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SOFTWARE ARCHITECTURE FOR CREATING A PSYCHOLOGICAL PORTRAIT OF A PERSON BASED ON SOCIAL MEDIA ACTIVITY

Abstract: The paper presents the design and implementation of a system for building a psychological portrait of a person based on activity in social networks. The problem is formalized, and a neural network approach is used to solve it. For the first time, the multitask finetuning approach is used for this task and its effectiveness is proved. The choice of the system architecture is substantiated and proposed architecture is implemented. The paper presents an example of using the created system in the HR industry.

Keywords: psychological portrait, social networks, large language models, neural networks, natural language processing, trait prediction..

1. Introduction

This paper is devoted to the description and implementation of the software architecture for building a psychological profile (portrait) of a person based on activity in social networks.

The psychological portrait of a person is a certain formalized representation of his/her personal characteristics, such as emotions, behavior or cognitive patterns. One of the approaches that allows to formalize the psychological characteristics of a person is personality models. The essence of the models is that each person has a certain set of basic personality traits, and the balance of these traits determines the unique psychological characteristics of a person.

In the modern world, social networks are one of the main means of communication. As a result, during interpersonal interaction, a large amount of information reflecting their psychological characteristics is accumulated in them. To have a superficial understanding of the person you are communicating with online, you need to identify the main patterns of their behavior. These patterns are also reflected in their activity on social networks. The set of these patterns is combined in this study into a psychological portrait of a person. This portrait is not a complete portrait from the point of view of qualified psychologists. However, it provides recommendations on what aspects of human behavior should be paid attention to. Thus, the system proposed in this paper allows us to solve the urgent task of determining the psychological characteristics of a person. It can be used in the selection of personnel for a particular position, in law enforcement agencies in the investigation of crimes. It can also provide significant assistance to psychologists in creating a complete psychological description of a person. In addition, this system can be used in everyday life when communicating with people on social media.

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It should be noted that this topic has been sufficiently researched. However, there are currently a small number of systems that automate and facilitate the construction of a psychological profile based on social media activity from start to finish. They are usually proprietary, and their results are quite difficult to explain. In addition, the approach of large language models used in this article is currently under-researched, but its application can significantly improve the accuracy of portrait building.

2. Literature review and problem statement

Modern research is actively exploring the possibility of creating psychological portraits of individuals based on the analysis of their digital footprints. This includes social media activity, including posts, likes, comments, and interactions with other users. Studies highlight the role of such data in predicting personality traits, psychological well-being and social attitudes. The most common approaches include:

Content analysis: the use of algorithms to identify psychological characteristics based on texts, images, and behavioural data on social media. For example, experiments show that the choice of content and its emotional colouring can indicate the level of well-being and emotional state of an individual [1-4].

The article [1] analyses how users' digital footprints (including text posts, likes, and demographic data) can predict personality traits according to the Big Five (OCEAN) model. Text analysis methods, demographic segmentation, and activity evaluation are used to create accurate predictions of personality traits.

Article [2] presents the results of using natural language processing (NLP) and machine learning tools in the analysis of individual profiling based on various data sources, including publicly available datasets, social media platforms, and modern frameworks.

Article [3] describes the connection between Facebook data (such as posts, photos, likes) and personality traits. The emphasis is placed on the use of machine learning algorithms to determine the accuracy of predictions. The results show that text analysis and image processing are important for assessing extraversion, neuroticism, etc.

Paper [4] discusses approaches to text analysis, including classification and sentiment analysis in the context of social media. Emotions expressed in texts help determine the psychological state and characteristics of a person.

Surveys and questionnaires: the use of traditional psychological tools adapted to study the impact of the digital environment [5].

Article [5] is devoted to the study of the use of social media data to predict personality traits. This research focuses on analysing user data, including behavioural patterns, interactions, and content preferences, to model personality, potentially using psychological theories or data-driven machine learning techniques. The work includes elements such as analysing textual and visual content on platforms such as Facebook or Twitter.

Machine learning models: automating the analysis of large data sets to create accurate profiles [6-7].

