Original Article

Recommending Profiles To Social Event Participation In Online Social Network Service Applications Using Deep Learning Techniques

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Abstract

Nowadays, organizing online Social events is growing especially in current pandemic situation due to corona. Thus social network services helps to organize the event oriented online social gathering. The events discussed on social networks can be associated with topics, locations, and time periods. Various literatures have employed clustering mechanism to group the profiles of the user of social networking applications. More research has been carried out in event based online network services as existing models leads to scalability and sparsity problems. Event-based online social networks are used to maintain interest-based groups with high relevancy rate, recommendation quality and predictive accuracy. In order to achieve the above goal, in this paper, we propose a novel framework named as Deep Influence Predict (DIP) which explores the features of Recurrent Neural Network in order identify the target or potential users through different patterns and behaviours of the profile on the social networking service applications. It learns multiple levels of representations and abstractions of the latent data through individual participation record. Further, it extracts the extrinsic and intrinsic properties of the profiles on their social connections and social effects. Specifically, it identifies the distinguishing social groups with different topics and categories as multifaceted interest in iterative process. Finally decision of recommendation for the event is integrated on outcomes of user behaviour model through personnel impact, social relation and equilibrium. Evaluation of the proposed model through various case studies has been implemented using hadoop architecture and validated across various measures such as accuracy on precision, Recall and f measure along scalability and Execution time.

Keywords: Event Driven Social Networking, Prediction, Deep Learning, Recurrent Neural Network

I. INTRODUCTION

Event driven social networking service has been emerging to provide opportunities for the peoples to gather together in online during pandemic situation like Covid-19. It attracts millions of users all around the world to create interest-based groups to organize and promote offline events ranging from parties to technical conferences as social platform[1]. Event can be generated by any user with event description, location, and time. Social event analysis generates the complexity for the participant recognition to the particular event. However, as profile of the users have become unstructured and noisy, and it is difficult for researchers to use them for social events analysis. Organizing numerous social media data and analyzing social trending events automatically are particularly helpful for improving event analysis on major challenges such as social connection, impact and multimodal properties. In order to establish a recommendation solution to event to eliminate those issues, extraction of the social factors has to be carried out on the user profiles or from the event log data. The Accuracy of the results becomes inevitable for offline social data gatherings [2]. Comprehensive modelling is still required for built recommendation system as statistical model on offline social data gathering provides the irrelevant prediction results on the event oriented applications. The existing model is also fails in clustering the extracted information from the social influential attributes and user diversity model in the distributed system[3]. It causes the uncertainty in complex decision making processes. Thus comprehensive modelling on social effects which is considered as feature or constraint is still important for the analysis of social event as it improves the prediction results.

In this paper, a novel framework named as Deep Influence Predict (DIP) which explores the features of Recurrent Neural Network in order identify the target or potential users on basis of social connection and social effects of the profiles on other similar events. In addition, geographical features, social features, and implicit patterns of the profile have been simultaneously considered[4]. It learns multiple levels of representations and abstractions of the latent data through individual participation record composed by sequential preference and contextual preference. Further, it extracts the extrinsic and intrinsic properties of the profiles on their social connections. Specifically, it identifies the distinguishing social groups with different topics and categories.

The rest of this paper is organized as follows. Section 2 explains the related work on basis on decision making process for participant recommendation to the event. In Section 3, we formulate the deep influence prediction framework for recommending profile to social event using Recurrent Neural Network. In Section 4, experimental validation has been carried out on proposed framework against state of art approaches using performance metrics on benchmark dataset. Finally, we conclude the paper in the section 5.

II. RELATED WORKS

In this section, many approaches related to the social event recommendation using decision making machine learning model has been analysed on various aspects. Besides some approaches provides solutions for the event participants.

