

A BRIEF OVERVIEW ON SENTIMENT ANALYSIS BASED RECOMMENDATION SYSTEM

Abstract

Many industries, including e-commerce, media, finance, and utilities, have embraced recommender systems. To maximize customer happiness, this type of technology uses a vast quantity of data. These recommendations assist customers in selecting items, while companies can enhance product use. When it comes to analyzing social data, sentiment analysis may be used to acquire a better knowledge of users' thoughts & feelings, which is useful for enhancing the dependability of recommendation systems. However, this data may also be utilized to supplement user ratings of items. According to some, SA (Sentiment Analysis) of articles that may be found in online news sources and blogs or even in the recommender systems themselves can provide better recommendations to users. Research trends that connect sophisticated technological components of recommendation systems utilized in many service domains with the commercial aspects of these services are reviewed in this article. We must first conduct an accurate evaluation of recommendations models for RS (Recommendation Systems) using data mining & application service research.

Deep learning architectures for breast cancer detection are the topic of this review. The following is a list of current machine-learning-based technologies that will be discussed in this survey. Research into recommendation systems is made possible by this study's examination of the numerous technologies and service trends to which recommendation systems may be applied, which gives a complete overview of the area.

Keywords: Recommendation System; Content-Based Filtering; Collaborative Filtering; Recommendation Technique

Authors

Sumit Kumar

Department of Computer Science and Engineering
Arya College of Engineering and IT
Jaipur, India

Dr. Vishal Shrivastava

Department of Computer Science and Engineering
Arya College of Engineering and IT
Jaipur, India

Dr. Vibhakar Pathak

Department of Computer Science and Engineering
Arya College of Engineering and IT
Jaipur, India

I. INTRODUCTION

The widespread use of Web 2.0 has created an atmosphere where customers may express themselves, be creative, communicate, and share. Many consumers use online ordering platforms (like Dianping & Trip Advisor) to share their thoughts about restaurants and their feelings about them. It's a great way to meet new people while doing something fun. A large number of restaurant evaluations written by customers themselves allows customers to communicate their wants and requirements while also supporting businesses in offering timely & personalized service [1,2]. With an average of 9 reviews per person each year, two-thirds of consumers have taken the time to evaluate local businesses [3]. Restaurant clients rely extensively on customer evaluations to determine the quality of service before spending money since goods and services are intangible and complicated. [4].

In addition to expressing the emotional requirements of customers, restaurant reviews serve as a significant source of information to which consumers may turn for information [5]. Consumers prefer to seek a high number of restaurant reviews from other users during the pre-consumer information search phase to lessen the perceived uncertainty & perceived risk created by information asymmetry [6].

The Recommendation System area has been of significant relevance in academia, business, & industry since its inception more than a few decades ago. Amazon, Pandora, Netflix, Trip Advisor, Yelp, Facebook, and articles are just a few of the places where they've been used articles (TED). As e-commerce websites have evolved, it has become clear that RSs can be a valuable tool for helping customers find products that are a good fit for their wants and requirements. As an example, 35 percent of Amazon sales/revenues came from user-recommended goods in 2015.

The three most common methods of making recommendations are collaborative-based, content-based, & hybridized versions of all three. According to what the user liked, purchased, or watched, CB(Content-Based) method mines relevant recommendations for the user [7]. A suggestion is generated for a user using the collaborative filtering (CF) technique, which compares his prior preferences and interests to those of other users [8]. For those who still want additional options, there's the hybrid method, which combines recommendations from several different sources into a single recommendation system [9]. Nevertheless, these conventional RS techniques rely on the recommendation process being based on a single-criteria rating (overall rating). For a suggestion, a single-criterion rating is insufficient since the overall ratings cannot represent the fine-grained understanding underlying the user's behavior. Study on how to improve the RS's performance has become a broad research issue as a result of this.

User suggestions are provided via recommender systems, which are software tools and techniques [10]. Recommender systems aid customers in making judgments about the products or things they want to buy. To produce suggestions, recommender systems process information from a variety of sources, including data that is being actively collected. Depending on the recommender system, different types of data were employed to process the information [11]. As a result of these structures, we can make suggestions regarding products or items based on information that is readily available through online social networks (OSN). The cloud platform provides an Automatic Recommender system that may propose products or things depending on the user's inquiries; this is done through the cloud platform. In the

cloud, users may share their thoughts and sentiments about things and items. For the recommender system, online social networks like Facebook or Twitter will be an excellent cloud platform.