Article [6] presents the results of a study of the use of deep learning methods for predicting personality traits based on text data. The focus is on such models as the Myers-Briggs Type Indicator (MBTI) and the Big Five Personality Model (also known as the OCEAN model): Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism). The article discusses various approaches, including the use of pre-trained models, such as BERT and LSTM (Long Short-Term Memory) networks, which increase the accuracy of personality prediction based on text data.

Article [7] presents a study of the impact of posts by famous personalities on social media on the cryptocurrency rate. This paper uses statistical methods (Pearson's correlation coefficient, Spearman's rank correlation coefficient, and t-test) to confirm the assumption of the significance of this influence.

From the above, we can conclude that personality analysis models are usually used to build a psychological profile (portrait). The main source of data is text messages on social media. As a result, the vast majority of models use NLP approaches.

The research presented in this paper develops the idea of developing the use of large language models and describes the architecture and training approach for the task of building a psychological profile (portrait).

3. The aim and objectives of the study

3.1. The aim and objectives

The aim of the study. To automate the creation of a psychological profile (portrait) of a person based on activity in social networks.

Object of research: software for creating a psychological profile (portrait) of a person based on activity in social networks.

Subject of the study: methods, approaches and tools for building a psychological profile of a person based on his/her activity in social networks.

To achieve this goal, the following objectives were formulated:

– to analyse modern approaches to determining a psychological portrait of a person based on activity in social networks;

– to analyse off-the-shelf software products that allow to build a psychological portrait based on data from social networks;

– to develop a neural network model for determining a person's portrait based on his/her posts in social media;

– to verify the correctness of the developed model;

– design the architecture and implement software for determining a psychological portrait.

3.2. Problem statement

The task of building a psychological profile (portrait) is formulated as follows:

The input is a dataset of textual data - posts in social networks.

Let a user u in a certain social network m writes P posts:

$$P_{um} = \{p_{um1}, p_{um2}, \dots, p_{umn}\}. \quad (1)$$

Each post is a sequence of words w:

$$p_{umk} = \{w_{k1}, w_{k2}, \dots, w_{kn}\}. \quad (2)$$

Let the true value of the user's psychological characteristics be an N-dimensional vector $T_u \in R^N$, where N is the number of basic personality traits in the model. Each value of this vector is a probability that a given personality trait is inherent in a person. A user can be active in different social networks M:

$$M = \{m_1, m_2, \dots, m_l\}. \quad (3)$$

The output for each dataset instance is the identification of its psychological traits.

Total user activity A_u is then defined as the union of sets of posts in all social networks:

$$A_u = \bigcup_{i=1}^{l} P_{um_i}. \quad (4)$$

The goal of solving this problem is to find the following function F over the array of posts A_u, that the difference between the obtained values and the true values is minimal:

$$F(A_u) = E_u,\ E_u - T_u \to min. \quad (5)$$

We used a neural network approach to find a function for mapping posts to the distribution of personality traits. In this case, the task is formalized as a multi-label classification problem, where the psychological traits present in each post are determined. After that, the traits are aggregated by their frequency to obtain the distribution.

4. The study materials and methods

4.1. Development of a neural network

The most common and popular models are the Myers-Briggs Type Indicator (MBTI) [8] and Big Five [9]. The MBTI model defines 4 basic personality traits, combinations of which create 16 archetypes. The main traits of the MBTI model are extraversion-introversion, intuition-sensing, thinking-feeling, and judgement-perception. The Big Five model is an extension of the MBTI model and consists of the following five basic traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism.

This task is a classical text classification task, so it is reasonable to use the transformer architecture, as it is currently the State-Of-The-Art (SOTA) for most Natural Language Processing (NLP) tasks. One of the main features that made transformers so performant is the use of attention mechanisms. In general, the development of large language models can be divided into discriminative (such as Bidirectional Encoder Representations from Transformers (BERT) [10]) and generative (Generative Pre-trained Transformer (GPT) [11], Large Language Model Meta AI (LLAMA) [12]). Currently, generative language models have gained the most popularity and accuracy due to their size and training on large amounts of data. We chose the LLAMA architecture, displayed in the Fig.1, for the solution of the following task, a model developed by Meta and released in 2023.

