Assignment 5

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Section – 001
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Total in points (Maximum 100 points)–

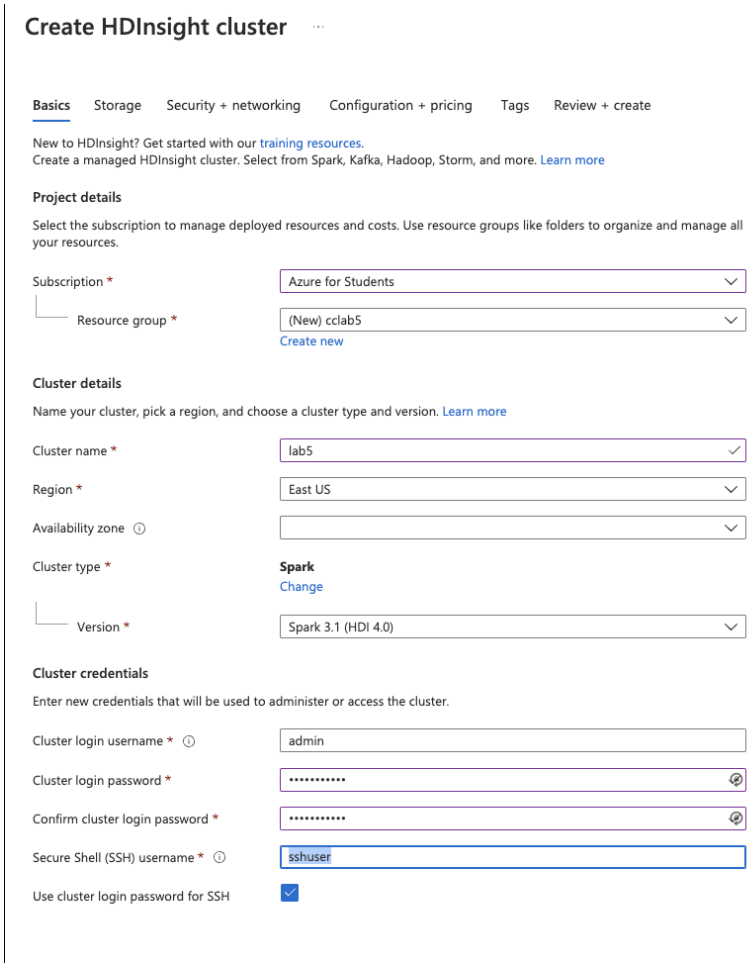
Professors Comments –

PART 1

Get familiar with Machine Learning using Spark; execute and document the following exercise

Step 1 –

This is like assignment 3 where we need to create a new cluster. All the required services are the part of the HDMI cluster and we need to push the ML doc as mentioned in the tutorial.



Step 2 – This uses logistic regression. Suppose you have a set of feature vectors xi ∈ Rn for i in in [0,m] . Associated with each feature vector we have a binary result yi . We are interested in the probability P(y=1|x) which we write as the function p(x) . However because p(x) is between 0 and 1 it is not expressible as a linear function of x so we can't use regular linear regression, so we look at the odds expression p(x)/(1−p(x)) and make the guess that its log is linear. In other words

ln(p(x)1−p(x))=b0+b·x

```
#inspections = spark.sparkContext.textFile('wasb:///HdiSamples/HdiSamples/FoodInspectionData/Food_Inspections1.csv')\
#               .map(csvParse)

inspections = spark.sparkContext.textFile('Food_Inspection.csv')\
              .map(csvParse)
```

Python

It is used frequently in machine learning to map a real number into a probabilty range $[0, 1]$.

```
In [1]: sc
```

Command finished at 03-26-2021 15:36:54.253 -04:00, execution took 75ms

Jobs: 1 COMPLETED Spark: 3 EXECUTORS 2 CORES

Job ID	Job Name	Status	Stages	Tasks	Submission Time	Duration
35	runJob	COMPLETED	2/2		2 minutes ago	2s

```
Starting Spark application
```

