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Trusted Knowledge Infusion Model-based Recommender System for IoT based B2B applications

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Abstract— The exponential growth and usage of Internet, social sites, and e-commerce results extensive amount of information everywhere. It becomes very difficult for the people to search something, so they go for the offered suggestions which are pertinent for them rather than searching from a potentially overwhelming number of options. Recommender Systems are the solutions for such difficulties. There are many powerful Recommender Systems available for e-commerce, websites, books, tourism, and documents, but recommendations for IoT-based applications need of new discoveries. Traditional recommendations methods are not sufficient for big data based scalable and heterogeneous IoT environment. In this paper, we propose a knowledge infusion model-based hybrid recommendation model for IoT-based B2B applications. The proposed model is analyzed with a real dataset, and the evaluation represents that model performs well in terms execution time, RMSE, precision and F1-score as compared with the existing models.

Keywords- Recommender System, Internet of Things, IoT Recommender system, Business to Business services, Knowledge infusion

I. INTRODUCTION

The amount, volume and complexity of data generated at every second, delivers information overload problem. Luckily, Recommender systems (RS) are performing a major role to cop the information overloading problem by offering personalized information to the users. The evolution of recommender systems can be divided into three generations, which are RS for handling e-commerce data, RS to handle social-aware data and RS to grip IoT data. As the applicability of IoT environment is everywhere, so it can be the source of rich information to develop a productive and diverse recommender system compatible for IoT scenario. IoT is the network of everything, which results heterogeneous and integral relations between entities, things, data, and information. The conduction of IoT based recommender system is very crucial.

Recommender Systems relates to information filtering and retrieval systems, typically developed to make suggestions that can be refer to any decision-making process. RS are useful when an individual wants to take a decision, such as what to order to eat, what product to buy, what book to read, what video or movie to watch, what music to listen, what app to install etc. Sometimes users even do not clear understanding about their needs and choices. But RS can help the users by studying their interesting patterns, history preferences and behavior. Recently RS acquire knowledge by processing real time data to generate accurate, diverse, and productive suggestion. There are many popular Recommender systems, which are deploying their services in many application areas like social media, e-commerce, online dating, financial services, OTT (over-the-top) platforms. Recommender systems can also be of type proactive and post active. Proactive RS suggest items without explicit user request and post active RS needs explicit request. In recent years, requirement and awareness of recommender systems has increased significantly. RS has proved their significance in online commercially business by uplifting their profit statistics and by improving customer satisfaction. In E-commerce most of the recommendation techniques are designed and developed for Business to Customer (B2C) environment. But for Business to Business (B2B) application models there are very less developed recommendations techniques that can enrich the suggesting options for Buyer-Supplier matching. RS can be an assistance tool for supply chain management and for matching buyers and supplier business partners. This can be helpful for business integration and for business intelligence. This demands researches to develop a scalable, powerful, and intelligent recommendation techniques that can cop up with the issue of Buyer-Supplier management. Machine learning technologies-based RS for B2B can give greater result and performances.

Basically, RS are categorized into two categories: content-based RS and collaborative filtering (CF) RS. Content-based RS use the filtering algorithms on user history profile that reflect user's interest and item description profile. Item description profile includes the similar item identified by the similarity measures like Cosine Similarity or Pearson co-efficient. After recommendation user get a list of suggested items which are alike the consumed items. These methods have restricted ability to expand or scale. Collaborative-filtering techniques gather the data about user's identity and behavior, analyze that to predict similar users' group. Recommendation list in this method is prepared by including the consumed items by the similar users' group members. CF-approaches are classified in model and memory-based approaches. In memory-based methods similarity between items or users is calculated by analyzing user rating matrix. This algorithm realizes on the vector space-based data structure so addition of new items becomes complicated and time consuming. Model-based approach use the algorithms of data mining, machine learning, and data science to predict the rating of unrated items with the inclusion of old rated database. Some hybrid RS are also developed by combining model and memory-based algorithms and overcome the limitation of each other. Success of a RS is measured by their real applicability and user satisfaction [1]. Although RS are applicable in many real domain applications but still there are some difficulties which should be attentive while developing a new such as cold-start, sparsity of data, extraction of features (items/users), accuracy, changing trends, scale in options, and diversity.

