REVIEW-BASED COLLABORATIVE RECOMMENDER SYSTEM USING DEEP LEARNING METHODS

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DEDICATION

To my beloved family

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ABSTRACT

Recommender systems have been widely adopted to assist users in purchasing and increasing sales. Collaborative filtering techniques have been identified to be the most popular methods used for the recommendation system. One major drawback of these approaches is the data sparsity problem, which generally leads to low performances of the recommender systems. Recent development has shown that user review texts can be exploited to tackle the issue of data sparsity thereby improving the accuracy of the recommender systems. However, the problem with existing methods for the review-based recommender system is the use of handcrafted features which makes the system less accurate. Thus, to address the above issue, this study proposed collaborative recommender system models that utilize user textual reviews based on deep learning methods for improving predictive performances of recommender systems. To extract the product aspects to mine users' opinion, an aspect extraction method was first developed using a Multi-Channel Convolutional Neural Network. An aspect-based recommender system was then designed by integrating the opinions of users based on the product aspects into the collaborative filtering method for the recommendation process. To further improve the predictive performance, the fine-grained user-item interaction based on the aspect-based collaborative method was studied and a sentiment-aware recommender system was also designed using a deep learning method. Extensive series of experiments were conducted on real-world datasets from the Semeval-014, Amazon, and Yelp reviews to evaluate the performances of the proposed models from both the aspect extraction and rating prediction. Experimental results showed that the proposed aspect extraction model performed better than compared methods such as rule-based and the neural network-based approaches, with average gains of 5.2%, 12.0%, and 7.5% in terms of Precision, Recall, and F1 score, respectively. Meanwhile, the proposed aspect-based collaborative methods demonstrated better performances compared to benchmark approaches such as topic modelling techniques with an average improvement of 6.5% and 8.0% in terms of the Root Means Squared Error (RMSE) and Mean Absolute Error (MAE), respectively. Statistical T-test was conducted and the results showed that all the performance improvements were significant at $P<0.05$. This result indicates the effectiveness of utilizing the multi-channel convolutional neural network for better extraction accuracy. The findings also demonstrate the advantage of utilizing user textual reviews and the deep learning methods for improving the predictive accuracy in recommendation systems.

