PersonaMovs: A Multimedia Conversational Personality Dataset

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Abstract

Automatic personality detection has evolved from simple text classification to sophisticated multimodal analysis, 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 PersonaMovs, a large, extensive and varied multimedia conversational dataset, built on 305 movies and 14 TV series, featuring over 46k dialogues, 552k utterances, 4016 characters, and 963 hours of video. PersonaMovs not only addresses the challenges of existing datasets by offering majority-voted personality annotations and detailed social relation networks but also paves the way for advanced analysis of interactions of personality across various contexts.

1 Introduction

Personalities is a comprehensive yet complex trait that encapsulates individual differences in patterns of thinking, feeling, and behaving (Costa and McCrae, 2002). Detecting personality automatically is of significant importance for improvement of machine's ability to have human-like cognition and engage in more natural interactions with humans, particularly in the context of advancing Artificial General Intelligence (AGI) and various practical applications such as reflective linguistic programming (Fischer, 2023), disease diagnosis (Tseng et al., 2013) and mental health prediction (Feng et al., 2024). At the very beginning, owing to the limitations of multimedia model and computational power, researchers initially approached personality prediction as a straightforward text classification task, focusing on deciphering personality traits from individuals' digital footprints online (Kerz et al., 2022; Yang et al.). However, as illustrated in Figure 1, there is now growing recognition that personality is expressed across multiple modalities, with nuances that cannot be fully captured through text-based analysis alone (Al Maruf et al., 2022; Zhu et al., 2022; Bose et al., 2023). This realization has driven the shift towards multimodal personality detection as the dominant methodology.

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

Personality datasets, integrating text, audio, visual information along with the manner of speaking, face expressions, body language and so on, offer a richer, more nuanced view of human behavior and personality expressions than text-based datasets alone. This comprehensive approach is vital for developing models that accurately cap-

ture the complexity of human personality. Consequently, numerous multimodal datasets have been released in recent years, and several efforts have focused on constructing such datasets specifically for personality analysis (Palmero et al., 2021; Junior et al., 2021; Jiang et al., 2020; Chen et al., 2022). Additionally, many multimodal datasets designed for other tasks have been adapted for personality prediction. For example, TVQA (Lei et al., 2018), a large-scale dataset originally created for visual question answering, is frequently utilized in personality research due to its extensive scope.

Recently Li et al.; Pal et al. state that personality is far beyond discrete and reveal that dynamic nature of personal identity. Although current datasets have evolved to include many features necessary for personality prediction, they still exhibit several limitations:

1) **Limited Data Source**: Previous datasets often select one or several famous movies or TV series as the raw data, resulting in a limited number of characters and personality types covered, which hinders the generalizability of model training.

2) **Manual Annotation Issues**: The process of manually annotating personality traits typically relies on a few numbers of volunteers with varying levels of expertise, leading to potential inconsistencies and biases in the annotations.

3) **Lack of Relations Representation**: Current datasets largely fail to account for the interactions of personality, which evolves over time in response to changes in life experiences and social environments. These datasets often provide static snapshots of personality traits, overlooking the psychological understanding that personality can vary across different contexts and stages of life.

In our study, we endeavor to partially eliminate the aforementioned limitations by providing a scale-up multimodal dataset that contains reliable labels. Specifically, we find a personality database website[1] that offers a large amount of personality types for virtual characters and (Zhu et al., 2023) have scraped the personality data from it to annotate TVQA dataset. Compared with previous datasets whose labelling commonly involved five to ten people, our datasets are labelled by about 160 voters on average. It shows the vote distribution rather than a single personality type which is more persuasive and operable.

Against these backdrops, we introduce the PersonaMovs, a comprehensive dataset that starkly contrasts with existing offerings in several key aspects. PersonaMovs is built on 305 movies and 14 TV series (894 episodes in total) 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) with more 28 personality classes, 7 kinds of Social Relations. Our analysis highlights substantial quantity and diversity in content, adequate experiments on different models with all modalities and personality interactions discovery.

Our contributions are as follows:

- We introduce PersonaMovs, the most comprehensive and varied multimodal personality dataset to date, surpassing existing datasets in **scope** and **diversity**. This dataset uniquely combines movie and TV genres with personality analysis via audio, video, and text, along with crowd sourced personality and social relations labels, unlocking new avenues in personality research[2].

