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The Lexical Hypothesis & the Big Five Model

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ABSTRACT

In the last decades, personality has become a major area of research in psychology. At the present time, the Big Five model is the most popular approach to personality, having been used in settings that include research, education, and employment. The HEXACO model, on the other hand, is a more recent approach to personality that includes an additional personality factor, namely Honesty-Humility (H).

The lexical approach on which the Big Five and the HEXACO models are developed does not come without limitations. On the assumption that measuring personality traits with language-based questionnaires is particularly problematic for the Honesty-Humility factor given the stigma associated with concepts indicating dishonesty, we propose an AI-based model for detecting deceptive responses during the assessment of the H factor. Our model is an adaptation of deception analysis reasoning engine (DARE), an AI system that uses high- and low-level facial features to predict deception in real-life trial videos.

Significance

The development of AI-based deception detection models may be an important milestone in the advancement of personality testing, especially in the case of psychological tests where deceptive answers are more likely to occur.

The deception reasoning engine we refer to as OceanH2.0 is meant to improve the detection of deceptive responses during personality assessment and, consequently, increase the accuracy of personality tests. Our work is focused on the H factor of the HEXACO model, an approach to personality based on the Big Five model.

We believe that our results will inspire future works that 1) advance the field of AI-based deception detection and 2) find new areas where the proposed model can be applied to detect deceptive behaviours with a higher accuracy rate.

Keywords

HEXACO model, Big Five model, Dark triad.

Introduction

The origin of the modern study of personality research can be attributed to the development of the lexical approach by Francis Galton [1], who counted the number and types of words used to describe a specific type of character.

Almost a century later, Goldberg [2] developed the lexical hypothesis, which assumes, among others, that the differences between individuals that are socially relevant have been encoded in language and that cross-cultural factor analysis of dictionary words that refer to individual differences can be used to find the most important dimensions of personality. Following the lexical hypothesis, the Big Five Model was developed, which includes the personality dimensions Extraversion, Emotional Stability/Neuroticism, Agreeableness, Conscientiousness, and Openness to Experience [3].

The Five-Factor Model has become the most popular approach to personality, as many studies support the reliability and validity of the model in assessing personality and making predictions based on it. For example, a longitudinal study suggested that personality traits and general mental abilities predict several facets of career success over a span of decades [4]. For instance, high conscientiousness was associated with intrinsic professional success while extrinsic professional success was associated with low neuroticism, low agreeableness, high extraversion, high conscientiousness, and high cognitive ability.

The HEXACO Model

Some studies using the lexical method have revealed the existence of a sixth personality factor, namely Honesty-Humility (H), while also giving a different interpretation of Emotional Stability and Agreeableness [1]. These developments have led to the emergence of the HEXACO model of personality.

The H factor is defined by traits which include greed-avoidance, sincerity, fairness, modesty, greediness, slyness, and pretentiousness [5]. In this model, Emotionality does not include the hostility elements that are present in the Big Five model, as hostility is associated with low Agreeableness. The elements associated with sentimentality, which in the Big Five model belong to the Agreeableness dimension, are associated with Emotionality in the HEXACO model.

The Honesty-Humility factor, while not universally embraced by the personality community, has been shown to explain variance in several antisocial behaviours, such as those related to psychopathy, narcissism, Machiavellianism, and egoism, as well as prosocial behaviours such as cooperation [1].

AI-Based Deception Detection

Automatic deception detection has gained substantial popularity in the last few years, as advances in artificial intelligence (AI) has made possible combining modalities such as video, audio, and text to detect deceptive behaviours in real life videos. Developing AI models that can be used to detect deception could be an important milestone in the advancement of fields such as forensic, which have relied on physiological measurements of deception for decades. The same applications could be used to detect deceptive behaviours during psychological testing, potentially increasing the accuracy of psychological tests that are more likely to induce deceptive answers.

Several models of AI-based deception detection have been proposed. For instance, Pérez-Rosas, Abouelenien, Mihalcea, and Burzo [6] built a multimodal deception detection system designed to differentiate between truthful and deceptive statements made by defendants and witnesses during trials. The proposed model was tested on 121 videos and achieved accuracy levels between 60 and 75% with a model that extracts and fuses features from gesture and linguistic modalities. It is worth mentioning that the authors also provided a human deception detection study where they compared the human capacity to detect deception in trial hearings with that of the system they developed; the proposed automated system provided a relative percentage improvement of up to 51%.

