Correlation based data unification for personality trait prediction

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ABSTRACT

The data points created by users with their online behavior are the primary source of data analysis in various research studies. One of such studies that even more contributes directly or indirectly to other application domains is personality trait analysis. There are well-defined models witnessed to be strong enough to characterize the individual personalities. Some prominent models are the Big Five, Interpersonal Circumplex, and DISC. To make it possible the model should always be fed with a huge amount of data. Here comes the limitation is that the user's online behavior is spread across various platforms resulting in various forms of data points. The segregated form of the data limits the model performance, which is the primary focus of the proposed work. Among these, the big five personality traits model has become so familiar because of its simplicity and dominance. The proposed work illustrated the mapping of various data forms namely measures of the source dataset (MBTI) and Interpersonal Circumplex data to Big five data.

Keywords: Correlation, Data consolidation, Heterogeneous, Neuroticism, Personality traits, Prediction

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1. INTRODUCTION

Earlier studies have witnessed how an individual personality can be drawn from his handwriting skills. This high dimensional online data availability has vanished the traditional approaches and forced us to come up with altered study models for human psychological behavior. As a result, The Big Five Personality trait model, the first-ever kind of psychological prediction model, has been introduced. Its main aim is to analyze the personality based on the responses given to the predefined psychology-based questionnaire [1]. To be more precise, the Big Five Personality Trait model [2], also known as the OCEAN model, identifies and maps the individual to one of the following assessment aspects [3].

- Openness: People with dynamic personalities, creative, attentive, and willing to take on more challenges come under this personality trait. Such people tend to be more curious and ready to explore new things.
- Conscientiousness: High levels of thought, carefulness, and discipline are the characteristics of this trait. They seem to be well organized and stick to the time in completing tasks.
- Extroversion: These people are too expressive and have good social behavior. They clearly show their excitement and enthusiasm and like to see the results quickly.
- Agreeableness: Cooperation, affection, trustworthiness, and kindness are the main characteristics of these people. They are considered to be generous and understanding.
- Neuroticism: These people are emotionally unstable and are highly prone to mood swings. High levels of this trait are irritable.

Human behavior is a complex interplay of actions, cognitions, and emotions, a deep understanding of it, will help in decision making, stress management, professional insights, setting and reaching goals, and emotion control [4]. The process of trait analysis has proportionately increased the complexity of the emerging technologies. Different sources will generate heterogeneous cross-domain and context-based data, however, mapping or consolidating such data to a uniform format well contributes to trait analysis [5].

2. RELATED WORK

Personality prediction is one of the prominent application areas in the field of individual counselling, personality trait detection, online marketing, recruitment agencies and many more [6]. This section presents the exiting work in the relevant field. Initially the personality prediction started along with sentiment on email data using Bayesian classifier [7]. Their work attempted to study the personality prediction on the social network data with a focus on email messages. Later it was extended to the correlation analysis over user’s personalities and their respective online behavior on social media platforms.

Han et al. [8], explored the challenges in predicting the Big Five Personality scores using Linear Regression and Support Vector Regression. Their study is carried on Facebook posts and status to predict the personality. Another study given in [9], highlighted the impact of social media addiction on their behavioral pattern. Their questionnaire-based study among the teenage students witnessed how the social media influenced the individual empathetic concern and perspective talking.

Aung and Myint [10], has came up with a novel personality recognition model that works on personality lexicon. Their word embedding techniques could come up with a lexicon-based approach for personality recognition. Dandannavar et al. [11], investigated the influence on demographics and Big Five personality dimensions on social media. The word vector-based Bi-RNN model is developed for personality prediction based on word vector representation [12].

The CNN based another model is proposed Thomas et al. [13] and applying different activation functions to detect personality of the individual purely on the text data. Christian et al. [14] explored the provision for personality detection using the mobile technology, in which correlation and clustering methods identify extroversion and neuroticism using BIG5 model. Another work proposed in Ren et al. [15] attempted to identify correlation among personality and handwriting data in which Convolutional neural network applied to find the correlation among human handwriting and personality detection on BIG5 model.

