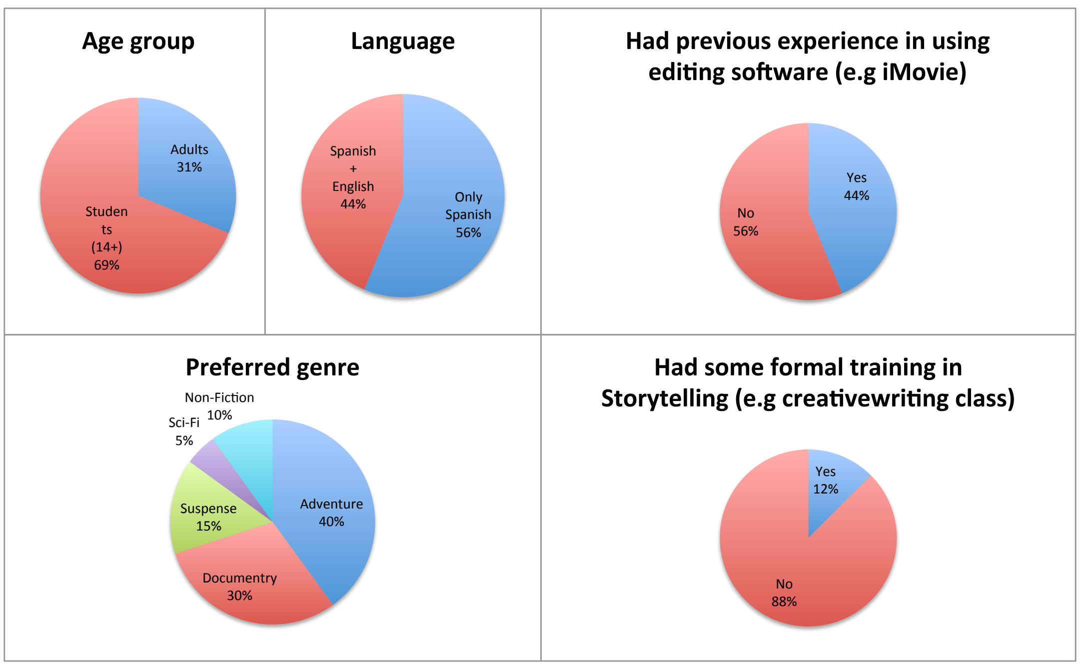


Figure 6.1: Participant Demographics

A total of thirty participants, twenty from Boyle Heights and ten from Maywood took part in our workshops. All thirty participants took part in the first workshop, which focused on an introduction to the user study and a hands-on training session with the Narreme tools. Unfortunately, we had a drop in participation in subsequent workshops, and only sixteen participants completed the entire study. The main reason for the high drop in the number of participants was because our final workshop coincided with the start of the school year and we lost many of the high school students and family members at this time.

Our study evaluation is based on the feedback of the 16 participants who finished the entire study and created final narratives using our tools. Figure 6.1 shows detailed demographics of these participants.

6.3 Study Methodology

We conducted three workshops with the participants. At the completion of the workshops they were expected to have created their own narrative using both existing data and new data that they could collect during the course of the study.

Figure 6.2: Participants working in teams in Workshop 1

1. The first workshop was an introduction to the project and a training session to use Narreme tools.

2. In the second workshop participants were given phones, which had an application to collect new data. Participants were asked to explore the existing data in the Narreme Clustering tool and use it as inspiration to start thinking about what stories they wanted to create. They were told that for their final stories they could use the existing data of 715 annotated images from the BHBH campaign as well as new data they collected with the phone application. They were given two weeks with the phones to collect new data. During the course of our study, participants collected an additional 248 annotated images that were added to the dataset.

Figure 6.3: Participants working on their individual narratives in Workshop 2

3. In the third workshop participants created their final stories and answered a questionnaire about the Narreme tools and the stories they created.

At the end of the study the final stories were screened for five judges who were bilingual in Spanish and English and had some formal background in storytelling. The judges ranked each story based on the content, structure and provided an overall score on a scale of 1-5.

6.4 Datasets

The initial dataset of 715 annotated images that were collected during the BHBH campaign were very specific for what was important to the Building a Healthy Boyle Heights Collaborative at that time. Participants were asked to focus on documenting the conditions of the community in and between work, school and home as they went about their daily routines.

Union de Vecinos did not have any specific things they wanted participants to document but would rather have the participants work on any topic of their own liking. They wanted the flexibility to allow participants to be able to collect new data if their narrative required it. We were happy to support this and set up an android data collection application to take annotated pictures and add them to our dataset. Our only criteria was that all the new data collected should be combined with the old data and available to all participants to use in their narratives. This was because we wanted all participants to have exactly the same dataset when creating their narratives. Participants ended up collecting 248 additional annotated images which were added to the database.

The new data was very different from the initial dataset and had a lot of variety. It had a lot of images related to summer activities with family and the community. There were more pictures of people, and things that were meaningful to the participants. Some participants felt the need to take pictures of images and illustrations from books and magazines to support their narratives. Some of the new data very specifically covered a particular event that took place over a week, such as the cleaning of a neighborhood park.

6.5 Evaluation

In the next sections we will provide results and describe the feedback from participants when they created narratives with the data using the Narreme tools.

6.5.1 Usability Testing

We wanted to learn if people liked using the kind of tools we developed and how useful they were in helping create stories. Our goal was not to build a commercial product, so we did not do rigorous usability testing using Accuracy, Efficiency and Recall metrics, which commercial user interfaces would use. We were more interested in the emotional response and usefulness of the tools.

For each of the tools we asked user the user to rank how they felt about using the tool on a seven point Likert scale (1=very poor, 2=poor, 3=fair, 4=good, 5=very good, 6=excellent, 7=exceptional).

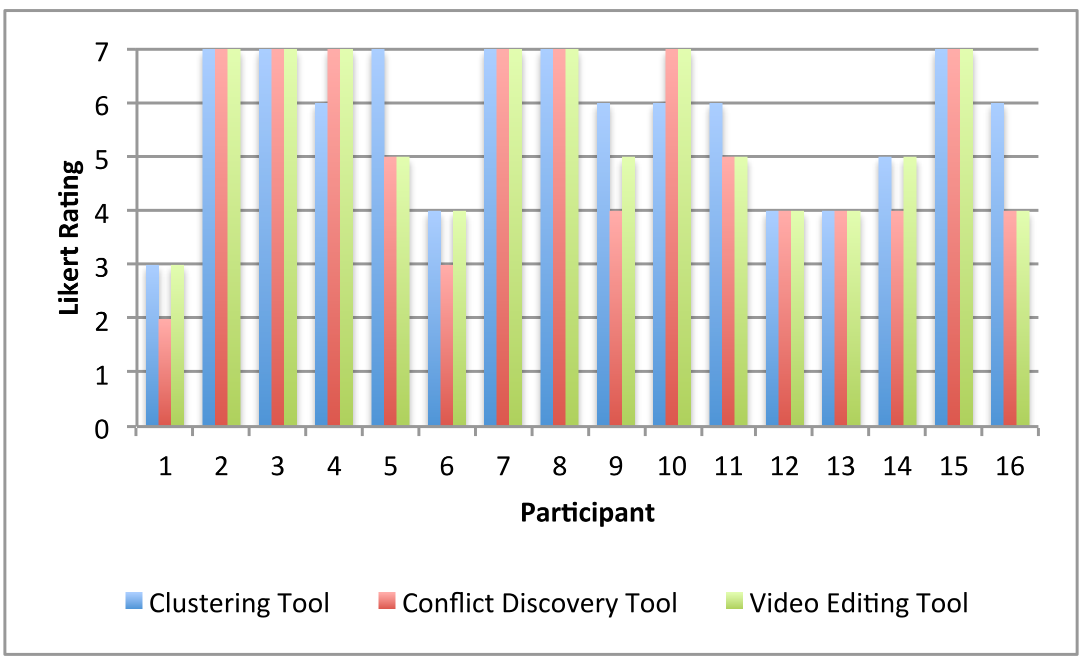


Figure 6.4: Distribution of user responses to the Likert scale for the usability of Narreme tools

Figure 6.4 shows a comparative distribution of all the user responses to the Likert scale for the three tools. We provide a summary in Table 6.1.

Tool	**Mean Score**	**Max Score**	**Min Score**
Narreme Clustering	5.75	7	3
Narreme Conflict Discovery	5.25	7	2
Narreme Video Editing	5.5	7	3

Table 6.1: Usability Results for Narreme Tools

All three tools received a mean rating of very good. Five participants out of the sixteen ranked all three tools to be exceptional. We received only one rating of poor, which was for Narreme Conflict Discovery tool, and one Fair for the Clustering and Video Editing tools. These were from the same participant, who had missed the first introductory workshop and training session. *This result probably concludes that the Narreme tools are harder to understand and use without any instruction.*

6.5.2 Evaluation of the Narreme Clustering Tool

We described the clustering tool in Chapter 3 Section 3.1. To recap, the tool has 3 columns: raw data, canvas for current cluster, and a column for saved clusters. This is split into two halves. The first half lists all the clusters the user saved for use in their narrative. This includes those they may have created manually or were automatically generated and modified. The second half has some options to generate clusters automatically and list them below. Clicking on any cluster opens it up in the middle window displaying all the images with annotations for that cluster, where the user could view and modify them by adding or removing elements.

The raw data column allowed the user to filter data with keywords or filter by categories used when data was captured. *Eleven of the sixteen participants said* *they found the filters useful to find data for their clusters.*

We asked users whether viewing data in the clustering tool influenced their narrative. All of them felt it influenced his or her narratives to some degree. *Five said the ideas for their narratives were very strongly influenced by looking at the data in the clustering tool. While the others felt their narrative ideas were at least somewhat influenced by it.*

Some users commented that they had preconceived ideas about the how they envisioned their final stories to be, but the clustering tool forced them to break down their ideas into groups, which enabled them to explore more possibilities.

6.5.2.1 Evaluation of the Automated Clustering

Thirteen participants of the sixteen tried using the automated clustering in creating their final narratives. Eleven of these said they found the results useful for their narratives. However, only six actually used one or more clusters that the automated clustering returned in their narrative. The rest looked at the results for inspiration only but created their own clusters manually and with the help of text filters.

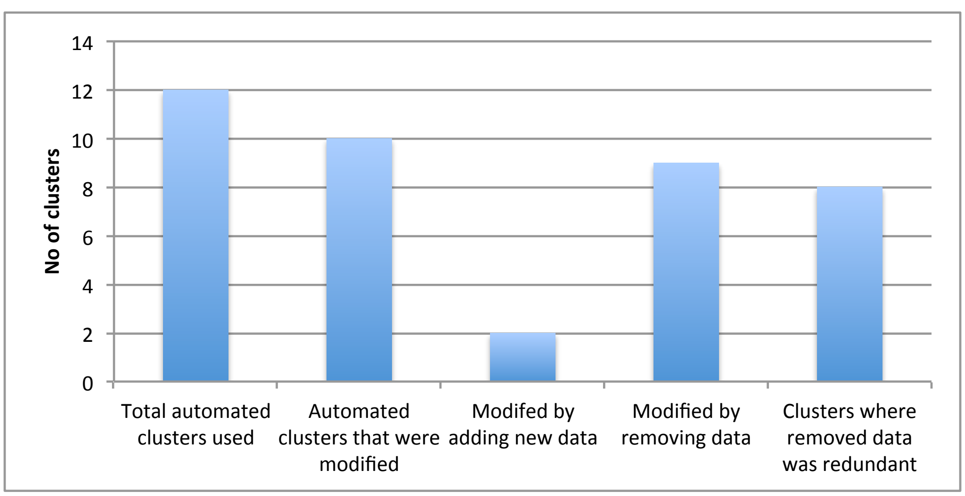


Figure 6.5: Results from Automated Clustering.