Internet of Things (IoT) is a giant network that connects everything from anywhere at any time with the internet. IoT is amalgamation of physical and cyber worlds [2]. It is the integration of extensive computing, ubiquitous computing, and seamless mobile computing. Now a days, IoT has proved their practical existence everywhere with a strong contemplation of user's interests. Use of IoT technologies rise with the advancement in sensor technologies, cloud computing, networking, big data computation, and artificial intelligence[3]. IoT services leads for collection and exchange of information with or without human intervention across the whole world. IoT also facilitates many real time applications by enhanced data collection and data analysis. IoT application generates the abundant amount of information, out of which recommendation of useful information can enhance the user's experience and enterprises responses. IoT applications need service recommendations and things recommendations dominantly. For recommender systems cold start is ordinary issue caused by scarcity of new user behavior data across the system. There are two types of cold starts: Complete Cold Starts when no rating at all is existing and Incomplete Cold Starts when some of rating records are obtainable for new items or users. Due to sparsity of the data, training samples for developing new recommendation models becomes insufficient. Most of the existing hybrid approaches were intended to solve these approaches but they use either implicit or explicit information in providing significant recommendations. In explicit information, user expresses his or her preference on an item consciously, usually using a discrete numerical scale. Implicit information refers to the interpretation of user behaviors or selections to obtain a preference, typically based on historical data. But the existing approaches were not providing significant solutions for problems such as sparsity, serendipity, privacy, cold start, and scalability due to random assumptions and improper recognition of unique characteristics in the correlation between user and item. Hence a new hybrid recommendation system should be developed to provide efficient recommendation without sparsity, confidentiality, scalability, and cold start issue by considering all unique characteristics without random assumptions.

In this paper, we suggest a novel recommender system using Knowledge Infusion technique for IoT enabled B2B applications that can overcome issues such as serendipity, over-personalization, confidentiality, cold start, and scalability. Business to Business distribution scenario has a wide range of items and customers to deal with. The purpose of suggested recommender system is to deal with the information overloading problem and to uplift the purchasing participation of customers. The key contribution of this work is summarized as follows:

- Proposing a knowledge infusion model-based recommendation approach.
- Implementation of the proposed model with a real data set.
- Comparison with the existing models.

The paper is organized in seven sections. First section is the introduction. Section 2 is the description of IoT Recommender systems. Section 3 is the review of state-of -the-art approaches. Problem formulation is defined in the section 4. Section 5 discusses the proposed approach. Evaluation and comparison of the proposed approach is done in section 6. The paper ends with the conclusion in section 7.

II. IoT Recommender System

Recommendations in IoT environment leads to IoT Recommender System (IoT RS). IoT recommendations play a vital role in promoting IoT application benefits for society and business. IoT Recommender System (IoT RS) exploit IoT generated data for recommendations. IoT generated data are continuously growing, more contextual, heterogeneous, and dynamic, which needs special analytical methods for recommendations. IoT recommendations are harder as compare to conventional recommendations due to extensive processing, resource constraints, massive and diverse contextual data. The main feature of IoT is the ability to exploit huge amount of information and knowledge to receive users' behavior and preferences. Acceptance of IoT enabled users' behavior can build an accurate and diverse recommender system. IoT RS are associated with the limitations like management of trust, security and privacy, interoperability, heterogeneity, scalability, and service quality. Increase in the number of smart devices and smart objects lead the growth of IoT services. Due to which user faces difficulties to find relevant and useful services, but recommender systems give the solution.

Conventional or traditional RS has been implemented using data which is related to users (customers) and items but the IoT RS also includes sensor-based real time data and diverse relations among users and things [4]. The used techniques for IoT RS are content-based, Collaborative filtering based, graph-based, Knowledge-based, context aware-based, Correlation-based and machine learning-based. Content based IoT RS recommend things of interest by comparing similarity with things used in past. Collaborative approach recommends things and services if similar users like or rated them. Contextual IoT recommender systems use user's contextual data gathered explicitly and implicitly and surrounding contextual data gathered from IoT sensors and devices. Further contextual recommender systems are categories as prefiltering contextual RS, postfiltering contextual RS and contextual modelling-based contextual RS. Correlation-based IoT RS incorporate social correlation between IoT objects and Social-IoT data. Knowledge-based IoT RS involves knowledge-based methods like ontology for IoT service recommendations. The approaches based on reinforcement learning, machine learning, and deep learning can capture temporal user activities and intentions and give more favorable outcomes. Hybrid techniques defined as the combination of any two or more techniques also give promising results.

