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Research on Recommendation Systems using Deep Learning Models

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Abstract*: *Recommender System is the effective tools that are accomplished of recommending the future preference of a set of products to the consumer and to predict the most likelihood items. Today, customers has the ability to purchase or sell different items with advancement of e-commerce website, nevertheless it made complicate to investigate the majority of appropriate items suitable for the interest of the consumer from many items. Due to this scenario, recommender systems that can recommend items appropriate for user's interest and likings have become mandatory. In recent days, various recommendation methods are applied to resolve the data abundance setback in numerous application areas like movie recommendation, e-commerce, news recommendation, song recommendation and social media. Even if all the available current recommender systems are successful in generating reasonable predictions, these recommendation system still facing the issues like accuracy, cold-start, sparsity and scalability problem. Deep learning, the recently developed sub domain of machine learning technique is utilized in recommendation systems to enhance the feature of predicted output. Deep Learning is used to generate recommendations and the research challenges specific to recommendation systems when using Deep Learning are also presented. In this research, the basic terminologies, the fundamental concepts of Recommendation engine and a wide-ranging review of deep learning models utilized in Recommender Systems are presented.

Keywords* : *Basic terminologies, Recommendation Systems, Deep Learning based models, Performance Metrics.

I. INTRODUCTION

The enormous stormy growth of internet results in a plenty of information. In a way we are drowning in information but starving for understanding and knowledge. Though abundant information is influx to the web by the user there is insufficiency of models and algorithms to process the information to knowledge. So the current scenarios claim new models that can support the users to discover resources of interest among the enormous opportunities. These paved ways for the foreword of recommendation model which attempt to predict most likelihood items to particular users by analyzing the user's likes and dislikes or preferences of a product depending up on the significant information related to products, consumers and the association among consumers and items.

Recommendation belongs to the category of information filtering system that utilizes information to predict customer's liking and interest of an item. They are primarily used in commercial applications. Recommender systems have revolutionized the way we interact by providing lots of services. Instead of producing static information to users, Recommender Systems bring interactive experience, an option to leave your feedback and to personalize the information you are given. A recommender system not only constructs the personalized informational flows independently for each user but also the behaviour of all users of a service are also taken into account.

Recommender systems are utilized in various applications such as playlist providers for movie and series recommendations in Netflix, Amazon Prime, YouTube recommendation service, news recommendation, e – commerce service recommendations like Amazon, Flipkart and recommendations for social media networks like Facebook, Instagram and Twitter. These classes of recommendation models has the ability to handle distinct input such as audio, videos, comments, ratings or several inputs in and transversely the fields like news, books and search queries.

II. BACKGROUND

Recommendation models are defined as systems that produce personalized predictions as an output. These recommendation systems are applicable in ecommerce, music, movies, videos, books, news and others. Based on how the recommendations are made, they are classified into: Content-Based recommender systems, Collaborative Filtering Recommender systems and hybrid recommender systems. Nevertheless, in all these methods, the accuracy of predicting target output is narrowly related to the quantity of information acquired from the active users to whom these predictions are generated. In the recommender systems user interest, their preferences and dislikes are utilized to design the user profile which is utilized as filters. Building of accurate user profiles is a prominent task and the accuracy of the system's performance is depending upon the capability of the trained active consumer profiles to represent the user's preferences.

The initial works on recommenders were using collaborative filtering that recommended news articles to users and music album and artist recommendations from social information. It was followed by a lot of works in the field of recommender systems which helped the consumers to identify items,

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services and content such as books, research articles, movies, news, retail business, digital products, consumer products etc by applying various algorithms which reviews the different users and items to give proper suggestions.

Though the recommendation model is traced as a specific category of data filtering system, deep learning is an upcoming technology in machine learning. Prior to exploring how these domains linked with each other, it becomes mandatory to explain the fundamentals of Recommender systems and Deep learning. In this research, a wide spread review of the relevant descriptions of deep learning based recommendation systems are presented. In background segment, the fundamentals and phases of recommender system, categorization of deep learning based recommendation engine and the issues of recommendation systems are precisely illustrated. Then the deep learning concepts were compared with its merits and demerits are introduced. Finally, the performance metrics that have been widely utilized in deep learning models for evaluation is analyzed.