Our tool was instrumented to track how these automated clusters were used and modified. We plotted the results in Figure 6.5

We found that *90% of the clusters that were used in a narrative were modified in some way before use. 14% of these modifications were to add new data to the cluster; the remaining 86% were to remove elements. 90% of the data that was removed had exactly the same annotation as other elements in the cluster which were retained, which shows that these results were not wrong but that the user preferred one picture over another which had similar content or they just wanted to trim down the size of a cluster.*

6.5.3 Evaluation of the Narreme Conflict Discovery Tool

The purpose of this tool was to help the user discover how events, people or things in the narrative interact with each other and thus determine which events were in conflict with each other and which were in harmony.

Typically in fictional narratives, conflict is introduced in the beginning and tension builds up in the story as events conflict with each other, until there is a climax and harmony is used to release this tension.

This format keeps an audience engaged. In non-fictional stories, too, it is important to understand where tension can be introduced to keep an audience engaged.

Understanding what events are in conflict is the first step towards introducing tension. The tool takes each cluster which the user created in the Narreme Clustering tool and presents it to her paired with all the other clusters the user created, with a slider below which goes between conflict and harmony. Internally, a score between -10 for (maximum conflict) and 10 (maximum harmony) is maintained for each pair of clusters.

To make the process quicker, the tool tries to predict a score for each pair based on Sentiment Analysis on the title of the cluster. This score is used to set the initial position of the slider.

We were interested to see how well Sentiment Analysis performed in providing a conflict score for the clusters, so the software tracked the predicted score and how much the user shifted the slider from the predicted position.

The results varied a lot for different user narratives. We present results from three different narratives here with 6, 3 and 4 clusters respectively.

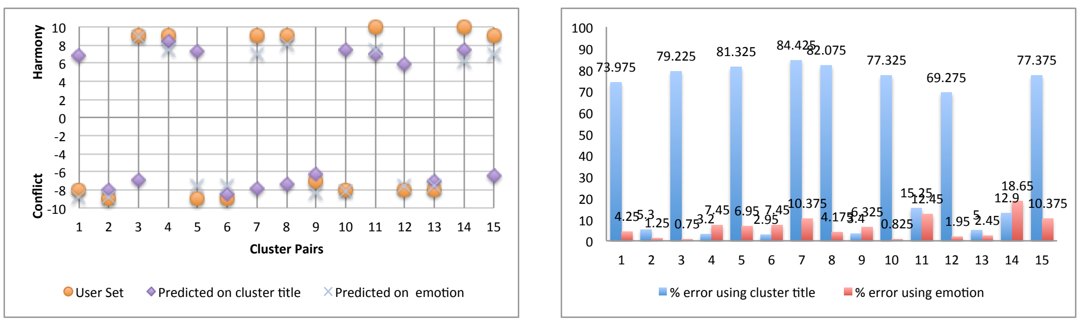


Figure 6.6: Comparison of conflict values set by a user to predicted values based on sentiment analysis on cluster titles and on cluster's associated emotions for narrative #7.

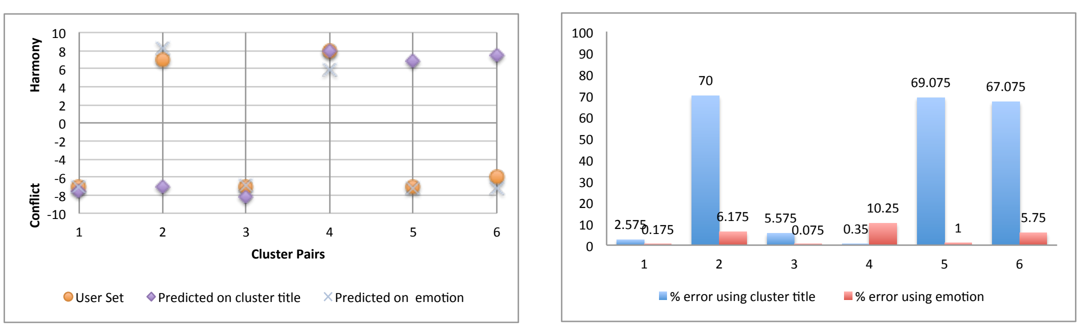


Figure 6.7: Comparison of conflict values set by a user to predicted values based on sentiment analysis on cluster titles and on cluster's associated emotions for narrative #3.

In the first narrative (#7) we found that our predicted score when using the

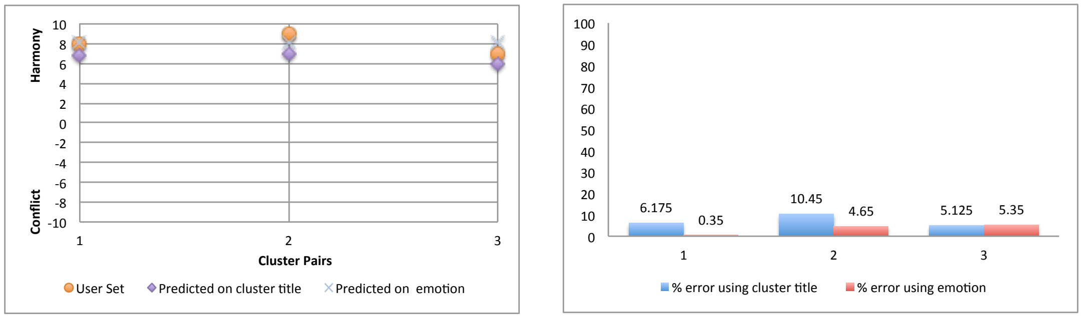


Figure 6.8: Comparison of conflict values set by a user to predicted values based on sentiment analysis on cluster titles and on cluster's associated emotions for narrative #4.

title (Figure 6.6) was more that 70% off for more than half of the pairs.

In the second narrative (#3) our predicted score had an error of 5-10% for all clusters. (Figure 6.7)

And in the third narrative (#4) our prediction was 67-70% off for half the pairs. (Figure 6.8)

These results were not promising and show that the title alone is not a good metric to gauge emotions associated with a cluster and predict conflict.

During the course of the study, users were given a worksheet and asked to track each cluster they created and write down what emotions they would attach to it .They were also asked what they would like to evoke in an audience through the images in the cluster.

This worksheet was to help them analyze clusters and think about where they would like to place the slider when comparing clusters.

After the user study we looked at the worksheets which were used for helping them with the conflict discovery, and fed the descriptions that people provided into prediction algorithm instead of the titles for the clusters.

We found a huge improvement. The maximum error between predicted value and user set value in the first narrative was 18%, in the second narrative it was 5%, and in the third it was 10%.

6.5.4 Narreme Video Editing Tool

The Narreme Video Editing Tool is the final tool in the narrative building tool chain. When a user enters this tool, the clusters created by users using the clustering tool are automatically placed in a video editing timeline, with a tension curve for the ordering of clusters on the timeline. Users can then manipulate the ordering of the clusters to produce different tension curves until they are happy with the final ordering. The users set the initial ordering in the clustering tool.

After users had created their final narratives, they were asked for feedback about the narrative curve and how it helped their narrative creation process. 87.5% of users said the tension curve was a useful tool. 75% of the users said it was an accurate representation.

25% of users who created final narratives changed the order of their narratives after looking at the narrative curve.

Two users commented that they went back to the clustering tool after looking at the tension curve because they felt they needed to introduce more conflict or harmony between clusters.

The video-editing module in the tool allowed users to change the font sizes in title cards and increase or decrease the default duration (2 sec) for which titles and images were displayed and add colors and effect. However, this had to be done separately for each image and each title card. Users commented that they would have liked the tool to be smarter to set the duration automatically based on length of text.

Many users captured portrait style pictures with their phones, which had to be squeezed, cropped or scaled to fit the landscape format of the video. This was also a manual process and some users found it frustrating. Automation of identifying what type of scaling, cropping or squeezing is required and providing a best guess could help here.

6.6 Evaluation of Narrative building process

6.6.1 Initial thoughts about story types by Participants

After the first training session, community members were asked for initial thoughts on what kind of stories they would like to tell. Some of the common themes were:

1. Concerns about the neighborhood and what made it interesting to live in,

2. What made their community interesting? One participant said she wanted to talk about "animals that live in our community" because they make it unique.

3. Participants also expressed a desire to mix reality and fiction; "I want to make a story about the community but add little fictional twists to it", "Maybe fiction or documentary".

4. History of the community was another theme that resonated among the participants;"I want to do a documentary about the history about the community and about what the future holds for the community " (My story) will be about where it (community) has been, where its at and where its going."

5. They also had a target audience in mind, some wanted to share their stores to make people outside the community aware of their community while others felt strongly about sharing within the community or for family who are part of the community but living away; "I want to do a story about the soccer

field for my son who lives in Mexico and plays soccer. I want to tell him a story about the soccer here."

The desire to fuse fiction and facts about their community strengthens our initial notions about using fictional storytelling ideas to make documentary stories more engaging. The conflict discovery and tension curve tools support this kind of storytelling.

6.6.2 Evaluation of the Narratives

We selected a panel of five judges who were bilingual in Spanish and English and had some background in story writing to help with ranking the final narratives that participants created. They were each asked to provide a score between 1-5 for the overall narrative and presentation and asked if the subject matter was interesting and if they liked the order of events. Three scores were generated from the means for each narrative. The first one was an overall narrative score, the second one for order of events score and the third a subject matter score. Each was on a 0-5 scale. Below we present the results based on the feedback from the judges.

6.6.2.1 Order of events and overall narrative rating

Figure 6.9 shows the relation between the order of events and narrative rating. This shows that for most of the narratives the rating is directly influenced by the order of events.