On social media, customers are increasingly discussing their experiences with one another. Many customers rely on their purchasing decisions on what other people think of service or product. As a result of this phenomenon, the number of online viewpoints has grown rapidly (that is, user reviews). It is the opinion of the customer that is expressed in each review, whether it be a purchase, a movie, or a lodging reservation. Consumers and companies alike value product reviews like this. However, despite the advantages of these assessments, it is extremely difficult to extract relevant information from them due to their massive scale and unique qualities [12]. The reviews' qualities make it harder for robots to understand written natural language compared to other structured data sources, hence most RSs do not use them in creating suggestions[13].

In addition to encouraging customers to consider the viewpoints of others, sentiment analysis aids in the selection of purchases based on the opinions of other customers. To meet the needs of advertising and product benchmarking in the industrial company, assessment mining may also be used to highlight product improvement. SA procedure is depicted in Fig.1

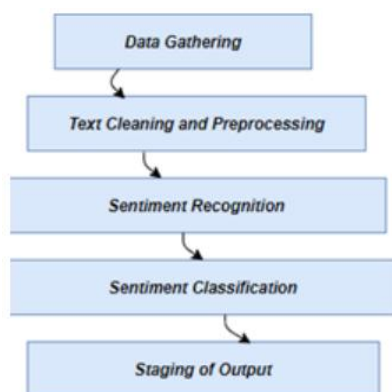


Figure 1: Sentiment Analysis Process

The goal of SA might be in the form of speech, text, pictures, or any other form of communication. Because restaurant reviews are often delivered as text, the majority of articles on sentiment analysis rely on text-based SA [14]. Consumers often establish a broad perception of a restaurant during the pre-purchase information-seeking stage, and the massive volume of restaurant review material surpasses consumers' capacity to comprehend it, and reading fewer reviews improves the probability of forming misperceptions [15]. The platform must be capable of processing information promptly to immediately detect the emotional information present in restaurant reviews.

II. BACKGROUND

1. Sentiment Analysis (SA): In addition to encouraging customers to consider the viewpoints of others, sentiment analysis aids in the selection of purchases based on the opinions of other customers. To meet the needs of advertising and product benchmarking

in the industrial company, assessment mining may also be used to highlight product improvement. The sentiment analysis procedure is depicted in Figure 1.

- Lexicon-based Techniques** were first to be utilized for SA. There are 2 schools of thought: lexical and corpus-based [17]. To classify emotions in the former case, a dictionary of words, like Senti Word Net or Word Net, is utilized. But SA based on corpus-based SA does not depend upon predetermined lexicon nonetheless on a statistical analysis of contents in documents collection, like k-NN [18], CRF [19], and HMM [20], among others.
- Machine Learning-based Techniques** [21] Traditional methods and deep learning are the two main approaches to solving sentiment analysis difficulties. Naive Bayes [22] maximum entropy [23, 24], and SVMs(Support Vector Machines) [25] are examples of traditional machine learning methods. Lexical and sentiment characteristics, sections of the speech, or adjectives and adverbs are all examples of input to these algorithms. How accurate these systems can be is based on the features that are selected. More effective than more conventional methods may be achieved using deep learning. SA may make usage of different types of DL (Deep Learning) models, like RNN, CNN, & DNN. This section discusses categorization models that handle issues at the document, phrase, or aspect levels.
- The Hybrid Approaches** [26] ML& lexicon-based techniques can be utilized together. For the most part, these tactics rely heavily on the use of emotive lexicons. Deep learning-based solutions for SA are depicted in Figure 2 using a taxonomy.

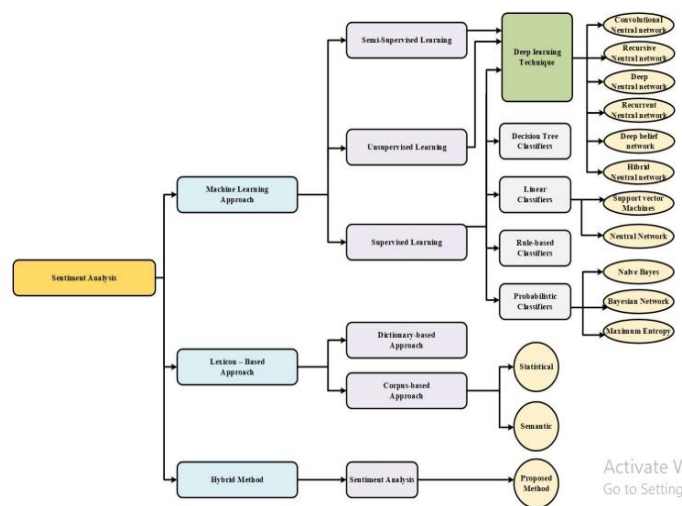


Figure 2: Taxonomy of SA Techniques.

Source: [27].