ID	YARN Application ID	Kind	State	Spark UI	Driver log	Current session?
7	application_1616777260895_0011	pyspark	idle	Link	Link	✔

```
SparkSession available as 'spark'.
<SparkContext master=yarn appName=remotesparkmagics>
```

```
In [2]: from pyspark.ml import Pipeline
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.feature import HashingTF, Tokenizer
from pyspark.sql import Row
from pyspark.sql.functions import UserDefinedFunction
from pyspark.sql.types import *
```

Command finished at 03-26-2021 15:36:54.531 -04:00, execution took 261ms

```
In [3]: def csvParse(s):
    import csv
    from StringIO import StringIO
    sio = StringIO(s)
    value = csv.reader(sio).next()
    sio.close()
    return value
```

Command finished at 03-26-2021 15:36:54.601 -04:00, execution took 48ms

Step – 3

If we do this another way, we can ask how accurate are we in finding the failing resturants? This is a bit harder because there are far fewer of them. In this case we are interested in true-negatives, so

Precision is the probability that a (randomly selected) negative prediction is correct.

```
df.show(5)
```

Python

```
+-------+--------------------+--------------+--------------------+
|     id|                name|       results|          violations|
+-------+--------------------+--------------+--------------------+
|1978294|KENTUCKY FRIED CH...|          Pass|32. FOOD AND NON-...|
|1978279|          SOLO FOODS|Out of Business|                    |
|1978275|SHARKS FISH & CHI...|          Pass|34. FLOORS: CONST...|
|1978268|CARNITAS Y SUPERM...|          Pass|33. FOOD AND NON-...|
|1978261|           WINGSTOP|          Pass|                    |
+-------+--------------------+--------------+--------------------+
only showing top 5 rows
```

```
print("passing = %d"%df[df.results == 'Pass'].count())
print("failing = %d"%df[df.results == 'Fail'].count())
```

Python

```
passing = 61204
```

Step 4-

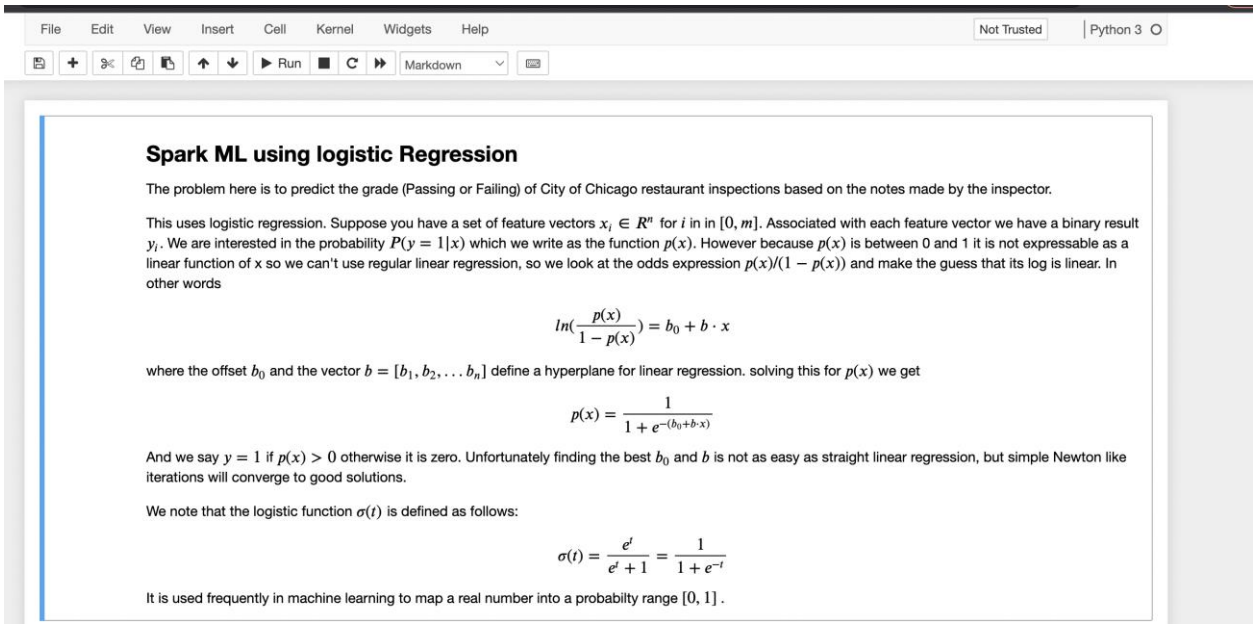
Precision and recall are then defined as:

