SentixScan: DEVELOPMENT OF A REAL-TIME SENTIMENT ANALYSIS APPLICATION FOR USER PRODUCT REVIEWS ON E-COMMERCE PLATFORMS

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ABSTRACT

Consumer preferences towards online shopping have increasingly grown due to the convenience given by the e-commerce platforms such as Amazon, Shopee, and Lazada. The user-generated product reviews on the platform have a high degree of influence towards the user's purchase decisions, but prove a struggle for businesses to gather valuable data from quickly. *SentixScan* is a real-time sentiment analysis application that has been developed in this study to handle analysis of product reviews and ratings. This is geared towards providing businesses solutions on how they can efficiently handle their user-generated reviews, thus helping them come up with informed and data-driven decisions for their businesses. The analysis only considered product reviews that were written in English language, taking into account accuracy for niche products. Significance lies in contributing towards e-commerce analytics, enhancing customer experiences, and aiding businesses to proactive decision making with a promise of improved brand management, marketing strategies, and market presence.

Keywords: Sentiment Analysis, Natural Language Processing (NLP), Machine Learning, E-Commerce, Product Reviews

Contents

Chapter 1

Introduction

1.1 Overview of the Current State of Technology

Nowadays, e-commerce is widespread, with online shopping becoming the preferred method due to its convenience. Consumers can browse and purchase the products and services of several shops online—in the comfort of their homes (Markellou et al., 2006). As evident in the Philippines, many online shopping platforms such as Shoppee, Lazada, TikTok Shop, and many more offer various products and services to consumers. Other international e-commerce platforms such as Amazon, Alibaba, eBay, and more have also transformed the global retail landscape (Hänninen et al., 2019).

These platforms have created global marketplaces where products from all over the world are available to consumers. They store consumer data regarding their product preferences and purchase patterns. Available data from these platforms provide opportunities for businesses and companies to monitor and analyze customer behavior to develop corresponding strategies in increasing their revenue and ensuring customer satisfaction.

User-generated product reviews play an integral role in shaping the reputation of products and influencing consumer decisions (Forman et al., 2008). They serve as a basis for other users who browse through the products in these e-commerce platforms, providing insights into their decisions whether they are going to commit to purchasing the item/s that they are interested in. These product reviews are valuable, not only to the other consumers, but also to the sellers themselves. They can serve as an assurance to the seller and add to the trustworthiness of their products, developing a good impact to their overall image and branding, or they can become a downfall to their business especially in the case of bad reviews. In general, these product reviews are opportunities for businesses to implement necessary improvements to their operations to enhance product offerings.

The emergence of sentiment analysis has become a vital method for analyzing user-generated product reviews (Jabbar et al, 2019). According to Tang and Zhang (2018), sentiment analysis utilizes natural language processing (NLP) and machine learning algorithms to identify emotions, opinions and contextual details in textual content. Depending on the goals set before it, sentiment analysis has a wide range of applications in many domains.

In social media, it has become an important tool in gauging how the public feel about products and brands. Sites such as Twitter and Facebook use sentiment analysis to follow users' vibes, key trends or issues that are hot, and measuring how successful an organization's marketing campaigns have been. In customer service, sentiment analysis is useful in quickly grasping customer perception in a manner that businesses can decisively address issues and improve on the total customer experience. Sentiment analysis has also been useful in the political discourse where the knowledge of the sentiments of the publics and their attitude can have tremendous implications (Neri et al., 2012; Süerdem & Kaya, 2015; Ahad, 2023).

Although sentiment analysis has been adopted in various domains, ranging from political and social networks to movie reviews, there is a lack of the utilization of sentiment analysis techniques in the context of e-commerce to user-generated product reviews. Huang et al. (2023) highlights the potential of sentiment analysis in e-commerce, focusing on machine learning algorithms that capture user opinions and improve product satisfaction.

To address this gap, the researchers aim to develop *SentixScan*—a real-time sentiment analysis application designed to address the challenges given by user-generated reviews of products on e-commerce platforms. This application will not just bridge the gap in sentiment analysis application for the e-commerce domain, but will also provide opportunities for business to gain better insights from product reviews and make data-informed decisions—thus helping in achieving better customer experience.

