Political Party Text Classification with Tweets*

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***Abstract*—Social media has evolved into a space where American politicians can engage with the public, sometimes promoting division. This study examines whether there is a difference in rhetoric between people commenting on posts from Democrats versus Republicans. Using an open-source dataset from Hugging Face, which includes comments by citizens on the Facebook posts of the members of U.S. Congress from 2018, a Multi-Layer Perceptron with two hidden layers was employed to predict the party of the original post. The model achieved 86.2 % accuracy, surpassing the random-chance goal of 50 %, indicating differences in rhetoric based on engaging with a specific political party.**

I. Introduction

A. American Social Media Practices

The surge of social media in the past twenty years has unfortunately led to an age of misinformation. In 2024, 54 % of U.S. adults often or sometimes got their news from social media, including Facebook, Youtube, Instagram, TikTok, and X [1]. Facebook has immense influence on its users, with 48 % getting their information regularly from the platform in 2024 [1]. Information on social media has not been controlled at the federal level, as fervent constitutionalists declare restrictions on content violates the First Amendment. This increase of consumption from unchecked sources has led to much of the division we have seen today.

B. Project Goals

This study analyzes comments from various individuals on the posts of U.S. Congress members, to see if there is an identifiable difference in the way people engage with content from Republican versus Democrat politicians. The goal of this project is to create a model with over 50 % accuracy, surpassing random political party assignment. This would suggest evidence that the way individuals communicate leads to the divisiveness of American politics today.

C. Literature Review

Natural Language Processing (NLP) algorithms have been in use since the 1980s, but recent work emphasizes deep learning models for text classification. The paper "Efficient Estimation of Word Representation in Vector Space," introduces Word2Vec, a method for computing word embeddings utilizing continuous bag of words and skip-gram models which outperform older methods [2]. Convolutional Neural Networks (CNNs) which are typically used for image classification, also perform quite well on pre-trained embeddings, explored in the paper "Convolutional Neural Networks for Sentence Classification" [3]. CNNs extract local features from text data which are used as the layers of the multi-layer perceptron (MLP) and utilized as the final decision making for the classification. Although a bit out of the scope of this project "Attention Is All You Need" [4] and "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding" [5] discusses transformers to capture semantic structure. In conclusion, Word2Vec allows meaningful word embeddings to be created which are then processed through multi-layer perceptrons for text classification, with possible extensions of using CNNs to extract local features before MLPs are trained or transformers to capture semantic context.

II. Methods

A. Dataset Description

The dataset used for this study was open-sourced from Hugging Face. It was previously generated for the study "RtGender: A Corpus for Studying Differential Responses to Gender" [6] and refined by the study "Style Transfer Through Back-Translation" [7]. The dataset is a robust set of the top comments on American Congressmembers' posts with 140,000 rows, already preprocessed into training, evaluation, and testing datasets (with 80,000; 4,000; and 56,000 rows respectively), with an even split of comments from Democrat versus Republican politicians' posts. The main columns of interest were the processed text, the data split category, and political party affiliation. The average number of words per comment was 14 with a standard deviation of 9 words. Fig. 1 below shows the distribution of comment length. When stratified by political party, there was not a significant difference in comment length.

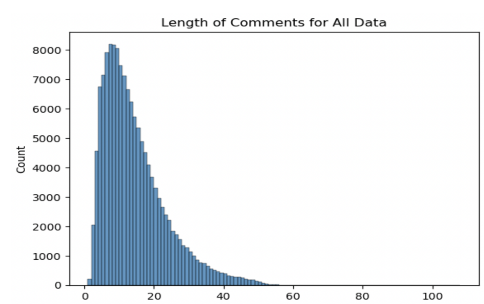

Fig. 1. Distribution of Comment Length.

