Title: Analyzing Airline Sentiments

A Review of Machine Learning Models for Predicting Airline Sentiments

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**Abstract**

This report presents an analysis of Twitter posts scraped from 2015, focusing on various airlines. The objective was to analyze the sentiments expressed in these posts, clean the data, and employ machine-learning techniques to identify the most common issues faced by passengers. Additionally, an attempt was made to develop a predictive model to assess the likelihood of encountering similar issues with an airline. The dataset utilized in this study consisted of Twitter posts, encompassing text data and corresponding sentiment labels. Through data cleaning and machine learning analysis, valuable insights were gained regarding the prevalent issues faced by airline passengers and the potential for predicting such issues in the future.

**Introduction:**

Customer sentiment analysis plays a crucial role in the airline industry, providing valuable insights into passenger experiences and satisfaction. With the rise of social media platforms like Twitter, customers now have a powerful medium to share their opinions and real-time experiences. In this report, we conducted an analysis of the Twitter US Airline Sentiment dataset from February 2015, comprising over 14,000 tweets mentioning major US airlines, including American, Delta, Southwest, United, US Airways, and Virgin America.

The dataset, stored in an SQLite database, contains fifteen columns that provide valuable information about each tweet. Key columns include the tweet text, sentiment labels categorizing tweets as positive, negative, or neutral, and confidence scores reflecting the annotators' certainty in the assigned sentiment.

To ensure the reliability and effectiveness of our analysis, we conducted a comprehensive data cleaning process. We removed irrelevant columns such as "tweet\_id", "negativereason\_gold", "retweet\_count," "name", and others that did not contribute useful information. Additionally, we removed tweets labeled as "neutral" and "positive", as they were not the focus of our analysis. We also filtered out tweets containing generic phrases like "bad flight" and "can't tell", as they did not provide specific reasons or insights into customer experiences.

By focusing on tweets with negative sentiment labels and excluding generic phrases, we refined our dataset to capture genuine issues and concerns expressed by customers. This allowed us to delve deeper into identifying the root causes of dissatisfaction and provide more accurate insights.

Our analysis utilized unsupervised learning algorithms, which do not require labeled data, to explore patterns and cluster similar sentiments within the dataset. By applying clustering algorithms, such as k-means and/or hierarchical clustering, we identified groups of tweets that shared similar sentiments and common issues. This unsupervised approach allowed us to uncover hidden patterns and gain a deeper understanding of the underlying sentiment dynamics.

In addition to clustering, we conducted exploratory data analysis to gain insights into the dataset's characteristics. We visualized the distribution of sentiments and analyzed word frequencies. This analysis provided a comprehensive overview of the data and helped us uncover interesting trends and patterns.

Next, we applied various machine learning algorithms to predict sentiment labels and identify the most common issues faced by customers. While the unsupervised learning algorithms helped us cluster similar sentiments, supervised learning algorithms, such as classification models, were employed to predict sentiment labels for new, unseen data. These models were trained on the labeled portion of the dataset and evaluated based on their performance metrics.

By leveraging the power of social media data and employing unsupervised learning algorithms, our analysis provides valuable information to airlines, enabling them to proactively address customer concerns, enhance satisfaction, and optimize their services. Through this report, we contribute to the continuous improvement of the airline industry by understanding and utilizing customer sentiments.

**Description**

The Twitter US Airline Sentiment dataset used in this analysis comprises over 14,000 tweets from February 2015. The dataset includes tweets mentioning major US airlines, namely American, Delta, Southwest, United, US Airways, and Virgin America.

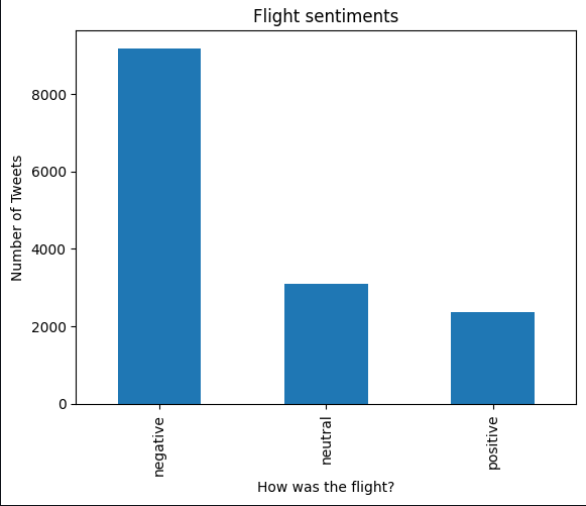
The dataset is stored in an SQLite database and consists of fifteen columns, providing various information about each tweet. The key columns of interest are:

