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Comparing LSTM and GRU for Multiclass Sentiment Analysis of Movie Reviews.

Pawan Kumar Sarika

Faculty of Computing, Blekinge Institute of Technology, 371 79 Karlskrona, Sweden

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The authors declare that they are the sole authors of this thesis and that they have not used any sources other than those listed in the bibliography and identified as references. They further declare that they have not submitted this thesis at any other institution to obtain a degree.

Contact Information:
Author(s):
Pawan Kumar Sarika
E-mail: pasr19@student.bth.se

University advisor:
Dr. Prashant Goswami
Department of Computer Science

Faculty of Computing
Blekinge Institute of Technology
SE–371 79 Karlskrona, Sweden

Internet : www.bth.se
Phone : +46 455 38 50 00
Fax : +46 455 38 50 57

Abstract

Today, we are living in a data-driven world. Due to a surge in data generation, there is a need for efficient and accurate techniques to analyze data. One such kind of data which is needed to be analyzed are text reviews given for movies. Rather than classifying the reviews as positive or negative, we will classify the sentiment of the reviews on the scale of one to ten. In doing so, we will compare two recurrent neural network algorithms Long short term memory(LSTM) and Gated recurrent unit(GRU).

The main objective of this study is to compare the accuracies of LSTM and GRU models. For training models, we collected data from two different sources. For filtering data, we used porter stemming and stop words. We coupled LSTM and GRU with the convolutional neural networks to increase the performance.

After conducting experiments, we have observed that LSTM performed better in predicting border values. Whereas, GRU predicted every class equally. Overall GRU was able to predict multiclass text data of movie reviews slightly better than LSTM. GRU was computationally expansive when compared to LSTM.

Keywords: Gated recurrent unit, Multiclass classification, Movie reviews, Sentiment Analysis, Recurrent neural network,

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Pawan Kumar Sarika

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Chapter 1

Introduction

Being in the digital world, we as humans constantly generate data knowingly or unknowingly. Every time we use the internet it is most likely our activities generate data in one way or another. Simple tasks like searching a keyword using a search engine and opening relevant website generate data for the search engines. At first glance, this data may seem useless but when we combine data of preferred website by thousands of users for a single keyword, we can find the most popular or most relevant website for that keyword which helps search engines to show relevant results. This encourages every internet-based entity to collect data.

We are getting increasingly dependent on the internet. If we want to know the meaning of a word, get to a location, send money or to search for a movie, we use the internet. Because of this, there is a surge in data generation. To administer this data there is a need for efficient and reliable data warehousing.

When a movie is released in theatres, television or online streaming sites (Amazon Prime, Netflix, Hulu, etc.), some people who have watched the movie express their views in the form of text (reviews). These reviews generally posted on websites such as IMDB(internet movie database), rotten tomatoes. It is a common scenario when a person wants to watch a movie they read reviews so they can have an insight into the movie. But we cannot tell if the movie is good or bad by simply reading two or three reviews. Following are the two contrasting reviews for the Oscar-winning movie 'Parasite' from IMDB website

Rating: 10/10
Review 1: *"The most original film of 2019 and it is wickedly funny and darkly disturbing all at the same time. The narrative and the actors were excellent. One of the better endings of a movie in quite a while. Class warfare at its best" [14].*

Rating: 1/10
Review 2: *"When I find myself constantly looking at my watch and asking when a film is going to deliver any of the promises that the Critics and Reviewers have seen fit to lavish on it then there's something awry. This isn't scathing socio-political cinema...it's not black comedy, in fact it's not remotely amusing or believable or even sympathetic to any of its characters. It's a simple hype job. The movie here is the real Parasite" [14].*

These contrast in reviews leads to a dilemma. Hence, we need to analyse a significant number of reviews. If we analyze enough number of reviews, we can classify the movie as good or bad. To be more precise we can classify the movie reviews on the scale of one to ten, one being worst and ten being excellent. To mine the opinion of the reviewer, there is a need for Sentiment analysis of text reviews. Sentiment analysis focuses on the analysis and understanding of the emotions from the text patterns. It identifies the opinion or attitude that a person has towards a topic or an object, and it seeks to identify the viewpoint underlying a text span [20].

1.1 Background

Sentiment analysis of text appears to be a simple task for humans but when we need to analyse thousands of text reviews at ones, sentiment analysis becomes a difficult and time-consuming task. This task can be automated using machine-learning techniques. Machine learning techniques are the computer algorithms that improve automatically through experience [2].

Using computer algorithms for sentiment analysis of text reviews can be a complex task. The reviewer generally write reviews in their natural language. These text reviews do not have a specific structure. When a human reads a sentence, he/she tends to understand the whole sentence rather than looking at the words. For instance, "The movie lacks good characters, simple plot, elegant theme, attention to details and satisfactory ending." a human reader could easily tell this is a negative review but for a computer this could be difficult to classify because when we look at the words there are five words that depict positive sentiment whereas there is only one word that depicts negative sentiment. Hence to classify the sentiments, in this research we use Neural networks one the subset of machine learning.

1.1.1 Neural Networks

Neural networks are a set of algorithms which are designed in such a way that they mimic a human brain. The execution of algorithms is similar to that of humans. They try random things, learn from previous experience, improve and make decisions accordingly.The ability of neural networks to learn can be key for sentiment analysis of text reviews. As we need to learn the dependency of words on one another.

The figure 1.1 represents a simple neural network structure. Neural network mainly constitutes of three layers, input layer, hidden layer and output layer. These three layers are built-up of neurons. Input layer is the data that is provided. hidden layer are the weights which are determined using special mathematical functions. Output layer is the final result of the input data.

Among the vast variety of neural networks. In this report, we concentrated on two variants of the recurrent neural network (LSTM and GRU).Recurrent Neural network (RNN) is a class of neural networks which remembers every information through time [22]. This is crucial as we need to understand the dependency of one word on another. During the time of training models on LSTM and GRU, we have observed that both the algorithms take 2-4 hours for each epoch. Due to the time constraints, we coupled LSTM and GRU with a convolutional neural network(CNN). This lead to a significant decrease in training time.

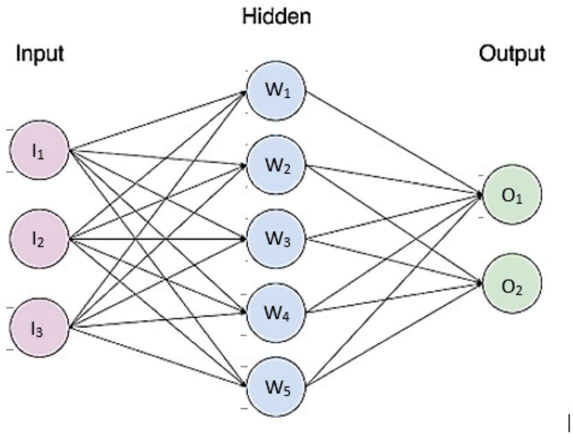


Figure 1.1: Simple Neural network Structure

In this research, we will conduct a study on two RNN algorithms, LSTM and it's variant GRU. We will try to classify text reviews of movies on the scale of one to ten using LSTM and GRU and determine how they compare for sentiment analysis.

The reason for selecting LSTM is because the study [25] states that "Experimental results show that the proposed method outperforms lexicon-based, regression-based, and NN-based methods for the text data resembling valence-arousal". In another study [18] which states "Each text is represented by a latent topic space instead of a word space, and the ability to process long-term sequences by CNN is improved by combining GRU, so as to achieve a highly accurate classifier". The reason for selecting GRU is because the mentioned study stated that it improved their results.

