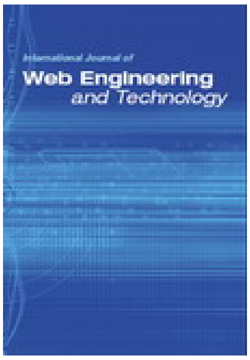


International Journal of Web Engineering and Technology

ISSN online: 1741-9212 - ISSN print: 1476-1289
https://www.inderscience.com/ijwet

The role of sentiment analysis in a recommender system: a systematic survey

Jitali Patel, Hitesh Chhinkaniwala

DOI: 10.1504/IJWET.2022.10049993

Article History:

Received:	09 February 2021
Last revised:	15 April 2022
Accepted:	18 April 2022
Published online:	25 August 2022

Copyright © Inderscience Enterprises Ltd.

The role of sentiment analysis in a recommender system: a systematic survey

Jitali Patel*

Nirma University – Institute of Technology,
Gujarat, India
Email: jitali.patel@nirmauni.ac.in
*Corresponding author

Hitesh Chhinkaniwala

Adani Institute of Infrastructure (AII),
Ahmedabad, Gujarat, India
Email: drhiteshrc1@gmail.com

Abstract: Currently, fields like e-commerce, education, social media, tourism, and the entertainment industry rely on recommender systems to provide personalised services to their clients. The most common and widely accepted technique – collaborative filtering, creates recommendations by examining the users' past rating patterns. Collaborative filtering assumes that a users' past rating data accurately reflects their actual preferences. However, different study found that the ratings may not accurately reflect user preferences in the real-world circumstances. Therefore, to deal with this problem, sentiment analysis of user-generated text is started to be used. It helps to improve the performance of recommender systems, as it provides more specific and trustworthy user preferences than ratings. A sentiment-aware recommender system captures sentiment from the user-generated content and provides most suited personalised services to the user. We have classified sentiment enhanced recommender systems according to the level of sentiment analysis and presented technical aspects such as datasets, methodologies and results.

Keywords: recommender system; sentiment analysis; user-generated text; collaborative filtering; sentiment-aware recommender system.

Reference to this paper should be made as follows: Patel, J. and Chhinkaniwala, H. (2022) 'The role of sentiment analysis in a recommender system: a systematic survey', *Int. J. Web Engineering and Technology*, Vol. 17, No. 1, pp.29–62.

Biographical notes: Jitali Patel is working as an Assistant Professor in Computer Science and Engineering Department at Institute of Technology, Nirma University. She has obtained her post-graduation degree ME(CE) from Dharmsinh Desai University in 2010. She has an experience of more than ten years in the field of teaching. Her area of interest and research are machine learning and its applications. She has published more than ten peer review research articles.

Hitesh Chhinkaniwala is an Associate Professor and the Head at the Department of Information and Communication Technology, Adani Institute of Infrastructure Engineering, India. His area of interest are data mining and knowledge discovery, privacy-preserving, text mining, text summarisation,

Copyright © 2022 Inderscience Enterprises Ltd.

information extraction, sentiment analysis, statistical data analysis and ontology learning. He has published more than 20 peer review research articles and a book. He is a reviewer of *Transactions on Knowledge Discovery from Data* (*TKDD*).

1 Introduction

In overcrowded search areas, recommender systems have proven to be an excellent information filtering approach for anticipating what users will be interested in and giving personalised suggestions of services to users (Lü et al., 2012). The conventional recommender system provides recommendations for books, movies, products/services, news articles and recommends like-minded personalities on social media. Traditional e-commerce recommender systems work on explicit ratings furnished by users and may also infer implicit evaluations, e.g., purchase implies high ratings. However, the problem with explicit ratings is that very few people rate any item explicitly, so from the universe of items, when a single user interacts with a small subset of items, the user-item rating matrix becomes very sparse. It is easy to learn user preferences from high ratings, but tough to extract them from low ratings. It is challenging to infer user preferences using the overall star rating; therefore, traditional e-commerce recommender systems which work on explicit ratings suffer from poor accuracy (Lei et al., 2016). Social media recommender systems utilise the number of likes and replies on the comments for the topic. However, the reactions to comments may not be indicative of the sentiments of users towards those comments. All these hindrances of traditional recommender systems, either for e-commerce or social media, can be resolved by analysing the sentiment of textual comments provided by users (Chen, 2019; Colace et al., 2015). Product reviews are analysed to extract feature level user preferences for e-commerce recommender systems (Ma et al., 2018). Social media comments should be analysed before giving a friend recommendation, topic recommendation, or suggestions for followee.

Valuable information like features and context can be extracted from user-generated text. Hence, along with overall rating, additional sentiment analysis of reviews generated by the users is also used to increase the recommendation's accuracy. For instance, a movie recommender system can infer a user's opinion for a movie from his social media comments, and based on a user's sentiment, recommendation accuracy can be improved (Selmene and Kodia, 2020). Therefore, researchers have started considering sentiment analysis of reviews and comments for improving the accuracy of recommender systems.

1.1 Scope of this survey

For the last two decades, the field of recommender systems have been a trending area of research, leading to many recommender system surveys being published. Our objective is different; we propose a survey of sentiment-aware recommender systems which remain in their initial stage. Bobadilla et al. (2013) surveyed traditional recommendation methods, their evaluation measures, and similarity measures to implement recommender system. They investigated a recommender system that uses social information for a recommendation. They also explored trust-aware and location-aware recommender systems, but not sentiment-aware recommender systems, which this survey aims to address.

Yang et al. (2014) presented how recommender systems can adopt social network information as an additional input for accuracy improvement. They investigated two different categories of collaborative filtering based social recommender systems, matrix factorisation based system and nearest neighbourhood based systems. The survey carried out in this research is different as the focus is not on sentiment analysis. Lu et al. (2015) conducted an exhaustive survey on recommender system's application domains. Different methodologies and application platforms were investigated; furthermore, new directions were identified for researchers to work on in this area. Ravi and Ravi (2015) presented an extensive survey on sentiment analysis by covering methodologies, application domains, data sets information, and open issues. Furthermore, the area of recommender systems is also mentioned as one of the application areas of sentiment analysis. However, sentiment-aware recommender systems are not in the scope of their survey.

Al-Ghuribi and Noah (2019) presented a comprehensive survey on recommender systems that considered multi-criteria. However, they do not furnish application domains and do not focus on the various levels of sentiment analysis. Additionally, a very few future directions are mentioned. So, as mentioned above, many surveys on conventional recommender systems and their applications already exist, and review articles on sentiment analysis are also available. Still, no one considered implementing a recommender system using sentiment analysis in their survey. The prime focus of our survey is on recommender systems that exploit sentiment analysis called sentiment-aware recommender system. Therefore, we try to cover the weaknesses discussed above in our systematic study on the role of sentiment analysis in recommender systems.

1.2 Motivation

The main motive of our survey on sentiment-aware recommender systems is as follows:

- Very few survey has considered the role of sentiment analysis in recommender systems. Rapid research advancements in sentiment-aware recommender systems have motivated us to conduct a systematic survey by exploring, selecting, and summarising relevant studies.
- Depth of sentiment analysis with different strategies has been introduced to implement personalised recommender systems.

1.3 Contribution

In this paper, we exhibit an extensive survey of recommender systems implemented using various levels of sentiment analysis. The main contributions of this paper are:

- We present rationales to incorporate sentiment analysis in a recommender system. Then we explained the architecture of a sentiment-aware recommender system.
- We provide a survey of pre-processing techniques that can be performed on text before applying sentiment analysis on it.
- We present an in-depth survey of sentiment enhanced recommender systems using various tools, machine learning, and deep learning models.
- We also highlight application domains and research opportunities.

1.4 Organisation

This research paper is organised as follows: Section 2 presents a systematic survey methodology. Section 3 describes the need for sentiment analysis in recommender systems. The phases of a recommender system using sentiment analysis are explained in Section 4. Data collection and pre-processing techniques used by various approaches are given in Section 5. Section 6 furnishes the details of different application domains. Section 7, the most important section, presents a literature survey of different levels of sentiment analysis with computational approaches and methods of recommendations. Section 8 presents evaluation measures for sentiment-aware recommender systems. Based on the literature survey discussed in Section 7, various research opportunities are stated in Section 9, and finally, the conclusion is presented.

2 Survey methodology

This section exhibits the methodology employed to conduct this survey.

2.1 Survey plan

Pre-planning is required before conducting an exhaustive survey (Kitchenham et al., 2009). Therefore, we started with survey planning, recognition of various research questions, associated data sources, identification of keywords for searching research material, the decision of material inclusion and exclusion. We explored literature to conduct this systematic survey. Before considering the proposed survey, the related studies, publications, and articles were acquired and scrutinised for quality.

2.2 Research questions

Some of the identified research questions used for the systematic survey, along with their objectives and section maps in the article, are listed in Table 1.

Table 1 Identified research questions and their aims

Q. no.	*Identified research questions*	*Objective*	*Mapped section*
RQ. 1	What characteristics of sentiment-aware recommender systems have drawn attention to providing better personalisation?	Its goal is to investigate why sentiment analysis using a recommender system is in such high demand.	Section 3
RQ. 2	How is sentiment analysis exploited in a recommender system?	Its goal is to provide information on how sentiment analysis approach is used by recommender systems.	Section 4
RQ. 3	What are the application domains, methodologies used, and the scope of improvement in a sentiment-aware recommender system?	Its goal is to present existing sentiment recommender system studies and information on research opportunities in the field.	Sections 6, 7 and 9

2.3 Source selection

We have selected only reputed and reliable data sources to prepare this systematic survey. We have explored various portals such as IEEEXplore, ACM Digital Library, Science Direct journals (Elsevier), Scopus, and Google scholar to furnish a comprehensive bibliography of research papers on recommender systems using sentiment analysis.

2.4 Search strategy and inclusion and exclusion criteria

In the proposed survey, terms like 'sentiment analysis and recommender system', 'recommender system using opinion mining' and other relevant keywords were used in our search, as shown in Figure 1. We executed a manual search process for research papers/articles in which these search terms are not mentioned in either the title or the abstract.

