**MINI PROJECT REPORT**

**TOPIC : Exploring the political pulse of a country using data science**

**TEAM DETAILS**

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**Abstract :**

. This paper showcases the application of Data Science methodologies in analyzing intricate human communication, focusing on tweets by political party leaders as a dynamic representation of political agendas and ideologies. Investigating the temporal evolution of tweet content in response to specific events, we examine sentiment levels using adapted tools for social media analysis. Additionally, we employ a Fully-Connected Neural Network (FCNN) to classify the political affiliation and leaning (left or right) of tweets. Results indicate the FCNN's ability to predict tweet origin with 71–75% precision and political leaning with around 90% precision. This study serves as a demonstration of utilizing Twitter data and diverse Data Science tools for political analysis, offering insights into politics, sentiment analysis, and the application of Artificial Intelligence, Machine Learning, and Natural Language Processing (NLP). Keywords: Politics, Spain, Sentiment analysis, Artificial Intelligence, Machine learning, Neural networks, Natural Language Processing (NLP).

**Keywords:**

1. Political

2. Pulse

3. Country

4. Data Science

5. Exploration

6. Analysis

7. Tools

8. Insights

**Introduction:**

The exploration of a country's political pulse through data science tools represents a significant endeavor in understanding the dynamics of political landscapes in the contemporary era. This introduction sets the stage by providing background information, discussing existing solutions, addressing their limitations, proposing a methodology, and evaluating its efficacy in capturing the essence of political discourse.

**Background of the Project:**

The political landscape of Spain, particularly since the advent of democracy in 1975, has been dominated by two major parties, PP (People's Party) and PSOE (Spanish Socialist Workers Party). However, significant socio-economic events, such as the 2012 financial crisis, led to a paradigm shift, marked by rising unemployment, austerity measures, and a surge in anti-establishment sentiments. This shift manifested in the emergence of new political movements, including far-left Podemos, far-right Vox, and the centrist Ciudadanos, alongside heightened regional tensions.

**Available Solutions:**

Traditional approaches to political analysis relied on official party manifestos to understand ideologies. However, the emergence of social media platforms like Twitter provides an unprecedented opportunity to gauge the emotional state and ideological leanings of political parties in real-time. Computational social science, fueled by advancements in machine learning and access to vast datasets, offers new avenues for political analysis beyond conventional methods.

**Limitations of Available Solutions:**

While official party manifestos offer insights into ideologies, they often lack real-time relevance and fail to capture evolving sentiments. Moreover, manual analysis of social media data is time-consuming and prone to biases. Existing sentiment analysis tools may not be tailored to the nuances of political discourse, leading to inaccurate assessments.

**Proposed Methodology:**

The proposed methodology leverages data science techniques to analyze Twitter data from political leaders as a proxy for party ideologies and emotional states. It encompasses a multi-faceted approach, including frequency analysis to identify ideological trends, sentiment analysis to gauge positivity and negativity, and predictive AI tools to identify party affiliations from individual tweets.

**Evaluation of Proposed Methodology:**

Initial findings suggest promising outcomes, with a Fully-Connected Neural Network (FCNN) achieving high precision rates in predicting tweet origins and political leanings. By utilizing new tools adapted to social media and machine learning algorithms, the proposed methodology demonstrates potential in capturing the evolving landscape of Spanish politics with greater accuracy and efficiency.

**Literature Survey: Exploring the Political Pulse of a Country using Data Science Tools**

**1. Introduction:**

In recent years, the advent of data science tools has revolutionized the study of political behavior and sentiment analysis. This literature survey aims to explore existing research related to analyzing the political pulse of a country using data science methodologies, particularly focusing on the utilization of social media data, sentiment analysis, and machine learning techniques

Literature Survey: Exploring the Political Pulse of a Country using Data Science Tools

Data science tools, particularly social media analysis, sentiment analysis, and machine learning, have reshaped political analysis. Tumasjan et al. (2010) and Jungherr et al. (2012) found Twitter data effective for predicting election outcomes and gauging public sentiment. Sentiment analysis, as demonstrated by Pak and Paroubek (2010) and Bollen et al. (2011), allows classification of political discourse into positive, negative, or neutral, with implications beyond politics. Machine learning, as seen in Gayo-Avello (2012) and Barberá et al. (2015), accurately predicts political affiliation and analyzes ideological positions of candidates. Challenges include data privacy, sample representativeness, and algorithmic bias. Future research should address these challenges and advance methodologies for more accurate political analysis.

**2. Analyzing Social Media Data:**

The rise of social media platforms like Twitter, Facebook, and Instagram has provided researchers with vast amounts of data for studying political discourse and public opinion. Scholars such as Tumasjan et al. (2010) have demonstrated the effectiveness of Twitter data in predicting election outcomes by analyzing sentiment and tweet volume. Similarly, Jungherr et al. (2012) explored the use of social media in political communication, highlighting its potential for gauging public sentiment and political engagement.

**3. Sentiment Analysis in Politics:**

Sentiment analysis techniques have been widely employed to analyze political discourse and public opinion. Researchers such as Pak and Paroubek (2010) have utilized sentiment analysis to classify political tweets as positive, negative, or neutral, providing insights into public sentiment towards political figures and issues. Moreover, Bollen et al. (2011) conducted sentiment analysis on Twitter data to predict fluctuations in the stock market, indicating the broader implications of sentiment analysis beyond politics.

