Proposal: From One-Fit-All to Perspective Aware Modeling

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Abstract

Variation in human annotation and human perspectives has drawn increasing attention in natural language processing research. Disagreement observed in data annotation challenges the conventional assumption of a single "ground truth" and uniform models trained on aggregated annotations, which tend to overlook minority viewpoints and individual perspectives. This proposal investigates three directions of perspective-oriented research: First, annotation formats that better capture the granularity and uncertainty of individual judgments; Second, annotation modeling that leverages socio-demographic features to better represent and predict underrepresented or minority perspectives; Third, personalized text generation that tailors outputs to individual users' preferences and communicative styles. The proposed tasks aim to advance natural language processing research towards more faithfully reflecting the diversity of human interpretation, enhancing both inclusiveness and fairness in language technologies.

1 Introduction

Understanding human perspectives and designing systems that cater to individual needs are critical goals in natural language processing (NLP) research. However, traditional approaches often rely on aggregated annotations in datasets and treat them as a singular ground truth for model training (Braylan and Lease, 2020; Qing et al., 2014).

In recent years, the assumption of a "single ground truth" has been increasingly challenged by researchers (Plank, 2022; Cabitza et al., 2023; Sap et al., 2022; Frenda et al., 2024), drawing attention to the limitations of conventional data construction and modeling practices in capturing the full spectrum of human perspectives. Beyond NLP research, similar concerns have arisen in related fields, such as the legal domain (Braun and Matthes, 2024; Xu et al., 2023), the medical domain (Miñarro-Giménez et al., 2018), and music annotation (Koops et al., 2019).

Growing evidence suggests that annotator perspectives are shaped by complex, context-dependent factors, including individual beliefs, their demographic backgrounds, context information, text ambiguity or interpretive uncertainty. Studies (Braun, 2024) also highlighted that human annotators frequently provide different but equally valid labels, challenging the assumption that there is always a single correct answer. This shift calls for a deeper investigation into annotation variation and human perspectives research in all stages: annotation (Plank, 2022), modeling (Uma et al., 2021; Mostafazadeh Davani et al., 2022; Mokhberian et al., 2024) and evaluation frameworks (Basile et al., 2021; Rizzi et al., 2024) in order to improve the inclusiveness and models' alignment of human perspectives.

This proposal aims to advance perspective-aware approaches in NLP by providing insights into annotation methodologies that better capture the complexity of human perspectives and improve modeling efficiency (Section 3), evaluating the influence of socio-demographic factors on annotation variation modeling (Section 4), and exploring methods to leverage persona information for personalized textual generation (Section 5). Three tasks are illustrated in Figure 1.

Annotation Format: This task explores different formats of annotation types in representing perspectives: binary labels vs. continuous or Likert scale values. We assess whether continuous values or Likert scales, rather than binary labels, better capture the uncertainty of annotators' tendencies and perspectives. The research outcome aims to improve annotation practices and derive more refined annotation methods for capturing the subtleties of diverse annotator perspectives.

Perspective Annotation Modeling: This task in-

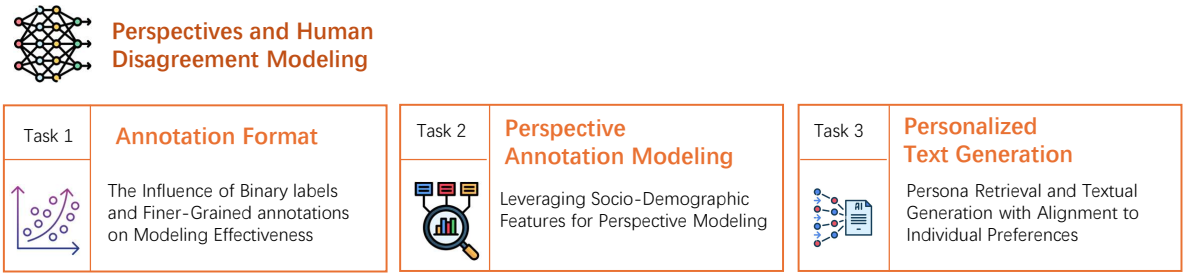

Figure 1: Proposed Tasks of Perspective Aware Modeling

vestigates the extent to which socio-demographic features can account for annotator perspectives or variation in humans' annotation patterns. We examine the effectiveness of predicting an individual's annotations based on their socio-demographic attributes in application domains that have not yet been explored.

