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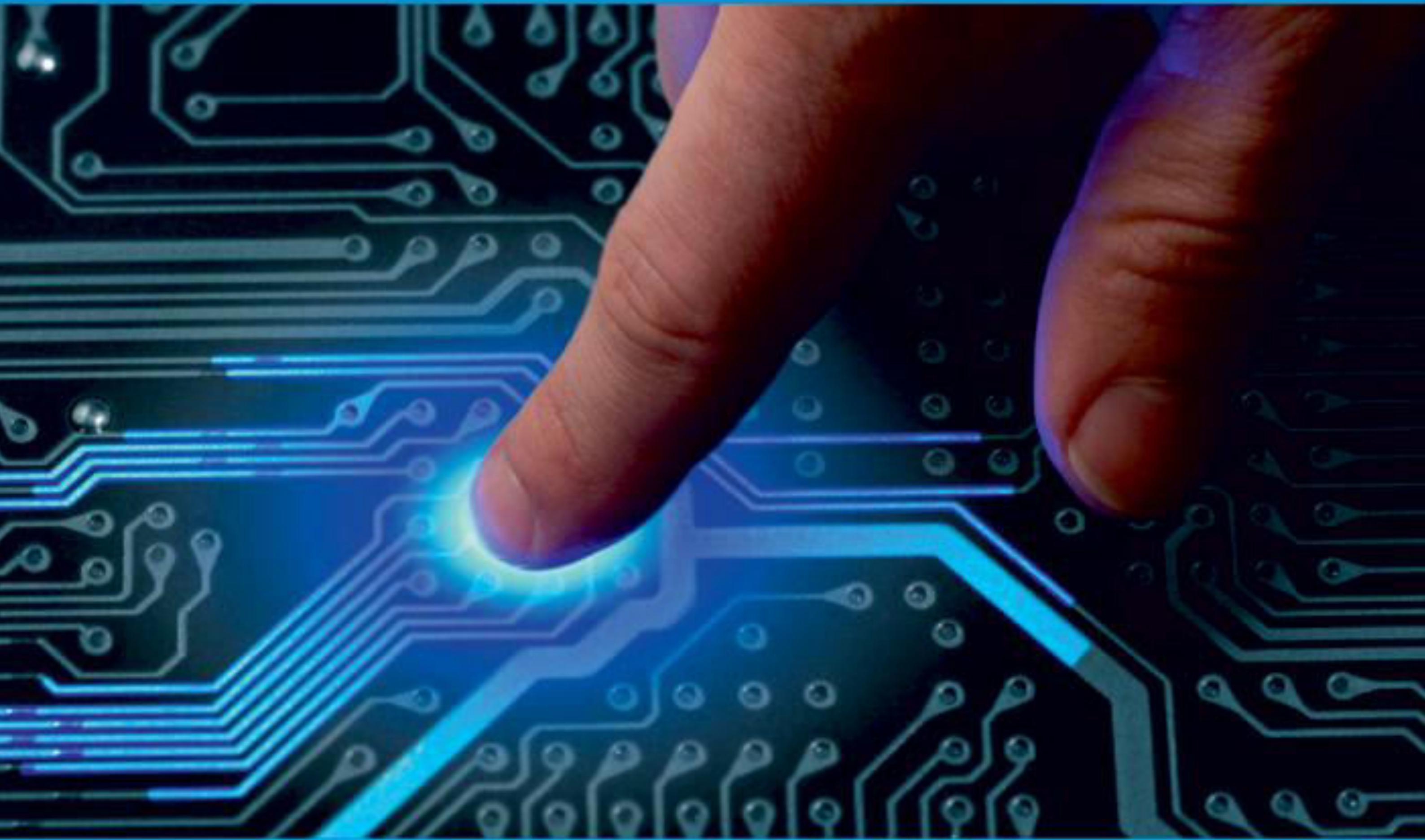

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A Review on Deep Learning Models for User Product Rating Analysis in E-Commerce Industry

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ABSTRACT: Recently deep learning models are showing impressive performance in natural language processing tasks like sentiment classification that include document and sentence classification. User comments are important for recommender systems because they include various types of emotional information that may influence the correctness or precision of the recommendation. A deep learning model is used to process user comments and to generate a possible user rating for user recommendations. This paper first gives an overview sentiment analysis and its applications. Then we have surveyed various deep learning architectures such as RNN, LSTM, DBN and HDBN and their applications in sentiment analysis.

