SENTIMENT ANALYSIS BASED ON DEEP LEARNING METHODS FOR EXPLAINABLE RECOMMENDATIONS WITH REVIEWS

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ABSTRACT: In recent years, there has been a lot of interest in recommendation systems that can explain their decisions. Most of them rely on written reviews to explain to customers why they appreciate or recommend a certain service or product. Online communities on social media platforms like Twitter, Facebook, and YouTube can benefit from sentiment analysis by learning how their users feel about various topics. However, it appears that sentiment analysis of textual evaluations in explainable recommendation systems is an extremely difficult task. To automatically forecast the tone of reviews, which may be thought of as justifications for recommendations, we describe a deep learning-based framework for sentiment analysis in this paper. Both the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) versions of the prediction model are included. We test their efficacy using a single Amazon real-world dataset and contrast their results to a single state-of-the-art technique. The experimental findings validate the superior performance of our methods compared to the reference method.

Sentiment analysis, explainable, recommendation, recommender system, deep learning, LSTM, and GRU are all terms that can be used to describe this technique.

1. INTRODUCTION

scientists that are considering implementing deep learning strategies into algorithm development. This new group of algorithms is having a profound effect on the recommender systems business, enhancing not only the quality of recommendations but also the user experience by catering to individual tastes, interactions, and product characteristics. The development of this technology has been especially beneficial to video streaming services like YouTube and Netflix, where recommendations account for 80% and 60% of traffic, respectively [1][2]. Several different methods for recommender systems that rely on deep learning have been created in recent years. RecDNNing, created by the inventors of [3], is a recommender system built on a deep neural network that uses the forward propagation method to anticipate users' ratings. The authors integrated a deep neural network with embeddings for people and

products to create a model with higher recommendation precision. Existing recommender systems have several shortcomings, but one of the most significant is their inability to provide explanations for their recommendations. Understanding why products are being recommended to users is a difficulty that must be addressed by explainable recommendation systems if they are to succeed in making their recommendations easily understood. Making use of terms from item reviews, which are helpful in ensuring online consumers can grasp suggestions, is one technique to guarantee the explainability task.

Fig.1: Example figure

2. LITERATURE REVIEW

RecDNNing: a recommender system using deep neural network with user and item embeddings

Interest in creating ground-breaking new recommender systems has surged due to the widespread success of using deep learning across a variety of areas. Few works have investigated the application of deep learning in these systems, and none have demonstrated how to integrate embedding of users and things with deep learning to improve the performance of recommender systems. To address this issue, the authors of this research offer a new method they term RecDNNing, which uses a mixture of embedded users and items to train a deep neural network. The two-stage process that is proposed for making recommendations is as follows. For the first step, we employ a process called user embedding and item embedding to generate a dense numerical representation for each user and item. Afterwards, the embeddings of items and users are averaged and then concatenated before being fed into a deep neural network. In the second stage, we use the forward propagation technique to the model of the deep neural network and feed it the combined user and object embeddings to forecast rating scores. As demonstrated by experimental findings on MovieLens, the suggested RecDNNing achieves better outcomes than state-of-the-art methods.

This article introduces a novel collaborative filtering recommendation system that makes use of dimensionality reduction and clustering strategies.

Over the past decade, e-commerce and Internet-based organizations like Google, YouTube, Facebook, Netflix, LinkedIn, Amazon, etc. have relied heavily on recommender systems to drive revenue and customer engagement. Since reaching out to new customers and marketing products and services is crucial to a company's success, collaborative filtering recommendation algorithms are invaluable. This research introduces a new collaborative filtering recommendation method based on dimensionality reduction and clustering techniques with the goal of enhancing the recommendation performance of such an algorithm. Both the k-means algorithm and the Singular Value Decomposition (SVD) are used to group users into groups with similar characteristics

and so reduce the number of dimensions. As such, it proposes and assesses a two-stage recommender system that can efficiently and accurately create recommendations. The trial outcomes demonstrate that the effectiveness of the recommendation systems is greatly enhanced by using this novel approach.

phrase-level sentiment analysis using explicit factor models for interpretable suggestion

Recommendation algorithms that rely on CF techniques, such as Latent Factor Models (LFM), perform admirably in terms of prediction accuracy. However, it can be challenging to explain the recommendation outcomes to users due to the latent properties. However, thanks to the explosion of user-generated content on the web, data for training a recommender system is no longer restricted to simple numerical star ratings or features of users and products. To better understand what features are important to a user, it is feasible to gain insight into the possibilities of making explainable suggestions by extracting clear user opinions about various parts of a product from the reviews. While maintaining a high level of prediction accuracy, the Explicit Factor Model (EFM) is proposed here to create explainable suggestions. By conducting phrase-level sentiment analysis on user reviews, we first identify explicit product features (i.e. aspects) and user opinions; then, we generate both recommendations and disrecommendations based on the relevance of these features to the user's interests and the hidden features we've discovered. Furthermore, the model generates intuitive feature-level explanations for why a product is or is not recommended. Experimental results on multiple real-world datasets conducted offline show that our framework outperforms state-of-the-art baseline algorithms in rating prediction and top-K recommendation tasks. Experiments conducted online reveal that both recommendations and disrecommendations have a greater impact on users' purchasing decisions when accompanied by thorough explanations.

