MMPD: A Multimedia Conversational Personality Dataset

Anonymous ACL submission

Abstract

Automatic personality detection has evolved from simple text classification to sophisticated multimodal analyses, recognizing the multi-dimensional manifestation of personality beyond textual data. This shift highlights the need for datasets that can accurately capture the complexity of human personality through diverse modalities. We introduce the Multimedia Conversational Personality Dataset (MMPD), a large, extensive and varied dataset, built on 305 movies and 14 TV series, featuring over 46k dialogues, 552k utterances, 4016 characters, and 963 hours of video. MMPD not only addresses the challenges of existing datasets by offering majority-voted personality annotations and detailed relationship networks but also provides a new method for matching subtitles with original scripts, paving the way for advanced analyses of personality dynamics across various contexts.

Figure 1: The Distinctive Features in Three Modalities for Personality Prediction

1 Introduction

Personality is a comprehensive yet complex trait that encapsulates individual differences in patterns of thinking, feeling, and behaving. In recent years, there has been a burgeoning interest in automatic personality detection, marking a significant shift from traditional methods to innovative computational approaches. Initially, the challenge of personality prediction was approached as a straightforward text classification task, aiming to decipher personality traits from the digital footprints individuals leave online (Kerz et al., 2022). However, as shown in Figure 1, researchers have increasingly recognized that personality is manifested multi-dimensionally, with nuances that pure text-based analysis cannot fully capture (Al Maruf et al., 2022). This revelation has propelled the move towards multimodal personality detection as the mainstream methodology.

Multimodal datasets, integrating text, audio, visual, and sometimes physiological signals, offer a richer, more nuanced view of human behavior and personality expressions than text-based datasets alone. This comprehensive approach is essential for developing models that accurately reflect the complexity of human personality. Naturally, a lot of multimodal dataset were released in recent years. There has been a few attempts in multimodal personality dataset construction (Palmero et al., 2021; Junior et al., 2021; Jiang et al., 2020; Chen et al., 2022). There are also many multimodal datasets used to perform other tasks and some of the personality prediction works will modify their datasets to adapt the personality context. For instance, TVQA (Lei et al., 2018) is a large dataset which is initially designed to do the visual question answering task. It is used frequently in our research field because of the its large scale.

However, current datasets still face certain challenges to support accurate personality prediction reserach. Firstly, the process of manually annotating personality traits often relies on a small number of volunteers, typically individuals with an interest in the subject matter but varying levels of expertise. This method introduces a substantial degree of subjectivity, as the annotations are heavily dependent on the volunteers' understanding and interpretation of the characters' personalities. Zhu et al. (2023) found that personality database website[1] has marked thousands of virtual characters in movies and TV shows and they scraped the personality data from it to annotate TVQA dataset.

On the other hand, most research in multimodal personality prediction has favored image-based over video-based analyses (Zhu et al., 2022; Kampman et al., 2018). This preference is attributed to the challenges associated with segmenting videos into discrete scenes and the lack of detailed annotations for each utterance within existing datasets.

From a psychological standpoint, it is essential to recognize that personality is not a static attribute but one that evolves in response to environmental contexts (Palmero et al., 2021). Incorporating relationship networks into personality prediction models offers a solution to this issue. Such networks provide a rich context for observing and understanding individual behaviors, preferences, and traits, reflecting the interconnectedness of personality with social and environmental factors.

