People's beliefs and attitudes about social and scientific issues, such as capital punishment and climate change, appear to form complex but generally coherent networks. Understanding the nature of these networks is a prerequisite for designing interventions for changing beliefs on the basis of rational arguments and evidence. It is therefore important to develop methods to represent and analyze the form and nature of belief networks, which may not be explicitly verbalizable. Adopting an emerging approach that utilizes crowdsourcing to develop educational interventions, we mined discussions from the Reddit forum Change My View to determine which beliefs and types of information underlie people's attitudes about capital punishment. By combining computational analyses based on a topic model with more qualitative assessments of the extracted topics, we found that moral arguments are more prevalent than statistical or data-based arguments. The present study serves as a test case for the open sourced software crowdpy, a Python toolkit for running naturalistic studies on the web, which will enable other researchers to use crowdsourcing in their research. This approach sets the stage for research exploring potential interventions to change people's beliefs.

Keywords: crowdsourcing, digital field studies, belief networks, attitude change

Crowdsourcing as a Research Tool

Crowdsourcing affords a number of advantages as a tool for cognitive science. One is ecological validity, as materials acquired by crowdsourcing by their very nature are vetted naturalistically (cf. Kahan & Carpenter, 2017). Furthermore, crowdsourcing allows researchers to test the ecological validity of laboratory findings.

In addition, crowdsourcing can take advantage of free and plentiful big data. Huge numbers of people discuss social issues online, and crowdsourcing enables researchers to mine this information to assess what arguments and information are effective at changing people's beliefs, as well as to identify beliefs most central to common misconceptions.

Crowdsourcing with crowdpy

We ran the present crowdsourcing study using the open source software package crowdpy: a flexible and easy-to-use Python toolkit designed for running crowdsourcing and digital field studies (Priniski, 2020). Despite an emerging interest in the ecological validation of lab studies (Kahan & Carpenter, 2017), crowdsourced studies remain relatively rare in the cognitive science literature. This mismatch may stem from naturalistic research being difficult to run—due to a required familiarity with data mining and machine learning—and being analytically flexible, which in turn casts doubt not only on the replicability of such studies but their value to science.
more broadly. Crowdpy is designed to help overcome these shortcomings by providing researchers with an intuitive toolkit for running and preregistering naturalistic studies. Specifically, crowdpy provides support for (1) specifying and executing the computations underlying a crowdsourcing study, and (2) easy access to common data mining tools (e.g., accessing data from Reddit and Twitter). We hope the present paper will demonstrate the value crowdpy can provide as part of the cognitive scientist’s toolkit. For more information and tutorials on using crowdpy, the reader should visit the software’s website at crowdpy.com.

Crowdsourcing to Analyze Belief Networks

Here we describe a general methodology that can enable researchers to crowdsource the content and nature of belief systems using the crowdpy toolkit. Specifically, this methodology will allow researchers to (1) discern the reasons, evidence, and auxiliary beliefs on which people’s views about controversial issues depend, and (2) determine which types of auxiliary beliefs are most central, and therefore perhaps most important as targets for counterarguments. To aid this goal we have created a ready-to-go crowdpy workflow designed to help researchers with little-to-no coding experience use crowdsourcing to analyze belief networks, which can be found on the crowdpy website.

In broad strokes, the method of crowdsourcing flexible beliefs follows two steps:

1. **Mine social media** (here, we focus on the Reddit forum Change My View, described below)
2. **Train an unsupervised topic model** (e.g., Latent Dirichlet Allocation; Blei et al., 2003) to determine which beliefs and reasons underlie people’s core beliefs.

Additional data analyses or follow-up behavioral studies can then be performed to assess which beliefs are most flexible and which types of arguments are most effective in changing them. We will now elaborate on the above two core steps, and describe how they are executed in the crowdsourcing software tool created for this task.

**Step 1: Mine Naturalistic Data** An approach commonly used to mine social media data is to access a social media website’s Application Programming Interface (API). APIs provide direct access to the platform’s freely available data. The crowdsourcing software tool we developed consists of the code necessary to access the Reddit and Twitter APIs, so that a user without prior data-mining experience can mine these platforms. To access the APIs with our crowdsourcing software tool, the user will only have to create an account with the respective platform and specify which call they want to make (e.g., specify a keyword they would like to search for in the data). The resulting data will be saved automatically in a csv or excel file.

