paper 9

by Hanafi Hanafi

Journal of Theoretical and Applied Information Technology
31st July 2018. Vol.96. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DEEP LEARNING FOR RECOMMENDER SYSTEM BASED ON APPLICATION DOMAIN CLASSIFICATION PERSPECTIVE: A REVIEW

[1,2]HANAFI, [3]NANNA SURYANA, [4]ABD SAMAD BIN HASAN BASARI.

[1]Department of Computer Science, University Amikom of Yogyakarta, Yogyakarta, Indonesia
[2,3,4]Faculty of Information and Communication Technology, University Teknikal Malaysia Melaka, Melaka, Malaysia.
Emails: [1]hanafi@amikom.ac.id, hanafiutem@gmail.com, [3]nsuryana@utem.edu.my, [4]abdsamad@utem.edu.my

ABSTRACT

Recommender system is critical equipment for establishing an effective communication between consumers and retailers in ecommerce business. Effective and enjoyable communication to find the fit product is considered to have a massive implication to increase of sales achievement. Recommender system established in the middle 90s. Based on technical approach, there are four of recommender system model namely Collaborative filtering, Contents Based, Knowledge Based and Demographic filtering. Collaborative filtering is considered to be more superior than another tree methods. It offers obviously advantages in terms of serendipity, novelty and accuracy. Although it has several benefits in recommendation result, in an effort to improve the weakness of the recommender system, many involving machine learning, machine learning with shallow layers was popular in the 90's for instance neural network, SVM. In the era of big data like now, where the amount of data is abundant, and the data variations are very diverse, this will become an increasingly interesting challenge in generating a recommender system results more appropriate in the present era of big data. in this literature review, researchers are trying to find answers to the weaknesses, challenges and opportunities forwards that exist in the method of deep learning for ecommerce recommender system.

Keywords: *Ecommerce, Recommender System, Recommendation System, Deep Learning, Deep Network*

1. INTRODUCTION

The first e-commerce recommender system was develop and introduce in the middle 90s, The objective background is how e-commerce users could finding the suitable product easily [1]. We can imagine, the growth of Internet users has increased significantly. These factors were influence number of users and number of products also growing significantly. Then e-commerce company must be providing millions of items for millions of consumers at any time and any places. Choosing among a lot of product is very difficult to be done by users. For example, what product needs to buy, what news should be read, what movie should be watched, what music to listen, what advertising should be looked etc.

Recommender system is also very useful for e-commerce company is to increase the number of sales. In e-commerce business, there is important mechanism how to provide better information between consumer and producer that namely recommender system. This mechanism aims to make effective communication for both. A wide range of companies such as Amazon.com, Netflix.com, eBay.com, Half.com, CDNOW, J.C. Penney, and Procter & Gamble have successfully deployed recommendation technologies to increase web and catalogue sales and improve customer loyalty [2].

E-commerce has changed the way in many companies do business. To them, e-commerce is no longer an alternative but an imperative. Many companies are struggling with the most basic problem: what is the best approach for establishing and doing business in the digital economy? Some companies are moving their businesses entirely to the Web (e.g.egghead.com). Some are establishing subsidiaries, then spinning them off as separate online business entities (e.g. barnesandnoble.com) [3]. The Internet has dramatically affected the conduct of business. Markets, industries, and businesses are being transformed. The new economy demands the exploitation of new models and paradigms. Information technology (IT) now drives businesses and markets. In the new

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

economy, the Internet has become a powerful and ubiquitous communication mechanism to facilitate the consummation and processing of business transactions. This has led to substantial changes in traditional industries and companies. Firms are attempting to understand and measure the impact of IT so that they can make intelligent decisions regarding crucial IT investments [4].

The flood of information on the big data era on a decade is one that causes so important of a recommender system. It also a consequences is the over flooded by unnecessary information. This is why the recommender system is very important in our living right now. The literature review in this research, has been conducted based on most recent related work. There is a need to understanding about the state of the art of recommender system including proposed a way to forward.

Figure 1. Example case for movie recommendation

How to make customer feeling happy to do online shopping in e-commerce is one of recommender system goal. Netflix is an example of large corporation on movie online streaming provider that concern to research and applied in recommender system approach become a strategy to increase their business revenue. Example display of recommender system on Netflix website shown on figure 1.

So many e-commerce business companies have been applied recommender system machine to help their business, for instance Netflix, Amazon, YouTube, Facebook, Google, MovieLens, Last.fm, Alibaba, eBay and etc. Following to research [5][6] There are four common majority technical goals of recommender system to implemented in e-commerce company as follow;

A. **To produce relevant product information**: The famous goal of a recommender system is to provide information about product that fit to users' interest. So, the product fit can obtained by users conveniently. Users or customers necessary to finding especially product in online commerce.
B. **To provide novelty product information**: Recommender system is quite useful to help a user for finding suitable products or items. The other essential things the objective of recommender systems are to provide information that has not seen before. Do over before to provide of favourite information possibly decrease in target of sales.
C. **To provide serendipity of product information**: that means item recommendation is unpredictable. Systems have ability to provide better information automatically, direct influence for customers, they startled to looks the information of product. There is no clear clarification and no agreement to define serendipity, but serendipity must have contains three element that are novel, relevant and unexpected.
D. **To provide diversity product information:** this aims to enhance recommendation diversity. That means diversity ensure to customers if the information shown is not repeated, then customers feeling enjoy and happy.

1.1. Basic Element of Recommender System

Recommender system is important field in data mining and machine learning research field. Before we discuss the topic about recommender system based on deep learning machine, we will convey some important and fundamental aspect to gaining comprehensive understanding about the recommender system in general.

1.1.1. Classification of Rating Type

Collaborative filtering approach have been most of successful approach in accuracy point of view [7]. However they are not robust in extreme sparse data, that mean just a little history of users activity in the past for instance explicit feedback come from customer include rating. One another of important thing to generate recommendation are user's activity for example user purchasing, and user clicks to product, items that were seen by user, sometimes, many e-commerce portal support available opinion, comment for his/her product, product interested by users as rating. Rating is a form of user interest in the product. Also become an indicator of degree of interesting user for product.

