

# **Assignment 2 Report**

Text Classification Using Deep Learning

CS6301.004 Data Science with R

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#### What is Text Classification?

Text classification (a.k.a. text categorization or text tagging) is the task of assigning a set of predefined categories to free-text. Text classifiers can be used to organize, structure, and categorize pretty much anything. For example, new articles can be organized by topics, support tickets can be organized by urgency, chat conversations can be organized by language, brand mentions can be organized by sentiment, and so on.

There are many approaches to automatic text classification, which can be grouped into three different types of systems:

- Rule-based systems
- Machine Learning based systems
- Hybrid systems

## **Classification using Deep Learning**

One way to classify Text Data is to use Deep Learning networks. Deep learning is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised. We have used Keras neural network packages to achieve our goals. We have selected Sentiment Labelled Sentences Data Set from the UCI Text Datasets for this Assignment. We have worked on the Amazon review dataset which has 1000 reviews with 50% positive reviews and 50% negative reviews which are labelled using 1 and 0 respectively.

## Goals

- 1. Preprocessing the dataset:
  - Removing stopwords, punctuations, numbers, single characters and whitespaces from the individual reviews.
  - Converting the words to list of integer indices and vectorizing the input data so that it can be fed to the neural network.
- 2. Splitting the dataset into training and testing data.
- 3. Create different deep network models and test their accuracy using GCloud.

# **Libraries Required**

library(keras)
library(tm)
library(stringr)
require(caTools)

## **Models and Performance**

No.	Code	Performance
1.	<pre>#model1 library(keras) model &lt;- keras_model_sequential() %&gt;%     layer_dense(units = 16, activation = "relu",</pre>	Loss: 0.6367 Accuracy: 0.6833  Link to Google Cloud Output

```
#model 2
                                                                Loss: 0.221
2.
     library(keras)
                                                                Accuracy: 0.6547
     model2 <- keras model sequential() %>%
      layer dense(units = 16, activation = "relu",
            input shape = c(10000)) %>%
      layer dense(units = 16, activation = "relu") %>%
                                                                Link to Google Cloud
      layer dense(units = 1, activation = "sigmoid")
                                                                Output
     model2 %>% compile(optimizer = "rmsprop",loss =
     "mse", metrics = c("accuracy"))
     model2 %>% fit(x train, y train, epochs = 10,batch size
     = 512)
     #plot of history based on validation data
     history <- model2 %>% fit(
      partial x train,
      partial_y_train,
      epochs = 20,
      batch size = 512,
      validation_data = list(x_val, y_val)
     results2 <- model2 %>% evaluate(x_test, y_test)
     #model 3
3.
                                                                Loss: 0.9546
     library(keras)
                                                                Accuracy: 0.6589
     model3 <- keras model sequential() %>%
      layer dense(units = 16, activation = "relu",
            input shape = c(10000)) %>%
      layer dense(units = 16, activation = "tanh") %>%
                                                                Link to Google Cloud
      layer dense(units = 16, activation = "tanh") %>%
                                                                Output
      layer_dense(units = 1, activation = "sigmoid")
     model3 %>% compile(optimizer = "rmsprop",loss =
     "poisson", metrics = c("accuracy"))
     model3 %>% fit(x train, y train, epochs = 10,batch size
     = 512)
     #plot of history based on validation data
     history <- model3 %>% fit(
      partial x train,
      partial_y_train,
      epochs = 20,
      batch size = 512,
```

