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Inferring Trust Using Personality Aspects Extracted from Texts

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***Abstract*— Trust mechanisms are considered the logical protection of software systems, preventing malicious people from taking advantage or cheating others. Although these concepts are widely used, most applications in this field do not consider affective aspects to aid in trust computation. Researchers of Psychology, Neurology, Anthropology, and Computer Science argue that affective aspects are essential to human's decision-making processes. So far, there is a lack of understanding about how these aspects impact user's trust, particularly when they are inserted in an evaluation system. In this paper, we propose a trust model that accounts for personality using three personality models: Big Five, Needs, and Values. We tested our approach by extracting personality aspects from texts provided by two online human-fed evaluation systems and correlating them to reputation values. The empirical experiments show statistically significant better results in comparison to non-personality-wise approaches.**

I. Introduction

Trust mechanisms are based on observations of people's behavior and the assignment of trust values to them. These values are often used in decision-making processes and are useful to indicate whether a person should interact or not with another. Differently from hard security, which is based on policies, cryptography or access control; trust mechanisms are related to soft security and are used to prevent malicious people from deceiving others.

To construct systems upon trust mechanisms, researchers have developed trust and reputation models. Such models are composed of a set of dimensions that aim at: (i) extract information from the environment or others (artificial agents or people), (ii) compute trust values, and (iii) help in decision-making processes about whether interacting or not with a particular partner. Most of the existing models rely on the numeric or cognitive paradigms, which are related to numerical aggregations and mental states, respectively [1]. Therefore, there is a lack of understanding of how trust is influenced by affective aspects, particularly in information exchange environments such as evaluation systems. This fact is also corroborated by [2], who argues that it is difficult to explain trust values in cognitive models since the parameters are usually random (using only artificial simulations) and trust values are often subjective.

The affective paradigm was introduced to fill this gap, which uses affective data to aid in trust computation [3]. An example of this paradigm is presented by [4], where the reputation of items (hotels and books) is calculated based on the emotions extracted from text reviews. Based on this, in this work we propose a trust model that considers the personality bound given by the Five Factor Model [5] – also called the Big Five Model [6], [7], Needs [8], [9], and Values [10], [11]. In other words, the main contribution of this paper is the usage of personality aspects to trust prediction. We hypothesize that our model will achieve higher correlation and accuracy when compared to purely numeric models that do not account for affective aspects. This new model can be applied to improve systems that already have trust or reputation mechanisms, as well as for systems that do not present such mechanisms. It will be possible to build predictive trust systems to indicate whether or not we can trust a person. Our approach is evaluated by extracting personality aspects from texts provided in two online human-fed evaluation systems. Empirical results show significant correlation and accuracy improvements with $p < .05$.

This paper is divided as follows. We start by discussing trust (Sec. II). Later, we focus on personality (Sec. III and how to perform their extraction from texts (Sec. IV). Afterwards we introduce our model (Sec. V), which was evaluated using several inductive machine learning algorithms in two real-world datasets (Sec. VI). Finally, we conclude this paper and state future work (Sec. VII).

II. Trust

Trust has been approached in several fields, such as Economy, Philosophy, Sociology, and Psychology [12], [13], [14], [15]. There are many trust definitions in the literature, and most of them are related to uncertainty about events, risk, and beliefs regarding partners [16]. We refrain from providing an extensive mapping of possible trust definitions since it has been surveyed in [1].

There are two types of trust: cognitive and affective. Cognitive trust is quickly constructed and it relies on opinions or knowledge about objects [16], [17]. Essentially, it involves conscious decisions about trust partners based on competence, responsibility, and dependence [18], [19],

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[20], [21]. Conversely, affective trust is related to affective content among individuals [22], [19], [3].

Although both influences the prediction of events [23], cognitive trust concerns to reasoning mechanisms that enable probability-based predictions, thus, becoming easier to build and update. On the other hand, affective trust is grounded on affective aspects. It is claimed to be more important since it is relevant during decision-making [4]. Finally, another concept related to trust is reputation, which is defined as the collection of opinions about other person and can be considered part of the user's trust [24].

