Analysis of Customer Reviews using Deep Neural Network

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***Abstract*— Customer Review Analysis has become a most important application of Businesses. This will enable the business to analyze the text data and know the sentiment of the customers on their business entities in the market. It requires a thorough computational study of the behavior of discrete entities with respect to customers purchasing affinity and extracting the customer's point of view about the business entity. The business performance is always measured with customers satisfaction. In this era of e- commerce and social networking, the launching of a new product has to undergo with deep study of customers views on existing products and their requirements in the product. Since a huge amount of reviews are being generated from various source, thereby it is becoming exceedingly difficult to make sense of the data. This project considers the problem of analyzing reviews by their overall semantic that is, positive, negative and neutral behavior. In this work a Webapp is developed that classifies the review to any of the 3 cases. The work here is analyzing and classifying the Product Reviews using Deep Learning.**

Keywords—Sentiment Analysis, Deep Learning, Convolutional Neural Network.

I. Introduction

The fast development of social media is causing explosive growth of digital content. Identifying sentiments in digital content have increased a lot of consideration overs the recent years. Accordingly, Sentiment Analysis has become one of the fundamental methods in predicting the tone of the sentence. This technique is proposed to distinguish people groups, conclusions that comprise of abstract articulations over an assortment of items or political choices. As of late, in India, people usually converse in social media. Business institutions need to process and study these sentiments to investigate data and to gain business insights. AI procedures such as Deep Learning techniques can exhibit promising performance, using Natural Language Processing (NLP), therefore, there is a lot of space to progress to higher-precision systems. To gain simple solutions using numerous algorithms in a progressive fashion in this work we are using deep learning techniques. It supports multilayered approach and shows better performance and accuracy[2]. Harnessing the power of deep learning, models can be trained to understand the underlying feeling or mood of the customer from a text review to determine the sentiment (positive, neutral and negative) of the customers[9].

II. Literature Review

Sentiment polarity or categorization is the primary issue in sentiment analysis. For a given review, the difficulty is to designate the review into one particular sentiment polarity that is, positive or negative or neutral. Depending on the scope of review, there are 3 measures of sentiment polarity differentiation viz the level of documentation, the level of the sentence, and the entity and aspect level[1-4]. Examination of a document, as a whole, which expresses negative or positive or neutral sentiment is the concern of document level, but the sentence level transacts with each sentence's sentiment codification. The main concern of the entity level is to figure out what the people are into or not precisely from their opinions. Sentiment classification is a grading problem, where features that involve perceptions should be recognized or identified before the classification[21]. The main concern of the entity level is to figure out what the people are into or not precisely from their opinions. Sentiment classification is a grading problem, where features that involve perceptions should be recognized or identified before the classification. The field of Sentiment analysis is widely used in Recommender systems[21-23]. Hence lot of research in this work is going on. In [22] an approach to identify Music Sentiment in Human using KNN, Apriori methods were explored for evaluation. Robotically classifying the themes based on Naïve Bayes, ML Models and HMM classifiers are applied on tweet data in [10]. Deep learning(DL) is a sub-category of Machine learning(ML) and is primarily based on studying data representations, in preference to task-specific algorithms. DL is gaining popularity due to availability of high speed machines at low cost and well proposed research solutions in the field of AI for over a decade, that has brought together both hardware and software to demonstrate powerful computational solutions for complex problems. The applications developed using DL from automated waiters to advanced Emotional speech Recognition, allows almost everything to be modeled. DL is affecting almost all Industries associated w-ith ML and AI. Learning can appear in a supervised, semi-supervised or unsupervised format[11-17]. Deep Learning : The "Deep" indicates the multiple hidden layers that exits in Artificial Neural Networks (ANN) modeling, in few solutions we notice more than 100 hidden layers in an ANN model. There are various ANNs models proposed in AI Research. DL is continuously evolving in terms of robust learning models with higher accuracy. It is an interconnection of artificial neurons, each neuron represents a node in ANN Layer. A neuron in the current layer, receives input from previous layer that constitutes output of neuron in previous layer with weight of the edge from the neuron in the previous layer to the neuron in current layer and processes the input using Activation function, the resultant output is sent to next layer. In the final layer if the expected outcome accuracy is poor then it readjusts the weights of neurons and repeat the process. In a DL model the input layer is the leftmost layer of neurons and vice versa, the rightmost layer is called the output layer. All the layers between input layer and output layer are known as hidden layers.

