Computational Analysis of Character Development in Holocaust Testimonies

Esther Shizgal[1] **Eitan Wagner**[1] **Renana Keydar**[2] **Omri Abend**[1]
[1] Department of Computer Science [2] Faculty of Law and Digital Humanities
Hebrew University of Jerusalem
{first_name}.{last_name}@mail.huji.ac.il

Abstract

This work analyzes character development by capturing both their religious behaviors and their expressed belief systems. We propose a computational analysis of the interplay of internal and external changes the protagonist undergoes within a narrative. Our framework employs a two-dimensional analysis, one dimension captures the protagonist's world of beliefs, and the other describes the practices that may express their inner life. As a test case, we view Holocaust testimony transcripts, each telling the story of an individual. We focus on exploring the protagonist's religious trajectory, examining the evolution of religious beliefs and practices throughout the narrative. The trajectories are extracted by prompting and fine-tuning LLMs. We cluster the resulting trajectories in the dataset, identifying common sequences in the data. Our findings highlight multiple common structures of religious activity across the narratives; most present a constant disposition toward religion, serving as valuable material for historical and sociological research.

1 Introduction

Characters in narratives are shaped by the continuous interplay of internal and external events they experience, each influencing their thoughts, feelings, and behaviors. As narratives progress, these events unfold across various dimensions, some are common to all narratives, such as changes in location, while others are specific to particular genres. Within the domain of holocaust testimonies, as people experience unimaginable atrocities, the change in religious dispositions takes a central role. To get a sense of the entire corpus of testimonies, we present a scalable computational method for extracting a representation of this progression along the narrative timeline.

We leverage off-the-shelf LLMs for automatic character arc inference, focusing on the protagonist's development. We explore the progression of their religious trajectory across the narrative. We focus on a dual perspective analysis, the first captures the protagonist's descriptions of their beliefs, while the other describes their religious practices.

As people change and adapt, their observance of religion and the world of beliefs constantly evolves. We define a *religious trajectory* as a series of changes in religiosity throughout a given storyline of an individual's life course. We view each trajectory as a combination of the evolution of religious practices and beliefs, assuming they each describe religiosity from a unique perspective.

For extracting the trajectories, we (1) identify the segments within the text that constitute the trajectory; and (2) assess the protagonist's religious valence and intensity in each segment. We then cluster the resulting trajectories, identifying common sequences, see Figure 1. Our research contributes to a deeper understanding of character evolution within narratives by highlighting the potential of machine learning techniques in studying thematic trajectories.

2 Related Work

Narrative Analysis. There has been significant attention in NLP research toward understanding narratives and their importance in studying human behavior and belief systems. While existing research in narrative comprehension often centers around event and location schemas (Wagner et al., 2023), the analysis of personalities, narrator intentions (Piper et al., 2021), (Zhu et al., 2023), or narrative structure (Wagner et al., 2022); there remains a gap in tracking the evolution of characters, particularly their development, throughout a narrative. This gap is critical, as understanding character evolution can provide deeper insights into how narratives convey complex human experiences.

Another aspect researched is character attribute inference, analyzing personas or archetypes, rela-

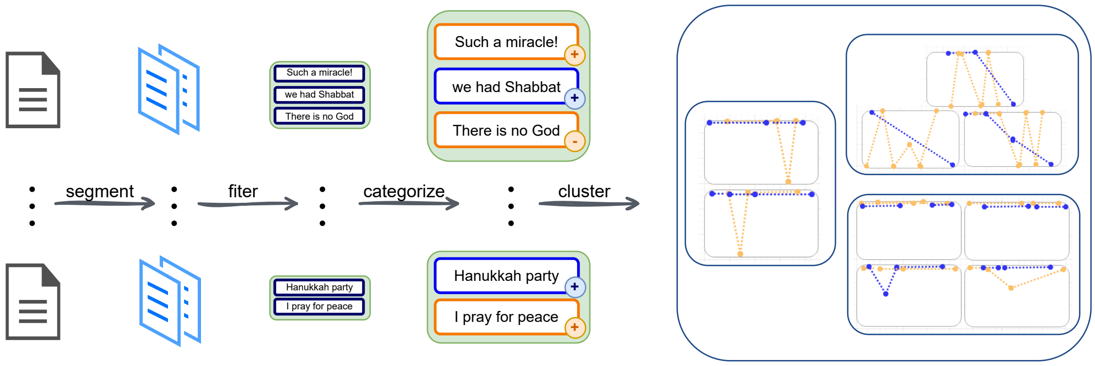


Figure 1: The general pipeline for identifying the religious trajectories from a set of Holocaust survivor testimonies: (1) **Segmentation:** segment the testimonies, beginning with question-answer pairs and then merging and dividing them so that the majority length is 50-100 words; (2) **Filtration:** train and run a classifier to filter all segments containing religious content; (3) **Categorization:** use LLMs to identify the protagonist's valence of religious practice and/or beliefs in a given segment; (4) **Clustering:** cluster the resulting trajectories to identify common patterns of evolution of religiosity in the testimony dataset.

tionships, and emotional trajectories (Chaturvedi et al., 2017). Analyzing characters' thematic trajectories is demonstrated by Brahman and Chaturvedi (2020), modeling the emotional trajectory of the protagonist in neural storytelling. Their work includes generating and modeling stories that follow various emotional arcs for the protagonist. Additional research (Brahman et al., 2021) focuses on Character Description Generation, emphasizing the need for better models of narrative comprehension.

This study builds upon these foundations by analyzing character development, focusing on the protagonist's religious practices and their expressed religious belief systems.

Religious Trajectories. Ingersoll-Dayton et al. (2002) explore religious trajectories, examining patterns of change and stability in religiosity over the life course. Their study employs a life course perspective to identify various dimensions of religiosity that exhibit change and uncovers four distinct patterns of religious trajectories: stable, increasing, decreasing, and curvilinear. Similarly, McCullough et al. (2005) examine religious trajectories among immigrant populations, focusing on how their religiosity evolves after settling in a new country. Exline et al. (2020) explore the religious and spiritual struggle of college students who have distanced themselves from religion. They discuss challenges such as ultimate meaning, interpersonal conflicts, doubt, divine struggles, and intellectual questioning about God's existence.

We leverage recent advances in NLP to analyze religious trajectories on a broader scale using a large dataset of personal testimonies. Rather than focusing on individual cases, our approach aims to uncover common patterns and sequences across many narratives, providing insights into how religious beliefs and practices evolve throughout the life course, and under trauma, within this context.

Trajectory Clustering. Alqahtani et al. (2021) hold a thorough review of time-series data analysis, focusing on deep time-series clustering (DTSC); their work proposes Deep Cluster – a clustering approach using deep convolutional auto-encoders (DCAE). Chang et al. (2023) discuss common methods for this task, including traditional metrics that operate on trajectories and deep learning methods that map the trajectories to embeddings and then apply distance measures to quantify similarity. However, these methods, typically require labeled data for supervised learning.

3 Task Definition

Given a segmented testimony $(x_1, x_2, \dots, x_n)$, our framework outputs a sub-sequence of segments representing its religious trajectory $(\langle b_1, p_1, t_1\rangle, \langle b_2, p_2, t_2\rangle, \dots, \langle b_k, p_k, t_k\rangle)$, where b_j are the labels for the belief trajectory, p_j for practice, and $t_j \in (0, 1)$ represents their position within the narrative. Each label describes a religious practice the protagonist engages in, a belief they hold on to, or both.

