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# DEEP LEARNING ARCHITECTURE TOWARDS PARTICIPANT PREDICTION FOR EVOLVING EVENTS IN EVENT BASED SOCIAL NETWORK

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***Abstract:*** **The Event Based Social Network(ESBN) is a distributed platform for organizing the online social events, in which events are submitted to the user groups on associated topic, location and time period. Usually, event based social network systems contain abundant events and large scale of user participating on event, there exist an overhead on clustering the user for the event. In order to model a participant prediction, deep learning architecture for the user recommendation has become necessary. However, many existing work using machine learning model leads to scalability and sparsity issues. Further events and user profiles continually arrive and evolve in terms of behaviour and knowledge, which leads to the issues of task cold-start. In order to overcome the above mentioned challenge, a novel dense recurrent neural network architecture using deep neural network for participant recommendation on basis of evolution of user knowledge and preference has been formulated in this research. Initially proposed idea deals with the dynamics of the user and event in the event based social network by extracting the features with multiple latent factors using feature extraction technique. Latent factor extracted on basis of the event and user features according to their experience and historical behaviors. Further deep neural network has been incorporated to model a participant recommendation system to event on basis of latent feature extracted towards prediction on timely basis to achieve high reliability, accuracy and latency. Deep learning architecture schedules the participants to event on embedding latent features on generation of the objective function to produce recommendation with minimum error. It results in significant increase on the prediction performance for discriminative information's of the event and user. Extensive experiments have been conducted on real datasets to compare proposed model with conventional. The experimental results show that deep learning architecture can achieve both effectiveness and good scalability on large scale data.**

***Index Terms*** **- Deep Learning, Event based Social Network, Participant Recommendation.**

## I. INTRODUCTION

Event Based Social Network has become a very useful and distributed event based data sharing application which encompassed the discussing the knowledge and experience on specified field. Specifically, these applications explore the participant to the event in collaborative manner using artificial intelligence capabilities [1]. In general, Event [2] is generated with event description by user along location and time. Event analysis generates the recommendation list containing the participants to the particular event. It generates complexity using machine learning architectures for participant recognition to the event on analysing the unstructured profiles. Further it produces the data sparsity and cold start issues

In order to provide reliable solutions for event recommendation, many latent social factor of the user has to be extracted. To accomplish the specified requirement, dense recurrent neural network is modelled. In this work, a Dense Recurrent neural network has been employed as proposed contribution to extract the latent factor of user dynamic and event dynamic in the event based social network as multiple latent factors using feature extraction technique. These extracted features applied to deep neural to model a participant recommendation to event to achieve high reliability, accuracy and latency. Deep learning architecture schedules the user to event on embedding latent features on generation of the objective function to produce recommendation with minimum error. Proposed results have been significantly increased the prediction performance for discriminative information's of the event and user.

The Remaining paper is organized as follows, related work are described in section 2, the architecture of the proposed deep neural network architecture for participant recommendation in event based social network is described in section 3 and experimental results and effectiveness of the proposed system is demonstrated in section 4 using real time dataset along performance comparison against state of arts approaches on various metric has been explained. Finally paper is concluded in section 5.

## II. RELATED WORK

In this section, event based social network using machine learning approaches has been examined in detail on basis of architectures on event representation and similarity measures of the processed participant to event. Each of those machine learning techniques which produce better performance in terms of effectiveness on the evaluation of the model has been represented in detail and some techniques which performs nearly similar to the proposed model is described as follows

A.Collaborative filtering learning

In this method, Task based Recommendation [6] has been proposed for predicting the task for crowdworker on basis of similarity and preferences. Correlation based Similarity [7] has been used to compute the correlation between the tasks. Pearson similarity measures the extent to which two task linearly relate with each other on preference of the crowd worker. It provides personalized task list to the user on implicit and explicit feedback model.

B.SERGE: Graph Entropy for Event-Based Social Networks

In this method, Concepts were weighted higher by the intension of the boosting the semantic concepts in user profiles.It use the preference on the user profiles for semantic enrichment and indexing to achieve the social aware prediction [16].

C.Event-Participant and Incremental Planning over Event-Based Social Networks

In this method, incremental planning on event participant is to identify user participating in different interesting social events using Greedy based technique as it accountable for changes to events[17]. .

