A PROPOSED MEMORY-BASED COLLABORATIVE FILTERING TECHNIQUE BASED ON A NEW SIMILARITY AND MADM METHODS (CF-NSMA) FOR IMPROVING THE RECOMMENDATION ACCURACY

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We hereby declare that We have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy.

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I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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for the award of the degree of
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ABSTRAK

Saringan Kolaboratif (CF), sebagai salah satu pendekatan yang paling banyak digunakan dan paling berjaya untuk menyediakan perkhidmatan cadangan, menyediakan pengguna dengan satu set cadangan yang berkaitan dengan apa yang mereka perlukan (minat mereka). Cadangan ini akan dihasilkan berdasarkan korelasi dalam kalangan pilihan pengguna seperti kedudukan dan tingkah laku. Walau bagaimanapun, bilangan pengguna dan item yang terdapat di Internet telah meningkat secara dramatik, dan kebanyakan pengguna tidak memberikan penilaian yang mencukupi untuk item tersebut. Selain itu, peningkatan/ pertumbuhan yang besar ini menjadikan matriks penarafan pengguna-item sangat besar dan jarang. Ini dianggap sebagai masalah dalam sistem memori berasaskan CF berdasarkan memori tradisional semasa mengira hubungan antara pengguna/item menjadi sangat sukar atau mungkin menyebabkan mencari jiran yang tidak berjaya yang seterusnya membawa kepada cadangan yang lemah. Oleh itu, kunci CF berasaskan ingatan memformulasikan kaedah korelasi yang betul yang dapat mengenal pasti kejiran yang berjaya. Sebaliknya, kaedah persamaan tradisional yang lazim tidak dapat menentukan pengguna yang sama efektif, terutamanya apabila bilangan penarafan oleh pengguna adalah kecil. Begitu juga, kaedah skor ramalan, yang menjadi tumpuan beberapa kajian juga berdasarkan tahap kepentingan yang sama. Oleh itu, kaedah ramalan masih merupakan kawasan terbuka untuk penambahbaikan untuk mendapatkan penilaian yang lebih baik dan kedudukan barang calon. Oleh itu, Teknik Memori Baharu–Berasaskan CF dicadangkan untuk meningkatkan ketepatan cadangan, ia dipanggil CF-NSMA. Teknik ini terdiri daripada tiga langkah utama: 1- Membina matriks baharu yang dinormalizasi untuk mengatasi isu sparsiiti; 2- Merumuskan ukuran matriks yang baru, berdasarkan pengajaran keadilan dan perkadaran faktor penarafan umum untuk mencari jiran yang tepat; 3- Mengaplikasikan kaedah MADM untuk mendapatkan penilaian yang lebih baik dan senarai kedudukan item calon. Fasa-fasa ini telah direka dan dilaksanakan dengan teliti untuk menyelesaikan isu-isu yang disebut tadi. Selain itu, untuk menilai ketepatan teknik CF-NSMA, beberapa eksperimen telah dijalankan menggunakan dataset awam (MovieLens 100K, DataLens 1M penanda aras dataran). Proses penilaian dilakukan untuk mengukur ketepatan teknik yang dibangunkan dengan menggunakan Ralat Mutlak Mutlak (MAE) untuk mengukur ketepatan ramalan dan Precision, Recall dan F-measure untuk mengukur ketepatan prestasi. Metrik yang dipilih dianggap sebagai metrik yang paling biasa digunakan dalam proses penilaian ketepatan teknik CF. Hasil eksperimen menunjukkan bahawa ketepatan teknik yang dicadangkan lebih baik berbanding dengan kaedah CF berasaskan memori berasaskan biasa. Peratusan ketepatan ramalan dari segi MAE adalah kira-kira 0.76 dan 0.74 melalui 100K dan 1M masing-masing. Walaupun, peningkatan teknik CF-NSMA dari segi ketepatan prestasi adalah lebih kurang tiga kali ganda ketepatan masa, sekitar empat kali ganda dari segi penarikan semula, dan sekitar tiga kali ganda dari segi ukuran F. Kesimpulannya, kerja ini menyumbang secara signifikan kepada bidang meningkatkan ketepatan CF berasaskan ingatan dengan membangunkan fasafa-fasa penting CF berasaskan memori tradisional, termasuk mewakili semula matriks penarafan, merumuskan kaedah persamaan baru dan menggantikan kaedah ramalan dengan kaedah MADM. Tambah pada, MADM berjaya meminimumkan kesan negatif kaedah ramalan dalam menilai dan menilai item calon. Oleh itu, aplikasi MADM dengan ketara meningkatkan ketepatan CF berasaskan ingatan dan menghasilkan hasil yang lebih tepat daripada kaedah asas. Oleh itu, objektif utama kajian ini telah dicapai.
ABSTRACT