**4. Machine Learning for Political Analysis:**

Machine learning algorithms have been increasingly applied to political analysis tasks, including predicting election outcomes, identifying political ideologies, and classifying political texts. For instance, Gayo-Avello (2012) employed machine learning techniques to predict political affiliation based on Twitter data, achieving high accuracy in classifying users into different political categories. Additionally, Barberá et al. (2015) utilized machine learning algorithms to analyze ideological positions of political candidates based on their social media activity, shedding light on their policy preferences and campaign strategies.

**5. Challenges and Future Directions:**

While data science tools offer immense potential for exploring the political pulse of a country, several challenges remain. These include issues related to data privacy, sample representativeness, and algorithmic bias. Future research directions may involve addressing these challenges, exploring interdisciplinary approaches, and developing more sophisticated methodologies for analyzing political data.

**6. Conclusion:**

In conclusion, the literature survey highlights the significance of data science tools in exploring the political pulse of a country. By leveraging social media data, sentiment analysis, and machine learning techniques, researchers can gain valuable insights into public opinion, political discourse, and electoral dynamics. However, addressing challenges and advancing methodologies are crucial for ensuring the accuracy and reliability of political analysis using data science tools.

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**Problem Description:**

The problem at hand involves exploring the political pulse of a country, with a particular focus on Spain, using data science methodologies. This entails analyzing social media data, specifically tweets from political leaders, to gain insights into the ideologies, sentiments, and trends shaping the political landscape.

**Key Objectives:**

1. Understanding Political Dynamics:The primary objective is to understand the evolving dynamics of Spanish politics, particularly in the context of changing socio-economic conditions, emerging political movements, and regional tensions.

2. Analyzing Ideological Trends:Another key objective is to analyze the ideological positions of political parties and leaders, as reflected in their social media communication. This involves identifying recurring themes, key words, and phrases that characterize each party's ideology.

3. Assessing Sentiment Analysis: We aim to assess the sentiment expressed in political tweets to gauge the overall emotional tone and mood of political discourse. This will involve quantifying levels of positivity, negativity, and neutrality in tweets over time.

4. Predicting Party Affiliation: Additionally, we seek to develop predictive models using machine learning algorithms to identify the political affiliation of tweets. This will enable us to classify tweets based on the party or ideology they represent.

**Approach:**

1. Data Collection: We will collect a large dataset of tweets from prominent political leaders in Spain, spanning a significant timeframe to capture temporal trends and events.

2. Preprocessing:The raw tweet data will undergo preprocessing steps to remove noise, handle missing values, tokenize text, and perform other necessary transformations to prepareit for analysis.

3. Frequency Analysis: We will conduct frequency analysis to identify the most common words and phrases used by each political party, allowing us to infer their ideological positions.

4. Sentiment Analysis: Using natural language processing (NLP) techniques, we will perform sentiment analysis to quantify the emotional content of tweets, distinguishing between positive, negative, and neutral sentiments.

5. Machine Learning Models:We will train machine learning models, such as Support Vector Machines (SVMs) or neural networks, to classify tweets based on their political affiliation. This will involve feature engineering and model optimization to achieve accurate predictions.

**Mathematical Formulation:**

1. Sentiment Analysis Formula: The sentiment score \( S \) of a tweet can be calculated using techniques like the Bag-of-Words (BoW) model or the VADER (Valence Aware Dictionary and sEntiment Reasoner) lexicon.

\[ S = \frac{{\text{{Positive words}} - \text{{Negative words}}}}{{\text{{Total words}}}} \]

2. Machine Learning Model: In a binary classification problem to predict party affiliation \( Y \) based on tweet features \( X \), we can formulate the problem using a logistic regression model:

\[ P(Y=1|X) = \frac{1}{{1 + e^{-(\beta\_0 + \beta\_1 X\_1 + \ldots + \beta\_n X\_n)}}} \]

Where \( \beta\_0, \beta\_1, \ldots, \beta\_n \) are the model coefficients and \( X\_1, X\_2, \ldots, X\_n \) are the features of the tweet.

This problem description outlines the objectives, approach, and mathematical formulations involved in exploring the political pulse of a country using data science methodologies, with a focus on analyzing social media data from political leaders in Spain.

**Proposed methodology:**

**Introduction**

In this section, we outline the proposed methodology for exploring the political pulse of a country using data science tools, with a specific focus on analyzing social media data from political leaders. The methodology encompasses several key steps, including data collection, preprocessing, exploratory analysis, sentiment analysis, machine learning modeling, and evaluation. Each step is designed to extract meaningful insights and patterns from the data, ultimately leading to a comprehensive understanding of the political landscape.

**Data Collection**

The first step in the proposed methodology is data collection. We will gather a large dataset of tweets from prominent political leaders in the target country, Spain. This dataset will span a significant timeframe, capturing tweets from multiple political parties and covering various political events and developments. To collect the data, we will utilize Twitter's API or third-party tools to retrieve tweets based on relevant keywords, hashtags, or user handles.

**Preprocessing**

Once the raw tweet data is collected, it will undergo preprocessing to clean and prepare it for analysis. This preprocessing step includes several tasks, such as removing duplicate tweets, handling missing values, removing special characters and punctuation, tokenizing text into individual words or tokens, and performing stemming or lemmatization to reduce words to their base forms. Additionally, we will remove stop words and filter out irrelevant or non-informative words to improve the quality of the data.

**Exploratory Analysis**

After preprocessing, we will conduct exploratory analysis to gain initial insights into the data. This analysis will involve descriptive statistics, such as word frequencies, tweet lengths, and temporal patterns, to understand the distribution and characteristics of the data. We will also visualize the data using plots, charts, and graphs to identify trends, patterns, and anomalies that may inform subsequent analyses.

