USDC: A Dataset of User Stance and Dogmatism in Long Conversations

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Abstract

Analyzing user opinion changes in long conversation threads is extremely critical for applications like enhanced personalization, market research, political campaigns, customer service, targeted advertising, and content moderation. Unfortunately, previous studies on stance and dogmatism in user conversations have focused on training models using datasets annotated at the post level, treating each post as independent and randomly sampling posts from conversation threads. Hence, first, we build a dataset for studying user opinion fluctuations in 764 long multi-user Reddit conversation threads, called USDC. USDC contains annotations for 2 tasks: i) User Stance classification, which involves labeling a user's stance in a post within a conversation on a five-point scale; ii) User Dogmatism classification, which involves labeling a user's overall opinion in the conversation on a four-point scale. Besides being time-consuming and costly, manual annotations for USDC are challenging because: 1) Conversation threads could be very long, increasing the chances of noisy annotations; and 2) Interpreting instances where a user changes their opinion within a conversation is difficult because often such transitions are subtle and not expressed explicitly. Hence, we leverage majority voting on zero-shot, one-shot, and few-shot annotations from Mistral Large and GPT-4 to automate the annotation process. Human annotations on 200 test conversations achieved inter-annotator agreement scores of 0.49 for stance and 0.50 for dogmatism with these LLM annotations, indicating a reasonable level of consistency between human and LLM annotations. USDC is then used to finetune and instruction-tune multiple deployable small language models like LLaMA, Falcon and Vicuna for the stance and dogmatism classification tasks. We make the code and dataset publicly available [1].

1 Introduction

Understanding fluctuations in a user's (or author's) opinions during a conversation is fundamental to successful interpersonal interactions. It is essential to develop better communication skills, fostering empathy, and making informed decisions. This understanding is particularly relevant in the context of dogmatism—a phenomenon observed in areas such as politics, religion, culture, intellect, and science—where rigid adherence to beliefs often hinders open-mindedness and empathy (Rokeach, 1954). By aligning with the opinions and stances of potential customers, advertisers can target their campaigns more effectively. Companies can leverage this information for market research, tailoring products and services to meet consumer needs and preferences. Similarly, political groups can gauge public reactions to policies and campaigns, adjusting their strategies accordingly. Identifying differing opinions can facilitate conflict resolution by helping to understand the perspectives of all parties. By recognizing and respecting diverse opinions, society can promote tolerance and maintain social harmony.

Fig. 1 illustrates a sample Reddit conversation on the topic of *Capitalism vs. Socialism.* In this context, an author's initial post—comprising the title and body—is referred to as a submission. Multiple authors can then share their opinions as comments on this submission. Specifically, this example contains 6 comments $\{c_i\}_{i=1}^{6}$ from 3 authors $\{a_j\}_{j=1}^{3}$. We also display stance and dogmatism predictions from two LLMs: Mistral Large and GPT-4. Some authors, like a_1, change their views during the discussion based on the beliefs or opinions of others. At the beginning of the dialogue, author a_1 somewhat favors socialism (in submission and c_2). However, after considering the viewpoints of author a_2 in comments c_1 and c_3, a_1 shifts their stance to somewhat favoring capitalism (in c_4), illustrating a firm yet open-minded approach. On the other hand, author a_3 seems very flexible based on their comment c_5. Conversely, author a_3 appears very flexible based on their comment c_5. Understanding such conversations requires comprehending the fine-grained topics being discussed and the dynamic viewpoints of individual users.

Given the importance of understanding these user dynamics in conversations, training language models to perform this task automatically at scale is critical. While

[1] https://github.com/mounikamarreddy/USDC

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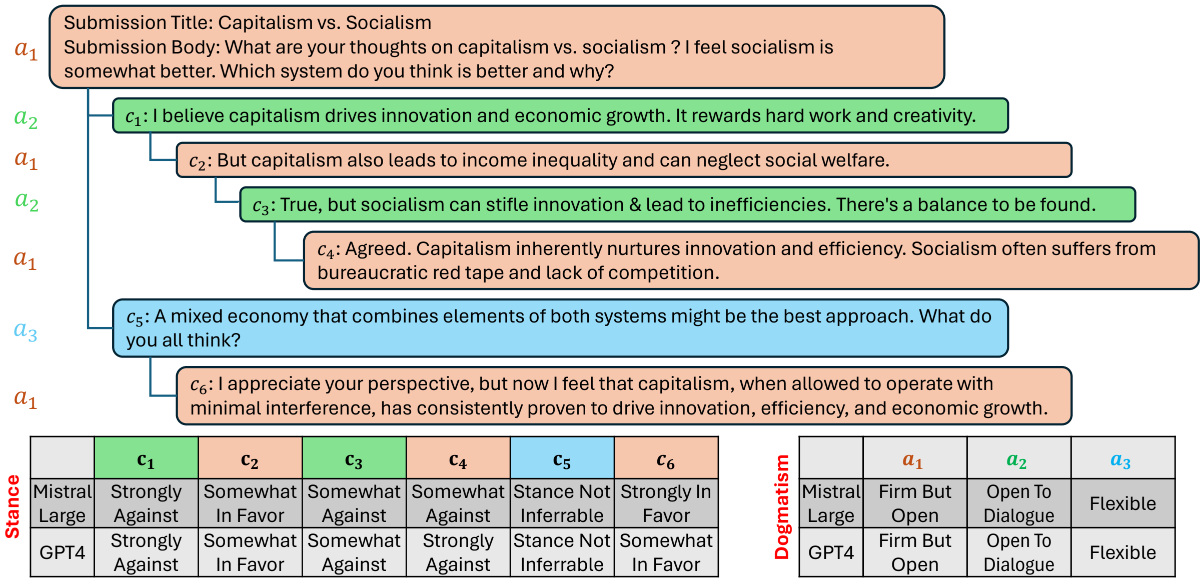


Submission Title: Capitalism vs. Socialism
Submission Body: What are your thoughts on capitalism vs. socialism ? I feel socialism is somewhat better. Which system do you think is better and why?

c_1: I believe capitalism drives innovation and economic growth. It rewards hard work and creativity.

c_2: But capitalism also leads to income inequality and can neglect social welfare.

c_3: True, but socialism can stifle innovation & lead to inefficiencies. There's a balance to be found.

c_4: Agreed. Capitalism inherently nurtures innovation and efficiency. Socialism often suffers from bureaucratic red tape and lack of competition.

c_5: A mixed economy that combines elements of both systems might be the best approach. What do you all think?

c_6: I appreciate your perspective, but now I feel that capitalism, when allowed to operate with minimal interference, has consistently proven to drive innovation, efficiency, and economic growth.

Stance

	c_1	c_2	c_3	c_4	c_5	c_6
Mistral Large	Strongly Against	Somewhat In Favor	Somewhat Against	Somewhat Against	Stance Not Inferrable	Strongly In Favor
GPT4	Strongly Against	Somewhat In Favor	Somewhat Against	Strongly Against	Stance Not Inferrable	Somewhat In Favor

Dogmatism

	a_1	a_2	a_3
Mistral Large	Firm But Open	Open To Dialogue	Flexible
GPT4	Firm But Open	Open To Dialogue	Flexible

Figure 1: Sample Reddit conversation on "Capitalism vs. Socialism" with Stance (for every comment $\{c_i\}_{i=1}^{6}$) and Dogmatism (for every author $\{a_j\}_{j=1}^{3}$) labels from Mistral Large and GPT-4. The submission content favors socialism and examines how the authors position their opinions regarding socialism vs. capitalism.

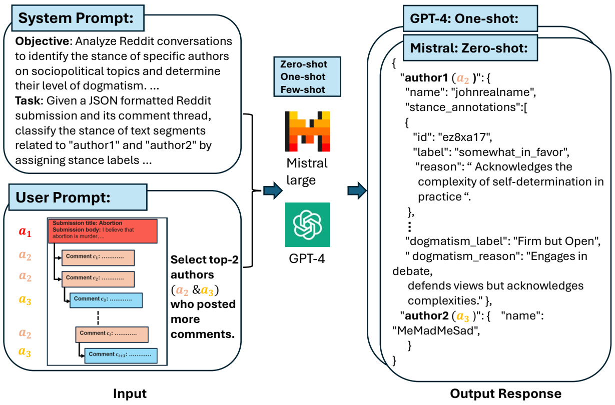
several prior studies have explored stance and dogmatism at the post level, and numerous datasets exist for analyzing individual user posts (Fast and Horvitz, 2016; Sakketou et al., 2022; Villa-Cox et al., 2020; Li et al., 2023; Niu et al., 2024), these typically involve random subsampling or selecting posts with a limited number of tokens, treating each post as independent. Consequently, the comprehensive exploration of a specific user's opinion fluctuations within an entire conversational thread remains underexplored.

Crowdsourcing is one possible approach to address the need for a suitable dataset. However, manually annotating datasets for user opinions is time-consuming and costly, as annotators must read entire conversations to label each user's posts. Additionally, manual annotation often faces challenges related to quality, as accurately labeling opinions requires understanding demographic details and domain-specific knowledge. Given these limitations, achieving a comprehensive and accurate set of user opinions corresponding to posts about a topic often requires multiple annotators or iterative rounds of annotation. Since users can change their opinion (often with subtle transitions and not with explicit statements) within a conversation, tracking such changes across multiple users manually becomes very cumbersome.

Recently, large language models (LLMs) (Touvron et al., 2023a,b; Jiang et al., 2023; Zhang et al., 2023b), especially those built on Transformer architectures (Vaswani et al., 2017) and pretrained on large datasets, have resulted in state-of-the-art accuracies on several complex natural language processing (NLP) tasks (Brown et al., 2020; Chung et al., 2024). LLMs are also frequently used for synthetic dialog response generation (Zhang et al., 2020; Bao et al., 2019; Roller et al., 2021; Adiwardana et al., 2020). Given the complex and cumbersome nature of conversation understanding, we hypothesize that LLMs can effectively capture the nuances involved in understanding user opinions and their shifts in multi-user conversational contexts. Furthermore, since these models possess long-range memory capabilities, we believe they can reason over extended conversational threads involving numerous participants, as good as human annotators, if not better.

We leverage LLMs like Mistral Large (Jiang et al., 2023) and GPT-4 (OpenAI, 2023) to perform two tasks: i) User Stance classification, which involves labeling a user's stance of a post in a conversation on a five-point scale; ii) User Dogmatism classification, which deals with labeling a user's overall opinion in the conversation on a four-point scale. In addition to the class labels, we also obtain the reasoning behind the selection of each label. We experiment with these two models as human-like annotators, generating user opinions in full-length, multi-user Reddit conversations in zero-shot, one-shot, and few-shot setups. Thus, for every sample, we obtain annotations in six settings ({Mistral Large, GPT-4}×{zero-shot, one-shot, few-shot}). Fig. 2 presents our LLM-based annotation pipeline for user-level Stance and Dogmatism tasks. We consider majority voting over these six settings as our final annotations. This approach enables us to curate our USDC (user stance and dogmatism in conversations) dataset, which consists of 764 multi-user conversations from 22 subreddits, including 1,528 user-level dogmatism samples and 9,618 stance samples across all posts from selected users. Annotations in USDC highlight specific user opinions in each post related to stance, track opinion fluctuations leading to dogmatism, and provide reasoning about why users hold specific opinions.

We conduct a comprehensive evaluation of USDC



Objective: Analyze Reddit conversations to identify the stance of specific authors on sociopolitical topics and determine their level of dogmatism. ...
Task: Given a JSON formatted Reddit submission and its comment thread, classify the stance of text segments related to "author1" and "author2" by assigning stance labels ...

User Prompt:
a_1
Submission title: Abortion
Submission body: I believe that abortion is murder....
a_2
Comment c_1: ....
a_2
Comment c_2: ....
a_3
Comment c_3: ....
a_2
Comment c_i: ....
a_3
Comment c_{i+1}: ....
Select top-2 authors (a_2 &a_3) who posted more comments.
Input
Zero-shot
One-shot
Few-shot
Mistral large
GPT-4
GPT-4: One-shot:
Mistral: Zero-shot:
Output Response

```
{
  "author1 (a2 )": {
   "name": "johnrealname",
   "stance_annotations":[
   {
     "id": "ez8xa17",
     "label": "somewhat_in_favor",
      "reason": " Acknowledges the
       complexity of self-determination in
       practice ".
    },
    ⋮
   "dogmatism_label": "Firm but Open",
   " dogmatism_reason": "Engages in
debate,
    defends views but acknowledges
    complexities." },
  "author2 (a3 )": {   "name":
"MeMadMeSad",
    }
}
```

Figure 2: Generating annotations using LLMs: We pass the entire conversation for each Reddit thread as JSON. The JSON includes top two authors who posted most comments, alongside annotation guidelines for stance and dogmatism labels in system prompt.

by incorporating human annotations on 200 test conversations and measuring inter-annotator agreement between LLM and human annotations. When we compare LLM-generated annotations with human annotations, it becomes evident that the "lost in the middle" phenomenon (Liu et al., 2024) is marginal in LLMs, whereas human annotators maintain a steady understanding and agreement throughout the conversation, regardless of its length or complexity. Additionally, our "recency bias" (Peysakhovich and Lerer, 2023) analysis shows that LLMs rely heavily on full context to maintain better inter annotator agreement with human annotators.

USDC addresses several weaknesses of existing post level stance and dogmatism datasets. First, the full-length multi-user conversation aspect of USDC enables it to capture contextual and opinion shifts of multiple users. This feature allows it to serve as both an instruction-tuning user opinion dataset and an evaluation benchmark. We believe that the ability to perform instruction-tuning for user opinions at a large scale can bridge the gap between open-source and commercial user trait understanding models. Additionally, the in-context learning annotations using state-of-the-art LLMs in USDC make it a more comprehensive measure of how current LLMs understand complex tasks like capturing opinions. Further, the USDC dataset offers several use cases that extend its value in various domains, including, (i) Improving moderation tools, (ii) Analyzing public opinion dynamics, (iii) Enhancing dialogue systems and (iv) Creating dynamic contextual user representations. These aspects make it a valuable resource, especially for social media agents seeking deeper insights into user behavior.

To demonstrate the utility of USDC, we utilize our dataset to fine-tune and instruction-tune open-source small language models (SLMs) for generating stance and dogmatism labels for users. We experiment with three pretrained SLMs like LLaMA-2-7B, LLaMA-3-8B (Touvron et al., 2023b), and Falcon-7B (Almazrouei et al., 2023). We also experiment with four instruction-tuned SLMs like LLaMA-2-chat-7B, LLaMA-3-8B-instruct, Vicuna-7B-v.1.5, and Falcon-7B-instruct.

We make the following contributions: 1) We introduce USDC, a dataset of user stance and dogmatism in conversations. 2) We provide human annotations on 200 test conversations, achieving inter-annotator agreement scores of 0.49 for stance and 0.50 for dogmatism, indicating a reasonable level of consistency between human and LLM annotations. 3) We benchmark initial results for the stance and dogmatism tasks using seven SLMs for UDSC. We find that stance performance improves with instruction-tuning (F1-score of 56.2) compared to finetuning (F1-score of 54.9). However, dogmatism performs worse with instruction-tuning (F1-score of 49.2) compared to finetuning (F1-score of 51.4), highlighting the complexity of this task. 4) We apply transfer learning by fine-tuning SLMs on USDC and assessing their performance on existing post-level stance datasets, like SPINOS, MT-CDS, and Twitter-stance. We find that our transfer learning results are either comparable to or outperform prior studies. 5) We make the code, models and dataset publicly available[1].

2 Related Work

Post level stance and dogmatism. Previous stance detection studies have primarily focused on evaluating stances within individual posts of users or through multi-party discussions on some specific topic in social media interactions (Villa-Cox et al., 2020; Sakketou et al., 2022; Li et al., 2023; Niu et al., 2024). Sakketou et al. (2022) introduced the post level Stance dataset, SPINOS, where each post is considered independently, without including submission posts for context, which affects the labeling by annotators. Recently, the MT-CSD dataset, introduced by Niu et al. (2024), addresses stance detection in multi-turn conversations with multiple targets, addressing different aspects of stance detection while the focus is on the multi-party discussions. In contrast to these two studies, Villa-Cox et al. (2020) specifically focus on extracting stances (denying vs. supporting opinions) from replies and quotes on controversial issues in Twitter conversations. Li et al. (2023) focus on target-specific stance detection, where the goal is to classify individual posts or comments into a stance class related to a specific issue, such as COVID-19 vaccination. From the above studies, we clearly observe that these works focus more on stance detection at the post level, while our work emphasizes user-level opinion fluctuations. Additionally, the prior studies are limited in scope, targeting specific issues (5 topics in (Villa-Cox et al., 2020), 1 topic in (Li et al., 2023)), whereas USDC covers a broader range of general subreddits across 22 different topics.

Similar to post level stance datasets, Fast and Horvitz (2016) predicted user dogmatism on randomly sampled Reddit posts from conversations, with each post limited to 200-300 characters. One major limitation of this work is the unavailability of a public dataset, and the treatment of each post as independent. Overall, all these prior studies contrast with the USDC dataset, which focuses on tracking user-level opinions across long, multi-user conversations, capturing the evolution of stance and dogmatism over extended discussions rather than just on a specific target issues.

Generating annotations for NLP tasks using LLMs. Our work also relates to a growing body of literature suggesting that LLMs can perform similarly to human annotators in labeling complex NLP tasks (Zhou et al., 2022; Zhang et al., 2023a; Bansal and Sharma, 2023; Lowmanstone et al., 2023; Wadhwa et al., 2023; Honovich et al., 2023; Zheng et al., 2024; Ye et al., 2022a; Meng et al., 2022). Several studies have explored LLM-based annotation generation in zero- or few-shot task settings (Ye et al., 2022a; Meng et al., 2022; Ye et al., 2022b), while others have compared pairs of language models to assess the quality of annotations generated by these LLMs (Zheng et al., 2024). However, these studies focused on generating annotations for NLP tasks such as sentiment analysis, natural language inference (Gilardi et al., 2023; Alizadeh et al., 2023), or creating synthetic dialogues, but only for dyadic conversations (Lee et al., 2023). Our approach complements these previous studies by focusing on generating annotations of user opinions in complex multi-user conversations.

3 USDC Dataset Curation

3.1 Collection of Reddit Conversation Threads

Initial crawl. We crawl a year (2019) of multi-user conversation data from 22 subreddits of Reddit using praw API [2]. This dataset includes submissions and all associated user comments. Each submission, which serves as the initial message of the conversation, contains a title and content body. This is followed by comments and replies to the submission or other comments. Overall, we crawled 3,619 Reddit conversations across the 22 subreddits. A sample Reddit thread is shown in Fig. 1.

Quality filtering of conversations. Since submission content on Reddit can sometimes include videos, we perform the following filtering steps. 1) We only consider submissions where the content is text. 2) We remove conversations with [deleted] tags and empty content. 3) We exclude conversations where the posts were discarded by users or removed by moderators.