The collaborative filtering (CF), as one of the most widely used and most successful approaches to provide service of recommendations, provides users with a set of recommendations related to what they need (their interests). These recommendations will be generated based on the correlation among the users’ preferences such as ratings and behaviour. Nevertheless, the number of users and items available on the Internet has increased dramatically, and most of the users do not give enough ratings for the items. Moreover, this vast growth has made the user-item rating matrix very large and sparse. This is considered a problem in the current traditional memory-based CF recommender system because the similarity calculation process between users/items becomes very difficult or may lead to locating unsuccessful neighbours which in turn to a weak recommendation. Therefore, formulating a right similarity method to identify the successful neighborhoods is a one key of memory-based CF. Similarly, the prediction method has the same level of importance in the process of improving the CF accuracy. Unfortunately, most studies on improving the accuracy of conventional CF systems have focused solely on enhancing the similarity measure. In contrast, improving the prediction method has been somewhat neglected. Consequently, the prediction method is still an open area for improvement to get better candidate items ranking and in turn increase the accuracy of CF. In the prediction process, the system predicts a user score for each item in the candidate set and promotes the highest-rated items as recommendations. This process of evaluating and ranking candidate items is therefore quite significant to the performance accuracy of the CF. Therefore, in this work, a new memory-based Collaborative Filtering (CF) technique is proposed to address the issue of sparsity data and improve the accuracy of recommendations, it is called CF-NSMA technique. The proposed technique consists of three main steps: 1- Constructing a new normalized matrix to overcome the sparsity issue; 2- Formulating a new similarity measure, based on adopting the fairness and the proportion of common rating factors to locate the accurate neighbours; 3- Applying the MADM method to get better evaluating and ranking list of candidate items. These phases were carefully designed and implemented to solve the issues that were mentioned earlier. Moreover, to assess the accuracy of CF-NSMA technique, several experiments were conducted using a public dataset (MovieLens 100K, MovieLens 1M benchmark datasets). The evaluation process was performed to measure the accuracy of the proposed technique using Mean Absolute Error (MAE) to measure the prediction accuracy and Precision, Recall and F-measure to measure the performance accuracy. These selected metrics are considered as the most common metrics to be used in an accuracy evaluation process of the CF techniques. The result of the experiments revealed that the accuracy of the proposed technique is better compared to the common base memory-based CF methods. The prediction accuracy percentage in terms of MAE was around 0.76 and 0.74 via 100K and 1M datasets, respectively. While, the improvement of the CF-NSMA technique in terms of performance accuracy was around more than three-fold in term precision, around four-fold in term of recall, and around three-fold in term of F-measure. In conclusion, this work contributes significantly to the field of improving the accuracy of memory-based CF by developing the critical phases of traditional memory-based CF, including re-representing the rating matrix, formulating a new similarity method and replacing the prediction method with the MADM method. Furthermore, MADM successfully minimizes the negative effect of the prediction method in evaluating and ranking the candidate items and significantly improves the accuracy of memory-based CF. Therefore, the primary objectives of this research were achieved.
## TABLE OF CONTENT

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>DECLARATION</td>
<td></td>
</tr>
<tr>
<td>TITLE PAGE</td>
<td></td>
</tr>
<tr>
<td>ACKNOWLEDGEMENTS</td>
<td>ii</td>
</tr>
<tr>
<td>ABSTRAK</td>
<td>iii</td>
</tr>
<tr>
<td>ABSTRACT</td>
<td>iv</td>
</tr>
<tr>
<td>TABLE OF CONTENT</td>
<td>v</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>x</td>
</tr>
<tr>
<td>LIST OF ABBREVIATIONS</td>
<td>iii</td>
</tr>
<tr>
<td>CHAPTER 1 INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Background</td>
<td>4</td>
</tr>
<tr>
<td>1.3 Problem Statement</td>
<td>7</td>
</tr>
<tr>
<td>1.4 Research Objectives</td>
<td>9</td>
</tr>
<tr>
<td>1.5 Research Scope</td>
<td>10</td>
</tr>
<tr>
<td>1.6 Significance of Study</td>
<td>11</td>
</tr>
<tr>
<td>1.7 Preliminary Definitions and Terminology</td>
<td>12</td>
</tr>
<tr>
<td>1.7.1 Formalization</td>
<td>12</td>
</tr>
<tr>
<td>1.7.2 Terminology</td>
<td>12</td>
</tr>
<tr>
<td>1.7.3 Traditional Common Memory-based CF Methods</td>
<td>14</td>
</tr>
<tr>
<td>1.7.4 Aggregation Methods</td>
<td>15</td>
</tr>
<tr>
<td>1.8 Organization of Thesis</td>
<td>15</td>
</tr>
<tr>
<td>CHAPTER 2 LITERATURE REVIEW</td>
<td>16</td>
</tr>
</tbody>
</table>
# 2.1 Introduction

