# DOGE's Downsizing, Can AI Read the Reddit Room?

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**Abstract**

We investigated public sentiment on Reddit regarding the Department of Government Efficiency's federal workforce reduction by classifying 400 labeled comments (28% favor, 18% neutral, 54% oppose) using supervised and unsupervised Large Language Models (LLMs). It turned out that supervised models showed low to moderate success, particularly with "oppose" comments, but struggled with "favor" and "neutral" stances. Similarly, LLMs best intent identified "oppose" sentiment but exhibited low precision for "favor" and "neutral." These findings highlight the challenges of accurately gauging nuanced public opinion on government policy changes through automated methods on social media data.

# 1 Introduction

The newly formed Department of Government Efficiency (DOGE) has reduced the federal workforce by almost 280,000 employees, a central pledge of the current administration. This action has generated significant apprehension among federal workers in regards to mental health and job security. To understand the impact of DOGE's actions on federal worker perceptions of job security, we labeled 400 Reddit comments on topics related to the current reduction in federal workforce by DOGE as whether the author favored, opposed, or had a neutral stance. We use these labels to build supervised learning models to predict stance. Additionally, we employ unsupervised large language models (LLMs) to detect the stance of these Reddit comments from text, to further explore appropriate models for this current topic.

# 2 Method

We collected a total of 12,553 Reddit comments in early March 2024 from subreddits relevant to the topic of interest. These comments were retrieved using keyword-based queries designed to capture posts of discussions that would reflect users' stances on the federal workforce reduction by DOGE. To prepare the data for analysis, a comprehensive preprocessing pipeline was conducted in Python 3. This process involved removing HTML tags and web-URLs, stripping special characters and tagging artifacts such as "@", and replacing emojis with textual descriptions. Also, it entailed eliminating punctuations and converting numerical values into their spelled-out forms. The text was standardized to lowercase, lemmatized using the SpaCy library, and further refined by removing stopwords per the Natural Language Toolkit (NLTK) lists. Spelling corrections were performed to improve textual coherence, while duplicate comments were identified and removed to maintain data integrity.

From this cleaned dataset, 400 unique comments without replacement were randomly sampled for manual annotation. Four graduate students independently coded and labeled each comment with one of three possible stances: favor, oppose, or neutral toward DOGE's approach to federal workforce reductions. As shown in Table 1, there were 28% favor, 18% neutral, and 54% oppose. These labeled comments were subsequently used for training and evaluating both supervised and unsupervised classification models.

Table 1: Distribution of Labeled Reddit Comment Data

| Stance | % |
|---|---|
| favor | 27.5% |
| neutral | 18.2% |
| oppose | 54.2% |

The feature set used in model training and evaluation consisted of two primary categories: metadata features and textual features. Metadata features included the Reddit comment's score, the subreddit in which it appeared in, and the search term that retrieved it. As the variables for score and upvotes were perfectly collinear in this dataset, only the score was retained. To ensure all values were non-negative, the score was adjusted by subtracting the dataset's minimum value from each score. The categorical variables, subreddit and search term, were numerically encoded using scikit-learn's label encoder.

Textual features were derived from each comment and represented using two distinct approaches: unigram term frequency and term frequency-inverse document frequency (TF-

IDF). The unigram used a bag-of-words model to represent each word as a feature based on its frequency in comment. The TF-IDF transformation built upon these raw counts by accounting for term importance across the corpus. For both unigram and TF-IDF methods, the total number of text-derived features was 2,102. Combined with the three metadata features, each dataset contained a total of 2,105 features. Two datasets were constructed for classification: one combining the metadata with unigram features, and another with metadata and TF-IDF features. Each dataset was divided into 80% training data and 20% test data. All supervised learning models were implemented using Python 3, with scikit-learn and XGBoost as the primary machine learning (ML) techniques. Classification was conducted using a diverse set of algorithms, including Extra Trees Classifier, Random Forest Classifier, Logistic Regression, Ridge Classifier, K-Nearest Neightbors (KNN), Nearest Centroid, Multi-layer Perceptron Classifier, Bernoulli Naive Bayes, Multino- mial Naive Bayes, Linear Support Vector Classifier, Decision Tree Classifier, Extra Tree Classifier, and the XGBoost Classifier.