ABSTRAK

Sistem pengesyoran telah diterima pakai secara meluas untuk membantu pengguna dalam pembelian dan peningkatan jualan. Teknik penapisan kolaboratif telah dikenal pasti sebagai kaedah yang paling dikenali yang digunakan untuk sistem cadangan. Salah satu kelemahan utama pendekatan ini adalah masalah ketahanan data, yang secara amnya menyebabkan prestasi rendah terhadap sistem pengesyoran. Perkembangan terkini menunjukkan bahawa teks ulasan pengguna boleh dieksploitasi untuk menangani isu ketahanandata seterusnya meningkatkan ketepatan sistem pengesyoran. Walau bagaimanapun, masalah dengan kaedah yang sedia ada untuk sistem pengesyoran berasaskan ulasan adalah penggunaan ciri-ciri kraftangan yang menjadikan sistem kurang tepat. Oleh itu, untuk menangani isu di atas, kajian ini mencadangkan model sistem pengesyoran kolaboratif yang menggunakan ulasan teks pengguna berdasarkan kaedah pembelajaran mendalam untuk meningkatkan prestasi ramalan sistem pengesyoran. Untuk mengekstrak aspek produk bagi mendapatkan pendapat pengguna, kaedah pengekstrakan aspek pertama kali dibangunkan menggunakan Rangkaian Neural Konvolusi Pelbagai Saluran. Sistem pengesyoran berdasarkan aspek kemudian dirancang dengan mengintegrasikan pendapat pengguna berdasarkan aspek produk ke dalam kaedah penapisan kolaboratif untuk proses cadangan. Untuk meningkatkan lagi prestasi ramalan, interaksi item pengguna yang halus berdasarkan kaedah kolaboratif berasaskan aspek telah dikaji dan sistem penyaran sedar sentimen juga dirancang menggunakan kaedah pembelajaran mendalam. Siri eksperimen yang meluas telah dijalankan ke atas data dunia nyata dari Semeval-014, Amazon, dan ulasan Yelp untuk menilai prestasi model yang dicadangkan dari aspekpengekstrakan dan ramalan penarafan. Keputusan eksperimen menunjukkan bahawa model pengekstrakan aspek yang dicadangkan menunjukkan prestasi yang lebih baik daripada kaedah perbandingan seperti pendekatan berasaskan peraturan dan rangkaian neural, dengan keuntungan purata masing-masing 5.2%, 12.0%, dan 7.5% dari segi Ketepatan, Ingat, dan skor F1. Sementara itu, kaedah kerjasama berasaskan aspek yang dicadangkan menunjukkan prestasi lebih baik berbanding pendekatan penanda aras seperti teknik pemodelan topik dengan peningkatan purata masing-masing 6.5% dan 8.0% dari segi Kesilapan Dataran Akar Bermakna (RMSE) dan Kesilapan Mutlak Min (MAE). Ujian-t statistik dijalankan dan keputusan menunjukkan bahawa semua peningkatan prestasi adalah signifikan pada $P<0.05$. Keputusan ini menunjukkan keberkesanan penggunaan rangkaian neural konvensional pelbagai saluran untuk ketepatan pengekstrakan yang lebih baik. Penemuan ini juga menunjukkan kelebihan menggunakan ulasan teks pengguna dan kaedah pembelajaran mendalam untuk meningkatkan ketepatan ramalan dalam sistem cadangan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	-	Artificial Neural Network
ADAM	-	Adaptive Moment Estimation
AE	-	Auto Encoder
AI	-	Artificial Intelligence
BN	-	Bayesian Network
CB	-	Content-Based
CBOW	-	Continuous Bag of Word
CF	-	Collaborative Filtering
CNN	-	Convolutional Neural Network
CP	-	Canonical Polyadic
CRF	-	Conditional Random Field
DBM	-	Deep Boltzmann Machine
FM	-	Factorization Machine
GRU	-	Gated Recurrent Unit
HMM	-	Hidden Markov Model
HOSVD	-	Higher-Order Single Valued Decomposition
LDA	-	Latent Dirichlet Allocation
LFM	-	Latent Factor Model
LSA	-	Latent Semantic Analysis
LSTM	-	Long Short-Term Memory
MAE	-	Mean Absolute Error
ME	-	Maximum Entropy
MF	-	Matrix Factorization
ML	-	Machine Learning
MLP	-	Multilayer Perceptron
NCF	-	Neural Collaborative Filtering
NLP	-	Natural Language Processing
PARAFAC	-	Parallel Factor
PMF	-	Probabilistic Matric Factorization
POS	-	Part of Speech

RBM	-	Restricted Boltzmann Machine
ReNN	-	Recursive Neural Network
RELU	-	Rectified Linear Unit
RMSE	-	Root Mean Squared Error
RNN	-	Recurrent Neural Network
RS	-	Recommender System
SDAE	-	Stack Denoising Auto Encoder
SEMEVAL	-	Semantic Evaluation
SGD	-	Stochastic Gradient Descent
SPSS	-	Statistical Package for Social Sciences
SVD	-	Single Value Decomposition
SVM	-	Support Vector Machine
TF	-	Tensor Factorization
TF-IDF	-	Term Frequency- Inverse document frequency

CHAPTER 1

INTRODUCTION

1.1 Introduction

With the advancement of the World Wide Web (WWW) and the explosive accumulation of information on the e-commerce platforms such as Amazon and Yelp, it becomes very difficult to search across all the alternative options in a bid to find what one most likely desire. In other words, the increasing growth of information on the web has brought about the information overload problem which makes it very difficult for effective information retrieval. Recently, to cope with these issues among other solutions, recommender system (RS) technology has been introduced to help customers by presenting products or services that are likely of their interest. Recommender systems can be viewed as a software tool that improves access and provides suggestions to users for the relevant product by considering the users' implicit and explicit preferences (Adomavicius and Tuzhilin, 2005).

