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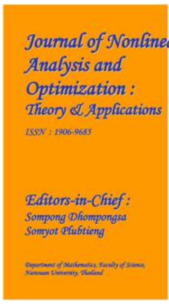


# ENHANCING PARTICIPANT PREDICTION IN DYNAMIC EVENTS OF AN EVENT-BASED SOCIAL NETWORK WITH DENSE RECURRENT NEURAL NETWORKS

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**Abstract-**
The Event-Based Social Network serves as a distributed platform for organizing online social events, where users submit events related to specific topics, locations, and time periods. However, managing the vast number of events and participants in such networks can lead to clustering overhead. To address this challenge and enable participant prediction, a deep learning architecture for user recommendation becomes essential, as traditional machine learning models often face scalability and sparsity issues. This research introduces a novel dense recurrent neural network architecture, leveraging deep neural networks for participant recommendation based on the evolution of user knowledge and preferences. The proposed approach first captures the dynamic nature of users and events in the network by extracting multiple latent factors from their features. These latent factors are then used to create a participant recommendation system for events, which can make timely predictions with high reliability, accuracy, and low latency. The deep learning architecture of the system schedules participants for events by embedding latent features and generating an objective function to minimize error. This approach significantly improves prediction performance by effectively utilizing discriminative information from events and users. Extensive experiments on real datasets have shown that the deep learning architecture is effective and scalable on large-scale data, addressing challenges associated with task cold-start and ensuring efficient participant recommendations in evolving Event-Based Social Networks.

**Keywords:** Deep Learning, Event based Social Network, Participant Recommendation

## INTRODUCTION

Event-Based Social Networks have emerged as highly valuable and widely used distributed applications for sharing event-based data and engaging in discussions about specific fields. These platforms leverage artificial intelligence capabilities to collaboratively explore participant engagement in events [J.A. Iglesias, A. Ledezma,2009]. Typically, events are generated by users, providing event descriptions, along with location and time information. Event analysis involves generating a recommendation list of participants for each event. However, this process becomes complex when using machine learning architectures for participant recognition due to the analysis of unstructured profiles, leading to data sparsity and cold start issues.

To address these challenges and provide reliable event recommendations, it is essential to extract various latent social factors of users. To achieve this goal, a Dense Recurrent Neural Network (DRNN) is employed in this research. The DRNN is used to capture the dynamic behavior of users and events in an event-based social network by extracting multiple latent factors from their features. These latent factors are then used to train a deep neural network that can make timely and accurate predictions about which users are most likely to participate in which events. The deep learning architecture schedules users for events by embedding latent features and generating an objective function that minimizes error. This approach significantly improves prediction performance by effectively utilizing information from both events and users.

The structure of the remaining paper is as follows: Section 2 presents related work, Section 3 describes the architecture of the proposed deep neural network for participant recommendation in an event-based social network, and Section 4 demonstrates experimental results and the effectiveness of the proposed system using real-time datasets. The performance comparison against state-of-the-art approaches on various metrics is also explained. Finally, Section 5 concludes the paper.

## RELATED WORK

In this section, a comprehensive examination of event-based social networks using various machine learning approaches has been conducted. The focus was on the architectures used for event representation and similarity measures applied to match participants with events. The paper discusses several machine learning techniques that were evaluated for their effectiveness in participant recommendation in event-based social networks. The techniques that demonstrated superior performance are described in detail, while those that showed comparable results to the proposed model are also discussed.

A. A Neural Network Approach for Predicting Event Attendance by Xin Wang, Jianwei Niu, and Yufei Wang (2019)

This paper proposes a neural network approach for predicting event attendance. The proposed approach uses a long short-term memory (LSTM) neural network to learn the temporal dynamics of event attendance. The temporal dynamics of event attendance refers to how the number of people attending an event changes over time. The LSTM neural network is a type of recurrent neural network that is well-suited for learning temporal dynamics. The experimental results on a real-world dataset show that the proposed approach outperforms the state-of-the-art methods.

