Personality traits analysis using Artificial Neural Networks : A Literature Survey

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***Abstract*—Personality traits analysis is becoming an attracting and challenging topic in the field of Artificial Intelligence. Moreover, with the inflation of Deep Artificial Neural Networks, many researches are being conducted in this subject showing significant results and achievements. This paper is a focused survey on personality traits analysis using Artificial Neural Networks. In this work we collected research papers from six research databases: IEEE Digital Library, Springer Link, Science Direct, Scopus, JStore and Web of Science for a topic modeling application using a Machine Learning technique known as Latent Dirichlet Allocation (LDA).**

Keywords—Artificial Neural Networks; Personality Traits; Topic Modeling; Latent Dirichlet Allocation.

I. Introduction

With the veil of the new millennium, Artificial Neural Networks have attracted wide spread attention, mainly by outperforming alternative machine learning in numerous important applications. Nowadays they are becoming an extremely active area and being paving the way for many scientific fields such as personality computing. Predicting someone's personality is certainly more and more important in the modern world, face, voice, handwriting, and more other aspects could be personality traits indicators. The need to assess links between those aspects and the personality is gaining increasing prominence in multiple domains such as biomedicine, education, recruitment, marketing… etc.

This paper represents a literature survey of Artificial Neural Networks applications in personality trait prediction. First, we describe some related terms and concepts in both personality and ANNs. Then we give a detailed explanation of our survey methodology followed by a results discussion, and finally a conclusion.

II. Personality and Artificial Neural Networks

A. Personality Traits analyisis

To model someone's personality we need to set a number of classification dimensions that we call traits and construct a questionnaire to measure those traits. In the field of psychology various schemes for personality modeling exists, such as 16PF[1], the three trait personality model PEN and EPQ-R[2], the Myers Briggs Type Indicator (MBTI)[3], and the Big-Five personality traits[4]. While MBTI is the most widely administered personality test in the world, the most popular measure used in the literature on automated personality detection is by far the Big-Five personality traits. Computerized personality analysis involves human behavior understanding, prediction and synthesis, and it deals with three main problems: Automatic Personality Recognition (APR), Automatic Personality Perception (APP) and Automatic Personality Synthesis (APS) [5]. In machine learning, any personality detection model relays on a set of inputs such as text, audio, video, or multimodal. Recent multimodal artificial neural networks models are starting to make reliable personality predictions. Offering a way to harness larger amounts of data and computation power, artificial neural networks are becoming the new state-of-the-art methods not only for personality recognition, but in other fields as well[6].

B. Artificial Neuarl Networks

Artificial neural Networks have offered several advantages in the emulation of many modern intelligent systems, it represents an advanced data modeling tool with the ability to capture and expose complex input/output relationships. In an Artificial Neural Network, each node performs a simple computation and each connection conveys a signal from one node to another labeled by a number called the "connection strength" or weight indicating the extent to which signal is amplified or diminished by the connection[7].

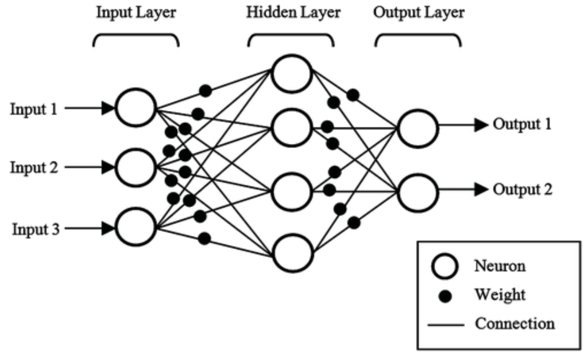

Fig. 1. General structure of an Artificial Neural Network [7]

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Different functions are being evaluated by the network which conducts to different choices of weight results. Considering a given network with initial random weights and knowing the task to be accomplished, a learning algorithm has to be used to determine the weight's values that in order to achieve the desired task. It is the learning algorithm that qualifies the computing system to be called Artificial Neural Network[8].

