BigFive: A Dataset of Coarse- and Fine-Grained Personality Characteristics

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Abstract

Obtaining the personalities of users conveyed by their published short texts has a wide and important range of applications, from detecting abnormal behavior of online users to accurately customization recommendation. Advancement in this area can be improved using large-scale datasets with coarse- and fine-grained typologies, adaptable to multiple downstream tasks. Therefore, this paper introduces $BigFive$, a large, high quality dataset manually annotated by experts. $BigFive$ contains 13,478 Chinese phrases that belong to five categories (coarse-grained) and 30 categories (fine-grained). The reliability of five categories grouped by personality level and 30 categories grouped by dimension level is demonstrated via a detailed data analysis. In addition, a strong baseline is build based on fine-tuning a BERT model. Our BERT-based model achieves an average F1-score of .33 (std=.24) in terms of 30 categories and an average F1-score of .66 (std=.05) in terms of five categories. The experimental results suggest that there is much room for improvement.

1 Introduction

Personality is of great significance in psychological research, since it represents a set of individual-derived, stable behavioral patterns and internal processing that can effectively make interpersonal distinctions between people (Pervin, 2003). In the field of psychology, the framework of big five personality theory is widely utilized to describe aspects of personality (McCrae and John, 1992). With the significant increment of online users in social networks, massive behavior data of online users are generated. Because of anonymity of social networks, these online data are much more indicative of the psychological characteristics of a user than behavioral data of the user generated in the real world. Therefore, Obtaining the personalities of users conveyed by their published short texts has a wide and important range of applications, from detecting abnormal behavior of online users to accurately customization recommendation.

Recently, many studies utilized statistical information of words appearing in web texts generated by users to achieve personality prediction. However, statistical information of appearing words lacks semantic information. Although some studies explored personality representations contained in semantic information in web texts, these methods lack universality since the employed datasets are not only small but also are only collected in terms of a small personality trait. In addition, by combining the questionnaire data of subjects, some studies utilized their personal data generated by social networks to conducted experiments for personality prediction (Li et al., 2014). Nevertheless, these methods still have much room for improvement as they lack large-scale textual datasets including personality labels.

In the field of psychology, it is difficult and expensive to obtain a large amount of personalities data, since the personalities of a user is only measured by questionnaires. By constructing personality prediction models, many scholars want to directly predict users' personality types from their text data in social networks, when a high-quality text dataset of personality types is especially important.Most of the current research related to Big Five personality prediction is still based on the LIWC lexicon(Pennebaker et al., 2001), and there is not yet a larger volume of Chinese textual dataset on Big Five personality types.

For this purpose, we provide two manually annotated datasets, one is a multi-label text dataset of Big Five personality types, and the other is a multi-label text dataset with each Big Five personality type more finely granularly divided into 6 dimensions with a total of 30 sub-dimensions.Table 1 shows an example from our dataset.We designed a personality classification for the BigFive5 dataset

Sample Text	Label1(s)	Label2(s)
今天天气很好，我们也很好。(It's a beautiful day and we're fine.)	Extroversion	Cheerful
不是一路人怎么抄近道都追不上。(Not all the way how to take a shortcut can not catch up.)	Neuroticism	Stress-prone
我在灰烬中看到了光?在光中看到了你。(I see the light in the ashes? I see you in the light.)	Openness	Imaginative; Emotionally-aware
已经在路上了?那就不要停了！(Already on the road? Then don't stop!)	Conscientiousness	Ambitious

Table 1: Example annotations from our dataset.

based on the Big Five personality theory(John et al., 2008), and a personality classification method for the BigFive30 dataset with reference to the studies of Costa Jr and McCrae (1995).

We performed hierarchical clustering of the 30 Big Five personality sub-dimensions and found that sub-dimensions of the same Big Five personality type can often be clustered together. In a downstream task, the potential relationships between the personality grid sub-dimensions were able to group them into higher-level categories, such as Big Five personality types.

We provide a power baseline for Big Five personality classification and more fine-grained 30-dimensional personality classification modeling on BigFive5 and BigFive30. By fine-tuning the BERT-based multi-label classification model(Devlin et al., 2019) and the Chinese BERT-wwm pre-training model(Cui et al., 2020), we obtained an average F1 score of 0.33 on the Big Five personality coarse category of BigFive5 and 0.66 on the Big Five personality fine-grained category of BigFive30.These results leave a lot of room for improvement and suggest that the most current and advanced NLU models do not yet fully address the subtask.