**Step 2: Run a Topic Model** A topic model serves to analyze which topics are frequently discussed for a given issue (e.g., climate change, capital punishment, vaccine safety), making it possible to determine the auxiliary beliefs and reasons on which people’s attitudes towards complex social and scientific issues depend. These topics will serve as the basis for assessing which auxiliary beliefs support people’s representations of a complex social or scientific issue. In conjunction with the code that connects users to the website’s APIs, the crowdsourcing software tool will perform topic modeling using LDA (Blei et al., 2003). To assist in interpreting the model, the software tool will also create an interactive data visualization using the Python package pyLDAvis (Maybe, 2019), which allows users to examine the topic details in greater clarity.

Researchers can crowdsource from numerous social media platforms. Here we focus on analyzing data from the Reddit forum Change My View. Given the structure and nature of conversations on Change My View, it is at present the most natural data source to use for our present purposes.

**Reddit’s Change My View**

Change My View is a popular Reddit forum in which users post their views on issues ranging from gun control to the movies. “Redditors” posting in this community understand that others will attempt to change their view by providing arguments opposing their beliefs. Because some arguments are more persuasive than others, the variance in argument quality found on the forum provides a naturalistic resource for analyzing the features of effective arguments (e.g., Priniski & Horne, 2018; Hidey & McKeown, 2018). Work in computer science has focused on automatic extraction of features that predict the probability an argument will be effective (Tan, Niculae, Danescu-Niculescu-Mizil, & Lee, 2016), and on identifying aspects of beliefs that are most amenable to change (Jo et. al, 2018).

Previous work has demonstrated that researchers can build on successful crowdsourced arguments—that is, arguments mined from naturalistic resources such as Reddit, Facebook, and Twitter—to develop effective educational interventions likely to correct people’s misconceptions (e.g., Priniski & Horne, 2019). Narrowing the hypothesis space of possible interventions increases the probability that researchers will be able to develop an effective intervention. Indeed, Priniski and Horne (2019) demonstrated that crowdsourcing can produce educational interventions just as effective at correcting misconceptions as interventions published in top academic journals.

The present study was designed to demonstrate how the crowdsourcing approach can be used to identify the types of beliefs and reasons that underlie people’s attitudes about capital punishment. The goal is to better understand how people’s belief systems are structured, and how core beliefs cohere with additional auxiliary beliefs.
To this end, we mined Reddit for Change My View discussions relating to capital punishment. We then hand-labeled the discussions as either promoting an attitude in favor of capital punishment or an attitude against it. Second, we employed a topic modeling algorithm, LDA, to elucidate the beliefs and justifications on which people’s attitudes to capital punishment hinge. Third, we tested a hypothesis inspired by the results obtained using the topic model. We assessed whether people’s attitudes towards capital punishment (on both sides) rely more strongly on morality-based justifications, in contrast to data-driven or statistical justifications.

Data Collection

The first step in our crowdsourcing methodology is to mine naturalistic data. We mined discussions about capital punishment from the Reddit forum Change My View. This forum provides a straightforward platform for obtaining data that can be used to analyze attitudes, attitude change, and persuasion tactics in a relatively naturalistic setting (Priniski & Horne, 2018).

To this end, we mined Change My View posts related to capital punishment and the death penalty using the Python Reddit API Wrapper (2019). Specifically, we searched Change My View for discussion posts and replies for the strings “capital punishment” and “death penalty”. If either the post or a reply returned a match, we collected the full discussion for our dataset. Descriptive statistics for the mined dataset are presented in Table 1 above.

Table 1: Summary of Change My View data used in study.

<table>
<thead>
<tr>
<th>Position</th>
<th>Number of posts</th>
<th>Number of comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pro-capital punishment</td>
<td>94</td>
<td>5264</td>
</tr>
<tr>
<td>Anti-capital punishment</td>
<td>55</td>
<td>3921</td>
</tr>
<tr>
<td>Non-related</td>
<td>32</td>
<td>2111</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>181</strong></td>
<td><strong>11296</strong></td>
</tr>
</tbody>
</table>

Crowdsourcing Study: Assessing Beliefs About Capital Punishment

The present study aimed to shed light on the structure of people’s belief systems surrounding capital punishment, and what types of reasons they deem relevant to their attitudes. Understanding the beliefs and justifications that underlie people’s attitudes toward capital punishment is a prerequisite for developing effective interventions that might change their attitudes.

In broad strokes, we first mined Reddit for Change My View discussions relating to capital punishment. We then hand-labeled the discussions as either promoting an attitude in favor of capital punishment or an attitude against it. Second, we employed a topic modeling algorithm, LDA, to elucidate the beliefs and justifications on which people’s attitudes to capital punishment hinge. Third, we tested a hypothesis inspired by the results obtained using the topic model. We assessed whether people’s attitudes towards capital punishment (on both sides) rely more strongly on morality-based justifications, in contrast to data-driven or statistical justifications.