2. Recommender System: Product or service suggestions are provided by a recommendation system to help consumers make better decisions as internet information continues to grow. E-business, E-government, and e-shopping or e-commerce are only a few of the many systems that have been developed and put into use in the three primary areas of government and business, as well as education [28]. Recommendation systems

are commonly used in e-commerce to help buyers pick from a variety of items. Using a filtering strategy, systems for delivering tailored options have improved [29].

Content-based, CF (Collaborative Filtering), &HRS (Hybrid Recommender Systems) are the three most prevalent methodologies for recommender systems. Based on the sort of social media data that is being analyzed, these strategies might differ. An analysis of common recommender systems by Lu and colleagues [28] efficiently reveals what is needed in the area. Additionally, our activity actively encourages & supports academics & practitioners to encourage widespread use & use of recommender systems in a variety of industries and contexts.

- **Content-based Recommender Systems:** Users' profiles and item attributes are used in content-based techniques. For instance, product characteristics can be utilized to generate user profiles from the content of products accessible over the Internet by the user. Using content-based similarity measurements between catalogue items and those that users have consumed, accessed, or rated favorably, recommender systems filter items. As a result, a user is shown things that are comparable to those that they have previously found interesting. A quantitative study of an item's information may be used to derive its utility for a particular user [31].
 - **Collaborative Filtering based Recommender Systems:** Cooperative filtering is a method for removing goods that people might appreciate based on the opinions of others who have used the same product. It does this by looking through a big number of individuals and identifying a smaller group of people whose likes are similar to the users. It analyses what the user likes and creates a ranked list of suggestions based on that. To utilize recommender algorithms, we require data that includes a collection of goods and a set of users. With this data, the matrix is comprised of the responses supplied by a group of users to certain objects within a collection. A user's ratings would appear in each row, and an item's ratings would appear in each column. [32].
 - **Hybrid Recommender Systems:** Any data that may be gleaned or inferred from online platforms, social media, or additional sources can be used in a hybrid approach. The typical issues in recommender systems can be addressed by a generic consolidative model based on a combination of individual deployment and accumulation of rankings and forecasts. Collaborative Filtering, for example, has sparseness, scalability, and cold-start difficulties [33, 34]. Each recommendation technique has advantages and drawbacks. When we have a lot of data, we have a sparseness problem. When a person or item is introduced to the system, a cold-start issue develops because of a lack of rating data. Solving these issues may be made easier by combining sentiment analysis and recommendation approaches.
- 3. Recommendation Techniques:** Data mining is a method for finding patterns and connections in massive datasets using statistical analysis [35]. To classify client or visitor clickstream data matching the client or visitor group, it analyses the item information, provides recommendations to the user, also builds comparable user groups amongst users. For fulfilling the demands of individual users, it can also offer personalized browsing alternatives. [36] Recommendations based on various data mining approaches can be

generated. Figure 3 provides a visual representation of the strategies that will be discussed in this section.

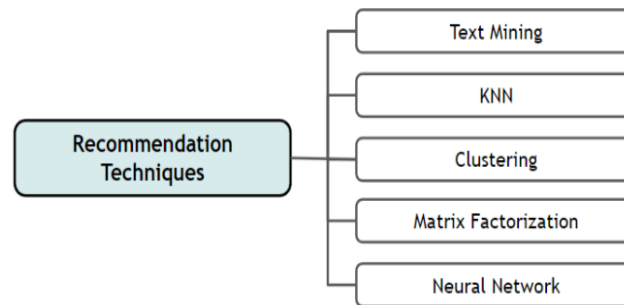


Figure 3: Technology mainly used in Recommendation System

- **Text Mining:** Data may be mined for important text information by extracting text-related information. The semantically relevant information has been retrieved from the accompanying text thanks to current advances in natural language processing technology. A limitation of comprehending semantics exists when NLP (Natural Language Processing) is utilized in various text analysis methods because of the inclination to assess texts based on the frequency of words [38]. As a result, the ontology [39], which specifies the common vocabulary of things & organizes meaning by establishing conceptual schema of text-domain, began to be employed to correctly comprehend the meaning of the text.
- **KNN (K-Nearest Neighbor):** To categorize a dataset, the K-Nearest Neighbor (KNN) method sorts test and training tuples based on their K-nearest neighbors. KNN uses distance-based weighting to compare the similarity between each piece of data to classify datasets [40]. Pearson correlation, Euclidean distance & cosine similarity are the most often used methods for comparing similarity. Using the KNN algorithm, a recommendation system may classify a user's search habits and forecast what products the user would like in the future. It is possible to categorize objects that are similar to user likes based on patterns in user activity data, like click stream data & web server logs, and then utilize the findings to propose appropriate goods.
- **Clustering:** It is common practice in recommendation systems to employ clustering as a method of classifying data into discrete categories or clusters [41]. K-means clustering is the most often used clustering approach in the recommendation system. A technique known as K-means clustering gathers data into groups centered on the mean once a predetermined number of K clusters has been selected. Following the computation of all of the data in RS, the data is allocated to the nearest cluster & calculation is repeated in a sequence of computing cluster centers [42]. It is, nevertheless, sensitive to the scalability problem, in which the computation performance reduces as the number of users and objects rises when a recommendation system is being serviced by K-means clustering.
- **Neural Network:** Speech and picture recognition, as well as photo search and language translation, have seen a rise in neural network utilization in recent times. However, although neural networks have only just been introduced and used in the

