DEEP REINFORCEMENT LEARNING APPROACHES FOR MULTI-OBJECTIVE PROBLEM IN RECOMMENDER SYSTEMS

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Chair : Assoc. Prof. Ts. Nurfadhlina Mohd Sharef, PhD
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Most of the recommender system merely focus on accuracy of rating prediction or recommendation of trendy items. Nonetheless, other non-accuracy metrics such as novelty and diversity should not be neglected to provide quality recommendation. The current major existing multi-objective recommendation approaches utilize collaborative filtering method as rating predictor to replenish the missing ratings and combined with evolutionary algorithm for only bi-objective optimization. However, collaborative filtering suffers from cold-start problem and incapable to predict rating on highly sparse user-item matrix besides difficulty to incorporate side features information such as user latent, which led to weak performance when encountering new items or users. On the other hand, the evolutionary algorithm is notorious with premature convergence issue and suffering from curse of dimensionality. This study proposes deep reinforcement learning approaches based on Deep Q-Network to improve multi-objective optimization in recommendation environment and investigated its capability to optimizing precision, novelty, and diversity concurrently. The MovieLens 100k dataset is applied to evaluate the performance of the proposed approaches, which do not require separate rating predictor such as done in benchmarked works. This is because the reinforcement learning agent is able to predict items directly by capture user latent information and explore large sparsity state space effectively. The experiment results demonstrated that embedding user latent features contributed to quality improvement in terms of precision by 19.80%, and novelty as well as diversity, by 20.46% and 1.60% respectively. Besides that, the experiment shows that agent which learning sequential data has earned lower precision by 17.57% and novelty by 4.68% compared to the agent that without learning sequential data, however, it achieved better diversity by 2.66%. In the performance comparison between proposed deep reinforcement learning with evolutionary algorithm, despite one of the variants of evolutionary algorithm has good performance in precision, it has rather weak performance in term of novelty and diversity. In contrast, the proposed approaches obtained better novelty and diversity results compared to

evolutionary algorithm with sacrificing a certain degree of precision. Overall, the deep reinforcement learning approaches are able to recommend accurate item concurrently with achieving good diversity and novelty as well.

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Sebilangan besar sistem cadangan hanya menekankan ketepatan ramalan penilaian di dalam meramalkan barang untuk pengguna ataupun pemberian cadangan barang yang popular. Namun, metrik selain ketepatan seperti kebaharuan dan kepelbagaian tidak patut diabaikan untuk memberikan cadangan yang berkualiti. Majoriti sistem cadangan yang sedia ada memfokuskan kepada dua objektif sahaja dengan menggabungkan penyaringan kolaboratif sebagai peramal untuk mengisi penilaian yang tertinggal dan algoritma evolusi untuk pengoptimuman. Walau bagaimanapun, kaedah penyaringan kolaboratif mengalami masalah “permulaan-sejuk” dan tidak dapat meramalkan penilaian pada matriks barang yang sangat jarang dinilai, selain itu, kaedah ini juga menpunyai kesukaran untuk memasukkan maklumat ciri sampingan seperti laten pengguna, menyebabkan prestasi lemah ketika memproses item atau pengguna baru. Di samping itu, algoritma evolusi umumnya diketahui mempunyai masalah penumpuan pramatang dan lemah dalam pemprosesan dimensi yang tinggi. Kajian ini mengusulkan pembelajaran pengukuhan mendalam berdasarkan algoritma Rangkaian-Q Mendalam dan menyelidiki kemampuannya bagi pelbagai objektif cadangan untuk mengoptimumkan ketepatan, kebaharuan, dan kepelbagaian secara serentak. Set data MovieLens 100k digunakan untuk menilai prestasi kaedah yang diusulkan, iaitu kaedah yang tidak memerlukan peramal penilaian yang berasingan seperti yang dilakukan dalam kaedah penanda aras kerana ejen pembelajaran pengukuhan dapat meramalkan item secara langsung dengan menangkap maklumat pendam pengguna dan meneroka ruang keadaan dengan berkesan. Hasil eksperimen menunjukkan bahawa mengambil kira ciri laten pengguna menyumbang kepada peningkatan kualiti dari segi ketepatan dengan 19.80%, kebaharuan, dan kepelbagaian, dengan 20.46% dan 1.60% masing-masing. Selain itu, penghasilan eksperimen juga menunjukkan ejen yang mengambil data berurutan memperoleh ketepatan yang lebih rendah dengan 17.57% dan kebaruan dengan 4.68% berbanding dengan ejen yang tidak belajar data berurutan, tetapi, ia mendapat kepelbagain yang lebih baik dengan 2.66%.

