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Sentiment_project

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Mosota-Kemunto-Gladys-2020 Final Presentation.pdf 5e61e8c · 3 minutes ago

Data	Renamed data file	4 days ago
Images	Image folder created	yesterday
Work	Deleted Sentiment-Analysis presenta...	3 hours ago
Presentation.pdf	Final Presentation.pdf	3 minutes ago
README.md	conclusion put after recommendations	yesterday
git.pdf	git.pdf	2 hours ago
index.ipynb	Final version of index.ipynb	11 minutes ago
index.pdf	Final Version of index.pdf	7 minutes ago

README

Sentiment_project

1. Project Overview

This project aims to develop a Natural Language Processing (NLP) model to analyze sentiment in Tweets related to Apple and Google products. By classifying the sentiment of these Tweets as positive, negative, or neutral, the model will provide valuable insights into public perception, aiding businesses in marketing strategies and product development.

Business Problem:

In an era dominated by social media, brands must continuously track customer sentiments expressed online. Twitter, in particular, has become a critical platform where users voice their opinions about products and brands. However, the vast volume and rapid pace of tweets make it impractical for businesses to manually analyze these opinions for insights. To address this, a Natural Language Processing (NLP) model needs to be developed to automatically classify the sentiment of tweets and determine which brand or product is the target of those sentiments.

The dataset from CrowdFlower includes over 9,000 tweets that have been evaluated for sentiment (positive, negative, or no emotion) and tagged with the associated brand or product. The goal is to build an NLP model that can accurately and efficiently:

1. **Classify Sentiments**: Identify whether a tweet expresses positive, negative, or no emotion.
2. **Identify Brand/Product**: Recognize which brand or product is being referred to in the tweet.
3. **Handle Ambiguity**: Deal with tweets that might reference multiple brands or unclear sentiments.

Key challenges include:

- **Textual Variations**: Dealing with informal language, abbreviations, emojis, and slang used on social media.
- **Context Understanding**: Ensuring the model understands subtle and implicit expressions of sentiment.
- **Real-Time Processing**: Building a scalable solution that can process large volumes of data in real time for timely insights.

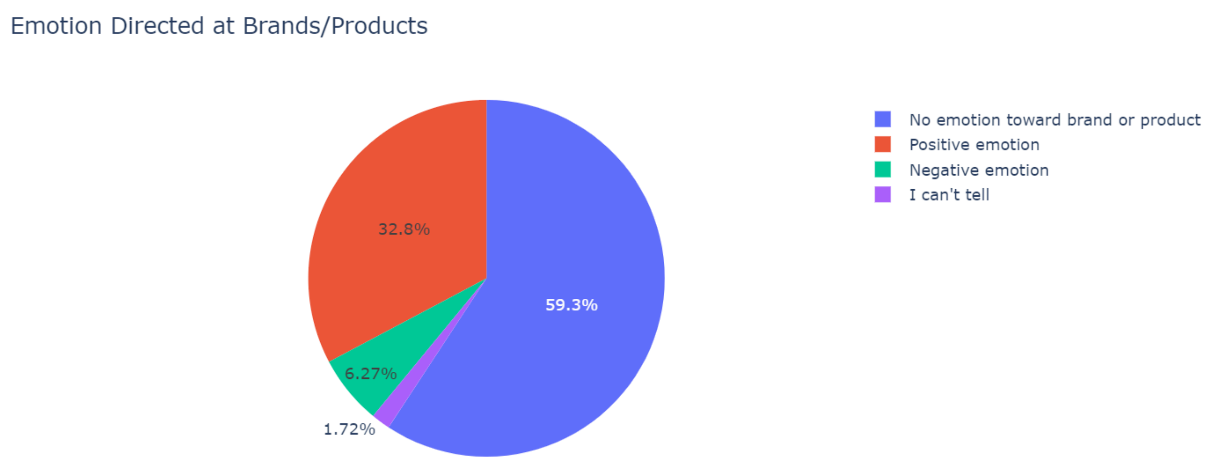
Solving this problem will help brands enhance their reputation management, respond promptly to consumer feedback, and optimize their marketing strategies based on real-time sentiment analysis.

