Proceedings of the International Conference on Artificial Intelligence and Smart Systems (ICAIS-2021)
IEEE Xplore Part Number: CFP21OAB-ART; ISBN: 978-1-7281-9537-7

A Systematic Review: Deep Learning based E-Learning Recommendation System

Mr. Roshan Bhanuse
Research Scholar, SCSE, VIT Bhopal University, Bhopal, India
Assistant Professor, Yeshwantrao Chavan College of Engineering.
Nagpur, India.
roshanbhanuse15@gmail.com

Dr. Sandip Mal
Assistant Professor, SCSE, VIT Bhopal University.
Bhopal, India
sandip.mal@vitbhopal.ac.in

2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS) | 978-1-7281-9537-7/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICAIS50930.2021.9395835

***Abstract*— Recently, there is notable development in usage of online learning resources by the learners. Increasing offerings of online materials to student creates complexity to locate particular data from data pools. Likewise, overloaded information in online makes the learner feel difficult to access needed information. The complexity is reduced with help of e-learning Recommendation System (RS). E-learning based RS try to suggest perfect learning resources to the learner depending on previous tasks done by him. High usage of internet by the learner includes more complexity to current E-learning system. Nowadays, e-learning RS depends on Deep learning technique for their progression. But still issues and challenges remains in form of accuracy, time consumption, and scalability, cold-start and data scarcity. So, in this survey, e-learning RS based on various DL approaches are reviewed. A taxonomy is created in which accounted for components needed to create efficient RS. Survey creates prominent contribution to filed e-learning RS by performing overview on current research and existing challenges.**

Keywords: Recommendation System, E-learning, Deep Learning, Cold-start, Scalability, Data Security, Taxonomy.

I. INTRODUCTION

Nowadays, internet offers numerous information to users and make them complex to choose most precise one. User might deal with numerous information, but it won't help them to take right decisions. The issue is referred as information overload. Where RS is one type of data filtering systems especially modelled to find user's preference/interest based on their requirements. RS provides list of items to users based on their past preference and needs or demographic information. RS is digital bookshelf in field of research [1]. RS is used in various areas like e-learning [2], products [3], social tags [4], music [5], research articles, books [6], news movies [7] and e-commerce . Intention of RS is to examine user data and mine needed data for further detection.

Learning is drastically shifted from traditional classroom to e-learning environment. E-learning is stated as learning with use of electronic media especially with use of internet. Main intention of extracting information from educational background is to find student's performance and to group them based on their similarities. It is helpful to determine student's undesirable behavior and suggest according to them. The way of extracting hidden information is most necessary for e-learning. Educational data mining (EDM) is an umbrella which also includes RS. Extracting current academic data for analysis and recommending course is called as EDM. LA (Learning Analytic) collects academic related data from various sources. Furthermore, needful data is mined from gathered data. LA and EDM contributes to e-learning RS. Figure 1 illustrates relationship between, 1). Extracting educational data, 2). Using LA by academician to find knowledge, 3). Create suggestion to learners.

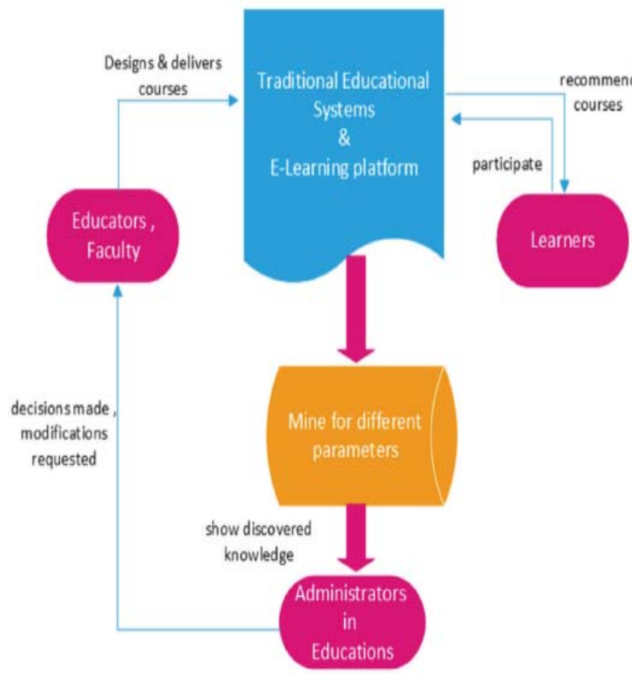

Fig. 1. E-Learning RS

In field of e-learning, RS would offer recommendation for activities related to learning modules. Task of e-learning RS is to suggest related learning materials to learner and supports them in taking right decision [8]. E-learning RS is one of information retrieval method which is used to filter and extract learning resources for learners. RS provide personalized suggestion for learning material depending on every individual's learning path or learning interest in online learning system and also creates user rating resource matrixes [9, 10]. Important advantage of e-learning are flexibility in time, free qualified resources, and interest of learner.

This paper provides review of existing RS on e-learning with DL algorithm. RS is an e-learning environment which tries to perfect suggestion to learners depending on their previous learners' tasks. Recommendation seekers are considered as users. User can directly request for recommendations. User could also give their interest or RS explicitly request for user's preference from them. On basis of interest given by target user and other similar users, the system would provide suggestion to the user. From the suggested list, user can choose the items.