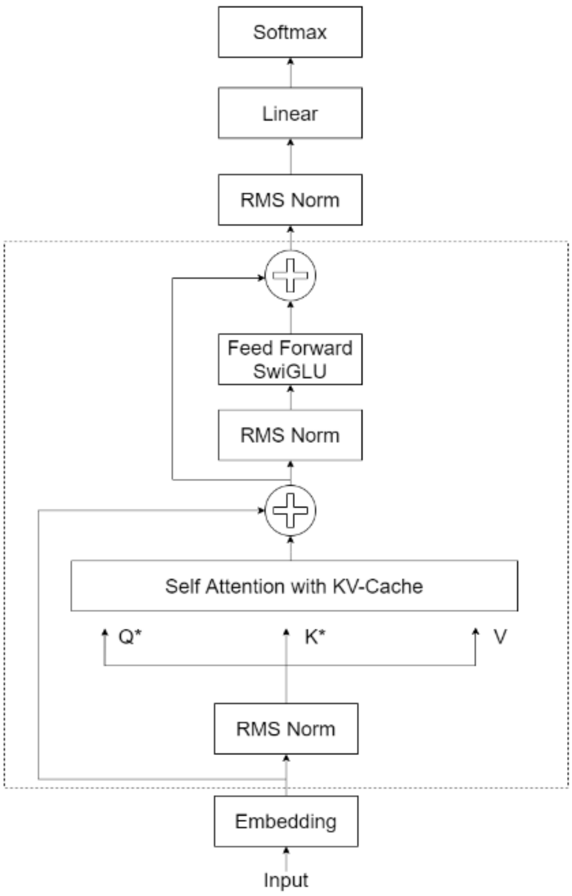

Figure 1. LLAMA model architecture

This architecture makes several changes to the classical transformer architecture. First, normalization is performed on the input values to the layer, which increases the stability of training. Secondly, the model uses the Rotary Position Embedding (RoPE) [13] approach for positional coding, which is to rotate the learnt word embeddings based on their position in the sentence. This encoding allows for caching and optimization at the inference stage. The last change is the use of the Swish+GLU (SwiGLU) [14] activation function in the fully connected layers. In this paper, we use a model with 7 billion parameters, which contains 32 heads and 32 layers. We chose this model because it will be easy to train on free hardware and not lose much accuracy due to the smaller number of parameters. The model also uses the Key-Value Caching approach to increase model throughput.

Currently, there is a rather small number of datasets for the task of building a psychological portrait of a person. To improve the accuracy of the model, we propose to use a multitask training approach. This approach implies that the neural network will be simultaneously trained to determine a portrait based on several personality models. Studies show that there is a correlation between such models as the Big Five and MBTI, so using this approach will improve the model's performance on each of these tasks by learning the correlations between them. Training of large language models consists of two stages: pretraining and finetuning. At the pre-training stage, the model is trained on a language modelling objective using large amounts of data, and as a result, we get a foundational model that is usually available for further development. After that, the model is retrained on a specific task using the instruction finetuning approach, which is presented in the Fig. 2. In our case, the model is trained on the instruction tuning dataset, which contains instructions for determining the Big Five and MBTI portrait.

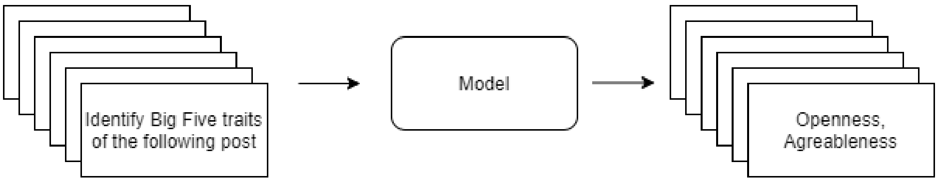

Figure 2. Multitask finetuning approach

The «Essays I» and «MBTI Dataset» datasets were chosen as training datasets and an instruction tuning dataset was built using the following prompt templates.