III. Personality

Personality is the affective state with longer duration, and it can last for years or even a lifetime [25], for this reason, it is essential in long-term social interactions since it contributes to consistent behaviors [3]. Regarding computers, one of the most used personality theories is the Big Five Model [7], which is composed of five traits: extraversion, agreeableness, conscientiousness, neuroticism, and openness [6]. Extraverted people are friendly, assertive, and inspired by social situations. Neurotics are anxious, insecure, impulsive, and tend to feel negative emotions. Agreeable people, in turn, are cooperative, pacific, optimist, and tend to avoid conflicts. Conscientiousness is a trait related to people responsible, organized, and persistent. Finally, the openness trait regards the following characteristics: curious, smart, imaginative, and the tendency to look for new experiences. Each one of these traits could also present facets, which are unique and specific aspects of the personality traits [26]. Table I shows the facets related to each Big Five personality trait.

Another personality model is the one based on Needs, which states that several types of human needs are universal and influence consumer behavior. This model was developed considering the marketing literature described in [8] and used by [9]. This model is composed by twelve Needs: excitement, harmony, curiosity, ideal, closeness, self-expression, liberty, love, practicality, stability, challenge, and structure. The personality model based on Values describes what is most important for an individual and serves as a guiding principle of people's lives. Values include people's behaviors considering people attitudes, beliefs, norms and traits [10]. According to Schwartz et al. [11] this model influences user's behavior as well as his/her decision-making process, and 19 basic individual Values compose it. However, as described in [10], those 19 fundamental Values are mapped onto four higher-level value dimensions: openness to change, self-enhancement, conservation, and self-transcendence. IBM Cloud [8] applied in the work of [9] 5 of those 19 values described as self-transcendence/helping others, conversation/tradition, hedonism/taking pleasure in life, self-enhancement/achieving success, and open to change/excitement.

IV. Personality and texts

One of the first tools for personality extraction from texts based on the Big Five Model was developed in [27] and was called Personality Recognizer. Since then other works have been developed, such as PR3 [28], Sentic Persona [29], Indico [30], and [31], [32], [33], [34]. Beyond the Big Five, in [9] an analysis was conducted to infer personality using the Need and Value models, which afterwards led to the creation of the Watson IBM Personality Insights [8]. All these works use linguistic features to aid in personality prediction, however, data from the environment is also claimed to help in personality estimation, specially social network information [35], [36], [37], [38].

In this work, we focus our study to the English language and personality extractors provided by public APIs or web interfaces. Precisely, we used Personality Recognizer [27], PR3 [28], Sentic Persona [29], Indico [30], and Personality Insights [8]. Given an inputted text, these tools return a value for each one of the personality aspects, depending on the personality model they were developed to work with. The first four tools are based only on the Big Five Model, so they return one value for each one of the five main traits. On the other hand, Personality Insights [8] returns values related to the Big Five facets [26], Needs [8], and Values [10] personality models.

According to Celli and Zaga [28], the performance of a personality extractor is directed related to the texts, since the most challenging datasets are the ones in which the texts were not spontaneous. Authors in [39] and [40] claim that texts can also vary given the writer gender, education, social status, culture, and the text purpose. None of those tools mentioned earlier consider such aspects. Personality extractors from texts may present different correlation coefficient for each one of the traits, so these tools can work better for some traits and worst for others due to bias.

V. Proposed model

Our approach computes the user's trust (how trustful a person is) using personality aspects extracted from text based on affective models (Sec. I). To validate our approach, we used benchmark datasets that included personality aspects and trust values, namely Trip Advisor and eBay. We modeled these datasets as regression and classification problems and assess our approach performance in terms of correlation and accuracy. In Trip Advisor users are allowed to write reviews which are evaluated by other users in the form of helpful votes. On the other hand, in eBay users are also entitled to write reviews about products, and additionally, they can write comments about purchase and sale transactions, since eBay is an e-commerce site. Trip Advisor dataset was extracted as part of the Twin Persona Research Project [41], while eBay dataset was obtained in September 2015 using crawler techniques.

