Leveraging genre classification with RNN for Book recommendation

Article *in* International Journal of Information Technology · July 2022

DOI: 10.1007/s41870-022-00937-6

Int. j. inf. tecnol.
https://doi.org/10.1007/s41870-022-00937-6

ORIGINAL RESEARCH

Leveraging genre classification with RNN for Book recommendation

Mala Saraswat[2] · Srishti[1]

Received: 25 November 2021 / Accepted: 8 April 2022

Abstract
Reviews of books and movies act as valuable source of user generated content that can be used for recommending books and movies respectively. Traditional recommendation algorithms have limitations as they ignore the combination factor of reviews and genre for book. Algorithms used in area of Natural Language Processing are based on similarity between word vectors in the two texts or documents. Often context between these words are missing leading to poor recommendation as it requires semantics to be analyzed between text from the given reviews. In this paper we use Recurrent Neural Networks (RNN) as a deep learning approach to classify books plots and reviews among various categories and recommend to the users or customers the books based on these categories. RNN is an improvement over traditional models as instead of each input unit being independent as in logistic regression and other neural networks each neuron can use its internal memory to maintain information about the previous units. Hence the context between reviews is maintained by memory units to provide more accurate classification leading to better recommendation. Our approach using RNN provides accuracy of 84% and F-measure of 0.80.

Keywords Reviews · Recommender Systems · Deep learning. Recurrent neural network · Genres

1 Introduction

Based on taste/preferences among a set of items of users, recommender system recommends items to users [1]. Recommenders are broadly classified into two categories: Collaborative filtering based recommender systems and content based recommender systems. In conventional memory-based Collaborative model (CF) techniques, similarity based on the ratings for different items, similar users are found. User based recommender system uses these similar users as the basis of their recommendations. In Model-based CF a rating patterns is examined and analyzed to estimate a model to recommend items [2]. Content or features of items based on user profile is utilized in content based recommender systems. Recommendations are based on user profile developed by user attributes [3]. Review based recommender system uses user generated content such as reviews to recommend items [4]. Review based recommender system exploit various review features such as topics [5], frequent terms [6], sentiments [7] and emotions [8] for recommending items. In [9], Chakraverty et al. further used emotion for recommending items of target domain to user in source domain using cross domain recommendations. Evaluation on emotion prediction further verifies the effectiveness of the proposed model in comparison to traditional rating based item similarity model [10]. Authors in their research further utilize fuzziness in emotion features for recommendations [11]. Saraswat et al. in their paper extract topics from reviews and combine them with reliable semantic coherence techniques to link different domains, using Wikipedia as a reference corpus [12] Conventional recommender systems based on reviews have certain shortcomings as they do not preserve the context between various reviews leading to ambiguous recommendations [1]. In this paper we propose an approach where we use deep learning model to process the book reviews and classify them into different genres. Based on this classification we recommend the books to different users.

Deep learning improves the shortcomings offered by other methods and gives us more efficient recommender systems [13]. Deep learning methods have become more

✉ Mala Saraswat
malasaraswat@gmail.com

1 ABES, Engineering College, Ghaziabad, U.P, India

2 Department of Computer Science and Engineering, The NorthCap University, Gurugram, India

powerful in tackling recommender systems such as news, music, mobile apps recommendations and fashion articles. For text classification or music lyrics categorization into genres deeper models with novel architecture and hundreds of layers have shown immense improvements reducing the classification error more than 25% points in past few time. One shortcoming related to recommendation is that basic neural networks like convolution neural networks does not work for sequence of data where inputs are presented based on the previous inputs. To make strong recommendations we need to take into consideration the context of the reviews that are being considered, so as to make a more coherent classification of genres. Hence we have used a Recurrent neural network (RNN) to process our user reviews, so that a more accurate prediction of book can be made for a user based on its genres. RNN carries along with its memory units which preserves the old information, hence an effective recommendation can be made [14]. Thus RNN applications include tasks such as speech recognition, connected handwriting recognition. For instance consider the phrase "This movie is bad". From simple recommendation and bag of words model we can easily recommend that user did not liked the movie. Let's now consider the phrase "This movie is not bad", by simple recommendation we may predict that user did not like the movie, but in actual user did like the movie. We overcome such problem by using Recurrent neural network which takes into consideration the word "not" before the word bad, and hence is more effective in making predictions.

