ILLINOIS INSTITUTE OF TECHNOLOGY

Implementation of Sentiment analysis with Sagemaker and Spark

Use of Big Data in Machine Learning Systems

BIG DATA TECHNOLOGIES
(CSP – 554)

Submitted by:

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INTRODUCTION

Machine learning is the process through which an algorithm makes predictions without having that function explicitly coded into it. Data is the machine learning model's primary input. Large dataset management can be accomplished via big data. We can process vast amounts of data and generate predictions by combining Big Data with machine learning. Using techniques known as regression and classification, it may forecast numerical values or categorical values. The input data must be organized and clean before predictions can be made; this procedure is known as data cleaning. Exploratory data analysis can be used to learn more about the dataset. Divide the input dataset into train and test datasets after which you can develop a model and predict the target variable on new or test datasets using the training dataset.

Apache Spark is a data processing platform that, either independently or in combination with other distributed computing technologies, can efficiently analyze big datasets and distribute data processing tasks across several machines. Apache Spark employs Spark MLlib to carry out machine learning. A scalable Machine Learning toolkit built on Spark called MLlib puts equal emphasis on quick performance and high-quality algorithms.

At a high level, it provides tools such as:

- **ML Algorithms:** common learning algorithms such as classification, regression, clustering, and collaborative filtering
- **Featurization:** feature extraction, transformation, dimensionality reduction, and selection
- **Pipelines:** tools for constructing, evaluating, and tuning ML Pipelines
- **Consistency:** saving and loading algorithms, models, and Pipelines
- **Utilities:** linear algebra, statistics, data handling, etc.

MLlib is a program that supports Java, Python, R, and Scala that can analyze big data on Hadoop, Apache Mesos, Kubernetes, standalone, or on the cloud. Java, Python, and R can be used to implement it, and it can run on Hadoop, Apache Mesos, and Kubernetes. Faster than Map Reduce, practically all machine learning techniques are now available with Spark MLlib.

LITERATURE REVIEW

1. Big Data Machine Learning using Apache Spark MLlib

A study paper by Mehdi Assefi, Ehsun Behravesh, Guangchi Liu, and Ahmad P. Tafti was utilized as a reference for this project implementation in Spark-MLlib. To evaluate the ability of the Apache Spark MLlib 2.0 library in analyzing big data sets, the project focused on a set of supervised (classification) methods, including SVM (Support Vector Machine), Decision Tree, Naive Bayes, and Random Forest, along with a widely used unsupervised (clustering) machine learning algorithm, namely K-Means.

A total of Six various big datasets were used to analyze and compare the Apache Spark MLlib 2.0 performance. Five datasets from the UCI Machine Learning Repository, and a dataset from the US government's Bureau of Transportation Research and Innovative Technology Administration (RITA) Web sites.

2. Sentiment Analysis

Machine Learning models take numerical values as input. The reviews are made of sentences, so in order to extract patterns from the data; we need to find a way to represent it in a way that a machine learning algorithm can understand, i.e. as a list of numbers. Emotions are essential, not only in personal life but in business as well. How your customers and target audience feel about your products or brand provides you with the context necessary to evaluate and improve the product, business, marketing, and communications strategy. Sentiment analysis or opinion mining helps researchers and companies extract insights from user-generated social media and web content.

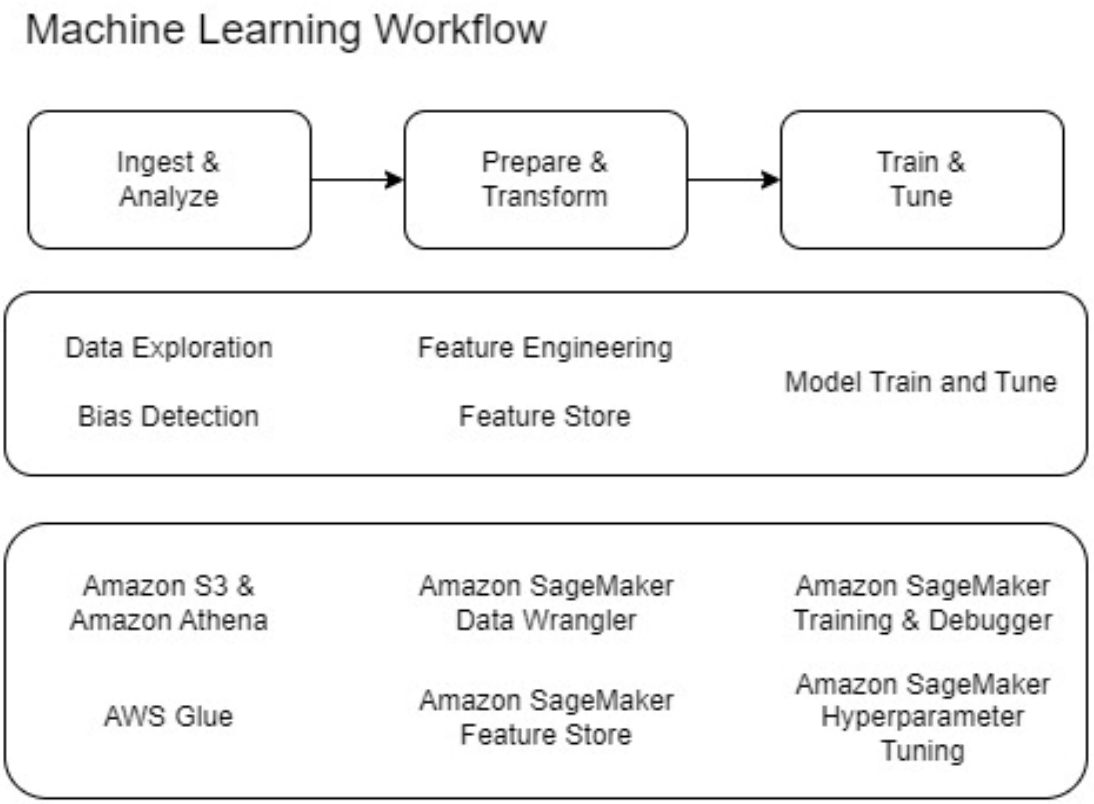
Irrespective of the industry or vertical, brands have become imperative to understand consumers' feelings about the brand and products. With cut-throat competition in the NLP and ML industry for high-paying jobs, a boring cookie-cutter resume might not just be enough. Instead, working on a sentiment analysis project with real datasets will help you stand out in job applications and improve your chances of receiving a call back from your dream company.

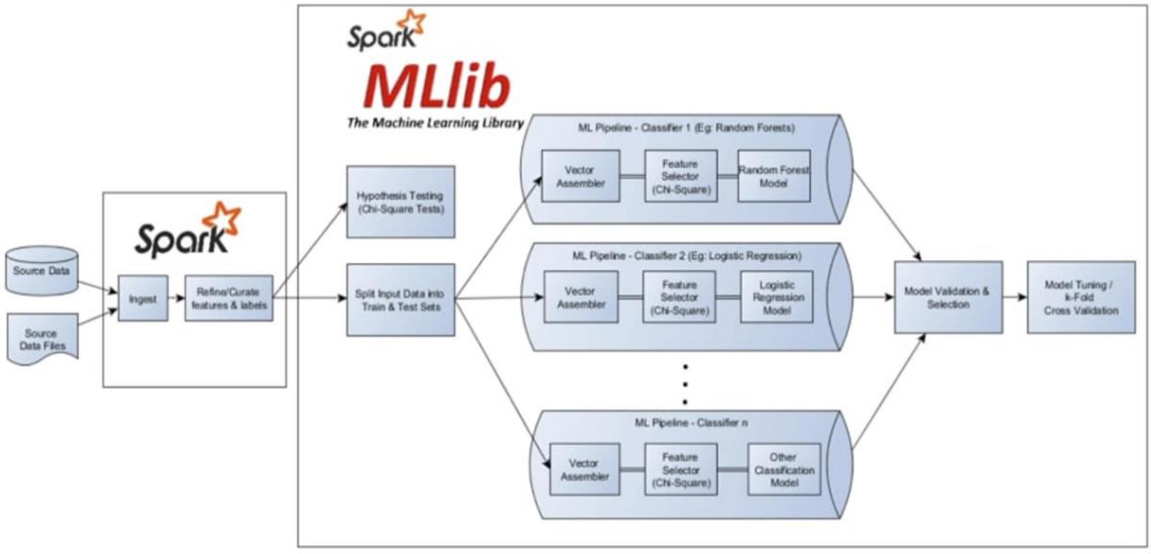
PROBLEM STATEMENT

It is considerably more difficult to discern someone's tone in writing than it is in conversation. For starters, you cannot infer an author's emotional condition from their facial expressions or body language. For instance, the tone of a message is typically not determined by a single characteristic. Numerous aspects are involved in effective communication. Because in some circumstances, what you say can be just as important as how you say it. Our approach is designed to offer feedback on a variety of keywords that represent the emotion of the message. It's also helpful in ensuring that your recipient will focus on the facts you are presenting rather than unintended consequences of your tone by making strategic judgments about how you convey your message.

WORK-FLOW

The steps implemented in this project are explained in the flowchart diagram below.





OBJECTIVE

To build a tone detector using Spark-MLibs and Sagemaker that performs better than or upto the state of-the-art models.

Bias Detection using AWS SageMaker Clarify

To demonstrate the effectiveness of Bias Detection solution we applied AWS SageMaker Clarify for bias detection on two datasets:

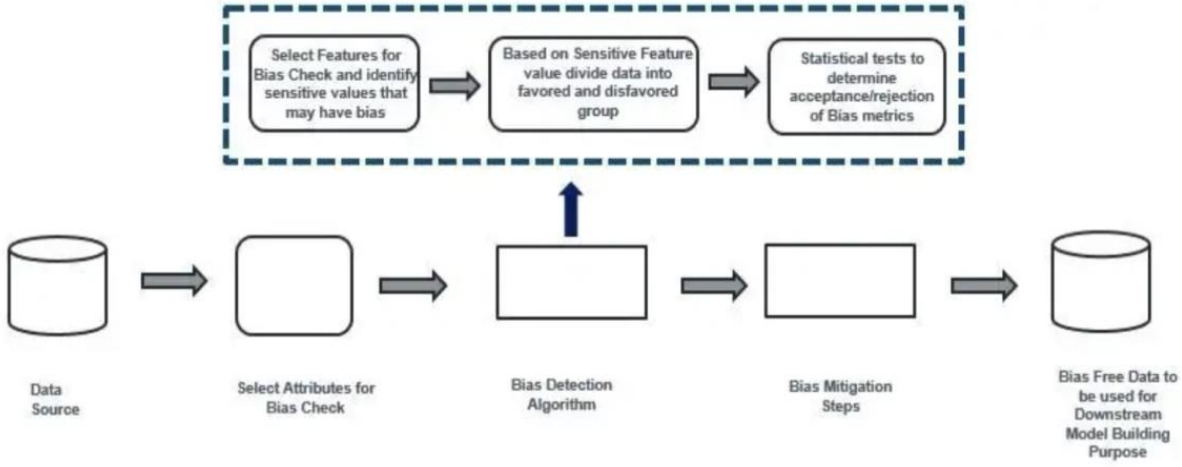
• Problem Statement:

1. Identify bias in datasets

2. Identify bias in Model Predictions.

• Data Source: //add data source here

• Solution Approach for Bias Detection using SageMaker Clarify: We leverage SageMaker Clarify to identify biases on above datasets. Below is a high-level solution approach for Bias Detection in datasets.



i. In the first step we identify those attributes that may cause bias.

ii. Once we have identified the sensitive attributes, we identify the range of values in these attributes which represent a disfavoured group.

iii. The sensitive attribute and sensitive value is fed to the Bias Algorithm.

iv. Within the Bias algorithm, the dataset is divided into a favored and disfavoured group based on the sensitive features and values specified.

v. Statistical tests are done, and pre-training and post-training metrics are computed for bias detection. Based on interpretation of statistical metrics, we identify the presence/absence of Bias.

• Exploratory Analysis Results: Data Exploration was done on the two datasets before the bias detection process.

AWS Sagemaker

SageMaker

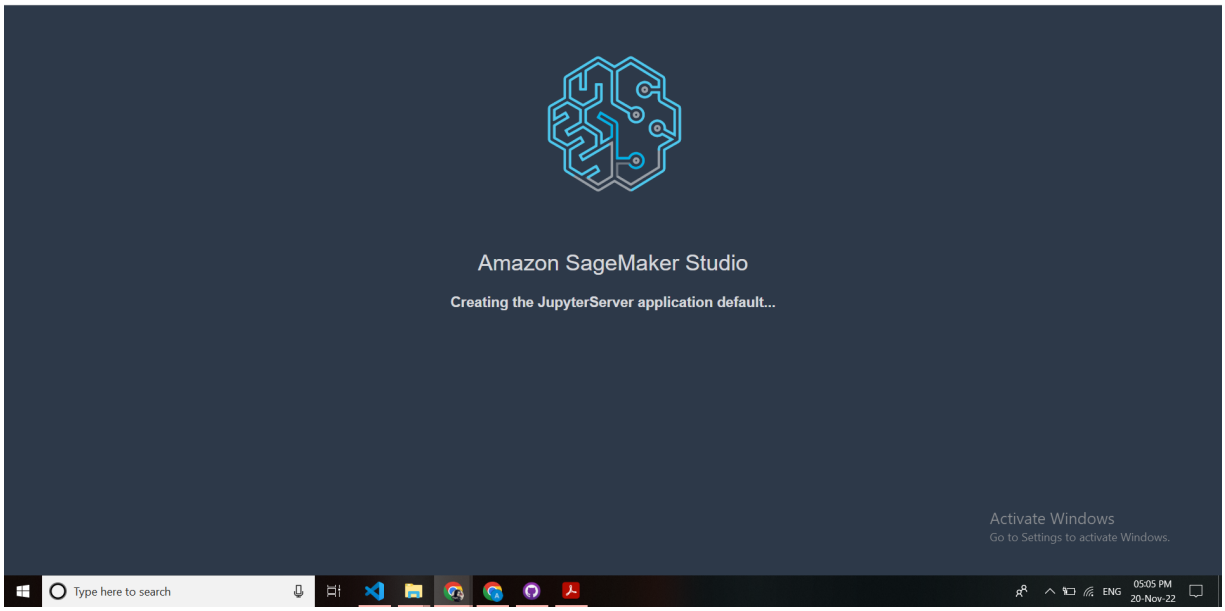
Amazon SageMaker automatic model tuning, also known as hyperparameter tuning, finds the best version of a model by running many training jobs on your dataset using the algorithm and ranges of hyperparameters that you specify. It then chooses the hyperparameter values that result in a model that performs the best, as measured by a metric that you choose. Amazon SageMaker automatic model tuning can use Amazon EC2 Spot instance to optimize costs when running training jobs. Before you start using hyperparameter tuning, you should have a well-defined machine learning problem, including the following:

- A dataset
- An understanding of the type of algorithm you need to train
- A clear understanding of how you measure success

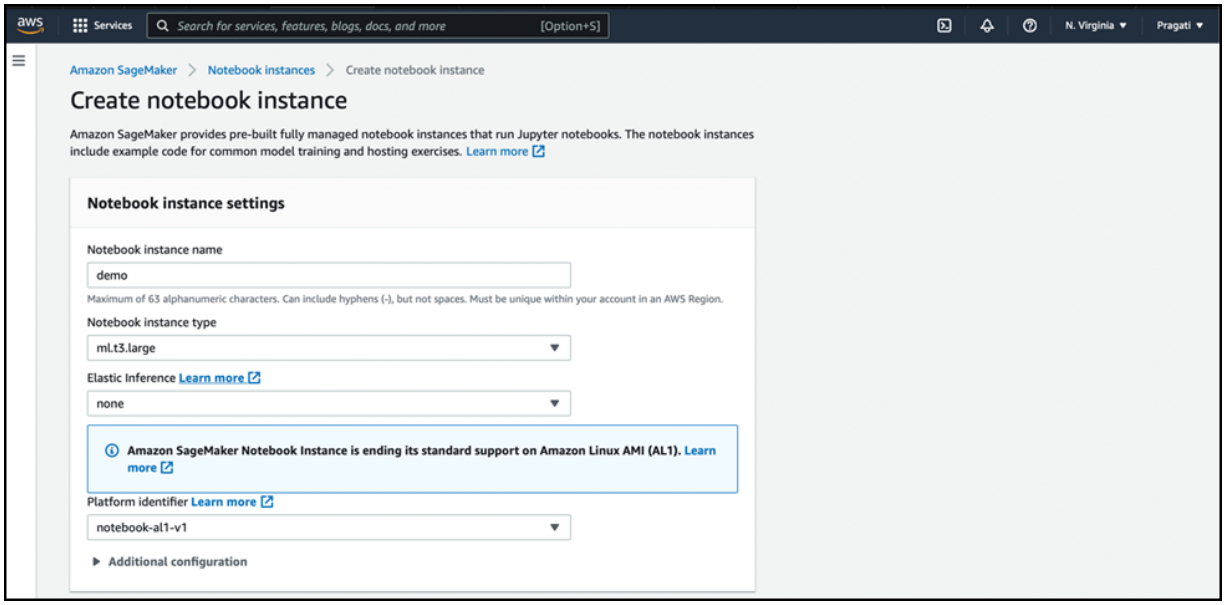
The complete machine learning pipeline, including labeling and prepping data, selecting an algorithm, training the model, fine-tuning and optimizing it for deployment, making predictions, and taking action, is covered by the fully-managed service Amazon SageMaker.

We have implemented the model with given dataset using sage maker, steps are represented below:

