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TOPIC MODELING AND SENTIMENT ANALYSIS FOR ENHANCED PERSONALIZATION IN RECOMMENDATION SYSTEMS

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Abstract: *More than 80% of today's available data are in the form of unstructured data, with text having the most representation. Texts hold information about customer preferences not visible in business data, such as customer emotions, explicit expressions of opinion, or focal aspects of customer satisfaction or dissatisfaction. Text data utilization has become paramount for businesses to achieve a market advantage. The introduction of text data into recommendation systems has shown to be beneficial, particularly in dealing with inherent development problems of recommendation systems, such as a cold-start problem, and in enhancing personalization of product and service recommendations. Two natural language techniques are particularly significant for utilizing text data in recommendation systems: sentiment analysis and topic modeling. This paper aims to systematize and present the advantages and challenges of applying these techniques in recommendation systems development and indicate how they contribute to enhancing personalization of the recommendations of products or services and addressing development issues, such as cold-start problem. For the research method the authors selected literature review, as it allows thorough examination of the current research and contextualization of the application of topic modeling and sentiment analysis to recommendation system development challenges.*

Key Words: ***Recommendation Systems, Topic Modeling, Sentiment Analysis***

1. INTRODUCTION

The development of information technology and wide access to the Internet has enabled the massive collection, storage, and processing of data, which have become the most important part of gaining a competitive advantage. A large part of data (around 80%), from which organizations strive to extract information for decision-making and business strategy development, is recorded in an unstructured form (Fadili & Jouis, 2016), such as data generated through the web, social media, mobile devices, and network sensors. Unstructured data is predominantly in textual form, although it can also include images, videos, and audio formats. In a business context, an indispensable source of customer knowledge lies in social media data, such as comments, online reviews, photos, or emoticons that customers utilize to express their opinions about products, services, or companies. Given the vast amount of data, it is necessary to find ways to extract information valuable for business. According to Davenport's research, only 18% of organizations utilize their unstructured data (Davenport T. H., 2019). Recognizing consumer preferences based on the information hidden in the unstructured data, such as whether a consumer likes a certain product or which characteristics of products customers prefer, offers a business advantage over competitors. On the basis of this information products/services are personalized and customized offers are delivered to each user, often without their awareness. The key role in this process belongs to recommendation systems (RS). They can be defined as software tools and techniques that provide meaningful suggestions of specific items to users who have an interest in them (Resnick & Varian, 1997), such as recommending items on online shopping platforms, e.g., Amazon, or content on streaming networks, e.g., Netflix (Davenport T. H., 2019).

Texts are handled using artificial intelligence techniques, particularly natural language processing (NLP). NLP refers to set of techniques dedicated to representation of human language and their analysis. It is applied in various tasks, such as indexing and searching through large texts, information extraction, text classification, automated translation, automated text summarization, question answering (QA), knowledge acquisition, text and dialogue generation, etc. (Chowdhary, 2020). In the context of recommendation systems, NLP techniques are used to extract metadata, such as specific keywords for topics, information on location and time, events and social activities from texts that can serve as item descriptors in content-based recommendation systems or attribute-aware collaborative recommenders (Manzato et al., 2016). Information that can be extracted from textual data can help with different problems in recommendation systems such as cold-start, novelty, diversity, etc. However, they can also contribute to the process of personalization of recommendations. Two NLP techniques that assist with this information extraction used in recommendation systems are sentiment analysis and topic modeling. The aim of this paper is to present the advantages and challenges of applying these techniques in recommendation systems and their beneficial effect on personalization of recommendations. To understand the current state of the research in the domain of topic modeling, sentiment analysis, and recommendation systems, as well as their intersection, particularly in terms of topic modeling and sentiment analysis contribution to solving development challenges in recommendation systems, authors opted for literature review as a main research method. The authors emphasize the research presented in this paper is part of a broader effort to explore the impact of topic modeling and sentiment analysis on recommendation systems and their contribution to enhanced personalization of recommendations that will result in a comprehensive framework as a guide to companies seeking assistance in this area.