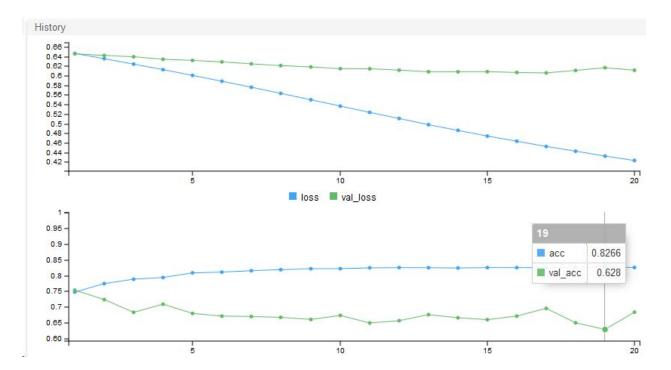
```
validation_data = list(x_val, y_val)
     )
     results3 <- model3 %>% evaluate(x_test, y_test)
     #model 4
                                                                Loss: 0.9333
4.
     library(keras)
                                                                Accuracy : 0.6505
     model4 <- keras model sequential() %>%
      layer dense(units = 16, activation = "tanh",
            input shape = c(10000)) %>%
      layer dense(units = 16, activation = "tanh") %>%
                                                                Link to Google Cloud
      layer_dense(units = 16, activation = "tanh") %>%
                                                                Output
      layer dense(units = 1, activation = "sigmoid")
     model4 %>% compile(optimizer = "rmsprop",loss =
     "poisson", metrics = c("accuracy"))
     model4 %>% fit(x_train, y_train, epochs = 10,batch_size
     = 512)
     #plot of history based on validation data
     history <- model4 %>% fit(
      partial_x_train,
      partial_y_train,
      epochs = 20,
      batch size = 512,
      validation data = list(x val, y val)
     results4 <- model4 %>% evaluate(x test, y test)
     #model 5
                                                                Loss: 0.9417
5.
     model5 <- keras_model_sequential() %>%
                                                                Accuracy: 0.6536
      layer_dense(units = 16, activation = "relu", input_shape
     = c(10000)) \% > \%
      layer dense(units = 16, activation = "tanh") %>%
                                                                Link to Google Cloud
      layer dense(units = 16, activation = "tanh") %>%
                                                                Output
      layer dense(units = 1, activation = "sigmoid")
     model5 %>% compile(
      optimizer = "rmsprop",
      loss = "poisson",
      metrics = c("binary accuracy")
     model5 %>% fit(x_train, y_train, epochs = 10,batch_size
     = 512)
```

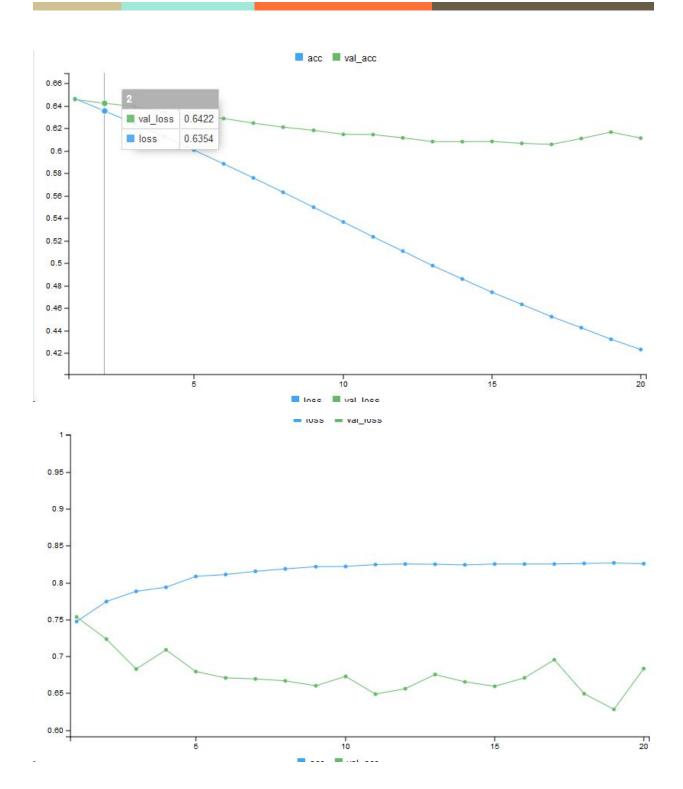
```
#plot of history based on validation data
history <- model5 %>% fit(
   partial_x_train,
   partial_y_train,
   epochs = 20,
   batch_size = 512,
   validation_data = list(x_val, y_val)
)

results5 <- model5 %>% evaluate(x_test, y_test)
```

### **Performance Plots**

We have just shown the plots for a single model. The rest of the plots and detailed outputs can be seen by going to the links given above.





job	cloudml_2019_03_10_012259742		
logs	View logs		
status	SUCCEEDED		
created	2019-03-10 01:23:36 GMT		
time	00:08:57		
ml_units	0.09		
Run			
context	cloudml		
script	TextClassification.R		
started	2019-03-10 01:27:33 GMT		
time	00:00:23		
Metrics			
loss	0.4233		
acc	0.8255		
val_loss	0.6113		
val_acc	0.6833		
Evaluation			
eval_loss	0.6367		

	Optimization				
Þ	loss binary_crossen		trop		
,	optimizer <tensorflow.python.keras.optimizers.rmsprop< td=""></tensorflow.python.keras.optimizers.rmsprop<>				
The same of the sa	lr				
	Training				
	samples	2,728			
	validation_samples	1,500			

20

512

\_

epochs

batch\_size

## **Conclusion**

We have performed the training, testing and validation on 5 different deep Learning models and have observed the accuracy and loss for each these models. The different models were created by changing different parameters like the activation function, the loss function, the optimizer and by varying the number of hidden layers and the number of units in each of them.