A. Analysis of Collaborative Filtering model

Social Influence Prediction Based on Combined Collaborative Filtering Model in Event- Based Social Networks estimates the unobserved entries of the constructed user-event on social influence matrix. Further Matrix Factorization with Event Neighborhood (MF-EN) model has been enabled to determine the event-specific features. It uses the two-stage discriminant framework which captures the users' preferences [5]. Collaborative future event recommendation estimates recommendation of the individuals' preferences on their past events in order to achieve the like and dislikes of each user in different clusters. Collaborative clustering predicts each user using ranking function on basis of their interest. Further the user parameters has been analysed on group and individual basis. Values of user parameters have been estimated using a similarity metric between users based on the degree to which they share these dimensions [6]. Group Event Recommendation in Event-Based Social Networks Considering Inexperienced Events estimates participant prediction mining implicit friendships between users on two-phase group event recommendation (2PGER) model for EBSNs by simulating the consulting process between users and their friends outside the groups, and simulating the negotiating process among members inside the groups. Initially online social behaviors, users' event participation records, and topological structures of EBSNs to establish a global trust network among users and establish ego trust networks of all users has been leveraged[18].

B. Analysis of Tree based model

Successive Event Recommendation Based on Graph Entropy for Event-Based Social Networks estimates list of upcoming events to a user according to his preference based on graph entropy (SERGE) to deal with the new event cold start problem by exploiting diverse relations as well as asynchronous feedbacks in EBSNs. Initially, it constructs a primary graph (PG) based on the entities and their relations in an EBSN and computes the user-event similarity scores by applying a random walk with restart (RWR) algorithm. At each recommendation time, it then constructs a feedback graph (FG) based on the up-to-date user feedbacks on event reservations and applies the RWR again on FG to compute new user-event similarity scores [19]. Tree-Based Mining for Discovering Patterns of Human Interaction in meetings estimates semantic knowledge for understanding and interpreting the user in the meeting. A mining method to extract frequent patterns of human interaction based on the captured content of face-to-face meetings has been analysed. Human interactions, such as proposing an idea, giving comments, and expressing a positive opinion, indicate user intention toward a topic or role in a discussion. Human interaction flow in a discussion session is represented as a tree. Tree based interaction mining algorithms are designed to analyze the structures of the trees and to extract interaction flow patterns [20].

C. Analysis of Temporal and Spatial based models

Participant Selection for Offline Event Marketing Leveraging Location-Based Social Networks estimates people to participate in a sponsored gathering, thus allowing marketers to have face-to-face, direct, and close contact with their current and potential customers by improving marketing on carefully selecting invitees to such sponsored offline events by leveraging location-based social networks with effect quantitative model that considers the distance and overlapping social influence to determine a participant team that can maximize the marketing effect while fulfilling the scale and item coverage constraints[21]. Organizing an Influential Social Event Under a Budget Constraint for the proliferation of event-based social services through organizing personalized offline events through the users' information shared online. The budget-constrained influential social event organization is carried out on basis of a group of influential users with required features to organize a social event under a budget. Further sub modular maximization problem with mixed packing and covering constraints several polynomial time algorithms he influence spread function is unknown and can be arbitrarily selected from a set of candidate submodular functions [22].

III. PROPOSED MODEL

In this section, proposed architecture to predict the participant for social event has been modelled using deep learning strategies and constraints. It is as follows in detail.

A. Transformation of event log and user profiles into matrix from meetup dataset

Meetup is real-world data set which is composed of event logs and user profiles. Collected event log and user profile are transmitted into social network matrix[7]. As matrix form as it comfortable to process further using probabilistic matrix factorization. Social network is represented as graph G=(V,E) , where V is considered as Vertex set representing user in the network and E is considered as edge representing the relation between the user.

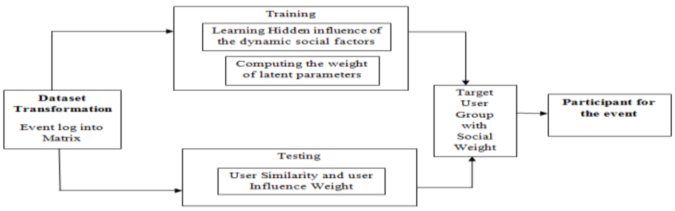

Fig 1: Architecture of proposed framework

Let C = {C_{ik}} denote the m × m matrix of G, which is also called the social network matrix in this paper. For a pair of vertices, V_i and V_k, let $C_{ik} \in (0, 1]$ denote the weight associated with an edge from V_i to V_k, and $C_{ik} = 0$, otherwise. C is an asymmetric matrix. The idea of social network matrix factorization is to derive a high-quality l-dimensional feature representation U of users based on analyzing the social network graph G. Let $U \in R^{l\times m}$ and $Z \in R^{l\times m}$ be the latent user and factor feature matrices, with column vectors U_i and Z_k representing user-specific and factor-specific latent feature vectors, respectively[8].