II. BACKGROUND WORK

Previously, internet has proved it rapid growth for learning resources. The expansion of learning resources over internet have speed-up extension of internet for online learning resources by learners in e-learning platform. The increased web dependent learning resources, user experience risk in making decision which is most important and relevant to their learning preference. RS resolve this problem by cleaning unnecessary learning resources and also suggest appropriate resources to learners based on their interest automatically. E-learning RS suggest task to learner based on their efforts and success undertaken by the learner. Certainly its new way to bring education in life compared to conventional learning system. E-learning RS recommends online learning objects to learner depending on learner's interest. Similarity among learners are grouped depending on their general previous access pattern.

III. RECOMMENDATION TECHNIQUES

There are seven recommendation approaches they are as follows:

A. Content Based Recommendation (CB)

Content Based Recommendation method depends on comparison of learner profile and learning object. For instance, collecting content information related to author, title, rate, etc. for books. Content information could fulfill gap among available and new learners and learning objects. There are two types of CB recommendation they are:

- Case dependent reasoning method
- Attribute dependent method

B. Case dependent reasoning method

It suggests learning objects which are in high association with objects which is liked by the learner previously. The method won't need content analysis. Quality of recommendation gets increased when learner rates with numerous learning objects. New learners address certain problem. Limitation is over specification, since it suggests only learning objects which are in high association with learner interest or profile.

C. Attribute dependent method

It suggests learning objects depending on connection of attributes to learner profile. It is sensitive to make modification over learner profile. Addition of new learner won't cause any issue. Limitation is static and wont study from network's behavior. It can manage cold-start issue since it directly links characteristics of learners to learning attribute. It does not require behavior of data.

D. CF (Collaborative Filtering)

It is one of broadly utilized technique in data mining. This technique depends on guess that similar users has similar interest. For instance, Amazon is a famous e-commerce site utilize its own RS. When product selected to buy, Amazon suggest a list of products purchased by other users. The method gathers similarities among learners and then provide new suggestion list depending on inter-learner comparison. Learner profile contains vector of learning objects and their rating. Where rating denote degree of user's interest. It might be real-value or binary. Collaborative recommendations are of two classes they are:

- Model-dependent recommendation
- Memory dependent recommendation

Memory dependent technique is categorized to item based and user based. User-dependent model means learner with similar behavior/preference. Lastly, it produces list of suggestion for the target learner. Item-dependent design finds set of learning object which is similar to interest of target learner's object. Then learning object's similarity is determined to suggest most common object as target object which have high rating within learning object.

Model dependent technique provides suggestion by examining statistical design for learner ratings. Probabilistic technique is utilized to find probability that learner would provide rating to novel learning object depending on object's previous rating. One constraint of CF is the cold-start issue where availability of learners and learning objects is possible deprived of rating.

E. Demographic Recommendation

Demographic Recommendation categorize learners depending on their personal characteristics and suggestion depends on demographic classes. It depends on assumption that entire learners belong to some demographic classes which has alike preference. It utilizes demographic data of learners and also utilize learner's viewpoint for suggesting learning objects. It creates people – people relationship like CB technique. But they utilize varied data. Let us consider an instance, if U1 (age of 21, male) purchase object X and Y from website, then U2 (female, age of 23) purchase object X, Y and Z from same website and U3 (male, age of 20) purchase object X and Q from same website. Now U1 needs to purchase object from suggested object. He would obtain suggestion for object Q depending on his demographic information because U3 and U1 belongs to same age and would have bought object of similar preference. In machine learning system, demographic data were utilized to reach classifier. Advantage considered as it's independent of history of learners rating.

F. Knowledge-dependent Recommendation

The RS tries to propose items depending on learner's preference and requirement. It includes information about how particular learning object satisfies particular learner requirements. It shows relationship between requirements and achievable suggestions. Learner profile could be of any information structure which must support the conclusion.

The method gathers information about learning object and learners to be utilized them within recommendation activity. It won't depend on learners rating. For instance, cars have various models, interior option, engine option and colors, and interest of users might be measured by very precise combination of these options. In the situation, time domain is difficult for various properties, and it's difficult to associate necessary ratings with huge number of mixtures at hand. It will not gather data for particular learner since institution wont depends on particular preferences. The method fit for hybridization with other recommendation methods for e-learning RS. One the restriction of the technique is needs knowledge acquisition.

G. Hybrid RS

It is a collaboration of two and more recommendation methods. Based on characteristic of data and domain, various hybridization techniques were utilized to combine CB and CD recommendation method to produce various output. Broadly utilized hybrid method is provided by combination of CB and CD recommendation technique. CD recommendation depends on similarity among access patterns of similar learners and learner's navigation path. Content dependent recommendation depends on correlation among content of learning object and learner's preference. Hybrid recommendation technique attempts to overcome all restrictions in every other method and also discover new domain to predict something which is interesting to learners.

H. Ontology-dependent Recommendation

It is an explicit description of conceptualization. It contains relationship, attributes, and entities. Ontology is utilized to design information about user background, domain, and item. Utilization of ontology could efficiently enhance personalized recommendation's quality. Ontology was utilized to design domain information about learner and learning objects. Learner model ontology consist of learner's knowledge level, learning style and personal information. Learning object ontology consist of resource format and types. Personalization through ontology offers most customized recommendations to target learner's interest. Ontology dependent recommendation will not experience any problems like traditional RS. It is based on domain knowledge not on rating. But one disadvantage is ontology construction is complex, costly and time taking process.

