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Using Big Data to Understand Memory and Future Thinking

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Abstract

Imagining the future and remembering the past both involve mental time travel. This commonality could indicate shared mental processes, as held by the Constructive Episodic Simulation Hypothesis (Schacter & Addis, 2008), or else interactive processes that complement one another, a possibility we call the Complementarity Hypothesis. According to the Complementarity Hypothesis, future thoughts are constructed from schemas making them episodically poor, whereas past thoughts are constructed from schemas and direct retrieval of memory traces, making them relatively episodically rich. We tested these hypotheses using machine learning to data mine mental operations in language, much as a geologist can recover physical processes from the geological record. People's natural, unprompted talk on web blogs was automatically analyzed for past, present, and future references using a temporal orientation classifier. In Study 1, we found that perceptual details were mentioned more often in past than future talk, implying greater use of episodic processing in past than future thinking. In Study 2, a neural network using schemas generated from Latent Dirichlet Allocation better predicted the content of references to the future than the past, implying that constructive processes are more common in future than past thinking. In Study 3, we used the results from the two prior studies to construct an episodic-by-constructive process space. We adapted techniques from fMRI analysis to analyze this space for clusters of activity, as if the frequency of past and future thinking were BOLD responses in cortical space. We found that past and future thinking occupy highly separable regions of processing space, supporting the Complementarity Hypothesis.

Keywords: Prospection; Memory; Future Thinking; Big Data; Naturally Occurring Datasets

Introduction

Memory is not just used to remember the past. It also helps people predict and plan for the future (Schacter & Addis, 2007; Klein, Robertson, & Delton, 2010). At a minimum, then, the cognitive process used to think about the future must be able to connect with those used to remember the past. Such a connection would be facilitated by overlap in the processes used to think about the future and past. According to the Constructive Episodic Simulations Hypothesis (Schacter & Addis, 2008) the overlap in these processes is considerable. An alternative possibility is that the thought processes used to think about the past and the future are largely unique and non-overlapping, but connect with each other in manner that complements the other. We will refer to this later possibility as the Complementarity Hypothesis. In this research, we seek to test between these two competing proposals using information afforded by machine learning and big data analytics.

The idea that thinking about the future and the past might involve similar kinds of process has received significant empirical support. Viard et al (2011) found that past and future thinking engage several common brain regions including the hippocampus, precuneus, prefrontal cortex, and posterior cingulate cortex. Addis, Wong, & Schacter (2007) found that past and future thinking both engage the left hippocampus, a region known to be involved in episodic memory. Meta-analyses suggest that the overlap between past and future thinking is robust and involves a broad set of regions in the brain's default network (Benoit & Schacter, 2015; Spreng, Mar, & Kim, 2009).

The evidence for common processes is not, however, uniform. Irish, Addis, Hodges, and Piguet (2012) found that conceptual knowledge impairments in semantic dementia were more severe in future thinking than past thinking. Craver, Kwan, Seindam, and Rosenbaum (2014) found that people who lost the ability to remember the past due to hippocampal amnesia often retained some ability to think about the future. Such patients make normal future-oriented decisions in delay discounting and score normally on surveys of future orientation. Findings such as these suggest that past and future thinking may rely on different cognitive processes.