A. Convolutional Neural Network.

It is a Deep Learning method for classification that relies on feed-forward architecture. Convolutional Neural Network(CNN) consists of three layers namely: input layer, hidden layers, and an output layer The middle layers are known as Hidden layers. Before the final convolution the activation module covers the inputs and outputs. A CNN typically consists of a multiplication or other dot product layer with a ReLU (rectified linear activation unit) as its activation function. After this layer there are many other layers such as pooling layers and fully connected layer. CNN has its foundations in image classification, object location, PC vision frameworks.

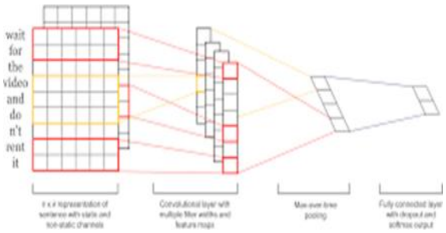

Fig. 1. CNN

B. Recurrent Neural Network

It is a Deep Learning method, that constitutes “memory”. It takes previous inputs as parameters to the next layer to determine the output. The output of the Recurrent Neural Network(RNN) depends on the sequence of inputs considered so far. The input is recurring therefore it is called recurrence neural network. In text classification such a model is needful to process a sentence. RNNs are most widely used in NLP data classification, sequential data processing, SpeechRecognition.

The input x_0 is processed to produce output h_0, the h_0 and x_1 input is processed to derive h_1 output and so on input x_t, h_{t-1} outputs h_t.

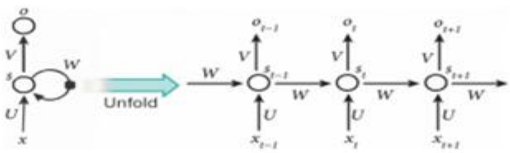

Fig. 2. RNN Framework

III. Problem Statement

Recent research for an effortless business approach requires customers opinion because it is the only gateway for the business entities to ensure a better relationship between the business and the customer. This is the very dynamic problem because customer reviews are subject to changes time to time because the customer is influenced by price, product delivery, quality, quantity etc. Recent studies show that for a rich customer experience the businesses need to ensure an effortless customer service by ensuring that each product review is taken seriously into account and then actions are taken to ensure the drawbacks addressed by the customer are responded correspondingly by enhancing the product service and quality. This study is aiming at developing an intelligent system based on deep learning classification algorithms for the prediction of the sentiment of the product reviews. This work considers the problem of analyzing reviews by their overall semantic that is, positive, negative and neutral. The Sentiment column corresponds to the label class taking three values, 1 if the review is positive, -1 if the review is negative and 0 if the review is neutral. This work aims to give the best results in analyzation and classification of the Products Reviews using Deep Learning Techniques.

IV. Methodology

Process of classification on Product Reviews is depicted in the diagram.

Fig. 3. Methodology Process

A. System Architecture

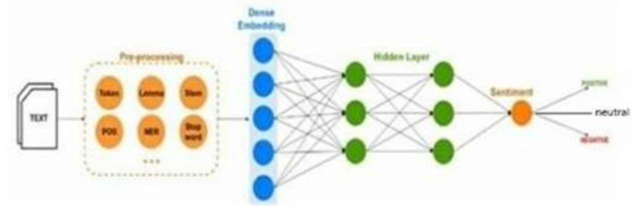

Fig. 4. System Architecture

B. Data Description

To evaluate the accuracy of our model, we have used Amazon reviews dataset of 2018 for sentiment analysis available in Kaggle. The dataset includes reviews (ratings, text, helpfulness votes), product metadata (descriptions, category information, price, brand, and image features), and links (also viewed/also bought graphs. The total number of reviews is 233.1 million. From such huge dataset we considered Electronics and Clothing, shoes and footwear data for this work. We have considered 1,98,503 reviews for analysis.