6.6.2.2 Subject matter and overall narrative rating

Figure 6.10 shows the relation between the subject matter and the narrative rating. This shows that overall rating is less influenced by the subject matter than the

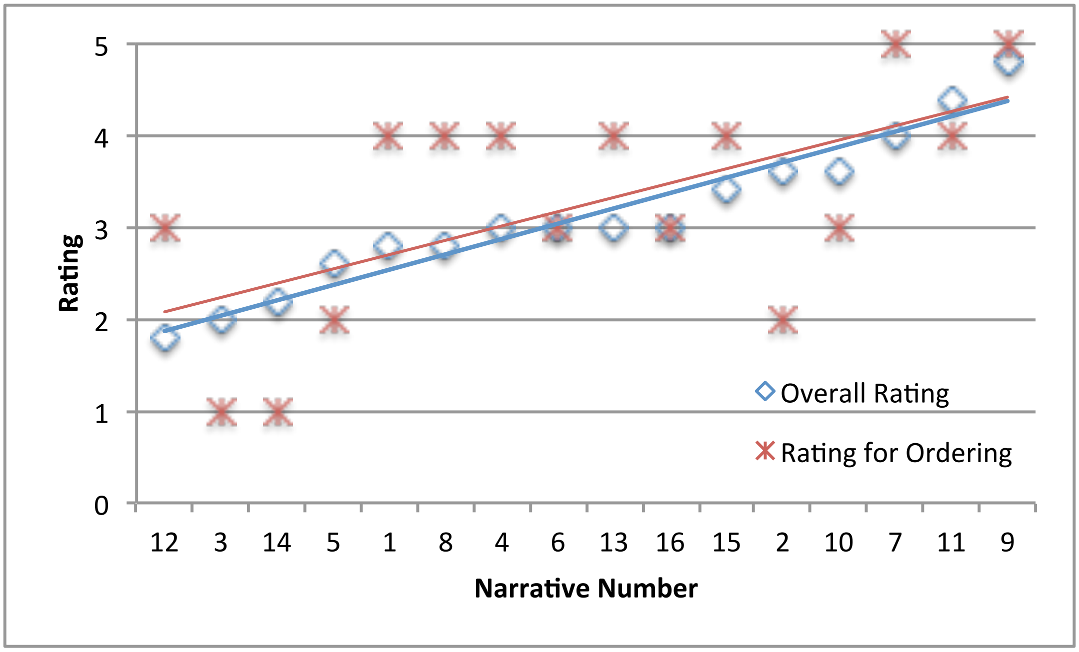


Figure 6.9: Comparison of Narrative Rating to the Rating of Order of Events in the Narrative

order of events.

6.6.2.3 Tension curves

Figure 6.11 shows plots of the narrative tension curves for all 16 narratives along with their rating and order of events scores. Overall there dont seem to be any very strong correlations between the tension curve and the narrative rating, but we can make a few observations:

1. The lowest rated narrative (#12) has a very flat tension curve compared to all the others.

2. Narratives where the order of events score are above 4 (#1, #4, #7, #9 , #11, #13, #16) seem to have at least 3 consecutive clusters that build on the same tension trend, i.e. the tension in 3 consecutive clusters is either all rising together or falling together.

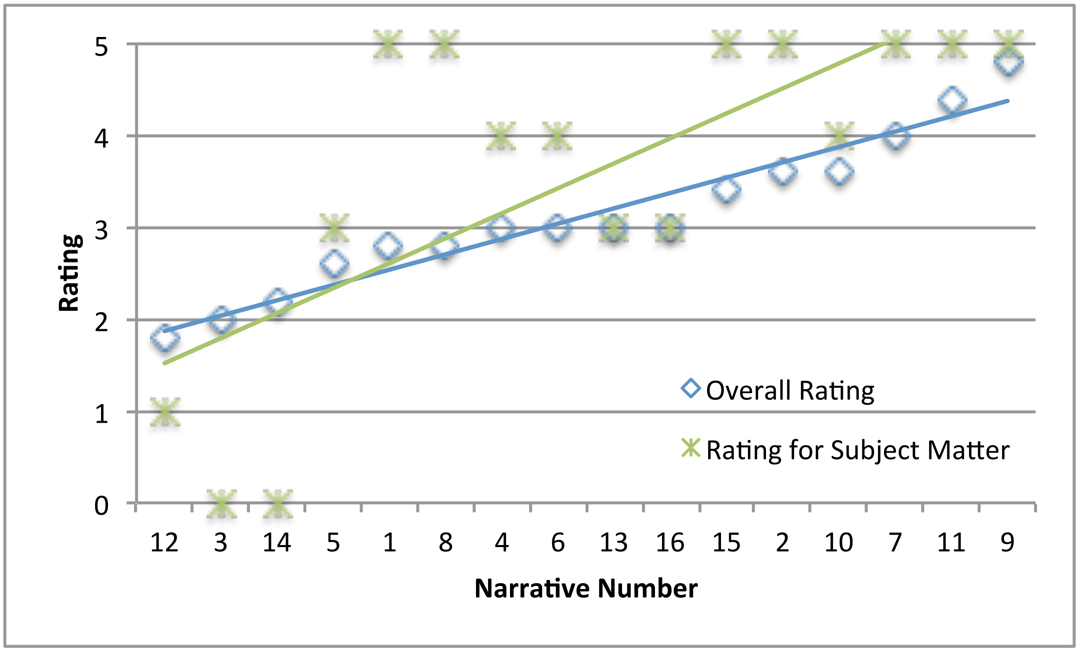


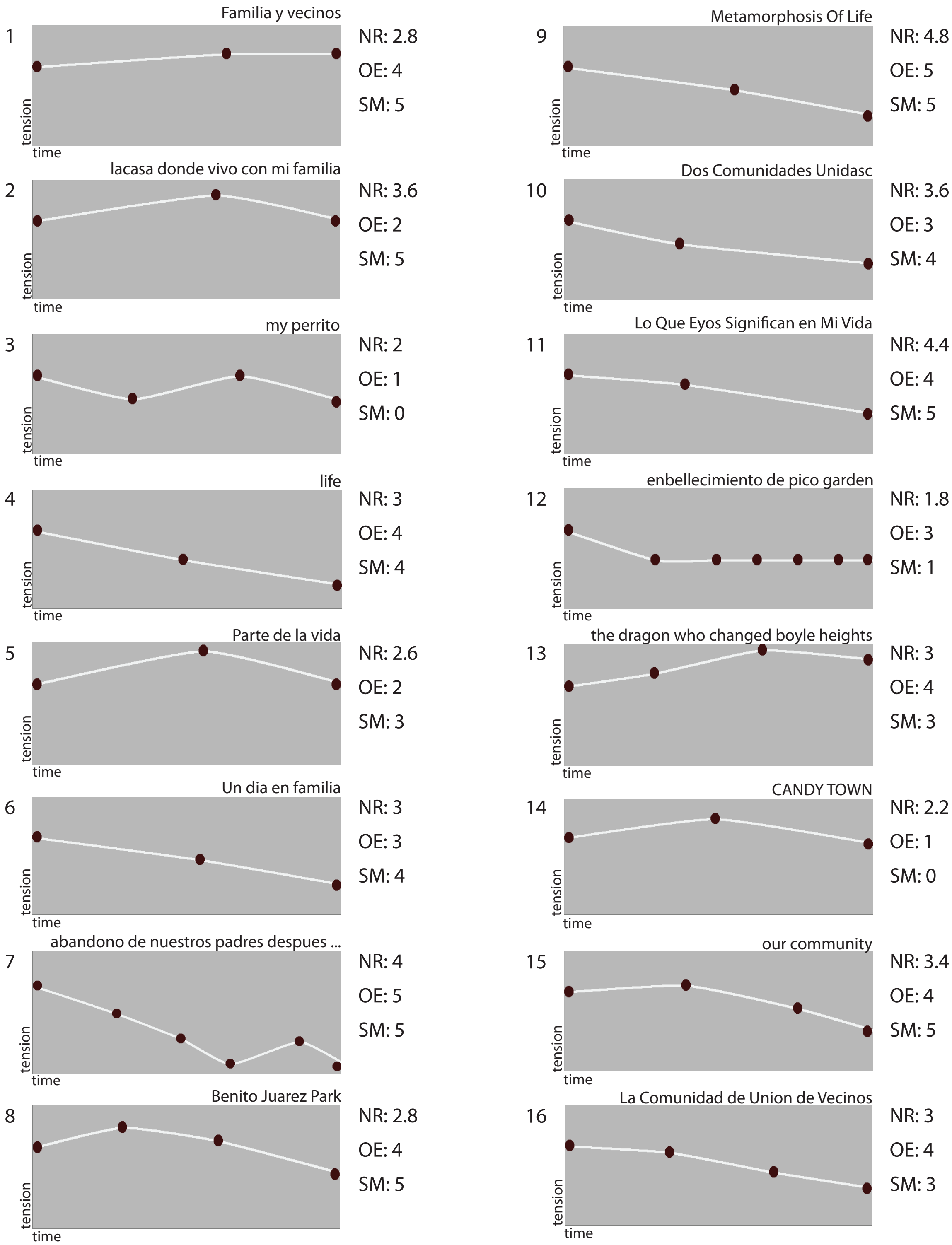
Figure 6.10: Comparison of Narrative Rating to the Rating of Subject Matter in the Narrative

3. Consequently, narratives #2, #3, #5 and #14 have do not have consecutive clusters that build upon the tension trend of the previous cluster and these have the lowest ordering scores.

6.6.3 Images Used

We did not have a way to track if pictures used by a participant were pictures they had taken because we did not maintain the user id of the person who collected images. But we asked participants about it in the final questionnaire. Their responses are tabulated in Table 6.2. Three participants used only their own new images which they collected themselves in their narratives. Six participants did not use any of their own images. This is probably because they did not take any new images of their own.

We also noticed that only about 10% of the images from the first BHBH dataset



Key: NR: Overall rating for the narrative , OE: Rating for order of events, SM: Rating for subject matter. All are on a 0-5 scale.

Figure 6.11: Tension curve of all 16 narratives along with narrative rating

were used by participants.

Narrative	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
% of images	-	100	80	90	0	0	100	100	0	0	0	10	-	0	10	50

Table 6.2: Percentage of images used in each narrative that were taken by the same participant.

6.7 Case Studies of Themes in the Final Narratives

Our initial notion was that people would create narratives about the community. Things that made it interesting, its history, its common concerns, its community pride and what the future holds for the community. These thoughts were reinforced when we talked to participants about what narratives they wanted to create after their first training session. However, the range of final narratives that were created surprised us. Only about half the narratives were directly related to the community. The following are the most common themes explored in the narratives that were created.

1. **Projects in building a healthy and beautiful community:** These narratives showed different projects that the communities worked on. Some of the activities that warrant a mention are:

Figure 6.12: Some of the images used in the narrative about transforming a disused park into a soccer field

(a) *The clean up of a disused community park:* Here the community got together to clean up the park and converted it into a soccer field and even created a youth soccer program.

(b) *The role of the community center:* Union de Vecinos plays a role in uniting the Maywood and Boyle Heights communities by organizing activities in the community building, beautification of the community and addressing common struggles of both communities.

(c) *The transformation and beautification of one neighborhood called Pico Aliso:* One of the narratives went into a lot of detail into all the changes that were made to this neighborhood; new-homes, security with new walls and fences, clean-streets, and a park for the children. This narrative however, received a very low rating because it only showed a lot of new and beautiful pictures of the transformed neighborhood but failed to communicate what the neighborhood was like before the transformation.

2. **Family activities:** Some narratives were very family oriented and focused on describing activities with ones family and close friends, some of these were about summer activities with the family. Much of this was spots and cooking and eating together.

Figure 6.13: Images used in narratives about family activities.