KEYWORDS: Sentiment Analysis; RNN; LSTM; HBDN; DBN;

I. INTRODUCTION

In the area of recommender systems and personalization, the inference of user sentiment can be very useful to make up for the lack of explicit user feedback on a provided service. In addition to machine learning, other methods, such as those based on the similarity of results, can be used for this purpose [1]. The sources of data for sentiment analysis (SA) are online social media, the users of which generate an ever-increasing amount of information. Thus, these types of data sources must be considered under the big data approach, given that additional issues must be dealt with to achieve efficient data storage, access, and processing, and to ensure the reliability of the obtained results [2].

The problem of automatic sentiment analysis (SA) is a growing research topic. Although SA is an important area and already has a wide range of applications, it clearly is not a straightforward task and has many challenges related to natural language processing (NLP). Recent studies on sentiment analysis continue to face theoretical and technical issues that hinder their overall accuracy in polarity detection [3,4]. Hussein et al. [4] studied the relationship between those issues and the sentiment structure, as well as their impact on the accuracy of the results. This work verifies that accuracy is a matter of high concern among the latest studies on sentiment analysis and proves that it is affected by some challenges, such as addressing negation or domain dependence.

Social media are important sources of data for SA. Social networks are continuously expanding, generating much more complex and interrelated information.
In recent years, several studies have proposed deep-learning-based sentiment analyses, which have differing features and performance. This work looks at the latest studies that have used deep learning models, such as deep neural networks (DNN), recurrent neural networks (RNN), and convolutional neural networks (CNN), to solve different problems related to sentiment analysis (e.g., sentiment polarity and aspect-based sentiment). Deep learning models with TF-IDF and word embedding to twitter datasets and implemented the state-of-the-art of sentiment analysis approaches based on deep learning.

1.1. Word Embedding
Many deep learning models in NLP need word embedding results as input features [5]. Word embedding is a technique for language modelling and feature learning, which transforms words in a vocabulary to vectors of continuous real numbers (e.g., $word$ "hat" → (…, 0.15, 0.23, 0.41,)). The technique normally involves a mathematic embedding from

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a high-dimensional sparse vector space (e.g., one-hot encoding vector space, in which each word takes a dimension) to a lower-dimensional dense vector space. Each dimension of the embedding vector represents a latent feature of a word. The vectors may encode linguistic regularities and patterns.
The learning of word embeddings can be done using neural networks [6], [9] or matrix factorization [10]. One commonly used word embedding system is Word2Veci, which is essentially a computationally efficient neural network prediction model that learns word embeddings from text. It contains Continuous Bag-of-Words model (CBOW) [7], and Skip-Gram model (SG) [8]. The CBOW model predicts the target word (e.g., "wearing") from its context words ("the boy is _ a hat", where "_" denotes the target word), while the SG model does the inverse, predicting the context words given the target word. Statistically, the CBOW model smoothens over a great deal of distributional information by treating the entire context as one observation. It is effective for smaller datasets. However, the SG model treats each context-target pair as a new observation and is better for larger datasets. Another frequently used learning approach is Global Vectorii (GloVe) [11], which is trained on the nonzero entries of a global word-word co-occurrence matrix.

II.LITERATURE REVIEW

The purpose of this study is to review different approaches and methods in sentiment analysis that can be taken as reference in future empirical studies. We have focused on key aspects of research, such as technical challenges, datasets, the methods proposed in each study, and their application domains.
Recently, deep learning models (including DNN, CNN, and RNN) have been used to increase the efficiency of sentiment analysis tasks. In this section, state-of-the-art sentiment analysis approaches based on deep learning are reviewed.

