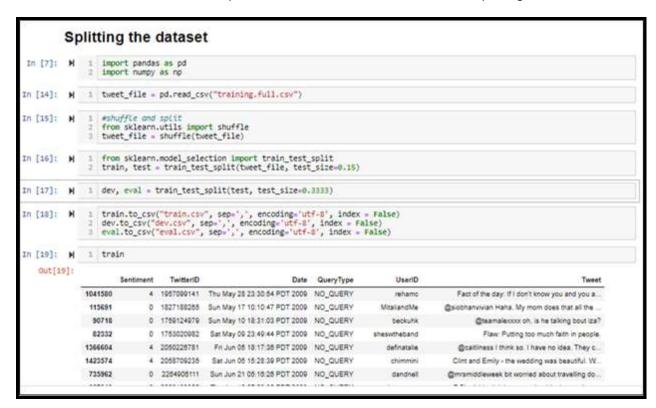
<u>Modelling Competition – Assignment 6</u>

1. Pre-processing

The data was downloaded using the link given in the prompt and then split into train, eval and dev with a 85%, 10% and 5 % split. The below code was used for the splitting.



This split csv file was uploaded on the S3 bucket and then we ran crawlers on them to make tables on AWS.



Integrating the code on our Git with TravisCI

Pylint and Pytest of the Preprocessing code

We were able to achieve a Pylint score of 10/10 after many iterations of updating the code and having the correct variables as well the correct alignment for each of the functions which are a part of our code.

```
The command "pytest --cov ./" exited with 0.
$ pylint ./twitter_file.py

Your code has been rated at 10.00/10

The command "pylint ./twitter_file.py" exited with 0.
$ pylint ./twitter_file_test.py

Your code has been rated at 10.00/10

The command "pylint ./twitter_file_test.py" exited with 0.
```

Coverage of the preprocessing code: We were able to get a coverage of 82% for our code. The images below report the coverage of our code:

Name	Stmts	Miss	Cover
nltoolkit.py	56	24	57%
twitter_file.py	59	2	97%
twitter_file_test.py	29	0	100%
TOTAL	144	26	82%

We then ran ETL jobs on them to make JSON files.



2. Tensorflow model using CNN

In order to do this step, we used the following code to -

- Load embedding into a dictionary and then making an embeddings matrix.
- Made a CNN model which will be trained on our data and saved it.
- The simple CNN model using Adam optimizer was taking around 2.5 hours for just 1 epoch on local system and around 1 hour on SageMaker.
- We did some research to reduce the computation time and found other optimizers such as SGD which runs in significantly lesser time.
- However, our accuracy was compromised while fitting the model on such large dataset
- Below is the change we did for SGD and our corresponding results.

The image below shows the CNN model with SGD optimizer.

```
model = Sequential()
model.add(Embedding(config['embeddings_dictionary_size'], config['embeddings_vector_size'], weight] [matrix_emb], no
model.add(Conv1D(filters [] 100, kernel_size [] 2Dectivation [] 'relu', padding [] 'valid', strides [] 1,))
model.add(GlobalMaxPoolID())
model.add(Dense(100, activation [] 'relu'))
model.add(Dense(100, activation [] 'sigmoid', name []'score'))
model.compile(optimizer='sgd', loss='binary_crossentropy', metrics=['accuracy'])
cnn_model = model
return cnn_model
```