$$\text{Precision} = \frac{tp}{tp+fp} \quad \text{Precision} = \frac{tp}{tp+fp}$$

$$\text{Recall} = \frac{tp}{tp+fn} \quad \text{Recall} = \frac{tp}{tp+fn}$$

Precision is the probability that a (randomly selected) positive prediction is correct.

Recall is the probability that a (randomly selected) resturant with a passing grade is predicted to be passing.



Spark ML using logistic Regression

The problem here is to predict the grade (Passing or Failing) of City of Chicago restaurant inspections based on the notes made by the inspector.

This uses logistic regression. Suppose you have a set of feature vectors $x_i \in R^n$ for i in in $[0, m]$. Associated with each feature vector we have a binary result y_i. We are interested in the probability $P(y = 1|x)$ which we write as the function $p(x)$. However because $p(x)$ is between 0 and 1 it is not expressable as a linear function of x so we can't use regular linear regression, so we look at the odds expression $p(x)/(1 - p(x))$ and make the guess that its log is linear. In other words

$$ln(\frac{p(x)}{1 - p(x)}) = b_0 + b \cdot x$$

where the offset b_0 and the vector $b = [b_1, b_2, \ldots b_n]$ define a hyperplane for linear regression. solving this for $p(x)$ we get

$$p(x) = \frac{1}{1 + e^{-(b_0 + b \cdot x)}}$$

And we say $y = 1$ if $p(x) > 0$ otherwise it is zero. Unfortunately finding the best b_0 and b is not as easy as straight linear regression, but simple Newton like iterations will converge to good solutions.

We note that the logistic function $\sigma(t)$ is defined as follows:

$$\sigma(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}}$$

It is used frequently in machine learning to map a real number into a probabilty range $[0, 1]$.

```
#sc = pyspark.SparkContext('local[*]')
sc
```

SparkContext

Spark UI

Version
`v3.2.1`
Master
`local[*]`
AppName
`PySparkShell`

```
2]: from pyspark.ml import Pipeline
    from pyspark.ml.classification import LogisticRegression
    from pyspark.ml.feature import HashingTF, Tokenizer
    from pyspark.sql import Row
    from pyspark.sql.functions import UserDefinedFunction
    from pyspark.sql.types import *
```

```
5]: def csvParse(s):
        import csv
        from StringIO import StringIO
        sio = StringIO(s)
        value = csv.reader(sio).next()
        sio.close()
        return value
```

The version in this notebook uses a slightly different input file from the one in the Azure HDInsight demo.