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
0	.@wesley83 I have a 3G iPhone. After 3 hrs twe...	iPhone	Negative emotion
1	@jessedee Know about @fludapp ? Awesome iPad/i...	iPad or iPhone App	Positive emotion
2	@swonderlin Can not wait for #iPad 2 also. The...	iPad	Positive emotion
3	@sxsw I hope this year's festival isn't as cra...	iPad or iPhone App	Negative emotion
4	@sxtxstate great stuff on Fri #SXSW: Marissa M...	Google	Positive emotion
...	...	...	...
9088	Ipad everywhere. #SXSW {link}	iPad	Positive emotion
9089	Wave, buzz... RT @mention We interrupt your re...	NaN	No emotion toward brand or product
9090	Google's Zeiger, a physician never reported po...	NaN	No emotion toward brand or product
9091	Some Verizon iPhone customers complained their...	NaN	No emotion toward brand or product
9092	Ï¡Ïàü_ÊÎÒ£Áââ_£â_ÛâRT @...	NaN	No emotion toward brand or product

9093 rows × 3 columns

In this project,we took sentiment as our target variable and tweets as our independent variable. Initially we did a binary classification of positive and negative sentiments.

We also did a multiple classification investigating effects of neutral sentiments. The following is a table for multiple classification:



We then removed class imbalances and the following is the summary of our results:

Sentiment Analysis Model Comparison

Results Summary

Binary Classification (Positive vs Negative)

Model	Accuracy (CW)	F1 Score (CW)	Accuracy (SMOTE)	F1 Score (SMOTE)
Logistic Regression	0.8333	0.8453	0.8630	0.8688
Random Forest	0.8842	0.8599	0.8884	0.8695
SVM	0.9054	0.8973	0.8955	0.8755
Gradient Boosting	0.8672	0.8280	0.8404	0.8401
Neural Network	0.8912	0.8873	0.8927	0.8890
XGBoost	0.8701	0.8486	0.8658	0.8492

Multi-class Classification (Positive vs Negative vs Neutral)

Model	Accuracy (CW)	F1 Score (CW)	Accuracy (SMOTE)	F1 Score (SMOTE)
Logistic Regression	0.8854	0.8848	0.8848	0.8845
Random Forest	0.8904	0.8763	0.8909	0.8798
SVM	0.8970	0.8903	0.8981	0.8903
Gradient Boosting	0.8893	0.8707	0.8815	0.8799
Neural Network	0.8501	0.8472	0.8281	0.8296
XGBoost	0.8909	0.8779	0.8909	0.8847

Results Summary Analysis:

1. Handling class imbalances significantly improved model performance, especially for the minority class (negative emotions).
2. In binary classification, SVM with class weighting performed best (Accuracy: 0.9054, F1 Score: 0.8973).
3. For multi-class classification, SVM with class weighting again showed the best results (Accuracy: 0.8970, F1 Score: 0.8903).
4. SMOTE and class weighting techniques showed similar improvements, with class weighting slightly outperforming SMOTE in most cases.
5. Neural Networks performed well in binary classification but lagged in multi-class scenarios.
6. Use SVM with class weighting as the primary model for both binary and multi-class sentiment analysis tasks.

Recommendations:

- **Primary Model Selection**: Based on the evaluation, SVM with class weighting consistently performed the best in both binary and multi-class classification tasks. It should be the preferred model for future sentiment analysis on this dataset.

- **Handling Class Imbalances**: The results show that class weighting slightly outperforms SMOTE in most

Releases

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Languages

- Jupyter Notebook 80.2%
- HTML 19.8%

Suggested workflows

Based on your tech stack

SLSA Generic generator Configure

Generate SLSA3 provenance for your existing release workflows

Jekyll using Docker image Configure

Package a Jekyll site using the jekyll/builder Docker image.

More workflows Dismiss suggestions