CSEE 5590 0001 Special Topics SPRING 2018

DEEP LEARNING LAB ASSIGNMENT - 3

Submitted On 5/9/2018

Name: Satya Sai Deepthi Katta

Class ID: 21



Department of Computer Science and Electrical Engineering

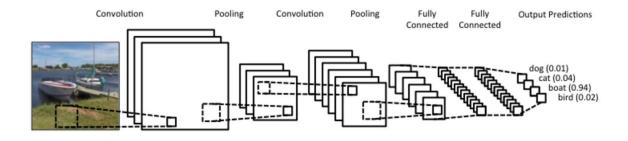
INTRODUCTION:

Text Classification is classifying the data based on some feature like email-spam filtering i.e, spam vs ham, sentiment analysis i.e; positives vs negatives. For most of the real world applications, text classification is used in many new stories developed by topics, product categories tags etc.

Three main techniques are used in classifying the text:

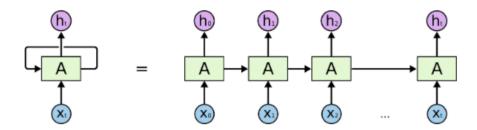
CNN - Convolutional Neural Network

This also known as ConvNet is used in analyzing visual imagery. The is class of deep learning technique part of feed forward neural network which doesn't contain any loop in the network.



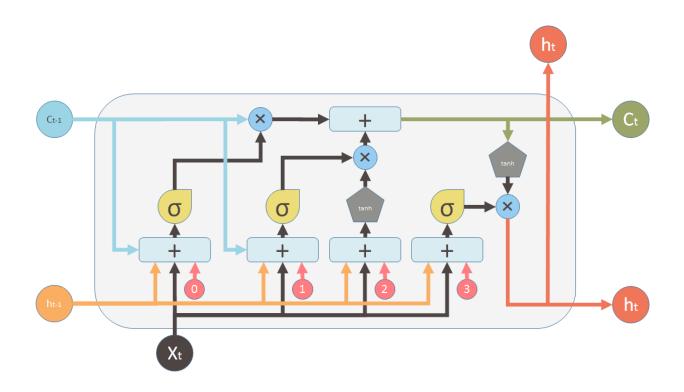
RNN - Recurrent Neural Network

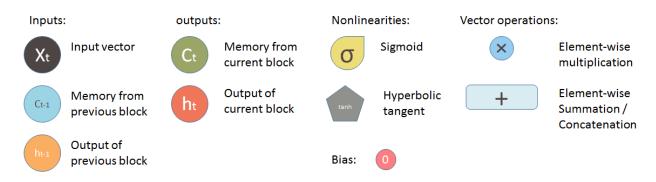
This is class of artificial neural network which follows a directed graph in a time sequence. Unlike feed forward network, these have loops which direct from output of input. RNN is used for unsegmented data like handwriting or speech recognition.



LSTM – Long Short-Term Memory

These are the unit blocks of the Recurrent neural networks which helps in building layers. These have cell, input, output and forget gates in the model. The cell usually has the remembering values which contribute to the "memory" segment of the RNN.





OBJECTIVE:

The object of the assignment is to give basic understanding behind the difference in using different text classification on a new dataset which is not used in the class.

And also, to compare the results plotting the workflows and graphs for scalars like accuracy and loss in tensor board.

APPROACH:

The approach is explained in simple steps below:

- Extract data from the dataset
- Weights and Bias assigned by Variables
- Inputs are given by Placeholders
- Prediction Model is built
- Trained using training data
- Optimizer used in reducing loss
- Loss and Accuracy Graphs Plotted
- Comparisons made using results

PARAMETERS:

Hyper parameters used for comparing the results by changing the values are listed below: Learning Rate = 0.001 Training Iterations = 10000 Displaying step = 1000

