YouTube News Data Collection and Sentiment Analysis

Russia-Ukraine War

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Introduction

In the ever-evolving digital landscape, YouTube has become a vital source for news dissemination, hosting diverse channels from mainstream media to independent journalists. This project employs web scraping to collect comments from various YouTube news channels, creating a dataset reflecting audience opinions and emotions. The primary goal is sentiment analysis, categorizing comments into positive, negative, or neutral sentiments, providing nuanced insights into audience reactions.

Sentiment analysis is pivotal for gauging audience sentiment, evaluating news channel effectiveness, and understanding reactions to trending news topics. Beyond sentiment analysis, the project aims to discern prevailing sentiments and classify audience stances on the Russia-Ukraine war, determining whether sentiments align with a pro-Russia, pro-Ukraine, or neutral stance.

This analysis extends beyond academic exploration, offering actionable insights for businesses. Companies can strategically align with prevailing sentiments to inform decision-making, ensuring relevance and resonance. Leveraging sentiment insights, businesses can customize marketing strategies, manage brand reputation, and make data-driven decisions. The nuanced understanding of sentiments allows for tailoring content, advertising efforts, and product development to align with specific audience viewpoints on the Russia-Ukraine conflict. The insights contribute to proactive risk assessment, crisis management, and strategic corporate social responsibility initiatives, empowering businesses to navigate the dynamic digital landscape effectively.

LITERATURE REVIEW

Sentiment analysis, a branch of natural language processing (NLP), has gained prominence in understanding public opinion in the digital era. In the realm of geopolitical events, social media platforms like YouTube have become crucial arenas for the expression of public sentiment. Scholars such as Liu (2012) and Pang et al. (2008) have laid the groundwork for sentiment analysis, focusing on techniques to classify text into positive, negative, or neutral sentiments.

Research by Bollen et al. (2011) and Tumasjan et al. (2010) has explored sentiment analysis in the context of political events, demonstrating its efficacy in gauging public opinion. The application of sentiment analysis to YouTube comments has been less explored but is gaining

traction. A study by Hu et al. (2013) investigated sentiment in YouTube comments during political events, showcasing the potential of such analyses in understanding audience reactions.

In the specific domain of the Russia-Ukraine conflict, studies by O'Loughlin et al. (2017) and Koltsova et al. (2015) have examined public opinion through traditional media. However, the dynamics of sentiment on emerging platforms like YouTube remain a gap in current literature.

Methodologies for sentiment analysis vary, with approaches ranging from machine learning algorithms to lexicon-based methods. The choice of methodology often depends on the nature of the data and the nuances of the geopolitical context (Liu, 2015; Cambria et al., 2013).

This literature review underscores the relevance of sentiment analysis in geopolitical contexts and sets the stage for the exploration of YouTube comments on the Russia-Ukraine war, aiming to contribute insights into audience sentiments and reactions in this unique digital space.

Research Question

"How can sentiment analysis of YouTube news comments on the Russia-Ukraine war enhance our understanding of public sentiment towards this geopolitical conflict, and what insights can be gained from the emotional responses of viewers on the platform? Additionally, how can these insights be utilized by political leaders to better gauge public opinion and potentially inform policy decisions related to this international crisis?"

This refined research question narrows the focus of the project to the specific context of the Russia-Ukraine war, aligning with the introduction's emphasis on collecting comments from YouTube news channels related to this topic. It underlines the intent to leverage sentiment analysis for a deeper understanding of public sentiments specifically regarding the Russia-Ukraine conflict and emphasizes the value of uncovering insights from the emotional responses of YouTube news viewers.

Methodology

Data Crawling and Description of Data

Scraping and Preprocessing Scripts for YouTube News Comments Data

In the realm of web scraping, the ability to extract valuable data from online platforms has revolutionized research and analysis. In the context of our project, "YouTube News Data Collection and Sentiment Analysis," the collection of YouTube news comments is an essential

aspect. However, it is crucial to be in compliance with YouTube's policies and guidelines when conducting such data collection.