4 Data and Annotation

We received 1000 Holocaust survivor testimony transcripts archived by the Shoah Foundation (SF).[1]

[1] https://sfi.usc.edu/

The interviews were recorded on video and transcribed as time-stamped text. Due to the lack of a structured format, our first step is to segment the data using natural divisions created by question-answer pairs. This strategy creates some very short and very long segments, leading us to merge segments with fewer than 10 words and divide those exceeding 100 words. The idea of this method is to create segments that contain just enough information to determine its relevance to the religious trajectory. Our segmentation method yields a dataset, with the majority length of the segments being between 50-100 words and reasonable paragraph breaks, mostly keeping separate ideas apart from each other. However, some of the samples may contain multiple topics or conflicting religious signals. For example: *"Saturday I would go, and I was encouraged to go to the synagogue. And Sunday, I was encouraged to go to church."*

4.1 Annotations

After segmenting the data, we randomly sample and annotate approximately 4000 segments. The trajectories are constructed from all religious content segments from the narrator's perspective; the first annotation assignment is for capturing descriptions of Jewish religious practices and beliefs. This is designed as a binary classification task. The annotators are directed to classify all segments that describe any Jewish religious practices or beliefs of the protagonist or indicate their absence, we provide the complete guidelines in Appendix A.

This complex annotation task involves knowledge of history and the Jewish religion. Many segments can be ambiguous, rely upon the context, or require an understanding of the context. Therefore, there may be a lack of consensus among the annotators on the exact classification of a given segment. All these factors contribute to the complexity of the annotation task and require careful consideration and attention.

To enhance the accuracy of the annotation process and the quality of its results, we recruit multiple annotators, each tasked with annotating over 2500 segments, with an overlap of 500, for measuring inter-annotator agreement (IAA). The overlap samples are selected randomly and the annotators did not know of the overlap. To evaluate the IAA, we use Krippendorff's alpha, obtaining a score of 0.64, indicating a substantial level of agreement.

The second annotation task is multi-label and consists of identifying the class of each sample and determining the speaker's valence toward the specific class. Each segment belonging to the trajectory is categorized by its content – practice, belief, or both. The segments are further categorized by their valence towards the specific practice or belief they describe. Specifically, we map each sample to one or more of the classes or mark it as falsely recognized religious content.

The classification schema is as follows: a segment describing a practice can be annotated with one of the classes *Active*, *Inactive* or *Other*; the first two classes identify descriptions of participating or violating religious practices while *Other* represents descriptions that do not meet the criteria of *Active* or *Inactive*, or match both of the classes simultaneously. For belief, the classification schema is similar, with the classes being *Positive*, *Negative*, and *Other*. An example of the annotation process is illustrated in Figure 2, and the annotation guidelines are detailed in Appendix B.

To construct the dataset for this task, we first run the religious content classifier to select positive predictions. Next, we use GPT-4o[2] to identify samples that belong to the minority classes, specifically the Belief classes and *Other-Practice*. The prompts used with GPT-4o include definitions of these minority classes. We then incorporate into the dataset all samples that GPT-4o classified as belonging to these minority classes. This approach helps balance the dataset by increasing the number of examples in the underrepresented classes, ensuring both positive and negative instances are well-represented. The resulting dataset is the one provided to the annotators.

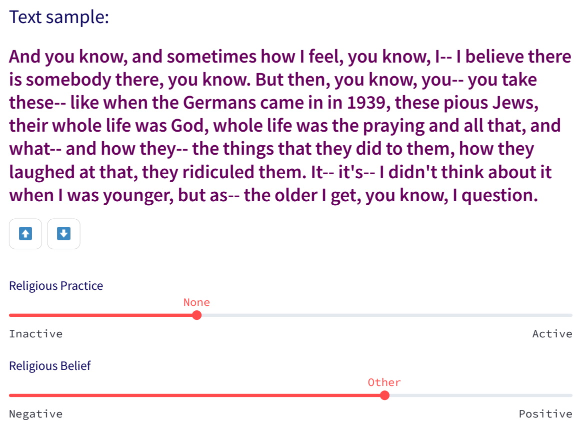
The Krippendorff's alpha score for the second task is 0.44, indicating moderate agreement, suggesting that this classification task is challenging even for human annotators. The Belief dataset contains 141 *Positive* samples, 76 *Negative*, and 42 *Other*. For Practice predictions, the class distribution is 351 *Active*, 76 *Inactive*, and 44 *Other*. We divide the data into three splits with equal portions of each class.

5 Modeling Trajectories

5.1 Experimental setup

Extracting the religious trajectory of a given segmented testimony consists of two annotation tasks followed by prompting and training adapters for

[2] https://platform.openai.com/docs/models/gpt-4o version gpt-4o-2024-05-13



Text sample:

And you know, and sometimes how I feel, you know, I-- I believe there is somebody there, you know. But then, you know, you-- you take these-- like when the Germans came in in 1939, these pious Jews, their whole life was God, whole life was the praying and all that, and what-- and how they-- the things that they did to them, how they laughed at that, they ridiculed them. It-- it's-- I didn't think about it when I was younger, but as-- the older I get, you know, I question.

Religious Practice: None

Religious Belief: Other

Figure 2: An annotation example from the platform we provided the annotators with to identify the survivor's valence of religious practice and belief in each segment.

LLM classification. The main steps are: (1) filter religious content, (2) identify practices and beliefs, and (3) measure the valence and intensity of the protagonist's expressed attitude towards religion.

We view the religious content filtration task as one that can be performed per segment. The annotation process yields approximately 700 positive samples with religious content and the rest negative. We fine-tune a RoBERTa (Liu et al., 2019) classifier on this task, using a balanced dataset of approximately 1400 segments, divided into three splits: train, validation, and test, by a ratio of 0.8, 0.1, and 0.1 respectively.[3] We evaluate the model on the test set, which gives accuracy and f1 scores of 95%. Additionally, cross-validation over 10 random splits produces an average accuracy of 92%. Given that the goal of this assignment is to identify segments that form a node in the trajectory – i.e., contain relevant practice and belief descriptions, these results demonstrate that the RoBERTa classifier is a reliable tool for this purpose.

For modeling the trajectories, we fine-tune LoRA adapters for Mistral-7B-instruct on data from the second annotation task and compare their performance with GPT-4o. Model selection was based on F1 scores across different classes. For training, we use Mistralai's mistral-finetune repository[4] with their default hyperparameters and test on multiple seeds.[5] For the four practice classes, the average F1 scores are 0.51 for GPT-4o and 0.55 for Mistral-7B. For the parallel belief classes, the scores are 0.57 and 0.56, respectively. In a zero-shot setting, the average F1 scores for practice are 0.45 for GPT-4o and 0.33 for Mistral-7B. For the parallel belief classes, the scores are 0.56 and 0.23, respectively. The performance of both models on our test data is comparable, leading us to choose Mistral-7B for generating the trajectories. The prompts we run for few-shot learning and training fit the format of Self-Consistency (Wang et al., 2022) and are carefully designed with guidance from Anthropic's prompt generator.[6] Additionally, we tested GPT-4[7] on a subset of the dataset, but it did not respond in the specified format. Considering the complicated annotation process and IAA, these moderate F1 scores are unsurprising.

While memorization is a valid concern when applying pre-trained LLMs, the specific combination of Holocaust testimony data with our labels is unlikely to have been seen in this exact form during pre-training, and therefore is not expected to limit the model's ability to generalize.

5.2 Evaluation

As we are not aware of any directly comparable reference for the trajectories, we evaluate them against two reliable proxies, albeit not directly comparable ones: a topic-modeling-based and a thesaurus-based.