reviewerI	asin	reviewerN	helpful	reviewTex	overall	summary	unixReviev	reviewTim	Division N	Department Name
A1YJEY40\	7.81E+09	Andrea	[3,4]	Very oily a	1	Don't wast	1.39E+09	01 30, 201	Initmate	Electronic
A60XNB87	7.81E+09	Jessica H.	[1,1]	This palett	3	OK Palette	1.4E+09	04 18, 201	General	Shoes
A3G6XNM	7.81E+09	Karen	[0,1]	The textur	4	great quali	1.38E+09	09 6, 2013	General	Dresses
A1PQFP6S	7.81E+09	Norah	[2,2]	I really car	2	Do not wo	1.39E+09	12 8, 2013	General Pe	Bottoms
A38FVHZT	7.81E+09	Nova Amo	[0,0]	It was a lit	3	It's okay.	1.38E+09	10 19, 201	General	Tops
A38TN14	7.81E+09	S. M. Ranc	[1,2]	I was very	5	Very nice	1.37E+09	04 15, 201	General	Dresses
A1Z59RFKI	7.81E+09	tasha "luv	[1,3]	PLEASE DC	1	smh!!!	1.38E+09	08 16, 201	General Pe	Tops
AWUO9P6	7.81E+09	TreMagnif	[0,1]	Chalky,No	2	Chalky, Nc	1.38E+09	09 4, 2013	General Pe	Tops
A3LMILRN	9.76E+09		[0,0]	Did nothin	2	no Lighten	1.41E+09	07 13, 201	General	Dresses
A30IP88Q	9.76E+09	Amina Bint	[0,0]	I bought th	3	Its alright	1.39E+09	12 27, 201	General	Dresses
APBQH4B	9.76E+09	Charmmy	[0,0]	I have mix	3	Mixed feel	1.4E+09	05 20, 201	General	Dresses
A3FE8WBL	9.76E+09	Culture C	[0,0]	Did nothin	1	Nothing	1.39E+09	02 18, 201	General Pe	Dresses
A1EVGDO	9.76E+09	Jessica "Ar	[0,1]	I bought th	5	This works	1.39E+09	01 23, 201	General Pe	Dresses
APSWTCM	9.76E+09	Layla B	[0,0]	This gell di	1	Does noth	1.39E+09	01 11, 201	Initmates	Intimate
A21IM16P	9.76E+09	mdub9922	[0,1]	i got this t	5	it works	1.39E+09	02 18, 201	General	Dresses
A1TLDR1V	9.76E+09	Mickey O I	[0,0]	I used it fo	2	burns	1.4E+09	04 6, 2014	General	Bottoms
A6F8KHDJ	9.76E+09	SanBen	[2,4]	I order thi	5	Did work f	1.38E+09	09 14, 201	General	Bottoms
AXPKZA7U	9.76E+09	Shirleyyy	[2,4]	Good proc	4	excellent	1.38E+09	10 18, 201	General	Tops
A2SIAYDK	9.76E+09	theredtran	[0,1]	I didn't use	3	weird sme	1.38E+09	11 1, 2013	General	Jackets
A1QVSIH6	9.79E+09	armygirl	[24,24]	I haven't b	5	Love the s	1.32E+09	09 19, 201	General	Dresses
A3UQXHI8	9.79E+09	D. Greene	[0,0]	We gave tl	5	Happy	1.38E+09	08 10, 201	General	Tops
A2EK2CJN	9.79E+09	Nikki	[1,1]	This is the	5	Very good	1.32E+09	11 28, 201	General	Dresses
A2GWNGC	9.79E+09	Pholuke "L	[2,4]	So I got thi	5	Lurrrrrrv.	1.34E+09	05 27, 201	General	Dresses
ABV67T13	9.79E+09	Sandra	[0,0]	This produ	5	Great Scer	1.36E+09	02 2, 2013	General	Dresses
A2FQZKL2	9.79E+09	Ellie B.	[1,1]	I'm very pi	5	Spring Gan	1.39E+09	03 11, 201	General	Tops