ANNs are more likely used in one of the two stages: The feature extraction stage or the classification and recognition stage. In the first one a given ANN is designed to find features within the preprocessed data(text, image, voice..), in the second one, which is more general, a given ANN can be designed and trained using sample from a data set for the purpose of classifying the data[9]. Many different ANNs algorithms and techniques exist since the veil of the 21st century[10], we give as examples: *Hopfield networks, Adaptive resonance theory (ART) networks, Kohonen networks, Backpropagation networks, Recurrent networks, Counterpropagation networks, Radial basis function (RBF) network, and every one of them is the best suited to a specific problem resolving.*

III. SURVEY METHODOLOGY

The aim of our work is to present an exploratory survey of the literature by exploring the diverse applications of Artificial Neural Networks in personality traits analysis. To do so, we give in the beginning a distribution of research papers by years and journals, followed by a word frequency of preprocessed "keywords", and we sum up with an in-depth analysis of our main research goal using a topic modeling approach. Figure 2 below shows an illustration of this exploratory survey methodology.

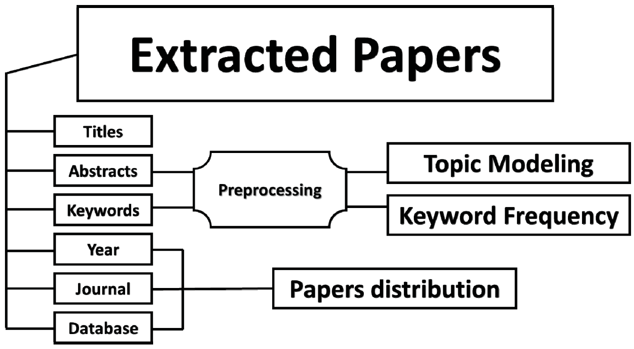

Fig. 2. Illustration of the proposed analysis aproach

A. Papers Extraction

We have extracted a collection of research papers on Artificial Neural Networks applications in personality traits analysis from six research databases. We used the keywords "Artificial Neural Network" and "Personality Traits" combined with the paper type filter option Journal papers in order to refine the search results. As described in Table 1, initially 159 papers were retrieved from the six databases, however we excluded 34 papers from the analysis due to redundancy and the out of subject cases. The final corpus consisted of 125 research papers dispersed as described in the same table above.

TABLE 1 : EXTRACTED PAPERS FROM EACH RESEARCH DATABASE

Research Databases	Initial extraction	Final selection
JSTORE	52	38
SCOPUS	69	58
WEB OF SCIENCE	21	13
SPRINGER LINK	7	6
SCIENCE DIRECT	6	6
IEEE DIGITAL LIBRARY	4	4
Total	**159**	**125**

Every one of the extracted papers are identified by a number of Metadata like the DOI, title, abstract, keywords, authors, journal,…etc. For our survey we only needed Titles, abstracts, keywords, journals, year of publication and database.

B. Papers Distribution

In this exploratory survey we used metadata like the publication journal, the year of publication and the database from where we extracted the papers, all in order to present representatives charts for the state of art related to the subject of this survey.

C. Preprocessing

The preprocessing step consisted of removing stop words from keywords and abstracts, the most familiar words in English that aren't offering any additional information to the analysis are like "for", "the", "about", "after"…etc. we also removed punctuations and transformed the text to the lowercase as fundamental steps in the preprocessing in order to make the text more amenable. Finally, we applied Lemmatization for grouping together the inflected forms of words so they can be analyzed as a single item, known as the word's lemma, or the dictionary form.

We used the preprocessed keywords for word frequency analysis, as for the preprocessed abstracts we used them in the Topic Modeling analysis.

D. Topic Modeling

Topic modeling is one of the most efficient methods used to find useful hidden structure in a collection of documents. Based on a clustering approach, it is considered as a powerful tool for modeling objects as latent topics to reflect meaning of a given collection of documents[11]. Many different methods exists in topic modelling, but resume them in two popular approaches: Probabilistic approaches where we consider each document as a mixture of a small number of topics where words and documents get probability scores for each topic (e.g. Latent Dirichlet Allocation (LDA) [12]); and matrix factorization approaches based on linear algebra methods where decomposing a single matrix into a set of smaller matrices can be interpreted as a topic model (e.g. Non-negative Matrix Factorization (NMF) [13]). Between the two approaches the most known and famous technique is the probalistic LDA, based on that fact we applied it to our corpus of preprocessed abstracts.