Personalized Generation: This task explores persona-based modeling and personalized textual generation that reflect users' preferences and communication styles. We incorporate structured persona information, such as socio-demographic features, sentiment orientation, and linguistic complexity as additional signals for text generation. The objective is to produce responses or texts that are not only contextually appropriate but also tailored in terms of individual preference.

2 Related Studies

Recent studies have increasingly recognized the presence of human disagreement and diverse perspectives in annotation tasks. Various terms have been used to describe this phenomenon, including subjectivity (Reidsma and Carletta, 2008), human uncertainty (Peterson et al., 2019), perspectivism or perspectivist (Cabitza et al., 2023; Frenda et al., 2024), human label variation (Plank, 2022) and pluralism (Sorensen et al.; Feng et al., 2024). Moreover, an increasing number of studies have released datasets (Wang et al., 2023; Kumar et al., 2021; Frenda et al., 2023; Passonneau et al., 2012; Dumitrache et al., 2018) annotated by multiple individuals, in contrast with the single label from the traditional majority-vote aggregation or score averaging.

Prior research (Plank et al., 2014; Sheng et al., 2008; Guan et al., 2018; Fornaciari et al., 2021; Xu et al., 2024; Casola et al., 2023) has demonstrated that incorporating labels from multiple annotators can enhance model performance by improving the model's generalization ability. Methods include the cost-sensitive approach, where the loss of each instance is weighted based on label distribution (Plank et al., 2014; Sheng et al., 2008), as well as soft-loss approaches (Peterson et al., 2019; Lalor et al., 2017; Uma et al., 2020; Fornaciari et al., 2021). Furthermore, researchers have explored leveraging additional metadata, such as socio-demographic features (Goyal et al., 2022; Gordon et al., 2022), annotator IDs (Mokhberian et al., 2024), and partial annotation histories (Milkowski et al., 2021; Sorensen et al., 2025), to characterize individual annotation patterns and refine learning procedures.

The alignment of large language models (LLMs) with human annotation has also gained increasing attention under the context of embracing human disagreement, particularly in evaluating their ability to capture diverse perspectives and which groups' perspective that LLMs reflect (Hu and Collier, 2024; Beck et al., 2024; Salemi et al., 2024; Muscato et al., 2024). In the generation domain, MORPHEUS (Tang et al., 2024) introduces a three-stage framework to model roles from dialogue history. It compresses persona information into a latent codebook, enabling generalization to unseen roles through joint training. Lu et al. (2023) disentangle multi-faceted attributes in the latent space and use a conditional variational auto-encoder to align responses with user traits.

3 Annotation Formats for Perspective Representation

This task explores two different annotation formats (binary classification versus Likert-scale or continuous values) for representing human perspectives and investigates their influence on modeling effectiveness. The study aims to provide guidance for

future dataset construction by identifying annotation formats that best support model learning and more accurately capture the nuance of human perspectives.

3.1 Motivation and Research Hypothesis

Previous research (Plank, 2022; Mostafazadeh Davani et al., 2022) has primarily focused on label variation using discrete labels. Many studies, particularly in domains such as hate speech and offensive language detection, rely on binary annotations (Mostafazadeh Davani et al., 2022; Akhtar et al., 2020). In some cases, ordinal Likert-scale ratings are converted into binary labels in modeling procedures (Orlikowski et al., 2023).

Ovesdotter Alm (2011) argues that acceptability is a more meaningful concept than rigid "right" or "wrong" labels. Human annotators exhibit varying degrees of uncertainty for specific items, and some tasks inherently involve continuous variation, such as the level of emotional arousal (Lee et al., 2022). Simple binary classes can obscure important nuances in annotation data. It may risk oversimplifying the granularity of human perspectives, ultimately impacting model reliability and the interpretability of annotator uncertainty.

We hypothesize that continuous values or Likert scales provide a more effective source for capturing and modeling annotation variation. From the perspective of machine learning, incorporating finer-grained annotations may help align better with human judgment and enhance model performance by smoothing the decision boundary compared to rigid binary labels.

3.2 Methodology

This study undertakes interdisciplinary approach to investigate the impact of the annotation format across multiple domains, including tasks such as hate speech detection, offensive language detection and sentiment analysis[1]. By examining diverse datasets and modeling techniques, we aim to assess whether adopting finer-grained annotation scales improves the representation and learning of annotators' perspectives in a cross-domain context.

Data Construction: Two types of datasets will be used for this purpose. First, for datasets with Likert scales or continuous values, we will train models using the original values and also targets that are transformed into binary labels[2] for comparison. Second, for datasets originally with discrete labels, such as natural language inference, where three labels (entailment, contradiction, and neutrality) exist, we will annotate with an additional scale representing human uncertainty of the label selection to capture the complexity inherent in human judgment.