recommendation system sector, a large number of studies are being undertaken as one of the most important areas of study in this domain. [44] This technique has been widely used in research to acquire more data in situations when it is tough to comprehend customer preferences depending upon previous data. Deep learning has the potential to enhance recommendation systems, as demonstrated by He et al. [45] who used DNN (Deep Neural Network) to model noisy implicit feedback data. As a result, neural networks are used in the creation of an RS to protect and supplement data to solve the difficulties of sparsity and cold start in Collaborative Filtering, as well as to enhance the performance of the recommendation system itself, among other factors.

4. Literature Review: For SA of online ordering platform reviews, we used an attention mechanism and a Bi-GRU. Online restaurant reviews and sentiment analysis approaches are discussed in this section.

- **Online Restaurant Reviews:** When it comes to choosing a restaurant, customers often look to customer evaluations in addition to further information offered by merchants, like expert advice, restaurant descriptions, & recommendations based on their preferences [46]. To build a general impression of a store, customers who read restaurant reviews would draw on their prior experiences to form an opinion of the business, which in turn influences their purchasing decisions. As a result of checking for internet restaurant evaluations, many consumers choose to dine at a well-known establishment.[47]

In online evaluations also other types of computer-mediated communication, consumers convey their emotions. [54] Emotional data from internet restaurant evaluations was gleaned by some academics to give practical advice. Xu & Luo utilized the DL method to investigate aspect restaurant sentiment during the COVID-19 pandemic period also found that the DL model performed better overall than machine learning algorithms [55]. Restaurant review sentiment is classified using Naive Bayes, a method that helps marketers understand the preferences and characteristics of their customers [56]. SA of restaurant reviews has been investigated from a methodological standpoint by certain researchers. For SA, Kim et al. utilized the word co-occurrence technique to determine how many times certain words occur together in a sentence. The authors then used this information to determine which sentences had the highest implicit feature scores, & findings demonstrated that this threshold-based approach performed well [57]. The emotional intensity of online reviews was assessed using a text-mining algorithm, & an experimental study indicated that pleasant emotions had a negative influence on reviews, while negative emotions had a beneficial effect, and expressing furious feelings was more effective than good emotions [58]. SA of online restaurant reviews was performed by Krishna et al. using ML techniques, and SVM produced the best results when applied to a specific data set [59].

- **Sentiment Analysis Method:** As a computer investigation of people's demands, attitudes, & feelings about a thing [60], SA is also called opinion mining. Findings of SA may be used in a variety of domains, like topic monitoring, online sentiment opinion analysis, word-of-mouth evaluation of enormous items, etc.

Selection of features from subjective texts is a critical part of sentiment analysis [61, 62], and doing so well may boost the accuracy of sentiment analysis greatly. Researchers have spent a great deal of time looking at features in an attempt to discover a good way to pick features. According to Zhang and colleagues, the Boolean weighting approach that they utilized to determine feature weights resulted in greater accuracy than the feature characterization methods they picked [62]. A more domain-specific approach to sentiment analysis necessitates domain-specific information to increase the system's performance; in this way, product feature selection may be viewed as a process of identifying domain-specific named entities. Sentiment analysis is less effective when it is applied outside of a specific context, and existing studies on feature selection are limited.

Sentiment dictionaries and machine learning approaches have been employed in some research to assess restaurant reviews [63], however, the data processing effort and the domain are less transferrable. As a result, deep learning-based sentiment analysis approaches are becoming more popular because they offer automated feature extraction, richer representation performance, & higher performance [64]. Traditional methods of sentiment classification lose both temporal and positional information, so Abdi et al. presented a DL-based method (called RNSA) to classify user opinions expressed in reviews [65]. This approach outperforms the traditional methods in terms of sentiment classification at the sentence level. Al-Smadi utilized LSTM (Long Short-Term Memory) to analyze reviews of Arabian hotels in 2 ways: First, by integrating Bi-LSTM and conditional random fields for the formulation of opinion requirements classification, and second, by employing LSTM for SA, which both surpassed the prior baseline research, it was discovered that both were superior to the prior baseline study[66].

