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A MULTIOBJECTIVE DEEP BELIEF NETWORK FOR EVENT PARTICIPANT PREDICTION IN ONLINE SOCIAL NETWORK SERVICE APPLICATIONS

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Abstract

Event based Social Networks provides convenient platform for knowledge enhancement to the participants from research communities and industrial communities in the social network but nowadays numerous event has been organized by the organizer which leads to the data overloading problem and it becomes complex to identify the suitable event and high influencing event by participant . Most previous works in participant prediction using machine learning and deep learning model focus on intrinsic and extrinsic properties of the user on their behavior and preference analysis in the social context. However multiple social events are hosted same time which it leads to high competition to obtain the influencing user to maximize the number of participants. In this paper, multiobjective deep belief network for event participant prediction is proposed to exploit the high influencing user to the various event. Typical task is to identify the user features and event features on its contextual information. Latent Dirichlet Allocation has been employed to extract the latent contextual information on the different perspective to increase the high relevancy rate. Extracted latent contextual information is projected to deep belief network to compute the participant prediction to event classes on processing the latent information in hidden layer and visible layer. Each visible layer enabled with representation learning of features. . Further influence weight has to be computed on both long term interest representation model and short term interest representation model to jointly represent user impact on the event. Interest model uses the multifaceted information ranking based on knowledge level, hierarchy level and participation level on the relevant events in the activation layer of deep belief function. Finally decision of the profile recommendation to the events is integrated on basis of influence weight to the correlation of similar preferences of the groups to the event in the visible layer. Evaluation of the proposed model through various case studies has been implemented and validated across various measures such as accuracy on precision, Recall and f measure along scalability and Execution time.

Keywords : Event Based Social Network, Event Participant Prediction ,Online Events, Latent Dirichlet Allocation , Deep Belief Network

1. Introduction

Event based Social Network is getting more attention in recent years among various user to enhance their knowledge sharing with each other on various topics. Especially Meetup, Douban and facebook provides online platform to create and distribute events in these networks. Event posted on the network is associated various attributes of the organizer. However various event is created on various themes mentioning the contextual information and published on various topic [1]. Due to huge number of events publishing continuously on various topic and theme in online social networks, it lead to complexity in computing the attractive events for users of the network is considered as cold start issues[2][3].

However conventional approaches using machine learning and deep learning architecture have been exploited to explore multiple contextual factors such as Social factors, Technical factors , location factors , Industrial factors and hierarchical factor along content, preference ,effects and social connection of the user to mitigate cold-start issues in participant recommendation to event in event based social network[4]. In addition, conventional model fails to compute the suitable event to individual as time varying factors is not incorporated. Hence efficient architecture has to be designed on incorporation of the time varying multi faced attributes of the user.

In this paper, a multiobjective deep belief network is architected as time based contextual preference model to recommendation of user profile to the competitive events. Initially architecture preprocess the dataset using missing value imputation and dimensionality reduction mechanism. Preprocessed matrix is capable of extracting the event features and user features using latent dirichlet allocation. LDA provides the marginal distribution of the features to event and user in order to compute the association in the deep learning architecture.

Deep belief network process the event features and user feature on its visible layer and hidden layer of the model. In this architecture, visible units of the visible layer enabled to process the event and user attributes features to associate on relationship as training data. Contrast divergence is applied to weight the feature in the visible layer. Relationship between the user features and event feature computed using weights which influences the association as unsupervised learning. Composite mapping of the feature is provided to hidden layer.

Hidden units in the hidden layer use the composite mapping to back propagation. Back propagation is considered as supervised learning to test data. Finally potential participants to the events is computed from back propagation process of the deep belief network using sigmoid based activation function to the various multi-faced information and it is validated using cross fold validation. Softmax operation is incorporated in this network for prediction purposed using random forest classifier.

