

Neural embedding of beliefs reveals the role of relative dissonance in human decision-making

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ABSTRACT

Beliefs serve as the foundation for human cognition and decision-making. They guide individuals in deriving meaning from their lives, shaping their behaviors, and forming social connections. Therefore, a model that encapsulates beliefs and their interrelationships is crucial for quantitatively studying the influence of beliefs on our actions. Despite its importance, research on the interplay between human beliefs has often been limited to a small set of beliefs pertaining to specific issues, with a heavy reliance on surveys or experiments. Here, we propose a method for extracting nuanced relations between thousands of beliefs by leveraging large-scale user participation data from an online debate platform and mapping these beliefs to an embedding space using a fine-tuned large language model (LLM). This belief embedding space effectively encapsulates the interconnectedness of diverse beliefs as well as polarization across various social issues. We discover that the positions within this belief space predict new beliefs of individuals. Furthermore, we find that the relative distance between one's existing beliefs and new beliefs can serve as a quantitative estimate of cognitive dissonance, allowing us to predict new beliefs. Our study highlights how modern LLMs, when combined with collective online records of human beliefs, can offer insights into the fundamental principles that govern human belief formation and decision-making processes.

Introduction

Beliefs are foundational for human cognition and decision making. The term ‘belief’ is often defined as “the feeling of being certain that something exists or is true”¹ or “confidence that something/somebody is good or right”². Guided by fundamental beliefs, individuals derive meaning in their lives, shape their behaviors, select the information they consume, and establish social connections that influence the networks and communities to which they belong^{3–6}.

Extensive research across multiple disciplines has been dedicated to quantitative understanding of human beliefs. In recent years, the accumulation of digitized behavioral data and the development of analytical tools have opened new avenues for exploring beliefs, leading to numerous studies aimed at the systematic description of human beliefs and their interactions, belief dynamics within individuals, and their spread and transmission in society. Notable approaches include modeling of belief dynamics based on diffusion models on social networks^{7–12} and models that take into account both individuals’ internal belief system and social influence, along with their empirical applications^{3,4,13–19}. Furthermore, researchers in the field of natural language processing (NLP) and social media have proposed various methods for detecting and predicting individuals’ beliefs based on their online activities and written texts^{20–26}.

Studies have revealed that human beliefs are interconnected, and understanding these relationships is crucial for comprehending the formation, updating, and spreading of human beliefs and related behaviors. For instance, individuals with similar beliefs can influence each other's lifestyle choices and lead to the clustering of behaviors and preferences within social groups³, explaining why seemingly unrelated beliefs (or preferences), such as being liberal and drinking lattes, are associated. The associative diffusion model⁴ also demonstrate the importance of relationships between beliefs, suggesting that the emergence of cultural difference may occur due to the transmission of perceptions regarding which beliefs or behaviors are compatible with each other, rather than the actual beliefs themselves, even in a community without any existing clustering structure. Another experiment suggests that the association between beliefs and political ideology initiated by small number of early movers can still lead to strong partisan alignments on beliefs that are substantially unrelated to political ideologies¹³. Other studies have proposed frameworks that consider both the interrelation between an individual's internal beliefs and the influence of social networks to model belief dynamics based on dissonance theory and network imbalance, shedding light on how discrepancies and imbalances between beliefs lead to different final distributions of social beliefs^{14–19}. The aforementioned studies demonstrate the importance of comprehending the interrelated nature of beliefs in order to better understand our society's fragmentation and polarization.

Yet, the relational landscape of human beliefs have not been comprehensively mapped and we still do not fully understand how such interactions form. Despite the advancements in quantifying and modeling human beliefs, significant challenges still persist. One major challenge in modeling belief systems is representing the nuanced *relationships* between beliefs. In network-based approaches to modeling human attitudes employing real data, researchers often rely on survey data on specific issues to explore the interrelationship of different beliefs (e.g., partial correlation between different questionnaires^{3, 14, 17}). However, survey-based methods are not scalable when we consider the entire “space” of beliefs. It is simply infeasible to capture the relationships between vast number of important human beliefs. Moreover, incorporating a new belief into existing belief system—inductive reasoning—is difficult.

Here, we construct a robust and general *representation space* for beliefs that enables both continuous and inductive reasoning about beliefs and their relationships. We largely draw our intuition from the vector space models for text representations that can encode semantic and contextual relationships between words into a geometric relations^{27–29}.

Our approach leverages large language models (LLMs), combined with revealed belief trajectories extracted from a series of online debates, to create a continuous, high-dimensional representation space of beliefs. Our

framework employs an empirical dataset of multiple beliefs held by individuals from an online debate forum to fine-tune a pre-trained LLM, which already hold a sophisticated understanding of human language. The fine-tuned belief-LLM translates belief statements into embedding vectors within a space where their spatial distance captures both the semantic relationship and socially perceived relevance between various beliefs. It also allows us to represent each individual as a vector in the belief space, which in turn allows us to infer other implicit beliefs that the person may possess.

We address the following research questions: Can we construct a reliable embedding space of general beliefs using LLMs integrated with online user activity data? What structural characteristics and patterns emerge in the resulting belief embedding space? What kinds of social issues exhibit pronounced clustering and polarization in the belief space? Can we predict an individual's belief or positions on new social issues based on the individual's prior beliefs by leveraging the belief space? Can we discover any underlying mechanisms for individual belief formation? What are the factors relating to accurately predicting individual's beliefs?

Results

Generating and validating the belief embedding space

Our first goal is to create a representation space that effectively encapsulates the interdependencies between diverse beliefs. We achieve this by fine-tuning pre-trained LLMs through contrastive learning³⁰. Contrastive learning enables models to learn a representation space by attracting similar (positive) belief pairs closely while repelling dissimilar (negative) belief pairs further away in the embedding space. Specifically, we use a contrastive learning task to distinguish belief pairs shared by many people from belief pairs in negative relationships.

We leverage user participation records from an online debate forum, Debate.org (DDO)^{20,21,31}. This dataset consists of online debates and corresponding voting records of the users; users can express their position by directly participating as debaters or voting for the PRO, CON or TIE position in the debates. We consider both debaters and voters simply as voters since they support a particular position in the debate. After pre-processing, we obtained a dataset of 59,986 unique debate titles voted on 197,306 times by 40,280 unique users which was used for fine-tuning LLMs (see Methods).

We operationalize each individual's belief as their expressed agreement or disagreement with a certain debate title. We transform voting records (PRO/CON) of users into belief statements by using predefined templates. For example, if a user voted PRO (CON) to a debate titled "Abortion is morally justified," we created a belief statement for the user as "I agree (disagree) with the following: Abortion is morally justified." (See SI Section 3, Table S2, S3,