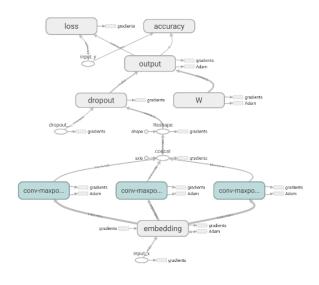
No. of inputs = 2

No. of hidden cells = 10

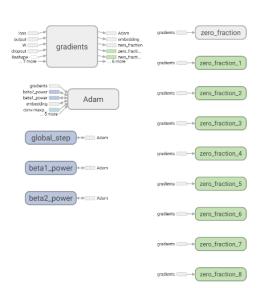
WORKFLOWS:

CNN

Main Graph

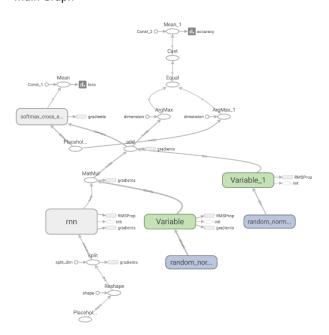


Auxiliary Nodes



RNN & LSTM

Main Graph



Auxiliary Nodes



DATASET

The dataset used here is few lines of text downloaded from GOOGLE Wikipedia. The text contains 500 words separated into 15 lines. The first paragraph of Google Wikipedia explaining company's history is considered as the dataset for text classification.

CONFIGURATION:

Code is built on PYCHARM Software using the advanced version of python programming language v3.6.4.

EVALUATION & DISCUSSION

Code snippets are provided below:

RNN

Importing required functions for the code. A start time is initiated as soon as the game begins.

```
import numpy as np
import tensorflow as tf
from tensorflow.contrib import rnn
import random
import collections
import time

start_time = time.time()

def elapsed(sec):
    if sec < 60:
        return str(sec) + " sec"
    elif sec < (60 * 60):
        return str(sec / 60) + " min"
    else:
        return str(sec / (60 * 60)) + " hr"</pre>
```

A training file is given as input where the text data is present. Read Data method helps to extract the data from the document.

```
# Text file containing words for training
training_file = 'google.txt'

def read_data(fname):
    with open(fname) as f:
        content = f.readlines()
        content = [x.strip() for x in content]
        content = [content[i].split() for i in range(len(content))]
        content = np.array(content)
        content = np.reshape(content, [-1, ])
    return content

training_data = read_data(training_file)
print("Loaded training data...")
```

The dataset is built into set of words storing in the dictionaries. Parameters are initialized which are used for changing for getting the outputs.

```
def build dataset(words):
    count = collections.Counter(words).most_common()
    dictionary = dict()
    for word, _ in count:
        dictionary[word] = len(dictionary)
    reverse dictionary = dict(zip(dictionary.values(), dictionary.keys()))
    return dictionary, reverse dictionary
dictionary, reverse dictionary = build dataset(training data)
vocab size = len(dictionary)
# Parameters
learning rate = 0.001
training iters = 10000
display_step = 1000
n input = 2
# number of units in RNN cell
n hidden = 10
```

Inputs are initialized using place holders, weights and bias are given initialized using variables.

```
# tf Graph input
x = tf.placeholder("float", [None, n_input, 1])
y = tf.placeholder("float", [None, vocab_size])

# RNN output node weights and biases

weights = {
    'out': tf.Variable(tf.random_normal([n_hidden, vocab_size]))
}

biases = {
    'out': tf.Variable(tf.random_normal([vocab_size]))
}
```

RNN function is used in defining the layers based on the no. of hidden layers initiated in the code.

```
def RNN(x, weights, biases):
    # reshape to [1, n input]
    x = tf.reshape(x, [-1, n input])
  # Generate a n input-element sequence of inputs
    # (eg. [had] [a] [general] -> [20] [6] [33])
    x = tf.split(x, n input, 1)
  # 2-layer LSTM, each layer has n hidden units.
    # Average Accuracy= 95.20% at 50k iter
    # rnn cell = rnn.MultiRNNCell([rnn.BasicLSTMCell(n hidden),rnn.BasicLSTMCell(n hidden)])
    # 1-layer LSTM with n hidden units but with lower accuracy.
    # Average Accuracy= 90.60% 50k iter
    # Uncomment line below to test but comment out the 2-layer rnn.MultiRNNCell above
    rnn cell = rnn.BasicLSTMCell(n hidden)
    # generate prediction
    outputs, states = rnn.static_rnn(rnn_cell, x, dtype=tf.float32)
   # there are n input outputs but
    # we only want the last output
   return tf.matmul(outputs[-1], weights['out']) + biases['out']
```