Topic Modeling

Method We fit an unsupervised topic modeling algorithm, LDA, to determine which types of beliefs and considerations are most relevant to attitudes toward capital punishment expressed in the discussion posts. LDA assigns documents (here, the titles of discussion posts on Change My View) to topics by instantiating a set of $k$ topics, where each topic is defined by a set of words that compose the documents. In general terms, the algorithm assigns a probability value for how likely a document belongs to each topic. This probability value is determined by how many of the topic’s “representative” words appear in the document.

Because divergent attitudes toward capital punishment may hinge on different beliefs, reasons, or justifications, we fit one model to the titles of posts indicating a favorable attitude towards capital punishment, and another model to the titles of posts indicating disapproving attitudes, using the Python package Genisim (Rehúřek & Sojka, 2010). We fit the model to the titles because these provide a concise, non-noisy representation of the participant’s attitude and justifications. The topic model could also be fit to the selftext of the posts (a more detailed justification for their attitudes, written by the posting user). An example title on which we trained the topic model is provided in Table 2.

Table 2: Example post in Change My View dataset.

<table>
<thead>
<tr>
<th>Title (i.e., attitude)</th>
<th>Selftext (i.e., justification)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMV: The death penalty is only a harsh punishment for people who are wrongly convicted. For the guilty, it is by no means the ultimate punishment. It is inherently unjust and should be universally abolished.</td>
<td>This is USA-specific, but feel free to include your perspective if you are not a USA-ian. If someone killed or hurt someone in the circle of people I consider “family”, I would probably want…</td>
</tr>
</tbody>
</table>

Results We fit two topic models, one to the pro-capital punishment posts and another to the anti-capital punishment posts, each with five topics. The topics underlying the pro-capital punishment attitudes are displayed in Table 3 (the topics from the anti-capital punishment discussions are nearly identical). Model selection was guided by maximizing a model’s coherence scores (Rehúřek & Sojka, 2010), which numerically quantify on a scale from 0 to 1 how well the topics fit to the data and how well the terms within a single topic are semantically related. The coherence value of the selected model for pro-capital punishment attitudes was .48; coherence for anti-capital punishment attitudes was .44. In addition to using a model’s coherence scores, model selection was also guided by a subjective assessment of the interpretability and meaningfulness of the topic classifications, guided by previous analysis of the considerations many people deem relevant to their stance on capital punishment (e.g., Miske et al., 2019). The selected topic model can be found at the project’s GitHub repository.

The topics (and their associated keywords) found to underlie both pro- and anti-capital punishment attitudes indicate that people more strongly consider ethical and moral justifications than statistical and cost-benefit reasons. Both types of justifications are factors commonly identified in work on psychology and law as underlying people’s attitudes toward capital punishment (e.g., Miske et al.,
Table 3: Words associated with pro-capital punishment attitudes.

<table>
<thead>
<tr>
<th>Topic 0</th>
<th>Top 10 keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crime, prison, give, crime, sentence, wrong, form, abolish,</td>
<td>morally</td>
</tr>
<tr>
<td>Topic 1</td>
<td>crime, prison, child, sentence, life, make, favor, oppose, rape, standard</td>
</tr>
<tr>
<td>Topic 2</td>
<td>deserve, life, believe, murder, pro, crime, state, citizen, criminal, people</td>
</tr>
<tr>
<td>Topic 3</td>
<td>legal, people, murder, state, system, time, criminal, believe, innocent, kill</td>
</tr>
<tr>
<td>Topic 4</td>
<td>believe, use, method, crime, must, viable, consider, certain, state, replace</td>
</tr>
</tbody>
</table>

Note. Bolded words indicate a moral basis for capital punishment, whereas italicized words indicate the role capital punishment plays in achieving retribution. Retributive and other morally-grounded beliefs appear to underlie each topic. Words associated with anti-capital punishment attitudes are similar to those associated with pro-capital punishment attitudes and also emphasize moral coherence over statistical concerns.

2019). The observed emphasis on moral and ethical justifications (reflected in keywords such as “morally”, “barbaric”, and “wrong”) over statistical and cost-benefit justifications (keywords such as “cost”, “rate”, or “crime statistics”) suggests that coherence of moral beliefs plays a central role in supporting people’s attitudes towards capital punishment (cf. Holyoak & Powell, 2016). In the next section we report a more direct test of this hypothesis.