This notebook will run on spark on your laptop.

```
5]: #inspections = spark.sparkContext.textFile('wasb:///HdiSamples/HdiSamples/FoodInspectionData/Food_Inspections1.csv')\
    #               .map(csvParse)

    inspections = spark.sparkContext.textFile('/users/dennisgannon/OneDrive/Docs7/Food_Inspections1.csv')\
                  .map(csvParse)
```

```
5]: inspections.count()
```

```
5]: 103994
```

```
5]: inspections.take(10)
```

```
5]: [['1978294',
  'KFC',
  'KENTUCKY FRIED CHICKEN',
  'Pass',
  '32. FOOD AND NON-FOOD CONTACT SURFACES PROPERLY DESIGNED, CONSTRUCTED AND MAINTAINED - Comments: OBSERVED THE FLOU
R BIN BROKEN/CRACKED AT CHICKEN FRIED PREP AREA, INSTRUCTED TO REPLACE. | 33. FOOD AND NON-FOOD CONTACT EQUIPMENT UTE
NSILS CLEAN, FREE OF ABRASIVE DETERGENTS - Comments: OBSERVED THE EXTERIOR OF THE FRYER, OVEN NOT CLEAN, INSTRUCTED T
O CLEAN. ALSO CLEAN AND SANITIZE REAR CHICKEN PREP TABLE. | 35. WALLS, CEILINGS, ATTACHED EQUIPMENT CONSTRUCTED PER C
ODE: GOOD REPAIR, SURFACES CLEAN AND DUST-LESS CLEANING METHODS - Comments: OBSERVED THE CEILING IN THE CHICKEN COOLE
R, NOT CLEAN, DUSTY. INSTRUCTED TO CLEAN. | 36. LIGHTING: REQUIRED MINIMUM FOOT-CANDLES OF LIGHT PROVIDED, FIXTURES S
HIELDED - Comments: OBSERVED BROKEN LIGHT SHIELD IN LADIES RESTROOM, INSTRUCTED TO REPLACE. | 21. * CERTIFIED FOOD MA
NAGER ON SITE WHEN POTENTIALLY HAZARDOUS FOODS ARE  PREPARED AND SERVED - Comments: VIOLATION CORRECTION'],
```

```
5]: df.show(5)
```

```
+-------+--------------------+---------------+--------------------+
|     id|                name|        results|          violations|
+-------+--------------------+---------------+--------------------+
|1978294|KENTUCKY FRIED CH...|           Pass|32. FOOD AND NON-...|
|1978279|          SOLO FOODS|Out of Business|                    |
|1978275|SHARKS FISH & CHI...|           Pass|34. FLOORS: CONST...|
|1978268|CARNITAS Y SUPERM...|           Pass|33. FOOD AND NON-...|
|1978261|            WINGSTOP|           Pass|                    |
+-------+--------------------+---------------+--------------------+
only showing top 5 rows
```

```
0]: print("passing = %d"%df[df.results == 'Pass'].count())
    print("failing = %d"%df[df.results == 'Fail'].count())
```

```
passing = 61204
failing = 20225
```

```
count_results_df = spark.sql("SELECT results, COUNT(results) AS cnt FROM \
        CountResults GROUP BY results").toPandas()
```

5]:
```
count_results_df
```

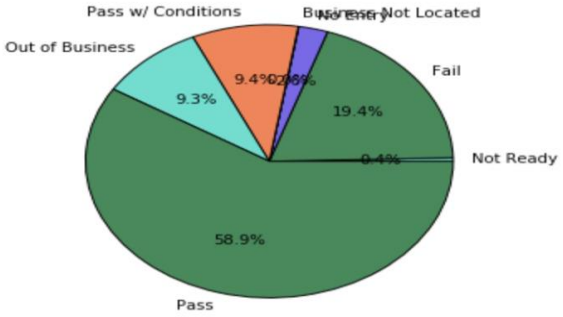
5]:

	results	cnt
0	Not Ready	429
1	Fail	20225
2	No Entry	2678
3	Business Not Located	44
4	Pass w/ Conditions	9725
5	Out of Business	9689
6	Pass	61204

5]:
```
%matplotlib inline
import matplotlib.pyplot as plt


labels = count_results_df['results']
sizes = count_results_df['cnt']
colors = ['turquoise', 'seagreen', 'mediumslateblue', 'palegreen', 'coral']
plt.pie(sizes, labels=labels, autopct='%1.1f%%', colors=colors)
plt.axis('equal')
```

5]:
```
(-1.0101138270539849, 1.0, -1.0114322486525658, 1.0040925495551682)
```



Precision and recall are then defined as:

$$Precision = \frac{tp}{tp + fp}$$
$$Recall = \frac{tp}{tp + fn}$$

Precision is the probability that a (randomly selected) positive prediction is correct.