Sentiment dictionaries and classical machine learning are commonly utilized in the field of SA. Because the performance of the model is largely influenced by the feature selection technique and parameter adjustment, these strategies are ineffective. CNN, RNN, LSTM, also other network topologies are included in DL. Neural networks are utilized in DL-based SA models because they can learn to extract complicated characteristics from data with minimum external contributions [67]. SA depends upon DL is more generalizable also has superior performance in terms of feature extraction and nonlinear fitting than sentiment analysis based on machine learning.

- 5. Applications:** The recommendation system has been employed in a wide range of service industries. These models and technology for recommendation systems outlined above will be examined in this research to see how they may be applied to a specific service field. Streaming services, social network services, e-commerce services, tourism services, education services, healthcare services, and academic information services were all included in the recommendation system's scope of use. Recommendation systems with rising user or commercial value and services that emerge often when 'Recommendation System' is searched in the Google Scholar search engine are broken down into seven primary categories. As seen in Figure 4, this section's recommendation system relies heavily on several services.

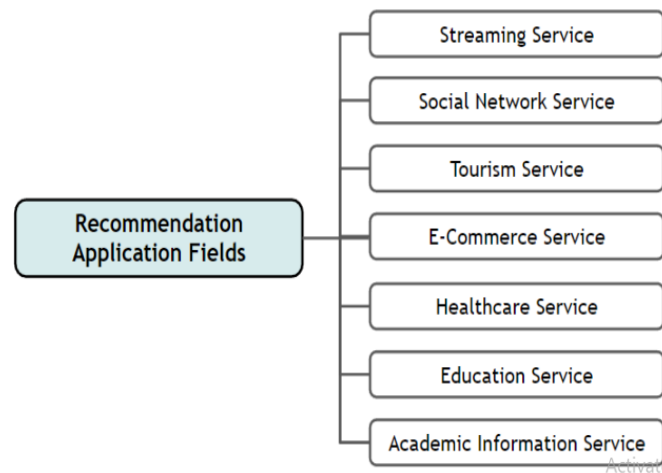


Figure 4: Recommendation systems used in this study may be found here.

Due to the growing popularity of Internet-connected smartphones, it is now possible to provide mobile users with personalized and context-sensitive suggestions, and hence, more mobile RSs are required. A more difficult problem arises when dealing with diverse, noisy, and time- and space-dependent mobile data. In the realm of RS, the more mobile-based analysis might have a substantial impact.

III. CONCLUSION

The proliferation of the Internet, mobile devices, and SNS (Social Networking Sites) has led to an increase in the number of online & application services. Thus, it is imperative to build a wide range of RSs that can assist consumers in quickly receiving and making selections in the face of an ever-increasing amount of item information. As a result, wearable gadgets and click stream data combined with real-time recommendation systems often lead to improved outcomes. A healthcare recommendation system's outputs, such as a diagnosis and treatment plan, have lower affinity than those depending upon clinical data. Real-time data, on the other hand, assures a more relevant outcome by reflecting patients' present state and can provide prompt advice for consultation services and urgent remedies.

Study on RSs was examined from a macro viewpoint, including instances of service applications & interconnection between RS-related study& business of application service. For academics interested in recommendation systems, this was meant to provide a general perspective. This work will serve as a foundation for future research into the creation of recommendation systems tailored to definite requirements of businesses operating in the application service sector.

REFERENCES

- [1] 1. Anaya-Sánchez, R.; Molinillo, S.; Aguilar-Illescas, R.; Liébana-Cabanillas, F. Improving travellers' trust in restaurant review sites. *Tour. Rev.* 2019, 74, 830–840.
- [2] 2. Chen, Y.; Xie, J. Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Manag. Sci.* 2008, 54, 477–491.
- [3] 3. Local Consumer Review Survey. Available online: <https://www.brightlocal.com/research/local-consumer-review-survey/> (accessed on 1 January 2019).