This paper is divided into the following sections: section two is literature review which briefly outlines the current state of the literature on different approaches to developing recommender systems. Third section addresses current challenges encountered in recommendation systems development and application. Section four describes the significance of topic modeling in addressing specific issues in recommendation systems. Section five shows the contribution of sentiment analysis to recommendation systems. In the final section authors provide concluding remarks.

2. LITERATURE REVIEW

The development of recommendation systems began in the 1990s with Belking and Croft (1992) research on information filtering and retrieval that made the foundation for recommendation system development and Goldberg et al. (1992) email filtering system, called the Tapestry. Today, recommendation systems are used in diverse information systems or individual applications, such as online shopping platforms, social networks, streaming services, healthcare, news platforms, advertisements, etc. Four different types of recommendation systems are utilized: collaborative filtering, content-based, knowledge-based, and hybrid which combine the previous three, Fig. 1.

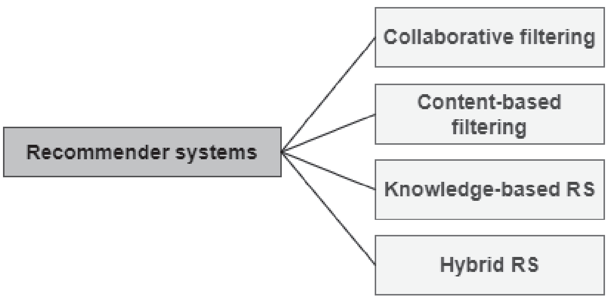

Fig. 1. *Types of recommender systems*

Collaborative filtering utilizes the ratings of other users to make recommendations. The basic idea is that the rating of items that the user has not rated can be imputed based on the existing ratings of other similar users. There is a correlation between the ratings that have not been determined and the assigned ratings of different users and items. Introducing extracted metadata from texts using NLP techniques, topic modeling, or sentiment analysis into recommendation systems aids the development of collaborative filtering recommender systems. Shoja and Tabrizi (2019) developed a specialized recommendation system that enhances the processing of customer feedback from texts. The authors identified relevant features from the reviews which served as the basis for measuring similarities among users and identification of users who share preferences. They employed Latent Dirichlet Allocation topic modeling to eliminate irrelevant keywords from reviews, deep learning to extract features, and collaborative filtering to generate recommendations. Manzato et al. (2016) constructed topic hierarchy, identified named entities and extracted domain terms to generate metadata used in recommendation system. These methods help generate structured data from item descriptions that content-based or attribute-aware collaborative recommendation system can use. In particular, this recommender system relies on collaborative recommenders. The authors utilized k-Nearest Neighbours and BPR-Mapping, and the resulting recommendation systems performed with improved accuracy when metadata extracted from texts were introduced.

Content-based filtering makes recommendations based on descriptive attributes of items. Item descriptions can be combined with user ratings and used to train regression or classification models. Like in collaborative filtering, text data can help enhance this type of recommender system. Protasiewicz et al. (2016) made recommender systems based on content-based filtering that suggests reviewers for scientific papers. They developed a system consisting of various separate parts. One part of the system extracts information from unstructured data, involving publication classification, keyword extraction, full-text indexing, etc. The recommendations are based on a combination of cosine similarity between keywords and full-text indexing.

Knowledge-based methods allow users to influence recommendation process by explicitly stating their preferences. Recommendations are generated based on the measured similarities between item descriptions and users' preferences. These methods are often used with luxury goods or items that are rarely purchased, such as real estate or cars. For such products, often there are only a few instances where ratings are assigned by users primarily because they are not purchased as often. The common problem is the so-called cold-start problem, where there is not enough information to provide recommendations based on historical data (Aggarwal, 2016). Integrating text data with this type of recommender system was the research objective of many authors. Tarnowska and Ras (2021) developed knowledge-based recommender systems that can handle unstructured data. Sentiment scores from the text are extracted with an opinion mining algorithm and then transformed into a structured format. After this, a rule mining algorithm was applied to this data, and these results were integrated into the recommender system. The purpose of these systems is to provide advice on profit maximization with minimal changes in services. This recommender systems approach can also help with the customization of products and services. Esheiba et al. (2021) proposed a hybrid knowledge-based recommender system that helps customers to select a customized product-service in near-mass production. Beam and Michael (2014) proposed a news recommender system, where the content of the recommendations is controlled by user input. The users have the opportunity to choose topics or sources of newspaper articles that they want to read. Pereira et al. (2018) contributed to the development of personalized recommender algorithms in the product-line configuration domain. Their approach allows consumers to go through a small set of product features that the algorithm recommends in order to perform the actual configuration. In this way, the product features that consumers configure are dynamically selected.