Recently, the differences between traditional RS and IoT RS and different techniques developed for IoT RS are discussed by Ahlawat and Rana [5]. IoT RS are utilized in many application areas like smart-mobile health, smart city, smart home, smart marketing, banking, agriculture, industries, transportation, and smart tourism. The number of developed models for IoT Recommendations have been increased gradually in last five to six years. Likewise of traditional recommender systems IoT recommender system also suffers with the problem such as cold start, data sparsity. The era of IoT recommender systems should need more notable advancements to handle trust-aware issues, multiple contextual correlations, and dynamicity of things.

III. LITERATURE REVIEW

Recommendation techniques are helpful to identify the relevant artifacts and grown up as a key IoT solution. IoT Recommender systems have gotten appreciable attention in recent years. These systems are developed on the idea of exploring user preferences, their spatiotemporal relations and their correlation with the things and services. Advanced gateways are developed which consists the innovative functionalities of configurators and recommender engine [6]. These gateways can recommend the useful recommendations like workflow, applications, services using their settings and user interactions. There are several developments [7]–[11] that have been focused to employ Recommender technologies using dynamisms of IoT like trust, scalability, security, SIoT, and correlations. Recently to solve the issue of scalability and sparsity in IoT Recommender systems, Kashef [12] proposed a clustering based recommender system with adoption of vector space model. Result evaluation done by prediction metrics shows that developed model out performs over collaborative-filtering approach.

Subramaniyaswamy et al. [13] developed a health-centric and intelligent RS known as ProTrip. It supports travelers by suggesting food choices with the consideration of climate conditions, users diet plans, users' diseases history, and nutritive value. The functionality of ProTrip is designed by blending ontology-based knowledge system and tailored filtering approach. Ensemble learning techniques also promised more accurate and efficient recommendations in IoT environment [14]. Abu-Issa et al. [15] presented a context-aware, proactive and multitype IoT Recommender System as a smart city mobile application. Amalgam of IoT and Artificial intelligence leads for a smart home automation recommender system for physically impaired persons for controlling and monitoring household work [16]. Using IoT knowledge-based data Gyrard and Sheth [10] developed a wellbeing recommender system (IAMHAPPY) to deal with users health issues by suggesting home remedies, physical activities and medicines. The system is applicable in naturopathy scenario. The integration of semantic-based repository and rule-based engine analyse emotions and health of users.

Ojagh et al.[17] developed a user orientation aware hybrid context-based recommender system to give more personalized recommendations. The system applied on users' contextual information (using smart devices) and social networks to capture user preferences dynamically. But the system suffers with privacy and data security issues. Shahbazi et al. [18] have presented a realistic CF-based recommendation model applicable by many E-commerce environment to enhance customer satisfaction and gross sales. The CF assumes that two like-minded people are most likely to exhibit a similar likeness pattern in the future. However, this model is vulnerable to both complete cold start (CCS) problem and incomplete cold start problem (ICS).

Mohamed et al. [19] developed a personalized CF-based recommendation algorithm by exploring users' hobbies and characteristics. But the system is not favorable to accept the changes in users' requirements and hobbies due to which it lacks in terms of prediction accuracy. With the progress of social media influencers, choices and preferences of users become more personalized and dynamic. Recently Yao et al. [20] have presented a model named GD-CFKG for IoT scenario to discover similarity user group using knowledge graph and CF. The model is composed in two stages, first stage identifies users' implicit preferences and second stage K-means clustering and hierarchical clustering are used to build the group of users with common preferences. Analysis of the model was done over real datasets using performance matrices recall and precision. Results are more promising than the baseline methods but the weakness is inability to consider dynamic preferences of users.