III. RECOMMENDER SYSTEM

A. Introductory and Fundamental Concepts of Recommender System

In Recommendation Systems, users and items are the two major top most objects that play a vital role. Users provide their interest about items and their interest and dislikes are accumulated as the input information. The information about the customer preference that is collected is denoted as a utility matrix. Utility matrix denotes the order of the preference for the particular items by the user in the combination of customer – item value. User-based recommender systems and Item-based recommender systems are the two classifications. In recommender system based on user, interest, dislikes and ratings are provided by the user to the items. Using user-based recommender systems, those items are recommended to the user, which is unrated already by that user considering the relationship among the users. On the other hand, in Item-based recommendation model, the closeness and the relationship among the items are utilized to generate recommendations from the users.

B. Phases of Recommender System

- *Data Acquisition Phase:* This segment of the recommender system gathers significant information regarding the users and generates a user summary based on the characteristics of the user's information, behaviours. Developing a precise description of user summary is mandatory for proper working of the recommender engine. A recommendation model works depending on the inputs which are acquired by using various ways like explicit review, implicit reviews and hybrid comments. Precise review accepts the input provided by the user depending up on their preferences on an item whereas implicit feedback takes user preferences indirectly through investigating the user's behaviour
- *Learning Phase:* This stage considers the evaluation of the input data gathered in the previous phase and processes this feedback by using a learning model to make use of the characteristics of user as output.
- *Prediction / Recommender Phase:* Most relevant items are recommended to the users in this stage. By investigating the feedback collected in the information collection segment, a recommendation will be generated by applying the appropriate algorithm by the system. The stages of recommendation system are denoted in Figure 1.

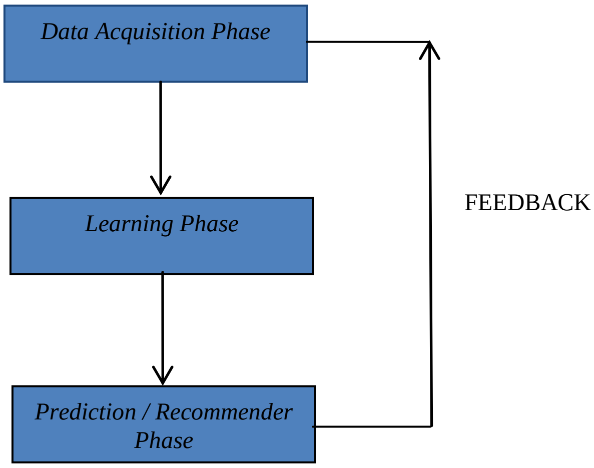

Figure 1. Phases of Recommendation System

C. Traditional Recommender System

Recommendation Engines are designed by utilizing various approaches like Content based Recommendation System, Collaborative filtering Recommendation Systems and Hybrid Recommendation Systems. Classification of Recommendation System is represented in Figure.2

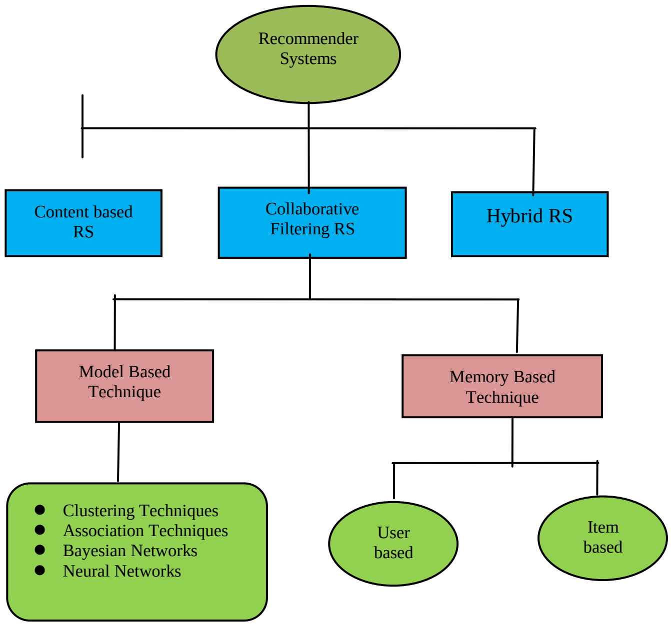

Figure 2. Classification of Recommender System

Content based Recommendation system:

CB recommender systems rely on both the attributes of the product and the active consumer's profile. This system works well when the attributes of the item such as name, place, availability etc are known even though the features of consumer are not known. In content based recommender system, the items are recommended based on the users past history of preferences. Content-based recommendation system is based on the classification problem related to the particular user and gain knowledge that a classifier for the user's preferences and disinterest based on the characteristics of the item.