<u>Big Five prompt template</u>

You are an expert in personality psychology, specializing in the analysis of text-based behavior. Your task is to analyze a user's social media posts to extract their Big Five personality traits. Based on the user's social media activity, identify and assess the following Big Five personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Examine the user's posts for language patterns, emotional expressions, and interaction styles that align with these traits. For each post, look for:

Openness: Signs of creativity, intellectual curiosity, or openness to new experiences.

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Conscientiousness: Indications of responsibility, organization, or a goal-oriented mindset.

Extraversion: Evidence of social engagement, assertiveness, and talkativeness.

Agreeableness: Displays of compassion, friendliness, trust, or cooperation.

Neuroticism: Clues of emotional instability, anxiety, mood swings, or stress.

Output Format:

Return the detected personality traits as a comma-delimited set.

Do not include any reasoning or arbitrary text in the response.

If a trait is not present, exclude it from the response.

Example Output: Openness, Neuroticism

Post: {post_content}

<u>MBTI prompt template</u>

You are an expert in personality psychology specializing in the Myers-Briggs Type Indicator (MBTI). Your task is to analyze a user's social media posts and identify the traits from the MBTI framework. Analyze the user's social media activity to determine their MBTI traits. Review the posts for behavior, language patterns, emotional tone, and interaction styles to assess the following dimensions:

Extraversion (E) vs. Introversion (I):

Extraversion: Signs of energy directed outwardly, frequent social interaction, or excitement from group activities.

Introversion: Focus on inner thoughts, solitary activities, or reserved communication style.

Sensing (S) vs. Intuition (N):

Sensing: Attention to details, practicality, and focus on concrete information.

Intuition: Preference for abstract thinking, ideas, future possibilities, and conceptual discussions.

Thinking (T) vs. Feeling (F):

Thinking: Emphasis on logic, objectivity, and analytical decision-making.

Feeling: Prioritization of emotions, personal values, and harmonious relationships in decision-making.

Judging (J) vs. Perceiving (P):

Judging: Preference for structure, organization, and a planned, decisive approach.

Perceiving: Flexibility, spontaneity, and an open-ended approach to tasks or decisions.

Output Format:

Return the detected personality traits as a comma-delimited set.

Do not include any reasoning or arbitrary text in the response.

If a trait is not present, exclude it from the response.

Example Output: Judging, Feeling

Post: {post_content}

The model was trained using the Low-Rank Adaptation (LoRA) approach [15] to optimize memory usage. This method involves learning the matrix ΔW, which is added to the original neural network weights. This matrix is represented as the product of matrices A and B with rank r (in this paper, $r = 8$):

$$\Delta W = A \times B. \tag{6}$$

As a result, the number of parameters to be trained was significantly reduced, which speeds up training and optimizes memory usage. The model is trained in accordance with the language modelling objective function.

4.2. System architecture

Conceptually, the system is an Extract-Transform-Load (ETL) pipeline with the following stages: extraction, processing and storage, which is displayed in the Fig. 3.

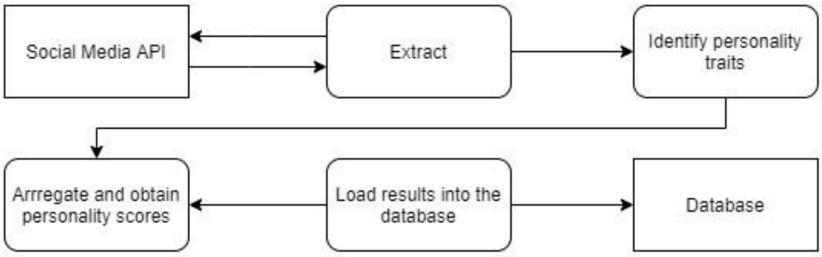

Figure 3. ETL pipeline

Data extraction: We introduced a concept of a *social media provider* that is responsible for extraction of latest posts from profile and personal information. Currently the system supports LinkedIn and Telegram data sources. Also, it is possible to combine different data sources for the same person, this may be useful in case a person has accounts in different social media. The result of data extraction step is a list of posts with the following JSON structure:

[{
“text”: “Happy 100th birthday…”,
“media”: “LinkedIn”,
“created_by”: “Bill Gates”,
“created_at”: “2024-10-01T23:42:59.137Z”
}]

Data processing: After the posts are extracted, we schedule a distributed workflow that analyzes the posts and aggregates the results. We utilize celery with a RabbitMQ

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transport as a workflow orchestrating engine. For each of the posts we call separately deployed model via http with the prompts mentioned above and extract the personality traits as a list. After that we can obtain personality scores based on the two following strategies: *distribution* and *frequency*. Let T_i be a personality trait in the model and P is the post set.