To recommend personalized IoT services to users, Bouazza et al. [11] suggested a hybrid recommendation model using ontology-based modelling of SIoT (Social IoT) and implicit CF. Ontology has been used to describe the relations between objects, users and services and to depict the discovery of services by calculating a confidence parameter. CF is also used to predict the choices of the users. Experiments shows that system deliver accurate and favorable services in IoT environment, but lacking behind in terms of trust and privacy conservation.

presented a hybrid technique that combines implicit collaborative filtering and ontology. Ontology is used to model the SIoT, in which the social relationships between objects are incorporated into the recommendation process alongside the ratings, while collaborative filtering predicts ratings and generates recommendations. However, there is a need to create a more powerful model by incorporating spatiotemporal criteria, such as time and location, to improve the accuracy of IoT service recommendations. Also, this method is not focusing on both user trust and privacy preservation.

By analyzing the literature, mostly developed models are exposed to CCS problem and ICS problem. and the prediction of relational personalization's are less accurate. In IoT User preferences are related to heterogeneous environments, but are computed relying only on the reviews of the things and services. Developed models are not accepting interactive data based on timely changes and not focusing on spatiotemporal relationship to enhance user's trust. From literature review, we observe that there is a research need to discourse a recommender system which is applicable in IoT scenario and resolve the issues of users trust and privacy, cold start problem and scalability.

IV. PROBLEM FORMULATION

Recommendation systems are important to handle unwanted traffic on internet caused due to data overloading by providing effective recommendations to internet users. Likewise, IoT also demands efficient and effective recommendation discovery to

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support various IoT based decision making activities. Traditional recommendation paradigms are not capable to deal with the dynamic nature of IoT caused by devices and social structure. Recommendations for IoT should entails with smart reasoning, intelligent discovery, and knowledge-based perceptions. As a result, many hybrid recommendation systems based on artificial intelligence techniques have been presented in the literature review to provide recommendations.

Generally, for recommendations the user-item matrix acquired from the dataset is sparse with uninhabited dimensions. Sparsity of data can be due to the lack of personal details or deficiency of items attributes. Most of the developed filtering and factorization techniques fill the missing entries across the matrix with ad-hoc assumptions or by zero based on user score and co-rated values. Due to which the filtering approaches suffers with serendipity, over-personalization, and confidentiality issues. Inclusion of existing similarity measure techniques in hybrid recommendation system produce linear latent features. Such systems do not take recency into account and are not able to recognize synonymy items. So, resulted recommendations did not include counter-attitudinal information of users and one-to-only-items.

Furthermore, while determining weighted average to predict unique recommendation list, existing weighted predictor methods assign equal weights to users based on group preference while ignoring the obscured correlation in user preference on sporadic and frequent items. This causes CCS (Complete Cold Start), ICS (Incomplete Cold Start) issues, and increasing MSE in recommendation generation. As a result, we propose a novel hybrid recommender system for IoT based B2B (Business to Business) applications using Trusted Knowledge Infusion ML model that can overcome issues such as serendipity, over-personalization, confidentiality, cold start, and scalability.

V. PROPOSED MODEL

Effective recommendations for B2B application in IoT have been provided by creating a novel model named “Stuffed Regression with Deep Knowledge Infusion Optimized M×N weighted predictor”. The proposed model initially collects business supplier-buyer data from the internet and performs two phases of operation as follows.

Phase 1: The input raw user-item sparse matrix is given to Stuffed Matrix Regression Encoder in which Gap Stuffed Golay regression fills sparse matrix data by predicting residual least square polynomials of independent 1-N parental id and user profiles that establish hidden correlation without ad-hoc assumptions, making it suitable to fill matrix even if user rating and appropriate parental detail are not present and eliminating serendipity and over-personalization. This newly filled matrix data is passed to Deep Fisher Tensor Orthogonal Encoder, which encodes it in geospatial-interaction tensor fisher vectors based on Jaccard orthogonal polynomials, eliminating confidentiality problems.

Phase 2: In this phase, both reputation score and weighted average for recommendation list generation has been measured by a novel Elevated Bi-level Deep Weighted Prediction.

Reputation score estimation: Encoded data are given to Deep Sporadic Attention NN which extracts non-linear latent semantic and trusted features based on timestamps and popularity drift-based recency. To recognise synonymy items, knowledge infusion from web data is incorporated, in which required synonymy item information is extracted via semantic graph-based attention, and a reputation score is obtained with counter-attitudinal information and one-to-only unique items.