The conflicting findings from past research are associated with different kinds of methodology. Studies supporting shared process have been those using brain imaging, while those indicating differences have been based on neuropsychological research investigating the effects of brain damage (although see Klein, Loftus, & Kihlstrom, 2002 for neuropsychological evidence for similar processing). Both kinds of research have their limitations. One of the challenges in neuroimaging work is the problem of how to elicit thoughts about the past and the future without bias to the results. Typically, temporal thoughts are elicited by explicit instructions to do so. The problem is that these instructions may alter the cognitive processes involved. For example, to image the future, participants are often instructed to imagine specific events that are highly likely to occur (e.g., Addis, Wong, & Schacter, 2007). These instructions might bias people to use their memory of the past to imagine future events because it requests that they offer specific details, a process that may not necessarily be associated with future thinking. Neuropsychological research investigating brain damage is limited by the (fortunately) relatively small numbers of participants. Most importantly, the research using both kinds of methodology has focused on people's ability to remember or imagine scenes with significant perceptual detail, but not all thoughts about the future and past are necessarily high in episodic detail. Certain thoughts about the future and past might be driven by abstract conceptual knowledge, possibly by schemas. Some research has investigated the role of cultural life scripts on future thinking (Bernsten & Bohn, 2010), but life scripts are only a small portion of people's abstract conceptual knowledge. In sum, prior research has been limited in its ability to study the potential impact of abstract knowledge and schemas on people's thoughts about the past and the future for lack of an inventory of the generic abstract knowledge structures that people are likely to possess.

The limitations of prior work can be addressed using big data methods. Big data methods involve mining large-scale naturally occurring behavior to provide insight into human cognition (Goldstone & Lupyan, 2016; Thorstad & Wolff, 2018a). In the case of mental time travel, people talk regularly about the past, such as what they did yesterday, and the future, such as what they plan to do tomorrow. This talk can be mined to understand the cognitive processes of memory and future thinking. These big data methods address some of the challenges of prior work. Big data methods avoid the explicit prompting in prior work by studying natural, unprompted talk about time. Big data methods also allow investigation of a much wider set of conceptual knowledge by learning the relevant concepts from the data.

Here, we examine people's temporal talk in a large web blog corpus. This corpus is ideal for studying mental time travel because people write without prompting about topics of their choosing. Once the sentences in the corpus are analyzed for their temporal orientation, we can investigate the cognitive processes associated with this talk to test between the Constructive Episodic Simulation and Complementarity hypotheses.

Study 1: What is the Content of Past and Future Thinking?

The view that past and future thinking share common cognitive processes makes a strong prediction about the content of people's temporal talk. Past and future thinking have been argued to rely on shared episodic processes (Schacter & Addis, 2008), and these episodic processes have characteristic types of representation that can be identified in text. Episodic thoughts are highly concrete and perceptual, with episodic future thinking typically described as a kind of pre-experiencing (Atance & O'Neil, 2001) or simulation (Schacter & Addis, 2008). Episodic thoughts also involve a spatial location (Tulving, 1993), as also reflected in work using spatial relations as a marker of episodic future thinking (Russell, Alexis, & Clayton, 2010). We measured these episodic representations in people's talk about the past, present, and future, based on psychometric dictionaries. If past and future thinking rely on common episodic processes as predicted by the Constructive Episodic Simulation Hypothesis, then we should observe similar amounts of episodic processing in past and future talk. By contrast, if past and future thinking rely on different processes as predicted by the Complementarity Hypothesis, then we should observe more episodic processing in talk about the past than the future. Such a pattern could occur if thoughts about the future are more constructed than thoughts about the past.

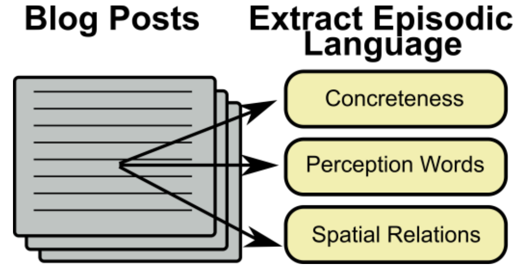

Fig. 1. Analyzing Episodic Language in Blog Posts. We extracted three episodic language indicators from a corpus of blog posts: concreteness, the amount of perceptual words, and the presence of spatial relation words.

Methods

All procedures were approved by the Emory University IRB.

Materials The analyses used the Blog Authorship Corpus (Schler, Koppel, Argamon, & Pennebaker, 2006). The corpus is demographically diverse, including 19,320 bloggers (50% female) from 40 different occupational categories and a wide range of ages (13-17y: N=8,240, 23-27y: N=8,086, 30-47y: N=2,994).