1.2 Statement of the Problem

Businesses are always challenged in harnessing the huge amount of information regarding user-generated reviews for products in an effective manner. The nature of the problem that is existing in the business world is striving to utilize meaningful value from the product reviews from e-commerce platforms in a quick and efficient manner. The challenge extends beyond simple data processing, to attempts at a complex analysis of people's sentiments expressed across different languages, cultural contexts, and product categories (Chen et al., 2011).

Such inefficiencies affect businesses due to a lack of any specialized and real-time sentiment analysis tool designed to customize the products for e-commerce platforms. Thus, the problem revolves around a tool that will quickly handle sentiment analysis over these platforms to enable businesses in maximizing value drawn from product reviews provided by the consumers.

1.3 Research Objectives

1.3.1 General Objective

The main objective of this special problem is to conduct a sentiment analysis on Amazon reviews and product ratings in the Philippines and develop a real-time sentiment analysis tool for e-commerce product reviews.

1.3.2 Specific Objectives

Specifically, this study aims:

1. to collect and compile data comprising product reviews and ratings from Amazon Philippines;
2. to analyze patterns within the dataset which underlies the classification of sentiments from customers;

3. to explore Natural Language Processing (NLP) algorithms and find the appropriate models that will be applied for this study; and
4. to design and implement a real-time web application that conducts a comprehensive analysis of customer reviews.

1.4 Scope and Limitations

This special problem will primarily focus on developing a real-time sentiment analysis web application. This application will have two major features: (1) using high-level Natural Language Processing (NLP) algorithms and machine learning models to analyze sentiments from Amazon reviews and products ratings, and (2) real-time capabilities that would provide dynamic feedback and immediate interpretation. Real-time sentiment analysis can be utilized by e-commerce platforms and businesses to observe the sentiments conveyed by users. Additionally, it can also benefit users by offering insights into the emotional tone of their feedback.

On a given note, the application will be aimed at sentiment analysis of user reviews about products expressed in English language, excepting analyses of reviews in other languages. Its effectiveness will depend on various platforms due to differences in formats of reviews and specifics typical for the given platform. Considerations for accuracy must be noted as the application may be limited in the ability to interpret sentiments of niche products or sentiments that are rare and not adequately represented in the training dataset.

The study also does not take on external factors such as market variation or changes in law that potentially impact e-commerce activities.

1.5 Significance of the Research

The main focus of this special problem aims to be significant across multiple domains, contributing to e-commerce analytics and customer experiences. The set of sophisticated tools cam change the business viewpoints and reactions to customers’ sentiments in the digital marketplace. The application promises to improve the overall customer experience by providing insights in real time, offering businesses an opportunity to address their concerns promptly, as well as mold their strategies aimed at increasing satisfaction and loyalty.

Businesses in the e-commerce sector may benefit from the research findings because a real-time sentiment analysis tool may give them the capacity to make informed and data-driven decisions. This capability will support proactive strategies for enhancing products, targeted marketing, as well as customer engagement to ensure businesses remain responsible to dynamic sentiments expressed by the users.

Moreover, the whole concept of *SentixScan* is strategic to marketing and brand management. Companies can take advantage utilizing real-time sentiment analysis in refining the marketing strategies, reaching at specific targeted customers on the personal level, as well as proactively managing their online brand reputation to gain a more strategic and effective market presence.

The research also extends its influences on the field of sentiment analysis for providing valuable insights specific to the user-generated sentiments pertaining to the product reviews within the e-commerce domain.

Lastly, the implications for this special problem may be applicable in an educational setting. The real-time sentiment analysis tool may be used for aiding training of individuals to acquire communication skills and emotional intelligence.

Chapter 2

Review of Related Works and Literature

The landscape for electronic commerce, or popularly known as e-commerce, has experienced an incredible transformation through the last few decades. It changed not only the business world, but also influenced significant consumer behaviors. A study conducted by Verma and Dixit (2023) brings out the exceptional rise of e-commerce driven by technological advancements and ever-changing consumer attitudes to position it for growth. This research opened up windows into the historical context of e-commerce, following its roots from the early days of the internet right to the extent in which the e-commerce enterprise is dominant today.