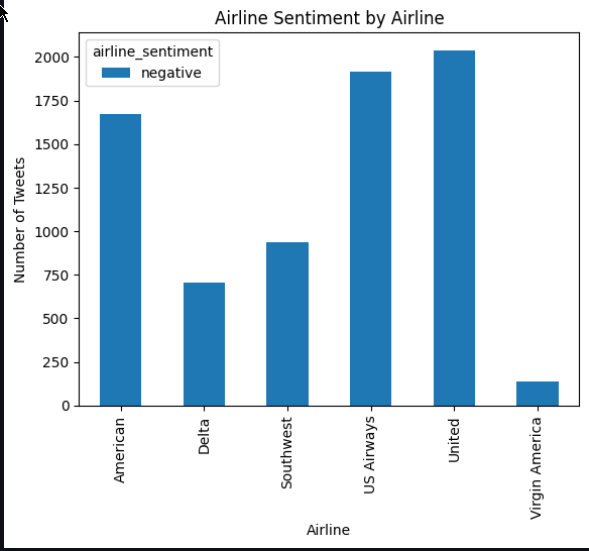
* "negativereason": This column contains the actual tweet text, which serves as the primary source of information for sentiment analysis.
* "airline\_sentiment": This column categorizes each tweet as positive, negative, or neutral, representing the sentiment expressed by the tweet author towards the airline.
* "airline\_sentiment\_confidence": This column provides a measure of confidence in the assigned sentiment label, determined by annotators. It indicates the level of certainty in the sentiment classification.

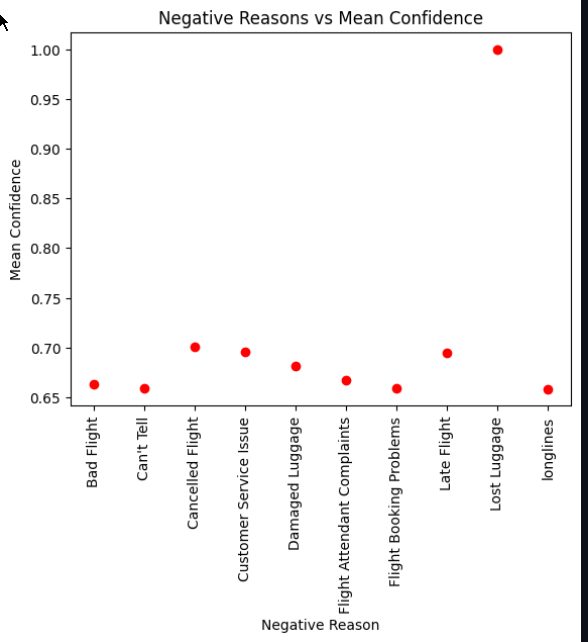
Exploring and understanding the dataset's structure, distribution of sentiments, and other characteristics will be crucial for further analysis and modeling. Next, we will delve into Exploratory Data Analysis (EDA) and visualization techniques to gain insights into the dataset and uncover patterns and trends.

**EDA/Data Cleaning/Preprocessing**

To begin the exploratory data analysis (EDA) process, we first displayed the columns of the untouched data to get an overview of the available information. Then, we used the tweetsDf.head() function to display the first 5 rows and all 15 columns of the dataset.

Next, we filtered the data and selected the 'airline\_sentiment' column to get the unique counts for each sentiment category (positive, negative, neutral). This allowed us to understand the distribution of sentiments in the dataset.