B. Extraction of user preference and social effects

In this module, user preference has been computed for predicting the participation of the target user group for the event without considering the social effects

α) Extracting User profile on Basis of Preference level

P_i is normalized vector representing the preference of the user. In order to represent user profiles, a vector pi to present the preferences of user u_i has been exploited, on exploration of elements, preference level on a specific aspect/topic has been denoted by the preference.

β) Extracting Attribute vector for event

Furthermore, a vector a_k for each event e_k to indicate the attributes which has been included as it has the same dimensions with pi.

χ) Participant prediction based on Similarity

Participant prediction to the event is computed based on the similarity between the vector of user preference and vector of attributes of the event. Computation has been done without social connection and social effects.

Target User Group = U

If ($p_{i==}$ a_k)

User has probability to the participate in the event e_k

Else

User will not participate in the event e_k

C. Extracting the social effects of the Target user towards participation prediction

User participation is considered as a discriminant problem, to tackle those issues, similarity function f(u_k, ek) and threshold function h(u_k,e_k) has used to compute the individual participation on basis of social effects. In this social effect has been merged with computation of threshold. Threshold depends on the participation of similar user[9]. Dependence of the user is reflected by variance of the threshold. Variance of the threshold is formulated using Classic Independent cascade [5] to simulate the dynamic mutual influence within the user.

Algorithm 1: Social Connection Extraction

Set Threshold = W_{ij}

W_{ij} is strength of the social connection

Case 1: W_{ij} = 0

Social Connection between U_i and U_j is low

User Participation is less

Case 2: W_{ij}=1

Social Connection between U_i and U_j is high

User Participation is high.

IV. DEEP INFLUENCE PREDICTION FRAMEWORK

Deep Influence prediction framework encompasses of Recurrent Neural Network to group the user based on the preference and social connection and further used to determine participation of the user in the event on latent influences. Framework is composed of training and testing phases.

a. Training phase

RNN are deterministic which is employed for Training with discrimination error. It is formulated using objective function

Target User Group U = {U_k}

Set of Event E = {e_k}

Participation of the user P= {$S_{i,k}$} for each pair of u_k and e_k

Event attributes a_k for each e_k.

In this phase, activity measures and connection strength for each u_i has inferred to the latent profile of the user.

RNN produces the hidden states of user profiles through the deterministic probability distribution using two properties, one is considered as distributed hidden state to store static social influence and social effects of the user and another is Non-linear dynamics to update dynamic social effects of the user. On incorporation of the linear constraints, back propagation algorithm on dynamic mutual influence can be modified easily between the weights of the social connection [10].

We compute the gradients as usual, and then modify the gradients so that they satisfy the constraints. Recurrent net as a layered, feed-forward net with shared weights and then train the feed-forward net with weight constraints.

Stack of activities of the entire user has been built on the forward pass at each time step. On other side, backward pass peels activities off the stack in order to compute the error derivatives at each time step. Finally derivatives at all the different times for each weight are added together after backward pass. The initial activity state of all the hidden and output units has been specified with some default value like 0.5 as threshold.

Dynamic influences through various connections contain the learned parameters on its initial states to learn the weights of the connection. Further initial states have been back propagated at the end of each training sequence to obtain the gradient of the error function. Finally, adjust the initial states by following the negative gradient.

α. Inputs to the Recurrent Networks

We can specify inputs in several ways:

- Specify the initial states of the entire group with social effects.
- Specify the initial states of a subset of group with weight of social effect.
- Specify the states of the same subset of the weight at every time step.

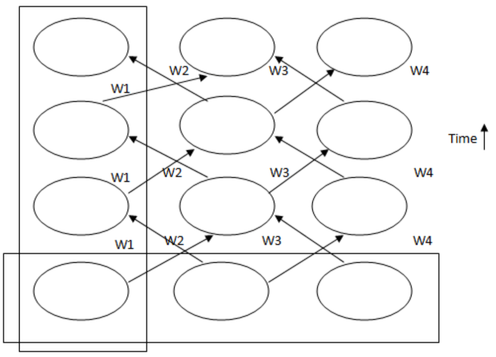

Fig 2: Input processing of the neural network

α. Training recurrent networks

We can specify targets in several ways:

- Specify desired final activities of all the groups with social effects to determine the participating user.
- Specify desired activities of all group for the last few participants for the event
- Good for learning attractors
- It is easy to add in extra error derivatives as back propagate.