Loss and optimizer are varied based on the learning rate and RMS propagation optimizer gives best optimizing results.

```
pred = RNN(x, weights, biases)

# Loss and optimizer
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=pred, labels=y))
optimizer = tf.train.RMSPropOptimizer(learning_rate=learning_rate).minimize(cost)

# Model evaluation
correct_pred = tf.equal(tf.argmax(pred, 1), tf.argmax(y, 1))
accuracy = tf.reduce_mean(tf.cast(correct_pred, tf.float32))

# Initializing the variables
init = tf.global_variables_initializer()
loss_summary=tf.summary.scalar('loss',cost)
accuracy_summary=tf.summary.scalar('accuracy',accuracy)
merged= tf.summary.merge all()
```

A session is created to store instances for every iteration.

```
# Launch the graph
with tf.Session() as session:
    session.run(init)
    writer = tf.summary.FileWriter('./graphs/rnn', session.graph)
    step = 0
    offset = random.randint(0, n_input + 1)
    end_offset = n_input + 1
    acc total = 0
    loss_total = 0
    while step < training_iters:</pre>
        # Generate a minibatch. Add some randomness on selection process.
        if offset > (len(training_data) - end_offset):
            offset = random.randint(0, n_input + 1)
        symbols in keys = [[dictionary[str(training data[i])]] for i in range(offset, offset + n input)]
        symbols in keys = np.reshape(np.array(symbols in keys), [-1, n input, 1])
        symbols out onehot = np.zeros([vocab size], dtype=float)
        {\tt symbols\_out\_onehot[dictionary[str(training\_data[offset + n\_input])]] = 1.0}
        symbols out onehot = np.reshape(symbols out onehot, [1, -1])
        _, acc, loss, onehot_pred,summary = session.run([optimizer, accuracy, cost, pred,merged], \_\
                                                 feed_dict={x: symbols_in_keys, y: symbols_out_onehot})
        loss_total += loss
        acc_total += acc
```

The loss and accuracy are displayed for every 100th step.

```
if (step + 1) % display step == 0:
        print("Iter= " + str(step + 1) + ", Average Loss= " + \
              "{:.6f}".format(loss total / display step) + ", Average Accuracy= " + \
              "{:.2f}%".format(100 * acc total / display step))
        acc total = 0
        loss total = 0
        writer.add summary(summary, step)
        symbols_in = [training_data[i] for i in range(offset, offset + n_input)]
        symbols out = training data[offset + n input]
        symbols_out_pred = reverse_dictionary[int(tf.argmax(onehot pred, 1).eval())]
       print("%s - [%s] vs [%s]" % (symbols in, symbols out, symbols out pred))
   step += 1
   offset += (n input + 1)
print("Optimization Finished!")
print("Elapsed time: ", elapsed(time.time() - start time))
print("Run on command line.")
```

If the given words are present in the dictionary then rest of sentence is printed. If the words are not present then it shows an error message that words are not present.

```
while True:
    prompt = "%s words: " % n_input
    sentence = input(prompt)
    sentence = sentence.strip()
    words = sentence.split(' ')
    if len(words) != n input:
        continue
    try:
        symbols in keys = [dictionary[str(words[i])] for i in range(len(words))]
        for i in range(32):
            keys = np.reshape(np.array(symbols in keys), [-1, n input, 1])
            onehot pred = session.run(pred, feed dict={x: keys})
            onehot pred index = int(tf.argmax(onehot pred, 1).eval())
            sentence = "%s %s" % (sentence, reverse dictionary[onehot pred index])
            symbols in keys = symbols in keys[1:]
            symbols in keys.append(onehot pred index)
        print(sentence)
    except:
        print("Word not in dictionary")
```