Weight prediction: From the determined reputation score, Bi-level Deep Quadratic critic network predict weight for sporadic long tail items and relevant frequent items based on obscured correlation in user preferences, producing multiscale user weightings with improved M X N prediction matrix and eliminating CCS, ICS problems, and MSE in recommendation.

Overall, the proposed model performs accurate matrix filling and appropriate reputation score measurement by providing improved weighted recommendations, thereby eliminating issues such as sparsity, serendipity, confidentiality, cold start, and scalability. Figure 1 gives the diagrammatic view of the proposed model. Table 1 summarizes our proposed algorithm.

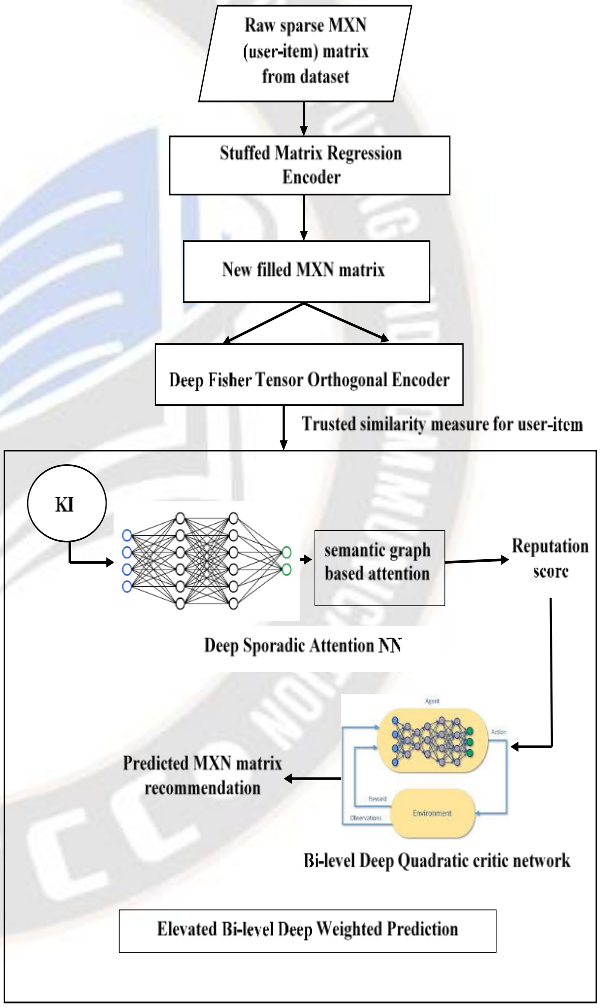

Figure 1: Diagrammatic view of proposed model

TABLE I ALGORITHM FOR THE PROPOSED MODEL

ALGORITHM	KNOWLEDGE INFUSION-BASED IOT RS ALGORITHM
INPUT	Retail Rocket Recommender dataset
OUTPUT	Set of top-ranked items
STEP 1:	Import python libraries and machine learning models from sklearn

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STEP 2:	Read the CSV data files from selected data set /*Freely available online*/		
STEP 3:	Stuffed Matrix Regression Encoder is used		
	Step 3.1:	Evaluation for regression training	
		Step 3.1.1:	Calculate the mean value
		Step 3.1.2:	Calculate covariance
		Step 3.1.3:	Calculate coefficients
		Step 3.1.4:	Apply Simple regression algorithm: simple_linear_regression(train, test): predictions = list() b0, b1 = coefficients(train) for row in test: yhat = b0 + b1 * row[0] predictions.append(yhat) return predictions
	Step 3.2:	Predict residual least square polynomials	
	Step 3.3:	Filling Null values using gap stuffed regression	
STEP 4:	Deep Fisher tensor orthogonal encoder		
	Step 4.1:	Finding teuss similarity /* elimination of serendipity */	
	Step 4.2:	Jarcos ortho polynomial used /* for ranking calculation*/	
		Step 4.2.1:	Random Forest Classifier is used
STEP 5:	Weight Prediction using elevated Bi-level deep neural network		
	Step 5.1:	Generation of reputation score and weighted average	
	Step 5.2:	Deep sporadic attention neural network is used with inclusion of popularity drift-based recency: words = array ([word_1, word_2, word_3, word_4]) random.seed(42) W_Q = random.randint(3, size=(3, 3)) W_K = random.randint(3, size=(3, 3)) W_V = random.randint(3, size=(3, 3)) $K = words@W_K$ $V = words@W\_V$ $Q = words@W_Q$ scores = Q @ K.transpose() weights = softmax(scores / K.shape[1] ** 0.5, axis=1) attention = weights @ V print(attention)	
STEP 6:	Bi-level deep quadratic critic network is used		
	Step 6.1:	Frequent items based on obscured correlation in users are suggested	
STEP 7:	End		