In our endeavor to address the limitations of existing datasets for personality prediction, we meticulously analyzed the requirements for an ideal multimodal personality dataset. Our analysis highlighted several critical needs: substantial quantity and diversity in content, majority-voted personality annotations to mitigate bias, temporal alignment in video data to capture dynamics accurately, and the inclusion of multiple characters and their relationships to reflect personality dynamics. Against this backdrop, we introduce the Multimedia Conversational Personality Dataset (MMPD), a comprehensive dataset that starkly contrasts with existing offerings in several key aspects. MMPD is built on 305 movies and 14 TV series in different genres, including more than **46k dialogues, 552k utterances, 4016 characters** and **963 hours videos**. With the rich annotation, our dataset supports 4 personality traits models (MBTI, Big Five, Enneagram and Instinctual Variant), 7 kinds of social relationship and 8 attitudes for the emotional relationship. Due to the size of our dataset, we have made a simple sample available at https://anonymous.4open.science/r/sample-of-MMPD-F26F/

[1] https://www.personality-database.com/

Our contributions are as follows:

- We introduce MMPD, the most comprehensive and varied multimodal personality dataset to date, surpassing existing datasets in scope and diversity. This dataset uniquely combines TV genres and character analyses via audio, video and text, along with crowd-sourced personality, emotion and social relationship labels, unlocking new avenues in personality research.

- We developed a novel annotation and matching method for each utterance, by segmenting scenes according to original scripts. This approach achieves 87% accuracy, thereby providing a reliable foundation for detailed personality studies.

- For the first time, we categorize several types of relationships to depict the dynamics of character interactions on a scene-by-scene basis, enabling a granular analysis of personality dynamics through social interactions.

2 Dataset Design

This paper introduces a new multimodal personality dataset, MMPD, consisting of 305 movies and 14 TV shows, which is the largest of existing multimodal datasets. In this section, we provide a specific description about our dataset in terms of design principles and the structure in details.

2.1 Design Principles

2.1.1 Personality Model Theory

In constructing such a dataset for personality prediction, incorporating four distinct personality models, provides a comprehensive framework for undersatanding the multifaceted nature of human Personality. To this end, envolving four distinct personality models—Myers-Briggs Type Indicator (MBTI), Big Five, Enneagram, and Instinctual Variant—into our dataset construction is essential. Each of these models provides a unique lens through which to

Dataset	Dialogues	Utterances per Dialogue	Characters	Source
MEmoR	8.53k	64.23	7	The Big Bang Theory
FriendsPersona	0.71k	27.61	7	Friends
CPED	12k	1	392	40 TV shows
UDVIA	188	65.31	147	Dyadic Interaction
The ChaLearn FI	10k	Unknown	3000	Youtube
TVQA	29.4k	2.2	Unknown	6 TV shows
Our Dataset	46.21k	12.42	4000+	300+ Movies and 14 TV Shows

Table 1: Comparison of different datasets and our MMPD

view and interpret personality traits, offering complementary insights that are critical for a holistic understanding. By integrating these four models, we aim to construct a dataset that not only captures the complexity of human personality but also facilitates nuanced predictions. This comprehensive framework acknowledges the diversity of human experience and the need for multidimensional analysis to truly understand and predict personality dynamics. The complete definitions can be found in Appendix A.

2.1.2 Definitions of Relationship Types

Each model offers unique insights and covers different aspects of personality making them collectively valuable for a multidimensional approach personality prediction. Besides these personality models, we introduce two main categories of relationship among characters.

The first one is social relationship, which provides a comprehensive canvas on which to observe and interpret the nuances of personality in action. We conclude 7 social relationship from the perspective of psychology and socialogy (Table 2), which recognizes that personality is not only a matter of internal traits and instincts but also fundamentally shaped and expressed through interactions with others in various domains of life.

The social relationships above are relatively non-changable, not depicting the attitudes towards someone else. So we define another 8 types for the emotional relationships (Table 3), as the aid for the comprehension of personality.

We choose affection, jealousy, dislike, pity, respect, hostility, envy and gratitude as our annotators for the emotional relationship, which concludes the diverse attitudes in human's daily life.

Thus, we select a binary tuple to annotate the pair of characters for each scene, as well as emotional relationship tag for each utterance.

2.2 Structure of MMPD

MMPD has a very large scale for the three modalitie: video, audio and text. We built a fine grained structure describing the interactions and corresponding personality traits for each utterance based on the original scripts.

