A research attempt to predict and model personalities through users' social media details

Muskan Goyal
Department of Information Technology
Dwarkadas J.Sanghvi College of Engineering
Mumbai, Maharashtra
muskangoyal4000@gmail.com

Prachi Tawde
Department of Information Technology
Dwarkadas J.Sanghvi College of Engineering
Mumbai, Maharashtra
prachi.tawde@djsce.ac.in

***Abstract*—Users of products and services, as human beings have a wide range of personalities. This is being experienced right from the initial days of e-commerce and m –commerce in India. In this research an attempt has been made to predict personalities using MBTI (Myers Briggs Type Indicator) based approach making use of natural language based processing, machine learning and transformer based modelling. As each human being is unique and exhibits different personality trait, therefore it is impractical to offer a generalized treatment for all users. But it is possible to categorize individuals, in terms of their defining characteristics based on MBTI based approach, which groups personalities/users into 16 groups and thus helps in predicting personalities. In this study authors made an attempt to extract social media based information of users through their accounts to characterize users into one of the 16 MBTI personality types. For this prediction and modelling, authors made use of pre-processed data from Kaggle, which was then fed into the transformer for modelling/processing. Based on the information it gets, like comments, post captions, reviews, etc., the transformer is fine-tuned to predict the user's personality. The required qualities of the model were taken into account while coding the transformer's parameters. Additionally, an attempt is also made to compare the outcomes of two trained transformer models. Authors report that the prediction accuracy of their modelling as 64%, outperforming all other models used. The testing data had a 76% precision.**

***Index Terms*—Natural language processing, Bert, Transformers, MBTI, personality prediction, social media, machine learning**

I. Introduction

Ever since the entry of e-commerce and m-commerce modes of doing business and offering services, an urgent need is being experienced to probe the mindset of users and personalities. If the personalities, perceptions and tastes of users are properly understood then it can be meaningfully leveraged in the favor of companies [1,2]. Accordingly, research attempts are being made to tap the details available on various social media platforms. These details which are available in various formats, influence an individual's life both directly and indirectly. It not only throws light about an individual's profile and likings but can also be explored to understand the personality of same individual, as these details are largely linked to individual's life. Owing to a significant amount of time spent by almost all humans on social media platforms, it generates a lot of information for every user. Data captured on social media sites not only include details about a person's likes and dislikes but also his/her activity and interests. The intelligent usage of these details efficiently is one of the hot areas of research and can be utilized in many different manners. How to infer meaningful information to understand user's personality using these details requires deep analysis and an innovative thought process. The challenge is, the personality of a user is very varied. As each individual is different in terms of background, upbringing and tastes/likings. Thus, It is challenging to classify and an individual but it is possible to offer a general description or characteristic traits to different users based on their personalities. This Personality based classification on classifying users into some specific groups, that although do not capture the essence of the person or their quirks but do give a basic sense of the characteristics of the person. MBTI (Myers Briggs Type Indicator) personality model is one developed by Myers and Briggs and it classifies based on 4 parameters namely Extraversion (E) – Introversion (I), Sensing (S) – Intuition (N), Thinking (T) – Feeling (F), Judging (J) – Perceiving (P). The combination of these 4 parameters gives us 16 different personality traits. With this premise, an attempt is being made to classify users into one of the 16 MBTI personality traits using the data from their social media accounts. The data that will be used for analysis will include the posts made by the user, the comments left by the user, the tweets, the captions, and any or all the text-related activity on the user's social media account. For this experiment, data has been taken from a popular Kaggle dataset, and that data was pre-processed and then passed into the transformer. The transformer was fine-tuned to predict the personality of the user based on the data it receives. The parameters of the transformer were coded in such a way as to fit the characteristics of the model required.