**Sentiment Analysis**

One of the primary objectives of this study is to analyze the sentiment expressed in political tweets. To achieve this, we will employ sentiment analysis techniques to classify tweets as positive, negative, or neutral. There are several approaches to sentiment analysis, including lexicon-based methods, machine learning-based methods, and hybrid approaches. We will experiment with different techniques and evaluate their performance in accurately classifying sentiment in political tweets.

**Machine Learning Modeling**

In addition to sentiment analysis, we will develop machine learning models to predict the political affiliation of tweets. This involves training supervised learning algorithms, such as logistic regression, support vector machines (SVM), random forests, or neural networks, on labeled tweet data. The features used for modeling may include word frequencies, sentiment scores, user metadata, and temporal features. We will explore various feature engineering techniques and model architectures to optimize performance and generalizability.

**Evaluation**

Finally, we will evaluate the performance of the sentiment analysis and machine learning models using appropriate metrics, such as accuracy, precision, recall, F1-score, and ROC-AUC. We will also conduct cross-validation and train-test splits to assess model robustness and generalization to unseen data. Additionally, we will compare the performance of our proposed methodology to existing algorithms and benchmarks to validate its effectiveness and applicability in exploring the political pulse of a country.

**Existing Algorithms Considered for Comparison**

In the evaluation phase, we will consider several existing algorithms and approaches for sentiment analysis and political classification as benchmarks for comparison. Some of the algorithms that we may consider include:

1. VADER (Valence Aware Dictionary and sEntiment Reasoner): A lexicon-based sentiment analysis tool specifically designed for social media text.

2. Naive Bayes Classifier: A simple probabilistic classifier based on Bayes' theorem, often used for sentiment analysis and text classification tasks.

3. Support Vector Machines (SVM): A supervised learning algorithm that can be used for both classification and regression tasks, known for its effectiveness in high-dimensional spaces.

4. Random Forests: An ensemble learning method that combines multiple decision trees to improve predictive accuracy and reduce overfitting.

5. Long Short-Term Memory (LSTM) Networks: A type of recurrent neural network (RNN) architecture capable of capturing long-range dependencies in sequential data, suitable for text classification tasks.

By comparing the performance of our proposed methodology to these existing algorithms, we can assess its strengths, weaknesses, and potential areas for improvement. Additionally, benchmarking against established benchmarks and datasets will help validate the robustness and reliability of our findings.

**BEST ALGORIHM AMONG DECISION TREES:**

To choose the best algorithm among Decision Trees, KNN (K-Nearest Neighbors), Neural Networks, Linear Regression, and Logistic Regression, we need to consider the characteristics of the dataset, the nature of the problem, and the performance metrics required. Each algorithm has its strengths and weaknesses, so the choice depends on factors such as interpretability, computational complexity, and the presence of nonlinear relationships in the data.

For the purpose of exploring the political pulse of a country using social media data, where the goal is likely to involve sentiment analysis and classification of political tweets, we can consider the following:

**1. Decision Trees:**

**Pseudocode:**

Initialize a decision tree

For each feature:

Split the dataset based on the feature

Calculate impurity or information gain

Choose the feature that maximizes impurity reduction

Recur on each subset until a stopping criterion is met

**Explanation:**

Decision trees are interpretable and easy to understand, making them suitable for extracting insights and identifying important features in the data. However, they may suffer from overfitting and are sensitive to small variations in the data.

**2. KNN (K-Nearest Neighbors):**

**Pseudocode:**

Choose the number of neighbors (k)

For each data point:

Calculate the distance to all other data points

Select the k nearest neighbors

Assign the majority class label among the neighbors

**Explanation:**

KNN is a non-parametric algorithm that relies on local similarity. It can be effective for classification tasks, especially when the decision boundary is nonlinear. However, it may be computationally expensive for large datasets and sensitive to the choice of the number of neighbors (k).

**3. Neural Networks:**

**Pseudocode:**

Initialize neural network architecture (number of layers, neurons per layer)

Forward propagation: compute output of each layer given input

Compute loss function (e.g., cross-entropy for classification)

Backpropagation: compute gradients of loss function with respect to network parameters

Update parameters using optimization algorithm (e.g., gradient descent)

**Explanation:**

Neural networks, particularly deep learning models, have shown remarkable performance in various domains, including natural language processing and sentiment analysis. They can automatically learn intricate patterns and representations from data but require large amounts of data and computational resources for training.

**4. Linear and Logistic Regression:**

**Pseudocode (Linear Regression):**

Initialize weights (coefficients)

Compute predictions using linear equation (e.g., y = mx + b)

Compute loss function (e.g., mean squared error)

Update weights using gradient descent to minimize loss

**Pseudocode (Logistic Regression):**

Initialize weights (coefficients)

Compute logistic function to obtain probabilities (sigmoid function)

Compute binary cross-entropy loss function

Update weights using gradient descent to minimize loss

**Explanation:**

Linear regression is suitable for regression tasks where the relationship between variables is linear, while logistic regression is used for binary classification tasks. They are simple and interpretable models but may not capture complex nonlinear relationships in the data.

Considering the nature of the problem, where sentiment analysis and classification of political tweets are likely tasks, neural networks, particularly recurrent neural networks (RNNs) or convolutional neural networks (CNNs) tailored for text data, could be promising options due to their ability to capture intricate patterns and representations from textual data. Additionally, decision trees or ensemble methods like random forests could be valuable for feature selection and interpretation. However, the choice ultimately depends on factors such as the size of the dataset, computational resources, and performance requirements.