Jaiswal, Tabibu, and Bajpai [7] proposed an automatic deception detection model with real-life visual and verbal data extracted from 121 videos. Their approach used Open Face with facial action unit recognition to analyse the movement of facial features of witnesses when they are asked questions and Open Smile to analyse acoustic data. Spoken words were analysed with a lexical analysis that emphasis pauses and utterance breaks that are sent to a Support Vector Machine to test deceit or truth prediction. Utterance-based fusion of visual and lexical analysis was incorporated with a string-based matching. The method of feature-level of fusion worked at an average of 78.95%.

Krishnamurthy, Majumder, Poria, and Cambria [8] developed an automatic deception detection model that combines video, audio, and text with Micro-Expression Features. The Micro-Expression Features were extracted from data containing 39 facial micro-expressions provided by Perez-Rosas, Abouelenien, Mihalcea, and Burzo [6] The proposed model was tested with 121 videos and obtained a deception detection accuracy of 96.14%. The performance of the model was largely influenced by visual and textual features, which suggests facial display features and unigrams are more important in detecting deception in videos.

Deception Analysis Reasoning Engine (DARE)

Wu, Singh, Davis, and Subrahmanian [9] proposed an automated deception detection system that was used with real-life courtroom trial videos. The system used classifiers trained on low-level video features to predict human micro-expressions and show that predictions of high-level micro-expressions can be used as features to predict deception. The performance of the training system was enhanced by fusing the score of classifiers trained on Improved Dense Trajectory (IDT) features and high-level micro-expressions and by using Mel-frequency Cepstral Coefficients (MFCC) from the audio domain.

DARE obtained an area under the precision-recall curve (AUC) of 0.877 when evaluated on individuals that were not part of the training set and outperformed acknowledged models that use human annotations of micro-expressions by 5%. When used with human annotations of micro-expressions, DARE provided an AUC of 0.922.

The results obtained by DARE suggest that a vision system based on high- and low-level features can provide a higher accuracy of deception prediction compared to humans and complementary information from audio and transcripts can further improve the performance.

Methodology

Sample

We started training the model with 54 volunteers from our own social network (family members, friends, and colleagues). The AI was later trained with 400 participants recruited from Amazon MTurk. For the next phase of the project, we seek to recruit 4000 participants.

Feature Extraction

The input sources are videos where individuals make truthful or deceptive statements. From the video input, the machine extracts the transcripts, audio, and video (Figure 1). Global Vectors for Word Representation (Glove) [10] is used as the transcript features, MFCC [11] is used as the audio features and Improved Dense trajectory (IDT) [12] as the video features.

Glove is a log-bilinear regression model for unsupervised learning of word representations which has provided good results on word analogy, similarity, and name entity recognition tasks. Glove represents words with vectors and uses word co-occurrence statistics for training. The MFCC features model hearing by adjusting the frequencies output from the DFT into a Mel scale and is used for speech recognition. Finally, the IDT model computers local feature correspondences in consecutive frames and uses RANSAC to estimate the camera motion. Following camera motion cancellation, IDT samples feature points densely at several spatial scales and track them through a limited number of frames.

Procedure

Humility and honesty are more difficult to assess compared to the Big Five personality traits, as responders are less likely to provide responses that reflect their actual behaviours. Respondents can provide deceptive responses intentional, due to the cultural stigma associated with being dishonest, or unintentional, as cognitive biases may prevent people from recognizing dishonesty to themselves.

In response to the limitations associated with assessing humility and honesty, we used a two-tiered system of evaluation and scaling framework to add the H factor to the Big Five scale. More specifically, the user was first asked to either confirm or deny a statement, which allowed the detection of potentially deceptive responses. The user was then asked to either concur or negative the same statement.

In order to ensure a higher accuracy level in the assessment of the H factor, an observational approach based on physiological parameters was used via artificial intelligence. More specifically, we have used an adaptation of DARE.

First, the user is asked to either confirm or deny a statement. This allows the detection of potentially deceptive responses. The user is asked to repeat, to either concur or negate the statement.

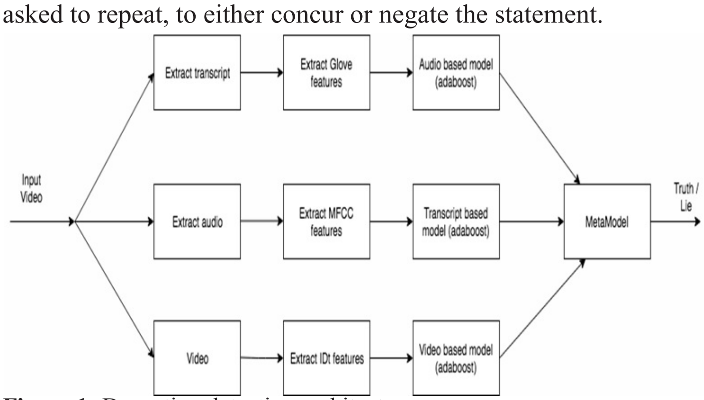

Figure 1: Deception detection architecture.