3. **Sharing personal life or a personal family situation:** We were surprised that people felt this was a good platform for sharing personal life

stories. Some of the most appreciated narratives, which received high ratings, told very personal stories. These stories struck a chord with people who viewed them even across cultures not just within the community. Three narratives in this category merit description here:

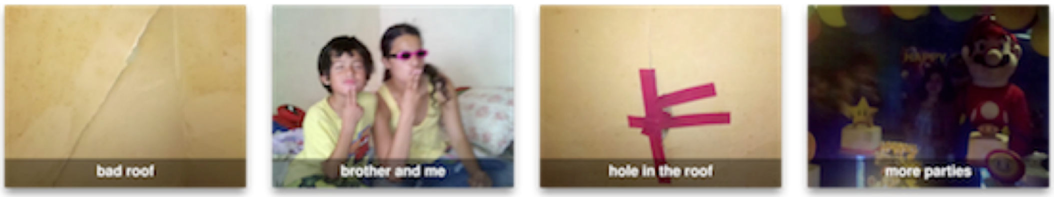


Figure 6.14: Images from "la casa donde vivo con mi familia"

(a) *la casa donde vivo con mi familia* which means "The house where I live with my family". This story gave a peek into the very personal living situation of a family. The story was about how the condition of the roof in this person's house was in complete disrepair, "the roof is falling", but the family was not concerned about it. They are enjoying life and having a lot of parties. The style of storytelling was very striking because of the way it intertwined images of the broken roof and a family that is happy and enjoying life. (Figure 6.14)

(b) *Lo Que Esos Significan en Mi Vida* "what they (my mom and step dad) mean in my life." This story had very few pictures but said a lot through the description on the title cards. It was about the bond between this person and her mom and stepfather, and how she feels closer to her stepfather than to her biological father, and realizes that the stepfather respects, appreciates and loves her mother and her "real Dad didn't know (how) to care."

(c) *Life* was about the life of the author who is a high school girl. She shares the things she cares about, her friends, and things around her that are meaningful to her.

4. **Philosophical about life and aging:** This was another theme that we did not expect. Three different narratives talked about life, growing up, and aging. They all had slightly different focuses.

Figure 6.15: Some of the images used in narratives that had a Philosophical theme about life and aging.

(a) *Parte de la vida*, which means "Part of life", was about how life starts and what people decide to do in life.

(b) *abandono de nuestros padres despus que dan su vida por nosotros* which means "abandonment of our parents after giving their life for us", went though the different stages of life from a mother giving birth, parents who nurture and care for their children as they grow and are proud when they achieve. Followed by parents growing old and needing help. And finally ending with a wish that their children should not abandon them in old age.

(c) *Metamorphosis of Life* was about the different stages of life. It starts with images of a baby being conceived and the stages in a mother's womb, the mother and infant, the little child going to school, playing in the playground, graduating from college, choosing a career, choosing a partner, starting a family and then the process of aging. It ends with the thought that some of us will get to our 100th birthday while some will die younger so we should enjoy life as best we can and live happily.

All three narratives used a lot of the same images even thought they had different focuses. The images were a mix of pictures from the community and others that seem to be taken from books or magazines. Figure 6.15 shows some of the interesting images that were used by participants to create these three narratives.

Though surprising, the last two themes are a good indicator of the success of our tools. Our goal was to build tools that helped people discover ideas in the data and look at it from different perspectives. Users initially mentioned (after the training session), that they wanted to create narratives around community. Despite that, the tools helped them see more in the data which inspired new ideas. Also, we can speculate that some of the personal narratives may have been motivated by the use of conflict discovery and the tension curve, as this might have led them to look for themes where they could introduce more conflict and create more compelling narratives.

CHAPTER 7

Conclusion

The proliferation of sensors in consumer mobile phones has made them a powerful participatory sensing platform. We have become more interested in collecting data to document and learn about our own lives, our relationships with the community and the environment we live in. The scale and richness of data we collect with our phones has being growing rapidly. However, current research is mostly focused on analysis of quantitative data, and a lot of important information that can be extracted from qualitative data such as images and text annotations is being ignored. The focus of this dissertation was to research and build techniques to help users analyze and make sense of the qualitative data they were collecting and communicate the information and knowledge they extract from the data.

We explored how ideas from narratology could be used as a means to understand and make sense of large datasets of qualitative data with many contributors. We also looked at how narratives could be used to communicate this knowledge to others in a form that is compelling and uses elements from the data to express our ideas. More specifically, the main contribution of this research is in the creation and evaluation of two techniques that are fundamental to narration tools: clustering and conflict discovery. We used these techniques in the Narreme Toolset. The toolset enables user assisted creation of compelling narratives with participatory sensing data.

Consumer movie making tools like iMovie, Microsoft Movie Maker, Final Cut, Muvee etc. allow the user to create video narratives with their own pictures and videos. Some even offer automated video creation scripts which can take a photo album and create a randomly arranged slide show. However, their main purpose is not for helping in organization of large datasets such as the participatory sensing database in meaningful ways. They lack in providing the user a structure for creating a meaningful narrative. They do not offer ways for discovering how and where to introduce conflict in your narrative or in understanding the emotional impact of narratives, and how the ordering of events might influence it. The Narreme toolset fills these gaps.

The Narreme toolset consists of three tools:

1. **Narreme Clustering Tool:** Helps a user organize her thoughts and identify supporting qualitative data consisting of images and text for her narratives. The tool allowed users to either manually use filters and search strings to sift though the data and create groups manually, or use our automated clustering suggestions which use lexical techniques to preprocess the annotations and relate them to the large WordNet lexical database.

2. **Conflict Discovery Tool:** The main purpose of this tool was to help the user better understand where conflict could be introduced in narratives created with participatory sensing data. The tool allowed a user to pairwise compare clusters of data based on the emotions each cluster hoped to evoke in an audience. We also developed a technique to try to predict the conflict between two clusters based on the sentiment analysis scores of user-assigned titles. Our goal was to help speed up the process for the user by allowing them to use our predicted score instead of having to assign one for each pair of clusters themselves.

3. **Video Editing Tool:** Users can view an automatically generated slide show video of the images on an editing timeline, along with a tension curve. The tension curve shows narrative tension over time for the narrative in the

present form. Users can try variations of the tension curve based on different orderings until they like an ordering.

The Narreme toolset helped the community members in the following ways:

1. It provided an effective way for community members to collaborate together, to analyze and organize the large datasets of qualitative participatory sensing data they collected, in meaningful ways.

2. It helped community members in constructing video narratives from this data where they could express their own point-of-view and share it with others.

3. It allowed multiple community members to re-use data that different members in the community had collected and create narratives within a common context.

4. The Narreme tools promoted community building as members helped each other in using the tools to create stories. Some users had little or no experience in using a computer, while others were proficient in using editing software and picked up the tools very quickly and became mentors for the less experienced.

5. Since, the Narreme tools worked off one large common database as opposed to individual datasets for each user's data, the resultant narratives, had a sense of being interlinked, and when viewed as a collection, gave a sense of collective authorship.

We partnered with the community organization Union de Vecinos and performed a formal user study with sixteen participants from Boyle Heights and Maywood communities in East Los Angeles to evaluate these tools.

We evaluated the Narreme toolset's usability, and effectiveness in creating narratives. We also looked at what aspects of our tools were effective in making the narratives compelling. We also had a panel of five judges rank all the final narratives and compared their ranking to the ordering and tension curves for the narratives.

7.1 Findings

Below is a list of our findings:

1. Our technique of preprocessing data using lexical techniques with the WordNet database helped in the clustering of annotations into meaningful clusters. User feedback from a pilot study revealed that when our technique was used with Hierarchical clustering there was a 30% improvement in the accuracy of the clusters. The user rating of the clusters produced, increased from 2.52/5 when no preprocessing was done to 4.03/5 when using our technique with Hierarchical clustering. When this technique was used in our tool eleven of sixteen participants in our user study said they found the clustering results useful for their narratives.

2. We received high usability scores from study participants. All three tools received a mean rating of very good (5/7). Five participants out of the sixteen ranked all three tools to be exceptional (7/7).

3. The user study revealed that our conflict prediction was not accurate. Our predicted scores had errors of up to 70%. We refined our technique to do the sentiment analysis on the users description of the cluster and emotions they wanted to evoke (which, we had asked them to fill-out on paper) instead of the titles we had used in our implementation of the tool. We found that the new predicted scores showed a big improvement. We compared results for

three different narratives and found that the errors had been reduced from a maximum of 70% to a maximum of 18%.

4. The tension curve in the video editing tool received a favorable feedback. 87.5% of users said the tension curve was a useful tool. 75% of the users said it was an accurate representation. 25% of users who created final narratives changed the order of their narratives after looking at the narrative curve. Two users commented that they went back to the clustering tool after looking at the tension curve because they felt they needed to introduce more conflict or harmony between clusters.

5. We also found that for most of the narratives the overall rating (given by the judges) was directly influenced by the order of events in the narrative and less influenced by the subject matter.

6. We did not find strong correlations between the tension curve and the narrative rating from the sixteen narratives. Nonetheless, we could make some observations:

   (a) lower rated narratives had very flat curves.

   (b) narratives were more appreciated if they had either rising or falling tension which built for at least 3 consecutive clusters.

   (c) narratives where tensions did not build on the previous tension trend were least appreciated.

7. One of our primary goals for the Narreme tools was to help users discover new ideas in the data and look at it from different perspectives. In our user study participants initially mentioned (after the training session), that they wanted to create narratives around their community. Despite that, the tools helped them see more in the data, which inspired new ideas. This is a good indicator of the success of our toolset.

8. From our case study of the final narratives we can speculate that some of the unexpected narratives may have been motivated by the use of conflict discovery and the tension curve as this might have led participants to look for themes where they could introduce more conflict and create compelling narratives.

7.2 Future Work

The techniques and tools developed during the course of this dissertation focused on building narratives as a way to make sense of qualitative data from participatory sensing campaigns, and to communicate the knowledge imbibed to the community.

There are many other fields and areas where our techniques and tools can be adapted. For example, it is also conceivable that the system can be used for creating videos for a family that returns from a vacation with photo-sets from every family member providing different perspectives.

Recent studies show that Storytelling with photos can be therapeutic for people with Dementia [FKG09]. The Narreme toolset could be extended to help in this area.

If extended to support source audio and video data, the system might also have applications as a tool in the creation of trailers for a feature film by indicating which segments from the film would be interesting enough for inclusion in the trailer. Among others, it could also function as a tool to help an editor in a reality show to find the most attractive sequences from all the footage.

The Narreme tools could be extended to produce interactive movies where data and statistics could be linked into the timeline of the movie. A viewer could then access these links from the timeline while watching the video and dig deeper into the data.

Finally, our aim was to add emotions to data which was lacking earlier. We hope that this work helps capture and preserve these feelings though Narratives.

APPENDIX A

Workshop Questionnaires

A.1 Narrative Creation Feedback Questionnaire

Below in Figures A.1,A.2,A.3 and A.4 is the questionnaire we used to get feedback from the participants while they created the final narratives. They were asked to fill out page 1 before starting their narratives, followed by page 2 while they were working on their narratives. Page 2 asked them to fill out each cluster as they created it in the Narreme Clustering Tool followed by what emotions they hope to evoke in an audience though the cluster. They were allowed to refer back to this when using the Narreme conflict discovery tool.

We have included only the english questionnaire here, we also had a spanish version for spanish speaking participants.

A.2 Narrative Evaluation Questionnaire

Figure A.5 shows the questionnaire we asked the judges to fill out to evaluate the final narratives that had been created. The same set of questions was repeated for each narrative.

