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A Review on Suggestion Mining from Online Reviews with Deep Learning Techniques

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Abstract—Opinion mining can be useful in several ways. i.e, in marketing it helps in judging the success of a new product launch, determine which versions of a product are popular and even differentiate which demographics like or dislike particular features. Online reviews are considered as one of the most essential sources of client opinion. In current scenario, consumers can learn about the products and services using online review resources to make decisions. Suggestion mining can be defined as the process of identifying and extracting sentences from unstructured text that contain suggestion. Suggestions in the form of unstructured text could be found in various social media platforms, discussion forums, review websites and blogs. Deep learning is often unsupervised, masterly regulated contrasting learning. It needs the development of large Neural Networks to make it possible for the machine to learn or compute itself without direct human intervention and we discuss the various types of deep learning techniques of Convolutional Neural Networks, Recurrent Neural Networks, An autoencoder, RBM or Deep Neural Networks. In this survey we have study about the opininonmining , Online reviews,Suggestion mining & also described these challenges, deep leaning & its various techniques.

Keywords—Opinion Mining , Online Reviews , Social Media ,Suggestion Mining , Deep Learning , Convolutional Neural Networks , RBM,RNN.

I. INTRODUCTION

Opinion mining can be useful in several ways. i.e, in marketing it helps in judging the success of a new product launch, determine which versions of a product are popular and even differentiate which demographics like or dislike particular features. There are many challenges in opinion mining. The first is that people don't always phrase opinions in a same way. A second challenge is an opinion word that is considered to be positive in one state may be considered negative in another state. Most traditional text processing depends on the fact that small differences between two pieces of text don't change the meaning very much. In opinion mining, however, "the camera was great" is very different from "the camera was not great". People can be dissimilar in their statements. Farthest reviews will have both positive and negative comments, which is slightly manageable by analyzing sentences one at a time. However, in the more annular medium like twitter or blogs, the more likely people are to join different opinions in the same sentence which is easy for a human to understand, but more difficult for a computer to parse. Sometimes even other people have difficulty recognizing what someone thought based on a short piece of text because it shortage context [1].

Now a day's online reviews has become an increasingly trendy approach for public to share their sentiments and opinions towards the product bought and services received. Online reviews become one of the most important part of any business today. Online reviews presents wealth of information on products and services, if the reviews are properly utilized then it is valuable for vendors in network and social intelligence so that business will be improved. A recent study focused on cost-effective values of online reviews and provides deep understanding between product reviews and their sales performanc. People tend to read online reviews understanding the opinions and sentiments and trust them as much as they are recommended by their friends or families. Twitter, a social networking service plays significant role in social networking research. Tweets give rich information about movie, product, or service [2]. Social media is defined as a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchanges of user-generated content. Social media is conglomerate of different types of social media sites including traditional media such as newspaper, radio, and television and nontraditional media such as Facebook, Twitter, etc. Social media gives users an easy-to-use way to communicate and network with each other on an unprecedented scale and at rates unseen in traditional media. The popularity of social media continues to grow exponentially, resulting in an evolution of social networks, blogs, microblogs, location-based social networks (LBSNs), wikis, social bookmarking applications, social news, media (text, photo, audio, and video) sharing, product and business review sites, etc [3].

Suggestion mining can be defined as the process of identifying and extracting sentences from unstructured text that contain suggestion. Suggestions in the form of unstructured text could be found in various social media platforms, discussion forums, review websites and blogs. They are often expressed in the form of advice, tips, recommendations, warnings, things to do, and various other forms in an explicit as well as an implicit way. Suggestion mining is a relatively new domain and is challenged by problems such as ambiguity in task formulation and manual annotation, understanding sentence level semantics, figurative expressions, handling long and complex sentences, context dependency, and highly imbalanced class distribution, as already mentioned by. Similar problems are also observed in the dataset shared by the organizers for the SemEval task, as it is obtained from a real-world application comprising of suggestions embedded in unstructured textual content [4].

Deep learning is often unsupervised, masterly regulated contrasting learning. It needs the development of large NNs to make it possible for the machine to learn or compute itself without direct human intervention. Learning in apps relies on arm-technical features where the researcher codes pertinent details manually about the task and then learning about it. This contrasts with the deep learning that makes the structure as viable as possible to develop its properties. Recent Google experiments on deep learning have shown that a very large, unsupervised NN can be trained to optimize the development of features for cat faces recognition. The data limitations associated with incredibly broad recommendation networks offer ample opportunities to discover new methods of transferring expertise through subsidiary sources of information. [5].