<table>
<thead>
<tr>
<th>2.2</th>
<th>Background of Recommender Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.2.1</td>
<td>Definition of Recommender System</td>
</tr>
<tr>
<td>2.2.2</td>
<td>The Importance of Recommender System</td>
</tr>
<tr>
<td>2.2.3</td>
<td>Evolution</td>
</tr>
<tr>
<td>2.2.4</td>
<td>Recommender Systems and Information Retrieval</td>
</tr>
<tr>
<td>2.2.5</td>
<td>Relevance Feedback</td>
</tr>
</tbody>
</table>

# 2.3 Recommender System Approaches

| 2.3.1 | Content-based Approach |
| 2.3.2 | Collaborative Filtering Approach |
| 2.3.3 | Hybrid Approaches |

# 2.4 Collaborative Filtering Models

| 2.4.1 | Model-Based CF Technique |
| 2.4.2 | Memory-Based CF Model |

# 2.5 Traditional Memory-Based CF Technique

| 2.5.1 | Base Related Work Review |
| 2.5.2 | Further Related Work |
| 2.5.3 | Memory-Based CF Challenges and Limitations |
| 2.5.4 | Finding Summary |

# 2.6 Multi-Attribute Decision Making Method

| 2.6 | Multi-Attribute Decision Making Method |

# 2.7 Evaluation of the Recommender System

| 2.7.1 | Evaluation metrics |
| 2.7.2 | Datasets |
| 2.7.3 | Splitting Methods |

# 2.8 Chapter Summary
# CHAPTER 3 METHODOLOGY 66

3.1 Introduction 66
3.2 Literature Review and Preliminary Phase 68
3.3 Design and Implementation Phase 68
   3.3.1 Selecting Dataset 69
   3.3.2 Constructing Normalized User-Type Matrix 70
   3.3.3 Formulating a New Similarity Measure (BSF) 70
   3.3.4 Applying MADM Method 70
3.4 Evaluation Phase 71

# CHAPTER 4 CF-NSMA: PROPOSED MEMORY-BASED COLLABORATIVE FILTERING TECHNIQUE 73

4.1 Introduction 73
4.2 Proposed Technique Architecture 75
   4.2.1 System Input 77
   4.2.2 Re-representing User Preference 77
   4.2.3 Neighbours Formation 82
   4.2.4 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) 89
   4.2.5 Generating Recommendations/Output 97
4.3 Implementation 97
4.4 Chapter Summary 98

# CHAPTER 5 RESULTS AND DISCUSSION 99

5.1 Introduction 99
5.2 Proposed Similarity Method (CF-BSF) Vs Traditional Similarity Methods 99
   5.2.1 Prediction Accuracy 100
5.2.2 Performance Accuracy 101