## III. PROPOSED MODEL

This section provides a detailed design specification of the proposed technique titled as dense Recurrent neural network employed for participant recommendation architecture on inclusion of parametric tuning of the deep learning layers to obtain the prediction of the participant to event on basis of latent factor of the event and participant behaviour analysis and experience analysis.

### *3.1 Event Based Social Network*

Event based Social Network consist of Event, User and Recognition model has been used for effective recommendation.

- Event

Event is set of m topic submitted by various Users on basis of various characteristics for increasing the knowledge by discussion. Event belong to various category, it is denoted by Ei

E = {E1,E2,E3....En} ....Eq.1

- User Profiles

The User profiles discusses the knowledge and experience on various category of the topic It will be evolved with various information along constraints and strategies with different location and different time frame.

U= {u1, u2 u3....un}...Eq.2

### *3.2 Extraction of User and Event*

In order to eliminate the intrinsic error rate, extraction based method has been employed on basis of category. Further, it is to identify user feature with respect to their behaviour and experience, latent discriminant analysis has been employed to determine the latent factor of participants for the event. Event profile has been represented in the matrix form as full projection matrix. The full projection matrix containing column represents the data point of the particpants on characteristics and row represents the behaviour characteristics [6].

Aggregated Vector for Single behavior characteristics

$$\boldsymbol{\lambda}_i = \frac{1}{n} \int \boldsymbol{d}\left(\frac{dy}{dx}\right)^{-2} \sum_{x \varepsilon C}^{n} C, (r - r_i) \qquad \ldots\text{Eq.3}$$

### *3.3 Dense Recurrent Neural Network.*

Dense Recurrent Neural Network is deep learning architecture employed for prediction of the participant for the event. In this part, parametric tuning of the activation function of the participant prediction on objective functions based on experience and Implicit behaviour of event as latent factors has been used. Training model uses hidden layer to maps the extracted latent features into pair wise features representation and these pair-wise representations have been processed in deep layers on basis of the user preference to reconstruct features into event [10].

The feature representations of the user and event that can enhance the separation of participant to the event have computed using the Pearson correlation similarity on preference of the user. The recognition components of the Recurrent Neural Network for participant prediction are given in table 1.

| **Hyper Parameters** | **Values** |
|---|---|
| Matrix Batch Size | 158 |
| Model Learning Rate | 0.03 |
| Size of User Dimensions | 15 |
| Epoch | 75 |
| No of Latent Features | 25000 |
| Error function | Cross entropy |

Table 1: Recognition Component for the Dense Recurrent Neural Network

## IV. EMBEDDING LAYER

The Embedding layers capture the preference feature subset through their inherent mechanism hierarchically as abstract features and learn the discriminative features with very few hyper parameters of softmax layer. Outcome of the feature space is latent dimension of the evolving user characteristics. In this layer, many evolving characteristics of the preference variable have embedded to activation function to identify the resultant user set to the event.

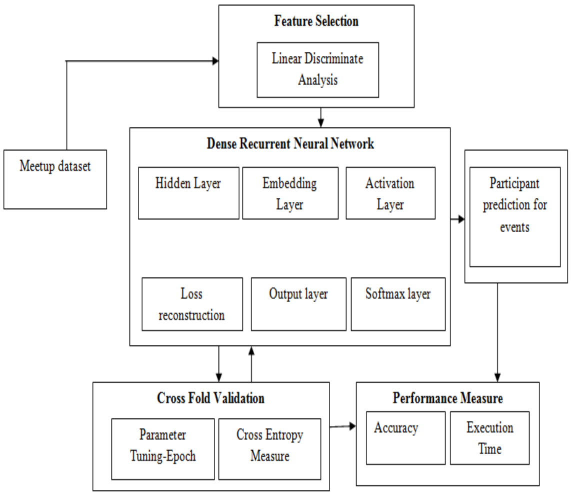


Fig 1: Architecture Diagram of the Participant Recommendation model

1In this layer, high-dimensional user features is linearly converted into low-dimensional embedded vectors by learning.

### *4.1 Activation Function*

The proposed architecture uses the rectified linear units (ReLU) activation function [11] for Participant recommendation to evolving event. Further it containing the preference vector and pair wise vector of event in the embedded layer. Activation function produces the appropriate participant on each element in the embedding matrix. Embedded vector has been processed with parameterized values to generate the appropriate prediction for the selected participant vector and to each epoch parameter updating.