Procedures Several preprocessing steps were taken to clean the corpus. Special characters, emoticons and URLs were removed. Misspellings were automatically corrected using a dictionary from Han, Cook, & Baldwin (2012). Extremely short posts with less than 10 words were dropped. Non-English sentences were removed using the Python library langdetect.

We extracted temporal talk from the corpus by automatically classifying the sentences using a temporal orientation classifier. As a first step, the sentences in the corpus were syntactically parsed using the Stanford Parser (Chen & Manning, 2014). These parses could then be used to determine temporal orientation using a set of 121 syntactic and lexical rules written in the regular expression-like language Tregex (Levy & Andrew, 2006). References to the past were flagged using rules like "VP>VG>have" and references to the future by rules like "MD>will" (Copley & Wolff, in prep.)

Before running the classifier on the corpus, the performance of the classifier was verified in a separate rating study where we recruited 30 human raters via Amazon Mechanical Turk. We obtained 3 ratings for each of 1,000 randomly drawn sentences from the blog corpus (100 ratings/participants), as to whether the sentences referred to the past, present, future, atemporal, or unintelligible. Participant quality was ensured using unmarked attention checks and by requiring participants to have completed 100 previous MTurk tasks with 95% approval rating. We found that the performance of the classifier, as indicated by the F statistic (Raschka, 2015), F = 0.61, where chance = 0.33, approached human-level accuracy, F = 0.67. We also compared the classifier to other classifiers based on the Linguistic Inquiry and Word Count psychometric dictionary (Pennebaker et al, 2015), a decision-tree model based on a variety of language features (Schwartz et al, 2015), and a

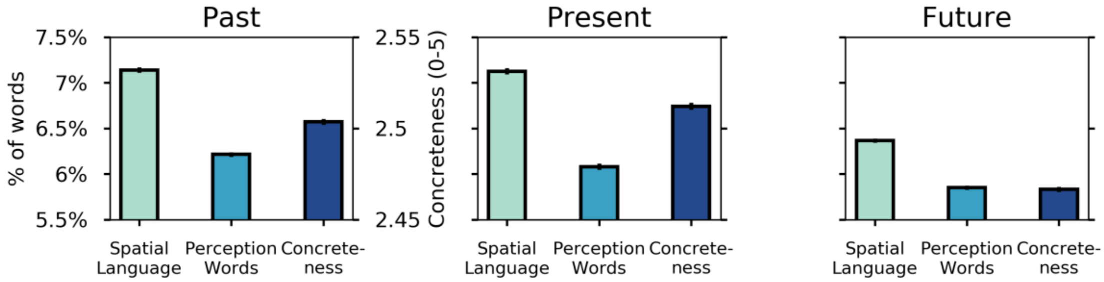

Fig. 2. Amount of episodic processing (+/- 95% CI) in sentences about past, present, and future.

regular-expression pattern-based temporal classifier known as SUTime (Chang & Manning, 2012). Our temporal orientation classifier outperformed these other temporal orientation classifiers, specifically SUTime, $F = 0.25$, decision trees, $F = 0.33$, and the Linguistic Inquiry and Word Count psychometric dictionary, $F = 0.56$.

Once applied to the blog corpus, the classifier was able to identify which sentences referred to the past (2,134,357 sentences, 39.5%), present (1,428,626 sentences, 26.5%), or future (1,834,206 sentences, 34.0%).

As shown in Fig. 1, we measured the episodic processing in each sentence in the blog corpus using three measures. We analyzed concrete language based on averaging the concreteness of the words in each sentence using concreteness ratings of 40,000 English lemmas from Byrsbaert et al (2014). We analyzed the perceptual and spatial language in each sentence by **c**alculating the proportion of words in the sentence matching predefined lists from the Linguistic Inquiry and Word Count psychometric dictionary (Pennebaker et al**.**, 2015).