- [4] 4. Yang, S.-B.; Hlee, S.; Lee, J.; Koo, C. An empirical examination of online restaurant reviews on Yelp.com: A dual coding theory perspective. *Int. J. Contemp. Hosp. Manag.* 2017, 29, 817–839.
- [5] Marine-Roig, E.; Clave, S.A. A. A method for analysing large-scale UGC data for tourism: Application to the case of Catalonia. In *Information and Communication Technologies in Tourism 2015*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 3–17.
- [6] 6. Hong, H.; Xu, D.; Wang, G.A.; Fan, W. Understanding the determinants of online review helpfulness: A meta-analytic investigation. *Decis. Support Syst.* 2017, 102, 1–11.
- [7] Pazzani, M. J. & Billsus, D. 2007. *Content-Based Recommendation Systems*. Dlm. (pnyt.). *The Adaptive Web*, hlm. 325-341. Springer
- [8] Aciar, S., Zhang, D., Simoff, S. & Debenham, J. 2007. Informed Recommender: Basing Recommendations on Consumer Product Reviews. *IEEE Intelligent Systems* 22(3):
- [9] Danilova, V. & Ponomarev, A. 2016. Hybrid Recommender Systems: The Review of State-of-the-Art Research and Applications. *PROCEEDING OF THE 20TH CONFERENCE OF FRUCT ASSOCIATION*.
- [10] Esmaeili L., Mardani S., Hashemi Golpayegani S.A., Zanganeh Madar Z. "A novel tourism recommender system in the context of social commerce" *Expert Systems with Applications*, 149 (1) (2020)
- [11] Hedge S.B., Satyappanavar S., Setty S. "Sentiment based food classification for restaurant business" *International conference on advances in computing, communications and informatics, IEEE, Bangalore, India (2018)*, pp. 1455-1462
- [12] Chen, L., Chen, G. & Wang, F. 2015. Recommender Systems Based on User Reviews: The State of the Art. *User Modeling and User-Adapted Interaction* 25(2): 99-154.
- [13] Musat, C.-C., Liang, Y. & Faltings, B. 2013. Recommendation Using Textual Opinions. *IJCAI International Joint Conference on Artificial Intelligence*, hlm. 2684-2690.
- [14] Kim, Y.; Shim, K. TWILITE: A Recommendation System for Twitter Using a Probabilistic Model Based on Latent Dirichlet Allocation. *Inf. Syst.* 2014, 42, 59–77.
- [15] Zhang, Y. GroRec: A Group-Centric Intelligent Recommender System Integrating Social, Mobile and Big Data Technologies. *IEEE Trans. Serv. Comput.* 2016, 9, 786–795.
- [16] Bhavitha, B.; Rodrigues, A. P.; Chiplunkar, N. N. In *Comparative study of machine learning techniques in sentimental analysis*, 2017 *International conference on inventive communication and computational technologies (ICICCT)*, 2017; IEEE: 2017; pp 216-221.
- [17] Salas-Zárate, M. d. P.; Medina-Moreira, J.; Lagos-Ortiz, K.; Luna-Aveiga, H.; Rodriguez-Garcia, M. A.; Valencia-García, R., *Sentiment analysis on tweets about diabetes: an aspect-level approach. Computational mathematical methods in medicine* 2017, 2017.
- [18] Huq, M. R.; Ali, A.; Rahman, A., *Sentiment analysis on Twitter data using KNN and SVM. Int J Adv Comput Sci Appl* 2017, 8, (6), 19-25.
- [19] Pinto, D.; McCallum, A.; Wei, X.; Croft, W. B. In *Table extraction using conditional random fields*, *Proceedings of the 26th annual international ACM SIGIR conference on Research and development in information retrieval*, 2003; 2003; pp 235-242.
- [20] Soni, S.; Sharaff, A. In *Sentiment analysis of customer reviews based on hidden markov model*, *Proceedings of the 2015 International Conference on Advanced Research in Computer Science Engineering & Technology (ICARCSET 2015)*, 2015; 2015; pp 1-5.
- [21] Zhang, X.; Zheng, X. In *Comparison of text sentiment analysis based on machine learning*, 2016 *15th International Symposium on Parallel and Distributed Computing (ISPDC)*, 2016; IEEE: 2016; pp 230-233.
- [22] Malik, V.; Kumar, A., *Sentiment Analysis of Twitter Data Using Naive Bayes Algorithm. International Journal on Recent and Innovation Trends in Computing and Communication* 2018, 6, (4), 120-125.
- [23] Mehra, N.; Khandelwal, S.; Patel, P., *Sentiment identification using maximum entropy analysis of movie reviews. Stanford University* 2002.
- [24] Wu, H.; Li, J.; Xie, J., *Maximum Entropy-based Sentiment Analysis of Online Product Reviews in Chinese. In Automotive, Mechanical and Electrical Engineering*.
- [25] Firmino Alves, A. L.; Baptista, C. d. S.; Firmino, A. A.; Oliveira, M. G. d.; Paiva, A. C. d. In *A Comparison of SVM versus naivebayes techniques for sentiment analysis in tweets: a case study with the 2013 FIFA confederations cup*, *Proceedings of the 20th Brazilian Symposium on Multimedia and the Web*, 2014; ACM: 2014; pp 123-130.
- [26] Pandey, A. C.; Rajpoot, D. S.; Saraswat, M., *Twitter sentiment analysis using hybrid cuckoo search method. Information Processing & Management* 2017, 53, (4), 764-779.
- [27] Medhat, W.; Hassan, A.; Korashy, H., *Sentiment analysis algorithms and applications: A survey. Ain Shams Engineering Journal* 2014, 5, (4), 1093-1113.
- [28] Lu, J.; Wu, D.; Mao, M.; Wang, W.; Zhang, G., *Recommender system application developments: a survey. Decision Support Systems* 2015, 74, 12-32.