Long Short Term Memory

Hochreiter and Schmidhuber initially proposed the long short term memory (LSTM) in the year 1997 [13]. LSTM is a type of Recurrent Neural Network (RNN). RNN neurons have a connection to the previous neuron state in addition to the layer inputs. RNNs are particularly benefitial to data that is sequential or that can value a contextual view. therefore, RNNs can be impressive in text classification [26]. RNN remembers every information through time [22]. While working with gradient-based learning algorithms we face an increasingly difficult problem, The problem occurs when there is an increment in the duration of capturing the dependencies while generating a model [6]. We can address this problem using Long short-term memory (LSTM) [13].

LSTM consists of a memory cell to store information. It computes input gate, forget gate and output gate to manage this memory. LSTM units can propagate an important feature that came early in the input sequence over a long distance. Hence, capturing potential long-distance dependencies [7]. Following equations computes time-step t for each hidden state [3]:

Forget gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] \; + \; b_f)$$

Candidate layer:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] \ + \ b_i)$$

Input Gate:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_c)$$

Output Gate:

$$C_t = f_t \ * \ C_{t-1} \ + \ i_t \ * \ \tilde{C}_t$$

Hidden state:

$$o_t = \sigma(W_o \ [h_{t-1}, x_t] \ + \ b_o)$$

Memory state:

$$h_t = o_t \ * \ \tanh(C_t)$$

Where W and b denotes weight vector for forget gate(f), scandidate(C), input gate(i), output gate(o). $*$ denotes element wise multiplication and σ is the sigmoid function. The figure 1.2 demonstrate the internal structure of LSTM at time-step t.

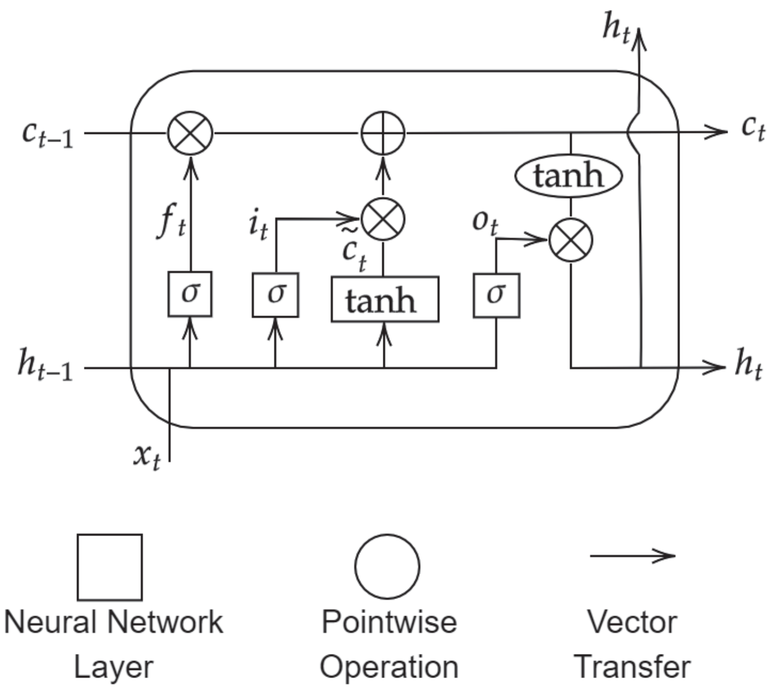


Figure 1.2: Internal structure of Long Short Term Memory [3]

Gated Recurrent Unit

Even though LSTM deals with the vanishing gradient problem, a generalised form of LSTM [4] is Gated Recurrent Unit (GRU) which was proposed in 2014 by Cho et al [11]. Similar to the LSTM unit, the GRU has gating units that modulate the flow of information inside the unit, however, without having a separate memory cells. Gated Recurrent Unit (GRU) calculates two gates called update and reset gates which control the flow of information through each hidden unit. Each hidden state at time-step t is computed using the following equations [7]:

Update gate:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

Reset gate:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

New memory:

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$

Final memory:

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Where W denotes weight vector, $*$ denotes element wise multiplication and σ is the sigmoid function. The figure 1.2 demonstrate the internal structure of LSTM at time-step t.

Convolutional Neural Network

Convolutional neural networks (CNNs), are a specialized kind of neural network for processing data that has a known grid-like topology, this was introduced by LeCun et. al. in 1998 [17]. The name "convolutional neural network" indicates that the network employs a mathematical operation called convolution. Convolution is a specialized kind of linear operation. Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers [12].

Even though CNNs were Originally invented for computer vision, the article by Yoon Kim has shown that a simple CNN with one layer of convolution performs remarkably well for convolutional neural networks built on top of word2vec [16]. In this research, convolutional neural network is adopted to increase the performance of LSTM and GRU. A study by Alec Yenter on CNN-LSTM has shown that performnce vastly improves upon the baseline CNN-LSTM model [27].

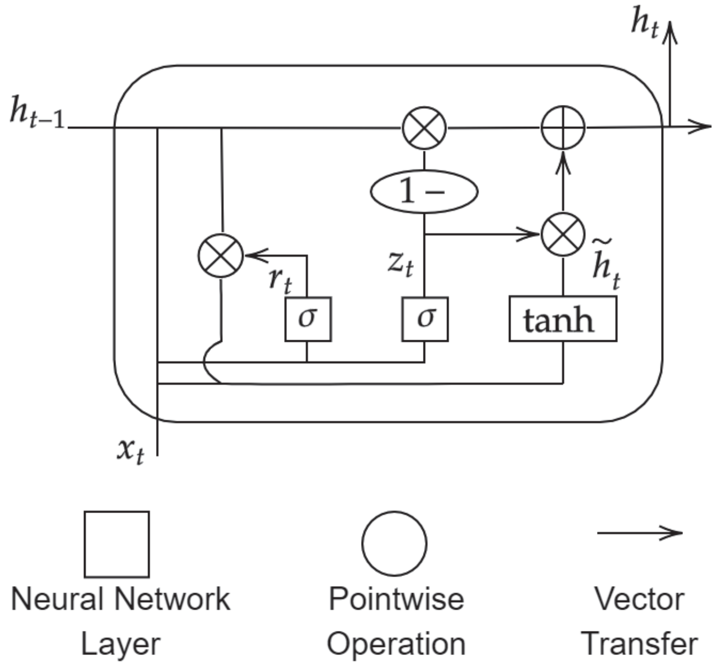


Figure 1.3: Internal structure of Gated Recurrent Unit[3]

1.2 Aim and scope

This research majorly focuses on the performance of LSTM and GRU in terms of accuracy for classifying text reviews given for movies on the scale of one to ten. We will try to answer the question:

- Which of the two, LSTM and GRU algorithms will have higher accuracy for multi-class classification of supervised textual data of movie reviews?

To answer this question, we set four main objectives. these objectives will eventually help us to achieve our aim to compare the accuracy of LSTM and GRU for text reviews. Following are the objectives:

1. Gathering data that can be used for training, validation and testing purposes.
2. Applying pre-processing to filter data.
3. Training and generating models using algorithms on supervised data of movie reviews that predicts the class of the review.
4. Analizing the final models using validation and testing data and then comparing the algorithms.

The sentiment analysis of movie reviews can be proven worthy for Blue-Ray retailers, TV channels and streaming services like Netflix, Amazon, HBO, etc. These entertainment services can use Sentiment analysis of the movie reviews to suggest movies of higher rating to their customers.

Chapter 2

Related Work

There are several pieces of research which when put together contribute to this study.