Beginning in 2015, many authors have since evaluated this trend. Tang et al. [12] introduced techniques based on deep learning approaches for several sentiment analyses, such as learning word embedding, sentiment classification, and opinion extraction. Zhang and Zheng [13] discussed machine learning for sentiment analysis. Both research groups used part of speech (POS) as a text feature and used TF-IDF to calculate the weight of words for the analysis. Sharef et al. [14] discussed the opportunities of sentiment analysis approaches for big data. In papers [15, 16, 17], the latest deep-learning-based techniques (namely CNN, RNN, and LSTM) were reviewed and compared with each other in the context of sentiment analysis problems.

Some other studies applied deep-learning-based sentiment analysis in different domains, including finance [18, 19], weather-related tweets [20], trip advisors [21], recommender systems for cloud services [22], and movie reviews [23]. In [20], where text features were automatically extracted from different data sources, user information and weather knowledge were transferred into word embedding using the Word2vec tool. The same techniques have been used in several works [24]. Jeong et al. [25] identified product development opportunities by combining topic modeling and the results of a sentiment analysis that had been performed on customer-generated social media data. It has been used as a real-time monitoring tool for analysis of changing customer needs in rapidly evolving product environments. Pham et al. used multiple layers of knowledge representation to analyze travel reviews and determine sentiments for five aspects, including value, room, location, cleanliness, and service .

Another approach [26] combines sentiment and semantic features in an LSTM model based on emotion detection. Preethi et al. [22] applied deep learning to sentiment analysis for a recommender system in the cloud using the food dataset from Amazon. For the health domain, Salas-Zárate et al. [27] applied an ontology-based, aspect-level sentiment analysis method to tweets about diabetes. Polarity-based sentiment deep learning applied to tweets was found in [28].
The authors described how they used deep learning models to increase the accuracy of their respective sentiment analysis. Most of the models are used for content written in English, but there are a few that manage tweets in other languages, including Spanish [29], Thai [30], and Persian [31].
Previous researchers have analyzed tweets by applying different models of polarity-based sentiment deep learning. Those models include DNN, CNN, and hybrid approaches.
Other works using neural network models are focused not only on the sentiment polarity of textual content, but also on aspect sentiment analysis.
Salas-Zárate et al. [27] used semantic annotation (diabetes ontology) to identify aspects from which they performed aspect-based sentiment analysis using SentiWordNet. Pham et al. [21] included the determination of sentiment ratings and importance degrees of product aspects. A novel, multilayer architecture was proposed to represent customer reviews aiming at extracting more effective sentiment features.

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From among 32 of the analyzed studies, we identified three popular models for sentiment polarity analysis using deep learning: DNN, CNN, and hybrid. Three deep learning techniques, namely CNN, RNN, and LSTM, were individually tested on different datasets. However, there was a lack of a comparative analysis of these three techniques.
Many studies use the same process for sentiment analysis. First, text features are automatically extracted from different data sources, and then they are transferred into word embedding using the Word2vec tool.
Sentiment analysis has also been the target of extensive research in the application domain of recommender systems. Most methods in this area are based on information filtering, and they can be classified into four categories: content-based, collaborative filtering (CF), demographic-based, and hybrid. Social media data can be used with these techniques in different ways. Content-based methods make use of characteristics of items and user's profiles, CF methods require implicit or explicit user preferences, demographic methods exploit user demographic information (age, gender, nationality, etc.), and hybrid approaches take advantage of any kind of item and user information that can be extracted or inferred from social media (actions, preferences, behavior, etc.).
Besides, when dealing with both explicit data (which are provided directly by users) and implicit data (which are inferred from the behavior and actions of users), hybrid methods and lifelong learning algorithms are considered as in-depth approaches for recommendation systems.
Shoham [32] proposed one of the first hybrid recommendation systems, which takes advantage of both content and collaborative filtering recommendation methods. The content-based part of the proposal involves the identification of user profiles based on their interest in topics extracted from web pages, while the collaborative filtering part of the system is based on the feedback of other users.