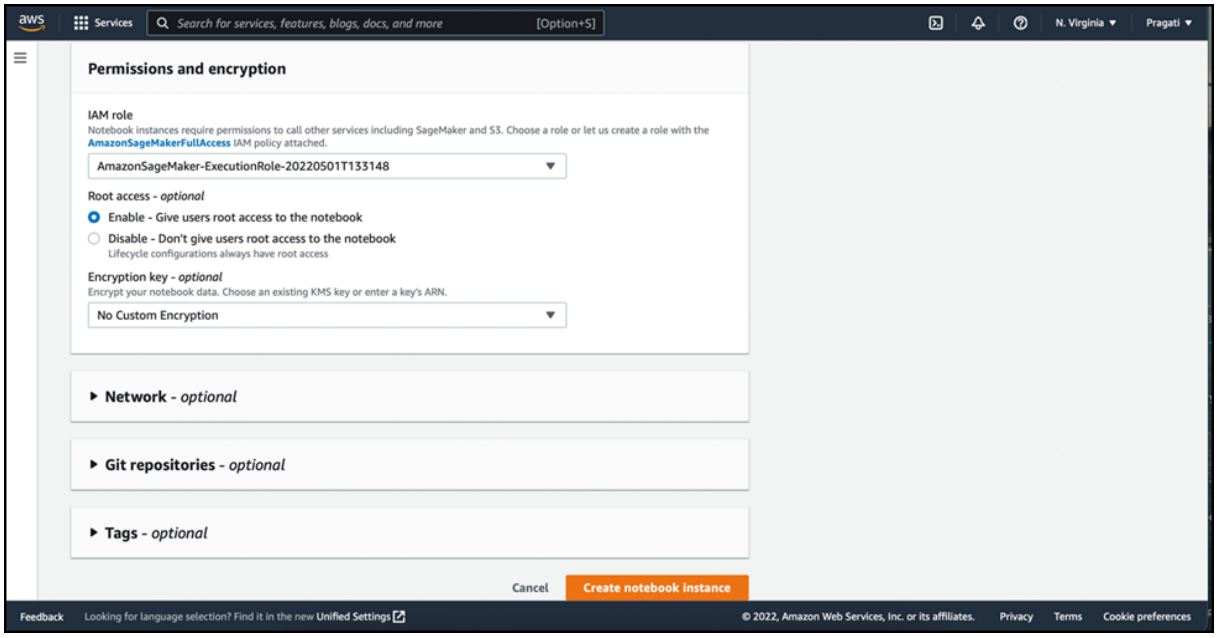
1.Starting up Amazon Sagemaker Studio



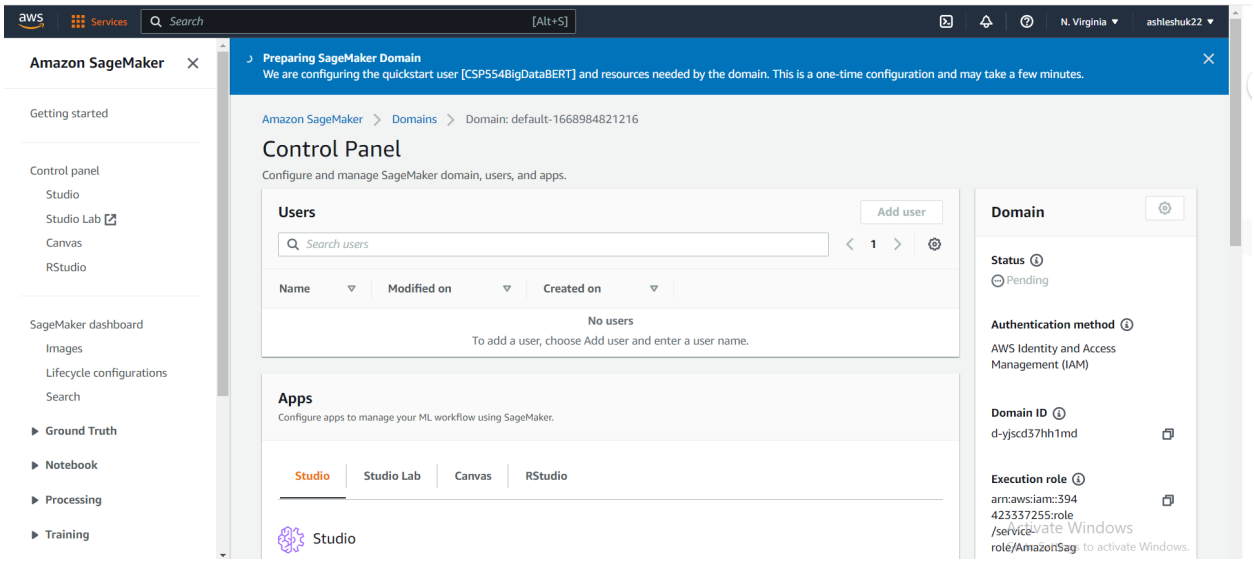
2.Create a notebook Instance



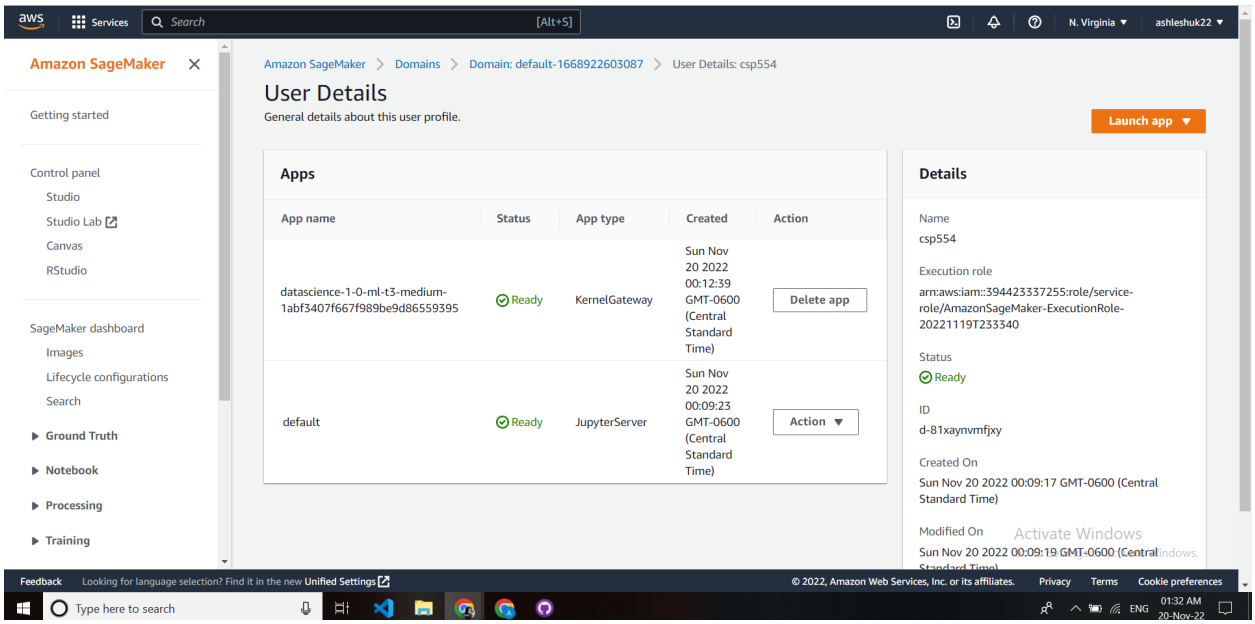
3. Configuring notebook instance for aws sagemaker



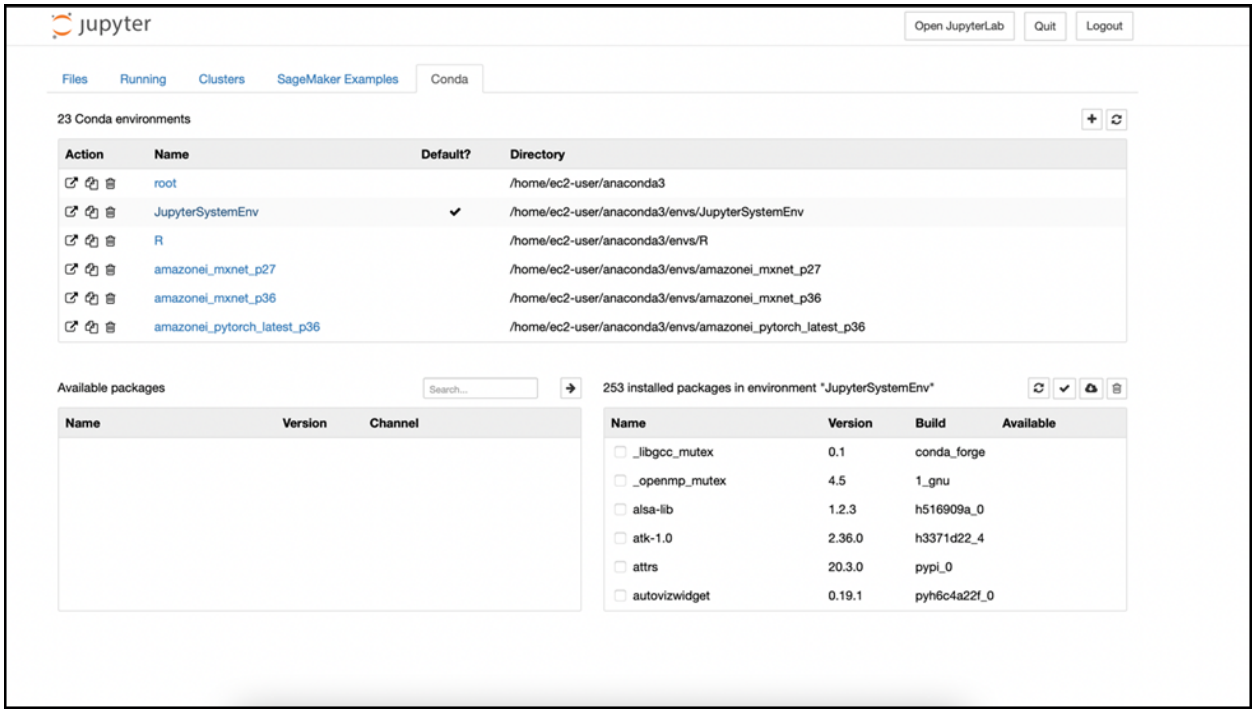
4.Setting up Studio prerequisites



5.Setting up User & Cluster configuration



6. Verify and check configuration for notebook instance we created



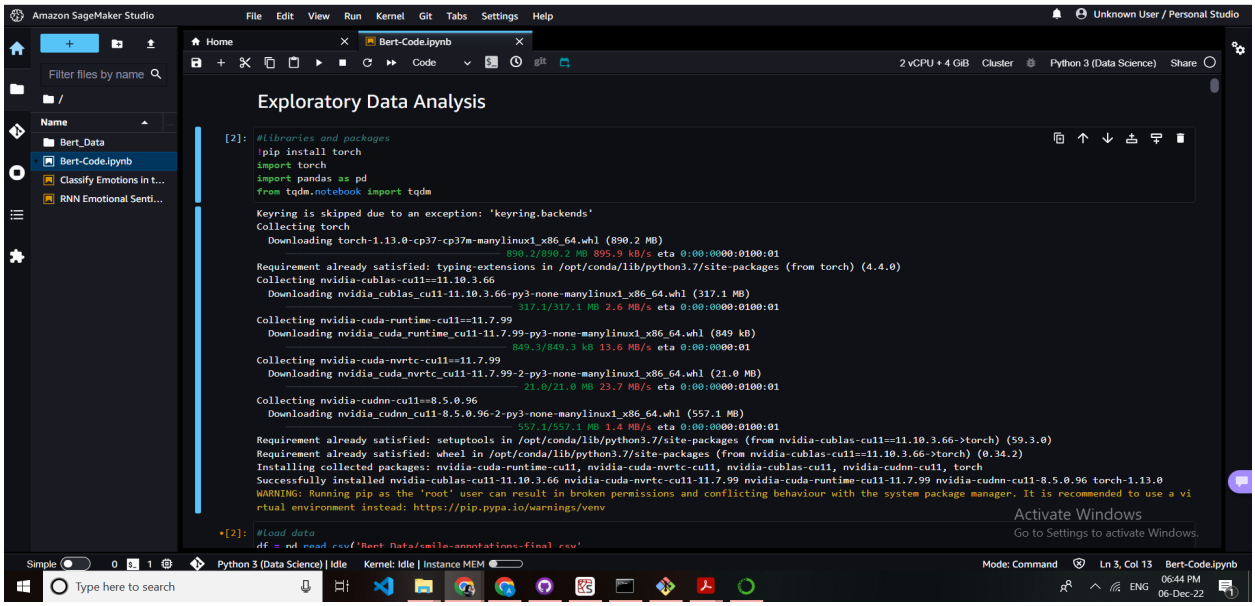
We also verified and checked configuration for notebook instances we created like the environment, programming language of your notebook, processing configuration (gpu, number of cores, etc.)

Implementation of Machine Learning Model in AWS Sagemaker

Stage-1 : Ingest And Analyze (Data Loading, Exploration & Data Preprocessing)

In this stage, we have cleaned and preprocessed data in order to fit the data into models. we started with following steps

- Installing required Python packages



- Then read the given data in your notebook (here we have used CSV format).

```
[2]: #load data
df = pd.read_csv('Bert_Data/smile-annotations-final.csv',
                 names = ['id', 'text', 'category'])

#reset index
df.set_index('id', inplace = True)
```

```
[3]: #preview
df.head()
```

[3]:

id	text	category
611857364396965889	@aandraous @britishmuseum @AndrewsAntonio Merc...	nocode
614484565059596288	Dorian Gray with Rainbow Scarf #LoveWins (from...	happy
614746522043973632	@SelectShowcase @Tate_StIves ... Replace with ...	happy
614877582664835073	@Sofabsports thank you for following me back. ...	happy
611932373039644672	@britishmuseum @TudorHistory What a beautiful ...	happy

- after loading the data, we start with data Exploration with understanding on **column type**, checking for **null values**

```
In [9]:
#info
df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 3085 entries, 611857364396965889 to 611566876762640384
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   text      3085 non-null   object
 1   category  3085 non-null   object
dtypes: object(2)
memory usage: 72.3+ KB

In [10]:
#check for null
df.isnull().sum()

Out[10]:
text        0
category    0
dtype: int64
```

- Following On same Line, we **calculated categorical classes** already mentioned in dataset

```
In [12]:
#count for each class
df.category.value_counts()

Out[12]:
nocode              1572
happy               1137
not-relevant         214
angry                 57
surprise              35
sad                   32
happy|surprise        11
happy|sad              9
disgust|angry          7
disgust                6
sad|disgust            2
sad|angry              2
sad|disgust|angry      1
Name: category, dtype: int64
```

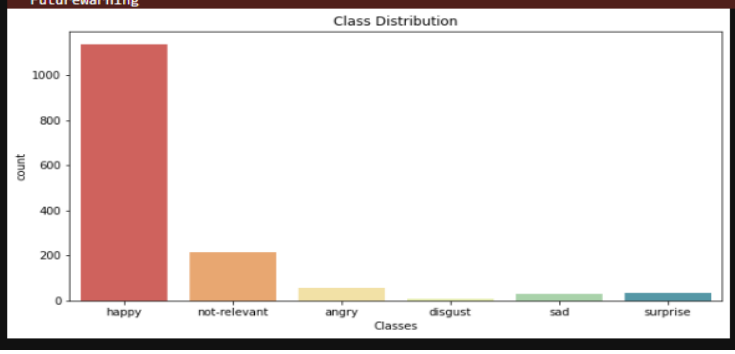
- Dropping unwanted/undefined classes for category

```
In [13]:
#drop irrelevent class
df = df[~df.category.str.contains('\|')]

In [14]:
#drop irrelevent class
df = df[df.category != 'nocode']

In [15]:
#final classes
df.category.value_counts()

Out[15]:
happy           1137
not-relevant     214
angry             57
surprise          35
sad               32
disgust            6
Name: category, dtype: int64
```

- Visualizing final Prepared Data

```
In [16]:
import matplotlib.pyplot as plt
import seaborn as sns

#plot class distribution
plt.figure(figsize=(10, 5))
sns.countplot(df.category, palette='Spectral')
plt.xlabel('Classes')
plt.title('Class Distribution');
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



- Finally, **Converted labels** to numerical values

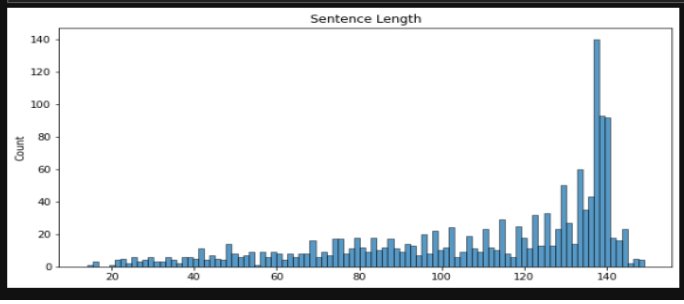
```
In [18]:
#convert labels into numeric values
label_dict = {}
for index, possible_label in enumerate(possible_labels):
    label_dict[possible_label] = index
```

```
In [19]:
label_dict
```

```
Out[19]: {'happy': 0,
 'not-relevant': 1,
 'angry': 2,
 'disgust': 3,
 'sad': 4,
 'surprise': 5}
```

- Plotting **histogram** to understand Sentence length

```
In [21]:
#need equal length sentences
#plot hist of sentence length
plt.figure(figsize=(10, 5))
sns.histplot([len(s) for s in df.text], bins=100)
plt.title('Sentence Length')
plt.show()
```



- Splitting dataset into Training dataset, validation dataset and Test dataset

```
In [23]:
from sklearn.model_selection import train_test_split

#train test split
X_train, X_val, y_train, y_val = train_test_split(df.index.values,
                                                  df.label.values,
                                                  test_size = 0.15,
                                                  random_state = 17,
                                                  stratify = df.label.values)
```

```
[20]: #fill in data type
      df.loc[X_train, 'data_type'] = 'train'
      df.loc[X_val, 'data_type'] = 'val'

[21]: df.groupby(['category', 'label', 'data_type']).count()

[21]:
```

			text
category	label	data_type	
angry	2	train	48
		val	9
disgust	3	train	5
		val	1
happy	0	train	966
		val	171
not-relevant	1	train	182
		val	32
sad	4	train	27
		val	5
surprise	5	train	30
		val	5

- **Now we are ready to develop models and implement them**.

- Here we have implemented 3 machine learning models for the classification of the given dataset:
  1) BERT NLP model
  2) RoBERTa model
  3) RNN Model

Analyzed the performance of all three models on amazon sagemaker using 2 parameters accuracy and loss.

Implementing Sentiment Analysis using BERT NLP Model

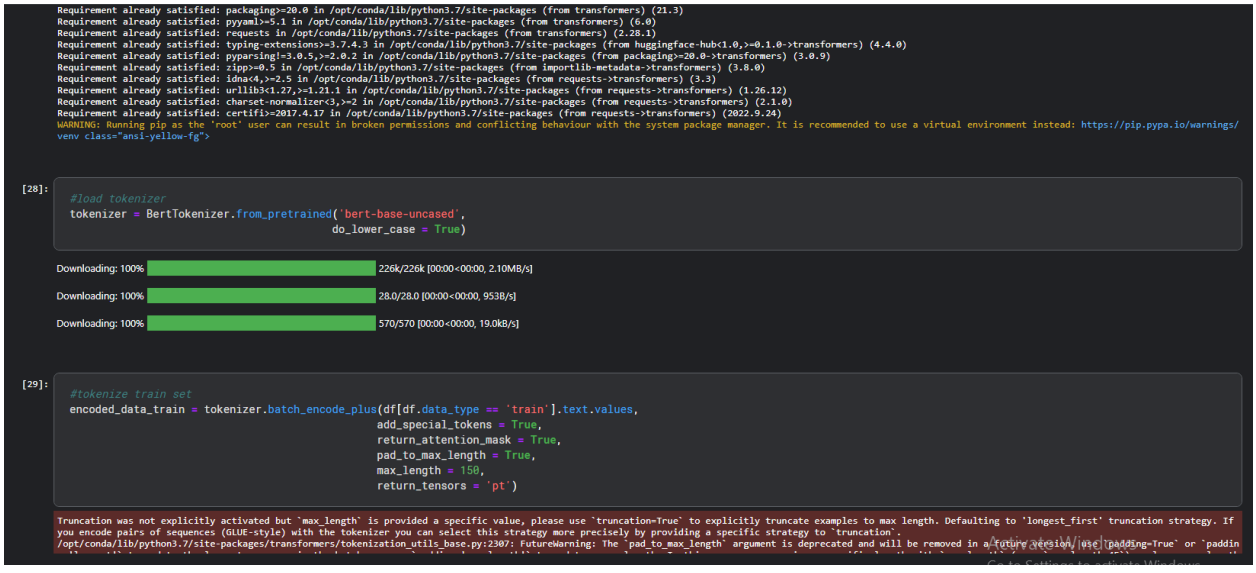
BERT:

Although BERT(Bidirectional Encoder Representations from Transformers) can be used without any further training, it's helpful to understand how it learns and understands language by simultaneously using word masking and next sentence prediction. The model hides 15% of the words in each sentence while BERT reads fresh text. Then BERT guesses the masked words and self-corrects, updating the model weights when it makes a mistaken prediction. The term "masked language model" or "masked LM" refers to this phase. The model must learn the surrounding words for each sentence as a result of masking. BERT simultaneously predicts and masks words, or to be more accurate, input tokens. Additionally, it employs NSP, or next sentence prediction, on pairs of input sequences.

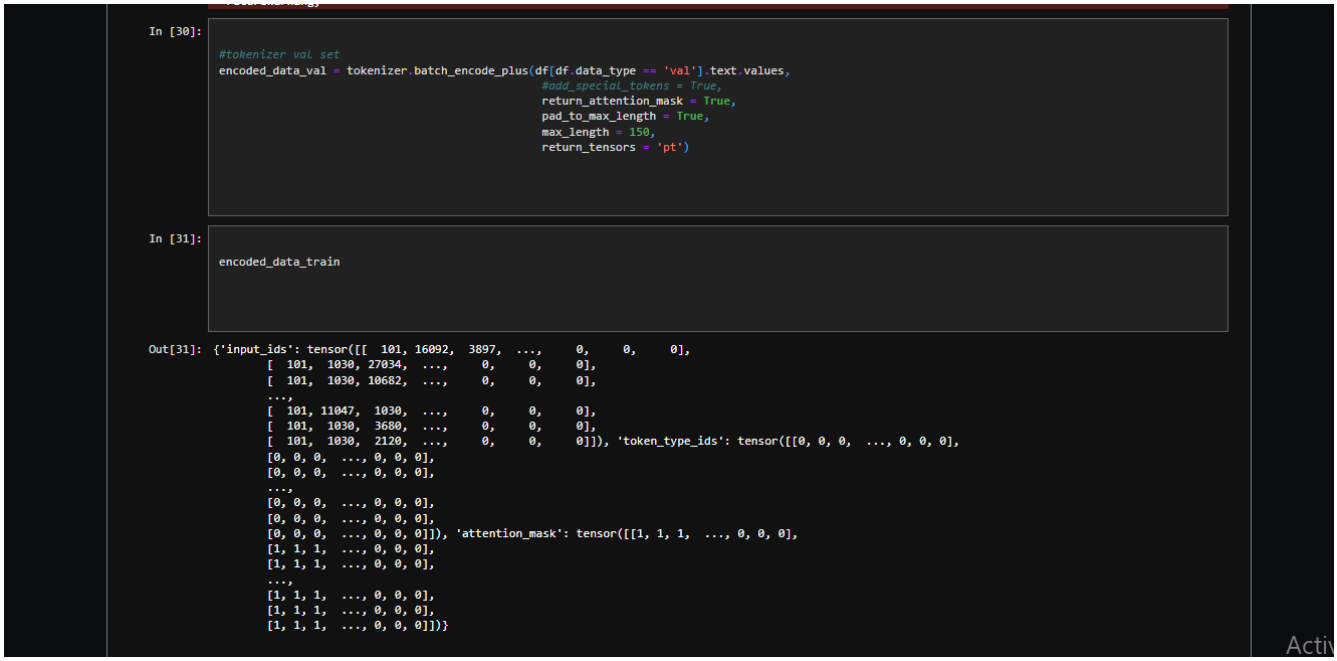
BERT randomly selects 50% of the sentence pairings and substitutes one of the two sentences with a random sentence from a different section of the document to conduct NSP. The validity of the two sentences as a sentence pair is then predicted by BERT. When it makes a mistaken prediction, BERT will once more correct itself. For the purpose of generating a single accuracy score for all of the training efforts, those two training tasks are carried out simultaneously. As a result, the model becomes more reliable and is able to anticipate words and sentences. Keep in mind that this pre-training phase is carried out using unsupervised learning. Large collections of unlabeled text make up the input data.

Following are steps involved in **Building Sentiment Analysis using the BERT model.**

1. We have already imported packages, explored, cleaned & prepared data. For NLP sentiment analysis, we are required to tokenize the words in sentences. **Tokenization** is used in natural language processing to split paragraphs and sentences into smaller units that can be more easily assigned meaning.



2. Result of Tokenization:

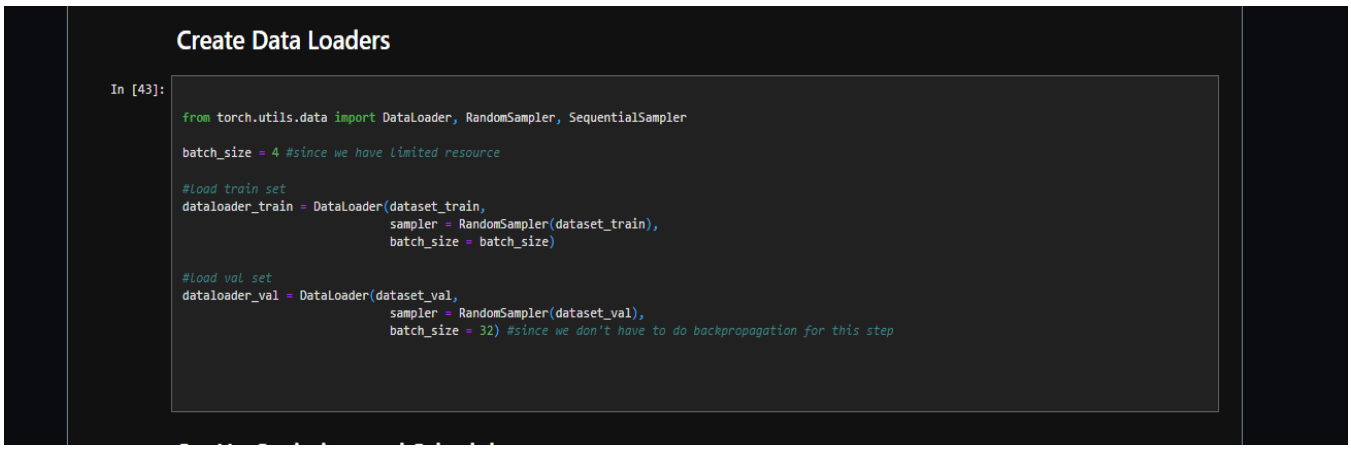