Aiming to deliver a tidy and readable structure, there is no more suitable file types than JSON format. We distribute different scenes in a single json file with index. For each movie or TV show, the video clips with the corresponding json and audio files are stored in the same directory.

As shown in Figure 2, each video clip of our dataset is tagged with a "scene" identifier, which likely refers to a specific segment or moment within a larger narrative or dataset. The "content" field contains an array of objects, each providing a detailed description of a scene and dialogues between characters. The dialogues are presented with time corresponding timestamps, too. The "relationship" field within this object provides a summary or interpretation of their interaction, in this case, indicating a professional relationship with an element of fondness between Travis and Betsy. Finally, the "personality annotation" section provides personality profiles for the characters mentioned in the scene, where their personality type distribution are listed along with a "distribution" field.

3 Methodology

3.1 Source of Data

Considering the unreliable labeling method of existing works, we collect the personality annotations from personality database website as well as the voting distribution that indicates the credibility of current personality type. We used some python scripts to scrape the personality data from the website and annotate them to the corresponding scripts. As for the scripts and subtitles, we also find some

Relationship type	Description
Family Relationship	Parents (grand parents) and children, siblings, etc.
Friendship	Based on common interest, mutual respect and affection, but not related to the blood
Romantic Relationship	Based on emotional attraction and include dating, marriage, etc.
Professional Relationship	Formed in a work environment, such as colleagues, superiors and subordinates, etc.
Social Relationship	Formed in a broader social context, such as neighbors, club members.
Academic Relationship	Formed in an educational setting, such as between teachers and students, classmates.
Online Relationship	Established in online spaces or through social media platforms.

Table 2: Descriptions of Social Relationship Types

Relationship type	Description
Affection or Fondness	A positive emotion characterized by a person's fondness for another.
Jealousy	Unhappy and angry because someone has something that you want
Dislike or Aversion	A negative emotion, referring to a feeling of disfavor towards someone
Pity or Sympathy	A feeling of sadness for someone else's difficult situation
Respect	Admiration felt or shown for someone that you believe has good ideas or qualities
Hatred or Hostility	An unfriendly or unkindness towards someone or something.
Envy	A discontented feeling when a person desires what someone else has
Gratitude	An emotion of being thankful for someone else's help or kind actions.

Table 3: Description of Emotional Relationship Types

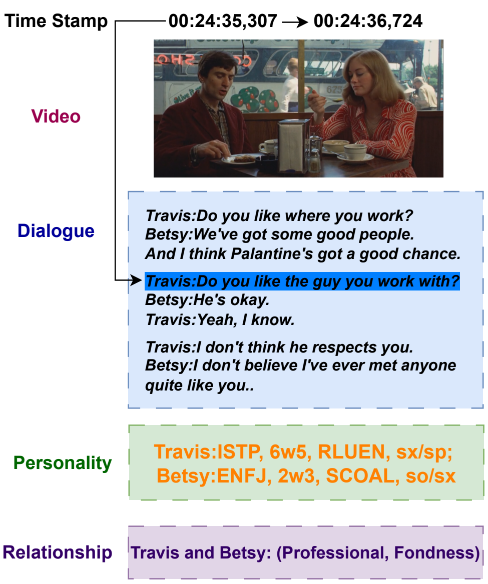

Figure 2: A sample from MMPD.

open-source websites[1,2] for research offering the free scripts and subtitles of many famous movie and television programs. To represent the diversity of the real world scenarios, we select various genres of the movies and TV series which includes action, thriller, romance, comedy, science fiction, etc.

[1] https://www.simplyscripts.com/
[2] https://subscene.com/

3.2 Data Alignment Process

As subtitle contain temporal information and original scripts associate utterances with characters, we are supposed to align them properly as efficient as possible. However, most of the existing multimodal datasets annotate the timestamps mannually with taking up a great deal of time. There are also some works which utlize different automatic tools to align the utterances with their corresponding information. For instance, Lian et al. (2024) uses an Automatic Sound Recognition (ASR) tool called Gentle to get the timestamps for the utterances. To streamline the process of aligning dialogue utterances with their respective timestamps and speakers from subtitles, we propose an efficient method leveraging a fuzzy matching algorithm (see Algorithm 1).