5.3 Proposed Technique (CF-NSMA) Vs Traditional Memory-Based CF Methods 104

5.3.1 Recall metric 104
5.3.2 Precision Metric 105
5.3.3 F-Measure Metric 107

5.4 Traditional Methods based on MADM Method 108

5.4.1 Recall Metric 108
5.4.2 Precision Metric 109
5.4.3 F-measure Metric 110

5.5 Chapter Summary 112

CHAPTER 6 CONCLUSION 113

6.1 Introduction 113
6.2 Summary of Thesis 114
6.3 Contributions 116
6.4 Future Work 117

REFERENCES 119

APPENDIX A SIMILARITY MEASURE DERIVATIONS 130

APPENDIX B EXPERIMENTS SETUP 138

APPENDIX C MOVIELENS 100K DATASET DESCRIPTION 154

APPENDIX D MOVIELENS 1M DATASET DESCRIPTION 158

APPENDIX E EXAMPLE RESULT 162

APPENDIX F EXPERIMENTS AND COMPARISON 168
<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 1.1</td>
<td>User-item matrix data structure R</td>
<td>12</td>
</tr>
<tr>
<td>Table 1.2</td>
<td>List of terminology</td>
<td>13</td>
</tr>
<tr>
<td>Table 1.3</td>
<td>Similarity measures frequently used in the traditional memory-based CF.</td>
<td>14</td>
</tr>
<tr>
<td>Table 1.4</td>
<td>Aggregation methods</td>
<td>15</td>
</tr>
<tr>
<td>Table 2.1</td>
<td>RS relevance feedback</td>
<td>23</td>
</tr>
<tr>
<td>Table 2.2</td>
<td>Content-based vs Collaborative filtering.</td>
<td>28</td>
</tr>
<tr>
<td>Table 2.3</td>
<td>Hybridization Methods</td>
<td>29</td>
</tr>
<tr>
<td>Table 2.4</td>
<td>Memory-based CF similarity measures.</td>
<td>32</td>
</tr>
<tr>
<td>Table 2.5</td>
<td>Drawbacks of existing similarity methods</td>
<td>55</td>
</tr>
<tr>
<td>Table 2.6</td>
<td>Summary of MADM Methods</td>
<td>58</td>
</tr>
<tr>
<td>Table 2.7</td>
<td>Classification of the possible result of a recommendation of an item to a user</td>
<td>60</td>
</tr>
<tr>
<td>Table 4.1</td>
<td>Conceptual rating matrix R</td>
<td>79</td>
</tr>
<tr>
<td>Table 4.2</td>
<td>User-item rating matrix example</td>
<td>80</td>
</tr>
<tr>
<td>Table 4.3</td>
<td>A conceptual time matrix T</td>
<td>81</td>
</tr>
<tr>
<td>Table 4.4</td>
<td>User-type time rating matrix example</td>
<td>81</td>
</tr>
<tr>
<td>Table 4.5</td>
<td>A conceptual normalized matrix W</td>
<td>82</td>
</tr>
<tr>
<td>Table 4.6</td>
<td>Normalized user-type matrix example</td>
<td>82</td>
</tr>
<tr>
<td>Table 4.7</td>
<td>A conceptual similarity matrix S</td>
<td>87</td>
</tr>
<tr>
<td>Table 4.8</td>
<td>A Conceptual decision matrix X</td>
<td>91</td>
</tr>
<tr>
<td>Table 4.9</td>
<td>A Conceptual normalized decision matrix R</td>
<td>92</td>
</tr>
<tr>
<td>Table 4.10</td>
<td>A Conceptual weighted normalized decision matrix V</td>
<td>92</td>
</tr>
<tr>
<td>Table 4.11</td>
<td>A Conceptual separation matrix ( V' )</td>
<td>94</td>
</tr>
<tr>
<td>Table 4.12</td>
<td>Decision matrix X</td>
<td>95</td>
</tr>
<tr>
<td>Table 4.13</td>
<td>Normalized decision matrix R</td>
<td>95</td>
</tr>
<tr>
<td>Table 4.14</td>
<td>Weighted normalized decision matrix V</td>
<td>96</td>
</tr>
<tr>
<td>Table 4.15</td>
<td>Separation matrix ( V' )</td>
<td>96</td>
</tr>
<tr>
<td>Table 4.16</td>
<td>The loseness to the ideal solution</td>
<td>97</td>
</tr>
<tr>
<td>Table 4.17</td>
<td>Alternatives ranking</td>
<td>97</td>
</tr>
<tr>
<td>Table 6.1</td>
<td>Chapters summary</td>
<td>114</td>
</tr>
<tr>
<td>Table 6.2</td>
<td>Objectives achievement</td>
<td>116</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