Reddit user conversations can be very long, and we observed up to 591 comments in a single crawled conversation data. Considering the maximum sequence length allowed by various language models, we retained only those conversations that contain at least 20 and, at most, 70 comments, as shorter conversations (fewer than 20 comments) are insufficient for accurately gauging user opinions. Further, we ensure that at least two users covering ∼50% of the comments in the conversations. We did not remove any comments or reduce the post length in the selected conversations. Out of the initial 3,619 conversations, these filtering steps result into 764 conversations getting selected. Table 3 in the Appendix A shows detailed subreddit level statistics.

3.2 Obtaining LLM Annotations

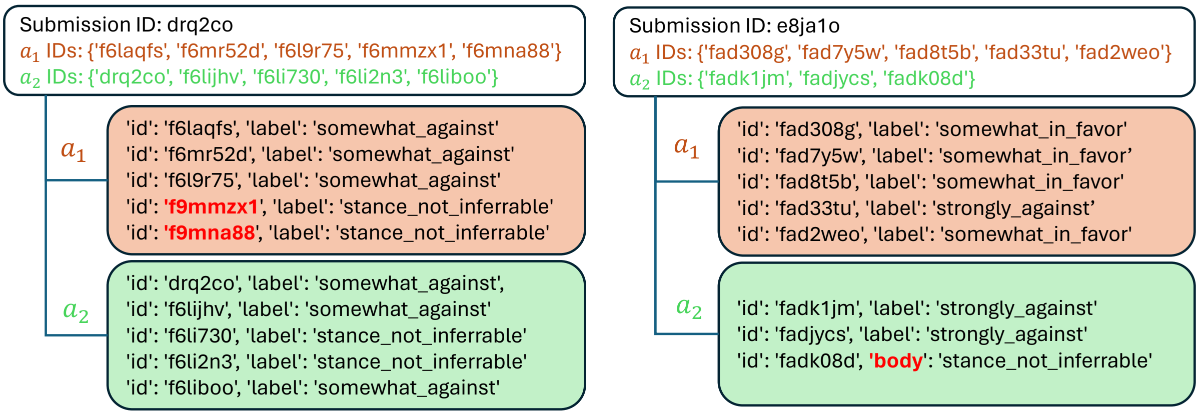
Representing Reddit conversations in JSON format. To create the prompt, we follow the nested hierarchical structure of Reddit conversations to maintain the context. Specifically, we maintain a JSON structure for each conversation, where each author has their post IDs, and comments or replies are available in the body section. An example of a Reddit conversation in JSON format is provided in Appendix B. Note that the JSON explicitly includes the top-2 authors who posted the most comments in the conversation, and their respective post IDs. Our emphasis on these top-2 users (covering 47% posts of total posts on average) aimed at accurately assigning Stance and Dogmatism labels, acknowledging the challenge of modeling a user's opinion belief based on a very limited number of posts within a conversation.

Using LLMs as human-like annotators. To annotate the stance of a user towards a submission at each individual post and to assess the overall level of dogmatism expressed by the user throughout the conversation, we employ two well-known commercialized API-based LLMs: GPT-4 (OpenAI, 2023) and Mistral Large (Jiang et al., 2024). OpenAI GPT-4 is a decoder-based language model with a context window of 32k to 128k tokens. Mistral Large features a context window of 32k tokens. Additionally, we examined other versions of these models, such as GPT-3.5 and Mistral-small and medium, but found that these models failed to produce annotations in the desired format. We briefly discuss these limitations, along with the situations where LLMs are prone to errors, in Appendix C.

For both GPT-4 and Mistral Large, we supplied a system prompt that contains the definitions of Stance and Dogmatism, guidelines for annotating each user conversation, and the necessary labels for Stance and Dogmatism, as shown in Fig 2. The system prompt is detailed in the Appendix D. Along with the system prompt, we provided a user prompt comprising the entire user conversation in a structured JSON format, as discussed above. Additionally, we prompted the model to generate reasoning for each label, explaining why the LLMs assigned a particular label to a specific user post. We used zero-shot, one-shot, and few-shot settings to get the LLM-based annotations. For the few-shot setting, we added two examples in the prompt. Samples of generated outputs using GPT-4 in zero-shot, one-shot, and few-shot settings are shown in Appendix F.1, F.2, F.3 respectively. Similarly, samples of generated outputs using Mistral Large in zero, one, and few-shot settings are shown in Appendix F.4, F.5, F.6 respectively.

Annotation tasks. We prompt the LLMs to perform two annotation tasks: 1) Stance detection, which determines if a user comment or post is *Strongly In Favor*

[2] `https://github.com/praw-dev/praw`



```
Submission ID: drq2co
a1 IDs: {'f6laqfs', 'f6mr52d', 'f6l9r75', 'f6mmzx1', 'f6mna88'}
a2 IDs: {'drq2co', 'f6lijhv', 'f6li730', 'f6li2n3', 'f6liboo'}
```

```
'id': 'f6laqfs', 'label': 'somewhat_against'
'id': 'f6mr52d', 'label': 'somewhat_against'
'id': 'f6l9r75', 'label': 'somewhat_against'
'id': 'f9mmzx1', 'label': 'stance_not_inferrable'
'id': 'f9mna88', 'label': 'stance_not_inferrable'
```

```
'id': 'drq2co', 'label': 'somewhat_against',
'id': 'f6lijhv', 'label': 'somewhat_against'
'id': 'f6li730', 'label': 'stance_not_inferrable'
'id': 'f6li2n3', 'label': 'stance_not_inferrable'
'id': 'f6liboo', 'label': 'somewhat_against'
```

```
Submission ID: e8ja1o
a1 IDs: {'fad308g', 'fad7y5w', 'fad8t5b', 'fad33tu', 'fad2weo'}
a2 IDs: {'fadk1jm', 'fadjycs', 'fadk08d'}
```

```
'id': 'fad308g', 'label': 'somewhat_in_favor'
'id': 'fad7y5w', 'label': 'somewhat_in_favor'
'id': 'fad8t5b', 'label': 'somewhat_in_favor'
'id': 'fad33tu', 'label': 'strongly_against'
'id': 'fad2weo', 'label': 'somewhat_in_favor'
```

```
'id': 'fadk1jm', 'label': 'strongly_against'
'id': 'fadjycs', 'label': 'strongly_against'
'id': 'fadk08d', 'body': 'stance_not_inferrable'
```

Figure 3: Failure cases of LLMs: Mistral Large few-shot output (left), the ids ("f6mmzx1","f6mna88") were mismatched with generated ids ("f9mmzx1","f9mna88"), GPT-4 zero-shot output (right), the key "label" was mismatched with generated key "body".

(SOIF), *Strongly Against* (SOA), *Stance Not Inferrable* (SNI), *Somewhat In Favor* (SIF), or *Somewhat Against* (SGA) towards specific subreddit submission content; Our 5-class stance detection scheme is inspired by the SPINOS dataset proposed by Sakketou et al. (2022). These labels provide a fine-grained analysis similar to sentiment labels, allowing for a more detailed understanding of user opinions. 2) Dogmatism identification, which evaluates the user's overall opinion in conversation and categorizes them into one of four categories: *Firm but Open*, *Open to Dialogue*, *Flexible* or *Deeply Rooted*. Our 4-class dogmatism task is inspired by Fast and Horvitz (2016), where the authors reported ratings that correspond to each level of dogmatism. We have adopted similar definitions for dogmatism labels and incorporated them into our system prompts to ensure consistency and accuracy in our annotations. This assessment reveals whether users are open to changing their beliefs or remain steadfast in their opinions based on interactions with other users.

Addressing failures in JSON parsing of LLM response. Sometimes, LLMs get confused with the author IDs and miss their Stance labels (Fig. 3 (left)). Sometimes, there were minor errors in key naming ('label' vs 'body' in Fig. 3 (right)). We observed such errors in ∼15 cases across LLM setting. We manually fixed JSON parsing errors and corrected author IDs for associated Stance labels.

Majority voting conflict. After obtaining six annotations ({Mistral Large, GPT-4}×{zero, one, and few-shot}) for each sample, we follow the two step process to obtain final gold annotations. (i) Majority voting: we aggregate using majority voting (i.e label that appears most frequently across models) to determine the final gold annotations for the Stance and Dogmatism tasks. (ii) Handling situations with no clear majority: when generating annotations using both GPT-4 and Mistral Large, it is possible that the two models might provide different annotations for the same conversation. In these cases, we use the annotation provided by GPT-4 in the few-shot setting as the deciding factor or "gold standard". We chose to prioritize GPT-4 few-shot annotations because human annotations have better IAA agreement with GPT-4 few-shot. Further, few-shot models, which are fine-tuned with a small amount of task-specific data, often provide more accurate and contextually relevant annotations.

Class distributions for stance task is as follows: 3117 (somewhat in favour), 2266 (stance not inferrable), 1998 (somewhat against), 1303 (strongly against) and 640 (strongly in favor). For dogmatism task, the distribution is as follows: 666 (open to dialogue), 653 (firm but open), 140 (deeply rooted), and 69 (flexible). We present the class distributions obtained from each model with the 3 settings (zero, one, and few-shot) for both the tasks in Figs. 4 and 5, respectively, in Appendix A.

3.3 Inter-annotator Agreement with LLMs as Annotators

As the quality of labeling on subjective tasks is challenging, we validate the inter-annotator agreement (IAA) between the two LLMs in three settings (GPT-4 Zero-shot, GPT-4 One-shot, GPT-4 Few-shot, Mistral Large Zero-shot, Mistral Large One-shot, and Mistral Large Few-shot) for the Stance and Dogmatism tasks. We perform IAA using two approaches: i) Cohen's kappa score (Cohen, 1960) and ii) Fleiss' kappa score (Fleiss, 1971). Cohen's kappa measures the agreement between two raters, while Fleiss' kappa extends this to multiple raters. Hence, we employed Cohen's kappa for pairwise comparisons and Fleiss' kappa for overall agreement across all models.

Fig. 6 in the Appendix A shows pairwise Cohen's kappa values for both tasks. We observe that Cohen's kappa values range from 0.36 to 0.72 for stance and 0.31 to 0.61 for dogmatism, indicating moderate agreement between the models. Broadly, kappa values are higher for model pairs within a family (GPT-4 or Mistral Large). Thus, the large variance in the kappa scores is not due to the various in-context learning settings (ZS, OS, FS) but rather due to architectural differences.

The overall Fleiss' kappa value was calculated as 0.485 for stance and 0.435 for dogmatism, suggesting moderate agreement among all six settings. Comparing LLM IAA with previous studies, we observe that for dogmatism, the LLM IAA of 0.435 matches with 0.44 as mentioned in (Fast and Horvitz, 2016). Similarly, for Stance, the LLM IAA of 0.485 is much higher than 0.34 as reported in (Sakketou et al., 2022). This suggests that LLMs can be considered as competent annotators for complex subjective tasks.

3.4 USDC Test Dataset Evaluation with Human Labels

Due to the time-consuming nature of the manual annotation process, we perform human annotations on a set of 200 test conversations. In the forms for human annotations, we displayed the top 2 authors Reddit posts from the conversation, along with the submission title and content. We also provided a link to the original Reddit URL so that annotators could look at the full conversation. We provided detailed annotation guidelines (similar to the ones mentioned in the prompt in Appendix D) to instruct human annotators in carrying out these tasks.

With three human annotators on a sample of 200 conversations, as shown in Appendix N Fig. 20, we achieved an inter-annotator agreement score of 0.49 for the stance detection and 0.50 for dogmatism tasks, indicating a reasonable level of consistency between human and LLM annotations. The annotators included two males and one female, affiliated with academia and industry, aged between 20 and 40, who were very familiar with Reddit topics. We calculated the inter-annotator agreement among the three human annotators themselves. Tables 12 and 13 in Appendix O report the IAA scores for both stance and dogmatism tasks among the human annotators. The results showed an agreement of 0.57 for the stance and 0.52 for the dogmatism. These findings demonstrate the level of consistency among human annotators, providing a more comprehensive understanding of the alignment between LLM-generated labels and human judgments.

4 Training SLMs

We train three pretrained SLMs (LLaMA-2-7B, LLaMA-3-8B, Falcon-7B) and four instruction-tuned SLMs (LLaMA-2-chat-7B, LLaMA-3-8B-instruct, Vicuna-7B-v.1.5, and Falcon-7B-instruct). We finetune and instruction-tune these models using the proposed USDC dataset. We use pretrained model checkpoints from Hugging Face (Wolf et al., 2020). All of these LLMs have a context length of 4096 tokens. Model details and hyper-parameter settings are in Appendix G.

Train-test setup. We conduct both finetuning and instruction-tuning of SLMs. We divide the dataset of 764 conversations into train ($\sim$ 75%) and test splits ($\sim$ 25%). The training dataset comprised 564 conversations, including 1128 samples of dogmatism labels and 7520 samples of stance labels. Conversely, the testing dataset consisted of 200 conversations, with 400 samples of dogmatism labels and 1831 samples of stance labels across two authors posts.

Finetuning of SLMs. For Stance classification, we treat each user post as an independent sample. In contrast, for the dogmatism classification, we consider the entire user conversation as a single sample by concatenating all the threads from a user in that conversation. To load the pretrained SLMs, we perform 4-bit quantization, and we finetune the models by apply the LoRA technique (Hu et al., 2021), with SFTT before saving the finetuned model. For finetuning, we used prompt for Stance classification as shown in Fig. 7 (see Appendix E). Similarly, Fig. 8 (see Appendix E) displays prompt for Dogmatism identification.

Instruction-tuning of SLMs. We instruction-tune the SLMs on user conversations along with their gold labels from the training part of the USDC dataset. For instruction-tuning, we use the same prompt as used for LLMs to generate the USDC dataset (also shown in Appendix D). Similar to finetuning, we use same train-test splits for instruction-tuning.

5 Results

Baseline (un-fine-tuned) model performance and what constitutes a "reasonable" F1 score? To establish a reasonable F1-score benchmark for fine-tuning and instruction-tuning (discussed in the next subsections), we evaluated the un-fine-tuned SLMs, GPT-4 and Mistral Large, in few-shot settings. This evaluation includes both stance and dogmatism tasks, using majority voting to enhance reliability. The results are summarized in the Tables 4, 5, 6 and 7 in Appendix H. We make the following observations: (i) Majority Voting generally provides a slight improvement over individual few-shot configurations, which suggests the value of combining predictions from multiple models. (ii) The difference between GPT-4 and Mistral Large in un-fine-tuned few-shot settings is relatively small, indicating that both models are fairly comparable in performance on these tasks when using the LLaMa-3-8B model.

As shown by the un-fine-tuned model's performance for stance classification in Table 6, an overall accuracy of 0.311 and F1 scores as low as 0.06 for certain classes, the baseline for this task is relatively low. Similarly, for dogmatism in Table 7, an overall accuracy of 0.40 and F1 scores as low as 0.00 for certain classes. In this context, an F1 score that significantly improves upon this baseline—especially if it approaches or exceeds 50%—could be considered reasonable.

Do SLMs finetuned with task-specific LLM annotations accurately perform Stance and Dogmatism tasks on user opinions?

We show the weighted F1 of various SLMs finetuned with task-specific LLM annotations on the stance and dogmatism detection tasks on the USDC test set in Table 1. We report AUC scores and other qualitative analysis in Appendix I (Fig. 10 and 11). We make the following observations from these results: 1) Compared to the baseline, while the un-fine-tuned models show moderate performance, the fine-tuned models nearly double their F1 scores, particularly for the Stance task. Even for dogmatism tasks, we saw better improvement in F1-score after fine tuning. 2) For both tasks when finetuning, the majority voting labels as ground truth has a relatively high performance, scoring above 50% weighted F1-score across several (7/7 for stance and 2/7 for dogmatism) models. 3) Finetuned LLaMa-3 models (LLaMA-3-8B and LLaMA-3-8B-instruct) perform better across both tasks. 4) For GPT-4 annotations, in most cases, SLMs finetuned with few-shot annotations outperform those trained with zero and one-shot annotations. For Mistral Large annotations, SLMs finetuned with one-shot annotations perform the best. 5) Specifically, for the stance detection task, Vicuna-7B-v.1.5 finetuned using few-shot annotations is the best model trained with GPT-4 annotations. Similarly, LLaMA-3-8B-instruct finetuned with one-shot annotations is the best model trained with Mistral Large annotations. 6) For the dogmatism detection task, LLaMA-3-8B-instruct finetuned using few-shot annotations is the best model trained with GPT-4 annotations. Similarly, LLaMA-2-chat-7B finetuned with one-shot annotations is the best model trained with Mistral Large annotations. 7) Overall, we observe that instruction-tuned SLMs perform better than the pretrained SLMs.

Do SLMs instruction-tuned with task-specific LLM annotations perform better than SLMs finetuned with task-specific LLM annotations for the Stance and Dogmatism tasks? We show the weighted F1 of various SLMs instruction-tuned with task-specific LLM annotations on the stance and dogmatism detection tasks on the USDC test set in Table 1. We report AUC scores and other qualitative analysis in Appendix J (see Fig. 12). We make the following observations from these results: 1) SLMs with instruction-tuning result in higher weighted F1-scores than SLMs with finetuning for stance detection, while SLMs with finetuning outperform SLMs with instruction-tuning in dogmatism detection. 2) Contrary to finetuning results, instruction-tuning results demonstrate that using majority voting labels as ground truth, SLM instruction-tuning yields relatively high performance only for the stance detection task, but not for the dogmatism detection. 3) Similar to finetuning results, LLaMA-3 models (LLaMA-3-8B and LLaMA-3-8B-instruct) perform better across both tasks. Additionally, GPT-4 annotations yield the best results in the few-shot setting, while Mistral Large annotations perform best in the one-shot setting.

Overall, we draw the following conclusions when comparing SLM finetuning and instruction-tuning: (1) Since dogmatism detection is inherently a more complex and varied than stance detection, the model might struggle to generalize from the instructional data. (2) The system prompt used in finetuning is much simpler than the original system prompt for instruction-tuning, making it challenging to handle the context length for longer conversations. We perform an error analysis to further analyze the results in the next subsection.

Qualitative Analysis

Error analysis. Table 2 illustrates the confusion matrix for stance detection for LLaMa-3-8B finetuning and instruction-tuning. We make the following observations from this table: 1) For both finetuning and instruction-tuning, there is a significant misclassification between "Somewhat Against" and "Somewhat In Favor," as well as between "Somewhat In Favor" and "Stance Not Inferrable." These overlaps suggest challenges distinguishing moderate stances, indicating a need for enhanced feature representation and clearer class definitions to improve model performance. We report the confusion matrix for dogmatism detection task in Fig. 9 in the Appendix. It shows significant misclassifications, especially for the "Deeply Rooted" and "Flexible" labels, with zero accuracy and F1-scores. On the other hand, the model performs moderately better for "Firm but Open" and "Open to Dialogue" classes with accuracies of 48.7% and 64.4%, respectively. The confusion matrix also indicates substantial confusion to distinguish between intermediate levels of dogmatism, such as "Firm but Open" and "Open to Dialogue". The area under the ROC curve (AUC) measures the model's ability to distinguish between classes. Hence, we further report the ROC curve, which shows the trade-off between the true positive rate (TPR) and false positive rate (FPR) for each class for stance and dogmatism tasks, see Figs. 10 and. 11 in Appendix I.