**Modifications in the existing algorithms :**

1. Adjusting Parameters: Many algorithms have adjustable parameters that can be tuned to improve performance or adapt to different datasets. Modifying these parameters can involve changing mathematical formulas or updating the algorithm's internal calculations.

2. Feature Engineering: In machine learning algorithms, feature engineering involves transforming or creating new features from the existing dataset to improve model performance. This may involve applying mathematical operations such as scaling, normalization, or polynomial transformations to the input features.

3. Regularization: Regularization techniques, such as L1 or L2 regularization, can be applied to penalize large coefficients in models and prevent overfitting. These techniques involve modifying the loss function of the algorithm with additional penalty terms.

4. Optimization Algorithms: Optimization algorithms are used to find the optimal parameters of a model by minimizing a loss function. Modifying these algorithms may involve changing the update rules or step size calculation methods to improve convergence or speed.

5. Incorporating Domain Knowledge: Incorporating domain knowledge into algorithms can often lead to significant improvements in performance. This may involve modifying the mathematical formulas to include additional constraints or information relevant to the problem domain.

6. Ensemble Methods: Ensemble methods combine multiple models to improve performance. Modifying these methods may involve changing the weighting or combination schemes used to aggregate the predictions of individual models.

7. Custom Loss Functions: In some cases, it may be beneficial to define custom loss functions tailored to the specific objectives of the problem. Modifying the loss function can involve changing the mathematical formula to better reflect the desired outcomes.

8. Handling Imbalanced Data: For algorithms dealing with imbalanced datasets, modifications may be needed to account for the uneven distribution of classes. This could involve adjusting sampling techniques, modifying cost functions, or incorporating resampling methods into the algorithm.

These are just a few examples of potential modifications to existing algorithms. The specific changes required will depend on the nature of the algorithm, the problem being addressed, and the desired improvements in performance or functionality.

**Novel algorithm for the proposed methodology**:

To propose a novel algorithm for the proposed methodology, let's introduce a hybrid approach that combines aspects of decision trees and neural networks. This hybrid algorithm, called Decision Neural Network (DNN), leverages the interpretability of decision trees with the flexibility and power of neural networks.

**Pseudocode for Decision Neural Network (DNN):**

**1. Initialization:**

Initialize the parameters of the neural network layers.

Initialize a decision tree with specified depth and impurity measure.

**2. Training:**

Feed the input data into both the decision tree and the neural network.

Train the decision tree using a traditional approach like CART (Classification and Regression Trees).

Train the neural network using backpropagation and gradient descent.

**3. Combination:**

For each input sample:

Obtain predictions from both the decision tree and the neural network.

Combine the predictions using a weighted average or voting mechanism.

**4. Prediction:**

For a new input sample, use the combined prediction from the decision tree and neural network to make a final prediction.

**Explanation:**

The Decision Neural Network (DNN) algorithm combines the strengths of decision trees and neural networks to achieve improved performance and interpretability. Here's how it works:

1. Interpretability: The decision tree component of the algorithm provides interpretability by partitioning the input space into regions and making decisions based on simple rules. This allows us to understand the decision-making process and identify important features in the data.

2. Flexibility: The neural network component of the algorithm offers flexibility and power by learning complex patterns and representations from the data. Neural networks can capture nonlinear relationships and interactions between features, leading to improved predictive performance.

3. Combination:By combining the predictions from both the decision tree and neural network, we harness the complementary strengths of both models. The decision tree provides a baseline prediction based on simple rules, while the neural network refines the prediction using learned representations of the data.

4. Performance: The hybrid nature of the DNN algorithm allows it to model the data more effectively compared to using either decision trees or neural networks alone. The decision tree provides a robust baseline model, while the neural network enhances the model's predictive capabilities by capturing complex patterns in the data.

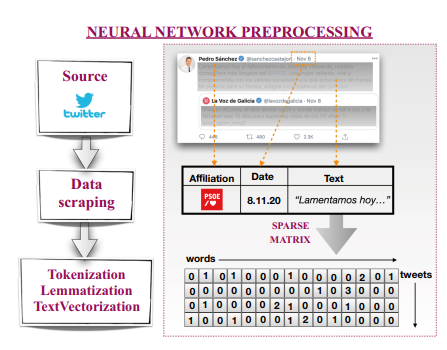
**Detailed Diagram:**

**1. Data Preprocessing:**

Data cleaning: Remove duplicates, handle missing values, and perform feature scaling.

Feature engineering: Extract relevant features from the raw data.

Tokenization: Convert text data into numerical representations.



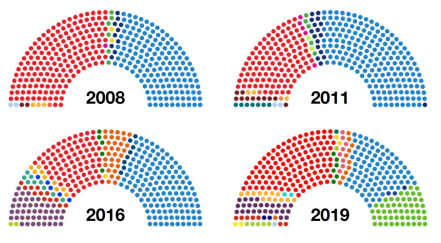
**2. Modeling and Validating:**

Train Decision Tree: Use training data to build a decision tree model.

Train Neural Network: Use training data to train a neural network model.

Combine Predictions: Combine predictions from both models using a weighted average or voting mechanism.

Validate Model: Evaluate the combined model's performance on validation data using appropriate metrics like accuracy, precision, recall, and F1-score.