The remaining article is sectionized into following parts. Section 2 details various related work of the participant prediction to the various event in the event based social network.. In Section 3, design and architecture of multiobjective deep belief network for participant prediction to events is formulated for time varying user information's. In Section 4, experimental analysis and performance evaluation of proposed architecture has been carried against conventional approaches using multiple performance metrics on benchmark dataset. Finally article has been concluded in section 5.

2. **Related work**

This article examines nearly similar event recommendation model which is employed using deep learning approaches in detail on basis of feature extraction and feature representations using similarity measures. Particular deep learning techniques produce better performance in terms of effectiveness on the evaluation of the model has been represented in detail and few approaches performing similar to the proposed architecture is represented as follows is described as follows

2.1. Deep Influence prediction

In this method, Deep Influence Prediction (DIP) has been analyzed in deep to explore the user and event features of Meetup dataset. Extracted feature is processed using the deep learning architecture entitled as Recurrent Neural Network. Particular architectures computes the potential participants to the event on processing the user implicit and explicit attribute information with and without social effects. Each layers of the RNN abstract the latent information of the user and predict the user participation of the social effects on similar topics multifaceted interest in iterative process [7].

3. Proposed model

A large variety of datasets of form of high dimensional data are curated. Data Pre-processing has been applied in form missing value prediction and dimensionality reduction to determine effective recommendation list on quality attribute set.

3.1. Missing Value Imputation

Missing Value Imputation has been used factor analysis. Factor Analysis determines maximum common variance on the particular data field. It follows the Kaiser criterion[9] which uses the Eigen value. It uses the score for the variance of the particular data field to fill the missed value of the data field. It can also compute using maximum likelihood method on basis of correlation of the data field [10].

3.2. Dimensionality Reduction -Singular Value Decomposition

Singular value decomposition is to reduce the entire dimension of dataset from high dimension dataset to event specific dimension of the dataset. It is carried out to reduce the time in building the predictive analytics learning model. It also score data on processing the quality dimension. Especially some attributes has no predictive value hence it reduces the accuracy of the model. Singular value decomposition uses the ranking approach which derives the event specific attributes based on the linear combinations on the transformed matrix to yield quality attributes. Consider the following visual representation of these matrices

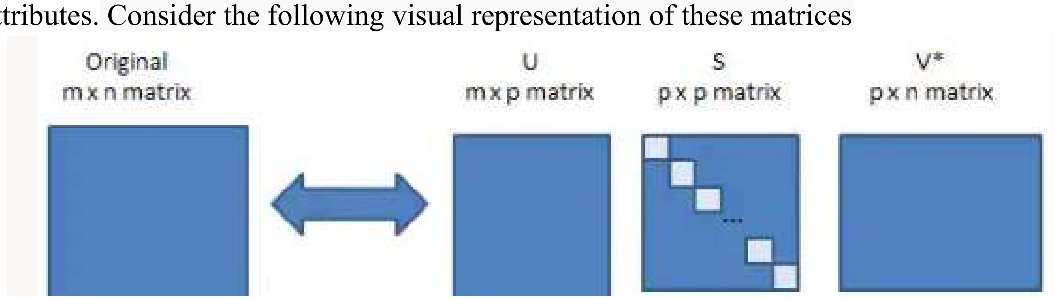

Figure 1: Transformation of High Dimensional dataset into Event specific dataset using SVD

Dataset Matrix M = m*n

Where m is real value and n is the complex value

Factorization of M = USV

U = m*p matrix

V = n*p matrix

S = diagonal matrix p*p

Diagonal value of S = singular value of data matrix M

where p represent rank

Singular Value decomposition generates the event specific attributes set as transformed dataset to build more accurate model in shorter time factorization has USV form The columns of *U* are typically called the left-singular vectors of *M*, and the columns of *V* are called the right-singular vectors of *M*. Important features of SVD in processing high dimensional data is that it provides the decomposition mechanism to the data matrix considered as *M* into *U*, *S*, and *V*. I

n this operation, original matrix can be reconstructed or approximated. The singular values in the diagonal matrix *S* is employed to determine the amount of variance on each attributes in the every singular vectors.

