# Research Plan

Arif Laksito (arif.laksito@amikom.ac.id)

## Research Title

Bi-directional LSTM and latent factor methods  on collaborative filtering recommender system.

## Background and General Description

The rapid development of the Internet and information technology makes knowledge has grown abundantly and it caused information overload in recent years. Although the information is easy to search and obtain, people might not get the information they want. To get valuable information, personalization or customization is consideration needed to screen and filter from the massive information. Personalization is a concept provides personalized products and information, and widely used as the service of recommendation. Personalization's service has been used in many online companies such as Amazon, Yahoo, eBay, Uniqlo and so on [1]. Recommendation systems provide a type of mass customization and also promises a firm greater customer loyalty, higher sales, more advertising revenue, and the benefit of targeted promotions [2].

Recommendation systems are commonly classified into content-based filtering(CBF) and collaborative filtering(CF). CBF recommends items for the user's consumption based on correlations between the content of the items and the user's preferences. However, CBF filtering has limitations: 1) Difficult to analyze sound, photographs, video, or physical items. 2) CBF techniques have no inherent method for generating serendipitous finds. It recommends more of what the user already has seen before [3].

The problem of CBF when items are difficult to analyze could be solve using CF which will make the recommendation to target users according to the clusters' interests, experiences, and preferences that are the same as the target users. CF does not require the analysis of product content. CF technology is now deemed as a very important technology for the recommendation systems, and it can generate the recommendation according to the quality, style, or attributes of items. It can also cooperate with users who have similar preferences to recommend the items outside of the predicted scope [1].

Generally, CF algorithms classified into two general classes: memory-based and model-based. The memory-based method uses records in the database for analysis. For example, after calculating the similarity and correlation, recommend the items that have the highest correlation with user preference. The closest user or items are calculated only by using Cosine similarity or Pearson correlation coefficients, which are only based on arithmetic operations. The nearest neighbor technique is the most common method for memory-based [4]. On the other hand, the model-based method uses a mathematical model or machine learning model to calculate and predict which items the users currently prefer or need. The concept of the model-based is to build a model based on the evaluation data or is to build some of the extraction of information from the data collection and dataset that used and to make recommendations without having to use the dataset at a time. This method consists of Bayesian classifiers, relapse based methods, and cluster-based CF [5].

CF algorithms have been widely used and achieved great success. However, some of the limitations of these algorithms, such as sparsity, cold start, and scalability need to develop further [6]. Some of the approaches to improve CF technique are adopting a deep learning method using the BP neural network [7] or matrix factorization based algorithms such as the SVD [8], PMF [9], and NMF [10]. Memory-based CF having a crucial problem in scalability [11]. It is a reason why many researchers have been tried to another strategy mostly focus on model-based. Although, recommender system which is using a deep learning technique having the ability to improve the result, cold start and sparsity as the major problem in model-based CF should be eliminating. Both problems will happen when new user and news item actually new come in table matrix of collaborative filtering [11].

## Problem Statement

Extracting auxiliary information from items to support a sparse matrix is needed to increase the performance of the CF recommender system. Several approaches are used to extract music [12], text [13], and color classifier [14] in order to improve the accuracy to reduce sparse data. Although the techniques of extracting auxiliary information have been successful in increasing robustness in sparse data, they ignore contextual information and do not explicitly consider Gaussian noise [15]. Disadvantages issue in extracting auxiliary information, i.e., music, fashion, sentiment analysis are not compatible with text sentence content. DCNN has been used to capture contextual meaning information from consumer product reviews and it can increase the level of accuracy [16]. Table 1 shows various approaches to capture contextual meaning information in the recommender systems in recent years.

Table 1. Comparison of several methods for extracting text and rating prediction.

| No | Methods | Conclusion | Ref. |
|---|---|---|---|
| 1 | LDA | Integrating LDA into CF to analyze item description documents (bag of word method) | [17], [18] |
| 2 | DCNN - PMF | DCNN is more effective than traditional methods bag of word or word order. | [16] |
| 3 | CNN - PMF | Considering contextual information using CNN deals with the sparsity problem. | [15], [19] |
| 4 | CNN - NMF | Integrating CNN into NMF so as to capture contextual information and mitigate the effect of negative values present in user/ item factors. | [20] |
| 5 | Bi-directional LSTM | - | Our approach |

## Propose Method

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) are two of the most popular deep learning techniques for sentiment analysis. LSTMs are more directly suited for text inputs since each word in a sentence has meaning based on the surrounding words. However, Bi-directional LSTM (Bi-LSTM) can obtain information from past and future states. Since this method allows the model to learn the text characteristics more complete. Bi-LSTM has proven better performance than LSTM for word embeddings [21][22].