Topic modeling based reference. Ifergan et al. (2024) conducted topic modeling using BERTopic, on the same set of testimony transcripts, which suggests multiple topics that align with our definitions of religious practices and beliefs. Using this prior knowledge, we extract the labeling by these topics as reference trajectories. Their segmentation method creates segments about three times larger than ours, leading to relatively sparse sequences. The topics we address, and their matching categories appear in Appendix D.

Thesaurus-based reference. The testimony transcripts we received from the SF, were divided into segments based on their duration – typically one per minute. Each segment was indexed with labels describing several terms from the SF highly de-

[3] Hyperparameters: 3 epochs, batch size=8, learning rate=1e-5, seed=33

[4] `https://github.com/mistralai/mistral-finetune`

[5] Hyperparameters: Lora Rank=64, sequence length=16,384, batch size=1, learning rate=1e-4 number of micro-batches=1. Number of training steps for belief=100; for practice=400, weight decay=0.1, pct-start=0.05. Seed for belief=1; for practice=5

[6] `https://console.anthropic.com/login`

[7] version: gpt-4-turbo-2024-04-09

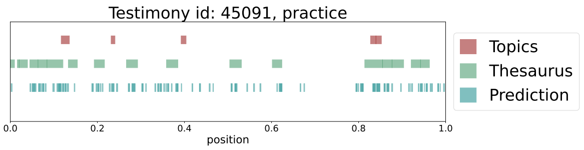


Figure 3: Alignment of predicted trajectories with reference trajectories for testimony ID: 45091. The colored rectangles' widths correspond to the segment lengths. The x-axis represents the normalized position within the testimony transcript. Color code: red denotes segments labeled by topic modeling (Topics), green represents segments labeled by the thesaurus-based approach (Thesaurus), and blue depicts the predicted labels (Prediction). This alignment illustrates the differences and overlaps between the predicted and reference trajectories.

tailed thesaurus, containing $\sim$ 8000 unique labels.[8] We leverage the terms related to religious practices and beliefs to extract reference trajectories. The terms we address include camp prayers, religious observances, Kaddish, Baptisms, religious identity, and other related terms. The full list can be found in Appendix E.

Both of these references have several limitations. First, the segments in the reference trajectories are larger than ours, which leads them to contain information irrelevant to the practice and belief labels. Second, the reference sequences are sparse compared to the predicted ones. For the topics, since our analysis for the topic model selects a single topic for each segment, rather than all the top relevant topics. For the thesaurus, despite the large number of terms, many segments lack the labeling of their matching terms. This may be a result of the exceedingly large label set ($\sim$ 8K labels), which may have resulted in recall issues in the SF annotation. In addition, the label set of the references is partial, meaning that the majority of the topics and terms that we address do not have a specific valence. Considering these points, the false positive rate of the predictions is unknown, making the references suitable only for measuring recall. An example illustrating the alignment of the references and predictions is shown in Figure 3.

We run the fine-tuned Mistral-7B model on the full dataset, producing 1000 trajectories. In this setting, relying on our fine-tuned classifier, only religious content predictions are prompted, and not every single one of the original dataset segments. For each of the reference and predicted sequences, we quantify their distance. For a given non-empty trajectory T and a reference path R:

Baseline	Definition
Equal	Scatter the points evenly between 0 and 1.
Original	Randomly select points from the original distribution of the predicted label.
Edges and middle	Randomly select points from three equal splits of (0, 1); each third containing the same percent of the point that it has in the predicted distribution of the label.
G-Edges and middle	Same as Edges&middle except we sample the point from the normal distribution.
2-Gaussian	All of the points sampled normally from the first half, same for the second half.
Normal-original	Sample from the Gaussian with the variance and mean values of the predictions.

Table 1: The different baseline definitions for evaluating the predicted trajectories.

$$min\_sum\_dist(T, R) = \sum_{r \in R} min_{t \in T}(|t - r|)$$

If T is empty, return the number of segments in R, and if R is empty, return 0. We compare the sum of the distances to baseline trajectories. These baselines are artificial sequences designed by using our prior knowledge about the distribution (Figure 5) of practice and belief segments in the full dataset; each is the same length as the predicted sequence. The different baselines for a given class are defined in Table 1.

6 Trajectory Clustering

After extracting the trajectories, we cluster them according to a predefined taxonomy and using unsupervised methods. We expect to identify a few main clusters, each representing a different trajectory prototype that can be identified by generating a path that is more similar to each one of the sequences within its cluster than to any of the other sequences.

6.1 Predefined Taxonomy

We divide the trajectories into classes based on their valence and structure; continuous positive/negative, oscillating, uni-modality, and the level of coverage relative to the testimony storyline. The full taxonomy is defined in Table 2. For this evaluation, each trajectory is filtered by removing any neutral values it contains and then shrunk by replacing a sequence of constant consecutive values with a single value. For example, [-1,1,0,1,1] was shrunk to [-1,1]. The coverage level is defined for a given

[8] sfi.usc.edu/content/keyword-thesaurus

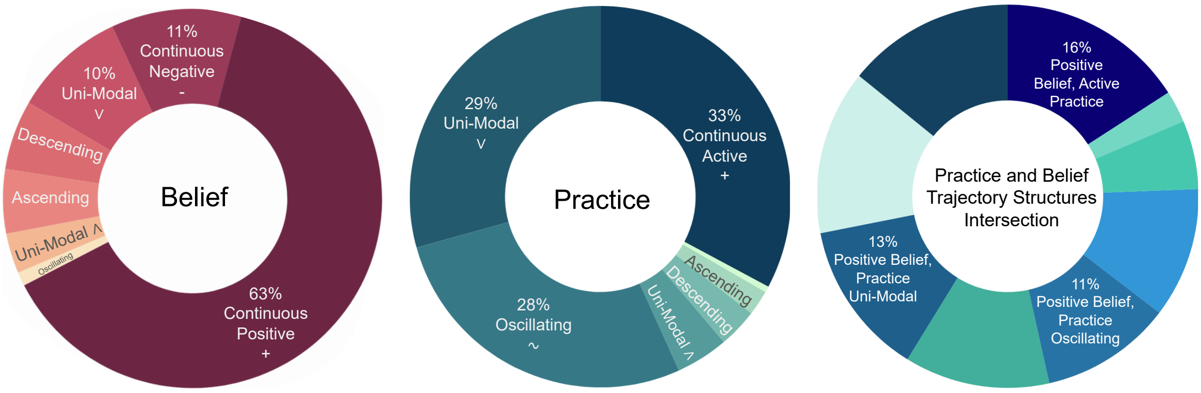


Figure 4: Religious Trajectory structure distributions, from left to right: 63% of the belief trajectories share a continuous positive trend; 11% are negative, and the rest are distributed among ascending (5%) descending (6%), oscillating, and uni-modality patterns (low: 10%). The practice trajectories have a more balanced distribution, having the three majority structures continuous-active, uni-modal-low, and oscillating. For the intersection of the two aspects, the three trends that we recognized, covering 40% of the intersection, all have a monotonic-positive belief structure, while the practice valence varies: 16% are monotonic-active, 13% have a uni-modal-low structure and the rest (11%) oscillate.

trajectory spanning between t_1 and t_k for some testimony positions in the interval (0,1).

We examine the different densities of trajectories and whether trajectories with the same structure share similar characteristics, such as events, topics, or places.