III. SENTIMENT ANALYSIS

Sentiment Analysis is a field of Natural Language Processing (NLP) that builds models that try to identify and classify attributes of the expression. Sentiment Analysis can help to automatically transform the unstructured information into structured data of public opinions about products, services, brands, politics or any other topic that people can express opinions about. This data can be very useful for commercial applications like marketing analysis, public relations, product reviews, net promoter scoring, product feedback, and customer service.
Sentiment analysis learns the positivity or negativity of products or services from user comments [33]. Sentiment analysis is based on an opinion lexicon. An opinion lexicon is a dictionary containing words, which express the polarity of words through positive or negative sentiments, such as happy, good, bad, or disgusting. These opinion words are used in sentiment analysis as the key indicator to calculate the opinions of the user. In recent years, many public lexical collections have become available, such as SentiWordNet [34], General Inquirer [35], and SenticNet [36]. The first important task in sentiment analysis is to identify the opinion targets (aspects, entities, and topic identification problems) about which opinions are expressed [37]. Next, the opinion lexicon must be constructed. For example, I am very disappointing with this restaurant's services. Although "disappointed" is the opinion target and "disappointing" is an opinion word as well.

3.1 Application of Sentiment Analysis

The title is 17 points in Times New Roman Bold font, left aligned, not justified, not indented. Leave 28 mm space above the title and 10 mm after the title. It is widely accepted that sentiment analysis is very useful in a wide range of application domains, such as business, government, and biomedicine.
In the fields of business intelligence and e-commerce, companies can study customers' feedback to provide better customer support, build better products, or improve their marketing strategies to attract new customers. Sentiment analysis can be used to infer the users' opinions on events or products. The results of SA help to gain greater insight into the customers' interests or opinions on industrial trends. In this context, Jain and Dandannavar [38] proposed a fast, flexible, and scalable SA framework for sentiment analysis of Twitter data that involves the use of some machine learning methods and Apache spark.
As pointed out in the introduction, the area of recommender systems has also benefited from sentiment analysis. A sample of this can be found in the work of Preethi et al. [40], where recursive neural networks were applied to analyze sentiments in reviews. The output was used to improve and validate the restaurant and movie recommendations of a cloud-based recommender system. Along with behavioral analysis, sentiment analysis is also an e cient tool for commodity markets [41].
The medical domain is another field of potential interest. The applications of opinion mining in health-related texts on social media and blogs were explored in [42]. In addition to traditional machine learning and text processing techniques, the author offers new approaches and proposes a medical lexicon to support experts and patients in the varied methodology that is used to describe symptoms and diseases. In the field of mental health, sentiment analysis is

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performed on texts written by patients' posts on social media as a means of supplementing or replacing the questionnaires they usually fill in [43].

1. Deep Learning Models For Sentiment Analysis

Application of multiple layers of artificial neural networks for the learning tasks is called deep learning [44]. In the research field, deep learning is a powerful machine learning technique. It has the ability to learn multiple levels of representations and abstractions from data, which can solve both supervised and unsupervised learning tasks [45] [46]. Deep learning uses multiple layers of non-linear processing units for feature extraction and classification. Sentiment analysis is one of the active research areas in Natural Language Processing.
There exist numerous techniques to perform sentiment analysis task, which include both supervised and unsupervised methods. Types of supervised machine learning method include Support Vector Machines (SVM), Maximum Entropy, Naïve Bayes, etc. Types of unsupervised machine learning methods include sentiment lexicons, grammatical analysis, and syntactic patterns. Application of deep learning to sentiment analysis has been very popular now a day. The reason to choose deep learning models, as it provides improved performance and accurate results over learning tasks. Deep neural network methods will perform both feature extraction and classification for document and short text.