The Result of this code on running locally was as follows:

```
lbase) dyn-168-39-142-39:model127 umeshbodwari$ gethon sentiment training.gy --train 'dots/train/' --dee 'dats/dev/'
                                                                                                               -eval "data/eval/" -raw esech 40 -config "training config.json" -model sutput dir
Entering training file
Entering dataset file
Entering model on file
Preparing for training...
Fetcking train data...
MANTAD:temporflow:From /Users/umeshbothworl/anacomde3/lin/python3.T/site-pockages/temsorflow/python/data/uril/random_meed.py:88: add_dispatch_mapport.wlecalsv.umapper (from temporflow.python.ops.array_ops)
ill be removed in a future version.
Instructions for updating:
Use of where in 2.6, which has the same broadcast cale as sp.where
WANKING: tensorflow: From / Obsers/smeshipetheani/Desktop/Conves/AI_Cloud/Initterh/teitier_compressed/model127/sentiment_datasot.pg: 85: Unitasotin.move_eno_shot_iterator (from tensorflow.pythom.data.eps.datasot_ap
Instructions for updating:
Use 'for ... in dataset: to iterate over a dataset. If using 'tf.estimator', return the 'Dataset' sbject directly from your legut function. As a last resort, you can use 'tf.compat.vi.data.make_one_shot_itm Fetching dev data...
Fotobing eval data...
MARTNO:tersorTlaw:From /Users/ameshandhwani/anacondu3/lia/pythor3,7/site-packages/tersorTlaw/python/kerse/init/alizers.py:159: calling Nundominiform.__imit__ (from tensorTlaw.python.ops.init_sps) with dtype will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of pessing it to the constructor
2022-03-09 13:29:51,734420: I temporfize/core/platform/cou feature quard.cc:142] Your CPU exports instructions that this Temporfize instructions that this Temporfize instructions that the time Temporfize instructions that the Temporfize instructions are considered to use: 4892 784
MARKAD:Tensorflow:From //mers/unes/pashwant/anacondu8/lib/python2.7/site-packages/tensorflow/python/ops/init_ops.py:2251; calling VarianceScaling, _init__ (from tensorflow.python.ops.init_ops) with dtype is I in removed in a future version.
Instructions for applicting:
Dall initializer instance with the dtype argument instead of passing it to the constructor
Starting training ...
                     13400/13600 [=
               13600/13600 [+
                       Epoch 4/48
13688/13688 [4
                       manusanananananananana) - 48s 4as/stap - loss: 0.6774 - acc: 0.5889 - val loss: 0.6719 - val acc: 0.5885
```

```
13600/13600
          Epoch 8/48
     13600/13600 [
Epoch 9/48
13600/13600
       Epoch 10/40
13688/13688
     Epoch 11/48
13600/13600
       Epoch 12/48
13600/13600
      Epoch 13/48
13600/13600
     Epoch 14/48
13600/13600
          Epoch 15/48
13600/13600
       Epoch 16/48
13600/13600
        Epoch 17/48
13600/13600
     Epoch 18/48
13600/13600
      Epoch 19/48
13600/13600
         Epoch 20/40
13600/13600
        Epoch 21/48
13600/13600
        Epoch 22/48
13600/13600
     Epoch 23/48
13600/13600
      Epoch 24/48
13600/13600
       Epoch 25/48
13600/13600
     -----1 - 55s 4ms/step - loss: 0.6580 - acc: 0.6058 - val loss: 0.6582 - val acc: 0.6055
Epoch 26/48
13600/13600
     ================================ ] - 56s 4ms/step - loss: 0.6577 - acc: 0.6061 - val_loss: 0.6579 - val_acc: 0.6068
Epoch 27/40
     13600/13600
Epoch 28/48
     13600/13600
Epoch 29/48
13680/13688
           ******************* - 55s 6ms/step - loss: 0.6570 - acc: 0.6660 - val_loss: 0.6573 - val_acc: 0.6662
Epoch 38/48
13600/13600
           31/46
13600/13600
Epoch 32/40
13600/13600
           Epoch 33/46
13688/13688
         ##################### - 49s Ams/step - loss: 8.6562 - acc: 8.6879 - val_loss: 8.6564 - val_acc: 8.6978
            Epoch 35/48
13600/13600
            ******************** - 55s Ams/step - loss: 0.6558 - acc: 0.6865 - val loss: 0.6561 - val acc: 0.6883
poch 36/48
13600/13600
           Epoch 37/40
13600/13600
              =======] - 57s Ams/step - loss: 8.6554 - acc: 8.6689 - val_loss: 8.6557 - val_acc: 8.6887
Epoch 38/48
13688/13688 [===
        39/40
13689/13688
          Epoch 40/40
13598/13600 [=
   13600/13600 [ ----
Test loss:0.6535608787889586
Test sccuracy:0.6125375032424927
e verocity to M (on Linux, export AutoMAPH_VENBOSITY=10 ) and attach the full butput. Gause: converting <function canonicalize_Name: 3, expecting 4
MARNING:tensorflew:Entity <function Function._initialize_uminitialized_variables.<locale>.initialize_variables at 0x647378c80> could
n filing the bug, set the verbosity to 10 (on Linux, 'export AUTOGRAPH_VERBOSITY=10') and attach the full output. Gause: converting
78c80>. AttributeError: module 'gast' has no attribute 'Num'
Model successfully saved at: ./sentiment_model.hb
```