1. *Data used in RS.*

RS are data dependent, so data are gathered explicitly or implicitly. Implicit data are raw data which are classified into two types they are: 1. Data collected from existing data stream like keystroke log, users click and search key. 2. Exhaust data refers to by-product of activities of users which could or couldn't be utilized [18]. Explicit data are gathered from profile information or registration forms given by the users. Similarly explicitly data can also be gathered from rating given by users in the online [19]. All these data combine together to form input data for design, which are developed with help of DL techniques to determine user's preference, where accuracy of prediction is based on volume and data quality [20]. Currently for processing data RS dependent on DL architecture offers strong structure for supervised learning [21].

2. *Deep Learning in RS*

[22] predicts "core parametric function approximation" as basic technology for FDN (Feed Forward Deep Network). FDN are utilized as building block for several modern Neural Network like (CNN).

Convolutional Neural Network, RNN (Recurrent Neural Network), DBN (Deep Belief Network), etc. These systems are broadly utilized in various industries, especially for NLP (Natural Language Processing) and speech Recognition and also utilized in RS [23]. [24] facilitates examination of user's interest and match result to current information to capture historical impact on current user decision. In [22] best result was obtained with supervised learning depending on supervised regression and classification, with known set of labels and techniques like logistic regression, Bayesian classifiers, rules, decision tree and KNN. Unsupervised classification mines labels from clustering techniques like Bayesian non-parametric, message parsing, hierarchy-dependent metrics or density, k-means, or association rules. [22] claims that though there is development of numerous algorithms to overcome problem of "high dimensionality of random variable", unsupervised learning remains infancy. However, both training approaches were utilized to design RS.

3. *Recommender System Evaluation*

Previous section clearly says that algorithm and architecture play significant role for designing RS. Decision for designing was made depending on evaluation metrics, performance and experiments which provide ranking for algorithm [25, 26]. There are three kinds of experiments for evaluation of RS they are: user studies, offline and online. Offline experiments utilize available protocols and datasets which replicates activities of users and also finds prediction's accuracy. User studies depends on RS with restricted users with their feedbacks. Online trials examine real time usage of RS [25, 26].

Algorithm and system were chosen depending on evaluation metrics. Generally utilized evaluation metrics are F-score, Mean Absolute Error, (RMSE) Root Mean Squared Error, Precision and Recall [27]. Recall examines user interest depending on RS recommendations, larger recall value result in most specific recommendations. Whereas precision measures percentage of user's preference, high value of precision results in qualified recommendations. RMSE finds error in determined rating which must be low[28, 29].

Previous work provides overview of recent recommendation techniques for e-learning system based on DL architecture.

Success of RS is based on training technique such as unsupervised or supervised, an innovative technique to model algorithm which breaks "box-like" of CNN, evaluation, validation, accuracy of datasets and area of application.

Table 1: Comparison of various Techniques of Recommendation

Technique	Description	Benefits	Limitation
Ontology-dependent recommendation.	Focusing on RS without ontology in e-learning and hybrid RS with ontology in e-learning. Ontology takes various forms based on the context. Using the Web Ontology language compared with other languages the ontology representing the XML scheme in database context.	Enhance quality of personalized recommendation. Traditional recommender system limitations overcame. Time-consuming Better performance in hybrid recommender system.	Need for domain knowledge. Identifying the correct recommendation approach combination and estimating the performance is difficult in case of hybrid recommendation-based ontology.
Context aware recommendation.	The recommendation provider for gathering the contextual data and feedback data from sensor and learner application module.	Recommendations can be adjusted based on context	Integrate contextual information
Hybrid filtering.	Book recommendation systems based on hybrid approach comprised of collaborative and content-based predictions and effective combination resulted.	No cold start issue is seen. Combined the Spark big data platform and obtains the personalized book recommendation and further utilization rate is enhanced.	Time complexity issue is seen.
Knowledge dependent recommendation.	Reviewed and divided the techniques based on knowledge dependent recommendation and ontology-based recommendation.	It is not based on user ratings. Effectiveness enhanced by using the hybrid recommendations.	Knowledge acquisition challenges.
Demographic recommendation.	Financial planning and for that recommendation process has to modify and improved in better way.	IT does not need rating history of particular learner. For various online and offline applications this system has used.	Learner must retrieve personal attributes.
Collaborative filtering recommendation.	Various algorithmic methods highlighted which is utilized to enhance information retrieval to gives learner an efficient recommendation by satisfaction level and performance improvement.	Domain knowledge is not required. Effectiveness obtained by improved information retrieval.	Effective utilization of recommender system is not seen in case of comparisons with other domains. Over specification
CD recommendation.	For generating recommendation, potential items have been compared with the rating items for determining the matching of the item. The user interest is oriented on the features based on objects rated.	No need of domain information	Few challenges such as scalability, data sparsity, cold-start issue.