II. OPINION MINING

OM is a promising discipline that is described as a crossroads between information recovery and computer linguistic techniques to address the views expressed in a document. OM is a promising subject, defined as a combination of information retrieval as well as language modeling techniques. OM or SA is the field to extract as well as summarize the opinionated text datasets in a comprehensible form. Opinion mining is to remove summer from unstructured data from the optimistic, negative, or neutral view.

A. ARCHITECTURE OF OPINION MINING

OM often referred to as sentiment study is a way to gain an opinion of the consumer on a product or topic. Opinion mining summarizes the good, neutral or poor opinion of the company on objects, incidents, themes, etc. Three main measures are taken in the mining opinion or resuming process: extraction of opinions, categorization of opinions, or overview opinion. The review term can be contained on websites of analysis. Opinion texts, which are contextual details on the topic, can be contained in forums, articles, analysis, tweets, etc. Examinations can be marked as negative or optimistic. Summary of opinions is then created by considering specific features on a topic dependent on features in opinion phrases.

Figure. 1: Architecture Of Opinion Mining

B. OPINION MINING TECHNIQUES

There are mainly three types of techniques:

a) Supervised Learning Techniques (SVM): SVM Neural Network, Multi-layer Perceptron (MLP), Decision Tree, NB, MaxEnt (MaxEnt) are the most widely-used controlled learning strategies.

b) Unsupervised Learning Techniques (ULT): Clustering method, probability maxing method, matrix factorization, key feature simulations are more widely employed strategies.

c) Case-Based Reasoning (CBR): It is an experimental strategy that arises. In such an in-depth situation, CBR is an analytical method in machine thinking. Within the CBR archive recognized as the case base, the answer is held.

C. APPLICATION OF OPINION MINING

The key uses of opinion or sentiment analysis as described below:

a) Opinion spam detection: Users will compose critical intense reviews of the drug. Opinion and emotions analysis will divide such comments into "spam" or "not spam" material.

b) Purchasing Product or Service: This approach allows users to accurately analyze a different product or service reviews and expertise and can therefore effectively assess rival products.

c) Quality Improvement in Product or service: The negative views or favorable views about the product or service growing to be gathered in this production sector to enhance product quality or service efficiency.

d) Marketing research: The new government strategy will evaluate goods or services. Both of these findings will lead to insightful collaborative work.

e) Policy-Making: Sentiment analyzes encourage politicians to take citizens ' attitudes of such policies and to use that knowledge to create different or improved citizen-friendly policies.

f) Decision Making: The views & understanding of citizens are a very significant aspect of decision-making. It includes the viewpoint of evaluated individuals who can be used to make decisions [6-11].

III. ONLINE REVIEWS

Online reviews have become an important source of information for consumers that significantly influence consumer choices and product sales. Research on online reviews has become an established field due to the rapid growth of electronic commerce. From the perspective of manufacturers, the selection of helpful online reviews and learning from online reviews for new product development have both become important. Big Data, i.e., the volume, velocity and variety of primary data, provides manufacturers with the opportunity to make use of online reviews for product designs.

Online reviews could be the source of innovative ideas, providing input for new product designs and enhancements. Co-creation, the active involvement of customers in the process of new product and service development, has been identified as a reliable source of competitive advantag. From the viewpoint of manufacturers, online reviews are appealing sources of customer requirements, especially for those manufacturers who must continually renovate their products in the competitive market. Through online reviews, manufacturers can listen to the voices of customers in the target market. In addition, manufacturers are able to draw knowledge about the market structure and competitive landscape to support their marketing decisions [12].

A. IMPLICATIONS OF ONLINE REVIEWS

The online reviews have a major impact on the customer's purchase intentions. These reviews leave a remarkable change in the customer's mind about a product or a brand. The customer will be positively or negatively affected by the nature of reviews hence the online website owners need to be proactive in understanding the customer's reviews and any negative comment must be immediately looked into. The feedback given by the customers will have a direct impact on the future customers hence a proper channel needs to be developed to understand and deal with the customers writing negative reviews.