A. Recurrent Neural Networks

Recurrent neural network models are a form of neural networks that is used to work for natural language processing tasks, without depending on window size. Most recurrent networks will process the sentence sequences of variable length.
Recurrent networks share parameters in a different way. Each member of the output is a function of the previous member of the output. Each member of the output is produced using the same update rule applied to the previous outputs. This recurrent formulation results in the sharing of parameters through a very deep computational graph [47]. The recurrent neural network model with three-time steps is shown in Figure 1.

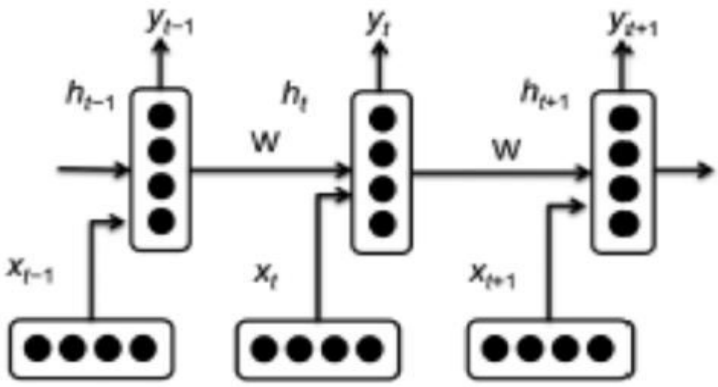

Figure 1: Recurrent Neural Network

B. LSTMs

Long Short-Term Memory networks — usually just called "LSTMs" — are a special kind of RNN, capable of learning long-term dependencies. LSTMs don't have a fundamentally different architecture from RNNs, but they incorporate additional components.
The key to LSTMs is the cell state C(t), the horizontal line running through the top of the diagram. A cell state is an additional way to store memory, besides just only using the hidden state h(t). However, C(t) makes it possible that LSTMs can work with much longer sequences in opposite to vanilla RNNs.
Furthermore, LSTMs have the ability to remove or add information to the cell state, carefully regulated by structures called gates. Gates are a way to optionally let information through. An LSTM has three of these gates, to protect and control the cell state.
Forget Gate: After getting the hidden state h(t-1) of the previous input x(t-1), Forget gate helps us to make decisions about what must be removed from h(t-1) state and thus keeping only relevant stuff.
Input Gate: In the input gate, we decide to add new stuff from the present input x(t) to our present cell state C(t).
Output Gate: The output gate as the name suggests, decides what to output from the current cell state C(t) to the next C(t+1). For the language model example, since it just saw a subject, it might want to output information relevant to a verb, in case that's what is coming next. For example, it might output whether the subject is singular or plural so that we know what form a verb should be conjugated into if that's what follows next.

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Behind each of these states are separate neural networks. As you can imagine this makes LSTMs quite complex. At this point, I won't go much more into the detail about LSTMs.

Tang's [47] work use several layers of LSTMs to build the document model, first LSTM layer is for sentence modeling, the sentence vectors are then fed into document level LSTM, the model proved to be efficient in classification problem. Another well-known use of LSTM is NMT-neural machine translation; a widely used model by researchers is sequence to sequence model. The model is composed of encoder and decoder part, both are LSTM chains, while the encoder part encodes input sentence, the decoder part output prediction result based on the previous word tokens, Zaremba [48] use this method in his work. Same idea can be used in figuring relation between sentence, or detect similiar sentences, as used in Sutskever [49]'s research.

A special type of RNN is long short-term memory (LSTM), which is capable of using long memory as the input of activation functions in the hidden layer. This was introduced by Hochreiter and Schmidhuber (1997). Fig 2 illustrates an example of the LSTM architecture. The input data is preprocessed to reshape data for the embedding matrix (the process is similar to the one described for the CNN). The next layer is the LSTM, which includes 200 cells. The final layer is a fully connected layer, which includes 128 cells for text classification. The last layer uses the sigmoid activation function to reduce the vector of height 128 to an output vector of one, given that there are two classes to be predicted (positive, negative).