Distribution strategy allows to obtain relative distribution of personality traits and is calculated based on the following formula:

$$Score(T_i) = \frac{|p_j|\ T_i \in Traits(p_j)\ for\ p_j\ in\ P|}{\sum_{T_k} |p_j|\ T_k \in Traits(p_j)\ for\ p_j\ in\ P|}. \quad (7)$$

Frequency strategy allows to directly measure how strong the personality trait of person is. This strategy is calculated based on the following formula:

$$Score(T_i) = \frac{|p_j|\ T_i \in Traits(p_j)\ for\ p_j\ in\ P|}{|P|}. \quad (8)$$

Data storage: We utilize MongoDB as a reliable and a distributed data storage for the analyzed posts and personality scores. After the analysis we store analyzed post and personality scores. Corresponding data examples can be found in the Fig. 4 and in the Fig. 5.


```
_id: ObjectId('673d3ba9cb86a9571f6a3284')
analysis_id : "94d9a462-cda0-48a1-b8a4-ee0430838ec5"
text : "Happy 100th birthday, President Carter. From peanut farmer to presiden…"
media : "LinkedIn"
created_by : "Bill Gates"
created_at : 2024-10-01T23:42:59.137+00:00
▾ traits : Array (2)
    0: "Openness"
    1: "Agreeableness"
```


Figure 4. Analyzed post


```
_id: ObjectId('673bcf2d2c64eeea5dc598c9')
analysis_id : "bf45dd48-a647-4769-9e13-a7a8f7dd7fa5"
type : "Big Five"
▾ scores : Array (5)
  ▾ 0: Object
      trait : "Agreeableness"
      score : 0.1282051282051282
  ▾ 1: Object
      trait : "Conscientiousness"
      score : 0.02564102564102564
  ▾ 2: Object
      trait : "Extraversion"
      score : 0.2564102564102564
  ▾ 3: Object
      trait : "Neuroticism"
      score : 0.23076923076923078
  ▾ 4: Object
      trait : "Openness"
      score : 0.358974358974359
```


Figure 5. Extracted personality scores

We decided to implement a distributed architecture with workers and queue. Detailed high level architecture is presented in the Fig. 6.

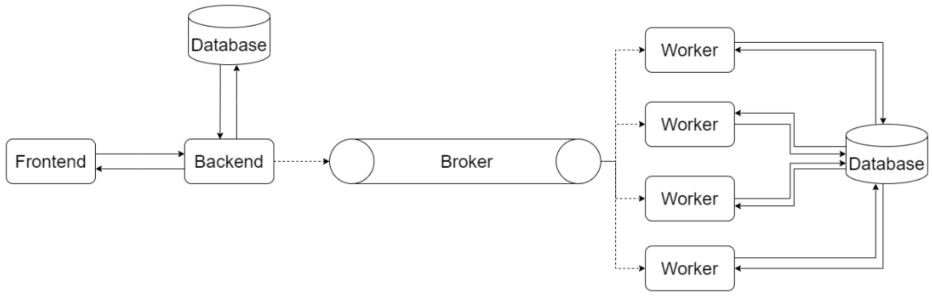

Figure 6. System architecture

This architecture allows for efficient and parallel processing of large amounts of data, in addition, the use of large language models is rather slow, and the use of parallelism can also significantly speed up the system.