2 Related Work

2.1 Personality Prediction

In recent years, researchers in the fields of natural language processing and psychology have become increasingly interested in using social network data for personality prediction(Nguyen et al., 2016).Many studies on personality prediction have focused on the Big Five personality theory model.Halim et al. (2019) used users' game data and their questionnaire data predictions to produce a dataset for predicting players' Big Five personality types.Azucar et al. (2018) predicts the Big Five personality type of users by using the image and text data posted by users in social networks.In a study by Golbeck et al. (2011) on Twitter, some Twitter data from 50 users were obtained for personality prediction.The datasets used in these studies are self-constructed, often relatively small, and difficult to generalize to different scenarios for personality prediction.

2.2 Personality Dataset

The largest developed dataset on personality is myPersonality(Kosinski et al., 2013), which is collected by Facebook through the myPersonality application and contains personality questionnaires and Facebook personal information data filled out by users.Such datasets are significant for studying personality prediction, but they are difficult to obtain and lack sufficient markers, and there is a lack of text classification datasets for similar sentiment classification tasks(Demszky et al., 2020) in the field of personality prediction.

2.3 Classification Models

Both feature-based models and neural network models have been used to construct automatic personality classification models. Feature-based models typically use hand-built dictionaries, such as SC-LIWC(Yuan et al., 2017).The personality prediction task is similar to sentiment prediction, where both the transformer-based model(Wolf et al., 2020) and the BERT model pre-trained with the language model achieved state-of-the-art performance in the sentiment prediction task. We used the BERT model in our experiments and also achieved better performance than the traditional model.

3 BigFive

Our dataset is composed of 13,478 Chinese phrases from social networks and labeled with one or more tags of the Big Five personality and two layers of tags, one for the Big Five personality dimensions of openness, responsibility, extraversion, agreeableness and neuroticism with five tags, and the other for the more fine-grained Big Five personality lattice dimensional traits of 30 labels.

3.1 Data Selection & Preprocessing

The data of this dataset comes from the real data of various social network platforms, mainly crawled from Weibo hometown, WeChat friend circle, Qzone, NetEase cloud music comments, Douban movie reviews, etc. Initially, 200k of rough data were obtained, non-Chinese phrase text was deleted, and the following processing was done on the text.

Filtering pornography. Phrases containing pornographic messages were removed, and phrases containing vulgarity and aggression were retained, because some negative personality traits in the Big Five need to learn traits from them.

Filtering discrimination. During the tagging process, taggers review phrases for discrimination on the basis of race, gender, sexual orientation or physical disability and remove them.

Text length filtering. After analyzing the crawled data, it was found that phrase texts with lengths above 10 Chinese characters were richer in personality traits, and phrase texts with lengths below 55 Chinese characters occupied more than 50% of the crawled data, so the phrase length requirement was set to 10-55 Chinese characters, including punctuation.

Special Noun Masking. Masking of human names and religious terms is usually done using named entity recognition techniques for identification masking.

Eliminate Popularity. In order to prevent hot events from taking up too large a proportion of the data, we crawled data from more than 200 microblogs in the same city by changing the positioning in the process of crawling microblog data; in the process of crawling NetEase cloud music reviews, we selected different songs of the top ten singers in the hotness list from different music genres to crawl review data; in the process of crawling Douban movie reviews, we selected the top ten rated movies from different film and TV genres to crawl In the process of crawling Douban movie reviews, the top ten rated movies from different movie genres were selected to crawl the review data; various constraints were also imposed on other platforms to ensure that the crawled data conformed to the real distribution and were not affected by the hot issues at specific time points.

3.2 Data Balance

Since the distribution of people's personalities in the real world is already extremely unbalanced, the data in social networks are inevitably unbalanced as well, but acceptable at the Big Five personality level.