Lost in the middle. To analyze the "lost in the middle" (Liu et al., 2024) phenomenon in our LLM-based user-stance annotations, for a given user, we divided the data into time segments and calculated inter-annotator agreement (IAA) using Cohen's Kappa scores across different models and settings. The data was segmented based on the submission_id, author_id, and stance_id_timestamp. For each group (i.e., each combination of submission_id and author_id), the timestamps were divided into equal segments. The number of entries for each group was divided by the desired number of segments (3), and the division was done as evenly as possible, with each segment containing a roughly equal number of time-stamped entries. Fig. 13 in Appendix reports the comparison statistics of IAA scores for the stance detection task across initial, middle, and later time stamps. From Fig. 13, we observe that the analysis across different time segments, especially when divided into three segments, clearly demonstrates that the "lost in the middle" phenomenon is marginal.

The partial decrease in inter-annotator agreement during the middle parts of the conversations suggests that as conversations progress, models might face challenges in maintaining consistent agreement; however, the decrease in agreement scores is minimal. The recovery in agreement towards the final segments could indicate that as conversations start to conclude, they become more

		Stance Classification							Dogmatism Classification						
	Model	GPT-4			Mistral Large			Maj	GPT-4			Mistral Large			Maj
		ZS	OS	FS	ZS	OS	FS		ZS	OS	FS	ZS	OS	FS	
Finetuning	LLaMA-2-7B	51.8	52.9	52.7	35.1	49.2	46.0	54.0	42.1	44.2	45.2	39.3	47.6	43.7	43.4
	LLaMA-2-chat-7B	52.8	51.4	51.8	34.7	47.5	46.5	51.3	42.1	42.5	48.8	41.1	49.7	45.5	48.3
	LLaMA-3-8B	51.3	52.2	52.9	34.9	48.5	47.0	**54.9**	42.0	47.8	45.3	39.9	47.4	36.3	**51.4**
	LLaMA-3-8B-instruct	51.2	52.6	52.7	33.9	49.5	45.6	54.5	44.8	46.2	49.7	46.1	45.8	46.1	50.8
	Falcon-7B	50.7	51.1	51.6	34.9	47.2	43.9	53.2	41.5	42.1	43.3	36.5	38.4	37.5	40.1
	Falcon-7B-instruct	51.2	51.5	51.6	35.1	47.7	44.2	51.0	41.7	42.1	42.9	36.8	38.5	36.9	39.7
	Vicuna-7B-v.1.5	51.0	53.0	53.2	35.1	48.5	45.8	54.7	42.9	48.3	40.8	45.9	42.6	46.2	42.3
Instruction-tuning	LLaMA-2-7B	53.2	54.0	54.5	36.8	50.3	47.2	55.5	43.0	45.0	46.3	40.6	48.2	45.0	44.0
	LLaMA-2-chat-7B	54.0	54.5	55.0	36.5	50.7	47.6	54.0	43.2	45.5	47.0	40.8	48.5	45.5	43.8
	LLaMA-3-8B	53.5	54.8	55.5	37.0	50.5	48.0	**56.2**	43.5	46.0	47.5	41.0	48.8	45.8	45.1
	LLaMA-3-8B-instruct	53.0	54.2	55.0	36.0	50.0	47.0	55.5	43.8	46.5	47.8	41.5	**49.2**	46.0	44.8
	Falcon-7B	52.8	53.4	54.0	36.5	49.5	46.5	54.8	42.5	44.6	45.8	39.8	47.0	44.0	43.8
	Falcon-7B-instruct	53.0	53.8	54.2	36.8	49.8	46.8	54.5	42.8	44.8	46.0	40.0	47.2	44.2	43.0
	Vicuna-7B-v.1.5	53.3	54.5	55.2	37.0	50.2	47.8	55.2	43.7	46.8	47.2	41.2	48.2	46.5	44.8

Table 1: Finetuning and instruction-tuning results: weighted F1-score for Stance and Dogmatism classification using SLMs on USDC test set. ZS: Zero-shot, OS: One-shot, FS: Few-shot. Maj=Majority.

		Predicted				
		SOA	SOIF	SNI	SGA	SIF
Actual	SOA	151	132	34	44	2
	SOIF	93	537	113	17	14
	SNI	23	78	259	5	0
	SGA	52	35	13	115	17
	SIF	18	50	12	25	27

		Predicted				
		SOA	SOIF	SNI	SGA	SIF
Actual	SOA	143	125	37	54	4
	SOIF	82	543	106	27	16
	SNI	22	82	253	6	2
	SGA	41	35	11	131	14
	SIF	16	53	10	23	30

Table 2: Confusion matrix for LLaMa-3-8B Stance detection on USDC (test): finetuning (top) instruction-tuning (bottom)

focused, or that the models are better able to align on concluding statements. This trend underscores the importance of considering segment-based analysis when evaluating model performance over long-form conversations. When comparing the model-generated annotations with human annotations, it becomes evident that we do not encounter the "lost in the middle" problem. The human annotations demonstrate a consistent level of inter-annotator agreement (IAA) across all three segments—initial, middle, and final. This suggests that human annotators maintain a steady understanding and agreement throughout the conversation, regardless of its length or complexity.

Recency bias phenomenon (prior context vs. full context). To investigate the impact of recency bias (Peysakhovich and Lerer, 2023) on LLM performance in user-stance annotations, we focused on verifying model annotations by examining the prior context for a given user, rather than considering the entire conversation. The goal was to determine whether assessing each response within its immediate context, followed by aggregation, would yield different results compared to analyzing the full conversation context. Further details about the prior context annotations using LLMs are discussed in Appendix N. Fig. 14 in Appendix L reports IAA scores, which contains a matrix of Cohen's Kappa scores across different models and settings, including GPT-4 Few-Shot (FS), Mistral Large FS, Majority Voting, as well as GPT-4 FS PC and Mistral Large FS PC (here, PC denotes prior context). From the figure, we observe that The agreement between GPT-4 FS and Majority Voting is higher when the full conversation is considered (0.75) compared to when only prior context is used. The agreement between GPT-4 FS PC and Mistral Large FS PC (both based on prior context) is lower than when using the full context, indicating that prior context alone may not capture all the necessary nuances for consistent annotation.

Human agreement. The comparison of human annotations with models like GPT-4 FS and Mistral Large FS shows that human annotators also rely heavily on the full conversation context to maintain agreement. The results from this additional experiment, supported by the data in Fig. 14 in Appendix, suggest that while prior context can provide some useful insights, it is not as effective as considering the entire conversation context for maintaining high inter-annotator agreement. In summary, the experiment highlights the importance of full context in LLM-based annotations and suggests that while recency can influence model performance, it should be supplemented with the entire conversation context to ensure higher accuracy and agreement.

Transfer learning evaluation of models trained on USDC. To evaluate the quality of LLM-generated annotations, the annotators labeled 200 conversations and transfer learning is applied by fine-tuning the SLMs on the USDC dataset. We subsequently tested the model's performance on several existing stance datasets, including SPINOS (Sakketou et al., 2022), MT-CDS (Niu et al., 2024), and the Twitter stance dataset (Villa-Cox et al., 2020). We observe that performance of models trained using USDC is better or comparable to that of models trained using individual datasets themselves. Detailed results and analysis of results for the three datasets are reported in Appendix M.

6 Discussion & Conclusion

We introduced USDC, a large-scale dataset of user stance and dogmatism in conversations, leveraging LLMs as human-like annotators. This dataset is used for various applications, including analyzing public opinions, enhancing dialogue systems, improving content moderation tools by identifying and flagging dogmatic or polarizing users in online discussions, and generating dynamic contextual user representations. The full-length multi-user conversation aspect of USDC allows it to capture the contextual and opinion shifts of multiple users in a conversation. We believe that the ability to perform finetuning or instruction-tuning SLMs for user opinions at a large scale can bridge the gap between SLMs and commercial LLMs for understanding user traits. While finetuning SLMs shows good F1-score on both stance and dogmatism tasks, the F1-score remains below 60% (54.9% for stance and 51.4% for dogmatism). On the other hand, instruction-tuning of SLMs only improves F1-score performance on stance, not the dogmatism task. Further, the performance still falls short of 60%, with weighted F1-scores of 56.2% for stance and 49.2% for dogmatism. These findings indicate that there is still significant room for improvement in understanding user opinions from a text segment. Human evaluation showed an agreement of 0.57 for the stance and 0.52 for the dogmatism tasks between LLM and human annotations. This indicates that LLM-generated annotations in USDC are close to human labels. Transfer-learning on 3 datasets also showed positive results.

7 Limitations

We plan to extend this work along the following directions in the future. 1) We would like to extend this work to multi-lingual conversations and verify how accurately SLMs and LLMs perform on the stance and dogmatism tasks in the multi-lingual scenario. 2) We analyzed user dogmatism based on their posts within a single conversation. This approach could be extended to include posts across multiple conversations and utilize similar profile information if available. 3) We analyzed dogmatism information for only the top two authors. Users with fewer comments often do not provide enough information to accurately assess their stance or dogmatism, as many contribute only one or two comments, which is insufficient to determine their overall opinion or dogmatic nature. Therefore, our study prioritizes the two most active users, who contribute approximately 50% of the comments in each conversation, to better capture opinion fluctuations and provide a more robust analysis of stance and dogmatism.

8 Ethics Statement

Personalized systems rely on understanding users, including their dynamic behavior and shifts in opinion over time. This is particularly relevant for tasks such as identifying changes in a user's dynamic opinion change across an entire conversation. Our study introduces the USDC dataset, which is built using publicly accessible Reddit posts and comments. While Reddit usernames are pseudonymous and not tied to real identities, we have taken additional steps to ensure privacy: the USDC dataset does not include any personal demographic information. We only use post IDs to associate content with users, strictly avoiding any form of user identification. For more details, please refer to Reddit's privacy policy[3].

Language generation grounded in personalized information can enhance the contextual relevance of outputs, such as Stances or opinions expressed on social platforms. However, the methods proposed in this work, though potentially valuable for understanding user behavior and alignment with social norms, should not be misused. We explicitly oppose any applications that could result in discrimination or undermine intellectual freedom (Richards, 2012). USDC enables automatic inference of user stance, dogmatism, and overall opinion dynamics. While such tools may offer benefits in certain contexts, they also present risks if misapplied. The ethical implications of these technologies depend on their use cases. Therefore, we advocate for responsible deployment, where users are made aware of how their data is being used and are given the option to opt out of automated inference or decision-making processes based on these predictions.

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Overview of Appendix Sections

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- Section P Robustness Analysis of Human-LLM Annotations
- Section Q Qualitative Examples Demonstrating Cases with High, Moderate, and Low Inter-annotator Agreement (IAA)
- Section R: Weighted Cohen's Kappa Score: IAA between Human Labels and LLM-generated Labels

A Detailed Statistics of the USDC Dataset

Table 3 shows the detailed statistics of our USDC dataset at the subreddit level. Fig. 4 shows the distribution of stance labels across LLM annotations across zero-shot, one-shot, and few-shot settings. Fig. 5 shows the distribution of dogmatism labels across LLM annotations across zero-shot, one-shot, and few-shot settings.

subreddit	num_conversations	min_total_token_count	max_total_token_count
DebateCommunism	73	529	11557
Abortiondebate	70	1271	7401
CapitalismVSocialism	61	665	16927
prochoice	60	582	7278
brexit	56	637	4553
climateskeptics	56	734	7550
prolife	54	672	13342
gunpolitics	52	683	7889
MensRights	52	623	5774
climatechange	49	520	7427
nuclear	41	572	5282
progun	39	436	3632
NuclearPower	23	629	4589
Vegetarianism	22	627	3958
AntiVegan	20	351	5052
climate	13	701	4678
Egalitarianism	10	665	4060
VeganActivism	8	460	3685
Veganism	2	1332	1738
AnimalRights	1	845	845
animalwelfare	1	1363	1363
GunsAreCool	1	2945	2945

Table 3: Statistics of the User Conversation Dataset.

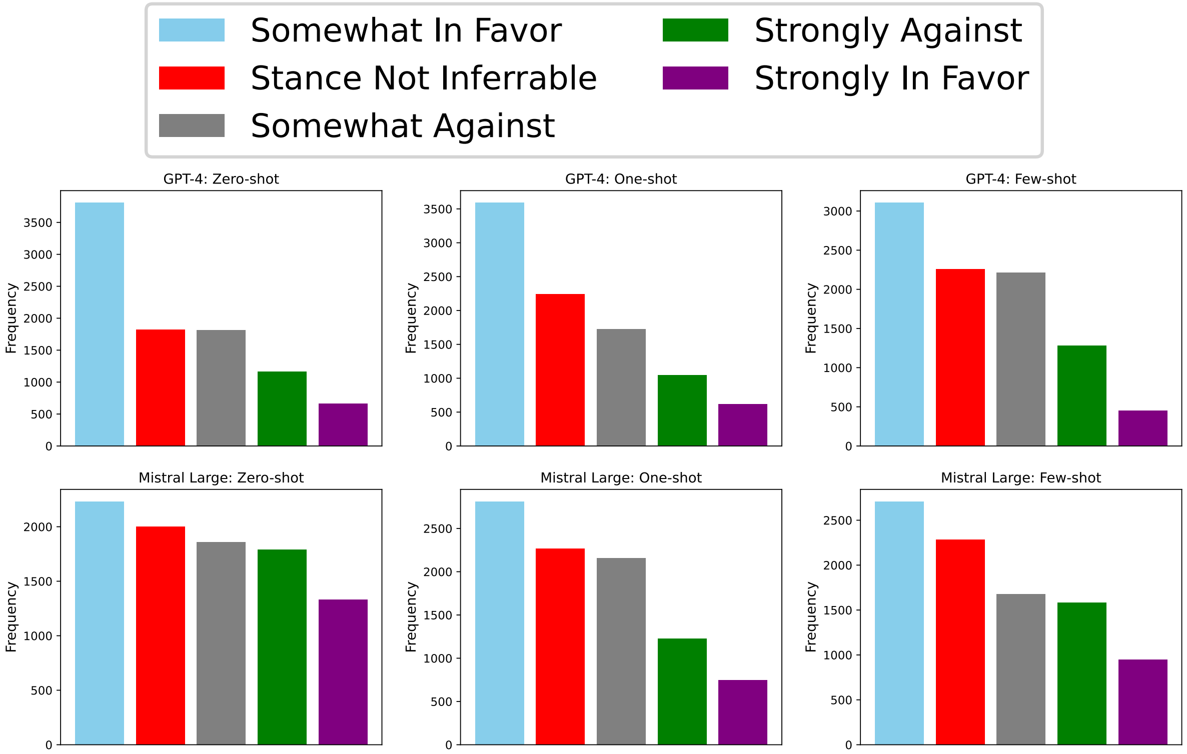


Figure 4: Distribution of Stance labels across LLM annotations in six settings: GPT-4, Mistral Large×Zero-shot, One-shot, Few-shot. Somewhat In Favor is the most frequent class across all six settings, while Strongly In Favor is the least frequent.

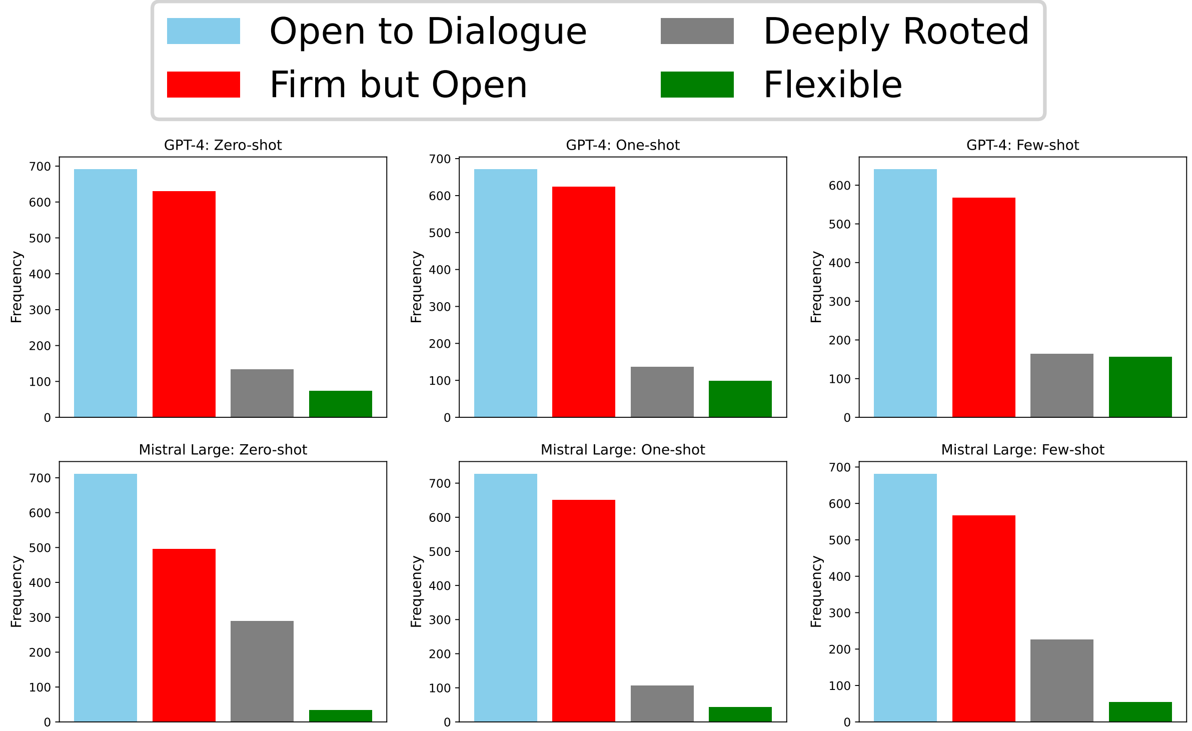
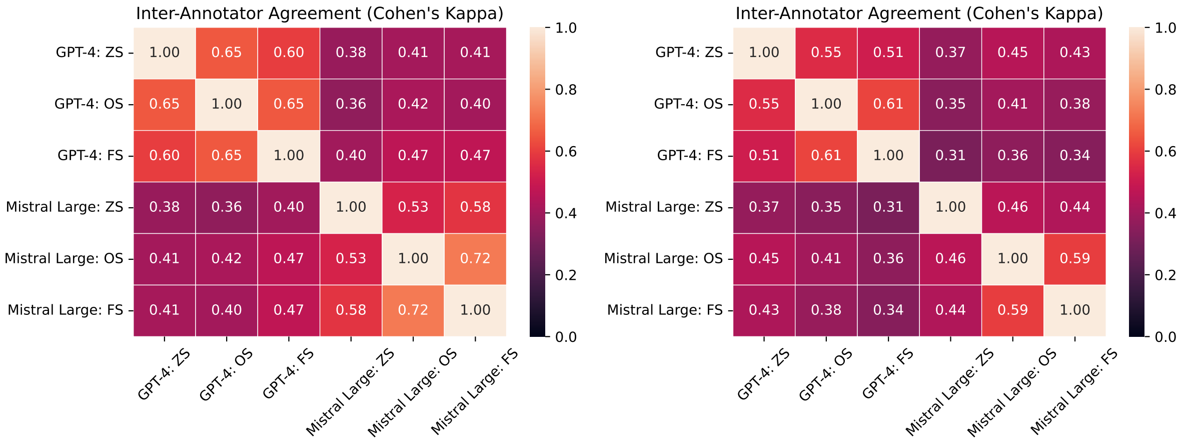


Figure 5: Distribution of dogmatism labels across LLM annotations in six settings: GPT-4, Mistral Large×Zero-shot, One-shot, Few-shot. Open to Dialogue is the most frequent class across all six settings, while Flexible is the least frequent.