A. Background And Related Work

Katharine Briggs and Isabel Briggs Myers, a mother- daughter team, developed the Myers-Briggs theory. The Myers-Briggs theory is a modification of Carl Gustav Jung's theory of psychological types. It is based on the 16 personality types that Carl Jung considered to be archetypes. They serve as helpful points of reference to comprehend one's unique

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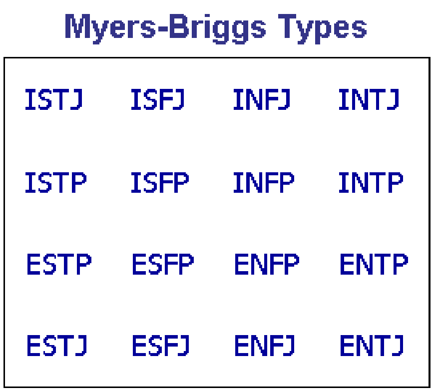
personality.Myers-Briggs theory comprises of four preferences [1].

- Ideas and information (Introversion or ”I”), or people and things (Extraversion or ”E”).
- Possibilities and potential (Intuition or ”N”), or facts and reality (Sensing or ”S”).
- Values and relationships (Feeling or ”F”), or logic and truth (Thinking or ”T”).
- One that goes with the flow (Perception or ”P”), or a well-structured lifestyle (Judgment or ”J”).

These four letters can be combined to create a personality type code. There are sixteen Myers-Briggs personality types, divided into four pairings.


Myers-Briggs Types

ISTJ	ISFJ	INFJ	INTJ
ISTP	ISFP	INFP	INTP
ESTP	ESFP	ENFP	ENTP
ESTJ	ESFJ	ENFJ	ENTJ

Fig. 1. Myers-Briggs Personality Types.

B. *Transformers Introduction*

Transformers and what is known as a sequence-to-sequence architecture are both discussed in the paper ”Attention Is All You Need”[3]. Sequence-to-Sequence (also known as Seq2Seq) is a neural network that changes one sequence of elements, such as the words in a phrase, into another. An input sequence is examined by the attention mechanism, which determines which additional sequence elements are significant at each stage. It can be observed that the modules mostly consist of layers for Multi-Head Attention and Feed Forward. The Equation is given below [2]:

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{1}$$

On the left is the encoder, and on the right is the decoder. According to Nx in the image, Encoder and Decoder are both made up of modules that can be stacked on top of one another several times. Since strings cannot be used directly, the inputs and outputs (target sentences) are first embedded into an n-dimensional space. The positional encoding of the various words is a small but significant component of the model.

For the task at hand, a classification problem, just the encoder component of the transformer is used.