β. Connectivity of the Network

Hidden Activity pattern in the three hidden units has been fully connected in the both direction to vote in the next step in one time step. In this feed forward connection which allows voting for next hidden activity pattern through input unit [11]. Finite state automaton was exponentially powerful as it is emulated by the recurrent network with n hidden neurons using 2^N possible binary activity vectors.

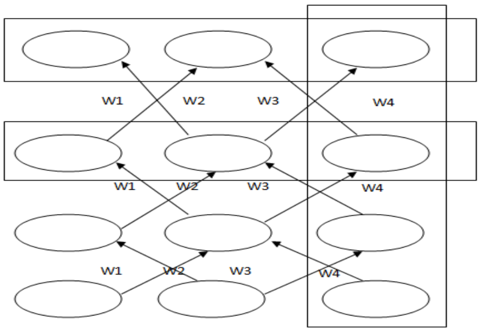

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Fig 3: Training of neural network

Algorithm 2: RNN Training of the adjacent matrix

Input: Adjacent Matrix

Process: RNN Training with Hidden Layers

Output: Target Group with user profile along strong dynamic social strength for events

1. Initialization of weight and biases for social connection of user
2. Set Input Bias= 0
3. Set output Bias =0.05
4. Apply Gradient Descent()

    Weights adjusted between the user profiles on error function derivatives

    Total Loss = weight of the group + derivative of error with respect to the weight

    Optimization weight update is given by

$$\theta t = \frac{\lambda}{U}\sum\theta$$

Where U is size of training set, λ is the learning rate, and θ is set of parameters

5. Compute error derivatives on Dynamic social effects
6. Group the user profile based on Back propagation
7. Merge user profile computed by back propagation on various intervals in social effects
8. Converge the user profile as user groups based on their social connections

a. Testing phase

On extraction of the user profile and mutual affection strength of the profile data in training stage, predicting the participants and participation of the user for the event for target user group is determined on varying social effects using time window to learn temporal strength. Testing phase is carried out with prediction on the test data.

Algorithm 3: Event Participant Prediction

Input: Target User Group

Output: Participants for the event

Process: Prediction

Compute Similarity among the user in the group against various influences

Compute the weight for each user based on the social effects

Aggregate the highest Weights of social effects profiles

Highest Weights of Social effects profile = Participant of the event

Compute User Similarity and Social influence of the participant of the event with Target group

Most influenced user on participating user= Participant of the user.

V. Experimental Analysis

The experimental results of the proposed framework have been evaluated on a real data set has been presented. The work has been validated on various case studies which is as follows

A. Experimental Setup

We implement DIP framework based on top of the latest version of Hadoop (Hadoop YARN 2.6.0). We consider Hadoop YARN 2.6.0 as the baseline, denoted as "Hadoop". Hadoop uses the default scheduler for processing data towards executions of prediction modules without delay. The local cluster consists of 10 nodes, each with two Intel Xeon X5675 CPUs (12 cores in total), 24 GB memory and 500G SATA disks[12]. We perform the execution on 10-node cluster using Hadoop API. The configured system undergoes following process.

Initially, Topic with similar categories to describe the user profiles and event attributes has been extracted using Latent Dirichlet Allocation model and it is represented as matrix. User profiles extracted are grouped using preference function $f(u_i,e_k)$ and represented in vectors has been further processed using RNN training and testing for participant prediction on target group. Cosine similarity and distance of the features and attributes of the user affects the decision. The evaluation of the decision has been carried out using following metrics such as precision and recall. The results and values of the metrics detailed in the next section.

B. 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.

C. Performance comparison

The performance of the prediction of the proposed framework and existing framework has been carried out to determine the robustness of the work. In this work, dataset is classified into training with 90% of the user profiles and testing with 10% of the user profiles [13]. The evaluation results of the precision and recall has been computed to the results of the participant prediction on the target group and depicted in the table 1 with less deficient profiles.