According to reference [1][8] rating plays an important role in producing recommendation products. There are several type of rating that were implemented in recommendation algorithm, for examples:

Journal of Theoretical and Applied Information Technology
31st July 2018. Vol.96. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A. Numerical Rating: the rating star model uses some number between 1-5 star. So many big e-commerce companies adopted this type of rating model for example Amazon, Lazada group, mobile application provider iTunes, play store, some product of Google etc.

B. Continues rating. The rating uses special on continuous scale. For instance, the model that were applied in Jetster joke recommendation engine take a value rating between -10 and 10.

C. Ordinal rating, for example model sentences "strongly agree, agree, neutral, disagree, strongly disagree.

D. Binary rating that uses a model choice in which involving the user is simply asked the opinion to decide if a certain item is good or bad.

E. The last model of rating is unary rating, include in this model are observation about user behaviour to item or history bought a product in the past.

1.1.2. Primary Challenge for Recommender System

One of several challenge in recommender system research field is cold start problem which a parts of extreme sparse data consist two categories; user cold start problem and item cold start problem. Item cold start happen when new user coming inside the system also new user. This problem causes both of them have no history activity in the past. Several research have deal to classified cold start problem into three categories. According [9][10] Complete argument shown in figure 2. Fully cold start happen when complete there is no rating from user to item and incomplete cold start happen when there is rating from user to item less than 10 percent, the last no cold start when there is rating from user to item more than 10 percent.

	(not cold start)				(incomplete cold start)				(cold start)			
	i 1	i 2	i 3		i1	i 2	i 3		i 1	i 2	i 3	
u1				-				-				-
u2				**				-				-
u3				-				-				-
u4				**				_				_
u5				-				*				-
u6				**				-				-
u7				-				-				-
u8				**				-				-
u9				**				-				-
u10				*				-				-

Figure 2. Classification of cold start problem

Reference authors [11][1] Based on explanation by researchers, mainly of the researcher who interesting to do study on recommender system is how to create improvement in some primary problems and challenges to the future study, on above is summarize some problem attempted to addressing by researchers:

A. Handling cold Start Problem
This trouble rises when new user/customer or new item/product come in the system, so the system failed to produce recommendation due no record users or product history in the past. The history can be term of a payment, purchase, click or rating to the product.

B. Increase accuracy
The system have performance to estimated product recommendation to the user or customers exactly, it is the explanation of accuracy. There are some aspect which influence the accuracy level are the availability of information, in which the cold start problem issue and sparsity data issue could be addressed.

C. Dealing sparsity Data
The serious problem emerge the reality when customer give the rating very poor to the items, unique case when the data table are very large, it is rises reason sparse user-item rating matrix with poor data for calculating similar users or item are very difficult. The situation like this will produce the final of product recommendation are not accurate. Lack of data is specific in collaborative filtering which rely on history feedback to provide recommendation.

D. Increase scalability
Scalability following to performance of the system to calculate user-item-rating matrix with no necessary a lot of time to compute. Classical collaborative filtering for instance memory based necessary a lot of time to calculate similarity based on item-item or user-user use nearest neighbourhood technique. This is one of many background why many researchers interested to established recommender system use model based approach.

E. Provide diversity information
Diversity following to the objective in which the prospective customers is faced with diverse choices. A prospective customers who is not interested in a product/item, certainly would not be interested also in item of the same variety.

Journal of Theoretical and Applied Information Technology
31st July 2018. Vol.96. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The other strategy to eliminate cold start and sparsity data by using location based [12] by this approach, some application suitable to applied for instance e-commerce delivery service. Another method by empowering matrix factorization technique. The shortcoming of the strategy is cannot handle cold start and sparsity data in extreme condition [13]. This method absolutely need external information to completion the matrix. Matrix factorization method has been applied to collaborative filtering by a variety of work. Matrix factorization focuses on factorizing the rating matrix into low dimension user latent vector and item latent vector [10]. The key idea in dimensionality reduction methods is that the reduced, rotated and completely representative can be robustly estimated from incomplete data matrix [5]. However, matrix factorization approach is not robust in handle extreme sparse data. Finally, it influent the result of recommendation inaccurate. Figure to illustration of matrix factorization process shown in figure 3.

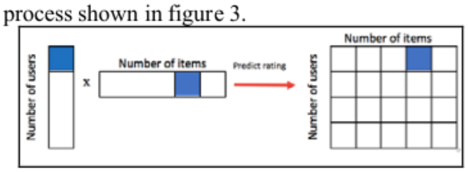

Figure 3. Matrix factorization approach

1.1.3. Classification Based on Algorithm Approach

The fundamental of thinking of recommender system is preference product by calculate and learning user's character, user's history behaviour, and the specification of product that already in the system. Several technical strategies have approach used by the e-commerce platform to generate preference products to buyers' candidate. It has been calculate by most fundamental and primary strategies for recommendation systems are content based, collaborative filtering, knowledge based and demographic filtering. Many practical industry and researchers also have been conducted as an attempt to find the possibility to mix between one approach to another one namely hybrid methods. The most useful and common approach and widely applied that called Collaborative filtering, this approach algorithm is the most efficient and accurate recommender systems [14].

Implemented recommender system aims to growing up marketing achievement[15][16][17]. Also another objective to increase customer service satisfied[18] Following researcher [19] based on algorithm approach, there are four type of fundamental algorithm that often used to establish recommender system also does combination between one approach to another. Four fundamental approach are:

A. Content based.

The system attempts to generate product or item recommendation which is equal to the ones that the user interested in the past. The equal of product will be compute by using the specification of contents related to the compared items. For instance, if a customer liked a film that belongs to the comedy genre, then the server can calculate to preference other movies from this genre. Older Content Based approach recommendation procedures go for coordinating the properties of the client profile against the properties of the items. In so many time, the properties of the product are importantly watchwords that are eliminate from the product depictions. Semantic requesting strategies communicate to the product and customer's profiles breaking down thoughts instead of keyword.

