MBTI Test-Informed Personality Prediction via Machine Learning

Akshat Sinha & Ankit Sharma

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1 Introduction

Machine learning has significantly shaped the field of cognitive science throughout its history. The origins of cognitive science in the mid-20th century brought together disciplines like psychology, linguistics, computer science, and neuroscience to explore human cognition. Early on, cognitive scientists primarily focused on symbolic models of cognition. However, as artificial intelligence (AI) and machine learning progressed in the 1970s and 1980s, these techniques found their way into cognitive science. Researchers began using expert systems, rule-based approaches, and early machine learning algorithms like decision trees to build cognitive models.

The 1990s and 2000s witnessed a significant shift as machine learning techniques, particularly neural networks, gained prominence in cognitive science. These approaches were applied to problems such as natural language processing, pattern recognition, and neuroimaging analysis. Neural networks, for example, were used to model human learning and decision-making processes.

Machine learning for personality prediction is a relatively recent development, closely intertwined with advances in artificial intelligence and data analytics. In earlier years, personality assessment primarily relied on traditional methods like self-report questionnaires and psychological evaluations. It wasn't until the late 20th century and the 21st century that machine learning techniques became integrated into personality prediction.

2 Myers-Briggs Personality Test

The Myers-Briggs Type Indicator (MBTI) is a renowned personality assessment tool originally developed by Katharine Cook Briggs and Isabel Briggs Myers in the mid-20th century. It is rooted in the theories of Swiss psychiatrist Carl Jung, aimed at providing a structured framework for understanding individual differences in cognition and behavior. The MBTI is frequently employed within academic, professional, and organizational contexts to categorize individuals into one of 16 distinctive personality types. These types are derived from four pairs of dichotomous preferences: Extraversion (E) versus Introversion (I), Sensing (S) versus Intuition (N), Thinking (T) versus Feeling (F), and Judging (J) versus Perceiving (P). By identifying an individual's preference on each of these dimensions, the MBTI yields a four-letter personality type, such as "ENFJ" (Extraverted, Intuitive, Feeling, Judging) or "ISTP" (Introverted, Sensing, Thinking, Perceiving).

The core concept underlying the traits are explained below.

1. Extraversion-Introversion dimension within the Myers-Briggs Type Indicator (MBTI) is to delineate and categorize fundamental variances in how individuals interact with their surroundings and derive energy from their experiences. Extraverts are typified by their proclivity to attend to the external milieu, deriving energy from social engagements and external stimuli. In contrast, Introverts draw their energy internally, frequently favoring solitary pursuits and contemplative activities. This dimension serves as a foundational framework for classifying individuals based on their cognitive and behavioral biases and how they manifest in their engagement with the external environment and interpersonal interactions.

2. Sensing-Intuition dimension in the Myers-Briggs Type Indicator (MBTI) is to capture and categorize how individuals prefer to perceive and process information. Sensing individuals tend to focus on tangible, concrete details and facts in the present, while Intuitive individuals are more inclined to explore patterns, possibilities, and abstract concepts. This dimension offers insights into cognitive preferences, problem-solving methods, and decision-making styles, helping individuals understand their own and others' approaches to learning, thinking, and decision-making. It serves as a framework for acknowledging and appreciating the diversity in how people interpret and interact with the world around them.

3. Thinking-Feeling dimension in the Myers-Briggs Type Indicator (MBTI) is to categorize and understand how individuals make decisions and assess information. Thinking individuals prioritize objective and logical analysis in their decision-making while Feeling individuals make choices based on personal values and empathy. This dimension helps shed light on an individual's approach to ethical and value-based decision-making, offering a framework to appreciate diverse perspectives and enhance communication in interpersonal relationships.

4. Judging-Perceiving dimension in the Myers-Briggs Type Indicator (MBTI) is to elucidate how individuals interact with the external world and structure their lives. Those who prefer Judging lean towards order, planning, and decisiveness, often embracing structure and goal-setting. Conversely, individuals who prefer Perceiving are characterized by flexibility and adaptability, as they thrive in unstructured and spontaneous environments, valuing open-ended possibilities and remaining comfortable with uncertainty. This dimension plays a pivotal role in understanding an individual's approach to time management, problem-solving, and overall lifestyle choices.