The study of the recommender system in the movie domain has a large number in the last decade [23][24]. Besides, the study of recommender systems in other domains also attracted many researchers. Zhang, et al [25] used five real-world datasets in movies, books, and music categories to develop cross-domain recommender system (CDRS) using consistent information transfer. Since movie datasets in MovieLens, IMDb, and Amazon can freely be accessed, auxiliary information from the reviews of IMDb and Amazon in the movies category will be extracted to support the sparse matrix in MovieLens. Other domains also will be evaluated like books, music, or e-commerce, it depends on the availability of the review data.

Table 2. Domain category plan.

| No | Domain | Auxiliary (Review text) | Target |
|---|---|---|---|
| 1 | Movies | IMDb, Amazon | MovieLens |
| 2 | Books | Amazon, Goodreads | LibraryThing |

This study will focus on extracting auxiliary and capturing contextual information using Bi-LSTM in movies and books domains of the recommender system. Some of the methods will be evaluated to predict sparse data on matrix ratings such as SVD, NMF, PMF or SVD++. Both RMSE and MAE will be used as evaluation metrics.

## Objectives

Extracting auxiliary information in the content filtering of recommender system.

## Study Plan

| Stage | Activity | Time |
|---|---|---|
| Stage 1<br>Literature Review | • Develop research design<br>• Search, capture and synthesize relevant literature<br>• Drafting detail research plan<br>• Submit paper | First year |
| Stage 2<br>Data collection | • Develop data collection instrument<br>• Propose new method<br>• Literature review (continue)<br>• Submit paper | Second year, first semester |
| Stage 3<br>Design Algorithm | • Design new algorithm<br>• Implement data to new algorithm<br>• Evaluation<br>• Conclusion and recommendation<br>• Submit paper | Second year, second semester |
| Stage 4<br>Finalizing | • Comparing algorithm<br>• Design new algorithm<br>• Implement data to new algorithm<br>• Evaluation<br>• Conclusion and recommendation<br>• Writing dissertation<br>• Submit paper | Third year |

## References


[1] L. Li, R. Hsu, and F. Lee, “Review of Recommender Systems and Their Applications,” *Int. J. Adv. Inf. Technol.*, pp. 63–87, 2012.

[2] A. Ansari, S. Essegaier, and R. Kohli, “Internet recommendation systems,” *J. Mark. Res.*, vol. 37, no. 3, pp. 363–375, 2000.

[3] U. Shardanand and P. Maes, “Social information filtering: algorithms for automating ‘word of mouth,’” *Conf. Hum. Factors Comput. Syst. - Proc.*, vol. 1, pp. 210–217, 1995.

[4] J. S. Breese, D. Heckerman, and C. Kadie, “Empirical Analysis of Predictive Algorithms for Collaborative Filtering,” pp. 43–52, 2013.

[5] N. Mustafa, A. O. Ibrahim, A. Ahmed, and A. Abdullah, “Collaborative filtering: Techniques and applications,” *Proc. - 2017 Int. Conf. Commun. Control. Comput. Electron. Eng. ICCCCEE 2017*, 2017.

[6] D. Liu, “A study on collaborative filtering recommendation algorithms,” *2018 IEEE 4th Int. Conf. Comput. Commun. ICCC 2018*, pp. 2256–2261, 2018.

[7] D. E. Chen, “The collaborative filtering recommendation algorithm based on bp neural networks,” *2009 Int. Symp. Intell. Ubiquitous Comput. Educ. IUCE 2009*, vol. 1, pp. 234–236, 2009.

[8] X. Zhou, J. He, G. Huang, and Y. Zhang, “SVD-based incremental approaches for recommender systems,” *J. Comput. Syst. Sci.*, vol. 81, no. 4, pp. 717–733, 2015.