In Content-based recommenders, the features of the products are described using keywords and a user profile is constructed to illustrate the type of item this user likes. Using algorithms, based on the past record of customer’s likelihood or by analyzing in the present, Recommender Systems of this category tries to predict items. In specific, a variety of product features are evaluated and related to the products which are shown interest by the consumer previously and the most appropriate products are predicted and suggested. Content Based Recommendation System is shown in Figure 3.

A user profile is generated by concentrating on the following category of data:

i. Representation of consumer’s interest and preferences.

ii. Consumer’s communication details in the past with the recommendation engine.

A commonly used model is the tf–idf illustration model. It is also named as vector space illustration model. A content-based user profile is generated depending on a weighted vector of item features. Many techniques are used to compute the weights from independent rated content vectors and these weights represent the importance of each feature. Simple methods like mean values of the item vector which is rated by the user is utilized to calculate the weights. Machine learning methods like Naïve Bayesian Classifiers, Clustering techniques, decision trees induction and ANN can be used to evaluate the likelihood of the item preferences by the user.

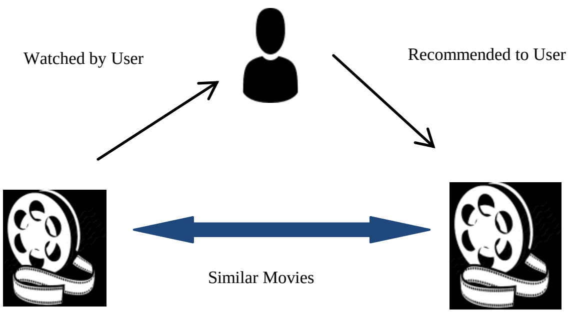

Figure. 3 Content Based Recommendation System

Collaborative filtering Recommender Systems

CF models are the most commonly used methods for Recommendation System. To provide recommendation of the user’s preferences on items, Collaborative Recommender systems depend on the history of the user -item interaction. Collaborative Filtering methods provide predictions by considering the correlation among consumer - consumer or item - item or both. Moreover optimization methods are utilized to create a training model in a same way in which classifiers are utilized in creating training models from the distinct data. Fundamentally, there are two categories of the Collaborative Filtering approaches, such as the memory-based approach and model-based approach. CF is the most salient approach in recommendation systems which works based on the hypothesis that the consumers has the same taste, likes and preferences both in the past and in the future, as well. In those kinds of systems, interest of neighbour users who have similar taste is considered as the foundation of all generated predictions rather than individual features of items. CF based Recommendation System is depicted in Figure 4.

Content-based recommendation engine utilize the description of the products and find the similarities among them. After examining adequate numbers of items that one user is interested with it and then the user interests profile is created. Finally the recommender system explores the user profile database and finds the list of products that match with the user profile.

The essential part of a Collaborative Filtering model is the dynamic user who tries to find out the prediction of the rating or ranking of the listed items. User interest and dislikes in the past history are considered to determine the similarity among the users. Typically, a CF system contains a record of n users $U = \{u_1, u_2,..., u_n\}$ and m item $I = \{i_1, i_2,..., i_m\}$. An $n \times m$ user-item matrix is constructed which consists of the ratings for the items given by the user, where each entry $r_{p,q}$ represents the dynamic user given ratings u_p for each product i_q. The recommendations were generated as output for the user with the ratings on the item q. The Collaborative Filtering approach will forecast rating for item or predicts an ordered list of preferable top-K items.