Page **1** of **4**

Workshop 2 Questionnaire

UCLA Study
'Making Data Tell Tales:
Using Narrative Tools to understand Annotated Images'

Thank you for participating in the two workshops to learn about and to use our web-based narrative building tool to help us evaluate the effectiveness and usefulness of this tool developed by Vids Samanta, UCLA computer science graduate student. We would now like you to take a moment to respond in writing to this questionnaire to provide feedback about this tool and about your narratives:

Background in storytelling and technology use

1. Rank your storytelling experience on a scale of 1-7 (where 1– Amateur and 7-Professional):

Circle your answer for the following questions:

2. Which of the following is your preferred type of story: (circle)
   a. Adventure
   b. Suspense
   c. Comedy
   d. Sci-Fi
   e. Non-Fiction
   f. Documentary
3. Do you have any formal training in storytelling e.g. creative writing class? (circle)
   a. Yes
   b. No
4. Have you ever used a video-editing program before? (circle)
   a. Yes
   b. No
5. Have you ever posted images or videos you took to the web (eg. on Flickr or Facebook etc.)? (circle)
   a. Yes
   b. No

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Figure A.1: Workshop 2 Questionnaire pg. 1, to be filled out before starting the narrative

Narrative

1. What is your narrative about?

____
____
____
____

2. How did you come up with the idea for your narrative?

____
____
____
____

3. List the clusters (each group of photos) you selected for your narrative in the order they appear in your narrative and describe in a few words for each what emotions you were hoping to evoke in the audience for each cluster as it plays out. (Use extra sheets if necessary)

Grp #1 Title____________________________

Emotion____

Grp #2 Title____________________________

Emotion____

Grp #3 Title____________________________

Emotion____

Grp #4 Title____________________________

Emotion____

Grp #5 Title____________________________

Emotion____

Grp #6 Title____________________________

Emotion____

Grp #7 Title____________________________

Figure A.2: Workshop 2 Questionnaire pg. 2, to be filled out while creating clusters

Page **3** of **4**

Emotion____

Clustering Tool

1. How much did looking at all the data in the clustering tool influence you in thinking about your narrative?

   Not at all — Hardly — Seldom — Somewhat — Often — Mostly — Very

2. Did you use the search filters to find annotations or categories in the data? (circle)
   a. Yes
   b. No

3. Did you use the automated clustering function? (circle)
   a. Yes
   b. No

4. Did the automated clustering provide useful results for your narrative? (circle)
   a. Yes
   b. No

5. How would you rank your overall experience in using the Clustering Tool?

   Very Poor — Poor — Fair — Good — Very Good — Excellent — Exceptional

6. Was it easy to find (data) images to support your narrative? (circle)
   a. Yes
   b. No

   Explain why?____
   ____

7. What percentage of images in your narrative were taken by you? ________

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Figure A.3: Workshop 2 Questionnaire pg. 3, to be filled out after finishing the narrative

Page **4** of **4**

Conflict Discovery Tool

1. How would you rank your overall experience in using the Conflict Discovery Tool?

Very Poor — Poor — Fair — Good — Very Good — Excellent — Exceptional

Video Editing Tool

1. How would you rank your overall experience in using the Video Editing Tool?

Very Poor — Poor — Fair — Good — Very Good — Excellent — Exceptional

1. Is the tension curve a good representation of the tension in your narrative? (circle)
   a. Yes
   b. No

2. Did you change the order of your final narrative based on the tension curve? (circle)
   a. Yes
   b. No

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Figure A.4: Workshop 2 Questionnaire pg. 4, to be filled out after finishing the narrative

#1 Familia y vecinos // Family and neighbors

- **clasificar la historia (un círculo)**
  Rate the overall story (circle one):

excelente	**muy bueno**	**bueno**	**satisfactorio**	**No me gustó**
Excellent	Very Good	Good	Was Ok	Didn't like it

- **¿Fue el tema interesante?** **sí** **no**
  Was the subject interesting? Yes No

- **¿La historia se refieren a su comunidad?** **sí** **no**
  Does the story relate to your community? Yes No

- **¿Te gustó el orden de los sucesos de la historia?** **sí** **no**
  Did you like the order of events in the story? Yes No

- **¿Qué le gusta más de la historia?**
  What did you like most about the story?

____
____
____

Figure A.5: Narrative Evaluation Questionnaire

APPENDIX B

Early Experimentation on Clustering Techniques

In this appendix we present our early experiments on clustering techniques for images in participatory sensing data based on annotations.

We built an application that uses lexical techniques to preprocess the annotations and relate them to the large WordNet lexical database [Mil95] and ran experiments with different clustering algorithms a dataset of 90 annotated images from the Boyle Heights School campaign. The results from our experiment show that using these techniques helps creating more relationships between data elements and in-turn improves clustering. (F1 scores increase from 66% to 83%, 80% to 100% and 46% to 88% for three different classes, and overall accuracy increased from 36% to 71%).

B.1 Dataset used in Experiments

We used a dataset of 90 images that were collected by students in the Boyle Heights community during the *BH-Escuela* campaign. Fifteen students participated in the campaign that ran for one week. The students contributed a total of 97 images relating to school conditions and things that needed repair, what they liked about school, what they ate at school and who supported them. We filtered out some of the images that did not have any annotations and images that were collected by the study organizer possibly for testing the application. This left us with a set of 90 images. Figure B.1 shows our complete un-clustered data set visualized with annotations in our tool.

Figure B.1: Un-clustered images with annotations that were used in our experiments as our test data set

B.2 Experimental Setup

Figure B.2 shows the set up of our clustering tool. The tool is written in Java and Processing and uses the R statistical computing language over RServe to run clustering algorithms. In the backend it uses a java API to communicate with WordNet and uses the Jazzy API which implements the Levenshtein spelling algorithm for getting spelling suggestions from a database of English language words. It uses a flat file system database of out test dataset images and annotations. Based on user specified options the tool reads the dataset of un-clustered

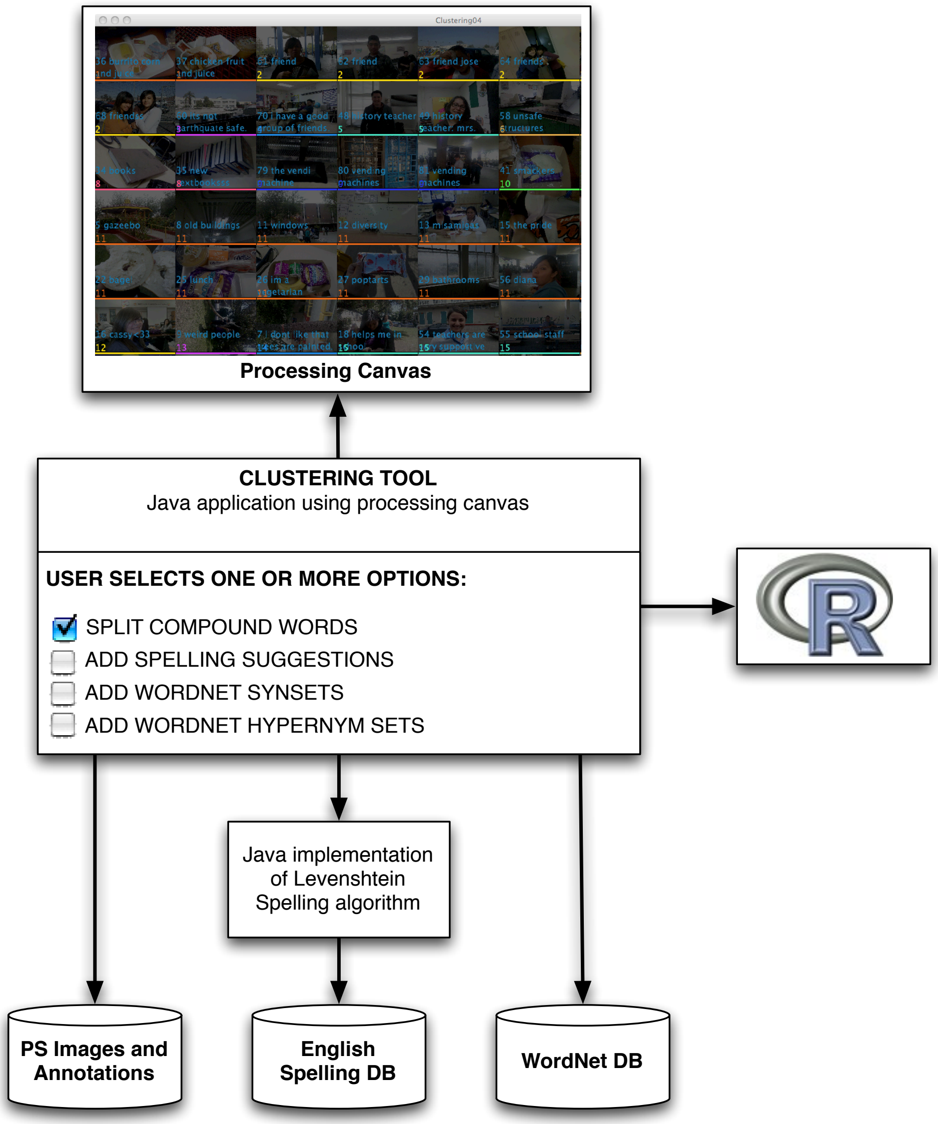


Figure B.2: Diagram showing clustering tool and experimental setup.

annotations and preprocesses the data into a table that can be passed to R for clustering. Once R is done clustering the data the clustered sets are read back into our tool and rendered on a processing canvas.

The clustering tool has four options that can be selected to run different linguistic and lexical analysis on the data before running a clustering algorithm. The first option splits compound words. Compound words in linguistics are comprised of two or more stems. For example:

$$textbook = text + books \tag{B.1}$$

When the word-splitting option is selected compound words are split into their stems and both the compound word and the stems are inserted into the feature set for the annotation.

The second option is spelling suggestions. When this option is selected all annotations are checked for spelling errors. A set of spelling suggestions for each misspelled word are added to the feature set for the annotation containing the misspelled word. The misspelled word is also left in the feature set.

Option 3, is used to add WordNet synsets to the feature set. WordNet is lexicon of the English language that also captures the semantic relationships between words. It contains information about different senses of words and combines synonyms into structures called synsets.

Most synsets are connected to other synsets through different semantic relationships:

Hypernyms: Word X is a hypernym of Y if every Y is a kind of X.

i.e. it is a **IS A** relationship.

e.g. collection is a hypernym of library.

Hyponym: The converse of a **hypernym.**

e.g. Surfing is a hyponum for Water Sport.

When option 4 is selected word Hypernyms are added to the feature set. This creates a hierarchal tree forming relationships between words.

Figure B.3 shows the clustering output of running Hierarchical cluster analysis [Jai88] with options for spelling suggestions, WordNet Syn Sets and WordNet Hypernym sets selected. The clusters are marked with a cluster number and color. Images that have the same color and number are in the same cluster for e.g. in the figure cluster three has eight images that all belong to the class of friends. The results can then be visually inspected for correctness.