Structure	Filtered&shrunk series
Continuous-Negative/Inactive	[-1]
Continuous-Positive/Active	[1]
Ascending	[-1, 1]
Descending	[1, -1]
Oscillating	$\{1, -1\}^n$
Unimodality Low	[1, -1, 1]
Unimodality High	[-1, 1, -1]
Coverage Level Definitions	
Low	$t_1 - t_k \leq 0.33$
Medium	$0.33 \leq t_1 - t_k \leq 0.33$
High	$0.67 < t_1 - t_k$

Table 2: Definitions of the structures and coverage levels for the predefined taxonomy.

6.2 Hierarchical Clustering

For the hierarchical clustering, we use Dynamic Time Warping (Berndt and Clifford, 1994) with multiple window sizes to measure the distances between the trajectories; and then run agglomerative (Zepeda-Mendoza and Resendis-Antonio, 2013) and HDBSCAN clustering methods (McInnes et al., 2017). Further details are in Appendix G.

7 Results

We evaluate the predicted trajectories against the references and present the results in Table 3. As anticipated, the alignment of the prediction trajectories with the references is almost a fully contained relation, validating the predictions' recall, as many reference points match predicted ones. Other than the evaluation of the full dataset, 101 testimonies are randomly sampled and their trajectories are predicted in three settings: prompting GPT-4o and the trained Mistral-7B on religious content predictions, and separately prompting Mistral on the full set of segments. The evaluation results for this subset are provided in Appendix F. We observe that prompting on all segments, as opposed to just religious content, leads to a significant over-prediction rate for each class. Specifically, when using the non-filtered data, the proportion of positive classes does not align with the proportion of religious content in the full dataset, as predicted by a reliable classifier trained on this data.

7.1 Clustering

Running the structure-based clustering gives 99% of the testimonies containing trajectories with at least two points, 68% of them include belief trajectories, and the others only practice. For the belief trajectories, more than half (63%) share a continuous positive shape, 11% negative, and the rest are distributed among ascending (5%) descending (6%), oscillating, and uni-modality patterns (low:

	Topic			Thesaurus				
	B	**P**	**P$^-$**	**B**	**P**	**P$^+$**	**B$^+$**	**B$^-$**
Predicted	**12**	**12**	**41**	**7**	**9**	**10**	**13**	**127**
Original scatter	22	104	48	16	71	54	14	139
Edges & middle	27	33	57	20	30	31	20	139
Equal scatter	35	24	53	23	18	25	14	180
Normal-original	24	62	51	21	52	60	20	141
# Reference paths	335	905	187	282	787	761	98	217
# predicted paths	874	996	665	874	996	988	659	278
# Reference points	456	2,768	301	439	2,434	2,214	171	253
# predicted points	4,500	21,193	1,719	4,500	21,193	17,462	2,339	427

Table 3: Sum of min_sum_dist for fine-tuned Mistral-7B predictions and baseline trajectories on the full dataset. **Original:** Sample from the distribution of the predictions. **Edges&middle:** Random sample from three equal splits of (0, 1); according to the predicted distribution of the label. **Equal:** Even scatter. **Normal-original:** Sample from the Gaussian with the variance and mean values of the predictions.

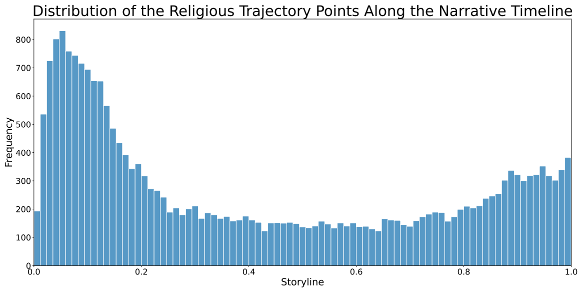


Figure 5: Distribution of all religious content, the distributions that we based the baselines on are according to each label separately.

10%). Among the positive trajectories, 52% cover a substantial portion of the plot, whereas negative trajectories are sparser, 58% covering up to two-thirds of the narrative. The practice trajectories vary in their structure, 33% follow a continuous-positive pattern, the majority with high coverage levels similar to the belief trajectories: 83% with high coverage, 11% medium, and only 6% cover just the first third. For the intersection of the two aspects, the three trends that we recognize, covering 40% of the intersection, all have a monotonic-positive belief structure, while the practice valence varies: 16% are monotonic-active, 13% have a uni-modal-low structure and the rest (11%) oscillate. These distributions are shown in Figure 4.

When analyzing the intersection of practice and belief structures within the trajectories, we find that 16% of the trajectories share a continuous-positive structure for both religious aspects. 13% of the trajectories show a positive trend in religious beliefs but a uni-modal pattern in practices. This discrepancy may reflect external circumstances the survivors went through that prevented them from practicing Judaism, or social changes.

For the hierarchical clustering methods, HDBSCAN points out clusters with fair separation. The clusters are similar to structure-based ones and are shown in Appendix G.

7.2 Comparison of Similarity Metrics

We compare the similarity metrics used for clustering; each has its own approach to reveal commonalities.

We examine the relationship between the similarity scores used to produce clusters in both methods by comparing the DTW distance distributions of trajectory pairs with identical structures to those with different structures, see Figure 6. The predefined taxonomy score indicates whether trajectories share the same structure, while unsupervised methods use the DTW distance matrix. The distribution of distances for pairs with the same structure centers around smaller values, with average distances of 0.10 (belief) and 0.48 (practice) for identical structures, compared to 0.16 (belief) and 0.56 (practice) for pairs with different structures. This highlights a link between the DTW distance and the structure taxonomy.

8 Discussion

Our analysis identifies common structures of religious trajectories, grouping those that share a similar structure.

The distinction between religious practices and beliefs is discussed in the sociology of religion.

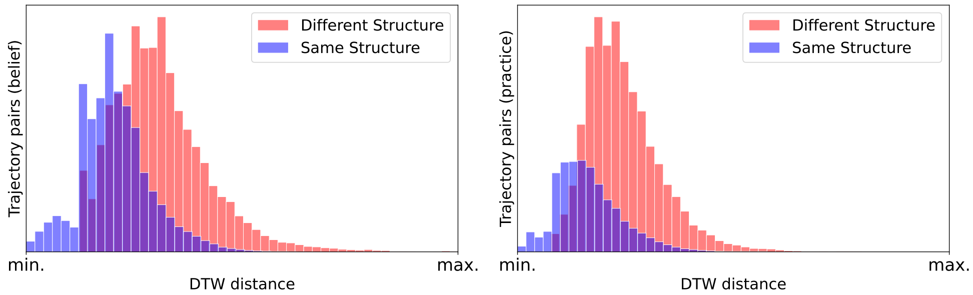


Figure 6: DTW distance distributions of trajectory pairs: the left plot represents belief and the right practice. Blue indicates pairs with the same structures, and red indicates pairs with different structures. The distribution for identical structures is shifted towards smaller DTW distance values.

Chaves (2010) describes common incongruities among religious observers. He states: *"Ideas and practices exist as bits and pieces that come and go as situations change, producing many inconsistencies and discrepancies... Religious ideas, values, and practices generally are not congruent."*

Our research focuses on Holocaust survivor testimony transcripts from video recordings filmed in English over the past 30 years. The significance of this dataset in the study and remembrance of the Holocaust cannot be overstated. As the number of surviving witnesses continues to diminish, there is an urgent need to find new approaches to engage with the extensive collection of testimonies. Applying NLP technology for analyzing these testimonies has been advocated (Artstein et al., 2016; Wagner et al., 2022), offering the potential to extract valuable insights from the vast number of testimonies, instead of relying on small-scale, manual studies. Holocaust testimonies also present unique value for NLP research due to the combination of many accounts within a relatively confined domain of topics and locations, distinguishing them from typical narrative datasets (Sultana et al., 2022).

