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Research Article

Deep Learning Social Filtering Model for Event Recommendation Services

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Abstract

In the contemporary time, technology has made the determination and discovery of human preferences, priorities and personal inclinations possible through the use of recommender systems. Activities of users on the internet can be monitored, extracted, stored, analyzed and used by the recommender systems for suggesting future events to users on the web. This paper aims at developing and analyzing a model for event services recommendation for visitors to events. Event seekers, organizers and event service providers get notified, plan and book for upcoming events from their comfort zones without hassles of gallivanting nooks and crannies to enquire about prospective events. There is not any compelling need to interface with under-enthusiasts and intermediaries in the course of organizing, visiting and providing services for an event. However, it is obvious that massive amount of available information on the web exhibit frustrating attributes, hence it is increasingly a difficult task for users to find the content of interest; in other words, a huge chunk of information undiscovered on the network is left behind as "dark information". In context, event service recommendation uses deep learning social filtering base techniques which adopt similarity computation measures with a bias for Pearson correlation coefficient, cosine similarity, and Euclidean similarity to recommend related and most relevant events/services to the targeted online audience. In this paper, the aim is to develop a deep learning model which integrates social filtering technique for enhancing the quality of event recommendation for users. A model based on the deep learning algorithm of multilayered perceptron and Neural Collaborative Filtering is proposed for event recommender services. The results from various simulations using meetup website dataset shows that the proposed model performs better than other techniques. The results yield 70% accuracy, 66% precision and 98% recall.

Keywords

Deep Learning, Multilayered Perceptron, Neural Collaborative Filtering, Event Service Recommender

1. Introduction

The web has experienced dynamicity and exponential growth due to the impact of rapid development in internet and information technology, resulting in an avalanche of information on the web space. It is obvious that massive amount of available information on the web exhibit similar attributes, hence it is increasingly a difficult task for users to find the content of interest; in other words, leaving behind a huge chunk of other user information undiscovered on the network as "dark information". Also, it is arguably known that in spite of efforts of researchers in the development of tools and

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methods to manage the deluge of web information to satisfying the regular demands and the limitations of proffered solution offered by one-size-fit-all search engines, more cutting edge tools are needed to eliminate the ambiguity by users in locating the appropriate content leading to making the right choices in satisfying their needs and expectation, thereby enhancing their commitment and overall satisfaction with online services. There is a lesser extent to which information retrieval technology can meet user's need due to its universal characteristic albeit it seldom satisfies user request for preferences and personalized contents.

The global rise in internet usage is an indication that there is a significant number of users to make the most use of the internet for purchase and delivery of services and whose lifestyle has been tremendously impacted by the trend of similar activities. Since its inception, researches on recommender system is continuing and has been applied in online services from diverse domains like music, commerce and movies. Big brands like Amazon and Netflix use recommendation extensively to reach out to a broad spectrum of customers by recommending products and services [1]. Extant conventional methods for classifying recommendation systems include content based, collaborative filtering and hybrid. The content-based method adopts user profile information and production /service description for recommendation. Collaborative filtering derives recommendation from behavior and preference information of user generated in the past such as users rating on items. The hybrid method seeks to generate the best recommendation result by combining features of the collaborative filtering and content-based methods [2].

Many current event recommender systems employ collaborative filtering algorithm to enable it suggest event to users based on the past preferences of items rated by all users. They allow events of interest to be displayed for users based on their records and also show great potential for improvement to intelligently recommend event services and related event /service information. The hype about deep learning has been enormous and could be sustained in years ahead due to its brilliant achievement in application areas such as computer vision and speech recognition. Hence the resolve that applying deep learning to a wide range of areas would replicate its capability of producing credible results from solving complex task has intensified [3]. Consequently, deep learning has played a significant role in transforming the recommendation architecture and progressively enhanced the prospect of having a glitch free recommendation.

Researches in recommender systems embedded with deep learning model have also been applauded for their tremendous ability to enhance recommendation quality through the development of recommendation systems that outweigh the obstacles of the traditional models. This is attributed to deep learning mastery in capturing nonlinear and non-trivial user -item relationship, in addition to simplifying hierarchical data representation [4].