Figure 1 Search strings (see online version for colours)

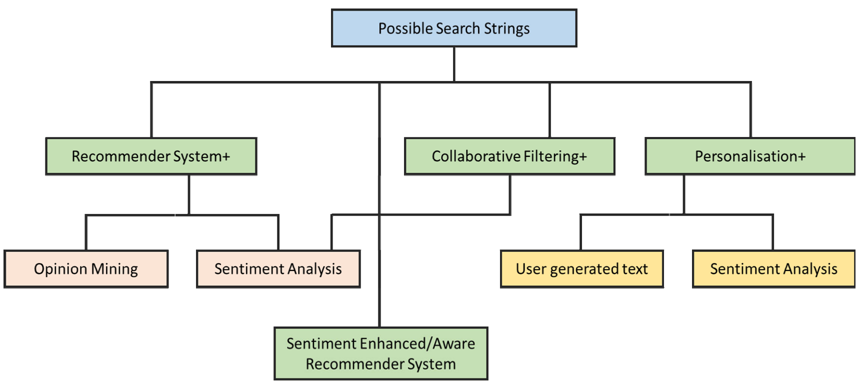
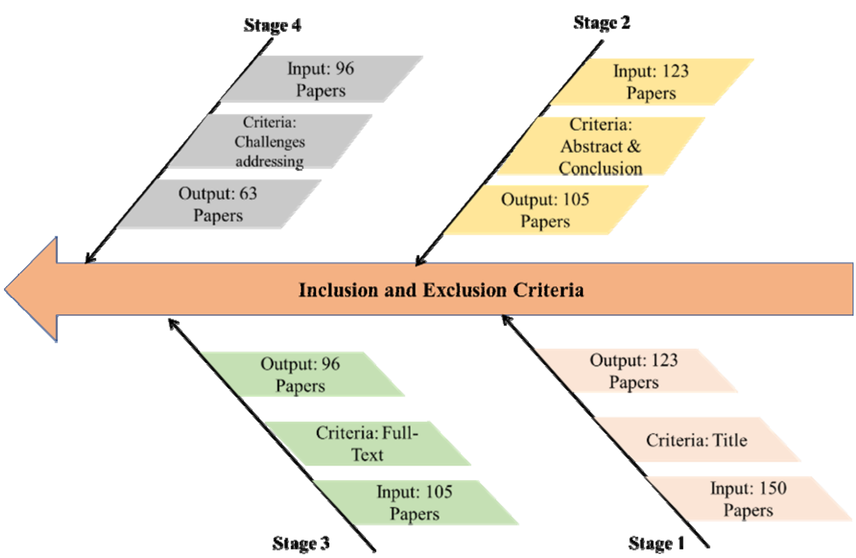


Figure 2 Inclusion and exclusion criteria (see online version for colours)



After applying the research criteria mentioned above, we consider recent and relevant papers to make an attractive and impactful survey along with early access articles. We select inclusion and exclusion criteria proposed by Gupta et al. (2020) to include and exclude articles for our survey. Figure 2 shows that the filtration procedure is divided into multiple phases. Different phases of inclusion criteria were designed based on title, abstract and conclusion, full text, and challenges. The articles that do not follow the inclusion principle were excluded, and eventually, relevant articles were identified and only the articles with good citations were considered.

2.5 *Quality assessment*

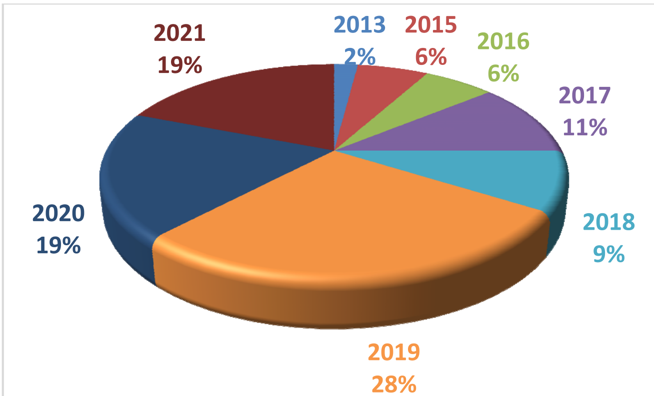
Each identified paper from the previous section was checked for quality assessment. We acquired the procedure proposed by Nazir et al. (2019) for quality check. Quality assessment questions were designed to select relevant articles and presented in Table 2. Each quality evaluation question is assigned a score of 1 if fully answered, 0.5 if partially answered, and 0 if not answered. Table 2 depicts the sample study of three articles after giving a quality score. The last row represents the normalised score of each article after the summation of three quality assessment questions. We set 0.5 as a threshold value for quality evaluation. Any article below this threshold value was not considered for further processing.

Table 2 A sample set of papers with quality assessment questions

Quality assessment criteria questions	*Example studies*		
	S1 Pappas and Popescu-Belis (2016)	*S2 Bansal and Srivastava (2018)*	*S3 Cai and Xu (2019)*
Does the research article refer to the recommender system implemented using sentiment analysis?	1	1	1
Does the research paper clearly state pre-processing techniques and the level of sentiment analysis technique?	0	1	0.5
Does the research paper describe a sentiment-aware recommender system by considering any real-life application?	1	1	1
Remarks	Though sample paper S1 describes the application domain, they do not define a pre-processing technique.	Sample paper S2 answers all the quality assessment questions.	Sample paper S3 describes very few pre-processing techniques in their work.
Summation	2	3	2.5
Normalised score (0–1)	0.66	1	0.83

Figure 3 exhibits the distribution of the surveyed papers according to the year of publication. Articles from 2013 to 2021 that were previously published in reputable journals are included in this survey. It can be easily seen from Figure 3 that compared to previous years, i.e., 2013 to 2016, more articles have been published since 2017 on a sentiment aware recommender system.

Figure 3 Statistics of surveyed papers by publication year (see online version for colours)



3 The need for sentiment analysis with recommender system

The performance of a recommender system improves by using sentiment analysis with it (Yu et al., 2017; Lei et al., 2016). Though it is cumbersome to perform sentiment analysis on user-generated text like reviews, posts, and tweets, there are various reasons for incorporating sentiment analysis into a recommender system. We briefly present them as follows.

- *Better understanding of user preference for an e-commerce recommender system*: It is tough to understand user preferences by using only star ratings as they cannot provide a user's personalised choice for different aspects of a product (Liu et al., 2013).
- *To deal with the data sparsity issue for an e-commerce recommender system*: Sparsity problems occur in any application domain with minimal user and item interaction. For example, consider an online purchasing dataset that contains a user-item rating matrix where a user provides a rating to an item. Very few star ratings are available for relatively expensive products like luxury automobiles, televisions, and air conditioners as people do not frequently buy high-risk products. Therefore, a very few star ratings are available, and the dataset becomes very sparse. Consider social media application domains, especially Facebook's dataset containing like and share information of Facebook posts; the user versus like/share rating matrix is also sparse. Hence, it is very tough to understand user preferences for any application domain using recommender System (Athira and Thampi 2018; Jiang et al., 2015; Lin et al., 2021).

- *To handle the COLD start issue for an e-commerce recommender system*: Identifying a correlation between various users is essential to deal with the cold start problem. This correlation can be inferred from social media comments and can overcome the cold start problem (Li et al., 2016).
- *To improve one-class collaborative filtering for an e-commerce recommender system*: Traditional recommender systems consider only explicit positive feedback to learn user preferences and do not differentiate between users who have not seen an item and users who did not like that item. When a recommender system considers only positive feedback, it is called one-class collaborative filtering, and it is a biased recommendation process. Sentiment information extracted from user-generated content can be incorporated to handle the one-class collaborative filtering problem (Pappas and Popescu-Belis, 2016).
- *To deal with rating bias for the e-commerce recommender system*: It is tough to infer user satisfaction level from star rating because strict users yield weak rating values (Shen et al., 2019). At the same time, liberal users give a very good rating value. ‘fake rating’, and ‘fake likes problem’ can also create problems in guessing correct user preferences (Zhang and Chow, 2019).
- *Additional*: It is challenging for traditional recommender systems to understand users’ attitudes and suggest friends/posts/videos on social media of interest of those users. By analysing user comments using sentiment analysis, inferring user attitudes becomes very easy for a social media recommender system (Gurini et al., 2018). A person’s emotional state needs to be considered for applications like depression detection and music recommendation; it is only possible through sentiment analysis (Rosa et al., 2015).

4 The stages of the recommender system using sentiment analysis

Figure 4 shows the different stages of a sentiment enhanced recommender system.

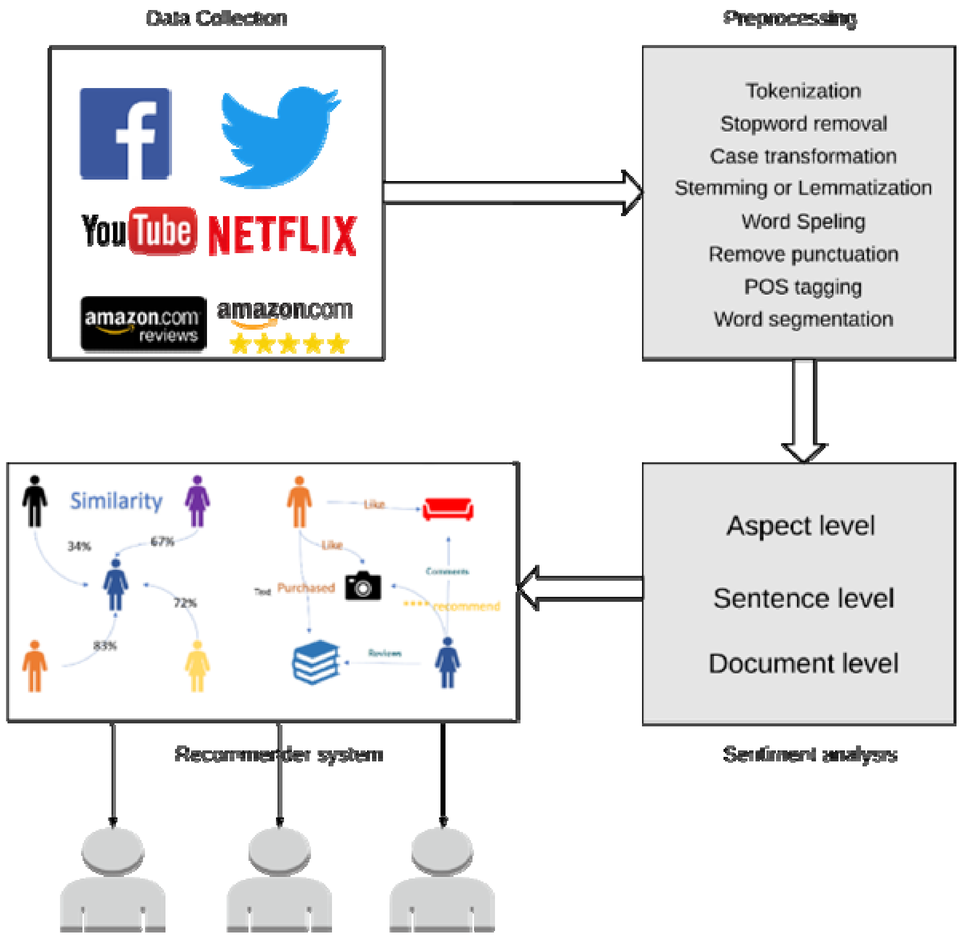
4.1 Data collection

The primary focus of this phase is to assemble data that will be utilised in subsequent phases. Various resources from which data can be obtained are mainly comments or reviews available on Twitter, Facebook, and online purchasing websites. Different proposed techniques accumulate data using either web scraping or using various open APIs.

4.2 Pre-processing

The principal intention of this phase is to clean the collected data and reduce dimensionality. Pre-processing tasks smoothen the sentiment analysis process by removing noisy data (Vijayarani et al., 2015). A detailed discussion of the pre-processing phase is given in the next section.