A paper 'Sentiment Analysis and Classification Based On Textual Reviews' by K.Mouthami proposed a new algorithm called Sentiment Fuzzy Classification algorithm is proposed to improve classification accuracy on the benchmark dataset of Movies reviews [20].

Even though the proposed method does not relate to our study, the problems addressed and the type of data set is similar. This paper helped us to determine several steps that are needed for sentiment classification approaches.

Architectures for text categorization and sentiment analysis[9] has shown the importance of pre-processing in neural networks. In this paper, researchers analyzed the impact of simple text pre-processing decisions on the performance of a standard word-based neural text classifier. There evaluations highlight the importance of being careful in the choice of how to pre-process our data and to be consistent when comparing different systems.

The study state that there is a high variance in the results depending on the pre-processing choice ($\pm 2.4\%$ on average for the best performing model)[9]. This study motivated us to investigate several pre-processing techniques which lead us to the next study.

V. Srividhya evaluated three important pre-processing techniques namely, stop word removal, stemming and TF/IDF on Reuters dataset[23]. This study has shown that pre-processing has a huge impact on performances of classification. From this study we have Incorporated two pre-processing techniques stop word removal and stemming.

The paper on sentiment analysis with gated recurrent units by Shamim Biswas is a major contributor to our research. In this paper, researchers did sentiment analysis at the paragraph level of movie reviews as positive or negative. Different approaches used by us are Tf-idf, Word2Vec (vector average), Word2Vec (k – means dictionary), GRU (gated recurrent units) and Ensemble model. and concluded that conclude that gated recurrent units are a suitable model for sentiment analysis especially at the paragraph level[7].

In our research, we will compare LSTM and GRU for multiclass sentiment analysis and will try to find out model with higher accuracy. we will also incorporate and test different pre-processing techniques.

Hadi Pouransari in his study 'Deep learning for sentiment analysis of movie reviews' implemented the recursive neural tensor networks(RNTN) to train a multi-class sentiment analyzer. The training of standard RNTN was computationally very expensive. To overcome the high computational cost of training the standard RNTN we introduce the lowrank RNTN, in which the matrices involved in the quadratic term of RNTN are substituted by symmetric low-rank matrices. We show that the low-rank RNTN leads to significant saving in computational cost, while having similar a accuracy as that of RNTN[21]. This study has shown how we can apply sentiment analysis on multiclass text data using neural networks.

A blog post on sequence classification with LSTM Recurrent Neural Networks in Python with Keras by Jason Brownlee[8] has shown the addition of convolutional layer to LSTM reduce the training time of LSTM without affecting the accuracy. Due to the time constrains we have incorporated this method.

Chapter 3

Method

To obtain a solution to the research question, the method used is a formal experiment. In a formal experiment, we create identical circumstances to test methods, activities, Algorithms, etc. to identify what effect they have. Artificial neural networks are a good example of the explorative mode of experimentation. After having been discarded on theoretical grounds, experiments demonstrated properties better than predicted [24]. For this project, We experiment on the LSTM and GRU Recurrent neural network algorithm which comes under Artificial neural networks, experimentation is better fitted.

To determine which of the two LSTM or GRU has algorithm has higher accuracy for multiclass classification of text data. We used text reviews given to the movies by the users. Here the reviews are classified into the scale of one to ten. We are adopting LSTM and GRU as a tool to processes the natural language of text reviews given to the movies. We generated separate models for each method using training data from the dataset. The models are then used to predict the class of reviews. We compare the predicted values to actual values in the test data to determine accuracy. In the experiment, we also used Porter stemming and Stop words (Natural language processing tools) to filter data. To improve the efficiency of LSTM and GRU, we coupled them with the convolutional neural network.

Further this chapter comprises details regarding Datasets, Algorithms, Experimental setup and Visualization techniques employed in this experiment.

3.1 Datasets

To train and test the RNN model for text reviews of movies to classify them from one to ten, There is a need for a large amount of data. Firstly we used Large movie review dataset V1.0 by Andrew L. Maas [19]. This dataset has a total of 50,000 IMDB movie reviews classified into positive and negative data. For more data, we included another dataset of kaggle's Bag of Words Meets Bags of Popcorn competition [1]. This dataset also has 50,000 IMDB movie reviews evenly distributed into Train and Test data.

Both the dataset are primarily meant for binary classification (positive or negative) of movie reviews. Since the aim is to predict multiclass sentiments of movie reviews, the dataset is also needed to be classified into multiclass (Scale of one to ten). Fortunately, both the datasets have unique ids for each review which incorporate a rating from one to ten given by the user while writing the review. For example, In the dataset by Andrew Maas, '11867_8.txt' is a file containing a single review. We can observe that the file name has two attributes separated by an underscore, '11867' refers to review id and '8' refers to the rating. Hence, to extract rating from the dataset we used python to automate the process. Section 3.1.1 Describes extraction process for Large movie review dataset V1.0 by Andrew L. Maas [19]. Section 3.1.2 Describes extraction process for kaggle's Bag of Words Meets Bags of Popcorn competition [1].Section 3.1.3 contains details of final dataset that is used for training and testing.

3.1.1 Dataset 1

In Dataset 1 there are two top-level directories [train/, test/] corresponding to the training and test sets. Each contains [pos/, neg/] directories for the reviews with binary labels positive and negative. Within these directories, reviews are stored in text files named following the convention [[id]_[rating].txt] where [id] is a unique id and [rating] is the star rating for that review on a 1-10 scale. For example, the file [test/pos/200_8.txt] is the text for a positive-labeled test set example with unique id 200 and star rating 8/10 from IMDb [19].

Firstly we manually copied every txt files in train and test directories into a single directory. While manually copying the file into a single directory, some of the files which may have some identical file name with different contents are renamed by default. We use code in Listing 3.1 to read and store names of each file to extract rating from the file name. The code in Listing 3.2 extracts ratings from the file names and also stores them in a new file along with the reviews. The new file consists of two columns 'Sentiment' and 'Review'.

```
#directory holding all files
mypath = os.path.join(mypath,"Combined_data")
for (dirpath, dirnames, filenames) in walk(mypath):
    #Adding all file name to the list
    filelist.extend(filenames)
```

Listing 3.1: Retrieving file names

```
for i in filelist:
    #Splitting file extension (txt)
    filename_complete = i.split(".")
    #Splitting id
    filename_splited = filename_complete[0].split("_")
    if(' ' in filename[1]):
        #Splitting rating if file is renamed
        renamed = filename_splited[1].split(" ")
        Sentiment = renamed[0]
    else:
        Sentiment = filename_splited[1]
    filename = os.path.join(mypath, i)
    file = open(filename, "r", encoding="utf-8")
    #writing sentiments and reviews in a new file
    newdataset.write("\""+Sentiment+"\"\t"+"\""+file.read()+"\"\n")
    file.close()
```

Listing 3.2: Seprating rating from filename

3.1.2 Dataset 2

The Dataset 2 consist of two files 'labeledTrainData.tsv' and 'testData.tsv'. Both the file contain 25,000 reviews each and has three columns 'id', 'sentiment', 'review'. In this dataset, the rating that is needed to be extracted are present in the 'id' column. every row of 'id' column follows the convention [[id]_[rating]] where [id] is a unique id and [rating] is the star rating for that review on a 1-10 scale.