Modeling framework: To test the hypothesis (numerical values better represent human perspectives than binary labels, and models based on values show better effectiveness in machine learning), we will implement the three modeling architectures (Figure 2) from Mostafazadeh Davani et al. (2022) to compare the results of two types of targets (binary encoding vs. continuous values):

- Individual Annotator Modeling: Each annotator's annotations will be modeled separately using distinct neural networks to capture individual perspectives.
- Multi-target Methods: A shared neural network will be trained with all annotators' annotations represented as target vectors, allowing the model to learn patterns across annotators.
- Multi-Task Learning: A partially shared neural network will be employed, with shared layers capturing common understanding and annotator-specific layers or heads capturing individualized annotation tendencies.

Evaluation and Result Analysis: Model performance will be evaluated using both traditional metrics based on aggregated labels, label distributions and specialized evaluation on individualized prediction accuracy to assess the advantages of finer-grained annotations compared to binary labels. Since direct comparison between binary classification and regression outputs is inherently challenging, we propose two complementary evaluation strategies to facilitate a meaningful comparison:

- Binary Label Conversion: Continuous regression outputs will be converted into binary labels using a predefined threshold (consistent with the threshold used during training for label derivation). We will then compute standard classification metrics such as F1 score

[1] These tasks are known that human annotation variation exists and with relatively richer datasets annotated by multiple individuals, seen Wang et al. (2023); Akhtar et al. (2020); Waseem (2016) and Gruber et al. (2024).

[2] Different threshold values can be set for partition to assess the robustness.

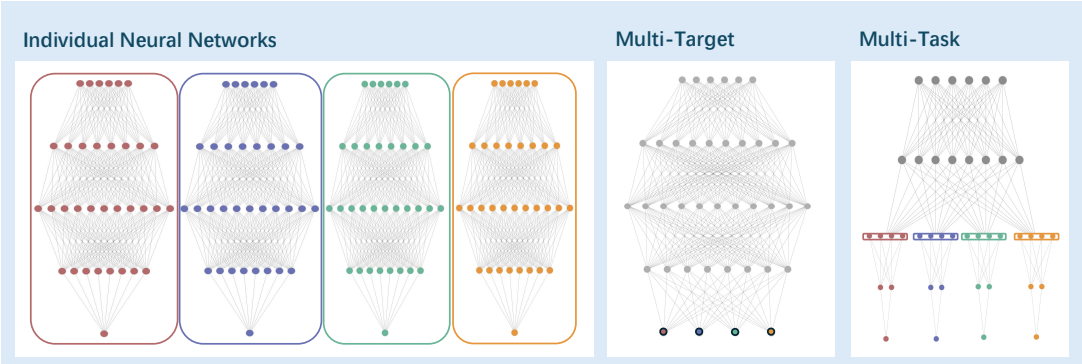

Figure 2: Neural Network Architectures for Perspective Annotation Modeling

and accuracy to evaluate the alignment between the binarized predictions and the target.

- Ranked Correlation Comparison: While classifier outputs do not offer the same level of granularity as regression values, the predicted probabilities or logits can serve as proxies for prediction confidence or intensity (e.g., degree of toxicity). These values enable a ranking-based comparison with the ground truth labels. We will compute the Spearman rank correlation (r) between the model predictions and the true target values, allowing us to compare the correlation strength across both classifiers and regressors.

4 Perspective Annotation Modeling with Demographic Features

This task investigates the extent to which socio-demographic features, such as age, gender, education level, political affiliation, and domain expertise contribute to explaining and modeling variation in human annotation.

4.1 Motivation and Research Questions

While prior research has explored this question in some NLP tasks, findings remain inconclusive with various methods and datasets. In toxicity classification, for example, Orlikowski et al. (2023) reports that incorporating group-level socio-demographic features does not significantly improve predictive performance in toxicity classification tasks, when compared to randomly assigned groups. In contrast, Gordon et al. (2022) discovered a correlation between annotator perspectives and their socio-demographic backgrounds, suggesting these features may meaningfully inform model learning of toxicity.

These conflicting results raise a question: in which application domains and with what modeling methods do socio-demographic features act effectively for modeling? Can we model the probability conditioned on socio-demographic features `Prob(annotation_pred|demographic_feature)` with a better accuracy than assuming an undifferentiated perspective `Prob(annotation_pred)` with neural networks?