3. CHALLENGES IN RECOMMENDATION SYSTEM DEVELOPMENT

Like all functional systems, recommender systems face challenges in their development and application. However, the problems they face differ depending on the applied methods. This paper summarizes the most frequently mentioned problems in literature and the potential solutions authors have offered.

The cold-start problem is one of the most common problems that arise in recommender systems. This problem is caused by a lack of information on user-item interactions, due to which the recommendation algorithm lacks data to provide recommendations. It is directly connected with the data sparsity problem, where there is a large number of users and items but a small number of their interactions. Three types of cold-start problems are often mentioned in the literature: recommendations for new users, recommendations of new items, and recommendations of new items for new users (Z.K. Zhang et al., 2010). This problem is related to situations where it is necessary to provide a recommendation for an item that no one has rated or a recommendation to a user who has not rated any items. Usually, it occurs with collaborative filtering, and its basic form is unable to solve the problem (Schein et al., 2002).

Data sparsity is addressed by many authors (Schein et al., 2002), (Gharahighehi et al., 2021), (Gonzalez Camacho & Alves-Souza, 2018), (Algarni & Sheldon, 2023), (Panda & Ray, 2022). Gharahighehi et al. (2021) mention the problem in real estate recommendation systems due to the small number of user interactions with real estate platforms, in addition to the fact that new properties that appear need to be recommended to users. Camacho and Alves-Souza (2018) discuss how this problem frequently arises in social networks. Algarni and Sheldon (2023) state that the same problem also occurs in course recommendation systems. This problem is specifically addressed by Panda and Ray (2022), who divided strategies for tackling this problem into two groups: data-driven and approach-driven strategies. Data-driven strategies use data like location, social network, trust, and cross-domain data. Approach-driven strategies are classified into deep learning, matrix factorization, hybrid recommender systems, novel approaches in collaborative filtering, and novel approaches in content-based recommender systems.

Every recommender system aims to provide the most relevant and precise recommendations for users, i.e., to increase *accuracy*, so this can be considered a general problem. Saifudin and Widiyaningtyas (2024) state in their research that this recommender system problem occurs in 65% of all cases. This issue is also discussed by Saraswathi et al. (2023), who state that social network recommender systems face the same problem.

With the grow of the number of users and items, the data processing requirements increase leading to scalability issues in recommendation systems development (Silva et al., 2022). The efficiency of recommendation system is reduced if the amount of stored data is limited. During development phase scalability should be considered, as an important issue, and techniques that can adapt to the growth of the data should be utilized (Saifudin & Widiyaningtyas, 2024).

Running time refers to the speed of the recommendation process. The goal is to minimize the time required to perform this process as much as possible until it reaches perfection (Saifudin & Widiyaningtyas, 2024).

Silva et al. (2022) emphasise *explainability* as one of the important issues in recommendation systems, as it can affect user’s trust in the system. It refers to the ability of recommendation system to explain offered recommendations to users, usually in a form "because you previously..." or "users with similar preferences liked...,".

Serendipity (over-specialization) problem is defined as surprise in recommendations or unusual, but relevant recommendations (Y. C. Zhang et al., 2012). In cases where the system consistently offers similar and predictable recommendations, users may become saturated and less active over time. Therefore, it is necessary to encourage a variety of recommendations that might appeal to the user. This problem is addressed by authors Abas and Niu (2019).