In this paper, we propose a review based recommender system using RNN to recommend items. Section 2 discusses the related work. In Sect. 3, we discuss the proposed approach. Experiments and results are discussed in Sect. 4. We conclude in Sect. 5.

2 Related work

- Recommender systems are one of the most successful and widespread application of machine learning technologies in business today. The user-based Collaborative filtering is very much similar to item-based collaborative filtering. In user based collaborative filtering rather than measuring the similarity between two items, similarity between two users is considered.

The item-based collaborative filtering is almost identical to user-based collaborative filtering. In item based collaborative filtering similarity between two items is computed rather than calculating similarity between two users.

Other important algorithm used for recommendation is matrix factorization which was established to reduce the problem dimensionality [15]. These algorithms are used for classification or regression and are much more computationally efficient on large sparse datasets. Also this algorithm is used to scale large datasets, like that of Netflix. This property of matrix factorization makes it widely used tool in Recommendation where user count and item count are very large and actual number of recommendations is small.

Some limitations offered by above mentioned algorithms are, first, it is difficult to generate features of items in certain areas, second it suffers from overspecialization problem and third, it is difficult to acquire recommendations from users, and hence recommendations are not validated.

In our approach we have tried classifying book reviews and story plots among various genres. Genres plays a very important role in learning user interests and recommending items for users. All entertainment domains are mostly categorized into different major genres. Literary genres, films genres and nowadays webseries genres are based on the concept of genres as prototypical narratives that invoke emotions [16]. Genres group books or movies into various categories. Genres play an important role for users for finding what they have in mind what is expected from the book while reading and whether to read it or not.

Carlsson built a recommendation engine which can predict a book's genre solely based on the book's cover [17]. In his work the author trained a convolutional neural network (CNN), which takes high dimensional book cover images as inputs and outputs a low-dimensional vector, consisting of book genre association probabilities. Then based on genre books are recommended of same genre.

. Taking cues from all above different approaches, we recommend our proposed approach that uses RNN for classifying the available reviews into genres and then using similar genres books are recommended.

Our work is different from work in [17] as this work uses textual reviews for genre classification using RNN whereas in [17] book cover images are used for genre classification using CNN.

3 Proposed Approach

Our proposed solution is to perform a recurrent neural network on book reviews by using word embedding which is used to produce a dense representation of review vectors. These embedding use a pre-trained model of glove embedding [18]. As inputs we have positive reviews (ratings $>=6$) and as outputs we have multivalued, multiclass classification of review vector into genres. As a result we can classify reviews into various genres based on user preferences.

Further, Fig. 1 depicts the structure of the proposed approach review based classification of Books into genres for recommender system. The RNN based genre classification approach illustrated in Fig. 1 can be extended to almost every domain of entertainment. Book reviews are used to exemplify our approach. Book crossing dataset from which books reviews are extracted from *amazon.com*[1] has been used to extract reviews of books. Each segment as shown in Fig. 1 are elaborated on as below:

All reviews corresponding to a particular book are appended to form a corpus of text. Hence, the result of this segment includes book title, book author and concatenated list of reviews for particular book.

a) **Input Data**: Dataset used for books is Book crossings [19]. The user-book ratings are extracted from Book crossings dataset consisting of 278,857 users who rate of 271,378 books on a rating scale of 1 to 10 with 1.08 million ratings.

a. **b) Preprocessing of review corpus**: Most of the times while reviewing the books users use a relaxed style of writing which results in noise and syntactic errors. This step refines the corpus of reviews by removing redundant and irrelevant content. In this module, given steps are incorporated. Preprocessing of the textual corpus removes noise and irrelevant details and now corpus can be fed as input to our Recurrent Neural Network.

i) Stop words Removal: ii) Stemming of words iii) Numeric character removal iv) Remove special characters.

