Myers-Briggs Personality Types Using Machine Learning Techniques

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Abstract

In this paper, we study the differences in machine learning techniques while applying them to a data set used to determine an individual's personality type with Myers-Brigg. Various methods of natural language processing are utilized when viewing a person's social media posts and their personality type is determined from such. It was found that through machine learning techniques that are prevalent in natural language processing, a person's personality type can be determined by the Myers-Briggs determination.

1. Introduction

The ability to understand people and a person's reasons for which they make the decisions they choose is a greatly resource many digital platforms are using to better expand their reach to the public. By understanding a user's personality type, these platforms can better understand the interests of that person to serve them better and offer a greater experience on their platform. Determining personality types used to be a long and tedious task that could only be done manually, but with machine learning techniques, the information a user provides to online resources can be used label their personality type much faster and without the use of the traditional assessments. This means that the user would no longer have to take these assessments and their personality type can be determined without any extra effort by the user. This calls into question privacy concerns, but that is a topic for another study.

The Myers-Briggs Type Indicator is the most widely used and accepted personality test currently available. While others are useful, the MBTI has been known to most accurately determine personality types of those who take their assessment. Personalities are broken down into sixteen sub-types that appear in pairs that oppose one another, such as extroverts and introverts. At the conclusion of the assessment, a personality is given by a four-letter combination that describes that person's personality type. There are 16 different combinations of personalities with some being very common, while others are very rare. The

Figure 1. Eight of the key personality types

most common being INFP and the most uncommon being ESTJ.

1.1. How it's Done Today

In today's practices, an emphasis on the communication between machines and humans is being used to predict an individual's personality type using machine learning techniques. In particular, neuro linguistic programming (NLP) is used to discern the different ways a person thinks, makes decisions, communicates with others, and act in their daily lives. NLP is a collection of techniques used to help to identify these personality traits and patterns that can be later used as features in any data collected.

Figure 3 shows some of the more common studies that have been conducted on determining personality types and the methods that have been tested of each. Not all the studies use the Myers-Briggs methods for determining types, and those other methods have different attributes and different classes of personality types. However, it should be noted that in many cases, the methods of determining a personality type can be closely related to another method. Various studies have shown that when using a similar data set and method of producing an output, simpler machine learning techniques produce higher accuracies than most other more complicated ones. This is due in part to the need for natural language processing.

Study	Personality Model	Method
Champa and Anandakumar (2010)	MBTI Network	Artificial Neural
Golbeck and et al. (2011)	MBTI Algorithms	Regression
Komisin and Guinn (2012)	MBTI Bayes and SVM	Naïve
Wan and et al. (2014)	Big Five Naive Bayes	Logistic Regression
Li, Wan and Wang (2017)	Big Five Learning	Multiple Regression and Multi-Task
Tandera and et al. (2017)	Big Five Architecture	Deep Learning
Hernandez and Knight (2017)	MBTI Networks	Recurrent Neural
Cui and Qi (2017)	MBTI Learning	Baseline, Naïve Bayes, SVM and Deep

Figure 2. Studies of determining personality types, the methods chosen, and the mode for which they were graded. [1]

1.2. Limitations

One of the biggest limitations when determine a personality type is choosing which information in a user's post is relevant to their personality and which is extraneous information that should not be included when examining the data. This can range from quoting a different user's words, common sayings and phrases, naming titles of journals or articles, and anything else that may not be the user's own words.

Avoiding algorithmic discrimination is an even that may occur when a particular algorithm or machine learning technique that is being used chooses to use information that does not concern the personality type. To avoid this, extensive data stripping can be used to remove any information from the comments and posts by the person that is manually chosen by the programmer. A deep understanding of how any machine learning model functions is needed to properly separate the information that is useful from the information that will cause outliers and false data.

1.3. Who is Interested

Since social media has had such a dramatic impact on how people view the content they're seeing and how they make decisions, it can be quite useful to predict a user's personality type. By studying their posts, comments, and any other information they may put on social media platforms, such as Facebook, Instagram, LinkedIn, and many others, companies will be able to better market resources that user sees and may interact with. Also, marketing social media ads to the appropriate types of people based on their personality can increase that user's engagement and increase revenue to those companies.

In recent years, the use of online dating platforms has become more prevalent as many more people are looking to digital resources to find personal connections over the more traditional methods. Companies that have developed these online dating resources find that knowing personality types of their users results in greater chances of those user matching with other and finding the personal relationships they seek. Additional research has been conducted to better understand the compatibility of various personality types. By leveraging this information, the chances of success greatly improve and thus, the dating platform's success rates improve.

Another use for predicting a person's personality type is to better provide help to that person in the form of clinical psychology, counselling, and therapy. This is the more traditional use because of the effects it may have on helping those individuals. Better care can be provided on a more individual level and that person might be able to better understand the reasoning behind their actions, how they connect, their personal relationships, and many other aspects of their lives.