```
In [30]:
#tokenizer val set
encoded_data_val = tokenizer.batch_encode_plus(df[df.data_type == 'val'].text.values,
                                               #add_special_tokens = True,
                                               return_attention_mask = True,
                                               pad_to_max_length = True,
                                               max_length = 150,
                                               return_tensors = 'pt')

In [31]:
encoded_data_train

Out[31]: {'input_ids': tensor([[  101, 16092,  3897,  ...,     0,     0,     0],
                [  101,  1030, 27034,  ...,     0,     0,     0],
                [  101,  1030, 10682,  ...,     0,     0,     0],
                ...,
                [  101, 11047,  1030,  ...,     0,     0,     0],
                [  101,  1030,  3680,  ...,     0,     0,     0],
                [  101,  1030,  2120,  ...,     0,     0,     0]]), 'token_type_ids': tensor([[0, 0, 0,  ..., 0, 0, 0],
                [0, 0, 0,  ..., 0, 0, 0],
                [0, 0, 0,  ..., 0, 0, 0],
                ...,
                [0, 0, 0,  ..., 0, 0, 0],
                [0, 0, 0,  ..., 0, 0, 0],
                [0, 0, 0,  ..., 0, 0, 0]]), 'attention_mask': tensor([[1, 1, 1,  ..., 0, 0, 0],
                [1, 1, 1,  ..., 0, 0, 0],
                [1, 1, 1,  ..., 0, 0, 0],
                ...,
                [1, 1, 1,  ..., 0, 0, 0],
                [1, 1, 1,  ..., 0, 0, 0],
                [1, 1, 1,  ..., 0, 0, 0]])}
```

3. Set Up BERT Model on our Dataset: we are using pre trained **BERT model named- "bert-base-uncased",** which was built on "BertForMaskedLM" architectures.

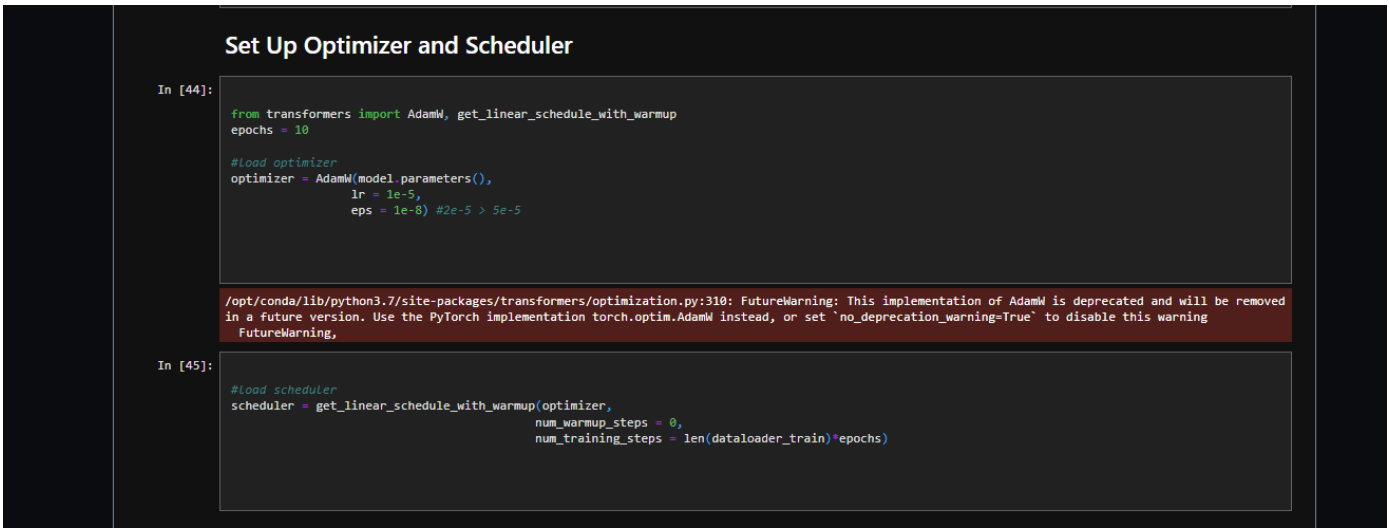
```
Set Up BERT Pretrained Model

[*]: from transformers import BertForSequenceClassification

#load pre-trained BERT
model = BertForSequenceClassification.from_pretrained('bert-base-uncased',
                                                      num_labels = len(label_dict),
                                                      output_attentions = False,
                                                      output_hidden_states = False)

Downloading: 100% [==========] 440M/440M [00:07<00:00, 58.7MB/s]
```

4. Create Data loaders:



```
Create Data Loaders

In [43]:
from torch.utils.data import DataLoader, RandomSampler, SequentialSampler

batch_size = 4 #since we have limited resource

#Load train set
dataloader_train = DataLoader(dataset_train,
                              sampler = RandomSampler(dataset_train),
                              batch_size = batch_size)

#Load val set
dataloader_val = DataLoader(dataset_val,
                              sampler = RandomSampler(dataset_val),
                              batch_size = 32) #since we don't have to do backpropagation for this step
```

5. Set up Optimizer and Scheduler



Set Up Optimizer and Scheduler

In [44]:

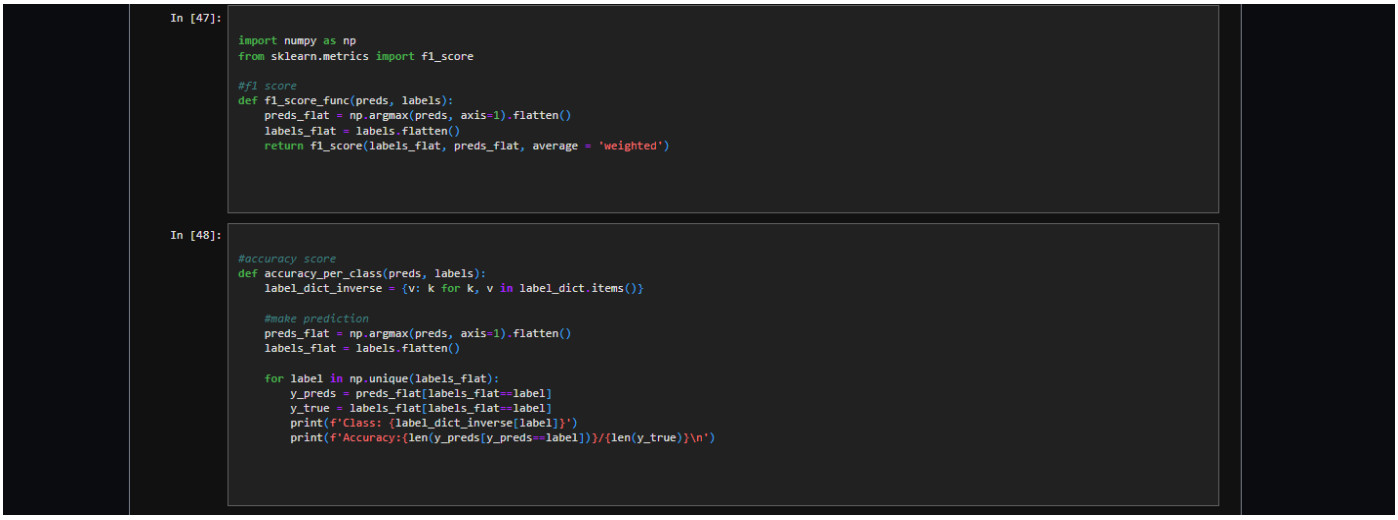
```
from transformers import AdamW, get_linear_schedule_with_warmup
epochs = 10

#Load optimizer
optimizer = AdamW(model.parameters(),
                  lr = 1e-5,
                  eps = 1e-8) #2e-5 > 5e-5
```

```
/opt/conda/lib/python3.7/site-packages/transformers/optimization.py:310: FutureWarning: This implementation of AdamW is deprecated and will be removed in a future version. Use the PyTorch implementation torch.optim.AdamW instead, or set `no_deprecation_warning=True` to disable this warning
  FutureWarning,
```

In [45]:

```
#Load scheduler
scheduler = get_linear_schedule_with_warmup(optimizer,
                                            num_warmup_steps = 0,
                                            num_training_steps = len(dataloader_train)*epochs)
```

6. Defining Evaluation Parameters



In [47]:

```
import numpy as np
from sklearn.metrics import f1_score

#f1 score
def f1_score_func(preds, labels):
    preds_flat = np.argmax(preds, axis=1).flatten()
    labels_flat = labels.flatten()
    return f1_score(labels_flat, preds_flat, average = 'weighted')
```

In [48]:

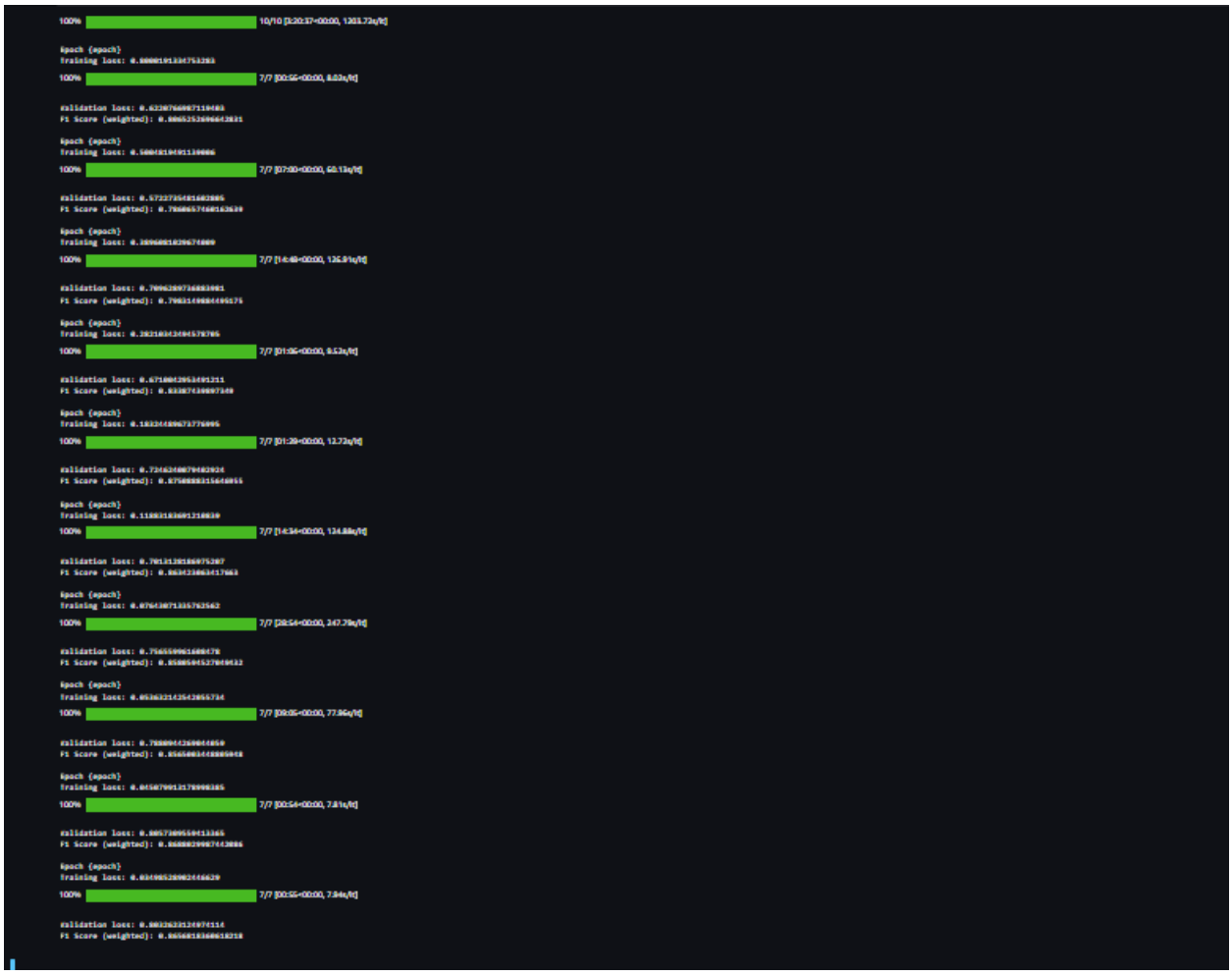
```
#accuracy score
def accuracy_per_class(preds, labels):
    label_dict_inverse = {v: k for k, v in label_dict.items()}

    #make prediction
    preds_flat = np.argmax(preds, axis=1).flatten()
    labels_flat = labels.flatten()

    for label in np.unique(labels_flat):
        y_preds = preds_flat[labels_flat==label]
        y_true = labels_flat[labels_flat==label]
        print(f'Class: {label_dict_inverse[label]}')
        print(f'Accuracy:{len(y_preds[y_preds==label])}/{len(y_true)}\n')
```

7. Training Model

[62]:

```
for epoch in tqdm(range(1, epochs+1)):

    #set model in train mode
    model.train()

    #tracking variable
    loss_train_total = 0

    #set up progress bar
    progress_bar = tqdm(dataloader_train,
                        desc='Epoch {:1d}'.format(epoch),
                        leave=False,
                        disable=False)

    for batch in progress_bar:
        #set gradient to 0
        model.zero_grad()

        #load into GPU
        batch = tuple(b.to(device) for b in batch)

        #define inputs
        inputs = {'input_ids': batch[0],
                  'attention_mask': batch[1],
                  'labels': batch[2]}

        outputs = model(**inputs)
        loss = outputs[0] #output loss
        loss_train_total +=loss.item()

        #backward pass to get gradients
        loss.backward()

        #clip the norm of the gradients to 1.0 to prevent exploding gradients
        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

        #update optimizer
        optimizer.step()

        #update scheduler
        scheduler.step()

        progress_bar.set_postfix({'training_loss': '{:.3f}'.format(loss.item()/len(batch))})

    tqdm.write(f'\nEpoch {epoch}')

    #print training result
    loss_train_avg = loss_train_total/len(dataloader_train)
    tqdm.write(f'Training loss: {loss_train_avg}')

    #evaluate
    val_loss, predictions, true_vals = evaluate(dataloader_val)
    #f1 score
    val_f1 = f1_score_func(predictions, true_vals)
    tqdm.write(f'Validation loss: {val_loss}')
    tqdm.write(f'F1 Score (weighted): {val_f1}')
```

8. Model Training results



9. Estimation : Accuracy

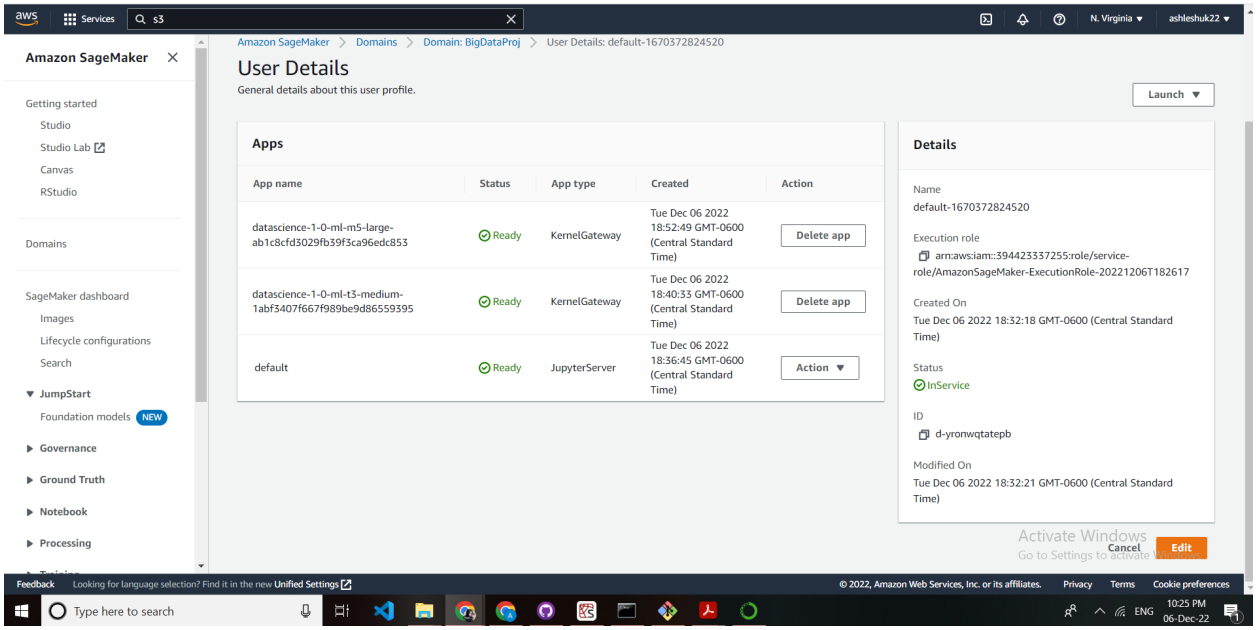
```
[53]: #get accuracy score
      accuracy_per_class(predictions, true_vals)

      Class: happy
      Accuracy:164/171

      Class: not-relevant
      Accuracy:20/32

      Class: angry
      Accuracy:8/9

      Class: disgust
      Accuracy:0/1

      Class: sad
      Accuracy:1/5

      Class: surprise
      Accuracy:2/5

[54]: print(f"Accuracy : {Accuracy}")