- [29] Betru, B. T.; Onana, C. A.; Batchakui, B., A Survey of State-of-the-art: Deep Learning Methods on Recommender System. *International Journal of Computer Applications* 2017, 162, (10).
- [30] Kardan, A. A.; Ebrahimi, M., A novel approach to hybrid recommendation systems based on association rules mining for content recommendation in asynchronous discussion groups. *Information Sciences* 2013, 219, 93-110.
- [31] Hdioud, F., Frikh, B. & Ouhbi, B. 2013. Multi-Criteria Recommender Systems Based on Multi-Attribute Decision Making. *Proceedings of international conference on information integration and web-based applications & services*, hlm. 203.
- [32] Yang, C., Yu, X., Liu, Y., Nie, Y. & Wang, Y. 2016. Collaborative Filtering with Weighted Opinion Aspects. *Neurocomputing* 210(185-196).
- [33] S. Sánchez-Moreno, D.; López Batista, V. F.; Muñoz Vicente, M. D.; Gil González, A. B.; Moreno-García, M. N., A session-based song recommendation approach involving user characterization along the play power-law distribution. *Complexity* 2020
- [34] 38. Adomavicius, G.; Tuzhilin, A.; engineering, d., Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge* 2005, 17, (6), 734-749.
- [35] Lika, B.; Kolomvatsos, K.; Hadjiefthymiades, S. Facing the Cold Start Problem in Recommender Systems. *Expert Syst. Appl.* 2014, 41, 2065–2073.
- [36] Gündüz, S.; Özsü, M.T. A web page prediction model based on a click-stream tree representation of user behavior. In *Proceedings of the 9th ACM International Conference on Knowledge Discovery and Data Mining (KDD)*, Washington, DC, USA, 24–27 August 2003; pp. 535–540.
- [37] Gómez-Pérez, A.; Corcho, O. Ontology languages for the Semantic Web. *IEEE Intell. Syst.* 2002, 17, 54–60.
- [38] Yu, Eunji; Kim, Jung-Cheol; Lee, Choon Yeul; Kim, Namgyu Using Ontologies for Semantic Text Mining. *J. Inf. Syst.* 2012, 21, 137–161.
- [39] 62. Noy, N.F.; McGuinness, D.L. *Ontology Development 101: A Guide to Creating Your First Ontology*; Stanford University: Stanford, CA, USA, 2001.
- [40] Guo, G.; Wang, H.; Bell, D.; Bi, Y.; Greer, K. KNN Model-Based Approach in Classification. In *On The Move to Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE.*; Meersman, R., Tari, Z., Schmidt, D.C., Eds.; *Lecture Notes in Computer Science*; Springer: Berlin/Heidelberg, Germany, 2003; Volume 2888, pp. 986–996, ISBN 978-3-540-20498-5.
- [41] Shepitsen, A.; Gemmell, J.; Mobasher, B.; Burke, R. Personalized Recommendation in Social Tagging Systems Using Hierarchical Clustering. In *Proceedings of the 2008 ACM Conference on Recommender Systems—RecSys '08*, Lausanne, Switzerland, 23–25 October 2008; p. 259.
- [42] Bilge, A.; Polat, H. A Comparison of Clustering-Based Privacy-Preserving Collaborative Filtering Schemes. *Appl. Soft Comput.* 2013, 13, 2478–2489
- [43] Gan, G.; Ma, C.; Wu, J. *Data Clustering: Theory, Algorithms, and Applications*; Society for Industrial and Applied Mathematics: Philadelphia, VA, USA, 2007
- [44] Wang, H.; Wang, N.; Yeung, D.-Y. Collaborative Deep Learning for Recommender Systems. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Sydney, Australia, 10–13 August 2015; pp. 1235–1244.
- [45] He, X.; Liao, L.; Zhang, H.; Nie, L.; Hu, X.; Chua, T.-S. Neural Collaborative Filtering. In *Proceedings of the 26th International Conference on World Wide Web*, Perth, Australia, 3–7 April 2017; *International World Wide Web Conferences Steering Committee*; pp. 173–182.
- [46] Mudambi, S.M.; Schuff, D. Research note: What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Q.* 2010, 34, 185–200.
- [47] Yang, S.-B.; Hlee, S.; Lee, J.; Koo, C. An empirical examination of online restaurant reviews on Yelp.com: A dual coding theory perspective. *Int. J. Contemp. Hosp. Manag.* 2017, 29, 817–839.
- [48] Nakayama, M.; Wan, Y. The cultural impact on social commerce: A sentiment analysis on Yelp ethnic restaurant reviews. *Inf. Manag.* 2019, 56, 271–279.
- [49] Jurafsky, D.; Chahuneau, V.; Routledge, B.R.; Smith, N.A. Narrative framing of consumer sentiment in online restaurant reviews. *First Monday* 2014.
- [50] Jia, S.S. Motivation and satisfaction of Chinese and US tourists in restaurants: A cross-cultural text mining of online reviews. *Tour. Manag.* 2020, 78, 104071.
- [51] Meek, S.; Wilk, V.; Lambert, C. A big data exploration of the informational and normative influences on the helpfulness of online restaurant reviews. *J. Bus. Res.* 2021, 125, 354–367.
- [52] Tian, G.; Lu, L.; McIntosh, C. What factors affect consumers' dining sentiments and their ratings: Evidence from restaurant online review data. *Food Qual. Prefer.* 2021, 88, 104060.