We aim to explore whether socio-demographic traits enhance the performance of predicting annotations, particularly in domains that have received limited attention in previous research. Prior research primarily focuses on subjective domains such as hate speech (Sachdeva et al., 2022; Kocoń et al., 2021) or toxicity classification (Goyal et al., 2022). In linguistic annotations, more objective tasks such as natural language inference (Huang and Yang, 2023; Jiang and de Marneffe, 2022) and part-of-speech tag (POS) (Plank et al., 2014) are detected with inherent human label variations.

Extending beyond tasks that received much attention in previous research, we apply this perspective modeling framework to financial or economic domains to investigate the interpretation variation of business trends and sentiment of economic statements[3] (Malo et al., 2014; Liu et al., 2023).

Specifically, we address the following research questions: First, to what extent do socio-demographic attributes and domain expertise account for variation in annotator judgments in business-related tasks? Second, which specific attributes, if any, serve as reliable predictors of annotation variation? And third, which modeling

[3]Related datasets such as Malo et al. (2014) and Liu et al. (2023) are available with a single annotator's decision. Datasets with meta information, particularly with various socio-demographic backgrounds, should be constructed for the purpose of the current study.

methods show advantages in modeling patterns of various socio-demographic groups?

4.2 Methodology

In this task, we will improve the modeling methods in prior research to model socio-demographic features and annotation variation more efficiently. The following modeling methods are proposed for exploration:

- Socio-Demographic Embedding Learning: Embedding layers will be incorporated into neural networks to encode socio-demographic attributes, enabling the model to capture correlations and patterns of annotator attributes such as gender, nationality, and political orientation. This embedding-based model will be compared against a baseline where these attributes are randomly shuffled to assess their genuine contribution to model performance.

- Demographics-Enriched Prompts in Large Language Models (LLMs): We will experiment with prompt-based approaches to incorporate socio-demographic features into LLM predictions. Specifically, we will present demographic features in prompts with either structured key-value formats or natural language descriptions for a comparison study.

- Lightweight Fine-Tuning of LLMs: To further enhance performance, this study will adopt parameter-efficient fine-tuning techniques such as prefix tuning (Li and Liang, 2021), the methods enable personalization without extensive retraining, making them suitable for incorporating socio-demographic signals.

To assess the effectiveness of the proposed methods for modeling human perspectives, we design comparative experiments to assess the effect of socio-demographic features. Specifically, we consider the following three experimental conditions: (1) Single annotation modeling, which only makes use of the aggregated annotations obtained from multiple annotators. (2) Annotation distribution modeling that leverages the distribution of annotations without additional annotator attributes. Methods in Section 3 or approaches such as soft-loss function (Fornaciari et al., 2021; Uma et al., 2021) can serve for this purpose. (3) Socio-demographic enriched learning with three proposed methods in this section, in which predictions are conditioned on socio-demographic features. This comparison will shed light on whether demographic factors serve as useful input features for the perspective modeling of financial trends perception.

4.3 Evaluation

In the evaluation stage, we consider multiple metrics under different conditions. These include (1) Accuracy and F1 score computed from aggregated labels; (2) Measures that capture the distributional alignment of prediction and annotation, metrics including cross-entropy loss, Kullback-Leibler (KL) divergence, and Jensen-Shannon divergence. While, this study mainly focuses on (3) Model performance within specific socio-demographic groups to evaluate its effectiveness across diverse populations. To examine the influence of particular socio-demographic features on perspective attribution, we will apply statistical tests, specifically, the Student's t-test for binary features and ANOVA for categorical features, to investigate correlations between these attributes and annotation behaviors or perspectives.

5 Personalized Text Generation

Building on the perspective exploration of annotation variation, namely **label and value prediction** in the previous tasks, this section extends the research to **personalized text generation**. The goal is to generate language that aligns with individual users' backgrounds, preferences, and communication styles. This includes conditioning generation on persona-related factors such as socio-demographic attributes, historical dialogue context, and language preferences. Personalized generation aims to adapt to user needs and enhance user engagement and satisfaction.

5.1 Motivation

Generative models have demonstrated impressive capabilities of text generation across a wide range of tasks, such as summarization (Wang and Cardie, 2013), question answering (Duan et al., 2017), or dialogue generation (Li et al., 2017). While models may excel at producing coherent texts in a more general setting, they lack the ability to adapt output text to the various profiles of individual users (Zhang et al., 2024). Personalized generation aims to address this problem by integrating user-specific data, such as stated preferences, topic familiarity,

language proficiency or cultural background, to dynamically shape the generated content. This focus on personalization unlocks potential across applications like adaptive education, health support, and personalized suggestions, such as a diet plan or career recommendations.