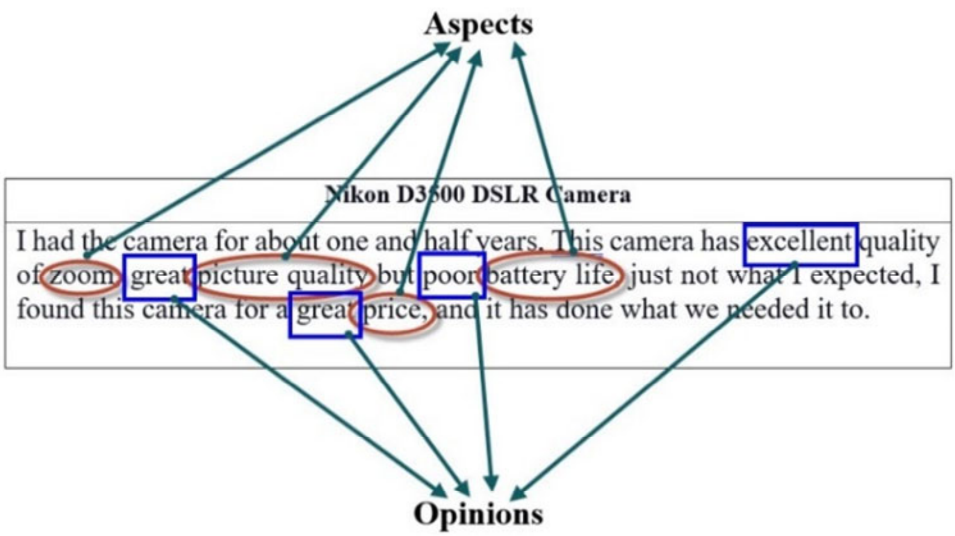
Figure 4 The stages of the sentiment enhanced recommender system (see online version for colours)



4.3 Sentiment analysis

This phase decides the sentiment orientation of user-generated reviews/comments/written text. Sentiment analysis can be applied at three distinct levels: document level, sentence level, and aspect/feature level (Devika et al., 2016). If document-level sentiment analysis is selected, the sentiment orientation of overall reviews/comments is considered for sentiment analysis. In sentence-level analysis, each sentence is considered a single section, and each sentence's sentiment orientation is determined. Another important task performed by sentence-level sentiment analysis is that it differentiates objective and subjective sentences. This difference is essential because objective sentences may not have opinionated words. The aspect/feature level of sentiment analysis is the fine-grained text analysis level (Qiu et al., 2018). This literature survey found out that social media recommender systems usually prefer document level sentence analysis to infer the sentiment of tweets or comments. In contrast, e-commerce recommender systems adopt aspect-based sentiment analysis for processing a user's product reviews. The aspect level is the most suitable level of analysis for the e-commerce domain. It analyses product reviews, and pulls out aspects and opinions (Qiu et al., 2016). It calculates the sentiment orientation of each extracted aspect using a matching opinion. As shown in Figure 5, words surrounded by red circles are extracted aspects, and words surrounded by blue squares indicate the opinions corresponding to those aspects. Various methodologies used for aspect and opinion extraction are discussed in Section 7.3.

Figure 5 Aspect and opinion extraction template (see online version for colours)



4.4 Prediction/recommendation

This phase is responsible for forming a list of recommendations. A user's preferences, past behaviour, and the sentiment of user's comments are considered to make predictions. Various recommendation approaches are available, but collaborative filtering is the well-accepted approach utilised with sentiment analysis (García-Cumbreras et al., 2013; Pappas and Popescu-Belis, 2016). Collaborative filtering analyses the similar user preferences to make recommendations. Matrix factorisation is the most successful method to implement collaborative filtering (Koren et al., 2009). The outcome of this phase changes depending upon the application's behaviour. Prediction gives a numerical rating, while the recommender system provides top N recommendations to each user from the calculated numerical score of each item (Wever and Frasincar, 2017).

A brief explanation of how a recommender system can incorporate extracted sentiment through aspect-based sentiment analysis for e-commerce applications is shown using Figure 5 and Table 3. As a demonstration, consider an e-commerce recommender system intended to recommend an item based on target user choices. In a traditional recommender system, a user only provides an overall star rating for an item. The recommender system calculates an unseen item's ratings based on other user's ratings who have the same choices as the target user. As depicted in Table 3, for all the three products, users U1 and U2 have similar overall ratings; therefore, they are considered as neighbours. The rating of an unseen item of user U1 is predicted through the star rating of that item given by user U2, even if the aspect level preferences of both the users are different. The sentiment-aware recommender system performs sentiment analysis on product reviews, extracts aspects and opinions, and assigns a polarity score to the extracted aspects.

Figure 5 shows four aspects zoom quality, picture quality, battery life and price along with their corresponding opinion excellent, great, poor and great. A1, A2, A3 and A4 represent these four aspects in Table 3. According to the opinion, a polarity score is assigned to every aspect by analysing the sentiments (positive or negative) associated with aspects. All three users are considered neighbours if only star ratings are counted even if their choices differ for every feature/aspect, which will affect the recommender system's accuracy. While in sentiment-aware recommender systems, the selection of neighbours is based on similar products' aspect preferences. As shown in Table 3, user U1 and user U2 do not share the same aspect preferences despite similar overall ratings, and hence they are not neighbours. User U1 and U3 share the same aspect preference and therefore, the predicted rating of user U1 for an unseen item is two and not five. We can infer aspect level ratings only through sentiment analysis and using this additional knowledge of aspect level preferences, a recommender system can enhance its performance.

Table 3 Sentiment-aware e-commerce recommender system (see online version for colours)

																
 U1	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4
	1	1	4	4	2	2	5	5	2	2	5	5				
		2				4				4				?		
 U2	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4
	4	4	1	1	5	5	2	2	5	5	2	2	4	5	5	4
		2				4				4				5		
 U3	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4	A1	A2	A3	A4
	2	2	5	5	3	3	4	4	2	2	4	4	1	1	4	4
		3				4				3				2		

5 Pre-processing

The prime intention of utilising pre-processing techniques before sentiment analysis is to remove noisy text. There are various pre-processing tasks, as shown in Table 4. Some approaches did not comment on the pre-processing tasks, while others used some of the pre-processing steps. If the content contains noisy text, the job of sentiment analysis turns out to be complex; additionally, noise present in the text expands the dimensionality of the text. Available approaches mainly use text from Twitter, Amazon reviews and YouTube comments to provide a recommendation to the user using sentiment analysis. Tweets, product reviews, and social media comments are unstructured/semi-structured data and contain noise; therefore, pre-processing is required before employing sentiment analysis. Table 4 presents the article reference number versus the utilised pre-processing techniques. A brief discussion of important pre-processing techniques is given below:

- *Tokenisation*: Tokenisation is a process that splits the text into a list of tokens. Primarily word tokenisation, and sentence tokenisation are the two types of tokenisation. Sentence tokenisation splits the sentences from a given text. Sentence level sentiment analysis utilises the sentence tokenisation technique. In contrast, word tokenisation generates a single token by splitting the word by spaces. Further, part of speech tagging is used to tag the generated tokens. It is an essential pre-processing step of aspect/feature-based sentiment analysis
- *Stop word removal*: Stop words are usually the most common and unavailing words in a language, but are necessary as a part of the language linguistic. These stop words might not be of much value for building sentiment analysis models. For example, the words ‘a’, ‘an’, ‘on’, ‘is’, ‘the’ convey no meaning while performing any level of sentiment analysis.
- *Stemming and lemmatisation*: Stemming cuts a suffix or prefix from a given word; on the other hand, lemmatisation transforms the word into its source form. After applying stemming and lemmatisation, the number of unique words is decreased which reduces the dimensions.
- *Word spelling*: The primary goal of pre-processing is to minimise errors before applying sentiment analysis; however, incorrect spellings are a significant barrier in text analysis. Wrong spellings may lead to erroneous interpretation and need to be dealt with.
- *POS tagging*: Part of speech tagging labels each word in a sentence with the part of speech for that word. These labelled words are used in later stages, specifically in aspect opinion extraction.
- *Bag of words*: The bag of words technique gives the frequency of occurrence of words in a document. The bag of word model is useful for aspect-based opinion mining.

Other pre-processing techniques are self-explanatory and are not discussed here due to space limitations.

Table 5 lists the available libraries to perform a pre-processing task.

Table 4 Pre-processing techniques

	Yu et al. (2017)	*Qiu et al. (2018)*	*Gurini et al. (2018)*	*Li et al. (2016)*	*García-Cumbreras et al. (2013)*	*Alahmadi and Zeng (2015)*	*Cai and Xu (2019)*	*Bansal and Srivastava (2018)*	*Sailunaz and Alhajj (2019)*	*Lei et al. (2016)*	*Athira and Thampi (2018)*	*Da'u and Salim (2019)*	*Chen (2019)*	*Irfan et al. (2019)*	*Shao et al. (2019)*
Tokenisation			•		•	•			•	•				•	
Stop word removal	•	•			•	•	•	•	•			•		•	
Stemming	•	•	•		•	•		•					•	•	
Remove hyperlinks			•				•		•		•				
Remove special characters			•												
Abbreviation						•									
Case transformation								•						•	
Remove punctuation								•						•	
Remove symbols								•							
Remove emojis									•						
Remove non-alphanumeric characters								•	•						
Remove redundant characters/words									•			•			
Remove repeated post											•				
Word spelling														•	
POS tagging		•							•					•	•
Bag of words															•

Table 5 Available libraries to perform a pre-processing task

NLTK	https://www.nltk.org/
Gensim	https://pypi.org/project/gensim/
spaCy	https://pypi.org/project/spacy/
TextBlob	https://pypi.org/project/textlob/
pyenchant	https://pypi.org/project/pyenchant/
Scikit-Learn	https://scikit-learn.org/

Embedding text is the process of converting text to numerical values. Experts in the domain of natural language processing (NLP) decided to develop an approach called word embeddings, which aims to convert words into their respective numerical representations. After using this algorithm, NLP algorithms can easily understand the transformed representations to process the provided textual data. In this article, various word embedding methodologies have been looked through, such as Bag of word, TF-IDF, and Word2Vec, GloVe, and BERT. The technique of word embeddings maps text to real-valued numerical representations. This is done by tokenising each term that might be a part of a sentence and translating it into a vector space. The word embedding technique aims to represent the semantic meaning of terms in a given sentence or a given sequence by assigning related numerical representations to terms with similar connotations.