CNN

Initiate code mu importing required functions. Parameters are defined for the dataset taken to display the results.

```
import tensorflow as tf
import numpy as np
import os
import time
import datetime
import data helpers
from cnn import TextCNN
from tensorflow.contrib import learn
# Parameters
# Data loading params
tf.flags.DEFINE_float("data_sample", .1, "Percentage of the training data to use for validation")
tf.flags.DEFINE_string("google_story", "./data/google.txt", "Data source for the google_story data.")
tf.flags.DEFINE string("google data file", "./data/google analysis.txt", "Data source for the google data.")
# Model Hyperparameters
tf.flags.DEFINE_integer("embedding_dim", 128, "Dimensionality of character embedding (default: 128)")
tf.flags.DEFINE string("filter sizes", "3,4,5", "Comma-separated filter sizes (default: '3,4,5')")
tf.flags.DEFINE_integer("num_filters", 128, "Number of filters per filter size (default: 128)")
tf.flags.DEFINE float("dropout keep prob", 0.5, "Dropout keep probability (default: 0.5)")
tf.flags.DEFINE float("12_reg_lambda", 0.0, "L2 regularization lambda (default: 0.0)")
# Training parameters
tf.flags.DEFINE integer ("batch size", 64, "Batch Size (default: 64)")
tf.flags.DEFINE_integer("num_epochs", 200, "Number of training epochs (default: 200)")
tf.flags.DEFINE integer("evaluate every", 100, "Evaluate model on dev set after this many steps (default: 100)")
tf.flags.DEFINE_integer("checkpoint_every", 100, "Save model after this many steps (default: 100)")
tf.flags.DEFINE integer("num checkpoints", 5, "Number of checkpoints to store (default: 5)")
# Misc Parameters
tf.flags.DEFINE boolean("allow soft placement", True, "Allow device soft device placement")
tf.flags.DEFINE_boolean("log_device_placement", False, "Log placement of ops on devices")
```

```
FLAGS = tf.flags.FLAGS
FLAGS. parse flags()
print("\nParameters:")
for attr, value in sorted(FLAGS. flags.items()):
    print("{}={}".format(attr.upper(), value))
print("")
# Data Preparation
# Load data
print("Loading data...")
x text, y = data helpers.load data and labels(FLAGS.google story, FLAGS.google data file)
# Build vocabulary
max_document_length = max([len(x.split(" ")) for x in x_text])
vocab_processor = learn.preprocessing.VocabularyProcessor(max_document_length)
x = np.array(list(vocab processor.fit transform(x text)))
# Randomly shuffle data
np.random.seed(10)
shuffle indices = np.random.permutation(np.arange(len(y)))
x 	ext{ shuffled} = x[	ext{shuffle indices}]
y shuffled = y[shuffle indices]
```

Dataset is split into training and testing data.

```
# Split train/test set
# TODO: This is very crude, should use cross-validation
dev_sample_index = -1 * int(FLAGS.dev_sample_percentage * float(len(y)))
x_train, x_dev = x_shuffled[:dev_sample_index], x_shuffled[dev_sample_index:]
y_train, y_dev = y_shuffled[:dev_sample_index], y_shuffled[dev_sample_index:]
print("Vocabulary Size: {:d}".format(len(vocab_processor.vocabulary_)))
print("Train/Dev split: {:d}/{:d}".format(len(y_train), len(y_dev)))
```

Graph sessions are taken to plot loss and accuracy for 10000 epochs displaying at each 1000 steps.

