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DOĞAL AFET SONRASI YORUMLARIN MAKİNE ÖĞRENMESİ YÖNTEMLERİ İLE SINIFLANDIRILMASI

Sentiment Classification of Post-Earthquake Consumer Brand Hate on Social Media Using Machine Learning Techniques

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Özet

Sosyal medya kullanımının yaygınlaşması, tüketicilerin markaları değelendirmesine, markalar ve aynı markanın diğer kullanıcılarına doğrudan etkileşimde bulunmasına olanak sağlamaktadır. 6 Şubat 2023 tarihinde meydana gelen depremin ardından Türkiye'nin on bir ilinde iki küresel marka olan Netflix ve Starbucks'a yönelik marka nefreti gözlemlenmiştir. Her iki marka da depremzedelere ve marka elçilerine gerekli hassasiyeti ve empatiyi göstermemekle suçlandı. Bu çalışmanın amacı, denetimli makine öğrenme yöntemlerini kullanarak tüketici tarafından oluşturulan içeriklerdeki marka nefretini incelemek ve sınıflandırmaktadır. Pazarlama disiplininde marka nefretinin yapısı çeşitli veri toplama yöntemleri ile kapsamlı biçimde araştırılmıştır ancak bu çalışma, marka nefretinin makine öğrenmesi yöntemleri ile incelendiği ilk girişimlerden biridir. Klasik polarizasyon işleminin aksine etiketleme işlemi yorumlardaki duygu yüküne bağlı olarak yapılmıştır; 0 nötr tepkileri, -1 negatif duygusal tepkileri ve -2 negatif ilişkisel tepkileri ifade etmektedir. Analiz sonuçlarına göre Destek Vektör Makineleri (DVM) yöntemi bu fenomenin açıklanmasında en başarılı algoritma olarak bulunmuştur.

Anahtar Kelimeler: *Duygu analizi, makine öğrenmesi yöntemleri, marka nefreti.*

Abstract

The widespread use of social media allows consumers to evaluate brands and to get into a direct interaction with brands and other followers of the same brands. After the devastating earthquake on February 6th, 2023, in ten provinces in Turkey a social media brand hatred was observed on two global brands Netflix and Starbucks. Brands were accused of not showing the necessary sensitivity and empathy towards the affected and the brand devotees. The objective of this study is to examine and classify brand hatred in online consumer-generated content using supervised machine learning methods. While the construct of brand hate has been extensively investigated in the discipline of marketing using different data collection methodologies, this is one of the first attempts to use machine learning methods for the analysis of the phenomenon. Unlike classic polarization, the labeling process was associated with the size of brand hatred; 0 denotes neutral reactions, -1 negative emotional reactions, and -2 negative relationship reactions. Support Vector Machines (SVM) was identified as the most successful algorithm for the explanation of the phenomenon.

Keywords: *Sentiment analysis, machine learning techniques, brand hate.*

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Introduction

Social media helps people to share their attitudes about a brand through several platforms (Cui et al., 2023). Twitter is one of the popular micro-blogging applications that allows users to share their views either publicly or privately. One of the most prevalent techniques for analyzing Twitter data is sentiment analysis (Sailunaz & Alhajj, 2019). Sentiment analysis refers to the process of collecting and analyzing individuals' perceptions about different topics (Wankhade et al., 2022). It is an essential tool in natural language processing that focuses on text classification (Tan et al., 2023). With the empowerment provided by the social media tools, consumers increasingly collect information about brands by considering other consumers' opinions expressed in text by extracting subjective information.

Increasingly, social media comments help firms to restructure their strategies and improve their performance (Taherdoost & Madanchian, 2023) all of which have a tremendous impact on institutions (Zhang et al., 2018). In recent years, sentiment analysis has received greater attention, not only by scholars in different disciplines but also by firms, governments, and organizations (Sánchez-Rada & Iglesias, 2019). For example, Lee et al. (2022) explored attitudes on the Taliban's reign over Afghanistan, Wang and Chen (2023) investigated sentiments towards COVID-19 vaccinations, Ounacer et al. (2023) analyzed customers' online hotel reviews and Alzate et al. (2022) employed text mining algorithms on online cosmetic product evaluations.

Web scraping and social media are used to collect data from several digital platforms such as social media, forums, web blogs and e-commerce websites (Wankhade et al., 2022) in different languages like Arabic (Ghallab et al., 2020), Spanish (Osorio Angel et al., 2021), and Turkish (Demircan et al., 2021). With regard to sentiment analysis on social media, Twitter is the most preferred social media channel, followed by Facebook (Ortigosa et al., 2014; Pratama, 2022), YouTube (Kim et al., 2022), Instagram (Alam et al., 2022), and Reddit (Li et al., 2023). Apart from these global social media channels, studies also employ local online channels that allow the generation of consumer content such as the online consumer dictionary Sourtimes in Turkey (Tekinbaş Özkaya et al., 2021).