- *Term frequency-inverse document frequency (TF-IDF)*: TF-IDF is quite a popular word weighting scheme for text-based recommender systems. It is used to assess the importance of a word in documents/reviews (Ray et al., 2021).
- *Word2Vec*: Word2vec processes the text of documents by vectorising the words. The output of the word2Vec model is a feature vector that represents valuable features from the given documents. A machine learning or deep learning model can derive semantic relationships among words by utilising this feature vector. With Gensim, it is extremely straightforward to create Word2Vec model (Ray et al., 2021; Zhao et al., 2018).
- *Global vector for word representation (GloVE)*: The word2vec considers nearby words for the word-to-word co-occurrence calculation matrix. Unlike word2vec, GloVe considers the entire corpus to calculate word-to-word co-occurrence. The GloVe is based on latent semantic analysis derived from matrix factorisation to obtain the vector.
- *Bidirectional encoder representations from transformers (BERT)*: BERT, a deeply bidirectional, massively pre-trained transformer model, relies on an attention mechanism. BERT produces good quality contextualised or alternatively context-aware word embeddings. These word embeddings are passed through each encoder layer of BERT to sift them in the training process. Based on the words on either side of the given word, the word associations are captured by the attention mechanism. Further, word embeddings are encoded positionally to keep track of the sequence of a particular word in a sentence. BERT is known to generate preferable word embeddings since the model is pre-trained on Wikipedia datasets and on a massive word corpus. Hence, it is known to be one of the most advanced techniques as compared to the techniques discussed above.

6 Application domains

It is observed from the survey of literature that sentiment analysis is not only used in the most common domains like product recommendation or social media recommendation, but it is also used in very diverse fields like depression detection and suicide prediction. Table 6 presents a distribution of articles based on an application with a utilised dataset.

Table 6 A summarised view of the adoption of sentiment-aware recommendation systems in different application areas

Area	*Application*	*Dataset utilised*	*Input consider for recommendation*	*Reference and total citation count*
E-commerce recommender system	Rating prediction of product for item recommendation to a user	Amazon review data set of various product categories	Reviews, overall ratings	Yu et al. (2017), 30
		Amazon review data set, Yelp dataset (comprises reviews of various businesses in various metropolitan regions across four countries)	Reviews, overall ratings	Da'u et al.(2020), 39
		Amazon review dataset	Rating, review, and helpfulness votes	Shen et al. (2019), 30
	Long-tail (less popular)product recommendation	Amazon, Airbnb	Reviews, product metadata information	Huang and Wu (2019), 7
	Predict user preferences	Amazon review for digital camera and laptop	Overall rating, review	Chen et al. (2019), 11
	Rating prediction of product for item recommendation to a user	Various categories from the YELP dataset	Overall rating, review	Zhao et al. (2018), 40
		Amazon and YELP	Review	Da'u and Salim (2019), 25
		Amazon, YELP and Trip Advisor	Review	Chen (2019), 23
Social media recommender system	Suggest relevant people to follow	Twitter	Tweets from Twitter	Gurini et al. (2018), 73
	Friend recommendation in social network	Weibo (Chinese micro-blog platform)	Microblog data	Cai and Xu (2019), 7
	Topic recommendation to user on Twitter	Twitter	Tweets, user information, emotion, sentiment information	Sailunaz and Alhajj (2019), 128
	suggest posts to user on Facebook	Facebook	Facebook posts	Athira and Thampi (2018), 5

Table 6 A summarised view of the adoption of sentiment-aware recommendation systems in different application areas (continued)

Area	*Application*	*Dataset utilised*	*Input consider for recommendation*	*Reference and total citation count*
Multimedia recommender system	Recommend YouTube videos to a user	Physiological signals and YouTube	YouTube textual comments and EEG signal data	Gauba et al. (2017), 68
	Recommend TV programs and movies to user	rating from Netflix and Twitter	Metadata of movie including director, genre, actor, producers from Netflix and comments from Twitter related to movie appear in Netflix dataset	Li et al.(2016), 38
	movie rating prediction for the user	Twitter, Movielens	Tweets	Alahmadi and Zeng. (2015), 72
	Recommend top N items to the user. For TED lectures, Vimeo videos and Flicker images	TED, Vimeo, Flicker dataset	Comments and indications of favourites (like)	Pappas and Popescu-Belis (2016), 24
	Recommend movies to users	IMDB and YELP dataset	Comments	Zhang and Chow (2019), 5
Travel and tourism	Personalised travel recommendation to a user	Trip and Tripadvisor	Comments	Shao et al. (2019), 10
	Suggest a suitable hotel to a user based on his customise preferences	Tripadvisor	Reviews from Tripadvisor	Ray et al. (2021), 23
	Provide personalised tourism recommendations to a user	Tripadvisor	Comments	Abbasi-Moud et al. (2021), 15
Other domains	Forecast product sales for the Automobile industry	Bitauto(auto trending platform)	Reviews	Fan et al. (2017), 231
	Recommend a candidate to voter	Twitter dataset	Tweets	Terán and Mancera (2017), 7
	Suicide prediction	Tweets	Tweets	Birjali at al. (2017), 69
	Election prediction of a political party	Twitter	Tweets	Bansal and Srivastava (2018), 39
	To detect the depression level of a person from his social media text	Facebook	Facebook messages	Rosa et al. (2018), 77
	E-learning: recommend personalised courses to users.	Coursera	Messages provided to courses	Mawane et al. (2020), 1

6.1 E-commerce recommender systems

Most of the work on recommender systems using sentiment analysis is on e-commerce product reviews. E-commerce websites use a recommender system to suggest personalised services to their customers and increase their business. The main intention of an e-commerce website by providing recommendations is customer retention. Currently, the user expresses their sentiment towards products through online reviews in addition to star ratings. Moreover, customers comment on different aspects of a product in a review. It is useful for e-commerce owners to understand user preferences towards their products better.

From the available approaches for e-commerce, the majority of them use aspect-based sentiment.

6.2 Social media recommender system:

Recommender system are mainly useful in social media for applications like friend recommendation on Facebook and followee recommendation on Twitter. A social graph represents the relationship among people, groups and organisations in a social network. As social network interactions increase on social media, the volume of the social graph also increases. Social media recommendation is challenging as social graphs are quite huge, and content is also growing and changing. Before sentiment analysis came into demand, friend/people recommendation on social media was based only on familiar friends and did not consider peoples' collective interests. Traditional recommender systems for social media ignore the social connections among the users. Therefore, Gurini et al. (2018) proposed a people-to-people recommender system that considers a user's beliefs on a debated topic and discovers that user's opinion on the subject before making recommendations. In order to improve the efficiency of the recommender systems, Cai and Xu (2019) also found relevance between users using sentiment analysis for friend recommendation. When recommending a post on social media, a conventional recommender system considers the replies received on that particular post. However, it can be biased because responses on that post can be positive or negative, which can only be analysed through sentiment analysis.

Therefore to find good communication between users, Sailunaz and Alhajj (2019) concentrated on the number of replies and performed sentiment analysis on responses. In the last few decades, most social media users have been suggested posts that are of no interest to them; due to this, people get irritated and lose interest in social media. Athira and Thampi (2018) suggested an excellent approach that provides personalised posts to social media users to deal with this issue. Various parameters, such as likes, shares, and sentiment analysis of comments, form a cluster of like-minded users and filter posts that are uninteresting to them.

6.3 Movie, video and music recommender system

Due to the COVID-19 pandemic and many other reasons, these days, people prefer to watch movies and videos on mobile devices. As there are many video/audio resources on the web, a user may feel frustrated if they cannot find a resource that is interesting to them. In order to provide personalised video/movie recommendations to users, many recommender systems have come into the market in the last few years. All of the proposed methods consider one of the following to provide recommendations: the user's historical records, the user's friendship networks, or overall ratings. However, friendship networks are relatively weak in online movie/TV streaming sites. A user's social media content should be explored before applying any recommendation technique to strengthen these networks. Alahmadi and Zeng (2015) proposed an approach to elicit user preferences by investigating users' online social network activities for movie recommendations. For sentiment analysis, tweets for that particular movie are extracted from Twitter using Twitter API. In an approach proposed by Li et al. (2016), metadata of the movie is extracted using Netflix API, but again comments related to the movie are crawled from Twitter. The methodology proposed by García-Cumbreras et al. (2013) and Zhang and Chow (2019) uses reviews available on the IMDB website to capture the implicit influence of movies. Pappas and Popescu-Belis (2016) conducted sentiment analysis on comments available on various platforms like Vimeo (a video sharing platform), TED lectures, and Flickr to deal with one-class collaborative filtering. A unique approach was proposed by Gauba et al. (2017) for rating prediction of video advertisements. This method combined electroencephalogram (EEG) waves and sentiment analysis of users' comments for rating prediction of video advertisements. EEG waves of a user are captured while that user watches video advertisements for his/her physiological analysis. Most people listen to songs according to their emotional state of being at that particular stage of their life. User sentiments are extracted from text posted on their social media and used for personalised song recommendations (Rosa et al., 2015). The sentiment-aware recommender system applies to the e-learning domain as well. Mawane et al. (2020) took the benefit of messages on all of the courses provided by Coursera and provided personalised recommendations of courses to users. The concept of a word matrix is utilised for aspect extraction, and an unsupervised deep learning methodology is used to generate a recommendation of courses.

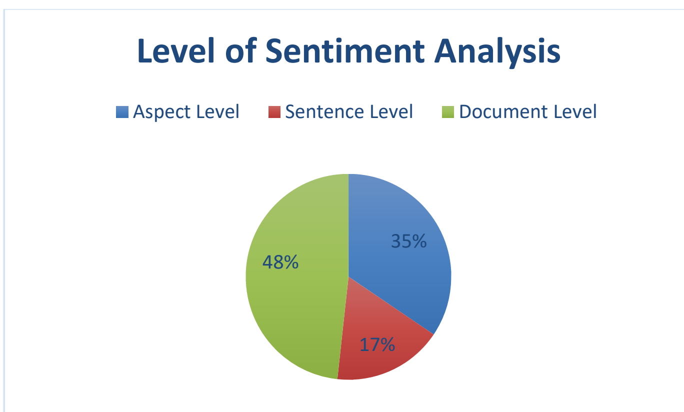
6.4 Hotel/tourism recommender system:

During the last few decades, almost all travel companies have provided services online, and the modern generation always prefers to plan their trips online. Before planning trips, people refer to reviews written by other users on the places they plan to visit. As many websites are available, and a massive amount of reviews are accessible, it is tough for users to choose a place/hotel to visit. Shao et al. (2019) gave personalised travel recommendations by processing textual reviews available on the Trip Advisor website using sentiment analysis to address this problem. Abbasi-Moud et al. (2021) also proposed a travel recommender system that considered contextual information like time, location and weather in addition to sentiment analysis to improve user satisfaction. In this approach, users' reviews are clustered semantically, after which sentiment analysis is performed on the reviews to infer user preferences for accurate travel destination recommendations. For the evaluation of their proposed system, reviews were taken from the Trip Advisor website (Abbasi-Moud et al., 2021).

6.5 Other domains

Social media conversations play a significant role in detecting depression levels. Suffering from depression can increase the risk for suicide. Rosa et al. (2018) proposed a system to recognise psychological disturbances in a user based on their Facebook conversations. It identifies depressive sentences using sentiment analysis and monitors a user's emotional health using deep learning techniques. If any user is found with a mental disorder, then this system alerts the authorised person. Another approach worked on a similar domain, presenting suicide attempt prediction from a user's tweets (Birjali et al., 2017). Politics is also greatly influenced by social media platforms. Terán and Mancera (2017) proposed an approach to suggest candidates and political parties to voters using social media discussions of the candidates and parties. This approach presents voting advice applications by employing sentiment analysis on a candidate's tweets. These days election results can also be predicted by online monitoring of Twitter using sentiment analysis. Bansal and Srivastava (2018) introduced a prediction method for elections that infers a voter's viewpoint by applying sentiment analysis on their tweets. Xu et al. (2019) proposed a very novel sentiment analysis application to detect slanderous users. Slanderous users confuse recommender systems by explicitly giving a fake low rating to a positive review. To address this problem, the opinion level of a review is assessed and further compared with its rating. Fan et al. (2017) offer a more diverse application to forecast the automobile industry's hike in sales using reviews. A mixture of past sales data and online reviews is used to predict sales.