TABLE I

BIG FIVE PERSONALITY TRAITS AND FACETS [26]

Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness
Friendliness	Trust	Self-efficacy	Anxiety	Imagination
Gregariousness	Morality	Orderliness	Anger	Artistic interests
Assertiveness	Altruism	Dutifulness	Depression	Emotionality
Activity level	Cooperation	Achievement-striving	Self-consciousness	Adventurousness
Excitement-seeking	Modesty	Self-discipline	Immoderation	Intellect
Cheerfulness	Sympathy	Cautiousness	Vulnerability	Liberalism

Fig. 1. Proposed model flowchart

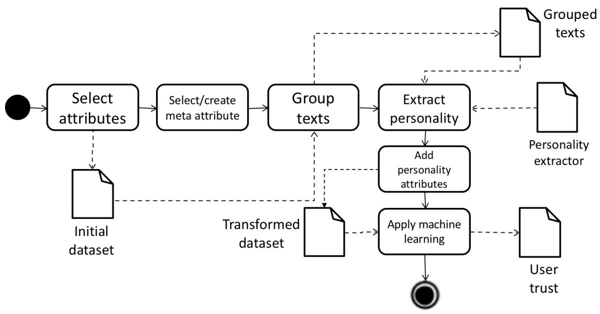


TABLE II

TRIP ADVISOR INITIAL DATA.

Field	Description
Age	Age of the user, ranging from 13-17, 18-24, 25-34, 35-49, 50-64 to 65+
Gender	Male or female
Reviewer badge	One of the following categories: Reviewer, Category, Passport, Helpful Votes, Explorer, or Traveler's Choice (provided by Trip Advisor)
Total number of evaluations	Total number of restaurant reviews + Total number of hotel reviews + Total number of attractions reviews
Average utility votes per review	An average calculated based on the utility votes the user received
Total of classifications	Total number of evaluations the user gave to others
Photos	Total number of photos in user's profile
Thumbs up photos	Total number of photos on the first page of user's profile
Percentage of world traveled	Percentage of the world the user had traveled, calculated by Trip Advisor
Number of visited cities	Total number of cities the user had been to
Total miles traveled	Total number of miles the user had traveled, calculated by Trip Advisor
Reputation	$hr/(hr+nhr)$, where hr is the total number of reviews set as helpful by others users at least once, and nhr is the total number of reviews that were not set as helpful at least once

A text corpus is compatible with our model if it contains: (i) data about users; (ii) texts written by these users; and (iii) data that characterizes the user's trust. Figure 1 presents our machine learning workflow. The first step is to **select attributes** with the intent to maintain only the attributes that represent useful data to model the user's trust. To illustrate the user's data, we show in Tables II and III sample data extracted from Trip Advisor and eBay, respectively. We use these additional data because according to [42], personality should be measured by the sum of experiences, including personal variables such as education, gender, number of close friends, among others.

TABLE III

EBAY INITIAL DATA.

Field	Description
Number of evaluations	Total number of evaluations the user gave to others
Number of reviews	Total number of reviews the user wrote about products
Blacklist	Indicates if the user has already been to the eBay's blacklist
Reputation	Given by eBay's own reputation system

The second step in Figure 1 is to **select/create the meta attribute**, which is related to the definition of the trust model. This attribute is used for inferences made by the machine learning algorithms and reflects the user's trust. Some datasets already include this data, while others may not present it explicitly, so the meta attribute needs to be generated considering the attributes extracted at the first step of the flowchart.

As Trip Advisor does not include a trust or reputation system, we have defined the meta attribute using a utility measure, which was based on the total number of reviews and the helpful votes the user had received. In short, a user's trust is given by his/her reputation as a reviewer. On the other hand, the user's trust in eBay is provided by the reputation value already presented in the system (both attributes can be seen in Tables II and III, respectively). Reputation on eBay is in the range of 0 and 100 with the majority of the users presenting the value 100 and the minority presenting other values. This is because eBay uses a decay function, so if a user goes too long without making transactions, his/her reputation can easily reach zero. To test our model under a classification scenario, we chose to apply classification rather than regression for this dataset. The classes were defined as follows: users with reputation greater than 50 belong to the "good" reputation class, while the others belong to the "bad" reputation class. This separation into only two classes was defined because of the distribution of reputation values as previously explained. It is also important to emphasize that in our experiments we correlate trust values from our model with actual reputation values. This was done because reputation was the only available data on the datasets, and as seen on the end of Sec. II, reputation is part of a user's trustworthiness.