1. *Preprocess the raw data*
   Firstly, we divide the scripts into several scenes according to the coherence in language of camera instead of ramdonly clipping in a certain time period. This segmentation is guided by explicit scene transition cues found in movie scripts, such as "*CUT TO:*" or scene location indicators. For TV show scripts, which might lack uniform scene transition markers, we identify scene changes by detecting pauses exceeding 3 seconds between utterances. And then we extract the character's name and its spoken utterances.

2. *Match the utterance*
   This algorithm is rooted in the comparison of

Algorithm 1 Scripts and Subtitles Matching

Input: $Script, Subtitles$
Output: Updated subtitles with speaker names

```
dial&speakers ← empty
threshold ← 0.8
for scene in Script do
    for Dials in scene do
        Extract speaker and dial from Dials
        dial&speakers ← speaker, dial
    end for
end for
for subtitle in Subtitles do
    match_score ← 0
    match_speaker ← Null
    for line in subtitle do
        for speaker, dial in dial&speakers do
            score ← Similar(subtitle, dial)
            if score > match_score then
                Update match_score and match_speaker
            end if
        end for
        if match_score ≥ threshold then
            Update line with match_speaker
        end if
    end for
    Update subtitle
end for
return Updated Subtitles
```

utterances from original scripts and subtitles based on a similarity threshold. If the similarity between a pair of utterances meets or exceeds this threshold, the character's name is accurately associated with the utterance.

3. *Rematch with the slide window*
Basically, the content in scripts is slightly different with the subtitles, because the director may have improvised on the set. Thus we introduce a slide window algorithm to evaluate the utterance-level similarity. As shown in Algorithm 2, we set a window to slide over the script and for each utterance, compare the content inside the window with each subtitle entry to get the similarity of the paragraph in the window. If the similarity is higher than the threshold, we will consider all the utterances in the window matched even though some of them are not matched in Algorithm 1.

Following successful alignment, we proceed to segment the video content into distinct scenes according to the timestamps. Besides, we use FFmpeg[1] to extract the audio track from the video clips and output it as a *.mp3* file.

[1] https://ffmpeg.org/

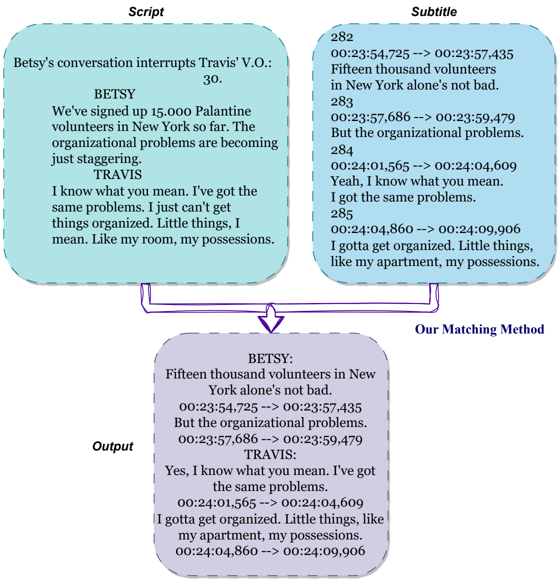

Figure 3: Process of Data Alignment

Algorithm 2 Slide Window Matching

Input: $Script, Subtitles$
Output: Updated subtitles

```
window_size ← 10
threshold ← 0.8
matches ← empty_list
for i ← 0 to Len(Script) − window_size do
    window ← slice(scriptTokens, i, i + window_size)
    match_score ← 0
    for j ← 0 to Len(Subtitles) − 1 do
        score ← Similar(window, Subtitles[j])
        if score > match_score then
            Update match_score
        end if
    end for
    if match_score ≥ threshold then
        matches ← Subtitles[j]
    end if
end for
return Updated Subtitles with matches
```