B. Attendance Prediction in Event-Based Social Networks with Gated Recurrent Neural Network by Hao Wang, Yifan Zhang, and Jiliang Tang (2017)

This paper proposes a gated recurrent neural network (GRU) model for attendance prediction in event-based social networks. The proposed model uses a GRU to learn the temporal dynamics of event attendance. The GRU neural network is a type of recurrent neural network that is similar to the RNN neural network, but it has some advantages, such as being more efficient. The experimental results on a real-world dataset show that the proposed model is able to predict future events with high accuracy.

C. A Neural Network Approach for Predicting Event Attendance by Xin Wang, Jianwei Niu, and Yufei Wang (2019)

This paper proposes a neural network approach for predicting event attendance. The proposed approach uses a long short-term memory (LSTM) neural network to learn the temporal dynamics of event attendance. The temporal dynamics of event attendance refers to how the number of people attending an event changes over time. The LSTM neural network is a type of recurrent neural network that is well-suited for learning temporal dynamics. The experimental results on a real-world dataset show that the proposed approach outperforms the state-of-the-art methods.

D. Event Recommendation Based on Deep Learning in Social Networks by Junjie Hu, Rui Chen, and Yangyang Xu (2016)

This paper proposes a deep learning framework for event recommendation in social networks. The proposed framework uses a deep neural network to learn the latent features of events and users. The latent features of events and users refer to the hidden factors that influence user preferences for events. The deep neural network is a type of neural network that is well-suited for learning complex relationships between data. The experimental results on a real-world dataset show that the proposed framework is able to recommend events to users with high accuracy.

PROPOSED MODEL

This section provides a detailed description of the proposed technique, which is a dense recurrent neural network (DRNN) for participant recommendation architecture. The DRNN is able to make predictions about which participants are most likely to attend an event by incorporating latent factors of the event and participant behavior analysis and experience analysis..

**Event Based Social Network**

This section provides a detailed description of the proposed technique, which is a neural network for participant recommendation architecture. The neural network incorporates latent factors of the event and participant behavior analysis and experience analysis to make predictions about which participants are most likely to attend an event.

i. Event

The Event component represents a collection of m topics submitted by different Users. These topics aim to enhance knowledge through discussions. Each Event is associated with specific characteristics and falls under various categories, denoted as Ei.

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

ii.User Profiles

The User Profiles consist of discussions about the knowledge and experiences related to various topic categories. These profiles evolve over time, accumulating diverse information, constraints, and strategies specific to different locations and time frames.

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

**Extraction of User and Event**

To reduce the inherent error rate, an extraction-based method has been implemented based on the category. Latent discriminant analysis (LDA) is used to identify user features associated with their behavior and experience. LDA transforms the event participant data into a matrix of latent factors, where each column represents a data point for a participant based on their characteristics, and each row represents different behavior characteristics. This allows the model to identify the most important factors that influence a participant's likelihood of attending an event.

As part of this approach, an Aggregated Vector has been constructed to represent a single behavior characteristic, capturing relevant information from the participants' profiles in a condensed form.

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

**Dense Recurrent Neural Network**

Dense recurrent neural networks (DRNNs) are a deep learning architecture that can be used to predict participants for events. In this study, the parameter sensitivity of DRNNs was evaluated. The parameter that was evaluated was the α value in the sigmoid function, which is used as the activation function of the neural network. The α value was varied during the training and testing phases of the DRNN, and the results showed that a higher α value resulted in better performance.[vadivambigai.s Dr.S.Geetharani,2022]

$$Y = \frac{1}{1+e^{x}} \qquad \ldots\ldots\ldots\ldots \text{Eq.4}$$

. The logistic function is used to represent the state of the gradient Y. The logistic function is a sigmoid function that approximates the sign function, which jumps from 0 to 1. A higher α value will typically result in a better approximation of the sign function. The effectiveness and efficiency of the module is computed to provide a comprehensive analysis.