      Accuracy : 0.97
```

10. Comparison of Performance on different Clusters:

After getting results on "**t3-medium**" (3 node) cluster instances, we also executed the above Machine Learning model on "**m5-large**" (5 node) cluster instances.

Observation:

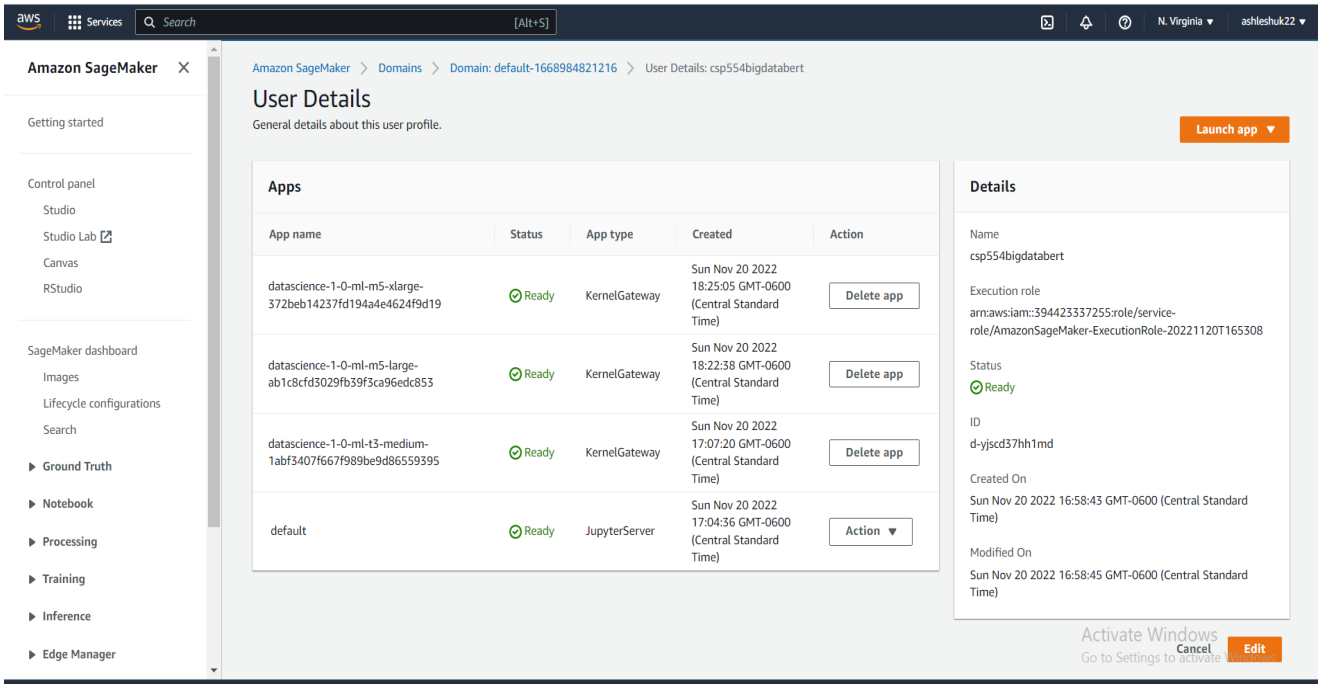
- The Code execution was fast, epochs estimation time were smaller in **m5-large** than **t3-medium**.
- The CPU utilization for **t3-medium** did reach 100% during training, while it did not maxed for **m5-large** instances.
- Hence we can say that, with better CPU configuration the execution speed is improved.



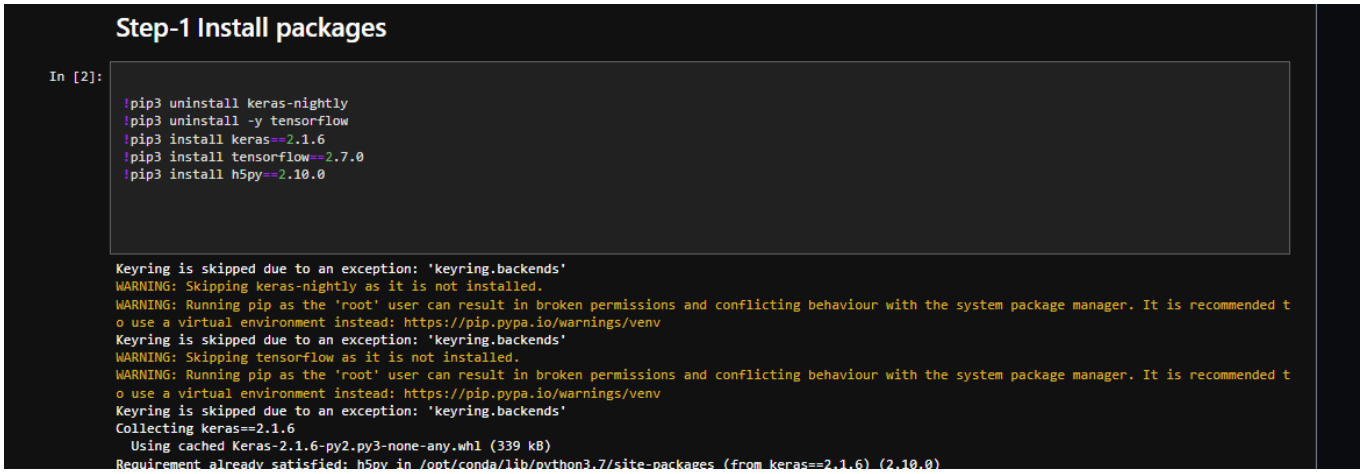
Implementing Sentiment Analysis using RobERTa Model

RoBERTa: RoBERTa(Robustly Optimized BERT pre-training Approach) expands on the BERT model architecture while changing some model hyperparameters and the model's training process, including the use of more training data. In contrast to BERT, this can actually result in notable performance gains in a number of NLP tasks.

1. **Sagemaker Domain-Cluster Setup for RoBERTa Model**



2. **Installing required Packages** for RoBERTa Implementation.



3. **Load dataSet** to Jupyter file using readCSV

```
In [8]:
train_data = pd.read_csv('emotions-dataset-for-nlp/train.txt', names=['text', 'emotion'], sep=';')
val_data = pd.read_csv('emotions-dataset-for-nlp/val.txt', names=['text', 'emotion'], sep=';')
test_data = pd.read_csv('emotions-dataset-for-nlp/test.txt', names=['text', 'emotion'], sep=';')
train_data.head()
```

Out[8]:

	text	emotion
0	i didnt feel humiliated	sadness
1	i can go from feeling so hopeless to so damned...	sadness
2	im grabbing a minute to post i feel greedy wrong	anger
3	i am ever feeling nostalgic about the firepiac...	love
4	i am feeling grouchy	anger

4. **Data Pre-Processing**

Data preprocessing

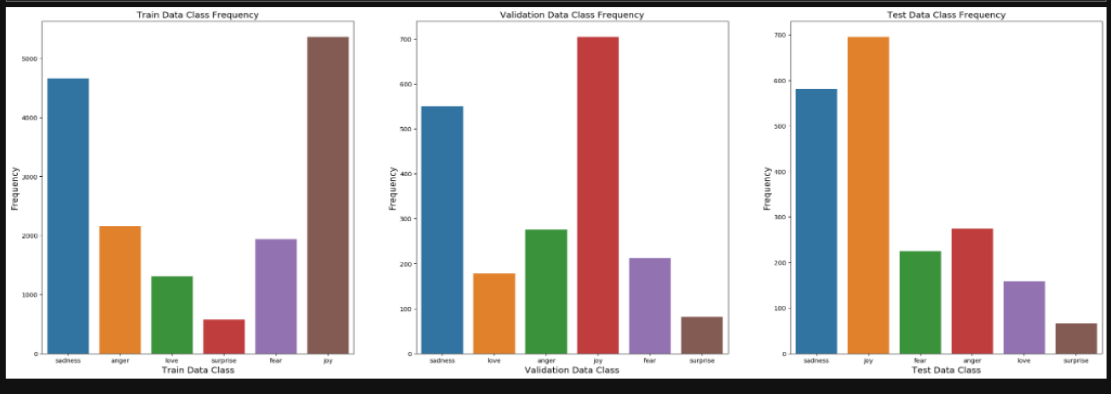
```
In [10]:
data = {'Train Data': train_data, 'Validation Data': val_data, 'Test Data': test_data}
for temp in data:
    print(temp)
    print(data[temp].isnull().sum())
    print('*'*20)
```

```
Train Data
text       0
emotion    0
dtype: int64
********************
Validation Data
text       0
emotion    0
dtype: int64
********************
Test Data
text       0
emotion    0
dtype: int64
********************
```

5. **Class Distribution** for Training, validation and Testing dataset

Class Distribution in Train, val and test dataset

```
In [11]:
bar, ax = plt.subplots(1,3, figsize=(30, 10))
for index, temp in enumerate(data):
    sns.countplot(ax = ax[index],x = 'emotion', data = data[temp])
    ax[index].set_title(temp+' Class Frequency', size=14)
    ax[index].set_ylabel('Frequency', size=14)
    ax[index].set_xlabel(temp+' Class', size=14)

plt.show()
```



6. Data Processing, Label Creation and Sentence Listing

Data Processing, Label Creation and Seentence Listing

In [14]:

```
def preprocess(sentence):
    stop_words = set(stopwords.words('english'))
    lemmatizer = WordNetLemmatizer()
    sentence = re.sub('[^A-z]', ' ', sentence)
    negative = ['not', 'neither', 'nor', 'but', 'however', 'although', 'nonetheless', 'despite', 'except',
                'even though', 'yet']
    stop_words = [z for z in stop_words if z not in negative]
    preprocessed_tokens = [lemmatizer.lemmatize(contractions.fix(temp.lower())) for temp in sentence.split() if temp not in stop_words] #Lemmatization
    return ' '.join([x for x in preprocessed_tokens]).strip()
```

In [16]:

```
train_data['text'] = train_data['text'].apply(lambda x: preprocess(x))
val_data['text'] = val_data['text'].apply(lambda x: preprocess(x))
test_data['text'] = test_data['text'].apply(lambda x: preprocess(x))
```

Note: As class imbalanced is evident, RandomOverSampler is used to add data(repetition) to all classes except highest frequency class.

In [17]:

```
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler(random_state=0)
train_x, train_y = ros.fit_resample(np.array(train_data['text']).reshape(-1, 1), np.array(train_data['emotion']).reshape(-1, 1))
train = pd.DataFrame(list(zip([x[0] for x in train_x], train_y)), columns = ['text', 'emotion'])
```

Applying OneHotEncoder on target of all dataset

In [18]:

```
from sklearn import preprocessing
le = preprocessing.OneHotEncoder()
y_train= le.fit_transform(np.array(train['emotion']).reshape(-1, 1)).toarray()
y_test= le.fit_transform(np.array(test_data['emotion']).reshape(-1, 1)).toarray()
y_val= le.fit_transform(np.array(val_data['emotion']).reshape(-1, 1)).toarray()
```

7. **Tokenizing Text** for Encoding

In [22]:

```
def roberta_encode(data,maximum_length) :
  input_ids = []
  attention_masks = []


  for i in range(len(data.text)):
      encoded = tokenizer.encode_plus(

        data.text[i],
        add_special_tokens=True,
        max_length=maximum_length,
        pad_to_max_length=True,

        return_attention_mask=True,

      )

      input_ids.append(encoded['input_ids'])
      attention_masks.append(encoded['attention_mask'])
  return np.array(input_ids),np.array(attention_masks)
```

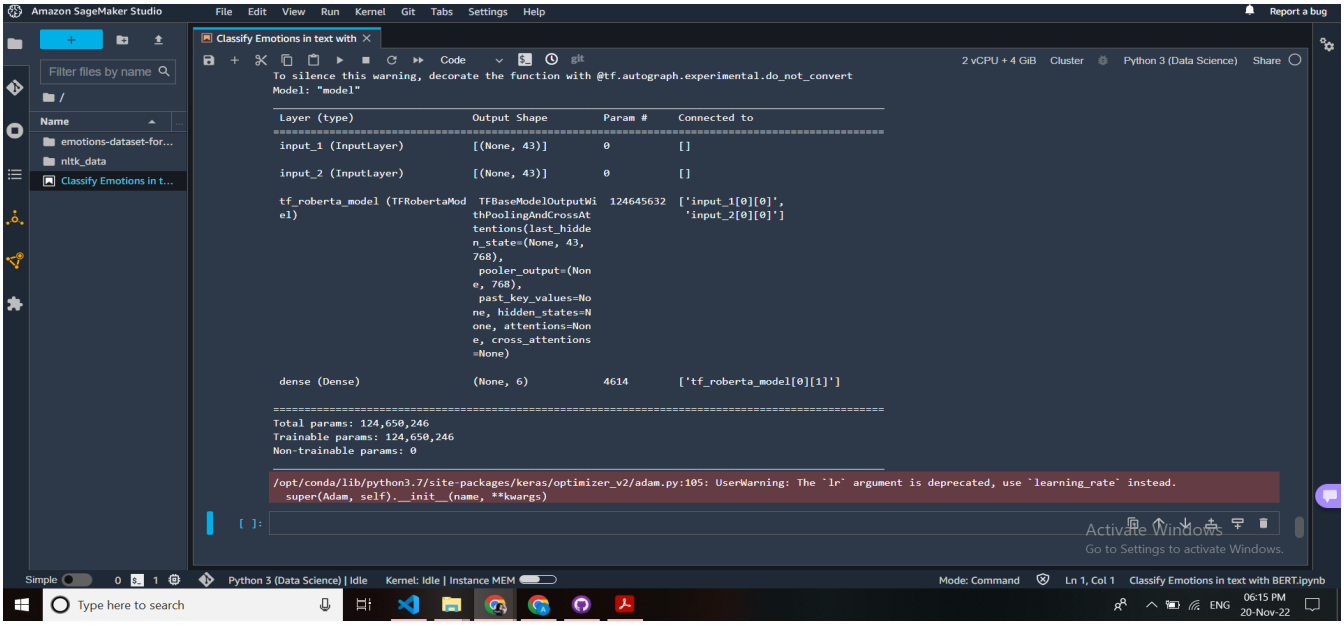
In [23]:

```
max_len = max([len(x.split()) for x in train_data['text']])
train_input_ids,train_attention_masks = roberta_encode(train, max_len)
test_input_ids,test_attention_masks = roberta_encode(test_data, max_len)
val_input_ids,val_attention_masks = roberta_encode(val_data, max_len)
```

8. Creating Model:

```
In [24]:

def create_model(bert_model, max_len):
    input_ids = tf.keras.Input(shape=(max_len,),dtype='int32')
    attention_masks = tf.keras.Input(shape=(max_len,),dtype='int32')

    output = bert_model([input_ids,attention_masks])
    output = output[1]

    output = tf.keras.layers.Dense(6, activation='softmax')(output)
    model = tf.keras.models.Model(inputs = [input_ids,attention_masks],outputs = output)
    model.compile(Adam(lr=1e-5), loss='categorical_crossentropy', metrics=['accuracy'])
    return model
```

9. RobertA Model Description



10. RoBERTa Model Training

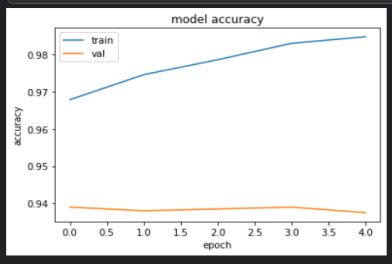
Model Training

```
[29]: history = model.fit([train_input_ids,train_attention_masks], y_train, validation_data=([val_input_ids,val_attention_masks], y_val), epochs=5,batch_size=100)

Epoch 1/5
322/322 [==============================] - 154s 479ms/step - loss: 0.0795 - accuracy: 0.9679 - val_loss: 0.1593 - val_accuracy: 0.9390
Epoch 2/5
322/322 [==============================] - 154s 479ms/step - loss: 0.0644 - accuracy: 0.9746 - val_loss: 0.1807 - val_accuracy: 0.9380
Epoch 3/5
322/322 [==============================] - 154s 478ms/step - loss: 0.0552 - accuracy: 0.9786 - val_loss: 0.1616 - val_accuracy: 0.9385
Epoch 4/5
322/322 [==============================] - 154s 479ms/step - loss: 0.0454 - accuracy: 0.9830 - val_loss: 0.1739 - val_accuracy: 0.9390
Epoch 5/5
322/322 [==============================] - 154s 479ms/step - loss: 0.0403 - accuracy: 0.9848 - val_loss: 0.1906 - val_accuracy: 0.9375
```

Plotting Accuracy and Loss (Training and Validation)

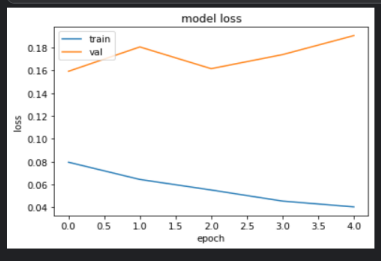
11. Plotting Model Accuracy of Training and Validation dataset

```
[30]: plt.plot(history.history['accuracy'])
      plt.plot(history.history['val_accuracy'])
      plt.title('model accuracy')
      plt.ylabel('accuracy')
      plt.xlabel('epoch')
      plt.legend(['train', 'val'], loc='upper left')
      plt.show()
```



12. Plotting Model Loss of Training and validation dataset

```
[31]: plt.plot(history.history['loss'])
      plt.plot(history.history['val_loss'])
      plt.title('model loss')
      plt.ylabel('loss')
      plt.xlabel('epoch')
      plt.legend(['train', 'val'], loc='upper left')
      plt.show()
```



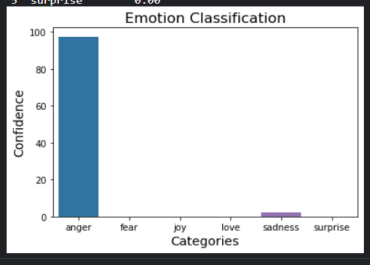
13. **Test results** on Different text example (**Note**: Text of inference is different)

```
[39]: result = inference("I am happy", max_len)
      print(result)
```

```
/opt/conda/lib/python3.7/site-packages/transformers/tokeniza
e `padding=True` or `padding='longest'` to pad to the longes
max_length` (e.g. `max_length=45`) or leave max_length to No
  FutureWarning,
   Category  Confidence
0     anger        0.02
1      fear        0.00
2       joy       99.97
3      love        0.00
4   sadness        0.01
5  surprise        0.00
```

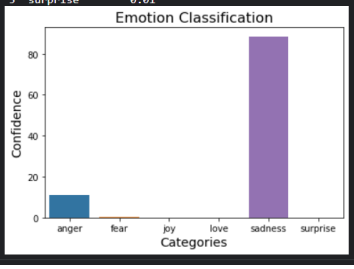

```
[40]: result = inference("I am unhappy", max_len)
      print(result)
```

```
/opt/conda/lib/python3.7/site-packages/transformers/tokeniza
e `padding=True` or `padding='longest'` to pad to the longes
max_length` (e.g. `max_length=45`) or leave max_length to No
  FutureWarning,
   Category  Confidence
0     anger       97.39
1      fear        0.01
2       joy        0.14
3      love        0.00
4   sadness        2.45
5  surprise        0.00
```

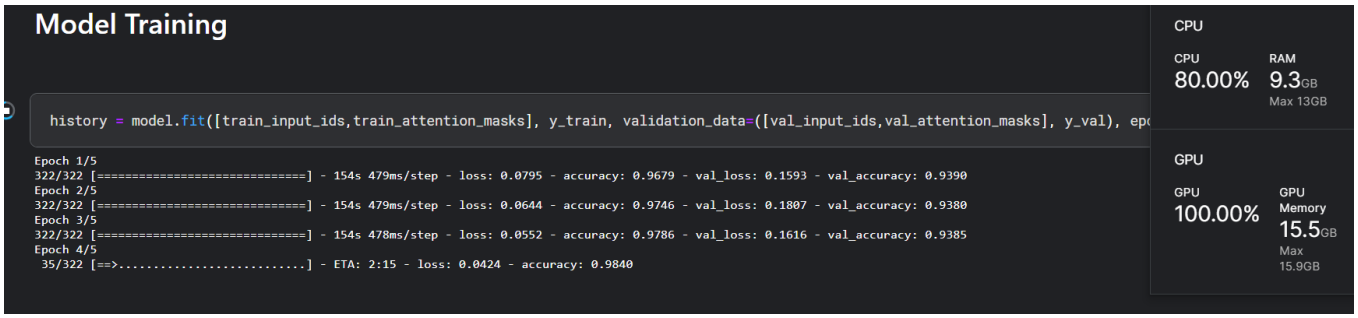