3.3. Latent Dirichlet Allocation

Latent Dirichlet Allocation is employed to analyze the event profile and user profiles to obtain the event feature vector and user feature vector containing attribute of the user and event from the analysis of the large dimensions of the dataset. Further it preserves the essential statistical relationship for prediction is follows.

3.3.1. User profiling

It attempts to describe set of observations of the user on the distinct categories to represent it is as user corpus. It is also used to enhance user coherence. Attribute of the user can be extracted from the following categories as

- Multi Valued Attributes : It contains multiple values to the attributes such as languages known , Jobs and Colleges Studied, Places visited

- Hierarchical Attribute : It contains different level to the attributes such as address, interest.

- Content Attributes : It includes the text from the user activities such as posting a comment or commenting a post.

3.3.2. Event profiling

It attempts to describe set of observations of the event on the distinct categories. Attribute of the user can be extracted from the following categories as

- Event Description Attribute : It contain the text description of the event

- Event URL : It is link to participate in the event

- Event RVSP count: No of user applied to the event

- Event Date : Date of event occurring

- Event Time: Time of event occurring

Dimensionality k of the dirichlet distributions related to the event is represented as Z

Probabilities of the distribution are parameterized by K*V is represented as matrix β Where $\beta_{ij} = p(u^j = 1 | e^i = 1)$ which contain attributes of the user or attribute of the event

Poisson Assumption is employed for discrete probability distributions as it provides probability of events in the specified time frame. It uses the one only variable λ representing the no of event in the time frame. It is capable of producing the prediction result on processing the distribution of the data with mean and variance computations on both integer and non - integer data. On inclusion of these properties it is possible to inference and estimate the parameter.

Dirichlet is a convenient distribution on the simplex which is considered as finite dimensional sufficient attributes and is conjugate to the multinomial distribution. A K dimensional dirichlet random attribute can take values in the (k-1) simplex. Simplex is a K vector containing user attributes or event attributes which is lies in the following range

$$\theta_i > 0 \text{ or } \sum_{i=1}^{k} \theta_i = 1$$

Where θ is the attribute composition of the user or event

Joint Distribution of the event and user feature is given as user-event association matrix

$$P(\theta, a, e \mid \alpha, \beta) = P(\theta \mid \alpha) \prod_{n-1}^{n} p(z_n \mid \theta)\, p(a_n \mid z_n, \beta)$$

Marginal Distribution of the user features is given by

$$P(a \mid \alpha, \beta) = \int P(\theta \mid \alpha) \left(\prod_{n-1}^{n} p(z_n \mid \theta)\, p(a_n \mid z_n, \beta)\right) d\theta$$

Marginal Distribution of the event features is given by

$$P(e \mid \alpha, \beta) = \int P(\theta \mid \beta) \left(\prod_{n-1}^{n} p(z_n \mid \theta)\, p(e_n \mid z_n, \beta)\right) d\theta$$

3.3. Bayesian Approach

Bayesian approach is used to compute the event parameter and user parameter on the marginal distribution of the event features and user features. Bayesian approach to represent the event parameter will be represented as

$$p(e, z) = \int p(\theta) \left(\prod_{n=1}^{N} p(z_n \mid \theta)\, p(e_n \mid z_n,)\right.$$

Where θ is considered as random parameter of marginal event.