All models were trained using default hyperparameter configurations. The number of neighbors for KNN model was set to three, and the mtry parameter for Random Forrest was fixed at two, reflecting the relatively small number of metadata features in those models. All experiments were conducted on a personal computer without the use of a GPU

In addition to traditional supervised models, we employed two instruction-tuned LLMs to perform zero- shot classification: Gemma 3.12B, developed by Google and based on the Gemini framework, and LLaMA 3.2B, developed by Meta AI. Gemma was deployed using the Great Lakes High-Performance Computing (HPC) cluster, while LLaMA was deployed locally on a GPU-enabled personal workstation using the rollama r-pacakge. These models were selected for their strong zero-shot classification capabilities and ability to be run locally or on cluster environments without reliance on commercial APIs. Both models were given the same prompt and tasks, which were developed by the research team to assess the effectiveness of classifying stance within our topic of interest (see Table 2).

Table 2. Example of Prompt and Task for LLMs

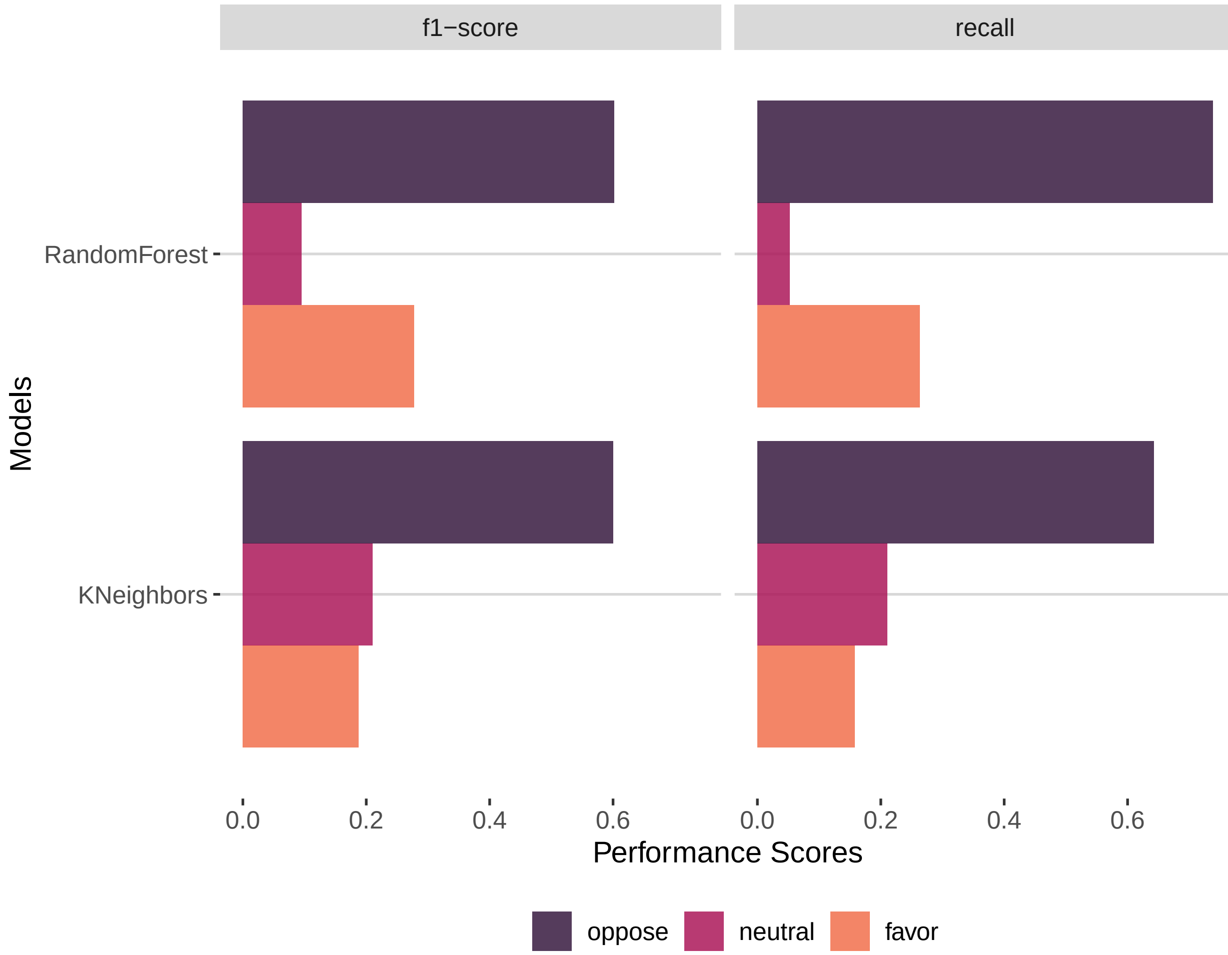
| | |
|---|---|
| **Prompt**: | "Is this comment in 'favor', 'neutral', or 'oppose' the reduction in federal workforce? Provide one word answer only! |
| **Task**: | "You have assumed the role of a stakeholder that is presented with a Reddit comment from a likely federal worker related to the current policies on reducing the federal workforce. Please determine the author's stance on this topic, and provide the answer only." |

