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Survey of Movie Recommendation System Using Varian of Recurrent Neural Network (Bidirectional GRU & ROA)

Ms. Gadakh Archana K.[1] , Dr. Pawar U. B.[2]

[1]PG Student , S.N.D.COE and RC,Yeola
[2]Asst. Professor, S.N.D.COE and RC,Yeola

ABSTRACT

The recurrent neural network (RNN) deeplearning algorithm, which mainly learns and predicts sequencedata and time series data, is mainly used in language modelling,stock price prediction, and chat bot. In this paper, we proposea method of predicting and recommending a movie byconsidering movie consumption patterns of users. We measurethe similarity between users based on movie rating data,classify users with similar movie preferences, and learn theconsumption pattern of each similar user group to improve theprediction accuracy by considering the change of preferenceover time. In order to show the effectiveness of the proposedmethod, we apply the collaborative filtering algorithm, thesimple RNN and our modified RNN and compare theirprediction accuracies.

Expressing reviews in the form of sentiments or ratings for item used or movie seen is the part of human habit. These reviews are easily available on different social websites. Based on interest pattern of a user, it is important to recommend him the items. Till today, a lot many recommendation systems are designed using several machine learning algorithms. Still, faster convergence speed, prediction accuracy, suitable optimization are the hurdles for the recommendation systems that must be resolved using hybrid algorithms. In this paper, we propose a system that uses Bidirectional Gated Recurrent Unit (BiGRU), the latest variant of Recursive Neural Network (RNN) collaborated with Remora Optimization Algorithm (ROA). Department of Information Technology, SND College of Engineering, Yeola Forecasting Movies to User Using Bidirectional GRU And Remora.

Keywords: Movie Recommendation, User Similarity, Consumption Pattern, Sequence Data, Recurrent Neural Network, BIGRU, ROA

INTRODUCTION

People are strongly connected to social media for sharing their emotions and reviews on different websites. These emotions are in the form of sentiments or ratings for a product or service. As a result, a huge amount of data is generated and is being studied to predict, recommend a user any product or service for his interest. The movie rating database with users and different parameters for movies is available on several popular websites like Kaggle. Decisions made by support of multiple stronger historical impressions to resolve an issue are always superior to the decisions made with single impression by any user. Rather than collecting all of the reviews or ratings, only the users having stronger relevance of ratings between them are collected.

Many researchers have taken efforts to enhance recommendation system using different machine learning techniques like GA, Neural Network (NN), Support Vector Machine (SVM) and many more. In this work, we proposed a movie recommendation system, based on BiGRU algorithm optimized through ROA. BiGRU algorithm is applied to 100 k IMDB dataset. The parameters user id, movie id and rating are considered only through pre-processing. Similarity between the users for rating similarity of same movies and also the weighting dissimilarity between the same movies are obtained. The weights for finding similarity between the users are optimized using ROA and finally top 10 movies are recommended to a user based on his interest pattern. The results are compared with the output from GA, MMDL and FFNN. It is observed that BIGRU shows better results obtained for all testing parameters we used for comparison. Recently, many studies are being conducted to predictand recommend products to be purchased in the near future through customized analysis of individual users, andapplications such as Netflix recommending movies andAmazon recommending products are increasing. In order topredict future consumption, user-based or item-basedcollaborative filtering algorithms are usually used. However,these methods areusually based on rating data provided byusers, and this means that it can’t be predicted without ratingdata. Therefore, a product without rating data can’t beincluded in the recommendation list, which causes a sparsityproblem. Also, since these conventional methods do not

consider the time changes, it does not reflect theconsumption pattern changes of users.

In this paper, we propose a method of predicting andrecommending a movie by considering movie consumptionpatterns of users. We measure the similarity between usersbased on movie rating data and classify users with similarmovie preferences. We then apply RNN to learn movieconsumption pattern of similar user groups and later topredict or recommend movies. To show the effectiveness of the proposed method, we apply the collaborative filteringalgorithm, the simple RNN and our modified RNN for theMovie Lens Latest Dataset and compare their predictionaccuracies.