Dalam perbandingan prestasi antara pembelajaran peneguhan mendalam yang diusulkan dengan algoritma evolusi, walaupun salah satu varian daripada algoritma evolusi menpunyai ketepatan yang baik, tetapi ia menpunyai prestasi yang agak lemah dari segi kebaruan dan kepelbagaian. Sebaliknya, kaedah yang diusulkan mencapai kebaruan dan kepelbagaian yang lebih tinggi dengan mengorbankan tahap ketepatan yang tertentu. Secara keseluruhan, hasilnya menunjukkan bahawa pendekatan pembelajaran peneguhan mendalam dapat mencadangkan item yang tepat sekaligus mencapai kepelbagaian dan kebaruan yang baik juga.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Master of Science. The members of the Supervisory Committee were as follows:

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LIST OF ABBREVIATIONS

RS	Recommendation system
DRL	Deep reinforcement learning
MORS	Multi-objective recommendation system
CF	Collaborative Filtering
EC	Evolutionary Computing
EA	Evolutionary Algorithm
MO	Multi-objective
DQN	Deep Q-Network
CB	Content-Based
MRR	Mean Reciprocal Rank
MAE	Mean Absolute Error
VSM	Vector Space Model
TF-IDF	Frequency-Inverse Document Frequency
ID	Identification number
RL	Reinforcement learning
MDP	Markov Decision Process
DDPG	Deep Deterministic Policy Gradient
AI	Artificial Intelligence
MOEA	Multi-objective Evolutionary Algorithm
NNIA	Nondominated Neighbour Immune Algorithm
MOEA/D	Decomposition-based MOEA
NSGA-II	Nondominated Sorting Genetic Algorithm II
TD	Temporal Differences

NSGA	Nondominated Sorting Genetic Algorithm
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
POMDP	Partially Observable Markov Decision Processes
CNN	Convolutional Neural Network
PMOEA	Probabilistic Multi-Objective Evolutionary Algorithm
GA	Genetic Algorithm

CHAPTER 1

INTRODUCTION

1.1 Background

Recommender system (RS) is one of the information filtering systems that aim to direct users across the vast information space, towards the area that meet user's needs and interests (Figure 1.1). The interaction patterns between user and item are crucial elements that enable RS to learn the hidden meaningful information, identify candidate items to be recommended, then filter the recommendation based on objectives and finally recommend relevant items to satisfy users. RS has benefited numerous domains in especially commercial applications such as online movie streaming, e-commerce shops, and social media platforms.

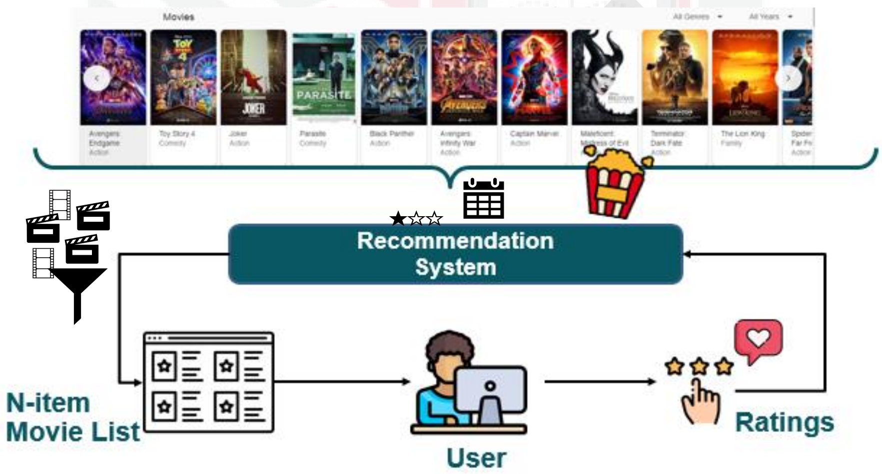

Figure 1.1: Movie recommendation system and the interaction between user and the platform

The traditional RS approaches [1]–[7] mainly can be categorized into collaborative filtering, content-based, and hybrid methods. In the past decades, more advanced methods for RS based on deep reinforcement learning (DRL) [8]–[11] emerged because of its monumental strength in solving many complex tasks and alleviated the shortcoming of conventional models.

Recently, multi-objective recommendation system (MORS) is gaining attention to complement single objective RS because MORS balances other non-accuracy objectives (Table 1.1) such as novelty and diversity to improve the recommendation quality, it is better than the typical single-objective RS that only focus on accuracy.