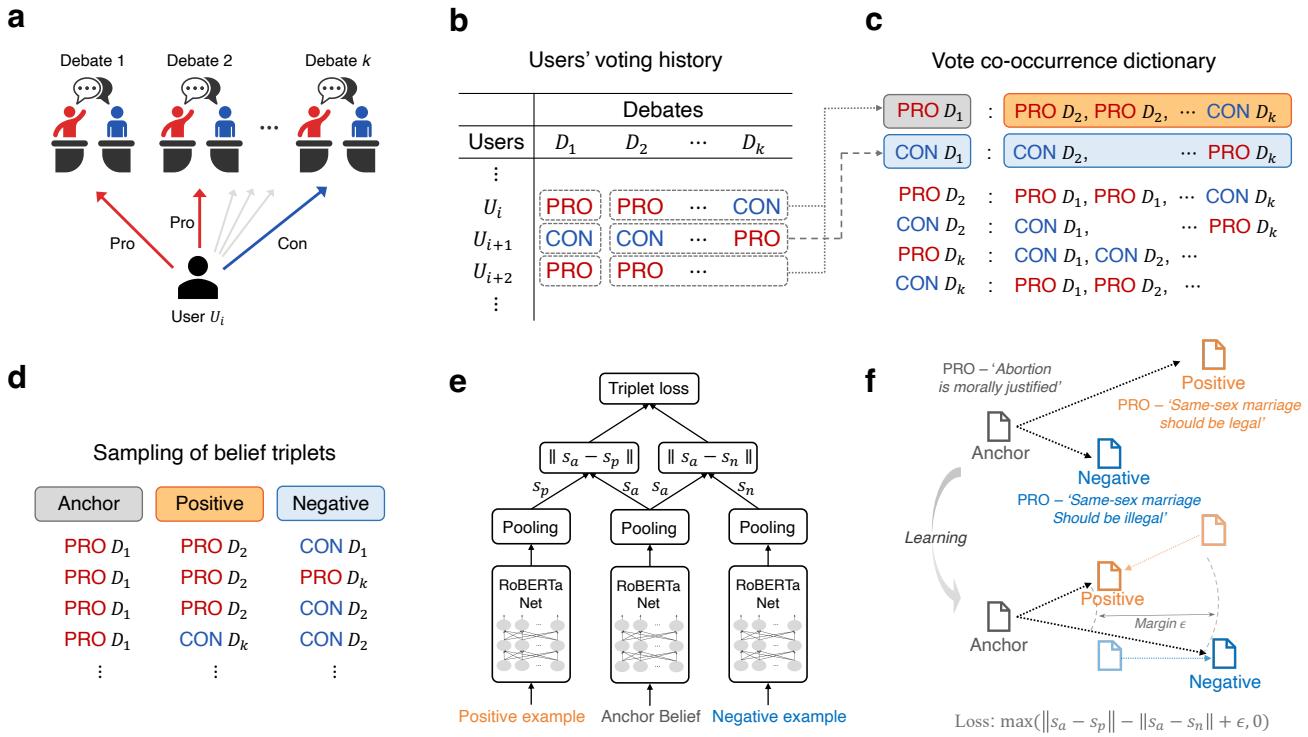


Figure 1. Fine-tuning an S-BERT using belief triplets to construct the belief space. (a) An illustration of a user's expressed positions in multiple debates. Each user can vote PRO or CON in each debate topic. (b) Voting histories of users represented as a matrix. (c) The vote co-occurrence dictionary captures how users who voted PRO/CON to a certain belief, voted on other beliefs. (d) From the vote co-occurrence dictionary belief triplets are sampled. Each belief triplet is composed of an anchor belief in addition to a positive and a negative belief in relation to the anchor. (e) A pre-trained S-BERT network is fine-tuned with the belief triplets in the form of triplet network. (f) An illustration of learning process happening within S-BERT. To minimize the triplet loss, an anchor belief and positive beliefs are drawn closer, whereas the anchor and negative examples are pushed apart.

and Fig. S5 for template variability on belief embeddings).

To encode these belief statements, we employ a pre-trained Sentence-BERT (S-BERT) with RoBERTa^{32,33}. Unlike the original BERT model³⁴, which is focused on token-level tasks, S-BERT is designed for generating semantically meaningful sentence-level embeddings and allows for efficient fine-tuning using sentence-level pairs or triplets. We fine-tune S-BERT with a triplet-based contrastive learning approach. As illustrated in Figs. 1a-d, we create belief triplets from user voting activities and use them as positive belief pairs, which are contrasted from negative examples. Note that the more two beliefs co-occur, the more likely they get sampled as positive examples. Conversely, negative pairs are derived from beliefs either from the opposite statement of the anchor belief or those frequently co-voted with the opposite statement (See Methods).

These triplets were then utilized to fine-tune the LLMs using a triplet loss function as depicted in Fig. 1e and f. The resulting model offers a 768-dimensional latent ‘Belief space,’ where vectors represent individual beliefs, and

Model type	Pre-trained model	Triplet evaluator		GLUE-STSB
		Train set	Test set	Spearman corr.
BERT (Before fine-tuning)	bert-base-uncased	37.67% (0.21)	35.89% (0.77)	0.615
S-BERT (Before fine-tuning)	roberta-base-nli -stsbs-mean-tokens	39.83% (0.19)	38.11% (1.01)	0.877
BERT (Fine-tuned)	bert-base-uncased	96.40% (0.35)	66.61% (0.46)	0.440 (0.027)
S-BERT (Fine-tuned)	roberta-base-nli -stsbs-mean-tokens	97.88% (0.18)	67.20% (0.68)	0.683 (0.016)

Table 1. Performance of various LLMs in the belief triplet evaluation task for both the training and test sets.

Scores represent the average accuracy obtained from a 5-fold validation task. A higher accuracy indicates that the model more accurately distinguishes positive examples from negative ones for a given anchor belief. Numbers in parentheses denote standard deviations. The last column demonstrates performance in the GLUE-STSB task³⁵, where the goal is to estimate semantic textual similarity between two texts. Performance is assessed through the Spearman correlation between the human-annotated benchmark score (rated on a scale of 1 to 5) and the cosine similarity between the vector representations of LLMs for the two texts.

distances between beliefs capture their closeness. We show that the distance between beliefs in the belief space is proportional to the likelihood that an individual has one belief given the other.

We use two different approaches, a triplet evaluator and a semantic similarity evaluation task, to evaluate the quality of the belief embeddings generated by the LLMs. We initially assessed the performance of various LLMs by employing a triplet evaluator for classifying belief pairs as either positive or negative relations. Table 1 compares triplet evaluation results from different models. The fine-tuned S-BERT model based on RoBERTa showed the highest performance with an average accuracy of about 98% for the train dataset and about 67% for the test sets (See Table 1).

Our model also shows good performance in capturing general semantic meaning of various texts beyond the range of our training dataset, which is directly related to how accurate a vector representation of a new, unseen belief would be. Even after proceeding with the fine-tuning process, the S-BERT still kept a relatively high performance score on the semantic textual similarity benchmark on general language understanding evaluation datasets (GLUE-STSB)³⁵ compared to other models. The Spearman rank correlation coefficient score of the S-BERT model was $r = 0.683 \pm 0.016$, while the fine-tuned BERT model showed relatively low correlation score ($r = 0.440 \pm 0.027$) (Table 1).

Belief landscape revealed by belief embeddings

PCA result of the belief space at a glance

To explore the structure of belief space, we perform Principal Component Analysis (PCA) on the output belief vectors. The distribution of beliefs in the belief space unveils both the proximity of beliefs regarding the same topic