3. MAPPING ILLUSTRATION

The Big Five Personality taxonomy was introduced in the 1980s with the basic idea of extracting the semantic associations among the words that actually describe the personality [16]. This has been carried out with the help of statistical-based factor analysis on personality survey data that gets mapped to one of the five dimensions namely openness, conscientiousness, extraversion, agreeableness, and neuroticism. To address this, the other sources of data are being considered to understand human behavior with respect to the context and content. As a consequence, dealing with this heterogeneous data under various contexts has become a challenging task. In this work, a mapping illustration is primarily focused on unifying various kinds of data gathered across different online platforms to the Big Five context model. Though accurate personality trait estimation is highly difficult from heterogeneous data, the advent of natural language processing (NLP) techniques gave a comfortable walkthrough to reach the goal [17]. This thought is extended in this work and experimented with mapping on various datasets as demonstrated below. Mapping illustration is given as follows. Firstly, an in-depth detail of the Big five model is presented. Secondly, the mapping process of each individual data with proper correlation of suitability is presented.

3.1. Big Five Personality Model

To begin with, a Big Five Personality Trait Model is chosen as a target model for data consolidation. In this, a sample questionnaire [8] is framed and the assessment procedure follows with a survey on a five-point scale of 1=disagree, 3=neutral and 5=strongly agree. Assuming no falsification from the participant will result in mapping an individual to one of its five dimensions which are presented along with their correlation analysis in the Table 1.

From the obtained values given in Table 1, it is clearly evident that all the five dimensions are uncorrelated with each other and thus can be considered as significant classes of personalities of human behavior. As shown in Figure 1, the datasets considered for fundamental mapping are MBTI dataset [18], Interpersonal Circumflex data [19], [20]. This way of consolidation would help the deep learning models in

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increasing the data size and also to carry the assessment on context and content-based data. The more detailed description of individual data unification is given as follows.

| Table 1. Correlation analysis on Big Five Dataset |
|-----------------|----------------|----------------|----------------|----------------|
|                | EXT            | NEU            | AGR            | CON            | OPN            |
| EXT            | 1              | -0.16          | 0.12           | 0.13           | 0.079          |
| NEU            | 1              | -0.089         | -0.148         | -0.047         |                |
| AGR            | 1              | 0.134          | 0.018          |                |                |
| CON            | 1              |                |                |                |                |
| OPN            |                |                |                |                | 1              |

Figure 1. System flow

3.2. Myers briggs type indicator or MBTI

MBTI in short, is a personality type detection system that categorizes the individual across four axes, for example someone who prefers to be extrovert, sensing, thinking and perceiving will be labeled as ESTP. The consistent four axis are: i) Introversion (I) – Extroversion (E), ii) Intuition (N) – Sensing (S), iii) Thinking (T) – Feeling (F), iv) Judging (J) – Perceiving (P). The personality type of the individual is represented as four letter MBTI code, and the 16 possible combinations of these four-letter codes [21] are given in Table 2.

| Table 2. MBTI - 16 Personality types with four-letter code |
|-------------|-------------|-------------|-------------|
| Sno    | four-letter code | Sno | four-letter code |
| 1      | ISTJ        | 8  | INFP         |
| 2      | ISTP        | 10 | INFP         |
| 3      | ESTP        | 11 | ENFP         |
| 4      | ESTJ        | 12 | ENFP         |
| 5      | ISFJ        | 13 | INTJ         |
| 6      | ISFP        | 14 | INTP         |
| 7      | ESFP        | 15 | ENTP         |
| 8      | ESFJ        | 16 | ENTJ         |

To ensure the uncorrelated or bipolar nature of four axes of MBTI, the correlation analysis is carried out on the experimental data. The linear correlation is extracted from the data using the Pearson correlation coefficient [22] whose values range from -1 to +1. To say that two sets are not correlated the respective correlation values should lie in -0.3 to 0.3, the values given in Table 3 clearly depicts that the pair of sets have no correlation and an individual personality can be categorized across these one of four axes.