Table 1.1: Objectives in Recommender Systems

Objective	Explanation	References
Accuracy	The accuracy is the prevalent objective emphasized in many recommender systems to ensure recommendation conforms to the correct target. The correctness of recommendation usually based on how many recommended items matched to target items or how close of the predicted rating value to the actual rating given. Accuracy can be measured by several metrics such as precision, recall, or mean absolute error.	[9], [12]–[21]
Novelty	Some recommender systems aim to recommend novel items or something new to the user in order to maintain fresh experiences for user, and this objective known as novelty. The evaluation metrics also commonly named as novelty. The novelty of recommendation is not only based on recommend new entry item to user, but also ability to recommend long tail items or unpopular items that user never experienced previously.	[12], [14]–[17], [22]
Diversity	The diversity objective in recommendation system is purpose to diversify the recommendation items and avoid to recommend similar items to user. Diversification of recommendation is referred as aggregation of the pairwise dissimilarities between recommended items. There are evaluation metrics for diversity measurement such as namely diversity or coverage.	[12], [14]–[17], [22], [23]

Most of the existing approaches for MORS are combination of collaborative filtering (CF) and evolutionary computing (EC) technique. The common technique of EC applied is evolutionary algorithm (EA) which uses genetic operator (including crossover and mutation) to generate new off springs as candidate items and search the Pareto optimal solutions. However, some unpreventable limitations from CF method such as cold-start issue (which happens when the user is new to the system and hence his past preferences are not known to the system) and premature convergence from EC technique (which has resulted to generation of solutions which have good performance initially but eventually dropped their performance) has urged academia to search for alternative potential solution.

DRL techniques have been proved of having better achievement on MORS problem in the aspect of solution convergence and sparsity data handling compared to the EC technique. Besides, DRL is able to predict the rating of items or items to be recommended directly, compared to EC technique that focuses only on the solution space exploration for preferred candidate items identification. Many advantages of DRL have motivated this research to propose a novel approach for solving multi-objective (MO) problem in RS application. After a thorough search of the relevant literature, there is no available research about applying Deep Q-Network (DQN) techniques in MO problem on RS domain. Therefore, this study demonstrates the capability of the DRL approaches based on DQN algorithm as non-iterative solver which is more effective in MO problem in RS. The proposed DQN for MORS approaches do not require additional rating prediction algorithm before generating recommendation, since it is able to work independently despite handling large sparse environment. Furthermore, the DQN approaches could effectively improve the recommendation quality because it is able to capture complex nonlinear abstraction and nontrivial information of user-item relationship as data representation.

This research works focuses on the development of MORS based on DQN approach and extend the experiments with different input states including user latent features and sequential rating information. To incorporate sequential rating input data, the DQN is enhanced with additional recurrent layer to capture sequence input and named as recDQNMORS, while the DQN without recurrent layer is named as DQNMORS. Furthermore, the hyperparameter tuning experiments for each algorithm are necessary at the beginning to identify the optimum values for essential hyperparameters including learning rate, discount factor, and epoch numbers. Subsequently, the comparison among proposed DRL approaches is accomplished to study the effect of different input features. Lastly, the comparison on performance between DRL with CF that combined with EC approaches were carried out. The results show that the proposed approaches are able to recommend accurate item concurrently with maintaining good item diversity and novelty as well. This study also contributes to proposing a novel DRL approaches for MO problem in RS.

1.2 Problem Statement

Most works in RS focuses on single objective approach specifically for achieving high accuracy by using CF [1]–[3] and Content-Based Filtering (CB) [4]–[6] and its hybrid techniques [7], [24]. In fact, a quality RS requires multiple metrics to be accounted including precision, novelty, and diversity as encouraged by [22], [23], [25]–[27], instead of just focusing only the accuracy.

There are some MORSs that used CF combined with EC [12], [15], [16] but only for dual-objective RS and evaluated in movie item datasets, such as precision and novelty [15], or precision and diversity [12], [14], [16] instead of all three quality indicators namely precision, novelty and diversity concurrently. This is because, CF based approaches suffered from cold-start issue and restricted by sparse matrix [28]–[30]. Besides, similar to other traditional RS approaches such as demographic and content approaches, the incorporating various features that potentially could advantage the MORS using the CF method is difficult [31] such as to learn user latent features and sequential rating data.

Although CF method could predict the rating for items to be recommended, this method itself is incompetent to tackle MO problem, so it relied on EC for optimization task despite EC suffering from its frequent premature convergence issue [32], [33]. The DRL approach has better performance for MO problems [34]–[36] but has not been explored for any recommendation system's problems. This indicates possibility to address MORS based on precision, novelty and diversity concurrently using DRL and relevant techniques such as pareto and scalarize weighting methods. The problem statement with subproblems and research questions have been determined as summarized in Table 1.2.