We got a Test accuracy of 61.2% with this SGD Optimization in our CNN Model.

We also tried to increase the number of layers and changed the optimizer to Adadelta this time.

Below is our modified code and the corresponding results.

```
model = Sequential()
          model.add(Embedding(config['embeddings_dictionary_size'], config['embeddings_vector_size'], weights=[matrix_emb], name='embedding', input_length
          model.add(ConviD(filters A 100, kernel_size A 2Dactivation A 'relu', padding A 'valid', strides ∏ 1,))
          model.add(Conv1D(filters A 50, kernel_size A 3)activation A 'relu', padding A 'valid', strides A(1,))
          model.add(ConviD(filters | 20, kernel_size | 2|activation | 'relu', padding | 'valid', strides | [1,))
          model.add(Flatten())
          model.add(Dense(180, activation f 'relu'))
          model.add(Dense(1, activation | 'signoid', name | 'score'))
          model.compile(optimizer='adadelta', loss='binary crossentropy', metrics=['accuracy'])
          cnn_model = model
           return cnn model
(base) 6yr-168-39-142-39:model127 uneshbodheuni$
       dyn-188-30-187-Winofelt?? unestandmani$ sytton sestiment training.sy --train "data/train/" -des "data/des/" -evel "data/essl/" -ran_esach 48 --config "training_config.jun" -model_output_dir "."
Estaring training file
Entering dataset file
Estaring model con file
Proposing for training...
Fetching train data...
WWRNDC:tenderflow.from /Usern/usesbbodhwini/anapomda3/lik/python3.7/site-packages/tenserflow/python/data/stil/random_seed.py:58: add_dispatch_mapport.
ill be renewed in a future version
Instructions for updating:
Use of where in 2.8, which has the same proadcast rule as sp. where
WWRING:tensorflow:Form (bers/unestbookmani/Desktop/Cannas/AL Cloud/twitters/twitter newsresset/model127/sortiment dataset.pv:88; Dataset/I.make one shot iterator (from tensorflow.puthon.data.uss.dataset oca) is d
Instructions for updating:
Des for ... in dataset: to iterate over a dataset. If using 'if.estimator', return the 'Dataset' object directly from your input function. He a lest resert, you can use 'tf.compat.et.data.make.one.akot_lineaturide
Fetching day data ....
WRRDNO:tensorflow:Form /bacts/unsabbethesni/anacenda3/lis/sython3.7/sito-packages/tensorflow/python/keras/initializers.by:13% celling RandosDelfore._init_ | from tensorflow.bythos.ops.init_ass| with dtype is dep
will be removed in a future estation.
Sestructions for updating:
     initializer instance with the dtype argument instead of passing it to the constructor
3839-88-89 12:34:43.472877; I temporflow/core/platform/cpu_feature_guard.cc:142) Your CRU supports instructions that this Temporflow binary was not compiled to use: NNO FRE WENTHOLOGIAL COLORS (Introduced Colors) And 
  be removed in a future version
Instructions for updating:
Call initializer instance with the otype argument instead of passing it to the constructor
Starting training...
13600/13680 |+
                              23689/13688
                             13600/13688 Ta
                            Epoch 4/48
13689/13689 [5
                            Epoch 5/48
15688/15688 To
                             Epoch 6/48
33680/13688
                            Epoth 7/48
13689/13688 [
                              Epoch 8/48
13688/13688 [
                             Esoth 9748
                              Exect 18/48
```

```
Epoch 12/48
13608/13600
               Epoch 13/48
13600/13600 [
                  Epoch 14/48
13600/13600
                 Epoch 15/40
13608/13600 [
                             - 174s 13ms/step - loss: 8.6629 - scc: 8.6833 - val loss: 8.6638 - val acc: 8.6637
