A LSTM based Tool for Consumer Complaint Classification

Thomas N T
thomasnt13@gmail.com
Tata Consultancy Services

***Abstract*— The work focuses on the issues in handling consumer complaints and queries in online platforms. In this digital era, the majority of complaints are posted in blogs, forums and social networking pages of companies. Users may not use official company websites or platforms to submit complaints. Thousands of queries and complaints are posted in digital platforms on a daily basis regarding different issues. It's a tedious process for a human to go through a database of such queries and manually tag each and every query to it's correct class or category. The consumer service representative who is handling that department can start working on the issue only after the tagging process. The manual intervention in this scenario is very high. A Long Short Term Memory (LSTM) based tool is proposed to automatically tag consumer queries to its corresponding class. Also, it identifies outliers or queries which are not related to the company issues or matters. The minimal manual intervention will reduce the response time. The model showed considerable accuracy when evaluated with validation data.**

Keywords— Artificial Intelligence; Deep Learning; Feed Forward Network; Recurrent Neural Network; Long Short Term Memory ;

I. INTRODUCTION

Machine learning algorithms need pre-defined features to work. It is a very difficult task to identify salient features from data. Domain data knowledge is very essential for applied machine learning. The process of transforming data into features is called feature engineering. The process of feature engineering is a time-consuming method. In deep learning, the neural network will learn the features automatically from raw data.

Feed Forward Network (FNN) is a type of Artificial Neural Network (ANN) where the information goes in forward direction only. The simple FNN has no hidden layers. In case of FNN with one perceptron, the computed output will be the sum of the product of their weights. When we step back and look at the data, we will understand the pattern of that data. By storing these patterns, we can predict the next sequence by just seeing the previous sequence.

Recurrent Neural Network (RNN) stores information in the memory over time. The vanishing gradient problem in RNN makes it difficult to store long term dependencies. The network is trained using backpropagation algorithm. It uses chain rule that gives derivatives or partial derivatives of a function.

RNN requires complex architecture than non recurrent networks. The chain rule requires lots of computation. The output of RNN is not only used for computing recurrent value but also for computing next value for time periods. In deep neural networks, there are lot of hidden layers. The fundamental flaw of recurrent neural network is the number of multiplications required to compute the updated weights. The computed coefficients or weights in the past hidden layers are small numbers. So it is hard for RNN to learn from the past. Consider this sample sequence A saw B, B saw C, C saw D. In this example, we need to predict the next sequence after 'A'. 'A' will strongly vote for 'saw' and 'B' will vote for comma. The word 'saw' has equal chances of predicting B,C or D. So there are chances to make wrong prediction. To predict correctly, we need to see what happened in the previous steps.

LSTM is a type of RNN with a set of gates to control the flow of information. The gates will select and forget information when it enters the memory. The on/off gates will decide what to release as prediction and what to keep internal.

The dataset used for this work is US Consumer Finance Complaints. It is about issues people experienced in marketplace. The 'issue' and 'sub_issue' columns in the data shows the problems faced by consumers. The product column shows products like mortgages, student loans, payday loans, debt collection, credit reports, and other financial products and services. Each record or sequence is a combination of 'issue' and 'sub_issue' column. The product column corresponding to each record is taken as class label.

II. RELATED WORK

Oguzhan Gencoglu [1] proposed a method to categorize the messages from Finland's largest online health forum. It is to reduce the manual effort in managing messages in the forum. He used a Naïve Bayes classifier to classify messages into 16 categories.

The Search result diversification enables the modern day search engines to construct a result list that consists of documents that are relevant to the user query and at the same time, diverse enough to meet the expectations of a diverse user population. However, all the queries received by a search engine may not benefit from diversification. Sumit bhatia, Cliff Brunk and Prasenjit Mitra [2] proposed an idea to analyze web search queries and classify those queries into one of the classes. They have achieved strong classification results for this classifier.

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Lorenxo A Rossi and Omprakash Gnawali [3] analyzed the discussion threads from coursera forums. They investigated several language independent features to classify the discussion threads based on the types of the interactions among the users. The features related to structure, popularity, temporal dynamics of threads are extracted.

Bernard J. Jansen and Danielle Booth [4] proposed a methodology to classify web queries automatically by topic and user intent. This technique can be used for real time query classification of web searches.

D. Irazú Hernández, Jansen Parth Gupta, Paolo Rosso and Martha Rochagy [5] proposed a method to automatically extract features from corpora and analyzed the distribution of features and used Naive Bayes and SVM to classify them.

Kristof Coussement and Dirk Van den Poel [6] introduced a technique to improve complaint-handling strategies through an automatic email-classification system that distinguishes complaints from non-complaints. This methodology reveals linguistic style differences between complaint emails and others.

III. Solution Approach

The workflow of the model is shown in figure 1. Dataset pre-processing is the primary step. Tokenization and stopword removal are the common pre-processing steps. Each record is converted into uni-gram tokens. Keras Tokenizer API is used for tokenization and other basic filtering of text. The most common words are removed from the raw text. Other unwanted symbols and numbers are also removed from the data using regex operations.

Also, there are queries which are not related to company products and services. These queries are considered as anomalies in this case. The anomalies are filtered before sending them to classifier. The classifier will give good results on filtered data. So an outer router is designed to handle outliers in data. The Outer router will check whether the input data is an outlier or not. The filtered query is then routed to the inner router. The LSTM network configured in the inner will tag the queries to its correct class.

Outer Router: An unsupervised mechanism is used to detect the anomalies in data. The outer router is shown in figure 2. The 'issue' and 'sub_issue' columns in the data are considered as good data. The good data is trained with One-class SVM.