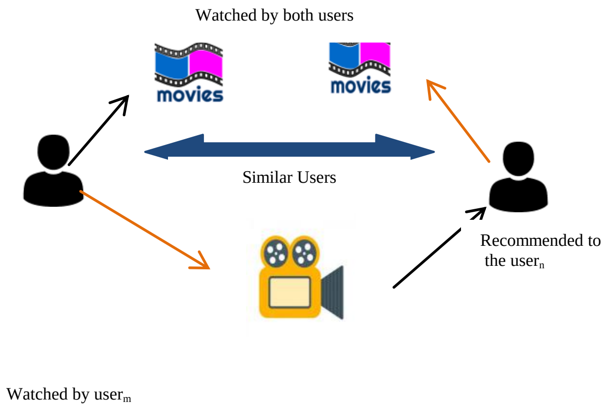

Figure 4. Collaborative Filtering Recommender System

Hybrid Recommender Systems

Most recommender systems are commonly using hybrid approach such as combining collaborative filtering, content-based filtering and other approaches in order to obtain better accuracy of prediction. Hybrid Recommender Systems works in numerous ways: by predicting CB and CF approach separately and then by uniting the results; by adding the content-based approach to a collaborative filtering model; or by unifying the approaches into one model. Through empirical evaluation the performance of the hybrid approach is compared with the pure collaborative and content-based methods. Several studies demonstrated that the hybrid methods will generate more accurate recommendations than pure independent approaches. Hybrid methods can also be used to overcome some of the common demerits in recommender systems such as cold start and the sparsity problem.

Netflix is referred as a great example for the use of hybrid recommender systems. The recommendations are generated by comparing the watching and searching history of like users (i.e., collaborative filtering) as well as by recommending movies that holds the similar characteristics with the movies that a user has given ratings highly in the earlier period (content-based filtering).

Various Hybrid Recommender techniques have been proposed and are summarized as,

- **Weighted**: Adding the weights of different recommendation components numerically.
- **Switching**: Depending upon the current situation, recommendations are generated by opting among various recommendation components and utilizing the selected appropriate one.
- **Mixed**: Predictions from different recommenders are combined together to produce single recommendation.
- **Feature Combination**: Features derived from different knowledge sources are combined together and given as input to a single recommendation algorithm.
- **Feature Augmentation**: Recommendation output obtained after computing a feature or set of features is then used as input to the next technique.
- **Cascade**: Recommenders are given strict priority such that the lower priority ones breaking ties in the scoring of the higher ones.
- **Meta-level**: One recommendation technique is applied and produces some sort of model, which is then utilized as the input by the other recommendation.

Table 1 represents the analysis of various recommender systems

IV. DEEP LEARNING-BASED RECOMMENDER SYSTEM

Najafabadi et al., [2] presented Deep learning is the fastest segment of machine learning that uses many layers of deep neural networks to learn levels of representation and abstraction that makes sense of data, typically by using artificial neural networks. Deep learning is driving significant advancements across industries, enterprises and e-commerce.

In this section, various deep learning algorithms used in recommender systems are briefly introduced. Deep Learning Algorithms can be applied for both unsupervised and supervised learning methods. Few examples of Deep learning algorithms that works on unsupervised category includes Autoencoders (AE), Restricted-Boltzmann-Machines (RBM), Deep Belief Networks(DBN), Deep-Boltzmann-Machines (DBM) and the recently developed Generative Adversarial Network (GAN). Other Deep learning architectures that are specifically applied for supervised deep learning models are Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Multi Layer Perceptron (MLP).

A. Deep Learning In Content-Based Recommender Systems

Batmaz et al., [5] proposed that Content-based recommendation system is primarily rely on items and user's supporting information. Supporting information can be viewed as various ranges like texts, images, audio and videos. Deep learning model based recommendation systems are used to generate a profile of the consumer's preferences from the samples depending on the descriptive features of the content. In addition to that, content - based recommender system identifies the complicate associations among the data itself, from accessible data rich sources like contextual, textual and visual information.

B. Deep Learning In Collaborative Filtering Recommender Systems

Zhang et al., [14] presented Collaborative Filtering (CF) as a commonly utilized model in recommendation systems to resolve the digital-world applications. Conventional Collaborative Filtering systems utilize the user-item matrix which is constructed by taking into account the individual interest of consumers for learning in order to predict the output. Weight of all users with respect to similarity with the active user is identified by using cosine similarity and Pearson coefficient. Select a Subset of the users (neighbors) are selected to use as predictors. Ratings are normalized and predictions are computed by utilizing the neighbor user's ratings as a combination by selection. Predicted items are ordered and the predicted items with highest ratings are provided as recommendations.