Since it was evolved over some decades ago, the field has grown dramatically in solving a variety of problems using various recommendation techniques in the domain of e-commerce, news, social media, services delivery, and many other services (Kunaver and Požrl, 2017). With the advancement of e-commerce, the benefits of the recommender systems cannot be overemphasized. According to research on Netflix[1], 60% of the movies watched on their platform are recommended to the users with the aid of the RSs. Similarly, 35% of sales at Amazon[2] comes from recommendations that are recommended to the users and users have shown great interest. At the same time, it has been shown that recommendation generates 38% more clicks reported by Google News[3].

[1]www.netflix.com
[2]www.amazon.com

[3]https://news.google.com/

Depending on the manner and the type of information being used, RSs can either be Content-Based (CB) (Smyth, 2016) which utilizes description of the items (features and attributes) to match the profiles of the users and provide a recommendation, or Collaborative Filtering (CF) approach (Shi *et al*., 2014) which relies on the information collected from users with similar behaviour in the past to provide a recommendation. However, these traditional RS approaches generally experience some major problems such as data sparsity and cold-start problems (Adomavicius and Tuzhilin, 2005). This made the RS became a wide research topic which raised the question of diving into more research works to finding effective solutions for further improvements.

With the recent remarkable success of deep learning methods in areas such as image processing, machine translation, and Natural Language Processing (NLP) (Hatcher and Yu, 2018), deep learning models have been widely used by many researchers for building the RS approaches (Cas *et al*., 2017; Zhang *et al*., 2017; Kim *et al*., 2016). As such deep learning-based RS brings more capabilities by addressing the inherent challenges of the traditional recommendation methods (Kunaver and Požrl, 2017). Deep learning techniques have been shown very effective in modeling the historical user/item interactions due to their capability in representation learning. Thus developing a personalized deep learning-based recommendation system became a promising research direction (Batmaz *et al*., 2019). In the recommendation system, deep learning methods are typically used to better learn user and item representation based on the user textual review for improving the rating predictive performance.

With the rapid advancement of E-commerce and social networks, recently opinion mining has been widely exploited for building the RSs. Sentiment analysis which involves the extraction of users' opinions/sentiments from the contents of review generally serves as a vital source of information for improving the performances of the RSs. Basically, opinion mining has been widely studied (Medhat *et al*, 2014; Ravi and Ravi, 2015) for many applications. It particularly focuses on determining the user preferences by classifying the user feedback polarity on a particular product. Feedback labelled 'positive' implies that the user who has posted the feedback has an interest in the product and vice versa. Thus, exploiting opinions for improving the performance of RS becomes a promising research direction recently.

Essentially, the user opinions contained in the textual review can help improve the performance of the recommendation system. Meanwhile leveraging deep learning methods for better learning user/item representation is an important driver towards improving the performance of the recommender system. This is the main idea behind the proposed methods in this thesis. The proposed models in this thesis aim to improve the accuracy of the predictive performances of the recommendation system. The related datasets used in this research include SemEval 2014 challenge, Amazon and Yelp datasets to evaluate the proposed models in Chapter 4, Chapter 5, and Chapter 6 respectively. To measure the effectiveness of the proposed models Precision, Recall, F1 score, Root Means Squared Error (RMSE), and Mean Absolute Error (MAE) metrics were used for the proposed models in Chapter 4, Chapter 5, and Chapter 6 respectively.

The rest of this chapter is organized as follows: Section 1.2 presents the background of the study which describes the problem background to identify the research gaps thereby proffering the desired solutions. Section 1.3 highlights the problem statement; section 1.4 presents the research objectives and section 1.5 summarizes the scope of the study.