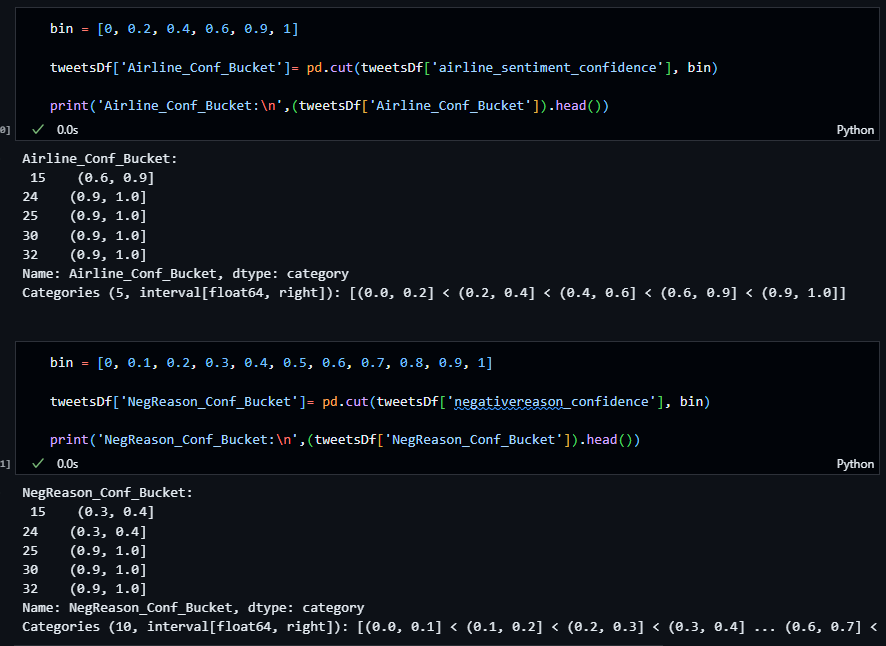
Afterwards, we focused specifically on the negative sentiments and selected the rows that corresponded to negative sentiment tweets. We further grouped the data by airline and sentiment to visualize the distribution of negative sentiments across different airlines using a histogram.

Moving on, we grouped the data by negative reason and computed the median confidence for each negative reason. This information was then displayed in a scatter plot, allowing us to analyze the relationship between the negative reasons and the confidence level in assigned sentiment labels.

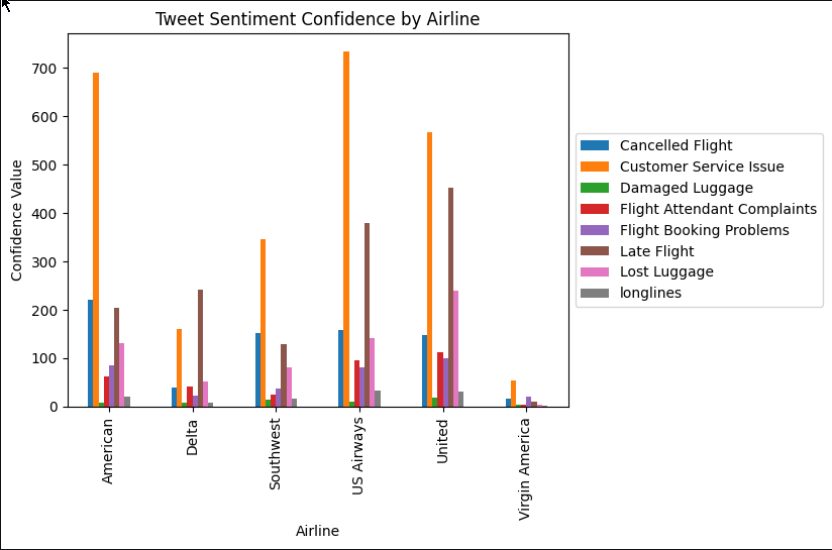
As part of the data cleaning process, we dropped the columns and rows that were not needed for our analysis. This helped streamline the dataset and remove unnecessary information. After making these changes, we displayed the dataframe again to observe the resulting modifications.