The third step in Figure 1 is to **group texts** for each

TABLE IV

TEXT CORPUS STATISTICS.

	Trip Advisor	**eBay**
Number of texts	65.535	394.149
Number of characters	52.480.378	4.226.218
Average characters per text	800	59
Number of users	1.641	7.313
Average of texts per user	40	55
Minimum number of texts	5	1
Maximum number of texts	795	386

TABLE V

DATASETS AND EXTRACTORS ADOPTED. PI STANDS FOR PERSONALITY INSIGHTS AND BF FOR BIG FIVE

Extractor	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Original data	X	X	X	X	X	X	X	X	X	X
Person. Recognizer [27]		X								X
PR3 [35]			X							X
Sentic Persona [29]				X						X
Indico [45]					X					X
PI BF [8]						X				X
PI BF Facets [8]							X			X
PI Needs [8]								X		X
PI Values [8]									X	X

user, receiving as input texts from the initial dataset and returning grouped texts. This stage is done because it is necessary to extract personality from all texts written by each user, so all reviews must be clustered. Additionally, studies claim that different observations on personality are needed since it is not a transitory factor [43]. For example, the Personality Insights [27] needs at least 70 words to compute personality aspects.

The fourth step is to extract personality aspects from the clustered texts using a personality extractor from text, as well as to add personality attributes returned by the personality extractor on a new dataset called **transformed dataset**. The transformed dataset contains the original data presented in Tables II and III with the addition of the personality aspects. As in our experiments we use the Big Five Model [20], Big Five Facets [26] Needs [8] and Values [10], we add in the transformed dataset all the attributes that correspond to each one of these theories, as seen on Section II.

Finally, the last step is to **apply machine learning** algorithms receiving as input the transformed dataset and the machine learning algorithms, returning user trust. This step will be discussed on Sec. VI. Table IV presents statistics about Trip Advisor and eBay datasets, and it is possible to observe that there is a big difference between the minimum and the maximum number of texts per users because we used the max quantity of data to avoid loss of useful information. The number of characters in eBay is lower than in Trip Advisor, which can be explained by the fact that in Trip Advisor the texts are more spontaneous and the users are allowed to write larger texts. We had initially 5.806 users in eBay (4.299 with "good" reputation and 1.507 with "bad" reputation), but as the dataset was unbalanced we applied the SMOTE [44] technique to resample the original data, resulting in 7.313 users with the same quantity of rows per class. This is an oversampling method which creates synthetic samples from the minor class.

VI. ANALYSIS

In this section, we access the performance of our proposal with several inductive machine learning algorithms in the task of predicting user's trust using personality aspects extracted from texts. In Table V we present the description of the datasets used during our analysis, as well as the features each one embeds, encompassing only social network data (D1), to the adoption of all possible features with personality (D10). The expected result is that the datasets from D2 to D10 present a higher correlation coefficient (Trip Advisor) and accuracy (eBay) when compared to D1. This is plausible because D1 is the only dataset that does not present personality aspects. Therefore, if these datasets have higher results with statistically significant differences, it is possible to claim that personality extracted from texts impact on user's trust so that we can confirm our hypothesis. Besides doing the experiments individually using the personality extractor tools (in datasets from D2 to D9), we have also created D10 which contains the data from all extractors, so we can evaluate what the best features in trust prediction are. In the following section, we state the experimental protocol adopted, allowing a robust discussion of the empirical results obtained.

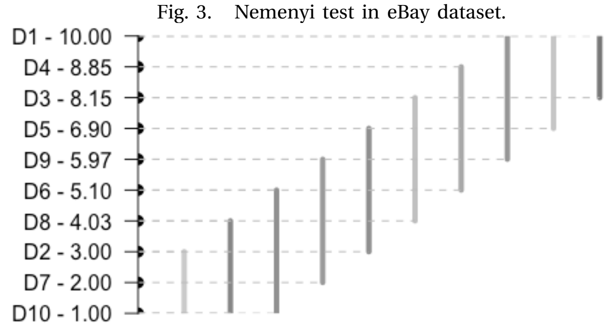
A. Experimental Protocol

To test our hypothesis, the datasets described on the last section were used to generate and evaluate models given the following inductive learners: Linear Regression, M5Rules, Random Forest, Multilayer Perceptron, Support Vector Machines, JRip, and BayesNet. These algorithms were chosen due to their usage in the machine learning community, different biases, results obtained in various applications, as well as different paradigm type.