Changes in religiosity are particularly relevant when discussing Holocaust testimonies, which follow survivors' experiences in extreme conditions that are expected to influence both their religious beliefs and practices (Machman, 1982). We expect different patterns of change in religiosity throughout the testimonies, each telling the story of an individual and covering a wide range of times and places in the narrator's life. Moreover, alignment with the literature on the sociology of religion, religion in the Holocaust, and faith after the Holocaust lends insights to the modeling.

This work reveals various patterns in religious trajectories. The SF volunteers who conducted the interviews were guided to discuss specific themes – including religious belief and activity, creating a common narrative sequence within the dataset, as demonstrated by the distribution of religious content throughout the testimonies (Figure 5).

We examine the trajectories without accounting for differences in their lengths and frequencies, although investigating these could provide a more nuanced understanding of the religious, social, and theological aspects reflected in the trajectories. In a way, omitting the blank trajectories from our study might overlook a significant aspect. The absence of a religious trajectory may itself convey a story, although the specific narrative behind it remains unknown. This absence could result from either a low level of religiosity or that religion did not come up during the interview.

Other directions we aim to cover include examining the testimonies that share structural similarities, exploring additional commonalities, and how these may correlate with metadata such as age, gender, pre/post-war hometowns, and experiences during the war. Any analysis will need to consider the general distribution of the data, as most survivors in our sample were born in Poland, with the majority of interviews conducted in the United States and Canada.

Another perspective expected to contribute to a more sophisticated picture of the patterns is to include the non-positive-or-negative parts of the trajectory in the structure taxonomy analysis. The importance of incorporating these segments into the analysis arises from the unsupervised clustering that points out a separation between trajectories with multiple non-positive or negative segments, suggesting that these play a separate role in the trajectories.

Another direction is to explore the relationship between the practice and belief trajectories, investigating whether one follows the other's pattern or is a shift of the other and whether one can be predicted based on the other.

9 Conclusion

This paper explores character development by analyzing religious trajectories from a dual perspective of practices and beliefs. We develop a framework to extract and cluster trajectories from 1,000 Holocaust testimony narratives, uncovering common structures across the dataset. We believe these findings encourage further research on utilizing LLMs to capture character development and thematic trajectories. Our study offers valuable material for historical and sociological research.

Ethical Considerations

Limitations

As for the limitations of the framework, it is important to consider the existence of a reporting bias. Our data is limited to interview transcripts, which capture the survivors' descriptions of their beliefs, without offering a broader understanding of their theological positions. Though the SF recorded testimonies in several languages and countries, it is important to note that our dataset is also biased toward the information collected from survivors in English-speaking countries.

Additionally, much of this work relies on human annotators. Despite their shared professional backgrounds, each annotator brings different prior knowledge, which can affect agreement levels. For the cluster similarity evaluation, our analysis is restricted to the subset of testimonies that the annotators reviewed and analyzed.

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A Religious Content Annotation Guidelines

We are working on exploring changes in religious beliefs as reflected in testimony transcripts of Holocaust survivors; through looking at Jewish practices and beliefs described in the text. We want to capture all data segments from the testimonies that hold to the definition of religious content, we will label “TRUE” all segments that describe any Jewish religious practices or beliefs of the interviewee, **as well as segments that indicate the absence of religious practices or beliefs.** In detail:

- Religious practices and beliefs: Content that describes *“Who we were, what we did, and what we believed in”*. For instance phrases in the style of:
  - *“We were orthodox” / “We were not religious”*
  - *“My family belonged to a synagogue” / “We didn’t keep the Sabbath”*
  - *“We hosted Pesach Seder” / “I wasn’t familiar with the Jewish holidays”*
- Descriptions of the interviewee’s theological inner life, giving the reader information about their faith in God. For example:
  - *“I looked up to the sky, there must be a God above”*
  - *“I didn’t believe that God can look at this cruelty and all these dreadful things”*
- If the sample is written in first person (We, us, I), it is telling the story of the interviewee or their family and not stories about others, and its content meets our description of religious practices and beliefs then it will be labeled True.
- We will consider samples written in the third person, only if they reflect on the interviewees’ beliefs, or describe the environment that he grew up in.
  - *“My parents explained that we were Jewish, secular Jews, nonbelievers”* - True
  - *“My elder brother Rabbi Yosef Meyer was with me”* - False
  - *“I think my brother probably was affected because he changed his religion, he became a Roman Catholic.”* - True, since implies that the speaker wasn’t affected.
- The phrases “Baruch Hashem ” and “Thank God ” are religious phrases and, therefore will be labeled True.
- Zionism descriptions will be considered False; since the Zionist movement saw the land of Israel and the Hebrew language as integral parts of the Jewish national heritage, and not necessarily of religious significance.
- Descriptions of Jewish Identity will be labeled False. We are focusing on **religious Identity and not Jewish Identity**, therefore we want to capture only segments that contain religious practices and beliefs, not signs of Jewish culture.
- Jewish food or music, or speaking Yiddish - Not considered religious content
- Hnnukah candles, Bris, Bat Mitzvah celebrations, and Friday night dinner - are considered positive religious content.

- Getting a Jewish education
  - Secular Jewish education, such as attending Hebrew School, or a Tarbut institution, or participating in secular youth movements - Not considered religious content
  - Studying at Yeshivas or in any Jewish religious school, Bnei Akiva or Mizrahi - Positive religious content.
- Mentions of miracles
  - If reflecting a belief will be labeled True, and not when used as a phrase.
  - It is suggested to view the wider context of segments that mention miracles.
- Description of friendship relations with the non-Jewish population will be considered False, unless it indicates a religious approach.
  - *“We were friendly with our gentile neighbors, though didn’t eat at their houses”* - True

Some Examples

1. *“He gave me a Brucha, a blessing. I was very sick, a very sick child. And he told, don’t worry. She’ll grow. She’ll be well, God will help her. ”*
2. *“he was able to survive, which it was a, a miracle. It was simply a miracle. Because, by rights, he was dying. He was on death’s door”*
3. *“I got my presents under the Christmas tree, and then my girlfriend came to Hanukkah to my place. She got a present.”*
4. *“I send them to the best yeshivas. This is the whole future of my life. And this was– baruch HaShem– always could be better. But I’m satisfied– baruch HaShem. I accomplished.“*
5. *“He will always tell you, if you ask him, what’s your religion, I am a Jew. And the boys really have neither been circumcised nor baptized. And it doesn’t seem to have done them any harm so far.”*
   - Although it uses the word religion, The first part alone would not be considered Religious Content: “If you ask him, what’s your religion, I am a Jew” since it is about Jewish identity, not Religion.
6. *“I don’t think God was absent, but I really don’t understand yet.”*
7. *“A lot of kids thought that I am just a Catholic like they are. But it came a time, that when we came to school we had to stand up to say the prayers. And, of course, the Jewish children, we stood up, but we didn’t say, and we didn’t cross ourselves.”*

B Practice and Belief Identification and Rating - Annotation Guidelines

We are working on exploring changes in religious beliefs as reflected in testimony transcripts of Holocaust survivors; through looking at Jewish practices and beliefs described in the text. This task has two parts: Identifying the class of each sample and then determining the speaker’s approach toward the specific class.

Part 1 - Practice and Belief Identification Practice and Belief Identification is a multi-label classification task. The dataset for this task was randomly sampled from data classified as religious content by a machine learning classifier with high accuracy. The task is to map each sample to one or more of the classes or mark it as falsely recognized as religious content.