Figure 6 Distribution of articles by the level of sentiment analysis (see online version for colours)



7 Different Level of sentiment Analysis with computational approaches

It can be seen from Figure 6 that from the available methods, most strategies worked on document-level sentiment analysis. Document level analysis determines the sentiment orientation of a document as a whole and the document is considered a single entity. Product reviews on an e-commerce website, tweets on Twitter, or social media comments can be considered documents. Methodologies used at various level of sentiment analysis are depicted in Figure 7. Table 7 gives available libraries useful for sentiment analysis.

Figure 7 Hierarchy of level of sentiment analysis (see online version for colours)

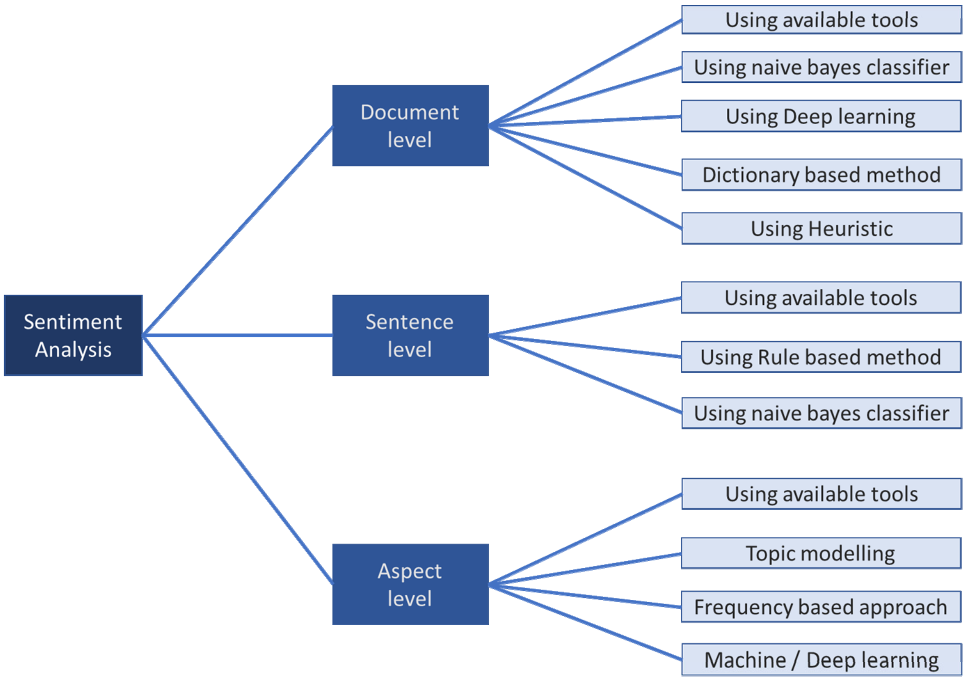


Table 7 Libraries for sentiment analysis

Useful libraries for sentiment analysis	*Website link*
SentiWordNet	https://www.nltk.org/_modules/nltk/corpus/reader/sentiwordnet.html
LingPipe	http://www.alias-i.com/lingpipe/
WordNet	https://wordnet.princeton.edu/
Alchemy language API	https://www.ibm.com/watson/alchemy-api.html
TextBlob of NLTK toolkit	https://textblob.readthedocs.io/en/dev/

7.1 Document-level sentiment analysis

7.1.1 Document-level sentiment analysis using available tools

For analysis of user-generated content at the document level, various methods use readily available tools. Alahmadi and Zeng (2015) proposed a lexicon based approach to exploit the sentiment intensity of a sentiment word using SentiWordNet. SentiWordNet is a sentiment lexicon correlating sentiment information to each wordnet synset. Li et al. (2016) developed a technique that extracts tweets related to TV programs or movies, as well as posts associated with a collection of movies. LingPipe tool is used to perform sentiment analysis on selecting movie tweets and assigning a score from 1 to 5. LingPipe is the best suitable toolkit to show text processing, as well as for topic modelling. Finally, for a recommendation, a correlation among users needs to be inferred. Therefore, association rule mining is exploited in this approach to figure out a correlation among users. To classify tweets related to suicide, Birjali et al. (2017) used different machine learning methods like SVM and naive Bayes. The polarity calculation is based on the semantic correlation between the vector of a stored word and a user's sentences. To find semantic relationships, the WordNet database is utilised. Eventually, for the prediction of suicide tweets, a heuristic-based algorithm is proposed. Athira and Thampi (2018) proposed an approach that recommends a post on Facebook by analysing clusters of like-minded peer groups based on sentiment analysis. The proposed method addresses the problem of unnecessary notifications received from various groups for a user. After pre-processing posts, a cluster is formed based on sentiment, theme, emotion, style, and psychology linguistics. A heuristic method is utilised to obtain a prominent keyword from the post. The proposed approach used Alchemy language API to determine the sentiment orientation of extracted keywords. A cluster of the posts is formed based on sentiment, using k-mean clustering. To make a recommendation, a post is reviewed based on the different mentioned aspects, and is suggested based on user interest. Pearson correlation measure is used to find the similarity among a cluster vector.

If a recommender system bifurcates recommendations among critical users and liberal users, it is called sentiment bias. Sentiment bias is a severe problem of traditional recommender systems, especially for long-tail products. Hence, Lin et al. (2021) proposed a recommender system based on the matrix factorisation technique and sentiment analysis to alleviate the sentiment bias problem. For sentiment analysis, Lexicon and rule-based available tools TextBlob and VADER are utilised. Likewise, Kumar et al. (2020) also used VADER to analyse movie tweets from the MovieLens dataset sentiment analysis. The intention of using sentiment analysis of movie tweets is to know the current trends, the sentiments of people, and the responses of viewers. A recommendation is provided using sentiment information and hybrid filtering of content-based and collaborative filtering.

7.1.2 Document-level Sentiment analysis using naïve Bayes classifier

The most popularly used classifier for emotion detection from text is naive Bayes. Alahmadi and Zeng (2015) developed a method to calculate the probability based rating of a sentiment based on the naive Bayes classifier. For overall rating prediction from sentiment ratings, three famous machine learning techniques: linear regression, support vector regression, and random forest, are utilised. Among these three, support vector regression performs very well for movie rating prediction. Fan et al. (2017) also proposed a similar approach where the sentiment index from an online review is computed using the naive Bayes method. The computed sentiment index is employed in the BASS Nortan model to enhance the forecasting accuracy of automobile sales. BASS Nortan model is an extension of the Bass diffusion model. One more approach uses a naive Bayes classifier to perform sentiment analysis on tweets (Sailunaz and Alhajj, 2019). In addition to naive Bayes, the maximum entropy machine learning technique is used to detect real emotion from tweets. In this approach, sentiment analysis on a tweet's reply is computed because it does not indicate agreement with the tweet; therefore, whether it is an agreement or disagreement can be decided using sentiment analysis only. K-mean clustering is used to provide a personalised recommendation of a topic on Twitter, which forms a cluster of people having the same emotional tendency.

7.1.3 Document-level sentiment analysis using deep learning

For a short review/text, a traditional classifier may fail to detect accurate level sentiment analysis. Xu et al. (2019) developed a method called hierarchical dual-attention recurrent neural network (HDAN) for slanderous user detection. HDAN finds the opinion level of each review. HDAN computes the sentiment analysis of reviews to discover the gap between ratings and reviews. Subsequently, joint filtering process filters slanderous user interaction if a discrepancy is noticed between ratings and reviews, and hence improves the recommender system's accuracy. Product recommendation is made using a non-negative traditional matrix factorisation method. A recurrent neural network based method named multi-objective, collaborative, and attentive framework (MOCA) was proposed by Zhang and Chow (2019) based on document-level sentiment analysis. Personalisation is provided to a user by reasoning implicit influence. For extraction of implicit influence from the content, this method used a multilayer perceptron and collaborative filtering. To obtain a word's semantic meaning, two independent RNNs called bidirectional recurrent neural networks are implemented together.

7.1.4 The dictionary-based approach

Shen et al. (2019) proposed a dictionary-based approach for document-level sentiment analysis. They created a sentiment dictionary (SD) from available reviews rather than using an available dictionary. To build a SD, reviews are first grouped based on their rating score. Then keywords from those reviews are extracted based on their term frequency. A sentiment score is assigned according to the rating score of a review. After creating the SD, sentiment analysis of review is determined based on the sum of sentiment scores of each word in the review. A recommendation is provided using the most popular method, matrix factorisation. The sentiment score obtained from the sentiment analysis phase is mapped into a latent space using conditional distribution. Sentiment probabilistic matrix factorisation is compared with other methods like basic matrix factorisation and probabilistic matrix factorisation. The proposed approach was tested on the Amazon review dataset.

7.1.5 Heuristic-based technique

Cai and Xu (2019) tackle the problem of poor prediction accuracy and provide personalised recommendations by using the social media details of users. They presented an SIO-TMF algorithm which was derived from basic matrix factorisation for a recommendation. The matrix is factorised, and a user-topic rating matrix is prepared based on sentiment information, objectives and the importance of user topic content dimensions. LDA is applied for the extraction of topical information. The importance of a topic is inferred through retweets and, likes on that topic and comment information. Now for friend recommendation, the matrix factorisation method is applied to the calculated rating matrix. They experimented on the Weibo topic Chinese platform. Li et al. (2021) presented a heuristic-based method to deal with inconsistency between user ratings and product reviews. This method considered review feedback to identify the noise ratings. Li et al. (2021) used a combined lexicon-based and semi supervised approach to calculate a review's sentiment score and then exploited a sigmoid function to normalise the sentiment score. A heuristic weighted average method was proposed that considered user consistency and review feedback to generate a recommendation. This approach may not work on a social media recommender system because reviews and ratings are not available. Karthik and Ganapathy (2021) proposed a sentiment-aware recommender system using fuzzy rule logic and ontology. The sentiment score of each targeted user is calculated; additionally, demographic information and the age group of customers are also considered. By analysing the sentiment polarity, the sentiment score of each customer's review is calculated, and the sentiment score of each user category is summed up to calculate the overall product rating. To compute a recommendation for each user's category, various designed fuzzy rules and adjustments of ontology are employed.