It is glaring that visitors to an event (event seekers), organizers and event service providers get notified, plan and book for upcoming events from their comfort zones without hassles of gallivanting nooks and crannies to enquire about prospective events. There is no compelling need to interface with under-enthusiasts and intermediaries in the course of organizing, visiting and providing services for an event. Long waiting queues on the checkout counter which often herald events are completely eliminated. The plaudit is ascribed to dynamics of e-commerce which has had a tremendous impact on the modus operandi for planning, organizing and booking events. However, the issue of inexact item recommendation that online users experience can be disincentive to online activity and hamper productivity in the long run. In context, event service recommendation uses deep learning social filtering base techniques which adopt similarity computation measures with a bias for Pearson correlation coefficient, cosine similarity, and Euclidean similarity to recommend related and most relevant events/services to the targeted online audience. The proficiency of the social filtering-based technique does have limitations resulting in inefficient feature extraction and will also allow for error prone computation and miscalculation in the evaluation process of user similarity. To avert this problem, the potential of deep neural network and inclusion of social information is employed for an effective feature mining which further enhances the recommendation quality. A model based on the deep learning algorithm of multilayered perceptron and Neural Collaborative Filtering is therefore proposed for event recommender services.

The remaining part of this paper is structured as follows. Section two covers the related works while materials and methods are discussed in section 3. Section 4 and section 5 focus on results and discussions respectively. The paper finally ends with the conclusion in section 6.

2. Related Works

In this section, related recommender systems are discussed.

Recommender systems have been proposed and applied by researchers covering diverse areas including domestic energy efficiency, industrial automation, fairness measurement, companies' internal recruitment, guests' hospitality, replicable knowledge awareness, tourists' destinations' selection, pervasive data streaming, public complaints and e-commerce [5-14].

A set of recommender systems focused on providing solutions to human health issues. In [15], a recommender system for the automation of clinical practice guidelines was proposed. Other studies in health care focused on recommender systems for the treatment of diseases, prediction of diseases and management of patients' diets [16-19].

Some computer science methods proposed and applied to recommender systems by authors in previous studies include particle swam optimization, deep reinforcement learning, natural language processing, knowledge graph, collaborative filtering and genetic algorithm [20-28]. Others include hybrid deep learning and other artificial intelligence models such as fuzzy logic recommender systems [29-31].

Macedo and Marinho [32] in their paper investigated and discussed important features of event-based social networks (EBSN). The author posited that previously published event-based networks could not match the performance of their preferences.

Cao et al. [33] proposed an event recommendation system based on multiple features and combined with a heterogeneous information network model, and having the capability of mining users' preferences.

Liao et al. [34] focused on group event recommendation using a two phase model. Their proposed model integrated online social network and random walk with restart.

This paper proposes the application of deep multilayered perceptron and neural collaborative filtering for events recommender. This approach has not been explored by previous researchers according to studies. This is the contribution of this paper.

3. Materials and Methods

The materials and research methods are provided in this section.

3.1. Deep Multilayered Perceptron (DMLP)

Multilayer perceptron is a computational neural network model in which layers consisting of neurons are connected to other neurons composed into a layer without a circular recourse. Also referred to as feed forward network due to the flow of information in a single direction from input layer via the hidden layers to the output layer. It is renowned for its efficiency in learning mapping function and a proven algorithm for universal approximation [35]. Multilayer perceptron is made up of input layer, one or more hidden layers and an output layer. A typical simple multilayer perceptron has a maximum of two neurons and usually utilizes tan h and sigmoid function due to the impact on performance especially for smaller to medium sized networks. Component neurons in the input layer and its associated weight are fed into training tuple. These inputs in numeric or binary form are forwarded to the hidden layer where computation is performed to generate a temporary result for each training tuple accepted into the network. The resulting output acquired are fed into the output layer and predicted value corresponding to the training tuple is derived based on an integral activation function [36].

Hanczar et al. [37] asserts that deep multilayer perceptron is an architecture based on the multilayer perceptron network model and it is usually the first option amongst model deployed from the catalogue of available deep learning techniques. Serin et al. [18] express that prediction models resulting from deep multilayer perceptron proffers solution to classification and regression issues and also can be applied to nonlinear complexities.