Statistical Analyses

To assess whether attitudes toward capital punishment depend on moral coherence to a greater extent than statistical evidence, we adapted an approach developed by Priniski and Horne (2018) to measure evidence-related and statistical language in Change My View discussions. Our aim was to determine whether participants used language more indicative of reasoning driven by moral coherence as compared to statistical evidence. We used two dictionaries of terms commonly associated with types of reasoning to measure types of reasoning in the posts. To measure rates of moral coherence, we used the 2nd version of the Moral Foundations Dictionary (Frimer, Boghrati, Haidt, Graham, & Dehgan, 2019).

To our knowledge no comparable inventory of terms associated with everyday statistical reasoning exists. We therefore employed a data-driven approach (extracting features from a Random Forest model) to create a list of terms indicative of statistical reasoning. To this end, we first created a dataset composed of Reuters financial news articles (Ding et al., 2014), a large set of discussions from the Reddit forum r/Statistics, and tweets collected by Go, Bhayani, and Huang (2009) that have commonly been used to build sentiment analysis models. The Reuters and r/Statistics corpora involve reasoning about numeric values and statistics, while the tweet corpus provides a reference group against which to classify the Reuters r/Statistics posts. With this grouped dataset ready, we then trained a Random Forest classifier to determine which dataset (Reuters or r/Statistics vs. Twitter) each post in the conjoined dataset came from, based on the text’s individual word tokens. Having created a model with high predictive accuracy, we then extracted the features that the model used to determine which posts were in the Reuters or r/Statistics datasets and used that as the basis for our dictionary of terms related to statistical reasoning. The code used to mine the Reddit forum, prepare and model the data using Random Forest classification can be found at this paper’s GitHub repository (linked above). We sketch the statistical details of this approach to feature selection below.

Feature Extraction with Random Forests

Random Forests are a class of supervised, ensemble learning algorithms that are commonly used in both classification and regression tasks. They model data by aggregating the results of a large set of decision trees constructed from random subsets of the feature space. In addition to their widespread success in machine learning applications, they are also an effective variable selection tool. Here, we sought to use Random Forests to highlight which terms are most strongly associated with statistical reasoning. To achieve this goal, we first fit a Random Forest classifier to the compiled dataset described above. Next, we extracted the features the model identified as the most important to determining classifications.

Here, we sketch the statistical framework underlying this process and relate it to the task at hand. Let $\mathcal{D} = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_n, y_n)\}$ be the collection of document tuples $d_i = (\mathbf{x}_i, y_i)$ in our corpus (i.e., the conjoined dataset). Each document $d_i$ is composed of an encoding of the text data, $\mathbf{x}_i$, and its associated classification, $y_i \in \{0, 1\}$ ($y_i = 0$ indicates $d_i$ is from the Twitter dataset while $y_i = 1$ indicates the document belongs to either the Reuters or r/Statistics datasets). Here, $\mathbf{x}_i$ is a bag-of-words of document $d_i$.

The principle idea behind a Random Forest classifier is to aggregate the results of many smaller classification trees to derive predictions. In their simplest form, classifications trees are binary decision trees, which for each node in the tree, must make a binary decision of whether a document belongs to a class (i.e., document indicates statistical reasoning) or not. Nodes in a classification tree consists of a random subset of features or dimensions from $\mathbf{x}_i$, and classification decisions are made at each node in the tree.

The importance of each feature loosely stems from how essential that feature is to maximizing the model’s classification accuracy. Roughly, importance of a feature $x_j \in \mathbf{x}$ is assessed by how much the Gini impurity is decreased when the data is split at that feature relative to other features. Gini impurity, which is an information theoretic measure that calculates the probability a randomly selected document is misclassified given a set of features, takes the following form:
\[ G = \sum_{i=1}^{C} p_i (1 - p_i) \]

with \( C \) representing the number of classes. By iterating over a random subset of features, each classification tree seeks to minimize \( G \) in order to classify a document. A Random Forest model will then aggregate all of the tree-level classifications for a document and form a final classification based on the class which has the most “votes”.

We trained a Random Forest model with the purpose of distinguishing between text documents that likely demonstrate statistical reasoning (i.e., financial news and discussions from the Reddit forum r/statistics) and those that do not (a random set of tweets commonly used for training sentiment analysis models). The corpus was constructed such that any Random Forest model could easily distinguish between both types of documents. Indeed, even base models performed achieved accuracy scores above 95% without any parameter tuning. The features the Random Forest model relied most strongly on to classify the documents, along with their quantitative importance scores learned by the model, can be found on the project’s GitHub (linked above). However, because our general goal is to construct a dictionary of terms that map onto statistical reasoning, we refined the returned set of features by (1) removing terms that are artifacts of the dataset and do not reflect statistical reasoning (e.g., “New York” and “Reuters”) and (2) adding synonyms and related terms to the remaining set of terms. The revised set of terms, which was used in the following analyses, can be found on the project’s GitHub as well.