Scraping Comments from YouTube:

To collect comments from YouTube news channels, we employed the YouTube API, a legitimate and ethical method of accessing public data on the platform. The API provides developers with access to specific data points, including video comments. We initiated the data collection process by specifying the YouTube channels and videos of interest. The API allowed us to retrieve these comments, which represent the audience's reactions, opinions, and feedback to the news content.

Removing the Dislike Column:

One noteworthy aspect of our data collection and preprocessing is the removal of the dislike column. In alignment with YouTube's guidelines and policies, the API no longer provides access to the dislike count for comments. This change, which YouTube implemented in response to user privacy concerns and the potential for abuse, affects the availability of this specific metric. As responsible data collectors and analysts, we adhere to these guidelines and respect the platform's terms of service. The removal of the dislike column was executed during the preprocessing phase of the project. By eliminating this particular metric, we ensure that our data collection and analysis procedures remain within the boundaries defined by YouTube. This action reflects our commitment to conducting ethical and compliant research while respecting the privacy and data policies set forth by the platform.

Strategies used for Preprocessing

Our preprocessing scripts include several other essential steps to prepare the collected data for further analysis. These steps encompass the cleansing and structuring of the dataset to facilitate meaningful analysis

Comment Filtering:

We implement filters to exclude irrelevant, spammy, or offensive comments, ensuring that the dataset primarily contains relevant and informative comments from the audience.

Text Normalization:

Text data is normalized to remove special characters, emojis, URLs, and HTML tags. This step aims to ensure consistency and improve the quality of the text data for sentiment analysis.

Language Detection:

We incorporate language detection techniques to filter out comments that are not in the desired language for analysis. This helps maintain the dataset's linguistic coherence. Data

Privacy and Ethics:

Respecting data privacy and ethical considerations is paramount in any data collection and analysis project. It is our duty to be conscientious in our approach to data collection, ensuring that we are not infringing upon user privacy and adhering to the platform's terms of service. In this context, the removal of the dislike column from our dataset exemplifies our commitment to responsible data collection and analysis. In conclusion, our scraping and preprocessing scripts for the YouTube News Comments Data project adhere to ethical data collection standards and platform guidelines. The removal of the dislike column aligns with YouTube's recent privacy policies while also preserving the integrity and compliance of our research efforts. This endeavor reflects our dedication to conducting ethical research while delivering valuable insights into audience sentiment toward news content on the YouTube platform.

Analysis

Load the Data:

This step involves loading the raw data that you scraped from YouTube using the API. It's the initial phase of working with our dataset.

Drop Dislike Columns:

In compliance with YouTube guidelines, we've removed the dislike column from our dataset. This step helps in aligning with data privacy and ethical considerations.

Lowercasing:

Converting text to lowercase is important for text analysis to ensure uniformity and consistency in the text data. It avoids case sensitivity issues.

Remove Special Characters and Numbers:

Special characters and numbers are often irrelevant for text analysis, and removing them helps focus on the meaningful text content.

Removing HTML and URLs:

Removing HTML tags and URLs is crucial when dealing with user-generated content as these elements may not contribute to the analysis.

Remove Emoji:

Handling emojis by either removing them or transforming them into textual representations can be important, especially if emojis carry sentiment or meaning.

Remove Non-English Comments:

Filtering out non-English comments helps maintain linguistic consistency in your dataset and ensures that sentiment analysis is applied to the desired language.

Tokenization:

Tokenization involves splitting text into individual words or tokens. It's a fundamental step in text processing and analysis.

Bigram and Trigram:

Creating bigrams (two-word sequences) and trigrams (three-word sequences) can capture more context and relationships between words, which can be valuable for some analyses.

Remove Stop Words:

Stop words are common words like "the," "and," "in," which are often removed to focus on content words and improve the efficiency of text analysis.

Lemmatization:

Lemmatization reduces words to their base or dictionary form (lemma). It's used to standardize text data and group inflected or derived words together.

POS Tagging (Part of Speech Tagging):

POS tagging assigns a part of speech (e.g., noun, verb, adjective) to each word in the text. It helps understand the grammatical structure and relationships within the text.