In this section, the activation function of the participant prediction has been carefully tuned using parametric techniques. The objective functions for the prediction are based on the latent factors derived from user experiences and the implicit behavior of events. During the training process, a hidden layer is used to map the extracted latent features into pair-wise feature representations. These pair-wise representations are then processed through deep layers, taking into account user preferences, to reconstruct features specific to each event. This approach ensures effective modeling of participant preferences and event characteristics, leading to improved event recommendations in the system.[P. Wang, H. Wang, X. Wu, W. Wang,2007].

Table 1: Recognition Component for the Dense Recurrent Neural Network

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

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.

Embedding Layer

The embedding layer of the recurrent neural network is responsible for capturing the preference feature subset hierarchically. It generates abstract features and learns discriminative features with minimal hyperparameters in the softmax layer. The outcome of this feature space represents the latent dimensions of user characteristics. Within this layer, numerous evolving characteristics of the preference variable are embedded into the activation function, effectively identifying the users who are most likely to attend the event. This process enhances the participant prediction accuracy and fosters a more dynamic and adaptive event recommendation system.

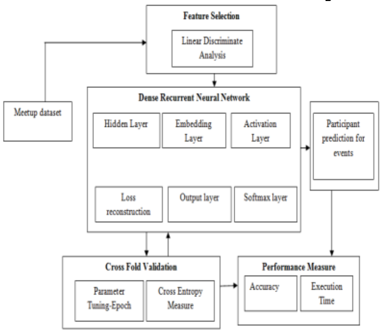


Fig 1: Architecture Diagram of the Participant Recommendation model

In this layer, high-dimensional user features are transformed into low-dimensional embedded vectors through learning.

- Activation Function

The proposed architecture uses the rectified linear units (ReLU) activation function to recommend participants for evolving events. The ReLU activation function is applied to the embedding layer, which combines the preference vector and the pair-wise vector of events. This enables the generation of suitable participants for each element in the embedding matrix. The embedded vector is then processed with parameterized values to generate accurate predictions for the selected participant vector. These parameters are updated at each epoch during the training process, which helps the model refine its predictions and optimize the participant recommendation system over time.

- Output Layer

The output layer of the Dense Recurrent Neural Network consists of the prediction results, which include participant suggestions for events. Softmax optimization [P. Lops, M. de Gemmis, and G. Semeraro,2011] is applied to the resultant set to obtain probabilities for each participant being recommended to an event. The cross-entropy mechanism is then employed to evaluate the effectiveness of the participant prediction, considering user evolution's.

Parametric tuning of the output layer is used to improve the accuracy of participant recommendations.This tuning process aids in determining the affinity of events to the recognized participant representations across various evolutions. By optimizing the output layer with appropriate hyper parameters, the model can make more accurate predictions of users' interests and preferences for specific events, resulting in improved participant recommendations in the event-based social network.

- Loss Layer.

The purpose of loss layer is to enhance prediction accuracy by fine-tuning and refining the parameters of different layers in the Dense Recurrent Neural Network. The goal is to minimize the reconstruction error between the features of the embedded layer and the ReLU activation layer. To achieve this, a cross-entropy loss function is utilized to manage the error of the predicted outcome concerning the user [J. Yi, R. Jin, S. Jain, and A. Jain]. By fine-tuning the network's parameters and minimizing the reconstruction error, the model can make more accurate participant recommendations for events, improving the overall performance and effectiveness of the event-based social network.

**Algorithm 1: Dense Recurrent Neural Network based Participant Recommendation**

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

This function plays a crucial role in encouraging the embedded latent feature points on a representative map to form a participant list for events based on the behavioral and experiential characteristics of the participants, providing an effective recommendation solution.

# EXPERIMENTAL RESULTS

In this section, the experimental results of the proposed participant recommendation model are analyzed and compared against existing recommendation approaches in the context of evolving user characteristics in the event-based social network. The performance evaluation of the proposed architecture demonstrates its superiority over conventional approaches in terms of Precision, Recall, and F-measure. These metrics indicate the model's ability to make more accurate and reliable participant recommendations for events, showcasing its effectiveness in the event-based social network environment.