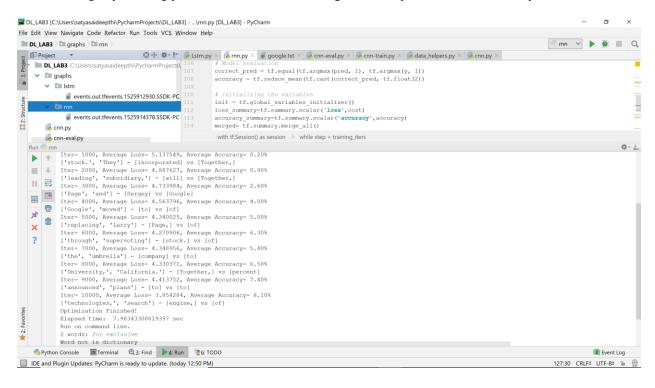
```
# Training
with tf.Graph().as default():
     session conf = tf.ConfigProto(
       allow soft placement=FLAGS.allow soft placement,
       log device placement=FLAGS.log device placement)
     sess = tf.Session(config=session conf)
     with sess.as default():
          cnn = TextCNN(
              sequence_length=x_train.shape[1],
              num classes=y train.shape[1],
              vocab size=len(vocab processor.vocabulary ),
              embedding size=FLAGS.embedding dim,
              filter sizes=list(map(int, FLAGS.filter sizes.split(","))),
              num filters=FLAGS.num filters,
              12 reg lambda=FLAGS.12 reg lambda)
          # Define Training procedure
          global step = tf.Variable(0, name="global step", trainable=False)
          optimizer = tf.train.AdamOptimizer(1e-3)
          grads and vars = optimizer.compute gradients(cnn.loss)
          train op = optimizer.apply gradients(grads and vars, global step=global step)
       # Keep track of gradient values and sparsity (optional)
       grad_summaries = []
       for g, v in grads_and_vars:
          if g is not None:
             grad_hist_summary = tf.summary.histogram("{}/grad/hist".format(v.name), g)
              sparsity_summary = tf.summary.scalar("{}/grad/sparsity".format(v.name), tf.nn.zero_fraction(g))
              grad summaries.append(grad hist summary)
              grad summaries.append(sparsity summary)
       grad summaries merged = tf.summary.merge(grad summaries)
       # Output directory for models and summaries
       timestamp = str(int(time.time()))
      out_dir = os.path.abspath(os.path.join(os.path.curdir, "runs", timestamp))
       print("Writing to {}\n".format(out_dir))
       # Summaries for loss and accuracy
       loss summary = tf.summary.scalar("loss", cnn.loss)
       acc_summary = tf.summary.scalar("accuracy", cnn.accuracy)
       # Train Summaries
       train_summary_op = tf.summary.merge([loss_summary, acc_summary, grad_summaries_merged])
       train_summary_dir = os.path.join(out_dir, "summaries", "train")
       train_summary_writer = tf.summary.FileWriter(train_summary_dir, sess.graph)
       # Dev summaries
      dev summary op = tf.summary.merge([loss summary, acc summary])
      dev_summary_dir = os.path.join(out_dir, "summaries", "dev")
       dev_summary_writer = tf.summary.FileWriter(dev_summary_dir, sess.graph)
```

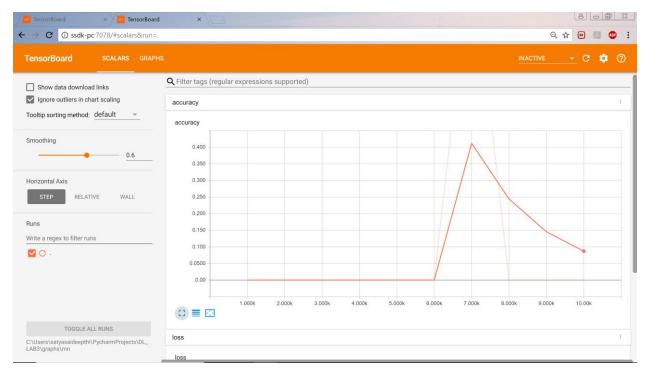
```
\# Checkpoint directory. \underline{\text{Tensorflow}} assumes this directory already exists so we need to create it
checkpoint dir = os.path.abspath(os.path.join(out dir, "checkpoints"))
checkpoint_prefix = os.path.join(checkpoint_dir, "model")
if not os.path.exists(checkpoint dir):
   os.makedirs(checkpoint_dir)
saver = tf.train.Saver(tf.global_variables(), max_to_keep=FLAGS.num_checkpoints)
# Write vocabulary
vocab processor.save(os.path.join(out dir, "vocab"))
# Initialize all variables
sess.run(tf.global_variables_initializer())
def train_step(x_batch, y_batch):
   A single training step
   feed dict = {
     cnn.input_x: x_batch,
     cnn.input_y: y_batch,
     cnn.dropout_keep_prob: FLAGS.dropout_keep_prob
   _, step, summaries, loss, accuracy = sess.run(
       [train_op, global_step, train_summary_op, cnn.loss, cnn.accuracy],
       feed dict)
   time_str = datetime.datetime.now().isoformat()
   print("{}: step {}, loss {:g}, acc {:g}".format(time_str, step, loss, accuracy))
   train_summary_writer.add_summary(summaries, step)
 def dev_step(x_batch, y_batch, writer=None):
     Evaluates model on a dev set
     feed_dict = {
       cnn.input_x: x_batch,
       cnn.input_y: y_batch,
       cnn.dropout_keep_prob: 1.0
     step, summaries, loss, accuracy = sess.run(
         [global_step, dev_summary_op, cnn.loss, cnn.accuracy],
          feed dict)
     time str = datetime.datetime.now().isoformat()
     print("{}: step {}, loss {:g}, acc {:g}".format(time str, step, loss, accuracy))
     if writer:
          writer.add summary(summaries, step)
```