B. USEFULNESS OF ONLINE REVIEWS

Most of the review studies have focused on features of the review content the information about the reviewer which includes his own character and his social relations have not been given much importance. Most of the reviews and information that are posted online have found to make a considerable difference depending upon the author's social relations the character of these reviewers needs to be keenly studied in order to find if the review is helpful or not. The quality of the review can also be decided by the readability and writing style as it will definitely have a major impact on the reader. In fact have found that readability does not have much impact in determining the quality and Ghose and Ipeirotis have put forth that the reviews do have an influence on the perceived usefulness and the subjective matter of information [13].

IV. SUGGESTION MINING

Suggestion mining can be characterized as separating suggestion from unstructured content, where the term ' recommendations' alludes to tips, counsel, suggestions, and so on articulations. Suggestion mining is a youthful issue contrasted with other entrenched errands of content grouping and in this way needs huge hand named datasets of benchmarks. In general, consumer views are expressed towards business entities such as blogs, services, brands and products through social media, online reviews, or discussion forums. Such views convey to a large degree positive and negative emotion about a particular entity but often tend to include recommendations for improvising the entity or advice for fellow customers. Classical opinion mining systems primarily focus towards automatic calculation of the distribution of sentiments to an entity of interest through methods of Sentiment Analysis. Separating suggestions that are communicated precipitously on various online stages permits associations to gather recommendations from a lot bigger and changed wellsprings of supposition than the conventional suggestion box or online feedback forms. It incorporates suggestion mining as a basic process of classifying certain sentences into suggestion and non-suggestion groups [14].

A. **CHALLENGES OF SUGGESTION MINING**

Some of the observed challenges in suggestion mining are:

- **Class imbalance:** Suggestions appear sparsely in domains like hotel reviews (6% - 13%), which leads to higher data annotation costs as well as results in a skewed class distribution for model training.
- **Figurative expressions:** The text from social media and other sources usually contain figurative use of language. For example, `Try asking for extra juice at breakfast - its 22 euros!!!!!' is more of a sarcasm than a suggestion. Therefore, a sentence in the form of suggestions may not always be a suggestion, and vice versa.
- **Context dependency:** At times, context plays a major role in determining whether a sentence is a suggestion or not. For example, `There is a parking garage on the corner of the Forbes showroom.' can be perceived as a suggestion (for parking space) when it appears in a restaurant review and the human

annotator gets to read the full review, while the same sentence would not be labeled as a suggestion if it is present in the description of the locality of a Forbes showroom.

- **Long and complex sentences:** Often, a suggestion is only expressed in one part of a long sentence, or appears as a very long sentence, like, `I think that there should be a nice feature where you can be able to slide the status bar down and view all the push notifications that you got but you didn't view, just like android and IOS, but the best part is that it fixes many problems like when people wanted a short cut to turn WiFi on and off and data on and off so that would be a nice feature to have 2'. This poses challenges to the training algorithms for learning effective features, as well as for certain pre-processing steps like part of speech tagging [15].

V. DEEP LEARNING

Deep learning is the idea of the human brain that has many kinds of depiction, which have simplistic characteristics at the lower levels and abstractions at high levels. Humans hierarchically order their thoughts and principles. People will learn basic concepts first and write them to represent more complex concepts. The human mind is like a DNN, composed of several neuron layers serving as role detectors, which sense more abstract characteristics as their levels increase. This is simpler for the computers to generalize knowledge in a more complex manner. The key value of DL is its condensed representation of a broader variety of functions than low networks used by the more common form of learning.

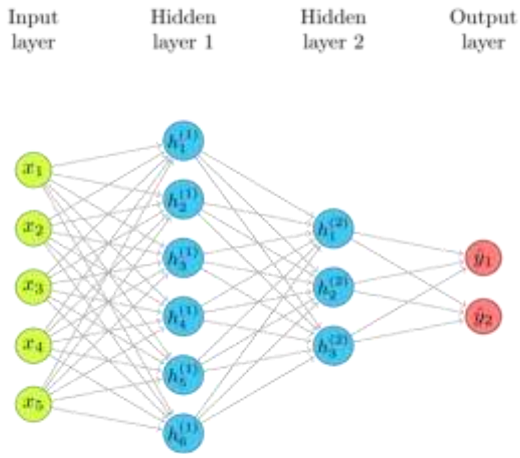

Fig. 2: Deep Learning

A. DEEP LEARNING TECHNIQUES

1. Deep Neural Networks

DL is a perceptron, which is a single neuron in a NN, the basic building block. If a set of m inputs is finished (e.g., m words or m-pixel), each input is increased by weight (that 1 to theta m), we sum up the weighted input mix, apply distortion and finish by a non-linear function of activation.