In academic settings, the MBTI is frequently employed for several purposes. It serves as a valuable tool for self-reflection, encouraging students and researchers to gain insights into their personality preferences and how these preferences may influence their cognitive processes and behaviors. Additionally, the MBTI is often utilized as a basis for understanding interpersonal dynamics, communication styles, and team composition. In educational psychology, it has been leveraged to foster effective learning environments by recognizing diverse learning styles and preferences.

3 Dataset Analysis

The dataset under examination encompasses a cohort of 8,675 individuals actively participating within the confines of the Personality Cafe forum (2). Within this dataset, one encounters 50 user-generated comments, constituting the primary data corpus. The overarching research objective centers upon elucidating the predictive potential of user-generated linguistic content for ascertaining the personality traits delineated within the Myers-Briggs Type Indicator (MBTI) assessment.

Comprehensive word clouds depicting various personality traits are readily observable in Figures 1 through 8. It is essential to acknowledge that, in light of certain inherent dataset constraints, instances of lexical overlap may happen between personality types belonging to a particular trait category.

1. Prominent terms such as "people", "thing","life", "know," and "tell" serve to illustrate the expressive and outgoing qualities associated with extroversion. In contrast, words such as "think", "one", "thought", and "know" are indicative of the introspective and contemplative aspects associated with introversion.

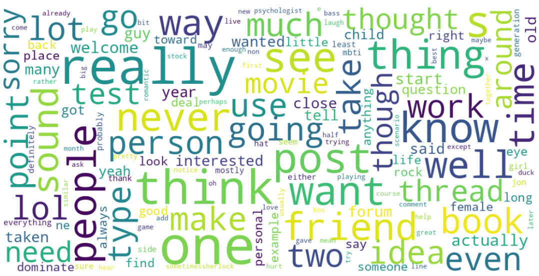

Figure 1: Introversion

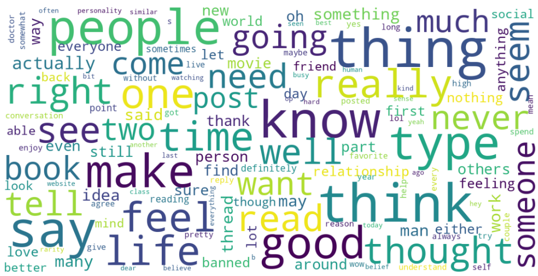

Figure 2: Extroversion

2. The usage of words like "thing", "know", and "think" suggests a predilection for empiricism among individuals in the sensing categories, highlighting a preference for concrete experiences. In contrast, individuals categorized as intuition types tend to employ more abstract terminology, as indicated by words such as "think" and "time" reflecting a propensity for abstract thinking and conceptualization.

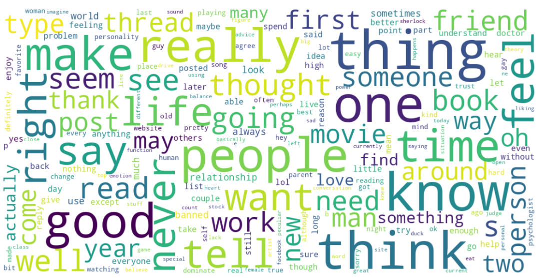

Figure 3: Sensing

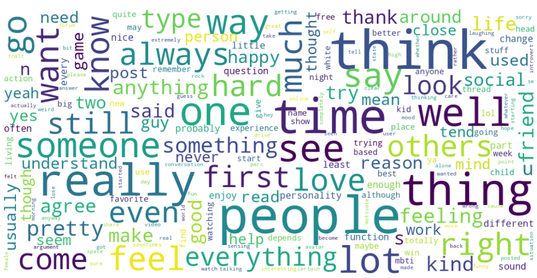

Figure 4: Intuition

3. The analysis of frequent words in the "Feeling" category, such as "feel", "people", and "good" suggests a preference for focusing on emotional experiences and a strong interest in the feelings of others. This indicates a social and empathetic nature. In contrast, the "Thinking" preference, featuring words like "thing" and "one" implies

a more detached and analytical decision-making approach that values objective criteria over emotions. Those with a Thinking preference prioritize logic and analytical thinking, evident in their frequent use of "think," and prioritize rational reasoning for decision-making, as indicated by "make"