REVIEW OFLITERATURE

Nowadays, increment, in E-commerce, has a big improvement in person inspections. The customers have modified their method of purchasing. The buy-choices need to be based on object facts introduced on a website. On-line carriers try to defeat this breaking-point with the aid of permitting the user to share the item checks online (Park 2007). Inside the net age, the maximum severe problem for an individual who desires to purchase something on the net isn't always simply the way to get sufficient statistics or desire and, from time to time, struggle to make an accurate choice with massive data. Nowadays, individuals continuously seek on the internet to discover the great viable items and offerings they need. Intentionally or unknowingly, they depend on the Recommendation System (RS) to conquer a facts over-burden. RS has been validated as a giant answer for the record’s over-burden issues, which offers more and more proactive and custom designed statistics services to the customers.

RSs are software program gadgets that suggest items that is probably a user-intrigue. The recommendation gadget is characterized because the helping system which is utilized to help the customers in locating the data offerings or the gadgets like internet destinations, television applications, track, movies, books, and virtual products based.

On the suggestions of the alternative customers. It gives customized recommendation services to numerous users. The recommendation machine is a statistics filtering machine, in any other case called a proposal engine, which is used to prescribe enlightening objects. They might be visible all around the region: there are RSs for song, movement pictures, the travel enterprise, books, look into articles, news, and fundamental things and they actually have grows to be a noteworthy segment in web sites like Netflix, Amazon, YouTube, Google, and others (Ricci 2015). RS makes use of diverse strategies like collaborative filter (CF), content material-based ones, and hybrid RS (Porcel et al. 2018). The CF techniques are all of the greater usually used; they don't need any preceding data about customers or matters; as an alternative, they make pointers with collaborations between them. Despite the fact that they are effective and simple, they revel in the unwell-consequences of a parcel of troubles, for example, expectation precision, cold starting, and absence of ability to take difficult collaborations among the patron and issue (Fu et al. 2018). The recommendation system contains of the following three elements.

Items: The outputs of recommendation are called items. The things that are recommended are referred to as items. Items may be portrayed as having a high value for complexity or service. In the great majority of recommendation systems, a thing's assessments may be certain if it is useful to the user. Things that are disliked are represented by negative attributes.

Via human-pc interactions, the give up-customers of a advice machine get the guidelines. The users of RSs are people; their interest differs one person to the opposite individual and the pointers given to each person may additionally exchange. For the reason that users have Numerous dreams and attributes, its miles essential to customize the tips which require a wide scope of facts. The statistics may be put away, controlled, and treated in various ways and to decide the method and the device with which we utilize the facts. The facts can be prepared in exceptional manners and also determine the model with which the information rely on the RSs.

Transactions: Exchange is a legitimate unit of work. In recommendation systems, an exchange is a recorded association between the user and the recommendation system. These exchanges are recorded in log documents to store all the data about the interactions of humans and RSs. These log records are given as contributions for the pattern discovery algorithms. These patterns are utilized by the recommendation system to anticipate things to the users.

1)(Cheng et al., 2020) proposed a movie recommendation model based on Recurrent Neural Network (RNN) and KG-RKAN (Knowledge Graph-Recurrent Knowledge Attention Network), which uses the auxiliary information in the KG to look for the potential interests of users for personalized recommendations. They solve the problem of user's individual interests, by designing an attention module in RKAN, using different weights to converge user's interest. For testing purpose, they mapped data collected from the real movie data set Movie lens and IMDB into a new data set for testing. Their model had significantly improved the recommendation accuracy.

2)(Pongpaichet et al., 2020) proposed rating prediction algorithm using singular value decomposition (SVD). They extended the singular value decomposition (SVD) based movie recommendation algorithm using Paralleled Stochastic Gradient Descent (PSGD) and improved its speed. They compared their proposed algorithm with the state-of-the-art rating prediction algorithm based on the traditional user-user collaborative filtering algorithm on Movie Lens dataset and their proposed algorithm outperforms the baseline in terms of accuracy, in both the rating prediction and movie recommendation tasks.

3) (W. Wang et al., 2020) proposed a combined recommendation model of LSTM and CNN. Their model combines CNN to fully mine the local information of movie data, and uses LSTM to capture the context of user ratings. They used the Movie Lens 1M data set. They compared with the traditional recommendation model and other recommendation models based on deep learning, the combined recommendation model of LSTM and CNN proposed in this paper have a MSE loss reduction of 4.4%~18.7% and a MAE loss reduction of 3.0%~52.2%.