| Table 3. Pearson Correlation Analysis on MBTI |
|-------------|-------------|-------------|-------------|
| IE       | NS          | TF          | JP          |
| IE       | 1            | -0.046      | -0.070      | 0.160       |
| NS       | 1            | -0.081      | 0.015       |             |
| TF       | 1            | -0.06447    |             |             |
| JP       |              |             | 1           |             |
3.3. Mapping procedure of MBTI to Big FIVE

As mentioned earlier, the personality trait of an individual is represented as a four-letter code, and the proposed work attempted to reinterpret this code representation in correlation with the Big Five model. The experimentation is aimed to find the correlated attributes among MBTI and Big Five, and so map the MBTI codes to Big Five dimensions. The partial correlation table in the literature is given in Table 4 from the source [23].

It is required to have an overlap between the measures of the source dataset (MBTI) and the target dataset (Big Five) to proceed further with the mapping process. The correlation values given in Table 4, clearly provides a feasible solution to obtain either a negative or positive correlation among the two trait models. The Pearson correlation analysis between two is summarized in Table 5.

Table 4. Correlation of MBTI and Big Five

| MBTI / Big Five | E   | I   | S   | N   | T   | F   | J   | P   |
|-----------------|-----|-----|-----|-----|-----|-----|-----|-----|
| Neuroticism     | -.30| .31 | .15 | -.14| -.13| .12 | .07 | -.07|
| Extraversion    | .71 | -.72| -.28| .27 | .00 | -.00| -.13| .16 |
| Openness        | .28 | -.32| -.66| .64 | -.17| .13 | -.25| .26 |
| Agreeableness   | -.02| -.02| .01 | -.00| -.44| .28 | .05 | -.06|
| Conscientiousness| .13 | -.13| .10 | -.13| .22 | -.27| .46 | -.46|

Table 5. Mapping Compatibility with Pearson Correlation Coefficient on MBTI and Big Five

| Big Five | MBTI | Correlation Score | Type of Correlation |
|----------|------|-------------------|---------------------|
| Extroversion (EXT) | Extroversion(E) | 0.7 | Positive |
| Openness (OPN) | Intuition(N) | 0.6 | Positive |
| Agreeableness (AGR) | Feeling (F) | 0.3 | Positive |
| Conscientiousness (CON) | Judging(J) | 0.4 | Positive |
| Neuroticism (NEU) | Introversion(I) | 0.3 | Positive |
| | Extroversion(E) | -.3 | Negative |

3.4. MBTI to Big five fusion analysis

From the observations recorded in Table 5, it is apparently visible that two trait models are compatible with each other for the fusion or unification process. Each sample in MBTI is mapped to Big Five traits on the bases of existing positive or negative correlation. Basing upon this relative analysis, further the fusion process with the possible options of these two trait models is illustrated in Table 6.

Table 6. MBTI 16 four-letter code classes to Big five dimensions

| Big Five | MBTI | Correlation Score | Type of Correlation |
|----------|------|-------------------|---------------------|
| ISTJ | N | N | N | Y | Y |
| ISFJ | N | N | Y | Y | Y |
| INFJ | N | Y | Y | Y | Y |
| INTJ | N | Y | N | Y | Y |
| ISTP | N | N | N | Y | N |
| ISFP | N | N | N | Y | N |
| INFP | N | Y | Y | Y | N |
| INTP | N | N | Y | Y | N |
| ESTP | Y | N | N | N | N |
| ESFP | Y | N | Y | N | N |
| ENFP | Y | Y | Y | N | N |
| ENTP | Y | Y | N | N | N |
| ESTJ | Y | N | N | N | Y |
| ESFJ | Y | N | Y | N | Y |
| ENFJ | Y | Y | N | Y | Y |
| ENTJ | Y | Y | N | N | Y |