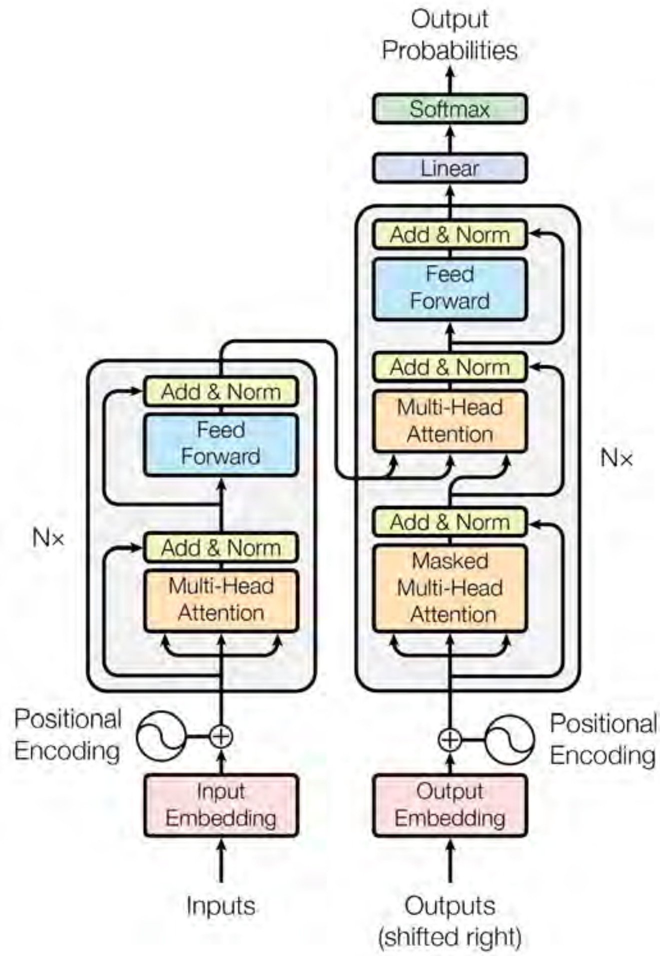


Fig. 2. The Transformer-model architecture.

II. Literature Survey

”Text based personality prediction from multiple social media data sources using pre-trained language model and model averaging” [4], this study suggested a deep learning architectural strategy that outperformed the majority of personality models built on the Facebook MyPersonality dataset and the Twitter dataset by using pre-trained language models like Bidirectional Encoder Representations from Transformers (BERT), Robustly Optimized BERT Pre-training Approach(RoBERTa), and XLNet, Natural Language Processing(NLP) statistical characteristics, and model averaging. Furthermore, the inclusion of NLP statistical features such as TF-IGM(term frequency & inverse gravity moment), sentiment analysis, and the NRC lexicon database significantly improved the performance of the personality prediction system on both datasets. These features can be used to extract features from a model rather than relying solely on a pre-trained model.

According to ”Comparative Study of Personality Prediction From Social Media by using Machine Learning and Deep Learning Method ”[5],for predicting personality positive and negative traits were used. Machine learning and deep learning neural network techniques were employed as two different types of categorization algorithms for determining personalities. Better accuracy than machine learning techniques was discovered when employing these deep learning techniques, such as LSTM(Long-Short Term Memory) .

On the basis of the personal Values and human Needs personality characteristics collected from users' postings on social media, a new method for predicting the Big Five personality traits is presented in the paper"Predicting the Big Five for social network users using their personality characteristics"[6]. The classification of the Big Five qualities is proposed using various supervised machine learning approaches. In order to determine the cut-off values for the classification boundary, two thresholding procedures are used. The best classification outcomes were produced by combining Needs and Values variables using regression approaches.

The paper"Machine intelligence based personality prediction using social profile data "[7] suggests that an effective way to predict a user's attributes is through social network user content. The article provides a method that applies traditional machine learning models and ensemble learning. The focus of the study was the practicality of modelling people's Big Five characteristics using data from their Facebook user profiles. With a variety of uses, this makes it possible to fairly accurately analyse a person's personality qualities.

In the paper "Personality predictions based on user behavior on the facebook social media platform "[8] it was proposed that users' behaviour and their OCEAN(Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism) personality score to be predicted using the MyPersonality dataset. There was a correlation score discovered, and it was noted that employing various linguistic dictionaries could enhance the correlation outcomes. In the previous stage, retrieved features were used to predict personality score. Using distinct SNA(Social Network Analysis) feature sets, the XGBoost machine learning approach produced the best personality prediction.

Various personality-based machine learning models were used to assess Turkish tweets rather than only utilising frequency-based statistical methodologies. Due to their pairwise associations, the number of word groups in this study was decreased. Different machine learning models are used to forecast each personality feature to provide successful outcomes in the paper "Predicting Personality with Twitter Data and Machine Learning Models "[9].

From the literature survey done , important research gaps were identified. For example, it was observed that most personality models created were based on OCEAN score for personality prediction. Where as not many cases were observed for predicting someone's MTBI personality. As we know that it is more prevalent and offers a more accurate representation of a person's characteristics. Also for many personality prediction models , it was observed that text data wasn't enough and other features such as user relation graphs of social media and emoticon data were required for an accurate prediction. Although it improved accuracy it is not as easy to find and store as text data and thus a little improbable for practical purposes. Hence the proposed model uses the research done before and builds upon it , in an attempt to predict MTBI personality type of the user using only text data available on their social media accounts.