Figure 1.1 Approaches of RS. 4
Figure 1.2 Content-based structure. 5
Figure 1.3 Memory-based CF method 6
Figure 1.4 User-based CF method 7
Figure 1.5 Item-based CF Method 7
Figure 2.1 Chapter's outline visualisation 18
Figure 2.2 Information retrieval system 22
Figure 2.3 Recommendation system 23
Figure 2.4 The description of the basic idea of the PIP 38
Figure 2.5 Holdout method 63
Figure 2.6 Holdout method procedure 63
Figure 2.7 Cross-validation method procedure 64
Figure 3.1 Research framework 67
Figure 4.1 Proposed technique structure 76
Figure 4.2 The Design-Implement-Test Cycle 83
Figure 4.3 Neighbours formation algorithm 89
Figure 4.4 Euclidean Distances to the Ideal and Negative-Ideal Solutions 94
Figure 5.1 Compare MAE between CF-BSF and traditional memory-based CF methods. 101
Figure 5.2 Recall rate on 100K & 1M datasets, using holdout and cross-validation. 102
Figure 5.3 Precision rate on 100K & 1M datasets, using holdout and cross-validation. 103
Figure 5.4 F-measure rate on 100K & 1M datasets, using holdout and cross-validation. 104
Figure 5.5 Recall comparison of traditional CF methods and CF-NSMA on 100K & 1M datasets, using holdout and cross-validation. 105
Figure 5.6 Precision comparison of traditional CF methods and CF-NSMA on 100K & 1M datasets, using holdout and cross-validation. 106
Figure 5.7 Precision comparison of CF-NSMA with baseline CF methods. 107
Figure 5.8 F-measure comparison of traditional CF methods and CF-NSMA on 100K & 1M datasets, using holdout and cross-validation. 108
Figure 5.9 Recall comparison of traditional CF methods with and without MADM method on 100K & 1M datasets, using holdout and cross-validation. 109
Figure 5.10  Precision comparison of traditional CF methods with and without MADM method on 100K & 1M datasets, using holdout and cross-validation.

Figure 5.11  F-measure comparison of traditional CF methods with and without MADM method on 100K & 1M datasets, using holdout and cross-validation.
LIST OF SYMBOLS

N  Natural numbers
Max Maximum value scale of ratings.
Min Minimum value scale of ratings
U  Set of users.
I  Set of items
R  Set of ratings
$r_{i,j}$ Rating value of user $i$ on item $j$
* Absence of ratings
$c_g$ A vector of category of items in the dataset.
$c_g^j$ Value of item $j$ belongs into $g^{th}$ type.
$t_{i,g}$ Number of items rated by user $i$ and belong to genre $g^{th}$
$w_{i,g}$ Normalized value of $t_{i,g}$, which represents the ratio of user $i$ preference on category $g^{th}$
$\theta$ Denominator of $S_f$, which represents the minimum size of co-rated items
$s_{j,i}$ Similarity value of user $i$ with user $j$
# LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RS</td>
<td>Recommender System</td>
</tr>
<tr>
<td>CF</td>
<td>Collaborative Filtering</td>
</tr>
<tr>
<td>CB</td>
<td>Content-Based</td>
</tr>
<tr>
<td>MADM</td>
<td>Multi-Attribute Decision Making</td>
</tr>
<tr>
<td>TOPSIS</td>
<td>Technique for Order Preference By Similarity to Ideal Solution Technique</td>
</tr>
<tr>
<td>BC</td>
<td>Bray-Curtis distance measurement</td>
</tr>
<tr>
<td>Ff</td>
<td>Fairness Factor.</td>
</tr>
<tr>
<td>Sf</td>
<td>Sigmoid Function.</td>
</tr>
<tr>
<td>BSF</td>
<td>A new similarity measurement based on merged BC, Ff and Sf.</td>
</tr>
<tr>
<td>CF-BSF</td>
<td>CF based on the combination similarity measurement (BSF)</td>
</tr>
<tr>
<td>CF-NSMA</td>
<td>CF based on the New Similarity and MADM methods.</td>
</tr>
<tr>
<td>CV</td>
<td>Cross-Validation Partition Method</td>
</tr>
<tr>
<td>HO</td>
<td>Hold Out Partition Method</td>
</tr>
<tr>
<td>CF-PCC</td>
<td>CF based on Pearson Correlation Coefficient.</td>
</tr>
<tr>
<td>CF-CPCC</td>
<td>CF based on Constrained Pearson Correlation Coefficient.</td>
</tr>
<tr>
<td>CF-SPCC</td>
<td>CF based on Sigmoid Function Based Pearson Correlation Coefficient.</td>
</tr>
<tr>
<td>CF-Cosine</td>
<td>CF based on Cosine similarity measure.</td>
</tr>
<tr>
<td>CF-JMSD</td>
<td>CF based on Jaccard and Mean Squared Difference MSD.</td>
</tr>
<tr>
<td>CF-NHSM</td>
<td>CF based on New Heuristic Similarity Model.</td>
</tr>
</tbody>
</table>
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