Results and Discussion

We found that past thoughts involved more of all three types of episodic representations than future thoughts. In all three cases, past thoughts were more similar to present thoughts, which do not require mental time travel, than to future thoughts. As shown in Fig. 2, references to the past were rated as more spatial, $t_{(18,808)} = 48.34$, $p < 0.001$, perceptual, $t_{(18,808)} = 23.27$, $p < 0.001$, and concrete, $t_{(18,806)} = 46.65$, $p < 0.001$, than references to the future. As also shown in Fig. 2, references to the past are as perceptually rich as references to the present. Together, the results suggest that past thinking is more episodic than future thinking, a result that is fully consistent with the Complementarity Hypothesis.

Study 2: What Processes are used for Future Thinking?

Study 1 suggests that past thoughts are more episodic than future thoughts. These results raise the question of what processes are used to think about the future. An intuitive possibility is that because the past has happened but the future has not, future thoughts may be more constructed than past thoughts. This construction could be performed by relying on stored knowledge structures known as schemas. While the possibility that future thoughts rely more on schemas is intuitive, it is broadly agreed that memory also relies on schemas (Bransford & Johnson, 1972), and so one could also predict that past and future thoughts rely equally on schemas. In Study 2, we therefore asked whether future thoughts rely more on schemas than past thoughts.

There are two challenges to quantifying the influence of schemas on temporal thoughts. First, it is difficult to know in advance which schemas people use to mentally time travel. It seems likely that the most important schemas may be used in everyday talk. With a large enough sample of everyday talk, it should be possible, then, to extract these schemas. To do this, we analyzed 1 month of posts from the social media website Reddit (307 million words). We extracted the 500 most common schemas using a machine learning model known as a topic model (Blei, Ng, & Jordan, 2003). As shown in Fig. 3, a topic model works by inferring the latent topics that organize people's choices of which words to write in certain documents, or Reddit posts. These topics can thought of as probability distributions over words. While these topics do not share every feature of schemas (for example they are not hierarchical), they share some of the essential features, such as the fact that the important words represent slots that can be filled by words, which are conceptually similar, but not necessarily semantically related.

The second important challenge is that the mere presence of a schema does not necessarily imply a cognitive process. It is necessary to ask whether an author used a schema to guide their writing or merely invoked the schema incidentally. To make this leap from describing schemas to cognitive processes, we capitalized on a key cognitive function of schemas: schemas are thought to fill in missing information. For example, if a person goes to a restaurant, they can use their schemas to know that there will be a waiter even before they have seen a waiter. We created an analogue of this prediction in text by asking whether, if only a part of a sentence is provided, the rest of the sentence can be filled in based on knowledge of the schema. We did this by training a neural network to use the schemas evident in people's blog posts to predict the words they wrote next. We performed this prediction separately for sentences about the past, present, and future, thus allowing us to investigate whether schemas are more involved in filling in missing information for the past, present, or future.

If past and future thinking rely on common cognitive processes as predicted by the Constructive Episodic Simulation Hypothesis, then we would expect schemas to be equally useful for predicting the content of people's past and future talk. By contrast, if past and future thinking rely on different cognitive processes as predicted by the Complementarity Hypothesis, then we would expect schemas to be more useful for predicting the content of people's past talk than future talk.