Recall is the probability that a (randomly selected) resturant with a passing grade is predicted to be passing.

2]:
```
print('so precision = %f'% \
      (float(true_positive['cnt'])/(float(true_positive['cnt'])+float(false_positive['cnt']))))
```
```
so precision = 0.911911
```

3]:
```
print('and recall = %f'% \
      (float(true_positive['cnt'])/(float(true_positive['cnt'])+float(false_negative['cnt']))))
```
```
and recall = 0.971670
```

If we do this another way, we can ask how accurate are we in finding the failing resturants? This is a bit harder because there are far fewer of them. In this case we are interested in true-negatives, so

Precision is the probability that a (randomly selected) negative prediction is correct.

Recall is the probability that a (randomly selected) resturant with a failing grade is predicted to be failing.

$$Precision = \frac{tn}{tn + fn}$$
$$Recall = \frac{tn}{tn + fp}$$

4]:
```
print('so the precision of failure prediction = %f'% \
      (float(true_negative['cnt'])/(float(true_negative['cnt'])+float(false_negative['cnt']))))
```
```
so the precision of failure prediction = 0.870579
```

5]:
```
print('and recall is = %f'% \
      (float(true_negative['cnt'])/(float(true_negative['cnt'])+float(false_positive['cnt']))))
```
```
and recall is = 0.670001
```

In [26]:
```
%%sql -q -o true_positive
SELECT count(*) AS cnt FROM Predictions WHERE prediction = 0 AND results = 'Fail'
```
Command finished at 03-26-2021 17:53:00.308 -04:00, execution took 3s 289ms

Jobs: 1 COMPLETED Spark: 3 EXECUTORS 6 CORES

Job ID	Job Name	Status	Stages	Tasks	Submission Time	Duration
34	runJob	COMPLETED	2/2		4 minutes ago	2s

In [27]:
```
true_negative = spark.sql("SELECT count(*) AS cnt FROM Predictions WHERE \
        (prediction = 0 AND results = 'Fail')").toPandas()
```
Command finished at 03-26-2021 17:53:03.605 -04:00, execution took 3s 286ms

Jobs: 1 COMPLETED Spark: 3 EXECUTORS 6 CORES

Job ID	Job Name	Status	Stages	Tasks	Submission Time	Duration
35	toPandas	COMPLETED	2/2		4 minutes ago	2s

In [28]:
```
%%sql -q -o false_positive
SELECT count(*) AS cnt FROM Predictions \
WHERE prediction = 0 AND (results = 'Pass' OR results = 'Pass w/ Conditions')
```
Command finished at 03-26-2021 17:53:09.801 -04:00, execution took 2s 274ms

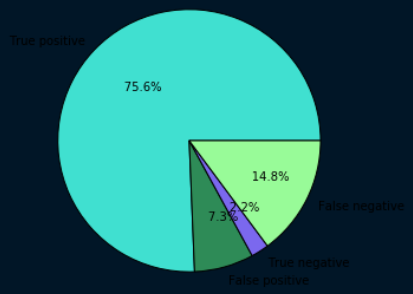
Jobs: 1 COMPLETED Spark: 3 EXECUTORS 6 CORES

Job ID	Job Name	Status	Stages	Tasks	Submission Time	Duration
36	runJob	COMPLETED	2/2		4 minutes ago	1s

```python
labels = ['True positive', 'False positive', 'True negative', 'False negative']
sizes = [true_positive['cnt'], false_positive['cnt'], false_negative['cnt'], true_negative['cnt']]
colors = ['turquoise', 'seagreen', 'mediumslateblue', 'palegreen', 'coral']
plt.pie(sizes, labels=labels, autopct='%10.1f%%', colors=colors)
plt.axis('equal')
```