III. Data Used

The Data that was used for the experiment, as well as the research, was the MBTI personality dataset which is opensource and available on Kaggle [10]. This dataset consists of mainly two columns, the personality type of the user from the 16 MBTI types and the social media activity of the user. The social media activity of the user can range from anything starting from the comments the users make to the captions on their posts to the tweets they have made and the various text data linked to a user's social media. It consists of a set of the last 50 things the user has posted on their social media accounts. The data consists of 8600 entries and was divided into a ratio of 8:2 for training and testing respectively. The individual posts were separated by '|||' symbol and hence the cleaning process consisted of removing this and combining all the posts.

Fig.3 shows the distribution of personality types in the dataset that we worked with. The data was severely imbalanced which could be a reason for overfitting and low accuracy and precision on actual test data not seen by the model.

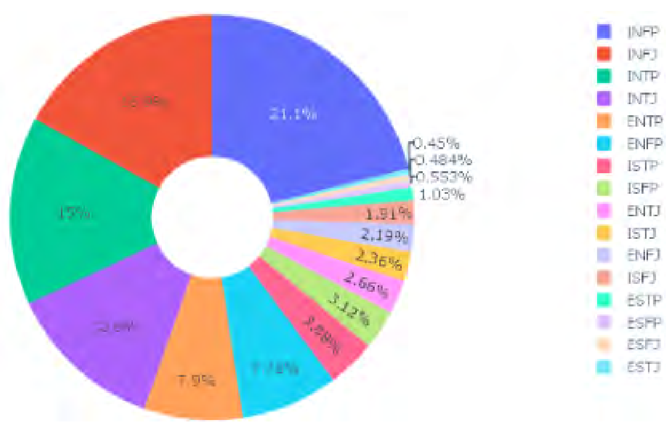


Fig. 3. Distribution of Personality types in the dataset.

IV. Methodology

A. Pre-processing

The data were first checked for missing and null values, when preliminary analysis of the data showed no null values further steps in the pre-processing were carried out. For preprocessing, since this experimental setup is working with transformers, it needed to only keep useful information from the dataset. Hence, the numbers, symbols as well as any sort of links were removed. The whole text dataset was then lemmatized. The dataset was divided into two parts in a ratio of 8:2. Since the size of the data being worked on was small , an 80-20 ratio had to be chosen rather than the much preferred 70-30 or 75-25 ratio. Since there was also a lot of disparity between data of various personality types and a few types had very little data , stratified sampling method was used to overcome this problem. The max length was set to 512 in the tokenizer. Various different max lengths were worked with but 512 had very obvious better results. The difference in performance metrics between the max length of 256 and 512 is seen in table 1. The personality types of the user were encoded using one hot label encoder to assign a label to each of the 16 personality types.

B. Performance Metrics

The performance metrics were defined to evaluate the workings of each model. Three criteria are defined as follows, f1 score, precision, and accuracy. Precision and accuracy were taken as the deciding factor in choosing the models as well as choosing parameter values while training. This had to be coded as Keras model requires it but the basic formulae [11] are given as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{t_p}{t_p + f_p} \tag{3}$$

$$F = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{4}$$

When trying to figure out the best model, one parameter out of precision, accuracy, recall and f1take priority. This is decided according to the use case for the model. Higher precision is preferred when the cost of false positive is high and a higher value of recall is preferred when the cost of false negative is high. Since here, the study is working on a classification task, the prediction of personality neither precision or recall will be given priority. The different parameters of the models will be judged based on F1 score which is used when a balance is needed between precision and recall values.