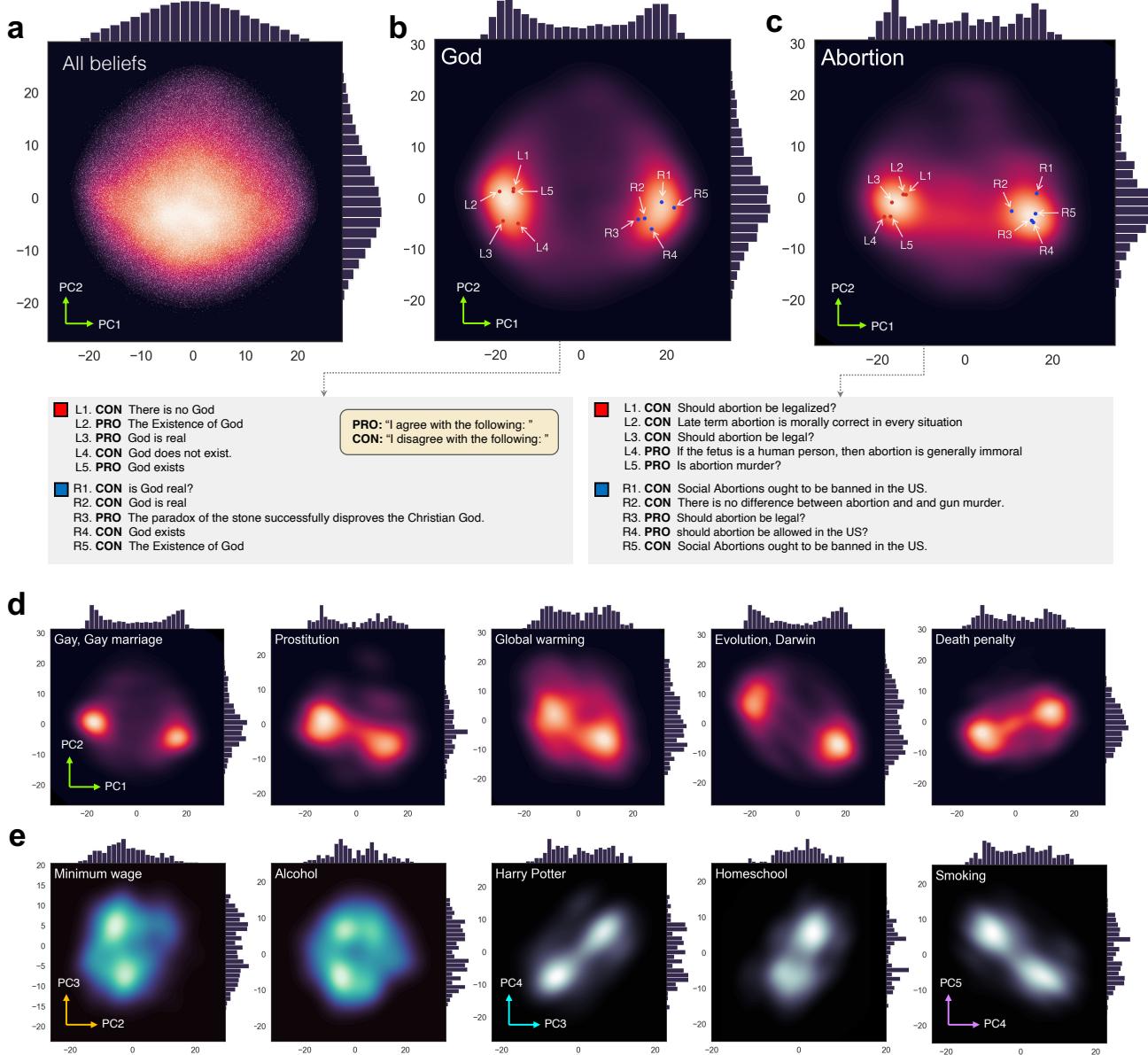


Figure 2. (a) The entire distribution of belief embeddings is represented in the first two principal components (PC1-PC2) space. The background heatmap reflects the density of beliefs, and the overlaid white dots indicate individual beliefs. (b) and (c) depict the distribution of beliefs related to the topics ‘God’ and ‘Abortion,’ respectively. Both belief distributions exhibit two highly clustered regions in the PC space, signifying the presence of two distinct groups of beliefs regarding these topics. Five example beliefs from each cluster are highlighted as red and blue points in the belief space, and the corresponding beliefs are presented in the gray boxes. (d) Distributions of beliefs corresponding to five different keyword sets, displaying two bimodal distributions in the first two principal components (PC1-PC2) space, similar to (a) and (b), are illustrated. (e) Additional belief distributions corresponding to five keyword sets, revealing unique structures in the higher PC axis, are displayed.

and the interconnections among beliefs across different topics. To analyze the overall distribution of beliefs on various topics, we compiled twelve example sets of beliefs chosen from various fields that exhibit distinct patterns in the PC space, each consisting of a unique set of keywords relevant to their belief statements. For example, there are

a total of 5,324 distinct beliefs featuring the keyword ‘God (god)’ and 1,053 beliefs associated with the terms ‘gay’ or ‘gay marriage.’

Figure 2 presents the density of beliefs along the first two PCs across major belief subgroups, each related to distinct topics. The entire belief set (Fig. 2a) exhibits a smooth, uni-modal, bell-shaped distribution along both the first and second principal component axes (PC1 and PC2). However, the density plots for beliefs related to specific topics, such as ‘God’ and ‘Abortion,’ reveal markedly different, polarized patterns (Fig. 2b and c), suggesting that beliefs regarding these topics are grouped into two clusters with contrasting opinions. These bimodal patterns of beliefs are also observed in belief spaces using other types of dimensionality reduction methods (see Fig. S6 for the UMAP³⁶ results).

Belief embeddings also reveals which beliefs are more closely associated to each other. For instance, beliefs favoring the existence of God or opposing abortion were predominantly found on the negative side of the PC1 axis. The positive side of this axis was associated with disbelief in God and support for abortion rights. Additionally, beliefs related to topics such as ‘Gay and gay marriage,’ ‘Prostitution,’ ‘Global warming,’ ‘Evolution and Darwin,’ and ‘Death penalty’ also exhibited two dense clusters along specific axes in the PC1 and PC2 space (Fig. 2d), reflecting the existing political polarization on various social issues^{37–39}.

Examining the other PC axes reveals another dimension of belief separation. For instance, beliefs concerning the ‘Minimum wage’ and ‘Alcohol’ exhibit bimodal distributions along the PC3 axis (Fig. 2b). Similarly, beliefs about ‘Harry Potter’ and ‘Homeschool’ cluster into two distinct groups on the PC3-PC4 plane, whereas they do not display a noticeable pattern on the PC1-PC2 plane. This indicates that the contextual relationships among these topics are encoded in the PC3 and PC4 axes. However, not all keyword groups show such polarized distributions; for example, beliefs related to ‘Society,’ ‘Education,’ and ‘USA’ tend to spread around in the PC space.

Overall, our results demonstrate that the distributions of beliefs related to various keywords show unique patterns in the belief space, often forming polarized clusters along specific axes. Furthermore, the association of belief positions of various polarizing issues in the PC space are generally aligned with the partisan polarization observed in public surveys. For instance, according to Gallup’s beliefs poll in 2019³⁷, American liberals were more likely to consider ‘abortion’ (73%), and ‘gay/lesbian relations’ (81%) morally acceptable. In contrast, only 23%, and 45% of conservatives believed these issues to be morally acceptable, demonstrating the interconnected nature of these beliefs.