1. Auto Encoder-Based Collaborative Filtering Method

F. Strub et al., [18] proposed as, Autoencoder is an ANN used to gain knowledge of an illustration (encoding) for an labeled input data which may be of audio, image or text. This model is commonly used to a attain the reduction in dimensions. Autoncoder maps the function f(x) = x. Architecturally, an Autoencoder is a neural network of composite functions which is of three layer network. An activation function is applied to the input and the output is given as input to the hidden layer in a compressed representation. The number of neurons present in the input and output layer should be the same since it has tom reconstruct the original data. Due to this Autoencoder is best suited for the application of dimensionality reduction.

Table 1: Analysis of various Recommender Systems

Technique	Commonly Used Techniques	Advantages	Disadvantages
Collaborative Filtering (CF)	o Nearest neighbor o Clustering o Graph Based o Bayesian networks o Neural networks o Linear regression o Probabilistic models	• Requ • ires minimal knowledge engineering efforts. • Adaptive: quality improves over time. • Produces good results.	• Huge number of user feedback data is required • Accuracy relies on large historical data set. • Since it works based on feedback, if no reviews available the system is not applicable • Gray sheep: Users having peculiar opinion will not get benefited. • Scalability Problem
Content-based	o TF-IDF o Clustering o Bayesian Classifier o Decision tree o Neural network	• Domain knowledge is not needed. • Adaptive: quality improves over time. • Implicit feedback sufficient • Descriptions of predicted items by providing the features of the content that leads to recommendation	• Recommendations will not be relevant if enough data is not available for item discrimination • Hard to exploit quality opinion of other users. • Accuracy relies on large historical data set.
Utility-based	o Implicit holistic utility rate o Genetic algorithm o Simple Multi-Attribute Rating Technique (SMART) o Radial Basis Function Networks (RBFN)	• Ramp-up is not necessary. • Adaptive to change in liking	• Utility function should b provided as input by the user • Ability of suggestion is not dynamic • Understanding of engineering is required.
Hybrid	o Linear combination of predicted ratings o Various voting schemes o Incorporating one component as a part of the heuristic for the other o Building one unifying model	Does not have following problems: • Content Description • Over-Specialization • Subjective domain problem • Sparsity Problem	• User ramp-up problem
Context Aware	o Incorporates contextual information. o Autoencoders and PCA are used to extract latent contents. o Gradient descent based ANN	• All kinds of heterogeneous ata are integrated to deal with data sparsity problem.	• Accuracy is still less.
Tag - aware	o Based on tag, predictions are made. o SDAE is utilized for feature extraction of users by using tags. o Extraction of user and item's latent features are done by utilizing AE.	• 3 Dimensional correlation between item, user and tags produce more accurate recommendations	• Sparsity Problem • Training time required is high.
Session based	o Next occurrence of an event is predicted by using RNN by investigating the series of clicks in a session	• Noisy clicks are handled by Data Augmentation. • Session clicks and content information are clicked together to avoid sparsity problem and to improve accuracy.	• Cold start problem.
Cross domain	o RNN and CNN are used together to extract the user features from different domain along with item features.	• Several types of cross platform data are integrated to overcome the data sparsity and cold start problem	• Generation of User model requires great effort • Datasets are fairly inadequate and difficult in Cross-domain to accomplish in reality

Autoencoder is utilized by having compressed form of hidden layer in addition to the input and output layer. Autoencoder consists of two step process encoder and decoder. First part of the model is the Encoder which encodes the input data to reduced dimensions to the hidden layer. Second, the decoder decodes the encoded data from the hidden layer to the original data as output. Here input and output are the same but the hidden layer consists of encoded data of the input. This cause makes the model to generate lower dimension representation of the information in the hidden layer by investigating the association among the input data.