7.2 Sentence-level sentiment analysis

7.2.1 Sentence level sentiment analysis using naïve Bayes classifier

This level is more specific as compared to document-level sentiment analysis. Sentence-level sentiment analysis calculates the sentiment orientation of every sentence of a document. Usually, researchers use sentence-level sentiment analysis when working with micro posts because, in a micro-post, there is a limitation of up to 140 characters. Gurini et al. (2018) proposed an approach to improve recommendation accuracy; user attitude towards a presented topic is inferred using sentence-level sentiment analysis. This proposed approach provides followee recommendation. Because there are many celebrities from different domains on social media, people are confused about whom to follow. For sentence-level sentiment analysis, the proposed method uses the multinomial naive Bayes classification, and this method mainly focuses on three parameters: sentiment, volume, and objectivity. The volume considers how many times a user discusses a particular topic. Objectivity prunes the sentences that do not contain any sentiment words, and these sentences are of no further use. For the recommendation of political leaders to people on Twitter, matrix factorisation is used. Matrix factorisation considers user attitude calculated using sentence-level sentiment analysis.

7.2.2 Sentence level sentiment analysis rule-based approach

Pappas and Popescu-Belis (2016) exploited a rule-based approach to estimate polarity at the sentence level. This proposed method determines the total polarity of comments by summarising each sentence's polarity in a comment. A rule based classifier with binary classification is used for sentiment analysis, and the preferences of a user are extracted from their comments. Similarity-based nearest neighbourhood models in collaborative filtering were utilised to combine explicit user ratings and user preferences inferred using sentiment analysis. The proposed method was tested on TED and, Vimeo video comments.

7.2.3 Sentence level sentiment analysis based on the available tool

The sentiment-Br2 word dictionary is used by Rosa et al. (2015, 2018) to calculate sentence sentiment intensity values. The eSM used by Rosa et al. (2015) is an improved sentiment matrix on sentiment-Br2 that considers user profile information like lifetime, gender, and education level to calculate sentiment intensity. Emotion-based music recommendation is offered by Rosa et al. (2015) using sentiment-Br2 and eSM. The sentiment intensity matrix of comments related to Brazillian songs is calculated using eSM. For recommendations, this proposed approach used a content-based filtering method and sentiment intensity calculated using eSM. A knowledge-based recommendation System generates recommendations based on domain knowledge and a user's profile information. Usually, it does not rely on the profile information of other users (Truşcă et al., 2020). Rosa et al. (2018) come up with a rare fusion of knowledge base methods and sentiment analysis. This method monitors the physiological state of a user using sentiment analysis. Facebook comments related to depression or stress of a user are extracted, and sentiment intensity is computed using the sentiment metric eSM2. The eSM2 is an improved version of eSM that considers user geographical information and studies the Portuguese language. A bidirectional long short-term memory (LSTM) recurrent neural network with an ontological approach is used to provide a recommendation. If any sentence indicates stress or depression, a positive message is recommended by this proposed method. Irfan et al. (2019) developed a lexicon-based method for sentence-level sentiment classification. As discussed by Irfan et al. (2019), feature extraction and feature reduction are two phases of sentence-level sentiment classification. The frequency of a noun is considered for feature extraction, and for polarity detection, SVM and naive Bayes classifiers are used at the sentence level. The hub-average model derived from the hub-authority model with sentiment orientation calculated from reviews is utilised to present venue recommendations.

7.3 Feature/aspect level sentiment analysis

7.3.1 Aspect-based sentiment analysis using available tool/library

BERT is adapted as a popular library for NLP tasks. It uses a bidirectional and an unsupervised technique for language representation. Bai et al. (2020) used the BERT model to extract aspects and polarity associated with those aspects. Further, with aspect information, external domain knowledge is combined to enhance the generated recommended reason. Ray et al. (2021) also applied BERT for aspect level sentiment analysis. For aspect-based sentiment analysis, a fusion of random forest and BERT model is utilised, and then reviews are categorised based on different aspects using fuzzy logic and cosine similarity measure. For classification of reviews, the BERT model and random forest are applied for aspect extraction. Afterwards, based on a user's query, a hotel is recommended according to the selected features.

7.3.2 Aspect-based sentiment analysis using topic modelling

Topic modelling is the most prevalent technique for aspect-based opinion mining, and LDA is the most practised method for topic modelling. A product review mostly contains the discussion of features of a product. Lei et al. (2016) presented a technique where LDA is used for feature extraction. The dictionary-based approach is employed for the polarity calculation of sentiment words. An enlarged version of the Hownet SD was created called the SD. For business recommendations, the result of sentiment analysis is fused as one additional dimension into matrix factorisation. The experiment was conducted on the YELP dataset. Yu et al. (2017) also proposed an approach called ratings are sentiment (RAS), which is an extended version of the hidden factors as a topics model (HFT). LDA is responsible for feature extraction and is further combined with the traditional latent factor model. Aspect-based opinion mining is responsible for the aspect and sentiment unification model (ASUM), an extensive LDA version. The latent factor model and LDA are combined into HFT. HFT does not examine the impact of user sentiments on rating score; RAS settled this problem and considers sentiment orientation as a dimension in the latent factor. An investigation of the proposed approach was done on the Amazon review data set. For long-tail products (hard to find), very few reviews are available. A topic modelling using LDA merely may not work precisely for feature extraction; therefore, Huang and Wu (2019) proposed an approach that extends LDA called the Biterm topic model.

For simultaneous mining of aspects and emotions, the Biterm topic model was combined with MaxEnt-BTM. The similarity among objects was computed through the K-medoids algorithm for a recommendation. Here, the object has both dimensions: numeric ratings and sentiment ratings. One more method used the same idea of topic modelling but added one more parameter: time. Li et al. (2020) proposed a matrix factorisation method that exploits time and aspect information for personalised product recommendations to deal with dynamic changes in user preference and an item's profile. LDA is used to extract aspects from Amazon reviews of laptops and smartphone products. An additional approach, LDA-LFM, attempted LDA for aspect extraction and the latent factor model for recommendations to improve an e-commerce recommender system's accuracy (Aslanyan and Frasincar, 2021). The main advantage of their work is that they can handle large datasets.

7.3.3 Aspect-based sentiment analysis using frequency-based methods

For many years, the frequency-based technique has been a relatively simple and effective method for feature extraction. Some commercial companies have adapted this technique with various enhancements for feature extraction. Hu and Liu (2004) proposed a feature-based opinion mining technique for the first time, where features are extracted based on the frequency of nouns or noun phrases. The frequent noun approach contains noise; therefore, some pruning techniques are also needed to improve the precision of the feature extraction task. Gauba et al. (2017) present a frequency-based procedure for feature extraction and a combination of text blob of NLTK tool and naive Bayes classifier for polarity detection of an extracted feature. The sentiment analysis phase consolidates the regression analysis of EEG signals and sentiment analysis of comments. Random forest regression is employed to predict advertisement preferences.

The feedback mechanism plays a vital role in a recommender system to solve the cold start problem and to better understand user preferences. Therefore, Chen et al. (2019) proposed a critiquing based recommender system using feature-level sentiment analysis to recognise user preferences. In this approach, frequent noun or noun phrases are extracted after part of speech tagging to discover product features from the available reviews. For opinion extraction corresponding to a feature, the nearest adjective is detected using the SentiWordNet dictionary. A statistical measure known as TF-IDF is also popular to find out the frequency of a word in a document. Huang et al. (2020) developed a method known as A2SPR to recommend personalised reviews to a user based on the users' choices on various aspects. Aspect extraction is achieved through TF-IDF and based on the user's aspect preferences, and identical users are discovered using a cosine similarity measure. By considering the review's helpfulness score and users' choices on various aspects, top n personalised reviews are recommended to a user.

7.3.4 Aspect-based sentiment analysis using machine learning/deep learning

Chen et al. (2019) developed a method called deep belief network and sentiment analysis (DBNSA) to predict ratings for a review. A vector is created from the words extracted from comments using the WordNet dictionary. DBNSA uses a noise reduction technique that removes short comments, non-opinionated sentences, and sarcastic sentences for dimensionality reduction. RBM is an ANN that learns probability distribution on a set of inputs. Here, RBM is used to extract features from an input vector of words. Then, the deep belief network predicts the ratings of reviews. The proposed approach was tested on three data sets: Yelp, Amazon, and Trip Advisor.

Da'u et al. (2020) also worked on a deep learning based technique for aspect-based sentiment analysis. Necessarily, there are three opinion mining steps: aspect extraction, aspect summarisation, and aspect rating calculation. For aspect-based sentiment analysis, a fusion of a deep convolution neural network and LDA methodology was used. This approach makes use of the SentiWordNet dictionary to produce an aspect rating matrix. Rating prediction was accomplished by integrating the aspect rating matrix and overall rating matrix into tensor factorisation. The performance of rating prediction is checked on two real-world data sets: Amazon and Yelp.

A user's internal factor should be analysed from the user's reviews to know their user preferences very well (Zhao et al., 2018). Information such as retweeting a topic, following people, and mentioning people on social media is not enough to infer a user's preferences. The word2vec model is used to pluck user sentiments, and for the classification of sentiments, the SVM classifier is utilised. For the prediction of emotion scores from the feature vector, support vector regression is used. For rating prediction of an item, the emotion score calculated by SVR and users' external factors are fused. In order to extract the aspect from product/ business reviews, Da'u and Salim (2019) proposed a sentiment-aware, deep recommender system. This method employed a semi-supervised topic model to pull off the aspect and sentiment lexicon associated with the aspect. It is semi-supervised because this method employs the seed word for the extraction of domain-specific aspects and sentiment lexicon. Extracted aspect and sentiment orientation of the aspect are consolidated into a LSTM kind of recurrent neural network. Furthermore, a co-attention mechanism is used to predict user-item ratings that help the model learn accurately.

8 Different measures to evaluate a sentiment-aware recommender system

This section discusses various measures such as recall, precision, F-measure, RMSE, MAE, and MSE to evaluate sentiment-based recommender systems. Usually, a sentiment-aware recommender system is made of two phases, one is sentiment analysis, and another is the recommendation. The effectiveness of sentiment classification or aspect extraction methods can be measured through recall, precision and F1-measure. Similarly, the effectiveness of a recommendation can be measured through RMSE and MAE.

8.1 Measurement criteria for sentiment analysis

8.1.1 Recall

For sentiment classification, precision is used to measure a classification model's exactness, and for aspect extraction, precision is the percentage of correctly extracted aspects. Higher precision is observed when the rate of false-positives is lower. The sensitivity of an aspect extraction/sentiment classification can be determined through recall. When the rate of false-negatives is lesser, a higher value of recall is observed. For aspect extraction, recall is the percentage of the correctly identified extracted aspects. F1-score gives a single metric that assesses a model by both recall and precision. F1-score is the harmonic mean of recall and precision. It is a good metric when the data is imbalanced.

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}} \tag{1}$$

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}} \tag{2}$$

$$\text{F1-score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

8.2 Measurement criteria for recommendation

It is necessary to assess the performance of a recommender system to confirm whether it functions accurately or not. Evaluation measures of sentiment enhanced recommender systems are the same as that of traditional recommender systems because the idea is the same, to match the prediction with the withheld rating.

$$MAE = \frac{1}{N}\sum_{j=1}^{N} | r_{xi} - r_{xi}^{*} | \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{(x,i)\in T} \left(r_{xi} - r_{xi}^{*}\right)^2}{N}} \tag{5}$$

Equation (4) shows the mean absolute error, and equation (5) shows the root mean square error where r_{xi} represents the actual rating, and r_{xi}^{*} represents the predicted rating. RMSE calculates the sum of the square difference between actual and withheld ratings divided by the total number of the test set N. RMSE is the most suitable measure for recommender systems as it considers both negative and positive inaccuracies. The mean absolute error metric calculates the mean of the absolute values of all the differences between actual and predicted scores. The values of both metrics mentioned above scale from zero to infinity, and the lower values indicate better predictions.