B. Collaborative Filtering.

The leading and most successful implementation of this approach creates prediction to the dynamic customer underlying of product that diverse customer with tantamount suggests a flavor like previously. The equal in flavor of two customer is calculate in perspective of the resemblance in the rating record of the customer. This is the inspiration driving why insinuates collaborative filtering as "personal to personal association." collaborative filtering is believed to be the most popular and for the most part executed strategy in recommender system.

C. Demographic Filtering

Demographic Filtering enhance demographic information like age, gender, education, etc. for learning to classification of users. It have ability more robust from the new user problem as is doesn't involve ratings to generate product recommendations. However, it is very hard today to accumulate enough demographic information that is required because of online privacy concerns, limiting the utilization of demographic filtering. It is still mixed with other recommenders as a enhancing method for better quality

D. Knowledge Based.

Knowledge based endeavors information about customer and product to reason about what product meet the customer prerequisites and produce prediction in like manner. A specific kind of knowledge based are limitation-based recommendation system which are able to preference complex products that are seldom purchased (i.e. cars, insurance or houses) and show essential limitation for the customer (cost). It is not probably to effectively utilize collaborative filtering or content based in this space of product as few customer connection information are accessible (people seldom to buy insurance service).

2. ENHANCE DEEP LEARNING FOR RECOMMENDER SYSTEM

Deep learning has become more powerful due the amount of available training data has massive growth. The trend of the use of deep learning technology was also influenced by the increase in the ability of hardware and infrastructure that qualified to perform computing. Recent 5 years, deep learning has ability to increase significant performance in several aspects like image processing, text mining, natural language processing, voice recognizing. Many researchers attending to conduct research in recommender system field involve deep learning technology. The world research organization for example ACM as a major research in recommender system field invited for people in around the world who interested in this research area to involved.

In this passage the author of the book [20] telling short history of deep learning machine. As general, deep learning have evolution for 3 time: deep learning machine recognize as cybernetics in the 1940s until 1960s, then in two decades about in 1980s-1990s recognize as connectionism, and the last decade recognizes as deep learning machine in the beginning 2006.

2.1. Deep Learning Classification Algorithm

Deep learning machine was classified a part of machine learning. It called deep due involve multi-layer of representation and abstraction from data. It can be term of supervised and unsupervised method. According [21] the authors have conduct classification based deep learning algorithm in their review research as explained on below:

A. Restricted Boltzmann Machine (RBM) is a type of deep learning involve two layer neural network divided into two later network namely of a visible layer and a hidden layer. It can be easily stacked to a deep network. Restricted here that means that there are no correspondences between intra-layer in visible layer or hidden layer.
B. Multilayer Perceptron (MLP) is type of deep learning a part of feedforward neural network with multiple (one or more) hidden layers between input layer and output layer. The mechanism to work in here, the perceptron can employ arbitrary activation function and does not necessarily represent strictly binary classifier.
C. Deep Semantic Similarity Model (DSSM), or more specific, Deep Structured Semantic Model, is a family of deep neural network for learning semantic portrayals of elements in a general continuous semantic space and estimating their semantic resemblance.
D. Autoencoder (AE) is an unsupervised type trying to remake its information in the output layer. In common, the bottleneck layer (the center most layer) is utilized as a striking element illustration of the input information. There are numerous variations of autoencoders, for example, denoising autoencoders, marginal denoising autoencoders, sparse autoencoders, contractive autoencoders and variational autoencoders.
E. Recurrent Neural Network (RNN) [20] is useful for establish modeling consecutive information. It is different feedforward neural system, there are circles and recollections in RNN to remember previous calculations. Variations, for example, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) network are frequently exploited in practice to handling vanishing gradient problem.
F. Convolutional Neural Network (CNN) [20] is specific type of feedforward neural network with convolution layers and pooling tasks. It is equipped for catching the global and local feature and noteworthy improving the proficiency and precision. It good ability in preparing information with grid like topology.

2.2. Single and Hybridization Approach in Deep Learning

In deep learning evolution, the use of deep learning has several dynamically evolution in order to achieve the best performance, there are some researchers who have a goal to optimize with single deep learning and hybridization deep learning, according researcher [21] to use the term composite deep learning.

Using single deep learning technique and deep composite model (recommender system

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

which involves two or more deep learning techniques).

- Model using Single Deep Learning Technique. In this category, models are divided into eight subcategories in conformity with the aforementioned eight deep learning models: MLP, AE, CNN, RNN, DSSM, RBM,NADE and GAN based recommender system. The deep learning technique in use determines the strengths and application scenarios of these recommendation models. For instance, MLP can easily model the non- linear interactions between users and items; CNN is capable of extracting local and global representations from heterogeneous data sources such as textual and visual information; RNN enables the recommender system to model the temporal dynamics of rating data and sequential influences of content information; DSSM is able to perform semantic matching between users and items.
- Deep Composite Model. Some deep learning based recommendation models utilize more than one deep learning technique. The motivation is that different deep learning techniques can complement one another and enable a more powerful hybrid model. There are many possible combinations of these eight deep learning techniques but not all have been exploited. We list the existing combinations in Section 5. Note that the deep composite model here is different from the hybrid deep networks in [22] which refer to the deep architectures that make use of both generative and discriminative components. Deep learning consist by two categories that are single method and another one combining between all of them namely composite deep learning, illustration figure shown in figure 4.

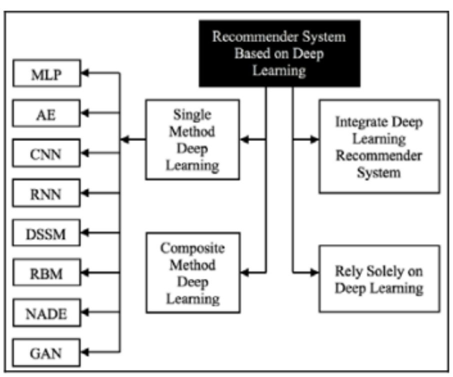

Figure 4. Deep Learning Hybrid Approach

3. LITERATURE REVIEW

In recent decade, deep learning become interesting machine learning to refine in many problem research, industry and business. Deep learning also successful improve the problem in image processing, natural language processing, text mining. Recommender system is software intelligent to support ecommerce company. In recent five years, some industrial company and researchers consider involving deep learning machine to increase performance or solving some existing problem. This research aims to investigate performance of deep learning to refine the problem, what deep learning kind often use in recommender system, are there any unique approach to increase performance in every ecommerce domain application?