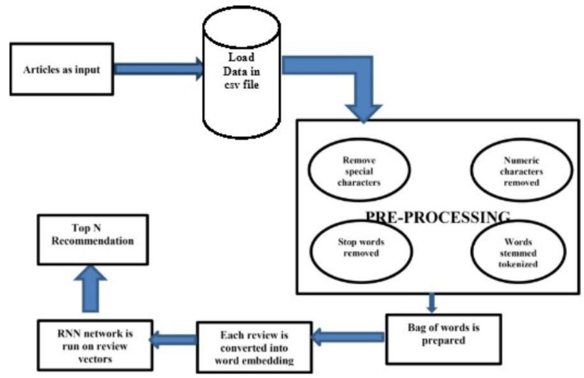


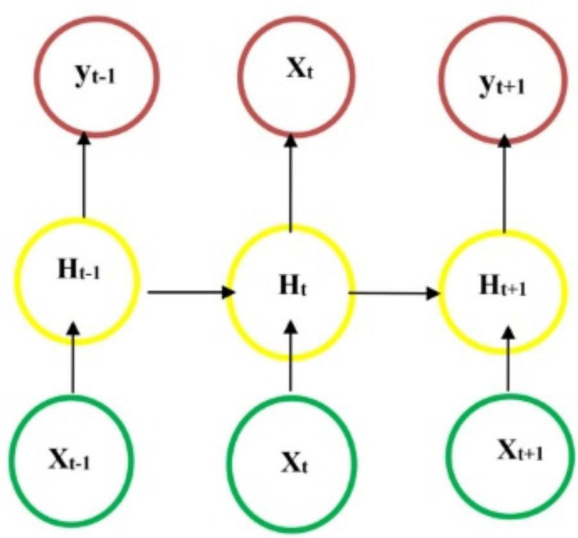
Fig. 1 Proposed approach of genre classification of Book reviews

Through reviews, users express their opinions, feelings and experiences of items bought by them on e-commerce websites. Also reviews are gathered for each of books in Book crossing dataset from amazon.com. Various reviews are taken from amazon.com for each book and are appended to form corpus of textual book reviews for different books.

c) **Recurrent Neural Network**..

Neural networks consisting of hidden layers and using backward propagation to correct the weights based on the labelled data gives an accuracy better than the existing Matrix factorization and collaborative filtering techniques. Based on the user's rating for all the movies in the dataset we could predict the dominant genres in which a user seems most interested in. Further, to recommend books for

Fig. 2 Architecture of a Recurrent Neural Network



[1] https://www.amazon.com/.

a particular user, we used various reviews and storylines of the books to classify into various genres.

RNN is a widely used neural network and is different from other neural networks in a sense that instead of treating each input unit independently, each input is dependent on previous units and this is done with the use of memory called Long Short term Memory (LSTM) [20]. Figure 1 shows the architecture of RNN. From the figure we can write equations from equation i to equation iv where:

U = Weight vector for hidden layer; V = weight vector for hidden layer; W = same weight vector for different layers; X = Word vector for input word; Y = Word vector for output word.

At time step(t),

$Ht = \sigma(U * Xt + W * Ht - 1)$ (i)
$yt = Softmax\,(V * Ht)$ (ii)
$J^t\,(\theta) = -\Sigma_{j=1}^{|M|} y_{t,j} log\overline{y}_{t,j}$ iii)
$J\,(\theta) = -\frac{1}{T}\Sigma_{t=1}^{T}\Sigma_{j=1}^{|M|} y_{t,j} log\overline{y}_{t,j}$ iv)

$$M = vocabulary, J\,(\theta) = Costfunction$$

Model used in RNN processing book reviews.