1.2 Problem Background

As stated earlier, RSs play a vital role in addressing the issue of information overload, having been widely applied in many online services including social media and e-commerce websites. Collaborative Filtering (CF) is the most widely used technique for RSs. The basic idea of this technique is that people who share similar behaviors in the past tend to have a similar preference in the future. Although CF methods have shown promising performances, one of its major challenges is the problem of data sparseness which is characterized by the insufficient number of user ratings with a high number of items. This, however, affects the effectiveness of the recommendation systems. With the recent advancement of e-commerce websites, it has been shown that user textual reviews that contain rich information on different products, can be utilized to alleviate the data sparsity problem thereby enhancing the effectiveness of RSs. Generally, user reviews contain not only the user's comments on different aspects of products but also the user's fine-grained opinions towards various aspects of products. Essentially, these opinions of users are very important as they reflect the user's preference towards products and consequently affect the accuracy of RSs. Thus, in order to get details of the user's opinions towards the item, essentially aspect extraction for opinion mining methods has to be conducted (Cheah, 2016; Hemmatian and Sohrabi, 2017). One of the earliest attempt to extract aspects of products was based on the frequency-based/rule-based methods (Hu and Liu, 2004; Popescu and Etzioni, 2005; Scaffidi *et al.*, 2007) for which some of the constraints are used for identifying the most frequent nouns or noun phrases as the aspects candidates. In this approaches nouns and noun phrases are usually identified using Part-of-Speech (POS) tagger and the names that have been frequently repeated are termed as the aspects. One of the drawbacks of the frequency-based method is that the method generally focuses on only the most popular aspects while the low-frequency aspects are generally neglected.

With the recent achievement of the artificial neural networks in NLP (Da'u and Salim, 2019; Kim, 2014), several methods have been introduced for the aspect extraction task. Most of these methods rely on the CNN model. For example, Poria *et al.*, (2016a) applied a multilayer convolutional model for aspect extraction by tagging words as aspects or non-aspects labels. To further improve the model performance, the authors additionally applied linguistic features which are then integrated with the pre-trained vectors. Toh and Su (2016) utilized the CNN model in the Semeval challenge for aspect detection. The model showed competitive results with the integration of two different machine learning methods. Pham and Le (2018) proposed a CNN based technique by utilizing multiple input vectors for aspect extraction. The model specifically integrates Word2vec, Glove, and one hot vector to generate a unified feature generation for a better extraction process. Xu *et al.*, (2018b) introduced a simple CNN based technique named DE-CNN that leverage double embeddings for the aspect extraction. The model uses the pre-trained Glove and a domain-dependent embedding that are trained on the Amazon and Yelp reviews using the convolution method. Although these methods have performed well, however, the major drawback of the existing CNN based methods is that they typically rely solely on word embedding models such as Google Word2vec (Mikolov *et al.,* 2013) or Glove (Pennington *et al.,* 2014) as the main semantic features. Even though word embeddings have been indicated to be effective in better learning both semantic and syntactic features of texts. However, due to their intrinsic issue of the *distributional hypothesis*, Word embeddings alone cannot guarantee to learn better semantic information of some aspect words (Young *et al*., 2018). For instance, "*good"* and *"bad"* are particularly mapped together as neighbours in a latent space while analysing these words is very critical in real-world applications.

The extracted aspect terms can essentially be utilized for building recommender system models (Cheng *et al*., 2018). Recently, several approaches have been proposed to directly exploit the product's aspects for building the aspect-based recommendation systems. Most of these approaches were typically based on the topic modelling (Cheng *et al*., 2018; Diao et al., 2014; McAuley and Leskovec, 2013; Tan *et al*., 2016) in which the main idea is to align topics and user/item latent factors for rating prediction. Other approaches utilized sentiment lexicons and heuristic methods for the rating prediction (Zhang *et al*., 2014a). Although these approaches have shown good performance, however, they generally rely on the Bag of Word (BOW) method which typically considers words in the document as a mere collection without considering the local contextual information of the words. Thus, in such approaches, the vital information in the form of phrase and sentences is usually lost and consequently leads to poor accuracy of the model.

To investigate the role of the deep learning method in exploiting the aspect terms along with reviews for improving the accuracy of the recommendation system, the study further seeks to explore a deep learning-based recommender system method. Recently, several approaches have been proposed to exploit user reviews based on the deep learning techniques for recommendation systems (Zhang *et al*., 2017). For example, (Kim *et al*., 2016) proposed Convolutional Matrix Factorization (ConMF) which simultaneously uses deep learning and Probabilistic Matrix Factorization (PMF) model for better user/item representation learning based on the contextual information of the words. A Deep Convolutional Neural Network (Deep-