In the more fine-grained sub-dimensional traits, the imbalance of the data is more obvious, and the requirement of the data volume is higher. For the imbalance problem of the personality grid sub-dimensional class, some measures have been taken, and the current main methods are: in terms of data sources, no more than 5% proportion of manually collected data is added, and this part of data requires the collector to go to the social network to collect according to a certain sub-dimensional personality trait, which This is equivalent to pre-labeling the collected data with a label, and from the experimental results, the imbalance of this dataset can be effectively mitigated by this method.

3.3 Data Annotation.

This dataset was labeled by experts, and for each sample at least three psychologists were assigned for labeling. For samples labeled by only one annotator, another annotator is assigned for annotation. All the labelers were native Chinese speaking psychologists.

Number of examples	13,478
Number of personalities	5 or 30
Number of unique raters	19
Number of raters/example	3 or 4
Number of labels per example	1: 60%
	2: 28%
	3: 10%
	4+: 2%

Table 2: Summary statistics of our labeled data.

The annotators were asked to identify the personality sub-dimension traits embedded in the author of the text, giving predefined definitions of the personality sub-dimensions and some sample texts for each emotion. The annotators were allowed to select multiple personality traits, but were asked to select only those that they had reason to believe were embedded in the text. For uncertain phrases, uniformly were asked to label as meaning unknown.

4 Data Analysis

Table 2 shows the summary statistics of the data. The majority of the samples (60%) are labeled as single labels, and 40% of the data have more than two labels.

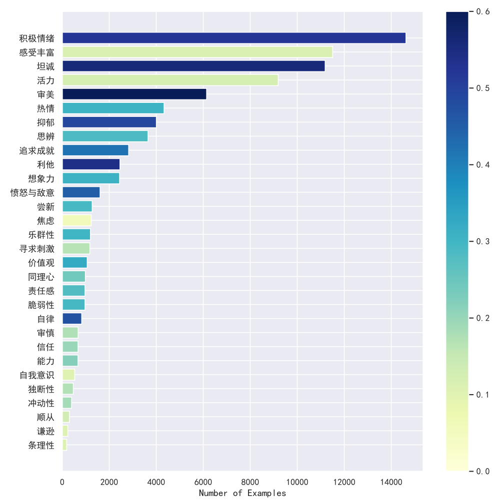

Figure 1: Our personalities categories, ordered by the number of examples where at least one rater uses a particular label. The color indicates the interrater correlation.

4.1 Interrater Correlation

Figure 1 shows the distribution of the personality grid sub-dimensional labels. It can be easily observed that even though some balancing steps of personality traits and sub-dimensional traits were performed in the data selection and screening process, there is a huge difference in the frequency of personality trait labels (e.g., $Cheerful$ appear more than 100 times more often than $Organized$). However, given the inherent unbalanced nature of personality traits that people exhibit in the real world, this presentation of the data results is reasonable.

The consistency of annotation is estimated for each personality type or person-grid dimension by calculating the correlation between annotators. For each annotator $r \in R$, Spearman's correlation of annotation results between annotators is calculated, and the range of data annotated by the annotators is consistent.

Figure 1 shows that $Cheerful$, $genuine$, and $artistic$ have the highest labeling consistency, and $anxiety - prone$, $self - conscious$, and $organized$ have the lowest labeling consistency. The frequency of most personality traits was positively correlated with labeling consistency, but there were exceptions; personality traits with low frequency could also have high labeling consistency (e.g., $disciplined$), while those with high frequency could also have low labeling correlations (e.g., $emotionally_aware$ and $energetic$).

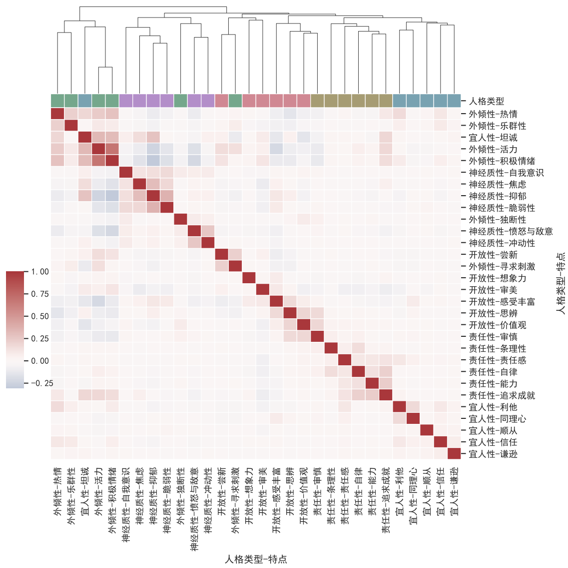

Figure 2: The heatmap shows the correlation between ratings for each personalities. The dendrogram represents the a hierarchical clustering of the ratings. The personalities labeling was done a priori and it shows that the clusters closely map onto personalities groups.