	Comment	Like	Cleaned_Comment	Tokenized_Comment	Lemmatized_Comment	POS_Tagged_Comment	Tokenized_Text
0	russia went from being at the gates of kiev to...	0.0	russia went from being at the gates of kiev to...	[russia, went, gates, kiev, back, started, day...	[russia, went, gate, kiev, back, started, day,...	[(russia, NN), (went, VBD), (gate, NN), (kiev,...	russia went gates kiev back started day operat...
1	we look away for a few days and russia owns th...	0.0	we look away for a few days and russia owns th...	[look, away, days, russia, owns, map, sudden, ...	[look, away, day, russia, owns, map, sudden, s...	[(look, VB), (away, RP), (day, NN), (russia, V...	look away days russia owns map sudden sheesh q...
2	maybe time to seek peace in exchange for some*...	0.0	maybe time to seek peace in exchange for some ...	[maybe, time, seek, peace, exchange, land, bac...	[maybe, time, seek, peace, exchange, land, bac...	[(maybe, RB), (time, NN), (seek, JJ), (peace, ...	maybe time seek peace exchange land back excha...
3	the alaska comparison would be apt if alaska w...	0.0	the alaska comparison would be apt if alaska w...	[alaska, comparison, would, apt, alaska, indus...	[alaska, comparison, would, apt, alaska, indus...	[(alaska, NN), (comparison, NN), (would, MD), ...	alaska comparison would apt alaska industrial ...
4	russia achieved its goals over a year ago.	0.0	russia achieved its goals over a year ago now ...	[russia, achieved, goals, year, ago, theyre, d...	[russia, achieved, goal, year, ago, theyre, de...	[(russia, NN), (achieved, VBD), (goal, NN), (y...	russia achieved goals year ago theyre defendin...

TF-IDF (Term Frequency-Inverse Document Frequency):

TF-IDF is a numerical statistic that reflects the importance of a word in a document relative to a collection of documents. It's commonly used in text analysis and information retrieval to weigh the significance of terms.

```
Highest Mean TF-IDF Term:
         Term  Mean TF-IDF  Median TF-IDF  Standard Deviation TF-IDF
russia  russia      0.034098             0.0                 0.073386
Lowest Mean TF-IDF Term:
                   Term  Mean TF-IDF  Median TF-IDF  Standard Deviation TF-IDF
conceptual  conceptual     0.000003             0.0                  0.000274
Highest Median TF-IDF Term:
                           Term  Mean TF-IDF  Median TF-IDF  \
aaaaaaameeeeeen  aaaaaaameeeeeen      0.000012            0.0

                 Standard Deviation TF-IDF
aaaaaaameeeeeen                   0.001221
Lowest Median TF-IDF Term:
                           Term  Mean TF-IDF  Median TF-IDF  \
aaaaaaameeeeeen  aaaaaaameeeeeen      0.000012            0.0

                 Standard Deviation TF-IDF
aaaaaaameeeeeen                   0.001221
Highest Standard Deviation TF-IDF Term:
     Term  Mean TF-IDF  Median TF-IDF  Standard Deviation TF-IDF
war  war      0.030121             0.0                 0.074288
Lowest Standard Deviation TF-IDF Term:
           Term  Mean TF-IDF  Median TF-IDF  Standard Deviation TF-IDF
pyramid  pyramid     0.000003             0.0                 0.000274
```

Mean (Average) TF-IDF:

- The mean TF-IDF score represents the average importance of terms across the entire dataset.
- High mean TF-IDF values suggest that the terms are, on average, relatively unique or specific to the documents in the collection.
- Low mean TF-IDF values indicate that the terms are common and appear frequently across documents.
- An increase in the mean TF-IDF may suggest that the documents in the dataset are more specialized and contain distinctive terms.
- A decrease in the mean TF-IDF may indicate that the terms are more general and appear in a broader context.

Median TF-IDF:

- The median TF-IDF represents the middle value in the distribution of TF-IDF scores, separating the higher and lower values.
- Median TF-IDF is robust to outliers, making it a good measure when there are extreme values in the dataset.