Utility as goodness-of-fit is computed accordingly to the correlation coefficient between the observed reputation y values and the predicted reputation $\hat{y}$ values. This method is used for the Trip Advisor experiments, in which we have a regression problem. On the other hand, for the eBay dataset, we used the accuracy score metric since it is a classification problem (number of correct predictions divided by the number of predictions). Our evaluation encompasses 30 executions using cross-validation 10-folds, therefore, diminishing the probability of overfitting. To verify if there are significant statistical differences between the usage of different subsets of features, we proceeded with a combination of Friedman [46] and Nemenyi [47] non-parametric hypothesis tests with a 95% confidence level. All algorithms implementations are provided in the Waikato Environment for Knowledge Analysis (WEKA) framework [48] with their default parameters.

Fig. 2. Nemenyi test in Trip Advisor dataset.

Fig. 3. Nemenyi test in eBay dataset.



B. Discussion

In Table VI we present the correlation coefficients obtained in the experiments using Trip Advisor data. From these results, one can see that there is no "one outperforms all" set of features, yet, D5 is the best ranked with slightly improvements using the Random Forest learner. We also can see that D2, D3, D4, D6, and D9 present better results than D1, which corroborates our initial hypothesis that personality aspects extracted from texts increase the correlation of trust-based systems. The interesting point is that D10 presented the worst results, which indicates that the combination of all personality aspects does not lead to better results in this particularly dataset.

As the correlation improvements in the Trip Advisor dataset are quite small, Figure 2 shows the Nemenyi graph to check if there are significant statistical differences among the approaches. The calculated critical distance (CD) is 2.473, so we can conclude that D5, D2, and D6 are statically better than D1 because the subtraction of their rankings compared to D1 is higher than the CD (6.13 – 2.17 = 3.96, 6.13 – 2.97 = 3.16, 6.13 – 3.30 = 2.83, respectively). This analysis corroborates our hypothesis.

To check the importance of the attributes to trust prediction, we used a measure of quality called average impurity decrease [49] applied to the Random Forest algorithm. Table VII shows the first five best-ranked attributes to D5, D2, and D6, therefore, the higher the value, the more important the feature is. We can realize that the average utility votes per review are the most important attribute; anyway, the personality aspects are listed in all datasets with similar importance as the purely numeric attributes. It means that although its average impurity decrease is not so high, these attributes can contribute to the learning algorithm and aid in trust prediction.

Table VIII presents the accuracy scores obtained in the experiments using eBay data. From these results, one can see that the datasets from D2 to D10 outperforms D1 in all executions using the Random Forest learner, which also leads to the validation of our hypothesis that personality aspects can help in trust prediction. Differently, from the experiments using Trip Advisor data, we can see great improvements comparing D10 and D1 and also, we can realize that the combination of all personality aspects leads to better results in this particularly dataset.

Figure 3 shows the Nemenyi graph to check if there are significant statistical differences among the approaches. The critical distance (CD) is 2.473, so we can conclude that except D4 and D3 all other datasets are statically better than D1. It happens because the subtraction of their rankings compared to D1 is smaller than the CD (10.00 - 8.85 = 1.15, 10.00 - 8.15 = 1.85, respectively).

To check the importance of the attributes for the trust prediction, we again used average impurity decrease [49] applied to the Random Forest algorithm. Table IX shows the first fifteen best-ranked attributes to D10. We can realize that the personality aspects from D2, D3, and D4 were considered the best ones because they are listed in the top positions of the ranking, outperforming the numeric attributes. As stated in Sec. IV, personality extractors may present different performance for each one of the traits. When analyzing Table IX, we can see that the openness trait in D4 (0.53) is better for the trust prediction than the openness trait in D3 (0.43), so this analysis can be used to choose the best set of attributes regarding the dataset. It is important to emphasize that the features from the other personality extractors present similar values from the ones shown on Table IX, so they can also be relevant for the trust prediction. A final discussion is that we also did experiments using only personality aspects, instead of combining them with the numeric features (Tabs. II and III). The correlation coefficient for Trip Advisor (D5) and Random Forest was only 0.0251. On the other hand, the accuracy score for eBay (D10) and Random Forest was 70.1354. Based on these results, we argue that although personality aspects are important, the combination with the attributes of the environment leads to better results.