4.2 Correlation Among Personalities

In order to better understand the relationship between the Big Five personality traits in this dataset, correlations between them were analyzed. Let T be the total number of samples contained in this dataset, and obtain a T-dimensional vector representation of each personality trait by averaging the annotations of each annotator, and use it to calculate the Pearson correlation coefficient between each pair of personality traits. The heat map in

Imaginative	Artistic	Emotionally-aware	Actions	Intellectual	Liberal
月亮(moon)	喜欢(like)	温柔(gentle)	尝试(try)	生活(life)	生活(life)
夏天(summer)	好听(nice)	喜欢(like)	第一次(first time)	人生(life)	永远(forever)
Self-assured	**Organized**	**Dutiful**	**Ambitious**	**Disciplined**	**Cautious**
天才(genius)	记录(record)	工作(work)	加油(come on)	打卡(Clock in)	止损(Stop loss)
目标(goal)	锻炼(exercise)	老师(teacher)	努力(strive)	努力(strive)	慎重(careful)
Friendly	**Sociable**	**Assertive**	**Energetic**	**Adventurous**	**Cheerful**
喜欢(like)	朋友(friend)	世界(world)	喜欢(like)	生活(life)	喜欢(like)
加油(come on)	快乐(happy)	真的(real)	快乐(happy)	快乐(happy)	哈哈(ha ha)
Trusting	**Genuine**	**Generous**	**Compliance**	**Humble**	**Empathetic**
喜欢(like)	喜欢(like)	加油(come on)	放心(relax)	低调(Low-key)	加油(come on)
陪伴(accompany)	真的(real)	希望(hope)	喜欢(like)	请教(consult)	心疼(feel sorry)
Anxiety-prone	**Aggressive**	**Melancholy**	**Self-conscious**	**Impulsive**	**Stress-prone**
讨厌(hate)	做作(affected)	不想(Don't want)	尴尬(awkward)	快快(hurry up)	孤独(lonely)
疫苗(vaccine)	无语(speechless)	难过(sad)	害怕(fear)	一秒(one second)	没意思(boring)

Table 3: Top 2 words associated with each personalities (Openness , Conscientiousness , Extraversion , Agreeableness , Neuroticism).

Figure 2 shows that there is usually a strong correlation between the sub-dimensions of a personality type.

In addition, hierarchical clustering was used to cluster these person-grid dimensional traits to reveal the relationship between the two layers of labels employed in this dataset. The distance and the sum of squares of deviations were used to calculate the correlations among the dimensions in the annotator evaluation score data. The dendrogram at the top of Figure 2 shows that the stronger correlations among personality traits are neighbors, with most of the sub-dimensions under the same type of Big Five personality clustered together. Some exceptions also occur (e.g., $actions$ and $extraversion$). The data were also categorized at the level of Big Five personality types with multiple labels and some correlation between the labels.

4.3 Linguistic Correlates of Emotions

In this paper, we utilize TF-IDF method to analyze the lexical correlations of personalities on each category of data text. The labels with top 2 TF-IDF values for each category are listed in Table 3. As shown in Table 3, some labels belong to important lexical sets of multiple personalities. For example, the label $like$ is an important word belongs to the lexical sets of personalities $aestheticfeelings$, $enthusiasm$, $vitality$, $trust$, $honesty$, $obedience$, etc. That is, the situation of multiple labels appeared in a same sample or a same label appeared in multiple samples is reasonable. Therefore, accurately obtaining personalities conveyed by labels requires more context, since it is unrealistic to explain the personality contained in samples only from the perspective of vocabulary.

5 Modeling

In this paper, a strong baseline personality prediction model is presented for BigFive.