3.3 Annotation Process

We construct a process to automatically annotate the social and emotional relationship types among characters by using ChatGPT API. Only text data are supposed to be processed, thus we choose *gpt-3.5-turbo-1106* pre-trained model to annotate our dataset. Since we preprocess the text data and divide them into scenes, we design a prompt to ask ChatGPT for identifying both social and emotional relationship types for every single scene.

Based on the definitions of relationship types, we design this prompt for relationship annotation (Fig 4). The prompt categorizes relationships into seven social and eight emotional types, ensuring comprehensive coverage of human interactions. By associating characters with both social and emotional relationship labels, the dataset supports multimodal personality prediction models that consider the interplay between social contexts and emotional responses. Note that we require ChatGPT to generate the responses following our format strictly so that we could better manipulate them flexibly.

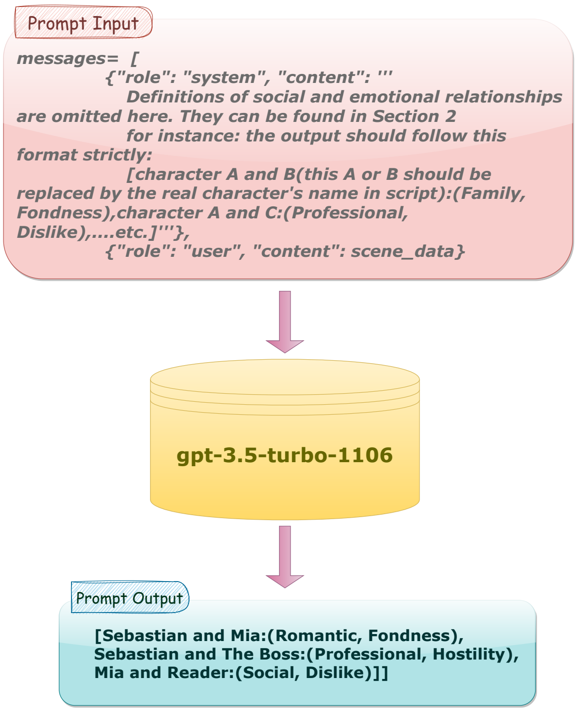

Figure 4: Prompt Design for Relationship Annotation

4 Evaluation

We first present the statistics of our dataset, then elaborate on stringent evaluation on our matching algorithm and relationship annotation, for a quantatative understanding of dataset quality.

4.1 Dataset Statistics

As we mentioned before, MMPD is not only the largest dataset containing a huge amount of text, audio and video corpus but also its data is highly diverse in terms of personality types, movie and television production genres, and relationship types. Furthermore, we get the distribution of MBTI personality types in real world as well as calculate the distribution in our dataset. The result is apparently similar, which proves that our dataset is able to represent the distribution of personality types in real world thus eliminating bias. Fig 6 and Fig 7 are the distribution of two types of relationship, which indicates the diversity in terms of interaction scenarios.