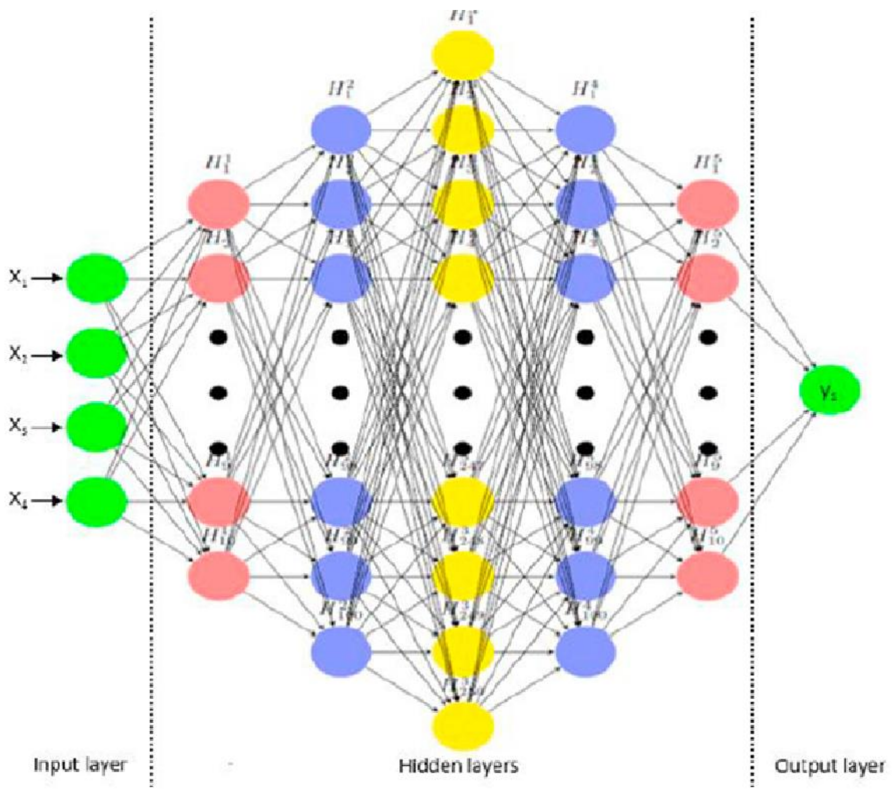

Figure 1. *Architecture of DMLP Algorithm with Multi-Layers [38].*

In Figure 1, features represented as vectors are indicated by X_i and are taken as input to the algorithm. A product of the weight W_i and the input vector with the addition of bias will give the output Y_i. The addition of all result gotten in the hidden layer gives a new output vector which is fed to the next hidden layer. The required result to determine the desired output is derived by updating the weights.

3.2. The Existing Model

The Neural Collaborative Filtering (NCF) model for the event recommendation service is adopted. In the NCF, interactions between user and item are used by a neural network to provide filtering. Matrix factorization is treated from a non-linearity viewpoint. A pair consisting of user ID and item ID are taken in by tensor flow as input sequence and directly fed into a matrix factorization step and a multilayer perceptron network. The combination of the matrix factorization and the MLP's output is fed into a single dense layer for prediction. The purpose of the prediction is to determine the state of interaction between the user and the input item [39]. The existing NCF model is shown in Figure 2.