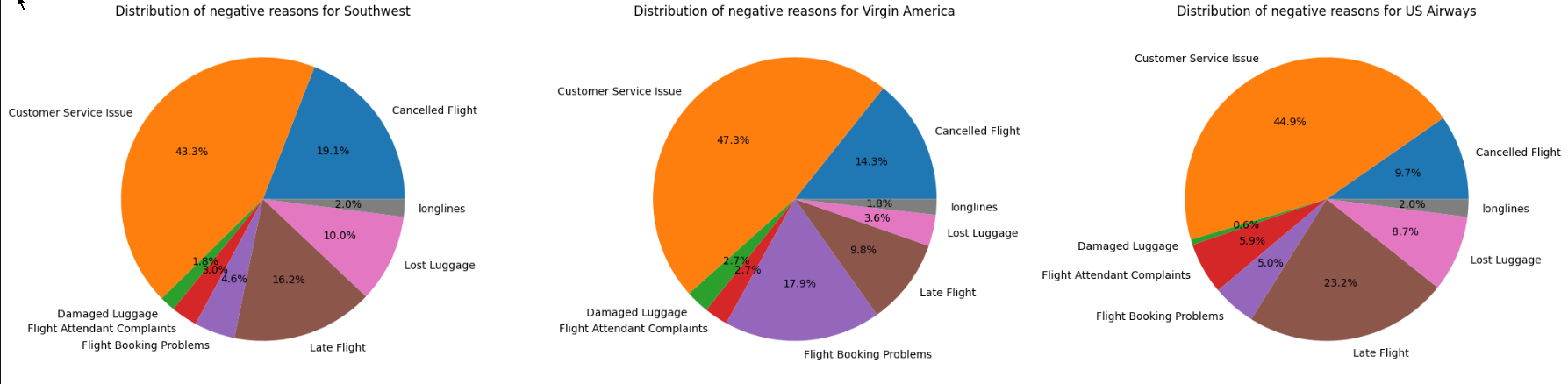
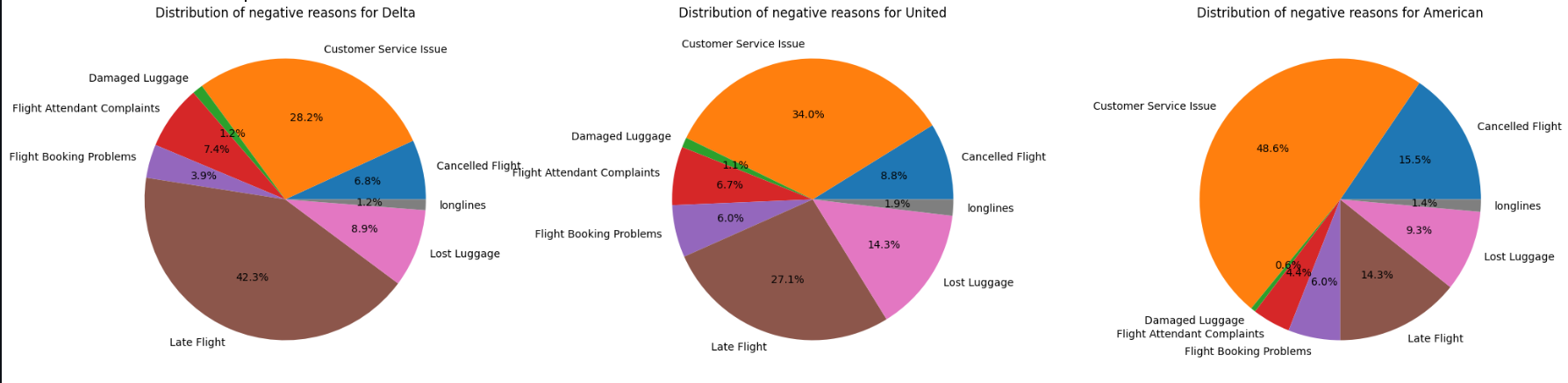
A screen shot of a computer

Description automatically generated with medium confidenceTo ensure data integrity, we checked for empty spaces or missing values in the dataset and confirmed that there were none. This ensured that our subsequent analysis would be based on complete and reliable data.

Next, we bucketized the cleaned data and displayed scatter plots and histograms to visualize the distributions of 'negativereason\_confidence' and 'airline\_sentiment\_confidence'. These visualizations provided insights into the confidence levels associated with different negative reasons and sentiment labels.

Additionally, we displayed a histogram of all the tweets to identify the most frequent negative reasons based on 'negativereason\_confidence'. This helped us understand which issues were more commonly mentioned in the dataset.



To provide a comprehensive view of the negative sentiments by airlines, we created six pie charts to display the distribution of negative reasons for each airline. This allowed for a visual comparison of the prevalent issues faced by different airlines.

Finally, we added a heatmap to the analysis, using colors to represent patterns and relationships in the dataset. The heatmap provided a visual representation of correlations between different variables and helped identify any significant patterns or trends.