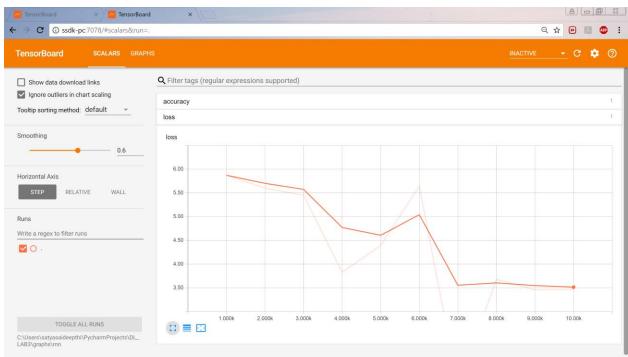
```
# Generate batches
batches = data_helpers.batch_iter(
    list(zip(x_train, y_train)), FLAGS.batch_size, FLAGS.num_epochs)
# Training loop. For each batch...
for batch in batches:
    x_batch, y_batch = zip(*batch)
    train_step(x_batch, y_batch)
    current_step = tf.train.global_step(sess, global_step)
    if current_step % FLAGS.evaluate_every == 0:
        print("\nEvaluation:")
        dev_step(x_dev, y_dev, writer=dev_summary_writer)
        print("")
    if current_step % FLAGS.checkpoint_every == 0:
        path = saver.save(sess, checkpoint_prefix, global_step=current_step)
        print("Saved model checkpoint to {}\n".format(path))
```

RESULTS:

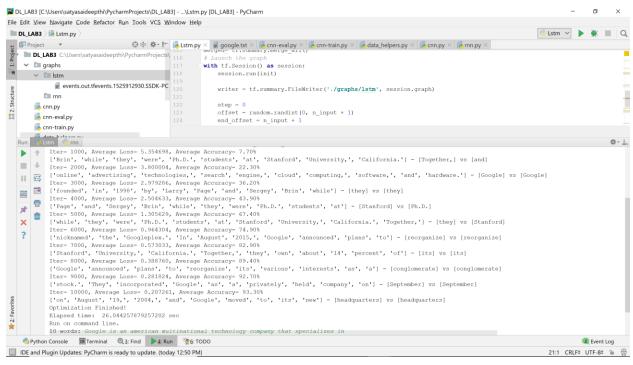
Code is deployed on pycharm console showing accuracy and loss for every 1000 iteration.