IV. Results and Discussion

A. Frequency Analysis of Keywords

The most frequent terms (Figure 3) in our corpus keywords of personality along with artificial neural networks are: ANN, personality, trait, analysis, disorder, performance, intelligence... Many of those words highlight domains and fields involving the use of artificial neural networks techniques. A further comprehension of this frequency analysis is explained in the topic modeling section.

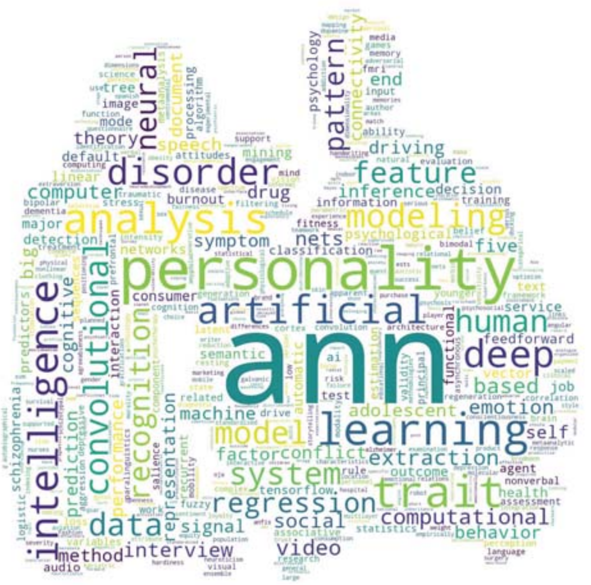

Fig. 3. Wordcloud of keywords frequency

B. Papers distribution analysis

The number of published research papers is growing number across the years since 2010, reaching the peak only in the last year (2019) with a number of 12 published papers leaded by the SCOPUS database (Figure 4). This tendency interpretation could be the result of the growing interest in Artificial Neural Networks algorithms after the new GPU-DBN implementation and the first official Competitions Won by RNNs and MPCNNs [14] in 2010.

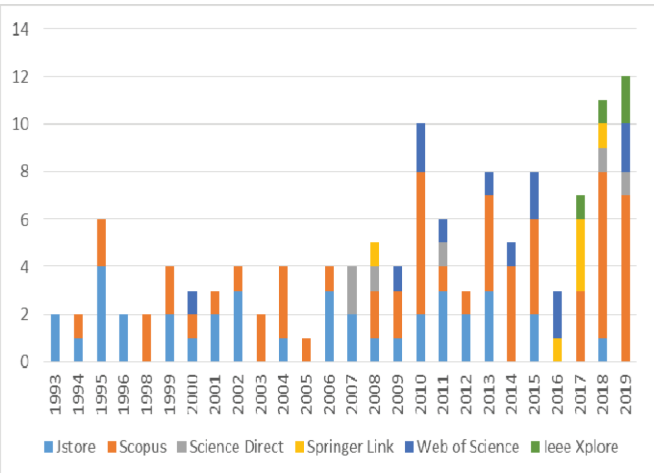

Fig. 4. Published research papers by years

As for the distribution of research papers across journals (Table 2), Neurocomputing represent the top publishing journal with 5 published papers, followed by Journal of Management Information Systems and The Journal of Mind and Behavior with 4 published papers for each. We interpret this ranking with the fact that we are indeed investigating neural networks applications (Neurocomputing) in personality detection which find resort in professional recruiting (Management) and psychological studies (Mind and behavior).

Table 2 : Number of research papers by Journals

Journal	Published papers
Neurocomputing	5
Journal of Management Information Systems	3
The Journal of Mind and Behavior	3
Philosophical Transactions: Biological Sciences	3
Plos One	2
The American Journal of Psychology	2
Journal of Science Education and Technology	2
Ergonomics	2
Expert Systems with Applications	2
Psychiatry Research	2
Schizophrenia Research	2
Neural Networks	2
EURASIP Journal on Image and Video Processing	2
IEEE Transactions on Affective Computing	1
Current Directions in Psychological Science	1
Journal of Consumer Psychology	1
...	1
Total	**125**

C. Topic modeling with LDA

In Topic modeling, the number of topics is the main parameter in any LDA model, and can be chosen manually or estimated on the basis of a parameter selection approach[15]. We used a topic coherence measure on the basis of a word embedding model constructed from our preprocessed corpus. In this step we used the GENSIM implementation of Word2Vec to build a Word2Vec model based on our preprocessed corpus. The resulted model was used to evaluate the different LDA topic models that we created with different number of topics (from 2 to 20) in order to calculate coherence (C_V, U_MASS) and Perplexity scores for each of these models. The Figure 5 below illustrates the coherence scores for each LDA model so as to select the best appropriate K value for number of topics.