We believe that the social stigma associated with behaviours suggesting dishonesty makes an accurate assessment of the H factor on a language-based questionnaire more difficult than with other personality factors. In order to address this potential limitation of the HEXACO model, we have designed an AI-based model of deception detection based on DARE.

At the present time, our model has been trained with over 400 participants. In the next phase of the project, the accuracy of the model will be tested with 4000 participants. A satisfactory level of accuracy will support the usefulness of the model in personality assessment and might be an important milestone in the introduction of AI in the world of personality research and assessment.

Mission Statement

We started this work because we wanted to develop new ways through which machines could gain a better understanding of human behaviour at the individual level. As the world is gradually transitioning from the information age to the age of augmentation, our digital identities grow in importance and we must understand what this means in terms of personality development.

A special focus of this project is on what has been referred to as "the dark triad", which refers to personality traits associated with stable maladaptive behaviours, namely those indicating narcissism, Machiavellianism, and psychopathy. It has been suggested that these behaviours are encouraged and exacerbated by technology, which might be explained by the fact humans can now digitally construct their identities and their digital identities can take precedence over the non-digital ones. If digital identities do not only express conscious desires and choices but also unconscious ones, negative behavioural tendencies left in "the dark" might become evident in some types of externalized events with negative consequences. This assumption encourages new approaches to understanding personality and predicting behaviour.

The proposed model is not only mean to detect behaviours from the dark triad but also behaviours indicating traits belonging to the triad of well-being.

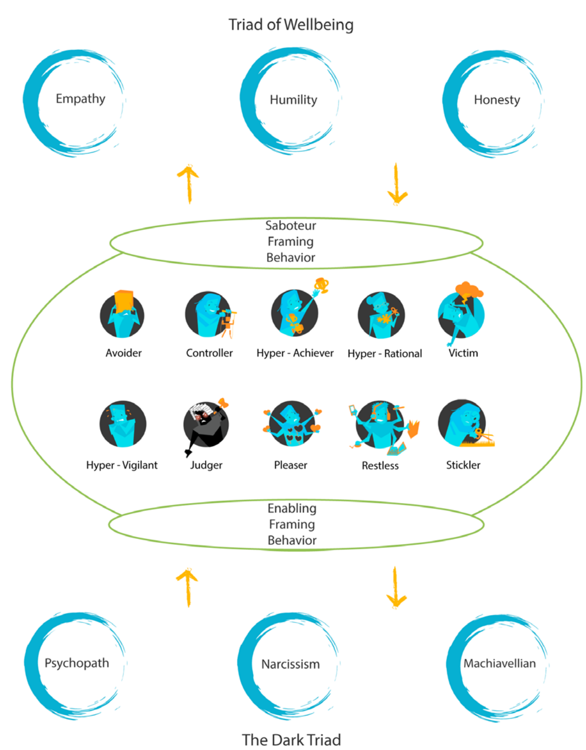

Figure 2: The triad of well-being and the dark triad.

As shown in Figure 2, the triad of well-being consists of empathy, humility, and honesty. It is worth noticing that the triad is conceptualized as containing the traits that are, in relative terms, opposed to the ones making the dark triad. Our goal is to make the proposed AI-based deception detection model to not only detect behaviours that lead to the development of digital identities where the traits from the dark triad manifest but also to find and encourage behaviours that enable the development of the traits forming the triad of well-being.

We do not believe that traditional personality testing can be used to detect the traits belonging to the dark triad, as the assessment of such traits require the use of words that indicate behaviours that are stigmatized and this can have a significantly impact on the accuracy of the answers.

For this reason, we use AI in order to identify attitudes and emotions based on visual, auditory, and transcript inputs. This approach provides an increased accuracy of trait profiling and can be used to detect behaviours pertaining to the dark triad before they result in negative consequences.

Conflict of Interests

We will have to mention the paper is published by authors associated with the company owning Ocean H2.0 If you will use your name as the author of the paper, you will have to indicate you are CEO at the company producing the AI model.

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