Lately research recommender system using deep learning more interesting, it was triggered by the era of big data where the availability of data much more and many variations, also influenced by the powerful hardware capabilities for computing. In this literature review research, the researcher aims to find the answers to the following questions below:

RQ 1. What kind of deep learning machine that often used in recommender system?
RQ 2. What application domain are used deep learning as recommender system?
RQ 3. What disadvantages of recommender system based on deep learning?
RQ 4. What advantages of recommender system based on deep learning?
RQ 5. What advantages of recommender system based on deep learning?

3.1. Selecting Paper Process

Deep learning is a technology that is included in relatively new machine learning. In this research paper, there is little problem because of the limited resources referred. Researchers in overcoming this problem by searching from prestigious digital library in computer science such as IEEE, ACM, Scopus, Sciencedirect, Springer as the main literary source and other relatively common sources from google scholar.

The search strategy for this recommender system study based on deep learning technology, used several combinations of keywords as follows: "recommender system*", OR, "recommendation*", OR, "recommendation system *", AND, "deep learning", OR, "deep", OR, "deep neural", OR, "deep network", AND "ecommerce", OR, "e-commerce". The selecting papers in this research within the span of 10 years between 2008 to 2017.

Journal of Theoretical and Applied Information Technology
31st July 2018. Vol.96. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Types of paper that comes from the paper conference and mostly derived from the journal. The following is the search result shown in figure 1 below. In the graphic picture shown the results of research interest in recommender system specific uses deep learning machine from year by year shows increase significant. Graphics figure distribution research by year shown on figure 5 on below.

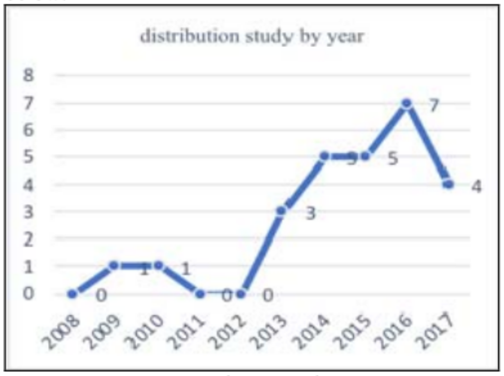

Figure 5. Distribution study per year

The result of selecting study that strong related in ecommerce recommender system use deep learning machine based on application domain found 20 papers, consist 6 group come from different application domain include; group movie application [23][24] [25] [26], group online music application [27][28][27][29], group fashion shop [30], group news, article, document, text [31] [32] [32] [33] [34] [35] [36], group of video or IPTV application [26] [37], group of social and community group[38][39], group of multi product, web services, advertising [26] [40][41], group of book store application [42]. Detail distribution of collecting paper base application domain shown in figure 6 on below.

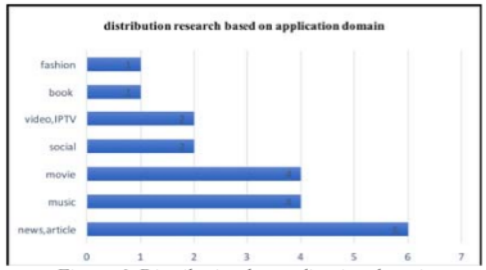

Figure 6. Distribution by application domain

Summary of result selecting paper, we have classified deep learning into the term include type of application domain, reference paper, year of publication, technical approach type, kind of deep learning are often used, then detail strategy approach and finally objective research. Complete summary explanation are shown in table 1 on below.

Table 1. Result selecting paper and detail technical approach by deep learning

Application domain	***Ref.***	***Year***	***Single/hybrid***				***Deep learning***		
Music			CF	CB	DM	KB	DEEP ALGORITHM	STRATEGY	RESULT
	[27]	2014	√	√	-	-	DBN	extract audio feature & probabilistic graphical model	Cold start
	[29]	2013	√	√	-	-	CoNN		Semantic gap
	[28]	2016	√	-	-	-	SAE	predict user tag	cold start
Movie	[42]	2015	√				MDAE		sparsity cold start
	[24]	2014	√	√			BAYESIAN SDAE	Item-item CF	Sparsity
	[25]	2016	√	√			SDAE	learn rating cold start & hybridization	cold start sparsity
	[43]	2016						Learn item feature	
Video/TV	[37]	2016		√	√	√	DNN	video watches,	cold start

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

								search query, geographic and demographics, uses corpus	accuracy
	[26]	2015	√	√			DNN		
Social/ Community	[39]	2015					RBM	detection content user community	
	[44]	2014					Collective DBN		
News, article, document, text	[31]	2017		√			CoNN		cold start accuracy
	[32]	2017		√			CoNN	joint user review text and item review text	Item cold start
	[33]	2013					BP [Back Propagation]		
	[34]	2014		√			RNN	feature learning then user preference	
	[35]	2016	√				TDSSM		
	[36]	2016	√				DNN		
	[45]	2016		√			CoNN + MF	Item review, abstract, item description	Contextu al aware
Multi Domain	[26]	2015	√	√			DNN		
	[41]	2010			√		RBM		
	[40]	2016		√			DBM		
Fashion shop	[30]	2015		√			CNN	Extract items feature	accuracy

3.2. Result and Analysis

3.2.1. Online Music

Online music application service is one that attracts many researchers in the field of recommender system in addition to other fields such as film, fashion, web service, news, video etc. After iTunes successful to create a new way of listening to music, the online music industry is growing up rapidly, this business is very promising for the future, it's the reason some new companies in this industry have coming in, then existing players compete with each other. One of the strategy to win the competition is how to serve the information satisfaction, recommender system is a tools attempt to serve information about music interesting to users.