The user interest decreases with system's provision of too many similar recommendations. The goal is to offer *diversity* in recommendations to avoid a lack of variety. This feature is important for user loyalty (Alamdari et al., 2020).

Novelty refers to the system's ability to recommend items with which the user has not interacted before. It can be measured and expressed as numerical indicator, as explained by Zhang et al. (2012). A novel item refers to items disimilar to previously purchased or observed items, the items a user is unuaware of but are relevant for them.

Alamdari et al. (2020) indicated that security and privacy should be of high priority during the development of recommendation systems, since while striving for improved recommendations developers often reach for personal information, such as information from social media profiles raising concerns about privacy or login times and location, rising conserns about security (M. Li et al., 2018).

With the rise of available unstructured data and the emergence of NLP techniques, researchers try to address identified development and/or application issues by introducing texts and applying topic modeling and sentiment analysis. Table 1 summarizes recommender system problems and papers that address them with topic modeling or sentiment analysis, while the consecutive sections explore these papers in more detail.

Table 1. *Overview of the papers addressing recommender systems challenges with topic modeling and sentiment analysis.*

Recommender system challenges	Topic modeling	Sentiment analysis
Cold-start	(R. Li et al., 2020), (J. Wu et al., 2014), (Gao et al., 2017)	(D'Addio et al., 2018), (Alahmadi & Zeng, 2015)
Sparsity	(N. Liu & Zhao, 2023), (He et al., 2017)	(L.-H. Wu, 2024), (N. Liu & Zhao, 2023)
Accuracy	(He et al., 2017), (Zhao et al., 2022), (Xie & Feng, 2015), (Zeng et al., 2018), (ZHAO et al., 2019)	(Tarnowska & Ras, 2019), (Subramanian et al., 2021), (Petrusel & Limboi, 2019), (Karabila et al., 2023)
Scalability	(Liang et al., 2017), (Dib et al., 2021)	
Explainability	(Padilha Polleti & Gagliardi Cozman, 2019), (Rossetti et al., 2013)	(Zarzour et al., 2021)
Serendipity, novelty and diversity	(Xiao et al., 2014), (Tomlein & Tvarožek, n.d.), (Yang et al., 2023)	(Cai & Xu, 2019), (Y. Zhang & Zhang, 2022)

4. TOPIC MODELING IN RECOMMENDATION SYSTEMS

Topic modeling identifies underlying thematic structures in a collection of documents, i.e., corpus (Blei, 2012) based on the co-occurrence of words (Barde & Bainwad, 2017). It can also serve as a dimensionality reduction technique. The basic idea is that each document is a random mixture of topics and words (Kherwa and Bansal, 2018). The approaches to topic modeling can be divided into probabilistic and non-probabilistic approaches, with Latent Semantic Analysis (LSA) and Non-negative Matrix Factorization (NNMF) as the most prominent non-probabilistic methods and LDA and Probabilistic Latent Semantic Analysis (PLSA) probabilistic methods (Kherwa and Bansal, 2018).

It is a technique used to extract usable information from texts, which aids in solving some of the recommender system development challenges. Authors of papers (Li et al., 2020), (Wu et al., 2014), (Gao et al., 2017) address the *cold-start* problem with topic modeling. Li et al. (2020) utilized topic modeling in an event recommender system. Events are real-time and occur daily. When they begin the system can receive feedback from users on their quality, leading to a cold-start problem. Traditional collaborative methods are ineffective in this context. In light of this, authors proposed a Spatial-Temporal Topic Model (STTM) to capture interactions among content, location, spatial, and temporal factors to enhance the efficiency of event recommendations in situations where there is no prior data, addressing the shortcomings of existing methods. A wide range of existing event recommendation methods has been used for recommendations (Li et al., 2020). Wu et al. (2014) used a collaborative filtering method by integrating matrix factorization with topic modeling. Their idea was based on collaborative filtering through matrix factorization, where the cold-start problem was addressed using a probabilistic topic model based on WSDL (Web Service Description Language) documents. The authors experimented on two real-world datasets and demonstrated improved accuracy when topic modeling was introduced. To recommend relevant items to users Gao et al. (2017) proposed the introduction of a PLSA topic modeling approach for extraction of user interests (dividing users with different interests into different subgroups) and uniform Euclidean distance for measuring similarities between users. The cold-start problem, manifested in missing rating values, was addressed with predictions of ratings based on similar neighbors' ratings.