B. Basic Model

The input for the model consisted of comment strings transformed into word embedding vectors, with the output being a binary classification of the post's party of origin (Republican or Democrat). Before the Multi-Layer Perceptron (MLP) became operational, text preprocessing involved tokenizing words and vectorizing them using Word2Vec, with a vector length of 100. The mean vector for each comment was computed, standardized, and turned into tensors. The data was already split into training, evaluation, and test sets. The basic MLP model (shown in Fig. 2) used the mean-pooled comment vector of length 100 as input and had three fully connected layers, including two linear hidden layers with ReLU activation (128 and 32 units respectively). Binary cross-entropy loss computed the class probabilities, and the Adam optimizer (learning rate 0.0001, batch size 128) was used for back propagation. The final classification used a sigmoid function, outputting a 0 for Republican posts and a 1 for Democrat posts.

III. Results

As stated above, the text data was tokenized, vectorized using Word2Vec, and pooled using the mean. The data was already split into train, evaluation, and testing splits from Hugging Face which was 57 %, 3 %, and 40 % of the data respectively. Cross validation was performed to find the optimal hyperparameters of how many units should be in each hidden layer, the batch size, and the learning rate, which were the hyperparameters used above. Fig. 3 below displays the confusion matrix, where 0 represents the classification of Republican and 1 represents Democrat.

The accuracy, precision, and recall (all applied to the test data set) are 86.2 %, 86.6 %, and 85.6 %. In Fig. 4 the ROC curve is displayed with an AUC of 0.94. These statistics show the model is highly accurate and has low Type I and II errors. These results exceeded the goal of the project which was an accuracy of 50 % which is equivalent to random label assignment.

Even using a simpler model, logistic regression, the accuracy was still 80 %, indicating that the MLP helped improve accuracy but only by 6 %. In a broader context, this might suggest that there is distinctly different rhetoric that people engaging with a certain political party use. This excellent performance may be due to the robust size of the data, as there were 80,000 rows to train on.

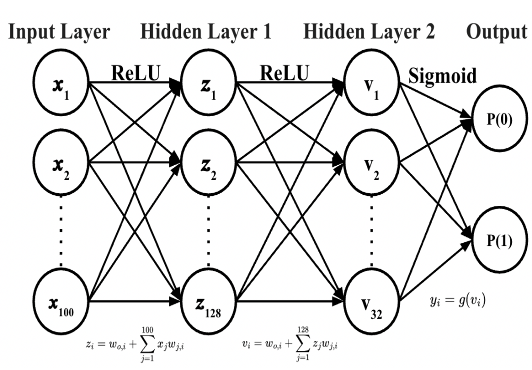

Fig. 2. Basic MLP Architecture.

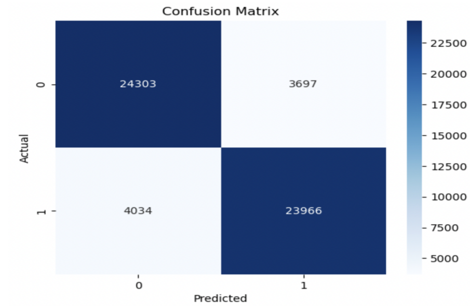

Fig. 3. Confusion Matrix on Test Data for MLP.

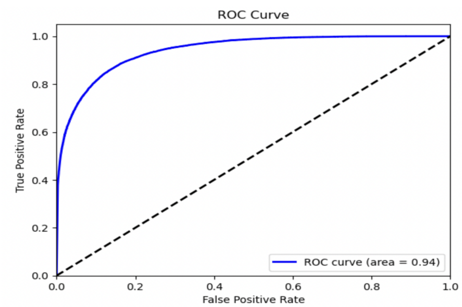

Fig. 4. ROC Curve for MLP.

IV. Conclusion

In this paper, comments from individuals on the posts of politicians were binary classified by the political party of the poster, using word embeddings from Word2Vec and a Multi-Layer Perceptron. This model was successful in its main goal of exceeding an accuracy of 50 % and demonstrates the political divisiveness in America through our rhetoric. Social media continues to be a major source of information for many people and the way we use it can lead to further disunion. With more time this research can be extended in the future by using different pooling methods, transformers, and word embedding lengths.

References

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