CONN) has been proposed by (Zhang *et al.*, 2017) to exploit two parallel CNN models to separately learn the textual contents from both the user and item side. The model uses the embedding layer to derive the user and item latent features which are then concatenated and finally fed to the output layer consisting of the Factorization Machine (FM) for the rating prediction. The model was later extended by introducing a method called Transnet (Seo *et al*., 2017). The model particularly utilized more layers in addition to the two parallel CNN layers for better learning of the representation of the user-item review at the training time and regularized the output of the source network using the learned representation. Recently, the deep learning-based attention mechanism has been successfully applied for building the deep learning-based recommender system. Seo *et al*., (2017) proposed an interpretable network model by exploiting the attention-based CNN technique. The model exploits different attention mechanisms: local and global attention mechanisms. Specifically, the local attention assist the model for better modelling users and item features while the global attention allows better learning the semantic information of words from the user texts. In this way, the combination of the local and global attention help the model to better learning interpretable item/user representations.

Despite the remarkable achievements of the abovementioned deep learning-based recommender system models compared to their prior methods, they experience some limitations: 1) they model latent feature vectors statically and independently in which the user and item factors are projected into fixed representations vectors in a shared space and the only interaction between user and item vectors occurs at the final prediction layer. Therefore, in these approaches, the fine-grained user/item interaction is generally lost which is very important for ensuring more accurate rating prediction. 2) Moreover, the existing deep learning methods generally ignore sentiment aware user/item representation in learning user/item latent factors for the rating prediction.

To better clarify the entire research problem background, Figure 1.1 below, provides a diagrammatic illustration with a summary of the research problem of the study, showing the key research gaps and the proposed solutions accordingly.

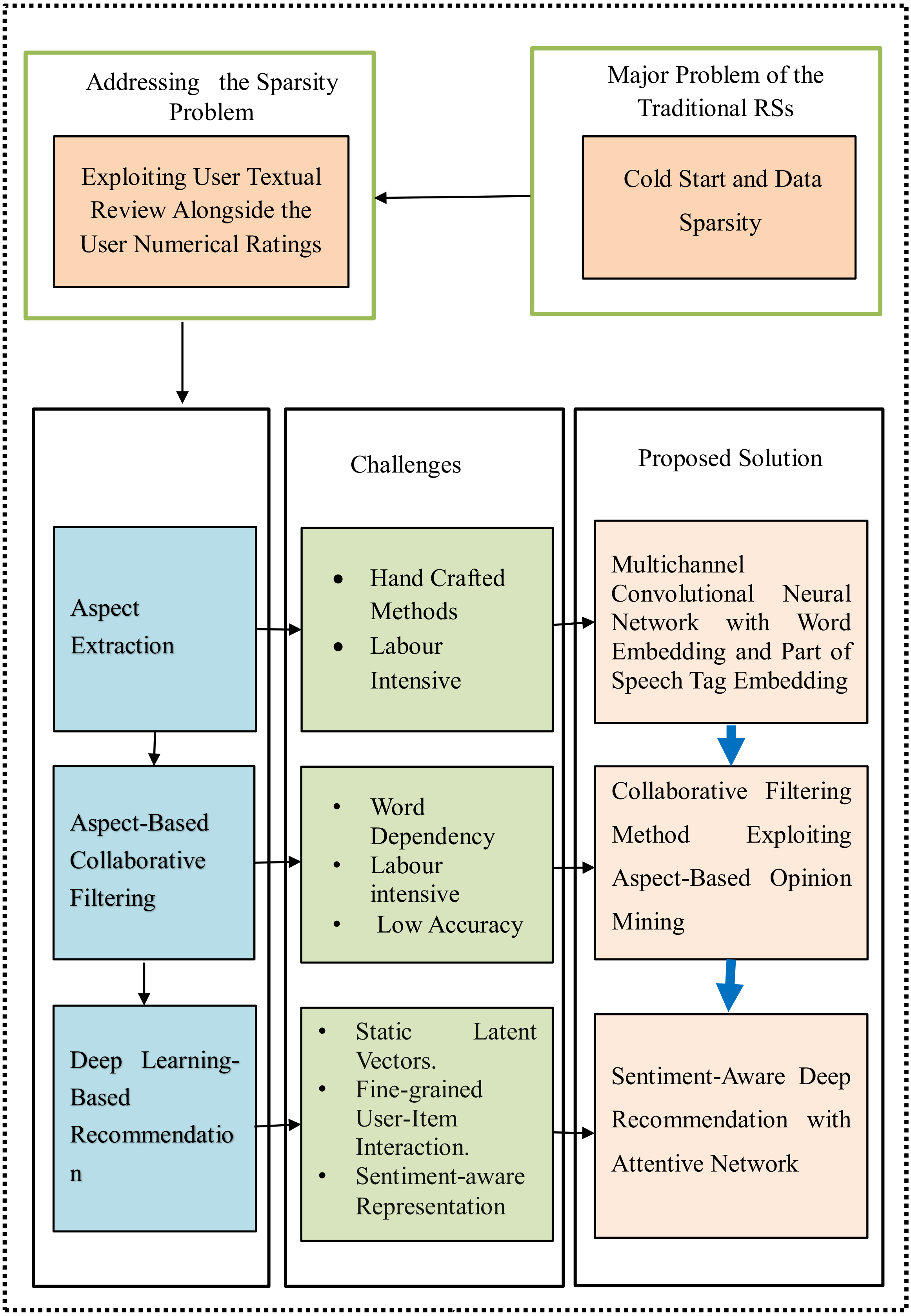
Addressing the Sparsity Problem
Exploiting User Textual Review Alongside the User Numerical Ratings
Major Problem of the Traditional RSs
Cold Start and Data Sparsity
Challenges
Proposed Solution
Aspect Extraction
Hand Crafted Methods
Labour Intensive
Multichannel Convolutional Neural Network with Word Embedding and Part of Speech Tag Embedding
Aspect-Based Collaborative Filtering
Word Dependency
Labour intensive
Low Accuracy
Collaborative Filtering Method Exploiting Aspect-Based Opinion Mining
Deep Learning-Based Recommendatio n
Static Latent Vectors.
Fine-grained User-Item Interaction.
Sentiment-aware Representation
Sentiment-Aware Deep Recommendation with Attentive Network