	GPT-4: ZS	GPT-4: OS	GPT-4: FS	Mistral Large: ZS	Mistral Large: OS	Mistral Large: FS
GPT-4: ZS	1.00	0.65	0.60	0.38	0.41	0.41
GPT-4: OS	0.65	1.00	0.65	0.36	0.42	0.40
GPT-4: FS	0.60	0.65	1.00	0.40	0.47	0.47
Mistral Large: ZS	0.38	0.36	0.40	1.00	0.53	0.58
Mistral Large: OS	0.41	0.42	0.47	0.53	1.00	0.72
Mistral Large: FS	0.41	0.40	0.47	0.58	0.72	1.00

	GPT-4: ZS	GPT-4: OS	GPT-4: FS	Mistral Large: ZS	Mistral Large: OS	Mistral Large: FS
GPT-4: ZS	1.00	0.55	0.51	0.37	0.45	0.43
GPT-4: OS	0.55	1.00	0.61	0.35	0.41	0.38
GPT-4: FS	0.51	0.61	1.00	0.31	0.36	0.34
Mistral Large: ZS	0.37	0.35	0.31	1.00	0.46	0.44
Mistral Large: OS	0.45	0.41	0.36	0.46	1.00	0.59
Mistral Large: FS	0.43	0.38	0.34	0.44	0.59	1.00

Figure 6: Inter-annotator agreement (IAA): Cohen's Kappa score across six different settings (2 models×3 settings) for Stance (left) and Dogmatism (right) tasks.

B Sample of User Input Prompt

```
"""
Now complete the given task for the respective authors i.e., author1 respective ids
    are ['dhoxyz', 'f3pghji', 'f3tywb4', 'f3uomn2']. author2 respective ids are ['
    f3rt0bf', 'f3rqu2u'] for the data in json format
{
   "id":"dhoxyz",
   "title":"This sub should encourage anti vs. pro-gun discussions instead of
       shutting them down instantly",
   "content":"Honesly, I followed this sub especifically to take part in these
       discussions, but everytime I see a comment that even remotely suggests anti
       gun ideals or a discussion on the subject just gets ignored and downvoted to
       hell. Kind of expecting this to go the same way (my karma anus is ready,
       downvotes) , but I have to hope for healthy discussions on the subject.",
   "comments":[
      {
         "id":"f3p9n2c",
         "body":"I think the problem now is the two sides are at an impasse.
             Everytime there is a "compromise" pro gun loses something. Now days pro
              gun is interpreting the Constitution more literal, which leaves even
             the most mild policies of anti gun as infringements. To further
             compound this anti gun is only considering the most extreme measures. "
             Assault Weapons" bans, mandatory buybacks, red flag laws, etc.. I think
              at this point there is just nothing left to talk about. The middle
             ground is gone.",
         "replies":[
            {
               "id":"f3pati9",
               "replies":[
                  {
                     "id":"f3pdu44",
                     "body":"You are exactly right. I'm done with the idea that
                         there can be real compromise. We should have at least
                         gotten national reciprocity and shall-issue in every state
                         in exchange for what we've given up. Now you have to be a
                         goddamn lawyer to exercise your rights without violating
                         the law."
                  },
                  {
                     "id":"f3rt0bf",
                     "body":"I am prepared for UBCs, if they do this:
                     1. Lower the age to buy handguns to 18, nationwide.
                     2. Repeal the Hughes Amendment:
                     3. A FOPA-like ban on assault weapon bans (what the FOPA did
                         with a registry)
                     4. The punishment for violation is a monetary fine only
                     5. A repeal of the GCA ban on foreign NFA weapons
                     6. A repeal of the National Minimum Drinking Age Act of 1984"
                  }
               ]
            },
            {
               "id":"f3pd55z",
               "body":"Everytime there is a "compromise" pro gun loses something.
                   That and today's compromise is tomorrow's loophole to be closed.
                   All such compromises do is push that policy off until the next
                   round."
            }
         ]
      },
      {
         "id":"f3paf0j",
         "body":"Yeah this sub it's not conducive to conversion. Its quickly
             devolving to little more than "Boogaloo" memes and shouting "SHALL. NOT
             ." at each other. However,  as far as I know, the mods won't delete
             your thread and ban you from the sub for trying to have a good faith
             discussion,  like some of the gun control subs will.",
         "replies":[
            {
```

```
            "id":"f3pusbm",
            "body":"Unfortunately this sub's mod team takes a very passive
               approach to moderation. With very little effort they could make
               this sub into a  quality progun meeting ground *without having to
                resort to censorship*. Instead they promote low-effort memes and
                endless duplication of posts through their inaction. whubbard
               has the chops to resurrect this sub. Let's see if he's up to the
               challenge.",
            "replies":[
               {
                  "id":"f3q8xj6",
                  "body":"We voted to ban memes last week. All about rolling it
                     out now.",
                  "replies":[
                     {
                        "id":"f3qn4p8",
                        "body":"Damn I might have to eat some crow here then..."
                     }
                  ]
               }
            ]
         }
      ]
   },
   {
      "id":"f3pafqa",
      "body":"Found the gun grabber!!",
      "replies":[
         {
            "id":"f3pcw4h",
            "body":"Witch hunter."
         }
      ]
   },
   {
      "id":"f3pal5l",
      "body":"I see people have discussions when it makes sense to. Not much
         reason to spend time responding to the same gun control measures over
         and over though."
   },
   {
      "id":"f3paw3h",
      "body":"I get where you're coming from, but people's ability to protect
         themselves and own their own property isn't something that is
         compromisable. Anything less, and they cease to own their own property.
          It's like breathing, there can be nothing less than total ability to
         breath when and how someone wants. It's just that simple."
   },
   {
      "id":"f3pax9m",
      "body":"My take on this, What kind of open discussion is possible for a
         right that is guaranteed and most importantly, not to be infringed upon
         ? They're making all these unlawful laws to portray it as it's somehow
         legitimate. They are not, We are at an apex, to which both political
         spectrums and even us to a degree are liable for.\nI certainly believe
         both sides are waiting for this to boil over so each can finger point.
         I just speculate it's going to be the hell humanity been whispering
         about but never thought it would ever occur."
   },
   {
      "id":"f3pb6ny",
      "body":"The time for discussion is over."
   },
   {
      "id":"f3pfqwq",
      "body":"I don't know what you're talking about. Sure people downvote, but
         they also talk. We get "why do you need guns" posts at least weekly,
         and several people will engage in actual conversation with them, citing
          facts, clearing up statistics, and telling stories to illustrate why
         this is important to them, but they are usually met with "you stupid @#
```

```
             $%, you think you're Rambo" or something equally clever. People who
             come here to discuss and learn will be treated well. People who are
             just trolling are treated like trolls.",
         "replies":[
            {
               "id":"f3pghji",
               "body":"I made this post because I'm always seeing rational,
                   conversation seeking comments getting blown to downvote hell.",
               "replies":[
                  {
                 "id":"f3pi9xv",
                 "body":"[Like this one?](https://www.reddit.com/r/progun/comments/
                     dhcu92/yup/f3p75tg/)> One smart man in a sub full of... welp...
                      "strong opinions". You start off with arrogance, as the sole
                     arbiter of what constitutes a "smart man". Then you back it up
                     with a dismissive swipe at what you term "strong opinions".>
                     Every other country can see that PROPER gun control reduces gun
                      violence by a ton, More arrogance. False equivalence.
                     Unsupported claims.> but the US refuses to let go of it's
                     antique laws In a shocking turn of events, more arrogance.>
                     Fully aware that this is a fully pro gun sub, willing to take
                     the downvotes in order to spark a discussion and crack some
                     heads. You aren't the first arrogant asshole to grace this sub
                     with posts like this. Try bringing something other than your
                     own self-importance to the discussion. Edit: And then there's [
                     this gem](https://www.reddit.com/r/unpopularopinion/comments/
                     d3w5z1/people_living_in_the_us_are_living_in_one_of_the/f06r3sg
                     /.> Wanna feel like you could be shot at every single moment?
                     Move to the US, it'll prob happen to you either as a bystander,
                      or you'd be shot by a random citizen (sometimes police)."
                  },
                  {
                     "id":"f3pj8k0",
                     "body":"As is tradition. We're done with that condescending
                         bullshit from antis, you dont come here for good faith
                         discussion and whether you get a reasonable response or not
                         , nothing ever changes, easier to downvote you and move on
                         because we get the same treatment anytime we attempt to
                         speak out in anti subs."
                  },
                  {
                     "id":"f3plgf4",
                     "body":"If downvotes hurt your feelings, you shouldn't be on
                         reddit. People tend to downvote anything they disagree with
                          (which is why some subs specifically ask you to only
                         downvote things that contribute nothing to the discussion).
                          It's a bad habit, but that's the way it is. People
                         downvote and *still* enage. You want to post a view
                         contrary to the prevailing view of the sub, take your lumps
                          and participate in what conversation you are offered. But
                         if you're only here to preach about how stupid, misguided,
                         unevolved, uneducated, irrational, and/or violent we are,
                         don't expect a polite response."
                  },
                  {
                     "id":"f3tcgf1",
                     "body":"An arrogant Israeli trying to tell another nation how
                         they should be run. You're just a walking stereotype aren't
                          you? And before you say anything, I popped into your
                         comment history. That's where the calling you Israeli comes
                          from.",
                     "replies":[
                        {
                           "id":"f3tywb4",
                           "body":"I thought that trying to tell other nations how
                               they should run was your guys's stereotype.",
                           "replies":[
                              {
                                 "id":"f3u0vkq",
                                 "body":"No we go in and try to make them work our
                                    way."
                              }
                           ]
                        }
                     ]
                  }
               ]
            }
         ]
      },
      {
         "id":"f3pzseh",
         "body":"It's a little unfortunate but the grabbers who come on here tend to
              be intellectually dishonest and/or uninformed. There was some
             Australian post a few days ago that pretty much asked why we like our
             guns more than children. No discussion to be had there. There's also
             some posts that clearly demonstrate the poster should inform himself or
              herself a little."
      },
      {
         "id":"f3rqu2u",
         "body":"Actually, do that. It shows everyone that they tend to be crazy,
             unstable, ignorant, stereotyping, arrogant bastards who hate black
             people with a hair trigger."
      },
      {
         "id":"f3t7tgg",
         "body":"Welcome to reddit, home of every single safe place for anything
             that doesnt violate the TOS. At least its slightly better than r/
             politics"
      },
      {
         "id":"f3unt9z",
         "body":"This isn't r/gundebate. This is a pro gun subreddit.  That said, we
              do allow some debate provided it remains civil.",
         "replies":[
            {
               "id":"f3uomn2",
               "body":"Sadly tho, r/gundebate is pretty dead..."
            }
         ]
      },
      {
         "id":"f4dip6o",
         "body":"Anything else you want to give away for free?"
      }
   ]
}
```

C Situations Leading to LLM Annotation Errors and Inconsistencies

Before proceeding with LLM annotation using larger models, we first tested other versions of GPT and Mistral models, such as GPT-3.5 and Mistral-small and medium. However, we found that these models failed to produce annotations in the desired format. Below are some specific situations where LLMs were prone to errors:

- **System Prompt Clarity:** The importance of a clear and precise system prompt cannot be overstated. When the prompt lacked clarity, LLMs often generated annotations for unspecified authors, indicating confusion about the task requirements.

- **Understanding Conversation Structure:** Without providing a clear example of the conversation structure, none of the LLMs were able to understand the task properly. This demonstrates the need for explicit guidance when dealing with complex conversation data.

- **Interface Issues:** Using an interface to facilitate LLM annotation proved problematic. After processing 2 to 3 examples, LLMs began providing annotations for previous user IDs, even when presented with new conversations. This suggests that the model lost track of the task and context.

- **Consistency in Annotations:** For smaller conversations, different LLMs tended to produce similar annotations. However, as the conversations grew longer, the annotations became inconsistent across different models, indicating challenges in maintaining accuracy over extended discourse.

- **Confusion with Author IDs:** Occasionally, LLMs confuse author IDs, resulting in missed stance labels for certain authors (as shown in Fig. 3 (left) in the main paper). Additionally, there were minor errors in key naming (e.g., ‘label’ vs. ‘body’ as shown in Fig. 3 (right) in the main paper), which further highlighted the model’s limitations.

D System Prompt for LLM Annotation

We used the following system prompt as annotation guidelines both to obtain annotations from LLMs and for the instruction-tuning of SLMs.

```
"""
### Introduction
**Objective**: Analyze Reddit conversations to identify the stance of specific
    authors on sociopolitical topics and determine their level of dogmatism.
**Stance Definition**: Stance is defined as the expression of the author’s
    standpoint and judgement towards a given topic.
**Dogmatism Definition**: Dogmatism is an opinion strongly believed as a fact
    to support a stance without a question or allowance for conversation.
**Task**: Given a JSON formatted Reddit submission and its comment thread,
    classify the stance of text segments related to ‘‘author1’’ and
    ‘‘author2’’ by assigning one of the following five predefined stance
    labels: ‘strongly_against’, ‘somewhat_against’, ‘somewhat_in_favor’,
    ‘strongly_in_favor’, ‘stance_not_inferrable’. Also, assign a dogmatism
    label for each author by assigning one of the following four predefined
    labels: ‘Deeply Rooted’, ‘Firm but Open’, ‘Open to Dialogue’, ‘Flexible’.

### Description of Stance Labels:
1. **strongly_against / strongly_in_favor**: Marks text showing strong
    opinions, emotional expressions, or argumentative tones.
2. **somewhat_against / somewhat_in_favor**: Identifies texts with openness to
    discussion, less certainty, or showing interest in different viewpoints.
3. **stance_not_inferrable**: Use for texts that are neutral, support both
    stances, or where the stance is unclear despite being on-topic.

### Description of Dogmatism Labels:
1. **Deeply Rooted**: Reflects a strong, unchangeable belief. This label
    conveys the idea of someone who is firm in their opinion and unlikely to
    be swayed.
2. **Firm but Open**: Indicates a person who is not likely to change their
    mind but does not impose their views authoritatively. It captures the
    essence of being steadfast in one’s beliefs without being dismissive of
    others.
3. **Open to Dialogue**: Describes someone who holds a certain opinion but is
    genuinely interested in considering other viewpoints. This label suggests
    a willingness to engage in meaningful conversation about differing
    perspectives.
4. **Flexible**: Denotes a person who is not firmly committed to their stance
    and is open to changing their opinion. This label is indicative of
    flexibility and openness to new information or arguments.

### Input Data Format
The input data will be in JSON format and will include several key elements to
    represent a Reddit submission and its associated comments. Each element
    provides specific information as described below:

- ‘id’: This is the unique identifier for the Reddit submission.
- ‘title’: The title of the post. This is what users see first and often
    summarizes or hints at the content of the submission.
- ‘content’: The main post’s detailed description. This text segment provides
    the core message or information the author wishes to communicate with the
    Reddit community. It may include narratives, questions, or any information
    relevant to the title.
- ‘comments’: An array (list) of comments related to the Reddit submission.
    Each comment in this array includes the following fields:
   - ‘id’: The unique identifier for the comment, allowing for identification
       and reference within the dataset.
   - ‘author1’ or ‘author2’: The username of the comment’s author, if it is
       made by one of our focus authors. This helps in tracking contributions
       by specific individuals.
   - ‘body’: The text of the comment. This is the main content of the comment
       where the author responds to the post or another comment, providing
       insights, opinions, or further information.
   - ‘replies’: An array of comments that are direct responses to this
       comment. The structure of each reply follows the same format as the
       initial comment, including ‘id’, ‘author1’ or ‘author2’ (if
```

~~~
       applicable), ‘body’, and potentially more ‘replies’.

### Output Data Format
Submit your annotations in JSON format, grouping all stance annotations under
    the key ``stance_annotations’’. Each entry should be a dictionary
    containing the segment’s ``id’’, your ``label’’, and the ``reason’’ for
    your choice. Include the dogmatism label and its justification under
    ``dogmatism_label’’ and ``dogmatism_reason’’ keys, respectively.

The output should follow this structure:
```json
{
  "author1": {
    "stance_annotations": [
      {
        "id": "[segment_id]",
        "label": "[chosen_label]",
        "reason": "[Justification in <50 words]"
      },
      ...
    ],
    "dogmatism_label": "[chosen_dogmatism_label]",
    "dogmatism_reason": "[Justification in <50 words]"
  },
  "author2": {
    "stance_annotations": [
      {
        "id": "[segment_id]",
        "label": "[chosen_label]",
        "reason": "[Justification in <50 words]"
      },
      ...
    ],
    "dogmatism_label": "[chosen_dogmatism_label]",
    "dogmatism_reason": "[Justification in <50 words]"
  }
}
’’’
### Instructions for Effective Annotation

1. **Labeling Stance**: For each segment (including the original Reddit
    submission, comments, or replies) where "author1" or "author2" is
    mentioned, assign a stance label that best represents the stance expressed
    towards the discussed topic in the submission. This comprehensive approach
    ensures no relevant contribution by "author1" or "author2" is overlooked.
    Evaluate the stance based on the content’s tone, argumentation, and
    engagement level with the topic.
2. **Providing Justification**: For each label assigned, include a concise
    reason, aiming for less than 50 words. Focus on the stance and
    argumentative indicators present in the text.
3. **Dogmatism Assessment**: After reviewing all segments from "author1" and
    "author2", assign a single dogmatism label reflecting the overall tone and
    approach in their contributions.
"""
~~~

E Prompts for Finetuning SLMs

Fig. 7 and 8 shows the prompts used for finetuning SLMs for the stance and dogmatism classification tasks respectively.

Stance Classification

Analyze the stance of the post enclosed in square brackets.
Categorize each post into one of the following categories based on its stance:

- Somewhat In Favor
- Somewhat Against
- Stance Not Inferrable
- Strongly In Favor
- Strongly Against

and return the answer as one of the corresponding stance labels.

```
[{data_point["stance_id_comment"]}]
```

Figure 7: Prompt for stance classification, for finetuning SLMs.

User Dogmatism Identification

Analyze the comments of a user in conversation enclosed in square brackets.
Categorize the opinion fluctuation of the user into one of the following categories based on its change:

- Open to Dialogue
- Firm but Open
- Deeply Rooted
- Flexible

Return the answer as one of the corresponding dogmatism labels.