Further, the path of e-commerce is intricately linked to technological advancement and patterns of consumer preference. Verma and Dixit's research provides such an in-depth view that one can understand, not just through numbers of the growth of e-commerce, but what has been at the root of changes over time. Moreover, it is important to recognize the transformative effect e-commerce has on both businesses and consumers. Such a rise on the online platform has been significant and facilitated not only the transactions, but also fundamentally redefines the way business operates and how the consumers interact with products and services (Deng, 2022).

2.1 Utilization of Sentiment Analysis for E-Commerce

Sentiment analysis, also known as opinion mining, is a field of study that systematically focuses on the computational extraction and exploration of opinions, sentiments, and emotions

(Kumar et al., 2021). It is one of the shaping elements that influence the experiences of customers in their purchasing decisions, as well as offering companies a chance for reviewing customers' sentiments. Positive sentiments in these reviews have a great impact that influences the overall establishment of brand credibility. A collection of favorable evaluations will serve as a strong endorsement that future clients can identify with, as well as a proof of the kind of quality and satisfaction that is tied to the products. It instills trust and reliability, both of which are important to online consumers in the process of decision-making (Xiao & Li, 2017). On the contrary, user-generated content that are categorized as negative sentiments encourages a call to action for businesses (Ott et al., 2013). It is a reflection of the areas where attention and improvement may be required. Negative feedback, if ignored, damages both the brand reputation and customer trust. By acknowledging these shortcomings, businesses that are involved proactively on sentiment analysis are best fit to identify and quickly address issues raised by their customers regarding their products. This proactive action mitigates not only future potential damage to reputation, but also positions the business responsive and committed to enhancing overall quality of products and customer satisfaction (Moghaddam, 2015).

The integration of sentiment analysis in e-commerce platforms is not merely technological enhancements anymore but has grown into strategic needs for businesses that desire to excel in this competitive digital marketplace (Sudhakaran & Jaiganesh, 2020). Decoding the sentiments inscribed within user-generated content provides businesses with insights on customer perception. Such understanding forms the basis on which businesses make informed decisions, carry out marketing strategies, and develop and foster a positive business image and brand to their clients (Shmunk et al., 2014). In essence, Plaza and Albornoz (2012) states that semantic sentiment analysis has turned out to be an essential component in the developing relationship between businesses and consumers, in which feedback acts as a fuel for continuous improvement and innovation.

2.2 Current Technologies and Tools for Sentiment Analysis

Machine learning algorithms have emerged as the most powerful tools in sentiment analysis which propose a data-centric approach towards understanding and predicting sentiments. Such algorithms use training datasets to learn the various patterns and relationships within the data. Particularly the supervised learning, unsupervised learning, and semi-supervised learning algorithms of machine learning have been used for sentiment classifications which made them versatile and widely accepted in sentiment analysis (Agarwal & Mittal, 2016).

Natural Language Processing (NLP) has become an essential part in sentiment analysis. This development gives the machines an ability to process, interpret and generate a human language in an advanced way. From the perspective of sentiment analysis, NLP allows achieving decisive insights out of textual data being capable to understand structures, grammars, and semantics of language (Kotapati et al., 2023). Moreover, neural networks revolutionized the methodologies in analyzing sentiments. Neural networks are such a powerful technique which can simulate the structure of a human brain to some extent, and it is capable enough to understand complex relationships and patterns within data. In sentiment analysis, neural networks—especially deep learning architectures—offer better performance in terms of analyzing text (Tang & Zhang, 2018).

There are numerous existing tools available that aid in making the sentiment analysis process easier. These tools can go from sentiment classification to sentiment polarity analysis. Nowadays, open-source algorithms such as the Natural Language Toolkit (NLTK), TextBlob, and VADER, are so popular because of their accessibility and good performances on many tasks related to sentiment analysis (Sunil & Beniwal, 2020). Similarly, other advanced sentiment analysis-based functionalities such as entity recognition and language support, along with commercial tools like IBM Watson and Microsoft Azure Text Analytics, also become an asset for organizations and researchers doing sentiment analysis and requiring assistance (Ziora, 2016; Harfoushi et al., 2018).

2.3 Synthesis

The literature synthesis forms part of a singular narrative that integrates with the primary objectives of this special problem. The literature provided a historical context through which to understand the development of e-commerce and contextual issues which pertain to user-generated content. The field of sentiment analysis arises as a starting point in response to businesses needing to find ways of navigating the complexities of consumer sentiments. Thus, the current technologies and tools under discussion in the literature influence more than just the development of *SentixScan*, but also contribute to the wider debate on the applications and advancements within the e-commerce landscape.