4)TimeFly algorithm is a novel behaviour-inspired recommendation algorithm that operates on the concept of changing the user's behaviour with respect to time. Their proposed model considers two recommendation problems (fluctuating user interest over time and high computation time when datasets go from scarcity to abundance) and shows a real-world implementation of the approach in the field of recommendation engines. On the Movie Lens 1M dataset, they compared the results of the TimeFly algorithm with the results of other well-known algorithms. They discovered that using TimeFly results in more accurate predictions in less time. (Sinha et al., 2020)

5)(Shen et al., 2020) used collaborative filtering algorithm to implement the movie recommendation system. They used the Movie Lens data set for experimentation. Their system achieved high efficiency and reliability in large datasets.

6) The system, which adopts the Hadoop technique, can meet the needs of the big data and the cloud computing environment (Shen et al., 2020). The KG provides an effective way for the design of recommendation systems in a big data environment. As an emerging type of auxiliary data, it can effectively solve data sparsity and cold start problems, thus improving the accuracy, diversity, and interpretability of recommendation results (Cheng et al., 2020).

SYSTEM ARCHITECTURE

A common architecture of RSs comprises the following three essential components as shown in Fig. 1.1

a) Candidate Generation This is the number one section of the RSs which takes the occasions from the consumers beyond movement as info and recovers a little subset (numerous) recording from a huge corpus. There are typically two primary competitor age attracts nearby:

- Content-based filtering Content-based totally isolating includes suggesting things that depend upon the characteristics of the things themselves. The gadget prescribes such things as what a consumer has cherished earlier than.
- Collaborative filtering CF relies on the consumer-object interplay and is predicated at the concept that comparative customerslike comparative things, as an example, customers who bought one element could buy any other factor

b) Scoring This establishes the second one level of RS wherein any other model positions and ratings the applicants on the whole on a scale of 10. As an instance, as a consequence of YouTube, the location device achieves this undertaking via allotting a score to each video as indicated through the correct goal work utilizing a rich association of highlights portraying the video and purchaser. The maximum elevated scoring recordings are introduced to the purchaser and positioned by way of their score.

c)Re-ranking Inside the 1/3 stage, the machine considers more necessities to assure a decent range, freshness, and reasonableness. For example, the structures expel the substance which has been expressly now not favoured by the consumer before and take into account any new thing at the web page.

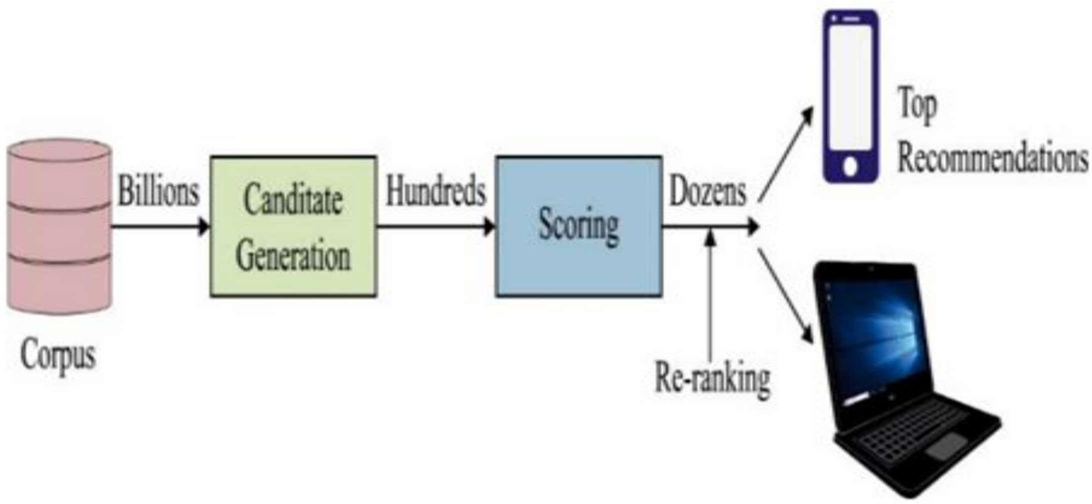

Fig. 1.1. Common Architecture for Recommender Systems Processes of recommender systems