- We study seven model architectures from different model families. Our results show that PersonaMovs is more **difficult** compared to other datasets, not only because it has a larger amount of multimedia data, but also due to its diversity and similarity to real life. Through our analysis, we found that our dataset provides a more realistic reflection of the distribution of personalities in the real world, further enhancing its value for personality-related tasks.

- For the first time, we categorize 7 types of social relations to depict character interactions on a scene-by-scene basis, enabling a granular analysis of personality through relations networks. Guided by the relations networks, we identify psychological phenomenons in conversational contexts, which largely explain the interaction of personality statistically.

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

[2] https://anonymous.4open.science/r/sample-of-MMPD-0177

Dataset	Dialogues	Utters. / Dial	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
PersonaMovs	46.21k	12.42	4000+	300+ Movies and 14 TV Shows

Table 1: Comparison of different datasets and our PersonaMovs

2 Dataset Design

2.1 Personality Theory

Personality refers to the combination of characteristics or qualities that form an individual's distinctive character. It encompasses a wide range of traits, behaviors, thoughts, and emotional patterns that evolve from biological and environmental factors (Lepri et al., 2012). A particular personality can determine various outward observable properties or features, including consistent behavioral patterns, communication style, emotional expression and so on. These traits manifest in how an individual consistently acts and reacts in different situations, their manner of speaking and body language, the openness or restraint of their emotional displays, their ways of relating to others, their approach to making decisions, and their preferences in activities, hobbies, and social engagements.

2.2 Multiple Personality Models are Needed

In constructing such a dataset for personality prediction, incorporating four distinct personality models, provides a comprehensive framework for understanding the multifaceted nature of human personality. To this end, evolving 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 view and interpret personality traits, offering complementary insights that are critical for a holistic understanding(See all details about each trait in Appendix A). For instances, MBTI has 16 unique personality types. Among these, INFJ is a personality type with the Introverted, Intuitive, Feeling, and Judging traits. They tend to approach life with deep thoughtfulness and imagination. Their inner vision, personal values, and a quiet, principled version of humanism guide them in all things.

2.3 Relations to Interpret Personality

Human social networks are complex and multifaceted. By categorizing relations, we can better understand the nuances of how people interact with each other. Different types of relations provide context for interactions, which is crucial for analyzing social behaviors and patterns, improving social network analysis, and applying this knowledge across various fields and applications.

Each personality model offers unique insights and covers different aspects of personality, making them collectively valuable for a multidimensional approach to personality prediction. In addition to these models, we introduce 7 categories of social relations among characters. These provide a comprehensive framework to observe and interpret the nuances of personality in action. We identify seven types of social relations from the perspectives of psychology and sociology. Based on various social environments, we categorize 7 kinds of social relations (shown in Table 2) including *family, friendship, romantic, professional, social, academic and online*.

2.4 Structure of PersonaMovs

Aiming to deliver a tidy and readable structure, we distribute different scenes in a single text file with corresponding audio and video clip. As shown in Figure 2, it provides a timestamp of the scene, a visual snapshot from the movie, and a transcription of their dialogue. The characters' personalities are profiled using various typologies, such as MBTI and Enneagram, with accompanying bar charts showing the distribution of votes or consensus on these personality assessments. Additionally, the social relations between Gatsby and Daisy is categorized as romantic, offering insights into their interaction.

3 Methodology

In this section, we outline the methodology employed to gather, process, and annotate the data