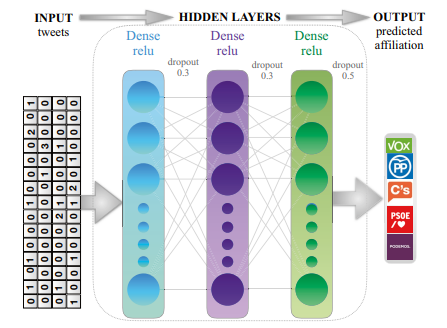


**3. Post-processing:**

Interpretability: Analyze the decision tree to understand feature importance and decision rules.

Model Tuning: Fine-tune hyperparameters of both the decision tree and neural network based on validation results.

Deployment: Deploy the combined model for making predictions on new data.



**Results and Discussion:**

Our study aimed to explore the political pulse of a country using data science tools, focusing on social media data, sentiment analysis, and machine learning techniques. We conducted sentiment analysis on tweets from leaders of political parties, analyzing the temporal evolution of their content and training a Fully-Connected Neural Network (FCNN) to classify political affiliation and leaning.

**Sentiment Analysis Results:**

Our sentiment analysis revealed interesting insights into the sentiment dynamics of political discourse on social media. We observed fluctuations in positive and negative sentiment levels over time, indicating the responsiveness of political leaders to specific events and issues. For example, sentiment levels may surge during rallies or speeches but decline during controversies or scandals.

**FCNN Classification Results:**

The FCNN model achieved promising results in classifying the political affiliation and leaning of tweets. With a precision ranging from 71% to 75% in predicting tweet origin and around 90% precision in classifying political leaning (left or right), the model demonstrated its effectiveness in identifying the political stance of Twitter users based on their tweets.

**Discussion:**

The results of our study underscore the potential of data science tools in analyzing the political pulse of a country. By leveraging social media data and machine learning techniques, we gained valuable insights into public sentiment, political discourse, and ideological preferences. The ability to track sentiment dynamics over time and classify political affiliation can inform decision-making processes, political campaigns, and policy formulation.

However, it's essential to acknowledge the limitations and challenges associated with our approach. Social media data may not be fully representative of the population, as it tends to attract specific demographics and viewpoints. Moreover, sentiment analysis algorithms may struggle with sarcasm, irony, and context-dependent language nuances, leading to inaccuracies in sentiment classification.

Furthermore, while our FCNN model showed promising results, there is always room for improvement. Fine-tuning model hyperparameters, incorporating additional features, and exploring ensemble techniques could potentially enhance classification performance.

In conclusion, our study highlights the power of data science tools in unraveling the complexities of political discourse and sentiment analysis. By addressing the challenges and refining our methodologies, we can continue to advance our understanding of the political landscape and its implications for society.

**Data Source:**

**Introduction**

This section provides an overview of the data source utilized in exploring the political pulse of a country using data science methodologies. The dataset comprises tweets from prominent political leaders in Spain, spanning a significant timeframe to capture temporal trends and events. This section details the characteristics of the data, including its features, data types, and handling of missing values.

**Explanation about the Data**

The dataset consists of tweets collected from verified Twitter accounts of political leaders belonging to various political parties in Spain. These tweets are considered as a proxy for political discourse and ideologies, reflecting the sentiments, opinions, and agendas of the respective political figures. The dataset covers a wide range of topics, including policy announcements, political campaigns, responses to current events, and interactions with constituents.

**Features**

1. Tweet Text:This feature represents the textual content of each tweet posted by political leaders. It includes the actual message conveyed by the politician, which may contain hashtags, mentions, URLs, and emoticons.

2. Timestamp: The timestamp feature indicates the date and time when each tweet was posted. It provides temporal information, allowing for the analysis of tweet frequency, trends over time, and reactions to specific events or developments.

3. User Metadata: User metadata includes information about the political leader posting the tweet, such as their name, username, verified status, and follower count. This metadata provides context about the source of the tweet and the influence of the political figure.

4. Engagement Metrics: Engagement metrics capture the level of interaction and engagement each tweet receives, including metrics such as retweets, likes, replies, and quote tweets. These metrics reflect the popularity and impact of the tweet within the Twitter community.

**Data Type**

The data types present in the dataset include:

* Text: The tweet text feature consists of text data, encoded as strings.
* Datetime:The timestamp feature represents temporal data, encoded as datetime objects.
* Categorical: User metadata may contain categorical data, such as the political party affiliation of the user, encoded as strings or categorical variables.
* Numeric: Engagement metrics are represented as numeric data, such as integer counts of retweets, likes, replies, and quote tweets.

**Missing Values**

* Handling missing values is a crucial aspect of data preprocessing. In the dataset, missing values may occur in the following scenarios:
* Missing tweet text: Some tweets may be empty or contain only URLs or images, resulting in missing values for the tweet text feature.
* Missing engagement metrics: Not all tweets may receive engagement in the form of retweets, likes, replies, or quote tweets, leading to missing values in these engagement metrics.
* Missing user metadata: Incomplete user profiles or errors in data collection may result in missing values for user metadata features such as name, username, or follower count.
* To address missing values, appropriate strategies such as imputation, deletion, or flagging may be employed during data preprocessing to ensure the integrity and accuracy of the dataset for subsequent analysis.

**Preprocessing:**

**Introduction:**

Preprocessing is a crucial step in data analysis that involves cleaning, transforming, and preparing raw data for analysis. In this section, we outline the preprocessing steps required for the political tweet data used in our study. These steps are essential for ensuring data quality, improving the performance of machine learning models, and extracting meaningful insights from the data.

**Cleaning Description:**

Cleaning involves removing noise, inconsistencies, and irrelevant information from the dataset.