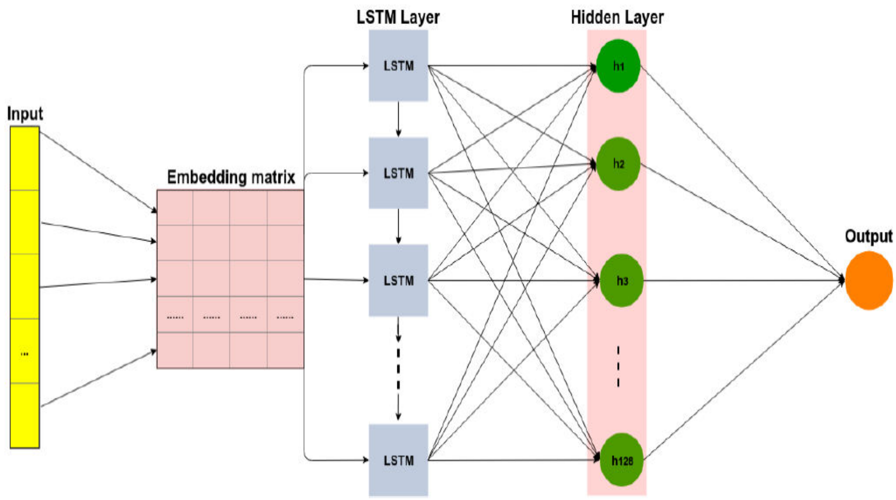

Figure 2: A long short-term memory network

C. Deep Belief Networks (DBN)

Deep belief network (DBN) is a generative graphics model, which consists of multiple layers of hidden units, with connections between layers wherein each layer unit does not have any connections. DBN can construct its input from the original input node to choose the significant features to be used as the input layer in the training phase. These capabilities are based on the probabilistic reconstruction of their input, as the layers act as features detectors [50]. DBN may also be used to perform classification problems from its training model [51].

Deep Belief Networks [52] shown in Figure 3 which helped to create unbiased values to be stored in leaf nodes. The first step is to train a layer of properties which can obtain the input signals from the pixels directly. The next step is to treat the values of this layer as pixels and learn the features of the previously obtained features in a second hidden layer. Every time another layer of properties or features is added to the belief network, there will be an improvement in the lower bound on the log probability of the training data set.

The Test Dataset is only used once a model is completely trained (using the train and validation sets). The test set is generally what is used to evaluate competing models. It includes only input data, not the corresponding expected output. The testing data is used to assess how well your algorithm was trained, and to estimate model properties. The test dataset is a dataset used to provide an unbiased evaluation of a final model fit on the training dataset. Prediction is the last step where the input is the text file that the user is uploaded. The input text file is pre-processed, trained, and

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classified to obtain theintent/domain. Based on the intent/domain identified, the sentences are loaded from the trained dataset. Accuracy is defined as the percentage of correct predictions for the test data. It can be calculated easily by dividing the number of correct predictions by the number of total predictions.

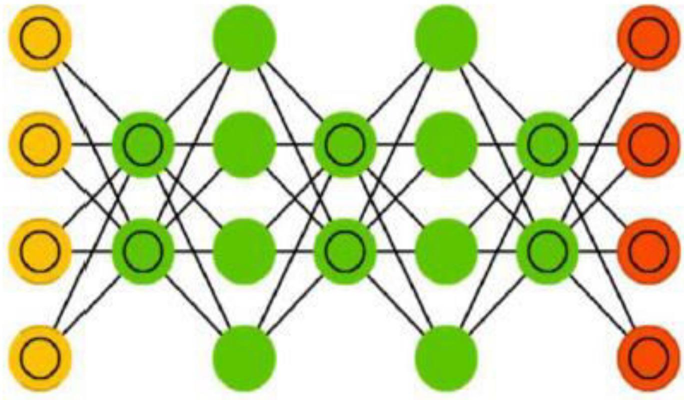

Figure 3: Deep Belief Networks.