Epoch 16/48
13600/13600
                            - 182s 13ms/step - loss: 8.6628 - acc: 8.6842 - val_loss: 8.6621 - val_acc: 8.6842
Epoch 17/48
13608/13600 [
                 Epoch 18/40
13608/13688 [
                   Epoch 19/48
13600/13600 [
                            - 177s 13ms/step - loss: 8.6599 - acc: 8.6862 - val loss: 8.6682 - val acc: 8.6868
Epoch 28/48
                            - 176s 13ms/step - loss: 0.6694 - acc: 0.6867 - val loss: 0.6598 - val acc: 0.6071
Fonch 21/48
13600/13600 [
                            - 194s 14ms/step - loss: 0.6590 - scc: 0.6872 - vel loss: 0.6594 - vel scc: 0.6878
Epoch 22/48
13600/13600 [
                          ==] - 181s 13ms/step - loss: 8.6586 - acc: 8.6876 - val_loss: 8.6598 - val_acc: 8.6688
Epoch 23/40
13608/13600 [
                   Fonch 24/48
13600/13600 [
                            - 183s 13ms/step - loss: 0.6579 - acc: 0.6884 - val_loss: 0.6583 - val_acc: 0.6086
Epoch 25/48
13600/13600
                    Ennch 2A/AB
13600/13600 [=
                    ============ ] - 175s 13ws/step - loss: 0.6673 - mcc: 0.6889 - val_loss: 0.6677 - val_ecc: 0.6892
Ennch 27/48
13600/13600
                   Epoch 28/48
13608/13600 [=
                  Epoch 29/48
13600/13600 [
                 Epoch 38/48
13600/13600 [
                     Epoch 31/48
13608/13600 [
              Epoch 32/48
                 ******************* - 181s 13ms/step - loss: 0.6558 - acc: 0.6103 - val_loss: 0.6562 - val_acc: 0.6109
13600/13600 [
Epoch 33/40
                  13608/13600
Epoch 34/48
13600/13600 I=
             Epoch 35/48
              13608/13600 E
13608/13600
         Enoch 34/48
13608/13680
                    Epoch 35/48
13608/13680 [
                   mmmmmmmmmm] - 207s 15es/step - loss; 0.6552 - scc: 0.6110 - val_loss; 0.6556 - val_scc: 0.6113
Enoch 36748
13600/13600
                    ============ ] - 247s 18ms/step - loss: 8.6558 - acc: 8.6118 - val_loss: 8.6553 - val_acc: 8.6116
Epoch 37/48
13608/13600 [=
                 Enoch 38/48
13608/13688
                 Enoch 39748
                13600/13600 [=
Epoch 48/48
13597/13600 [=
                        ====>.] - ETA: 0s - loss: 0.6542 - acc: 0.6118WARNING:tensorflow:Your dataset iterator ran out of data;
 steps + epochs' batches (in this case, 1601 batches). You may need touse the repeat() function when building your dataset
13600/13600 [===
                 Test loss:0.6533593118190766
Test accuracy:8.6151624917984889
Saving model
2028-03-09 15:37:33.748003: W tensorflow/pythan/util/util.cc:280] Sets are not currently considered sequences, but this may change in the fut
MARNING: tensorflow: Entity < function Function, initialize uninitialized variables. < locals. initialize variables at 8x62f861a68> could not be t n filing the bug, set the verbosity to 18 (on Linux, 'export AUTOGRAPH_VERBOSITY=18') and attach the full output. Cause: converting < function
61a60>: AttributeError: module 'gast' has no attribute 'Num'
MARNING:tensorflow:Entity <function canonicalize signatures.<locals>.signature_wrapper at 0x62f861a60> could not be transformed and will be e
 verbosity to 18 (on Linux, 'export AUTOGRAPH_VERBOSITY=18') and attach the full output. Cause: converting ∢function canonicalize_signatures
Name: 3, expecting 4
MARNING:tensorflom:Entity <function Function._initialize_uninitialized_variables.<locals>.initialize_variables at 8=644ea6378> could not be
 n filing the bug, set the verbosity to 18 (on Linux, 'export AUTOGRAPH VERBOSITY=18') and attach the full putput. Cause: converting <function
a6378>: AttributeError: modula 'gast' has no attribute 'Num'
Model successfully saved at: ./sentiment_model.h5
```