Overall, this review of the related literature and studies, basically set the stage for the succeeding chapters by providing the basis for the development, implementation, and evaluation of *SentixScan* as a real-time sentiment analysis application designed for e-commerce platforms.

Chapter 3

Materials and Methods

3.1 Development Tools

SentixScan's development will utilize the following tools: (a) Visual Studio (VS) Code, which will serve as the project's integrated development environment; (b) Google Colab, which will be used as a tool for data training and implementing machine learning algorithms; and (c) Github as both the version control system and repository for the project's source code.

Visual Studio (VS) Code

Visual Studio Code is a powerful source code editor with built-in support for languages such as JavaScript and TypeScript while also having an extensive collection of extensions for other languages and runtimes such as Python, C, C++, PHP, .NET and more. The editor also offers features that eases the work of programmers such as code completion, streamlined debugging, easy code navigation, and in-product source control.

Google Colab

Able to harness the full functionality of python libraries in analyzing and visualizing data, Google Colab offers an interactive environment called Colab notebook that enables writing and executing lines of code. Students and data scientists alike can import datasets, and train and evaluate machine learning models for their projects.

GitHub

GitHub is built on the top of web and offers a hosting service providing version control using Git and some other features, which allows for the integration of various services to collaborate with developers on software code. It provides all the distributed revision control and some extra features.

3.2 Data Gathering

The dataset for this project consists of user-generated reviews and ratings information on the products of Amazon platform. The dataset was obtained from Kaggle which is a popular website for finding all sorts of data science and machine learning datasets. Kaggle is a large repository of various datasets contributed by the community members themselves and serves as an invaluable and handy resource for researchers, data scientists, and developers.

The researchers will use Amazon product reviews and ratings dataset sourced from Kaggle as the basis for their analysis or any machine learning application that follows. The dataset contains various categories such as products reviews, users' rating, and other relevant attributes.

3.3 Machine Learning Model

3.3.1 Count Vectorizer

Count vectorizer is a text preprocessing technique that transforms a collection of text in a document into numerical representations. It is crucial in machine learning as some algorithms require values in numeric form by tokenizing the text data, counting the occurrence of each token and creating a matrix with the cell values as the frequency of each token.

3.3.2 Term Frequency – Inverse Document Frequency

Term frequency (TF) looks at the frequency of a particular term that in relation to the document and this can be achieved by the raw count of the words, logarithmically scaled frequency, or Boolean frequency. Inverse Document Frequency (IDF) looks at how common or uncommon a word is among the collection of words. Altogether, TF-IDF gives information on how often the word appears in the document as well as how rare the word is.

3.3.3 Logistic Regression

Logistic Regression is a supervised machine learning algorithm that predicts the probability of an event or observation.

3.3.4 Naïve Bayes

Naïve Bayes operates under a couple of key assumptions, implying that the predictors in the model are independent or unrelated to other features in the model. This technique simplifies the classification by needing only one probability per variable, thus streamlining the calculations.

3.3.5 Support Vector Classification

Support vector classification is a specific implementation of support vector machine (SVM) that performs optimal data transformations with the aim to determine the best hyperplane or boundaries to separate data points into different classes.

3.3.6 Voting Classifier

Voting classifier is an ensemble model that combines predictions from other base classifiers to create a single accurate prediction. The model aggregates the predictions from individual classifiers and decides based on highest voting or prediction.

Chapter 4

Preliminary Results and Discussion

The machine learning models generated by running the data in Google Colab are discussed in this chapter. The models used were Term Frequency-Inverse Document Frequency (TF-IDF) and Logistic Regression, Count Vectorizer and Logistic Regression, TF-IDF and Naïve Bayes, Count Vectorizer and Support Vector Classification (SVC), TF-IDF and SVC, and Voting Classifier with TF-IDF Logistic Regression and TF-IDF Naïve Bayes.

4.1 Classification Report

This section displays all classification reports of all models on the 5 ratings. Precision defines the ratio of true positives to the sum of false positives. Recall defines the ratio of true positives to the sum of true positives and false negatives. The F1-score is the harmonic mean of precision and recall.