A. Significance of Novelty

Gap Stuffed Golay regression fills the sparse matrix data by predicting residual least square polynomials of independent 1-N parental id and user profiles that establish hidden correlation without ad-hoc assumptions. Deep Fisher Tensor Orthogonal Encoder that encodes this matrix in geospatial-interaction tensor fisher vectors based on Jaccard orthogonal polynomials. Deep Sporadic Attention NN that extract non-linear latent semantic and trusted features with considering timestamps and popularity drift-based recency. Knowledge infusion from web data is incorporated in which required synonymy item information is extracted via semantic graph-based attention thereby reputation score is obtained with counter-attitudinal information and one-to-only unique items**.** Bi-level Deep Quadratic critic network is used to predict weight for sporadic long tail items and relevant frequent items based on obscured correlation in user preferences.

This novelty approach eliminates serendipity problem, confidentiality issues as well as over-personalization problem. It also helps to mitigate CCS, ICS problems and MSE in recommendation. In this model, for the first-time sparsity in dataset is eliminated without ad-hoc assumption and matrix filtering. Recency and synonymy are also considered for the first time in reputation score prediction with providing multiscale weighting for each user.

VI. EVALUATION

In this section, we introducing the evaluation of the proposed model. First, we describe the used data set, which is followed by description of used metrics and of results.

A. Dataset

The Retail Rocket Recommender dataset[1] has been used to assess the performance of our proposed model. It is publicly available recommender dataset and downloaded from the Kaggle website. Dataset contains four files: events, category_tree, item_properties_part1 and item_properties_part2. We split our dataset in two parts: 75% as a training dataset and 25% as a test dataset. The model was implemented in Python and compiled in Jupyter notebook because it includes various modules to make implementation easier.

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B. Evaluation Metrics

A recommender system builds a list of recommendations for the users. To provide insight for the relevancy to the list of recommendations, we must evaluate the system using different evaluation techniques. The evaluation metrics used in our work are Execution time, RMSE (Root Mean Square Error), Precision and F1 measure. Execution time metric is used to measure the performance and effectiveness of the model. To measure the accuracy, we use RMSE metric. RMSE square the errors before calculating their average and provide more weight to large error. RMSE is computed as:

$$RMSE = \sqrt{1/N \sum_{i,u}(P(u,i) - A(u,i))}^2$$

Where N is total users, P(u,i) represents predicted rating for user u and item i. A(u,i) shows actual rating. Precision metric is used to calculate the used predicted recommendation value over the total recommendation value, whereas recall is defined as used values over total related values. F-measure is computed as a harmonic mean of recall and precision measures. F-measure is also called F1-Score. Equations for precision and F-measure are as follow:

$$Precision = \frac{Recommended\ values\ used\ by\ user}{Total\ recommended\ value}$$

$$F - measure = 2 * \frac{Precision * Recall}{Precision + Recall}$$

[1] https://www.kaggle.com/datasets/retailrocket/ecommerce-dataset/code

C. Results

In this section, to assess the effectiveness and accuracy of proposed model experimental results are presented. Table1: summarizes the results. It shows that increase in the iterations to train the model with all training data in one cycle (Epoch), the model performs well with decrease in Execution time and RMSE. It is also observed that with increase in iterations, there is an increase in precision and recall which is valuable for increasing the performance. Figure 2,3,4 and 5 are demonstrating the graphical view of the observed experimental results. The results can differ with other datasets because we observed the results only on specific data set.