Figure 1.1: Summary of the research background

1.3 Problem Statement

In view of the problem background as discussed in Section 1.2 above, it could be deduced, that despite numerous achievements of the existing RS approaches they still experience major problems of the data sparsity which could lead to the low accuracy of the recommendation performance. Therefore more research efforts are still needed to fill the gaps thereby addressing the existing shortcomings by developing enhanced recommender system methods. Thus, to achieve that, the research put forward the following main research question:

"How can the accuracy of the collaborative recommender systems be improved by exploiting the user textual reviews using deep learning methods? "

To answer the main research question (RQ) the following sub-research questions are put forward to answer:

- **RQ1**: How can the product's aspects be extracted from the user textual review by using a Multi-Channel Convolutional Neural Network (MCNN) model for opinion mining?

- **RQ2**: Can the user opinions based on the product's aspects be integrated into the collaborative filtering technique for better predictive performance?

- **RQ3:** How can the recommendation accuracy be improved by utilizing the aspect-based collaborative method based on the deep learning technique?

1.3 Objectives of the Research

The main goal of this research is to design collaborative recommender system models that leverage user textual reviews using deep learning methods to provide robust and reliable predictive performances with high accuracy**.** Therefore, to achieve the main goal, the following research objectives (**RO**) will be put into consideration:

- **RO1**: To propose a multichannel convolutional neural network (MCNN) model to extract the product's aspects from the user textual review for opinion mining.
- **RO2**: To propose an aspect-based collaborative method by incorporating user opinions based on the product's aspects into the collaborative filtering technique for better predictive performance.
- **RO3**: To propose a sentiment-aware deep recommender system by utilizing the aspect-based collaborative method for improving the recommendation accuracy.