Figure 5: Thinking

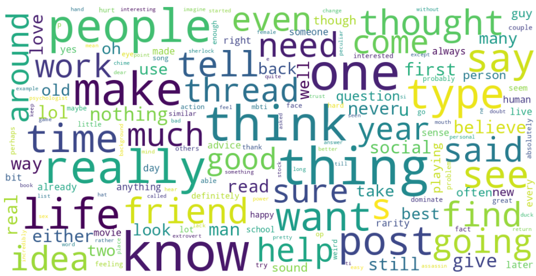

Figure 6: Feeling

4. Word frequencies in the Judging preference (J) category reveal the significance of "really", "type", and "time." These words imply that Judging preference people favor structured, planned decision-making, with "really" showing commitment to clear choices and plans. "Type" suggests categorization and organization, while "time" reflects efficiency, punctuality, and goals. "Think" and 'know" indicate well-informed decisions. In contrast, the Perceiving preference (P) is marked by words like "know", "thing" and "think," indicating adaptability and open-mindedness. "Know" shows interest in information and new insights. "Thing" and "think" show curiosity and learning. "People" show desire for diverse perspectives, demonstrating flexibility and adaptability.

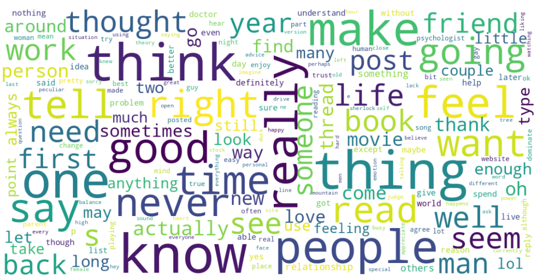

Figure 7: Judging

Figure 8: Perceiving

The correlation matrix depicted in Figures 9 through 14 unveils noteworthy patterns in the data. A prominent observation is that the majority of correlations between any two personality traits hovers around an approximate value of 0.5. This outcome suggests that these traits are not strongly interrelated, indicating a limited degree of significant association between them. This observation affords the opportunity to streamline our predictive models through the judicious assumption that personality traits can be reasonably treated as independent variables. Consequently, rather than necessitating the formulation of 16 distinct class predictions, we can streamline our approach by generating four binary class predictions.

This recognition of equal intercorrelation underscores the intricate diversity inherent within the spectrum of human personality. It underscores the notion that individuals are not relegated to rigid personality categories; instead, they manifest a broad spectrum