The primary cause of the cold-start problem is data *sparsity*. To address the sparsity issue in collaborative filtering, Liu and Zhao (2023) created a recommender system based on sentiment analysis and matrix factorization using topic modeling and deep learning to extract implicit information from reviews to get more information about user ratings. They generated user-topic and item-topic distributions from reviews using LDA, which are represented in a matrix form. Later, these two matrices were integrated to obtain the user-item matrix, which was then merged with the original rating matrix to create the user-item rating matrix. He et al. (2017) used topic modeling methods on item tags to enhance a user-topic interaction, which served as a solution to the sparsity problem in collaborative filtering. Based on this matrix, the authors calculated similarities between users by measuring their preferences towards topics and found that introduction of LDA-based topic modeling and Hierarchical Clustering provides higher accuracy compared to traditional approaches to collaborative filtering.

The introduction of topic modeling in a recommendation system development has a proven effect on increased accuracy, as documented in (He et al., 2017) (Zhao et al., 2022) (Xie & Feng, 2015) (Zeng et al., 2018) (Zhao et al., 2019).

Scalability, alongside sparsity, is a standard problem in collaborative filtering recommender systems. Since topic modeling algorithms are complex, they require large computing, resulting in low scalability. Liang et al. (2017) propose a solution for both problems. They have introduced the topic clustering recommendation (TCR) model, which integrates three ideas: matrix decomposition, clustering, and topic modeling using the LDA method with Gibbs sampling. In this way, they have reduced the model's complexity by employing a simpler latent factor extraction technique. Dib et al. (2021) created a recommender system whose purpose is to find users with similar interests on the Twitter network. Their model was based on long short-term memory (LSTM) along with an LDA output vector for recommendations. Through their study, they demonstrated that this model provided good scalability and effectiveness, but they noted that a drawback of this approach is the cold-start problem.

Polleti and Cozman (2019) proposed a content-based recommender system model based on topic modeling to generate *explanations*. The idea is that a user's preferences are related to the topics to which the items belong, and these topics are the result of the topic model algorithm. As the system makes suggestions based on content similarity, the explanation should follow the same principle. The same problem was addressed by Rosseti, Stella, and Zanker (2013). In their work, they aimed to explain the latent factors derived from the factorization of the user-item matrix along with the topics extracted from the item descriptions.

Topic modeling can also help with *serendipity, novelty,* and *diversity*. Xiao et al. (2014) addressed the problem of searching scientific papers, considering that it is difficult for new researchers in a given field to discover relevant and new papers. They propose a ranking topic model based on semantic recommendation that can assist with serendipity in the system. The ranking topic model rearranges the topic distributions according to users' intentions. Then, this arrangement of topics is used as a feature to rank scientific papers according to the user's search query. This approach also ensures novelty.

Content-based filtering methods often fail in situations where there are a large number of similar items. Analyzing the novelty of recommendations, Tomlein and Tvarožek (2014) developed a model that uses topic modeling to address this problem. Their method ranks topics by their significance and novelty, recommending articles based on these topics. The model has shown success compared to other models that focused on the same problem. To achieve high diversity and accuracy, Yang et al. (2023) created a model that uses LDA and the locality-sensitive hashing (LSH) algorithm in creating the recommender system. In this work, it is also significant that accuracy did not decrease with the increase in diversity.

5. SENTIMENT ANALYSIS IN RECOMMENDATION SYSTEMS

Sentiment analysis deals with the recognition of human opinion, sentiment, attitude, and emotions toward a specific entity, such as a product, service, organization, individual, event, topic, and their attributes. It is referred to as opinion mining, sentiment mining, opinion extraction, or emotion analysis (B. Liu, 2012). Sentiment analysis is performed on the document-, sentence-, or word-level (Tomlein & Tvarožek, 2014). It can be used to determine the sentiment orientation of the analyzed text segment, or it can be performed as aspect-oriented sentiment analysis where the goal is to identify the sentiment orientation towards a particular aspect of the observed entity. Subjective information is extracted from text using NLP techniques (Yang et al., 2023).