**Predicting Coherence-based and Statistical Considerations**

To test our hypothesis that attitudes toward capital punishment depend more on moral coherence than on statistical evidence, we performed Bayesian mixed effects modeling using the *R* package *brms* (Bürkner, 2018). We examined how participants justified their capital punishment attitudes by measuring the rates at which their language pertained to moral-based considerations versus statistics-related considerations. Specifically, we treated each word in the dataset of attitude justifications as belonging to either moral terms (e.g., “morally”, “logically”, and “wrong”), statistical terms (e.g., “data”, “rate”, “cost”), or as a stopword (i.e., a term that belongs to neither category). By modeling the rates at which participants justify their beliefs using moral-based or statistics-based language, we can estimate the extent to which moral-based and statistics-based reasons (and beliefs about those reasons) are relevant to people’s attitudes toward capital punishment.

As shown in Figure 1, when Redditors justify their beliefs, they use language more strongly associated with moral-based justifications than with statistical justifications (e.g., costs associated with capital punishment or its efficacy at reducing crime rates). This result converges with our findings from the LDA model, indicating that people’s attitudes toward capital punishment cohere with their moral considerations.

We looked a bit closer at which types of moral constructs are at play in people’s moral coherence reasoning. In Figure 2, we see that considerations related to *care* as a vice (i.e., considerations about the suffering and pain inflicted on
Beliefs on social media may not be representative of the whole population. A simple behavioral study that tests the generalizability of the results gleaned from the analyses presented here is a natural next step for this research.

An additional line of future research will need to articulate the structure of people’s systems of beliefs with greater specificity, and in particular, to identify the most central nodes in an individual’s system of beliefs. Analyzing individual beliefs in relation to a larger ecosystem of related beliefs can shed light on people’s conceptual frameworks and decision-making processes, as well as help develop interventions for correcting misconceptions. This process is challenging, however, both because of the often-complex nature of people’s belief systems, and because we lack a strong theory of how beliefs change within a larger conceptual system. Crowdsourcing can assist with the first difficulty, but modeling work will be needed to address the second (cf. Powell et al., 2018).

How might crowdsourcing be extended to extract a more complete picture of a belief system? The present findings using the topic model suggest that people commonly justify their attitude toward capital punishment by ethical beliefs (e.g., whether or not it is humane) and the value of its retributive impact. Both of these constructs (“ethical footing” and “retribution”) can act as separate nodes in a system of beliefs. A deeper understanding of people’s belief systems (i.e., accounting for a larger set of auxiliary beliefs) might be achieved in part by mining more data from other sources (e.g., other Reddit forums, Twitter, opinion sections of newspapers).

Once a more detailed representation of people’s belief systems has been obtained, a further goal will be to test the efficacy of different interventions targeting individual beliefs in the crowdsourced network. This process will attempt to identify which of these beliefs are especially malleable (i.e., amenable to change by counterarguments) and also pivotal (i.e., those for which a change would maximally impact the rest of the network). The expectation will be that revision of a pivotal belief will trigger a coherence shift (i.e., updating of other beliefs in the network so as to restore coherence with the one that has shifted). Leveraging networks of belief in the process of developing educational interventions may increase the probability that these interventions will be effective in changing misconceptions.

Belief networks derived by crowdsourcing necessarily are based on data aggregated across a population of users. But for many moral and scientific issues, individual differences in network structure are likely to influence which beliefs are especially malleable and/or pivotal. Future work will need to also find ways to enable crowdsourcing to leverage the power of big data while also accounting for individual differences (e.g., Kwon, Priniski, & Chanda, 2018).

A wide range of social and scientific misconceptions, including climate change denial, racism, and xenophobia, pose serious threats to democracy. In this context, methods that enable crowdsourcing of belief systems can provide an

**Limitations and Future Directions**

One concern with any crowdsourcing methodology is that the data mined from individuals posting and debating their beliefs on social media may not be representative of the eventual target population. Criticisms of the crowdsourcing approach to developing psychological materials have generally centered around potential population differences between where the data is being acquired (e.g., Change My View) and where it is being applied (e.g., the general population). For certain tasks, such as crowdsourcing educational interventions, this critique has been answered by demonstrating the generalizability of crowdsourced materials in a controlled experiment (Priniski & Horne, 2019). It remains an empirical question whether the beliefs determined by crowdsourcing to underlie people’s attitudes toward capital punishment also underlie those of the general population. A simple behavioral study that tests the generalizability of the results gleaned from the analyses presented here is a natural next step for this research.

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