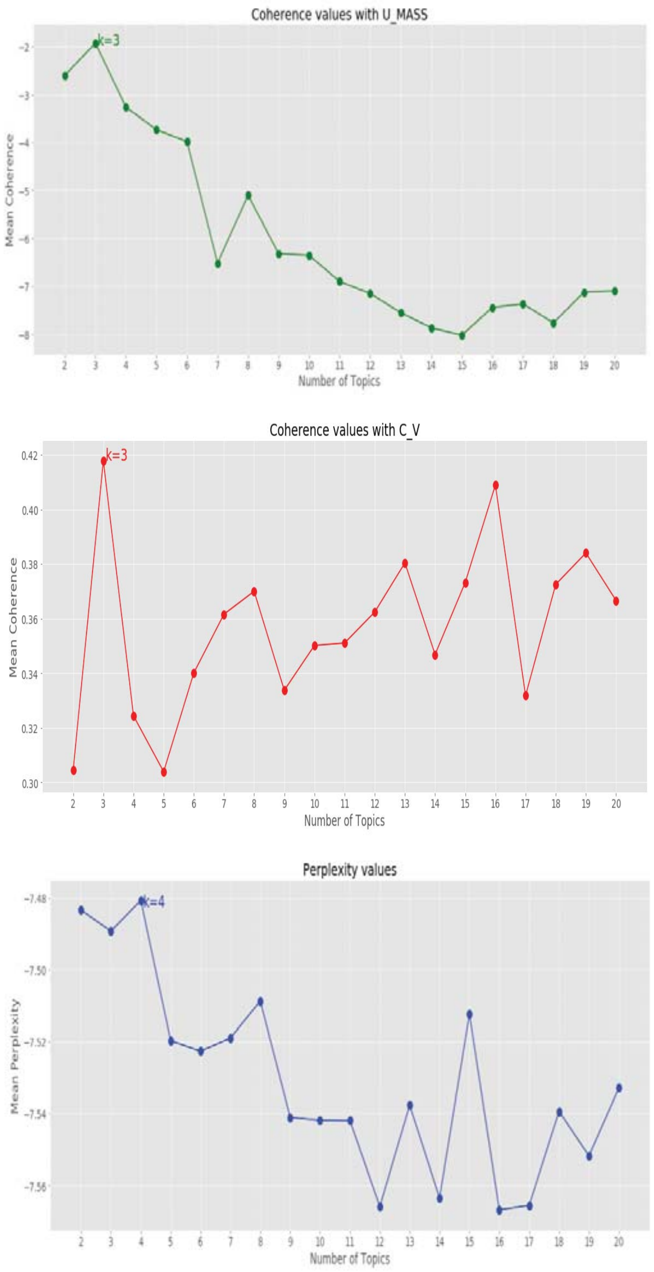

Fig. 5. Mean topic coherences and perplexity scores for k ε [2-20]

The most coherent LDA model is the one with three topics as resulted in the C_V and U_MASS coherences estimation, as for the Perplexity, the most coherent LDA model is the four topics model. To confirm the final selection of number of topics we used the interactive topic model visualization provided by the PyLDAvis[16] library. The PyLDAvis library plots topics as circles, whereas the surface represents the percentage of words (tokens) under each topic compared to the corpus, and the distance between circles reflect the coherence of the LDA model (the more distant the better the model).