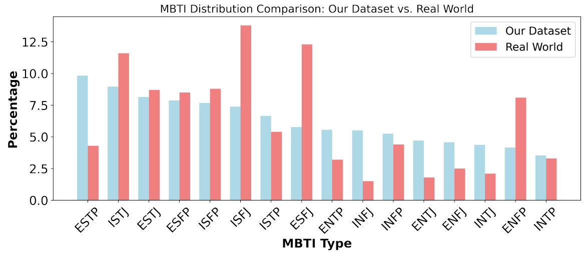

Figure 5: Distribution of comparing our data and real world MBTI type

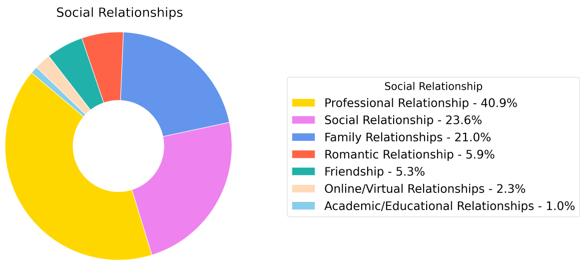

Figure 6: Distribution of Social Relationship Types

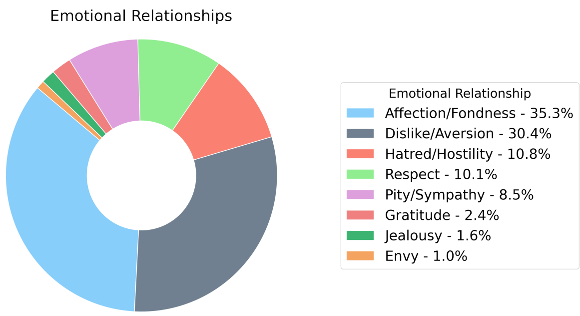

Figure 7: Distribution of Emotional Relationship Types

4.2 Algorithm Evaluation

To evaluate the performance of our character-to-subtitle matching algorithm, we randomly sample a test case comprising over 50 dialogues and 600 utterances from a variety of genres, including 10 films and TV series. We mannually check the aligned characters' name based on the script. Our primary metrics for assessment is accuracy. The algorithm demonstrate an accuracy of about 88%, indicating a high level of accuracy in correctly identifying character names within subtitles across diverse content types.Compared to existing ASR matching algorithm, our approach gains an improvement by 5% in accuracy. Besides, our algorithm shows a very strong efficiency comparing the ASR method, of which accelerating almost 7 times.

Method	Movies	TV	Exec. Time (s)
Gentle (ASR)	82.71%	85.21%	26.51
Our algorithm	87.53%	88.98%	3.55

Table 4: Accuracy and running time per dialogue of subtitle matching algorithm

4.3 Annotation Accuracy

Using ChatGPT to annotate relationship types for the characters is not a completely worthwhile method. To measure the automatic annotation accuracy, we sampled 235 scenes randomly and involved 5 human labellers on relationship annotation. These labellers are of about 25 age, undergraduate or higher education background, english language background with majors in psychology, filmography and socialogy, who were instructed to select one of the designated social and emotional relationship types after watching each aligned video. We continue to compare the automatically annotated results to the human-labeled ground truth. The outcome shows that both social and emotional relationship annotations are dependable, with the accuracy reaching 95% and 84% respectively.

Task	Movies	TV	Total
Social Relationship	98.21%	93.91%	95.78%
Emotional Relationship	82.04%	84.46%	84.01%

Table 5: Accuracy of Relationship Annotation.

5 Discussion

The introduction of MMDP, a new multimodal personality dataset, represents a significant advancement in the field of personality research, particularly in the context of media psychology and computational social science. Given the specific focus on personality prediction, the dataset structured in JSON format, containing aligned dialogues, timestamps, and speakers, alongside corresponding video and audio files, offers a unique and powerful resource for advancing research and applications in personality analysis. This dataset, which encompasses a variety of TV genres and characters along with crowd-sourced personality labels, emotions, and social relationships, presents a unique opportunity to explore several under-researched areas. Below are key research avenues that could be supported and enriched by such a dataset.

Personality Dynamics Through Social Interactions By including data on social relationships between characters, the dataset opens new pathways for exploring the dynamics of personality through interactions. This aspect can support research into how different personality types influence and are influenced by social networks, both within narrative contexts and in real-life implications. It provides a basis for computational models that simulate personality dynamics in social networks, potentially informing theories on social behavior, conflict resolution, and group dynamics.