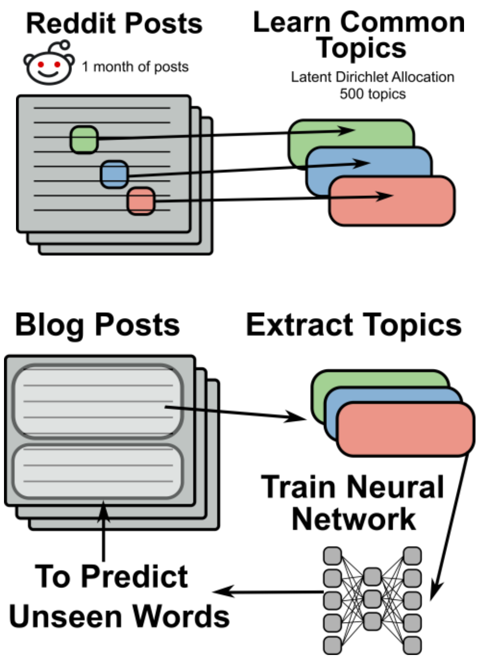

Fig. 3. Learning and Identifying Schemas in Temporal References. (Top) We identified the most prevalent schemas in a large social media corpus using Latent Dirichlet Allocation, which learns the 500 most common topics across many social media posts. (Bottom) For a particular blog post, we identified the schemas implicit in the post, and then trained a neural network to use those schemas to predict words in the unseen last sentence of the post. We conducted this prediction separately for sentences referring to the past, present, and future, allowing us to ask whether schemas were more useful for filling information for particular kinds of temporal references.

Methods

Schema Identification As shown in the top row of Fig. 3, we identified common schemas in a large corpus based on every post to the social media website Reddit in the month of January 2017 (307 million words). As shown in the top row of Fig. 3, we identified schemas in the posts by training a type of topic model known as Latent Dirichlet Allocation (Blei, Ng, & Jordan, 2003). The model was trained using the Python library *gensim* with the parameters α = 0.002, η = 0.002, *number of topics* = 500, using 100 training iterations.

Using Schemas to Fill in Information As shown in the bottom row of Fig. 3, for every post in the blog corpus, we used the LDA model to identify the schemas in the post based on every sentence except the last sentence in the post. Next, we created a dataset where the input was the schema of the post, and the output was a randomly selected word from the unseen last sentence in the post, restricting to the 5,000 most common words in the corpus. We then trained a neural network model to use the schema to predict the unseen word (out of 5,000 possible words). The model had a relatively simple architecture, with a single hidden layer with 500 units and a *relu* activation function, and was trained to minimize cross-entropy loss with *Adam* optimization, based on 25,000 training batches with a minibatch size of 100. The model was evaluated using unseen test data (10%). As described in the main text, we also trained a scrambled version of the model using the same procedure but randomly assigning words to Reddit posts.

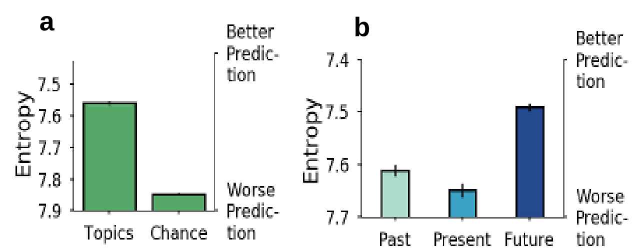

Fig. 4. Schema Usage. (A) The schemas learned by our model could predicted unseen words better than random schemas, replicating a key property of schemas. (B) These schemas were more useful for filling in unseen words for future references than past or present references.

Table 1. Schemas learned by the topic model.

Feelings	Reading	Studying	Food	Sounds	Health-care
Feeling	Read	Study	Food	Hear	Care
Feels	Reading	Subject	Eat	Sound	Health
Felt	Book	Passed	Eating	Sounds	Insuran-ce
Pain	Books	Studying	Healthy	Audio	Letter
Worse	Library	Studies	Diet	Hearing	Legal
Bad	Stuff	Exam	Dinner	Noise	Medical

Results and Discussion

We found that our model learned semantically coherent schemas from social media. We also found that future thoughts drew more on these schemas than did past thoughts, consistent with the Complementarity Hypothesis.