The goal recommendation is to make music that listened in accordance with the taste of the user. Most previous researchers used semantic analysis such as playlists, user's tags, user opinions, comment and others. Author [28] in their research, author consider to generate item recommendation using collaborative filtering involve users tag. Normally, human social tagging system typically consists three entities include users, items and tags. In principle basic, the recommendations in social tagging systems have three entities types include: items, tags and users. Tag recommendation expect relevant tags of items to a target user based on the tags other users have served for the same items. In this research author have different approach with another researcher who have conduct research by traditional approach. The main research objective is to address from many problems, such as sparsity, redundancy, and ambiguity. The stage of process, the first process, the users' profiles are modelled as vectors over tags. To discover the latent features of the users' tag space is used a deep neural network. Finally, aggregate the extracted features and items information to generate recommendations.

Usage collaborative filtering to produce recommendation in online music that rely on community opinion have shortcoming, they only capturing community interest to detected popular song. Because of reason, there is opinion from expert, when predict music interest for user based on information retrieval is more proper and powerful due music is tended to personality and psychological domain. Author[28] [29] proposed capture all of music content feature. This method truly can capture "colour of music", then music classification can be recommended to user interest exactly. Another function of capturing music content feature is to decrease of gap solution for item cold start problem also to anticipate new song and unpopular music always never recommend to user.

According author [29], there is problem between developing recommendation uses customer corresponding to produce recommendation and using classification type of music by extract audio signal. The fundamental problem namely semantic gap. To eliminate the problem, author proposed high level engineering audio sound by deep convolutional neural network. The main objective of research by author [29] In this research, they attempt to bridge the semantic gap in music recommendation by training deep convolutional neural networks to predict latent factors from music audio feature.

Different approach by [27] combining deep believe network and probabilistic graphical model to generate automatic music recommendation. According their knowledge, many online music recommendations that involve extract traditional audio content features such as Mel Frequency Cepstral Coefficients (MFCC) cannot capture music content accurately due MFCC technical method specific for speech recognition.

3.2.2. Online Movie

The 1990s was the year of the rapid development of the internet both in terms of deployment, capacity and media to access. This also affects the behaviour of watching movies where most of them change from traditional movie provider (VCD, Laser Disk, Cinema) to using movie online service. Netflix is very popular as a provider of this service as well as a business pioneer in this field. The company held a competition to improve the performance accuracy of the recommender system in 2006 [46]. Reference Author [24], in this work, Author addressing sparsity data with exploit content feature. Background of research problem is when product information is sparse, it will have impact degrade of recommendation result. Author in this work proposed stacked denoising auto encoder (SDAE) and inject Bayesian probabilistic to SDAE. This strategy to joining deep item information representation and collaborative filtering for rating feedback. Result of testing on three real industrial datasets from multi domain show that collaborative deep learning can improve significantly for the start of the art.

In this study [23] enhance external information to eliminate sparse data and exploit hybrid auto encoder and matrix factorization regard movie domain datasets, also reference [25], in this work author conduct hybridization between collaborative filtering based on TimeSVD++ and content based by extract items feature use deep learning. This study aims to addressing sparsity data and cold start problem. Author declare when their proposed method is unique and novel namely hybrid recommendation model with CF and deep learning (shorted HRCD). In this research, the researcher proposed hybrid model to handle sparsity data and cold start problem. The first stage, they divide matrix column (user, item, rating) into 3 categories include non-cold start, semi cold start and extreme cold start (extreme condition happens when there is no rating from the user to the item). the second stage is to create new matrix vector on non-cold start and semi cold start. The third stage, based on the item features obtained from the SDAE deep learning process, they compute the similarity measure between non-cold start and cold start use Pearson Correlation as results produced in the second stage with raw column on cold start.

The experiment results that measure by RSME show that HRCD model is effective on rating prediction for both cold start and non-cold start items. The result have compare with four baseline method includes ALS, SGD, timeSVD++ and CDL, finally HRCD more effective that all of them. Equal with author on above, Author [42], in this work, they proposed model to handle problem of cold start and sparsity uses deep learning with different strategy, according their knowledge, deep learning machine models have been proven to be very effective in extracting high-level representations from the raw input data in several learning tasks. The learned features represent high-level knowledge. They proposed strategy to integrate matrix factorization with deep feature learning. Framework proposed by researcher are shown in Figure 7 taken from [42]. Deep collaborative filtering is a hybrid based on collaborative filtering recommender system model, as it trains very effective latent factors from both user and item ratings also side information from user and item. Applied this hybrid model, they show the mDA-CF and mSDA-CF approaches by combining the probabilistic matrix factorization and marginalized denoising auto-encoders. They declare that their proposed model efficient optimization algorithms to improve the models. The result of testing shows mDA-CF and mSDA-

CF approaches outperform related methods on the tasks of movie recommendation.

The result of testing measure with RSME metric on MovieLens dataset, their approaches (mDA-CF and mSDA-CF) achieve much better performance than PMF and Biased PMF, which are special cases of author approach. It demonstrates the effectiveness of incorporating side information and deep architectures, detail construction of deep model shown on figure 7.

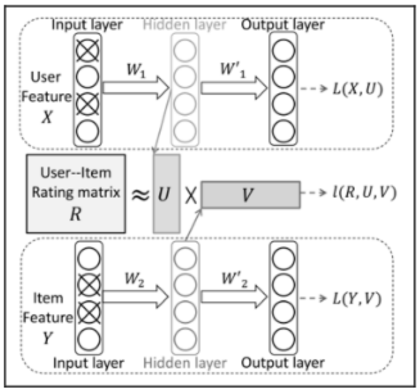

Figure 7. Matrix factorization and deep item feature

Another approach by author [43] semantic item vector to produce recommendation was proposed Recommender systems bargaining both item and customer interactions to bring about recommendations that suitable users suggestion. The recent gat back in shape of success in deep learning showing good opportunities for exploring these both sources of information. To prefer items, they ask for first learn a user independent high dimensional semantic space in which items are positioned according to their substitutability, and then train a user-specific transformation field to bring up to code this past into a ranking contained in each the user's in the past preferences. The benefit of the expected architecture is that it can be implemented to optimum recommend items by other content that defined the item or customer-product ratings. They declare that their approach significantly best performs start of the art recommendation system. Detail linkage structure model who have proposed by researcher shown on figure 8 on below.