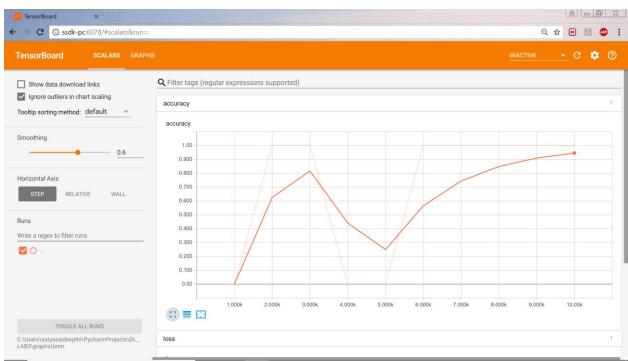


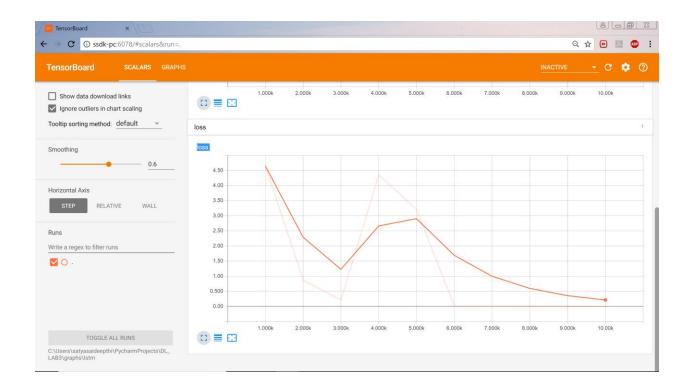




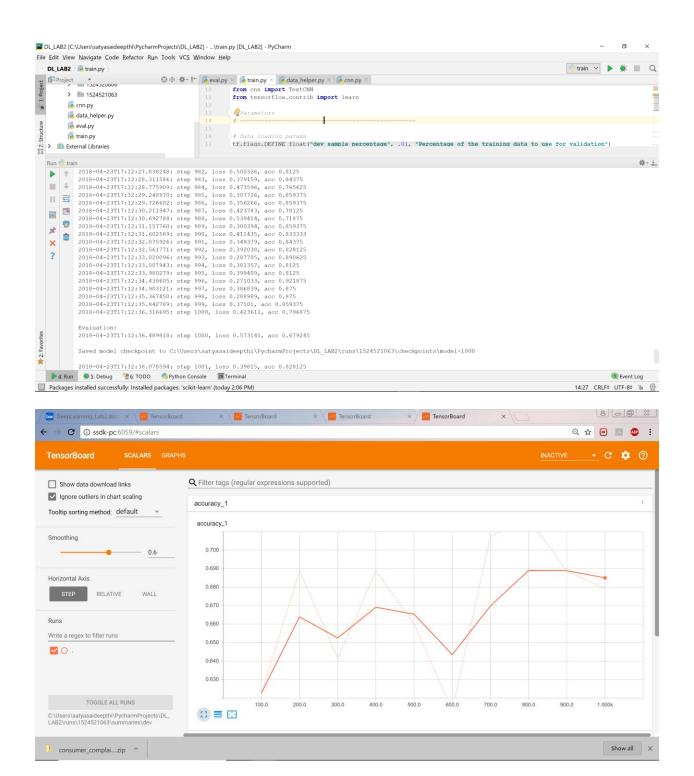
LSTM

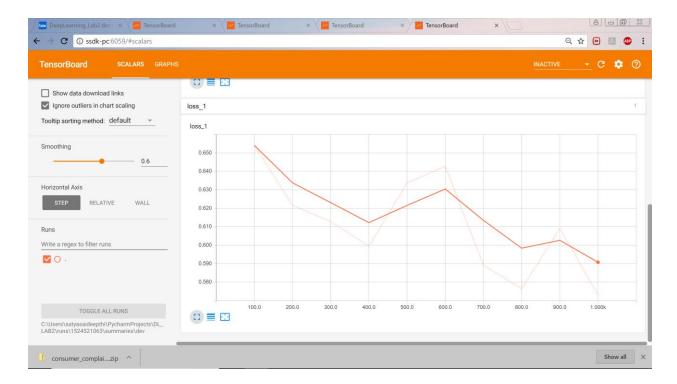






CNN





CONCLUSION:

We observe that the text is short and sentimental analysis is less but the text considered is about the company, RNN gives best results. When the text classification is based on the feature detection like giving sentimental analysis example angry, sadness etc CNN gives more accuracy than recurrent networks.