- [53] Li, H.; Qi, R.; Liu, H.; Meng, F.; Zhang, Z. Can time soften your opinion? The influence of consumer experience valence and review device type on restaurant evaluation. *Int. J. Hosp. Manag.* 2021, 92, 102729.
- [54] Lee, M.; Jeong, M.; Lee, J. Roles of negative emotions in customers' perceived helpfulness of hotel reviews on a user-generated review website: A text mining approach. *Int. J. Contemp. Hosp. Manag.* 2017.
- [55] Luo, Y.; Xu, X. Comparative study of deep learning models for analyzing online restaurant reviews in the era of the COVID-19 pandemic. *Int. J. Hosp. Manag.* 2021, 94, 102849.
- [56] Micu, A.; Micu, A.E.; Geru, M.; Lixandroi, R.C. Analyzing user sentiment in social media: Implications for online marketing strategy. *Psychol. Mark.* 2017, 34, 1094–1100
- [57] Schouten, K.; Frasincar, F. Finding implicit features in consumer reviews for sentiment analysis. In *International Conference on Web Engineering*; Springer: Berlin/Heidelberg, Germany, 2014.
- [58] Li, H.; Liu, H.; Zhang, Z. Online persuasion of review emotional intensity: A text mining analysis of restaurant reviews. *Int. J. Hosp. Manag.* 2020, 89, 102558.
- [59] Krishna, A.; Akhilesh, V.; Aich, A.; Hegde, C. Sentiment analysis of restaurant reviews using machine learning techniques. In *Emerging Research in Electronics, Computer Science and Technology*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 687–696.
- [60] Medhat, W.; Hassan, A.; Korashy, H. Sentiment analysis algorithms and applications: A survey. *Ain Shams Eng. J.* 2014, 5, 1093–1113.
- [61] Li, L.; Goh, T.-T.; Jin, D. How textual quality of online reviews affect classification performance: A case of deep learning sentiment analysis. *Neural Comput. Appl.* 2020, 32, 4387–4415.
- [62] Zheng, L.; Wang, H.; Gao, S. Sentimental feature selection for sentiment analysis of Chinese online reviews. *Int. J. Mach. Learn. Cybern.* 2018, 9, 75–84.
- [63] Sun, Q.; Niu, J.; Yao, Z.; Yan, H. Exploring eWOM in online customer reviews: Sentiment analysis at a fine-grained level. *Eng. Appl. Artif. Intell.* 2019, 81, 68–78.
- [64] Zhang, L.; Wang, S.; Liu, B. Deep learning for sentiment analysis: A survey. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* 2018, 8, e1253.
- [65] Abdi, A.; Shamsuddin, S.M.; Hasan, S.; Piran, J. Deep learning-based sentiment classification of evaluative text based on Multi-feature fusion. *Inf. Process. Manag.* 2019, 56, 1245–1259
- [66] Al-Smadi, M.; Qawasmeh, O.; Al-Ayyoub, M.; Jararweh, Y.; Gupta, B. Deep Recurrent neural network vs. support vector machine for aspect-based sentiment analysis of Arabic hotels' reviews. *J. Comput. Sci.* 2018, 27, 386–393.
- [67] Araque, O.; Corcuera-Platas, I.; Sánchez-Rada, J.F.; Iglesias, C.A. Enhancing deep learning sentiment analysis with ensemble techniques in social applications. *Expert Syst. Appl.* 2017, 77, 236–246.