TABLE II. EXPERIMENTAL RESULTS OF PROPOSED MODEL OF MEASURES RMSE, EXECUTION TIME, PRECISION AND F1-SCORE FOR DIFFERENT VALUES OF EPOCH

Epoch	RMSE	Execution Time(sec)	Precision (%)	F1-Score (%)
100	0.54	0.12	96.25	97.45
200	0.54	0.12	96.35	97.65
300	0.52	0.11	96.56	97.85
400	0.49	0.09	97.21	97.98
500	0.49	0.08	97.32	98.17

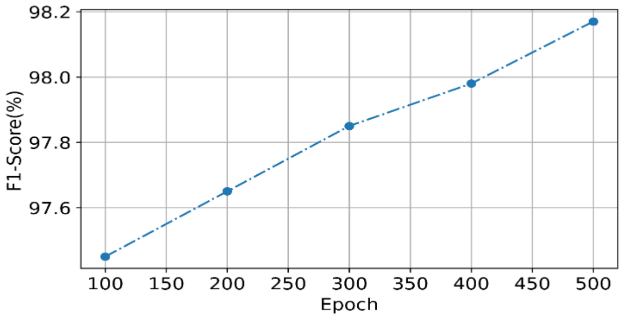

Figure 2: Performance of proposed model on measure F1-Score with increase in Epoch

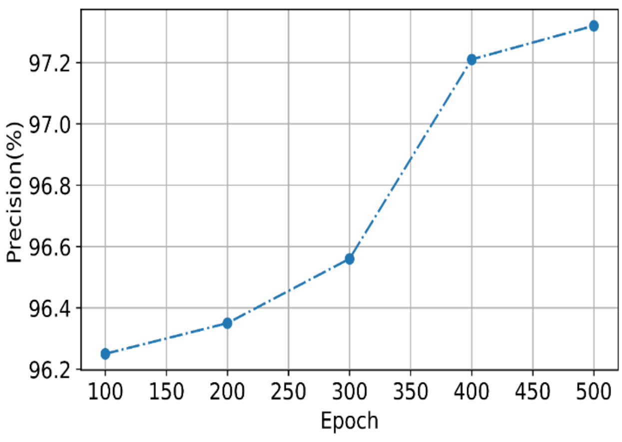

Figure 3: Performance of Proposed model on Precision with Increase in Epoch

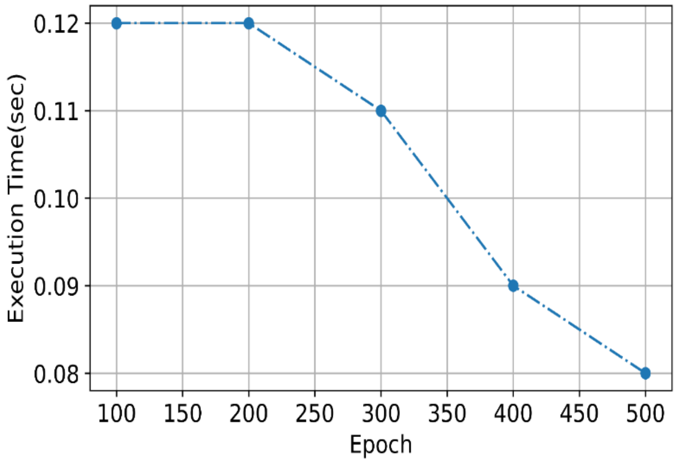

Figure 4: Performance of proposed model with execution time

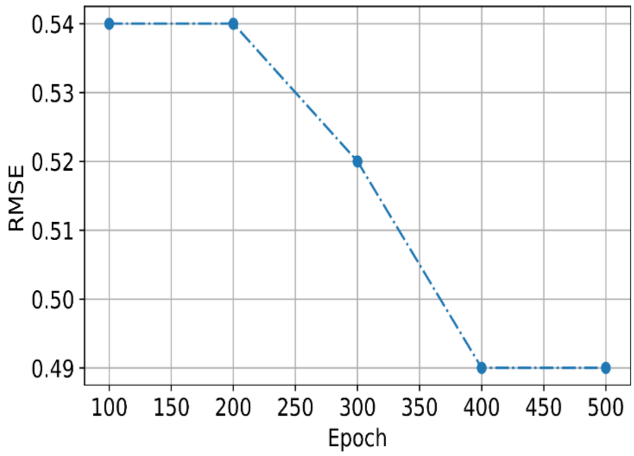

Figure 5: Performance of Proposed model with measure RMSE

We also compare our model with the developed models of our base paper [21] to evaluate results. Table 2: Represents the comparison on the measure of Execution time, F1-Score and Precision. The Execution time of the proposed model is better as compared to the basic collaborative approach, collaborative filtering with k-means clustering algorithm and collaborative filtering with self-organizing map. F1-score and precision of the proposed model is also remarkable as compared with the popularity-based filtering, content-based filtering and with a hybrid filtering approach based on k-means and self-organizing map algorithm. Figure 6, 7 and 8 represents the graphical view of our comparisons.