After the pre-processing data is fed into a Recurrent Neural Network. Here word embedding's that is a dense vector representation of reviews is created. Word embedding's is again 2 layered neural network which itself learns context of each word with respect to its use with neighboring terms in reviews. This dense representation of vectors help us make strong relation of the reviews to their corresponding outputs, hence a more effective performance. Our proposed approach divides the data into a training set and test set. RNN model consists of 4 layers. First, is the Embedding layer or the Input layer, second and third layers are the LSTM (Long short time memory) layers. LSTM layers are to prevent exploding and vanishing gradient in a Recurrent neural network. Also two dropout layers (with a fraction of 0.3) were added to prevent overfitting of the RNN. Dropout basically drops some portion neurons so that network becomes less sensitive to specific weight of neurons. This results in a network that is capable of better generalizations and is less likely to overfit the data. Finally, the fourth layer is the output dense layer with sigmoid activation function was added. Model was compiled with a RMS prop optimizer, loss Binary Cross entropy and accuracy metrics. Our model was run on 20 epochs and a batch size of 256. The optimized weights for the model are saved to be used later so as to train the network once only.

d).**Genre Classification based on RNN model**.

In this step, reviews corresponding to a book are given as input based on the already trained model generated by RNN, genres are generated for that book based on its reviews. We took our datasets from Amazon book reviews which consisted of ISBN, Title and the Author of the book. Also 'books2' dataset included Review Count and Reviews of the books. Also a labelled dataset books_gen.csv was taken from amazon dataset. This module then classifies the books based on these genres. Books belonging to same set of genres are recommended. These predictions have been verified by comparing with genres of actually rated books by the user. The results have been illustrated in results section. These recommendations further can be used to recommend items in other aspects of entertainment such as movies, gaming, television series and many more.

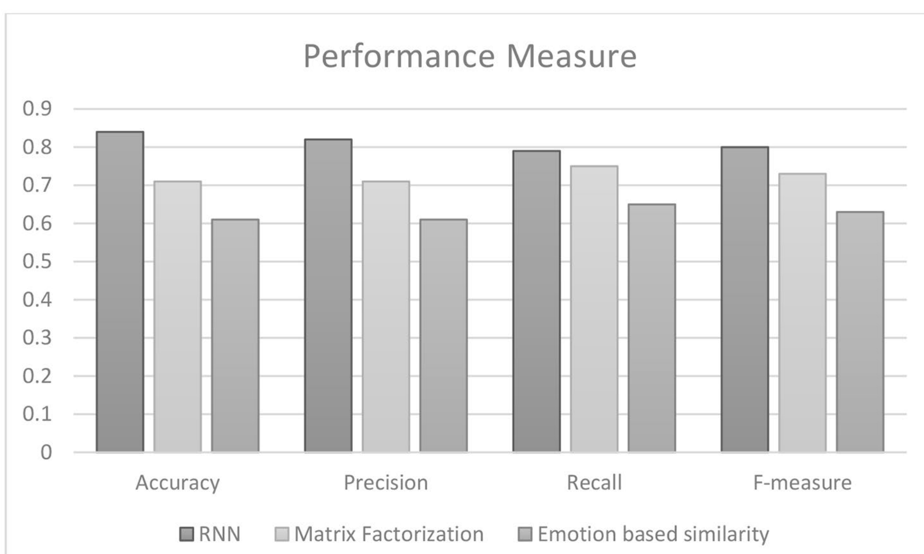


Fig. 3 Comparison of performance measures for Book recommendation

Table 1 Performance of RNN network and Matrix factorization on book reviews for genre classification for TOP 10 Recommendations

S. No	Accuracy	Precision	Recall	F-measure
RNN	0.84	0.82	0.79	0.8
Matrix Factorization	0.71	0.71	0.75	0.73
Emotion based similarity	0.61	0.61	0.65	0.63

Table 2 Performance of book leveraging RNN network on book reviews for genre classification