CF recommendation using AutoEncoder-based method (AutoRec), ratings based on items or users is given as input and it generates the ratings matrix. Output is generated by the reducing the error developed in reconstruction. Depending on the application domain any number of input layers, output layers and hidden can be used. Collaborative Denoising Auto-Encoder (CDAE) is mainly used for rating the recommendation. The input of CDAE is user partial observed implicit feedback. The input of CDAE is corrupted by Gaussian noise. CDAE initially updates its parameters using SGD over all feedback.

2. Restricted Boltzmann Machine-Based Collaborative Filtering Method

Su X et al., [11] presented as Restricted Boltzmann machine RBM is an undirected graphical model that plays a major role in the deep learning framework. In general RBM comprised of a couple of layers of neurons, the visible input layer and hidden layers. The unsupervised data is fed as input and the features are learned by the hidden layer.

These models are basically the neural network that belongs to energy based models that are trained with contrastive divergences (CD). RBM models are the algorithms used for processing unsupervised data into dimensionality reduction, regression, classification, feature learning. RBM model endures many limitations such as high parameterization which leads training of the model as computationally expensive one. Nevertheless, many hidden layers can be learned efficiently by composing RBM using the feature activation of one as the training data for the next. This elicits the rise of Deep Belief Network (DBN).

3. Recurrent Neural Network-Based Collaborative Filtering Method

Y. K. Tan et al., [17] proposed as, Recurrent Neural Network RNN model is exclusively used to process the sequential data to learn the user preferences by using their reviews. RNN is a type of Neural network designed to recognize the patterns in sequence of data such as text, genomes, handwriting, the spoken word or numerical time series data emanating from sensors, stock markets and government agencies. RNN model is trained using Back Propagation Through Time (BPTT) algorithm. RNN model is used to train the user events in a session such as products viewed, purchased to predict the next item in the session. However RNN models have the drawback of exploding gradients – clip scale gradients or vanishing gradient which learn to problem in training the model is solved by BPTT. Different architectures such as GRU (Gated Recurrent Unit) network and LSTM (Long Short Term Memory) are a special kind of RNN utilized to deal with the drawback of the vanishing gradient and are capable of learning long term dependencies. Although, GRU has the drawback that it can predict only the items present in the training set. Recently, in order to provide better performances BiLSM which is an alternate of the LSTM have been developed.

4. Generative Adversarial Network-Based Collaborative Filtering Method

Da'u, A et al., [16] represented Generative Adversarial Network GAN is a newlyy developed method which has two neural networks i) Generative ii) Discriminative. Generative model is used to generate the relevant items to the given query where as Discriminative model is utilized to discriminate the most relevant items among the given query document pairs. Unsupervised and supervised learning methods where used to generate the new instances of data that is similar to the training data. Two neural networks Generative model, to generate the expected target output and Discriminative Model, which is used to distinguish the true data from the output produced by the Generative model were used Generative Adversarial Network model is an effective way to evaluate the distribution of target data from the actual training data. GAN suffers from various limitations such as vanishing gradients, mode collapse and failure to convergence. Many variants of GAN have been developed such as Progressive GANs, Conditional GANs and Cycle GANs to improve the performance.

C. Deep Learning - Based Hybrid Recommender Systems

Burke, R et al., [8] proposed that the fundamental idea behind the development of deep learning-based hybrid recommendation method is to combine two or more recommendation systems namely the content-based recommendation methods and collaborative filtering recommendation methods are combined together benefit from their contemporary advantages. The features of the user or item learned from the different recommender systems are integrated and the recommendation process is united to form a single framework. Individual preferences of users are generated by employing the user – item matrix. Cold start and Data sparsity are the two top most traditional problems faced by the recommender systems. Apart from this, various latest issues are also identified such as reacting to the disparity of individual user context, growing user tastes or generating cross-domain recommendations.

V PERFORMANCE EVALUATION METRICS

The efficiency and effective performance of deep learning based recommender systems are assessed by means of evaluation. Different approaches are compared and assessed by utilizing predictive accuracy metrics, classification accuracy metrics and rank accuracy metrics. A perfect recommender system should predict both relevant and useful recommendations. Using a combination of multiple evaluation metrics, the performance of a model by more than just relevancy is assessed.