```
[{data_point["comments_string_for_dogmatism"]}]
```

Figure 8: Prompt for dogmatism classification, for finetuning SLMs.

F Samples of JSON Outputs from LLMs

F.1 Sample JSON Output from LLM: GPT-4 Zero-shot

```
{
    "author1": {
    "stance_annotations": [
    {
        "id": "dhoxyz",
        "label": "somewhat_in_favor",
        "reason": "Advocates for open discussions, showing interest in dialogue."
    },
    {
        "id": "f3pghji",
        "label": "somewhat_in_favor",
        "reason": "Expresses desire for rational discussions, despite downvotes."
    },
    {
        "id": "f3tywb4",
        "label": "somewhat_against",
        "reason": "Sarcastic retort, but lacks strong emotional language."
    },
    {
        "id": "f3uomn2",
        "label": "stance_not_inferrable",
        "reason": "Comment is factual, no clear stance on the debate itself."
    }
    ],
    "dogmatism_label": "Open to Dialogue",
    "dogmatism_reason": "Shows interest in discussion, acknowledges downvotes."
    },
    "author2": {
    "stance_annotations": [
    {
        "id": "f3rt0bf",
        "label": "somewhat_in_favor",
        "reason": "Proposes conditions for UBCs, indicating some openness."
    },
    {
        "id": "f3rqu2u",
        "label": "strongly_against",
        "reason": "Uses strong negative descriptors for opponents, indicating firm
            stance."
    }
    ],
    "dogmatism_label": "Firm but Open",
    "dogmatism_reason": "Mixed; proposes solutions but also dismisses opposition."
    }
}
```

F.2 Sample JSON Output from LLM: GPT-4 One-shot

```
{
    "author1": {
    "stance_annotations": [
    {
        "id": "dhoxyz",
        "label": "somewhat_in_favor",
        "reason": "Advocates for open discussions, indicating a pro-discussion
            stance."
    },
    {
        "id": "f3pghji",
        "label": "somewhat_in_favor",
        "reason": "Expresses desire for rational conversation, showing a supportive
            stance for dialogue."
    },
    {
        "id": "f3tywb4",
        "label": "somewhat_against",
        "reason": "Uses sarcasm to counter a stereotype, indicating a stance against
             the opposing view."
    },
    {
        "id": "f3uomn2",
        "label": "somewhat_in_favor",
        "reason": "Expresses disappointment in lack of active debate, supporting
            open discussion."
    }
    ],
    "dogmatism_label": "Open to Dialogue",
    "dogmatism_reason": "Shows a consistent preference for discussion and engagement
        , without dogmatic assertions."
    },
    "author2": {
    "stance_annotations": [
    {
        "id": "f3rt0bf",
        "label": "somewhat_in_favor",
        "reason": "Lists conditions for agreement, showing openness to compromise."
    },
    {
        "id": "f3rqu2u",
        "label": "strongly_against",
        "reason": "Uses strong language to describe opponents, indicating a firm
            stance against them."
    }
    ],
        "dogmatism_label": "Firm but Open",
        "dogmatism_reason": "While showing strong opinions, also lists specific
            conditions for compromise."
    }
}
```

F.3 Sample JSON Output from LLM: GPT-4 Large Few-shot

```
{
    "author1": {
    "stance_annotations": [
    {
        "id": "dhoxyz",
        "label": "somewhat_in_favor",
        "reason": "Expresses desire for open discussions, indicating a stance in
            favor of dialogue."
    },
   {
        "id": "f3pghji",
        "label": "somewhat_in_favor",
        "reason": "Advocates for rational conversation despite observing negative
            reactions."
    },
   {
        "id": "f3tywb4",
        "label": "somewhat_against",
        "reason": "Uses sarcasm to counter a stereotype, showing a stance against it
            ."
    },
   {
        "id": "f3uomn2",
        "label": "stance_not_inferrable",
        "reason": "Comment on the state of another subreddit does not reveal a
            stance on the gun debate."
    }
    ],
    "dogmatism_label":  "Open to Dialogue",
    "dogmatism_reason": "Shows a consistent
    preference for discussion over confrontation."
    },
    "author2": {
    "stance_annotations": [
    {
        "id": 'f3rt0bf",
        "labe"': 'somewhat_in_favor",
        "reason": 'Lists conditions for accepting UBCs, indicating some openness to
            compromise."
    },
    {
        "id": 'f3rqu2u",
        "label": "strongly_against",
        "reason": "Uses derogatory language to describe opponents, showing strong
            opposition."
    }
    ],
    "dogmatism_label": "Firm but Open",
    "dogmatism_reason": "While showing strong opinions, also suggests conditions for
         policy acceptance."
    }
}
```

F.4 Sample JSON Output from LLM: Mistral Large Zero-shot

```
{
    "author1": {
    "stance_annotations": [
    {
        "id": "dhoxyz",
        "label": "somewhat_in_favor",
        "reason": "Author expresses desire for open discussions on anti-gun ideals."
    },
    {
        "id": "f3pghji",
        "label": "stance_not_inferrable",
        "reason": "Author is commenting on downvotes, not expressing stance."
    },
    {
        "id": "f3tywb4",
        "label": "stance_not_inferrable",
        "reason": "Author is making a stereotypical comment, not expressing stance."
    },
    {
        "id": "f3uomn2",
        "label": "stance_not_inferrable",
        "reason": "Author is commenting on the state of another subreddit, not
            expressing stance."
    }
    ],
    "dogmatism_label": "Open to Dialogue",
    "dogmatism_reason": "Author expresses desire for open discussions and does not
        dismiss opposing views."
    },
    "author2": {
    "stance_annotations": [
    {
        "id": "f3rt0bf",
        "label": "strongly_in_favor",
        "reason": "Author lists conditions for accepting UBCs, showing strong pro-
            gun stance."
    },
    {
        "id": "f3rqu2u",
        "label": "strongly_in_favor",
        "reason": "Author"s comment is dismissive of anti-gun advocates, showing
            strong pro-gun stance."
    }
    ],
    "dogmatism_label": "Deeply Rooted",
    "dogmatism_reason": "Author"s comments are dismissive of opposing views and show
         a strong, unchangeable belief in pro-gun ideals."
    }
}
```

F.5 Sample JSON Output from LLM: Mistral Large One-shot

```
{
    "author1": {
    "stance_annotations": [
    {
        "id": "dhoxyz",
        "label": "somewhat_in_favor",
        "reason": "Expresses desire for open discussions on gun control, but follows
             pro-gun subreddit."
    },
    {
        "id": "f3pghji",
        "label": "stance_not_inferrable",
        "reason": "Comments on downvotes, but no clear stance on gun control."
    },
    {
        "id": "f3tywb4",
        "label": "stance_not_inferrable",
        "reason": "Comment about stereotypes, but no clear stance on gun control."
    },
    {
        "id": "f3uomn2",
        "label": "stance_not_inferrable",
        "reason": "Mentions r/gundebate being dead, but no clear stance on gun
            control."
    }
    ],
    "dogmatism_label": "Open to Dialogue",
    "dogmatism_reason": "Seeks open discussions and does not express strong dogmatic
         views."
    },
    "author2": {
    "stance_annotations": [
    {
        "id": "f3rt0bf",
        "label": "somewhat_in_favor",
        "reason": "Lists conditions for supporting UBCs, showing openness to
            compromise."
    },
    {
        "id": "f3rqu2u",
        "label": "strongly_in_favor",
        "reason": "Strong negative language against gun control advocates,
            suggesting strong pro-gun stance."
    }
    ],
    "dogmatism_label": "Firm but Open",
    "dogmatism_reason": "Expresses strong pro-gun views but open to compromise under
         certain conditions."
    }
}
```

F.6 Sample JSON Output from LLM: Mistral Large Few-shot