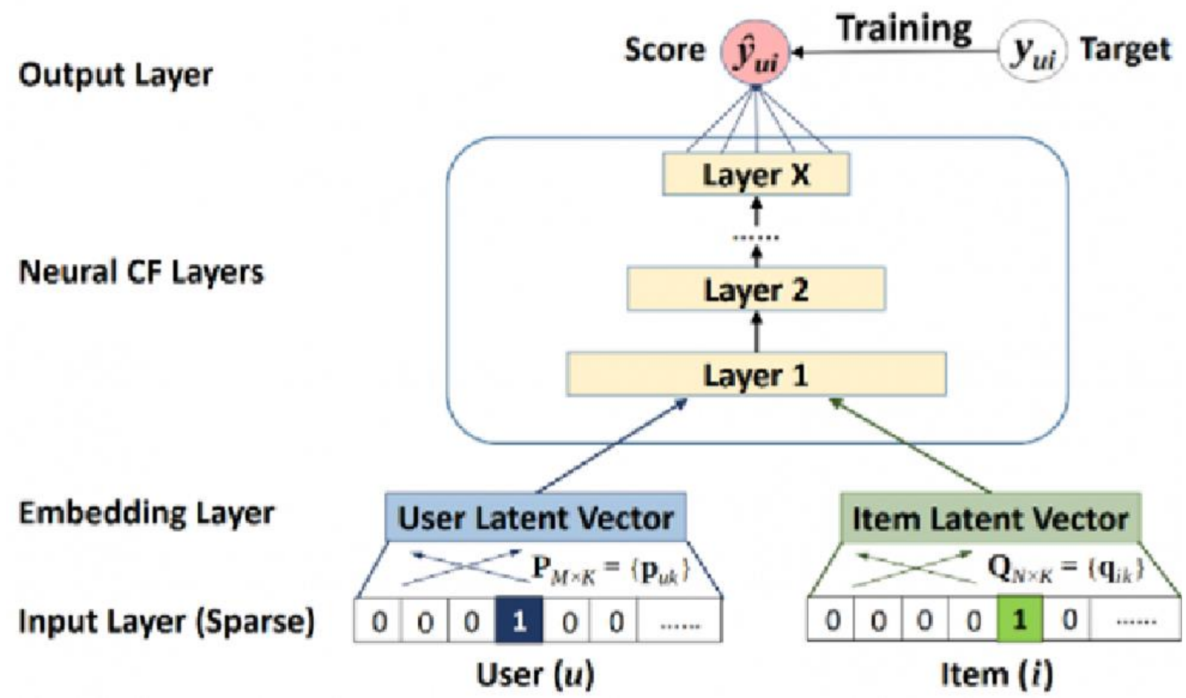

Figure 2. *The Existing NCF Model [39].*

3.3. The Proposed Model

Basically, machine learning tasks typically follow the same pattern. The proposed model begins from the dataset and it consists of phases and deliverables which are represented with a set of grey and white rectangles. The different phases and deliverables are connected with pointed and labelled arrow which represents the processes and a set of activities. These are organized into two major groups: the basic machine learning group and neural collaborative filtering group. The grey white rectangles and their processes form the machine learning group while the white boxes and their processes form the neural collaborative filtering group which is integrated with the DMLP. The graphical illustration of the proposed model is shown in Figure 3.

As illustrated in Figure 3, the dataset is preprocessed and this produced the cleaned data. This is followed by vectorising which yields the selected data, split into training data and test set. The activities of training, validation and evaluation are linked up with the neural collaborative filtering group. In the neural collaborative filtering group, the new data is preprocessed and the selected and optimized data with the inference are fed into the NCF and DMLP model. This is followed by the activity of prediction which produces the modelled data.

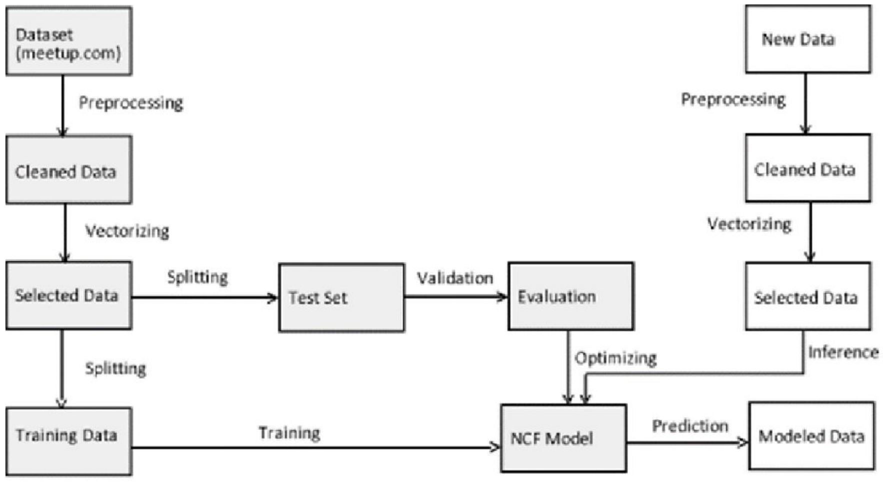

Figure 3. The Conceptual Architecture of the Proposed Model.