3.5. Interpersonal circumflex data model

In Figure 2 gives the details about another personality trait model namely, Interpersonal Circumflex or circle- a well-known conceptual model for assessing individual interpersonal traits. This circumplex is represented by two orthogonal axes [24]. The vertical axis signifies Status, Dominance, Power, Ambitiousness.
where as horizontal axis meant for Agreeableness, Compassion, Solidarity, Friendliness, Warmth, Love. This interpersonal circumplex can be divided into two or four broad segments, or sixteen narrow segments [25], [26] shown in Figure 2(a). But most of the studies considered the circle into eight partitions/octants which implies a blend of the two axial dimensions. Each octet is spread across 45 degrees and their correlation angle subtend is presented in Figure 2(a), and the mapping of corresponding Big five traits are given in Figure 2(b). The correlation among the dimensions ranges will be figured as -1 for linear angles, 0 for orthogonal angles +1 for 00 and for the sample dimension “Dominance” with other measures at different angles is given in Table 7.

![Figure 2. Details about another personality trait model (a) Interpersonal Circumplex to Big five Traits and (b) Correlation among dimensions Range](image)

| Angle subtend with dominance | Correlation |
|----------------------------|-------------|
| Gregarious Extraverted     | 0.5         |
| Friendliness; Agreeableness| 0           |
| Unassuming-Ingenious       | -0.5        |
| Submissiveness             | -1.0        |
| Aloof-Introverted           | -0.5        |
| Hostility/Coldness         | 0           |
| Arrogant-Calculating       | 0.5         |

Table 7. Correlation summary of Interpersonal Circumplex
3.6. Mapping from IC to Big Five

From the understanding of blended concepts given in Figures 2(a) and (b), the relative mapping of IC to Big Five model with angle subtend is given in Table 8. Using this mapping Table 8, any data sample on the interpersonal circumplex can be mapped to Big Five.

| IC Angle | E       | O       | A       | C       | N       |
|----------|---------|---------|---------|---------|---------|
| 0°       | Positive| Positive| Positive| Positive| Negative |
| 45°      | Positive| Positive| Positive| Positive| Negative |
| 90°      | Negative| Negative| Positive| Positive| Negative |
| 135°     | Negative| Negative| Positive| Positive| Negative |
| 180°     | Negative| Negative| Negative| Negative| Positive |
| 225°     | Negative| Negative| Positive| Positive| Positive |
| 270°     | Negative| Negative| Negative| Negative| Positive |
| 315°     | Positive| Positive| Negative| Negative| Positive |
| 360°/0°  | Positive| Positive| Positive| Positive| Negative |

Table 8. Correlation of Interpersonal Circumplex angles to Big Five

Figure 3 gives a view on how a user profile can be shown on Interpersonal circumplex. Each of the intersection point over IC octants represents user behavioral towards that dimension. If the distance from circle center to the octet intersection point is high, that is towards circumplex then it implies a positive correlation and if the distance is less, it implies a negative correlation with that dimension. In order to map the IC to Big five, for any user profile, the octet with the first largest distance towards circumplex is considered and proceeds further for the second largest circumplex and so on until the complete mapping of all Big Five-dimensional set is obtained. Mapping or Consolidation of two samples given in figure 3 are presented in Table 9. The existing personality trait prediction model has given less attention to multiple forms of data, because of which the behavioral analysis is restricted to a single vertical aligned to BIG Five data model [D12].

Figure 3. Octet Representation of the interpersonal circumplex source

| Largest Circumplex Angle | Big Five | E   | O   | A   | C   | N   |
|--------------------------|----------|-----|-----|-----|-----|-----|
| Sample 1                 | 45°      | Positive | Positive | Positive | Positive | Negative |
| Sample 2                 | 90°      | Positive | Positive | Positive | Positive | Negative |
| Final Mapping            | 0°       | Positive | Positive | Positive | Positive | Negative |
| Final Mapping            | 45°      | Positive | Positive | Positive | Positive | Negative |

Table 9. Mapping of IC data sample to Big Five

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