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

Table 2: Descriptions of social relations

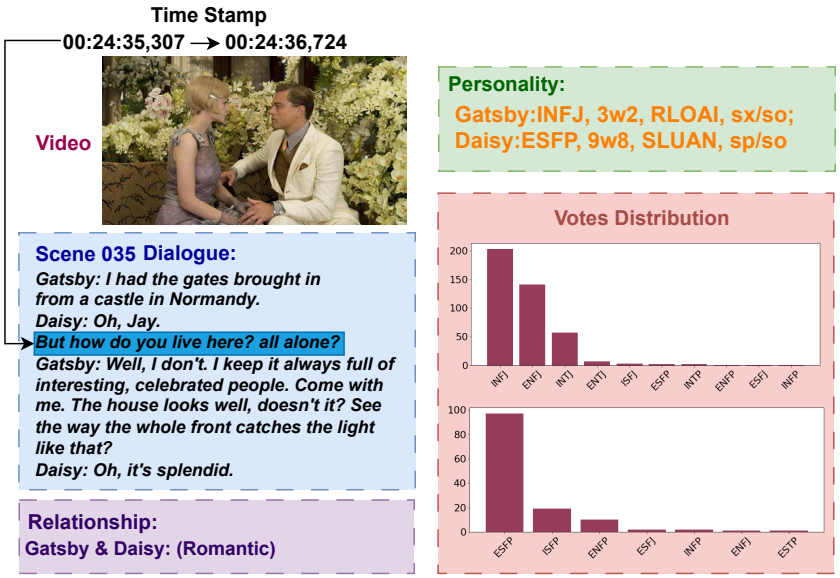


Figure 2: A sample from PersonaMovs, which includes full modality data along with timestamps, personality label, relationship label, and personality vote distribution.

for our study. We begin by detailing the sources of our multimodal video data and personality labels, focusing on how we efficiently align subtitles with original scripts to ensure accurate temporal and character associations. And we also present our annotation process, explaining how we leverage the ChatGPT to automatically annotate social relations among characters within the text data.

3.1 Source of Data

Our data source contains mainly two parts, the multimodal video data and personality labels. For video data, we include 14 different genres of TV series and movies via an open-source website[1], and for the scripts and subtitles, we also find other open-source websites[2][3] for research offering the free scripts and subtitles of many famous movie and television programs. Considering the insufficient labeling method of existing works, we collect the personality annotations from personality database website as well as the voting distribution and align them to correctly scripts.

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 manually with taking up a great deal of time. There are also some works which utilize different automatic tools to align the utterances with their corresponding information. For instance, (Lian et al., 2024) use an Automatic Sound Recognition (ASR) tool called Gentle[4] 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 effi-

[1]https://yts.mx/
[2]https://www.simplyscripts.com/
[3]https://subscene.com/
[4]https://github.com/lowerquality/gentle

cient method leveraging a fuzzy matching algorithm (details in Appendix B). 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.

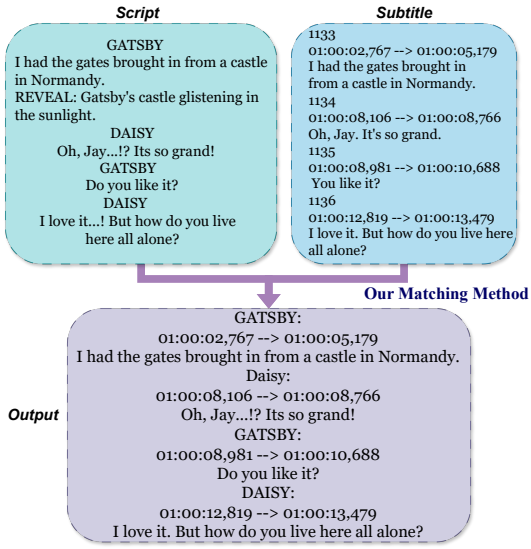


Figure 3: Process of data alignment

3.3 Annotation Process

In this study, we propose a method to automatically annotate social relations among characters in scripted text using the GPT-3.5 model (OpenAI, 2023), which is well-suited for processing natural language data. Our approach begins by preprocessing the text and dividing it into scenes. For each scene, we design a specific prompt (Figure 4) that guide ChatGPT in identifying the social relations among characters.

The rationale for using ChatGPT in this context is based on the model's general understanding of the show, its characters, and the roles they play. Given that GPT has been trained on a vast corpus of text, it is able to infer the dynamics of social interactions, even without explicit annotations. This capability allows the model to effectively detect and label social relations in scenes, making it a plausible tool for this task.