2. Approach

After obtaining a data set suitable for such determinations, the various types of machine learning algorithms needed to be decided. Originally, the methods there were chosen were gradient ascent, descent, and boosting, but after several failed attempts to produce any amount of usable model outputs, those methods were traded out for other. After testing other methods and studying the Sklearn library, I had decided to compare the results from using nearest neighbor, logistic regression, and random forests. Sklean is a library in python that contains many machine learning methods and makes it more convenient for users to utilize various algorithms instead of developing their own and risking errors in their implementation.

These methods were chosen because of their simplicity and their prevalence in natural language processing. Since the data set contains comments and posts written by users,

the ability to manage the text used is of great importance. There are several algorithms that are common in NLP, so it was decided that using these methods would produce the most meaningful and useful outputs. Additional methods would have required a deeper understanding of more complex algorithms in order to implements them.

NLP has been a growing area of research in recent years, and because of this, the methods used in this experiment are largely well known in similar testing. However, not many other cases compared these methods side by side to show their similarities and their differences. Also, the failure of using other methods to produce a usable output proved that a different course of action should be taken. Thus, the following methods were chosen for the reasons described below.
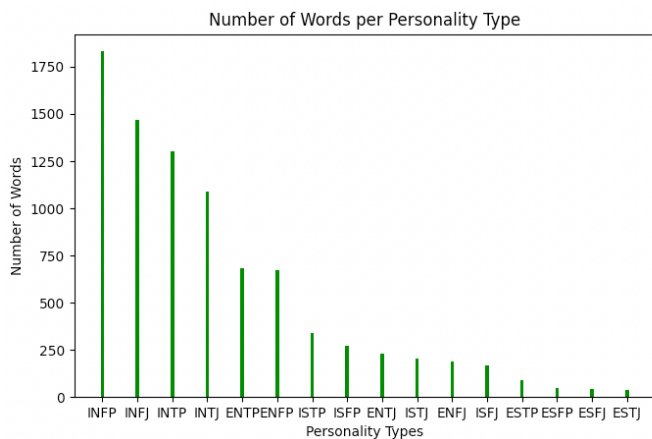

Figure 3. Number of words in each comment or post by the user and the personality type of each.

2.1. K-Nearest Neighbors

K-nearest neighbors is a type of supervised leaning mainly used in classification problems. Objects are classified by voting on its neighbors while that object is assigned to a class that is most common amongst its neighbors. The value of k, or the number of neighbors that that compared to the object. This method was chosen because of its ability to classify a piece of data into categories or classes. This is quite similar to classifying a piece of data to a personality type. The limitation of this method, however, is that it is very susceptible to outliers and missing values. Also, some experimentation may be necessary to choose the right value of k to produce the more accurate output. However, choosing the value of k can be done by repeating the method and comparing the outputs when using various k values. Values of k usually vary from 1 to the number of points in a data set. In my experiments, various stepping values of k were tested, but those values that were less than 10 usually performed greatest. Any values higher produced diminishing returns.

2.2. Logistic Regression

This method is named for its origin from statistics and probability coming from the logistic function. Inputs to the algorithm are given weights and through iterations of the function, those weights are updates until we know the predicted outputs. Below is the equation for logistic regression.

$$y = e^{\wedge}(b0 + b1*x) / (1 + e^{\wedge}(b0 + b1*x))$$

Text classification is the main concern when choosing an algorithm and logistic regression is a popular choice for such. Its ability to weight those words and discern the importance of that word make it an excellent and very common choice for natural language processing.

One of the common limitations of linear regression is that it must assume linearity between dependent and independent variables. Linear regression models can also perform poorly from a lack of correlation between the target labels and features of the data set.

2.3. Random Forest

Decision trees are among some of the most prevalent of algorithms used in computer sciences. A random forest is a collection of decision trees that take in various sub samples of a data set and averages the outputs of those trees. This can improve the predicted accuracy over using just a single tree. It can also help to prevent overfitting, which many algorithms are subject to in which a model fits against the training data and cannot provide accurate predictions with outliers and unseen data.

The decision to use random forests is because of its prevalence in NLP and the simplicity of decision trees. Decision trees tend to be very fast when searching through data and have been highly optimized. Its uses are similar to those of k-nearest neighbors in its classification of text and its ability to accurately classify objects into classes.

2.4. Problems

At the beginning of the project, I had anticipated being unsuccessful at comparing more complex machine learning algorithms being able to outperform simpler ones. I had believed that complex neural networks would be able to better identify a personality type due to the nature of human speech and translating it thought text. This was due to a lack of understanding of now natural language processing worked and how prevalent earlier techniques are in the use of.

The first several techniques that I had attempted to implement were unsuccessful.

Throughout the process, it had been determined that my skills in implementing some machine learning techniques was quite limited and caused issues when adapting a technique to fit the data set. Because of this, the original techniques that I had chosen to use were abandoned and replaced with other techniques that were better suited for the type of data that was chosen.