Table 1.2: Research problem statement with the detailed subproblems and research questions

Research Problem Statement	
The major existing approaches for MORS deployed CF method associated with EC to handle multi-objective problem [12], [14]–[16]. However, CF approaches not only seriously affected by cold-start issue and vulnerable to highly sparse environment [1]–[3], it also hard to incorporate side features and sequential rating data [12], [14]–[16]. Other than that, the EC techniques are mostly suffering from premature convergence issues. In addition, most of the existing MORS works only focus on bi-objective optimization instead of all the precision, novelty and diversity concurrently which equally important for quality recommendation [22], [23], [25]–[27].	
Subproblems	**Research Questions**
Since CF approach itself is incapable to optimize multi-objective problem, it required to collaborate with EC technique which are mainly suffered from premature convergence.	How to model the multi-objective recommendation system based on Deep Q-Network algorithm that able to avoid premature convergence?
Combination of CF approach with evolutionary computing technique difficult to incorporate the side latent features and sequential rating information that potentially benefits recommender prediction.	How to incorporate user features and sequential rating information into multi-objective recommendation system based on Deep Q-Network algorithm?

1.3 Objectives

The objectives of the research are:

i. To propose a multi-objective recommendation system using deep reinforcement learning framework that optimize precision, novelty, and diversity concurrently.
ii. To propose the deep reinforcement learning algorithms based on DQN approach and recurrent enhanced DQN in order to incorporate user latent and sequential rating features as additional side feature input.

1.4 Scope

This research focuses on the movie recommendation. The multi-objectives covered for the movie recommendation are based on precision, novelty, and diversity. The proposed deep reinforcement learning approaches based on Deep Q-Network for multi-objective recommendation system (namely DQNMORS and recDQNMORS) are purposed to be alternative to evolutionary computing and standard recommendation system approaches.

1.5 Significance of Contribution

The thesis has proposed the first MORS framework based on DQN with user latent and sequential rating features that handle three metrics (precision, novelty, diversity) concurrently. This research has addressed the limitation of existing approaches that using EC method that suffered from premature convergence and dependency on CF method to predict the sparse rating data of unrated items in MORS problem. The research findings prove that the proposed DQN based approaches with both Pareto and scalarized method are capable to optimize MORS problem with comparable result against the benchmark without relied on any rating predictor. In addition, the proposed approaches able to incorporate additional side features such as user latent to improve quality of recommendation. On the other hand, the experiment results also indicated that intake sequential rating data input did not improved precision and novelty, but increased diversity of recommendation. In overall, there is no single approach that can achieve highest value in all metrics and the trade-off between each objective is inevitable.

1.6 Thesis Organisation

The thesis comprised of 6 chapters and each chapter consists of few sections and subsections. The Chapter 1 briefly introduced about the research background, main problem of existing approach in recommendation system including multi-objective recommendation techniques, and the objectives of this research. The specific scope of the research was discussed on the section in Chapter 1 followed by the significance of contributions in this work.

Chapter 2 discussed the literature review on evaluation metrics that commonly used in MORS and followed by RS approaches in details from traditional classical techniques to state-of-the-art advanced techniques including DRL approaches. The working principle of the traditional recommendation approaches are reviewed and the limitations of the current existing approaches are analysed in order to determine the research gap for this work. Afterwards, the MORS and the optimization methods are discussed.

Chapter 3 presented the overview of research frameworks that initiated with research planning to the proposed algorithm. The approaches that introduced in the research are named as Multi-Objective Recommendation System based on Deep Q-Network (DQNMORS) and based on Recurrent enhanced Deep Q-Network (recDQNMORS). Subsequently, the experiment settings and evaluation metrics used are briefly introduced in last section of Chapter 3.

Afterwards, Chapter 4 demonstrated the experiments on the proposed DQNMORS approaches including the framework of the algorithms, the designed environment, and the settings of each approach. A total of three experiments have been carried out and reported in the Chapter 4 where each result is discussed comprehensively in the corresponding subsections. The summary of the findings is summarized at the end of chapter.

The proposed recDQNMORS approach that dealing with sequential input data is introduced in Chapter 5. Total three experiments are conducted and the results obtained from each experiment are analysed in the subsection of the chapter respectively. The comparison between the proposed approaches and the benchmark work result were investigated in the Chapter 5 as well.

Lastly, all the research findings and summary of contributions are presented in Chapter 6. Besides that, the limitation of the research work and future direction are discussed in the chapter.

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