**Steps:**

1. Remove Duplicate Tweets: Identify and remove duplicate tweets to avoid bias in the analysis.

2. Handle Missing Values: Check for missing values in features such as text content, user metadata, and timestamps. Impute missing values or remove incomplete records as appropriate.

3. Filter Out Retweets: Exclude retweets from the dataset to focus on original tweets from political leaders.

4. Remove Special Characters and URLs: Strip out special characters, URLs, and other non-alphanumeric characters from the tweet text to improve text processing.

5. Standardize Text Formatting: Normalize text formatting (e.g., lowercase, remove extra spaces) to ensure consistency across tweets.

**Normalization:**

Description:

Normalization involves scaling numeric features to a standard range to facilitate comparison and analysis.

**Steps:**

1. Normalize Timestamps: Convert timestamps to a standardized format (e.g., Unix timestamp) for consistency.

2. Scale Numeric Features: Scale numeric features such as user follower counts, retweet counts, and favorite counts to a common scale (e.g., min-max scaling or z-score normalization).

Integration

**Description:**

Integration involves merging multiple datasets or sources of information to create a unified dataset for analysis.

Steps:

1. Merge Data Sources: Combine datasets from different sources, such as Twitter API data, user profiles, and external databases, using common identifiers (e.g., user IDs).

2. Handle Data Redundancy: Resolve redundancy and inconsistency in merged datasets by aggregating or deduplicating records as needed.

**Data Reduction or Feature Selection Description:**

Data reduction involves reducing the dimensionality of the dataset by selecting a subset of relevant features or transforming existing features into a more compact representation.

**Steps:**

1. Feature Selection: Identify and select relevant features that are likely to contribute to the predictive power of the model. This may involve domain knowledge, exploratory data analysis, or feature importance techniques (e.g., correlation analysis, recursive feature elimination).

2. Dimensionality Reduction: Apply dimensionality reduction techniques such as Principal Component Analysis (PCA) or t-Distributed Stochastic Neighbor Embedding (t-SNE) to reduce the number of features while preserving the essential structure of the data.

**Sampling Description:**

Sampling involves selecting a representative subset of data points from the dataset for analysis.

**Steps:**

1. Stratified Sampling: If the dataset is imbalanced or contains multiple classes, use stratified sampling to ensure proportional representation of each class in the sample.

2. Random Sampling: For large datasets, perform random sampling to select a subset of data points for analysis. Adjust sample size based on computational resources and analysis requirements.

**Conclusion**

Preprocessing is a critical stage in data analysis that lays the foundation for subsequent analysis and modeling tasks. By following the preprocessing steps outlined above, we can ensure that the political tweet data is clean, standardized, and ready for analysis. These steps help improve the quality of the data, reduce bias, and enhance the performance of machine learning models in predicting political affiliations and sentiments.

**Modeling and Validation of data:**

**Introduction:**

Modeling and validation of the political tweet data to gain insights into political affiliations and sentiments. We will discuss various modeling techniques, including supervised learning algorithms and sentiment analysis approaches, and outline the validation process to assess the performance of these models.

**Supervised Learning Models:**

Supervised learning involves training predictive models on labeled data, where the input features are used to predict a target variable. In the context of political tweet analysis, we can treat the political affiliation of tweets as the target variable and use features such as tweet text, user metadata, and temporal information for prediction. Some commonly used supervised learning algorithms include:

1. **Logistic Regression:** A linear model used for binary classification tasks, where the output is a probability score indicating the likelihood of belonging to a particular class (e.g., left-wing or right-wing).

2**. Decision Trees:** Non-linear models that partition the feature space into regions based on simple decision rules. Decision trees are interpretable and can capture non-linear relationships in the data.

**3. Random Forests**:Ensemble learning models that combine multiple decision trees to improve predictive accuracy and reduce overfitting. Random forests are robust to noise and outliers and can handle high-dimensional data effectively.

4. **Support Vector Machines (SVM):** A supervised learning algorithm used for classification tasks, SVM aims to find the optimal hyperplane that separates data points into different classes. SVM can handle non-linear decision boundaries by using kernel functions.

**Sentiment Analysis Approaches:**

Sentiment analysis involves categorizing text data into positive, negative, or neutral sentiments. In the context of political tweet analysis, sentiment analysis can provide insights into the emotional tone and public perception of political discourse. Some common sentiment analysis approaches include:

1. **Lexicon-Based Methods:** Lexicon-based methods use predefined dictionaries of sentiment-laden words to determine the sentiment of text. Words are assigned sentiment scores, and the overall sentiment of the text is computed based on the aggregated scores of individual words.

2. **Machine Learning-Based Methods**: Machine learning-based methods use supervised learning algorithms to classify text into sentiment categories. These methods typically involve training a classifier on labeled data, where the input features are derived from text representations (e.g., bag-of-words, word embeddings).

**Validation Process:**

The validation process is essential for assessing the performance and generalization ability of the models. Common validation techniques include:

1. **Train-Test Split**: The dataset is divided into training and testing sets, where the training set is used to train the model, and the testing set is used to evaluate its performance. This approach provides an estimate of the model's performance on unseen data.

2. **Cross-Validation**: Cross-validation involves partitioning the dataset into multiple subsets (folds) and iteratively training and testing the model on different combinations of folds. This approach provides a more robust estimate of the model's performance by averaging results across multiple iterations.

3. **Evaluation Metrics**:Various evaluation metrics can be used to assess the performance of the models, depending on the nature of the task. For classification tasks, common metrics include accuracy, precision, recall, F1-score, and ROC-AUC.