4 Evaluation

We present the basic statistics of our dataset in the first part, and then we evaluate the accuracy

[1]https://ffmpeg.org/

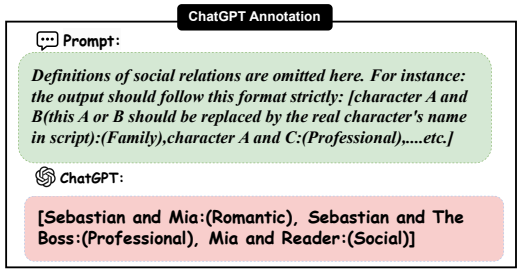


Figure 4: Prompt design for relations annotation

of our alignment and annotation process to ensure their reliability. Additionally, we not only test our dataset on different advanced models but also do ablation experiment on both modality and social relations annotation. To discover interesting topics about interaction of personality, we focus on those changes of personality and discover several interesting psychological phenomenons.

4.1 Dataset Statistics

As we mentioned before, PersonaMovs is not only a large 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. Fig 5 are the distribution of MBTI types and social relations, which indicates the diversity in terms of diversity of personality labels and interaction scenarios.

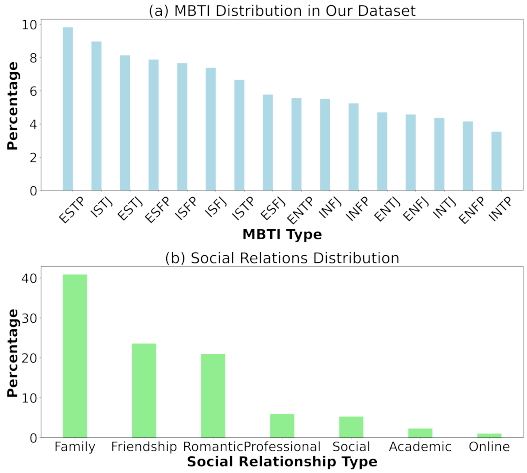


Figure 5: Distribution of MBTI types and social relations

Algorithm Evaluation

To evaluate the performance of our character-to-subtitle matching algorithm, we manually check

the aligned characters' name based on the script. The annotators were a group of five human volunteers with backgrounds in filmography and literary. They are in their mid-twenties and had at least an undergraduate education. The protocol involves the following steps:

- 1) Annotators independently reviewed a randomly selected sample of 50 dialogues from the dataset. By given relevant scripts and subtitle files, they are required to match each utterance in subtitle with corresponding names.
- 2) The annotations were compared against the results generated by our algorithm to evaluate accuracy.

The algorithm demonstrates 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 3: Accuracy and running time per dialogue of subtitle matching algorithm

Annotation Accuracy

Despite ChatGPT's impressive capabilities, the labels annotated by it are not completely correct and its automated annotations require validation through human expertise. To measure the automatic annotation accuracy, we sampled 235 scenes randomly and involved 5 human labelers on relations annotation. These labelers are in their mid-twenties, undergraduate or higher education background, proficient in English with majors in psychology, filmography and sociology, who were instructed to select one of the designated social relations after aligned video. We continue to compare the automatically annotated results to the human-labeled ground truth. The outcome shows that both social relationship annotations are dependable, with the accuracy reaching aroud 98% and 93%.

The dataset's foundation on crowdsourced 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.

Relations type	Accuracy in Movies	Accuracy in TV
Family	99.18%	93.27%
Friendship	95.35%	92.65%
Romantic	95.21%	91.93%
Professional	98.29%	95.10%
Social	97.13%	94.07%
Academic	98.50%	91.54%
Online	99.00%	93.15%
Overall	98.21%	93.91%

Table 4: Accuracy of each category of social relations annotation

4.2 Experiment Results

Dataset Difficulties

We test our dataset on popular models including BERT (Devlin et al., 2019), D-DGCN (Yang et al., 2023), Roberta (Liu et al., 2019), AttR-CNN (Xue et al., 2018), GPT-3.5 (OpenAI, 2023), GPT-4 (OpenAI, 2024) and MCT (Sun and Zhang, 2023). We use the MBTI framework, which includes 16 distinct personality types, as the labels for our dataset. As shown in Table 5, the accuracy of our dataset is lower than that of other comparable datasets. Accuracy here refers to the proportion of correctly predicted personality types out of the total number of predictions. One of the key challenges contributing to this lower accuracy is the increased complexity and diversity of our dataset, which encompasses a broader range of multimedia content compared to other datasets.