An Explainable Recommendation Framework Based on Deep Learning with a Long Short-Term Memory

Since there is so much data available online now, recommender systems are essential to the success of e-commerce websites. Unfortunately, most present recommender systems focus solely on better recommendation results and overlook the importance of providing an explanation for such results. To address this issue, we offer a long short-term memory deep learning architecture for explainable recommendation in this research, which can effectively create an explanation for every rating given by users of the recommended item. If our framework could automatically provide an explanation for a product, it would assist users feel more comfortable making a purchase. One example of an explanation that can be generated is a short sentence outlining the rationale behind a product suggestion. Extensive experiments on a real-world Amazon dataset are done to evaluate the efficacy of the suggested strategy in terms of loss and accuracy measures. Experimental results show that our approach is effective in providing diverse, explainable recommendations.

Gradient descent is a challenging method for learning long-term interdependence.

It is possible to employ recurrent neural networks to solve problems involving recognition, production, and prediction by mapping input sequences to output sequences. However, it has been observed that there

are practical difficulties in training recurrent neural networks to carry out tasks where long-term temporal contingencies are included in the input/output sequences. With longer dependencies, we demonstrate why gradient based learning systems confront a more challenging situation. These findings reveal a trade-off between learning quickly via gradient descent and remembering details for extended periods of time. Based on this comprehension, we investigate potential replacements for traditional gradient descent.

3.METHODOLOGY

- The vast majority of these sites rely on reviews posted by past customers to justify the popularity or recommendation of particular services or products. Understanding user sentiment on social media platforms like Twitter, Facebook, and YouTube could benefit from sentiment analysis. But it seems that with explainable recommendation systems, analyzing the tone of reviews written by actual people is a challenging problem.
- Limitations: • It seems that sentiment analysis of textual assessments in explainable recommendation systems is a challenging task.
- To automatically forecast the tone of reviews, which may be thought of as justifications for recommendations, we describe a deep learning-based framework for sentiment analysis in this paper. Both the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) versions of the prediction model are included. We test their efficacy using a single Amazon real-world dataset and contrast their results to a single state-of-the-art technique.
- Advantages:
- Results from experiments validate the superiority of our methods over the gold standard.

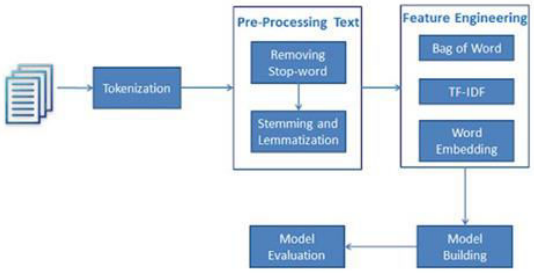

Fig.2: System architecture

Extracting sentiment and detecting emotion from reviews, as well as creating useful and meaningful profiles about the attitudes and preferences of the users, are just a few of the ways in which the developers of explainable recommendations models can benefit from the field of artificial intelligence known as sentiment analysis. However, it appears that sentiment analysis of textual evaluations in explainable recommendation systems is an extremely difficult task. As a result, in this research, we propose to employ deep learning techniques to construct a strong method for predicting the mood of the reviews, which are used as explanations in explainable recommendation systems. The deep learning-based sentiment analysis model is implemented twice, once with a long short-term memory (LSTM) neural network and once with a generalized recurrent unit (GRU) neural network. Positive, negative, or neutral, the approaches tell a user community of what they need to know about the attitude. Experiments show that our approaches effectively anticipate sentiment.

MODULES:

- Data Exploration
- Data Preprocessing
- Data Visualization
- Feature Selection
- Data Splitting
- Model Generation
- Build LSTM,Bi-LSTM,GRU & Hybrid Model CNN+LSTM Classifiers
- Comparison Graph
- Model Build
- Create Flask Object
- Load Model
- Signup & Signin
- Upload Test Data
- Recommending customer to buy or not product

4. ALGORITHMS

Gated recurrent units:

Since their introduction in 2014, recurrent neural networks have made use of a gating mechanism known as gated recurrent units (GRUs) developed by Kyunghyun Cho et al. Comparable to an LSTM with a forget gate, the GRU lacks an output gate, resulting in fewer parameters. It was shown that GRU and LSTM performed similarly on some tasks including the modeling of polyphonic music, speech signals, and natural language processing. On some smaller and less frequent datasets, GRUs have been proven to perform better.

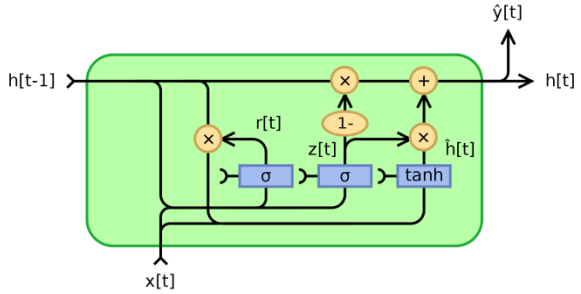

Fig.3: Gated recurrent units

NLTK:

Natural Language Toolkit (or NLTK for short) is a set of Python tools and programs for symbolic and statistical NLP of English. The University of Pennsylvania's Department of Computer and Information Science's Steven Bird and Edward Loper created it. [4] Visual representations and example data are both available in NLTK. This toolkit comes with a book that describes the concepts behind the language processing jobs it can perform, as well as a cookbook.