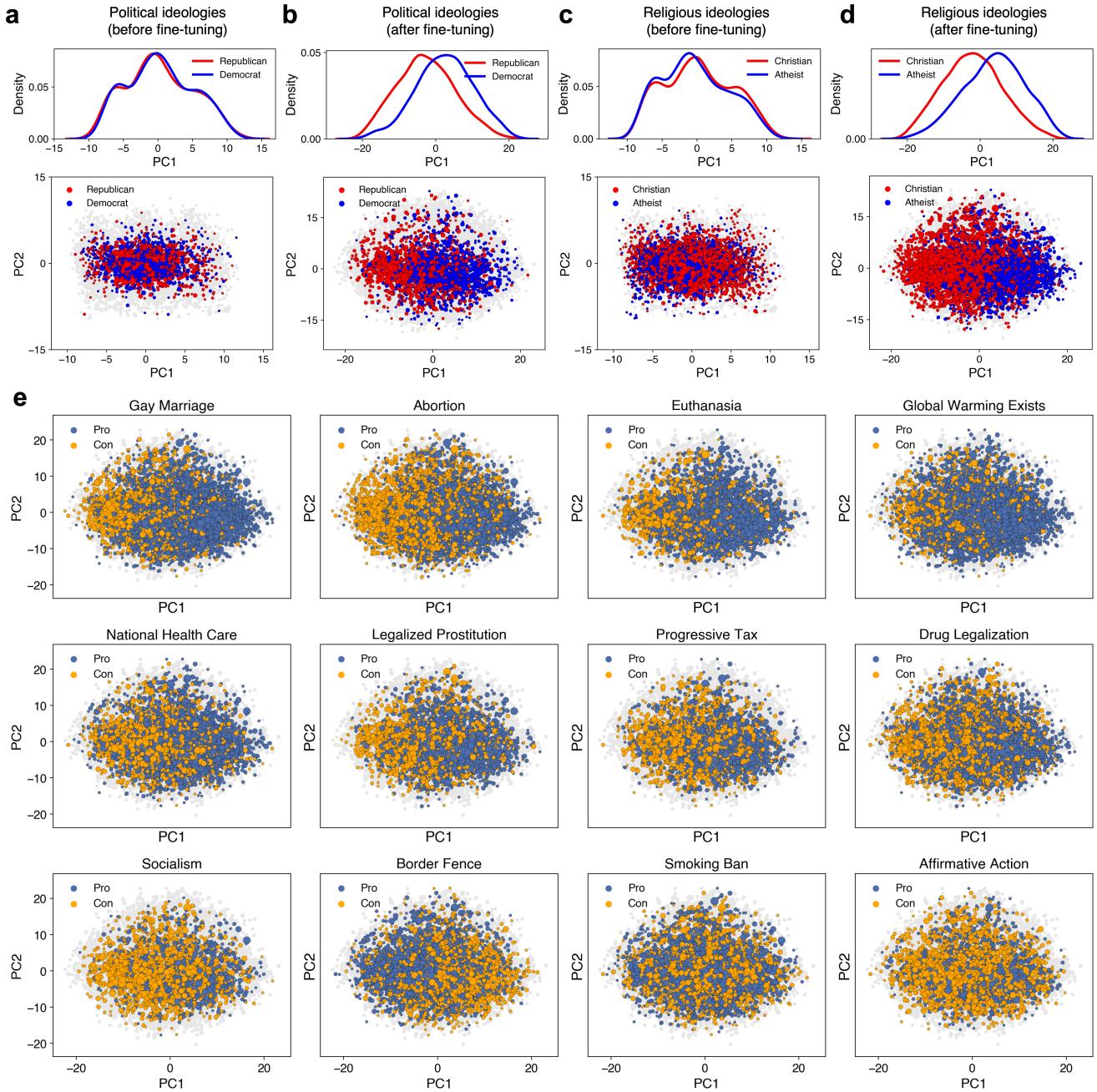


Figure 3. Visualization of user embeddings in the belief space. (a)-(d) depict the positions of two user groups in the belief space along the first two principal components (PC) axes, colored based on their supporting political parties (Republican vs. Democrats) and religious ideologies (Christians vs. Atheists), as identified by their self-reported data. (a) and (c) illustrate user embeddings obtained by averaging their belief embeddings from the base S-BERT model without fine-tuning, while (b) and (d) present embeddings from the fine-tuned S-BERT model. The fine-tuned model exhibits a clearer separation of users from different groups in the belief space, whereas users in the non-fine-tuned model are more mixed. (e) displays users grouped by their stances on various controversial social issues, as identified through their self-reported data on ‘big issues.’

Representation of individuals in the belief space reveals group polarization on various topics

The presence of topic-specific bimodal belief distributions prompts a question: Do individuals with distinct ideologies also exhibit polarized clusters within the belief space? To address this, we examine each individual user, represented by the averaged associated belief vectors. This approach allows us to investigate how close or distant individuals are based on their beliefs.

To validate if the resulting user representations properly locate the users, we visually mapped users according to their self-reported survey responses. In DDO, users can self-report their positions on major social issues via pre-survey participation, independently from their debate participation. This includes specifying their supporting political parties, religious beliefs, and positions on 48 key social issues, referred to as *big issues*. The big issues encompass a range of controversial social issues such as ‘abortion,’ ‘drug legalization,’ ‘gun control’, and others.

We projected the users onto the PC space of the belief space. Figs. 3a-d illustrate the positions of users in the belief space along the first two PC axes. These positions are calculated by averaging all belief vectors for each user using S-BERT both before and after fine-tuning. The color coding in these figures reflects the users’ political ideologies (i.e., Democrat vs. Republican) and religious ideologies (i.e., Christian vs. Atheist), as reported in their self-reported data. Remarkably, even though user embeddings were calculated solely using belief vectors derived from their voting records, without incorporating any metadata, users still formed two distinct clusters that correspond to their political and religious ideologies.

Notably, we observed a significant separation of user groups along the PC1 axis, suggesting that this axis primarily captures the alignment of beliefs or users with political and religious ideologies (Figs. 3b and d). By contrast, the base S-BERT model without fine-tuning did not exhibit such clear ideological group separations (Figs. 3a and c and Fig. S7). This supports the notion that the fine-tuned S-BERT model more effectively captures the contextual relationships between beliefs, positioning related beliefs closer within the space.

The fine-tuned model also effectively reveals the alignment of partisan identity with beliefs on other disparate social issues. We observed the pattern of user groups dividing under various social issue categories in other big issues. As shown in Fig. 3e, distinct user groups on various issues such as ‘gay marriage,’ ‘abortion,’ ‘euthanasia,’ and ‘global warming exists’ exhibit separations along the same PC1 axis, which represented the partisan polarization. However, user groups displayed a mixed pattern for some issues such as ‘smoking ban’ and ‘affirmative action’ in the PC space. It may be due to the fact that these issues do not usually align neatly with traditional political or social dichotomies. For example, individuals from both liberal and conservative backgrounds might either support or oppose smoking. Additionally, ethnicity may have a greater influence on perspectives on affirmative action than

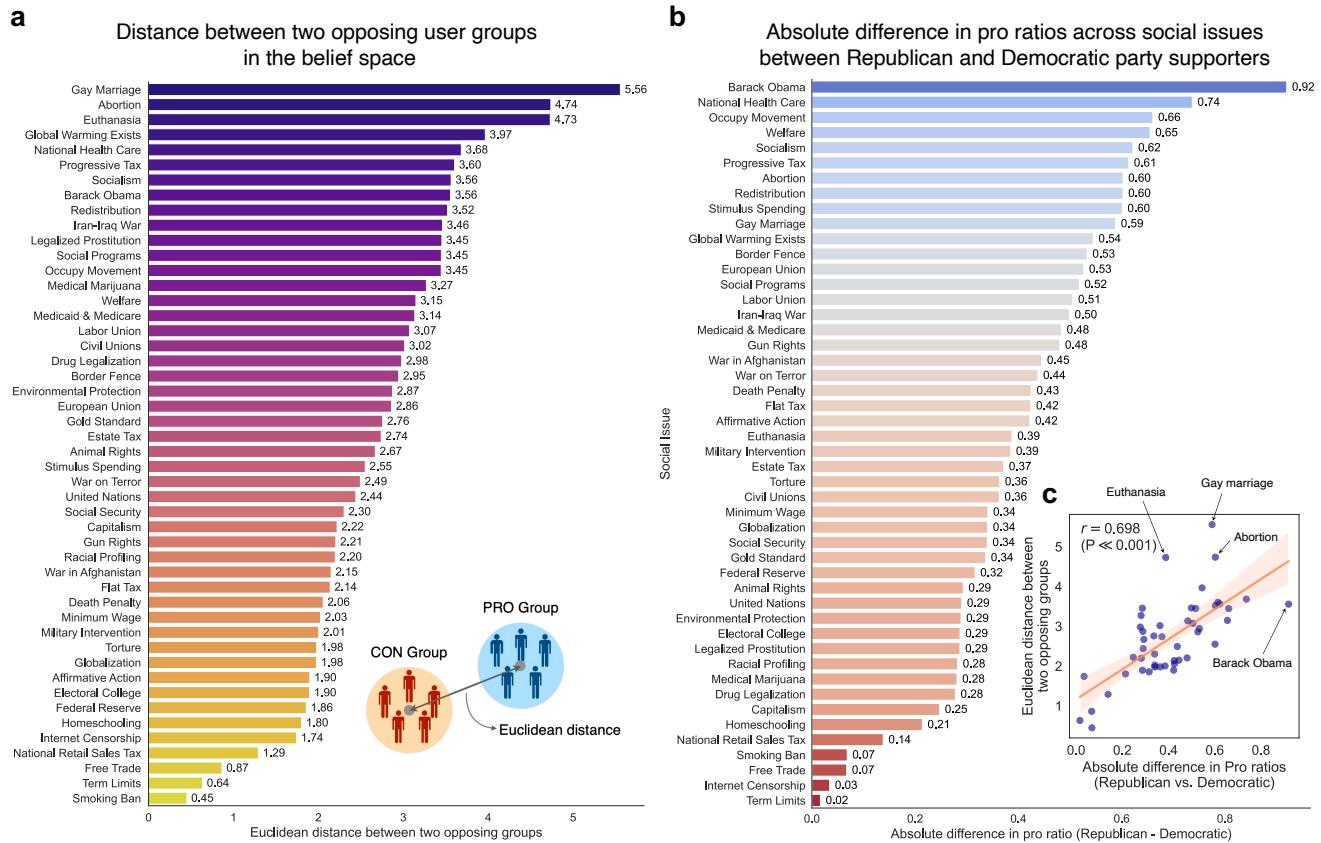


Figure 4. (a) Euclidean distance in the belief space between user groups with contrasting stances on 50 different social issues, based on the self-reported survey results. The distance between two opposing user groups is calculated by measuring the distance between the average positions of CON users and PRO users for each issue. This distance between two user groups on an issue demonstrates the degree of separation between the groups, highlighting the extent of polarization between them. (b) The absolute difference in pro ratios across social issues between supporters of the Republican and Democratic parties reveals the degree of partisan polarization in social issues. The pro ratios are calculated using self-reported data from users, independent of the belief embedding. (c) The Euclidian distance between two opposing groups in the belief space and the degree of partisan polarization across social issues exhibit a significantly high correlation ($r = 0.698$).

one's political position.