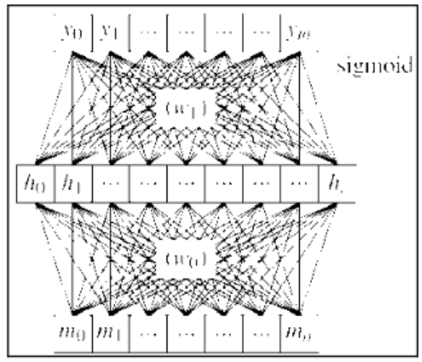

Figure 8. Semantic Item Vector Structure

3.2.3. Video/IPTV

In the last decade, video streaming become favourite application for internet user, more than 80% traffic internet consuming was used by users to access video. The most video portal is YouTube. Author who affiliate with YouTube company was proposed Video recommendation [27]. They develop system consist of two deep neural networks: first one for generate candidate and second one for generate ranking. The preview of general model shown on Figure 9.

YouTube is the largest online video streaming service for generating, providing and inventing video content portal. YouTube recommendation system have a task to assist more than a billion of users to invent specific from large corpus of video knowledge. In this work, author concern on the tremendous effect deep learning on the YouTube video recommender system. They are three major big challenge on video recommendation system on YouTube.

- Scale: on existing recommender system technique really operate maximum on little problem ignored to work on their scale. Specifically, distributed learning technique and efficient providing system is important for handling YouTube significant user based and corpus.
- Freshness: YouTube have dynamic environment corpus for example the number or video have upload per second. The recommender system absolute must be adaptive enough to method recently uploaded content as well as the final response taken of user.
- History user environment on system inherently very hard to estimate because for example cold start and sparsity data and several external factors. According author, they hardly ever the

Journal of Theoretical and Applied Information Technology
31st July 2018. Vol.96. No 14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

truth opinion about user satisfaction and critique feedback are so noisy. Instead, metadata that related with item are badly organized a good explained by knowledge. Their algorithm requires to be firm for a part feature of learning data. The illustration figure of the architecture shown in figure 10.

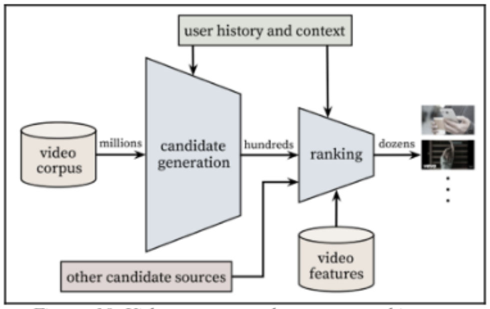

Figure 10. Video recommender system architecture

Deep nominee produces technique architecture proven inject rare attribute merge with solid feature. Injecting was averaged before combining to change attribute sized bags of rare name to permanent width vector fit for input to latent factor layer. All latent layer was all connected. Preview system are shown on figure 11.

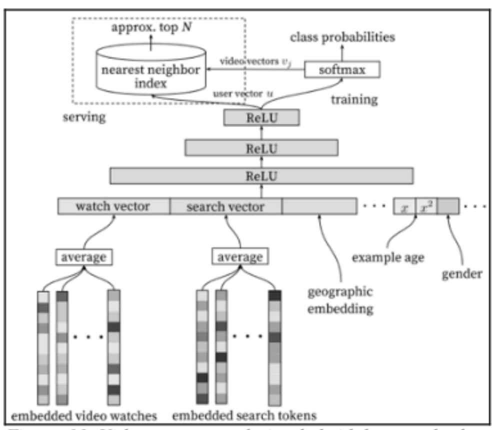

Figure 11. Video recommendation hybrid deep method

3.2.4. Social Network and Community

Refer to study [39], Online social network has becoming popular application in recent years. In social network have possibility to identify to other user with common interest. Comment opinion exchange. Finding user communities come from social network have become a major challenge that it can help member to interact with relevant people have equal interest. There are two ways to detect community member: the first is considering user network while the other user generated content. In this work, a multi-layer model community detection model based on identification of interest topic from user content presented. Author proposed to apply Gaussian Restricted Boltzmann Machine for user posts within social network to detect topic interest and community construction. The result test using KL divergence to measure similarity between user and equal community on Twitter dataset show that deep model outperforms than traditional community detection model that directly maps user into corresponding community use some baseline model. The complete illustration model in this research show on figure 12.

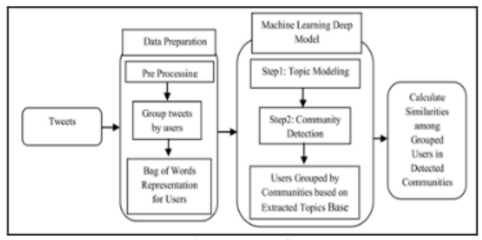

Figure 12. Recommender system for content community

In last decade, mainly recommender system aims to produce recommendation items for customer. According study [44] Because of basic human character, group behavior activities become an integral in human activities. Because of this, objective research on group recommendation system. However, mainly older algorithm created by group recommender system used recommendations via aggregating personal ratings or personal estimate results than considering the collective attribute that manage user decision decided within a group. In fact, this approach model is very sensitive to data. Based on this, they heavy risk to fail learn group recommendation. In this study author proposed novel recommendation which incorporate personal decision and group decision in combine model. In detail model, they proposed deep framework develop with collective deep belief network (DBN) and double function restricted Boltzmann machine (RBM). Finally, the result in real dataset show their experiment highly superior over existing method. Preview detail framework shown in figure 13.