TABLE III. COMPARISON OF PROPOSED MODEL ON THE BASE OF EXECUTION TIME, PRECISION AND F1-SCORE

Models	Execution Time(sec)	Models	F1-Score (%)	Precision (%)
CF	0.75	Poularity	0.68	0.52
CF_Kmeans	0.36	Content-Based	0.48	0.68
CF_SOM	0.32	Kmeans+SOM	0.83	0.78
Popose d	0.3	Proposed	0.9782	0.96738

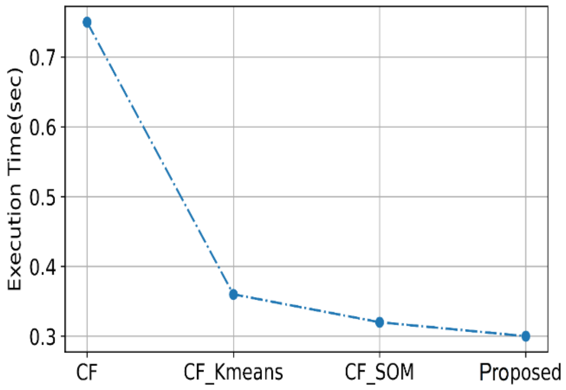

Figure 6: Comparison of Proposed model with other models on the measure of Execution Time

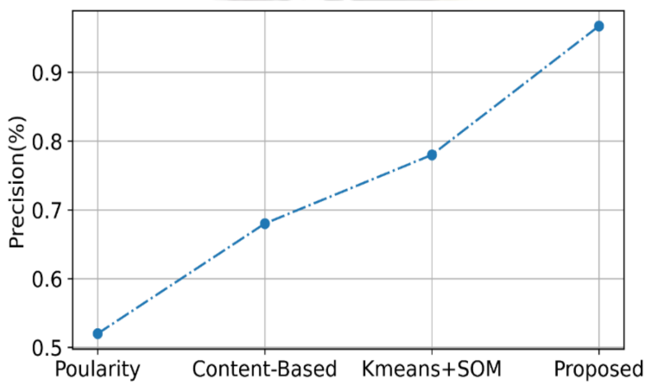

Figure 7: Comparison of Proposed model with other models on the measure of Precision

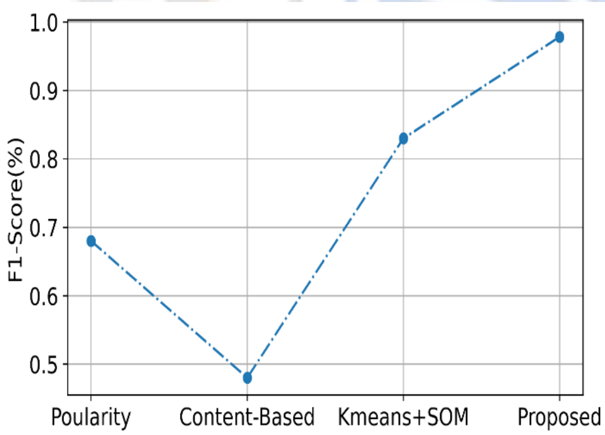

Figure 8: Comparison of Proposed model with the other models on the measure of F1-Score

VII. Conclusion

Overloading of information causes difficulties in acquiring relevant, interested, and useful services, but recommendations techniques provide efficient and promising solution. Advancement in knowledge infusion models can intensify the recommendations in IoT technologies. In this paper, we purpose a hybrid recommendation model for B2B applications based on trusted knowledge infusion model to address the cold start problem, confidentiality, and serendipity. We experiment the model on a real-world dataset and the evaluation reveals the better performance over the other models. In future, we would like to add temporal and context-aware information to enhance the performance specially for IoT context.

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