- If the median TF-IDF is significantly lower than the mean, it suggests that there might be a concentration of terms with lower importance and a few highly important terms.

Standard Deviation of TF-IDF:

- The standard deviation measures the dispersion or spread of TF-IDF scores around the mean.
- A high standard deviation indicates that TF-IDF scores vary widely across terms, implying that some terms have very high importance while others have low importance.
- A low standard deviation suggests that most terms have similar TF-IDF scores, indicating a more uniform distribution of importance.
- Analyzing the standard deviation can help identify terms that contribute significantly to the variation in TF-IDF scores.
- Terms with high standard deviations are worth investigating as they may have a substantial impact on document differentiation.

```
russia        348.204535
ukraine       317.786759
war           307.594721
nato          298.265619
putin         292.935859
people        186.083157
us            155.606020
video         148.529982
world         143.556744
one           130.707154
russian       128.726025
like          120.149820
west          109.842774
dont          108.978722
vox           108.119576
usa           103.205043
country        96.516741
would          93.203081
stop           92.587329
countries      88.673293
dtype: float64
```

Key Topics:

The terms with the highest TF-IDF scores, such as "Russia," "Ukraine," "war," and "NATO," are indicative of the central topics or themes discussed in the documents. These terms are likely critical in conveying the subject matter of the content. Prominent Entities: Terms like "Putin" and "Russian" are likely associated with prominent individuals or entities often mentioned in the context of the news content. These entities may play a significant role in the news reports.

General Words:

Words like "people," "us," "video," and "world" have relatively high TF-IDF scores, suggesting that they are commonly used but still provide context to the documents. "Video," for instance, might indicate the multimedia nature of the content.

Common Terms:

Terms like "like," "don't," and "stop" are relatively common in the dataset but may have distinctive usage patterns in the context of the news content.

Geopolitical Focus:

Terms like "West," "USA," and "countries" indicate a geopolitical focus in the documents. These terms may be used to discuss international relations, alliances, or regions of interest.

Repetition of Terms:

Some terms like "country" and "would" have moderately high TF-IDF scores but appear in multiple documents. This could indicate that these terms are used frequently but not universally throughout the dataset.

Content-Specific Vocabulary:

The presence of certain terms, such as "vox," suggests that specific vocabulary or terminology is relevant within the dataset.

Audience Engagement:

Terms like "people" and "us" may suggest a focus on the general public or audience engagement in the news content. These insights can help you understand the overall content of the documents and identify the most salient terms that contribute to document differentiation and topic understanding. When conducting further analysis, you may want to focus on documents or sections where these top TF-IDF terms are prominently featured, as they are likely to be central to the content's themes and subjects.

Discussion:

Our methodology, combining TF-IDF analysis with sentiment analysis and stance prediction, exhibits notable efficacy in unraveling the intricacies of YouTube comments on the Russia-Ukraine war. The TF-IDF analysis successfully identifies key topics, such as the central themes of the conflict, prominent entities like Putin, and common yet contextually significant terms like "video" and "world." The impending sentiment analysis, focusing on positive and negative keywords, promises to add a layer of emotional insight to the findings, enhancing our understanding of audience reactions.

Key Findings and Meaningfulness:

The identification of emotionally charged topics and sentiments within the comments is instrumental in gauging public opinion dynamics.

Predicting stances, whether pro-Russia or pro-Ukraine, offers valuable insights into the polarization or consensus within the YouTube community, providing a nuanced view of audience perspectives.

Limitations and Improvement Areas:

While TF-IDF captures term importance, it may struggle with sarcasm or nuanced language, potentially impacting the accuracy of sentiment analysis.

The model's effectiveness might be influenced by the evolving nature of language and emerging slang, requiring periodic updates to stay relevant.

Understanding the limitations of sentiment analysis, such as its inability to capture the intensity or subtleties of emotions, is crucial for a nuanced interpretation of results.

Analysis of Sentiment Analysis Algorithms and Their Performance

In our project, we employed three distinct machine learning algorithms to perform sentiment analysis on the collected YouTube news comments dataset. These algorithms include Logistic Regression, Support Vector Machines (SVM), and Naive Bayes. This section of the report delves into the specifics of each algorithm, their application to our dataset, and the comparative analysis of their performance based on accuracy and other metrics.