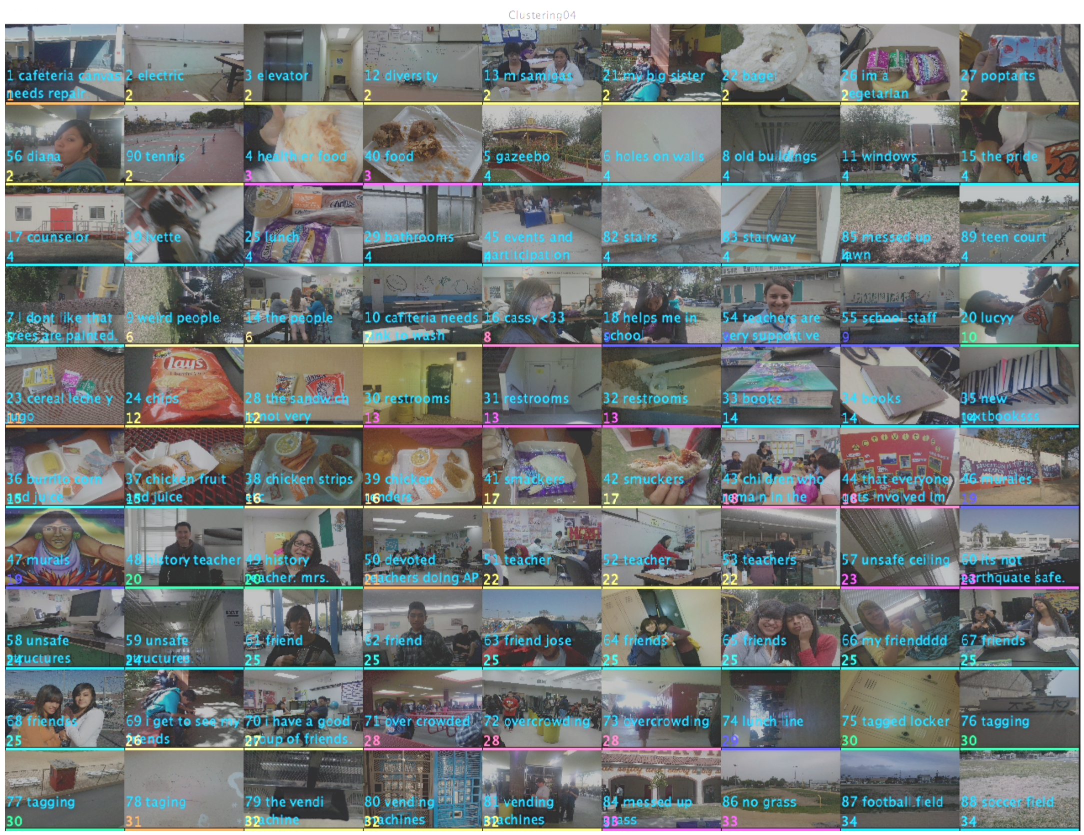


Figure B.3: Clustering results from running Hierarchical cluster analysis on data that is pre-processed with options for spelling suggestions, WordNet Syn Sets and WordNet Hypernym sets.

B.3 Results

First, we manually observed the data and decided on the following five clustering categories that we would compare across different runs:

1. *Toilet*
2. *Books*
3. *All Friends*
4. *Grass of field needing repair*
5. *Friends that support you*

We manually created the optimal cluster for these five sets and recorded this for comparing results from the test runs.

Next, we ran test runs selecting different options from our clustering tool and using the *k-means* clustering analysis algorithm in R. For each run we observed the results and recorded the precision, recall and F1 scores for five clustering categories. We also observed all the other clusters returned and the overall accuracy as defined in [Cho02]. Where accuracy of clustering is given by,

$$Accuracy = \frac{Number of elements correctly clustered}{Total number of elements} \tag{B.2}$$

Table B.1, shows the accuracy recorded for various runs of selecting differed options from our tool. The baseline in with no options selected. The results indicate that you can dramatically improve the clustering by using some of the techniques we implemented. The accuracy of the baseline in 37%. Adding spelling suggestions improved the accuracy by 6% to 43%, spell suggestions and splitting compound words increased the accuracy further to 48%. Adding synsets and hypernyms also shows an improvement. One interesting result is that there was a 10% increase in clustering accuracy when hypernyms were introduced after spelling suggestions were added to the feature set. This is because the annotations have a lot of misspelled words.

Test	**Accuracy**
baseline + k-means	0.37
baseline + spell + k-means	0.43
baseline + spell + split + k-means	0.48
baseline + syn + spell + split + k-means	0.49
baseline + syn + hyp + spell + split + k-means	0.47
baseline + spell + syn + hyp + k-means	0.59

Table B.1: Accuracy of running k-means on different tests

Next, we picked the same options that gave us the highest accuracy with k-means and ran tests with 3 other clustering algorithms. These results are presented in Figure B.2. The algorithms we chose are:

1. Hierarchical cluster analysis: Where we used the R implantation with is Agglomerative, so it begins with each object in its own cluster and pairs of clusters are merged as one moves up the hierarchy.

2. The K-medoids algorithm: Which is very similar to k-means but uses k randomly selected data points to begin instead of centroids.

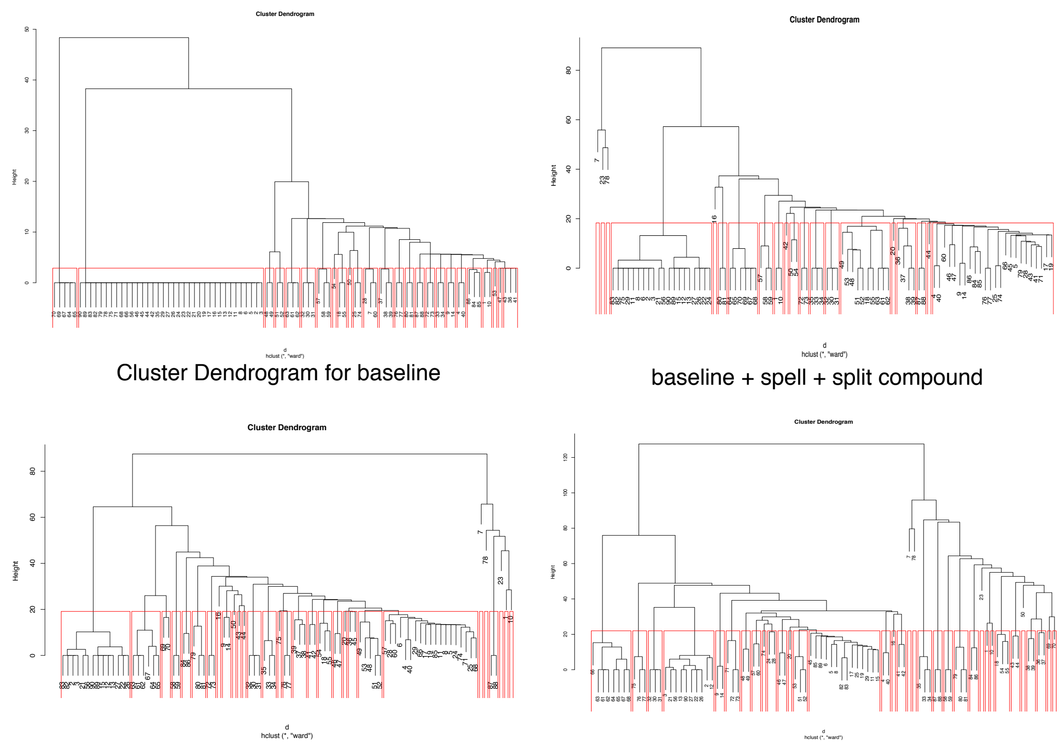
3. Spectral Clustering: Where clustering is performed by embedding the data into the subspace of the eigenvectors of an affinity matrix.

The Hierarchical clustering algorithm clearly outperformed all the rest, with an 11% improvement in accuracy over k-means. This was a bit surprising at first because in an initial test when we chose to use k-means for our experiments we had tested with hierarchical clustering as well on the baseline but its performance was not as good as k-means. However, from the results we can hypothesize that hierarchical clustering start to perform better once the WordNet hierarchical structure is added to our feature set. To test our hypothesis we plotted dendrograms of baseline and baseline with various options turned on Figure B.4. We can see that there is a visible improvement in the hierarchical structure that might be contributing to the performance improvement.

Test	**Accuracy**
baseline + spell + syn + hyp + k-means	0.59
baseline + spell + syn + hyp + k-means	0.71
baseline + spell + syn + hyp + k-means	0.52
baseline + spell + syn + hyp + k-means	0.54

Table B.2: Accuracy of running different clustering algorithms.

In Figure B.5 we present the precision, recall and F-scores of our test runs. The F1 score shows an improvement over the baseline for tests for all classes. Also, precision was 1 for almost all the tests we ran. Except for one in the *Toilet* class and three in the *Friends* that support you class. For the *Friends that support you* class this is exactly what we had expected. Once the synsets and hypernyms are introduced there are so many more correlations between the word friend that it dominates all other features. In case of the *Toilet* class it is unclear why the precision was so low.



Cluster Dendrogram for baseline

baseline + spell + split compound

baseline + spell + split compound + synsets

baseline + spell+ synsets + hypernyms

Figure B.4: Dendrograms for different selected options

	Precision	Recall	F-Score
Toilet			
baseline + kmeans	1.00	0.75	0.86
baseline + spell + kmeans	1.00	0.75	0.86
baseline + spell + split + kmeans	1.00	0.75	0.86
baseline + syn + spell + split + kmeans	1.00	1.00	1.00
baseline + syn + hyp + spell + split + kmeans	0.13	1.00	0.22
baseline + spell + syn + hyp + kmeans	1.00	0.75	0.86
Books	**Precision**	**Recall**	**F-Score**
baseline + kmeans	1.00	0.67	0.80
baseline + spell + kmeans	1.00	0.67	0.80
baseline + spell + split + kmeans	1.00	1.00	1.00
baseline + syn + spell + split + kmeans	1.00	1.00	1.00
baseline + syn + hyp + spell + split + kmeans	1.00	0.67	0.80
baseline + spell + syn + hyp + kmeans	1.00	1.00	1.00
All Friends	**Precision**	**Recall**	**F-Score**
baseline + kmeans	1.00	0.30	0.46
baseline + spell + kmeans	1.00	0.50	0.67
baseline + spell + split + kmeans	1.00	0.60	0.75
baseline + syn + spell + split + kmeans	1.00	0.60	0.75
baseline + syn + hyp + spell + split + kmeans	1.00	0.60	0.75
baseline + spell + syn + hyp + kmeans	1.00	0.80	0.89
Grass or field needing repair	**Precision**	**Recall**	**F-Score**
baseline + kmeans	1.00	0.40	0.57
baseline + spell + kmeans	1.00	0.60	0.75
baseline + spell + split + kmeans	1.00	0.60	0.75
baseline + syn + spell + split + kmeans	1.00	0.40	0.57
baseline + syn + hyp + spell + split + kmeans	1.00	0.40	0.57
baseline + spell + syn + hyp + kmeans	1.00	0.40	0.57
Friends that support you	**Precision**	**Recall**	**F-Score**
baseline + kmeans	1.00	0.50	0.67
baseline + spell + kmeans	1.00	0.50	0.67
baseline + spell + split + kmeans	1.00	0.50	0.67
baseline + syn + spell + split + kmeans	0.83	0.83	0.83
baseline + syn + hyp + spell + split + kmeans	0.83	0.83	0.83
baseline + spell + syn + hyp + kmeans	0.75	1.00	0.86

Figure B.5: F-1 Scores for five different classes of running k-means on different sets.