```
[41]: result = inference("I am depressed", max_len)
      print(result)
```

```
/opt/conda/lib/python3.7/site-packages/transformers/tokeniza
e `padding=True` or `padding='longest'` to pad to the longes
max_length` (e.g. `max_length=45`) or leave max_length to No
  FutureWarning,
   Category  Confidence
0     anger       11.15
1      fear        0.19
2       joy        0.09
3      love        0.00
4   sadness       88.56
5  surprise        0.01
```



14. Capturing CPU & GPU utilization



15. **Comparison of Performance on different Clusters:**

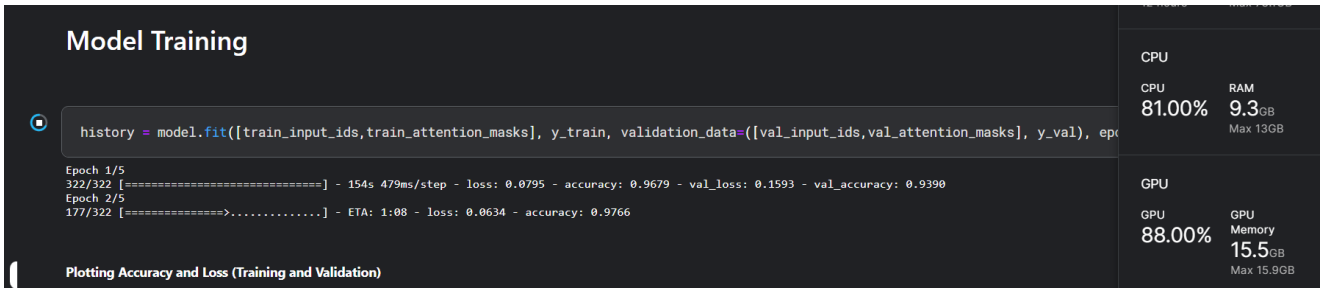
After getting results on "**t3-medium**" cluster instances (3 node), we also executed the above Machine Learning model on "**m5-large**" (3 node) and "**m5-xlarge**" (5 node) cluster instances.

Observation:

- The Code execution was fast, epochs estimation time were smaller in **m5-large** than **t3-medium**. it was even quicker in the "**m5-xlarge**"cluster.

- The CPU utilization for **t3-medium** did reach 100%(above snap) during training, while it reached 88% for **m5-large** and **m5-xlarge** instance.

- Hence we can again say that, with better CPU configuration the execution speed is improved.



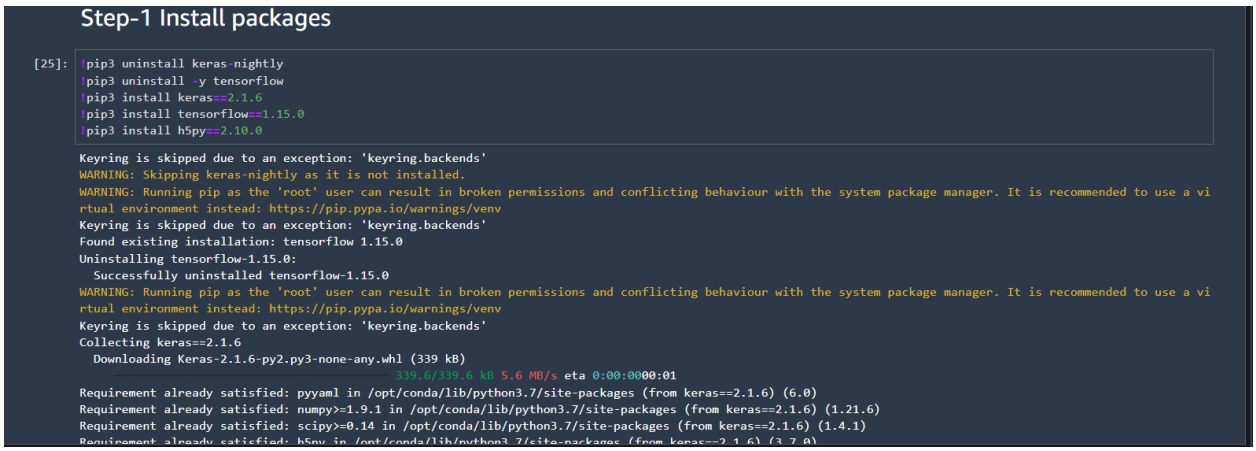
Implementing Sentiment Analysis using RNN Model

The most fundamental and potent neural networks are recurrent neural networks (RNN). These algorithms have gained a lot of popularity since they have produced promising outcomes for several technologies. RNN's main goal is to process sequential data effectively. The idea of internal memory sets RNN apart from conventional neural networks.

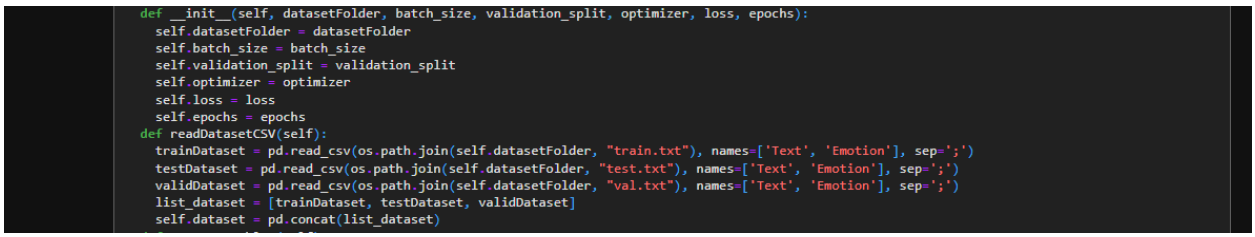
Recurrent neural networks are somewhat more established than other types of neural networks, having existed since the 1980s, although recently gaining popularity. With the advancement of technology, RNN has taken the lead because we now have greater computing power and a lot of data that has been collected recently.

for the implementation of this, we wrote a class called 'Emotions' comprised of following steps:

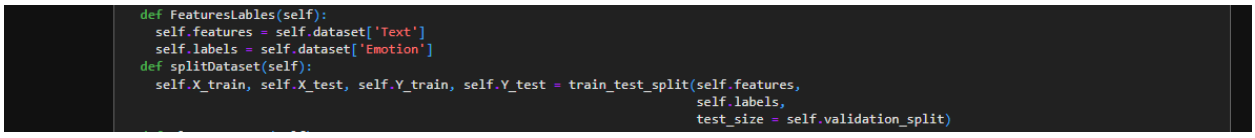
1. Installing Required packages.



2. Loading Dataset into Notebook

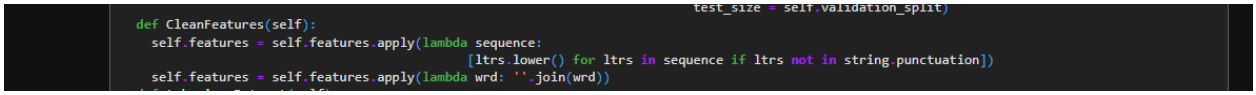


2. **Feature Labeling & splitting dataset**



3. **Cleaning Dataset feature**

- in our dataset we had Capital letters, camel-cased Alphabets, for sentiment analysis we figured out we don't need these, hence converted data into lowercase.
- remove unwanted Spaces, punctuation etc. hence finishing off with the Data preparation stage.



4. **Tokenizing** textual part of data and developing Word Embedding using **GloVe**
   - **GloVe :** GloVe model is an unsupervised learning algorithm for obtaining vector representations for words. This is achieved by mapping words into a meaningful space where the distance between words is related to semantic similarity.[7] Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space.

```
def tokenizerDataset(self):
  self.tokenizer = Tokenizer(num_words=5000)
  self.tokenizer.fit_on_texts(self.features)
  train = self.tokenizer.texts_to_sequences(self.features)
  self.features = pad_sequences(train)
  le = LabelEncoder()
  self.labels = le.fit_transform(self.labels)
  self.vocabulary = len(self.tokenizer.word_index)
def label_categorical(self):
  self.labels = to_categorical(self.labels, 6)
def glove_word_embedding(self, file_name):
  self.embeddings_index = {}
  file_ = open(file_name)
  for line in file_:
      arr = line.split()
      single_word = arr[0]
      w = np.asarray(arr[1:],dtype='float32')
      self.embeddings_index[single_word] = w
  file_.close()
  max_words = self.vocabulary + 1
  word_index = self.tokenizer.word_index
  self.embedding_matrix = np.zeros((max_words,300)).astype(object)
  for word , i in word_index.items():
        embedding_vector = self.embeddings_index.get(word)
        if embedding_vector is not None:
            self.embedding_matrix[i] = embedding_vector
```

5. **Defining function** with **activation** function, Dropouts, **Regularizers**, metrics & **fit function**.
   - here we have defined the function related dropouts, regularizers, function to compile and fit the model.
   - We have called this function to compile and fit the model on training data

   .

```
def model(self):
  m = Sequential()
  m.add(Input(shape=(self.features.shape[1], )))
  m.add(Embedding(self.vocabulary + 1,300))
  m.add(GRU(128, recurrent_dropout=0.3, return_sequences=False, activity_regularizer = tf.keras.regularizers.L2(0.0001)))
  m.add(Dense(6, activation="softmax", activity_regularizer = tf.keras.regularizers.L2(0.0001)))
  self.m = m
def compiler(self):
  self.m.compile(loss= self.loss,optimizer=self.optimizer,metrics=['accuracy'])
def fit(self):
  earlyStopping = EarlyStopping(monitor = 'loss', patience = 20, mode = 'min', restore_best_weights = True)
  self.history_training = self.m.fit(self.X_train, self.Y_train, epochs= self.epochs,batch_size = self.batch_size,
                                     callbacks=[ earlyStopping])
```

6. Complete picture of Class Emotions

- After defining all the above functions, we decided to put everything together into a class called "**Emotion**", whose object will be created to access all this functions.

In [10]:

```
class Emotion:
  def __init__(self, datasetFolder, batch_size, validation_split, optimizer, loss, epochs):
    self.datasetFolder = datasetFolder
    self.batch_size = batch_size
    self.validation_split = validation_split
    self.optimizer = optimizer
    self.loss = loss
    self.epochs = epochs
  def readDatasetCSV(self):
    trainDataset = pd.read_csv(os.path.join(self.datasetFolder, "train.txt"), names=['Text', 'Emotion'], sep=';')
    testDataset = pd.read_csv(os.path.join(self.datasetFolder, "test.txt"), names=['Text', 'Emotion'], sep=';')
    validDataset = pd.read_csv(os.path.join(self.datasetFolder, "val.txt"), names=['Text', 'Emotion'], sep=';')
    list_dataset = [trainDataset, testDataset, validDataset]
    self.dataset = pd.concat(list_dataset)
  def FeaturesLables(self):
    self.features = self.dataset['Text']
    self.labels = self.dataset['Emotion']
  def splitDataset(self):
    self.X_train, self.X_test, self.Y_train, self.Y_test = train_test_split(self.features,
                                                                            self.labels,
                                                                            test_size = self.validation_split)
  def CleanFeatures(self):
    self.features = self.features.apply(lambda sequence:
                                        [ltrs.lower() for ltrs in sequence if ltrs not in string.punctuation])
    self.features = self.features.apply(lambda wrd: ''.join(wrd))
  def tokenizerDataset(self):
    self.tokenizer = Tokenizer(num_words=5000)
    self.tokenizer.fit_on_texts(self.features)
    train = self.tokenizer.texts_to_sequences(self.features)
    self.features = pad_sequences(train)
    le = LabelEncoder()
    self.labels = le.fit_transform(self.labels)
    self.vocabulary = len(self.tokenizer.word_index)
  def label_categorical(self):
    self.labels = to_categorical(self.labels, 6)
  def glove_word_embedding(self, file_name):
    self.embeddings_index = {}
    file_ = open(file_name)
    for line in file_:
        arr = line.split()
        single_word = arr[0]
        w = np.asarray(arr[1:],dtype='float32')
        self.embeddings_index[single_word] = w
    file_.close()
    max_words = self.vocabulary + 1
    word_index = self.tokenizer.word_index
    self.embedding_matrix = np.zeros((max_words,300)).astype(object)
    for word , i in word_index.items():
            embedding_vector = self.embeddings_index.get(word)
            if embedding_vector is not None:
                self.embedding_matrix[i] = embedding_vector
  def model(self):
    m = Sequential()
    m.add(Input(shape=(self.features.shape[1], )))
    m.add(Embedding(self.vocabulary + 1,300))
    m.add(GRU(128, recurrent_dropout=0.3, return_sequences=False, activity_regularizer = tf.keras.regularizers.L2(0.0001)))
    m.add(Dense(6, activation="softmax", activity_regularizer = tf.keras.regularizers.L2(0.0001)))
    self.m = m
  def compiler(self):
    self.m.compile(loss= self.loss,optimizer=self.optimizer,metrics=['accuracy'])
  def fit(self):
    earlyStopping = EarlyStopping(monitor = 'loss', patience = 20, mode = 'min', restore_best_weights = True)
    self.history_training = self.m.fit(self.X_train, self.Y_train, epochs= self.epochs,batch_size = self.batch_size,
                                       callbacks=[ earlyStopping])
```

7. Result of DataSet Reading, getting glimpse of Data using data.head()

In [25]:

```
emotion = Emotion(dataset_emotion, 256, 0.1, 'adam', 'categorical_crossentropy', 20)
emotion.readDatasetCSV()
emotion.dataset.head()
```

Out[25]:

	Text	Emotion
0	i didnt feel humiliated	sadness
1	i can go from feeling so hopeless to so damned...	sadness
2	im grabbing a minute to post i feel greedy wrong	anger
3	i am ever feeling nostalgic about the fireplac...	love
4	i am feeling grouchy	anger

8. Result of **Data Cleaning**, **feature labeling** (step of Data Preparation)

```
In [26]:
emotion.FeaturesLables()
emotion.CleanFeatures()
emotion.features.head()

Out[26]: 0                            i didnt feel humiliated
         1    i can go from feeling so hopeless to so damned...
         2     im grabbing a minute to post i feel greedy wrong
         3    i am ever feeling nostalgic about the fireplac...
         4                              i am feeling grouchy
         Name: Text, dtype: object
```

9. Result of TokenizerDataSet function()

```
In [28]:
emotion.tokenizerDataset()
emotion.features

Out[28]: array([[   0,    0,    0, ...,  138,    2,  625],
                [   0,    0,    0, ...,    3,   21, 1383],
                [   0,    0,    0, ...,    2,  495,  420],
                ...,
                [   0,    0,    0, ...,    5,  215,  191],
                [   0,    0,    0, ...,   30,   57, 2181],
                [   0,    0,    0, ...,   75,    5,   70]], dtype=int32)
```

10. Summary of RNN neural network

```
In [35]:
emotion.compiler()
emotion.m.summary()

Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, 63, 300)           5129100

 gru_2 (GRU)                 (None, 128)               165120

 dense_2 (Dense)             (None, 6)                 774

=================================================================
Total params: 5,294,994
Trainable params: 165,894
Non-trainable params: 5,129,100
_________________________________________________________________
```

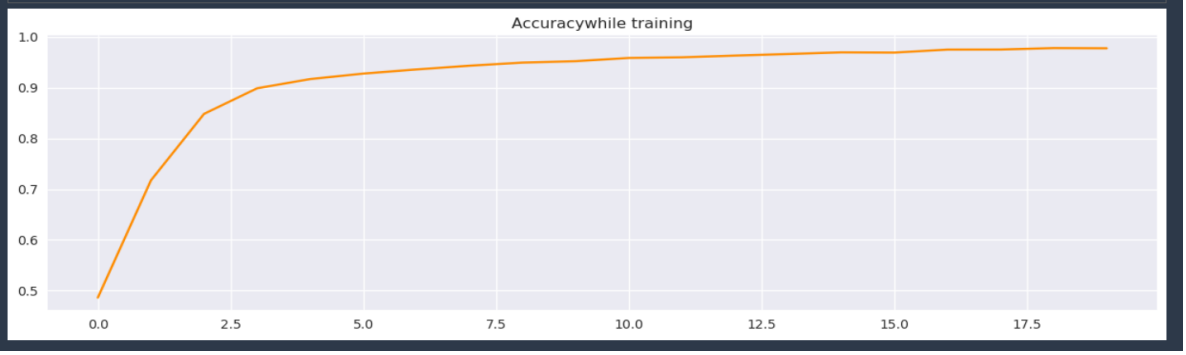
11. Training RNN Model

```
In [36]:
emotion.fit()

Epoch 1/20
71/71 [==============================] - 39s 519ms/step - loss: 1.3828 - accuracy: 0.4860
Epoch 2/20
71/71 [==============================] - 35s 499ms/step - loss: 0.8182 - accuracy: 0.7173
Epoch 3/20
71/71 [==============================] - 38s 542ms/step - loss: 0.4484 - accuracy: 0.8485
Epoch 4/20
71/71 [==============================] - 38s 539ms/step - loss: 0.2896 - accuracy: 0.8990
Epoch 5/20
71/71 [==============================] - 38s 532ms/step - loss: 0.2210 - accuracy: 0.9172
Epoch 6/20
71/71 [==============================] - 38s 531ms/step - loss: 0.1796 - accuracy: 0.9279
Epoch 7/20
71/71 [==============================] - 36s 512ms/step - loss: 0.1543 - accuracy: 0.9361
Epoch 8/20
71/71 [==============================] - 35s 497ms/step - loss: 0.1355 - accuracy: 0.9435
Epoch 9/20
71/71 [==============================] - 36s 504ms/step - loss: 0.1205 - accuracy: 0.9496
Epoch 10/20
71/71 [==============================] - 35s 495ms/step - loss: 0.1127 - accuracy: 0.9524
Epoch 11/20
71/71 [==============================] - 35s 495ms/step - loss: 0.1017 - accuracy: 0.9588
Epoch 12/20
71/71 [==============================] - 35s 497ms/step - loss: 0.0951 - accuracy: 0.9601
Epoch 13/20
71/71 [==============================] - 35s 499ms/step - loss: 0.0885 - accuracy: 0.9634
Epoch 14/20
71/71 [==============================] - 35s 498ms/step - loss: 0.0830 - accuracy: 0.9666
Epoch 15/20
71/71 [==============================] - 35s 499ms/step - loss: 0.0746 - accuracy: 0.9698
Epoch 16/20
71/71 [==============================] - 36s 500ms/step - loss: 0.0752 - accuracy: 0.9694
Epoch 17/20
71/71 [==============================] - 36s 505ms/step - loss: 0.0660 - accuracy: 0.9753
Epoch 18/20
71/71 [==============================] - 36s 500ms/step - loss: 0.0626 - accuracy: 0.9754
Epoch 19/20
71/71 [==============================] - 35s 498ms/step - loss: 0.0587 - accuracy: 0.9783
Epoch 20/20
71/71 [==============================] - 35s 496ms/step - loss: 0.0577 - accuracy: 0.9779
```

12. **Evaluation of Model:**

a) **Accuracy during Training**

```
[38]: import matplotlib.pyplot as plt
      mpl.style.use('seaborn')
      figure = plt.figure(figsize=(15, 4))
      plt.plot(emotion.history_training.history['accuracy'], 'darkorange', label = 'Accuracy')
      plt.title("Accuracywhile training")
      plt.show()
```

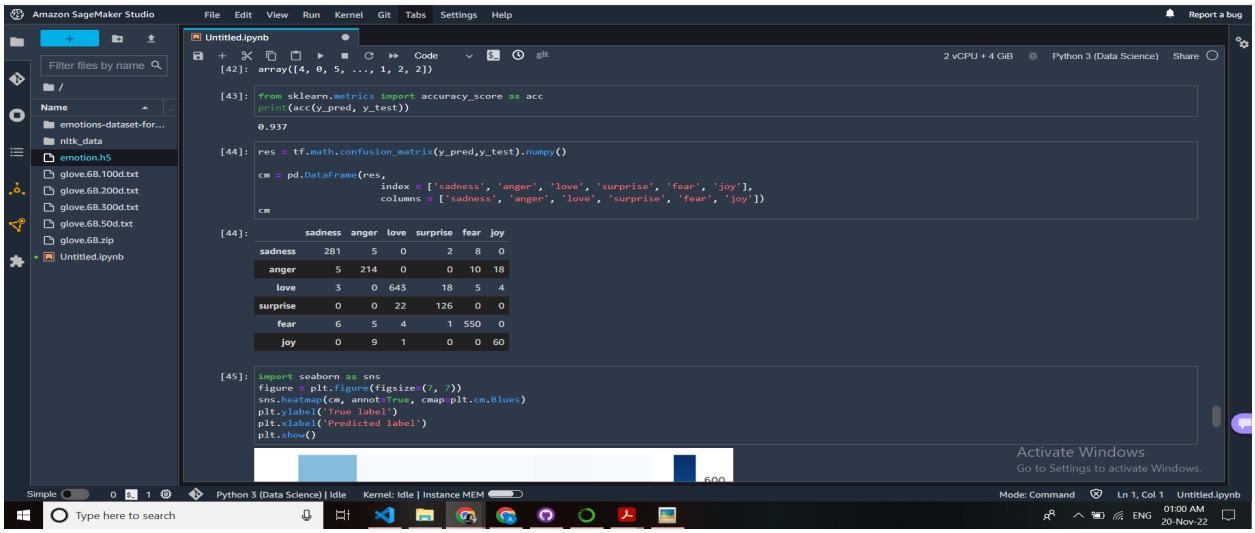


b) **Plotting Loss Function During Training**

```
[39]: figure = plt.figure(figsize=(15, 4))
      plt.plot(emotion.history_training.history['loss'], 'darkblue', label = 'Loss')
      plt.title("Loss while training")
      plt.show()
```


```
[40]: emotion.m.evaluate(emotion.X_test, emotion.Y_test, batch_size = 256)
```

c) **Confusion Matrix**

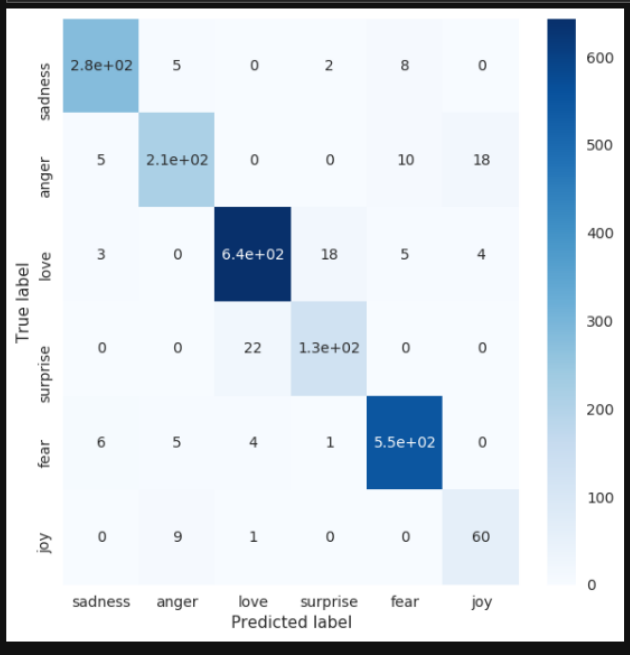


d) Predicting on Test Data

```
[41]: y_pred = emotion.m.predict(emotion.X_test)
      y_pred = np.argmax(y_pred, axis = 1)
      y_pred

      63/63 [==============================] - 2s 21ms/step
[41]: array([4, 0, 5, ..., 0, 2, 2])
```

e) Heatmap Visualization of Predicted labels