Technique	Precision	Recall	Training time	Testing time	Computation Cost
Deep Influence Prediction	98	97	125ms	101ms	215ms

Dynamic Mutual Influence	96	89	189ms	151ms	290ms

Table 1: Performance evaluation of the prediction model with less Deficient Profiles

D. Performance Analysis

The Deep Influence prediction framework describes the event participation on basis of the social spread which is to represent the social effects on computation of pair wise similar preference. Performance of the model is determined further against following categories

a. Parameter Sensitiveness

In this category, parameter sensitivity has been evaluated. The parameter used in sigmoid function towards training and testing phase of the RNN. It is considered as Activation function of the neural network[14]. Parameter of sigmoid function represented as gradients and weights of the event attributes and user profiles. Sigmoid function is represented as

$$Y=\frac{1}{1+e^{x}}$$

In this e^x is the logistic function representing the state of the gradient Y.

Sigmoid function to approximate the sign function jumping from 0 to 1, thus a higher α might be better for approximation. The effectiveness and efficiency of the module is computed to provide comprehensive analysis. Also, the sensitiveness of the training sample proportion has been discussed and which is summarized.. The execution time for training sample and testing sample has been measured in the figure 2 towards meetup dataset with less deficient profiles. The performance of the proposed model with less number of training samples indicates that proposed framework is sensitive in the social network structure towards participant prediction to the event.

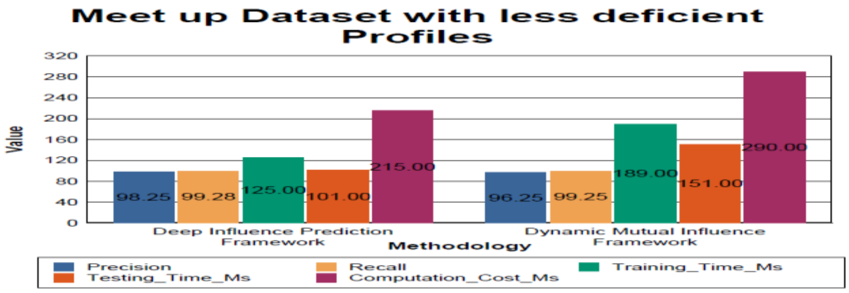

Fig 4: Performance Analysis of the Prediction model with less deficient profile on dataset

Indeed, each group containing more than 20 events in mean is constituted as classes, in those classes, process with only a few milliseconds on prediction of potential individual for participating the particular event in the extracted event list. Furthermore, towards managing the frequent updates of the social data of users, model could achieve the better stability between prediction accuracy and data update frequency.

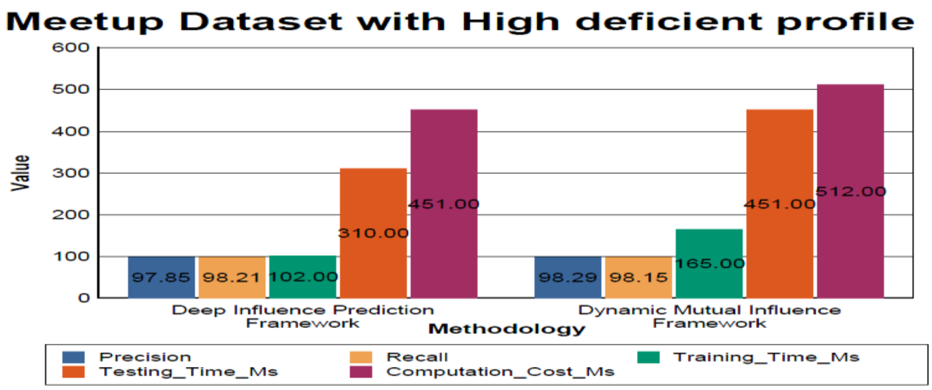

Fig 5: Performance Analysis of the Prediction model with high deficient profile on dataset

Validation has been resulted. Table 2 provides the performance evaluation on the prediction model with high deficient profiles. Deficient profile indicates the social influence [15].