We used the code in Listing 3.3 to extract ratings from the 'id' column. After extracting we again store the ratings and reviews into a new file under the column name 'Sentiment' and 'Review'.

```
#Read from file
data_test = pd.read_csv(Filename, delimiter="\t", encoding="utf-8")
#Separating rating from the id
data_test["sentiment"] = data_test["id"].map(lambda x: int(x.strip('"').split("_")[1]))
for i,j in data_test.iterrows():
    #writing sentiments and reviews in a new file
    newdataset.write("\""+str(j["sentiment"])+"\"\t"+"\""+str(j["review"])+"\"\n")
```

Listing 3.3: Seprating rating from id

3.1.3 Final datasets

After combining data from dataset 1 and 2 we generate a new dataset which consists of 100,000 samples. After combining the dataset we shuffle the rows randomly to avoid any bias or patterns. The table 3.1 depicts a sample of the final dataset.

sentiment	review
1	Just a stilted rip-off of the infinitely better...
10	This has to be the all time best computer...
7	Ok, so it may not be the award-winning...
2	I loved the first movie, the second one was...
3	Pretty poor Firestarter clone that seems more...

Table 3.1: Sample Dataset

Since the Both the parent datasets are for binary classification, they does not have neutral reviews, which means they have excluded reviews with rating '5' and '6'. Hence the final dataset also does not have any reviews with ratings '5' and '6'. Therefore, there are eight different classes (1,2,3,4,7,8,9,10) of reviews in the final dataset. the figure 3.1 shows the count of each class for reviews.

We divide the final dataset two sets for training and testing. The training dataset has 80% of total data i.e 80,000 samples, the testing dataset holds the rest of the 20,000 samples. We again divide 80% of the training dataset into training (64,000) and validation dataset (16,000).

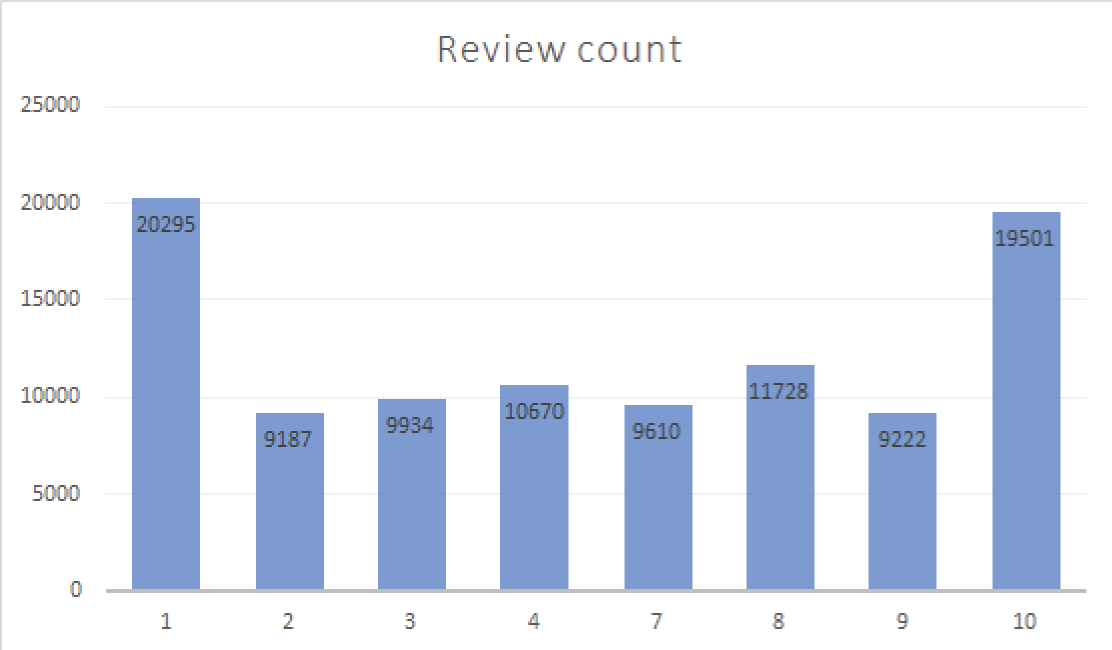


Figure 3.1: Final Dataset count

3.2 Pre-Processing Algorithms

This section consists of details about methods used for data pre-processing. Since we are dealing with text reviews that are written by the humans in there natural language, the text reviews may or may not be structured. Hence, there is a need for pre-processing text reviews. The study on the role of text pre-processing in neural network architectures has shows that there is a high variance in the results depending on the pre-processing choice [9].

To make all the text reviews uniform, we apply several filters like converting text into lowercase, removing HTML tags, etc. I this experiment we also test Porter Stemming and Stop Words techniques.

3.2.1 Filtering text

The text reviews in the dataset contains HTML tags.for example,

*"This German horror film has to be one of the weirdest I have seen.

I was not aware of any connection between child abuse and vampirism"*

The above review consist of HTML tag '
', which does not have any significance. Hence, HTML tags can be excluded, following is the processed text for above example.

"This German horror film has to be one of the weirdest I have seen. I was not aware of any connection between child abuse and vampirism"

Similarly, We Replace or convert characters which are insignificant. For this experiment we convert all the reviews into lower case, replace digits with the text 'number' and removing all the punctuation's with spaces. Here is an example,

Review:
"I first viewed They Died With There Boots On,about 1970 and though it has been many years since,this film and its impression remain."

Processed Review:
"i first viewed they died with there boots on about number and though it has been many years since this film and its impression remain"

3.2.2 Porter Stemming

Online reviews are generally used with informal language and they include internet slang and contemporary spellings like use of apostrophes, ing form of words to name a few. So such words must be re-visited and stemmed for correct data retrieval [5].

Porter stemming is a technique used to extract the root of words by eliminating suffixes like 'ing', 'ly', 's' etc. based on a rule. In this experiment we used PorerSremmer in nltk(Natural Language Toolkit) library for python language. Following is an example for porter stemming,
Review:
"what s inexplicable firstly the hatred towards this movie it may not be the greatest movie of all time but gimme a break it got number oscars for a reason it made eighteen hundred million dollars for a reason it s a damn good movie which brings to the other inexplicable aspect of it i have no idea whatsoever why this movie left such an impression on me when i saw it in theaters"

Processed Review:
"what s inexplic firstli the hatr toward thi movi it may not be the greatest movi of all time but gimm a break it got number oscar for a reason it made eighteen hundr million dollar for a reason it s a damn good movi which bring to the other inexplic aspect of it i have no idea whatsoev whi thi movi left such an impress on me when i saw it in theater"

3.2.3 Stop Words

Many of the most frequently used words in English are useless in Information Retrieval (IR) and text mining. These words are called 'Stop words'. Stop-words, which are language-specific functional words, are frequent words that carry no information (i.e., pronouns, prepositions, conjunctions) [23]. Examples of such words include 'the', 'of', 'and', 'to'.

Review:
"i have to say i quite enjoyed soldier russell was very good as this trained psychopath rediscovering his humanity very watchable and nowhere near as bad as i d been led to believe yes it has problems but provides its share of entertainment"

Processed Review:
"say quite enjoyed soldier russell good trained psychopath rediscovering humanity watchable nowhere near bad led believe yes problems provides share entertainment"

3.3 Experimental setup

The experimental setup is to generate and test models for text review classification using LSTM and GRU Recurrent neural networks. All the experiments are carried on identical hardware and operating system.

Operating System:	Windows 10 Education 64-bit (10.0, Build 18363)
System Manufacturer:	Dell Inc.
System Model:	Precision 5720 AIO
Processor:	Intel(R) Xeon(R) CPU E3-1275 v6 @ 3.80GHz (8 CPUs), ~3.8GHz
Memory:	16384MB RAM (16 GB)
GRU:	Radeon (TM) Pro WX 7100 Graphics

Models are generated and teased in Python 3.7.6 environment. List of several library functions used are given in table 3.2.