There are progressions of steps that are followed to attempt the process of the recommender frameworks. The various steps involved are as follows:

- Collection of data
- Storing of data
- Analysis of data
- Filtering of data (Rehman 2019)

i.Collecting the data: On this step, artificial Intelligence (AI) device makes use of the information which is obtainable and found in numerous systems, no matter whether implicit or specific. The information which is known as specific can be collected by engaging in the surveys and comments sharing of the users approximately exceptional gadgets. Be that as it may, the information of implicit nature is recognized with the pursuit log and records of the facts which is acquired in various bureaucracy. This information can be gotten efficaciously by means of viewing the search log or the historic backdrop of the consumer which notes down or collect the record approximately the consumer pastimes and the items.

ii.Storing of data: The previous assembled information is put away or sparing in the systems which helps in giving the suggestions later. Therefore, the storage of the given data helps in bringing out the recommendations which can be 6 made about the system and can support the assistance of recommendations about users.

iii.Analyzing the data: After going thru the above-given steps, one may additionally find the records shifting in the direction of the analysis stage in which the records are analysed thoroughly

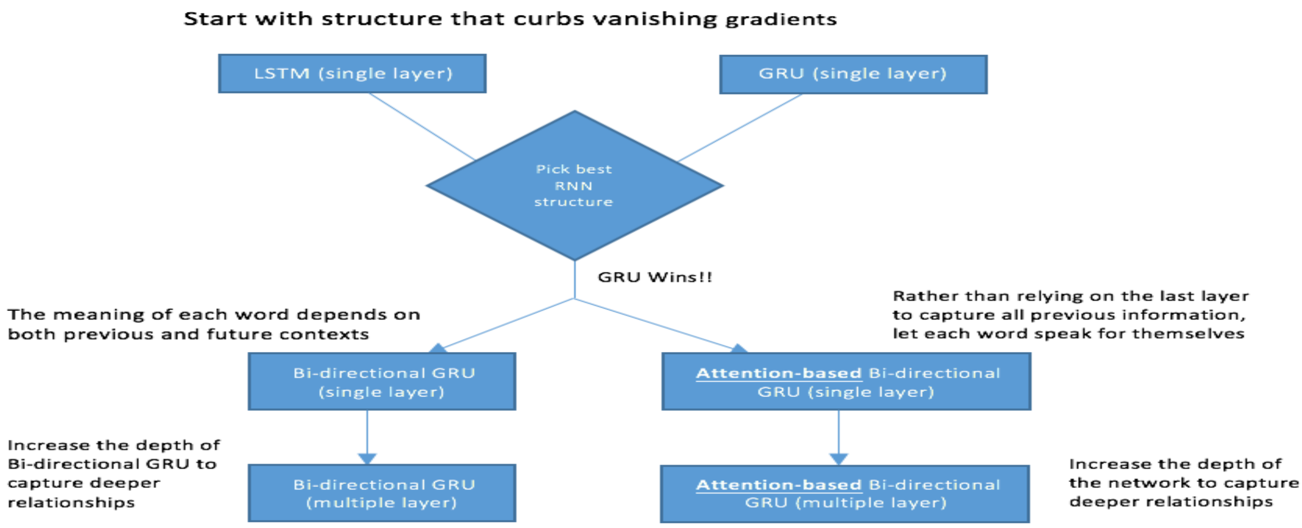

Figure 1.2: Model Selection Flow

We first compare the performance between GRU and LSTM on this specific prediction task,the result indicates the GRU structure performs slightly better than LSTM. Using the GRUas the RNN cell, we implement single, double, triple, and quadruple stacked bi-directionalmodel; the same implementation procedure is also employed to implement four stacked bi-directional attention-based structure.

BiRNN consists of forward and backward RNN structure (GRU cell). In the forward RNN,the input sequence is arranged from the first word to the last word, and the model calculatesa sequence of forward hidden states. The backward RNN takes the input sequence in reverseorder, resulting in a sequence of backward hidden states. To compute the final prediction, weaverage the output from RNNs in both direction and then apply linear transformation togenerate the input to the SoftMax prediction unit.