### *4.2 Output Layer*

The output layer of the dense recurrent neural network composed of the prediction result containing participant suggestion to event. Soft max optimization [12] is carried out the resultant set and cross entropy mechanism has used to evaluate the effectiveness of the participant prediction on user evolutions using Hyper parameter tuning has been enabled in the output layer to make the Prediction of the user to event by determining the affinity of the event to the recognized participant representation on various evolutions.

*4.3 Loss Layer.*

This layer is to ensure the prediction accuracy on fine tuning against refine parameter of different layers of dense recurrent neural network to ensure the minimum reconstruction error between features of embedded layer and ReLu activation layer. Further cross entropy loss function has been utilized to manage the error of the predicted outcome to the user [13].

***Algorithm 1: Dense Recurrent Neural Network based Participant Re**commendation*

Input: Discriminative Event and User set
Output: Participant Prediction for Event
Process
Linear Discriminant Analysis ()
Compute latent feature Set $F_s$
Apply Dense Recurrent Neural Network Learning
Hidden latent feature ()
Embedded Layer ()
Activation Layer ()
Parameterized Tuning of ReLu Function
Output Layer()
Softmax()---Participant Recommendation list

This function encourages the embedded latent feature points on representative map to form participant list to event on basis of behavioural and experience of the participant for recommendation solution.

## V. EXPERIMENTAL RESULTS

In section, experimental results of the proposed participant recommendation model has been analysed against the existing recommendation approaches on evolution of the user characteristics in the event based social network. Further performance evaluation on the proposed architecture has been depicted as it outperforms the conventional approaches in terms of Precision, Recall, F-measure.

### *5.1 Dataset Description*

Meetup data set is most popular EBSNs. It contains an online platform to the user to create, identify and share online and offline events for group of user as collection which is mostly frequently used bench mark dataset for many recommendation based applications. Specifically, dataset extracted event logs and user profiles via the official APIs of Meetup, which totally consists of 422 user groups, 9,605 social events and 24,107 related users.

### *5.2 Evaluation*

The proposed Framework for participant recommendation is evaluated against the following measures

### *5.3 Precision*

Positive predictive value of the user characteristics is the ratio of relevant instances to the retrieved instances from the event characteristics. The evaluation is evaluated against dataset is depicted in the figure 2.

$$\text{Precision} = \frac{\text{True positive}}{True\ positive + False\ Positive} = \frac{\text{TP}}{TP+FP}$$

### *5.4 Recall*

It is the ratio of relevant characteristics of the participant to the retrieved characteristics over the total amount of relevant participant to event..

$$\text{Recall} = \frac{\text{True positive}}{True\ positive + False\ negative} = \frac{\text{TP}}{TP+FN}$$

On recall analysis, the time-dependence relationship between event and participant on choosing the latent pattern and preference of the participant on basis of experience.

Deep learning based prediction algorithms is capable of identifying the participant based on their behaviors and experience to event. It effectively addresses the scalability problem in large scale data explorations by gathering participant recommendation within smaller and highly similar list instead of the extracting from the entire dataset.

### *5.5 F Measure*

It is a metric used to measure of a test's accuracy of the recommendation result of user to the event is defined as the weighted harmonic mean of the precision and recall [15] of the training or test data and performance values of the evaluated model has described in Table 2 on recommendation system.

Table 2: Performance Comparison of Methodology

| Dataset | Technique | Precision % | Recall % | Fmeasure % | Computation Time(s) |
|---|---|---|---|---|---|
| Crowd sourcing Dataset | Proposed | 97.37 | 86.23 | 97.23 | 10 |
| | Existing | 94.61 | 84.23 | 95.26 | 20 |

As shown in Table 2, proposed techniques provides high scalable and reliable recommendation list to event.

## IV. CONCLUSION

We designed and implemented Dense Recurrent Neural Network for predicting participant for recommending to events with high accuracy and scalability in the event based social network. The architecture uses Dense Recurrent Neural Network along Hyper parameter tuning to eliminate the reconstruction error and loss function for high accuracy prediction Further deep learning architecture utilizes the latent feature in embedding layer to represent sparse feature for prediction using activation layer. Finally softmax layer and loss layer has been embedded to generate the highly discriminative prediction results to participant recommendation to events

## REFERENCES

**[1]** J.A. Iglesias, A. Ledezma, and A. Sanchis, "Creating User Profiles from a Command-Line Interface: A Statistical Approach," Proc. Int'l Conf. User Modeling, Adaptation, and Personalization (UMAP), pp. 90-101, 2009.