Top N Recommendation	Accuracy	Precision	Recall	F-measure
Top 5	0.77	0.79	0.81	0.79
Top 10	0.84	0.82	0.79	0.80
Top 15	0.81	0.84	0.77	0.803
Top 20	0.82	0.85	0.77	0.808

4 Experimental results

Experimental results conducted on Book dataset are discussed in this section. After preprocessing the books dataset as discussed our proposed approach divide the data into training and test set, where specified labels are multivalued multiclass classification of genres. One hot encoding is applied to the dataset and feature scaling is done after that to improve the training process. Then, once the data is modeled, it is fed into an RNN architecture consisting of input layer, hidden LSTM layer and an output layer. Appropriate parameters are chosen such as learning rate = 0.001 and number of epochs = 50. After applying the RNN model as discussed in Sect. 3.1.3.We could classify our book reviews into 28 genres some of them being action, adventure, comedy, drama, family, mystery, romance, science and others. From the results elaborated in Table 1, we can clearly see that Recurrent Neural network based recommendation has precision of 0.82 as compared to 0.77 for matrix factorization approach for top 10 recommendations. Figure 2 illustrates the results graphically.

Table 2 shows the variation of precision, accuracy, recall and F-measures for Top –N recommendations. Figure 3 also compares accuracy, precision, recall for RNN based recommendations in book domain for Top N recommendations. From above observations, we infer that using a Deep Learning model using recurrent neural network increases our accuracy of the ratings and decreases the validation loss, hence the Root mean squared Error as compared to standard artificial neural network approach.

5 Conclusions

This paper presents and scrutinize recommendation model based on genre classification of the book reviews by various users. We examined our genre classification based on book reviews with reference Book crossings dataset. The results achieved show that review based genre classification provides high accuracy recommendations using recurrent neural network than any other neural networks. An improved user model is generated as user reviews for the books are used as intermediate source to boost recommendations. Personalization cannot be provided to a good extent by using user-user recommendations since it is based on preferences of other similar users. For future work, more features can be extracted from reviews such as emotions, latent topics etc. for recommender system and also use it for cross domain recommendations.

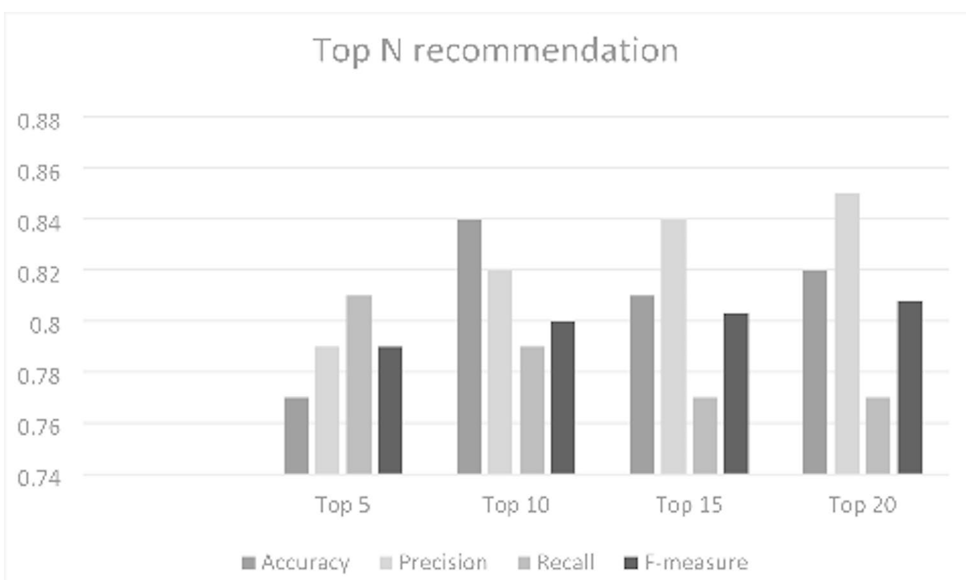


Fig. 4 Comparison of performance measures RNN based recommendation in Books domain

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