Machine Learning-Based Sentiment Analysis of YouTube Comments

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Project Overview

- Examine toxicity of YouTube comments
- Clean the data by dropping spam, duplicates, different languages
- Label our data using ML
- Create a Visualization for the data

Data

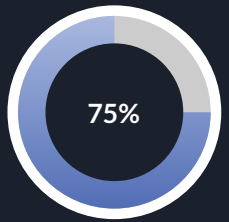
- 300 YouTube videos
- YouTube API (253,000 comments)
- ML Spam + Processing (189,000 comments)
- Labeling

- Dashboard (45% of data ~85,000 comments)
- ML Optimization (100 % of data)

kaggle

Spam Model Accuracy

- Feature extraction transforms raw text into numeric values that machine learning models can understand.
- Raw text cannot be used directly - it must be converted into numerical features.
- MultinomialNB is a Naive Bayes text classification algorithm well-suited for the task of YouTube comment spam detection.



Target

```
# Calculate the accuracy score of the model
print("Accuracy of Model",clf.score(X_test,y_test)*100,"%")
```

```
Accuracy of Model 91.67950693374422 %
```

Actual

RoBERTa Model Accuracy

The results of the research were conducted by comparing three models, such as (1) BERT; (2) Generalized Autoregressive Pretraining for Language Understanding (XL-Net) [40]; and (3) RoBERTa. This study shows that the result of RoBERTa has a higher accuracy than BERT, with an accuracy of 92.5%.[1]

RoBERTa Scores

RoBERTa provides percentage scores for sentiment, and we map the highest score to a categorical label to generate discrete negative, neutral or positive sentiment annotations.

```
example = "sugar with a little bit of coffee"
```

✓ 0.0s

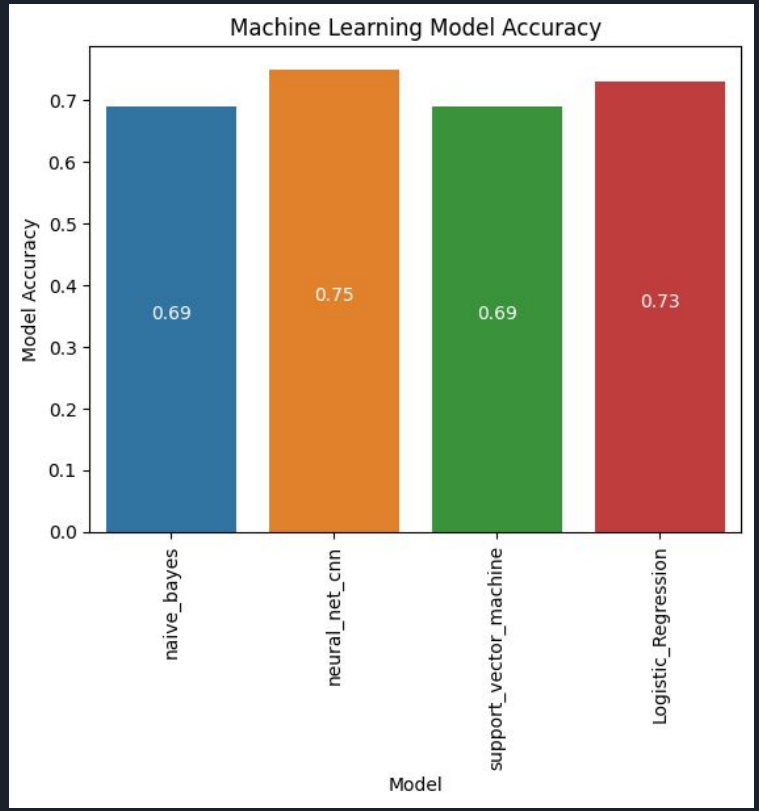
```
encoded_text = tokenizer(example, return_tensors= 'pt')
output = model(** encoded_text)
scores = output[0][0].detach().numpy()
scores = softmax(scores)
scores
scores_dict = {
    0: scores[0],
    1: scores[1],
    2: scores[2]
}

print(scores_dict)
```