METHODOLOGY & ALGORITHM

A) Bidirectional Gated Recurrent Unit (BiGRU)

BiGRU is version of RNN newer than LSTM gaining lot of popularity now days. RNN has a very deep calculation graph as it repeats the same operation at every time point. Long- and Short-Term Memory technique of Neural Network is proposed to solve RNN issues but it’s structure becomes more complicated and it is difficult for it to converge at higher speed. BiGRU speed is much faster than that of LSTM.

B) Remora Optimization Algorithm (ROA)

ROA [52] is a well-known bionics-based meta-heuristic algorithm inspired by the parasitic behaviour of remora during foraging in the ocean. Unlike other fishes, remora usually attach to other hosts (humpback whales or sailfishes) to complete long and short-distance movement in the ocean. Like other MAs, ROA also has three different phases: initialization, exploration, and exploitation.

- **Initialization**

Like other various meta-heuristic algorithms, ROA initializes the search agents using a random approach in the search space, which is calculated by:

$X_i = lb + rand \times (ub - lb);\ i \in \{1, 2, \dots, N\}$ (1)

where rand denotes a random variable between [0, 1]. ub and lb indicate the search space's upper and lower bounds. i represents the number of Remora, and N denotes population size.

- **Generate Initial Population**

Here population is a parameter for search agent. In our system the search agent is remora that we have to initialize the number of remora or search agent.

- **Define Network Weight:**

Here Neural Network weight values will be defined. These are randomly generated weight values close to 0.

- **Amendment of Search Agents**

In all optimization algorithms we are defining a solution space initially. We define the search area and number of search agents also. If the search agents exceed beyond threshold in a search space, then we amend the value of search agents. Only the search agents below threshold will be allowed in a search space.

- **Error Minimization**

Here we use error function or loss function for minimizing the error.

- **Store Fitness and Position of Current Search Agent**

In the search space different network weights are there. The network weight which is optimal one will be stored.

- **Find Near Optimal Weight**

First weight value is known and next weight value which is optimal weight can be found by evaluating the fitness value of every weight value we chosen initially. For every iteration we are evaluating fitness function.

- **Evaluate Fitness (Error Minimization)**

For each network weight we evaluate the fitness value. We are comparing new weight vale with the previous weight value.

- **Stopping Criteria:**

Initially we are defining the number of iterations that will be stopping criteria for us.

INCORPORATED PACKAGES

- Flask
- gunicorn
- Jinja2
- MarkupSafe
- Werkzeug
- numpy
- scipy

- nltk
- scikit-learn
- pandas
- beautifulsoup4
- jsonschema
- tmdbv3api
- lxml
- urllib3
- requests
- pickleshare

CONCLUSION & FUTURE SCOPE

We proposed ROA for BiGRU to recommend movies to user, based on his interest pattern. Then the obtained results are tested for the parameters like MAE, RMSE, accuracy, F measure, precision and recall. We compared these results with GA, MMDL, FFNN and we found that, BGRU with ROA has 97% accuracy,97.5 % F measure, 97% precision,98% recall which is greater than rest of all and MAE 0.03, RMSE 0.17 which are lowest than all remaining. Hence, we conclude that BiGRU with ROA has better performance for movie recommendation. In future, ROA can be used for newest machine learning algorithm for movie recommendation.

In this paper, we classify similar user groups with similartaste preferences through movie rating data set for 'movie'items, and apply RNN learning method to them. In this way,the movie consumption pattern of the similar user group islearned, and a model which recommends movies to users isproposed. This model overcomes the sparsity problem whichis the biggest problem in the current recommendationsystems based on the existing rating data. Also, it canrecommend movies by considering the dynamically changing consumption patterns over time.In addition to the 'movie' item, the recommendationmodel can also be used as a recommendation system in areassuch as books and clothing that have individual taste and arelikely to change with the passage of time.

In this paper, we predicted a single movie which is likelyto be consumed by the given user from 45,000 movies. Formore practical applications, multiple recommendationmethods that recommend multiple similar movies at the sametime, considering genre, actor, director, etc., will be moredesirable.

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