Test accuracy at local system using Adadelta optimizer: 61.5%

(base) dyn-160-39-142-39; model127 umeshbodhwani\$

While Adadelta took more time than SGD, the difference in their results was not significant.

Our best model:

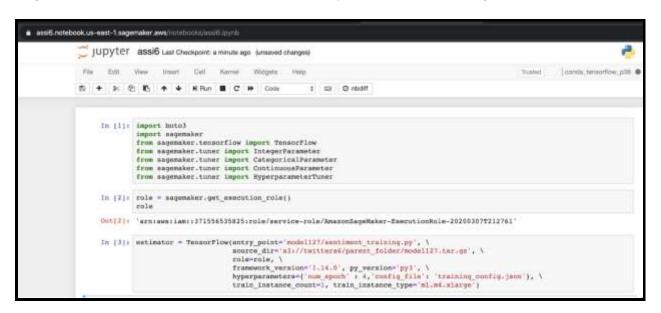
The best accuracy was obtained using the Adam optimizer with more hidden layers, but it took quite a lot time. Hence we decided to run the model on SageMaker with just 4 epochs.

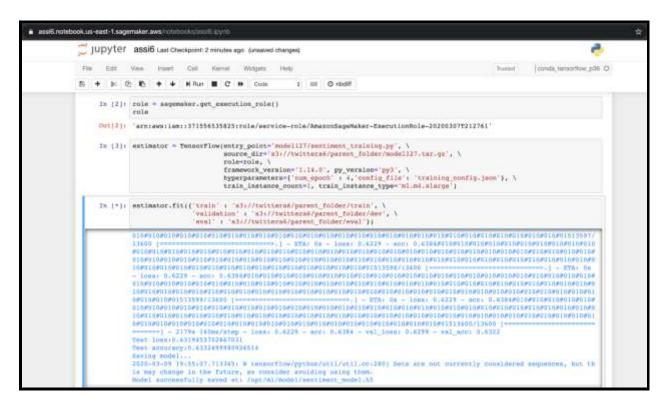
- 1) We were able to run our model successfully on SageMaker.
- 2) We faced a lot of issues in running SageMaker with the Educate account. It runs when we upload all our files into SageMaker Jupyter, but even that fails given the huge amount of data for this assignment.
- 3) We did some research on this and found that the only way to run SageMaker on such huge data was that we save our data in S3 bucket and let SageMaker pick our data from there. For this, we used our personal account on AWS.

3. Sagemaker Training

As part of this step, we started a Notebook Instance (Jupyter) on AWS SageMaker and deployed our model.

While doing this through the Educate account, we were not able to get access to the required instances and hence we used a Private account in order to deploy our model on AWS SageMaker. With this we were able to successfully run our model on SageMaker.