3. Experiments and Results

At the start of the project, I wanted to see an increase in training accuracy between the methods in order to define one method better than the other for this set of circumstances. However, after modifying the methods used, the measurement of success has altered from one that's quantitative to one that is qualitative. Qualitative in the sense that the method is better understood when applying it to the data set and the type of data provided. In this case the quality of understanding the simpler machine learning techniques against those that are more complex.

The first iteration of the project would be a failure due to not producing any sort of outcome that could be deemed accurate or usable. However, this led to deeper research on the subject matter and ultimately a better understanding of when to choose any of the various machine learning methods.

3.1. The Data Set

The data set consists of more than 8000 data points that correlate a social media comment or post with that person's personality type. The data is compiled form fifty different posts from each individual user. The data was consistent with that of the normal distribution of personality types of randomly selected people.

The data did contain information that was not needed for use such as hyperlinks, type characters, emojis, and other text that did not provide any useful meaning. For this reason, that text was removed prior to processing it in the various algorithms.

3.2. Results

The personality types were broken down into 4 subcategories for ease of use. When applying the methods mentioned earlier, it was discovered that random forest produced the greatest accuracy averaging greater that 98%, logistic regression varying between 60-86%, and lastly k-nearest neighbor producing a prediction accuracy of 76-88%. Therefore, from just these experiments, random forest produces the highest consistent accuracy when determining a personality type with the information given.

3.3. Lessons Learned

Throughout this project, I had learned many lessons that would have helped to produce a better product and more usable information at the conclusion of my findings. The greatest lesson I had learned is the importance of understanding the various studies that had been previously collected so that any findings that I had were not duplicates of those found in other studies. For example, a greater understanding of natural language processing would have helped me to understand how to better choose the machine learning methods that were to be used in this experiment. I would have known that the methods I had chosen to use were already being used in many techniques for discerning a personality type based on social media posts. I would have been able to find a different path that may not have been explored or had little research done so that any findings I may have would be relatively useful and new.
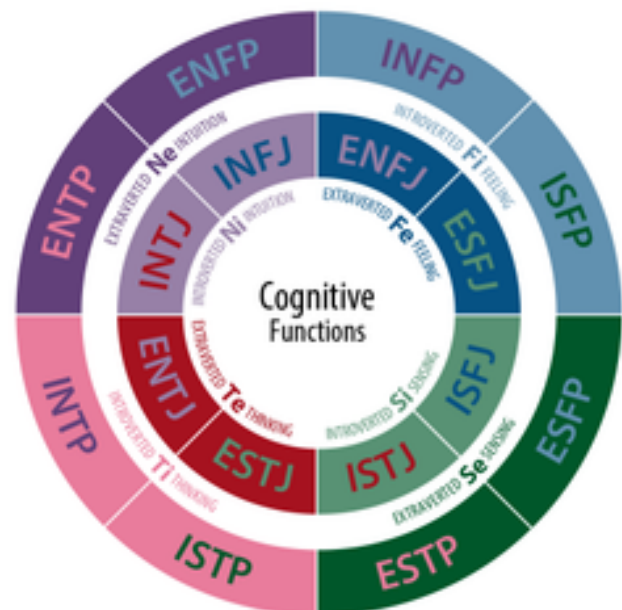

Figure 4. Relation of personality types to one another

It should be noted that while many sources do show that some similar techniques as those used here may outperform more complex ones, there are sources that prove just the opposite. In reference number 7, the user had proved that a convolutional neural network was able to outperform Naïve Bayes, support vector machine, and random forests while using the same data set as this project. The creator had said that there is a severe class imbalance problem in the data set [7], which would lead to inaccuracies in comparing each of the techniques.

3.4. Conclusion

Overall, I would consider this project a great learning lesson in how to research, implement, and conclude a topic in such a way that was useful and teaches me a great

number of subjects. My findings may have been relatively insignificant, but the research done, and the understanding of that research proved to be of much more importance. New information was continuously sought out during the entirety of the project, and with that came new information that contradicts what I had been led to believe up to that point. This is an important lesson to note that can occur in any research study and may occur and any future endeavors.

4. Availability

The code I used is available in a GitHub repository under the email given to me by Virginia Tech. It contains the code used for the machine learning programs and the data set used. This report will also be available in the repository as well.

https://github.com/calenfarmer/ML_personality

My findings are freely available to anyone who wishes to use them. My hope is that the lessons I had learned in this process may be of use to others that have interests in the same or similar topics.

5. Reproductivity

If any other researcher would like to attempt to reproduce the same outcomes that have been achieved in this experiment, they would only need to download and run the same programs I have written. The program and data set are freely available on the provided GitHub repository. Since the data set is quite large, additional data sets would not be necessary to reproduce similar results. If one were to use additional data sets or provide an additional data set/sets, similar results would be concluded at the end of the program. Instructions on running the program and the details of the code provided are in the README.txt file located in the repository alongside all other data and programs.

Since the machine learning algorithms are relatively simple when compared to other more complex methods, such as neural networks and deep learning, the model is highly reproducible. Additional data sets would provide similar outcomes, but there are few similar data sets that are readily available, so any others would have to be produced similarly to how the original data set was obtained

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