5.2 Methodology

To achieve the goal of personalized generation, we proposed a two-stage framework: (1) Persona Retrieval and Representation; and (2) Generation with Alignment to Individual Preferences.

In the first stage, persona information can be composed of both **explicit** and **implicit** sources. Explicit features include annotator metadata such as age, gender, education level, and profession, which were collected during the dataset construction phase. Implicit cues, on the other hand, are derived from users' historical text, such as writing style, expressed interests or behaviors. These require a preliminary persona prediction or persona representation. Two strategies will be pursued for persona representation: (1) Structured persona representation, where retrieved information is formatted as key-value pairs and provided as additional context in the input prompts. (2) Latent persona embedding, building on approaches like MORPHEUS (Tang et al., 2024) and MIRACLE (Lu et al., 2023), which encode user attributes into latent vectors. These embeddings can then serve as conditioning signals during the generation phase, enabling fine-grained personalization.

In the second stage, we focus on aligning the language model's generation behavior with the identified user preferences and persona attributes. Two methodologies will be explored:

- Prompt-Based Personalization: Persona attributes will be incorporated into structured or natural language prompts to gauge the generation task with an explicit user role. This approach leverages the in-context learning capabilities of large language models (LLMs) and offers a transparent, controllable mechanism for personalized input.

- Latent Representation Learning and LLM Fine-tuning: To enable integration of personalization signals into neural networks, we will investigate lightweight fine-tuning techniques such as prefix tuning (Li and Liang, 2021), LoRA (Low-Rank Adaptation, Hu et al., 2022). These methods allow LLMs to condition on user-specific embeddings with minimal training and data requirements. Beyond model tuning, this stage may also include reinforcement learning with user feedback (RLHF) or preference modeling, where iterative refinement is guided by explicit or implicit user evaluations.

5.3 Evaluation

Evaluating personalized generation poses additional challenges besides the conventional evaluation of text generation quality. Multiple evaluation strategies will be adopted to assess generation performance: (1) Standard Generation Metrics: Including BLEU, ROUGE and METEOR to assess content quality, coherence, and relevance. While these metrics may not capture personalized generation, they are useful for verifying baseline generation quality. (2) Persona-Based Metrics: We will evaluate the alignment between generated outputs and persona information by measuring the overlap or differences between generated texts and persona sentences in datasets like PersonaChat (Jandaghi et al., 2023). To assess whether generated texts reflect target attributes, we will use classification or clustering-based evaluations, measuring whether the generated texts reflect certain persona attributes. (3) Human Evaluation: For a subset of outputs, human annotators will be used to rate the relevance, fluency, and personalization of responses with respect to their persona profiles.

6 Conclusion

This proposal advances perspective-aware modeling in natural language processing by addressing three key components: annotation format design, annotation variation modeling by leveraging socio-demographic features, and personalized text generation. First, it investigates how finer-grained annotation formats, such as Likert scales, better capture the nuances of human perspectives compared to binary labels. Second, it examines the extent to which socio-demographic features influence annotation variation, particularly in relatively underexplored domains of business and economics. Finally, methods for personalized generation that align output with user-specific attributes are proposed. These tasks aim to enhance the inclusivity and fairness of NLP systems by modeling the diversity of human perspectives.

Limitations

This proposal does not aim to comprehensively resolve all challenges associated with human annotation variation and annotator perspectives, particularly given its cross-domain property. In addition, the availability of suitable datasets for certain tasks, especially those that include detailed annotator background information required for certain modeling and generation tasks, poses challenges to this research. To address this, the study will involve the construction of new datasets or the design of additional annotation tasks tailored to perspective research.

Ethical Considerations

Research involving socio-demographic attributes and personal perspectives inherently carries ethical risks, particularly concerning the privacy and potential misuse of annotators' personal information. This study will take careful measures to protect the identities and privacy of all participants. All collected and analyzed data will be fully anonymized and handled in accordance with privacy-preserving protocols.

Special attention will be given to the ethical challenges of persona inference and demographic modeling. Minority and underrepresented viewpoints, which are essential to the study's objectives, will be treated with care and used solely for academic purposes to prevent any harm or stigmatization. Moreover, in the analysis and presentation of findings, efforts will be made to use neutral, respectful language and to avoid reinforcing stereotypes or generalizations associated with specific demographic groups.

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