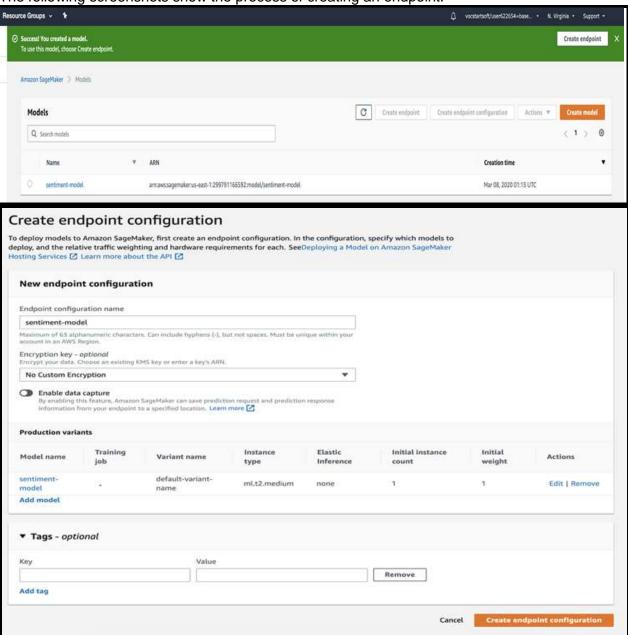


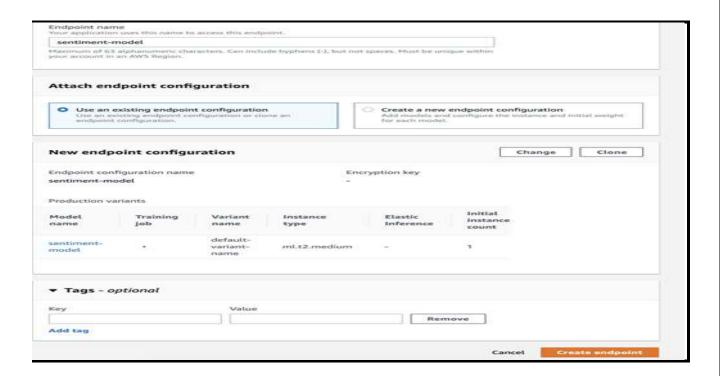
We used the Adam optimizer for training our model on SageMaker. We noticed that each epoch took around 1 hour to run. Hence we could only train our sagemaker model on 4 epochs and got an accuracy of around 64%.

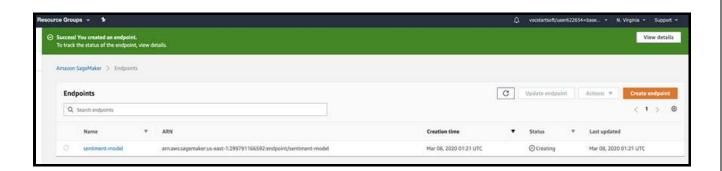
Had we been given more computation power, we would have run our CNN model on a larger number of epochs and achieved a better accuracy

Sagemaker Inference

In this step, we then deployed our model as a SageMaker inference endpoint. While doing this, in the endpoint configuration we used the cheapest instance "ml.t2.medium". The following screenshots show the process of creating an endpoint.







4. Model Deployment

As part of this step, we have made a Lambda Function that does the following:

- Pre-process with our code for the pipeline
- Model inference with the SageMaker endpoint
- · Post processing

The lambda function takes JSON input with a "tweet" key and produces a JSON output with a "sentiment" key and a value that can either be "positive" or "negative" based on the model prediction.

In order to test this part, we are giving a sample tweet and then checking if its been identified as positive or negative.

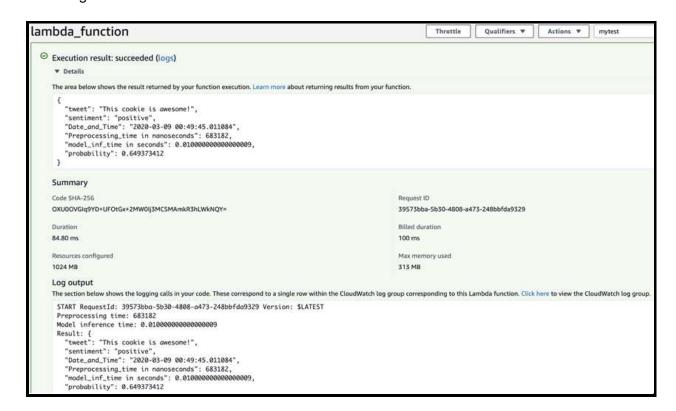
```
lambda_function.py ×
      twitter_file im
                          or TwitterClass
tw = TwitterClass()
sage_maker_client( = boto3.client("runtime.sagemaker")
def lambda_handler(event, context):
     now = datetime.datetime.now()
    Date_and_Time str(now)
    initial_time time.time_ns()
    tweet = event["tweet"]
    features = tw.processed(tweet)
    final_time | time.time_ns()
    Preprocessing time | final time initial time print('Preprocessing time: 'Preprocessing time)
    model_payload = {
    'embedding_input': features,
    model_initial_time@ time.clock()
    model_response = sage_maker_client.invoke_endpoint(
         EndpointName="sentiment-model",
ContentType="application/json",
         Body | json.dumps(model_payload))
    model_final_time( time.clock()
    model_inf_time = model_final_time = model_initial_time
print('Model inference time: 'Qmodel_inf_time)
    result = json.loads(model_response["Body"].read().decode())
    response = {}
    response ["tweet"] tweet
    result["predictions"][0][0] == 0.5:
response["sentiment"] = "positive"
         response["sentiment"] = "negative"
    response['Date and Time'] = Date and Time
    response['Preprocessing_time in nanoseconds'] = Preprocessing_time response['model_inf_time in seconds'] = model_inf_time
     response['probability'] = result["predictions"][0][0]
    print () Result: " | json.dumps(response, indent () 2))
             response
```