Package name	Version
Keras	2.3.1
matplotlib	3.1.3
nltk	3.4.5
numpy	1.18.3
pickle	4.0
pandas	1.0.1
re	2.2.1
sklearn	0.20.3
tensorflow	1.14.0

Table 3.2: Python Packages

In section 3.1.3 we have seen that there are eight different classes (1,2,3,4,7,8,9,10), we can observe that class labels are not continues. Since we need to define output parameters, we modify the class labels to be continues. Modified class labels are shown in table 3.3.

We will be using Using keras open-source neural-network library [10] for generating models. The keras only takes real numbers as input, hence we need to vectorise data (converting words into numbers). In order to do so we first tokenize the data, We tokenize text review given for movies using 5000 most frequently occurred words. The tokenized words are then vectorised, following example demonstrate how this is done. We apply sequence padding of 500 to ensure each reviews are are of same length.

Review:

Class lable	New Class lable
1	0
2	1
3	2
4	3
7	4
8	5
9	6
10	7

Table 3.3: Class labels for data

"This movie is amazing because the fact that the real people portray themselves and their real life experience and do such a good job it's like they're almost living the past over again."

Tokenised Review:

'This', 'movie', 'is', 'amazing', 'because', 'the', 'fact', 'that', 'the', 'real', 'people', 'portray', 'themselves', 'and', 'their', 'real', 'life', 'experience', 'and', 'do', 'such', 'a', 'good', 'job', "it's", 'like', "they're", 'almost', 'living', 'the', 'past', 'over', 'again.'

Vectorise Review:

[4, 5, 6, 7, 8, 1, 9, 10, 1, 2, 11, 12, 13, 3, 14, 2, 15, 16, 3, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 1, 27, 28, 29]

Keras sequential is needed to be compiled after defining features, Listing 3.4 describe how the model was generated and tested. Convolutioal layer and Pooling layer are add to increase the performance the Model.

```
model = Sequential()
# Embedding layer
model.add(Embedding(input_dim = 5000,
                            output_dim = 32,
                            input_length = 512))
model.add(Dropout(0.2))
# Convolutional layer
model.add(Conv1D(filters = 32, kernel_size = 3,
                            padding = 'same',
                            activation = 'relu'))
# Pooling layer
model.add(MaxPool1D(pool_size = 2))
if lstm == True:
    # LSTM layer
    model.add(LSTM(256))
else:
    # GRU layer
    model.add(GRU(256))
model.add(Dropout(0.2))
```

```
model.add(Dense(8, activation = 'softmax'))
model.compile(loss = 'categorical_crossentropy',
                        optimizer = 'adam', metrics = ['accuracy'])
# Training model on training data
model.fit(x_train_data, y_train_data,
            batch_size=128, epochs=100,
            validation_data=[x_val_data, y_val_data])
# Making predictions for test data
prediction = model.predict_classes(x_test_data, batch_size=64)
```

Listing 3.4: Keras model

We have conducted 18 different tests, table 3.4 lists tests conducted with different arguments.

S.No.	Model	Pre-processing	Epochs	CNN layer
1	LSTM	Porter Stemming	10	No
2	LSTM	Stop Word	10	No
3	LSTM	Basic	10	No
4	GRU	Porter Stemming	10	No
5	GRU	Stop Word	10	No
6	GRU	Basic	10	No
7	LSTM	Porter Stemming	200	Yes
8	LSTM	Stop Word	200	Yes
9	LSTM	Basic	200	Yes
10	GRU	Porter Stemming	200	Yes
11	GRU	Stop Word	200	Yes
12	GRU	Basic	200	Yes
13	LSTM	Porter Stemming	500	Yes
14	LSTM	Stop Word	500	Yes
15	LSTM	Basic	500	Yes
16	GRU	Porter Stemming	500	Yes
17	GRU	Stop Word	500	Yes
18	GRU	Basic	500	Yes

Table 3.4: Experiment Conducted

3.4 Data Visualization

Data visualization is the representation of data or information in a graph, chart, or other visual format. It communicates relationships of the data with images. This is important because it allows trends and patterns to be more easily seen. With the rise of big data upon us, we need to be able to interpret increasingly larger batches of data. Machine learning makes it easier to conduct analyses such as predictive analysis, which can then serve as helpful visualizations to present [15].

In this research, line chart and confusion matrix heat map is used for data visualization. Figure 3.2 is a sample of line graph which plots accuracy (y-axis) for training data and validation data with respect to each epoch (x-axis). Figure 3.3

visualizes confusion matrix for actual (y-axis) versus predicted (x-axis) values of test data.

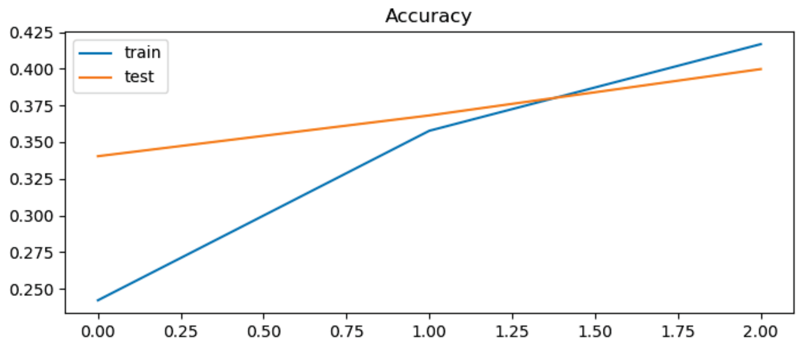


Figure 3.2: Line Graph for Accuracy

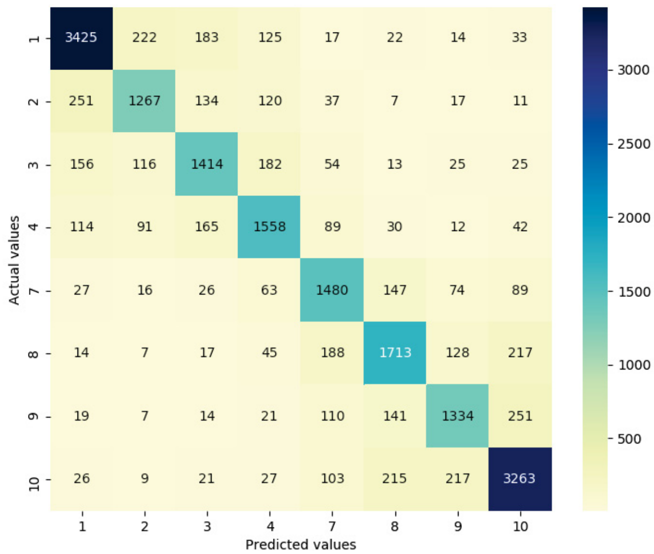


Figure 3.3: Confusion matrix heat map

Chapter 4

Results and Analysis

In this chapter, the outcomes of each test is placed together. We divided all the tests listed in table 3.4 into three sets based on number of epochs. Tests 1-6 are addressed in section 4.1, tests 7-12 are addressed in section 4.2 and tests 13-18 are addressed in section 4.3.

4.1 Experiment 1

This section consists of the tests that were conducted without the convolutional layer. This test is conducted to check the computational cost of LSTM and GRU.We conducted a similar test, where LSTM and GRU are coupled with convolutional neural network.

The table 4.1 illustrates average training time for each epochs and accuracy achieved after ten epochs on test data for the simple model and model coupled with CNN.