Method	Modalities	FP	TVQA	PM
BERT	T only	61.14	60.61	**52.94**
D-DGCN	T only	69.56	70.21	**68.47**
Roberta	T only	62.58	69.24	**60.37**
AttRCNN	T only	65.01	67.25	**62.44**
GPT-3.5	T only	69.21	66.89	**64.08**
GPT-4	T & V	79.14	78.33	**76.90**
MCT	T, A & V	71.67	69.93	**68.47**

Table 5: Accuracy of different methods on Friends Persona (FP), TVQA, and PersonaMovs (PM). T, A, & V stand for text, audio and video respectively. Lowest accuracy in each row is bolded.

A more challenging dataset, such as the one we have developed, offers several advantages in terms of personality detection: 1) Our dataset captures a wide range of real-life situations and intricate contexts, which better mirrors the complexity of human interactions. This realism is crucial for developing models that can perform well in practical applications. 2) Training on a more difficult dataset forces models to learn more nuanced patterns and relationships, leading to better generalization capabilities. 3) A difficult dataset sets a high standard for model evaluation, ensuring that only the most effective models are considered successful. This helps in distinguishing truly advanced models from those that perform well only on simpler tasks. Additionally, one notable observation from the results is that the MCT model, which leverages three modalities (text, audio, and video), does not outperform the GPT-4 model, which uses only two modalities (text and video). This performance gap suggests that Large Language Model outperforms the small model on this task, even though the latter uses more modalities.

The Importance of Multi-Modality

We conducted a series of ablation experiments to assess the impact of different modalities and relations annotations on the performance of personality prediction models. The experiments were designed to understand how the exclusion of specific modalities or relations annotations affects the overall prediction accuracy.

Method	Modality	Accuracy
MCT	T & A	66.13
	T & V	67.91
	T only	63.43
	T, A & V	68.47
GPT-4	T only	70.20
	T & V	76.90

Table 6: Ablation experiment on different modalities

Table 6 presents the results of ablation experiments where different combinations of video and audio modalities were excluded. The result underscore the critical importance of using multiple modalities to achieve higher accuracy in personality prediction tasks. Models that leverage both audio and video data, in addition to text, consistently outperform those that rely solely on textual data.

Table 7 shows the results of ablation experiments focusing on the inclusion or exclusion of social relation annotations which finds the relations annotations tend to slightly enhance the performance. This highlights the importance of including rich contextual information to improve the accuracy of personality prediction models.

Method	With Relations	Without Relations
BERT	54.16	52.94
Roberta	59.04	58.39
GPT-4	74.49	71.20

Table 7: Ablation experiment on social relation annotations.

The multimodal nature of the dataset 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.

Personality Analysis

As mentioned in the Introduction, personality can change depending on various contexts. To explore this, we studied the relationship between the diversity of personalities and prediction accuracy. For each character, we calculate the entropy of the vote distribution to represent the uncertainty of personality as well as predicting their personalities using GPT-3.5.

Entropy, denoted as $H(X)$, is a measure of the uncertainty or complexity in a probability distribution. It is calculated using the formula:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_b(p(x_i))$$

where X is a random variable representing the personality distribution, $p(x_i)$ is the probability of each personality type x_i, and b is the base of the logarithm, typically 2 when measuring entropy in bits.

Figure 6 shows that as the complexity of a character's personality increases, the corresponding prediction accuracy decreases. This finding suggests that personality should be considered an attribute based on different context rather than a static one.

According to our finding, we conduct statistical analysis based on our dataset to figure out if there exists certain personalities that are easily attracted to each other. To analyze the patterns of personality attraction, we focus on identifying pairs of