APPENDIX C

Source Code

Due to the enormous amount of code developed through the course of this dissertation, we are not including it here, but all of the source code is available on the Narreme git repository :

git clone https://code.google.com/p/narreme/

References

[AAB10] Amelia Acker, Raquel Armenta, Elizabeth Blaney, Deborah Estrin, Isela Gracian, and Martin Lukac. "Boyle Heights Planning for Place: Mobile Participatory Sensing Project." Whitepaper, November 2010. 5

[ABF61] Aristotle, S.H. Butcher, and F. Fergusson. *Aristotle's Poetics*. Hill and Wang, 1961. 36, 46

[Abo10] M.Y. Abolafia. "Narrative construction as sensemaking: How a Central Bank thinks." *Organization Studies*, **31**(3):349–367, 2010. 3, 47

[ABT00] E. André, K. Binsted, K. Tanaka-Ishii, S. Luke, G. Herzog, and T. Rist. "Three RoboCup simulation league commentator systems." *AI Magazine*, **21**(1):57, 2000. 49

[Art05] Procedural Arts. "Facade." http://www.interactivestory.net, 2005. 47

[AST06] A.Parker, S.Reddy, T.Schmid, K.Chang, G.Saurabh, M.Srivastava, M.Hansen, J. Burke, D. Estrin, M. Allman, and et. al. "Network System Challenges in Selective Sharing and Verification for Personal, Social, and Urban-Scale Sensing Applications." *Hotnets*, 2006. 8

[BA06] E. Byrne and P. M. Alexander. "Questions of ethics: participatory information systems research in community settings." In *Proceedings of the 2006 annual research conference of the South African institute of computer scientists and information technologists on IT research in developing countries*, SAICSIT '06, pp. 117–126, , Republic of South Africa, 2006. South African Institute for Computer Scientists and Information Technologists. 13

[BB84] R. Beach and L.S. Bridwell. *New Directions in Composition Research. Perspectives in Writing Research.* ERIC, 1984. 32

[BBZ07] Jordan Boyd-Graber, David Blei, and Xiaojin Zhu. "A Topic Model for Word Sense Disambiguation." *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*, 2007. 44

[BCM11] Carolina Bigonha, Thiago Cardoso, Mirella Moro, Marcos Gonçalves, and Virgílio Almeida. "Sentiment-based influence detection on Twitter." *Journal of the Brazilian Computer Society*, pp. 1–15, 2011. 35

[Beg06] Grigory Begelman. "Automated Tag Clustering: Improving search and exploration in the tag space." In *In Proc. of the Collaborative Web Tagging Workshop at WWW'06*, 2006. 43

[BEH06] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M.B. Srivastava. "Participatory sensing." In *World Sensor Web Workshop, ACM Sensys*, Boulder, Colorado, 2006. 3

[BGP94] R. Basili, F. Grisoli, and M.T. Pazienza. "Might a semantic lexicon support hypertextual authoring?" In *Proceedings of the fourth conference on Applied natural language processing*, pp. 174–179. Association for Computational Linguistics, 1994. 45

[Blu88] W.E. Blundell. *The art and craft of feature writing: based on the Wall Street Journal guide*. New American Library, 1988. 38, 46

[BPM09] Johan Bollen, Alberto Pepe, and Huina Mao. "Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena." *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media*, 2009. 35

[BSN08] A.D. Brown, P. Stacey, and J. Nandhakumar. "Making sense of sensemaking narratives." *Human relations*, **61**(8):1035–1062, 2008. 3, 47

[Cam03] J. Campbell. *The hero's journey: Joseph Campbell on his life and work*, volume 7. New World Library, 2003. 37, 46

[CEN08] CENS. "Personal Environmental Impact Report." http://peir.cens.ucla.edu/, 2008. 8

[Cho02] Choudhary. "Text clustering using semantics." *In The Eleventh International World Wide Web Conference*, 2002. 93

[CKH07] Sung-Bae Cho, Kyung-Joong Kim, and Keum-Sung Hwang. "Generating cartoon-style summary of daily life with multimedia mobile devices." In *Proceedings of the 20th international conference on Industrial, engineering, and other applications of applied intelligent systems*, IEA/AIE'07, pp. 135–144, Berlin, Heidelberg, 2007. Springer-Verlag. 49

[CKT06] Deepayan Chakrabarti, Ravi Kumar, and Andrew Tomkins. "Evolutionary clustering." In *Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*, KDD '06, pp. 554–560, New York, NY, USA, 2006. ACM. 27, 44

[CL87] M Csikszentmihalyi and R Larson. "Validity and reliability of the Experience-Sampling Method." *J Nerv Ment Dis*, **175**(9):526–536, 1987. 13

[CM08] Margaret Cargo and Shawna Mercer. "The Value and Challenges of Participatory Research: Strengthening Its Practice." *Annual Review of Public Health*, **29**(1):325–350, 2008. 13

[Cor03] J. Corburn. "Bringing localknowledge into environmental decision making: Improving urban planning for communities at risk." *J Plan Edu Res*, 2003. 13

[Cra04] Chris Crawford. *Chris Crawford on Interactive Storytelling*. New Riders Games, 2004. 46

[De 84] R. De Beaugrande. *Text production: Toward a science of composition*. Ablex Publishing, 1984. 32

[Dew08] R. Dewsbury. *Google web toolkit applications*. Addison-Wesley, 2008. 26

[Dic12] Dictionary.com. *Collins English Dictionary - Complete & Unabridged*. Harper Collins Publishers, 10th edition, Nov 2012. 3

[DSB12] Cheryl Diermyer, Susan Simmons, and Chris Blakesley. "Using Narrative Structures to Inspire and Improve Writing for Digital Media Assignments." http://narrativestructures.wisc.edu/aristotle, 2012. 37, 38, 46

[Ela02] K. Elam. *Semiotics of theatre and drama*. Routledge, 2002. 34

[Elb89] P. Elbow. "Toward a phenomenology of freewriting." *Journal of Basic Writing*, **8**(2):42–71, 1989. 32

[Emi71] J. Emig. *The composing processes of twelfth graders*. ERIC, 1971. 32

[EP06] Nathan Eagle and Alex Pentland. "Reality mining: sensing complex social systems." *Personal Ubiquitous Comput.*, **10**(4):255–268, 2006. 2

[ES06a] Elwood and Sarah. "Critical Issues in Participatory GIS: Deconstructions, Reconstructions, and New Research Directions." *Transactions in GIS*, **10**(5):693–708, 2006. 13

[ES06b] A. Esuli and F. Sebastiani. "Sentiwordnet: A publicly available lexical resource for opinion mining." In *Proceedings of LREC*, volume 6, pp. 417–422, 2006. 21

[FC02] Chris Fairclough and Padraig Cunningham. "An Interactive Story Engine." In *AICS*, pp. 171–176, 2002. 46

[Fel98] C. Fellbaum. *WordNet: An Electronic Lexical Database (Language, Speech, and Communication)*. The MIT Press, illustrated edition edition, 1998. 27

[Fie84] S. Field. "The Screenwriter's Workbook: Exercises and Step-by-Step Instruction for Creating a Successful Screenplay.", 1984. 36, 46

[FKG09] Thomas Fritsch, Jung Kwak, Stacey Grant, Josh Lang, Rhonda Montgomery, and Anne Basting. "Impact of TimeSlips, a Creative Expression Intervention Program, on Nursing Home Residents With Dementia and their Caregivers." *The Gerontologist*, **49**(1):117–127, 2009. 80

[Fro07] Jon Froehlich. "MyExperience: a system for in situ tracing and capturing of user feedback on mobile phones." In *Proceedings of the 5th international conference on Mobile systems, applications and services*, 2007. 8, 14

[GBH10] A. Go, R. Bhayani, and L. Huang. "Twitter sentiment classification using distant supervision." *CS224N Project Report, Stanford*, pp. 1–12, 2010. 35

[GBL06] Jim Gemmell, Gordon Bell, and Roger Lueder. "MyLifeBits: a personal database for everything." *Commun. ACM*, **49**(1):88–95, 2006. 45

[GFA08] TF Gharib, MM Fouad, and MM Aref. "Web document clustering approach using wordnet lexical categories and fuzzy clustering." In *Computer and Information Technology, 2008. ICCIT 2008. 11th International Conference on*, pp. 48–55. IEEE, 2008. 44

[GKS05] M. Groden, M. Kreiswirth, I. Szeman, and R. Macksey. *The Johns Hopkins guide to literary theory & criticism*. Johns Hopkins University Press, 2005. 37

[Gor99] A.S. Gordon. *The design of knowledge-rich browsing interfaces for retrieval in digital libraries*. PhD thesis, Northwestern University, 1999. 48

[Gre97] S.J. Green et al. "Building hypertext links in newspaper articles using semantic similarity." In *Third Workshop on Applications of Natural Language to Information Systems (NLDB'97)*, pp. 178–190, 1997. 45

[GWW04] Jim Gemmell, Lyndsay Williams, Ken Wood, Roger Lueder, and Gordon Bell. "Passive capture and ensuing issues for a personal lifetime store." In *Proceedings of the the 1st ACM workshop on Continuous archival and retrieval of personal experiences*, CARPE'04, pp. 48–55, New York, NY, USA, 2004. ACM. 2, 45

[HA68] O.B. Hardison and Aristote. *Aristotle's Poetics: A translation and commentary for students of literature*. Prentice-Hall Englewood Cliffs, NJ, 1968. 36

[Har79] J. A. Hartigan. "A k-means clustering algorithm." *Applied Statistics*, pp. 100–108, 1979. 20

[Her11a] D. Herman. *The Living Handbook of Cognitive Narratology*. Hamburg University Press, last modified July, 2011. 3, 47

[Her11b] Erik Hersman. "SwiftRiver Throws a Lifeline to People Drowning in Information." http://www.pbs.org/idealab/2011/12/swiftriver-throws-a-lifeline-to-people-drowning-in-information340.html, 2011. 49

[Hil11] Peder Hill. "The Elements of a Novel." http://www.musik-therapie.at/PederHill/Structure&Plot.htm, 2011. 39

[HTF09] Trevor Hastie, Robert Tibshirani, and Jerome Friedman. *The Elements of Statistical Learning, Second Edition: Data Mining, Inference, and Prediction*, chapter 14.3.12 Hierarchical clustering. Springer, 2nd ed. 2009. corr. 3rd printing 5th printing. edition, 2009. 20

[Inc12] Qwiki Inc. "Qwiki Storytelling." www.qwiki.com, 2012. 49

[Jai88] A.K. Jain. *Algorithms for Clustering Data*. Prentice Hall, 1988. 92

[Kar10] A. Karandikar. *Clustering short status messages: A topic model based approach*. PhD thesis, University of Maryland, 2010. 44

[Kea02] R Kearney. *On Stories*. Routledge, 2002. 16, 34

[KNS92] S. Kurohashi, M. Nagao, S. Sato, and M. Murakami. "A method of automatic hypertext construction from an encyclopedic dictionary of a specific field." In *Proceedings of the third conference on Applied natural language processing*, pp. 239–240. Association for Computational Linguistics, 1992. 46

[KRC12] SR Kannan, S Ramathilagam, and PC Chung. "Effective fuzzy c-means clustering algorithms for data clustering problems." *Expert Systems with Applications*, **39**(7):6292–6300, 2012. 20

[Kul11] Kullect. "http://www.kullect.com." (accessed May 19, 2011), 2011. 4, 8, 14

[Lai08] Mathew Laibowitz. "Spinner." http://www.media.mit.edu/resenv/spinner/, 2008. 46

[Lai10] Mathew Laibowitz. *Creating Cohesive Video with the Narrative-Informed use of Ubiquitous Wearable and Imaging Sensor Networks.* PhD thesis, MIT Media Lab, 2010. 46

[Lau90] B. Laurel. *The art of human-computer interface design.* {Addison-Wesley Professional}, 1990. 3, 48