LDA distribution on the marginal distributions of the event features is given as hidden latent features . It is computed through inference on approximation. variation approximation is used to inference the features of user . Further values of the variational features is computed on minimizing the kullback-leibler divergence. KL divergence is reduced using the

$$\phi_{ni} = \beta_i \exp(\log(\theta_i)$$

Reduced KL divergence on the marginal distributions yields the expected event features and user features for the event participant prediction under the variational inference

3.4. Deep Belief Network

Deep Belief Network is composed both supervised and unsupervised learning process on several RBN stacked Sequentially as Primary elements. Each elements of DBN on unsupervised learning uses the contrast divergence to allocates weights to the entities or features whereas supervised learning is implemented with back propagation. Back Propagation fine tunes the initial weights to obtain final weights. Each layers in the DBN is considered as joint distributions of other layers. Contrast divergence is used to the allocate weight to the event features and user features. Figure 2 represents the

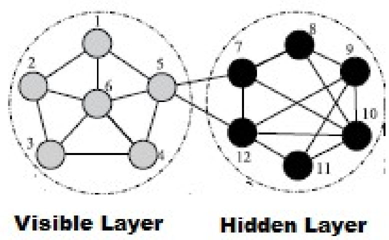

Figure 2: Illustration of Function Mapping

3.4.1. Visible layer

Initially unsupervised learning determines the initial weights of the feature inferred from the LDA model. DBN network is trained with weights sequentially. Let provide the parameter set of event feature and user features to partitions of the visible layer. Each visible layer fixed with partial feature and its weight computed using contrast divergence In this W^R is the weight matrix connecting the visible and hidden layers. The states of the visible layer is represented as

Visible layer is represented as $V = \{v_1, v_2, v_3 ... v_m\}$

3.4.2. Hidden Layer

Hidden layer is used to capture dependency between the event and user. Each unit contains the observed association of the feature and event. It is represented as high level representation. The states of the hidden layer is represented as

Hidden layer is represented as $H = \{h_1, h_2, h_3 .... h_n\}$

3.4.3. Contrast Divergence

It is used to allocate weight to the user feature and event feature on the time varying factors. Weight is derived from layer by layer using optimization of each layer on the contextual and preference factor of the user profile. Table 1 represents the optimized hyper-parameter of the deep belief network.

Table 1: Optimized Hyper Parameterized Component to the Deep Belief Network

Hyper Parameter	**Values**
Batch Size of the cluster	158
Learning Rate	0.01
Dataset Dimensions	65
Epoch	100
Activation Function	Sigmoid
Loss function	Cross entropy

The visible layer uses the computes the association of the user feature vector and event feature vector using its attributes weights. Further association of the feature is computed using activation function. Association matrix is processed in the softmax which uses the random forest classifier. Further uses bagging and boosting model to predict the potential participant to the available events and it generates the composite maps. Model uses the hyper parameter tuning to obtain increased prediction performances. Figure 3 represents the proposed architecture of the work.

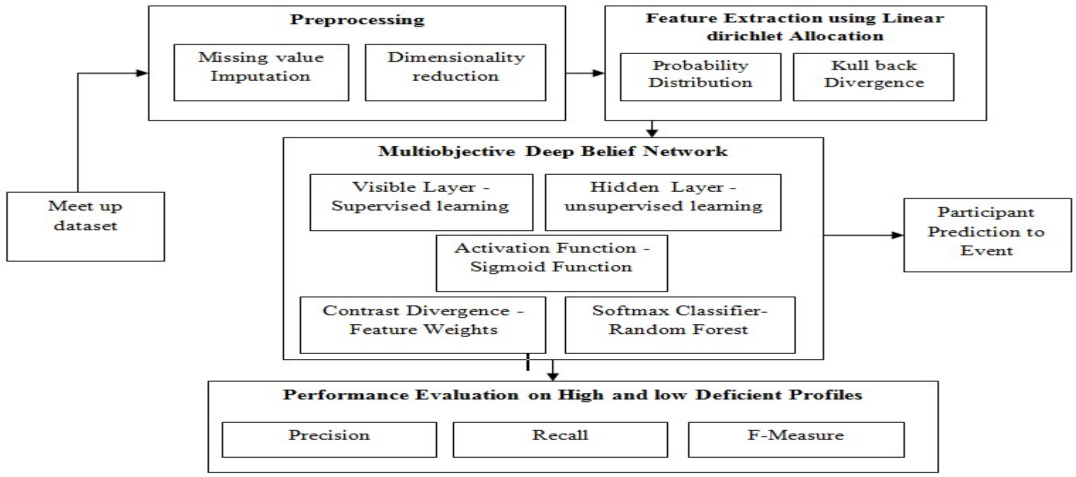

Figure 4: Architecture Diagram of proposed architecture

After an adequate number of sampling of the boosting and bagging iterations, the approximated marginal posteriors can be utilized to determine potential participants. Algorithm 1 gives the procedure of the potential participant prediction using multiobjective deep belief network.