4. *Research in CB RS*

CB recommendations depends on previous interest of users, where suggestions were done to users with similar dislikes and likes. For learning domain, [30] utilized correlation examination to gather courses related learning. They created 3 types depending on 'rule-space' design following CB to receive learning objects for every skill group and the enhanced learning path order for every learner. Similarly [31] created rule-dependent adaptive UI (User Interface) to offer learning components and to recommend learning objects to learners, depending on set of rules. Figure 2 illustrates architecture of CB RS which have three components such as: filtering component, profiler learner and content analyzer [32] where content analyzer gathers item's content from various information sources and mines item representation with help of feature extraction methods. Profile learner use DL method to item illustration and simplify user data to develop user profile depending on past dislikes and likes. Finally, filtering component match user profile with items to be suggested.

[33, 34] used history of student data to determine learning material with help of CB algorithm. [35] depends on decision tree and fuzzy clustering method to categorize learners into master, intermediate and beginner depending on their learning behavior and academic records. This facilitates RS to suggest learner-centered material on e-learning platform. [36] created novel technique for utilizing link data and social network interaction with help of CB technique to suggest suitable online resources. Most general learning algorithm like fuzzy-dependent and rule-dependent clustering methods depends on probabilistic technique, k-nearest neighbor, and relevance feedback. There are some limitations with CB method that it relays on previous user experience and won't suggest novel material which might

minimize motivation of user and leads to undesirable narrow focus. This represents that CB not able to overcome accuracy, time consumption, scalability, cold-start and data scarcity.

5. *Research on CF*

CF is one of famous recommendation method and numerous RS was created depending on this technique and it overcomes CB technique's limitation [37, 38]. CF depends on users. It suggest products liked by similar kind of users and discovers various feasible content [39]. By retrieving learner profile, RS could easily retrieve data about past learning activity, country, educational background, age, etc. With these data, RS could determine learners with similar learning interest and recommends appropriate learning material [40]. CF algorithms determine prediction rating or sometime suggest a list with top M number of items as illustrated in figure 3.

As depicted in figure 3, 'b' denotes 1st actor of CF system who is an active user, needs rating. Here, correlation was assumed with help of previous preferences between users. Depending on this, CF will develop suggestion to 'b' depending on interest of corresponding users. Generally, CF system would have m users V = {v1, v2, …vm}and m items Q={q1, q2,….qm}. System formulates nYm user-item matrix including user rating per item where user entry sj, i denotes rating provided by user vj for item qi. To obtain suggestion for 'b' for target item p, CF algorithm would find rating for 'p' or develop list of most interested top M number of items. [41] introduced CF depending on behavior of e-learning group which enhance recommendation's accuracy even in data sparsity [39]. Depending on CF recommendation model, [40] introduced noise management method and problem matrix which develop specific neighborhood and accurate suggestions. CF was used with sequential structure mining to create score design to gather feedback and preference of learners to weigh the learning objects and develop suitable one in RS created by [27]. Similarly, [42] utilized sequence behavior pattern to find learning style of user [43]. [44] followed CF method with use of k-mean algorithm for unsupervised learning design to mine learning sequence and also map learning objects with respect to the learner style.[46] had implemented novel creativity in CF depending on confidence relationship of target users with the neighbor to receive suggestion list with use of harmonic parameter and user-item rating matrix [47, 48]. However, model-dependent factorization matrices will not combine context with models. To resolve this problem, [49] presented multi-dimensional trust model depending on tensor factorization which consider learner's past history, rating dependent on behavior and viewing structure to share online materials. [50] developed his work depending on genetic algorithm following CF method to create optimal learning path for learners with use of variable length genetic algorithm. [51] presented deep belief network with online course to improve efficiency of learners with use of prediction rating [52]. Constraints of CF method is its complex to attach attributes to items, sometime which might lead to unclear suggestion. It's also consumes more time for an item to get necessary ratings to give perfect suggestions, which is also because of issues like data sparsity, scalability and cold start. CF by its own wont function as satisfactory component of effective RS. [53] finds relationship among activity of students with help of association rule technique in a way to support student to select more suitable learning materials. Extracted rules was utilized to determine catalog of most appropriate course with respect to interest and behavior of learners. Here FP growth algorithm offered by spark framework and Hadoop ecosystem was utilized. Figure 4 depicts RS for e-learning, it consists of 3 layers. 1st, storage, and replication layer denoted by HDFS. Where HDFS (Hadoop Distributed File System) [54] is file system utilized to manage data over huge cluster with master/slave architecture. In 2nd layer, Yarn [55] is utilized as cluster resource manager of nodes. Where Yarn is structure for cluster resource management and job scheduling. The topmost layer is spark, which was responsible for data processing and examining. Where Apache spark [56] is a structure utilized for processing of distributed big data. This work utilized (JDBC) spark SQL and (parallel FP-growth) MLlib libraries of spark framework.