C. Training

The model architecture was that of a transformer. Since the task was of classification only the encoder part of the transformer model was used. For training, the pretrained Bert model was used from the transformer library. The first hidden state from BERT output corresponding to the CLS tokens is taken and fed into the dense layer with 16 neurons and SoftMax activation functions. Adam optimizer was used from tensorflow library while creating the model.Several different values were tried and tested for the parameters batch size and epochs. Refer Table I and Table II for their metrics.

Both the models, the bert-base-uncased and the bert-large-uncased one performed similarly in similar conditions. After the testing period, the parameters that gave the best values were chosen as the final parameters. Here bert-uncased series is preferred because it automatically uses the lowercase form and hence works better for the problem statement in hand.

During the training, it was observed that the validation loss seems to decrease in the initial epochs and then come to the best value after which it would only increase, even though training loss seems to decrease. It was concluded that overfitting was occurring and hence two models were saved the best model which had the best validation loss and the last model which was received after the end of the whole training. In the testing phase, these two models were compared according to the performance metrics. All in all, the study had four models by the end of the training phase, two for the bert-large-uncased and two for bert-base-uncased.

TABLE I
RESULTS OF DIFFERENT VALUES OF ESSENTIAL PARAMETERS OF BERT-BASE-UNCASED

Max Length	Batch size	Epochs	Precision	Accuracy	F1score
256	8	4	0.6021	0.5182	0.4834
256	16	4	0.6187	0.5164	0.4939
256	32	4	0.6049	0.5084	0.4877
256	64	4	0.6553	0.5268	0.4799
512	8	4	0.7078	0.6340	0.6382
512	8	5	0.6873	0.6219	0.6199
512	8	10	0.6271	0.6035	0.6043
512	16	4	0.7471	0.6346	0.5515
512	16	5	0.6703	0.6104	0.6107
512	16	10	0.6492	0.6173	0.6236
512	32	4	0.7312	0.6357	0.6267
512	32	5	0.7072	0.6300	0.6326
512	32	10	0.6472	0.6121	0.6144
512	64	4	0.7464	0.6507	0.6369
512	64	5	0.7208	0.6398	0.6451
512	64	10	0.6873	0.6334	0.6347

TABLE II
RESULTS OF DIFFERENT VALUES OF ESSENTIAL PARAMETERS OF BERT-BASE-UNCASED

Max Length	Batch size	Epochs	Precision	Accuracy	F1score
512	8	4	0.6801	0.6173	0.6102
512	8	5	0.6205	0.5550	0.5261
512	8	10	0.6502	0.6242	0.6240
512	16	4	0.7534	0.6565	0.6385
512	16	5	0.6852	0.6323	0.6292
512	16	10	0.6544	0.6300	0.6299
512	32	4	0.7369	0.6559	0.6416
512	32	5	0.7316	0.6323	0.6084
512	32	10	0.6714	0.6386	0.6435
512	64	4	0.7032	0.6150	0.6096
512	64	5	0.7339	0.6305	0.6267
512	64	10	0.6564	0.6311	0.6307

V. RESULT

The results of the best model used after training are shown in Table III and Table IV.

During training, the evaluation of the models was performed on the last model saved for the values. These evaluations are the best models of each fine-tuned parameter. The max length parameter value was kept 526 and all other values were discarded as the results of those were clearly much better than the rest. Models were created for different values of batch sizes

TABLE III

RESULTS FOR THE BERT-BASE-UNCASED MODEL

Batch size	Epochs	Precision	Accuracy	F1score	Recall	Loss
8	4	0.7471	0.6346	0.6322	0.5515	1.2671
8	5	0.7439	0.6385	0.6462	0.5745	1.2450
8	10	0.7660	0.6342	0.6441	0.5607	1.2234
16	4	0.7569	0.6417	0.6495	0.5473	1.2268
16	5	0.7021	0.5958	0.5964	0.5209	1.3473
16	10	0.7417	0.6379	0.6250	0.5430	1.2669
32	4	0.7326	0.6337	0.6417	0.5734	1.2878
32	5	0.7570	0.6166	0.6248	0.5360	1.2765
32	10	0.7355	0.6448	0.6379	0.5675	1.2502
64	4	0.7295	0.6234	0.6333	0.5624	1.2826
64	5	0.7437	0.6394	0.6452	0.5735	1.2613
64	10	0.7316	0.6469	0.6537	0.5926	1.2832