[Lau91] B. Laurel. *Computers as theatre.* Addison-Wesley, 1991. 3, 48

[LBL12] G. Lee, V. Bulitko, and E. Ludvig. "Sports Commentary Recommendation System (SCoReS): Machine Learning for Automated Narrative." In *Eighth Artificial Intelligence and Interactive Digital Entertainment Conference*, 2012. 50

[LEM08] Nicholas D. Lane, Shane B. Eisenman, Mirco Musolesi, Emiliano Miluzzo, and Andrew T. Campbell. "Urban sensing systems: opportunistic or participatory?" In *Proceedings of the 9th workshop on Mobile computing systems and applications*, HotMobile '08, pp. 11–16, New York, NY, USA, 2008. ACM. 8

[Liu12] Bing Liu. "Sentiment Analysis and Opinion Mining." *Synthesis Lectures on Human Language Technologies*, **5**(1):1–167, 2012. 35

[Mad08] K.S. Madej. ""Traditional Narrative Structure"–not traditional so why the norm?" In *5th International Conference on Narrative and Interactive Learning Environments Edinburgh, Scotland 6th–8th August 2008*, 2008. 36

[Mar83] Chris Marker. "Sans Soleil.", 1983. 47

[Mat87] A. Matsuhashi. *Writing in real time: Modelling production processes*, volume 16. Ablex Publishing Corporation, 1987. 32

[McK97] R. McKee. *Story: Style, Structure, Substance, and the Principles of Screenwriting.* It Books, 1997. 39

[MHM10] Min Mun, Shuai Hao, Nilesh Mishra, Katie Shilton, Jeff Burke, Deborah Estrin, Mark Hansen, and Ramesh Govindan. "Personal data vaults: a locus of control for personal data streams." In *Proceedings of the 6th International COnference*, Co-NEXT '10, pp. 17:1–17:12, New York, NY, USA, 2010. ACM. 8

[Mil95] George Miller. "WordNet: a lexical database for English." *Commun. ACM*, **38**(11):39–41, 1995. 27, 88

[Moo05] Margaret Moore. "What's An Aspiring Author To Do?" http://www.margaretmoore.com/Tension.html, 2005. 9

[Moo11] D.T. Moore. "Sensemaking: a structure for an intelligence revolution." Technical report, DTIC Document, 2011. 6

[Mor06] B. Morgan. *Learning commonsense human-language descriptions from temporal and spatial sensor-network data*. PhD thesis, Massachusetts Institute of Technology, 2006. 48

[Mov12] MovieMasher. "http://www.moviemasher.com/." (accessed Oct 23, 2012), 2012. 22, 26

[MRS09] Min Mun, Sasank Reddy, Katie Shilton, Nathan Yau, Jeff Burke, Deborah Estrin, Mark Hansen, Eric Howard, Ruth West, and Péter Boda. "PEIR, the personal environmental impact report, as a platform for participatory sensing systems research." In *Proceedings of the 7th international conference on Mobile systems, applications, and services*, MobiSys '09, pp. 55–68, New York, NY, USA, 2009. ACM. 8

[MS02] M. Mateas and A. Stern. "A behavior language for story-based believable agents." *Intelligent Systems, IEEE*, **17**(4):39–47, 2002. 47

[Mul03] M.J. Muller. "Participatory design: the third space in HCI." *Human-computer interaction: Development process*, pp. 1051–1068, 2003. 3, 48

[Mur72] D. Murray. "Teach writing as a process not product." *The Leaflet*, **71**(3):11–14, 1972. 32

[Mus04] Robert B. Musburger. *Introduction to Media Production: The Path to Digital Media Production*. Focal Press, 2004. 34

[MVM09] F.P. Miller, A.F. Vandome, and J. McBrewster. "Levenshtein Distance: Information theory." *Computer science, String (computer science), String metric, Damerau? Levenshtein distance, Spell checker, Hamming distance*, 2009. 26

[Naa07] Mor Naaman. "How flicker helps us make sense of the world: context and content in community-contributed media collections." In *In Proceedings of the 15th international conference on Multimedia*, 2007. 27, 44

[Nar12] Narrative Science Inc. "Quill by Narrative Science." http://www.narrativescience.com, 2012. 48

[Nel65] T.H. Nelson. "Complex information processing: a file structure for the complex, the changing and the indeterminate." In *Proceedings of the 1965 20th national conference*, pp. 84–100. ACM, 1965. 45

[New06] M.Z. Newman. "From beats to arcs: Toward a poetics of television narrative." *The velvet light trap*, **58**(1):16–28, 2006. 38, 46

[Nob85] June Noble. *Steal This Plot: A Writer's Guide to Story Structure and Plagiarism.* Paul S. Eriksson, 1985. 47

[Nok08] Nokia. "Nokia Simple Context." https://simplecontext.com/eb2/, 2008. 14

[Oxf10] Oxford Dictionaries, editor. *Oxford Ameriacan English Dictionary.* Oxford University Press, April 2010. 3

[Pac12] Pacoapp. "Personal Analytics Companion." http://www.pacoapp.com/, 2012. 4

[Pag01] Philip Page. "Furrowing all the brows: Interpretation and the transcendent in toni morrison's paradise." *African American Review*, 2001. 34

[Pen04] A Pentland. "Healthwear: medical technology becomes wearable." *Computer*, **37**(5):42–49, 2004. 2

[Pin12] Pinterest. "http://www.pinterest.com." (accessed Oct 23, 2012), 2012. 4

[PLL10] Daniel Peebles, Hong Lu, Nicholas D. Lane, Tanzeem Choudhury, and Andrew T. Campbel. "Community-Guided Learning: Exploiting Mobile Sensor Users toModel Human Behavior." *Association for the Advancement of Artificial Inteligence*, 2010. 44

[PLV02] Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. "Thumbs up? Sentiment Classification using Machine Learning Techniques." *CoRR*, **cs.CL/0205070**, 2002. 35

[Pol24] Georges Polti. *The Thirty-Six Dramatic Situations.* James Knapp Reeve, 1924. 47

[Pro28] Vladimir Propp. *Morphology of the Folktale (Publications of the American Folklore Society).* University of Texas Press, 1928. 37, 46

[qua12] quantifiedself. "http://quantifiedself.com/." The Quantified Self, 2012. 4

[RAF12] N. Ramanathan, F. Alquaddoomi, H. Falaki, D. George, C. Hsieh, J. Jenkins, C. Ketcham, B. Longstaff, J. Ooms, J. Selsky, et al. "ohmage: An open mobile system for activity and experience sampling." In *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2012 6th International Conference on*, pp. 203–204. IEEE, 2012. 4, 14

[RBE08] Sasank Reddy, Jeff Burke, Deborah Estrin, Mark Hansen, and Mani Srivastava. "Determining transportation mode on mobile phones." In *Proceedings of the 2008 12th IEEE International Symposium on Wearable Computers*, pp. 25–28, Washington, DC, USA, 2008. IEEE Computer Society. 8

[Red10] Sasank Reddy. *Towards Design Guidelines for Participatory Sensing Campaigns*. PhD thesis, University of California, Los Angeles, 2010. 8

[Ric83] G.L. Rico. *Writing the natural way*. Tarcher Los Angeles, 1983. 32

[Ric86] GL Rico. "Clustering: A prewriting process." *Practical Ideas for Teaching Writing as Process. Sacramento, CA: California State Department of Education*, 1986. 32

[Rob86] Jacobs Roberts, Edgar; Henry. *An Introduction to Reading and Writing*. Prentice-Hall, 1986. 9, 35

[RPH07] Sasank Reddy, Andrew Parker, Josh Hyman, Jeff Burke, Deborah Estrin, and Mark Hansen. "Image browsing, processing, and clustering for participatory sensing: lessons from a DietSense prototype." In *Proceedings of the 4th workshop on Embedded networked sensors*, EmNets '07, pp. 13–17, New York, NY, USA, 2007. ACM. 8

[Rya01] M.L. Ryan. *Narrative as virtual reality*. Johns Hopkins University Press Baltimore, MA, 2001. 3, 48

[Rya03] M.L. Ryan. "Cognitive maps and the construction of narrative space." *Narrative theory and the cognitive sciences*, pp. 214–242, 2003. 3, 47

[Rya06] M.L. Ryan. *Avatars of story*, volume 17. University of Minnesota Press, 2006. 3, 48

[SA77] R.C. Schank and R.P. Abelson. *Scripts, plans, goals and understanding: An inquiry into human knowledge structures*. Lawrence Erlbaum, 1977. 48

[SB05] Er Schutz and Paul Buitelaar. "Relext: A tool for relation extraction from text in ontology extension." In *In: Proceedings of the 4th International Semantic Web Conference (ISWC). (2005*, p. 05, 2005. 44

[Sch90] R.C. Schank. *Tell me a story: A new look at real and artificial memory*. Charles Scribner's Sons, 1990. 48

[Sea12] Karl Stolley Sean M. Conrey. "Literary Terms." Purdue Online Writing Lab (http://owl.english.purdue.edu/), 2012. 9

[SHJ06] Christoph Schmitz, Andreas Hotho, Robert Jaschke, and Gerd Stumme. "Mining Association Rules in Folksonomies." *Data Science and Classification*, pp. 261–270, 2006. 44

[Siv09] Derek Sivers. "Kurt Vonnegut explains drama." http://sivers.org/drama, 2009. 39

[SM07] Lucia Specia and Enrico Motta. "Integrating Folksonomies with the Semantic Web." *The Semantic Web: Research and Applications*, pp. 624–639, 2007. 44

[Sny05] Blake Snyder. *Save The Cat! The Last Book on Screenwriting You'll Ever Need*. Michael Wiese Productions, 2005. 38, 46

[SRC07] Vidyut Samanta, Jason Ryder, Sona Chaudhuri, Jeff Burkey, Deborah Estrin, and Fabian Wagmister. "UCLA/Cisco Metropolitan Wi-Fi Research Network." In *IEEE LANMAN Workshop*, June 2007. 8

[Ste12] Joanna Stern. "Qwiki Aims To Turn Everyone into a Multimedia Storyteller." http://abcnews.go.com/Technology/qwiki-aims-turn-multimedia-storyteller/, May 2012. 49

[Stm12] Stm. "Storytelling Machines." http://www.stm.io/, 2012. 49

[TJ05] J. Taeho and N. Japkowicz. "Text clustering with NTSO (neural text self organizer)." *IEEE International Joint Conference on Neural Networks*, 2005. 44

[TNK10] T.T. Thet, J.C. Na, and C.S.G. Khoo. "Aspect-based sentiment analysis of movie reviews on discussion boards." *Journal of Information Science*, **36**(6):823–848, 2010. 21

[Vir12] Viralheat. "Viral Heat Sentiment Analysis API." https://viralheat.com/developer/sentiment_api, 2012. 27, 35

[Wan96] C. Wang. "Chinese village women as visual anthropologists: a participatory approach to reaching policymakers." *Soc Sci Med*, 1996. 13

[WBS05] R. Williams, B. Barry, and P. Singh. "ComicKit: acquiring story scripts using common sense feedback." In *Proceedings of the 10th international conference on Intelligent user interfaces*, pp. 302–304. ACM, 2005. 48

[Wor04] S.E. Worth. "Narrative understanding and understanding narrative." *Contemporary Aesthetics*, 2004. 7

[Yau12] Nathan Yau. "Your Flowing Data." http://your.flowingdata.com, 2012. 3