The model performance was evaluated by the F1-score and recall. The F1-score, a harmonic mean of precision and recall, serves as a balanced indicator of a model's ability to correctly identify relevant instances while minimizing both false positives and false negatives. Recall was also independently assessed to evaluate the proportion of true positive cases accurately identified by each model. While a high recall may increase the risk of false positives, its combination with the F1-score allows a more robust evaluation of model performance, especially for addressing the challenges inherent in imbalanced classification tasks

# 3 Results

Our machine learning models revealed a mix of performance results in classifying the stance of Reddit comment into “favor”, “neutral”, and “oppose.” Both models exhibited low recall and F1-scores for the “favor” stance (see Figure 1), and the random forest model (recall .26: F1-score .28) slightly outperformed KNN (recall .16: F1-score .19). The “neutral” class presented a significant challenge for the random forest with very low scores (recall .05: F1-score .10), while KNN exhibited slightly better performance (recall .21: F1-score .21). Both models showed the strongest performance in identifying comments expressing opposition. The random forest correctly identified 74% of all the actual Reddit comments expressing opposition compared to KNN at 64%, suggesting that KNN missed a larger proportion of true “oppose” comments. Both models obtained similar F!- scores of 60%, suggesting that KNN may have slightly higher precision, given its lower recall compared to the random forest model. This implies that when KNN predicts comments for the “oppose” class, its accuracy is comparable to that of the random forest model.

Figure 1. Recall and Precision Scores for Random Forest and KNN Models




The LLMs, showed poor performance in classifying the "favor" stance, with very low F1-scores (Llama .07: Gemma .02) despite moderate recall (Llama .29: Gemma .33), indicating low precision (see Figure 2). For the "neutral" class, both models showed modest results, with Llama achieving a slightly better F1-score (.23) compared to Gemma (.18), although Gemma had a higher recall (Gemma .50: Llama .25), again suggesting lower precision for Gemma. Similar to the supervised models, both LLMs performed best in classifying the "oppose" stance, with relatively high and similar F1-scores (Llama .67: Gemma .70) and comparable recall (Llama .56: Gemma .56), suggesting a better balance between precision and recall for this category. Both models correctly identified

67% to 70% of all the actual Reddit comments expressing opposition. Overall, both LLMs struggled with the "favor" and "neutral" stance but demonstrated a stronger ability to identify opposing comments.

Figure 2. Recall and Precision Scores for LLMs


Gemma and Llama demonstrated only fair agreement in stance classification (Cohen's Kappa = .24). The contingency table ( see Table 3) reveals the highest agreement for "oppose" (.80), indicating some consistency in identifying a strong negative stance. However, agreement was substantially lower for "neutral" (.03) and "favor" (.01), highlighting the divergent interpretations of more nuanced language. The off-diagonal values further illustrates these discrepancies, suggesting the fundamental differences in how the models process ambiguous cues and establish classification boundaries, particularly for less extreme stances.

Table 3: Aggreement Between LLMs, Cohen's Kappa, 0.24

| | favor | neutral | oppose |
|---|---|---|---|
| favor | 3 | 1 | 10 |
| neutral | 0 | 10 | 49 |
| oppose | 0 | 5 | 317 |

# 4 Conclusion

Public sentiment on Reddit were explored in terms of the DOGE federal workforce reduction through supervised learning (KNN, Random Forest) and unsupervised LLMs ( Gemma 3.12b and Llama 3.2 3B) for stance classifications. Our supervised learning models overall achieved low to moderate success in this classification task, with the strongest performance in identifying opposing viewpoints, which were also the most prevalent in our labeled data. Moreover, both models struggled with the "favor" and "neutral" stances, suggesting limitations in our features to capture these nuances. Our unsupervised learning models also showed the best ability to classify "oppose" comments, yet exhibited significant challenges with the "favor" and "neutral" categories, particularly demonstrating low precision.

This study had limitations such as the small size of our labelled dataset of 400 Reddit comments, the imbalance in the stance categories, and few features in the supervised approach. The zero-shot capabilities of the LLMs are suitable for topic exploration but may require fine-tuning for optimal performance on this specific domain, particularly with nuance language used in "favor" stance. To deepen the understanding of federal worker perceptions and enhance stance classification, future research may further expand the labeled datasets and incorporate more contextual text, rather than relying on single comments. Fine tuning LLMs on a larger corpus with relevant comments could render more accuracy in the classification task.