```
{
    "author1": {
    "stance_annotations": [
    {
        "id': "dhoxyz",
        "label": "somewhat_in_favor",
        "reason": "Expresses desire for open discussions on anti vs. pro-gun debates
            ."
    },
   {
        "id": "f3pghji",
        "label": "stance_not_inferrable",
        "reason": "Comments on downvotes, but no clear stance on the topic."
    },
   {
        "id": "f3tywb4",
        "label": "stance_not_inferrable",
        "reason": "Makes a stereotypical comment, but no clear stance on the topic."
    },
   {
        "id": "f3uomn2",
        "label": "stance_not_inferrable",
        "reason": "Mentions r/gundebate being dead, but no clear stance on the topic
            ."
    }
    ],
    "dogmatism_label": "Open to Dialogue",
    "dogmatism_reason": "Seeks open discussions and engages in conversation without
        strong dogmatic language."
    },
    "author2": {
    "stance_annotations": [
    {
        "id": "f3rt0bf",
        "label": "somewhat_in_favor",
        "reason": "Lists conditions for supporting UBCs, showing openness to
            discussion."
    },
    {
        "id": "f3rqu2u",
        "label": "strongly_against",
        "reason": "Uses derogatory language to express strong opposition to '
            grabbers'."
    }
    ],
    "dogmatism_label": "Firm but Open",
    "dogmatism_reason": "Expresses strong opinions but also shows willingness to
        consider certain conditions for compromise."
    }
}
```

G Details of Small Language Models and Hyper-parameter Settings

LLaMA models (Touvron et al., 2023a) are decoder-only LLMs trained on 1.6 trillion tokens from a mixture of corpora including C4, English CommonCrawl, Wikipedia, Github, and more. We use two versions of models in our study: LLaMa-2-7B (Touvron et al., 2023b) and LLaMa-3-8B and their instruction-tuned variants.

Falcon models (Almazrouei et al., 2023) are decoder-only LLMs trained on ≥ 1 trillion tokens of text, particularly emphasizing the RefinedWeb corpus. For Falcon, we use the pretrained and instruction-tuned 7B parameter variants in our study.

Vicuna model (Chiang et al., 2023) is finetuned from the LLaMA 7B model on approximately 70K user-shared conversations gathered from ShareGPT.com and we used the 7B parameter variants.

Implementation details for reproducibility. All experiments were conducted on a machine equipped with an NVIDIA A100 GPU with 80 GB of GPU RAM, partitioned into two devices of 40 GB each. We employed 4-bit quantization with normalized floating precision (nf4) from the bitsandbytes library [4]. Additionally, we utilized LoRA (Hu et al., 2021) with a rank of 64 and an alpha value of 16 during task-based instruction-tuning. Finally, we use PEFT (Parameter Efficient Finetuning) [5] library to train LLMs with the SFTT (Supervised Finetuning Trainer) setting. To further enhance performance, we divided the training dataset into a validation set comprising a randomly chosen 10% subset from the training set, used exclusively for hyperparameter tuning.

H Baseline (un-fine-tuned) Model Performance

To establish a reasonable F1-score benchmark for fine-tuning and instruction-tuning (discussed in the next subsections), we evaluated the un-fine-tuned SLMs, GPT-4 and Mistral Large, in few-shot settings. This evaluation includes both stance and dogmatism tasks, using majority voting to enhance reliability. The results are summarized in the Tables 4, 5, 6 and 7.

I SLM Finetuning: AUC (Area Under the Curve) Analysis

Fig. 9 illustrates the confusion matrix for dogmatism detection for LLaMa-3-8B finetuning and instruction-tuning. We make the following observations from Fig. 9: 1) For both finetuning and instruction-tuning, there are significant misclassifications, especially for the “Deeply Rooted” and “Flexible” labels, with both having zero accuracy and F1-scores. While “Firm but Open” and “Open to Dialogue” perform moderately better, with accuracies of 48.7% and 64.4% respectively. The confusion matrix indicates substantial confusion to distinguish between intermediate levels of dogmatism, such as “Firm but Open” and “Open to Dialogue”. We further report the ROC curve shows the trade-off between the true positive rate (TPR) and false positive rate (FPR) for each class for stance and dogmatism tasks, in Figs. 10 and. 11. The area under the ROC curve (AUC) measures the model’s ability to distinguish between classes.

J SLM Instruction-tuning: AUC (Area Under the Curve) Analysis

Fig. 12 shows the ROC curve trade-off between the true positive rate (TPR) and false positive rate (FPR) for each class for stance task using LLaMa-3-8B instruction-tuning. This instruction-tuning is performed on GPT-4 (zero-shot, one-shot, few-shot) and majority voting labels from the USDC dataset. We make the following observations from Fig. 12: 1) Across all four settings, the area under the curve (AUC) for all stance labels is $>= 0.5$. This indicates that the model predicts each stance label more accurately than random guessing for all classes. 2) Among all settings, the majority voting labels from the USDC dataset show a higher AUC for each class compared to zero-shot, one-shot, and few-shot labels. 3) Among all stance classes, the “Stance Not Inferrable” class has the highest AUC (0.8), while the “Strongly In Favor” class has the lowest AUC (0.6). Overall, LLaMa-3-8B instruction-tuning demonstrates superior performance in the stance detection task. However, there is still significant room for improvement in understanding user opinions from text segments.

[4] https://pypi.org/project/bitsandbytes/

[5] https://github.com/huggingface/peft

Class	Precision	Recall	F1-Score	Support
Somewhat Against	0.26	0.67	0.38	400
Somewhat In Favor	0.45	0.21	0.28	624
Stance Not Inferrable	0.35	0.11	0.16	454
Strongly Against	0.25	0.38	0.30	261
Strongly In Favor	0.13	0.02	0.03	128
Accuracy		0.29		1867
Macro avg	0.29	0.28	0.23	1867
Weighted avg	0.33	0.29	0.26	1867

Table 4: Classification Report for GPT-4 Few-shot as target labels: Un-finetuned performance: weighted F1 score for Stance classification using SLMs on USDC test set.

Class	Precision	Recall	F1-Score	Support
Somewhat Against	0.20	0.69	0.31	316
Somewhat In Favor	0.39	0.24	0.30	458
Stance Not Inferrable	0.41	0.08	0.14	567
Strongly Against	0.29	0.32	0.30	336
Strongly In Favor	0.31	0.02	0.04	190
Accuracy		0.26		1867
Macro avg	0.32	0.27	0.22	1867
Weighted avg	0.34	0.26	0.23	1867

Table 5: Classification Report for Mistral Large few-shot as target labels: Un-finetuned performance: weighted F1 score for Stance classification using SLMs on USDC test set.

Class	Precision	Recall	F1-Score	Support
Somewhat Against	0.30	0.71	0.42	443
Somewhat In Favor	0.41	0.20	0.27	625
Stance Not Inferrable	0.34	0.09	0.14	452
Strongly Against	0.26	0.39	0.31	256
Strongly In Favor	0.19	0.03	0.06	91
Accuracy		0.31		1867
Macro avg	0.30	0.28	0.24	1867
Weighted avg	0.34	0.31	0.27	1867

Table 6: Classification Report for Majority Voting as target labels: Un-finetuned performance: weighted F1 score for Stance classification using SLMs on USDC test set.

Class	Precision	Recall	F1-Score	Support
Deeply Rooted	0.17	0.54	0.26	28
Firm but Open	0.50	0.25	0.34	131
Flexible	0.00	0.00	0.00	14
Open to Dialogue	0.48	0.55	0.51	134
Accuracy		0.40		307
Macro avg	0.29	0.33	0.28	307
Weighted avg	0.44	0.40	0.39	307

Table 7: Classification Report for Majority Voting as target labels: Un-finetuned performance: weighted F1 score for Dogmatism classification using SLMs on USDC test set.

K Lost in the Middle

To analyze the "lost in the middle" (Liu et al., 2024) phenomenon in our LLM-based user-stance annotations, for a given user, we divided the data into time segments and calculated inter-annotator agreement (IAA) using Cohen's Kappa scores across different models and settings. The data was segmented based on the submission_id, author_id, and stance_id_timestamp. For each group (i.e., each combination of submission_id and author_id), the timestamps were divided into equal segments. The number of entries for each group was divided by the desired number of segments (3), and the division was done as evenly as possible, with each segment containing a roughly equal number of time-stamped entries. Fig. 13 in Appendix reports the comparison statistics of IAA scores for the stance detection task across initial, middle, and later time stamps. From Fig. 13, we observe that the analysis across different time segments, especially

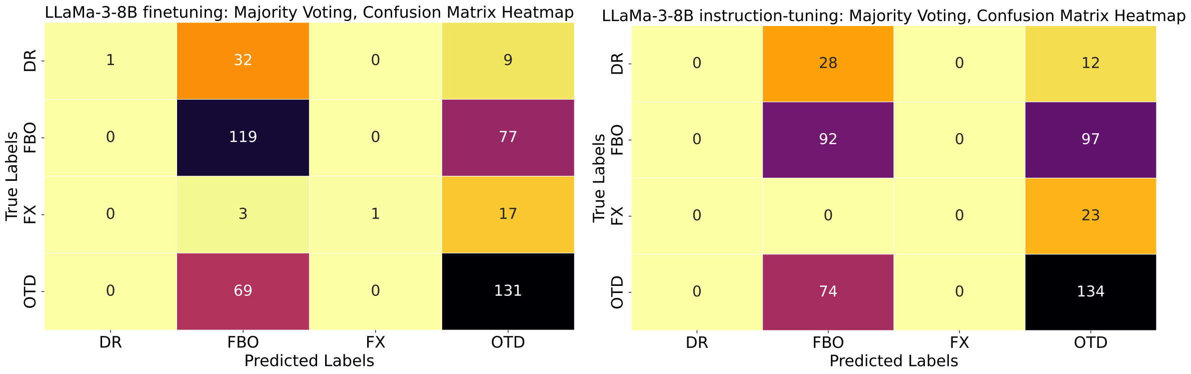


Figure 9: Confusion matrix for LLaMa-3-8B Dogmatism detection models on USDC test set: finetuning (left) and instruction-tuning (right). Here, DR: Deeply Rooted, FX: Flexible, FBO: Firm but Open, OTD: Open to Dialogue

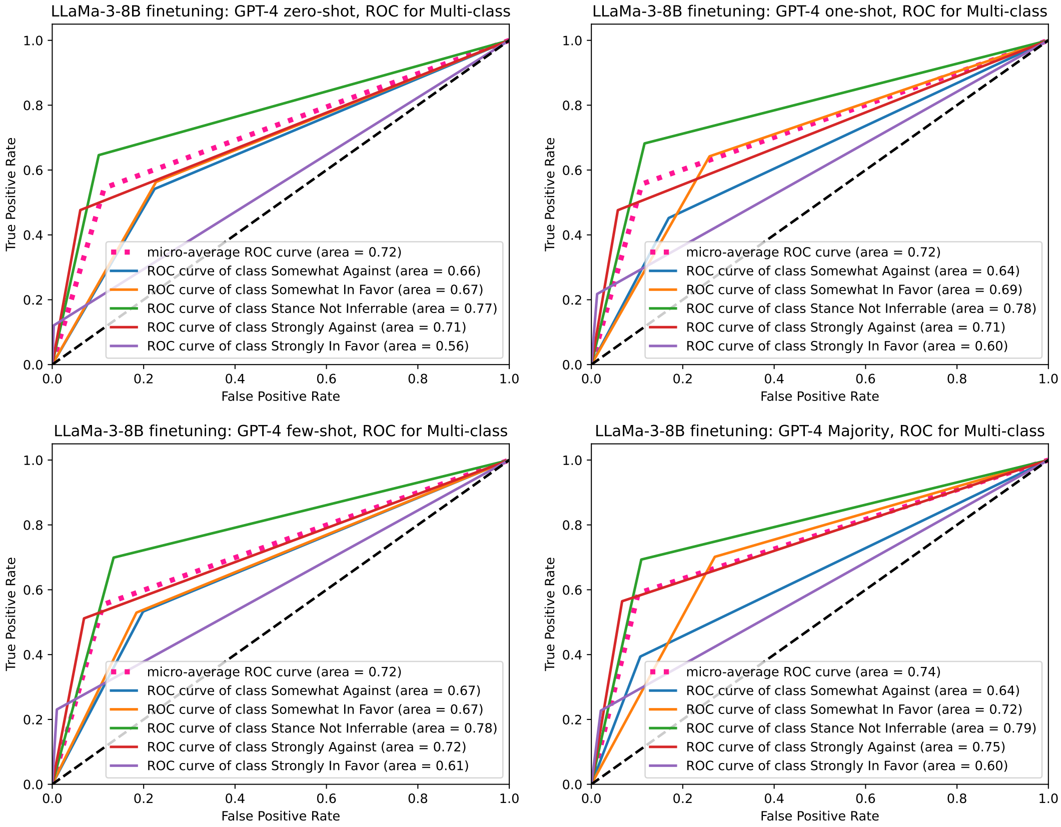


Figure 10: LLaMa-3-8B finetuning for stance detection task: Visualize the ROC curves for each class along with their AUC values for GPT-4 annotations across zero-shot, one-shot, few-shot and majority labels.

when divided into three segments, clearly demonstrates that the "lost in the middle" phenomenon is marginal.

The partial decrease in inter-annotator agreement during the middle parts of the conversations suggests that as conversations progress, models might face challenges in maintaining consistent agreement; however, the decrease in agreement scores is minimal. The recovery in agreement towards the final segments could indicate that as conversations start to conclude, they become more focused, or that the models are better able to align on concluding statements. This trend underscores the importance of considering segment-based analysis when evaluating model performance over long-form conversations. When comparing the model-generated annotations with human annotations, it becomes evident that we do not encounter the "lost in the middle" problem. The human annotations demonstrate a consistent level of inter-annotator agreement (IAA) across all three segments—initial, middle, and final. This suggests that human annotators maintain a steady understanding and agreement throughout the conversation, regardless of its length or complexity.

L Recency Bias

Fig. 14 reports IAA scores, which contains a matrix of Cohen's Kappa scores across different models and set-

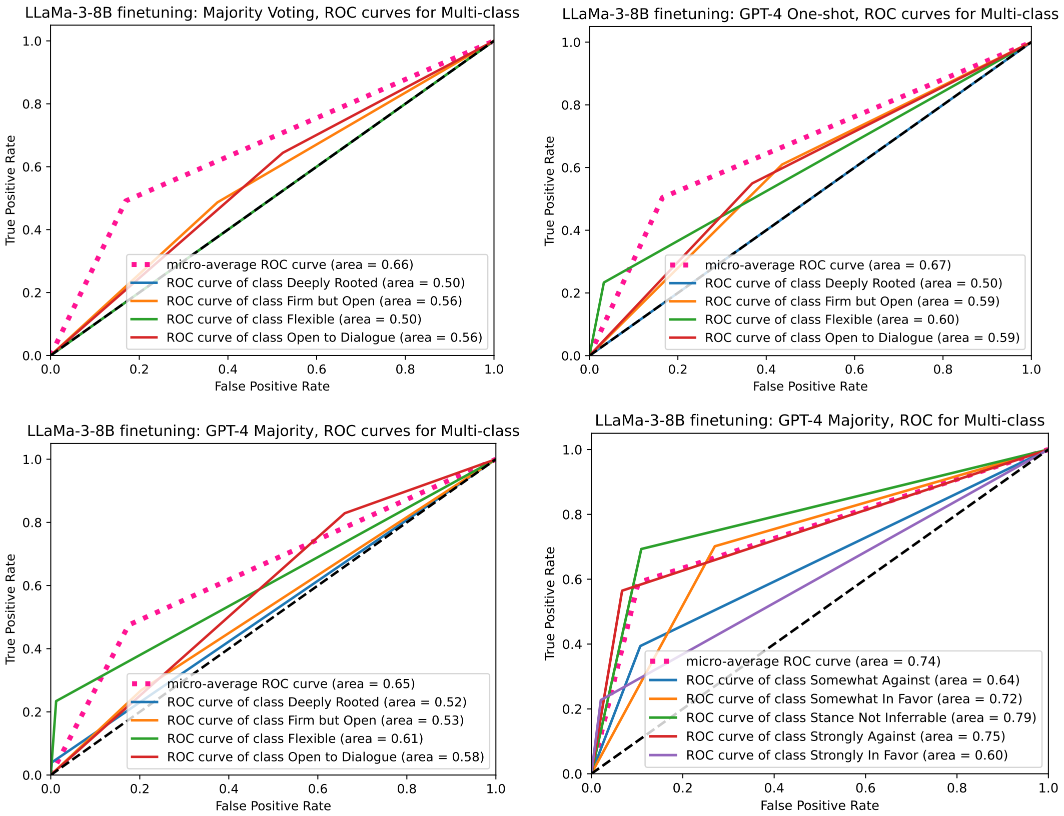


Figure 11: LLaMa-3-8B finetuning for dogmatism task: Visualize the ROC curves for each class along with their AUC values for GPT-4 annotations across zero-shot, one-shot, few-shot and majority labels.

tings, including GPT-4 Few-Shot (FS), Mistral Large FS, Majority Voting, as well as GPT-4 FS PC and Mistral Large FS PC (here, PC denotes prior context). From the figure, we observe that the agreement between GPT-4 FS and Majority Voting is higher when the full conversation is considered (0.75) compared to when only prior context is used. The agreement between GPT-4 FS PC and Mistral Large FS PC (both based on prior context) is lower than when using the full context, indicating that prior context alone may not capture all the necessary nuances for consistent annotation.

M SLM finetuning: Transfer Learning Performance

M.1 Stance Detection Evaluation on SPINOS Dataset:

To evaluate the quality of LLM generated annotations, we perform transfer learning by finetuning the SLMs on the USDC dataset. We then test the model's performance on the SPINOS dataset for a 5-class Stance detection task, as described by (Sakketou et al., 2022). We use the USDC training dataset. For testing, we use the SPINOS dataset, which consists of 3,238 post level examples across five stance labels.

Fig. 15 in Appendix M illustrates the confusion matrix for stance detection for LLaMa-3-8B finetuning on USDC and testing on SPINOS. We make the following observations from Fig. 15: 1) There is a significant misclassification across all classes, with the "Stance Not Inferrable" label being the most commonly predicted class, resulting in many false positives for this label. 2) The model performs best in terms of accuracy for three stance classes: "Somewhat In Favor" (0.456), "Strongly Against" (0.400), and "Somewhat Against" (0.381), while performing the worst for the "Strongly In Favor" stance (0.115). These overlaps suggest challenges in distinguishing whether a post contains stance or not, indicating a need for enhanced feature representation and clearer class definitions to improve model performance.

In comparison to the SPINOS dataset results reported in the paper by (Sakketou et al., 2022), where the best model (traditional machine learning classifier) achieved an F1-score of 0.341, a random baseline achieved 0.230, and a majority baseline achieved 0.124. Our approach using LLaMa-3-8B finetuning on the USDC dataset achieved a weighted F1-score of 0.320 on SPINOS. This score is close to the best model performance on the SPINOS dataset, indicating that our LLM-generated annotations on the USDC dataset are close in quality to human annotations. It is important to note that our weighted F1-score is significantly impacted by the "Stance Not Inferrable" class, which comprises the majority of samples in the SPINOS dataset. Our finetuned SLM struggled to classify this class accurately, leading to a lower overall weighted F1-score.

We also validated the SPINOS performance using

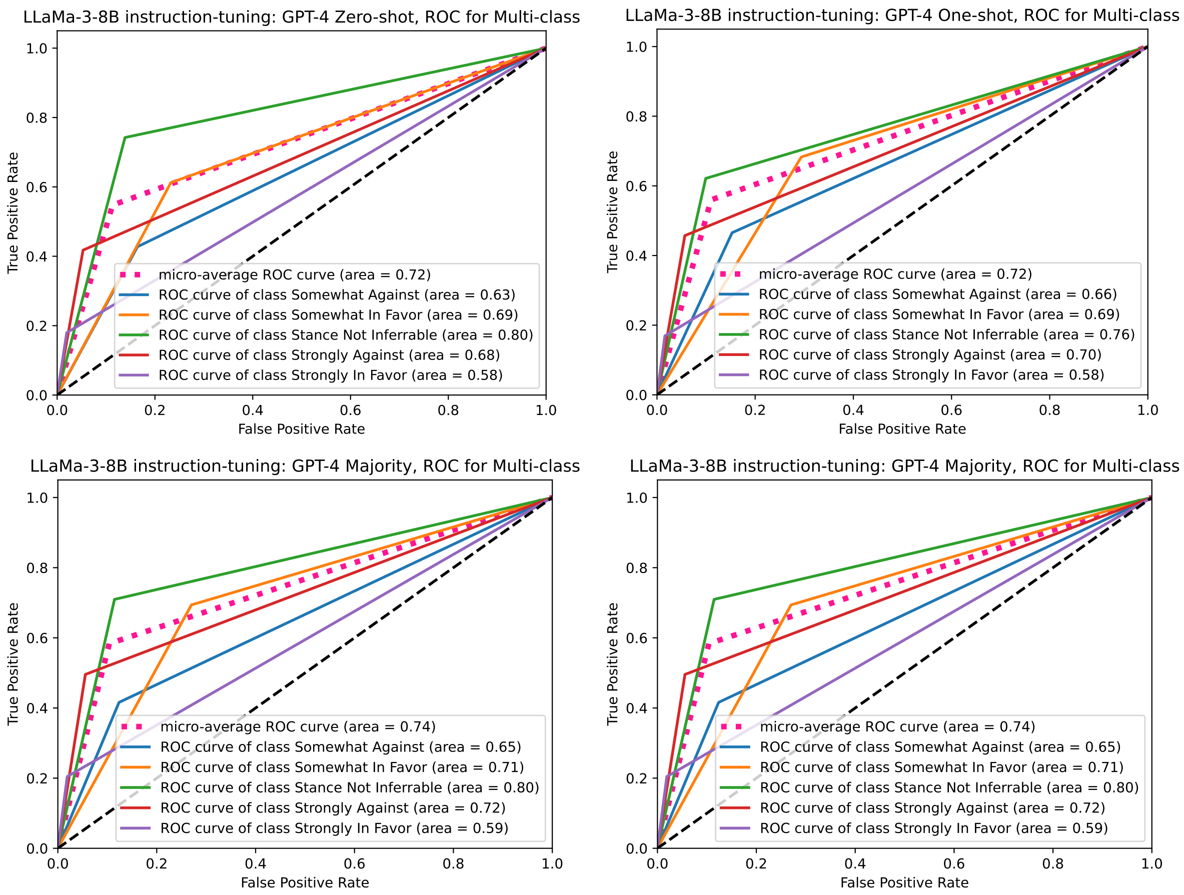


Figure 12: LLaMa-3-8B instruction-tuning for stance detection task: Visualize the ROC curves for each class along with their AUC values for GPT-4 annotations across zero-shot, one-shot, few-shot and majority labels.

other SLMs such as LLaMa-3-8B-Instruct, LLaMa-2-7B, LLaMa-2-7B-Chat, and Vicuna-7B models. Figs. 16, 17, 18 and 19 in Appendix M display these model results. These figures indicate that these models report weighted F1-scores of 0.320, 0.305, 0.286, and 0.291 respectively. These results show that all models perform better than the random and majority baselines. Additionally, the LLaMa-3-8B-Instruct model's performance is close to the SPINOS benchmark on the 5-class stance detection task.

Fig. 15 illustrates the confusion matrix for Stance detection for LLaMa-3-8B finetuning on USDC and transfer learning on SPINOS. We also validated the SPINOS performance using other SLMs such as LLaMa-3-8B-Instruct, LLaMa-2-7B, LLaMa-2-7B-Chat, and Vicuna-7B models. Figs. 16, 17, 18 and 19 display these model results.

M.2 SLM finetuning: Transfer Learning Performance on MT-CDS Dataset

The transfer learning accuracies using the USDC dataset on the MT-CSD dataset (Niu et al., 2024) is tailored for stance detection in multi-turn conversations with multiple targets, addressing different aspects of stance detection. This dataset consists of human annotated labels across 5 stance datasets (Biden, Bitcoin, SpaceX, Tesla, and Trump) in testing. This MT-CDS stance dataset contains 3-class labels such as favor, against and neutral. Therefore, we combined our Strongly Against and Somewhat Against as one class, Strongly In Favor and Somewhat In Favor as one class and Stance Not Inferrable as one class. Below are the accuracies we obtained on 5 datasets. From the Table 8, we observe that our transfer learning results are closer or performing better than results reported in Table 6 of Niu et al. (2024). This implies that our LLM generated annotations are closer to human-level performance on MT-CDS stance detection dataset.

Dataset	Best Accuracy	USDC accuracy
Biden	45.09	46.60
Bitcoin	56.95	51.40
SpaceX	55.94	54.80
Tesla	52.38	58.30
Trump	48.31	60.50
Avg	51.73	54.32

Table 8: Stance Detection Evaluation on MT-CDS Dataset: USDC dataset in training and MT-CDS dataset in testing.

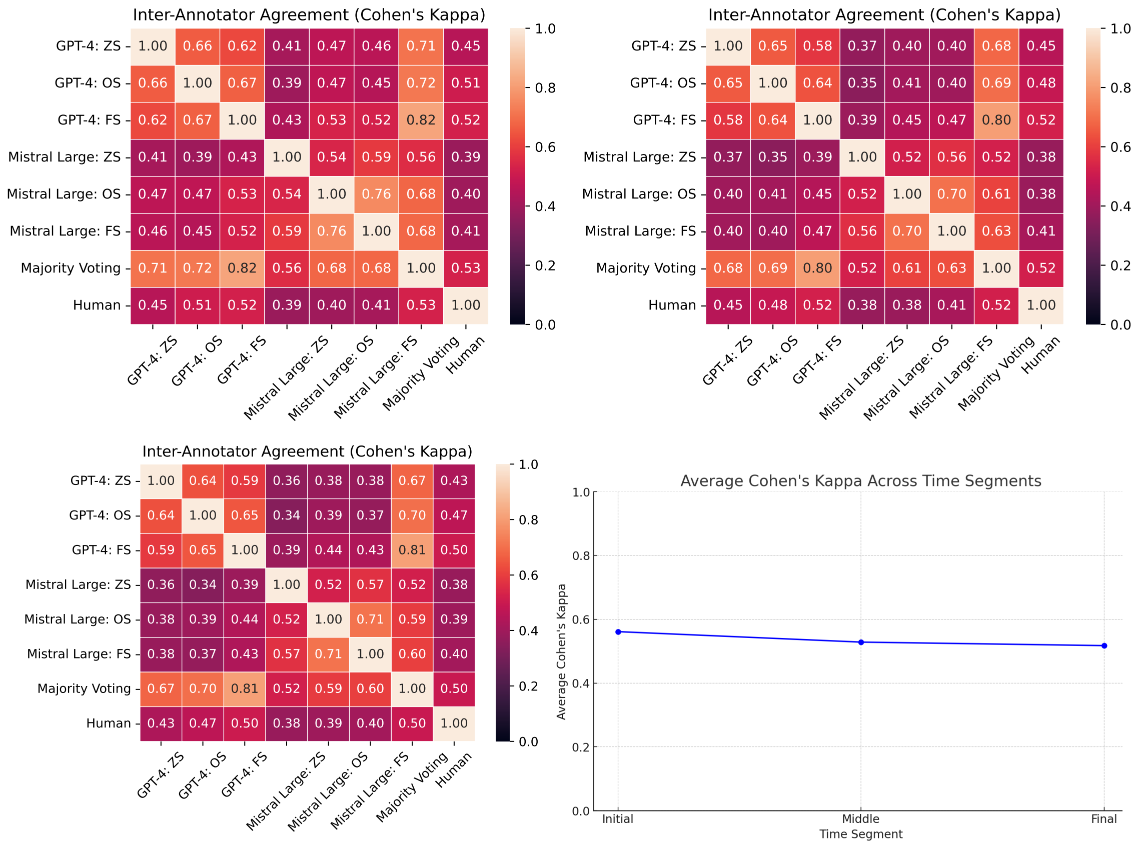


Figure 13: The inter-annotator agreement (IAA) on the USDC test dataset (Stance) was measured using Cohen's Kappa score across three segments: initial, middle, and later time stamps. The top two rows represent the initial and middle time stamps, while the bottom left corresponds to the later time stamp. The bottom right reports the average Kappa score across all time segments.

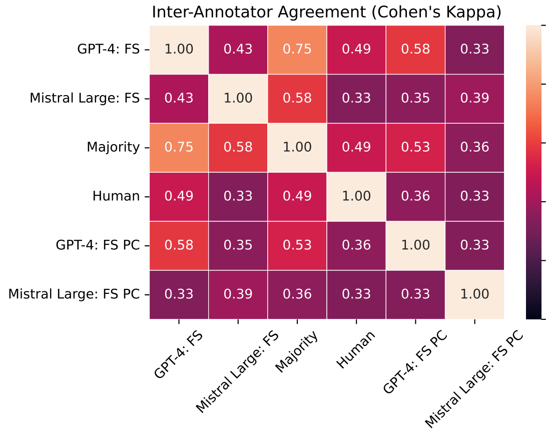


Figure 14: Inter-annotator agreement (IAA) on the test dataset was calculated for both the full conversations and the prior context for a given user. In this context, "GPT-4 FS PC" and "Mistral Large: FS PC" refer to the annotations based on prior context.

M.3 SLM finetuning: Transfer Learning Performance on Twitter-stance Dataset

This dataset focuses on extracting stance (denying vs. supporting opinions) from Twitter posts, specifically targeting replies and quotes on controversial issues. It is tailored to the specific challenges of stance detection on

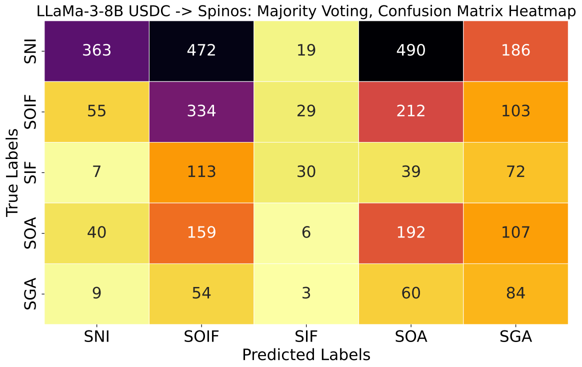


Figure 15: Confusion matrix for LLaMa-3-8B Stance detection models on SPINOS test set: finetuning on USDC and test it on SPINOS. SOA: Somewhat Against, SOIF: Somewhat In Favor, SNI: Stance Not Inferrable, SGA: Strongly Against, SIF: Strongly In Favor.

Twitter, particularly in controversial and rumor-related contexts. This dataset consists of 5 classes such as Implicit denial, Explicit denial, Implicit support, Explicit support, and Quotes. These classes are similar to our USDC 5-class stance labels. Below are the accuracies we obtained on twitter-stance dataset. We also report individual class labels F1-score as follows: Denial (0.53), Support (0.32), Stance Not Inferrable (0.184). From

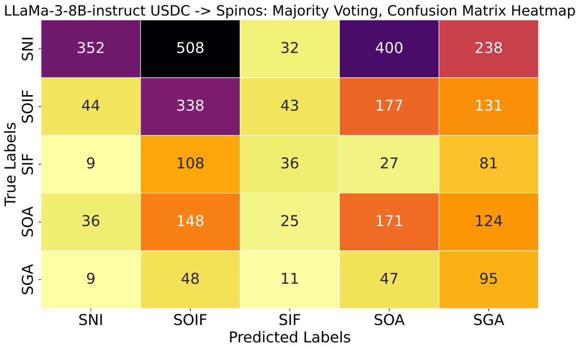


Figure 16: Confusion matrix for LLaMa-3-8B-instruct Stance detection models on SPINOS test set: finetuning on USDC and test it on SPINOS. SOA: Somewhat Against, SOIF: Somewhat In Favor, SNI: Stance Not Inferrable, SGA: Strongly Against, SIF: Strongly In Favor.

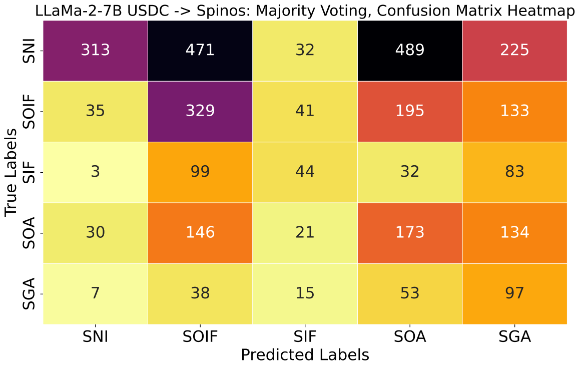


Figure 17: Confusion matrix for LLaMa-2-7B Stance detection models on SPINOS test set: finetuning on USDC and test it on SPINOS. SOA: Somewhat Against, SOIF: Somewhat In Favor, SNI: Stance Not Inferrable, SGA: Strongly Against, SIF: Strongly In Favor.

Dataset	Against	Favor
Biden	34.40	58.80
Bitcoin	41.40	61.30
SpaceX	44.10	65.50
Tesla	49.0	67.50
Trump	54.5	66.4

Table 9: Stance Detection Evaluation on MT-CDS Dataset w.r.t each class: USDC dataset in training and MT-CDS dataset in testing.

Table 10 in Villa-Cox et al. (2020), we observe that the combined quotes and replies achieve a micro F1-score of 0.45, while our approach obtained a score of 0.43, which is close to the performance of human-annotated labels. Additionally, similar to Villa-Cox et al. (2020), our results show that the denial class performs better than the support class.

In conclusion, the results indicate that LLM-generated annotations of the USDC dataset are a viable alternative to human labels for stance detection tasks, demonstrating the substantial potential for automating and scaling up such complex annotation processes in long user conversation data.

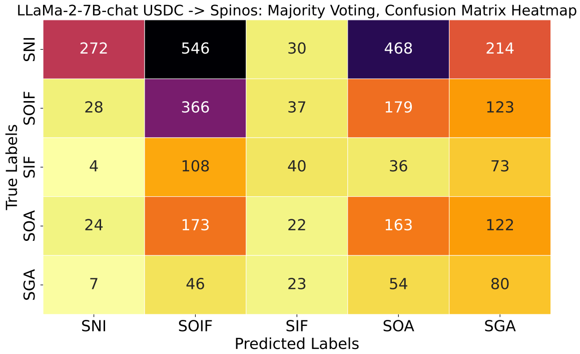


Figure 18: Confusion matrix for LLaMa-2-7B-chat Stance detection models on SPINOS test set: finetuning on USDC and test it on SPINOS. SOA: Somewhat Against, SOIF: Somewhat In Favor, SNI: Stance Not Inferrable, SGA: Strongly Against, SIF: Strongly In Favor.

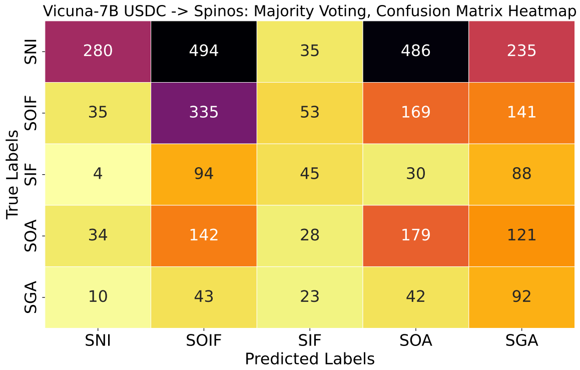


Figure 19: Confusion matrix for Vicuna-7B Stance detection models on SPINOS test set: finetuning on USDC and test it on SPINOS. SOA: Somewhat Against, SOIF: Somewhat In Favor, SNI: Stance Not Inferrable, SGA: Strongly Against, SIF: Strongly In Favor.

Dataset	Best Micro F1-score	USDC Micro F1-score
Twitter-stance	0.45	0.43

Table 10: Stance Detection Evaluation on Twitter-stance Dataset w.r.t each class: USDC dataset in training and Twitter-stance dataset in testing.

N Individual User Responses within their Specific Context vs. Entire Conversation at once for Stance and Dogmatism

For a given user, we consider each of their responses in the context of the topic and the comment they are responding to. We then use GPT-4 and Mistral-Large settings to assess annotations for the stance and dogmatism tasks. Using these generated annotations, we compare them to the annotations extracted from full-context conversations. The comparison statistics for stance and dogmatism tasks are reported in the Table 11 (Appendix).

The results from this experiment suggest that assessing each response individually within its context, and then aggregating the results, produces labels that are not identical to those derived from analyzing the entire conversation context. The higher percentage match with GPT-4 indicates that this method is fairly reliable. However, the differences in labels (30% with GPT-4 and 50% with Mistral-Large) highlight the importance of considering the full context for optimizing stance and dogmatism assessments.

Comparison	**Percentage Match**
GPT Labels Equal	70.37%
GPT Labels Not Equal	29.63%
Mistral Labels Equal	53.70%
Mistral Labels Not Equal	46.30%

(a) Dogmatism Labels

Comparison	**Percentage**
GPT Labels Equal	68.54%
GPT Labels Not Equal	31.46%
Mistral Labels Equal	52.40%
Mistral Labels Not Equal	47.60%

(b) Stance Labels

Table 11: Individual user responses within their specific context vs. entire conversation at once for stance and dogmatism

O Inter-Annotator Agreement (IAA) between Human Annotators

We computed the Inter-Annotator Agreement (IAA) between human annotators as well. The Tables 12 and 13 report the IAA scores for both stance detection and dogmatism detection tasks among the human annotators.

	Human1	Human2	Human3
Human1	1.00	0.62	0.55
Human2	0.62	1.00	0.57
Human3	0.55	0.57	1.00

Table 12: Stance Detection

	Human1	Human2	Human3
Human1	1.00	0.57	0.51
Human2	0.57	1.00	0.52
Human3	0.51	0.52	1.00

Table 13: Dogmatism Identification

P Robustness Analysis of Human-LLM Annotations

Fig. 21 presents a heatmap comparing human-annotated labels and majority voting labels from LLMs, illustrating the class-specific agreement for Stance and Dogmatism tasks. From Fig. 21, we make the following observations for Stance classification task: (i) The “Stance Not Inferrable” (SNI) and “Strongly Against” (SGA) classes exhibit high agreement between human annotations and LLM predictions, as indicated by the strong diagonal values for these categories. (ii) “Somewhat in Favor” (SIF) and “Somewhat Against” (SOA) show substantial mismatches with human labels, leading to higher rates of false positives in LLM predictions. (iii) Notably, “Somewhat Against” (SOA) demonstrates the greatest level of disagreement, with frequent misclassification into neighboring categories such as “Strongly Against” (SGA) or “Somewhat in Favor” (SIF).

For Dogmatism task, we make following observations from Fig. 21 (right): (i) The “Firm but Open” (FBO) and “Open to Dialogue” (OTD) classes exhibit relatively high agreement, with strong diagonal values in the confusion matrix. These classes show better alignment between human labels and LLM predictions compared to other dogmatism categories. (ii) The “Deeply Rooted” (DR) and “Flexible” (FX) classes have significantly fewer samples and exhibit frequent misclassifications. For instance, “Deeply Rooted” (DR) is often misclassified as “Firm but Open” (FBO), indicating challenges in detecting extreme levels of dogmatism.

Overall, the significant mismatch for intermediate stance classes, particularly “Somewhat Against” in the stance detection task and “Open to Dialogue” in the dogmatism task, likely explains the moderate inter-annotator agreement (IAA) observed between human and LLM-generated labels.

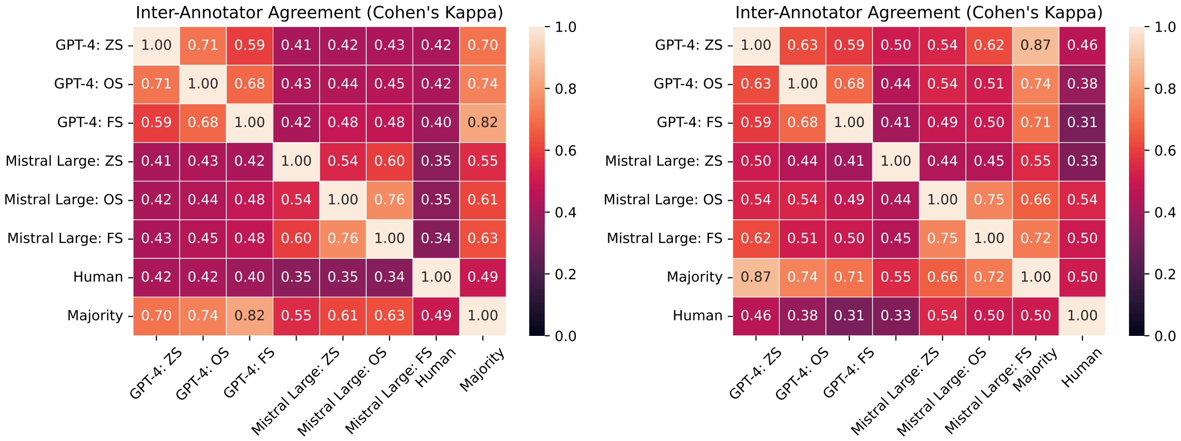


Figure 20: Inter-annotator agreement (IAA) on test dataset: Cohen's Kappa score across 8 settings: two different models (2 models×3 settings), majority voting and human annotations for Stance (left) and Dogmatism (right) tasks.

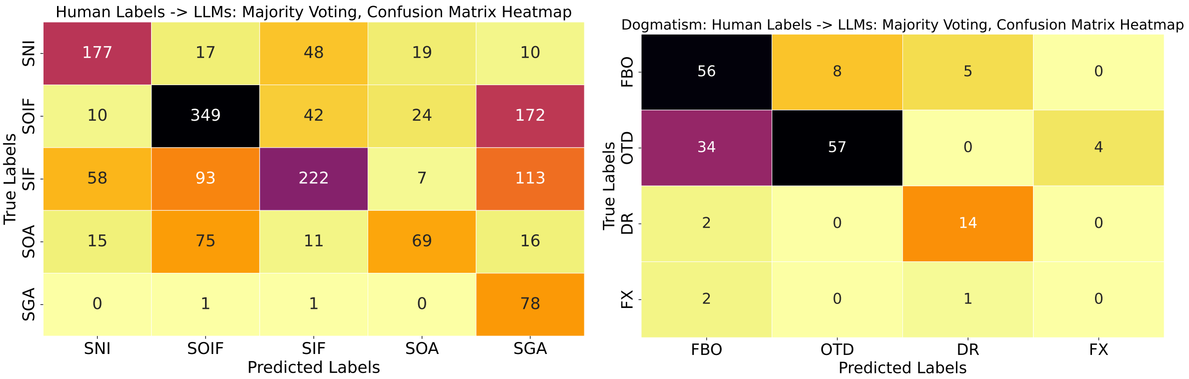


Figure 21: Confusion matrix between Human annotations and Majority voting labels of LLM annotations: (left) Stance Classification, (right) Dogmatism Identification.

Q Qualitative Examples Demonstrating Cases with High, Moderate, and Low Inter-annotator Agreement

We now include qualitative examples demonstrating cases with high, moderate, and low inter-annotator agreement (IAA) for the Stance and Dogmatism tasks, as shown in Figs. Q.1, Q.2, Q.3, Q.4, Q.5, Q.6. In cases of high agreement, all LLMs consistently assign the same stance label to a user comment. For moderate agreement, some LLMs assign one stance class while others assign a neighboring stance class. For low agreement, GPT-4 assigns consistent stance labels across its three settings, but Mistral Large outputs differ for each setting.

Q.1 High Inter-Annotator Agreement Stance Examples