Algorithm 1: Multiobjective Deep Belief Network

Input: High Dimensional Event based Social Network Dataset
Output: participant list to the events
Process
Data Pre-Process ()
Calculate Missing value Imputation ()
Kaiser based Criteria ()
Determine the mean and variance of the missingdata field
Dimensionality Reduction ()
Feature reduction_SVD()
Feature reduction _Ranking matrix ()
User and Event feature extraction_LDA ()
Return user feature Set U_s with Event feature set E_s
Association F_s on User_Event Matrix
Apply Multiobjective Deep belief Network ()
Visible Layer ()
Compute Gradient descent & weight Constraints on User Event Matrix
Contrast Divergence ()
Set Weight to feature of event and user
Activation Layer()

Sigmoid () for composite mapping

Softmax layer ()

Prediction using Random Forest on Boosting and Bagging in the bootstrapped maps

Loss Layer()

Cross entropy on the weights of features Parameterized Tuning of ReLu Function

Output Layer()

Participant prediction to the event classes

Top rated Event = { Electric vehicles, Internet of things, Stock Market, Modern Agriculture, Future Investment, Cancer treatment }

The algorithm outcomes the participants to the events handled by organizer with various related content. Along this, the association among the user content and event context has designed to mitigate the data sparsity with high quality. It is significant to eliminate the sparsity of textual content and to enhance the performance of participant prediction to the event.

4. Experimental Results

Experimental analysis of proposed multiobjective deep belief network using hyper parameter tuning towards processing the high dimensional data is carried out in this section. Architecture designs the prediction model using deep belief network including the hidden layer and visible layer for processing the event-user feature matrix obtained from the LDA process. Visible Layer of the model contains multiple visible unit to computes association of user event matrix on weight computation of multiple factors. weight of features is computed through contrast divergence. composite mapping of the weighted user and event associated feature is projected as supervised learning model to hidden layers.

Hidden layer composed of unit uses the softmax operation , activation function and loss layer to generate the participant prediction to the event using random forest classifier in softmax on boosting and bagging operations. Random forest compute the list of participant to each event on computing the correlation of event and user. Loss layer eliminates the maximum reconstruction error of the prediction result using cross entropy.

. The performance of the proposed architecture is evaluated against the conventional classifier using precision, recall and f-measure. Further it is model efficiency is evaluated with respect to cosine similarity and Euclidean distance on obtained prediction list. The proposed model is implemented and evaluated using python technology. In this particular platform, processing of the profile for participant prediction to event is flexible to train and validate using cross fold validation.

In this work, 60% of meet up dataset [18] is projected to train the prediction model of the proposed architecture to generate the participant prediction list and 20% of dataset is employed used to test proposed model and remaining 20% is evaluate the model on the 10 fold cross fold validation.

4.1. Dataset Description - Meet Up

We have carried out extensive experiments on Meet up datasets. Meet is online platform which is popular Event based social network to create and distribute the event for the user in the network. It contain the event information and user profile represented as high dimensional data incorporating attribute the personnel , technical , professional , social and contextual information. Further it uses the location factors.

4.2. Evaluation

The proposed architecture is evaluated against various performance measures against conventional Deep Influence prediction. In this article, proposed architecture is accessed employing 10 fold validation to calculate the performance of prediction model produced on processing the dataset using deep learning model along the activation functions, hidden layer, visible layer, loss function and hyper parameter of model.