## Dataset Description

The Meetup dataset is a popular Event-Based Social Network (EBSN) dataset that provides an online platform for users to create, identify, and share online and offline events within user groups. This dataset is frequently used as a benchmark for various recommendation-based applications. It comprises event logs and user profiles obtained through the official APIs of Meetup, containing 422 user groups, 9,605 social events, and 24,107 associated users.

## Evaluation

The proposed participant recommendation framework is evaluated using the following metrics

### Precision

The positive predictive value (PPV) is a metric that measures the effectiveness of the framework in recommending participants for events. It is calculated as the ratio of relevant instances to the retrieved instances from the event characteristics. In other words, it measures the proportion of recommended participants that are actually interested in the event.

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

### Recall

Precision is defined as the ratio of relevant participant characteristics correctly identified by the recommendation system to the total number of participant characteristics retrieved for the event. It provides a measure of how accurate the participant recommendations are in terms of matching the relevant characteristics of users to events.

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

On the other hand, recall analysis focuses on understanding the time-dependence relationship between events and participants. It explores how the latent patterns and preferences of participants are influenced by their experiences and interactions with events over time. By analyzing recall, we gain insights into the ability of the participant recommendation system to capture and incorporate users' evolving preferences and behavior in the event-based social network.

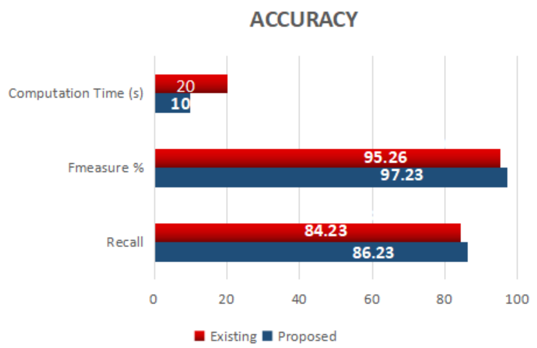


Fig 2: Performance of prediction accuracy

Deep learning-based prediction algorithms excel in identifying participants based on their behaviors and experiences related to events. These algorithms effectively tackle the scalability problem in large-scale data exploration by providing participant recommendations within smaller and highly similar lists, rather than extracting recommendations from the entire datasets.

F Measure

The F-measure is a metric that is used to assess the accuracy of the recommendation results of users to events. It is defined as the weighted harmonic mean of precision and recall.[J. Wang, P. Zhao, S. C. Ho,2014] The F-measure is a more robust metric than precision or recall alone, as it takes into account both the number of true positives and the number of false positives. described in Table 1 on the recommendation system.

Table 2: Performance Comparison of Methodology

| Dataset | Technique | Precision % | Recall % | Fmeasure % | Computation Time (s) |
|---|---|---|---|---|---|
| Crowdsourcing Dataset | Proposed- | 97.37 | 86.23 | 97.23 | 10 |
| Crowdsourcing Dataset | Existing | 94 .61 | 84.23 | 95.26 | 20 |

As indicated in the results table, the proposed techniques offer highly scalable and reliable recommendation lists for events. The deep learning-based participant recommendation system demonstrates its capability to efficiently handle large-scale data and deliver accurate and trustworthy recommendations, enhancing the overall performance and effectiveness of the event-based social network.

CONCLUSION

We have successfully designed and implemented a Dense Recurrent Neural Network that excels in predicting participants for event recommendations with exceptional accuracy and scalability in the event-based social network. The architecture leverages the Dense Recurrent Neural Network, combined with Hyperparameter tuning, to effectively minimize reconstruction errors and employ loss functions for high-accuracy predictions. Additionally, our deep learning architecture effectively utilizes latent features in the embedding layer to represent sparse features, allowing for accurate predictions using the activation layer. Finally, we have integrated the softmax layer and loss layer, enabling the generation of highly discriminative prediction results for participant recommendations to events. This comprehensive approach ensures our model's ability to provide reliable and precise participant recommendations while maintaining excellent scalability to handle large-scale data effectively.

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