3.4. The Dataset

The dataset for this study is provided on Kaggle [40] for event recommendation application covering a period of years and containing a number of csv files. The data in user.csv features the following columns: user_id, locale, birth year, gender, joined at, location, and time zone. It contains demographic information on a subset of users, including all of the people that appear in the train and test files. In the system, the user is identified with user_id. The user's locale is represented by the string locale, which has the format language territory. The year of the user's birth is indicated by a 4-digit integer called birth year. Depending on the gender of the user, there are two possible genders. The time string in ISO-8601 UTC indicates the user's initial use of the application. A string called "location" indicates the user's location. Other items in the dataset include user_friends.csv, events.csv and event_attendees.csv. The dataset consists of 38,210 users and 1,048,576 events.

4. Results

The data and its peculiarity are examined and analysed in this section.

4.1. Users' Statistical Features

The demographic and statistical features of the participants of events are represented with a histogram as shown in Figure 4 which portrays the participants' age. It can be seen from Figure 4 that most of the participants are young.

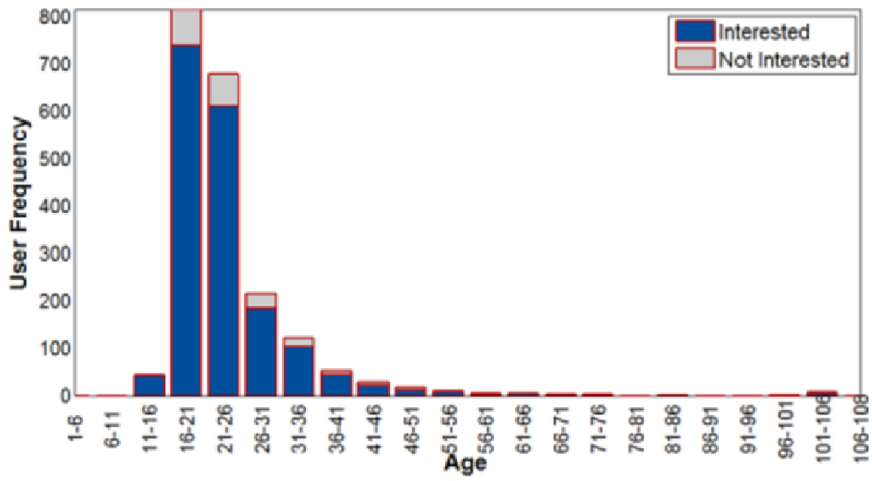

Figure 4. Number of Users of Different Ages.

The frequency of events during weekdays and weekends is shown in Figure 5. It is evident from Figure 5 that more events occurred during the weekdays.

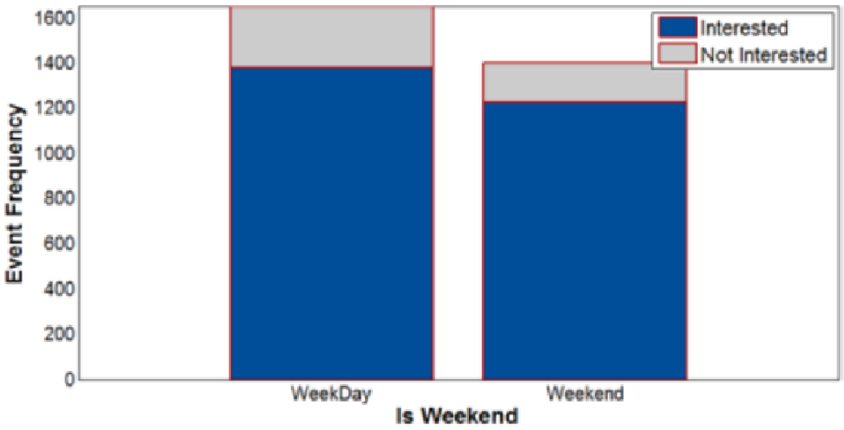

Figure 5. *Frequency of Events During Weekdays and Weekends.*

4.2. Evaluation Metrics

Event recommendation problem is categorized as a classification problem. Therefore, metrics employed for the evaluation of the proposed model are: accuracy, precision, recall and *F*-measure. Accuracy evaluates how well a classifier works. It is defined as the ratio of true results.

$$\text{Accuracy} = (TR + TN) / (TR + FR + TN + FN) \quad (1)$$

where TR represents the number of really relevant and recommended events.