Label Definitions

- Practice - A ritual, action, or activity motivated by the Jewish religion. Also descriptions reflecting an absence of Jewish religious practices will be mapped to this label.
  - Not including descriptions of Jewish communities or culture.
  - Examples: Saying prayers, going to synagogue, keeping Kosher.
- Belief - Inner life descriptions of ideas or thoughts related to God or religion. Including philosophy and feelings about God, and descriptions of miracles.
  - Excluding descriptions of Jewish identity or Zionism.
- Other - Samples that were falsely recognized as religious content

A general note: We will consider samples written in the third person, only if they reflect on the interviewees’ beliefs, or describe the environment that he grew up in.

Some Examples Practice

1. *"He gave me a brucha, a blessing. I was very sick. He gave me a blessing. I was usually a very sick child– wild, spoiled, and sick. And he told, don't worry. She'll grow. She'll be well, – God will help her. "*
   - *Note: Although phrased in the third person this example is relevant since the narrator of the text went to get the Bracha. It is also considered Belief, since it contains the phrase "God will help her".*
2. *" I got my presents under the Christmas tree, and then my girlfriend came to Hanukkah to– to my place. She got a present."*

Belief

1. *"He gave me a brucha, a blessing. I was very sick. He gave me a blessing. I was usually a very sick child– wild, spoiled, and sick. And he told, don't worry. She'll grow. She'll be well, – God will help her. "*
2. *"he was able to survive, which it was a, a miracle. It was simply a miracle. Because, by rights, he was dying. He was on death's door"*
   - Note: While the text is written in the third person point of view, it reflects the narrators faith.
3. *"I had the will, strong willpower to live. Every night I would take my prayer book. Every night somebody was in charge from the twins to look out. Each bunk beds, everybody is asleep, it's quiet. Then came my turn. One night, I would take my prayer book and cry. Say Psalms. It's so good. I felt close and came–"*
   - Note: this example is also considered Practice, since it describes a daily ritual.

Other - Neither a practice or belief descriptions

1. *"Was there any particular reason for going to a Jewish school for secondary school? The reason was that I didn't want to sit in exam to go to grammar school. I was too frightened. It was a grave mistake."*

Part 2 - Rating Jewish Practice and Belief Text Samples After identifying the classes of a text sample, our task is to rate the narrator's approach to the specific class on a scale from -1 to 1.

Rating Definitions:

- Active - Actively practicing a Jewish religious ritual
- Inactive - Violating Jewish religious practices, descriptions of not observing, actively not practicing a Jewish religious ritual, or practicing a different religion.
- Neither active or inactive valence of Jewish religious practice, or both simultaneously.

Practice examples Active

1. *"How would you describe your family's religious life? Orthodox."*
2. *"When did you have a Bar mitzvah? When I was 13. In the– in the main synagogue."*

Inactive

1. *"And did you– did you observe Shabbat in any way, light candles, go to synagogue? No, no, no candles, no Shabbat."*
2. *"The church became a very important part of my life. Although we didn't go often, any time that I went with my Catholic family, the Leszkowicz or Maciejewski family, I felt safe. And this cross that you're looking at was given to me by my Catholic grandmother."*

Other

1. *"Was there davening on the train? Yeah. Sure, they were davening."*
2. *"We were sleeping in an attic, in a cellar, here. If we were caught, that would be the end. Meanwhile, Rosh Hashanah– and– and don't forget."*
   - We don't know whether the speaker celebrated Rosh Hashana or is just mentioning the time od the year, therefor it's valence is "other".
3. *"You said your family was not religious. So in what way did you identify with Judaism? I would say– ethnically and community feeling.*

my grandmother and also my maternal grandparents, they went also only I think mainly Rosh Hashanah and Yom Kippur, not more than that."

- On the one hand, going to synagogue on the high holidays - Active.
  On the other, not a religious family - Inactive.
  → Altogether the signal is "other".

Belief examples Positive

1. *"And my mother kept on saying, this is going to be the Passover of Passovers, because we were liberated. Moses took us out of Egypt. And now, the world is going to take us out of Egypt from Hitler. But it didn't happen. The Jews fought for a month there. They fought most– the strongest army in the world. They, of course, at the end, lost."*
   - Note: This is a practice example as well.

2. *"What did you do when you saw that being done to the children? You think I could go up and say don't do it? Nothing. I just prayed. I just prayed. But I had to look. When I look at this now, that's what I saw. That's what had happened. And still Germany is so strong. And Germany is a country."*

3. *"But I still belong– believe in God. And if he's good, or if he can close his eyes, and then see us, and not to see and not to hear, but it comes a time when he takes his hands away, and from his eyes and ears, and he sees. And I hope that I will see, too. If I don't see, as my children, grandchildren will see and hear that he took his hands away from his eyes and ears, and he can help them."*

Negative

1. *"Why not? How can I believe? How is it possible? I just keep the tradition for my children and grandchildren sake and my friends who don't even keep the tradition. So they come. And we have nice dinner. And we try to be in good mood, but nothing Jewish in us anymore, no."*

2. *"How were you mentally at this stage, Leah, after all your experience? Very angry, very bitter. I didn't believe there was a god. I didn't want to know such a thing as a god. Very guilty."*

3. *"And that was our religion. But we didn't keep Shabbat. We didn't keep kosher. Nothing. And during the time in Auschwitz, I didn't even believe in religion. I didn't believe that the God can look at this cruelty and at all these dreadful things. I didn't believe in God. Maybe it was just a shock to the– I don't know."*
   - Note: This is a practice example as well.

Other

1. *"What do you think kept you going? What kept me going? Good question that, obstinacy– I didn't want to die. And however much I didn't want to die, the decision didn't rest with me. This– this is the interesting– it didn't rest with me at all. Maybe God helped– helped me to– to somehow that Dr. Mengele didn't pick me every time he went through these selections. I don't know. I don't know. It certainly wasn't me."*

2. *"And what about your beliefs? Do– do you practice Judaism? Do you believe in a deity? And is that in any way impacted by your experiences one way or the other? Well, I believe very much in the importance of what I would call tradition. And I think that our tradition is– is something to be very proud of. I think we have a very rich tradition, we have very rich history, a very unique history in the world. And I think it is– it is very much part of us."*
   - The speaker doesn't deny or assure faith in God.

3. *"What has– have you inherited that's helped you survive it? Well, I have more questions, I mean, about God than my father does, I'll tell you that. But I do respect very much my father's faith in God and feel that, if he can live though that and believe in God, then I certainly don't have a right to question that. So I've learned that people can go through hell, still believe in God, and go on in, in most ways in their lives, go on and enjoy life, and enjoy children. My father loves young children. He loves children. His whole life is children."*

C Instruction Prompts

The Instruction prompts we ran for GPT4o and Fine-tuning Mistral:

Prompt for Belief Classification

> Your task is to carefully read this text and determine the speaker's valence of Jewish religious belief in God, based on the following classification system: POSITIVE: The text expresses the narrator's belief in God according to the Jewish religion, or his existing relationship with God.
>
> NEGATIVE: The text expresses the narrator's lack of belief in God according to the Jewish religion, or a rejection of religious beliefs.
>
> AMBIGUOUS: The text expresses a relationship with God that does not meet the criteria of the classes POSITIVE or NEGATIVE. This includes questioning Gods while believing in his existence.
>
> NONE: The text does not directly imply the speaker's belief in God and religion, or their lack. This includes texts written in the third person that do not describe the speaker's personal beliefs or family environment.
>
> First, write out your reasoning for classifying the text inside <reasoning> tags. Consider the content and tone of the text, and how it aligns with the definitions provided above.
> After writing your reasoning, output your final classification as a single word (POSITIVE, NEGATIVE, AMBIGUOUS, or NONE) inside <classification> tags.
> Use HTML tags in your response.
> Do not add any words after </classification>.