Based on distinct clustering patterns of opposing user groups on various issues, we examined what the most polarizing topics were in the belief space. We quantified user polarization on specific issues by measuring the Euclidean distance between the centroids of PRO and CON user groups on the big issues, in the original high-dimensional belief space. Fig. 4a displays social issues ranked according to the Euclidean distances between two opposing user groups. Users with differing views on 'Gay marriage' showed the greatest separation distance, indicating significant polarization. Other highly polarized topics include 'Abortion,' 'Euthanasia,' and 'Global warming.' Conversely, users on issues such as 'Smoking ban,' 'Term limits,' and 'Free trade' exhibit relatively weaker polarization in the belief space. We note that the cosine distances between user groups were also highly

correlated with the Euclidean distances (Pearson's $r = 0.991$, $P \ll 0.001$) (Fig. S8).

To examine if the Euclidean distance between two groups in belief space actually reflects the degree of conflict over significant issues, we compared these distances with the degree of partisan polarization based on the self-reported user survey data. We measured the absolute differences in pro-ratios across 48 big issues between supporters of the Republican and Democratic parties (Fig. 4b). The pro-ratio for a social issue of a particular party is determined by the percentage of users who support the issue within the party based on their self-reported data. Fig. 4c shows that the Euclidean distance in the belief space and the degree of partisan polarization across the big issues are highly correlated ($r = 0.698$, $P \ll 0.001$), indicating that the distance between different user groups in the embedding space can be a useful metric for characterizing conflict levels over various social issues.

Downstream task: Predicting user beliefs on unseen debates based on belief embedding

Our results suggest that like-minded individuals with similar beliefs on specific social issues tend to cluster together in the belief space. This observation raises two further questions: Can we utilize the user embeddings to predict an individual's belief on unseen debates? Can we uncover any underlying mechanisms of human decision-making through the collective belief selection patterns of users? To explore these questions, we designed a binary belief classification task aimed at predicting a user's voting position (PRO or CON) in new debates. For this, we divide the entire set of debates into an 8:2 ratio and evaluate the model's performance using 5-fold cross-validation, considering users who appear at least once in both the train and test sets (Table S4). We leverage user embeddings, learned from a training set, to anticipate a user's views on debates they have not encountered before, as presented in the test set. We compare our results with multiple baselines and existing models.

According to the literature on dissonance theory of human attitudes, people tend to experience cognitive dissonance when they are exposed to information that are not in alignment with their existing beliefs^{14,40}. Moreover, the feeling of personal discomfort created by the conflict between the new information and one's own beliefs can possibly lead to selective exposure to belief-confirming information⁴¹. Similarly, we can consider a user's set of prior beliefs toward various debate issues constitutes an individual's existing belief system. Choosing a new belief towards a new debate is akin to adding a new belief to a user's existing belief system.

Our model employs a straightforward approach: it predicts a user's choice based on the Euclidean distance between the user's position and two opposing belief vectors from a new debate. For each new debate in the test set, we created two opposing belief statements for the debate title and generated corresponding belief vectors using the fine-tuned S-BERT model (Fig. 5a). Our model predicts the user's choice with the belief closest to the Euclidean distance for the user's embeddings.

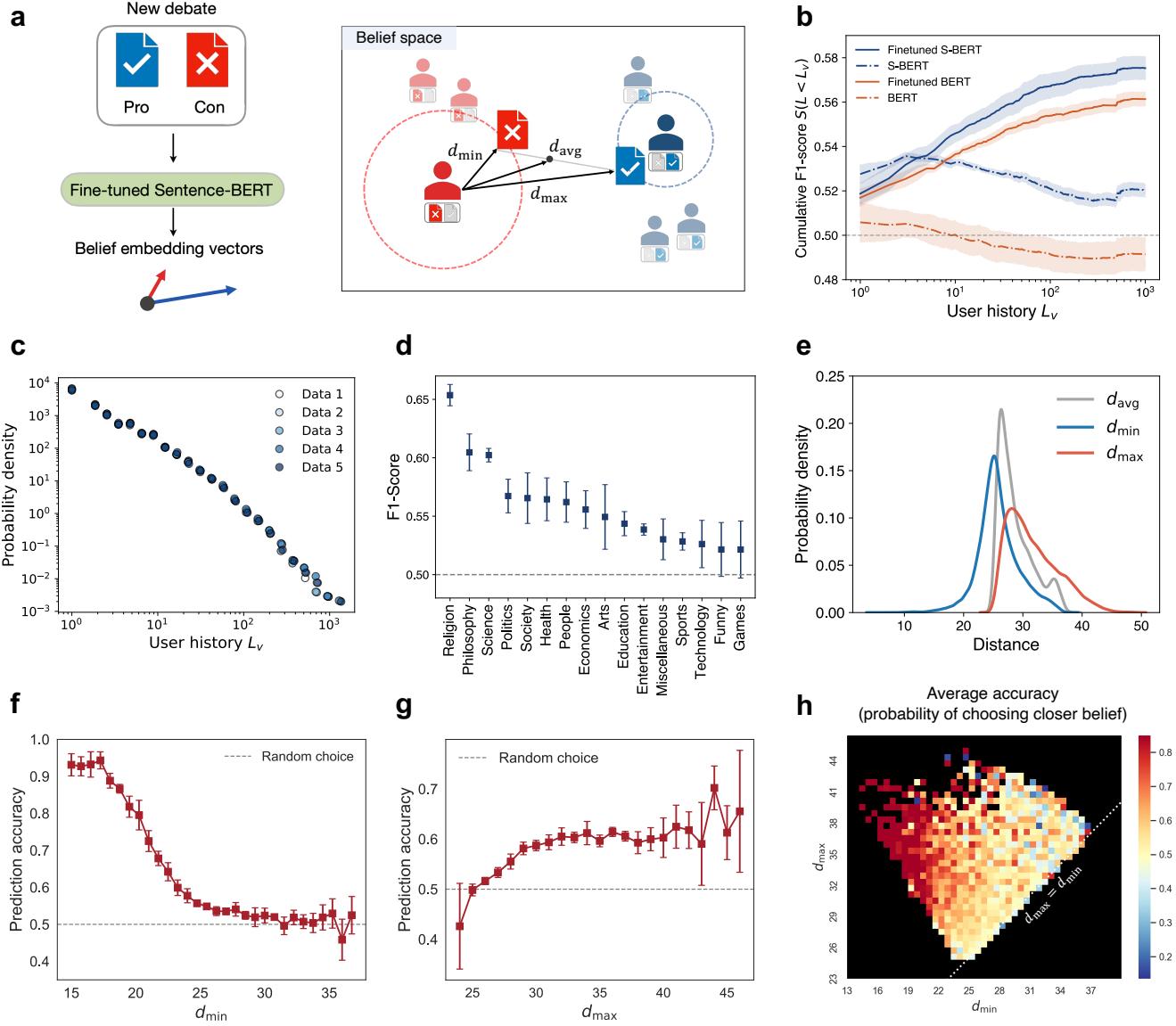


Figure 5. Predicting users' beliefs about new debates. (a) We generate two opposing belief vectors for an unseen debate and calculate the distances between these vectors and a given user's position in the belief space. The minimum and maximum distances are denoted as d_{min} and d_{max} , respectively, with their average labeled as d_{avg} . The model predicts the user's choice as the nearest belief vector. (b) Relationship between the F1-score $S(L < L_v)$ and the length of user history L_v , where $S(L < L_v)$ represents the F1-score for users with voting records shorter than L_v . (c) Distribution of user history L_v (number of votes) in a 5-fold dataset. (d) Variation in belief prediction accuracy, quantified using the F1-score, across diverse debate categories. (e) The distribution of d_{min} , d_{max} , and d_{avg} distances in the belief prediction task, indicating user proximity to candidate beliefs. (f) and (g) Average accuracy trends across d_{min} and d_{max} distances of candidate beliefs in the belief prediction task. (h) The heatmap illustrates the average prediction accuracy across various ranges of d_{min} and d_{max} .