```
In [45]:
import seaborn as sns
figure = plt.figure(figsize=(7, 7))
sns.heatmap(cm, annot=True, cmap=plt.cm.Blues)
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()
```



13. **Comparison of Performance on different Clusters:**

RNN being a very powerful Model we were getting results on "**t3-medium**" cluster instances (3 node) itself within seconds for the same dataset so kept.

Hence RNN is a very good Model to implement sentiment analysis on NLP Problems.

2. Implementing ML Model using Spark MLlib

An important task in ML is model selection, or using data to find the best model or parameters for a given task. This is also called tuning. Tuning may be done for individual Estimators such as LogisticRegression, or for entire Pipelines which include multiple algorithms, featurization, and other steps. Users can tune an entire Pipeline at once, rather than tuning each element in the Pipeline separately.

MLlib supports model selection using tools such as CrossValidator and TrainValidationSplit. These tools require the following items:

• **Estimator**: algorithm or Pipeline to tune
• **Set of ParamMaps**: parameters to choose from, sometimes called a "parameter grid" to search over
• **Evaluator**: metric to measure how well a fitted Model does on held-out test data

At a high level, these model selection tools work as follows:

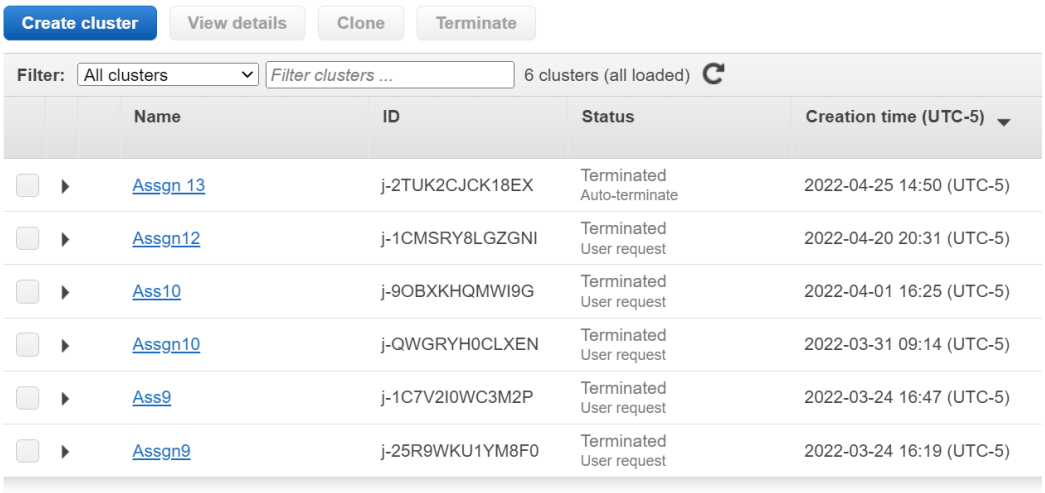
- They split the input data into separate training and test datasets.
- For each (training, test) pair, they iterate through the set of ParamMaps: For each ParamMap, they fit the Estimator using those parameters, get the fitted Model, and evaluate the Model's performance using the Evaluator.
- They select the Model produced by the best-performing set of parameters.

The Evaluator can be a Regression-Evaluator for regression problems, a Binary-Classification-Evaluator for binary data, a Multiclass-Classification-Evaluator for multiclass problems, a Multilabel Classification-Evaluator for multi-label classifications, or a Ranking-Evaluator for ranking problems.
The default metric used to choose the best ParamMap can be overridden by the set-Metric-Name method in each of these evaluators.

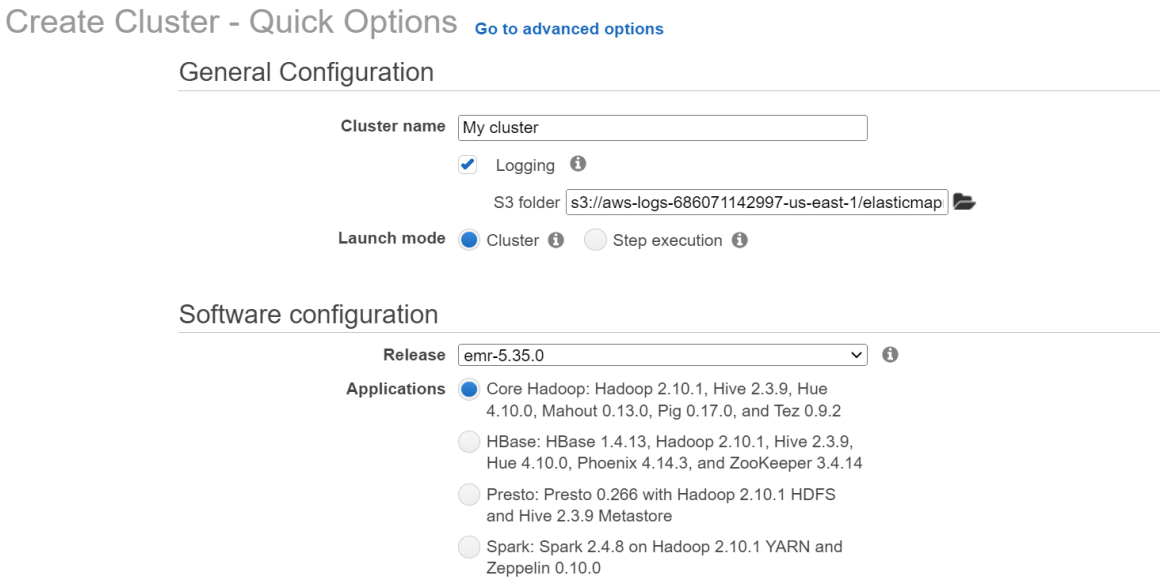
Below we have implemented this part in the following steps -

There are multiple cloud providers available to choose from in order to analyze spark R services so a few are AWS, Azure, Cloudera, data bricks, google cloud, etc. Here we choose AWS EMR using spark to run.

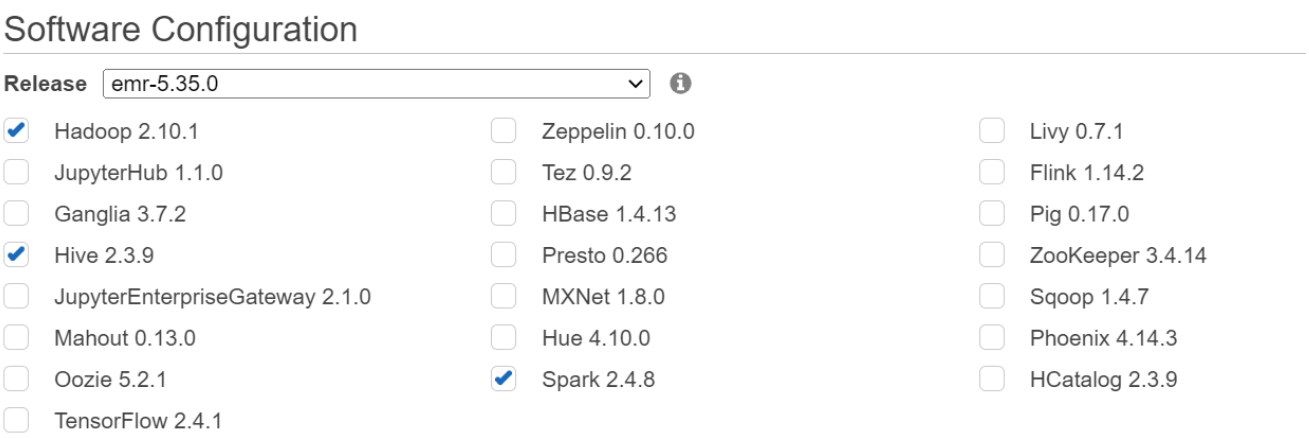
1. **Create an EMR Cluster on your AWS Account.**



2. **Go to advanced options**



3. **In the first step, Configure Software and Steps, please choose the latest EMR release in Software Configuration and select the below options**



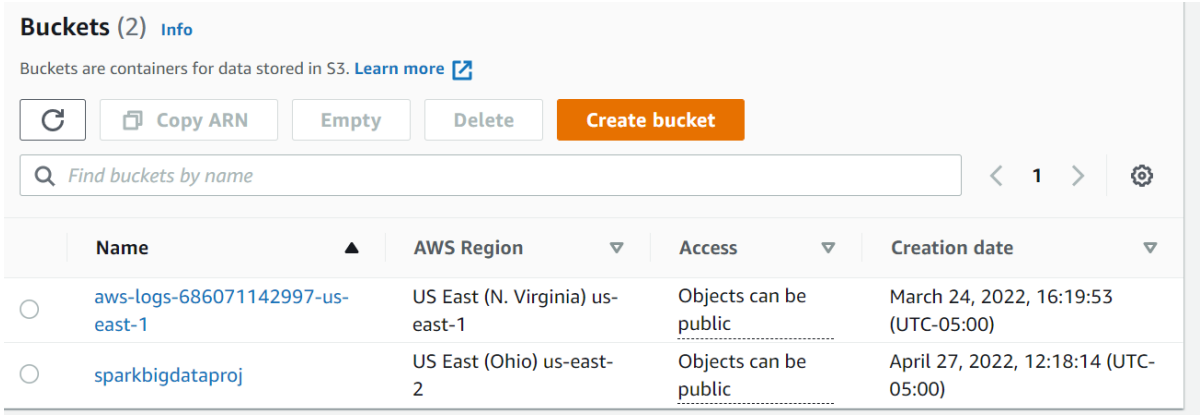
4. **Maximize resource allocation for your current EMR cluster using the below configuration**

```
{
        "Classification": "spark",
        "Properties": {
                "maximizeResourceAllocation": "true"
                }
}
```

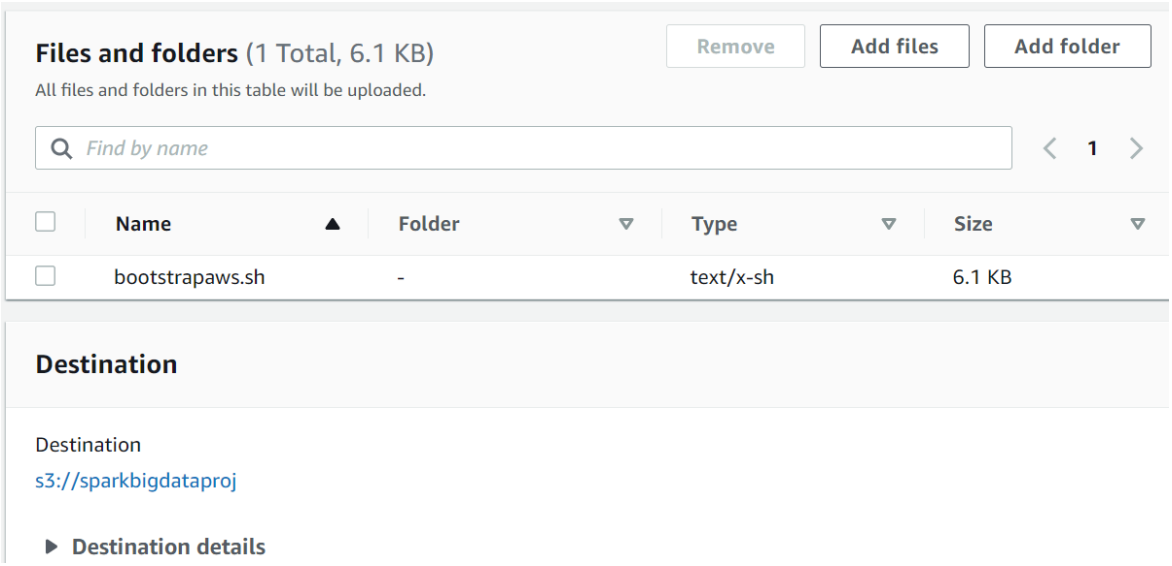
5. **In the second step, configure the Hardware as below**

Node type	Instance type	Instance count	Purchasing option
Master Master - 1	**m4.2xlarge** 8 vCore, 32 GiB memory, EBS only storage EBS Storage: 100 GiB Add configuration settings	1 Instances	**On-demand** **Spot** Use on-demand as max price
Core Core - 2	**m4.2xlarge** 8 vCore, 32 GiB memory, EBS only storage EBS Storage: 100 GiB Add configuration settings	0 Instances	**On-demand** **Spot** Use on-demand as max price
Task Task - 3	**m4.2xlarge** 8 vCore, 32 GiB memory, EBS only storage EBS Storage: 128 GiB Add configuration settings	0 Instances	**On-demand** **Spot** Use on-demand as max price

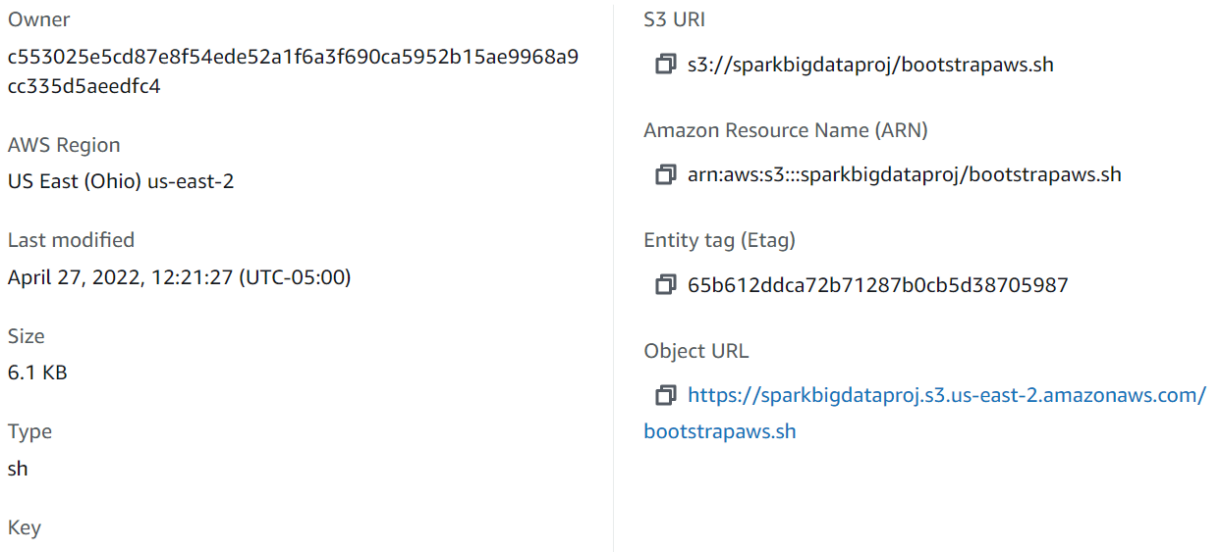
6. **Go to third step, to configure general cluster settings so here we configure bootstrap action**.
   - Next go to amazon blog - https://aws.amazon.com/blogs/big-data/running-sparklyr-rstudios-r-interface-to-spark-on-amazon-emr/
   - and edit the shell script as below and save it as a .sh file in R: https://aws-bigdata-blog.s3.amazonaws.com/artifacts/aws-blog-emr-rstudio-sparklyr/rstudio_sparklyr_emr5.sh
   - Go to aws and open S3, Create a bucket - sparkbigdataproj



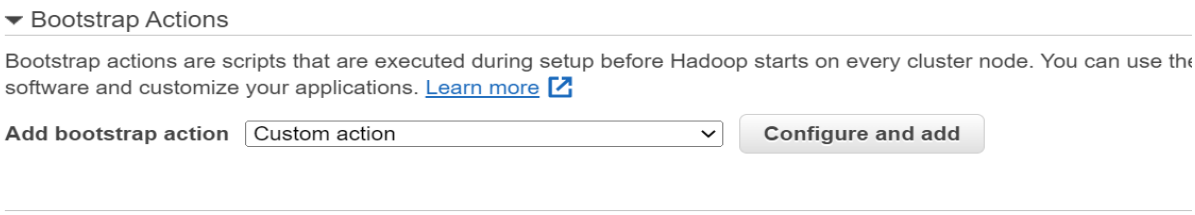
7. **Upload the sh file into it**

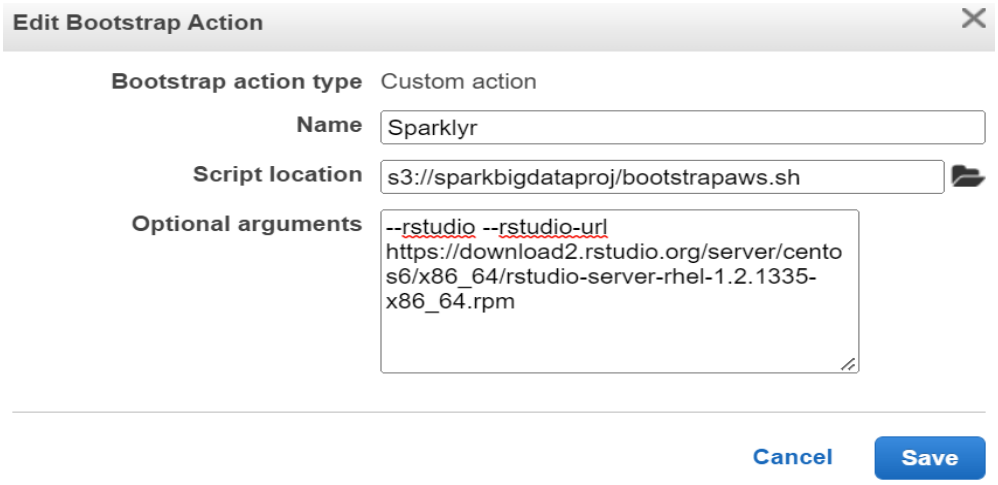


8. **Open the object and Copy the S3 URI Path**

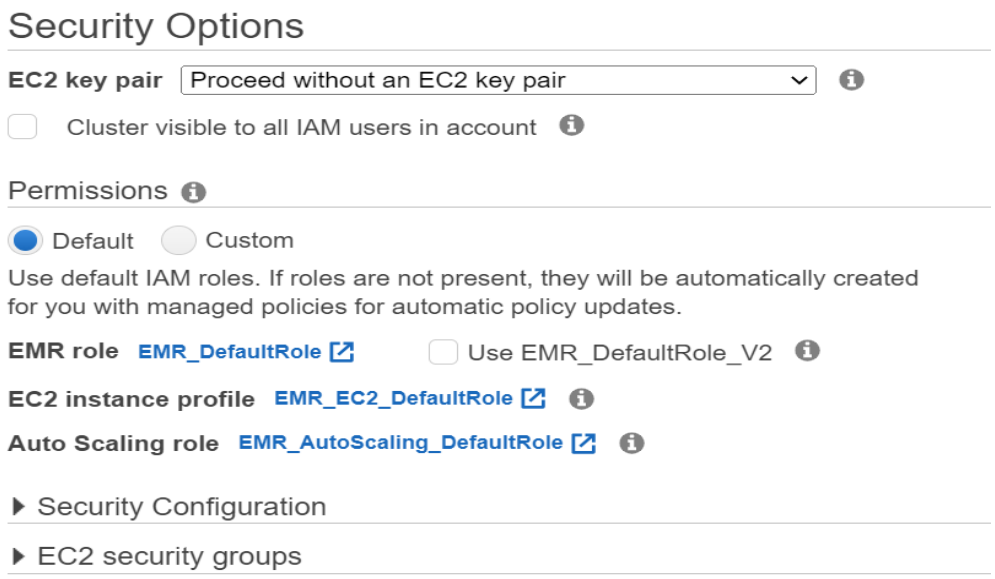


9. **Choose Custom Action then Configure and add the URI Path in emr cluster.**

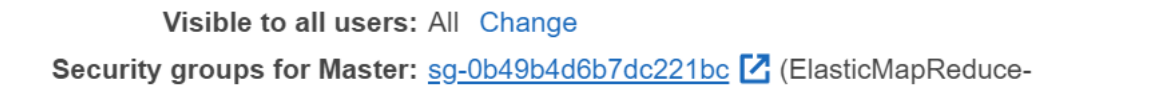


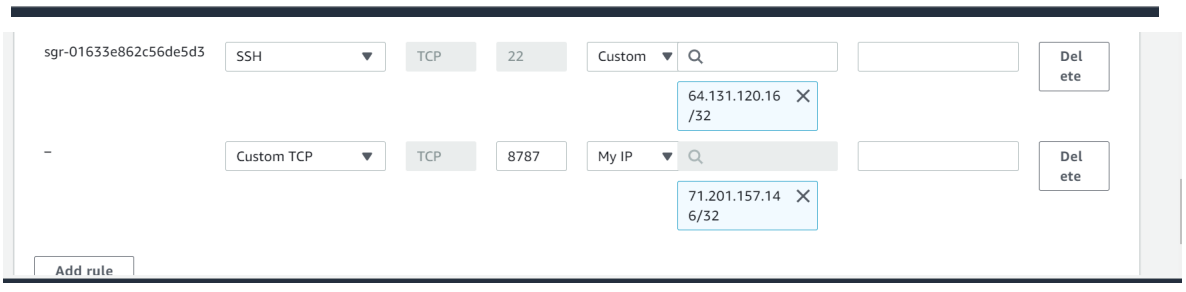


10. Go to last step, Security unselect the cluster visible option and create a cluster

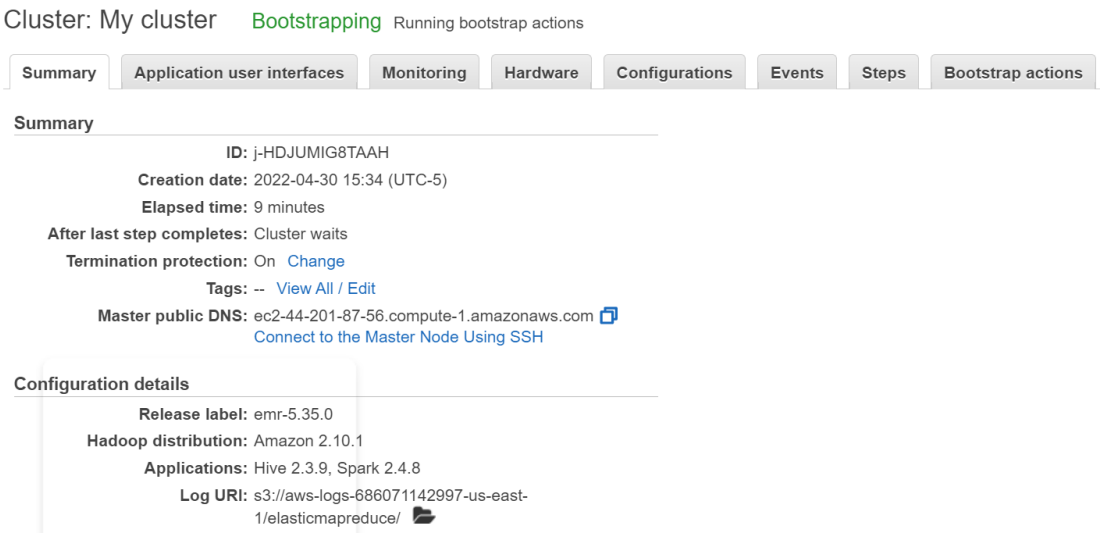


11. We will wait cluster to start and then configure the security groups for Master and add the edit inbound rules as below:

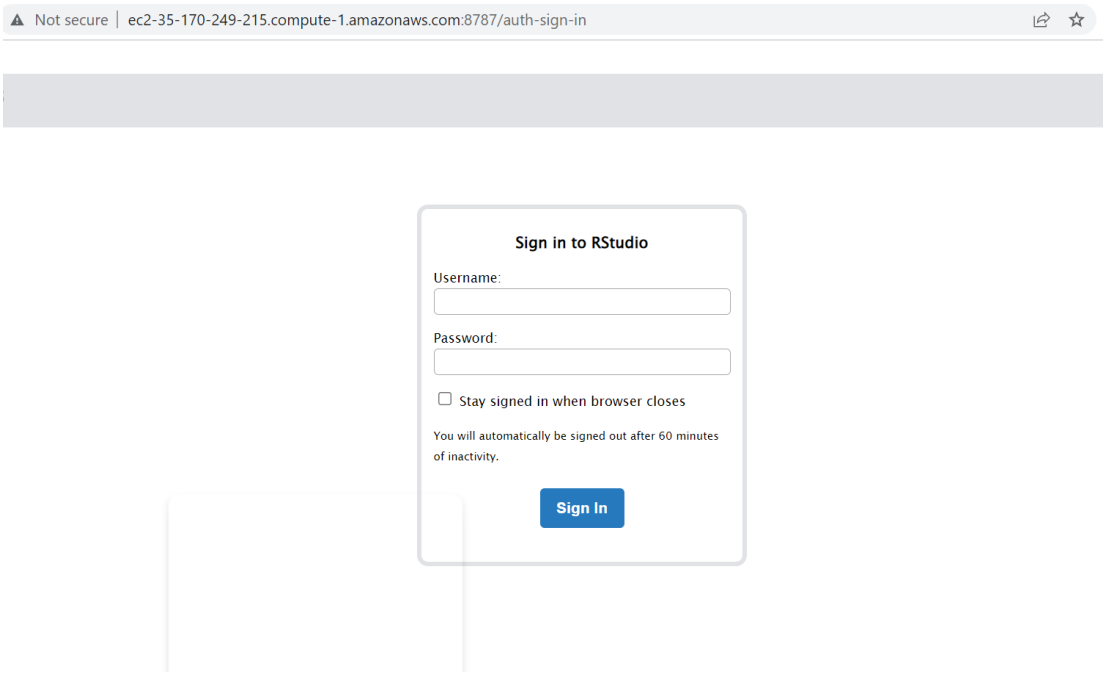




12. **Then, create a cluster, after sometime the cluster status changes to bootstrapping.**



13. **Add the 8787 port to the url - http://ec2-35-170-249-215.compute-1.amazonaws.com:8787/ and open it in a new tab- you will be able to see the login page of R studio**.



Now we are ready to implement the Machine Learning Model using the Spark-R configuration we just set up.

What are we implementing in Spark-MLlib

1. Determining Sentiment using **Random Forest**.
2. Determining Sentiment using **Logistic Regression**

14. Installed the required packages