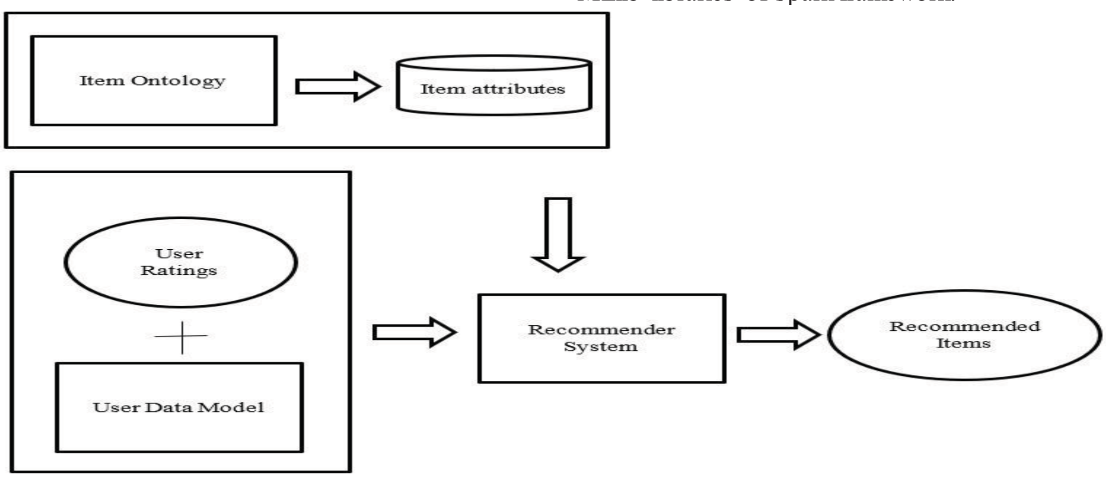

Fig. 2 High Level of Architecture for Content-dependent RS [32]

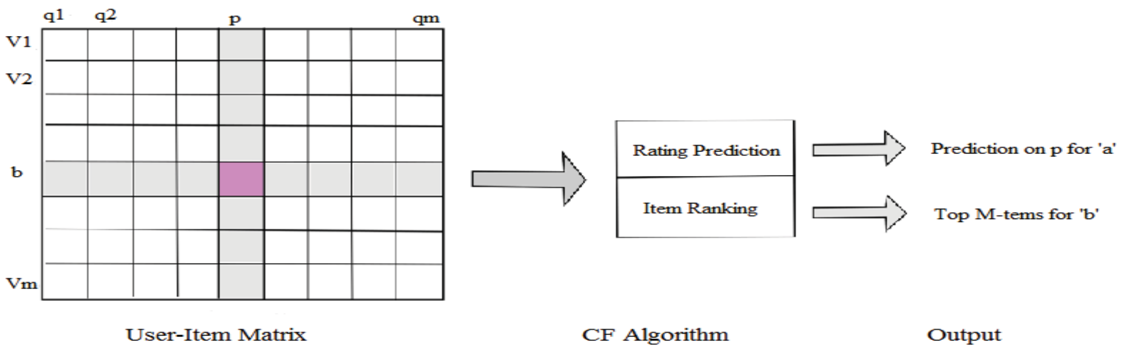

Fig. 3. CF dependent RS [45]

[46] had implemented novel creativity in CF depending on confidence relationship of target users with the neighbor to receive suggestion list with use of harmonic parameter and user-item rating matrix [47, 48]. However, model-dependent factorization matrices will not combine context with models. To resolve this problem, [49] presented multi-dimensional trust model depending on tensor factorization which consider learner's past history, rating dependent on behavior and viewing structure to share online materials. [50] developed his work depending on genetic algorithm following CF method to create optimal learning path for learners with use of variable length genetic algorithm. [51] presented deep belief network with online course to improve efficiency of learners with use of prediction rating [52]. Constraints of CF method is its complex to attach attributes to items, sometime which might lead to unclear suggestion. It's also consumes more time for an item to get necessary ratings to give perfect suggestions, which is also because of issues like data sparsity, scalability and cold start. CF by its own wont function as satisfactory component of effective RS.

Recommendation System based on Sentiment Analysis

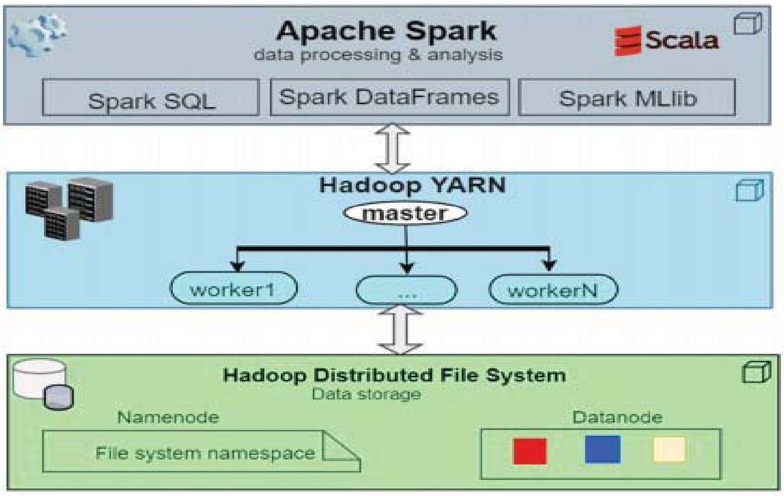

Fig. 4. Distributed Environment for E-learning RS [53]

[53] finds relationship among activity of students with help of association rule technique in a way to support student to select more suitable learning materials. It also concentrates on examining history of previous data of log data or course enrollments. This research mainly discusses frequent item sets to find rules in transaction database. Then extracted rules was utilized to determine catalog of most appropriate course with respect to interest and behavior of learners. Here FP growth algorithm offered by spark framework and Hadoop ecosystem was utilized. Figure 4 depicts RS for e-learning, it consists of 3 layers. 1st, storage, and replication layer denoted by HDFS. Where HDFS (Hadoop Distributed File System) [54] is file system utilized to manage data over huge cluster with master/slave architecture. In 2nd layer, Yarn [55] is utilized as cluster resource manager of nodes. Where Yarn is structure for cluster resource management and job scheduling. The topmost layer is spark, which was responsible for data processing and examining. [56] Introduced an intelligent RS (Recommender System) by utilizing a strategy named split-and-conquer which rely on clustering. It has the ability to automatically adapt to the interests, requirements, and knowledge levels of the learners.