Comparative evaluation with other LLMs reveals that the fine-tuned S-BERT model exhibits the highest performance. It achieves an F1-score of 57.6% with $\sigma = 1.2$ and an accuracy of 57.7% with $\sigma = 1.2$. This performance is notably superior when compared to other models, including the base S-BERT model, both the base

Model type	Accuracy	F1-Score
BERT	53.89%	49.10%
(Before fine-tuning)	(0.51)	(1.68)
S-BERT	56.14%	51.97%
(Before fine-tuning)	(0.50)	(0.64)
BERT	56.33%	56.17%
(Fine-tuned)	(0.71)	(0.70)
S-BERT	57.66%	57.57%
(Fine-tuned)	(1.18)	(1.16)
Baseline 1	49.85%	49.79%
(Random choice)	(0.12)	(0.12)
Baseline 2	53.24%	34.74%
(Majority rule)	(0.29)	(0.12)
LLama2-13b-chat	53.66%	36.90%
	(0.65)	(0.45)

Table 2. Performance of various LLMs in a downstream task on predicting users’ beliefs for unseen debates. Numbers in parentheses denote standard deviations obtained from 5-fold validation results.

and fine-tuned versions of the BERT model and other baseline models as detailed in Table 1. For instance, the base BERT and base S-BERT models recorded F1-scores of 49.10% ($\sigma = 1.68$) and 51.97% ($\sigma = 0.64$), respectively.

We also benchmarked our model against two baseline models: the random choice model (baseline 1) and the majority selection model (baseline 2). The random choice model randomly predicts a user’s belief between two given belief options. By its random nature, it is expected to achieve a 50% F1-score and accuracy. The majority selection model is used to deal with the asymmetric ratio of PRO and CON beliefs in the train set. It predicts all users will consistently choose a side either PRO or CON, whichever are more prevalent in the train set. The majority model registers higher accuracy (53.24%) but a reduced F1-score (34.74%). The fine-tuned S-BERT model outperformed both of these baselines.

Furthermore, we extended our evaluation in a few-shot setup using Llama2 (LLama2-13b-chat)⁴², a recent language model with much larger parameters (~ 13 billion). Llama2 exhibits strong few/zero-shot performance across a variety of tasks, including common sense reasoning, question answering, reading comprehension, and more. In our scenario, Llama2 was prompted with a set of user’s prior beliefs from the training set and tasked to predict the user’s belief (PRO or CON) on unseen debates (See Methods). Llama2 performed less effectively with an F1-score of 36.9% and an accuracy of 53.7%, slightly better than the majority baseline (Table 1).

The limited performance of the base LLMs without fine-tuning may be attributable to their structuring of the belief space. These models tend to cluster beliefs, which for the same debate title, differ only in the “agree” or “disagree” word in a compact area. That is, regardless of their positions, the models cluster similarly worded beliefs together. Hence, PRO and CON statements on the same issue more likely to be positioned closely, complicating

the prediction. Furthermore, these models fail to capture nuanced contextual relationships between topics. For example, these models do not adequately represent the correlation between beliefs regarding political parties and religious ideologies. This deficiency in understanding complex relationships reduces their accuracy in representing user stances (Fig. 3).

Although the fine-tuned S-BERT model shows relatively superior performance in belief prediction compared to other LLMs and baseline models, its overall F1-score is not exceptionally high (57.57%). To understand the intricacies affecting the performance of the belief prediction, we explored various factors and found the three critical factors: the length of individuals' vote history, debate category, and the relative distance between a user and two beliefs under consideration.

First, our findings indicate that the prediction accuracy largely depends on the extent of a user's voting history in the training set. Fig. 5b and S9 show that as we sequentially include users with more vote history, the average F1-score of users almost monotonically increased. This result shows that the beliefs of users are more accurately predicted when we know more about their prior beliefs. However, a fundamental obstacle to accurate prediction is that the degree of user participation activities in DDO follows a highly skewed distribution (Fig. 5c), which is commonly found in many online human activities^{43,44}.

Second, the diverse nature of debate topics also poses a significant challenge. While debates related to politics and religion are common, many debates in the DDO dataset focus on issues closely tied to personal preferences, such as 'Batman could beat Spiderman in a fight' or 'Soccer as the best sport.' Beliefs on such topics often show little correlation with those on other issues, complicating predictions unless the user has previously engaged in similar topics. We utilized the topic categories provided in the DDO dataset and measured prediction performance across different debate categories. As highlighted in Fig. 5d, the prediction performance varies considerably over debate topics. For instance, the user beliefs related to debates under the topics 'religion' and 'philosophy' are more predictable than those under 'sports,' 'funny,' and 'games.'

Third, the proximity of a user to the beliefs under consideration in the belief space significantly impacts prediction accuracy (Figs. 5e-h). When two contrasting belief vectors for a new debate are introduced during the prediction task, we measure two distances between the user and the two beliefs, denoted as d_{\min} for the closer belief and d_{\max} for the farther belief. Our analysis shows that these distances play an important role in the user's decision. The accuracy for the prediction task inversely correlates with d_{\min} and positively with d_{\max} (Figs. 5f and g). In our prediction setting, the prediction accuracy can be directly interpreted as the probability of a user choosing the closer belief, as our model always predicts the belief closer in distance to be the user's choice. Therefore, for the remaining

analyses, we use the accuracy score instead of the F1-score for clearer interpretation, even though the two scores are highly correlated. The heatmap in Fig. 5h demonstrates that the probability of choosing closer belief decreases with d_{\min} and increases with d_{\max} , suggesting that more accurate predictions are possible in cases where the closer belief is significantly nearer (i.e., smaller d_{\min}) to the user, and the farther belief is more distant (i.e., larger d_{\max}).

We further assessed the impact of the average distance d_{avg} between the user and two opposing beliefs on the accuracy of belief prediction for a given debate (Fig. S10). As d_{avg} increases, the accuracy tends to level off at 0.5, akin to random choice. This finding suggests that when both beliefs are distant enough from the user's position (around $d_{\text{avg}} \simeq 33$), predicting the user's choice becomes extremely difficult. In such scenarios, users' decisions appear to be independent of the distances, resembling random selection. In other words, a large d_{avg} implies that the debate topic is less relevant to the user's previous engagements, thereby diminishing the correlation between existing vote history and beliefs on new debates.

Understanding the role of relative dissonance in belief prediction

Our findings from belief prediction task reveal that the distances between a user and two opposing beliefs under consideration (d_{\min} and d_{\max}) significantly impact prediction accuracy. The underlying patterns of belief selection provide important insights into human decision-making mechanisms.

Based on the empirical observation, we devise a new metric termed ‘relative dissonance’, denoted as d^* :

$$d^* = \frac{d_{\max} - d_{\min}}{d_{\min}}, \quad (1)$$

to better quantify this decision-making process. d^* represents the absolute difference in distances from a user to two contrasting beliefs relative to the shorter distance, d_{\min} .

From the perspective of cognitive dissonance, one can interpret that a belief closer to the user's existing beliefs (smaller d_{\min}) would result in less dissonance, while a belief that is farther away would generate more dissonance (Fig. 6a). Thus, d^* acts as a relative indicator of dissonance reduction when a user opts for the belief closer to their current standpoint instead of choosing a belief that is farther away.

Fig. 6b illustrates a compelling relationship between d^* and the average prediction accuracy of users' beliefs on new debates: the average accuracy shows a linear increase with the rise of d^* . As we noted previously, the prediction accuracy can be interpreted as probability of a user selecting a belief that is closer to their position in the belief space. This observation implies that the probability of a user selecting a belief closer to their existing beliefs depends on relative dissonance. In other words, when the potential reduction of dissonance associated with one belief outweighs