FR represents the number of events recommended as relevant although they are not, and FN represents the number of events considered as non-relevant although they are relevant.

Precision is the probability that a truly relevant event has been recommended (TR). It is the ratio of truly relevant events among all the recommended events, i.e.,

$$\text{Precision} = TR / (TR + FR) \quad (2)$$

Recall evaluates the probability that a relevant event will be recommended, i.e.,

$$\text{Recall} = TR / (TR + FN) \quad (3)$$

The *F*-measure is given in Equation 4 and it captures the harmonic mean of precision and recall.

$$F1 = 2 \times (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall}) \quad (4)$$

4.3. Comparison of Recommenders Methods

A number of algorithms were simulated and compared to determine which performance is better. The proposed model is compared with neural network, support vector machine and Na ïve Bayes. The comparison chart with Accuracy, Precision, Recall and F-measure is shown in Figure 6 using the complete test data, that is, including missing data.

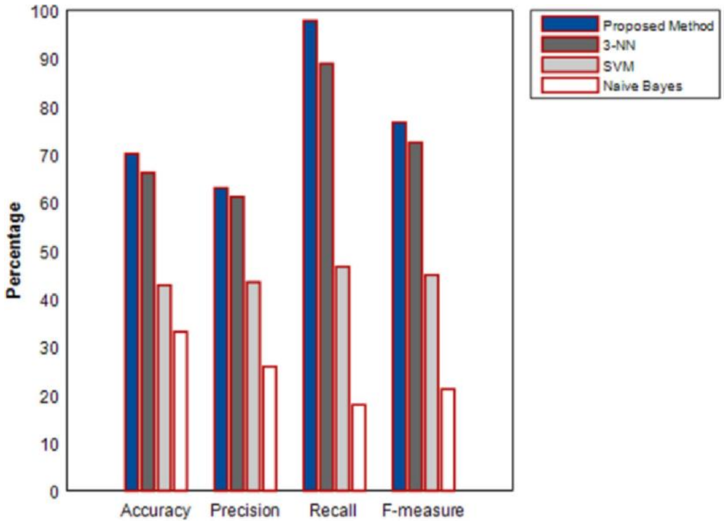

Figure 6. *Comparison of different methods using the complete test data, including missing data.*

Other baseline methods are also used for comparison. These includes K-nearest neghbors (KNN). The result of the performance of different machine learning algorithms is shown in Figure 7.