Table 2: Performance evaluation of the prediction model with High Deficient Profiles

Technique	Measures	Cosine Similarity	Euclidean Distance	Gaussian Probability time
Deep Influence Prediction Framework	Precision	99.21	99.28	99.21
	Recall	99.88	99.78	97.28
Dynamic Mutual Influence Framework	Precision	87.58	87.54	87.98
	Recall	87.39	87.56	85.56

The proposed framework performs with good computation results with less number of training samples and meanwhile effectiveness of time varying social factors with proposed model also been ensured . According to the experimental results of the proposed model, it outperforms with precision as 89.72% and recall with 95.25%. In addition, computation cost of the model is 0.22 milli seconds for training process and 0.92 milliseconds for evaluating the participant to the each event .

Table 3: Performance Evaluation of methodologies on Meet up dataset on other similarity metrics

Technique	Precision	Recall	Training time	Testing time	Computation Cost
Deep Influence Prediction Framework	97.85	98.21	102ms	310ms	451ms
Dynamic Mutual Influence Framework	98.29	98.15	165ms	451ms	512ms

DIP framework achieves better prediction on the multifaceted interests of the user profiles employing the latent constraints on the each layer of the RNN to increase the performance of the prediction [16]. Table 3 provides the performance analysis on different similarity metrics. Euclidean distance could be similar with cosine (if the vector is normalized via 2-norm), their performance are quite similar and unified variance is in appropriate. Time varying factors on the connection of profile determines the variation of the data on computing the participants to the event.

Normally each group contains average 20 to 30 user profiles which makes easy to predict the potential participants with high precision and recall values. The figure 4 indicates the precision and recall values of the prediction results of proposed and baseline framework on the time varying social factors of the user information.

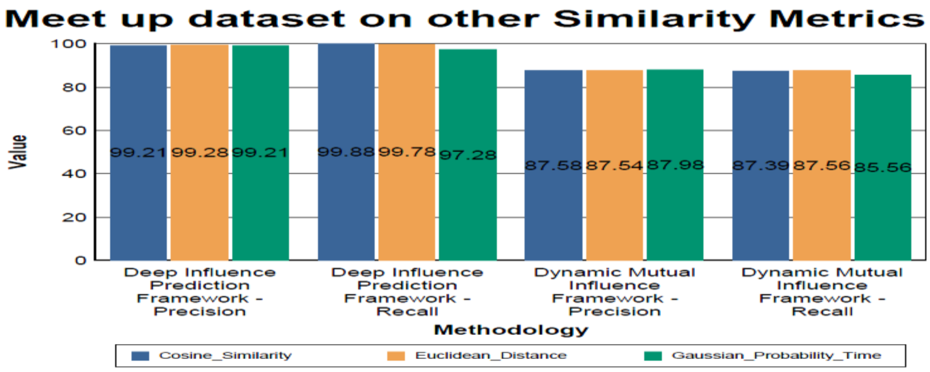

Fig 6: Prediction Performance Evaluation among various similarity metrics

The pruning validation is performed on the dataset with considering user influence has been summarized in figure 5 on measures of the precision, Recall and f measure.