Long-term Personality Modelling in Narrative Contexts TV series and their characters often evolve over time, offering a fertile ground for studying personality dynamics. The dataset allows for longitudinal studies on how characters' personalities change in response to narrative events, relationships, and challenges. This could lead to new models that explain personality development and dynamics in complex social settings, bridging narrative theory and psychological research. Moreover, it could enhance our understanding of how audiences' perceptions of characters change over time and what narrative elements trigger significant shifts in these perceptions.

Understanding Subjective Bias in Personality Perception The dataset's foundation on crowd-sourced voting allows for an in-depth analysis of subjective biases in personality perception. Researchers can investigate how different demographics (age, gender, cultural background) perceive personality traits and emotions in characters, revealing biases that may exist in personality assessment. This could also extend to studying the impact of viewer's own personality traits on their perceptions of characters, thus contributing to a deeper understanding of projection and identification processes in media consumption.

Enhancing Personality Theory with Multimodal Data Finally, the multimodal nature of the dataset (incorporating video, audio, textual, and crowd-sourced data) enables comprehensive studies that integrate different data types to understand personality. This could lead to the development of new theories or the refinement of existing ones that account for the complexity of personality as depicted through various media. It could also foster interdisciplinary research, combining insights from psychology, computer science, linguistics, and media studies.

From psychological research to personalized AI interactions and beyond, the potential uses of this multimedia dataset underscore the growing importance of personalized approaches in technology and media. As the field of personality prediction evolves, such datasets will become increasingly valuable in crafting experiences and technologies that are more closely aligned with the complexities of human personality.

6 Conclusion

In this study, we introduce MMPD, an outstanding multimodal dataset tailored for personality prediction. Built upon a foundation of varied movies and TV shows, MMPD enriches with precise annotations for personality traits based on different psychological personality models. Beyond mere text and video, MMPD innovates by incorporating detailed relationship networks, capturing the dynamic interplay of characters' interactions and emotional connections. By integrating multimodal data and emphasizing the fluid nature of personality within social contexts, MMPD opens new avenues for comprehensive analysis in personality psychology, offering valuable insights into how personality traits manifest and interact in varied narratives.

Copyright Concerns

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Limitations

While our multimedia dataset designed for personality prediction shows superiority in most aspects, it also comes with inherent limitations.

Dialogues and character behaviors extracted from movies or TV shows may not always accurately reflect real-life personality traits due to the scripted nature of these interactions. Fictional characters are often designed to serve a narrative purpose, which might exaggerate or oversimplify certain personality traits for dramatic effect, leading to potential biases in personality prediction.

The process of annotating dialogues, character relationships, and personality traits, even if partially automated, involves a degree of subjectivity. Different annotators might interpret the same dialogue or behavior differently based on their own biases and experiences, leading to inconsistencies in the dataset.

The dataset may predominantly reflect the cultural norms and values of the society in which the content was produced, potentially limiting its applicability across different cultural contexts. Our dataset is based on English movies and TV shows so it may not interpret other non-English cultural contexts properly.

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A Definitions of Personality Models

- Myers–Briggs Type Indicator (MBTI): The MBTI is utlized for its popular four dimensional categorization of personality types, offering a straightforward way to undersatand how individuals engage with the environment and make decisions.

- Big Five: The Big Five personality trait model is included for its empirical support and broad acceptance within the psychological community. It covers a range of personality dimensions (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism) that are universally recognized and have been linked to various outcomes in personal and professional contexts.

- Enneagram: The Enneagram adds depth to this dataset by introducing a typology of nine interconnected personality types, offering a dynamic perspective on individual differences. Its inclusion is strategic, as it provides insights into core motivations, fears, and desires that underpin behavior, thus allowing for a more detailed exploration of personality dynamics and potential growth paths for individuals.

- Instinctual Variant: The concept of Instinctual Variants (or Subtypes) within the Enneagram framework enriches the dataset by addressing the fundamental survival drives—Self-Preservation, Social, and Sexual (One-to-One)—that influence an individual's priorities and interactions.