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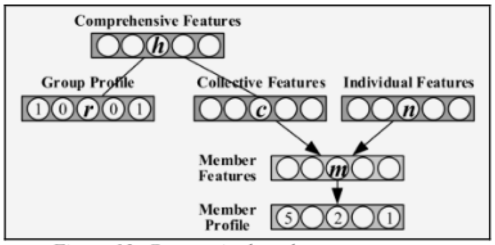

Figure 13. Community based content structure

Defined architecture on figure are Left side, preview of double layer collective DBN help to disentangle high-level collective and personal information. Right side, explanation of collective RBM for top level where collective attribute is linked to member attribute.

3.2.5. News, Article, Document, Text

In this section, we show selecting study in recommender system based on text management research field, refer author [21] Portal news online beat serious challenge in selecting candidate article to submit to their customer. Mainly, those articles recommend by human decision expected by editor. We can imagine, it's very difficult decision when the editor face too much information that will be candidate article come from large source and also this method need time consuming. In this work, author proposed selecting article selection behaviour. They propose learning model with demonstration system to automatically choose subset of article candidate from a large pool.

According their analysis, there are two shortcomings in traditional model to decided article candidate, first editors' selection criteria is based on more depending on the quality and attractiveness, following author knowledge they prefer according in the keywords or topics. Existing method have impact very difficult to catch based on traditional bag-of-words article representation. Because of the problem on above, author proposed Automate capture the editor underline selection category by the automate representation learning of each article and their correspondent with the meta data. Propose architecture by author are shown in figure 14, Explanation of proposed method are, first they use (convolutional neural network) CNN to take general document representation. Second, combining linier model and particular of CNN parallel to create modelling based on meta-information criteria and sequence criteria (document textual content). Third, to related editor behaviour adaptive, they proposed a model that concern via multiple deep network which jointly considers the specialty and the timeliness of each model trained in previous days.

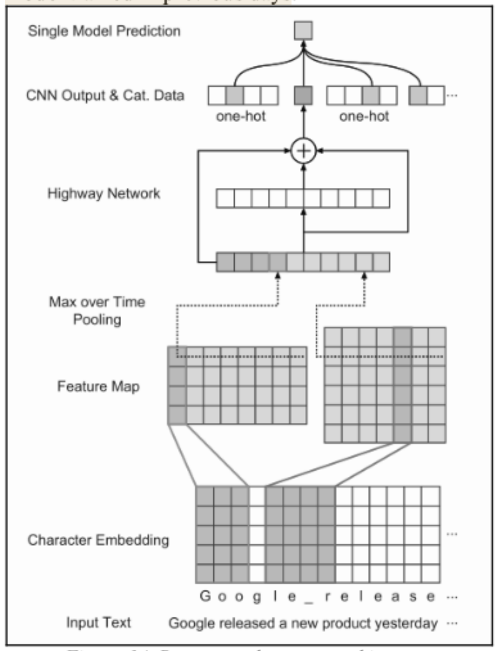

Figure 14. Recommender news architecture

The result of the test shown the model have proposed by test perdition use AUC and F1 show the best perform.

Reference Author [22] Mostly useful information is available in review have written by users. Source of information have ignored by most of current recommender system while they have become candidate to eliminate sparsity problem and improve performance recommendation. In their work, they show deep model for learning item feature and user behaviour jointly from review text. This model called deep cooperative neural network (DeepCoNN), divide into two parallel neural networks. The task of first network focuses on learning user behaviours explored review have written by users, and second network is learning item feature from review for the item. A joint layer is recognizing on the top to couple these of two networks together. Joining layer allow latent factor learning for user and item to communicate with each other in a manner equal to matrix factorization technique. Test result show that DeepCoNN dramatically outperform than all baseline recommender system on a variety dataset.

Complete architecture of this model are shown on figure 15.

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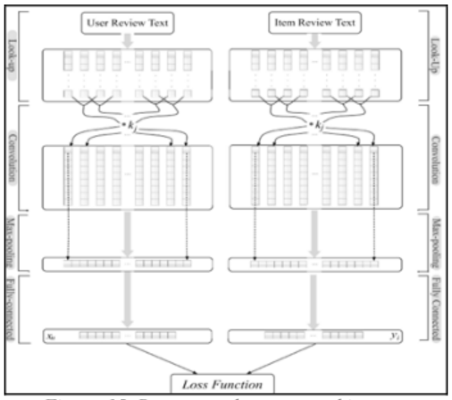

Figure 15. Recommender news architecture

3.2.6. Fashion Shop

Online fashions shop also become one of most popular ecommerce in the world. Although there is still a fairly noticeable gap between the fashion shown on the ecommerce portal with real clothing. The gap needs to be improved if the fashion shop expects to increase sales and increase profits in this business sector. One of the efforts done by author [30], this researcher is with recommendation approach in item feature extraction based on color specification. They have built hierarchical deep search framework to handle problem. It consists 2 modules, first they develop pre-trained network model that has learned in the middle level visualization. Second, they embedded a latent layer to the network layer. Finally, third layer resulting information retrieval for clothes, this technique uses coarse to fine strategy. Dataset they use exactly 161.123 clothes images. The architecture was proposed by author shown on figure 16.

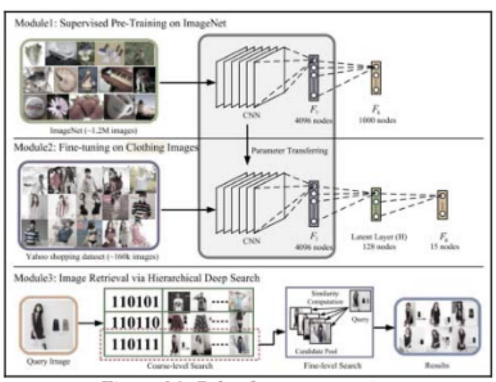

Figure 16. Color feature extraction

The final experimental result on large clothing dataset testing show that deep CNN framework outperforms and achieving speed up until 10x and 50x compared handcrafted baseline features item and exhaustive search using CNN.