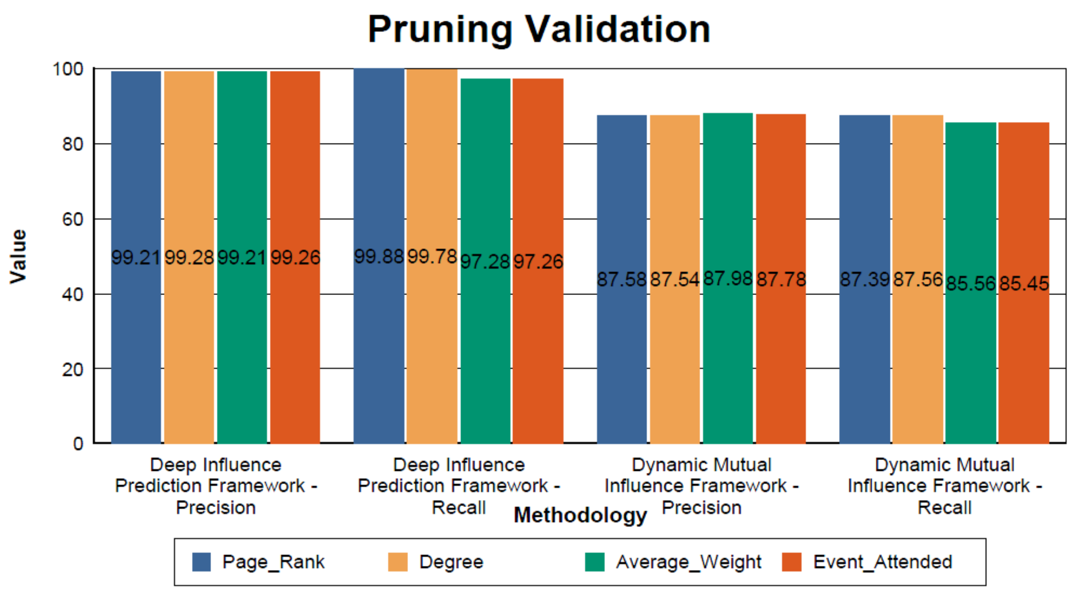

Fig 7: Pruning Validation against various models

α. PageRank: It is a familiar algorithm employed to determine the importance of the web page or data on the particular web document structure, it follows the assumption of the data significance on the particular web page which spread across the entire web document structure. In this work, it has been extracted to determine the event on basis of significance of the event information's.

β. Degree: It is a measure to determine the evolution of the data from its origin. It helps to identify the stronger influence of the participant to the event on these varying social factors to his profile on various heuristics conditions [17].

χ. Average Weight: It is used to compute weight of event on various social factors of the users to determine the participant and influence to participate on the event..

δ. Counts of Event Attended: It is considered as heuristic algorithm to compute the interest of the user on the various similar events to determine the influence of the user to the specified event.

Table 4: Pruning Validation on different perspectives of prediction accuracy

Technique	**Measures**	**Page Rank**	**Degree**	**Average Weight**	**Event Attended**
Deep Influence Prediction Framework	Precision	99.21	99.28	99.21	99.26
	Recall	99.88	99.78	97.28	97.26
Dynamic Mutual Influence Framework	Precision	87.58	87.54	87.98	87.78
	Recall	87.39	87.56	85.56	85.45

The overall performance on the pruning validation has been depicted in the table 4 on the computed value of measure such as precision, recall and time cost under various data settings. Especially to those computations, the X-axis of performance graph has been fixed with the percentage of users available i.e., only 90% -50% of users can make effective decisions, while remaining users, could able to accept social influence , but those user will not influence the others user for participation to the event. Performance of the complicated objective function has been revealed that latent user profiles and social connections with given event produces the maximum participant to the any event description.

E. Validation for Designed Event Attraction

It is complicated to carry out validation with direct ground truth data to measure the influence of the user to the event. However, target group will share common factors among the most popular events on assumption towards the direct validation. Meanwhile, indirect validation on participants to the event design has been compared with existing events, in that five top ranked event has been approximated towards computation of preference on the various social factors. Target group to the event has been considered as a social spread maximization problem. From the perspective of group decision-making, various metric has been employed to calculate the weighted voting. Specifically, it is composed of four important metrics namely PageRank, Degree, Average Weight and Number of count on Event Attend, those metrics has been defined above. Those metrics determines the weights of each user to specified event. Generally, weighted voting based evaluation proved as strong, it could be employed to increase the attendance rate of the participant to the designed event and it is considered as designed event influenced for target group.

F. Validation on Event Attendance Prediction

The designed events are likely to be similar with other pervious designed highly-attractive events in order measure the prediction effectiveness of the event designed. To be particular, event attribute vector to the key words (terms) of the user social profile has to be transferred through incorporation of the topic generation model. Finally, on availability of users' profiles and historic event attendance records of the user, each target users to particular event are labelled by multiple users with a score range of 1-5, in this, 5 means highest positive intentions to join the event and 1 means the lowest interest on going the event.

G. CONCLUSION

We designed and implemented a deep influence prediction framework to enhance the prediction of social event participation especially in pandemic period on exploring the social behaviours and interest on various factors in the latent information. Model extends the RNN architecture to obtain the high relevant results with good scalability in the hadoop architecture. Specifically, we designed a deep learning architecture towards prediction on basis of users' preferences and their latent social connections. Furthermore, validations on efficiency improvement have been carried with network pruning. The proposed model effectively uses the objective function for decision-making process of event participation.

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