VII. Conclusions

In this work, we proposed a personality bound trust model based on the affective paradigm, which was tested in the scenario of two real-world evaluation systems. To validate and experiment our approach we used data obtained from Trip Advisor and eBay websites. Experimental results confirmed our initial hypothesis that personality aspects extracted from texts increase the correlation and accuracy of trust-based systems with $p < .05$. The most significant results were obtained using data from eBay. We hypothesize that it happened because the reputation value is already present in this dataset. Differently, in Trip

TABLE VI

CORRELATION COEFFICIENTS OBTAINED DURING TRIP ADVISOR EXPERIMENTS.

Learner	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Random Forest	0.7968	0.7999	0.7987	0.7972	**0.8011**	0.7999	0.7472	0.7931	0.7991	0.7365
M5Rules	0.7039	0.7915	0.7867	0.7879	0.7935	0.7906	0.7637	0.7841	0.7896	0.7608
Multilayer perceptron	0.6528	0.6529	0.6552	0.6469	0.6588	0.6611	0.6278	0.6386	0.6364	0.6244
SVM	0.63	0.6301	0.6291	0.6356	0.6313	0.6303	0.6384	0.6308	0.6284	0.6393
Linear Regression	0.6169	0.6143	0.6161	0.6229	0.617	0.6189	0.619	0.6154	0.6124	0.6143

TABLE VII

AVERAGE IMPURITY DECREASE FOR THE TRIP ADVISOR EXPERIMENTS.

D5	**D2**	**D6**
0.28 - Average utility votes per review	0.27 - Average utility votes per review	0.28 - Average utility votes per review
0.04 - Total reviews about restaurants	0.05 - Total reviews about restaurants	0.04 - Total reviews about restaurants
0.04 - Reviewer badge	0.04 - Conscientiousness	0.04 - Reviewer badge
0.04 - Openness	0.04 - Reviewer badge	0.04 - Agreeableness
0.04 - Total miles traveled	0.04 - Agreeableness	0.04 - Neuroticism

TABLE VIII

ACCURACY SCORE OBTAINED DURING EBAY EXPERIMENTS.

Learner	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Random Forest	63.4669	69.5661	64.5171	64.4414	66.8627	68.0127	70.4822	68.7155	67.54	**72.8019**
JRip	62.1405	61.8579	62.0525	62.2667	62.2043	62.3497	61.8383	61.9408	62.8789	62.5521
Multilayer perceptron	60.4467	60.4435	60.303	60.5255	60.4079	60.4376	60.382	60.4663	60.4417	61.8898
SVM	60.454	60.454	60.454	60.3077	60.454	60.454	60.454	60.454	60.454	60.3077
BayesNet	61.031	61.7713	61.0383	60.9704	61.6054	62.3014	58.2775	61.0999	60.8638	59.9344

TABLE IX

AVERAGE IMPURITY DECREASE FOR THE EBAY EXPERIMENTS.

D10
0.55 – Agreeableness D4
0.55 – Neuroticism D4
0.53 – Openness D4
0.50 – Conscientiousness D4
0.50 – Conscientiousness D3
0.49 – Neuroticism D3
0.48 – Extraversion D3
0.47 – Neuroticism D2
0.47 – Extraversion D2
0.45 – Agreeableness D3
0.44 – Conscientiousness D2
0.44 – Feedbacks
0.43 – Blacklist
0.43 – Openness D3
0.43 – Agreeableness D2

Advisor we had to create this attribute, and one hypothesis is that this value may be not as accurate. As a pioneering study in this field, we think that with the evolution of the personality extractors from texts, the proposed model can present better results without the need to use data from the environment to trust prediction. It is a promising field of research to predict trust using personality aspects.

Future work includes (i) a more sophisticated analysis on feature selection, as well as more discussions about the personality aspects and their importance to the model; (ii) the usage of other datasets in order to test the model in different scenarios; and (iii) the usage of others personality extractors from texts.

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