Payload Logging using Lambda Function

Here we modified the Lambda Function (above) created to calculate and display the following:

- Date and time of the request
- Tweet
- Sentiment
- Probability from the model
- Pre-processing time
- Model inference time

Then the lambda function logs a JSON object to the bucket in S3 with the above details. The image below shows our result on AWS.

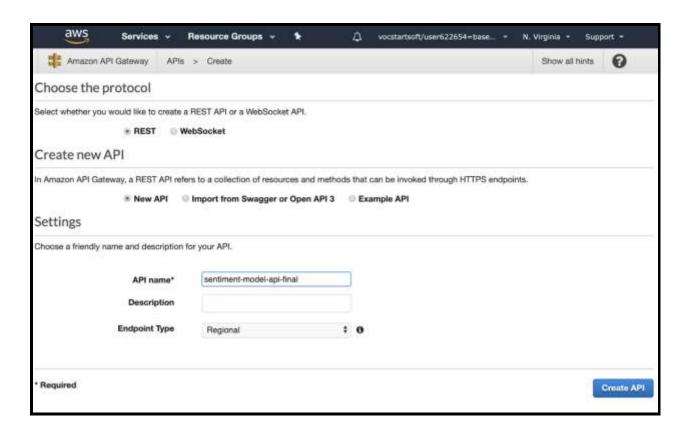


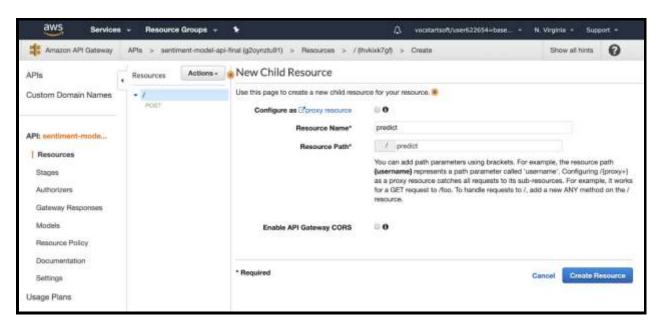
REST API

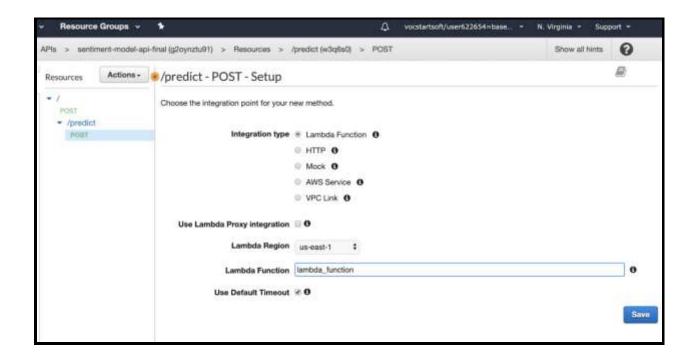
Here in this step we created an API Gateway to expose our lambda function.