We first asked whether our topic model learned semantically coherent schemas. Several of the schemas are shown in Table 1. The schemas are highly coherent on visual inspection. For example, the model learned a schema about feelings including the words *feeling*, *feels*, *felt*, *pain*, *worse*, and *bad*. We quantified this semantic coherence by training a second model but ablating the semantic information by randomly assigning words to documents in the Reddit corpus. We asked human raters to judge which model generated more semantically coherent topics. Raters judged the topics from the real model as more semantically coherent than the semantically ablated model, $t_{(22)} = 11.68$, $p < 0.001$, a difference that was observed in every individual rater (23/23 raters).

We next asked whether these schemas fill in missing information in a sentence. We trained a neural network to predict the words in people's talk in the blog corpus based on either the real schemas, or based on ablating schema knowledge using randomly generated schemas. As shown in Fig. 4A, we found that the model based on real schemas outperformed the model based on scrambled schemas, $t_{(220,174)} = 174.26$, $p < 0.001$, suggesting that these schemas do indeed fill in missing information.

Finally, we asked whether these schemas fill in more information for references to the past, present, or future. We found that past references drew on schemas, evidenced by increased prediction performance for past relative to present thoughts, $t_{(110,952)} = 4.60$, $p < 0.001$ (Fig. 4B). However, we found that future references drew more on schemas than did past references, $t_{(175,248)} = 18.53$, $p < 0.001$ (Fig. 4B). This increased prediction for future thoughts relative to past thoughts suggest that thoughts about the future rely more on schemas than thought about the past. This result is consistent with the predictions of the Complementarity Hypothesis.

Study 3: Are these Findings the Result of Different Processes?

Studies 1-2 suggest differences in the cognitive processes used for past and future thinking. However, these results are also open to an alternative interpretation, which we may call the Difference-in-Amount view. On this account, past and future thinking rely on the same basic cognitive processes, but to different extents.

Testing between the Difference-in-Amount and Complementarity Hypothesis requires an analysis for determining whether two operations reflect different underlying cognitive processes. Our key idea is that such a procedure exists in cognitive neuroscience, and can be adapted to big data. In fMRI studies, it is widely accepted that there are different cognitive processes if the two processes activate non-overlapping patterns of voxels in the brain. Indeed, the spatial overlap between past and future thinking in the brain has been taken as evidence for common processing. While this analysis is based on a brain space, a similar logic should hold for operations projected into what we will call a cognitive process space. As shown in Fig. 5, a process space can be created by projecting the candidate operations into a space composed by two or more cognitive processes. Evidence for a single process would be largely overlapping representations in process space (Fig. 5A), while evidence for multiple processes would be largely non-overlapping representations in process space (Fig. 5B). To evaluate the Difference-in-Amount and Complementarity Hypotheses, we pooled the data from Studies 1 and 2 to create a cognitive process space defined by constructive and episodic processing. We projected both past and future thinking into the process space, and quantified the amount of overlap between the processes. We asked whether this overlap was better explained by the Difference-in-Amount view or the Complementarity view.

Methods

Materials We combined the data from Studies 1-2. We created an aggregate measure of episodic processing by separately z-scoring the concreteness, spatial relation, and perceptual measures and then averaging the resulting z-scores for each sentence.

Process Space Creation We created a 10x10 cognitive process space using the episodic and constructive processing scores. For each measure we calculated 10 deciles. For example the bottom-left corner represents 0-10% episodic processing and 0-10% constructive processing. We then calculated the proportion of past and future thoughts falling in each region of process space. We stored the difference score (future - past) for each region and retained only scores larger than 0.25 in magnitude to avoid false positives.

Cluster Permutation Test We next tested how large a cluster would be obtained in the process space by chance. We did this by creating 10,000 permutations of the data by shuffling the past and future labels. In each permutation we repeated the cognitive process analysis and stored the size of the largest cluster, again retaining only scores large than 0.25 in magnitude. We used these cluster sizes to create a chance distribution (Fig. 5D, green distribution).