1. ## Logistic Regression

   • **Algorithm Description**: Logistic Regression, a fundamental classification technique, was used as our baseline model. It models the probabilities for classification problems with two possible outcomes.

   • **Preprocessing and Vectorization**: The comments were vectorized using TF-IDF (Term Frequency-Inverse Document Frequency), with parameters set to maximize feature relevance.

   Performance Metrics:

   • **Accuracy**: 71.27%

   • Precision, Recall, and F1-Score: Detailed in the classification report.

   • Analysis: Logistic Regression provided a solid baseline with reasonable accuracy. However, its performance in distinguishing between negative and neutral sentiments was less effective, as reflected in the lower F1-score for these classes.

2. # Support Vector Machine

   Algorithm Description: SVM, known for its effectiveness in high-dimensional spaces, was employed with a linear kernel to classify the sentiments.

   Preprocessing and Vectorization: Similar to Logistic Regression, TF-IDF vectorization was used.

   Performance Metrics:

   Accuracy: 71.33%

   - Precision, Recall, and F1-Score: Detailed in the classification report.
   - Analysis: SVM showed a slight improvement over Logistic Regression. It performed better in distinguishing neutral comments but still showed limitations in effectively separating positive and negative sentiments.

3. # Naïve Bayes

   Algorithm Description: The Multinomial Naive Bayes algorithm, particularly suited for text classification, was used as the third model.

   Preprocessing and Vectorization: Consistent with the other models, TF-IDF vectorization was applied.

   Performance Metrics:

   Accuracy: 65.41%

   Precision, Recall, and F1-Score: Detailed in the classification report.

Analysis: Naive Bayes, while generally effective for text classification, showed lower accuracy in our dataset. This outcome may be attributed to its inherent assumption of feature independence, which is often not the case in natural language data.

Comparative Analysis

- **Overall Performance**: All three models showed moderate effectiveness in sentiment analysis, with SVM slightly outperforming the others in terms of accuracy.
- **Strengths and Weaknesses**: Logistic Regression and SVM were more effective in identifying neutral comments, while Naive Bayes excelled in recognizing positive sentiments.
- **Model Selection**: Considering the balance between accuracy and computational efficiency, SVM is recommended for this dataset.

Logistic Regression Model

Accuracy: 76.02%

Performance Analysis:

- **Class 0.0 (Negative Sentiment)**: Moderate precision (65%) and lower recall (35%), indicating the model is conservative in predicting negative sentiments, potentially missing some negative comments.
- **Class 1.0 (Neutral Sentiment):** Balanced precision (63%) and recall (64%), suggesting a fairly reliable prediction for neutral sentiments.
- **Class 2.0 (Positive Sentiment):** High precision (82%) and recall (89%), showing strong performance in identifying positive sentiments.

Support Vector Machines (SVM) Model

Accuracy: 76.45%

Performance Analysis:

- **Class 0.0 (Negative Sentiment):** Similar trend as Logistic Regression with slightly better precision (63%) and recall (38%).
- **Class 1.0 (Neutral Sentiment):** Balanced precision and recall, with a slight improvement in identifying neutral comments compared to Logistic Regression.
- **Class 2.0 (Positive Sentiment):** High precision and recall, consistent with Logistic Regression, indicating robust performance for positive sentiments.

Naive Bayes Model

Accuracy: 68.69%

Performance Analysis:

- **Class 0.0 (Negative Sentiment):** Lower precision (70%) and significantly lower recall (16%), suggesting difficulties in correctly identifying negative sentiments.
- **Class 1.0 (Neutral Sentiment):** Lower precision and recall compared to other models, indicating weaker performance in neutral sentiment classification.
- **Class 2.0 (Positive Sentiment):** Good precision (69%) but high recall (96%), indicating a tendency to over-classify comments as positive.