Sentiment analysis has gained significant importance as it facilitates companies to gain insights into consumers' opinions regarding company activities and products and provides the possibility to conduct industry benchmarking. Extracted user opinions can be used in recommender systems to provide better, more personalized recommendations. This paper summarizes the advantages of applying sentiment analysis in recommender systems and how it can aid in resolving certain development issues.

Sentiment analysis can help address the *cold-start* problem. Item features can be extracted from user reviews, and in this way, additional information about user preferences and item descriptions is obtained. D'Addio et al. (2018) mitigated the cold-start problem by introducing four item features: sentiment concepts (an average sentiment that the user assigns to concepts) obtained through sentiment analysis, item embeddings (concepts mentioned in the item's reviews) obtained through sense embeddings, full similarity (similarity between items and all the concepts in the vocabulary), and mentioned similarity (similarity between items and the concepts that they have in their reviews). Alahmadi et al. (2015) extracted opinions from short texts, i.e. tweets, from the user's network and expressed sentiment as a scale of ratings. The authors combined this with collected information on trust from the friends' accounts and optimized the information using a genetic algorithm. Finally, they used the Support Vector Regression (SVR) algorithm to predict the ratings of the active user. In this way, their model contributed to solving the cold-start problem.

The *sparsity* problem can be mitigated using sentiment analysis, as mentioned in the papers (L.-H. Wu, 2024) and (N. Liu & Zhao, 2023). Wu (2024) proposed a solution to the cold-start and sparsity problem by integrating semantic and visual sentiment enabling the introduction of more advanced features on user preferences. For this purpose, the author utilized Bayesian personalized ranking (BPR) that manifested better results than traditional BPR models, not introducing advanced features. The use of sentiment analysis for addressing the sparsity problem with the help of matrix factorization and topic modeling is presented in the paper (N. Liu & Zhao, 2023).

Sentiment analysis can also help increase the recommender systems' *accuracy*, which is one of the most important evaluation measures. Users' opinions about a particular item are an important factor for improving recommender systems. The use of sentiment analysis to increase accuracy has been explored in papers (Tarnowska & Ras, 2019), (Subramanian et al., 2021), (Petrusel & Limboi, 2019), (Karabila et al., 2023).

A large number of recommender systems use textual reviews to *explain* the suggested products or services. Sentiment analysis can help determine users' opinions in online social communities. Deep learning architecture for sentiment analysis can predict users' opinions in reviews, which also serves as an explanation for the recommendation (Zarzour et al., 2021).

The use of sentiment analysis can also result in better *diversity* and *novelty* compared to traditional recommender algorithms. For example, matrix factorization and sentiment analysis have been used in social networks (Cai & Xu, 2019). Diversity can be achieved with a combination of topic modeling and sentiment analysis, such as the authors Zhang and Zhang (2022) did. They used the LDA algorithm combined with sentiment classification to build a movie recommendation system.

6. CONCLUSION

Recommender systems play a very important role in the process of personalization in the modern commercial environment and help businesses suggest and recommend products or services to users that would satisfy their preferences. All types of data on user activities can support recommender systems, but unstructured data have a special role. As the amount of recorded unstructured data grows, businesses must use various techniques to extract information that can be useful to recommender systems. Some of the most commonly used techniques for this purpose are topic modeling and sentiment analysis. However, these techniques do not only extract data, they can also help address the most common problems faced by recommender systems, such as the cold-start problem, sparsity, low accuracy, scalability, novelty, diversity, serendipity, explainability, security, etc. This paper presents ways in which topic modeling and sentiment analysis can help solve these problems faced by recommender systems and how they can do so. The methods and techniques that are most commonly used for this purpose are presented, as well as the areas in which recommender systems are applied.

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