2. Convolutional Neural Networks

CNN's are very much the same as common NNs, they comprise of neurons with learning weights and preconditions. Every neuron receives such inputs, generates a dot product & follows it with non-linearity optionally. A single differential score function is now represented in the entire network, from raw pixels on one end to class scores on the other. The later (completely connected) stage still has a missing purpose and we still apply all the tips and tricks we have learned to learn standard NNs. CNN uses the fact that the feedback consists of pictures to more sensitively limit the architecture.

3. Recurrent Neural Networks

RNN is the basic algorithm for more popular and robust sequential data. Even Siri Apple uses profoundly slow RNN to process speech. RNN has a clear memory that recalls the memory input. This segment consists of the RNN principles and Process. RNN works, which are more common because of the super memory it remembers and forecasts future events. In time-series data, speech data, and other uses, RNN is commonly used. Their profound interpretability makes them more valuable. The names are made up of FFNN and RNN channel information.

4. An autoencoder

A feedforward neural network is historically An autoencoder to learn a compact or distributed data set representation. A 3-layer neural network is a self-encoder, that is learned to construct its inputs by with them as output. It has to learn features that capture data variation to duplicate it. If a linear activation function is only used to minimize dimensionality, it can be shown to be equal to PCA. The triggering of the secret layer is used as the trained features during training and the first layer can be disabled. Auto parts encoders are trained using noise, contraction & sparseness.

5. RBM

RBM is an undirected, visible layer and hidden layer, two-layer NN. Within-layer there are no links, but the links are concealed to clear. It is learned to optimize the expected data log opportunity. Binary vectors are the inputs since each input receives Bernoulli distributions. In the same way, as in a normal NN, the activation function is determined & the logistic function commonly used is from 0 to1. every neuron is activated if activation is higher than the random variable and is viewed as a chance. Seen units are used by the secret layer neurons. Seen neurons are the original input of binary input vectors or hidden layer probabilities. [16,17].

VI. LITERATURE REVIEW

Feng Liu (2020) In this paper, we propose a new deep learning based method for suggestion mining. The major challenges of suggesion mining include cross domain issue and the issues caused by unstructured and highly imbalanced data structure. To overcome these challenges, we propose to apply Random Multimodel Deep Learning (RMDL) which combines three different deep learning architectures (DNNs, RNNs and CNNs) and automatically selects the optimal hyper parameter to improve the robustness and flexibility of the model. Our experimental results on the SemEval-2019 competition Task 9 data sets demonstrate that our proposed RMDL outperforms most of the existing suggestion mining methods [18].

Du, Y., & Yang, L. (2019) In order to analyze the polarity and intensity of the fine-grained emotion based on online reviews of complex products, and to verify the difference between the rating and the sentiment of reviews, a sentiment measurement model based on a domain ontology, named DO-SSM(Sentiment Score Measurement model based on the Domain Ontology, DO-SSM) is proposed. Firstly, build a fine-grained domain ontology based on features of the complex product, then leverage the fine-grained emotional intensity quantification method to obtain the emotional intensity taxonomy of online reviews. Empirical study indicates that the resulting emotional intensity taxonomy of the complex product online reviews of the model can achieve high accuracy and interpretability. The proposed model can provide decision support for users and enterprises, offering corrective information for online review sites [19].

Zhao, Z., et al. [2019] This paper proposes an SFNN (a sales factor model using a neural network), which uses a back-propagation multilayer perceptron neural network and weight matrix operation, to study the mechanism of the influencing factors of online product sales in the e-commerce platform. To achieve this objective, this study analyzes the factors and relative strength of online product sales based on four aspects: online reviews, review system curation, online promotional marketing, and seller guarantees. The empirical analysis of the SFNN model based on the data of Taobao.com shows whether the 14 factors, in relation to the four aspects, have any impact on product sales. In addition, the findings indicate that the number of sentiment words greatly affects product sales. Other factors affecting online product sales significantly include the review volume, the number of uploaded pictures, the negative review rate, the discount rate, 7+day returns and money-back guarantees, and the freight insurance. This study examines the interactions among the various factors affecting product sales on the e-commerce platform and provides management inspiration for e-commerce enterprises to manipulate online reviews, undertake effective promotion and fulfill after-sales promises [20].