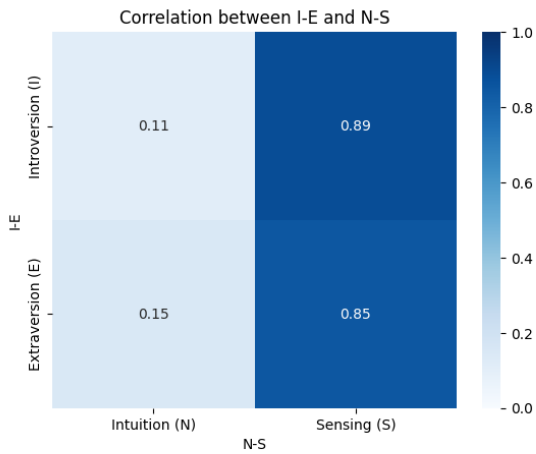

Figure 9

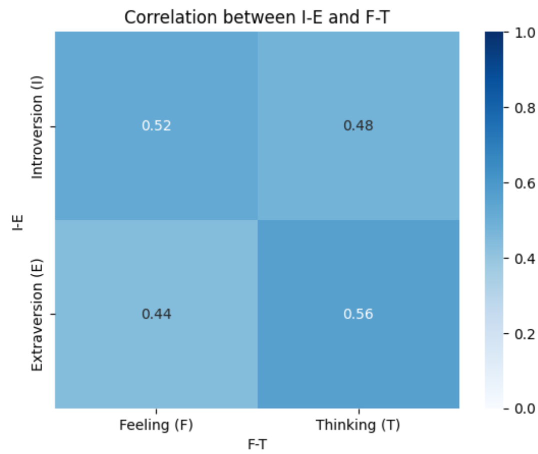

Figure 10

of preferences and inclinations. This insight can be instrumental in fostering a robust model. Evident in Figure 9, a notable disparity in color intensity stands out compared to the other heatmaps, highlighting the influential role of Sensing (S) on the degree of Introversion/Extroversion.

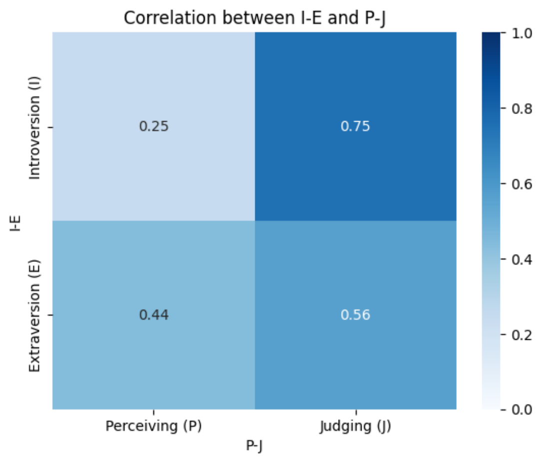

Figure 11

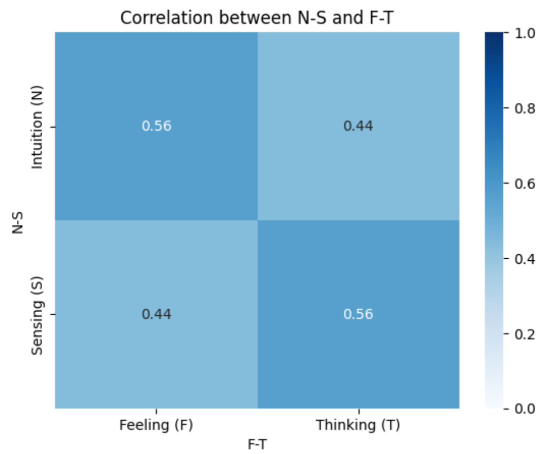

Figure 12

In summation, the equal correlation between personality traits as delineated by the MBTI test promotes a comprehensive view of personality dynamics, accentuating the multifaceted and heterogeneous nature of human conduct. This perspective, in turn, empowers individuals to embrace their distinctiveness, adapt to varying situations, and cultivate effective communication and collaboration with others. It reinforces the concept that one's personality is not static but rather adaptable and amenable to evolution over time, thereby enhancing both personal and professional development.

Figures 15 through 18 present the data distribution, and it's apparent that there's an uneven representation, particularly within the Extraversion-Introversion and Intuition-Sensing personality traits. This imbalance in the dataset sheds light on certain insights regarding our online presence.

One striking observation is that a significant proportion of individuals who engage online tend to exhibit introverted tendencies. The online environment often provides a virtual