5.1 Data Preparation

To reduce noise in the data, this dataset was filtered out of samples with only one annotator label, and then samples with at least one label were retained, and the amount of data remaining after this operation was 86% of the original annotated data. It was randomly divided into training, development, and test sets in the ratio of 8:1:1, and the test set was evaluated only after the model was finalized.

Grouping personalities. Following Costa Jr and McCrae (1995), a hierarchical grouping of big five personality is created, and the performance that the model performs on each level of the hierarchy is also evaluated. A personality level, which is called $BigFive5$, divides labels into five categories, i.e., $openness$, $accountability$, $extroversion$, $agreeableness$ and $neuroticism$. A dimension level, which is denoted as $BigFive30$, divides labels into 30 categories, such as $aestheticfeelings$, $enthusiasm$, $vitality$, $trust$, $honesty$, $obedience$, etc. The corresponding mapping relations are shown in Figure 2.

5.2 Model Architecture

Experiments are conducted using the BERT-based model. This model adds a dense output layer on top of the pre-trained model for fine-tuning, and uses a sigmoid cross-entropy loss function to support multi-label classification.

5.3 Parameter Settings

For the hyperparameters set by Devlin et al. only the batch size and learning rate were changed. it was found that at least 12 epochs were required to learn the data, but training more epochs would lead to overfitting. After extensive experiments, it was found that a small batch size of 16 and a learning rate of 5e-6 yielded the best performance.

5.4 Results

Table 4 summarizes the performance of our BERT-based model on the dataset $BigFive30$, which achieves an average F1-score of .33 (std=.24). As shown in Table 4, our BERT-based model performs well on personality labels with explicitness, such as $Anxiety-prone$(.81), $Empathetic$(.71) and $Self-conscious$(.67), while achieving an average F1-score of 0 on personality labels with very low frequency, such as $Liberal$, $Organized$ and $Cautious$, etc.

Table 5 summarizes the performance of our BERT-based model on the dataset $BigFive5$, which achieves an average F1-score of .66 (std=.05). As shown in Table 4 and Table 5, the performance of our BERT-based model significantly increases when the number of label categories goes from 30 to five. This demonstrates that grouping with personality level significantly reduces confusions and uncertainties among categories grouped by dimension level.

6 Conclusion

In this paper, we present $BigFive$, a large, high quality dataset manually annotated by experts for coarse- and fine-grained personality prediction. A detailed data analysis, which demonstrates the reliability of five categories grouped by personality level and 30 categories grouped by dimension level, is provided. In addition, a strong baseline is build based on fine-tuning a BERT model. However, the experimental results suggest that there is still plenty of room for improvement. In the future, we will explore the intelligence of big five personality scale in terms of user psychological assessment, and extend to the other domains of personality theories.

Data Disclaimer: We are aware that the dataset contains biases and is not representative of global diversity. We are aware that the dataset contains

BigFive30	**Precision**	**Recall**	**F1**
Imaginative	0.25	0.05	0.09
Artistic	0.57	0.68	0.62
Emotionally-aware	0.35	0.47	0.4
Actions	0.6	0.35	0.44
Intellectual	0.18	0.17	0.18
Liberal	0.00	0.00	0.00
Self-assured	0.71	0.53	0.61
Organized	0.00	0.00	0.00
Dutiful	0.47	0.28	0.35
Ambitious	0.44	0.33	0.38
Disciplined	0.53	0.58	0.55
Cautious	0.00	0.00	0.00
Friendly	0.43	0.27	0.33
Sociable	0.63	0.4	0.49
Assertive	0.38	0.12	0.19
Energetic	0.42	0.41	0.42
Adventurous	0.14	0.03	0.05
Cheerful	0.51	0.62	0.56
Trusting	0.38	0.10	0.16
Genuine	0.44	0.57	0.49
Generous	0.46	0.43	0.44
Compliance	0.00	0.00	0.00
Humble	0.00	0.00	0.00
Empathetic	0.83	0.63	0.71
Anxiety-prone	0.77	0.86	0.81
Aggressive	0.55	0.32	0.40
Melancholy	0.41	0.36	0.38
Self-conscious	0.76	0.6	0.67
Impulsive	0.50	0.12	0.19
Stress-prone	0.00	0.00	0.00
macro-average	**0.39**	**0.31**	**0.33**
std	**0.25**	**0.25**	**0.24**

Table 4: Results based on BigFive30 taxonomy.