Zhu, S., Ge, J., & Yue, D. (2018). Whether and how online reviews of one commodity's homogeneous goods affect the sales of itself. By using multiple linear regression model, We find the number of reviews, the score of products, the percentage of positive or negative reviews, the number of words of reviews, and the level of the commentators do have impacts on the sales of product. We also find the online review valence and volume of itself have a positive impact on the sales of its own products, but the online review valence and volume of their market substitute products have a negative impact on the sales of its own product [21].

Gobinath, J., & Gupta, D. (2016). The technology scape has undergone tremendous changes in the last couple of decades. With increased changes in technology a lot of changes have occurred in the way consumers behave. One major change area is in the way consumers gather information about the products to make purchase decisions. Online reviews have become the major source of information and have taken over many traditional sources that existed earlier. The quality of information obtained from any source plays a major role in the consumer decision making. In this study the factors that influence the consumer perception of information quality of online reviews are identified. For this purpose a conceptual model was developed by reviewing literature in the following areas, online reviews, electronic word of mouth, and information quality. The model was tested using a pan India survey. The sample size included 155 online consumer review readers in their product purchase to identify the impact of various factors on perceived quality of information. The data was analyzed using ordered logistic regression. This study identified that factors such as Perceived Informativeness, Perceived Persuasiveness, Source Credibility, and Attitude towards Online Reviews have significant positive impact on the consumer's perception of quality of information obtained from online reviews [22].

Pitchayaviwat, T. (2016). This study was collected text that contains customer suggestion on insurance services from various online social media and extract some specific word via Thai text segmentation and coverts text to Vector Space Model (VSM) based on TF-IDF. We performs experiment by used 800 records of textcrawler and implement two clustering models algorithm which include K-Means and Self-Organization Map (SOM) for clustering suggestion text into three cluster groups as follow Cluster_0 is about to customer feedback on Car Insurance Policy, Car Insurance Premium or Insurance Renewal, Cluster_1 is contains customer feedback on insurance claim services, Cluster_2 is about customer enquired general information. We use “Davies-Bouldin index” method[3] for evaluating both clustering algorithms. A result of experiment shows that K-Means has a significant performance higher than SOM. Finally, The benefit of this study able to help insurance company improve their products and services and increase customer satisfaction and retention strategies planning [23].

S. J. et al. (2014) Online consumer reviews have shown as an important source of information that affects individuals' purchase decision making. To understand the influence of massive online reviews in online communities, this study extends prior research on information adoption by incorporating the perspective of herd behavior. We develop and empirically test a research model using data collected in an existing book review site. Our results illustrate two major aspects of findings. First, informational factors, including argument quality and source credibility, predict the adoption of online reviews. Second, we find strong empirical support for the impacts of herd factors, that is, discounting own information and imitating others posit significant influences on the adoption of online reviews. Our findings suggest that herd behavior plays an important role in consumers' information adoption in online review communities. Discussions on both theoretical and practical implications are provided [24].

Santosh, D. T., & Babu, K. S. (2014) Online reviews have a telling and profound impact on the customer or newbie who want to purchase or consume the product via e-commerce. The deluge of the reviews which are regularly fed into the site can't be read by the customers completely to make decisions. To make this simple, many summarization systems have come to provide a constructive view of the reviews. Customer does this by building trust on the reviews on the basis of 4 major points: (1) Electronic Word-of-Mouth [1] by close friends, family members, neighbors (2) Standard Expert reviews on that particular product (3) Customer who comments on the reviews on a regular basis in a transparent manner and (4) A good number of positive reviews. This paper talks about these points in web 3.0 perspective which can lay the foundation for automated knowledge gain through Linked Data [2] through a generic search interface [25].

VII. CONCLUSION

Now a day’s online reviews has become an increasingly trendy approach for public to share their sentiments and opinions towards the product bought and services received. Online reviews have become the major source of information and have taken over many traditional sources that existed earlier. The quality of information obtained from any source plays a major role in the consumer decision making. Suggestion mining can be defined as the extraction of suggestions from unstructured text, where the term 'suggestions' refers to the expressions of tips, advice, recommendations etc. Deep learning is the idea of the human brain that has many kinds of depiction, which have simplistic characteristics at the lower levels and abstractions at high levels. Also, DL methods were considered ideal for big data analysis with active computer vision, pattern recognition, speech recognition, NLP, or recommendation systems implementations. An updated survey of four DL techniques is available. The DPP is a big step into the information exploration process which involves an autoencoder, CNN, a DNN, and a restricted Boltzmann machine. Finally, conclude that this survey will very helpful for further research.

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