Fig. 6. PyLDAvis visulisation of three and four topics LDA models

In Figure 6 given above it is evident that the most coherent LDA model is the three topics one, we see clearly in the PyLDAvis visualization for the four topic model the intersection between topic 1 and 2 which shows less efficiency for this model compared to the three topic one. The PyLDAvis visualization also allows us to give the distribution of tokens under each topic which is apparently more balanced in the three topic model:

- Topic 1 (**39.1%** of tokens)
- Topic 2 (**30.7%** of tokens)
- Topic 3 (**30.3%** of tokens)

As results of the three topics LDA model application on our corpus, we give the most ten frequent word (weight) followed by a three ranked documents (papers) under each topic.

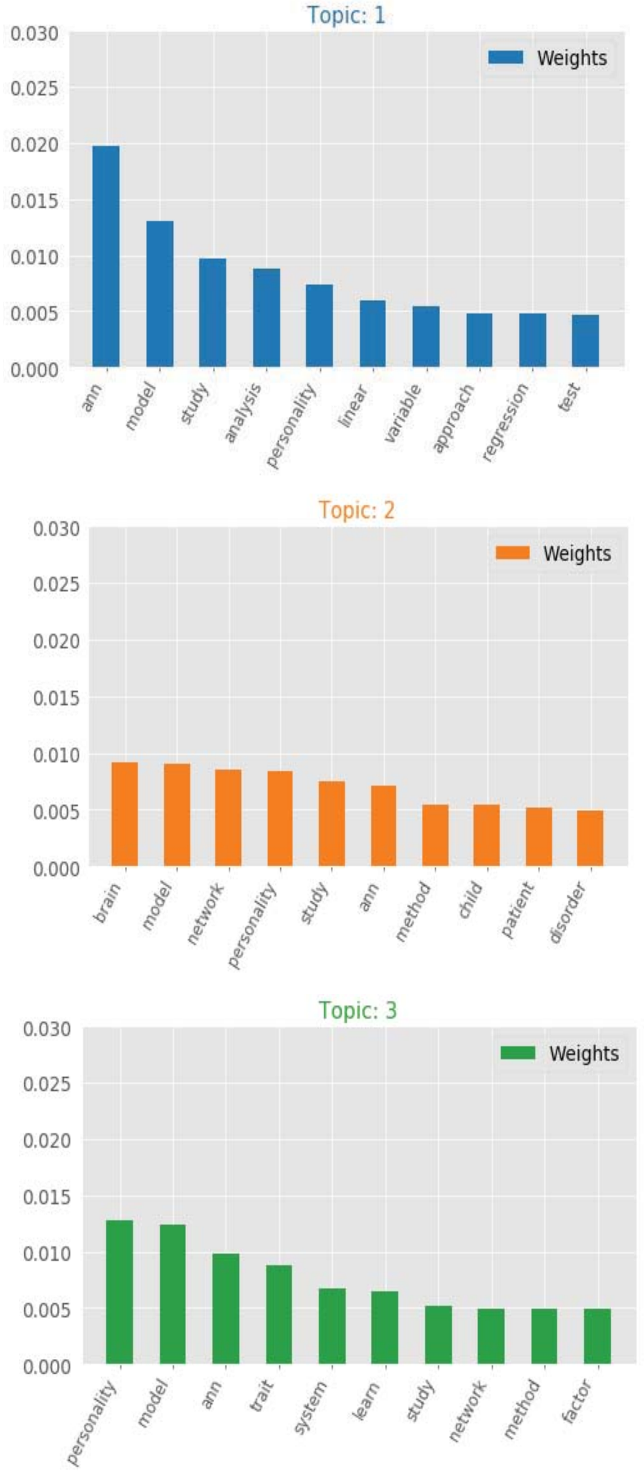

Fig. 7. Words wieghts under each topic

TABLE 3 : TOP 3 PAPERS UNDER EACH TOPIC

Topics	5 ranked documents (papers)
Topic 1	1) cultural differences in organizational communication: a semantic network analysis 2) a hybrid sem-neural network analysis of social media addiction 3) the social side and time dimension of self-representation in agents using modular neural networks
Topic 2	1) the common brain structures correlated with personality traits in healthy mothers and their daughters 2) personality disorders disturbances of the physical brain 3) neural networks underlying trait aggression depend on MAOA gene alleles
Topic 3	1) intuition and reason: re-assessing dual-process theories with representational sub-activation 2) a comparison of machine learning with human judgment 3) resting state low-frequency fluctuations in prefrontal cortex reflect degrees of harm avoidance and novelty seeking: an exploratory NIRS study Personality disorders disturbances of the physical brain