Table 4.1

Classification Report of TF-IDF and Logistic Regression			
Rating	Precision	Recall	F1-Score
1	0.40	0.25	0.31
2	0.42	0.15	0.22
3	0.47	0.27	0.35
4	0.41	0.21	0.28
5	0.69	0.93	0.79

Table 4.1 displayed the classification report of using TF-IDF vectorizer and Logistic Regression.

Table 4.2

Classification Report			
Rating	Precision	Recall	F1-Score
1	0.44	0.24	0.31
2	0.37	0.11	0.16
3	0.55	0.28	0.37
4	0.37	0.17	0.23
5	0.67	0.93	0.78

Table 4.2 displayed the classification report of using Count Vectorizer and Logistic Regression.

Table 4.3

Classification Report			
Rating	Precision	Recall	F1-Score
1	0.40	0.25	0.31
2	0.42	0.15	0.22
3	0.47	0.27	0.35
4	0.41	0.21	0.28
5	0.69	0.93	0.79

Table 4.3 displayed the classification report of using TF-IDF and Naïve Bayes.

Table 4.4

Classification Report			
Rating	Precision	Recall	F1-Score
1	0.44	0.24	0.31
2	0.37	0.11	0.16
3	0.55	0.28	0.37
4	0.37	0.17	0.78
5	0.67	0.93	0.78

Table 4.4 displayed the classification report of using Count Vectorizer and SVC.

Table 4.5

Classification Report			
Rating	Precision	Recall	F1-Score
1	0.40	0.25	0.31
2	0.42	0.15	0.22
3	0.47	0.27	0.35
4	0.41	0.21	0.28
5	0.69	0.93	0.79

Table 4.5 displayed the classification report of using TF-IDF and SVC.

Table 4.6

Classification Report			
Rating	Precision	Recall	F1-Score
1	0.52	0.16	0.25
2	0.78	0.11	0.19
3	0.53	0.28	0.37
4	0.40	0.14	0.20
5	0.65	0.96	0.78

Table 4.6 displayed the classification report of using Voting Classifier with TF-IDF Logistic Regression and TF-IDF Naïve Bayes.

As observed, the f1-scores are varied across all models and rating, indicating that the models may need finetuning and stratification in order to have an accurate validation of the report metric.

4.2 Validation Comparison

A comparison of all machine learning models in terms of accuracy score allows the observation of the best model that may be used in refining the system.

Table 4.7

Model	Accuracy on Training	Accuracy on Validation
TF-IDF and Logistic Regression	0.682	0.627
Count Vectorizer and Logistic Regression	0.674	0.620
TF-IDF and Naïve Bayes	0.647	0.615
Count Vectorizer and SVC	0.673	0.622
TF-IDF and SVC	0.577	0.577
Voting Classifier with TF-IDF Logistic Regression and TF-IDF Naïve Bayes	0.665	0.623

Table 4.7 displayed the accuracy score of the machine learning models.

Comparing all models and their scores, TF-IDF and Logistic Regression yielded the highest accuracy on both training and validation while TF-IDF and SVC had the lowest accuracy on both tests. This implied that using TF-IDF and Logistic Regression model may be used in creating the system, once refined, and tuned to further increase its accuracy score.

Literature Cited

[1] Agarwal, B., Mittal, N., Agarwal, B., & Mittal, N. (2016). *Machine learning approach for sentiment analysis*. Prominent feature extraction for sentiment analysis, 21-45.

[2] Ahad, M. (2023). *A REVIEW ARTICLE: USE OF SENTIMENT ANALYSIS IN SOCIAL MEDIA*. International Journal of Engineering Applied Sciences and Technology.

[3] Chen, Y. Y., & Lee, K. V. (2011). *User-Centered Sentiment Analysis on Customer Product Review*. World Applied Sciences Journal, 12, 32-38.

[4] Deng, J. (2022). *How customer behavior has transformed as e-commerce has developed in the digital economy*. BCP Business & Management.

[5] Forman, C.M., Ghose, A., & Wiesenfeld, B.M. (2008). *Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets*. Inf. Syst. Res., 19, 291-313.

[6] F. Neri, C. Aliprandi, F. Capeci, M. Cuadros and T. By, "*Sentiment Analysis on Social Media*," 2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, Istanbul, Turkey, 2012, pp. 919-926, doi: 10.1109/ASONAM.2012.164.