IV. CHALLENGES & ISSUES

Recommendation technique had been successful in previous years but because of vast usage have addressed few challenges they are:

i. Cold-start Issue

This issue is mainly addressed by new item or users. This issue arises because of primary lacking rating, which means new user might not have rated any item or any new item might not have been rate by any users. Hence this case becomes impossible to create best recommendations.

New users: when new user enter a system, he won't have made any rating to an items/object so its complex to find item for new user since it needs history of rating done by users to find similarity, which is used to predict neighbors. In this case, suggestion is provided based on rating given by target user and other users. User with minimum rating are complex to classify. New item: whenever new items are launched, it addresses cold-start issue since it doesn't have sufficient previous rating.

ii. Data Sparsity

It occurs when learning object have least rating compared to existing number of learning objects. If learning object have least rating, then it's difficult to provide suitable recommendation list to target user. Data sparsity is because of the learner who doesn't rate existing learning objects. It creates negative impact on CB recommendation method, since CB recommendation depends on similarity.

iii. Scalability

With increase in learning objects and learners, traditional CB recommendation would suffer serious scalability problem. But in CB based RS, increased number of learning object and learner result in inaccurate recommendation list.

iv. Over Specialization

This is one of major issue addressed by CB RS. It is insufficient to suggest alternate learning objects. Learners are suggested with learning objects who are previously known with it. It avoids learner in determining novel learning objects and its alternatives. Extra method must be added with system to provide recommendation outside choice of learner's preference. By combining additional techniques, learners would be provided with set of options.

v. Privacy

Privacy is a major problem with demographic recommender. In a way to provide most accurate suggestion to learner, it requires personal data from the learner. Personal data includes location, position, and time of learner which might breach privacy of learner.

V. CONCLUSION AND DISCUSSION

A RS attempts to suggest actions which are advantageous to users. Growth of comfortable e-learning platform offers education path to learners. According to e-learning, RS attempts to provide suggested learning objects to learner depending on previous activity of learner. This paper reviews different recommendation techniques utilized for e-learning environment and also discussed its benefits and constraints.

With enhancement of e-learning platform, personalization has become important feature in e-learning. This is because of dissimilarities in goals, capabilities, and backgrounds of learners. It has various other merits. They are, it minimizes the difficulties in feature design that are hand crafted. It permits the recommendation models (RM) to incorporate heterogeneous content such as images, audio, text, images and video. Personalization is attained with use of recommendation technique, user models and heuristic rules. Additionally, future work concentrates on using auto-encoder with RS to improve accuracy and performance. E-Learning RS (Recommendation System) have to be developed by utilizing trust and several other aspects in the near future.

REFERENCES

[1] V. Gupta and S. R. Pandey, "Recommender Systems for Digital Libraries: A review of concepts and concerns," *Library Philosophy and Practice,* pp. 1-9, 2019.

[2] M.-I. Dascalu, C.-N. Bodea, M. N. Mihailescu, E. A. Tanase, and P. Ordoñez de Pablos, "Educational recommender systems and their application in lifelong learning," *Behaviour & information technology,* vol. 35, pp. 290-297, 2016.

[3] S. Akram, S. Hussain, I. K. Toure, S. Yang, and H. Jalal, "ChoseAmobile: A Web-based Recommendation System for Mobile Phone Products," *Journal of Internet Technology,* vol. 21, pp. 1003-1011, 2020.

[4] M. Pennacchiotti and S. Gurumurthy, "Social media user recommendation system and method," ed: Google Patents, 2020.

[5] R. Wang, X. Ma, C. Jiang, Y. Ye, and Y. Zhang, "Heterogeneous information network-based music recommendation system in mobile networks," *Computer Communications,* vol. 150, pp. 429-437, 2020.

[6] G. Ramakrishnan, V. Saicharan, K. Chandrasekaran, M. Rathnamma, and V. V. Ramana, "Collaborative Filtering for Book Recommendation System," in *Soft Computing for Problem Solving*, ed: Springer, 2020, pp. 325-338.

[7] S. Kumar, K. De, and P. P. Roy, "Movie recommendation system using sentiment analysis from microblogging data," *IEEE Transactions on Computational Social Systems,* 2020.

[8] J. Aguilar, P. Valdiviezo-Díaz, and G. Riofrio, "A general framework for intelligent recommender systems," *Applied computing and informatics,* vol. 13, pp. 147-160, 2017.

[9] J. Xiao, M. Wang, B. Jiang, and J. Li, "A personalized recommendation system with combinational algorithm for online learning," *Journal of Ambient Intelligence and Humanized Computing,* vol. 9, pp. 667-677, 2018.

[10] A. Klašnja-Milićević, M. Ivanović, B. Vesin, and Z. Budimac, "Enhancing e-learning systems with personalized recommendation based on collaborative tagging techniques," *Applied Intelligence,* vol. 48, pp. 1519-1535, 2018.