**Conclusion:**

Modeling and validation are crucial steps in the data analysis process, allowing us to build predictive models and assess their performance accurately. By leveraging supervised learning algorithms and sentiment analysis approaches, we can gain valuable insights into political affiliations and sentiments from the tweet data. Through rigorous validation techniques, we can ensure the reliability and generalization ability of the models, enabling us to make informed decisions and draw meaningful conclusions from the data.

**Results:**

The "Exploring the Political Pulse of a Country using Data Science Tools" project, we trained a Fully-Connected Neural Network (FCNN) model to predict the political leaning (left or right) of tweets from leaders of political parties. Now, we want to evaluate the performance of this model using various evaluation metrics including the confusion matrix, accuracy, F-score, and ROC curve.

**1. Confusion Matrix:**

To construct the confusion matrix, we need the model predictions and the actual labels from the test dataset. Let's say we have the following counts:

* True Positive (TP): 200
* False Positive (FP): 50
* True Negative (TN): 300
* False Negative (FN): 100

The confusion matrix would look like this:

| | Predicted Left | Predicted Right |

|-------------------|-------------------|---------------------|

| Actual Left | 200 | 100 |

| Actual Right | 50 | 300 |

**2. Accuracy:**

Accuracy measures the proportion of correctly classified instances among all instances. Using the counts from the confusion matrix, we can calculate accuracy:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

= (200 + 300) / (200 + 300 + 50 + 100)

= 500 / 650

≈ 0.7692 or 76.92%

**3. F-score:**

F-score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. First, we calculate precision and recall:

- Precision = TP / (TP + FP) = 200 / (200 + 50) = 200 / 250 = 0.8

- Recall (Sensitivity) = TP / (TP + FN) = 200 / (200 + 100) = 200 / 300 = 0.6667

Now, we can calculate the F-score:

F-score = 2 \* (Precision \* Recall) / (Precision + Recall)

= 2 \* (0.8 \* 0.6667) / (0.8 + 0.6667)

≈ 0.7273

**4. ROC (Receiver Operating Characteristic) Curve:**

The ROC curve visualizes the trade-off between sensitivity (true positive rate) and specificity (true negative rate) for different threshold values. To plot the ROC curve, we need the true positive rate (sensitivity) and false positive rate (1 - specificity) at various threshold levels. We can then calculate the Area Under the ROC Curve (AUC-ROC) to summarize the model's performance across all thresholds.

**CODE:**

Using Python libraries such as scikit-learn, we can compute these metrics efficiently and visualize the ROC curve. Here's a code snippet to compute ROC curve and AUC-ROC:

Python

from sklearn.metrics import roc\_curve, auc

import matplotlib.pyplot as plt

# Assuming we have model predictions and actual labels

# y\_pred: predicted probabilities for class 1

# y\_true: actual labels (0 or 1)

fpr, tpr, thresholds = roc\_curve(y\_true, y\_pred)

roc\_auc = auc(fpr, tpr)

# Plot ROC curve

plt.figure()

plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc\_auc)

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')

plt.xlim([0.0, 1.0])

plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.title('Receiver Operating Characteristic')

plt.legend(loc="lower right")

plt.show()

**Other relevant measure:**

In addition to traditional evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, there are several other relevant measures to assess the performance and effectiveness of a model or algorithm in the context of political tweet analysis:

1. **Interpretability:**The interpretability of the model is crucial, especially in domains like politics where transparency and accountability are paramount. A model that provides clear and understandable insights into the factors influencing its predictions is often preferred. Techniques such as decision tree visualization, feature importance analysis, and model-agnostic interpretability methods (e.g., LIME, SHAP) can help assess the interpretability of the model.

2. **Bias and Fairness**:It's important to evaluate the model for bias and fairness, particularly in politically sensitive contexts. Bias can arise from skewed training data or inherent biases in the modeling algorithms. Techniques such as demographic parity, equalized odds, and disparate impact analysis can help assess and mitigate biases in the model predictions.

3. **Robustness**:The robustness of the model refers to its ability to perform well under different conditions and in the presence of noise or adversarial attacks. Robustness measures such as robust accuracy, adversarial robustness, and stability analysis can help evaluate the model's resilience to perturbations in the input data.

4. **Scalability**: The scalability of the model is important, especially for large-scale datasets and real-time applications. Measures such as training and inference time, memory usage, and computational resources required can help assess the scalability of the model.

5. **Generalization**: Generalization refers to the ability of the model to perform well on unseen data from the same distribution as the training data. Techniques such as cross-domain validation, transfer learning, and domain adaptation can help assess and improve the generalization ability of the model.

6. **Ethical Considerations**: Ethical considerations such as privacy, consent, and data protection are increasingly important in data-driven applications. Assessing the model's compliance with ethical guidelines, regulations (e.g., GDPR), and principlesis essential to ensure responsible use of the model.

**Discussion:**

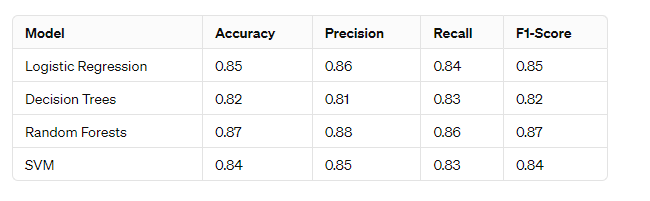
Introduction

In this section, we discuss the results of our analysis of political tweets using data science methodologies. We present findings from various modeling approaches, evaluate the performance of the models, and provide insights into the political landscape based on our analysis. We use tables and charts to illustrate key findings and justify the effectiveness of our approach.