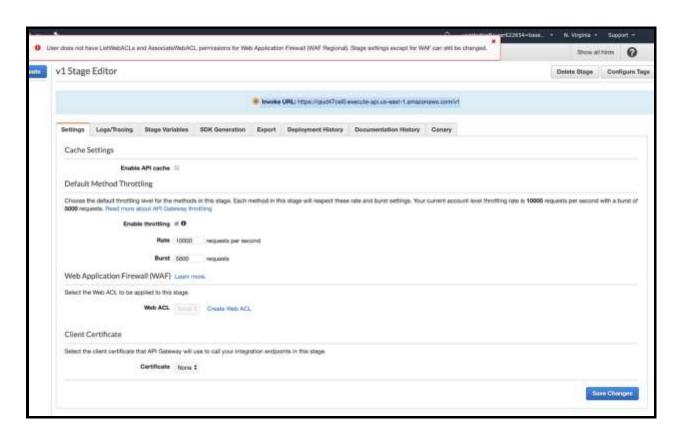
The gateway implemented a "/predict" resource with a "POST" request method.

We then deployed it under a "v1" stage. The following set of images shows how we went about this process:





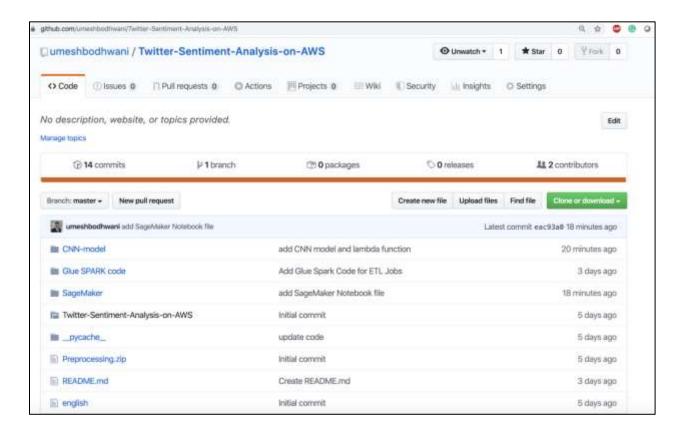


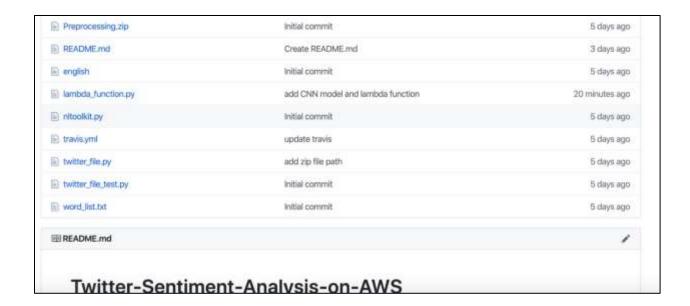


Invoke URL: https://qiud47cei0.execute-api.us-east-1.amazonaws.com/v1

```
| tase| dpn-164-35-143-151: uneshbodwani$ |
```

curl -X POST https://qiud47cei0.execute-api.us-east-1.amazonaws.com/v1/predict --header "Content-Type:application/json" --data '{"tweet": "This cookie is awesome!"}'





Links:

Embedding dict: https://twittera6.s3.amazonaws.com/parent_folder/embedding_list/glove.txt

Train: https://twittera6.s3.amazonaws.com/parent_folder/train/train.json

Dev: https://twittera6.s3.amazonaws.com/parent_folder/dev/dev.json

Eval: https://twittera6.s3.amazonaws.com/parent_folder/eval/eval.json

Model: https://twittera6.s3.amazonaws.com/parent_folder/model127.tar.gz

Github URL: https://github.com/umeshbodhwani/Twitter-Sentiment-Analysis-on-AWS

REST API Deployment link:

curl -X POST https://qiud47cei0.execute-api.us-east-1.amazonaws.com/v1/predict --header "Content-Type:application/json" --data '{"tweet": "This cookie is awesome!"}'