1.4 The Scope of the Study

This research provides an in-depth study of the collaborative recommendation system based on user review using the deep learning method. In essence, the recommender systems field is a broad research area that includes cross-domain RSs, rating-only-based RSs, review based RSs, etc. In essence, this study specifically focuses on the review-based recommender system perspective which utilizes user textual review for the rating prediction. More specifically, this research was confined to the following scopes:

- The proposed study is focused on the literature review related to the aspect extraction, deep learning methods, aspect-based recommender systems, and deep learning-based recommender system.
- Regarding the models' evaluations, for the rating prediction, the study focused on the three different datasets: Instant video, Musical instrument, and Yelp challenge datasets. The first two datasets were taken from the

Amazon review datasets out of the 23 categories of different products (McAuley and Leskovec, 2013) and the third dataset is taken from the Yelp challenge competition platform. Similarly, for the aspect extraction, the study particularly focused on the Semeval-014 Restaurant and SemEval-014 Laptop datasets which are taken from the SemEval (semantic evaluation) challenge competition (Pontiki and Pavlopoulos, 2014).

- Regarding the collaborative filtering algorithms used for the rating prediction, the study specifically focused on the Tensor Factorization (TF) and Matrix factorization (MF) for the proposed RS models in Chapter 5 and Chapter 6 respectively.

- Regarding the proposed models' performances, the study focused on the accuracy performance for both the aspect extraction and the recommendation relevance. Thus for the evaluation metrics, the study specifically focused on the MAE and RMSE metrics to evaluate both the proposed RS models. While the F1 score, Precision, and Recall metrics were used for the aspect extraction.

- The experiments for all the algorithms were carried out using Python 3.7 programming language with the Keras, Pytorch, and the Tensorflow backend.

1.5 Significance of the Study

As mentioned earlier, RSs have become ubiquitous in recent times due to their popularity in the e-commerce and social media domains. Companies such as Yelp, Amazon, and eBay have introduced a large number of products for meeting the satisfaction of their customers. The market value of recommendations in the companies is very important in the domain of service delivery and many sectors of e-commerce. According to research, over 30% of the sales in *amazon*[1] comes from recommendations that are provided to the customers and customers have shown a great satisfaction.

As noted in the literature, the existing RS methods have been shown to be suffered form the problem of the data sparseness which leads to a poor and inaccurate recommendation. This research aims to fill this gap by first proposing an aspect extraction method to extract product aspects from user textual review and then incorporate the extracted aspect opinions into a collaborative filtering method for improving the accuracy of the recommendation system. Meanwhile, we believe that incorporating the user sentiments into collaborative filtering based on the deep learning method would address the data sparsity problem thereby improving the accuracy of the recommendation system. Therefore, this study further investigates exploiting deep learning-based methods and neural attention mechanisms to propose a sentiment aware deep recommender system with neural co attention (SDRA).

Another significance of this study is that; our proposed recommender system models specifically utilizes user textual reviews in addition to the user numerical ratings. This is particularly very important in a domain where numerical ratings on products are very scarce, not available due to the difficulty to collect or where the opinions of a user towards domain items are too complex to express as scalar ratings.

1.7 Thesis Organization

This section describes the organization of the thesis. There are seven chapters in this thesis, which are arranged as follows:

Chapter 1, Introduction: This chapter presents a general introduction regarding the concept of the research work which includes an overview of the proposed research study. A comprehensive background of the study is also presented in this chapter. Further, the chapter includes the problem statement, objective of the study, research scope and the significance of the study.

Chapter 2, Literature review: This chapter provides an overview of the recommender system which includes the basic techniques for the recommender system, the main challenges of the recommender system and the evaluation measures used for the recommender systems. The chapter also discusses an overview of the deep learning techniques including the major deep learning methods uses for recommender systems. Furthermore, this chapter reviews the previous research works on the aspect-based recommender systems, and deep learning-based recommender systems accordingly.

Chapter 3, Research methodology: This chapter presents the detailed methodology used in this study. It encompasses the generic framework of the research and the steps required to carry out the research systematically. This chapter outlines detailed procedures involved in solving the research problems and answering the research questions to achieve the research goal and objectives. The chapter describes various stages to carry out the research, which includes a discussion of the research components such as the research phases, techniques, and the tools involved

Chapter 4, Aspect extraction on user textual reviews using deep convolutional neural network: This chapter addresses the first objective of the research. Specifically, the chapter presents an approach to extract the item aspects from the user review using a multichannel convolutional neural network (MCNN) model. The MCNN model comprises of word embedding and POS embedding channel. The main goal of this chapter was to propose a model for the aspect extraction from the user textual review using a multi-channel convolutional neural network for better predictive accuracy.