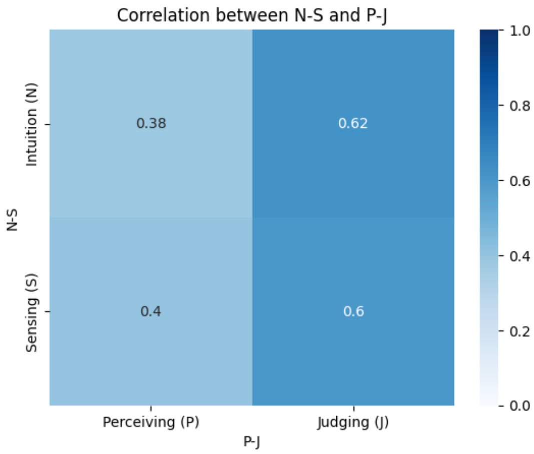

Figure 13

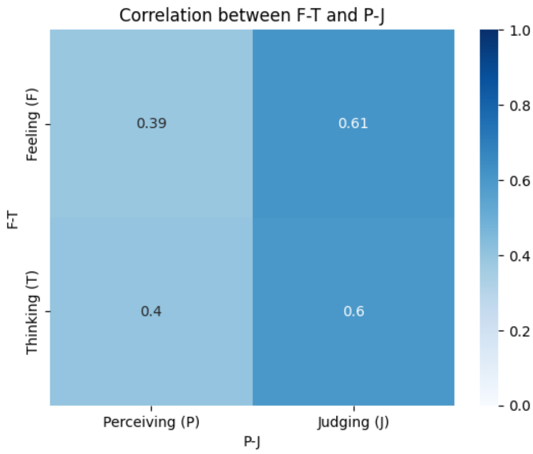

Figure 14

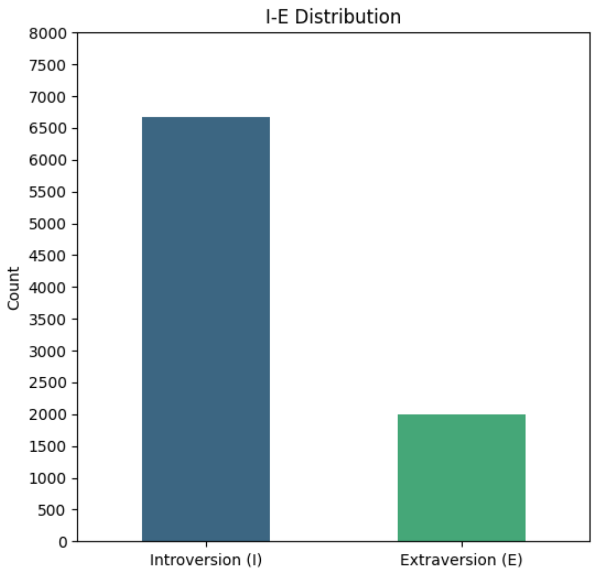

Figure 15: I-E

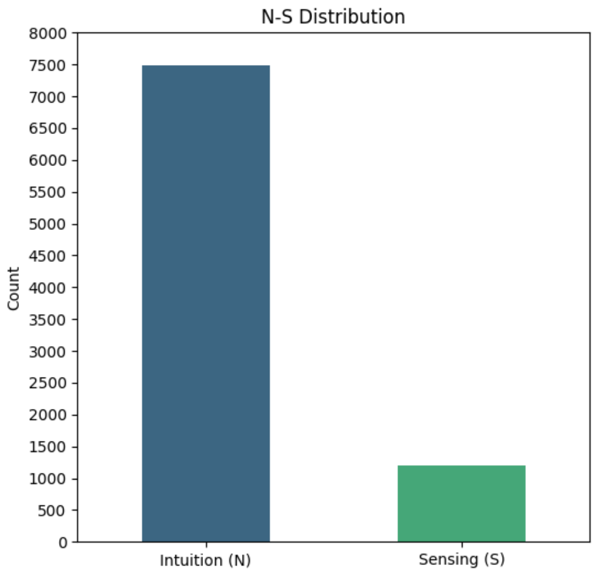

Figure 16: N-S

mask and a comfort zone, where people feel less exposed to judgment compared to face-to-face interactions. This sense of privacy and anonymity is a characteristic unique to the digital realm, which is not as readily attainable in the physical world. A similar argument applies to the prevalence of intuition traits, as frequent online participation in data collection processes tends to diminish sensing abilities. The high-speed data consumption patterns on social media platforms can erode our attention spans and, consequently, reduce our sensing abilities—a phenomenon that broadly applies to internet users.