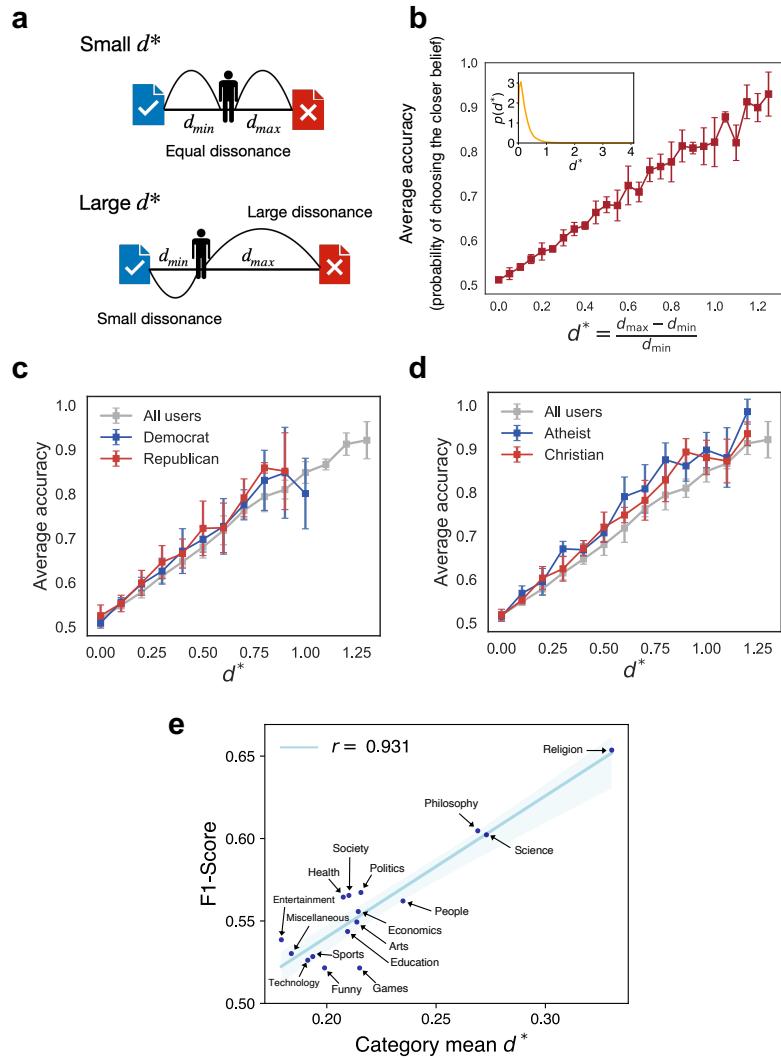


Figure 6. Effect of relative dissonance on belief selection. (a) Illustrates two scenarios a user may face when selecting a belief for a debate, contrasting cases of small and large relative dissonance. When the two beliefs under consideration are equally distant from the user, the selection of either belief may generate an equal amount of dissonance. Conversely, when one belief is significantly farther than the other, the potential dissonance the user experiences differs based on their selection. (b) The likelihood of a user choosing a closer belief linearly increases with relative dissonance d^* . The inset shows the distribution of d^* . (c) and (d) The linear relationship between average accuracy in the belief prediction task and d^* for distinct user groups: Democrats vs. Republicans (c), and Christians vs. Atheists (d). The results show a similar linear relation regardless of users' political or religious ideologies. (e) Average d^* for different debate topics within the prediction task and the corresponding average prediction score categorized by topic areas. Topics with higher mean d^* demonstrated a greater likelihood of accurate prediction compared to those with lower d^* cases.

the other, users are more likely to choose the belief that is closer to them.

For the conditions where d^* is near 0, the probability of a user choosing a closer belief is around 50%, suggesting their decisions are largely independent of their existing beliefs (Fig. 6b). Conversely, for debates where d^* nearing 1.2, users show a strong preference for beliefs closer to their position, with probability close to 1. d^* close to 1

implies that d_{\max} is about twice as large as d_{\min} (i.e., $d_{\max} = 2d_{\min}$). In this scenario, users are highly inclined to select beliefs closely related to their existing ones, implying a significant reduction in potential dissonance that might arise from choosing an alternative belief.

We further investigate whether user groups with distinct political or religious ideologies, such as Democrats vs. Republicans and Christians vs. Atheists, exhibit varied decision-making patterns in relation to relative dissonance d^* . As shown in Figs. 6c and d, we found no significant variation in the influence of relative dissonance on their belief selection process between two user groups ($P > 0.05$ in two-sample t-tests across all d^* ranges). This uniformity suggests that the impact of relative dissonance on the belief selection process is remarkably similar across different political and religious groups.

The concept of relative dissonance also helps to explain why users' beliefs on certain topics of debate can be more accurately predicted than others. We found a strong correlation between the average d^* of a debate category and its corresponding prediction F1-score, with Pearson correlation coefficient, $r = 0.931$ (Fig. 6e). This high correlation partly explains why the belief choice of users on certain topics (e.g., 'religion' or 'philosophy') are more predictable compared to others (e.g., 'funny' or 'entertainment') based on the relative difference in distance within the belief space. For example, the difference in distance from a user to two conflicting beliefs tends to be much larger in the belief space for debates involving 'religious' topics compared to the topics such as 'funny' or 'entertainment.'

Discussion

Here, we demonstrate that neural embedding approaches based on LLMs offer a powerful and scalable solution for understanding the complex and nuanced relationships among human beliefs. While previous approaches provide insightful theoretical bases for modeling belief systems that incorporate belief relationships, there has been a lack of robust frameworks to comprehensively represent the space of beliefs encompassing a wide range of topics^{14, 15, 24}. Existing methods, which often rely on surveys and small, topic-specific datasets, lack scalability and face challenges in capturing the full spectrum of beliefs individuals hold.

In this perspective, LLMs integrated with user activity data can open a new avenue for modeling human beliefs. Pretrained language models, which already possess a strong understanding of complex language patterns and contextual information, can be fine-tuned using extensive belief records to create a comprehensive "embedding space of human beliefs." This embedding space maps a wide range of topics and enables inductive reasoning about new beliefs. Furthermore, this approach enhances our ability to represent an individual's belief system efficiently and supports various downstream tasks such as quantifying polarization or predicting beliefs.

The key findings from our study offer several insights into the characterization of human beliefs. First, our study

introduces a representative learning framework for constructing a belief embedding space in a continuous high-dimensional vector space, using online user activities and LLM. This space effectively reveals the interconnected structure of various human beliefs and polarization of beliefs related to representative social issues. The continuous belief space created using the fine-tuned LLM facilitates inductive reasoning, enabling the addition of new beliefs.

Second, the vector representation of individuals allows us to uncover how people with different opinions are clustered and polarized. While the fine-tuned S-BERT model reveals a relatively clear segregation of people with similar political or religious ideologies, the base S-BERT model without fine-tuning do not exhibit such patterns. Our results demonstrate the usefulness of the belief space in measuring the polarization of certain social concepts. The distance between groups of individuals with opposing beliefs on a given issue within the belief space is highly correlated with the degree of political polarization associated with that issue.

Third, the downstream task for belief prediction shows that the proposed belief space is useful for predicting individuals' beliefs on new debates based on their pre-existing beliefs. We uncover three critical factors that influence the prediction outcome of an individual's choice of a new belief: the length of individuals' voting records, debate categories, and the distances between an individual and the two beliefs under consideration.

Most importantly, our empirical observations highlight that the relative distance between an individual and two contrasting beliefs of a new debate is a reliable predictor of their decision. This insight led us to develop a novel metric called 'relative dissonance' d^* , which quantifies the relative inconsistency a person may experience when adopting a belief into their pre-existing belief system compared to its opposite belief (Fig. 6). Our analysis reveals that the higher relative dissonance (higher d^*) is, the higher the likelihood of a person choosing a belief closer to their current position in the belief space is. In other words, the greater the difference in dissonance a person experiences between two beliefs, the more likely they are to choose the belief that causes less dissonance. This finding provides a quantitative measure of cognitive dissonance, linking it to distances within the belief space and supporting conventional theories of cognitive dissonance.

While our model captures many aspects of human belief dynamics, our study does have limitations that will guide future research. First, the reliance on a single online debate platform for data collection may limit the generalizability of our findings. Incorporating broader datasets from diverse platforms will help understanding the universal properties of belief systems and their cultural and social variations. Additionally, the dataset used in this study is primarily based on U.S. data, which may not fully represent global perspectives and cultural diversity in human beliefs. Future research should include data from various societies to improve broader relevance of the findings across different cultural contexts.

Second, the DDO dataset used in this study, where users' preferences are easily inferred from explicit voting records, represents a specific data type. Developing methods for extracting human beliefs from more general texts on diverse platforms, such as social media postings, news interviews, and movie scripts, would provide a deeper understanding of human beliefs and significantly increase the applicability of our framework.

Third, our study does not investigate the temporal and dynamical properties of the belief space. Although our study indirectly assumes the stability of the belief space, in reality, a society's beliefs on social issues can continuously change. Investigating how the shape of the entire belief space, which reflects the interconnections of collective societal beliefs, transforms over time would be an interesting avenue for future research.