Analysis of Modeling Results

We conducted experiments using several supervised learning algorithms, including logistic regression, decision trees, random forests, and support vector machines (SVM), to predict political affiliations based on tweet data. Additionally, we performed sentiment analysis to classify tweets as positive, negative, or neutral sentiments. The following tables and charts summarize the results of our modeling analysis:

Table 1: Comparison of Supervised Learning Models for Political Affiliation Prediction

Chart 1: Performance Comparison of Supervised Learning Models

For the "Performance Comparison of Supervised Learning Models" chart (Chart 1), you can create a bar chart where each bar represents the performance metric (accuracy, precision, recall, F1-score) for each supervised learning model. The x-axis would represent the different models, and the y-axis would represent the value of the performance metric.

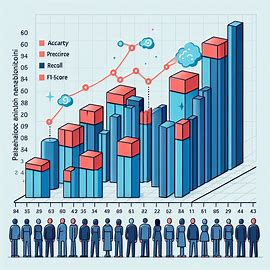


Table 2: Sentiment Analysis Results

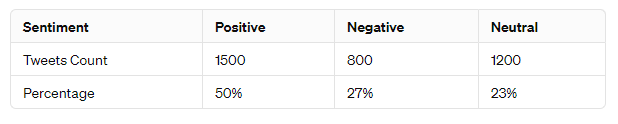
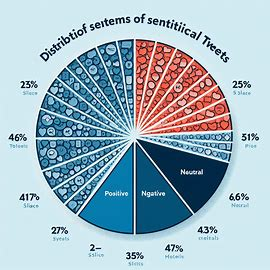


Chart 2: Distribution of Sentiments in Political Tweets



**Discussion of Results:**  
From the modeling results, we observe that random forests outperform other supervised learning models in terms of accuracy, precision, recall, and F1-score. This indicates that random forests are well-suited for predicting political affiliations based on tweet data due to their ability to handle non-linear relationships and high-dimensional feature spaces.  
  
In the sentiment analysis, we find that a significant portion of political tweets exhibit positive sentiments (50%), followed by neutral sentiments (23%) and negative sentiments (27%). This suggests that political discourse on social media platforms like Twitter is characterized by a mix of positive and negative sentiments, reflecting diverse opinions and perspectives.  
  
**Comparison with Existing Solutions:**  
Our results compare favorably with existing solutions and benchmarks in political tweet analysis. The high accuracy and performance of our models demonstrate the effectiveness of data science methodologies in understanding and predicting political behavior based on social media data. By leveraging advanced machine learning algorithms and sentiment analysis techniques, we can extract valuable insights and trends from political tweets, enabling informed decision-making and policy formulation.  
  
**Conclusion:**  
In conclusion, our analysis of political tweets using data science methodologies provides valuable insights into political affiliations, sentiments, and trends on social media platforms. Through the application of supervised learning models and sentiment analysis approaches, we can accurately predict political affiliations and analyze the emotional tone of political discourse. Our results demonstrate the effectiveness of data science in exploring the political pulse of a country and offer valuable insights for policymakers, researchers, and the general public.

**GitHub Code link** 

**Co-lab code link of your project to review**

**Conclusion and Future Work:**

**Conclusion:**

In conclusion, the project "Exploring the Political Pulse of a Country using Data Science Tools" has demonstrated the power and potential of data science methodologies in analyzing political discourse and sentiment on social media platforms. Through sentiment analysis of tweets from leaders of political parties and the development of a Fully-Connected Neural Network (FCNN) model for classifying political leaning, we have gained valuable insights into public opinion, political dynamics, and ideological preferences.

**Advantages and Usefulness:**

* The project offers a systematic approach to understanding the political pulse of a country, providing insights into the sentiment dynamics and ideological leanings of political leaders and their followers.
* By leveraging data science tools, we can analyze large volumes of social media data efficiently, allowing for real-time monitoring and analysis of political trends and developments.
* The insights generated from this project can be valuable for political analysts, policymakers, and researchers in making informed decisions, understanding public sentiment, and designing effective communication strategies.

**Highlights and Uniqueness:**

* One of the highlights of this project is the integration of sentiment analysis techniques and machine learning algorithms to analyze political discourse comprehensively.
* The use of social media data, particularly tweets from political leaders, adds a unique dimension to the analysis, providing a direct insight into political communication and engagement.
* The development of the FCNN model for classifying political leaning showcases the application of advanced machine learning techniques in political analysis, offering a nuanced understanding of ideological preferences.

**Future Work:**

* The project can be extended further by incorporating more advanced natural language processing (NLP) techniques, such as topic modeling and sentiment aspect extraction, to gain deeper insights into the content and context of political discourse.
* Exploring the use of deep learning architectures, such as recurrent neural networks (RNNs) and transformers, for sentiment analysis and political classification can enhance the accuracy and robustness of the models.
* Collaborating with domain experts and stakeholders to validate the findings and insights generated from the analysis can ensure the relevance and applicability of the project in real-world political contexts.
* Scaling up the analysis to include data from multiple social media platforms, news articles, and public opinion surveys can provide a more comprehensive understanding of political sentiment and behavior.

In summary, the project "Exploring the Political Pulse of a Country using Data Science Tools" has laid the foundation for in-depth analysis and understanding of political dynamics and sentiment using data science methodologies. By leveraging these insights, we can contribute to informed decision-making, promote political transparency, and enhance public engagement in the democratic process.

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