TABLE IV

RESULTS FOR THE BERT-LARGE-UNCASED MODEL

Batch size	Epoch	Precision	Accuracy	F1score	Recall	Loss
8	4	0.7944	0.6201	0.6022	0.4919	1.2508
8	5	0.6303	0.5625	0.5467	0.4861	1.5012
8	10	0.7560	0.6412	0.6398	0.5590	1.2181
16	4	0.7526	0.6483	0.6548	0.5822	1.2559
16	5	0.7647	0.6431	0.6590	0.5822	1.2110
16	10	0.7639	0.6493	0.6448	0.5612	1.2359
32	4	0.7534	0.6404	0.6467	0.5695	1.2047
32	5	0.7359	0.5991	0.6041	0.5166	1.2926
32	10	0.7561	0.6437	0.6407	0.5603	1.2263
64	4	0.7174	0.6052	0.5953	0.5134	1.3092
64	5	0.7359	0.5991	0.6041	0.5166	1.2926
64	10	0.6564	0.6311	0.6307	0.6131	2.1360

and epochs. For the model created on bert-base-uncased, the best results were obtained for batch size 16 and epoch value 4. On the other hand, for the model based on bert-large-uncased the best results were obtained for batch size 16 and number of epochs 5.

The trends for results are very similar in both the models trained. The precision value is better for smaller batch sizes while the accuracy value is the best for higher number of epochs amongst both the models. There is no obvious trend for recall value but it seems like the recall value is higher fir higher batch sizes and higher epoch values. F1 score is the score on the basis of which the models were judged. F1 score also has no obvious trends like accuracy or precision but it seems like it is the best for batch sizes 16 and 32 for both the models.

During an in-depth analysis of the result, it was found that many misclassifications occurred. ISFJ and ESTP personality types often got classified as other personality types. A reason why this could be prevalent is because of the lack of data for these two personality types. Since training data for these weren't sufficient the model is not able to recognize the types. Another reason can be that out of the four attributes consisting of the personality type (I-S-F-J), three attributes(I-F-J) played a bigger role in the text data and hence had a more probability and the fourth attribute played a smaller role and hence was not distinguishable from its counterpart. These reasons are proposed because on numerous occasions ISFJ personality type was classified as INFJ and ESTP was classified as INTP. The third reason for this disparity could be that the personality that is given as a result had more training data. INFJ label was given to 16.9% of the data and the INTP label consisted of 15% of the data that was worked with.

The results of the model are shown in figure 4. As seen in the figure, the output given by the model is in the form of percentages. Each personality type is given a percentage that represents the likelihood of the input being written by a person of that personality type.

The result for the bert-base-uncased models is as follows

Fig. 4. Actual Prediction of the best model.

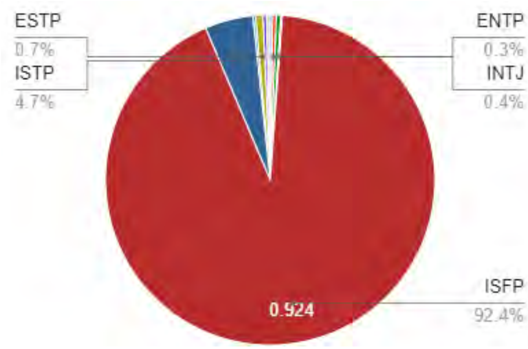


Fig. 5. Predicted probability of users personality

As seen in the above figure , the output of the code shows the prediction of the model in the form of a pie chart. It gives the user's personality type in terms of probability. So every one of the 16 personality type is associated with a probability. The