Lastly, there is a concern regarding the inherent biases present in the pre-trained LLMs used in our study⁴⁵. For example, LLMs trained predominantly on English-language internet data may inadvertently reflect Western-centric viewpoints, underrepresenting or misrepresenting beliefs prevalent in non-Western cultures. These models might exhibit biases related to gender, race, and socioeconomic status, which could skew the analysis of the belief relationships. Ongoing efforts to improve fairness and reduce biases in LLMs are crucial for future research to ensure more equitable and accurate representations of human beliefs.

In essence, our research establishes a foundational framework for an advanced, data-driven analysis of human beliefs using LLM. We anticipate that this work on the complex landscape of human beliefs would provide both theoretical insights and practical applications in understanding and modeling human behavior in the fields of cognitive science, social psychology, political science, and beyond.

Methods

Debate.org dataset and extraction of belief statements

The Debate.org (DDO) dataset used in this study contains a corpus of 78,376 debates (68,900 unique debate titles excluding duplicates) by 42,906 debaters from October 15, 2007, to September 19, 2018 (Figs. S1 and S2). In DDO, each debate features two debaters, one supporting the proposition (PRO) and the other opposing it (CON). In each debate, other users can engage by voting on seven different items. Notably, the option "Agree with after the debate" enables users to express their position on the debate topic as either PRO, CON, or TIE, reflecting their belief on the issue. To extract belief pairs which reveal clear positive and negative relations, we only considered the PRO and CON votes and excluded TIE votes. We also treated debaters and voters equally as voters as our study utilizes users' positions various debate topics as their beliefs.

Most debate titles in DDO represent beliefs on various topics (e.g., 'Abortion should be legal,' 'God exists,' 'All

morals are relative’). Thus, users’ votes on these titles as PRO or CON can be considered as revealing their beliefs on these topics. To generate a complete belief statement for a user, we appended a template phrase that explicitly describe the user’s stance. For example, a PRO (or CON) vote on a debate title leads to the belief statement “I agree (disagree) with the following: [DEBATE TITLE].” For instance, a PRO vote on ‘Abortion is morally justified’ results in the belief statement “I agree with the following: Abortion is morally justified.” These belief statements are then fed into LLMs.

We performed data filtering on the DDO dataset to make it suitable for our analyses. While most debate topics in DDO can be considered in the form of beliefs that allow for support or opposition, there are also incomplete or unsuitable titles that cannot be regarded as beliefs. We filtered these unsuitable debate titles using GPT-4^{46,47}, one of the most advanced and reliable artificial intelligence language model. We asked GPT-4 to determine whether a given statement (debate title) can be considered a human belief (See SI Section 2, Table S1, and Figs. S3 and S4).

Among 68,900 unique debate titles, GPT-4 classified 8,914 as unsuitable for consideration as belief statements. The unsuitable debate titles include titles that use *versus* or *vs.*, such as ‘Batman vs. Spiderman’ and ‘atheism vs. agnoticism’, titles denoting battle content like ‘Rap battle,’ ‘music battle,’ and ‘Video Rap battle,’ titles with single words without meaningful context or incomplete sentences, for instance, ‘fox news,’ ‘useless,’ ‘Media are ...,’ titles posing how questions like ‘How many donuts are too many donuts,’ ‘How can you be an atheist?’, as well as titles expressing personal resolutions or suggestions like ‘I will not contradict myself’ and ‘I will lose this debate.’ Removing 8,914 inadequate debate titles resulted in 59,986 unique debate titles that were voted by 192,307 times by a total of 40,280 users.

To assess the consistency of classification results using GPT-4 with human annotations, we compared its classifications of 50 randomly sampled debate titles against those determined by three human annotators. We equally sampled 25 titles from each category of ‘True’ and ‘False,’ as classified by GPT-4, to ensure balanced representation. The annotators were requested to indicate whether or not the debate titles qualify as belief statements. The inter-annotator reliability using Fleiss’ Kappa, which quantifies the level of agreement beyond what would be expected by chance, was 0.866, indicating a high level of agreement among the human annotators. GPT-4’s classifications showed an 88% agreement rate with the majority vote of the human annotators. This high agreement rate suggests the strong consistency between GPT-4’s classifications and the consensus among human annotators in identifying belief statements.

Training LLMs with belief triplets and construction of the belief space

We employed a pre-trained S-BERT model (roberta-base-nli-stsb-mean-tokens)³², based on the RoBERTa model³³, to learn relationships between beliefs across multiple topics. Using belief triplets, we applied a contrastive learning technique to fine-tune the model. We explored various LLMs, from the original BERT³⁴ to other S-BERT models pre-trained with different sources. The RoBERTa-based model exhibited superior performance in diverse tasks and was thus selected for our study (See Table 1 and Table 2).

For the fine-tuning process, we created belief triplets using the voting records of users. A user's voting records on various debates create a sequence of beliefs. Using these belief sequences, we produced a set of belief triplets. Each of the belief triplets comprises three distinct beliefs: an anchor belief statement B_a , a positive example belief B_p , and a negative example belief B_n . We went through all belief statements as anchor beliefs and find corresponding positive and negative examples. The positive example beliefs to a given anchor were sampled from the beliefs that were voted together with the anchor belief weighted by its frequency (the more often two beliefs are voted on by the same users, the more likely they are to be sampled as positive examples). Conversely, the negative example beliefs of an anchor belief were selected from either the directly opposing belief statement (expressing an opposite opinion towards the anchor belief) or from the beliefs that were co-voted with the opposite belief statement.

For example, assume that many users frequently voted as PRO to the debates titled ‘Abortion is morally justified’ and ‘Same-sex marriage should be legal.’ Then, for the anchor belief “I agree with the following: Abortion is morally justified,” a possible positive example could be “I agree with the following: Same-sex marriage should be legal,” and a negative example could be “I disagree with the following: Abortion is morally justified.” In this way, we sampled at most five positive examples and five negative examples for a given anchor belief statement, and generated all possible combinations of belief triplets based on these examples; A maximum of 25 triplets can be created for one anchor belief.

The belief triplets were fed into the pre-trained S-BERT model. We divided debates into training and test data in an 8:2 ratio, repeating this process 5 times for 5-fold validation datasets. On average, 1,358,138 triplets were used for the fine-tuning process as train sets. The model was fine-tuned to minimize the triplet loss function L ,

$$L = \max(\|s_a - s_p\| - \|s_a - s_n\| + \varepsilon, 0), \quad (2)$$

where s_a , s_p , and s_n are the 768-dimensional output vectors of S-BERT corresponding to the sentence embedding of an anchor belief B_a , a positive belief B_p , and a negative belief B_n , respectively. ε is the triplet margin term, which

guarantees that the negative belief vector s_n must be farther away from the anchor s_a than the positive belief vector s_p . We used the default parameter $\varepsilon = 5$.

During training, the weight parameters of the S-BERT model are updated in order to minimize the Euclidean distance between s_a and s_p , while simultaneously maximizing the gap between s_a and s_n . The fine-tuned model thus provides a comprehensive 768-dimensional latent representation of human beliefs, termed the *belief space*. When belief statements are inputted into the LLM, it outputs their vector representations that form this belief space, where the positions and distances between beliefs reveal interdependencies between them.

Belief prediction with a bigger LLM in a few-shot setting

During the downstream task, which involves predicting user beliefs on unseen debates, we benchmarked our results against the performance of Llama2 (LLama2-13b-chat)⁴², a recent LLM with much larger parameters, for few-shot tasks. We chose Llama2 as it exhibits strong zero/few-shot performance across a variety of tasks such as question answering and natural language reasoning. For our task, Llama2 was prompted with a user's existing beliefs from the training set and tasked with predicting the user's stance on new, unseen debates. After testing several prompts, we chose a prompt for Llama2 that includes a user's prior belief statements, followed by a query: "Based on these statements, do you think you might agree or disagree with the following: {DEBATE TITLE}? Please choose from one of these options: agree or disagree. Do not explain your choice." This approach required the model to make a binary decision, answering either 'agree' or 'disagree'. We were able to test only on approximately 85% of the dataset due to the context-size limitations of Llama2.

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Data availability

The original DDO dataset^{20,31} is publicly accessible and can be downloaded from <https://esdurmus.github.io/ddo.html>. For the replication of our study, the processed dataset will be made available at <https://github.com/ByunghweeLee-IU/Belief-Embedding> upon publication.

Code availability

The replication code will be made available at <https://github.com/ByunghweeLee-IU/Belief-Embedding> upon publication.

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Competing interests

The authors declare that they have no competing interests.