To address these dataset biases in our modeling and prediction efforts, we have employed a specialized metric known as the F1-score. This metric is particularly valuable for validating models in scenarios marked by dataset bias, as is evident in our case.

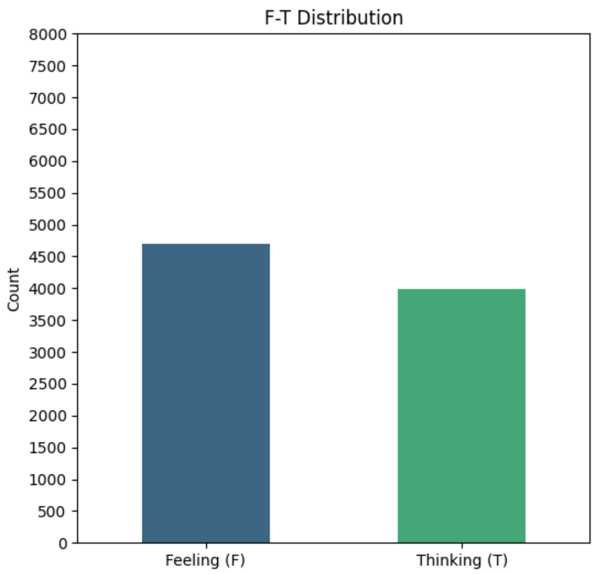

Figure 17: F-T

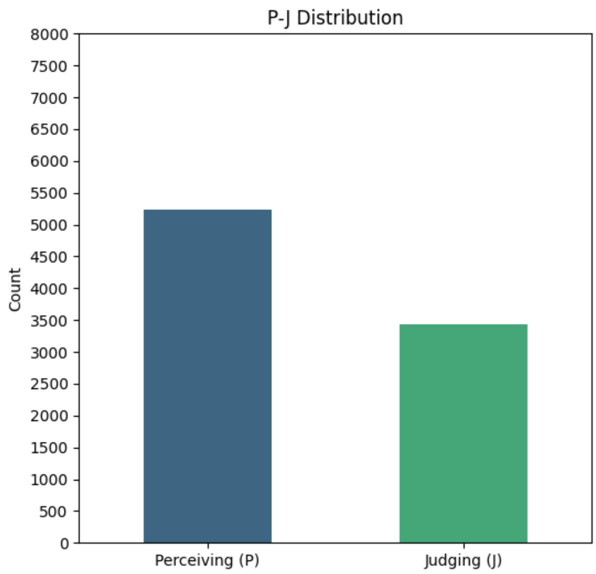

Figure 18: P-J

4 Methods

4.1 Models

Machine learning is a subset of artificial intelligence that focuses on developing algorithms and models that enable computers to learn and make predictions or decisions from data without being explicitly programmed. It is inspired by how humans and animals learn from experience, which is why it has strong connections to cognitive science. In cognitive science, machine learning techniques are often used to model and simulate human learning and decision-making processes. Two common machine learning algorithms used in cognitive science:

1. Support Vector Machine: SVM is a supervised learning algorithm used for classification and regression tasks. It's based on the idea of finding a hyperplane that best separates data points into different classes or predicts a continuous outcome. In cognitive science, SVM can be used to model human decision-making and categorization processes.

2. Logistic Regression: LR is a supervised learning technique used to model the relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the variables. In cognitive science, linear regression is often used to analyze and predict cognitive performance based on various input factors.

In the interest of clarity and ease of understanding, we have omitted detailed mathematical explanations and derivations.

4.2 Metrics

In the realm of machine learning, the evaluation of models and theories often relies upon metrics. Two key metrics utilized for this purpose are accuracy and the F1 score.

1. Accuracy measures the proportion of correctly predicted instances out of all instances in the dataset. Mathematically, accuracy is calculated as:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

2. The F1 score is a metric that balances precision and recall, making it particularly useful when you need to consider both false positives and false negatives in your classification problem. Precision measures the percentage of true positive predictions out of all positive predictions, and recall (sensitivity) measures the percentage of true positives out of all actual positives.

$$\text{F1-score} = \frac{\text{2*Precision*Recall}}{\text{Precision + Recall}}$$

5 Results

We conducted experiments (1) using multiple machine learning models and have shared the outcomes of the top-performing ones, namely Logistic Regression and Support Vector Machine. These models consistently delivered an average accuracy of 75.75%, a performance level comparable to the existing benchmark for this dataset.