The predictive accuracy metrics is utilized to evaluate the accuracy of the rating predicted by the recommender system, with the actual value of that rating given by the user. Predictive accuracy metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Normalized Mean Absolute Error (NMAE). The classification accuracy metrics is used to identify how accurate the predictions made by the recommender system process for identifying and generating a right product to the right user. Precision, Recall, F1 Measure and Receiver Operating Characteristic (ROC) Curve are the metrics that comes under the Classification Accuracy category. In recommender systems, the measure that belongs to Ranking accuracy is to analyze the proximity between the ordering of predicted items by the system to the ordering of the items given by the user for the same set of items.

The M ean Squared Error (MSE) and Root Mean Squared Error (RMSE) are the most popularly used evaluation measure. The performance of various recommendation approaches are measured based on the accuracy of the predictions. Table 3 provides the various evaluation metrics of recommender systems.

Table 3: Evaluation Metrics of Recommendation Systems

Evaluation metrics		Formula	Description
Predictive / Rating Accuracy Metrics	Mean Squared Error (MSE)	MSE = $\frac{1}{n}\sum_{i=1}^{n}(p_i - r_i)^2$	yi: predicted rating of the system xi: actual user given rating for the same itm n: items in the test set that are not rated
	Root Mean Squared Error (RMSE)	RMSE = $\frac{\sqrt{\sum_{i=1}^{n}(y_i - x_i)^2}}{n}$	
	Mean Absolute Error (MAE)	MAE = $\frac{\sum_{i=1}^{n}\lvert y_i - x_i\rvert}{n}$	
	Normalized Mean Absolute Error (NMAE)		
Classification Accuracy Metrics	Precision	Precision = $\frac{tp}{tp + fp}$	TP: True Positive: remarkable items that are predicted and provided to the user TN: True Negative: unremarkable items are not predicted to the user FN: False Negative: unremarkable items are not predicted to the user FP: remarkable items that are predicted and provided to the user
	Recall	Recall = $\frac{tp}{tp + fn}$	
	F1 Measure	F1 Measure = $\frac{2 * precision * recall}{precision + recall}$	
	Receiver Operating Characteristic (ROC)	A graphical technique that uses two metrics: TPR (True Positve Rate) and FPR (False Positive Rate) TPR = $\frac{TP}{TP + FN}$ FPR = $\frac{FP}{FP + FN}$	
Rank Accuracy Metrics	Normalized Discounted Cumulative Gain (NDGC)	$NDCG = \frac{DCG}{IDCG}$ $Discounted\ CG_p = \sum_{i=1}^{p}\frac{rating_i}{\log_2(i+1)}$ $IdealDCG_p = \sum_{i=1}^{\lvert REL_p\rvert}\frac{2^{rel_i} - 1}{\log_2(i+1)}$	DCG is the Discounted Cumulative Gain rel_i is the graded relevance at position IDCG is Ideal Discounted Cumulative Gain
	Mean Reciprocal Rank (MRR)	$MRR = \frac{1}{\lvert q\rvert}\sum_{i=1}^{\lvert q\rvert}\frac{1}{rank_i}$	Q is the query $rank_i$ refers to the rank position of the first relevant document for the i-th query.
	Hit Ratio (HR)	$HR = \frac{num_{hits}}{n}$	num_{hits} is the items included in the recommended list n is the number of users
	Mean Average Precision (MAP)	$MAP = \sum_{q=1}^{Q}\frac{AveP(q)}{Q}$	Q is the number of queries

VI CONCLUSION AND FUTURE WORK

Deep learning method supports a wide range of sub domains of computer science such as NLP, image and video processing, speech recognition to collaborate with each other to solve the complexity of utilized techniques. The objective of this research to review the state of art approaches on deep learning-based recommendation system and the measures utilized in evaluating the performance of recommender system to support budding researchers to enhance a widespread knowledge of the domain. Nevertheless, deep learning can be applied to recommender systems domain in order to generate trivial and promising results, issues like accuracy, efficiency of performance and scalability are still unwrap for enhancement and guarantee future scope.