CNN:

In this example, we will construct a 6 layer neural network to demonstrate how to create an image classifier using a convolutional neural network. The network we're going to construct is so simple that it can even be run on a central processing unit. If trained on a standard CPU, traditional neural networks, which are exceptionally proficient in picture classification, take a relatively long time and have a large number of parameters. Yet, our aim is to demonstrate how to construct a practical convolutional neural network utilizing TENSORFLOW.

(Long Term Short-Term Memory)

An artificial recurrent neural network (RNN) architecture, long short-term memory (LSTM) is utilized in deep learning. With LSTM, there are feedback connections, which is not the case with regular feedforward neural networks. Single data points (like photos) aren't all it can handle, though; it can also handle data sequences in their entirety (such as speech or video). Unsegmented, linked handwriting recognition, speech recognition[3],[4], and anomaly detection in network traffic or intrusion detection systems (IDSs) are just a few examples of the many areas where LSTM can be put to use (intrusion detection systems). Cells, input gates, output gates, and forget gates make up the other parts of a typical LSTM unit. The three gates control the entry and exit of data into and out of the cell, and the cell's memory can store values for an indefinite amount of time.

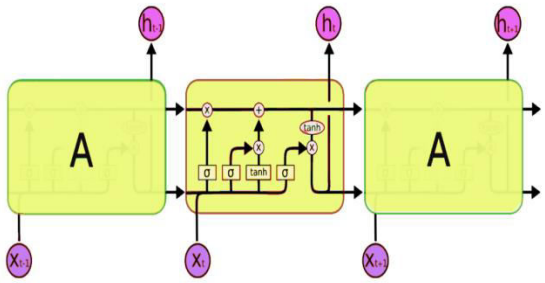

Fig.4: LSTM model

5. EXPERIMENTAL RESULTS

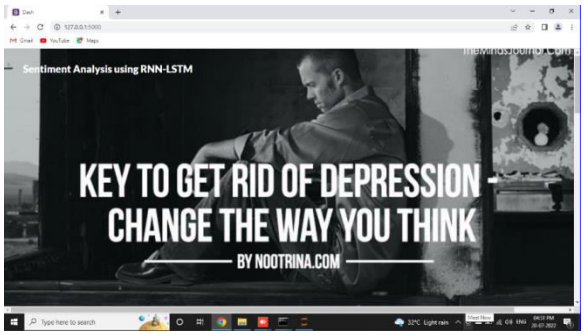

Fig.5: Home screen

Fig.6: Signup here

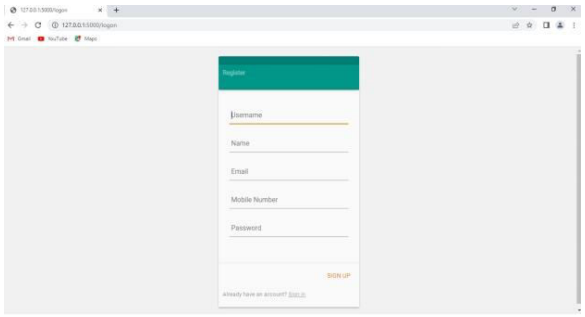

Fig.7: Login

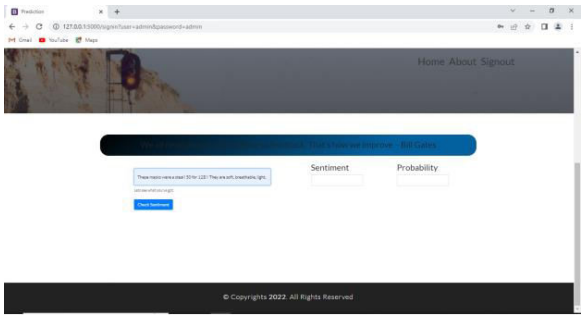

Fig.8: Input screen

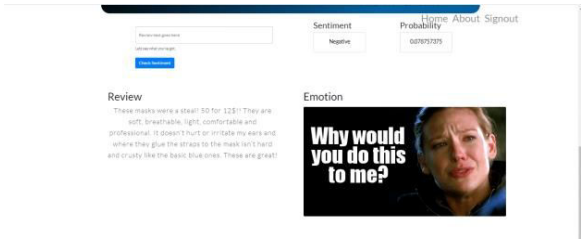

Fig.9: Prediction result

6. CONCLUSION

To automatically forecast the tone of reviews, which serve as justifications for recommendations, we describe a deep learning-based system for sentiment analysis. Both the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) versions of the prediction model are included. We test their efficacy using a single Amazon real-world dataset and contrast their results to a single state-of-the-art technique. The experimental findings validate the superior performance of our methods compared to the reference method.

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