```
> install.packages("dplyr")
also installing the dependencies 'glue', 'cli', 'rlang', 'vctrs'

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/glue_1.6.2.tgz'
Content type 'application/x-gzip' length 155475 bytes (151 KB)
==================================================
downloaded 151 KB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/cli_3.3.0.tgz'
Content type 'application/x-gzip' length 1171398 bytes (1.1 MB)
==================================================
downloaded 1.1 MB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/rlang_1.0.2.tgz'
Content type 'application/x-gzip' length 1822104 bytes (1.7 MB)
==================================================
downloaded 1.7 MB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/vctrs_0.4.1.tgz'
Content type 'application/x-gzip' length 1761486 bytes (1.7 MB)
==================================================
downloaded 1.7 MB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/dplyr_1.0.9.tgz'
Content type 'application/x-gzip' length 1327720 bytes (1.3 MB)
==================================================
downloaded 1.3 MB


The downloaded binary packages are in
        /var/folders/d_/23y7m6ns5kg1n8jjr5kh1cbc0000gn/T//Rtmp0wXCK8/downloaded_packages
>
```

```
> install.packages("sparklyr")
also installing the dependencies 'htmlwidgets', 'config', 'forge', 'r2d3', 'rprojroot', 'tidyr'

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/htmlwidgets_1.5.4.tgz'
Content type 'application/x-gzip' length 898177 bytes (877 KB)
==================================================
downloaded 877 KB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/config_0.3.1.tgz'
Content type 'application/x-gzip' length 78547 bytes (76 KB)
==================================================
downloaded 76 KB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/forge_0.2.0.tgz'
Content type 'application/x-gzip' length 38522 bytes (37 KB)
==================================================
downloaded 37 KB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/r2d3_0.2.6.tgz'
Content type 'application/x-gzip' length 1905942 bytes (1.8 MB)
==================================================
downloaded 1.8 MB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/rprojroot_2.0.3.tgz'
Content type 'application/x-gzip' length 100267 bytes (97 KB)
==================================================
downloaded 97 KB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/tidyr_1.2.0.tgz'
Content type 'application/x-gzip' length 1022523 bytes (998 KB)
==================================================
downloaded 998 KB

trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/sparklyr_1.7.5.tgz'
Content type 'application/x-gzip' length 5785886 bytes (5.5 MB)
==================================================
downloaded 5.5 MB
```

```
The downloaded binary packages are in
        /var/folders/d_/23y7m6ns5kg1n8jjr5kh1cbc0000gn/T//Rtmp0wXCK8/downloaded_packages
> install.packages("data.table")
trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/data.table_1.14.2.tgz'
Content type 'application/x-gzip' length 2354815 bytes (2.2 MB)
==================================================
downloaded 2.2 MB


The downloaded binary packages are in
        /var/folders/d_/23y7m6ns5kg1n8jjr5kh1cbc0000gn/T//Rtmp0wXCK8/downloaded_packages
> install.packages("ggplot2")
trying URL 'https://cran.rstudio.com/bin/macosx/big-sur-arm64/contrib/4.1/ggplot2_3.3.6.tgz'
Content type 'application/x-gzip' length 4122229 bytes (3.9 MB)
==================================================
downloaded 3.9 MB


The downloaded binary packages are in
        /var/folders/d_/23y7m6ns5kg1n8jjr5kh1cbc0000gn/T//Rtmp0wXCK8/downloaded_packages
>
```

Once we have set up the environment, we are now implementing the actual part. Importing necessary libraries. We'll be using a number of Python tools and frameworks. Using the function readFile(filename), we will read the contents of a text file and output the contents of the file as a list containing single words. Using this function, we will read all the CSV files, in which each row represents a text file and the columns contain the counts of each word in that specific text file. Read the CSV files and display data(training testing validation)

1. Training Data Image

```
> glimpse(df_train)
Rows: 170,883
Columns: 31
$ Time   <dbl> 51742, 61413, 74745, 144191, 77866, 138901, 28314, 119597, 161002, 121976, 42390, 123162, 48874, 21503, 140347, 169847, 39258, 40772, 55256, 143400, 4076, 1…
$ V1     <dbl> 1.21777027, 0.66529375, 1.27217637, -7.72533613, -0.51741575, 2.14992728, -0.51959247, -0.69251468, -0.69582680, 1.95734543, -5.45335867, -0.23939182, -1.63…
$ V2     <dbl> 0.077243995, -0.779358247, 0.169924869, -2.354525834, 0.313685579, -1.955008075, 0.887040653, 1.074982165, -0.292627271, 0.110680440, -0.231388334, -0.23551…
$ V3     <dbl> 0.498320921, 1.680699937, -0.179971299, -4.607707356, 1.537755598, -0.511217981, 1.440903939, -0.214693143, 1.243020585, -1.632382884, -1.507947139, -1.6858…
$ V4     <dbl> 0.52081540, 3.15837257, 1.06222072, 0.16461745, -1.55839611, -1.85509676, 1.33028614, -0.48961654, -1.96064228, 1.42177447, -1.05100263, 1.02082718, -1.0151…
$ V5     <dbl> -0.57493216, -1.44556215, 0.52113991, -6.98564210, 0.70002786, -1.40519345, 0.28485258, 1.19239059, -1.01894794, 0.38608355, -0.88952104, 1.19676810, 1.7418…
$ V6     <dbl> -0.70860220, 0.72112018, 0.61467613, 5.63762828, 1.28801100, 0.88406274, -0.01240266, -0.51072267, -0.05348007, -1.13756538, -2.14250592, -2.85250088, 0.510…
$ V7     <dbl> -0.15910140, -0.73334910, 0.01776800, 5.31388329, 0.27189790, -1.99249895, 0.54990329, 1.17717094, -0.92444059, 0.69048453, -0.69071343, 0.83313809, -0.1646…
$ V8     <dbl> 0.03974627, 0.35181687, 0.08778932, 0.66060851, 0.50785636, 0.35322381, 0.11750182, -0.37740411, 0.50319274, -0.42686523, 1.62623071, -0.37323827, 0.5443738…
$ V9     <dbl> 0.04662027, 0.94769094, 0.41939825, 0.06467695, 0.03874012, -0.67957025, -0.28542418, 0.44992879, -2.38251375, 0.20385026, 0.28120308, -0.24838164, -0.31510…
$ V10    <dbl> 0.15416414, 0.24338193, -0.11428525, -1.27791475, -0.46023339, 1.65873457, -0.09904113, -0.71702185, 0.65392202, 0.24216188, -1.88736834, -1.46248628, -0.57…
$ V11    <dbl> 1.18739570, -1.65843187, -1.82494214, 0.51420147, 2.21283228, -0.39765542, -0.62739817, -0.77397431, -1.32835501, -0.97896262, -0.95992515, 0.81502624, 2.13…
$ V12    <dbl> 0.14041972, -0.19943952, -0.04508140, 0.56761746, 0.73287217, -0.91132998, 0.15465282, -0.46458157, -1.48685407, 0.30331634, 2.05764194, -0.74798787, 0.0202…
$ V13    <dbl> -1.49365270, -1.25173693, -0.09806199, 0.59535051, -0.61883494, -0.20927264, -0.16824800, -0.30603555, -0.07741579, -0.29891972, 1.58922066, -1.07850222, -1…
$ V14    <dbl> 0.778755068, -0.703287023, 0.022784387, 0.737137725, 0.113775958, -0.542535017, 0.026868926, -2.148160000, -0.144727134, 0.550597636, 1.247583973, -2.677376…
$ V15    <dbl> 0.52057694, -1.44303735, 0.03103779, 1.40786805, 0.98407363, -0.07748705, 0.22485432, -0.69270992, 0.44892596, -0.50939667, 0.07651487, 0.60025407, 1.119257…
$ V16    <dbl> 0.58043838, 0.23800276, -0.30547969, 1.83604611, -0.48070189, 0.53662657, -1.22143933, -0.03052407, -0.78638800, -0.73258439, -0.21621394, 0.38071848, -0.78…
$ V17    <dbl> -0.57581565, 0.08258451, -0.23349454, -0.18545377, 0.18041636, -0.30796733, 0.63322382, 1.00386814, 1.08161413, -0.12311094, 0.61404035, 2.79859005, 0.53151…
$ V18    <dbl> 0.164915866, -0.091704277, -0.496386172, -0.439953804, -1.792958946, 1.278902925, -0.670814150, 0.278332173, 0.385911950, -0.647856510, -0.287374850, 0.9238…
$ V19    <dbl> 0.183083986, -0.587018607, 0.162940224, -0.642606025, -2.015641436, 0.175551053, 0.722868501, -0.227393384, 0.882431905, -0.235162987, 0.323835153, -0.35551…
$ V20    <dbl> -0.194238948, 0.173779642, -0.167845299, -5.028522602, -0.062245780, -0.292541879, 0.186150070, -0.021684075, -0.208347522, -0.229382732, -0.967483857, 0.47…
$ V21    <dbl> -0.226153731, 0.046142968, -0.199115064, -1.073900540, 0.010926041, -0.091000411, -0.019202261, -0.022695751, -0.087784279, 0.071818891, -0.117051821, 0.171…
$ V22    <dbl> -0.77301817, -0.01765075, -0.32912090, 1.17360022, 0.33847836, 0.02869474, 0.26010819, 0.42127313, -0.04729308, 0.35135162, 0.12359577, 0.04862732, 0.594241…
$ V23    <dbl> 0.145242554, -0.209463297, -0.228424917, -0.183291096, 0.066528800, 0.204367543, -0.106747404, -0.165215854, -0.236493437, -0.033844403, -0.579949776, 0.606…
$ V24    <dbl> 0.276868331, 0.385114789, -1.313536521, -0.584830819, -0.989922227, -0.412525548, 0.096712750, 0.530683751, 0.654293114, -0.006930706, 0.569689850, 0.665258…
$ V25    <dbl> 0.129511016, 0.296199660, 0.844640504, 0.008990326, -0.638208162, -0.503210266, -0.081635853, -0.191540072, 0.384780489, 0.443082256, 1.236152967, -0.528511…
$ V26    <dbl> 0.083098376, 0.082171404, -0.224776172, 0.618217507, 0.806935439, -0.217686199, -0.223809540, 0.500289835, 0.103345352, -0.493266120, -0.604587731, 0.640381…
$ V27    <dbl> -0.04399679, 0.02549195, 0.03753611, -0.57952974, 0.07574998, 0.04153347, 0.42188220, -0.14282286, -0.04176558, -0.02190505, 0.38435179, -0.13437705, -0.221…
$ V28    <dbl> 0.0049825747, 0.0710640262, 0.0005805126, -0.6069469475, -0.1814167096, -0.0347870456, 0.2076466615, 0.0168861053, -0.0229249781, -0.0556870970, -1.13190491…
$ Amount <dbl> 0.99, 214.04, 3.76, 1395.00, 7.68, 73.50, 17.18, 14.99, 15.00, 45.50, 7.50, 145.00, 28.75, 14.19, 22.08, 0.99, 830.78, 2.99, 1.46, 9.39, 9.60, 56.00, 19.99,…
```

2. Validation Data glimpse(df_val)

```
> glimpse(df_val)
Rows: 170,883
Columns: 31
$ Time   <dbl> 51742, 61413, 74745, 144191, 77866, 138901, 28314, 119597, 161002, 121976, 42390, 123162, 48874, 21503, 140347, 169847, 39258, 40772, 55256, 143400, 4076, 1…
$ V1     <dbl> 1.21777027, 0.66529375, 1.27217637, -7.72533613, -0.51741575, 2.14992728, -0.51959247, -0.69251468, -0.69582680, 1.95734543, -5.45335867, -0.23939182, -1.63…
$ V2     <dbl> 0.077243995, -0.779358247, 0.169924869, -2.354525834, 0.313685579, -1.955008075, 0.887040653, 1.074982165, -0.292627271, 0.110680440, -0.231388334, -0.23551…
$ V3     <dbl> 0.498320921, 1.680699937, -0.179971299, -4.607707356, 1.537755598, -0.511217981, 1.440903939, -0.214693143, 1.243020585, -1.632382884, -1.507947139, -1.6858…
$ V4     <dbl> 0.52081540, 3.15837257, 1.06222072, 0.16461745, -1.55839611, -1.85509676, 1.33028614, -0.48961654, -1.96064228, 1.42177447, -1.05100263, 1.02082718, -1.0151…
$ V5     <dbl> -0.57493216, -1.44556215, 0.52113991, -6.98564210, 0.70002786, -1.40519345, 0.28485258, 1.19239059, -1.01894794, 0.38608355, -0.88952104, 1.19676810, 1.7418…
$ V6     <dbl> -0.70860220, 0.72112018, 0.61467613, 5.63762828, 1.28801100, 0.88406274, -0.01240266, -0.51072267, -0.05348007, -1.13756538, -2.14250592, -2.85250088, 0.510…
$ V7     <dbl> -0.15910140, -0.73334910, 0.01776800, 5.31388329, 0.27189790, -1.99249895, 0.54990329, 1.17717094, -0.92444059, 0.69048453, -0.69071343, 0.83313809, -0.1646…
$ V8     <dbl> 0.03974627, 0.35181687, 0.08778932, 0.66060851, 0.50785636, 0.35322381, 0.11750182, -0.37740411, 0.50319274, -0.42686523, 1.62623071, -0.37323827, 0.5443738…
$ V9     <dbl> 0.04662027, 0.94769094, 0.41939825, 0.06467695, 0.03874012, -0.67957025, -0.28542418, 0.44992879, -2.38251375, 0.20385026, 0.28120308, -0.24838164, -0.31510…
$ V10    <dbl> 0.15416414, 0.24338193, -0.11428525, -1.27791475, -0.46023339, 1.65873457, -0.09904113, -0.71702185, 0.65392202, 0.24216188, -1.88736834, -1.46248628, -0.57…
$ V11    <dbl> 1.18739570, -1.65843187, -1.82494214, 0.51420147, 2.21283228, -0.39765542, -0.62739817, -0.77397431, -1.32835501, -0.97896262, -0.95992515, 0.81502624, 2.13…
$ V12    <dbl> 0.14041972, -0.19943952, -0.04508140, 0.56761746, 0.73287217, -0.91132998, 0.15465282, -0.46458157, -1.48685407, 0.30331634, 2.05764194, -0.74798787, 0.0202…
$ V13    <dbl> -1.49365270, -1.25173693, -0.09806199, 0.59535051, -0.61883494, -0.20927264, -0.16824800, -0.30603555, -0.07741579, -0.29891972, 1.58922066, -1.07850222, -1…
$ V14    <dbl> 0.778755068, -0.703287023, 0.022784387, 0.737137725, 0.113775958, -0.542535017, 0.026868926, -2.148160000, -0.144727134, 0.550597636, 1.247583973, -2.677376…
$ V15    <dbl> 0.52057694, -1.44303735, 0.03103779, 1.40786805, 0.98407363, -0.07748705, 0.22485432, -0.69270992, 0.44892596, -0.50939667, 0.07651487, 0.60025407, 1.119257…
$ V16    <dbl> 0.58043838, 0.23800276, -0.30547969, 1.83604611, -0.48070189, 0.53662657, -1.22143933, -0.03052407, -0.78638800, -0.73258439, -0.21621394, 0.38071848, -0.78…
$ V17    <dbl> -0.57581565, 0.08258451, -0.23349454, -0.18545377, 0.18041636, -0.30796733, 0.63322382, 1.00386814, 1.08161413, -0.12311094, 0.61404035, 2.79859005, 0.53151…
$ V18    <dbl> 0.164915866, -0.091704277, -0.496386172, -0.439953804, -1.792958946, 1.278902925, -0.670814150, 0.278332173, 0.385911950, -0.647856510, -0.287374850, 0.9238…
$ V19    <dbl> 0.183083986, -0.587018607, 0.162940224, -0.642606025, -2.015641436, 0.175551053, 0.722868501, -0.227393384, 0.882431905, -0.235162987, 0.323835153, -0.35551…
$ V20    <dbl> -0.194238948, 0.173779642, -0.167845299, -5.028522602, -0.062245780, -0.292541879, 0.186150070, -0.021684075, -0.208347522, -0.229382732, -0.967483857, 0.47…
$ V21    <dbl> -0.226153731, 0.046142968, -0.199115064, -1.073900540, 0.010926041, -0.091000411, -0.019202261, -0.022695751, -0.087784279, 0.071818891, -0.117051821, 0.171…
$ V22    <dbl> -0.77301817, -0.01765075, -0.32912090, 1.17360022, 0.33847836, 0.02869474, 0.26010819, 0.42127313, -0.04729308, 0.35135162, 0.12359577, 0.04862732, 0.594241…
$ V23    <dbl> 0.145242554, -0.209463297, -0.228424917, -0.183291096, 0.066528800, 0.204367543, -0.106747404, -0.165215854, -0.236493437, -0.033844403, -0.579949776, 0.606…
$ V24    <dbl> 0.276868331, 0.385114789, -1.313536521, -0.584830819, -0.989922227, -0.412525548, 0.096712750, 0.530683751, 0.654293114, -0.006930706, 0.569689850, 0.665258…
$ V25    <dbl> 0.129511016, 0.296199660, 0.844640504, 0.008990326, -0.638208162, -0.503210266, -0.081635853, -0.191540072, 0.384780489, 0.443082256, 1.236152967, -0.528511…
$ V26    <dbl> 0.083098376, 0.082171404, -0.224776172, 0.618217507, 0.806935439, -0.217686199, -0.223809540, 0.500289835, 0.103345352, -0.493266120, -0.604587731, 0.640381…
$ V27    <dbl> -0.04399679, 0.02549195, 0.03753611, -0.57952974, 0.07574998, 0.04153347, 0.42188220, -0.14282286, -0.04176558, -0.02190505, 0.38435179, -0.13437705, -0.221…
$ V28    <dbl> 0.0049825747, 0.0710640262, 0.0005805126, -0.6069469475, -0.1814167096, -0.0347870456, 0.2076466615, 0.0168861053, -0.0229249781, -0.0556870970, -1.13190491…
$ Amount <dbl> 0.99, 214.04, 3.76, 1395.00, 7.68, 73.50, 17.18, 14.99, 15.00, 45.50, 7.50, 145.00, 28.75, 14.19, 22.08, 0.99, 830.78, 2.99, 1.46, 9.39, 9.60, 56.00, 19.99,…
$ Class  <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
> |
```

3, Viewing Glimpse of Dataset and Preprocessing

```
+    select(Class) %>%
+    group_by(Class) %>%
+    summarise(count = n()) %>%
+    glimpse
Rows: 2
Columns: 2
$ Class <fct> 0, 1
$ count <int> 170588, 295
```

4. **Implement logistic regression in Spark-R**

Now we train a basic logistic regression model to classify the sentiment of the reviews. Make sure you do not use the filename as a feature if you previously included it in the Dataframe. Compare the accuracy of this basic model on the training set and the validation set. Are you overfitting? Try changing the parameters of the logistic regression, such as adding a regularization term, to reduce the overfitting.