It's worth noting that further enhancements can be achieved through advanced techniques such as ensembling. The MBTI test lays a robust groundwork for developing personalized app workflows and educational programs tailored to individual personalities.

6 Discussion

In our project, we're basically working on the idea that the way we talk can give insights into our personality. By analyzing how people use language, we aim to predict personality traits and behaviors. This idea isn't new; many psychologists also believe that how we talk is linked to our personality.

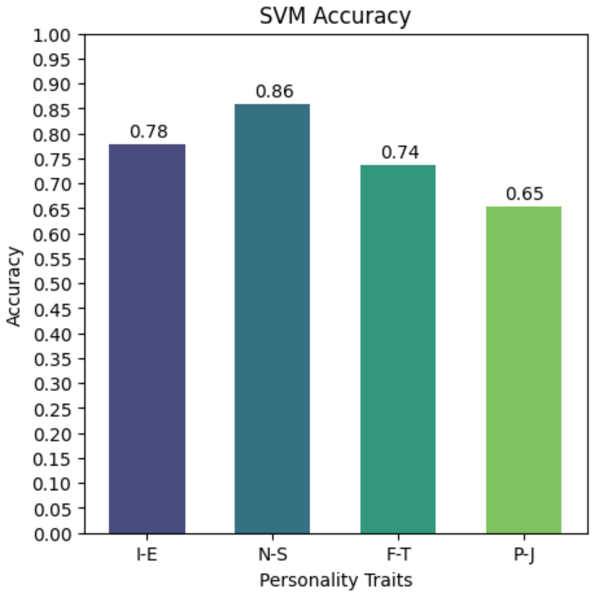

Figure 19: SVM Accuracy

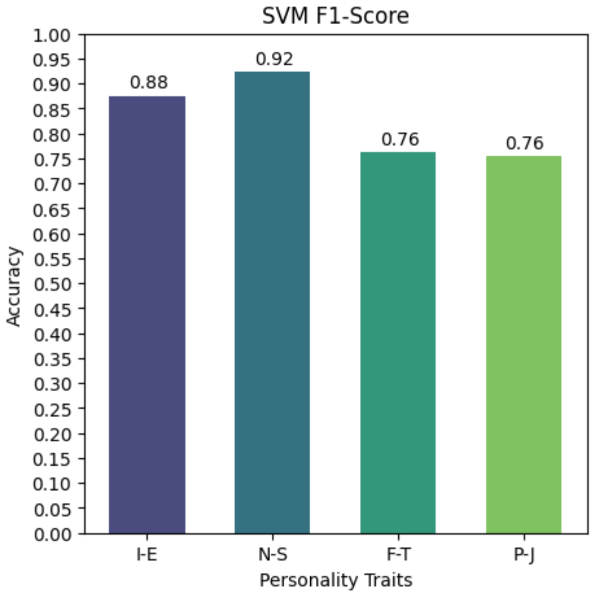

Figure 20: SVM F1

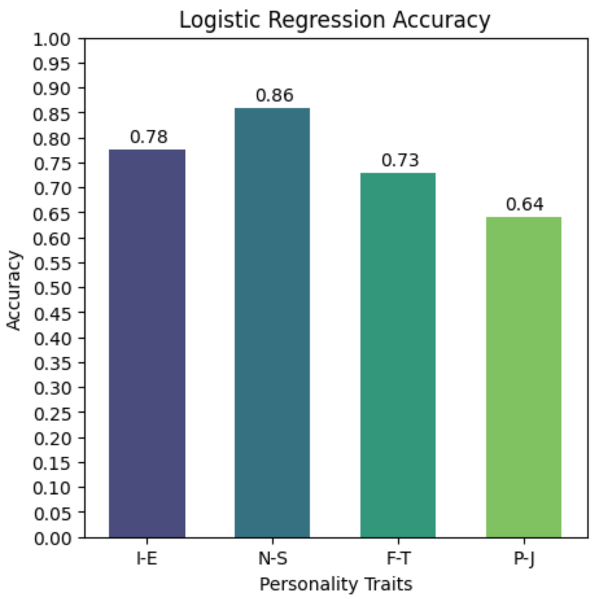

Figure 21: LR Accuracy

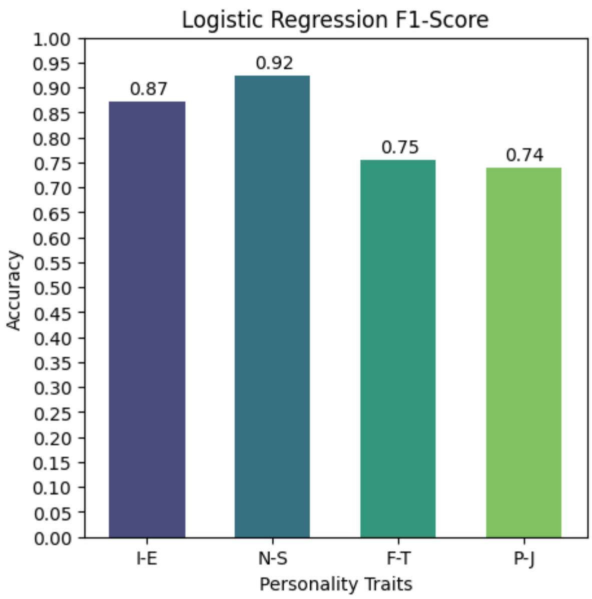

Figure 22: LR F1

What's interesting is that personality tests like MBTI can do more than categorize people. They can help identify groups of individuals who might be at risk for things like depression, ADHD, OCD, and other mental health conditions. They also hold the potential to personalize learning methods, showing how different personality traits impact how we handle emotions and other aspects of how our brains work.

Building models to predict MBTI personality types can really make a difference in the world of cognitive science, addressing some of these complex aspects of human behavior and psychology.

6.1 Procedure

Our model operates by taking user comments or sentences as input, depending on the context, and endeavors to predict personality traits within the MBTI framework. To prepare the text data for analysis, we undertake a series of preprocessing steps.