```
{
    "submission_id": "abi4d2",
    "stance_id": "ed8f1x2",
    "stance_id_comment": "I'm not sure, but people like you speaking up helps. My
        new year's resolution is to promote what I think father's rights should be
        both here and in r/menslib. We don't get enough exposure and there are many
        misconceptions. But for your specific situation you could try r/legaladvice
        .",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/abi4d2/
        mens_issues_regarding_child_custody_and_child",

    "gpt41106preview_zero_shot_stance_label": "somewhat_in_favor",
    "gpt41106preview_one_shot_stance_label": "somewhat_in_favor",
    "gpt41106preview_few_shot_stance_label": "somewhat_in_favor",
    "mistrallargelatest_zero_shot_stance_label": "somewhat_in_favor",
    "mistrallargelatest_one_shot_stance_label": "somewhat_in_favor",
    "mistrallargelatest_few_shot_stance_label": "somewhat_in_favor",

    "gpt41106preview_zero_shot_stance_reason": "Author expresses intent to promote
        father's rights, showing support.",
    "gpt41106preview_one_shot_stance_reason": "Expresses a desire to promote father'
        s rights, indicating support for change.",
    "gpt41106preview_few_shot_stance_reason": "Expresses a commitment to promoting
        father's rights, showing support for the cause.",
    "mistrallargelatest_zero_shot_stance_reason": "Author offers advice and
        expresses a desire to promote father's rights.",
    "mistrallargelatest_one_shot_stance_reason": "The author encourages someone to
        speak up about father's rights and offers advice.",
    "mistrallargelatest_few_shot_stance_reason": "Encourages speaking up for father'
        s rights."
}

{
    "submission_id": "abt6bj",
    "stance_id": "ed2y40j",
    "stance_id_comment": "So many untested kits are by request from the \"victim\"
        and not due to discrimination or police failure",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/abt6bj/
        sane_sexual_assault_nurse_examiner_nurse_story",

    "gpt41106preview_zero_shot_stance_label": "somewhat_against",
    "gpt41106preview_one_shot_stance_label": "somewhat_against",
    "gpt41106preview_few_shot_stance_label": "somewhat_against",
    "mistrallargelatest_zero_shot_stance_label": "somewhat_against",
    "mistrallargelatest_one_shot_stance_label": "somewhat_against",
    "mistrallargelatest_few_shot_stance_label": "somewhat_against",

    "gpt41106preview_zero_shot_stance_reason": "Claims many untested kits are due to
         'victim' requests.",
    "gpt41106preview_one_shot_stance_reason": "Claims many untested kits are due to
        victims' requests, showing some skepticism.",
    "gpt41106preview_few_shot_stance_reason": "Claims many untested kits are due to
        false accusers, showing distrust.",
    "mistrallargelatest_zero_shot_stance_reason": "Author claims that many untested
        rape kits are due to victim's request.",
    "mistrallargelatest_one_shot_stance_reason": "Implies that untested rape kits
        might be due to false accusations.",
    "mistrallargelatest_few_shot_stance_reason": "Believes many untested rape kits
        are due to false claims."
}

{
    "submission_id": "acnfv1",
    "stance_id": "acnfv1",
    "stance_id_comment": "The 2AF has received over $86,000 in donations just from
        Amazon Smile. That should be even higher! \n\nIf you haven't already, set
        them as who you donate to, and then **remember to checkout with smile.amazon
        .com, if you do regular amazon.com or the app, it won't donate anything.** \
        n\nIt will donate .5% of anything you purchase. That's $5 per every $1000
        you spend, which adds up fast if you use Amazon a lot. 2AF and Alan Gura won
         us *Heller* and continue to try and get gun cases to the Supreme Court.
        Help them keep doing so with a little of Amazon's money!",
    "reddit_link": "https://www.reddit.com/r/gunpolitics/comments/acnfv1/
        psa_set_your_amazon_smile_to_the_second_amendment",

    "gpt41106preview_zero_shot_stance_label": "strongly_in_favor",
    "gpt41106preview_one_shot_stance_label": "strongly_in_favor",
    "gpt41106preview_few_shot_stance_label": "strongly_in_favor",
    "mistrallargelatest_zero_shot_stance_label": "strongly_in_favor",
    "mistrallargelatest_one_shot_stance_label": "strongly_in_favor",
    "mistrallargelatest_few_shot_stance_label": "strongly_in_favor",

    "gpt41106preview_zero_shot_stance_reason": "Advocates for donations to 2AF,
        emphasizing its importance.",
    "gpt41106preview_one_shot_stance_reason": "Promotes 2AF donations through Amazon
         Smile, indicating strong support.",
    "gpt41106preview_few_shot_stance_reason": "Promotes Amazon Smile for 2AF
        donations, showing strong support.",
    "mistrallargelatest_zero_shot_stance_reason": "Author promotes donating to 2AF
        through Amazon Smile, emphasizing its impact.",
    "mistrallargelatest_one_shot_stance_reason": "Promotes Amazon Smile donations to
         2AF, emphasizing its impact.",
    "mistrallargelatest_few_shot_stance_reason": "Promotes donating to 2AF through
        Amazon Smile, highlighting its achievements."
}

{
    "submission_id": "abt6bj",
    "stance_id": "abt6bj",
    "stance_id_comment": "A female coworker of mine who is also a nurse was telling
        me that she took the SANE the class to become a nurse that assists patients
        in emergency rooms that claim they were raped. \nShe told me that if the
        dozens of patients she examined and collected evidence on their behalf, she
        only believed one of the \"victims\". \nThat one victim was a prostitute
        that was held against her will for 2 days repeatedly given heroin and raped.
         \nEvery other person she examined was highly suspicious for deception but
        she had to treat every single one like they were telling the truth. \
        nUltimately she quit because she felt she was just enabling women to file
        false reports against men, or feeding their desire to be victims or be
        manipulative. \nThese false accusers either need to be prosecuted or court
        ordered mental health services. This is not ok. It is why I rarely believe
        women when they say they were victims. It is unfortunate because rape is
        absolutely a horrible crime and should be punished severely when a criminal
        rapist is caught. But women need to stop lying. ",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/abt6bj/
        sane_sexual_assault_nurse_examiner_nurse_story",

    "gpt41106preview_zero_shot_stance_label": "strongly_against",
    "gpt41106preview_one_shot_stance_label": "strongly_against",
    "gpt41106preview_few_shot_stance_label": "strongly_against",
    "mistrallargelatest_zero_shot_stance_label": "strongly_against",
    "mistrallargelatest_one_shot_stance_label": "strongly_against",
    "mistrallargelatest_few_shot_stance_label": "strongly_against",