Prompt for Practice Classification

> Your task is to carefully read this text and determine the speaker's valence of Jewish religious practice described in the text, if any, based on the following classification system:
>
> 1. ACTIVE = The text expresses the narrator actively practicing a Jewish religious ritual.
> 2. INACTIVE = The text expresses the narrator violating Jewish religious practices or not observing/actively not practicing a Jewish religious ritual.
> 3. AMBIGUOUS = The narrator of the text expresses a Jewish religious practice, that does not meet the criteria of the classes ACTIVE or INACTIVE, or the text matches both of the classes at the same time.
> 4. NONE = The text does not directly discuss the speaker participating in a religious practice or violating one. This includes texts written in the third person that do not describe the speaker's personal valence of practicing religion or family environment.
>
> First, write out your reasoning for classifying the text inside <reasoning> tags. Consider the content and tone of the text, and how it aligns with the definitions provided above.
> After writing your reasoning, output your final classification as a single word (ACTIVE, INACTIVE, AMBIGUOUS, or NONE) inside <classification> tags.
> Use HTML tags in your response.
> Do not add any words after </classification>.

D Topic Model Based Evaluation

The topics we address, and their matching categories are in Table 4.

Topic	Class	Sub-Class
Synagogue, holiday(s), Shabbos, religious, Shabbat, Shul, Friday, Passover, Jewish	practice	-
Bar, Mitzvah, Torah, Synagogue, Mitzvahed, Shul, Rabbi, religious	practice	-
God, believe, religion/religious, faith, question	belief	-
Catholic, church, priest, baptized, communion, religion, Catholicism, convert, prayers	practice	inactive

Table 4: Practice and belief-related topics from (Ifergan et al., 2024), and a partial list of the words they contain.

E Thesaurus Based Evaluation

List of terms from the thesaurus that align with our definitions for religious content:

- **Active Practice**
ritual circumcision (bio) mohelim Jewish religious observances Jewish schools synagogue attendance mikva'ot Yahrzeit Jewish dietary laws ghetto Jewish religious observances camp Jewish religious observances refugee camp Jewish religious observances hiding-related Jewish religious observances Islamic prayers yizkor Kaddish prison Jewish religious observances Jewish mourning customs yeshivot forced labor battalion Jewish religious observances Hasidic rebbes (bio) synagogue organizations (bio) Baalei Keriah (bio) Baalei Tefillah (bio) synagogues' sisterhood (bio) synagogues' men's clubs deportation Jewish religious observances Jewish Theological Seminary of America transfer Jewish religious observances Beth Jacob schools b'nai mitzvah b'nai mitzvah (stills) Borerim Jewish religious observances (stills) Institute of Jewish Studies shamas Jewish Institute of Religion Mitnagdim observant/practicing Ramah Camping Movement Shema Yisrael

- **Inactive Practice**
Christian religious observances church attendance religious identity communions (stills) confirmations (stills) Jehovah's Witness missionary activities Jehovah's Witness religious observances Mormon missionary activities Jehovah's Witness religious beliefs camp Jehovah's Witness religious observances baptisms forced labor battalion Jehovah's Witness religious observances camp Christian religious observances Eucharist Islamic religious observances baptisms (stills) prison Jehovah's Witness religious observances ghetto Christian religious observances Christian religious observances (stills) confirmations Islamic dietary laws Seventh-Day Adventist missionary activities non-observant/non-practicing Buddhist religious observances Buddhist lunar days karma Christian missionary activities Christian prayers

- **Practice - Other**
rabbis

- **Positive Belief**
prayers Jewish prayers camp Jewish prayers Jewish religious beliefs prison Jewish prayers forced labor battalion Jewish prayers camp prayers ghetto prayers deportation Jewish prayers hiding-related prayers forced march Jewish prayers

- **Negative Belief**
Christian religious beliefs camp Jehovah's Witness prayers Jehovah's Witness prayers Islamic identity Buddhist religious beliefs Islamic religious beliefs Armenian Genocide faith issues Bosnian War and Genocide faith issues Guatemalan Genocide faith issues Holocaust faith issues Rwandan Tutsi Genocide faith issues

F Evaluation on a Subset of Trajectories

Evaluating a subset of the predicted trajectories presents similar trends to the evaluation in the complete dataset, results in Tables 5, 6 and 7.

G Hierarchical Clustering

Belief Clustering Example An example from running HDBSCAN on the belief trajectories: 19
We first truncated the values of the position points of the trajectories to two decimal points, then calulated their distance matrix using dtw_ndim.distance_matrix from the *dtaidistance* Python module, with window=7 and the default values for the rest of the hyper-parapeters; followed by calling HDBSCAN from the *hdbscan* module, with: min_cluster_size=30, min_samples=1, cluster_selection_epsilon=1 and alpha=1.

Practice Clustering Example An example from running HDBSCAN on the practice trajectories: 11
Hyper-parameters: window=6, min_cluster_size=30, min_samples=1, cluster_selection_epsilon=1 and alpha=0.95.

	Topic			**Thesaurus**				
	B	**P**	$\mathbf{P^-}$	**B**	**P**	$\mathbf{P^+}$	$\mathbf{B^+}$	$\mathbf{B^-}$
Predicted	**3.92**	**32.53**	**18.46**	**6.74**	**21.87**	**25.64**	**2.74**	**8.06**
Original scatter	5.60	33.33	***17.99***	8.22	23.39	30.81	4.80	8.92
Edges & middle	5.89	33.33	19.64	8.90	23.72	26.82	5.26	9.69
Gaussian	6.62	41.80	19.53	8.89	29.57	34.95	3.19	9.71
G- Edges & middle	7.07	41.30	20.47	9.65	29.05	33.70	5.17	9.54
Equal scatter	7.31	33.15	19.81	10.47	23.07	27.89	3.06	14.0
Normal-original	8.40	33.50	17.92	10.58	23.88	25.39	2.89	13.08
# Reference paths	38	91	26	31	79	76	8	22
# predicted paths	71	88	60	71	88	81	56	35
# Reference points	50	264	40	48	233	206	19	27
# predicted points	368	1279	157	368	1279	639	189	80

Table 5: Sum of min_sum_dist for GPT-4o on a subset of trajectories

	Topic			**Thesaurus**				
	B	**P**	$\mathbf{P^-}$	**B**	**P**	$\mathbf{P^+}$	$\mathbf{B^+}$	$\mathbf{B^-}$
Predicted	**2.81**	**0.45**	**1.87**	**0.93**	**0.34**	**0.68**	**2.23**	**10.35**
Original scatter	5.27	1.22	***3.38***	3.71	2.33	1.84	2.36	13.00
Edges & middle	5.00	2.16	2.77	2.53	2.65	2.32	4.67	12.31
Gaussian	4.13	7.07	3.03	3.02	5.81	6.10	2.38	13.38
G- Edges & middle	5.96	7.47	4.25	4.53	6.07	6.56	4.71	12.44
Equal scatter	3.07	0.90	3.56	2.36	0.95	1.36	1.98	16.41
Normal-original	3.89	3.80	2.89	2.68	3.43	3.95	3.89	12.81
# Reference paths	38	91	26	31	79	76	8	22
# predicted paths	93	101	86	93	101	101	63	29
# Reference points	50	264	40	48	233	206	19	27
# predicted points	507	2967	328	507	2967	2385	206	54

Table 6: Sum of min_sum_dist of fine-tuned Mistral7B on a subset of trajectories, prompting all content