8.2.1 Mean reciprocal rank

A recommender system evaluates a list of items generated by a query through mean reciprocal rank (MRR). MRR is a measure in statistics indicating the closeness of the first relevant object from the starting point on an average for different users (Luo et al., 2014). In layman's terms, it is the mean of the reciprocal ranks for a particular system. For example, if the reciprocal ranks of five users are ⅕, ⅓, 1, ⅕ and ½, their MRR is (⅕ + ⅓ + 1 + ⅕ + ½) / 5. It is a simple method that is easy to calculate and understand. While it does not evaluate the rest of the list to look for relevant items, it focuses on the first relevant element in the list.

$$MRR(0,U) = \frac{1}{|U|} * \sum_{u \in U}^{N} \frac{1}{ku} \tag{6}$$

In equation (6), $\frac{1}{ku}$ represents the reciprocal rank. $|U|$ denotes the length of list U, which is the list of users. Therefore, $|U|$ also denotes the number of users.

8.2.2 Mean average precision

Mean average precision (MAP), as the term explains, is the mean of the average precisions. Average precision for a class is the area under its PR curve or the precision-recall curve. It is mainly used to measure the performance of information retrieval models, recommender systems, etc. In a given recommender system, we can find the precision and recall for various queries, after which the area under the precision-recall curve or the average precision is found, which is further used to calculate MAP (Majid et al., 2013). Equation (7) shows the calculation where $AP(q)$ denotes the average precision of query q among a set of queries Q.

$$MAP = \frac{\sum_{q=1}^{Q} AP(q)}{|Q|} \tag{7}$$

8.2.3 Normalised discounted cumulative gain

Similar to MAP, normalised discounted cumulative gain (NDCG) also puts highly relevant documents at the top of the list of documents. It is essentially defined as the statistical measure of ranking quality that is generally used to measure a given recommender system's effective working and other relevant applications. A knowledge of cumulative gain and discounted cumulative gain is necessary before understanding NDCG. Cumulative gain is said to be the sum of the relevance scores for each item. Discounted cumulative gain [equation (8)] uses the concept of penalisation for relevant objects appearing lower in the system. This value has to be normalised to get a more accurate perspective of the recommender system. The NDCG [equation (9)] is calculated as the overall DCG divided by the ideal DCG (Vilakone et al., 2020).

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel(i)} - 1}{\log(i+1)} \tag{8}$$

$$NDCG = \frac{DCG_p}{IDCG_p} \tag{9}$$

9 Research opportunities

Though several approaches have been proposed for sentiment-aware recommender systems, there are still several significant related research areas that are yet to be explored as mentioned below.

1 Another research area for the improvement of sentiment-aware recommender systems is to recognise contextual information of a user. A smart recommender system can be built by utilising a specific contextual situation of a user. Contextual information is very much crucial for e-commerce personalisation. Therefore, besides sentiment and rating information, other elements can be added for a recommendation, like geographical information of the user, gender identity and climate information (Patel and Chhinkaniwala, 2021; Liu et al., 2021). Thus, recommender system accuracy can be improved by a fusion of sentiment enhanced and context-aware recommender systems (Asani et al., 2021).

2 For a sentiment-aware recommender system, reviews and comments are essential inputs; hence, it becomes essential to know whether reviews or comments used for recommendation are genuine (Revar et al., 2017). Moreover, sarcastic reviews need to be filtered out as they mislead the prediction accuracy. It was observed from the literature review that before employing sentiment analysis, very few approaches applied spam detection and sarcasm detection on reviews/comments. Hence, if reviews/comments are pruned using these techniques before applying sentiment analysis, the performance of a recommender system can further be enhanced.

3 The accuracy of sentiment analysis must be improved to enhance a recommendation's quality in a sentiment-aware recommender system. To further increase the accuracy of sentiment analysis, it is necessary to understand user emotions better. Therefore, emojis can also be scanned to better understand user emotions (Shiha and Ayvaz, 2017). The effect of emojis can be explored in a sentiment-aware recommender system. As emojis play a vital role in deciding the polarity of sentiments, the sentiment orientation of text and emojis should be considered for sentiment analysis to make it more accurate.

4 In addition to sentiment orientation extraction, some more parameters need attention, such as grouping or clustering users with an identical opinion or different opinion with the review. Moreover, while performing recommendations on social media, parameters like the number of times a user tags a friend's post as their favourite can be considered.

5 Social media is a perfect platform for entrepreneurs to advertise their brands/products across the globe. Users are also from various countries. Therefore, there is time to develop a multilingual social media platform to support the enterprise's new market. The majority of the sentiment enhanced recommender systems only consider reviews/comments of English or a particular language.

However, the futuristic trend demands a multi-linguistic platform. Therefore one can propose an approach that can deal with a multi-linguistic platform.

6 Health care is always a crucial domain for study, although a sentiment enhanced health recommender system is not explored enough. Sentiment-aware health recommender system may generate a recommendation using the information available on the internet, such as drugs used to prepare medicine and test recommended by doctor's suggested treatment. This type of system may help a patient in finding proper and nearby doctors for proper medication.

7 Traditional database systems and platforms have limitations, and supporting exponentially increasing information such as user reviews and comments can be challenging. System strategies and algorithms to support a large variety of voluminous data are highly in demand to improve sentiment-aware big data recommender systems for real-time processing. Various horizontal and vertical scaling platform-based customisations can be addressed to achieve high speed and parallel operations (Sharef et al., 2016).

10 Conclusions

In the new age scenario, sentiment analysis is applied to the text generated by users to improve the accuracy of recommender systems. Our aim by presenting this survey is to focus on state-of-the-art sentiment-aware recommender systems. We investigated the need to incorporate sentiment analysis methodologies with recommender system techniques. The survey is divided into five parts. The first part discusses the architecture components of a sentiment-aware recommender system. The second part examines pre-processing and word embedding techniques applied to text before using sentiment analysis algorithms. This research paper also presents various applications of sentiment-aware recommender systems in the third part. The fourth part discusses articles that used different levels of sentiment analysis and provides an analysis of the approaches that implement a different level of sentiment analysis. Finally, the fifth part discusses the research opportunities of using sentiment analysis in a recommender system. Using this survey, a researcher working in this area gains a deep understanding of the role of sentiment analysis in improving a recommender system's accuracy. This survey will encourage researchers to work in this area.

References

Abbasi-Moud, Z., Vahdat-Nejad, H. and Sadri, J. (2021) 'Tourism recommendation system based on semantic clustering and sentiment analysis', *Expert Systems with Applications*, Vol. 167, p.114324.

Alahmadi, D.H. and Zeng, X.J. (2015) 'ISTS: implicit social trust and sentiment based approach to recommender systems', *Expert Systems with Applications*, Vol. 42, No. 22, pp.8840–8849.

Al-Ghuribi, S.M. and Noah, S.A.M. (2019) 'Multi-criteria review-based recommender system – the state of the art', *IEEE Access*, Vol. 7, pp.169446–169468.

Asani, E., Vahdat-Nejad, H. and Sadri, J. (2021) 'Restaurant recommender system based on sentiment analysis', *Machine Learning with Applications*, Vol. 6, p.100114.

Aslanyan, T.K. and Frasincar, F. (2021) 'Utilising textual reviews in latent factor models for recommender systems', in *Proceedings of the 36th Annual ACM Symposium on Applied Computing*, March, pp.1931–1940.

Athira, U. and Thampi, S.M. (2018) 'Linguistic feature based filtering mechanism for recommending posts in a social networking group', *IEEE Access*, Vol. 6, pp.4470–4484.

Bai, P., Xia, Y. and Xia, Y. (2020) 'Fusing knowledge and aspect sentiment for explainable recommendation', *IEEE Access*, Vol. 8, pp.137150–137160.

Bansal, B. and Srivastava, S. (2018) 'On predicting elections with hybrid topic based sentiment analysis of tweets', *Procedia Computer Science*, Vol. 135, pp.346–353.

Birjali, M., Beni-Hssane, A. and Erritali, M. (2017) 'Machine learning and semantic sentiment analysis based algorithms for suicide sentiment prediction in social networks', *Procedia Computer Science*, Vol. 113, pp.65–72.

Bobadilla, J., Ortega, F., Hernando, A. and Gutiérrez, A. (2013) 'Recommender systems survey', *Knowledge-based Systems*, Vol. 46, pp.109–132.

Cai, C. and Xu, H. (2019) 'A topic sentiment based method for friend recommendation in online social networks via matrix factorisation', *Journal of Visual Communication and Image Representation*, Vol. 65, p.102657.

Chen, L., Yan, D. and Wang, F. (2019) 'User perception of sentiment-integrated critiquing in recommender systems', *International Journal of Human-Computer Studies*, Vol. 121, pp.4–20.

Chen, R.C. (2019) 'User rating classification via deep belief network learning and sentiment analysis', *IEEE Transactions on Computational Social Systems*, Vol. 6, No. 3, pp.535–546.

Chen, R.C. (2019) 'User rating classification via deep belief network learning and sentiment analysis', *IEEE Transactions on Computational Social Systems*, Vol. 6, No. 3, pp.535–546.

Colace, F., De Santo, M., Greco, L., Moscato, V. and Picariello, A. (2015) 'A collaborative user-centered framework for recommending items in online social networks', *Computers in Human Behavior*, Vol. 51, pp.694–704.

Da'u, A. and Salim, N. (2019) 'Sentiment-aware deep recommender system with neural attention networks', *IEEE Access*, Vol. 7, pp.45472–45484.

Da'u, A., Salim, N., Rabiu, I. and Osman, A. (2020) 'Recommendation system exploiting aspect-based opinion mining with deep learning method', *Information Sciences*, Vol. 512, pp.1279–1292.

Devika, M.D., Sunitha, C. and Ganesh, A. (2016) 'Sentiment analysis: a comparative study on different approaches', *Procedia Computer Science*, Vol. 87, pp.44–49.

Fan, Z.P., Che, Y.J. and Chen, Z.Y. (2017) 'Product sales forecasting using online reviews and historical sales data: a method combining the Bass model and sentiment analysis', *Journal of Business Research*, Vol. 74, pp.90–100.

García-Cumbreras, M.Á., Montejo-Ráez, A. and Díaz-Galiano, M.C. (2013) 'Pessimists and optimists: improving collaborative filtering through sentiment analysis', *Expert Systems with Applications*, Vol. 40, No. 17, pp.6758–6765.

Gauba, H., Kumar, P., Roy, P.P., Singh, P., Dogra, D.P. and Raman, B. (2017) 'Prediction of advertisement preference by fusing EEG response and sentiment analysis', *Neural Networks*, Vol. 92, pp.77–88.