[7] Harfoushi, O., Hasan, D., & Obiedat, R. (2018). *Sentiment Analysis Algorithms through Azure Machine Learning: Analysis and Comparison*. Modern Applied Science, 12(7), 49.

[8] Hänninen, M., Mitronen, L., & Kwan, S. K. (2019). *Multi-sided marketplaces and the transformation of retail: A service systems perspective*. Journal of Retailing and Consumer Services, 49, 380-388.

[9] Huang, H., Asemi, A., & Mustafa, M.B. (2023). *Sentiment Analysis in E-Commerce Platforms: A Review of Current Techniques and Future Directions*. IEEE Access, 11, 90367-90382.

[10] J. Jabbar, I. Urooj, W. JunSheng and N. Azeem, "*Real-time Sentiment Analysis On E-Commerce Application*," 2019 IEEE 16th International Conference on Networking, Sensing and Control (ICNSC), Banff, AB, Canada, 2019, pp. 391-396, doi: 10.1109/ICNSC.2019.8743331.

[11] Kotapati, G., Gandhimathi, S. K., Rao, P. A., Muppagowni, G. K., Bindu, K. R., & Reddy, M. S. C. (2023, July). *A Natural Language Processing for Sentiment Analysis*

from Text using Deep Learning Algorithm. In 2023 2nd International Conference on Edge Computing and Applications (ICECAA) (pp. 1028-1034). IEEE.

[12] Liu, B., & Zhang, L. (2012). *A survey of opinion mining and sentiment analysis*. In Mining text data (pp. 415-463). Springer, Boston, MA.

[13] Markellou, P., Rigou, M., & Sirmakessis, S. (2006). *A Closer Look to the Online Consumer Behavior*. IGI Global: International Academic Publisher. https://www.igi-global.com/chapter/closer-look-online-consumer-behavior/12522

[14] Moghaddam, S. (2015). *Beyond Sentiment Analysis: Mining Defects and Improvements from Customer Feedback*. European Conference on Information Retrieval.

[15] Neri, F., Aliprandi, C., Capeci, F., Cuadros, M., & By, T. (2012). *Sentiment Analysis on Social Media*. 2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, Istanbul, Turkey, 919-926.

[16] Ott, M., Cardie, C., & Hancock, J.T. (2013). *Negative Deceptive Opinion Spam*. North American Chapter of the Association for Computational Linguistics.

[17] Plaza, L., & de Albornoz, J. C. (2012). *Sentiment analysis in business intelligence: a survey*. In Customer Relationship Management and the Social and Semantic Web: Enabling Cliens Conexus (pp. 231-252). IGI Global.

[18] Schmunk, S., Höpken, W., Fuchs, M., & Lexhagen, M. (2013). *Sentiment analysis: Extracting decision-relevant knowledge from UGC*. In Information and Communication Technologies in Tourism 2014: Proceedings of the International Conference in Dublin, Ireland, January 21-24, 2014 (pp. 253-265). Springer International Publishing.

[19] Süerdem, A.K., & Kaya, E. (2015). *Using Sentiment Analysis to Detect Customer Attitudes in Social Media Comments*. Res. Comput. Sci., 90, 207-215.

[20] Sunil, K., & Beniwal, S. (2021, December). *Sentiment analysis: A tool for mining opinions and emotions*. In Proceedings of the International Conference on Innovative Computing & Communication (ICICC).

[21] Tang, D., Zhang, M. (2018). *Deep Learning in Sentiment Analysis*. In: Deng, L., Liu, Y. (eds) Deep Learning in Natural Language Processing. Springer, Singapore. https://doi.org/10.1007/978-981-10-5209-5_8

[22] Verma, S., & Dixit, G. (2023). *The Future of E-commerce: Trends, Challenges, and Opportunities*. International Journal & Research Paper Publisher | IJRASET. https://www.ijraset.com/best-journal/the-future-of-ecommerce-trends-challenges-and-opportunities

[23] Xiao, L., & Li, Y. (2019). *Examining the Effect of Positive Online Reviews on Consumers' Decision Making: The Valence Framework*. J. Glob. Inf. Manag., 27, 159-181.

[24] Ziora, L. (2016). *The sentiment analysis as a tool of business analytics in contemporary organizations*. Studia Ekonomiczne, 281, 234-241.