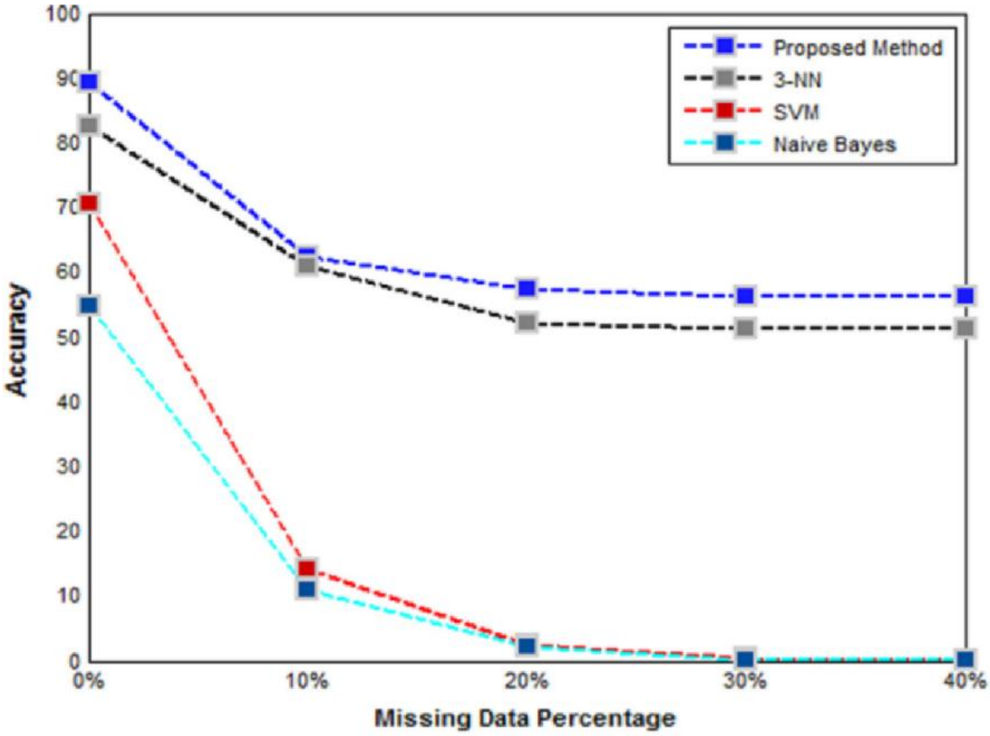

Figure 7. *Performance of Different M/L Algorithms.*

5. Discussion

In creating Figure 6, the meetup.com dataset was used to train and test the different models. The dataset is split into 70% for the training and 30% for the testing. The model learns on the training set; in other words, the set is used to assign the weights and biases that go into the model. A fraction of 20% is used while training the model, evaluating initial accuracy, and to see how the model learns and fine-tuning hyperparameters. While the 10% left is used for the final evaluation. After training the model, the performance is gauged using precision/accuracy/recall metrics.

In Figure 7, the performance of the proposed model is compared with KNN, SVM and Naïve Bayes which are baseline methods.

6. Conclusions

Artificial intelligent methods enable activities of users on the internet to be monitored, extracted, stored, analyzed and used by the recommender systems for suggesting future events to users on the web. This paper presents an experimentally evaluated approach based on deep learning in improving the accuracy of collaborative recommender systems. A deep learning model which integrates social filtering technique for enhancing the quality of event recommendation for users has been developed. The proposed model is compared with baseline machine learning methods. The results from various simulations data show that the proposed model performs better than other techniques evaluated. Future work shall focus on the application of hybrid systems with modified machine learning algorithms to event recommendation services.

Abbreviations

EBSN	Event-Based Social Networks
RWR	Random Walk with Restarts
MLP	Multilayer Perceptron
DMLP	Deep Multilayer Perceptron
NCF	Neural Collaborative Filtering
KNN	K-nearest Neighbors
SVM	Support Vector Machines

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Author Contributions

David Ademola Oyemade: Writing – review & editing, Supervision, Methodology

Linda Chioma Aworonye: Conceptualization, Data curation, Writing – original draft, Formal Analysis, Software, Writing – review & editing

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Data Availability Statement

The data can be provided upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Biography

David Ademola Oyemade is an Associate Professor of Computer Science at the Federal University of Petroleum Resources, Effurun, Delta State, Nigeria. He holds a PhD degree in Computer Science obtained from the University of Benin, Benin City, Nigeria in 2014. He also holds M.Sc. degree in Computer Science obtained from the University of Benin, Benin City, Nigeria in 2007 and a postgraduate diploma in Computer Science obtained from the University of Benin, Benin City, in 2004. He is a life member of Nigeria Computer Society (NCS) and a professional member of Association for Computing Machinery (ACM). He has served as a lecturer in the Department of Computer Science, Federal University of Petroleum Resources, Effurun and rose through various ranks. He has supervised several students at undergraduate and postgraduate levels at the department of Computer Science, Federal University of Petroleum Resources, Effurun. He has many articles in international and local journals. His research area is Software Engineering, Software Architecture, Intelligent Systems and financial market algorithms and modelling.

Linda Chioma Aworonye is a lecturer at Novena University Ogume. She obtained her B.Tech. Degree in Mathematics and Computer Science in 2006 from the Federal University of Technology, Minna and M.Sc. in Computer Science 2018 from the Federal University of Petroleum at Resources, Effurun, Delta State, Nigeria, respectively. She has a Master's in Business Administration (MBA) 2010 from Delta State University, Abraka., and P.G.D (2016) in Health Environmental Safety and Security from Federal University of Petroleum Resources, Effurun, Delta State, Nigeria. She has participated in multiple international research collaboration projects in recent years. She's currently lecturing at Novena University Ogume, Delta State, in the department of Computer Science and Telecommunication.

Research Field

David Ademola Oyemade: Software Engineering, Software Architecture, Intelligent Software Systems, Financial Market Algorithms, Deep Learning.

Linda Chioma Aworonye: Software Engineering, Deep Learning.