	Topic			**Thesaurus**				
	B	**P**	$\mathbf{P^-}$	**B**	**P**	$\mathbf{P^+}$	$\mathbf{B^+}$	$\mathbf{B^-}$
Predicted	**3.62**	**30.09**	**17.38**	**5.68**	**19.62**	**15.78**	**3.66**	**12.35**
Original scatter	5.20	33.23	***18.34***	9.20	23.99	18.53	**3.39**	15.70
Edges & middle	4.86	31.78	18.47	7.33	22.37	18.47	6.02	14.26
Gaussian	5.65	36.84	19.29	8.40	25.58	21.22	4.14	14.83
G- Edges & middle	6.16	38.46	19.67	9.16	27.13	23.73	6.09	14.02
Equal scatter	4.04	31.45	18.93	8.22	21.14	17.43	3.75	17.99
Normal-original	4.23	33.91	19.26	8.13	23.51		5.53	14.65
# Reference paths	38	91	26	31	79	76	8	22
# predicted paths	77	88	69	77	88	86	51	26
# Reference points	50	264	40	48	233	206	19	27
# predicted points	391	1816	199	391	1816	1468	198	46

Table 7: Sum of min_sum_dist of fine-tuned Mistral7B on a subset of trajectories, prompting filtered content

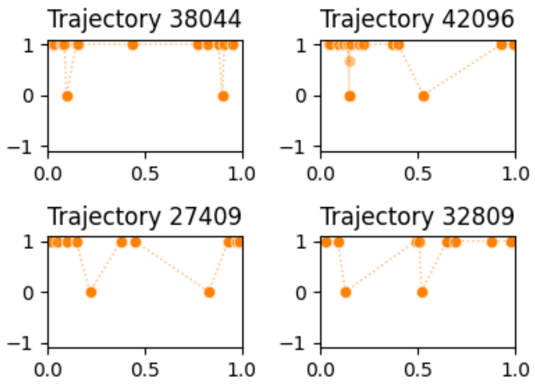

Figure 7: (a) Active - Med

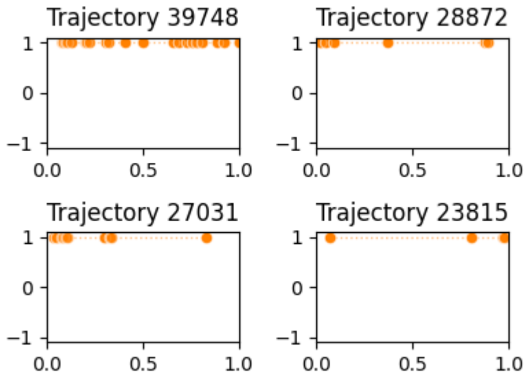

Figure 8: (b) Active

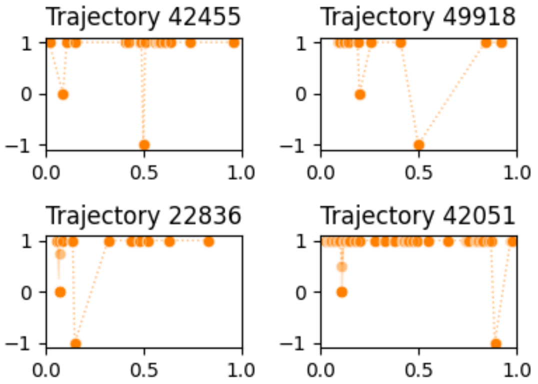

Figure 9: (c) Uni-Modal Low

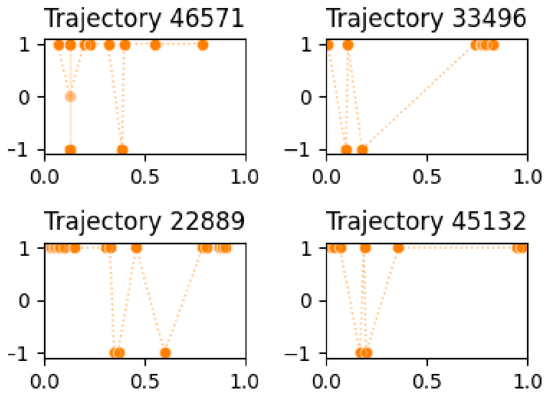

Figure 10: (d) Oscillating

Figure 11: Overall figure caption

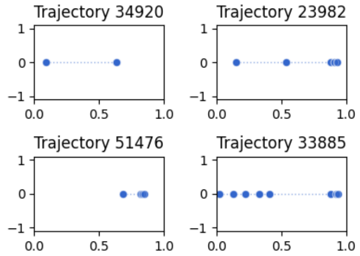

Figure 12: (a) Neutral

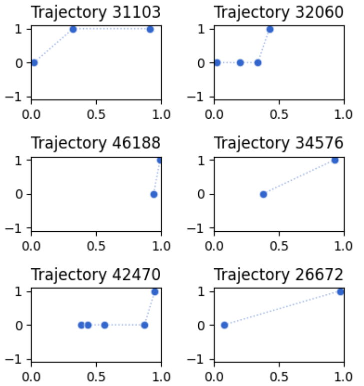

Figure 13: (b) Ascending from neutral

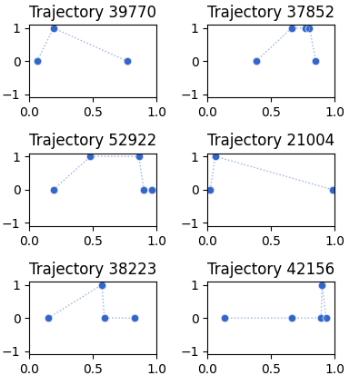

Figure 14: (c) Uni modal Neutral-Positive

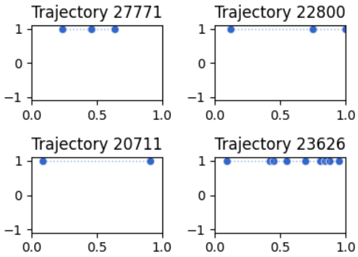

Figure 15: (d) Positive

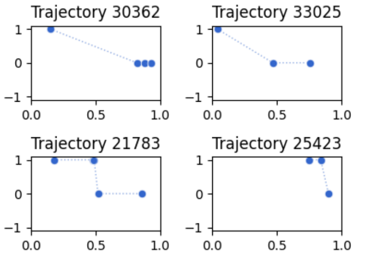

Figure 16: (e) Descending Positive Neutral

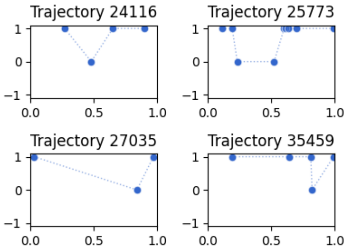

Figure 17: (f) Uni modal Positive Neutral

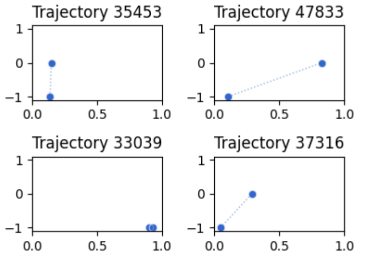

Figure 18: (g) Negative to Neutral

Figure 19: Belief cluster examples

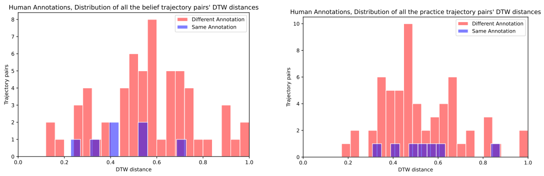

Figure 20: DTW distributions