[11] G. George and A. M. Lal, "Review of ontology-based recommender systems in e-learning," *Computers & Education,* vol. 142, p. 103642, 2019.

[12] S. A. Moghaddam and E. M. Tapia, "Context-aware recommendation system for adaptive learning," ed: Google Patents, 2018.

[13] Y. Tian, B. Zheng, Y. Wang, Y. Zhang, and Q. Wu, "College library personalized recommendation system based on hybrid recommendation algorithm," *Procedia CIRP,* vol. 83, pp. 490-494, 2019.

[14] J. K. Tarus, Z. Niu, and G. Mustafa, "Knowledge-based recommendation: a review of ontology-based recommender systems for e-learning," *Artificial intelligence review,* vol. 50, pp. 21-48, 2018.

[15] N. Pereira and S. L. Varma, "Financial Planning Recommendation System Using Content-Based Collaborative and Demographic Filtering," in *Smart Innovations in Communication and Computational Sciences*, ed: Springer, 2019, pp. 141-151.

[16] Z. Gulzar, L. A. Raj, and A. A. Leema, "Towards Increasing the Efficiency of E-Learning Systems Using Recommendation System Approach," in *Utilizing Educational Data Mining Techniques for Improved Learning: Emerging Research and Opportunities*, ed: IGI Global, 2020, pp. 35-55.

[17] V. Lytvyn, V. Vysotska, V. Shatskykh, I. Kohut, O. Petruchenko, L. Dzyubyk, *et al.*, "Design of a recommendation system based on collaborative filtering and machine learning

considering personal needs of the user," *Восточно-Европейский журнал передовых технологий,* pp. 6-28, 2019.

[18] R. Lovelace, "Book Review: The Data Revolution: Big Data, Open Data, Data Infrastructures and Their Consequences, by Rob Kitchin," *Journal of Regional Science,* vol. 56, pp. 722-723, 2016.

[19] T.-C. Huang and Y.-M. Huang, "Where are my cooperative learning companions: designing an intelligent recommendation mechanism," *Multimedia Tools and Applications,* vol. 76, pp. 11547-11565, 2017.

[20] T. Horváth and A. C. de Carvalho, "Evolutionary computing in recommender systems: a review of recent research," *Natural Computing,* vol. 16, pp. 441-462, 2017.

[21] A. Singhal, P. Sinha, and R. Pant, "Use of deep learning in modern recommendation system: A summary of recent works," *arXiv preprint arXiv:1712.07525,* 2017.

[22] I. Goodfellow, Y. Bengio, and A. Courville, "Deep feedforward networks," *Deep learning,* pp. 168-227, 2016.

[23] S. Zhang, L. Yao, A. Sun, and Y. Tay, "Deep learning based recommender system: A survey and new perspectives," *ACM Computing Surveys (CSUR),* vol. 52, pp. 1-38, 2019.

[24] D. Z. Liu and G. Singh, "A recurrent neural network based recommendation system," *tech. rep., Stanford University,* 2016.

[25] C. C. Aggarwal, "An introduction to recommender systems," in *Recommender systems*, ed: Springer, 2016, pp. 1-28.

[26] C. C. Aggarwal, "Evaluating recommender systems," in *Recommender systems*, ed: Springer, 2016, pp. 225-254.

[27] O. Bourkoukou, E. El Bachari, and M. El Adnani, "A recommender model in e-learning environment," *Arabian Journal for Science and Engineering,* vol. 42, pp. 607-617, 2017.

[28] S. Bhaskaran and B. Santhi, "An efficient personalized trust based hybrid recommendation (tbhr) strategy for e-learning system in cloud computing," *Cluster Computing,* vol. 22, pp. 1137-1149, 2019.

[29] L. Krithika and L. P. GG, "Student emotion recognition system (SERS) for e-learning improvement based on learner concentration metric," *Procedia Computer Science,* vol. 85, pp. 767-776, 2016.

[30] Y.-H. Chen, C.-H. Tseng, C.-L. Huang, L. Y. Deng, and W.-C. Lee, "Recommendation system based on rule-space model of two-phase blue-red tree and optimized learning path with multimedia learning and cognitive assessment evaluation," *Multimedia Tools and Applications,* vol. 76, pp. 18237-18264, 2017.

[31] S. V. Kolekar, R. M. Pai, and M. P. MM, "Rule based adaptive user interface for adaptive E-learning system," *Education and Information Technologies,* vol. 24, pp. 613-641, 2019.

[32] S. S. Khanal, P. Prasad, A. Alsadoon, and A. Maag, "A systematic review: machine learning based recommendation systems for e-learning," *Education and Information Technologies,* pp. 1-30, 2019.

[33] J. Shu, X. Shen, H. Liu, B. Yi, and Z. Zhang, "A content-based recommendation algorithm for learning resources," *Multimedia Systems,* vol. 24, pp. 163-173, 2018.

[34] L. Tian, C. Fan, and Y. Ming, "Multiple scales combined principle component analysis deep learning network for face recognition," *Journal of Electronic Imaging,* vol. 25, p. 023025, 2016.

[35] M. M. Rahman and N. A. Abdullah, "A personalized group-based recommendation approach for Web search in E-learning," *IEEE Access,* vol. 6, pp. 34166-34178, 2018.

[36] C. K. Pereira, F. Campos, V. Ströele, J. M. N. David, and R. Braga, "BROAD-RSI–educational recommender system using social networks interactions and linked data," *Journal of Internet Services and Applications,* vol. 9, p. 7, 2018.