**[2]**A. Cufoglu, M. Lohi, and K. Madani, "A Comparative Study of Selected Classifiers with Classification Accuracy in User Profiling," Proc. WRI World Congress on Computer Science and InformationEng. (CSIE), pp. 708-712, 2009.

**[3]**F.J. Ferrer-Troyano, J.S. Aguilar-Ruiz, and J.C.R. Santos, "Data Streams Classification by Incremental Rule Learning with Parameterized Generalization," Proc. ACM Symp. Applied Computing (SAC), pp. 657-661, 2006.

**[4]**R.K. Agrawal and R. Bala, "Incremental Bayesian Classification for Multivariate Normal Distribution Data," Pattern Recognition Letters, vol. 29, no. 13, pp. 1873-1876, http://dx.doi.org/10.1016/ j.patrec.2008.06.010, 2008.

**[5]**J.A. Iglesias, A. Ledezma, and A. Sanchis, "Sequence Classification Using Statistical Pattern Recognition," Proc. Int'l Conf. Intelligent Data Analysis (IDA), pp. 207-218, 2007.

**[6]** Bo Tang, Steven Kay, Haibo He "Toward Optimal Feature Selection in Naive Bayes for Text Categorization "in IEEE Transactions on Knowledge and Data Engineering in Volume: 28, Issue: 9, Sept. 2016

**[7]**H. Ma, D. Zhou, C. Liu, M. Lyu, and I. King, "Recommender systems with social regularization," in Proceedings of the 4th ACM International Conference on Web Search and Data Mining (WSDM), 2011, pp. 287–296.

**[8]**Y. Koren, "Factor in the neighbors: Scalable and accurate collaborative filtering," ACM Transactions on Knowledge Discovery from Data (TKDD), vol. 4, no. 1, pp. 1:1–1:24, 2010.

**[9]**P. Wang, H. Wang, X. Wu, W. Wang, and B. Shi, "A Low- Granularity Classifier for Data Streams with Concept Drifts and Biased Class Distribution," IEEE Trans. Knowledge and Data Eng., vol. 19, no. 9, pp. 1202-1213, Sept. 2007.

**[10]** I. Katakis, G. Tsoumakas, and I. Vlahavas, "Dynamic Feature Space and Incremental Feature Selection for the Classification of Textual Data Streams," Proc. Int'l Workshop Knowledge Discovery from Data Streams (ECML/PKDD), pp. 102-116, 2006.

**[11]** Y. Li, Z. Niu, W. Chen, and W. Zhang, "Combining Collaborative Filtering and Sequential Pattern Mining for Recommendation in E-Learning Environment," Proc. 10th Int'l Conf. Advances in Web- Based Learning, pp. 305-313, 2011.

**[12]**P. Lops, M. de Gemmis, and G. Semeraro, "Content-Based Recommender Systems: State of the Art and Trends," Recommender Systems Handbook, pp. 73-105, Springer, 2011.

**[13]**J. Yi, R. Jin, S. Jain, and A. Jain, "Inferring users preferences from crowdsourced pairwise comparisons: A matrix completion approach," in Proc. 1st AAAI Conf. Human Comput. Crowdsourcing, 2013, pp. 207–215.

**[14]** W. Lu, S. Ioannidis, S. Bhagat, and L. V. Lakshmanan, "Optimal recommendations under attraction, aversion, and social influence," in Proc. 20th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2014, pp. 811–820.

**[15]**J. Wang, P. Zhao, S. C. Hoi, and R. Jin, "Online feature selection and its applications," IEEE Trans. Knowl. Data Eng., vol. 26, no. 3, pp. 698–710, Mar. 2014.

**[16]**.Shenghao Liu, Bang, Minghua Xu "SERGE: Successive Event Recommendation Based on Graph Entropy for Event-Based Social Networks" IEEE Access, 2020

**[17]**Yurong Cheng; Ye Yuan; Lei Chen; Christophe Giraud-Carrier; Guoren Wang"Event-Participant and Incremental Planning over Event-Based Social Networks" IEEE Transactions on Knowledge and data engineering, Volume: 33 Issue: 2,pp:478-488