4. DISCUSION

This section focus to answer the research question that is become the focus of this research review, there are five important research question to guidance this research stay concern on the track.

RQ 1. What kind of deep learning machine that often used in recommender system?

The type of deep learning machine that often used is dependent on the type of business application domain built. In this research, example case for domain business applications for clothing and music products have a tendency to use the convolutional deep neural network. information retrieval to enrich hidden content feature. Another model of deep learning machine for instance DBN (deep belief network) concern to improve recommender system based on collaborative filtering that very fragile in cold start and sparsity, produce side information is a strategy use DBN to handle major problem in collaborative filtering.

Another technique deep learning machine is Boltzmann Machine for increase performance collaborative filtering. They proposed the parameterizations for the established of multiple Boltzmann machines (RBM) for user based and item-based processes. In some study, RBM proven more powerful implemented to the recommendation problem and outperforms over traditional Matrix Factorization.

There is important technique, in this work, author invent several hybrids deep learning for example case RBM and DBN,

RQ 2. What application domain are used deep learning as recommender system?

Based on the invent of many studies, whether all types of business in the field of e-commerce has conduct study and some of them have applied in deep learning, in some research is not known at all or limited to research. YouTube, as the world's largest online video service provider and the most accessible portal of internet users worldwide has implemented a deep learning engine.

Music streaming is one of business commerce company who concern to increase service satisfaction with develop auto generate playlist recommender system use learning audio content based on deep learning. This method having

Journal of Theoretical and Applied Information Technology
31st July 2018. Vol.96. No 14

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ability to capture the feature of audio content perfectly over existing technique. Author named this work with colour of music.

RQ 3. What disadvantages of recommender system based on deep learning?

In general classical problem applied deep learning is heavy computation. As specifically for RBM no need content information, such as user profiles or review texts. RBM well done to tracking missing value. Thus the result cannot deal in case to solve cold start problem. However, content information proven to eliminate cold start problem on items. In another cased, CoNN heavy effective to tackling image and sound extracting to enrich content feature. It a reason there is study to combining both of deep model due to upgrade performance to another one. In another case especially collaborative filtering, CoNN cannot compromise without rating. To maximum generating recommendation should be consideration involve side information to predict rating.

RQ 4. What advantages of recommender system based on deep learning?

We have explain on above, some benefit of deep learning in the case sound extraction and image extraction, however it have fragile to face review from user to product in the form of text. Deep learning have not fully exploit used recommender system. In several domain such image processing, text mining, voice recognizing, deep learning is successful to applied. There is opportunity to applied deep learning recommender system with different approach.

Deep learning successful to applied in real-world industry that has a high level of complacency and huge amount of data like in the video streaming industry like YouTube with the number of videos uploaded per hour reaching millions.

RQ 5. Is there any unique approach between application domain in e-commerce business kind?

As results of development and research on deep learning machine, they have the ability and character of each type of deep learning. It also affects the type of deep-learning use in different types of ecommerce businesses such as content-based models that use image and sound for information enrichment, involving CoNN as the main instrument in generating recommendation.

DBN is applied recommender system, however DBN is not robust to handle sparsity and cold start problem, thus require exploit another information from other deep learning family model. Its potential to improve recommendation with hybridization to other machine learning.

5. CONCLUSION

Even though deep learning machine technique having incredible ability in several field such as image processing, natural language processing, speech recognizing, deep learning machine which adopted in recommender system have not fully maximum work. In traditional recommender system gravitates to recommend items by rating. Thus, due cold start and sparsity data problem, the power of available rating are not enough to estimate latent factor between customer and product. This problem must be eliminating, content based is one of solution that probably to combine with collaborative filtering. In this situation, deep learning plays important role to extract auxiliary information resource for could be exploits to additional information such review texts, images, user profile, sound and etc., then can be utilized. The strategy often used by content based is exploring hidden information to learn by user recommendation and item feature. Nevertheless, mainly of content-based recommender system strategy are use hand-crafted feature usually needed rely on knowledge. Deep learning machine possibly to generate automatically learn character for users and items from more variety resources. This method is produce better performance and could be effective to increase performance quality of product recommendation, for example case in music and fashion shop.

According to our best knowledge which the recommender system having some major issues in experiences, and the underlying problem also following phenomenon of technological growth, user behaviour and the scheme of ecommerce business. The most common problems are cold start problem, sparsity data, accuracy and contextual improvement. There are several strategies have been doing to handle the problem on above by enhancing deep learning machine those auxiliary information enrichment. According the authors observation based on evidence above, to enrichment the source of information in the part of auxiliary item information (the term of images and sounds) have trend strongly to use convolutional neural network (famous called CoNN). In case for online music recommendation to extract content audio feature and extract image content feature for fashion shop recommendation. This approach very robust to tackling item cold start problem in which

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type collaborative filtering vulnerable to extreme sparse data (cold start problem). Another case enhancing CoNN implemented to capture contextual aware regarding review feedback, abstract, product description [45]. In recent year several researcher convey this method could increase contextual aware in recommender system research field.

According the author observation, enhance auxiliary information become an favourite model to finalize some existing problem, due availability information come from external factor is very possible in big data era for today. Information resources for instance social network activity, mobile device highly rich user information behaviour. the using of hybrid deep learning also will be trend to conduct research, also combining between one deep learning approach to another (hybridization) proven the better result performance to solving the problem. Combining between type of deep learning approach tend to complexity combination method in the future.

ACKNOWLEDGMENT

We said to thank for those support our literature research. The organization that support our research is University Teknikal Malaysia Melaka, Melaka, Malaysia. Also funded by University Amikom of Yogyakarta, Yogyakarta, Indonesia and Time Excelindo Private Limited IT Company located in Yogyakarta, Indonesia, the Holding Company member of AMIKOM Group in Indonesia.

I never forget my family, my deepest thank to my family member includes in there my beautiful wife and my lovely children who always allow me to spend a lot of time to reading, writing and conduct the research. And, Allah, thank you for big opportunity always you gave me.

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