Fig. 5. Dataset

C. *Feature Extraction*

It is an important Phase, in data science process. It is important to convert the text data into a feature vector so as to process text in an efficient manner. Dropped the records with null value columns. Then preprocessing is applied on text reviews, at first removed special characters, punctuations, numbers, spaces from the review text. Performed text tokenization of the review text, removed stop words, identified ∑ *Positive*, ∑ Negative and ∑ Neutral tokens in the text. The inherent polarity of words in the text is shown in below fig 6.

Clearly the dataset is imbalance, and considering this dataset may lead to biased classification, hence to deal with imbalanced dataset, we performed random over-sampling and tried to collect 8000 records per polarity category. This studyconsidered 24000 sample data.

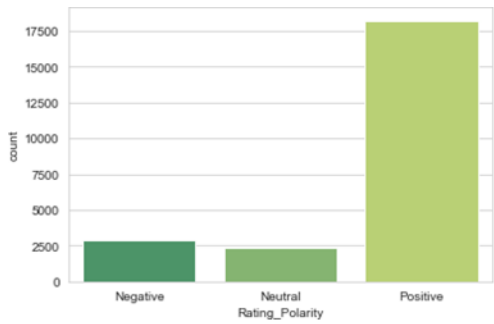

Fig. 6. Imbalanced Data Visualization

D. *Model Building*

CNNs can observe multiple words at a time and can realize the different arrangements. Different arrangements of words may have different contexts. A word may lose its meaning when separated from its context. Consequently, convolutional layers can be used for retaining context using n-grams. CNN has a filter to scan across the width and height of the data. Typical 1D convolution layer of filter size of 2- gram will process the inputs with a window shape of 32X2.

The preprocessed data after tokenization is a sparse collection of feature vector[20]. To form dense features for the purpose of neural networks classification, the word embedding is performed to determine the contextual words. A word vocabulary is determined using top frequently occurring 5000 words[20]. Word embedding is applied to determine the real valued vector for each word in the vocabulary by which contextual information is retained in the dataset. For CNN Modeling input is a series of words encoded with one hot encoding, activation function ReLu(rectified linear activation unit), Max-Pooling and dropout of 0.5, then Dense Layer is built with ReLu activation and dropout of 0.5, then another dense layer with sigmoid activation and Adam optimizer are applied to train the model.

Next we built an RNN model of Dense Layer with ReLu(rectified linear activation unit) activation and dropout at 0.5 of 2 more layers, then a dense layer with softmax activation with Adam optimizer are applied to compile the model.

V. Result

A. *Convolutional Neural Network*

1) *Model Fit :*

```
1 history = model.fit(X_train, y_train, batch_size=128, epochs=6, verbose=1, v
2
3 score = model.evaluate(X_test, y_test, verbose=1)
Epoch 1/6
114/114 [==============================] - 4s 39ms/step - loss: 0.6658 - acc:
1.0000 - val_loss: 0.6383 - val_acc: 1.0000
Epoch 2/6
114/114 [==============================] - 4s 38ms/step - loss: 0.6132 - acc:
1.0000 - val_loss: 0.5881 - val_acc: 1.0000
Epoch 3/6
114/114 [==============================] - 6s 54ms/step - loss: 0.5651 - acc:
1.0000 - val_loss: 0.5421 - val_acc: 1.0000
Epoch 4/6
114/114 [==============================] - 7s 61ms/step - loss: 0.5211 - acc:
1.0000 - val_loss: 0.5001 - val_acc: 1.0000
Epoch 5/6
114/114 [==============================] - 6s 52ms/step - loss: 0.4810 - acc:
1.0000 - val_loss: 0.4618 - val_acc: 1.0000
Epoch 6/6
114/114 [==============================] - 6s 54ms/step - loss: 0.4443 - acc:
1.0000 - val_loss: 0.4268 - val_acc: 1.0000
142/142 [==============================] - 1s 6ms/step - loss: 0.4268 - acc: 1.
0000
```