✓ 0.0s

```
{0: 0.043299638, 1: 0.8685472, 2: 0.08815308}
```

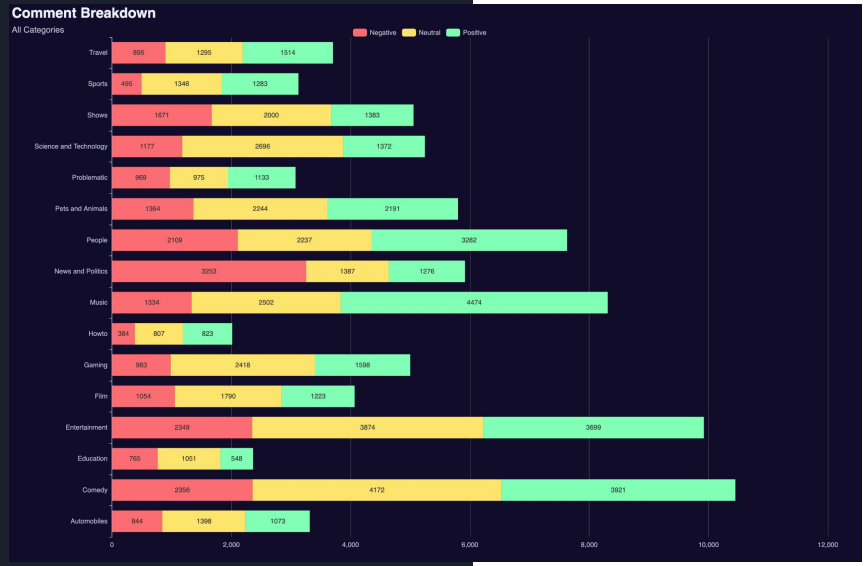
Data Model Optimization

- Testing the accuracy of our labels
- Used 100% of the cleaned, labeled dataset
- Ran 4 supervised learning models
  - MultinomialNB
  - Keras NN
  - SGD (labeled as SVM)
  - Logistic Regression



HTML and Tableau Dashboard Demos

The demo will highlight the visualizations on the dashboard, including some extra, bonus Tableau visualizations.



This bar chart visualization breaks down sentiment of YouTube comments across different video categories, with negative, neutral and positive sentiment.

Challenges

- Training the models to accurately label and filter our data- more time could be spent going through every model for further optimization.

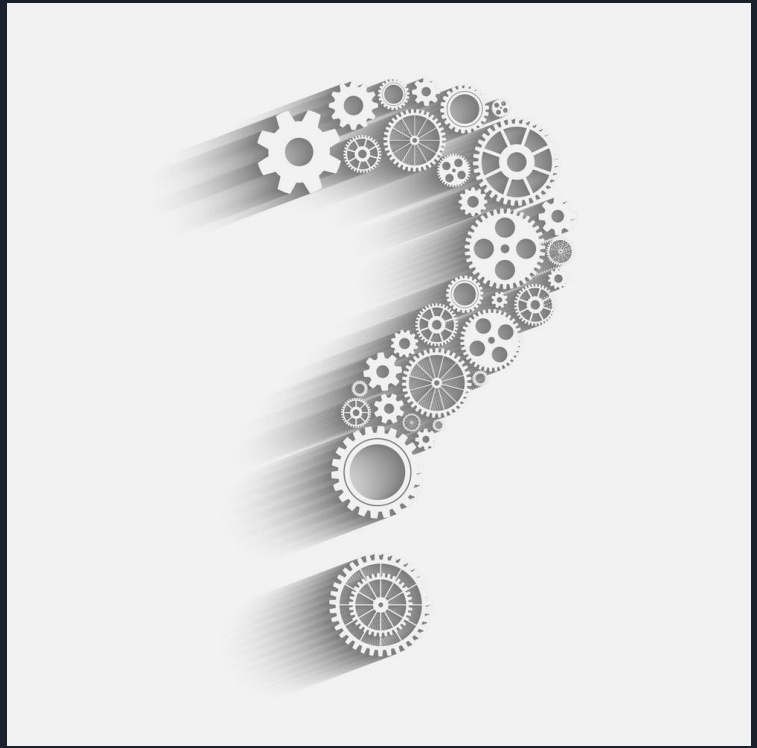
- We found that natural language processing and linguistic analysis was more complex than we expected so we shifted our goals for this project toward sentiment analysis.

Future Plans

- Create a tool that creators can use to further analyze their communities, and have a better understanding of negative comments for better moderation.

-Streamline the process, actively gather the comments and process them in a live format for active moderation.

QUESTIONS?



References

Naseer M, Windiatmaja JH, Asvial M, Sari RF. RoBERTaEns: Deep Bidirectional Encoder Ensemble Model for Fact Verification. Big Data and Cognitive Computing. 2022; 6(2):33. https://doi.org/10.3390/bdcc6020033