S. No.	Model	Pre-processing	Training Time per Epochs (Average)	Training Time per Epochs (Average) CNN	Test data Accuracy	Test data Accuracy CNN
1	LSTM	Porter Stemming	50.83 min	8.45 min	49.69	51.095
2	LSTM	Stop Word	47.5 min	8.36 min	50.059	51.39
3	LSTM	Basic	45.5 min	9.08 min	50.035	51.78
4	GRU	Porter Stemming	252.76 min	18.53 min	47.965	49.39
5	GRU	Stop Word	230.26 min	19.66 min	47.76	48.85
6	GRU	Basic	192.18 min	23.25 min	47.305	48.575

Table 4.1: Experiment 1 Summary

In the table 4.1, we can observe that training time for simple LSTM and GRU is far more than LSTM and GRU coupled with CNN. However, the accuracies of LSTM and GRU with and without CNN has reached a similar mark for the same number of epochs.

To make models predict classes with full potential, we need to train the models for a much higher number of epochs. Due to limited resources and time constraints, we decided to use LSTM and GRU with CNN for further tests.

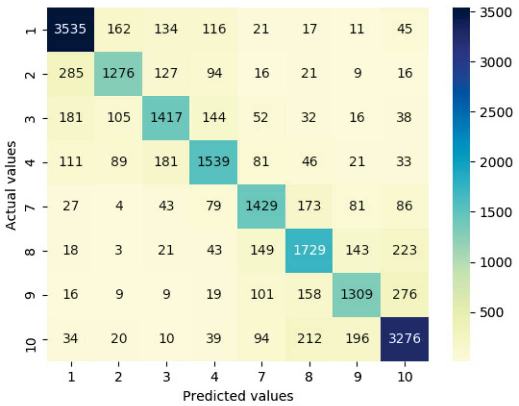
4.2 Experiment 2

This section, we present and compare the results of LSTM and GRU (coupled with CNN)with there corresponding pre-processing techniques. We will perform an in-depth analysis of the confusion matrix generated on test data. We will also go through accuracy graph generated during the training of models on test and validation data.

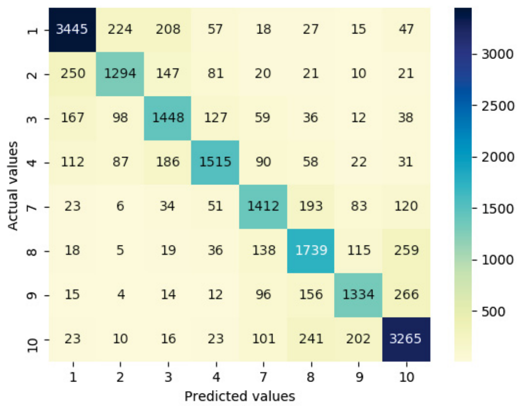
After training the model for 200 epochs, we use test data to predict the class of each review. We compare the predicted values with actual values and visualize them in the form of confusion matrix.

The figure 4.1, 4.1a is a confusion matrix for LSTM using porter stemming and 4.1b is a confusion matrix for GRU using porter stemming. When we observe the true-positive values of LSTM and GRU, there is some contrast. we can observe that LSTM has higher true-positive values for the class of sentiments 1, 4, 5 and 10 but on the other side, GRU has higher true-positive values for the class of sentiments 2, 3, 8, and 9.

If we look at false-positive and false-negative values, we can observe that LSTM has less false-positive values, whereas GRU has less false-negative values. It can be argued that LSTM in combination with porter stemming predicts border values more accurately. We can observe that there is very less difference between overall predicted values of LSTM and GRU. We can say that GRU predicts better when compare to LSTM for every class.



(a) LSTM-PS



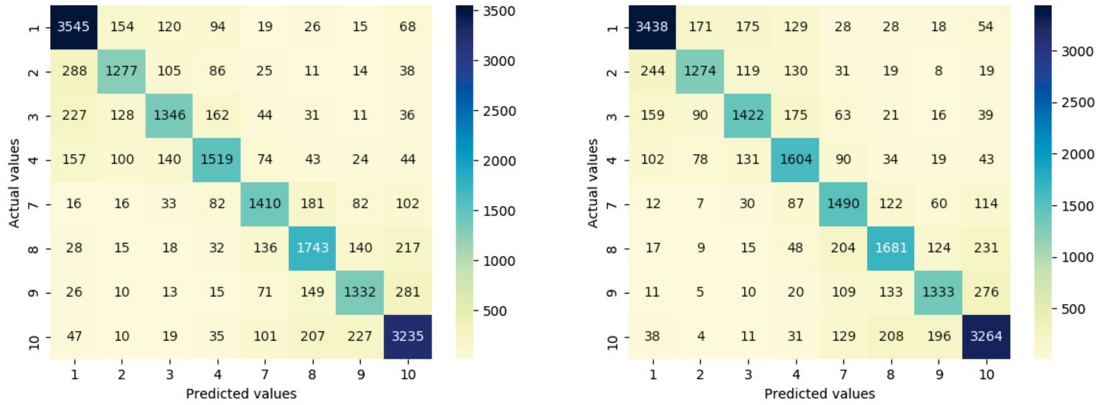
(b) GRU-PS

Figure 4.1: Confusion matrix heat map for Porter Stemming

In the figure 4.2, 4.2a and 4.2b are confusion matrix for LSTM and GRU when we use stop words pre-processing technique. Overall GRU has more true positive values than LSTM. This implies GRU works better with stop words than LSTM.

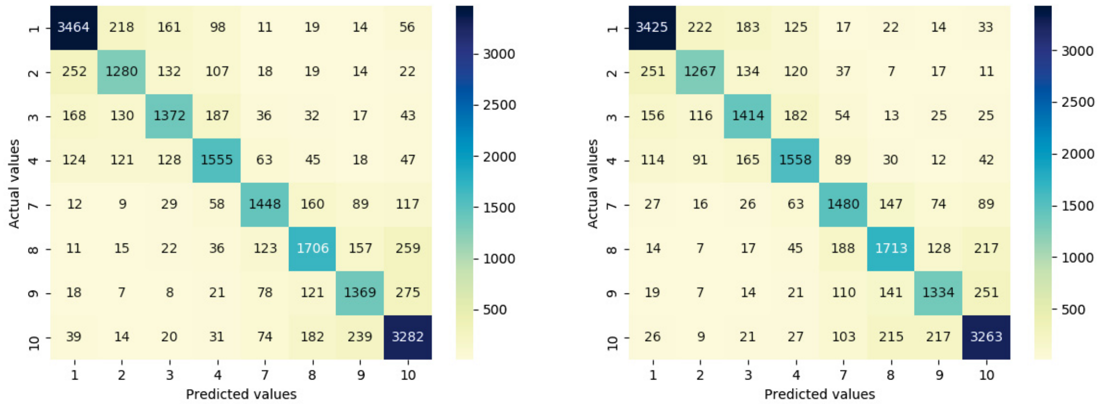
In the figure 4.3, 4.3a and 4.3b are confusion matrix for LSTM and GRU when we use basic pre-processing technique. When we compare the two matrices, there is not much of a difference in the overall values of true positive, false negative and false positive values. LSTM predicts better for class of sentiment 1 and 10 but overall both LSTM and GRU performed similarly.

