Real-Time Brand Sentiment Analysis of Social Media Text Content

Proposal (Juliet revisions)

Jonathan Agustin

Fernando Calderon

Juliet Lawton

University of San Diego

Introduction

Businesses increasingly leverage social media platforms to track brand perception using Natural Language Processing (NLP), Classification, and Sentiment Analysis. Machine Learning (ML) models are trained with a large corpus of social media text data using Deep Learning to classify a brand and categorize sentiment towards the brand as positive, negative, or neutral. The objective of this project is to train a ML model on the Sentiment140 dataset to classify the sentiment of tweets, allowing brands to quickly react to shifts in public sentiment and maintain a positive brand image. We will experiment with a variety of different ML algorithms, such as Naïve Bayes and Logistic Regression, to find the best fit.

Problem

Given a set B of strings representing brand names $B = \{b_1 = \texttt{"Nike"}, b_2 = \texttt{"Google"}, b_3 = \texttt{"Disney"}, \ldots, b_i\}$ and a set P of strings representing Twitter posts

$$
\begin{aligned}
p_1 &= \texttt{"Celebrating my birthday"} \\
p_2 &= \texttt{"I could care less about the new Air Force 1s"} \\
p_3 &= \texttt{"Happiest place on Earth"} \\
&\vdots \\
p_j &\in P
\end{aligned}
$$

the goal is to build a $\text{BrandClassifier}(p)$ model that predicts whether a Twitter post p expresses a brand, and returns a brand name b when the post expresses the brand, or `No-Brand` when the post does not express any brand. The model also returns a confidence score $c \in [0, 1]$ that indicates how confident the model is in its prediction.

$$
\text{BrandClassifier}(p) \to \begin{cases} (b, c) & \text{if } p \text{ expresses a brand } b \in B \\ (\texttt{No-Brand}, c) & \text{otherwise} \end{cases}
$$

We also build a $\text{BrandSentimentAnalyzer}(p, b)$ model that predicts the sentiment of a Twitter post towards a brand, and returns a sentiment label

$$
s \in S = \{s^+ = \texttt{Positive}, s^- = \texttt{Negative}, s^0 = \texttt{Neutral}, s^? = \texttt{Mixed}\}
$$

when the post expresses sentiment towards the brand, or `No-Sentiment` when it does not express any sentiment. The model also returns a confidence score $c \in [0, 1]$.

$$
\text{BrandSentimentAnalyzer}(p, b) \to \begin{cases} (s, c) & \text{if } p \text{ expresses sentiment } s \in S \text{ about brand } b \in B \\ (\texttt{No-Sentiment}, c) & \text{otherwise} \end{cases}
$$

Example. Given the following Twitter post $p_3 = \texttt{"I could care less about the new Air Force 1s"}$ and $b_3 = \texttt{"Nike"}$:

$$
\begin{aligned}
&\text{BrandClassifier}(p_3) \to (b_3, 0.68) \\
&\text{BrandSentimentAnalyzer}(p_3, b_3) \to (s^-, 0.82)
\end{aligned}
$$

For this problem, the primary machine learning algorithms for consideration are Naïve Bayes, Logistic Regression, Support Vector Machines, Recurrent Neural Networks, and Transformers (such as BERT).

Related Course Topics

This project will cover a variety of topics from AAI 501, patricularly Natural Language Processing and Classification. More topics may also be covered depending on which model is selected. The potential topics covered include:

1. Natural Language Processing
2. Classification
3. Regression
4. Supervised Machine Learning
5. Bayesian Networks
6. Deep Learning

Methodology

The work is divided into three stages: assessment, development, and evaluation. Each stage informs and refines previous stages, creating a feedback loop that continuously improves the overall system.

1. **Assessment.** The stage involves analyzing the dataset and selecting and testing appropriate models. The specific requirements of the sentiment analysis task, the characteristics of the available data, and the nature of the problem guide this selection process.
2. **Development.** This stage involves training and tuning the selected models. This process involves handling invalid values and discarding non-textual content such as images, videos, or audio. Automation ensures efficiency in this process. The selected models are trained to identify a brand or align with the sentiment expressed in a tweet, and then tuned to improve performance.
3. **Evaluation.** This stage measures the models' ability to identify brands and predict sentiment in Twitter posts. The tweets used for validation can come from a test set partitioned from the original dataset, as well as from the Twitter API. Standard classification metrics such as Accuracy, Precision, Recall, and F1 Score are used to evaluate the models. The models are then ranked by performance.

Expected Behaviors & Outcomes

We expect our models to demonstrate a nuanced understanding of the English language, accurately identifying brands and sentiments. Despite the inherent challenges associated with sentiment analysis and brand identification in text data, we anticipate that our models will achieve an accuracy rate exceeding 50%. We foresee our models to have real-world applicability, serving as a valuable tool for businesses to accurately analyze sentiment from social media data. The proposed system is expected to provide actionable insights that enable companies to make informed decisions.

Known Challenges A well-known problem in sentiment analysis is the "aboutness" problem. This problem refers to the challenge of determining the subject of the sentiment expressed in a sentence. For our scenario, this may manifest in one of two ways - complex sentences and ambiguous subjects. In the first instance, take for example the sentence "I love Disneyland but hate how expensive the tickets are." This sentence expresses both positive and negative sentiment towards the brand, Disney, but the overall sentiment is positive. In the second scenario, take for example the sentences "Google is a great company" and "You should google that." The first sentence refers to Google the brand with positive sentiment, and the second sentence refers to google as a verb and should not be regarded as an expression of sentiment towards the brand.

Limitations The primary limitation of the model is that it is trained on Twitter posts, so it is not yet able to classify posts from other social media sites, such as Facebook. Another limitation is the unimodal nature of the model. It processes only text data, ignoring non-textual elements like images, videos, and audio clips. Often found in social media posts, these elements can contain significant sentiment-related information. This information can support, contradict, or add nuance to the sentiment expressed in the text. Audio clips, for example, can provide sentiment-related cues through tone, pitch, and other features. Future work should consider generalizing the model to work with other kinds of social media posts, as well as expanding the model to a multimodal framework to provide a more comprehensive sentiment analysis of social media posts.

References

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