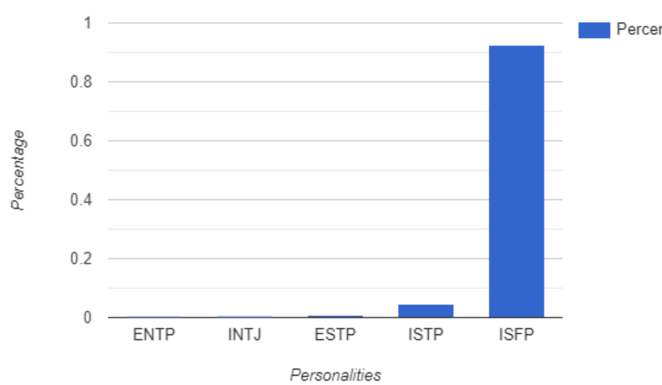


Fig. 6. Top 5 Probabilities

Fig. 6 given above , shows the top 5 probabilities predicted by the model and its corresponding personality types in a bar graph for better understanding.

In the following comparison table(Table 5), the best models (according to their f1 score) of bert-base-uncased and bert-large-uncased are compared.The best hyper parameters are taken and the Precision for bert-base-uncased model is noted as 75.69% and the Precision for the bert-large-uncased model is noted as 76.47%. As seen in table 5, the bert-large-uncased model performs slightly better than the bert-base-uncased one. Although the difference is slight, the size of the models trained varied by a lot, 488MB for bert-base-uncased and 1.2GB for bert-large-uncased. Even though both had similar parameters while training, both max length values were 512, and batch sizes were 16.

TABLE V
RESULTS OF DIFFERENT VALUES OF ESSENTIAL PARAMETERS

Parameters	Loss	Accuracy	F1	Precision	Recall
Bert-base-uncased	1.2268	0.6417	0.6495	0.7569	0.5473
Bert-large-uncased	1.2110	0.6431	0.6590	0.7647	0.5822

VI. Conclusion

In this paper, using transformers to predict personality is proposed. The following experiment concludes that transformers can and should be used for predicting personalities based on social media text data. In this paper, the working and training of both the bert-base-uncased as well as the bert-large-uncased were compared. The conclusion for it would be that model trained with bert-large-uncased performs slightly better than the model trained with bert-base-uncased. If the comparison in terms of speed and storage is done, the model trained on bert base-uncased performs much better. It takes far lesser time to train as well as loading of weights. If an application is made, the performance of the model trained on bert-base-uncased will be much better overall according to the experiment. The precision for the best model is coming out to be 76.47% and Accuracy came out to be 64.31%.

VII. Limitations and Future Scope

Authors acknowledge that the proposed model over fits the data. The probable reasons may be due to use of smaller sized dataset, which may invite some bias during its usage and predictions due to overfitting. It can be partially addressed if pre-processing is done on the data. Very humbly authors accept dataset size based limitations. As future scope of study and further extensions authors appeal to scholars to use bigger dataset and attempt even simulation [12] and mapping [13] of various scenarios to facilitate meaningful comparisons in terms of results. In previous works referred, the interaction pattern, as well as other factors, were taken into consideration while evaluating the personality of a user but passing the text data is a much simpler and faster way to predict the personality and distinguish users into sixteen different categories rather than the traditional five categories. For future work, other transformer models can be explored, for this study only two of them were, tried like bert- base-uncased and bert-large-uncased. Similarly, other models can also be studied for the same problem and the with bigger and alternative dataset . Similarly, one can try this model to different datasets to map similar social media texts to MBTI personality types to compare the accuracy and precision of the chosen model. Authors very humbly accept that the results discussed may exhibit mis-classifications owing to disparity in the distribution of data for different personality types. For future studies, a comprehensive dataset may be tried with better distribution of data and the results can then be compared with this study.

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