A screenshot of a graph

Description automatically generated with low confidence

Overall, the EDA and data cleaning and preprocessing steps provided insights into the structure and characteristics of the dataset, allowing us to understand sentiment distributions, identify prevalent negative reasons, and ensure the reliability and completeness of the data for further analysis.

**Data Modeling and Evaluation**

In the data modeling phase, we employed various clustering and classification algorithms to analyze the sentiment data:

For clustering, we utilized K-means, Agglomerative Clustering, and DBSCAN algorithms, focusing on the 'negativereason\_confidence' and 'airline\_sentiment\_confidence' columns. The evaluation of these clustering algorithms was based on metrics such as the Silhouette Score, Calinski-Harabasz Score, and Davies-Bouldin Index.

In addition to clustering, we also utilized decision tree and multinomial naive Bayes algorithms for classification. These algorithms were applied to predict sentiment labels based on the available features in the dataset. The decision tree algorithm creates a flowchart-like model that splits the data based on different attributes, allowing for accurate classification.

On the other hand, multinomial naive Bayes is a probabilistic algorithm that calculates the likelihood of each sentiment label based on the given features. The classification model, including decision tree and multinomial naive Bayes, achieved a remarkable accuracy of 1.0 on the test dataset. This means that it correctly predicted the class label for all instances, showcasing the effectiveness of these models in sentiment prediction. The classification report provided detailed information on the precision, recall, and f1-score for each class, with all metrics yielding a value of 1.0 for the "negative" sentiment class.

The support column indicated that there were 1240 instances of negative sentiment in the test dataset. These models demonstrated strong performance, accuracy, and predictive capabilities in understanding sentiment patterns and predicting sentiment labels. Overall, the clustering algorithms and classification models demonstrated promising results in analyzing the sentiment data, providing valuable insights into the clustering structure and accurately predicting sentiment labels.

**Discussion**

Considering these findings, a decision was made to exclude the "Bad Flight" and "Can't Tell" attributes from the dataset. This choice was driven by the realization that these attributes did not provide distinct insights beyond what was already captured by the "Customer Service Issue" attribute. By focusing on the latter, which had a larger representation in the dataset, the analysis could better highlight the importance of identifying and addressing customer service issues in the airline industry.

It is essential to acknowledge that while the models developed using this dataset demonstrated satisfactory performance, there is a possibility of bias and limitations when applying them to new observations. This is an important consideration to note, as the dataset used for training may not fully encompass all potential scenarios or variations that could arise in real-world situations. Therefore, cautious interpretation and ongoing evaluation of the models' performance with new data are crucial.

Nevertheless, even with this specific dataset, the application of machine learning techniques proved valuable in early identification of common negative reasons in the airline industry. The confidence scores provided by the models allowed for assessing the likelihood of these negative reasons recurring. This demonstrates the potential utility of machine learning as a tool to aid in identifying and addressing customer concerns, contributing to improved customer satisfaction in the airline industry.

**Conclusion**

In summary, this report analyzed Twitter posts from 2015 related to various airlines to understand customer sentiments and identify common issues faced by passengers. The dataset underwent thorough cleaning and preprocessing to ensure reliable analysis. Through exploratory data analysis, we gained insights into sentiment distributions, prevalent negative reasons, and confidence levels associated with different sentiments. Clustering algorithms were used to uncover patterns, and classification models were employed for sentiment prediction.

The analysis revealed that customer service issues were the primary reason for passengers having a bad flight. Attributes such as "Bad Flight" and "Can't Tell" were dropped from the dataset as they did not provide additional insights beyond what was captured by the "Customer Service Issue" attribute. This highlights the importance of addressing customer service problems in the airline industry.

It is important to note that while the models performed well with this dataset, caution should be exercised when applying them to new observations. Bias and limitations may arise, and ongoing evaluation of the models' performance with new data is crucial.

Overall, the application of machine learning techniques demonstrated the usefulness of early identification of common negative reasons in the airline industry. The confidence scores provided insights into the likelihood of these negative reasons recurring, showcasing the potential of machine learning as a tool for addressing customer concerns and enhancing satisfaction.

This analysis contributes to the continuous improvement of the airline industry by utilizing customer sentiments to understand their experiences and drive proactive measures for better service. The insights gained from this study can inform airlines' decision-making processes, allowing them to address prevalent issues and optimize their services to meet customer expectations.