REFERENCES

1. Gheisari, Mehdi & Wang, Guojun & Bhuiyan, Md Zakirul Alam. (2017). A Survey on Deep Learning in Big Data. 173-180. 10.1109/CSE-EUC.2017.215.
2. Najafabadi, Maryam & Villanustre, Flavio & Khoshgoftaar, Taghi & Seliya, Naeem & Wald, Randall & Muharemagic, Edin. (2015). Deep learning applications and challenges in big data analytics. Journal of Big Data. 2. 10.1186/s40537-014-0007-7.
3. Deng, Li & Yu, Dong. (2013). Deep Learning: Methods and Applications. Foundations and Trends in Signal Processing. 7. 10.1561/2000000039.
4. Kumar, P & Ravichandran, Suban & Satyala, Narayana. (2018). Deep Learning Analysis: A Review. 7. 24-28.
5. Batmaz, Zeynep & Yürekli, Ali & Bilge, Alper & Kaleli, Cihan. (2018). A review on deep learning for recommender systems: challenges and remedies. Artificial Intelligence Review. 10.1007/s10462-018-9654-y.

6. Beel, J.; Genzmehr, M.; Gipp, B. (October 2013). "A Comparative Analysis of Offline and Online Evaluations and Discussion of Research Paper Recommender System Evaluation" (PDF). Proceedings of the Workshop on Reproducibility and Replication in Recommender Systems Evaluation (RepSys) at the ACM Recommender System Conference (RecSys)..
7. Bashiri, Pedram. (2018). Recommender systems: Survey and Possible Extensions. 10.13140/RG.2.2.15714.63685.
8. Burke, R. : Hybrid recommender systems: Survey and experiments. User Modeling and User-Adapted Interaction, vol. 12, pp. 331-370 (2002)
9. Adomavicius, G.; Tuzhilin, A.Toward.: The next generation of recommender systems: a survey of the state-of-the-art. IEEE Transactions on Knowledge and Data Engineering, v. 17, n. 6, p. 734-749 (2005)
10. Redpath Jennifer, Shapcott M., McClean S. and Chen L., A Study of Evaluation Metrics for Recommender Algorithms. In: The 19th Irish Conference on Artificial Intelligence and Cognitive Science. (2008)
11. Su X, Khoshgoftaar TM (2009) A survey of collaborative filtering techniques. Advances in Artificial Intelligence, 2009(Section 3), 1–19. https ://doi.org/10.1155/2009/42142 5
12. Suglia A, Greco C, Musto C, De Gemmis M, Lops P, Semeraro G (2017) A deep architecture for content-based recommendations exploiting recurrent neural networks. In: UMAP 2017—proceedings of the 25th conference on user modeling, adaptation and personalization. https ://doi. org/10.1145/30796 28.30796 84
13. Zuo Y, Zeng J, Gong M, Jiao L (2016) Tag-aware recommender systems based on deep neural networks. Neurocomputing 204(C):51–60. https://doi.org/10.1016/j.neucom.2015.10.134
14. Zhang F,YuanNJ, Lian D, XieX,MaWY(2016a) Collaborative knowledge base embedding for recommender systems. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, ACM, San Francisco, CA, USA, pp 353–362
15. Wang H,Wang N, Yeung DY (2015b) Collaborative deep learning for recommender systems. In: Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining, Sydney, NSW, Australia, pp 1235–1244
16. Da'u, A., & Salim, N. (2019). Recommendation system based on deep learning methods: a systematic review and new directions. *Artificial Intelligence Review*, 1 - 40.
17. Y. K. Tan, X. Xu, and Y. Liu, ``Improved recurrent neural networks for session-based recommendations,'' in Proc. 1st Workshop Deep Learn. Recommender Syst., Boston, MA, USA, 2016, pp. 17_22.
18. F. Strub and J. Mary, ``Collaborative filtering with stacked denoising
19. autoencoders and sparse inputs,'' in Proc. NIPS Workshop Mach. Learn.e Commerce, Montreal, QC, Canada, 2015, pp. 150_158.

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Ongoing Research Projects

- UGC-Minor Research Project (MRP) titled "Multiple Classifier for E-mail Spam Classification in a Distributed Environment for reducing Network Traffic and improving the Network Performance" for an amount of Rs.3,90,000.
- AICTE –MODEROBS (Data Analytics Tool) Rs. 2,00,000/-
- "Design and Implementation of E-Learning System using Deep Learning Based on Audio-Video Speech Recognition for Hearing Impaired in Native Language" funded by DST - ICPS , for an amount of 70,00,000/-