Firstly, we eliminate common stop words from the comments. Stop words are typically conjunctions, prepositions, and other words that are essential for the structure of sentences but often carry little information about personality traits. Additionally, we remove any numerical values and special characters present in the text to ensure that the focus is on textual content rather than extraneous symbols. Next, we apply lemmatization to the words, a process that reduces them to their base forms. This step aids in standardizing and simplifying the vocabulary for analysis.

For the conversion of words into numerical representations, we employ both the count vectorization method and the TF-IDF (Term Frequency-Inverse Document Frequency) transformation. Subsequently, we proceed with the training and testing of our predictive models, culminating in the calculation of results to assess the model's efficacy in predicting personality traits.

6.2 Limitations

The MBTI system acknowledges that people can adjust their behavior and preferences based on the situation. For example, someone who tends to be more introverted might appear more extroverted in specific circumstances. This adaptability is a valuable trait, particularly in social and professional settings. However, it does present a challenge for our models.

Our dataset was collected by third parties on Kaggle, and it's not straightforward to verify the data collection process. Nonetheless, given the challenges, we've opted for a practical compromise by focusing on developing innovative methods for personality prediction.

We ventured into using advanced deep-learning techniques for predictions, which seemed like a step in the right direction. However, we encountered an obstacle when it came to converting sentences into numerical values or vectors suitable for neural networks. Transformers didn't quite do the trick, and the resulting feature vectors didn't exhibit strong associations with personality traits, leading to reduced predictive accuracy.

References

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[2] Mitchell J, K. (mbti) myers-briggs personality type dataset, 2020. https://www.kaggle.com/datasets/datasnaek/mbti-type.