[37] Y. Zhou, C. Huang, Q. Hu, J. Zhu, and Y. Tang, "Personalized learning full-path recommendation model based on LSTM neural networks," *Information Sciences,* vol. 444, pp. 135-152, 2018.

[38] D. Wang and M. Li, "Stochastic configuration networks: Fundamentals and algorithms," *IEEE transactions on cybernetics,* vol. 47, pp. 3466-3479, 2017.

[39] J.-w. Han, J.-c. Jo, H.-s. Ji, and H.-s. Lim, "A collaborative recommender system for learning courses considering the relevance of a learner's learning skills," *Cluster Computing,* vol. 19, pp. 2273-2284, 2016.

[40] R. Yera and L. Martínez, "A recommendation approach for programming online judges supported by data preprocessing techniques," *Applied Intelligence,* vol. 47, pp. 277-290, 2017.

[41] X. Liu, "A collaborative filtering recommendation algorithm based on the influence sets of e-learning group's behavior," *Cluster Computing,* vol. 22, pp. 2823-2833, 2019.

[42] S. Fatahi, F. Shabanali-Fami, and H. Moradi, "An empirical study of using sequential behavior pattern mining approach to predict learning styles," *Education and Information Technologies,* vol. 23, pp. 1427-1445, 2018.

[43] H. M. Truong, "Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities," *Computers in human behavior,* vol. 55, pp. 1185-1193, 2016.

[44] M. M. El-Bishouty, A. Aldraiweesh, U. Alturki, R. Tortorella, J. Yang, T.-W. Chang*, et al.*, "Use of Felder and Silverman learning style model for online course design," *Educational Technology Research and Development,* vol. 67, pp. 161-177, 2019.

[45] Z. Batmaz, A. Yurekli, A. Bilge, and C. Kaleli, "A review on deep learning for recommender systems: challenges and remedies," *Artificial Intelligence Review,* vol. 52, pp. 1-37, 2019.

[46] L. Guo, J. Liang, Y. Zhu, Y. Luo, L. Sun, and X. Zheng, "Collaborative filtering recommendation based on trust and emotion," *Journal of Intelligent Information Systems,* vol. 53, pp. 113-135, 2019.

[47] G. Guo, J. Zhang, and N. Yorke-Smith, "A novel recommendation model regularized with user trust and item ratings," *ieee transactions on knowledge and data engineering,* vol. 28, pp. 1607-1620, 2016.

[48] R. Wang, Y. Jiang, Y. Li, and J. Lou, "A collaborative filtering recommendation algorithm based on multiple social trusts," *Journal of Computer Research Device,* vol. 53, pp. 1389-1399, 2016.

[49] S. Kim and Y. Yoon, "Recommendation system for sharing economy based on multidimensional trust model," *Multimedia Tools and Applications,* vol. 75, pp. 15297-15310, 2016.

[50] P. Dwivedi, V. Kant, and K. K. Bharadwaj, "Learning path recommendation based on modified variable length genetic algorithm," *Education and Information Technologies,* vol. 23, pp. 819-836, 2018.

[51] H. Zhang, T. Huang, Z. Lv, S. Liu, and H. Yang, "MOOCRC: A highly accurate resource recommendation model for use in MOOC environments," *Mobile Networks and Applications,* vol. 24, pp. 34-46, 2019.

[52] P. Holtz, J. Kimmerle, and U. Cress, "Using big data techniques for measuring productive friction in mass collaboration online environments," *International Journal of Computer-Supported Collaborative Learning,* vol. 13, pp. 439-456, 2018.

[53] K. Dahdouh, A. Dakkak, L. Oughdir, and A. Ibriz, "Large-scale e-learning recommender system based on Spark and Hadoop," *Journal of Big Data,* vol. 6, p. 2, 2019.

[54] S. Bende and R. Shedge, "Dealing with small files problem in hadoop distributed file system," *Procedia Computer Science,* vol. 79, pp. 1001-1012, 2016.

[55] A. Hadoop, "Apache Hadoop & YARN," ed: The Apache Software Foundation, http://hadoop. apache. org/docs/current …, 2016.

[56] V. Suma and S. M. Hills, "Data Mining based Prediction of Demand in Indian Market for Refurbished Electronics," *Journal of Soft Computing Paradigm (JSCP),* vol. 2, pp. 153-159, 2020

.[57] Sandip Mal and Kumar Rajnish, "New Quality Inheritance Metrics for Object-Oriented Design", International Journal of Software Engineering and Its Applications, Scopus, Vol.7, No.6,pp.185-200,2013.

[58] Sandip Mal and Kumar Rajnish, Sanjeev Kumar, "Package Level Cohesion Metric for Object-Oriented Design", International Journal of Engineering and Technology (Engineering Journal publishers),Vol-5, No.3, PP: 2523-2528, 2013.

[59] Sandip Mal and Kumar Rajnish, "New Class Cohesion Metric: An Empirical View", International Journal of Multimedia and Ubiquitous Engineering, Vol.9, No.6, pp.367-376, 2014

[60] Sandip Mal and Kumar Rajnish, "Validation of new cohesion metric against Braind properties", Advances in Intelligent Systems and Computing Vol: 243, PP: 591-597, Springer, 2014.