The ranked documents (Table 3) are measured on the basis of the ranked words weighs under each topic (Figure 7), the results are clearly highlighting different aspects of neural networks application and interactions with personality traits. In the following, we give our best suggestion for naming those three topics:

- Topic 1 – Cultural and socio-cognitive effect on personality traits
- Topic 2 – Correlation between brain structure and personality traits
- Topic 3 – Human decisions and judgments interactions based on personality

D. Discussion

Going through the extraction and processing of our corpus we have noticed that the majority of research papers are about experimenting approaches or proposing new models, which means that only few numbers provides a review, study or a survey on Artificial Neural Networks applications in personality traits analysis. Using keywords like “study”, “review” and “survey” we have found less than 10 papers. Table 4 below gives a selection of related works to our survey, we have selected one research paper under each topic as mentioned in the topic modeling results.

Even if the papers mentioned in Table 4 seem to be about studying or reviewing existing works, they all are focusing on the efficiency of the approaches or the models by experimenting and comparing results on different aspects of artificial neural network models. We could say that none of them represents a global exploratory research of the subject. Compared to our work, we believe that we have given a solid overview of the subject, we also think that our distributions charts and topic modeling clustering give more insights to future researches.

TABLE 4 : RELATED WORKS UNDER EACH TOPIC

TITLE	AUTHORS	METHODOLOGY AND RESULTS	DOMINANT TOPIC
A survey of personality and learning styles models applied in virtual environments with emphasis on e-learning environments [17]	S. Fatahi H. Moradi L. Kashani-Vahid 2016	The authors reviewed the psychological models of personality used in the field of computer science, and discussed the relationship with various learning style models used in e-learning environments such as MBTI, Felder-Silverman, Cattell's 16PF, and Eysenck. As results they found that MBTI and Felder-Silverman are used more often than the others, and that artificial neural networks are more used with the Five Factor Model and the MBTI.	**Topic 1** with a topic percentage contribution of **0.9531**
The Use of Spatio-Temporal Connectionist Models in Psychological Studies of Musical Emotions [18]	E. Coutinho A. Cangelosi 2009	The work presented a novel methodology to analyze the dynamics of emotional responses to music, using spatio-temporal connectionist network. Based on the dynamics of affective responses to music on continuous measurements of two pervasive dimensions (arousal and valence), authors investigated the relationships between perceptual features of sound and reports of subjective feelings of emotions. The results provided evidence suggesting that spatiotemporal patterns of sound resonate efficiently with affective features underlying judgments of subjective feelings.	**Topic 2** with a topic percentage contribution of **0.9908**
Applying artificial neural network models to clinical decision making [19]	R. K. Price et al. 2000	Authors introduced in their work artificial neural networks as a suitable tool for a variety of clinical decision problems such as assessment of psychological state, diagnosis of psychiatric disorders, and prediction of behavior outcomes such as suicide attempts, hospitalization, and death. Using two large-scale psychiatric surveys, they described applications and differences between ANNs and common linear statistical methods in two problems of psychological assessment: computer diagnosis and behavior prediction. As results, ANNs outperformed linear and quadratic discriminant analyses in a psychiatric diagnosis assessment when a set of clinical measures is provided.	**Topic 3** with a topic percentage contribution of **0.9857**

V. CONCLUSION

In this work, we have presented a literature survey of Artificial Neural Networks applications in personality traits analysis. This was achieved by analyzing a collection of published research papers that we extracted from six research databases: IEEE Digital Library, Springer Link, Science Direct, Scopus, JStore and Web of Science. First, we provided a papers distribution across journal and years, then a keywords frequency examination, and finally we proposed three topics as our LDA topic modeling model suggested. Considering the middling number of analyzed research papers due to the "Journal" publication limitation, in addition to the fact that we collected them only from six indexed scientific databases, this literature review might not cover all applications of Artificial Neural Networks in the research field of personality traits analysis. This being said, we assume that the results in this paper have to be interpreted with caution.

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