Gupta, R., Tanwar, S., Tyagi, S. and Kumar, N. (2020) Machine learning models for secure data analytics: a taxonomy and threat model', *Computer Communications*, Vol. 153, pp.406–440.

Gurini, D. F., Gasparetti, F., Micarelli, A. and Sansonetti, G. (2018) 'Temporal people-to-people recommendation on social networks with sentiment-based matrix factorisation', *Future Generation Computer Systems*, Vol. 78, pp.430–439.

Hu, M. and Liu, B. (2004) 'Mining opinion features in customer reviews', in *AAAI*, July, Vol. 4, No. 4, pp.755–760.

Huang, C., Jiang, W., Wu, J. and Wang, G. (2020) 'Personalised review recommendation based on users' aspect sentiment', *ACM Transactions on Internet Technology (TOIT)*, Vol. 20, No. 4, pp.1–26.

Huang, X. and Wu, F. (2019) 'A novel topic-based framework for recommending long tail products', *Computers & Industrial Engineering*, Vol. 137, p.106063.

Irfan, R., Khalid, O., Khan, M.U.S., Rehman, F., Khan, A.U.R. and Nawaz, R. (2019) 'SocialRec: a context-aware recommendation framework with explicit sentiment analysis', *IEEE Access*, Vol. 7, pp.116295–116308.

Jiang, C., Duan, R., Jain, H.K., Liu, S. and Liang, K. (2015) 'Hybrid collaborative filtering for high-involvement products: a solution to opinion sparsity and dynamics', *Decision Support Systems*, Vol. 79, pp.195–208.

Karthik, R.V. and Ganapathy, S. (2021) 'A fuzzy recommendation system for predicting the customers interests using sentiment analysis and ontology in e-commerce', *Applied Soft Computing*, Vol. 108, p.107396.

Kitchenham, B., Brereton, O.P., Budgen, D., Turner, M., Bailey, J. and Linkman, S. (2009) 'Systematic literature reviews in software engineering – a systematic literature review', *Information and Software Technology*, Vol. 51, No. 1, pp.7–15.

Koren, Y., Bell, R. and Volinsky, C. (2009) 'Matrix factorisation techniques for recommender systems', *Computer*, Vol. 42, No. 8, pp.30–37.

Kumar, S., De, K. and Roy, P.P. (2020) 'Movie recommendation system using sentiment analysis from microblogging data', *IEEE Transactions on Computational Social Systems*, Vol. 7, No. 4, pp.915–923.

Lei, X., Qian, X. and Zhao, G. (2016) 'Rating prediction based on social sentiment from textual reviews', *IEEE Transactions on Multimedia*, Vol. 18, No. 9, pp.1910–1921.

Li, G., Chen, Q., Zheng, B., Hung, N.Q.V., Zhou, P. and Liu, G. (2020) 'Time-aspect-sentiment recommendation models based on novel similarity measure methods', *ACM Transactions on the Web (TWEB)*, Vol. 14, No. 2, pp.1–26.

Li, H., Cui, J., Shen, B. and Ma, J. (2016) 'An intelligent movie recommendation system through group-level sentiment analysis in microblogs', *Neurocomputing*, Vol. 210, pp.164–173.

Li, W., Li, X., Deng, J., Wang, Y. and Guo, J. (2021) 'Sentiment based multi-index integrated scoring method to improve the accuracy of recommender system', *Expert Systems with Applications*, Vol. 179, p.115105.

Lin, C., Liu, X., Xv, G. and Li, H. (2021) 'Mitigating sentiment bias for recommender systems', in *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, July, pp.31–40.

Liu, H., He, J., Wang, T., Song, W. and Du, X. (2013) 'Combining user preferences and user opinions for accurate recommendation', *Electronic Commerce Research and Applications*, Vol. 12, No. 1, pp.14–23.

Liu, P., Zhang, L. and Gulla, J.A. (2021) 'Multilingual review-aware deep recommender system via aspect-based sentiment analysis', *ACM Transactions on Information Systems (TOIS)*, Vol. 39, No. 2, pp.1–33.

Lu, J., Wu, D., Mao, M., Wang, W. and Zhang, G. (2015) 'Recommender system application developments: a survey', *Decision Support Systems*, Vol. 74, pp.12–32.

Lü, L., Medo, M., Yeung, C.H., Zhang, Y.C., Zhang, Z.K. and Zhou, T. (2012) 'Recommender systems', *Physics Reports*, Vol. 519, No. 1, pp.1–49.

Luo, Y., Xu, B., Cai, H. and Bu, F. (2014) 'A hybrid user profile model for personalized recommender system with linked open data', in *2014 Enterprise Systems Conference*, IEEE, August, pp.243–248.

Ma, Y., Peng, H., Khan, T., Cambria, E. and Hussain, A. (2018) 'Sentic LSTM: a hybrid network for targeted aspect-based sentiment analysis', *Cognitive Computation*, Vol. 10, No. 4, pp.639–650.

Majid, A., Chen, L., Chen, G., Mirza, H.T., Hussain, I. and Woodward, J. (2013) 'A context-aware personalised travel recommendation system based on geotagged social media data mining', *International Journal of Geographical Information Science*, Vol. 27, No. 4, pp.662–684.

Mawane, J., Naji, A. and Ramdani, M. (2020) 'Recommender e-learning platform using sentiment analysis aggregation', in *Proceedings of the 13th International Conference on Intelligent Systems: Theories and Applications*, September, pp.1–6.

Nazir, S., Nawaz, M., Adnan, A., Shahzad, S. and Asadi, S. (2019) 'Big data features, applications, and analytics in cardiology – a systematic literature review', *IEEE Access*, Vol. 7, pp.143742–143771.

Pappas, N. and Popescu-Belis, A. (2016) 'Adaptive sentiment-aware one-class collaborative filtering', *Expert Systems with Applications*, Vol. 43, pp.23–41.

Patel, J. and Chhinkaniwala, H. (2021) 'A fusion of aspect and contextual information for rating prediction in recommender system using a latent factor model', *International Journal of Web Engineering and Technology*, Vol. 16, No. 1, pp.30–52.

Qiu, J., Liu, C., Li, Y. and Lin, Z. (2018) 'Leveraging sentiment analysis at the aspects level to predict ratings of reviews', *Information Sciences*, Vol. 451, pp.295–309.

Qiu, L., Gao, S., Cheng, W. and Guo, J. (2016) 'Aspect-based latent factor model by integrating ratings and reviews for recommender system', *Knowledge-Based Systems*, Vol. 110, pp.233–243.

Ravi, K. and Ravi, V. (2015) 'A survey on opinion mining and sentiment analysis: tasks, approaches and applications', *Knowledge-based Systems*, Vol. 89, pp.14–46.

Ray, B., Garain, A. and Sarkar, R. (2021) 'An ensemble-based hotel recommender system using sentiment analysis and aspect categorisation of hotel reviews', *Applied Soft Computing*, Vol. 98, p.106935.

Revar, P., Shah, A., Patel, J. and Khanpara, P. (2017) 'A review on different types of spam filtering techniques', *International Journal of Advanced Research in Computer Science*, Vol. 8, No. 5, pp.2720–2723.

Rosa, R.L., Rodriguez, D.Z. and Bressan, G. (2015) 'Music recommendation system based on user's sentiments extracted from social networks', *IEEE Transactions on Consumer Electronics*, Vol. 61, No. 3, pp.359–367.

Rosa, R.L., Schwartz, G.M., Ruggiero, W.V. and Rodríguez, D.Z. (2018) 'A knowledge-based recommendation system that includes sentiment analysis and deep learning', *IEEE Transactions on Industrial Informatics*, Vol. 15, No. 4, pp.2124–2135.

Sailunaz, K. and Alhajj, R. (2019) 'Emotion and sentiment analysis from Twitter text', *Journal of Computational Science*, Vol. 36, p.101003.

Selmene, S. and Kodia, Z. (2020) 'Recommender system based on user's tweets sentiment analysis', in *2020 The 4th International Conference on E-commerce, E-Business and E-Government*, June, pp.96–102.

Shao, X., Tang, G. and Bao, B.K. (2019) 'Personalised travel recommendation based on sentiment-aware multimodal topic model', *IEEE Access*, Vol. 7, pp.113043–113052.

Sharef, N.M., Zin, H.M. and Nadali, S. (2016) 'Overview and future opportunities of sentiment analysis approaches for big data', *J. Comput. Sci.*, Vol. 12, No. 3, pp.153–168.

Shen, R.P., Zhang, H.R., Yu, H. and Min, F. (2019) 'Sentiment based matrix factorisation with reliability for recommendation', *Expert Systems with Applications*, Vol. 135, pp.249–258.

Shiha, M. and Ayvaz, S. (2017) 'The effects of emoji in sentiment analysis', *Int. J. Comput. Electr. Eng. (IJCEE.)*, Vol. 9, No. 1, pp.360–369.

Terán, L. and Mancera, J. (2017) 'Dynamic profiles using sentiment analysis for VAA's recommendation design', *Procedia Computer Science*, Vol. 108, pp.384–393.

Truşcă, M.M., Wassenberg, D., Frasincar, F. and Dekker, R. (2020) 'A hybrid approach for aspect-based sentiment analysis using deep contextual word embeddings and hierarchical attention', in *International Conference on Web Engineering*, Springer, Cham, June, pp.365–380.

Vijayarani, S., Ilamathi, M.J. and Nithya, M. (2015) 'Pre-processing techniques for text mining – an overview', *International Journal of Computer Science & Communication Networks*, Vol. 5, No. 1, pp.7–16.

Vilakone, P., Xinchang, K. and Park, D.S. (2020) 'Movie recommendation system based on users' personal information and movies rated using the method of k-clique and normalised discounted cumulative gain', *Journal of Information Processing Systems*, Vol. 16, No. 2, pp.494–507.

Wever, T. and Frasincar, F. (2017) 'A linked open data schema-driven approach for top-N recommendations', in *Proceedings of the Symposium on Applied Computing*, April, pp.656–663.

Xu, Y., Yang, Y., Han, J., Wang, E., Ming, J. and Xiong, H. (2019) 'Slanderous user detection with modified recurrent neural networks in recommender system', *Information Sciences*, Vol. 505, pp.265–281.

Yang, X., Guo, Y., Liu, Y. and Steck, H. (2014) 'A survey of collaborative filtering based social recommender systems', *Computer Communications*, Vol. 41, pp.1–10.

Yu, D., Mu, Y. and Jin, Y. (2017) 'Rating prediction using review texts with underlying sentiments', *Information Processing Letters*, Vol. 117, pp.10–18.

Zhang, J.D. and Chow, C.Y. (2019) 'MOCA: multi-objective, collaborative, and attentive sentiment analysis', *IEEE Access*, Vol. 7, pp.10927–10936.

Zhao, G., Lei, X., Qian, X. and Mei, T. (2018) 'Exploring users' internal influence from reviews for social recommendation', *IEEE Transactions on Multimedia*, Vol. 21, No. 3, pp.771–781.