BigFive5	**Precision**	**Recall**	**F1**
Openness	0.65	0.70	0.68
Conscientiousness	0.68	0.66	0.67
Extraversion	0.63	0.79	0.70
Agreeableness	0.55	0.59	0.57
Neuroticism	0.70	0.70	0.70
macro-average	**0.64**	**0.69**	**0.66**
std	**0.06**	**0.07**	**0.05**

Table 5: Results based on BigFive5 taxonomy.

potentially problematic content. Potential biases in the data include: Inherent biases and user base biases in $Weibo$, $Netease\ cloud\ review$, $Douban\ film\ review$ and other social networks, the offensive/vulgar word lists used for data filtering, inherent or unconscious bias in assessment of offensive identity labels. All these likely affect labeling, precision, and recall for a trained model. Anyone using this dataset should be aware of these limitations of the dataset.

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A Personality Definitions

Openness: It shows that a person is emotional, creative, and imaginative.

Imaginative: It shows that a person likes to be full of fantasy and create a more interesting and rich world. Imaginative and daydreaming.

Artistic: It shows that a person values aesthetic experience and can be moved by art and beauty.

Emotionally-aware: It shows that a person easily perceives his emotions and inner world.

Actions: It shows that a person likes to touch new things, travel outside and experience different experiences.

Intellectual: It shows that a person is curious, analytical, and theoretically oriented.

Liberal: It shows that a person likes to challenge authority, conventions, and traditional ideas.

Conscientiousness: It shows that this person is very organized, disciplined, and thoughtful.

Self-assured: It show that this person is confident in his own abilities.

Organized: It shows that this person is well organized, likes to make plans and follow the rules.

Dutiful: It shows that this person is responsible, trustworthy, polite, organized, and meticulous.

Ambitious: It shows that this person pursues success and excellence, usually has a sense of purpose, and may even be regarded as a workaholic by others.

Disciplined: It shows that this person will do his best to complete work and tasks, overcome difficulties, and focus on his own tasks.

Cautious: It shows that this person is cautious, logical, and mature.

Extraversion: It shows that this person is very sociable, outgoing, and socially confident.

Friendly: It shows that this person often expresses positive and friendly emotions to those around him.

Sociable: It shows that this person likes to get along with others and likes crowded occasions.

Assertive: It show that this person likes to be in a dominant position in the crowd, directing others, and influencing others' behavior.

Energetic: It shows that this person is energetic, fast-paced, and full of energy.

Adventurous: It shows that this person likes noisy noise, likes adventure, seeks excitement, flashy, seeks strong excitement, and likes adventure.

Cheerful: It shows that this person easily feels various positive emotions, such as happiness, optimism, excitement, etc.

Agreeableness: It shows that this person is very cooperative, trusting and well-loved.

Trusting: It show that the person believes that others are honest, credible, and well-motivated.

Genuine: It show that the person thinks that there is no need to cover up when interacting with others, and appear frank and sincere.

Generous: It show that this person is willing to help others and feel that helping others is a pleasure.

Compliance: It show that this person does not like conflicts with others, in order to get along with others, willing to give up their position or deny their own needs.

Humblel: It shows that this person does not like to be pushy and unassuming.

Empathetic: It show that the person is compassionate and easy to feel the sadness of others.

Neuroticism: It show that the person is extremely anxious, unhappy, pessimistic or depressed.

Anxiety-prone: It shows that this person is easy to feel danger and threat, easy to be nervous, fearful, worried, and upset.

Aggressive: It shows that this person is easy to get angry, and will be full of resentment, irritability, anger and frustration after feeling that he has been treated unfairly.

Melancholy: It shows that this person is easy to feel sad, abandoned, and discouraged.

Self-conscious: It shows that this person is too concerned about how others think of themselves, is afraid that others will laugh at themselves, and tend to feel shy, anxious, low self-esteem, and embarrassment in social situations.

Impulsive: It shows that when the person feels strong temptation, it is not easy to restrain, and it is easy to pursue short-term satisfaction without considering the long-term consequences.

Stress-prone: It shows that this person has poor ability to cope with stress, becoming dependent, losing hope, and panicking when encountering an emergency.