If we look at the test data accuracy in table 4.2, there is a very small difference



(a) LSTM-SW (b) GRU-SW

Figure 4.2: Confusion matrix heat map for Stop Words



(a) LSTM-B (b) GRU-B

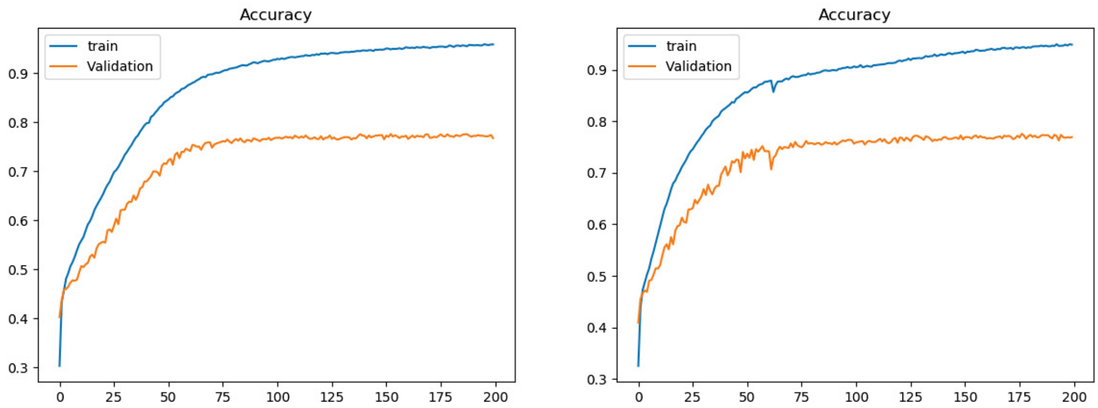
Figure 4.3: Confusion matrix heat map for Basic

between the accuracies of LSTM and GRU. Hence, we use another method to compare these two algorithms. We compared the learning rate for both LSTM and GRU to find out which algorithm has higher learning rate.

To compare the learning rate, we selected accuracy graph of LSTM and GRU with basic pre-processing shown in the figure 4.4. The reason for selecting basic pre-processing is because the accuracy is quite similar for both LSTM and GRU. Moreover, earlier we have seen LSTM and GRU performed similarly when we compared confusion matrices for basic pre-processing.

In the figure 4.4, 4.4a and 4.4b is a line graph that visualizes the accuracy gained for each epoch on training and validation data for 200 epochs. If we look at the structure of the curve, GRU attains higher accuracy before LSTM. Hence, this indicates GRU has higher learning rate than LSTM.

The table 4.2 summarizes the results for all the six models. When we compare the training time of these models with models addressed in section 4.1, there is a



(a) LSTM-B (b) GRU-B

Figure 4.4: Accuracy line graph for Basic

significant drop in training time for both LSTM and GRU models when we combine them with CNN. The training time of LSTM is dropped by approximately 6 times, whereas training time for GRU is dropped by approximately 14 times. Hence, this shows there is a major improvement in performance when we couple the convolutional layer with LSTM and GRU.

When we examine the maximum accuracy achieved on training data for LSTM and GRU, we can see that LSTM has slightly higher accuracy than GRU. We can argue that LSTM fits well for training data which is not essential. GRU predicts slightly better than LSTM, this can be implied when we compare the maximum accuracy achieved on validation data. The maximum accuracy of GRU on validation data is equal or slightly higher for all the three pre-processing techniques (PS, SW, B) when compared to LSTM.

S. No.	Model	Pre-processing	Time per Epochs (Average)	Max Training accuracy	Max Validation test Accuracy	Test data Accuracy
1	LSTM	Porter Stemming(PS)	8.37 min	95.58	77.70	77.55
2	LSTM	Stop Word(SW)	7.98 min	95.95	77.22	77.035
3	LSTM	Basic(B)	8.13 min	95.88	77.56	77.38
4	GRU	Porter Stemming(PS)	18.20 min	95.01	77.87	77.26
5	GRU	Stop Word(SW)	17.51 min	94.35	77.39	77.53
6	GRU	Basic(B)	17.33 min	94.96	77.56	77.27

Table 4.2: Experiment 2 Summary

4.3 Experiment 3

The tests addressed in this experiment are identical to experiment 2, the only difference is we increased the number of epochs to 500. The motive behind performing this experiment is to check how much accuracy can be gained when we train the model for a longer period. This is important for justifying how much we need to train the model to achieve reasonable accuracy with the minimal computational cost.

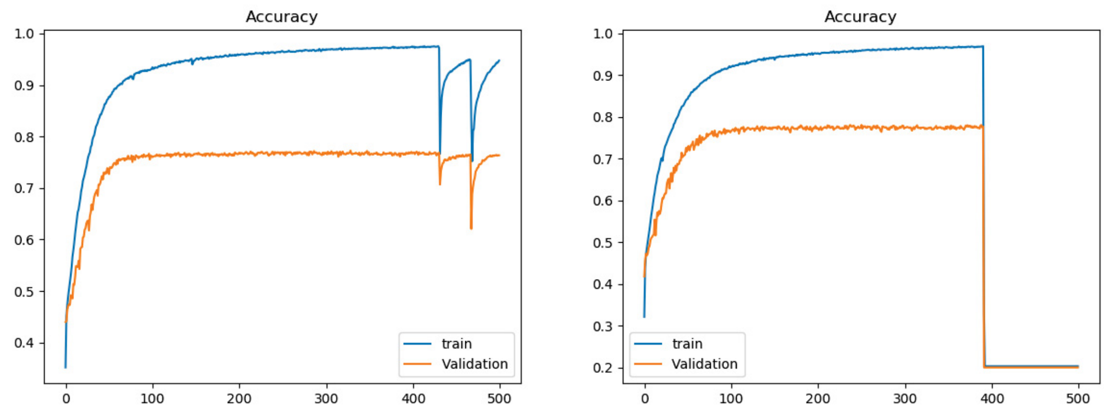
When we compare the results in table 4.3 and table 4.2, there is a rise in maximum accuracy on training data. This could lead to overfitting as we can observe a decline of accuracy for training data. There is a small increase in maximum accuracy on validation data but the difference is not significant enough to justify the computational cost.

S. No.	Model	Pre-processing	Max Training accuracy	Max Validation test Accuracy	Test data Accuracy
1	LSTM	Porter Stemming	97.47	78.11	77.59
2	LSTM	Stop Word	97.53	77.23	76.98
3	LSTM	Basic	97.08	77.63	77.23
4	GRU	Porter Stemming	96.90	78.04	20.20
5	GRU	Stop Word	95.01	77.46	76.6
6	GRU	Basic	96.70	77.66	76.88

Table 4.3: Experiment 3 Summary

When we train a model for a longer time, the final model's accuracy may drop to the extent that it becomes useless. This can be observed in the figure 4.5, 4.5a show there is fluctuation in the accuracy after 400 epochs. During the test, one of the model's accuracy falls to 20% and was never recovered, this can be seen in 4.5b.

After analyzing the results we can say that GRU performs slightly better than LSTM, hence this answers the research question.



(a) LSTM-SW (b) GRU-PS

Figure 4.5: Accuracy line graph for Basic

Chapter 5

Discussion

After looking at the test results, we could say that both LSTM and GRU irrespective of pre-processing techniques used achieved the accuracy of 77%. Hence, both LSTM and GRU are similar in terms of accuracy. This deduction may be incorrect as several other things needed to be considered.

Firstly, 77% accuracy may seem ok if we compare it with the general mark of 90% and above. Here we need to consider the number of classes for classification. As for binary classification, the minimum accuracy baseline is 50% (100/2) or above. Whereas in our model, there are eight different class labels. Hence, the baseline would be 12.5% (100/12). When we compare 77% with 12.5% baseline the resultant accuracy is quite good.

The dataset also plays a significant role in determining features of the mode. As we see in the figure 3.1, the class label 1 and 10 have nearly double the number of reviews than any other class label. Moreover, other class labels are also not balanced. This imbalance in class labels may make models more sensitive to some classes than others.