    "gpt41106preview_zero_shot_stance_reason": "Author expresses strong disbelief in
         most rape claims.",
    "gpt41106preview_one_shot_stance_reason": "Author expresses strong disbelief in
        most rape claims and suggests severe consequences for false accusers.",
    "gpt41106preview_few_shot_stance_reason": "Author expresses strong disbelief in
        most rape claims.",
    "mistrallargelatest_zero_shot_stance_reason": "Author expresses skepticism
        towards rape claims and believes most are false.",
    "mistrallargelatest_one_shot_stance_reason": "Expresses strong disbelief in rape
         claims and blames women for lying.",
    "mistrallargelatest_few_shot_stance_reason": "Expresses strong disbelief in rape
         claims and blames women for lying."
}
```

Q.2 Moderate Inter-Annotator Agreement Stance Examples

```
{
    "submission_id": "abi4d2",
    "stance_id": "ed8gah6",
    "stance_id_comment": "No, people need to hear this. When they talk about \"best
        interest standards\" for kids, the top thing on that list should be not one,
         but two loving parents. If you have two people who want to be with their
        children how can you deny them that? Instead they push \"stable home\"
        meaning a preference for one parent over another. I have 50/50 custody and
        my kids are very well adjusted, and I would say more adaptable than other
        kids.",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/abi4d2/
        mens_issues_regarding_child_custody_and_child",

    "gpt41106preview_zero_shot_stance_label": "somewhat_in_favor",
    "gpt41106preview_one_shot_stance_label": "strongly_in_favor",
    "gpt41106preview_few_shot_stance_label": "somewhat_in_favor",
    "mistrallargelatest_zero_shot_stance_label": "strongly_in_favor",
    "mistrallargelatest_one_shot_stance_label": "somewhat_in_favor",
    "mistrallargelatest_few_shot_stance_label": "strongly_in_favor",

    "gpt41106preview_zero_shot_stance_reason": "Author argues for equal parenting,
        indicating a supportive stance.",
    "gpt41106preview_one_shot_stance_reason": "Strongly advocates for equal
        parenting, criticizing the current system.",
    "gpt41106preview_few_shot_stance_reason": "Advocates for equal parenting,
        criticizing the preference for one parent over another.",
    "mistrallargelatest_zero_shot_stance_reason": "Author advocates for equal
        custody rights for both parents.",
    "mistrallargelatest_one_shot_stance_reason": "The author advocates for children
        having two loving parents and shares their positive experience with 50/50
        custody.",
    "mistrallargelatest_few_shot_stance_reason": "Advocates for equal custody and
        adaptability of children."
}

{
    "submission_id": "abp7hw",
    "stance_id": "ed3dbvc",
    "stance_id_comment": "Uh, yeah it's about attacking female privilege too.\n\nAnd
         yeah it's against \"SJW bullshit\" meaning anti-male prejudice and hate
        speech.\n\nI'm guessing the many women here would be surprised to learn any
        of that is attacking women.  Can I still criticize the KKK?  Or is that anti
        -White racism in your opinion?",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/abp7hw/
        a_reminder_that_this_sub_is_about_mens_rights_and",

    "gpt41106preview_zero_shot_stance_label": "strongly_in_favor",
    "gpt41106preview_one_shot_stance_label": "strongly_in_favor",
    "gpt41106preview_few_shot_stance_label": "strongly_against",
    "mistrallargelatest_zero_shot_stance_label": "strongly_in_favor",
    "mistrallargelatest_one_shot_stance_label": "strongly_against",
    "mistrallargelatest_few_shot_stance_label": "strongly_against",

    "gpt41106preview_zero_shot_stance_reason": "Author strongly supports attacking
        female privilege and anti-male prejudice.",
    "gpt41106preview_one_shot_stance_reason": "Asserts that attacking female
        privilege and opposing 'SJW bullshit' is part of the subreddit's purpose.",
    "gpt41106preview_few_shot_stance_reason": "Clearly opposes the idea that
        attacking female privilege is wrong and equates it with fighting prejudice
        .",
    "mistrallargelatest_zero_shot_stance_reason": "Author is in favor of attacking
        female privilege and criticizing the KKK.",
    "mistrallargelatest_one_shot_stance_reason": "Criticizes female privilege and
        SJWs, implying a negative stance towards them.",
    "mistrallargelatest_few_shot_stance_reason": "Criticizes female privilege and
        anti-male prejudice, implying a strong stance against them."
}
```

Q.3 Least Inter-Annotator Agreement Stance Examples

```
{
    "submission_id": "ach1kf",
    "stance_id": "ed83u16",
    "stance_id_comment": "It has nothing to do with logic it\u2019s all faith and
        emotion. I am always amazed that the atheist subs are so anti gun. ",
    "reddit_link": "https://www.reddit.com/r/gunpolitics/comments/ach1kf/
        a_easy_way_to_shutdown_anyone_who_brings_up",

    "gpt41106preview_zero_shot_stance_label": "somewhat_against",
    "gpt41106preview_one_shot_stance_label": "somewhat_against",
    "gpt41106preview_few_shot_stance_label": "somewhat_against",
    "mistrallargelatest_zero_shot_stance_label": "strongly_in_favor",
    "mistrallargelatest_one_shot_stance_label": "stance_not_inferrable",
    "mistrallargelatest_few_shot_stance_label": "somewhat_in_favor",

    "gpt41106preview_zero_shot_stance_reason": "Claims anti-gun sentiment is based
        on faith and emotion, indicating disagreement.",
    "gpt41106preview_one_shot_stance_reason": "Criticizes anti-gun sentiment as
        based on faith and emotion.",
    "gpt41106preview_few_shot_stance_reason": "Expresses a negative stance towards
        anti-gun views, attributing them to emotion rather than logic.",
    "mistrallargelatest_zero_shot_stance_reason": "Author dismisses anti-gun
        arguments as illogical.",
    "mistrallargelatest_one_shot_stance_reason": "Mentions atheist subs being anti-
        gun but does not express a clear stance.",
    "mistrallargelatest_few_shot_stance_reason": "Expresses disbelief towards anti-
        gun atheists, implying support for guns."
}

{
    "submission_id": "ach1kf",
    "stance_id": "edb7w5z",
    "stance_id_comment": "Sure but let\u2019s blame the tool as well, that is the
        point. Booze does not make someone a molester and a gun does not make
        someone a killer. ",
    "reddit_link": "https://www.reddit.com/r/gunpolitics/comments/ach1kf/
        a_easy_way_to_shutdown_anyone_who_brings_up",

    "gpt41106preview_zero_shot_stance_label": "somewhat_against",
    "gpt41106preview_one_shot_stance_label": "strongly_against",
    "gpt41106preview_few_shot_stance_label": "strongly_against",
    "mistrallargelatest_zero_shot_stance_label": "strongly_in_favor",
    "mistrallargelatest_one_shot_stance_label": "somewhat_against",
    "mistrallargelatest_few_shot_stance_label": "somewhat_in_favor",

    "gpt41106preview_zero_shot_stance_reason": "Argues against blaming tools (
        alcohol/guns) for actions, indicating stance.",
    "gpt41106preview_one_shot_stance_reason": "Strongly argues against blaming tools
         (guns) for actions of people.",
    "gpt41106preview_few_shot_stance_reason": "Clearly opposes the idea of blaming
        tools for actions, aligning with pro-gun stance.",
    "mistrallargelatest_zero_shot_stance_reason": "Author argues against blaming
        tools (guns) for crimes.",
    "mistrallargelatest_one_shot_stance_reason": "Suggests not blaming the tool (gun
        ) but does not directly express a stance on gun control.",
    "mistrallargelatest_few_shot_stance_reason": "Suggests not blaming tools (guns)
        for the actions of people."
}
```

Q.4 High Inter-Annotator Agreement Dogmatism Examples

```
{
    "submission_id": "abp7hw",
    "author_key": "author1",
    "author_key_name": "DavidByron2",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/abp7hw/
        a_reminder_that_this_sub_is_about_mens_rights_and",
    "gpt41106preview_zero_shot_dogmatism_label": "Firm but Open",
    "gpt41106preview_one_shot_dogmatism_label": "Firm but Open",
    "gpt41106preview_few_shot_dogmatism_label": "Firm but Open",
"mistrallargelatest_zero_shot_dogmatism_label": "Firm but Open",
"mistrallargelatest_one_shot_dogmatism_label": "Firm but Open",
"mistrallargelatest_few_shot_dogmatism_label": "Firm but Open",
    "gpt41106preview_zero_shot_dogmatism_reason": "Author holds strong views against
         SJWs but engages in discussion.",
    "gpt41106preview_one_shot_dogmatism_reason": "Strong views on the subreddit's
        purpose but engages without dismissing others.",
    "gpt41106preview_few_shot_dogmatism_reason": "Strongly opposes certain ideas but
         does not dismiss opposing views outright.",
    "mistrallargelatest_zero_shot_dogmatism_reason": "Author expresses strong
        opinions but also engages in discussion and asks questions.",
"mistrallargelatest_one_shot_dogmatism_reason": "Expresses strong opinions but
    engages in discussion and asks questions.",
"mistrallargelatest_few_shot_dogmatism_reason": "Expresses strong opinions but
    engages in discussion and asks questions, showing openness to dialogue."
}

{
    "submission_id": "abp7hw",
    "author_key": "author2",
    "author_key_name": "goodmod",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/abp7hw/
        a_reminder_that_this_sub_is_about_mens_rights_and",

    "gpt41106preview_zero_shot_dogmatism_label": "Open to Dialogue",
    "gpt41106preview_one_shot_dogmatism_label": "Open to Dialogue",
    "gpt41106preview_few_shot_dogmatism_label": "Open to Dialogue",
"mistrallargelatest_zero_shot_dogmatism_label": "Open to Dialogue",
"mistrallargelatest_one_shot_dogmatism_label": "Open to Dialogue",
"mistrallargelatest_few_shot_dogmatism_label": "Open to Dialogue",
    "gpt41106preview_zero_shot_dogmatism_reason": "Author enforces rules but is open
         to different opinions and dialogue.",
    "gpt41106preview_one_shot_dogmatism_reason": "Welcomes different opinions and
        upholds subreddit rules fairly.",
    "gpt41106preview_few_shot_dogmatism_reason": "Supports subreddit rules while
        acknowledging the validity of critical opinions.",
    "mistrallargelatest_zero_shot_dogmatism_reason": "Author is open to different
        viewpoints and engages in meaningful conversation.",
"mistrallargelatest_one_shot_dogmatism_reason": "Focuses on enforcing rules and
    addressing concerns without expressing personal opinions or dogmatic views.",
"mistrallargelatest_few_shot_dogmatism_reason": "Focuses on enforcing rules and
    engaging in conversation without expressing personal opinions on the topic."
}

{
    "submission_id": "acmcge",
    "author_key": "author1",
    "author_key_name": "Will_Power",
    "reddit_link": "https://www.reddit.com/r/climatechange/comments/acmcge/
        how_important_is_wind_power_and_what_is_its",

    "gpt41106preview_zero_shot_dogmatism_label": "Deeply Rooted",
    "gpt41106preview_one_shot_dogmatism_label": "Deeply Rooted",
    "gpt41106preview_few_shot_dogmatism_label": "Deeply Rooted",
"mistrallargelatest_zero_shot_dogmatism_label": "Deeply Rooted",
"mistrallargelatest_one_shot_dogmatism_label": "Deeply Rooted",
"mistrallargelatest_few_shot_dogmatism_label": "Deeply Rooted",
    "gpt41106preview_zero_shot_dogmatism_reason": "Consistently dismisses
        counterarguments, maintains strong stance without considering alternative
        views.",
    "gpt41106preview_one_shot_dogmatism_reason": "Consistently dismisses
        counterarguments and maintains a rigid stance.",
    "gpt41106preview_few_shot_dogmatism_reason": "Consistently argues against wind
        power with strong conviction, dismissing opposing views.",
    "mistrallargelatest_zero_shot_dogmatism_reason": "Author is firm in their stance
         against wind power and refuses to consider alternative viewpoints.",
"mistrallargelatest_one_shot_dogmatism_reason": "Shows a strong, unchangeable belief
     in the negative impact of wind power and is unlikely to be swayed.",
"mistrallargelatest_few_shot_dogmatism_reason": "Consistently maintains their stance
     against wind power and accuses the other author of being influenced by ideology
    ."
}

{
    "submission_id": "brn0ti",
    "author_key": "author1",
    "author_key_name": "immibis",
    "reddit_link": "https://www.reddit.com/r/prolife/comments/brn0ti/
        what_do_prolifers_think_about_those_with_a_high",

    "gpt41106preview_zero_shot_dogmatism_label": "Flexible",
    "gpt41106preview_one_shot_dogmatism_label": "Flexible",
    "gpt41106preview_few_shot_dogmatism_label": "Flexible",
"mistrallargelatest_zero_shot_dogmatism_label": "Flexible",
"mistrallargelatest_one_shot_dogmatism_label": "Flexible",
"mistrallargelatest_few_shot_dogmatism_label": "Flexible",
    "gpt41106preview_zero_shot_dogmatism_reason": "Author's comments are off-topic,
        showing no strong beliefs.",
    "gpt41106preview_one_shot_dogmatism_reason": "The author's comments are
        unrelated to the topic, indicating a lack of strong opinion on the matter.",
    "gpt41106preview_few_shot_dogmatism_reason": "The author's comments are
        consistently off-topic, indicating a lack of engagement with the issue.",
"mistrallargelatest_zero_shot_dogmatism_reason": "The author does not express a
    clear stance on the topic and seems open to different interpretations.",
"mistrallargelatest_one_shot_dogmatism_reason": "The author does not express a clear
     stance or engage in meaningful discussion on the topic.",
"mistrallargelatest_few_shot_dogmatism_reason": "The author does not express a clear
     stance or opinion on the topic."
}
```

Q.5 Moderate Inter-Annotator Agreement Dogmatism Examples

```
{
    "submission_id": "acqq1a",
    "author_key": "author1",
    "author_key_name": "Meyright",
    "reddit_link": "https://www.reddit.com/r/MensRights/comments/acqq1a/
        ive_noticed_a_worrying_trend_in_the_mensrights",

    "gpt41106preview_zero_shot_dogmatism_label": "Open to Dialogue",
    "gpt41106preview_one_shot_dogmatism_label": "Firm but Open",
    "gpt41106preview_few_shot_dogmatism_label": "Firm but Open",
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"mistrallargelatest_few_shot_dogmatism_reason": "Engages in thoughtful discussion,
    acknowledges different perspectives, and remains open to various viewpoints."
}


{
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    "author_key_name": "TBTop",
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        meaning_of_well_regulated_militia",

    "gpt41106preview_zero_shot_dogmatism_label": "Deeply Rooted",
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    "gpt41106preview_one_shot_dogmatism_reason": "Author is steadfast in their pro-
        gun stance but engages in discussion.",
    "gpt41106preview_few_shot_dogmatism_reason": "Presents strong support for gun
        rights but engages in discussion and historical context.",
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        showing a strong, unchangeable belief.",
"mistrallargelatest_one_shot_dogmatism_reason": "Author presents strong opinions but
     engages in discussion and responds to counterarguments.",
"mistrallargelatest_few_shot_dogmatism_reason": "Consistently argues in favor of the
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}
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Q.6 Least Inter-Annotator Agreement Dogmatism Examples

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{
    "submission_id": "ar65mb",
    "author_key": "author2",
    "author_key_name": "CarolusMinimus",
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    "gpt41106preview_zero_shot_dogmatism_label": "Flexible",
    "gpt41106preview_one_shot_dogmatism_label": "Flexible",
    "gpt41106preview_few_shot_dogmatism_label": "Open to Dialogue",
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    "gpt41106preview_few_shot_dogmatism_reason": "Limited data, but shows a negative
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}

{
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    "gpt41106preview_one_shot_dogmatism_label": "Firm but Open",
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"mistrallargelatest_few_shot_dogmatism_label": "Firm but Open",
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    "gpt41106preview_few_shot_dogmatism_reason": "Strong opinions on diet but shows
        some openness to moderation and clarification.",
"mistrallargelatest_zero_shot_dogmatism_reason": "Author engages in conversation and
    shares opinions without imposing them or dismissing others.",
"mistrallargelatest_one_shot_dogmatism_reason": "Encourages flexibility in diet
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}
```

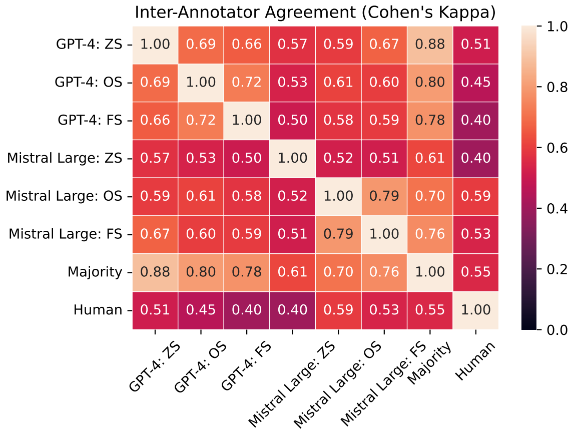

	GPT-4: ZS	GPT-4: OS	GPT-4: FS	Mistral Large: ZS	Mistral Large: OS	Mistral Large: FS	Majority	Human
GPT-4: ZS	1.00	0.69	0.66	0.57	0.59	0.67	0.88	0.51
GPT-4: OS	0.69	1.00	0.72	0.53	0.61	0.60	0.80	0.45
GPT-4: FS	0.66	0.72	1.00	0.50	0.58	0.59	0.78	0.40
Mistral Large: ZS	0.57	0.53	0.50	1.00	0.52	0.51	0.61	0.40
Mistral Large: OS	0.59	0.61	0.58	0.52	1.00	0.79	0.70	0.59
Mistral Large: FS	0.67	0.60	0.59	0.51	0.79	1.00	0.76	0.53
Majority	0.88	0.80	0.78	0.61	0.70	0.76	1.00	0.55
Human	0.51	0.45	0.40	0.40	0.59	0.53	0.55	1.00

Figure 22: Inter-annotator agreement (IAA) on test dataset: Weighted Cohen's Kappa score across 8 settings: two different models (2 models×3 settings), majority voting and human annotations for the Dogmatism task.

R Weighted Cohen's Kappa score: IAA between human labels and LLM-generated labels

We used the weighted Cohen's Kappa metric to compute the inter-annotator agreement (IAA) between human labels and LLM-generated labels across six settings, as well as majority voting, for the dogmatism task. Figure 22 reports the IAA on the test dataset, presenting the weighted Cohen's Kappa score across eight settings: two different models (2 models × 3 settings), majority voting, and human annotations for the dogmatism task. * This figure highlights that the weighted Cohen's Kappa metric improves the IAA between human annotations and the majority voting approach to 0.55, compared to the earlier score of 0.5 using the standard Cohen's Kappa metric. This indicates that the weighted Cohen's Kappa score effectively penalizes more distant disagreements, potentially leading to an improved measure of partial agreement.