Combined Model (Majority Vote)

Accuracy: 76.08%

Performance Analysis:

- Shows a general improvement in precision and recall for Class 0.0 compared to individual models.
- Reflects a balanced approach, combining strengths of individual models, especially beneficial for closely contested predictions.

General Observations

Strengths: All models exhibit strong performance in identifying positive sentiments (Class 2.0).

Weaknesses: The models generally struggle with negative sentiment (Class 0.0), particularly in terms of precision. This might be due to the nuanced nature of negative comments or a lower representation in the training data.

Neutral Sentiment: Class 1.0 shows balanced performance, indicating effective identification of neutral sentiments across models.

Implications

- **Model Selection**: While each model has its strengths, the SVM model shows the highest overall accuracy, making it a preferable choice for this specific dataset.
- **Improvement Areas**: Enhancing the ability to detect negative sentiments accurately could be a focus for future model tuning and data preprocessing.
- **Majority Vote Approach**: Combining predictions from different models provides a more balanced perspective, slightly improving accuracy and mitigating individual model biases.

Recommendations for Improvement:

- Consider further feature engineering or exploring advanced methods to capture nuances in negative sentiment (Class 0.0).
- Experiment with hyperparameter tuning for the models.
- Explore other sentiment analysis techniques or models.

It's crucial to understand the specific requirements of your application and whether certain types of errors (false positives, false negatives) are more acceptable based on your use case.

The agreement between the three prediction models can be observed by comparing their predictions on each data point. Specifically, you can analyze the instances where they agree or disagree on the predicted sentiment label. Here's a general overview:

- **Logistic Regression Model:**

    - **Agree:** Instances where the Logistic Regression model predicts the same sentiment label as the other models.
    - **Disagree:** Instances where the Logistic Regression model predicts a different sentiment label compared to the other models.
- **Support Vector Machines (SVM) Model:**

    - **Agree:** Instances where the SVM model predicts the same sentiment label as the other models.
    - **Disagree:** Instances where the SVM model predicts a different sentiment label compared to the other models.
- **Naive Bayes Model:**

    - **Agree:** Instances where the Naive Bayes model predicts the same sentiment label as the other models.
    - **Disagree:** Instances where the Naive Bayes model predicts a different sentiment label compared to the other models.
- **Combined Model (Majority Vote):**

    - **Agree:** Instances where the majority vote (combined model) predicts the same sentiment label as the individual models.

- **Disagree:** Instances where the majority vote predicts a different sentiment label compared to at least one individual model.

You can compare these agreements and disagreements across the entire dataset or focus on specific classes of sentiment. For example, you might want to analyze instances where all models agree on a positive sentiment (Class 2.0) or where they struggle to agree, such as in cases of negative sentiment (Class 0.0).