The objective of this study is to apply machine learning (ML) techniques in the brand management construct of brand hate. Brand hate is defined as "consumers' detachment from a brand and its associations as a result of consumers' intense and deeply held negative emotions such as disgust, anger, contempt, devaluation and diminution..." (Kucuk 2019, as cited in Kucuk, 2021: 432). While the initial operationalization of the construct focused on emotional dimensions, another stream of research focused on the negative brand-consumer relationships, where relationship encompasses apart from emotional also cognitive and behavioral dimensions (e.g., Fournier, 1988; Alba and Lutz, 2013; Brandao and Popoli, 2022).

The theoretical construct of brand hate has been examined thoroughly using different methodologies. Primary data was mainly collected using surveys, experiments, in-depth interviews, or triangulation of research methods by collecting data from a retrospective sample that is asked to recall hated brands (e.g., Fetscherin, 2019, Kucuk, 2019; Zarantonello et al., 2018, Zhang and Laroche, 2020). Secondary data was collected by observing consumer created brand hate content in websites and blogs (e.g., Kucuk, 2018; Kucuk, 2010; Kucuk, 2008; Krishnamurthy and Kucuk, 2009). The study will be the first in the field to use machine learnings techniques for the analysis of consumers' brand hate comments on brands' official social media accounts in the presence of a crisis.

For the research objective data was collected from the official Twitter and Sourtimes accounts of Starbucks and Netflix. On February 6th, 2023, a disastrous earthquake affected ten provinces in Turkey leading to the death of thousands and the loss of physical, psychological, and material well-being for millions. On the same day, consumers in all social media platforms started a call to firms for help. For the surprise of many two global brands remained silent on social media: Starbucks and Netflix. Three days after the earthquake both brands shared their first post. But the content of these brand crisis communication intensified consumers' comments on brand hate.

The objective of this research is to analyze consumer generated brand hate content in social media platforms using machine learning techniques. Mitchell (1997) developed a widely accepted machine learning definition in the field defined machine learning as *"a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E"*. Since then, artificial intelligence and ML evolved remarkably. Several tasks like image recognition and speech recognition are successfully implemented using ML. This transformation affected various fields from education to finance including marketing. Captured data is distilled and extracted to get valuable insights, assisting practitioners in the improvement of marketing operations and strategies (Cui et al., 2006). Even though the advancements have shaped the marketing literature, the use of ML methods in this area are still scattered (Ma and Sun, 2020) and limited (Ngai and Wu, 2022). In marketing, scholars investigate ML algorithms along with their applications in the 7Ps of marketing (Ngai and Wu, 2022) and on the opportunities for prediction, feature extraction, causal and descriptive interpretation for consumer purchase tracking and market analysis (Ma and Sun, 2020). One of the applications in the field of marketing is text classification since analyzing the huge amount of text stored in Internet has become challenging (Saigal and Khanna, 2020). Natural language processing is a technique that measures the frequency of words used to train a model/classifier. Machine learning algorithms are classified as supervised, unsupervised, and semi-supervised approaches. The supervised learning technique employs the strategy of training the system based on output labels, followed by testing the model on raw data. Popular supervised algorithms are reviewed below.

Random Forest. Random Forest, proposed in 2001 by Breiman and Cutler (Al Amrani et al., 2018), is one of the most popular and widely used classification algorithms. It is especially useful when working with large datasets with multiple features or when dealing with noisy data. Random Forest, also known as an ensemble learning algorithm, combines several decision trees to produce accurate and reliable predictions for various classification problems.

AdaBoost. AdaBoost (abbreviation for Adaptive Boosting) is a classification and regression machine learning ensemble method developed by Freund and Schapire in 1995 (Schapire & Singer, 1997). AdaBoost combines the predictions of numerous weak learners (often simple and weak classifiers) to produce a single strong classifier. On a given task, classifiers that are "weak" perform just marginally better than random guessing. The main idea behind AdaBoost is to iteratively train a series of weak learners on the same dataset, while giving the training samples various weights. The system prioritizes the samples that were incorrectly identified by the previous weak learners throughout each iteration, thus giving them greater weight. In this manner, weak learners in the future are compelled to focus on the occurrences in the data that are challenging to categorize.

Gradient Boosting. Gradient Boosting Classifier, one of the most powerful machine learning methods, is an ensemble method consisting of various weak learners like in decision trees (Bentéjac et al., 2021). Although it is highly preferred due to its success in complex datasets, the fact that it consists of several hyperparameters makes it difficult to decide on the most suitable one.

Support Vector Machine. Developed by Vapnik (2000), support vector machine is based on identifying an appropriate hyperplane in order to split data points into distinct classes. Because of its proven success in regression as well as classification problems, it is a widely recommended method that has different tuning parameters such as kernel, margin, gamma and regularization (Singh & Singh, 2023).