5. Results

5.1. Accuracy

To verify the correctness of the model, the dataset was split into training and validation datasets with a 20% share of validation. For a more accurate accuracy assessment, the validation dataset retained the same class distribution as the training dataset. The quality of the model was assessed by the values of the accuracy and $F1$ metrics, which are calculated using the following formulas:

$$Accuracy = \frac{1}{N}\sum_{i=1}^{N}\frac{|Y_i \cap \hat{Y}_i|}{|Y_i \cup \hat{Y}_i|}, \tag{9}$$

$$Recall = \frac{1}{L}\sum_{j=1}^{L}\frac{TP_j}{TP_j + FN_j}, \tag{10}$$

$$Precision = \frac{1}{L}\sum_{j=1}^{L}\frac{TP_j}{TP_j + FP_j}, \tag{11}$$

$$F1 = \frac{1}{L}\sum_{j=1}^{L}\frac{2 * Precision_j * Recall_j}{Precision_j + Recall_j}. \tag{12}$$

We also evaluated the quality of other architectures for this task and the results are shown in table 1.

Table 1. **Results comparison for the different models**

	Big Five		**MBTI**	
Model	Acc	$F1$	Acc	$F1$
Conv+features	0.58	0.55	0.65	0.61
LSTM	0.55	0.54	0.67	0.64
GPT-4o	0.67	0.65	0.77	0.75
GPT-o1	0.68	0.66	0.78	0.74
LLAMA 7b	0.22	0.18	0.26	0.23

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End of the table 1

	Big Five		**MBTI**	
LLAMA 7b+LoRA	0.59	0.59	0.68	0.65
LLAMA 7b+LoRA+multitask	0.64	0.63	0.74	0.72

5.2. Example usage

Suppose there is a job V that requires a certain set of personality traits from a candidate T_V, there is a certain set of candidates for this vacancy $C=\{c_1,c_2,\ldots c_n\}$. With the help of the created system based on social media activity, we get a set of features according to the model Big Five $P=\{P_{(c_1)},P_{(c_2)},\ldots {P_c}_n\}$. Results inside the system are presented in the Fig. 7 and in the Fig. 8.

Figure 7. Personality trait scores

Figure 8. Detailed post analysis

Let's define a function for evaluating the similarity of two psychological portraits S, since the value of a portrait is the distribution of personality traits, it is advisable to use relative entropy (Kullback-Leibler (KL) divergence):

$$S(P_i, P_k) = \sum P_{ix} \, log\left(\frac{P_{ix}}{P_{kx}}\right). \quad (13)$$

Based on the above evaluation function, we calculate the value for each candidate $Scores = \{S_1, S_2, \dots, S_n\}$ and rank the candidates. Since the smaller the value of the function, the smaller the difference between the distributions, the candidate with the lowest value will be the most suitable for the vacancy.

6. Discussion of results

The zero-shot learning approach does not work well and the model training approach is more appropriate. Training the model on each of the tasks separately allows us to obtain better accuracy than the SOTA architectures used before the transformers. On the Big Five problem, we obtained an accuracy of 0.59 and on MBTI of 0.68. The reason for the difference in accuracy is the availability of a larger data set for MBTI. The multitask fine-tuning approach allowed us to significantly improve the model's performance (5% improvement in accuracy and F1) due to the correlation of different personality models. As for now, the created model is inferior in accuracy to commercial models from OpenAI, but since the model is much smaller, it runs faster and takes up fewer resources. In addition, the model used is open source, so it can be deployed on your own hardware. This advantage can be useful for using this model in corporate circles with private information.

The created system can be used for automated analysis of a person's activity in social networks, searching for certain patterns of behavior or signals. This system is not an accurate reflection of a person's psychological profile, and the accuracy of the system highly depends on the quality and the amount of data provided. The system shows good results for profiles where there are at least 50 posts, and the average frequency of posts is at least 2 times a week. The values of personality traits and detailed analysis of posts obtained by the system can be used to build a more detailed and accurate psychological portrait.

Conclusion

In this work, a system for constructing a psychological portrait of a person based on activity in social networks was designed and implemented. The subject area analysis and mathematical formalization of the problem were carried out. A neural network based on the LLAMA architecture was implemented and trained using the instruction fine tuning approach. The use of this approach has improved the quality of the model's performance on each of the subtasks. The choice of the application architecture is substantiated and an example of using the system for the task of selecting candidates for a vacancy is presented.

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