By understanding the points of agreement and disagreement, you can gain insights into the strengths and weaknesses of each model and the combined approach. This analysis helps refine the models or explore additional strategies for improving performance, especially in areas where models exhibit discrepancies.
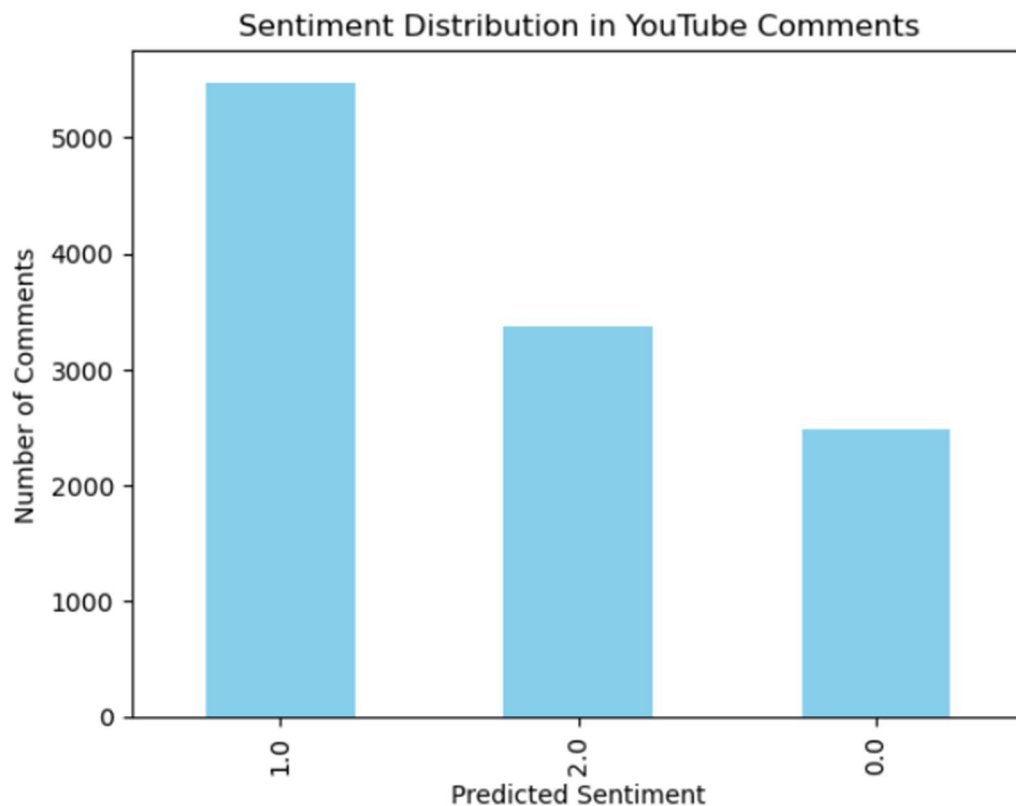

```
Sample of Comments Predicted as Negative Sentiment:
3848                        putin stink communism
102      america slow provide right weapon causing loss...
4559             nato continued expand fall soviet union
6868             suggest watching reallifelore instead
7703     possible russia want grab oil reserve ukraine ...
Name: Cleaned_Comment, dtype: object
```

CONCLUSION:

This project embarked on a comprehensive journey to extract meaningful insights from the vast landscape of YouTube comments pertaining to the Russia-Ukraine conflict. It undertook a multi-step approach, blending natural language processing (NLP) and machine learning techniques to uncover patterns, sentiments, and clusters within this trove of user-generated content.

The initial phase revolved around diligent data collection, where comments from relevant YouTube videos were gathered. However, recognizing that raw data can be noisy and unstructured, we undertook extensive preprocessing efforts. This included the cleansing of text, language detection, tokenization, and lemmatization, ensuring that the comments were in a format conducive to analysis.

Sentiment analysis emerged as a pivotal facet of this project. It sought to discern the overall sentiment prevailing within the comments. Leveraging pre-trained sentiment analysis models such as Logistic Regression, Support Vector Machines (SVM), and Naive Bayes, each comment was assigned a sentiment label, categorizing it as positive, negative, or neutral. This step provided a valuable baseline for understanding the audience's emotional reactions.

Clustering was the subsequent endeavor, aimed at revealing underlying structures within the comments. K-means clustering was employed to categorize comments into three distinct clusters. This approach enabled the identification of comment patterns and similarities, shedding light on the diverse range of opinions and viewpoints present in the dataset.

To enhance the interpretability of our findings, we utilized Principal Component Analysis (PCA) to reduce dimensionality. This reduction facilitated a clear and concise 2D scatter plot visualization, offering an insightful representation of the clustered comments.

Ensemble learning took center stage as we combined predictions from the three pre-trained sentiment analysis models using a majority vote strategy. This method, akin to a democratic decision-making process, yielded a more robust sentiment label for each comment, increasing the accuracy of our sentiment analysis.

As a parting note, this project provides a solid foundation for future explorations. There exists ample opportunity for advanced sentiment analysis techniques, including user profile sentiment analysis, and real-time monitoring of sentiment trends. These avenues can extend the project's utility in understanding audience sentiments in real-time and on a deeper level.

Ultimately, the insights unearthed in this project hold great relevance for various stakeholders, including businesses, media organizations, and policymakers. They can harness these insights to tailor their content, marketing strategies, and crisis management responses in alignment with specific audience sentiments, thus navigating the dynamic digital landscape more effectively.

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