Method

Data was gathered from the official Twitter accounts and Sourtimes entries of Starbucks and Netflix. Data from both channels was collected just before the earthquake until the date that regular posts and entries were shared about the products and services offered. Regarding the Twitter account, both brands shared their first post three days after the earthquake on the 9th of February 2023 leading to a significant increase in the number of consumer comments shared from that date onwards.

The collected data was initially preprocessed by transforming text to lowercase, removing numerical values, tokenizing (dividing a text into smaller pieces) and removing stop words which are often used in the text such as “a”, “an”, “the”, “is”, “was”, “will”, “would”. Then the data was labelled manually using the following numeric codes: “0” for neutral emotions, “-1” for negative emotions, “-2” for negative relationship reactions. To increase the reliability of the findings, the data was labelled independently by each researcher and then collectively until a consensus was formed. 454 of the 2581 observations were coded as neutral reactions, 1216 as negative emotional reactions and 911 as negative relational reactions (for a qualitative analysis of the codes check Omeraki Çekirdekci and Erarslan, forthcoming). TF-IDF (Term Frequency–Inverse Document Frequency) was used to vectorize (feature extraction by converting text to numerical vectors) data. It is basically a measure of the originality of each word by comparing the number of times words are used in a text.

Using Google Colab (https://colab.research.google.com/), the classification success of the models created using the following machine learning methods – Random Forest, AdaBoost, Gradient Boosting, and Support Vector Machine – was tested. Figure 1 presents the data analysis process.

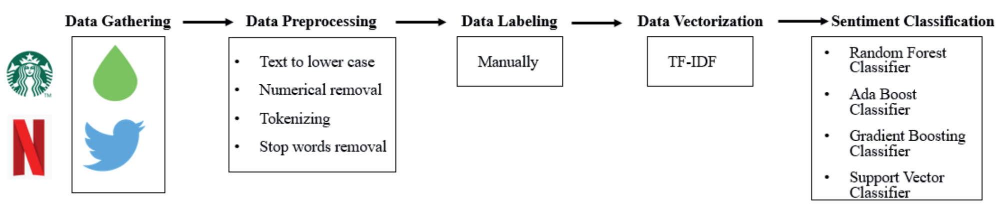

Figure 1. Data Analysis Process

Findings

The objective of this study is to use supervised machine learning approaches to classify consumers’ social media comments and entries about Starbucks and Netflix. 66.6% of 2541 comments are related to Starbucks and 33.4% are related to Netflix. 17.6% of these comments were labeled as 0, 47.1% as -1 and 35.3% as -2. After 80% of the dataset was split as training and 20% as test, data was classified using the selected four machine learning methods. Performance metrics for the methods are provided in Table 1.

Table 1. Performance metrics of classification algorithms

Algorithm	Class	Precision	F1 Score	Recall	Accuracy
Random Forest (RF)	-2	0.79	0.73	0.68	0.67
	-1	0.64	0.73	0.86	
	0	0.43	0.21	0.14	
AdaBoost (AB)	-2	0.78	0.48	0.35	0.58
	-1	0.64	0.69	0.95	
	0	0.00	0.00	0.00	
Gradient Boosting (GB)	-2	0.81	0.71	0.64	0.66
	-1	0.62	0.73	0.89	
	0	0.39	0.16	0.10	
Support Vector Machines (SVM)	-2	0.81	0.79	0.76	**0.71**
	-1	0.68	0.75	0.83	
	0	0.55	0.36	0.27	

Discussion and Conclusion

Advances in technology allowed consumers to create content moving from passive to active receivers and producers of information (Sohaib and Han, 2023). In the highly competitive marketplace consumers' online comments and their level of satisfaction prioritize the agenda of decision-makers in organizations. Consumers' comments include emotions, cognitions and behaviors about the brands providing valuable source for the development of strategies. Systematically obtaining and analyzing comments will allow firms to take early measures thus, supporting the effective management of customer satisfaction, brand loyalty and brand engagement.

This study used sentiment analysis and machine learning techniques to evaluate consumers' comments on social media platforms. The Turkish language comes with some additional challenges than the other languages. Since it is an agglutinative language, it may pose issues in the pre-processing stages of NLP and text mining. Models for predicting the sentiments, which are stored as raw data, were extracted, and labeled manually as -2, -1, 0 based on the content of comments. Especially, RF, AB, GB and SVM classifiers have been used to classify processed data. Results show that the SVM classifier outperformed other algorithms with 71% accuracy rate. Considering its success, it can be concluded that SVM algorithm can be used as an automatic brand hate classifier with an acceptable error rate. Future studies can use deep learning algorithms for the exploration of the phenomenon.

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Çıkar Beyanı: Yazarlar ve herhangi bir kurum/ kuruluş arasında çıkar çatışması yoktur.

Teşekkür: Yayın sürecinde katkısı olan hakemlere teşekkür ederiz.

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