```
install.packages("dplyr")
df_train <- read.csv("/usr/mounika/Desktop/CSP_Project/Dataset/
train.csv")
df_test <- read.csv("/usr/mounika/Desktop/CSP_Project/Dataset/train.csv")
df_val <- read.csv("/usr/mounika/Desktop/CSP_Project/Dataset/train.csv")

spark_write_parquet(df_train, path="/user/rstudio-user",
mode="overwrite")
spark_write_parquet(df_test, path="/user/rstudio-user", mode="overwrite")
spark_write_parquet(df_val, path="/user/rstudio-user", mode="overwrite")

dim(df_train)
dim(df_val)
dim(df_test)

df_train$Class <- factor(df_train$Class)

train  %>%
  select(Class) %>%
  group_by(Class) %>%
  summarise(count = n()) %>%
  glimpse

test %>%
  select(Class) %>%
  group_by(Class) %>%
  summarise(count = n()) %>%
  glimpse

#Logistic Regression model
Logistic_Model=glm(Class~.,test_data,family=binomial())
summary(Logistic_Model)
```

Logistic Regression output-1

```
> summary(Logistic_Model)

Call:
glm(formula = Class ~ ., family = binomial(), data = df_test)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.7005  -0.0290  -0.0177  -0.0101   4.1608

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -8.525e+00  3.399e-01 -25.080  < 2e-16 ***
Time        -4.941e-06  2.860e-06  -1.727 0.084110 .
V1           1.397e-01  5.491e-02   2.544 0.010966 *
V2           5.574e-02  8.832e-02   0.631 0.527959
V3          -9.386e-02  6.724e-02  -1.396 0.162740
V4           7.831e-01  1.153e-01   6.793 1.10e-11 ***
V5           1.679e-01  9.973e-02   1.683 0.092324 .
V6          -1.671e-01  9.540e-02  -1.752 0.079845 .
V7          -9.329e-02  9.375e-02  -0.995 0.319690
V8          -1.979e-01  3.831e-02  -5.166 2.39e-07 ***
V9          -5.196e-02  1.761e-01  -0.295 0.767896
V10         -7.846e-01  1.478e-01  -5.310 1.09e-07 ***
V11         -7.781e-02  1.055e-01  -0.738 0.460796
V12          1.511e-01  1.114e-01   1.356 0.174961
V13         -3.745e-01  1.058e-01  -3.540 0.000400 ***
V14         -6.649e-01  8.045e-02  -8.265  < 2e-16 ***
V15         -1.838e-01  1.084e-01  -1.696 0.089825 .
V16          1.898e-02  2.211e-01   0.086 0.931600
V17         -2.416e-02  9.246e-02  -0.261 0.793863
V18         -1.596e-01  2.121e-01  -0.752 0.452002
V19          2.615e-01  1.470e-01   1.778 0.075333 .
V20         -3.901e-01  1.128e-01  -3.457 0.000545 ***
V21          4.734e-01  8.580e-02   5.517 3.45e-08 ***
V22          8.765e-01  1.803e-01   4.860 1.17e-06 ***
V23         -1.337e-01  7.490e-02  -1.785 0.074310 .
V24          1.602e-01  1.848e-01   0.867 0.385821
```

Logistic Regression output-2

```
V10         -7.846e-01  1.478e-01  -5.310 1.09e-07 ***
V11         -7.781e-02  1.055e-01  -0.738 0.460796
V12          1.511e-01  1.114e-01   1.356 0.174961
V13         -3.745e-01  1.058e-01  -3.540 0.000400 ***
V14         -6.649e-01  8.045e-02  -8.265  < 2e-16 ***
V15         -1.838e-01  1.084e-01  -1.696 0.089825 .
V16          1.898e-02  2.211e-01   0.086 0.931600
V17         -2.416e-02  9.246e-02  -0.261 0.793863
V18         -1.596e-01  2.121e-01  -0.752 0.452002
V19          2.615e-01  1.470e-01   1.778 0.075333 .
V20         -3.901e-01  1.128e-01  -3.457 0.000545 ***
V21          4.734e-01  8.580e-02   5.517 3.45e-08 ***
V22          8.765e-01  1.803e-01   4.860 1.17e-06 ***
V23         -1.337e-01  7.490e-02  -1.785 0.074310 .
V24          1.602e-01  1.848e-01   0.867 0.385821
V25          3.093e-02  1.659e-01   0.186 0.852130
V26         -1.228e-01  2.433e-01  -0.505 0.613668
V27         -9.467e-01  1.409e-01  -6.718 1.85e-11 ***
V28         -4.860e-01  1.389e-01  -3.498 0.000469 ***
Amount       1.151e-03  4.907e-04   2.346 0.019001 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 4342.9  on 170882  degrees of freedom
Residual deviance: 1375.6  on 170852  degrees of freedom
AIC: 1437.6

Number of Fisher Scoring iterations: 12
```

4. **Implement Random Forest in Spark-R**

A Random Forest classifier random forest classifier. It is a type of ensemble learning method, where many decision trees (hence forest) make different predictions, and the majority outcome is chosen as the prediction. Random forest methods are also known for their resistance to over-fitting and are a widely used technique for classification problems. It prevents overfitting by using a series of weaker trees that cannot themselves overfit the training set and takes a majority vote from them to classify. Training a Classifier on the same dataset trains weak learners sequentially, so they focus on the points that are hard to classify, so we made sure to limit each individual tree so it is individually weak.

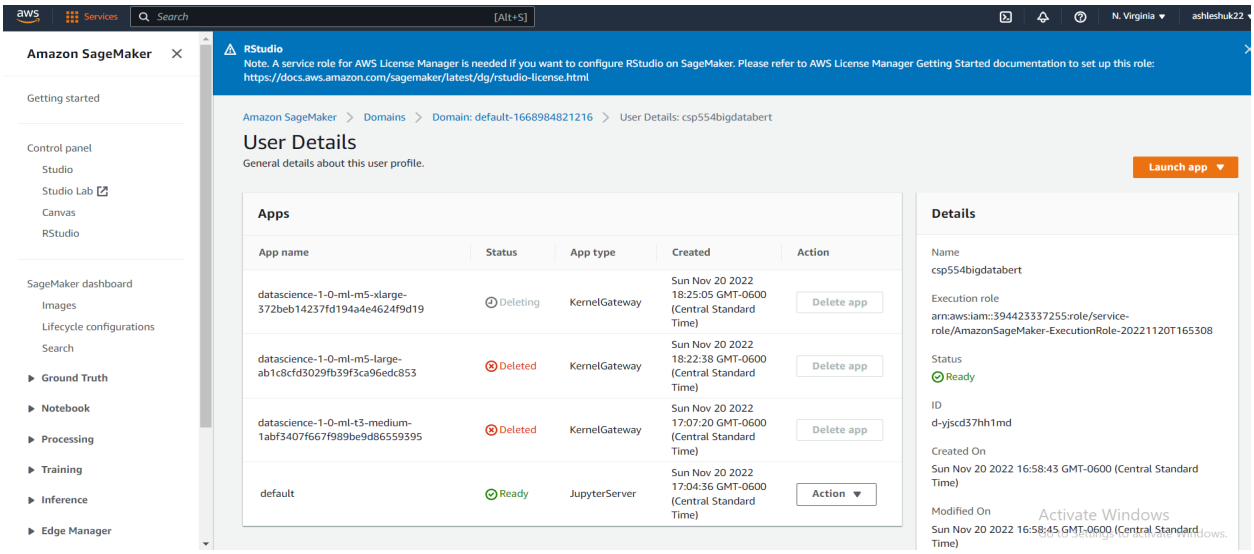
```
test$predictedTrim10 <- predict(rfModelTrim10, test)

F1_10 <- F1_Score(test$Class, test$predictedTrim10)
F1_10

# build dataframe of number of variables and scores
numVariables <- c(1,2,3,4,5,10,17)
F1_Score <- c(F1_1, F1_2, F1_3, F1_4, F1_5, F1_10, F1_all)
variablePerf <- data.frame(numVariables, F1_Score)


# plot score performance against number of variables
options(repr.plot.width=4, repr.plot.height=3)
ggplot(variablePerf, aes(numVariables, F1_Score)) + geom_point() + labs(x
= "Number of Variables", y = "F1 Score", title = "F1 Score Performance")
```

```
# build random forest model using every variable
rf.fit <- randomForest(Class ~ ., data=df_train, ntree=1000,
                       keep.forest=FALSE, importance=TRUE)
```

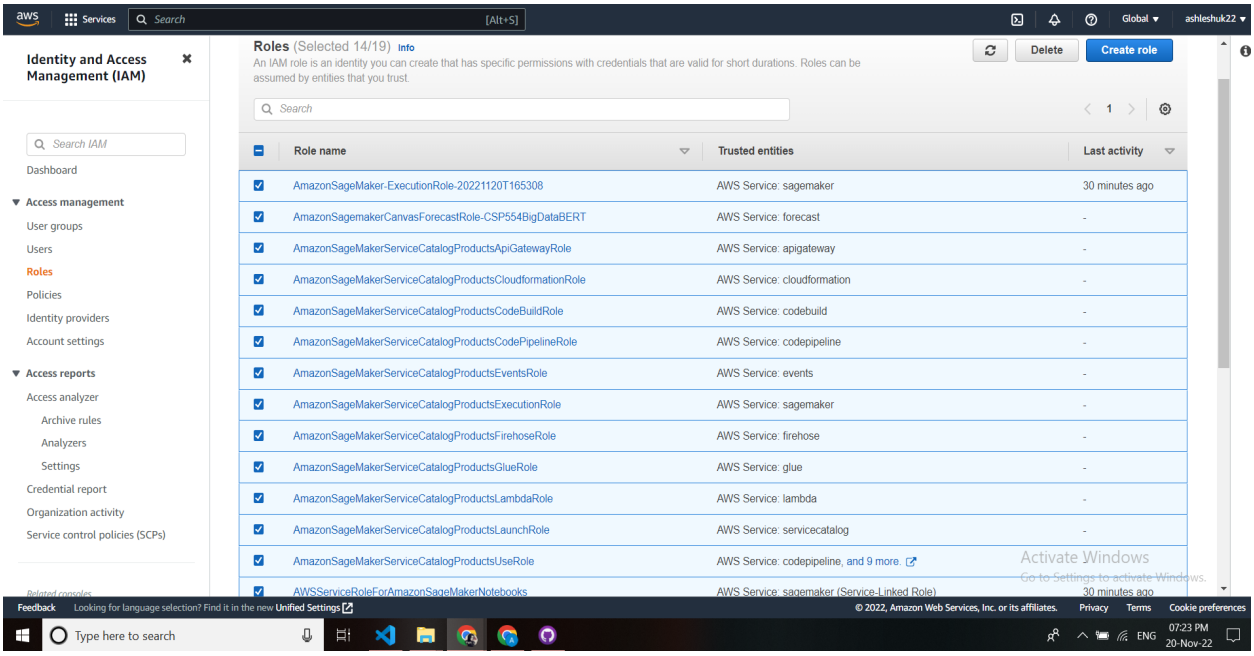
```
Training acc: 0.935714285714
Validation acc: 0.817857142857
```

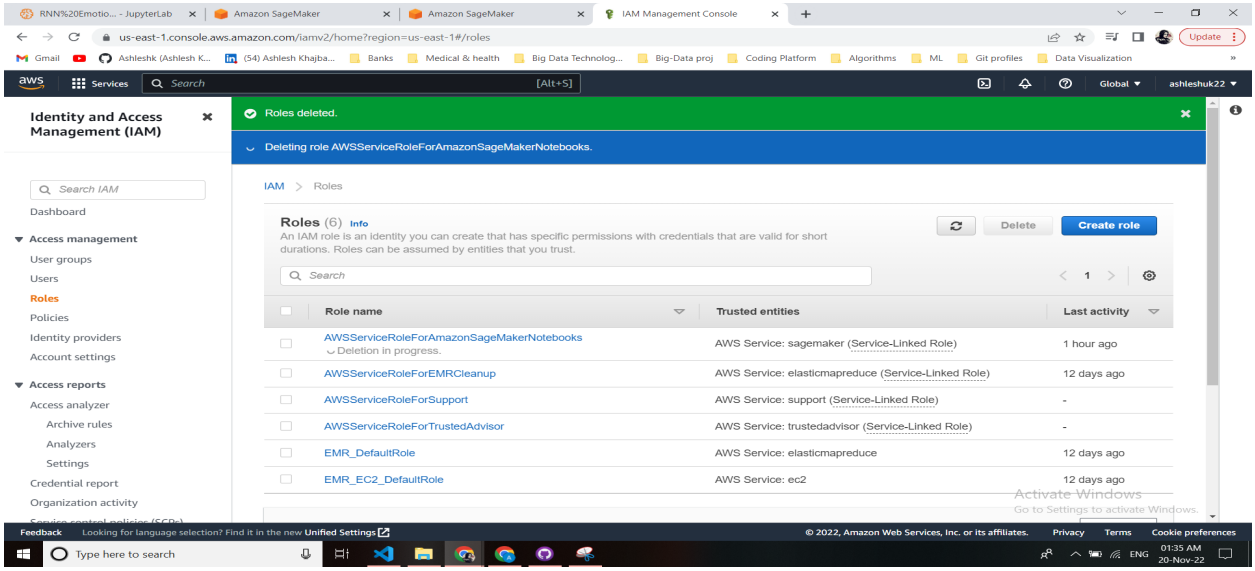
Closing AWS Services and Releasing Resource Utilized

1. Deleting Cluster-Instances after completing project

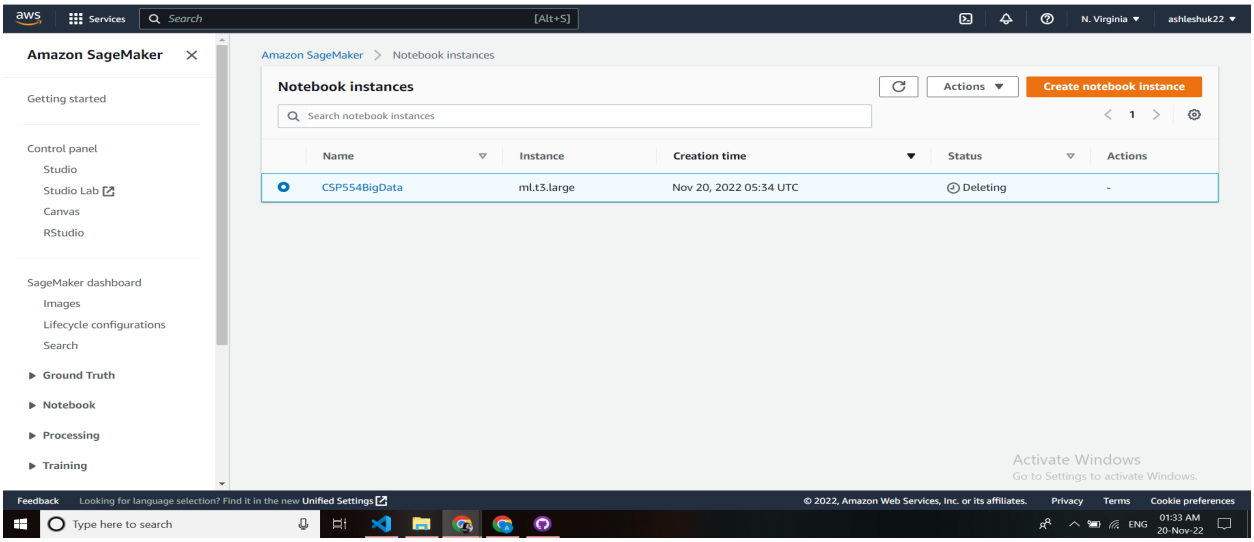


2. Removing Roles after completing Project

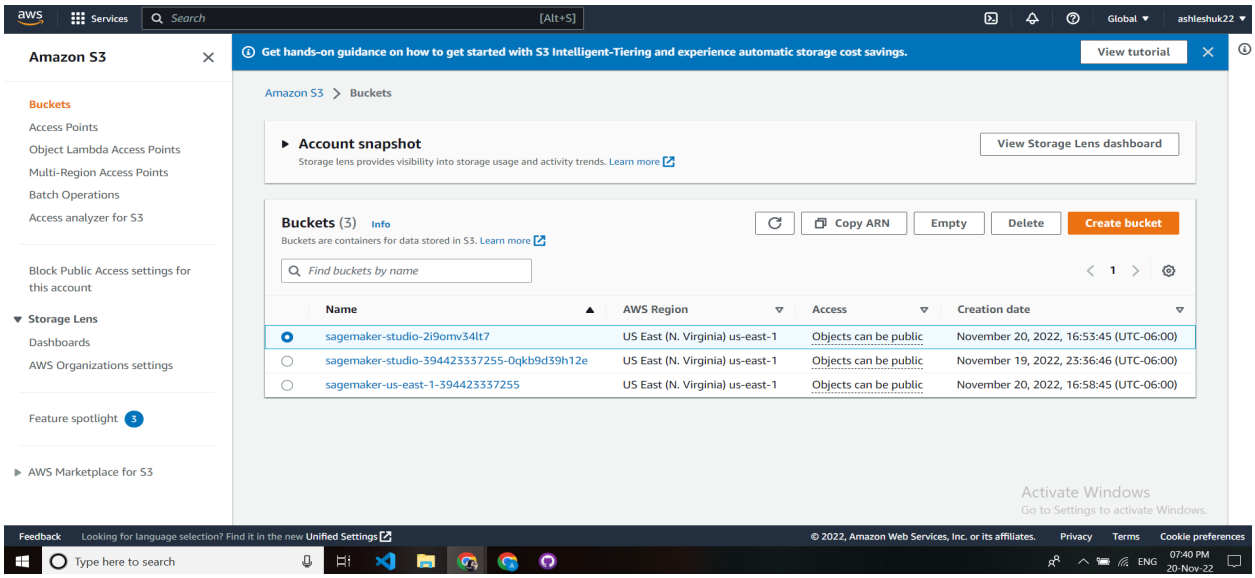




3. Removing Notebook Instances after Completing Project



4. Removing AWS S3 Buckets Created during Project



CONCLUSION

This project aimed to explore, analyze, and build a machine learning algorithm using Python, R, SageMaker, Spark-MLlib, SparkR, TensorFlow. We implemented various ML models to perform Sentiment Analysis of Emotions on a Text Dataset containing 20000 records. We implemented a few Deep Learning classifier models using BERT, RoBERTa and RNN on AWS Sagemaker and SparkMLlib.

The Model with BERT provided us with an accuracy of 97% while the RoBERTa provided 93.75%, and RNN classifier with 97.79% accuracy. The Loss parameters were similar and small for all of these models. Hence, the RNN model appears to be a better option for such data. Although RoBERTa is a BERT model without NSP objective & improved dynamic mask generation, we found BERT worked better for our data. Additionally, we compared performance of these models on different Cluster instances with distinct nodes. We found better CPU/GPU configuration definitely impacts execution speed in AWS.

One of the drawbacks of the data however is that it is past data. We might use a recent data frame that has been updated in future. These new data points can then be used to make predictions or train new models for more accurate results. With larger dataset tuning parameters, we may try to improve the model's accuracy.

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