[9] W. F. Yang, M. Wang, and Z. Chen, “Fast probabilistic matrix factorization for recommender system,” *2014 IEEE Int. Conf. Mechatronics Autom. IEEE ICMA 2014*, no. 1, pp. 1889–1894, 2014.

[10] M. H. Aghdam, M. Analoui, and P. Kabiri, “Collaborative filtering using non-negative matrix factorisation,” *J. Inf. Sci.*, vol. 43, no. 4, pp. 567–579, 2017.

[11] Hanafi, N. Suryana, and A. S. B. H. Basari, “AN UNDERSTANDING AND APPROACH SOLUTION FOR COLD START PROBLEM ASSOCIATED WITH RECOMMENDER SYSTEM : A LITERATURE REVIEW,” *J. Theor. Appl. Inf. Technol.*, vol. 96, no. 09, pp. 2677–2695, 2018.

[12] A. van den Oord, S. Dieleman, and B. Schrauwen, “Deep content-based music recommendation,” *Adv. Neural Inf. Process. Syst.*, pp. 2643–2651, 2013.

[13] L. Qu, G. Ifrim, and G. Weikum, “The bag-of-opinions method for review rating prediction from sparse text patterns,” *Coling 2010 - 23rd Int. Conf. Comput. Linguist. Proc. Conf.*, vol. 2, no. August, pp. 913–921, 2010.

[14] S. Jaradat, “Deep cross-domain fashion recommendation,” *RecSys 2017 - Proc. 11th ACM Conf. Recomm. Syst.*, pp. 407–410, 2017.

[15] D. Kim, C. Park, J. Oh, and H. Yu, “Deep hybrid recommender systems via exploiting document context and statistics of items,” *Inf. Sci. (Ny).*, vol. 417, pp. 72–87, 2017.

[16] Hanafi, N. Suryana, and A. S. H. Basari, “Dynamic convolutional neural network for eliminating item sparse data on recommender system,” *Int. J. Adv. Intell. Informatics*, vol. 4, no. 3, pp. 226–237, 2018.

[17] G. Ling, M. R. Lyu, and I. King, “Ratings meet reviews, a combined approach to recommend,” *RecSys 2014 - Proc. 8th ACM Conf. Recomm. Syst.*, pp. 105–112, 2014.

[18] J. McAuley and J. Leskovec, “Hidden factors and hidden topics: Understanding rating dimensions with review text,” *RecSys 2013 - Proc. 7th ACM Conf. Recomm. Syst.*, pp. 165–172, 2013.

[19] D. Kim, C. Park, J. Oh, S. Lee, and H. Yu, “Convolutional matrix factorization for document context-aware recommendation,” *RecSys 2016 - Proc. 10th ACM Conf. Recomm. Syst.*, pp. 233–

240, 2016.

[20] Z. Khan, N. Iltaf, H. Afzal, and H. Abbas, “Enriching Non-negative Matrix Factorization with Contextual Embeddings for Recommender Systems,” *Neurocomputing*, vol. 380, pp. 246–258, 2020.

[21] Z. Li, F. Yang, and Y. Luo, “Context Embedding Based on Bi-LSTM in Semi-Supervised Biomedical Word Sense Disambiguation,” *IEEE Access*, vol. 7, pp. 72928–72935, 2019.

[22] G. Xu, Y. Meng, X. Qiu, Z. Yu, and X. Wu, “Sentiment analysis of comment texts based on BiLSTM,” *IEEE Access*, vol. 7, no. c, pp. 51522–51532, 2019.

[23] D. H. Park, H. K. Kim, I. Y. Choi, and J. K. Kim, “A literature review and classification of recommender systems research,” *Expert Syst. Appl.*, vol. 39, no. 11, pp. 10059–10072, 2012.

[24] E. Çano and M. Morisio, “Hybrid recommender systems: A systematic literature review,” *Intell. Data Anal.*, vol. 21, no. 6, pp. 1487–1524, 2017.

[25] Q. Zhang, D. Wu, J. Lu, F. Liu, and G. Zhang, “A cross-domain recommender system with consistent information transfer,” 2017.