- **Precision**

It is to compute the relevancy of the clustered profile to the event. It is defined as ratio of the relevant user features extracted from the user profile compared to other list of the user features to determine the model outcome. It is measured on the composite functions of the hidden units of the layer in the network on processing the user-event association. It is given as

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

True positive is a number of similar feature in the prediction class set and false negative is number of real dissimilar feature in the prediction class set [19].

- **Recall**

It is to compute the resultant clustered profile to the event. It is defined as ratio of the resultant user features extracted from the user profile compared to other list of the user features extracted to determine the model outcome. It is measured on the composite functions of the hidden units of the layer in the network on processing the user-event association. It is given as

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

True negative is a number of dissimilar feature in the prediction class set and false negative is number of real dissimilar feature in the prediction class set [19].

- **F measure**

It is the number of correct predictions class to the user -event weighted features to the features of the user profile and event

Accuracy is represented as

$$\frac{\text{True positive} + \text{True Negative}}{True\ positive + True\ Negative + false\ positive + False\ negative}$$

Although different user -event weighted matrix may have different association to event on outcomes obtained on the various behavioral and contextual factors of the dataset. Figure 4 represents the performance of the proposed architecture with respect to the various measure against conventional approaches for exact profile recommendation prediction to the event. However, after a certain point, this data vector is diminished because of curse of dimensionality. On the other hand, for the Meet up data set, the recommendation lists generated are less separable

Gibbs sampling function termed as normalization function to map the user -event category into a new visible distribution on event participation. Then, the generative Bayesian probabilistic function used to produce the original vector by means of conditional probability and pairwise similarity. Table 2 presents the performance value of the technique for result analysis.

Table 2: Performance Analysis of Deep learning architecture against state of art approaches to dataset with less deficient profiles

Technique	Precision	Recall	F measure
Multiobjective Deep Belief Network - Proposed	98.45	97.56	98.16
Deep Influence prediction– Existing 1	98.10	89.24	94.14

Correlation of the user and event and divergence describes the user participation to event. Further multiple factor is cross validated in confusion matrix as represented below to the validation dataset. on basis of the social spread which is to represent the social effects on computation of pair wise similar preference as influence weight. User profile to the multiple event organized across the various location is analyzed.

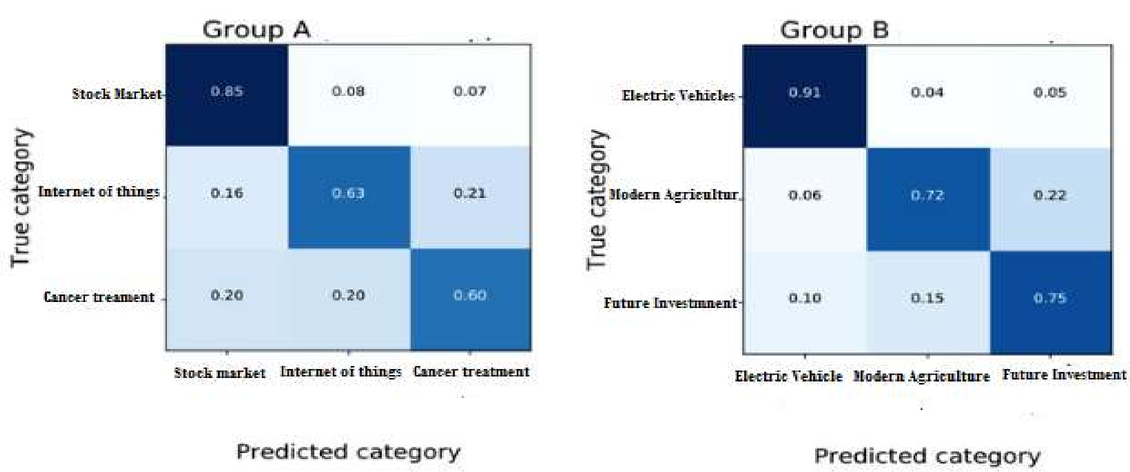

Figure 5: Confusion matrix for two fold validation

Confusion matrix for the validation data in multi fold using the user profile extracted on the events such as {Stock Market, Internet of things, Cancer treatments} in one fold and event such as { electric vehicle, Modern Agriculture, future Investment } in second fold. Matrix compute the association of event with user profile on the prediction value between 0 to 1. In this o represent least influencing and 1 refers the high influence of participating.