Fig. 7. CNN model Fit

B. *Recurrent Neural Network*

1) *Model Fit:*

```
1 model.fit(x=X_train, y=y_train, batch_size=256, epochs=100, validation_data=
Epoch 1/100
66/66 [==============================] - 919s 14s/step - loss: 0.6137 - accurac
y: 0.7361 - val_loss: 0.2783 - val_accuracy: 0.9026
Epoch 2/100
66/66 [==============================] - 1169s 18s/step - loss: 0.0795 - accura
cy: 0.9743 - val_loss: 0.2357 - val_accuracy: 0.9229
Epoch 3/100
66/66 [==============================] - 2901s 44s/step - loss: 0.0090 - accura
cy: 0.9980 - val_loss: 0.2816 - val_accuracy: 0.9356
Epoch 4/100
66/66 [==============================] - 2168s 33s/step - loss: 0.0026 - accura
cy: 0.9995 - val_loss: 0.3280 - val_accuracy: 0.9331
Epoch 00004: early stopping
```

Fig. 8. RNN model Fit

2) *Accuracy:*

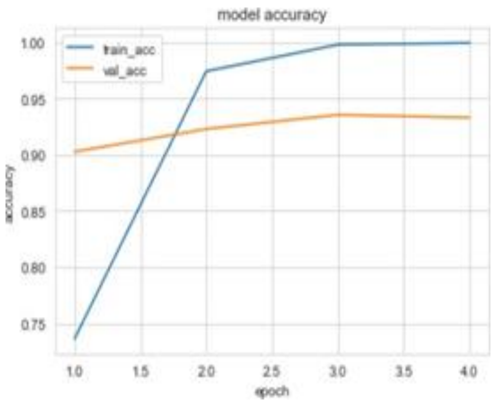

Fig. 9. RNN Accuracy

3) Evaluation models:

	precision	recall	f1-score
0	0.96	0.94	0.95
1	0.92	0.95	0.93
2	0.92	0.91	0.92

Fig. 10. Evaluation models performance

C. Comparison Study

In the comparison study of these two models, CNN model exhibited 85% Precision and RNN model exhibited 93% Precision of sentiment classifications. In literature CNN can be applied on text classification for sentiment analysis when the context information is not necessary. But it is observed that RNN improves classification accuracy and outperforms CNN model in product review analysis.

Table 1. Model Comparison

Model	Accuracy
RNN	85%
CNN	93%

CONCULUSION AND FUTURE SCOPE

In this work a sentiment analysis model using deep learning algorithms were developed. By using our model, you can gauge how customers feel about different areas of the business without having to read thousands of reviews at once and you can easily drill deep into customer groups of the business and better understand the product sentiment. In literature CNN can be applied on text classification for sentiment analysis where the context information is not necessary. But it is observed that RNN outperforms CNN model in sentiment analysis. Sentiment Analysis is a social analytic tool with a wide scope of research, still robust models are yet to develop. The future of sentiment analysis is going to continue to increase significantly in the coming decades, from mere likes, rating to automatically know the customer likes from his buying patterns and expect the features, a customer would prefer in a new product. Researchers and Businesses are interested in understanding the thoughts of people and how they respond to everything happening around them.

AI based product promotions are evolving using the sentiment analysis applications. Hence in our future work we want to explore this study to consider multi-model inputs and study the behavior of customer and their product ratings. We work with Big data technologies such as Spark and Hadoop to deal with huge product review data and come up with a much efficient model.

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