Similarly, there is also an disproportion in test dataset as we can see in the table 5.1. This may have a significant impact on the overall accuracy of the model on the test dataset. After a detailed analysis in the section 4.2, we could say that GRU has performed better in predicting all classes for every pre-processing technique. Hence, this answers the research question.

Class labels	Count
1	4041
2	1844
3	1985
4	2101
7	1922
8	2329
9	1897
10	3881

Table 5.1: Test dataset

Another important aspect is the computational cost. After coupling LSTM and GRU with the convolutional neural network, we were able to reduce the training time for each epoch significantly. Even though we can still observe that GRU takes double the time for training when compared to LSTM. Hence we conclude that LSTM is computationally cheaper than GRU.

One thing that we have to keep in mind is that the data which is used in training and testing the models are generated by humans. The class labels are extracted from the ratings given with the reviews. There may be several occurrences like two different reviews may convey the same sentiment but have a distinct rating and vice-versa.

Chapter 6

Conclusions and Future Work

In this dissertation, we tried to compare the prediction accuracies of LSTM and GRU for multiclass classification of text reviews given for movies. During the time of testing, we found out that both LSTM and GRU were computationally expensive. We coupled LSTM and GRU with CNN, which reduced the training time significantly. After in-depth analysis, we found out that GRU is slightly better than LSTM and also computationally expansive.

For future work, we can conduct the same experiments using properly balanced dataset and study how this effect the models. An in-depth study can be conducted on how CNN layer increased the performance of LSTM and GRU.

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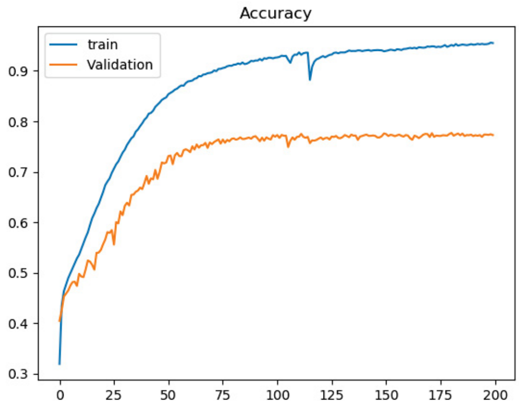
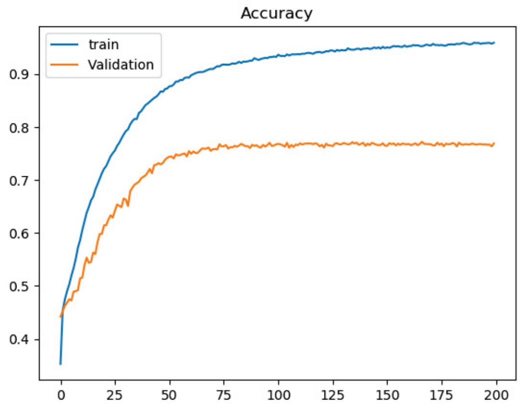
Appendix A

Supplemental Information

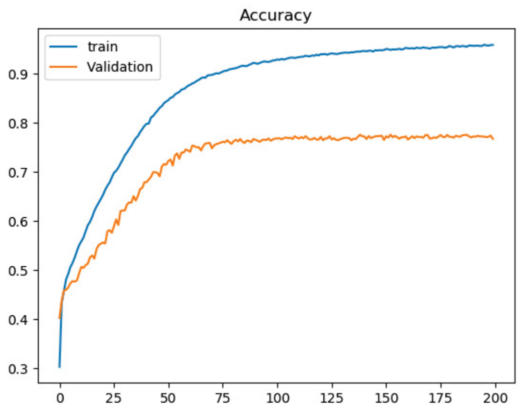


(a) LSTM-PS

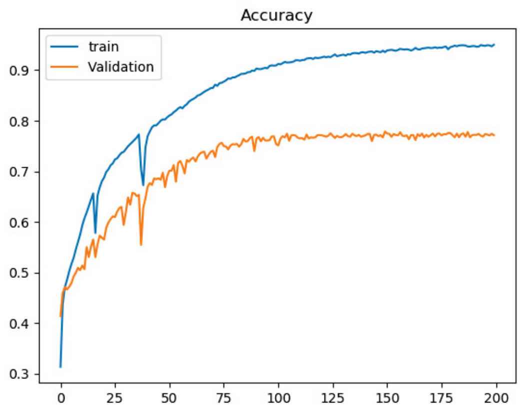


(b) GRU-PS

Figure A.1: Accuracy Line graphs for Porter Stemming

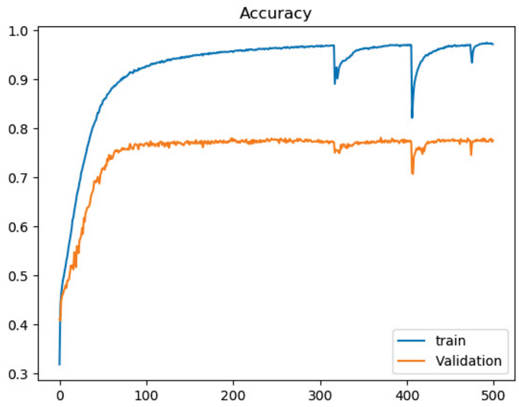


(a) LSTM-SW

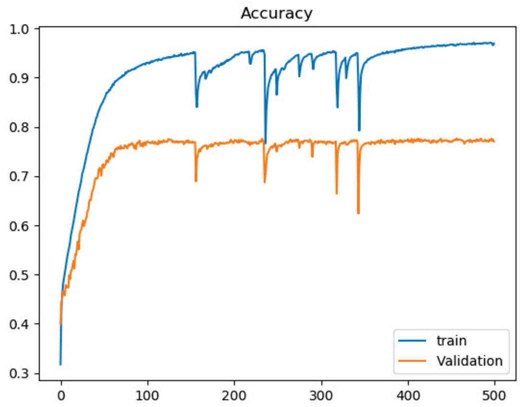


(b) GRU-SW

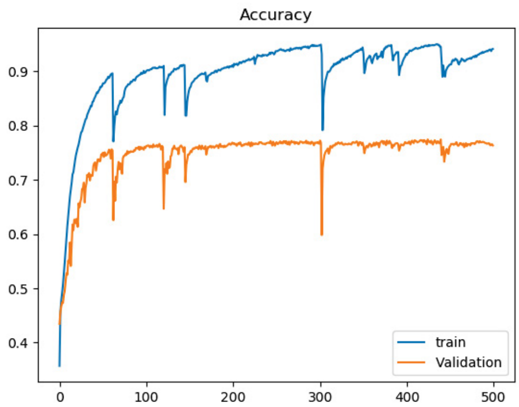
Figure A.2: Accuracy Line graphs for Stop words



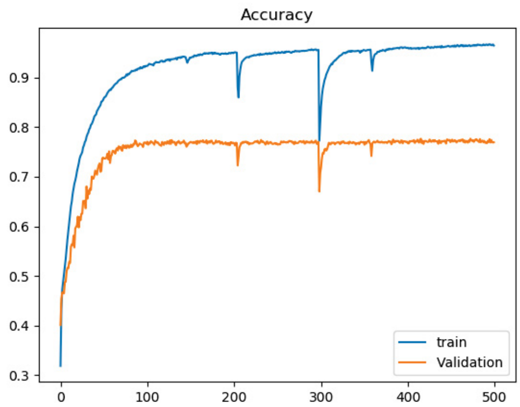
(a) LSTM-PS



(b) LSTM-B



(c) GRU-SW



(d) GRU-B

Figure A.3: Accuracy Line graphs for 500 Epochs

Faculty of Computing, Blekinge Institute of Technology, 371 79 Karlskrona, Sweden