Hyper-parameter is a very important component of the proposed deep contextual learning. Figure 4 represent the performance evaluation of the participant prediction architecture with respect to high deficient profiles.

Figure 4: Performance Evaluation of participant prediction architecture on high deficient profiles

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 has been achieved using gibbs sampling as it is to find the best value of the hyper-parameters. Table 3 represents the performance evaluation of the deep learning architectures to the analysis of low deficient profile for participant prediction.

Table 3: Performance Analysis of Deep learning architecture against state of art approaches to dataset with High deficient profiles

Technique	**Precision**	**Recall**	**F measure**
Multiobjective Deep Belief Network - Proposed	98.45	98.89	98.54
Deep Influence prediction– Existing 1	97.85	98.21	98.08

The evaluation of result is described in the table 3 for dataset with high defieicient profiles of meet up dataset. Figure 5 represent the performance evaluation of the low deficient profiles on predicting the participants to the event. Performance of the complicated objective function has been revealed that latent user and its social connections with event produce the maximum participant to the any event description.

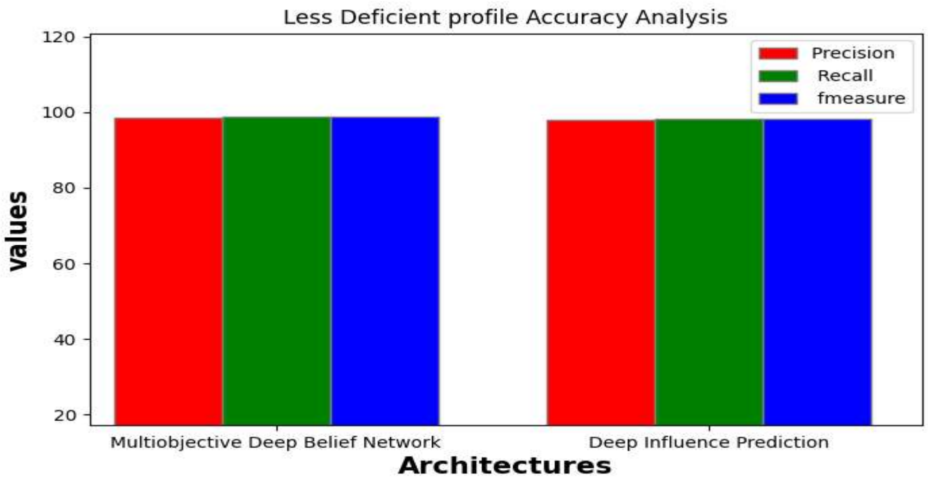

Figure 5: Performance Evaluation of participant prediction architecture on low deficient profiles

The modeled events are likely to be similar with other already modeled events especially which termed as high attractive events is accessed with similarity measure to compute the prediction effectiveness of the event modeled.

Conclusion

We designed and implemented a multiple objective deep belief network to enhance the prediction of user participation to various events is explored on association of user and event matrix on basis of event contextual information and user latent information's. User Latent information and event contextual information are computed using Latent Dirichlet allocation to enhance the prediction accuracy and high relevancy rate in hidden layer of the deep learning architecture. Gibbs sampling inferred using influence weight computed on the contrast divergence function. Influence weight of the user associated with event in prediction range of 0 to 1 is computed to various event it is mapped as composite function. Mapping function is provided to the hidden layer of the model to acts the supervised model to test data as back propagation network. Further hidden unit of the hidden layer use the sigmoid activation function and random forest softmax classifier and cross entropy loss function to generate the optimal participant list to the events.

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