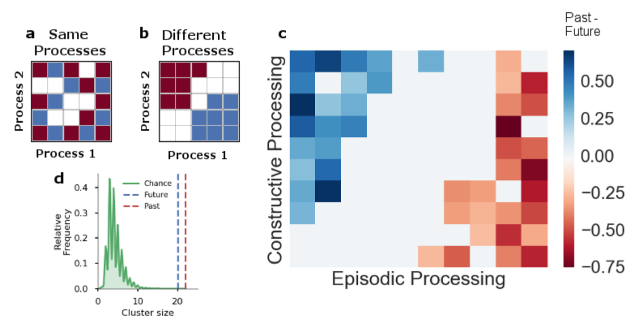

Fig. 5. Cognitive Process Space. (a-b) Hypothetical results in cognitive process space that would indicate reliance on the same or different processes. (c) Past thinking (blue) and future thinking (red) projected into cognitive process space. (d) Chance distribution of clusters in process space (green) compared to observed cluster sizes (vertical dotted lines).

Results and Discussion

We found that past and future thinking occupied largely non-overlapping clusters of the process space, supporting the predictions of the Complementarity hypothesis.

As shown in Fig. 5C, when past and future thinking were projected into cognitive process space, they occupied largely non-overlapping regions of the space. As shown in Fig. 5D, we quantified whether this pattern would be expected due to chance. We did this by creating 10,000 random permutations of the data, and recording the largest cluster size observed in each permutation (Fig. 5D, green distribution). We found that both the past thinking cluster (red dotted line) and the future thinking cluster (blue dotted line) were larger than those observed in any of the 10,000 permutations, suggesting dissociable cognitive processes that would not be likely observed due to chance (e.g. $p < 0.0001$). This result suggests that past and future thinking rely on different cognitive processes, consistent with the Complementarity Hypothesis.

General Discussion

There is growing consensus that memory is not just for remembering the past, but also for imagining the future. Here, we considered a strong version of this idea that past and future thinking could rely on largely similar cognitive processes. In a series of three studies based on people's natural talk about time, we found support for the alternative hypothesis that past and future thinking rely on different cognitive processes. In Study 1, we found that thoughts about the past were more episodic than thoughts about the future, as revealed by the increased presence of concrete words, perceptual words, and spatial relation words. In Study 2, we found that thoughts about the past were less constructed than thoughts about the future, as revealed by the decreased ability of a machine learning model to use the topics of people's writing to predict the contents of future references compared to past references. Finally, in Study 3 we found that these findings were better explained by differences in cognitive processing than by a Difference-in-Amount view, a conclusion supported by projecting the data into cognitive process space.

While we believe that the schemas learned by our model are quite general, a limitation of the current analysis is that the schemas are only derived from a single social media corpus. The social media corpus spans a broad range of topics and covers millions of posts, but it may be limited in some ways; for example, social media users may be younger than or more likely to be male than the general population (Duggan & Brener, 2013). Future work should address whether similar schemas would be discovered in other kinds of corpora.

Beyond future thinking, our results have implications for the role of big data in psychology. It has previously been shown that big data can predict many psychological traits, including personality (Youyou, Kosinski, & Stillwell, 2015), mental illness (Thorstad & Wolff, 2018b), and decision-making (Thorstad & Wolff, 2018a). However, psychologists are often interested in going beyond prediction to make inferences about the underlying cognitive processes. It is not obvious that cognitive processes are recoverable from big data, since in written text the cognitive processes that generated the text have already occurred. Our findings suggest that big data can in fact recover cognitive processes, in two ways. First, big data can be used to look for characteristic representations of a cognitive process, such as the episodic language markers in Study 1. Second, big data can be used to train a model to mimic the cognitive process used to generate the text, as in the schema-based prediction model in Study 2. Both of these techniques suggest that big data may be useful not just for predicting human psychology, but also for understanding cognitive processes, a kind of data mining the mind.

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