Chapter 5, Recommender system exploiting aspect-based opinion mining using deep learning methods: This chapter presents an approach to incorporate the user opinions/sentiments into the collaborative filtering algorithm for the recommender system. The main goal of this chapter is to address the problem of the cold start by utilizing the specific aspect ratings in addition to the overall ratings provided by the user in the review text. To achieve that a tensor factorization technique was employed which is very effective in dealing with a high order decomposition.

Chapter 6, Sentiment aware deep recommender system using neural attention mechanism: This chapter addresses the third objective of this thesis which aims to investigate how deep learning methods could be exploited along with neural attention mechanisms for improving the accuracy of the recommender systems. This chapter was motivated by the recent success of deep learning techniques in representation learning and the recommendation systems. In this chapter, the study proposed a deep recommender system that uses a neural co-attention mechanism to better learning fine-grained user/item interaction for improving the accuracy of the rating predictive performance of the recommendation system.

Chapter 7, Conclusion and Future Work: This chapter provides the conclusions of the research work discussed throughout this study. The chapter also presents and highlights the contributions of the research and puts forward some recommendations for future studies.

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APENDIX A: LIST OF PUBLICATIONS

1. **Da'u, Aminu**, and Naomie Salim. (2019). Recommendation System Based on Deep Learning Methods: A Systematic Review and New Directions. Artificial Intelligence Review. Springer Netherlands. (Published_WOS and SCOPUS Indexed Impact **Factor: 5.10, Q1**)

2. **Da'U, Aminu**, and Naomie Salim. (2019). "Sentiment-Aware Deep Recommender System with Neural Attention Networks." IEEE Access 7: 45472–84. (Published WOS and SCOPUS Indexed Impact **Factor: 4.098, Q1**)

3. **Da'u, Aminu**, Naomie Salim, Idris Rabiu, and Akram Osman. (2020). "Weighted Aspect-Based Opinion Mining Using Deep Learning for Recommender System." Expert Systems with Applications 140: 112871. **Published** WOS and SCOPUS Indexed Impact **Factor: 4.292, Q1**)

4. **Da,u Aminu**, Naomie Salim, Idris Rabiu, and Akram Osman.(2019). "Recommendation System Exploiting Aspect-Based Opinion Mining with Deep Learning Method." Information Sciences, no. xxxx. **Published** WOS and SCOPUS Indexed Impact **Factor: 5.524, Q1**)

5. **Da'u, Aminu**, and Naomie Salim. (2019). "Aspect Extraction on User Textual Reviews Using Multi-Channel Convolutional Neural Network." PeerJ Computer Science 2019 (5): 0–16. **Published** WOS and SCOPUS Indexed)

6. **Da,u Aminu**, Naomie Salim, Idris Rabiu, and Akram Osman. (2019). "Aspect Extraction on User Textual Reviews Using lexicon enhanced Deep Convolutional Neural Network. PARS 2019. Conference paper**: Best Presenter Award.**

7. **Da,u Aminu**, Naomie Salim, Idris Rabiu, .(2020). "Aspect-Opinion Terms Co-Extraction Based on the Lexicalized Convolutional Neural Network." International Graduate Conference Engineering, Science and Humanities (IGCESH 2020).

8. **Da,u Aminu**, Naomie Salim, Idris Rabiu, (2020). "Adaptive Context-Aware Recommender System with Neural Network." Knowledge-based System, no. xxxx. **Accepted** WOS and SCOPUS Indexed Impact **Factor: 5.921, Q1**)

9. **Da,u Aminu**, Naomie Salim, Idris Rabiu, (2020). "Multi-level Attentive Deep User-Item Representation Learning for Recommendation System "Neurocomputing", no. xxxx. **Accepted** WOS and SCOPUS Indexed Impact **Factor: (4.38, Q1**

10. **Da,u Aminu**, Naomie Salim, Idris Rabiu, (2020). "Lexicon augmented aspect extraction using deep learning methods." Applied Soft Computing. (Under **Review** WOS and SCOPUS Indexed Impact **Factor: 4.21, Q1**)