Unraveling MBTI Types from Online Posts

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Introduction

Understanding human personality traits is crucial for applications like personalized content recommendation. The Myers-Briggs Type Indicator (MBTI) classifies people into one of 16 personality types based on four binary attributes. Our algorithm analyzes individual online forum posts, using Naive Bayes and GPT-4 models to predict the person's overall MBTI type. We also use Neural Networks to predict each of the four MBTI attributes of the individual.

Data Preprocessing

- 1. Data cleaning: remove irrelevant characters (e.g., punctuation), eliminate stopwords (common words lacking meaningful context), lemmatization (simplifies words to their base form), and Synthetic Minority Over-sampling Technique a.k.a. SMOTE (creates synthetic instances of the minority class).
- 2. Feature Extraction:
 - TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical measure used to evaluate the importance of a word within a document relative to a corpus, resulting in a sparse vector representation of documents that emphasizes unique terms.

$$\mathsf{TF}(t,d) = \frac{\mathsf{Number\ of\ times\ term\ } t \ \mathsf{appears\ in\ document\ } d}{\mathsf{Total\ number\ of\ terms\ in\ document\ } d}$$

$$\mathsf{IDF}(t,D) = \log\left(\frac{\mathsf{Total\ number\ of\ documents\ }D}{\mathsf{Number\ of\ documents\ containing\ term\ }t+1}\right) + 1$$

$$\mathsf{TF}\text{-}\mathsf{IDF}(t,d,D) = \mathsf{TF}(t,d) \times \mathsf{IDF}(t,D)$$

• Word2Vec is a technique that leverages neural networks to map words into a high-dimensional vector space. It learns embeddings that cluster similar words together in this space, enabling the capture of complex word relationships and similarities.

Models

• Naive Bayes: Assumes all features are independent of each other within each class, simplifying calculations.

$$P(\mathsf{MBTI}_k|\mathbf{x}) = \frac{P(\mathsf{MBTI}_k)P(\mathbf{x}|\mathsf{MBTI}_k)}{P(\mathbf{x})}$$

$$P(\mathbf{x}|\mathsf{MBTI}_k) = \prod_{i=1}^n P(x_i|\mathsf{MBTI}_k)$$

$$P(x_i|\mathsf{MBTI}_k) = \frac{\mathsf{Number\ of\ times\ } x_i \ \mathsf{appears\ in\ MBTI}_k + \alpha}{\mathsf{Total\ number\ of\ words\ in\ MBTI}_k + \alpha \times D}$$

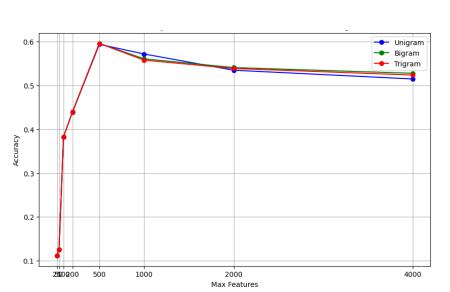
- Neural Networks: Tested various models including SimpleRNN, LSTM with Bidirectional LSTM, LSTM with Conv1D, and Conv1D alone
- **GPT**: Large Language Models (LLMs) like GPT use Transformer architecture for text generation, learning from vast text corpora through pretraining and fine-tuning for specific tasks. They employ self-attention to understand context and generate coherent text.

Results

- **GPT-4**: Experiment was conducted on $15 \times 16 = 240$ data points, with 15 data points for each personality type. Achieved accuracy **71%** in correctly predicting all 4 attributes and **88%** in predicting 3 correct attributes.
- Neural Networks:

MBTI Dichotomy	Best Threshold	Accuracy	ROC-AUC Score	G-Mean Score	F1-Score (avg/total
Extrovert vs Introvert	0.93	0.7804	0.68	0.51	0.72
Intuition vs Sensing	0.33	0.8599	0.69	0.39	0.80
Thinking vs Feeling	0.59	0.7925	0.87	0.79	0.79
Judging vs Perceiving	0.68	0.6594	0.68	0.61	0.64

Naive Bayes



Discussion

- Despite higher test set accuracy with LSTM (65%) compared to our primary model (59%), their ROC-AUC scores around 0.5 for each MBTI dichotomy suggest these architectures may not effectively generalize, and highlighting the necessity of using diverse metrics to evaluate true model performance.
- Naive Bayes is a simple yet effective classification method, typically bounded by a maximum achievable accuracy

Future Work

- Refine Preprocessing & Sentiment Analysis: Enhance text preprocessing to include sentiment analysis for capturing language nuances related to MBTI types.
- Tackle LSTM Overfitting: Explore novel regularization techniques and model adjustments
- Fine-tuning GPT to see what is the maximum achievable accuracy by an LLM for this task