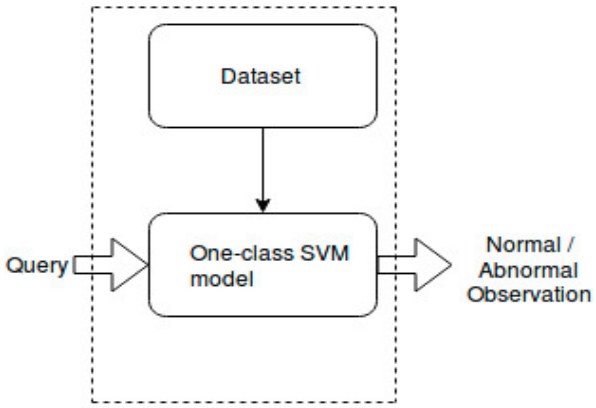

Fig.2. Outer Router

The features are inferred from the data and classifier is able to predict outliers in test data. The outer router will identify unlike queries in test data.

Inner Router: The filtered queries routed from the outer router is then send to the inner router for further classification. The LSTM sequence classification is used here. The queries may have similarity with other queries. Similar queries dealing with different issues can cause misclassification.

The long distance dependency and memory units of LSTM will solve this issue while dealing with similar queries. The inner router is shown in figure 3. The approach of sequence inner router is explained below.

Sequence processing: The first step is to transform each records to sequences. A vocabulary is created based on tokens. Each word in the dictionary is represented with a unique number. The next step is to pad the sequence length to the defined size. If the sequence length is smaller than the defined size, zeros will be added to pad the sequence. We can discard it if the size is higher than maximum sequence length.

Label Encoding: The algorithm will not be able to read class labels. The class labels are transformed into an array of numbers.

Word Embedding: The process of representing words in a continuous vector space based on position of words. This representation gives semantic similarity between words. The representation of words are given as an input to the embedding layer.

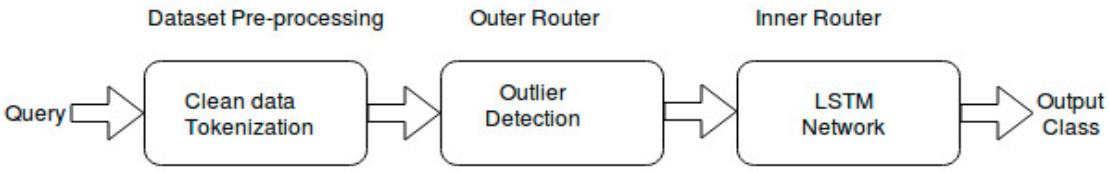

Fig.1. Tool Workflow

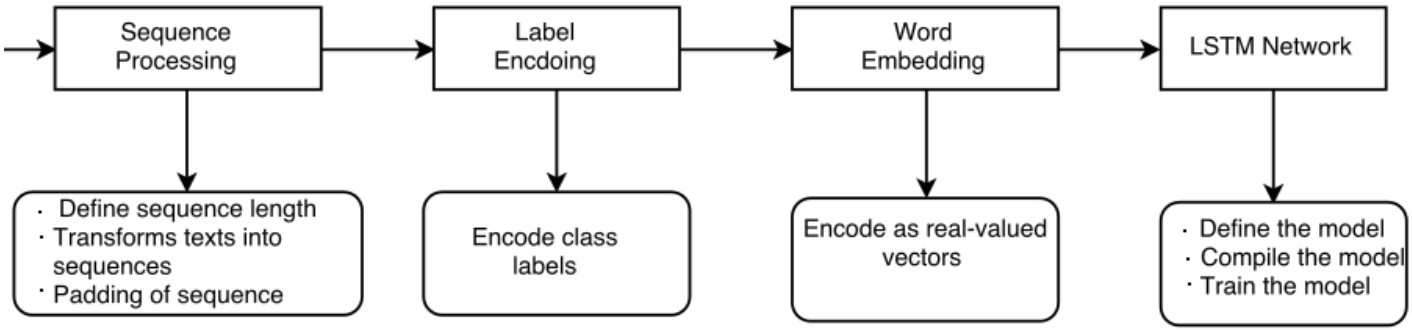

Fig.3. Inner Router

LSTM Network: The model is defined by giving the number of memory neurons, activation function etc. I have used softmax as the activation function. The total dimension represents the features. These features are converted into memory units. It is a fully connected network. LSTM network learns what to select and forget from the features. The model is then complied by defining the optimization algorithm and loss function. Adam optimizer algorithm is used in the network. It is then fitted to the model. The model is evaluated with the validation data. The dropout layers will assign zeros to a percentage of data for each epoch. The loss functions are used by the optimization algorithm in every epoch to update the weights in every epoch.

IV. RESULTS

The number of total records is 555957. A sample of 500 instances is taken from each class and a test set is generated. The evaluation score was 64 when tested with validation data by the inner router. Also, the model accuracy is manually tested using 4 different sets of unseen data. The outer router showed 90.67 an accuracy of 90.67 and inner router with a percentage accuracy of 62.825.

V. CONCLUSION

In this work, the main focus is automatic classification of complaints and queries in internet forums or sites. Overfitting is the main problem in LSTM topology and the network will not be able to predict for unseen data. The dataset may have thousands of parameters or dimensions. In this case, the parameters will try to adjust with the noise in the data. The training accuracy will go high and out of sample data gives low accuracy. Adding drop out layers reduced the overfitting in LSTM networks The future plan is to optimize the model and maximize the accuracy by tuning parameters. The hyper parameter tuning includes tuning of batch size, epochs, learning rate, activation functions, dropout layers, number of neurons etc. Also, model needs to be evaluated with different parameters using grid search process. Many predictive modeling problems can be solved using sequence models.

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