TWITTER SENTIMENT ANALYSIS

For enhanced brand management

PRESENTED BY
THE NEXUS NLP

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BUSINESS UNDERSTANDING

- Effective brand management involves not only monitoring brand mentions but also discerning the underlying emotions expressed by consumers.
- Positive sentiments signify brand advocacy, while negative sentiments may indicate dissatisfaction or potential issues.
- Moreover, understanding the target audience's emotional connection with the brand aids in crafting personalized marketing campaigns and product offerings.
- Sentiment analysis serves as a strategic tool for branding managers to gauge consumer sentiment accurately and tailor brand strategies accordingly, ultimately driving brand growth and profitability.

PROBLEM STATEMENT

Incorporating sentiment analysis from social media offers insights into public perception of specific stocks, complementing traditional methods. Understanding customer sentiment towards products like Google and Apple is crucial in the evolving technology market.

Automating sentiment analysis with Machine Learning provides a scalable solution, analyzing vast customer feedback on platforms like Twitter. This project aims to develop Machine Learning models for sentiment analysis of customer feedback towards Google and Apple products, benefiting investment managers, traders, and technology companies.

PROPOSED OBJECTIVES

Objective 1

Construct a machine learning model for automated sentiment analysis of tweets related to Google and Apple products, utilizing NLP techniques.

Objective 2

Collect and analyze sentiment data from Twitter for Apple and Google stock options to augment traditional financial analysis and improve investment decision-making.

Objective 3

Use social sentiment analysis to gain alternative insights into potential investment opportunities or risks, enhancing investment decision-making processes.

DATA UNDERSTANDING

The dataset was collected from Data World, containing 9000 rows and 3 columns of customer tweets related to various products, including popular brands like Apple and Google.

Twitter was chosen as the primary platform for data collection due to its rich source of real-time customer opinions and feedback, making it ideal for sentiment analysis.

The dataset allows for detailed sentiment analysis, providing insights into customer sentiments towards different products and brands.

METHODOLOGY

PREPROCESSING

Tweet text is preprocessed using custom Python functions, including regular expression search, punctuation removal, lowercase conversion, and stopword removal.

LEMMATIZATION

NLTK's lemmatizer actively reduced related words to common roots during the preprocessing stage, enhancing data consistency.

VECTORIZATION

Two vectorization techniques were actively employed: a simple bag-of-words approach integrated with sklearn's CountVectorizer for efficient data transformation.

MODELING

Model accuracy underwent thorough evaluation using the Complement Naive Bayes classifier, assessing performance through four classification metrics with precision. Deep learning was also used to extract actionable insights from social media data.

MODELLING

1	A new DataFrame was created, containing only the cleaned tokens column and emotions column. Prior to modeling the data, a train-test split was executed to partition the data into training and test sets, mitigating data leakage
2	Given the substantial class imbalance, Synthetic Minority Over-sampling Technique for Nominal and Continuous (SMOTENC) was employed to generate synthetic samples for the minority class, balancing the class distribution and enhancing the model's performance.
3	The baseline model was established as the XGBoost classifier with default parameters, achieving an accuracy score of 60% on the training set but with a recall score of 43%, indicating room for improvement.
4	Alternative models, such as the complement-based Naive Bayes, were explored, demonstrating an improved recall score of 71%, suggesting their effectiveness in capturing positive sentiment nuances.
5	Deep learning techniques were leveraged to analyze sentiment expressed in tweets related to Google and Apple products, offering valuable insights to investment managers, traders, and technology companies.

Deep
LEARNING

- Leveraging deep learning for sentiment analysis involves employing advanced neural network architectures to extract actionable insights from social media data, particularly tweets related to Google and Apple products.

- Loss and Accuracy Trends: The training loss decreases gradually indicating that the model is learning from the training data.

- The Deep Learning model is identified as the optimal choice based on metric evaluation, providing a competitive advantage in financial markets through advanced sentiment analysis techniques.

- Real-time analysis capabilities of deep learning models enable investment managers to stay updated with the latest market sentiments, facilitating timely adjustments to investment strategies for enhanced decision-making.

LIMITATIONS

In sentiment analysis, effective interpretation of textual data hinges on navigating through a myriad of inherent complexities.

While deep learning offers promising capabilities for Twitter sentiment analysis in investment management, investment managers must carefully consider its benefits and limitations when incorporating it into their decision-making process

01. Limited Dataset Size: Dataset for sentiment analysis is small, hindering the model's ability to capture diverse sentiments effectively.

02. Deep learning models demand large volumes of labeled training data, which can be time-consuming and resource-intensive to acquire and label, particularly in subjective or context-dependent domains like sentiment analysis.

03. Training deep learning models, especially those with multiple layers, requires substantial computational resources in terms of processing power and memory, posing challenges for investment firms with limited infrastructure or budget constraints.

RECOMMENDATIONS

1	Explore additional features to enhance predictive power, such as sentiment analysis of influential users or accounts.
2	Conduct time series analysis to track brand mentions over time, identifying trends and patterns.
3	Incorporate information about specific events influencing sentiment to enrich analysis.
4	Implement real-time sentiment trend monitoring and integrate insights into decision-making processes for investment.

NEXT STEPS

Integrate the deep learning sentiment analysis model into the investment decision-making process, merging sentiment-based insights with traditional financial analysis.

Utilize sentiment predictions to guide investment strategies, such as portfolio allocation, stock selection, and risk management.

Establish a system for real-time monitoring of Twitter sentiment towards selected stocks, enabling prompt adjustments to investment strategies based on evolving sentiment trends.

Continuously optimize the deep learning model by retraining it with updated data and fine-tuning parameters to ensure its ongoing relevance and effectiveness.

THANK YOU!