D. Hybrid Deep Belief Networks (HDBN)

HDBN is a novel semi-supervised learning method. The sentiment datasets have high dimension (about 10,000), and computation complexity of convolutional calculation is relatively high, so RBM is used to reduce the dimension of review with normal calculation firstly. Figure. 4 shows the deep architecture of HDBN, a fully interconnected directed belief nets with one input layer h0, N hidden layers h1, h2, ... , hN, and one label layer at the top. The input layer h0 has D units, equal to the number of features of sample review x. The hidden layer has M layers constructed by RBM and N −M layers constructed by CRBM. The label layer has C units, equal to the number of classes of label vector y. The numbers of hidden layers and the number of units for hidden layers, currently, are pre-defined according to the experience or intuition. The seeking of the mapping function X ! Y, here, is transformed to the problem of finding the parameter space W = {w1, w2, . . . ,wN} for the deep architecture [53].

The training of the HDBN can be divided into two stages:

1. HDBN is constructed by greedy layer-wise unsupervised learning using RBMs and CRBMs as building blocks. L labeled data and all unlabeled data are utilized to find the parameter space W with N layers.

2. HDBN is trained according to the exponential loss function using gradient descent based supervised learning. The parameter spaceWis refined using L labeled data.

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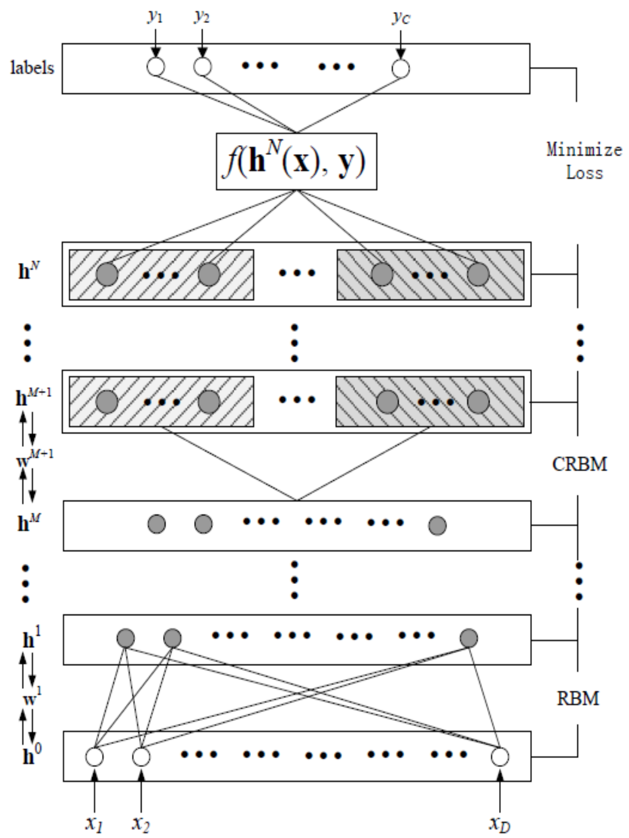

Figure 4: Architecture of HDBN.

IV. CONCLUSION

Applying deep learning to sentiment analysis has become a popular research topic. A deep learning model is used to process user comments and to generate a possible user rating for user recommendations. In this paper, we have reviewed various deep learning architectures such as RNN, LSTM, DBN and HDBN and their applications in sentiment analysis. Many of these deep learning techniques have shown state-of-the-art results for various sentiment analysis tasks. With the advances of deep learning research and applications, we believe that there will be more exciting research of deep learning for sentiment analysis in the near future.

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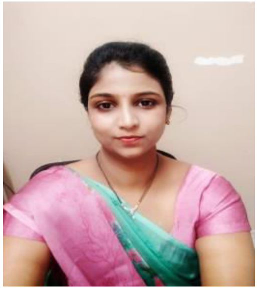

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