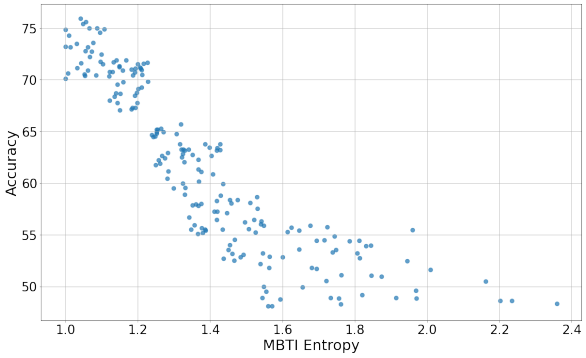
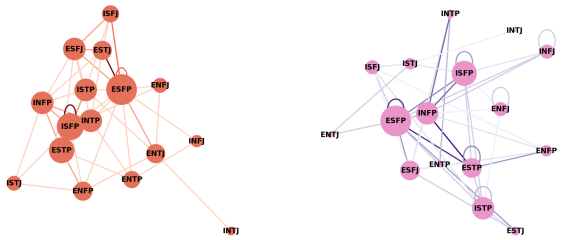


Figure 6: Relationship between MBTI entropy and prediction accuracy

personalities that frequently appear together in romantic and friendship relations. Figure 7 presents the favorite network with 16 MBTI personality types, providing a clear visual summary of statistical findings. The size of each node is proportional to the number of connections (degree) it has, which means personality types with more relationships are represented by larger nodes. The color of the edges represents the weight of the relationship between the personality types. Darker edges indicate a higher frequency or stronger relationship. For instance, ESFP is the most popular personality since almost every other personality has a friendship relation with it, and ESTP prefers to be around INFP, ESFP and people with the same personality as themselves. Another interesting pattern emerges in ESTP relationships: while they frequently form friendships with ESFPs, romantic relationships between these types are uncommonly rare in our observations. Thus, these potential findings may inspire the research on psychology and other social science.



(a) Romantic (b) Friendship

Figure 7: Favorite betworks with different personalities about two relations

By including data on social relations between characters, the dataset opens new pathways for exploring the interaction of personality. This aspect provides a basis for computational models that simulate personality in social networks, potentially informing theories on social behavior, conflict resolution, and group dynamics.

5 Copyright Considerations

The movies and TV series incorporated in this dataset are under the copyright of their respective holders. They are utilized in this academic and research work in accordance with the fair - use principles as defined in relevant international copyright agreements such as the Berne Convention for the Protection of Literary and Artistic Works (Berne Convention) (Ber) and the Universal Copyright Convention (Uni), or based on specific permissions obtained from the copyright holders. It must be clearly stated that this usage does not imply any form of endorsement or affiliation with the copyright owners. The use of these materials is strictly restricted to the scope of the permission granted, and any commercial distribution is explicitly prohibited.

6 Conclusion

In this study, we introduce PersonaMovs, an outstanding multimodal dataset tailored for personality prediction. Built upon a foundation of varied movies and TV shows, PersonaMovs enriches with precise annotations for personality traits based on different psychological personality models and detailed relations networks, capturing the interplay of characters' interactions. By integrating multimodal data and emphasizing the nature of personality within social contexts, PersonaMovs opens new avenues for comprehensive analysis of personality interaction, offering valuable insights into how personality traits manifest and interact in varied narratives.

Limitations

While our PersonaMov 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 categorizes personality into four dimensions. Extraversion (E) vs. Introversion (I): Extraverts are outgoing and energized by social interactions, while Introverts are reserved and energized by solitude. Sensing (S) vs. Intuition (N): Sensors focus on present, concrete information, valuing practicality, whereas Intuitives are imaginative and future-oriented, valuing abstract ideas. Thinking (T) vs. Feeling (F): Thinkers base decisions on logic and fairness, prioritizing objectivity, while Feelers base decisions on personal values and the impact on others, prioritizing harmony. Judging (J) vs. Perceiving (P): Judgers prefer structured and organized lives, liking plans and decisiveness, while Perceivers prefer flexibility and spontaneity, liking to keep their options open. Each MBTI type is defined by a combination of four cognitive functions, which can be either introverted (i) or extraverted (e). Extraverted Sensing (Se): Focuses on the present moment and physical reality, highly attuned to sensory experiences. Introverted Sensing (Si): Relies on past experiences and memories, valuing tradition and consistency. Extraverted Intuition (Ne): Sees patterns and connections, focusing on future possibilities and abstract ideas. Introverted Intuition (Ni): Focuses on internal insights and foresight, seeing underlying meanings and future potentials. Extraverted Thinking (Te): Organizes and structures the external world, prioritizing logic and efficiency. Introverted Thinking (Ti): Analyzes and categorizes information internally, valuing logical consistency and understanding. Extraverted Feeling (Fe): Prioritizes harmony and social values, focusing on the needs and feelings of others. Introverted Feeling (Fi): Values personal beliefs and feelings, making decisions based on inner values and ethics.

- **Big Five Personality Traits**: The Big Five model describes personality using five broad traits. Openness to Experience: High openness involves imagination and insight, while low openness involves practicality and routine. Conscientiousness: High conscientiousness is characterized by organization and dependability, while low conscientiousness is characterized by spontaneity and flexibility. Extraversion: High extraversion includes sociability and assertiveness, while low extraversion (introversion) includes reserve and solitude. Agreeableness: High agreeableness involves trust and altruism, while low agreeableness involves skepticism and competition. Neuroticism: High neuroticism involves emotional instability and anxiety, while low neuroticism involves emotional stability and calmness.

- **Enneagram**: The Enneagram classifies per-

sonality into nine types, each representing different motivations and fears. Type 1: The Reformer, driven by a need for perfection. Type 2: The Helper, driven by a need to be loved. Type 3: The Achiever, driven by a need for success. Type 4: The Individualist, driven by a need for uniqueness. Type 5: The Investigator, driven by a need for knowledge. Type 6: The Loyalist, driven by a need for security. Type 7: The Enthusiast, driven by a need for variety and fun. Type 8: The Challenger, driven by a need for control. Type 9: The Peacemaker, driven by a need for harmony. A 2w3 individual is likely to be more ambitious, charming, and goal-oriented than a typical Type 2. They still seek to help others but are also motivated by a desire for success and recognition.

- **Instinctual Variants**: The Instinctual Variants theory describes three primary instinctual drives influencing behavior. Self-Preservation (SP): Focuses on safety, health, and comfort. Social (SO): Focuses on relationships, status, and community. Sexual (SX): Focuses on intimacy, attraction, and one-on-one connections. For instance, an 8w7 with a Sexual variant, is highly charismatic and seeks intense and passionate connections with others. He or she is bold and assertive, often focusing his or her energy on building strong, impactful relationships.

B Data Alignment Algorithm

The details of data alignment algorithm are as follows:

1. *Preprocess the raw data* Firstly, we divide the scripts into several scenes according to the coherence in language of camera, instead of randomly 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.

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

Algorithm 1: Scripts and Subtitles Matching

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

$dial\&speakers \leftarrow empty$
$threshold \leftarrow 0.8$
for $scene$ in $Script$ **do**
  for $Dials$ in $scene$ **do**
    Extract $speaker$ and $dial$ from $Dials$
    $dial\&speakers \leftarrow speaker, dial$
  end for
end for
for $subtitle$ in $Subtitles$ **do**
  $match\_score \leftarrow 0$
  $match\_speaker \leftarrow Null$
  for $line$ in $subtitle$ **do**
    for $speaker, dial$ in $dial\&speakers$ **do**
      $score \leftarrow Similar(subtitle, dial)$
      if $score$ ¿ $match\_score$ **then**
        Update $match\_score$ and $match\_speaker$
      end if
    end for
    if $match\_score \geq threshold$ **then**
      Update $line$ with $match\_speaker$
    end if
  end for
  Update $subtitle$
end for
return Updated $Subtitles$

Algorithm 2: Slide Window Matching

Input: $Script, Subtitles$
Output: Updated subtitles

$window\_size \leftarrow 10$
$threshold \leftarrow 0.8$
$matches \leftarrow empty\_list$
for $i \leftarrow 0$ to $Len(Script) - window\_size$ **do**
    $window \leftarrow slice(scriptTokens, i, i + window\_size)$
    $match\_score \leftarrow 0$
    for $j \leftarrow 0$ to $Len(Subtitles) - 1$ **do**
        $score \leftarrow Similar(window, Subtitles[j])$
        if $score$ ¿ $match\_score$ **then**
            Update $match\_score$
        end if
    end for
    if $match\_score \geq threshold$ **then**
        $matches \leftarrow Subtitles[j]$
    end if
end for
return Updated $Subtitles$ with $matches$