Python

```
(-1.0045326948165894, 1.0, -1.0032166242599487, 1.0048178434371948)
```



PART 2

Get familiar with Machine Learning using Azure ML; execute and document the following exercise

Step 1 - This notebook illustrates invoking the webservice for the three way classifier with the Arvix data. The three way example uses three classifiers: a multiclass neural net, a multiclass logistic regression and a random forest classifier. The three way classifier uses a popularity vote system. If any two of the classifiers agree that is the main reply of the three way. the third case is always put forward as a second choice.

Azure ML service sample.

This notebook illustrates invoking the webservice for the three way classifier with the Arvix data. The three way example uses three classifiers: a multiclass neural net, a multiclass logistic regression and a random forest classifier. The three way classifier uses a popularity vote system. If any two of the classifiers agree that is the main reply of the three way. the third case is always put forward as a second choice.
The python code for the three way python module is here

```
import pandas as pd
labels = { 1: "'bio'", 2: "'compsci'", 3: "'finance'", 4: "'math'"}
   #The entry point function can contain up to two input arguments:
   #Param: a pandas.DataFrame
   #Param: a pandas.DataFrame
def azureml_main(dataframe1 = None, dataframe2 = None):

    tclass = dataframe1["Col1"]
    scored1 = dataframe1["Scored Labels"]
    scored2 = dataframe2["Scored Labels"]
    scored3 = dataframe2["Scored Labels (2)"]
    scored = []
    second = []
    lclass = []
    for i in range(0, len(tclass)):
        lclass.extend([tclass[i]])
        if scored2[i] == scored3[i]:
            scored.extend([labels[scored2[i]]])
            second.extend([labels[scored1[i]]])
        elif scored2[i] == scored1[i]:
            scored.extend([labels[scored1[i]]])
            second.extend([labels[scored3[i]]])
        elif scored1[i] == scored3[i]:
            scored.extend([labels[scored1[i]]])
            second.extend([labels[scored2[i]]])
        else:
            scored.extend([labels[scored1[i]]])
            second.extend([labels[scored3[i]]])

    data = {'Col1': lclass, 'Scored Labels': scored, 'second': second}
    df = pd.DataFrame(data, columns=['Col1', 'Scored Labels', 'second'])
    return df
```

```
import sys
import azure
import socket
import csv
import urllib2
import json
import pandas as pd
import numpy as np
import urllib
import json
import pickle
import unicodedata
```

```
The following establishes the urls and keys for each of the three classifiers
```

```
url = []
api_key = []
# the first is the neural net versionn
url.append('https://ussouthcentral.services.azureml.net/workspaces/38d1439e6956413e9fe2950b6530c117/services/281bbba94a
api_key.append('5dtOV9rJgoI8LtnX4N7vNMfhW4vdSPHcpCq1IUNQyTPTSwzIHQ4NADF1KkKvI/Q4mJSVFQh7JQcVyVxk7yuG/Q==')
# the second is the logistic regression version
url.append('https://ussouthcentral.services.azureml.net/workspaces/38d1439e6956413e9fe2950b6530c117/services/08e77a94e7
api_key.append('RkHxsJXpnBFv3CVeL5B927VlKgUbQZBaHp8BbQ2QeMgPkCqUG+W9QY9RanTO3zMXnTywpQBX+db5+n6xxWkugA==')
# this is the url and key for the threeway version
url.append('https://ussouthcentral.services.azureml.net/workspaces/38d1439e6956413e9fe2950b6530c117/services/462fccc1e3
api_key.append('e7iaNA+Pi9KdKZ70+Vv7JvZ81E3vKfqQShFuMf+a89GfGrixAHNq4HaHJZhpCY3TBujJmJh3hfKNtoYY3eKvnw==')
```

```
: def sendrequest(datalist, url, api_key):
    #datalist is a list ["class", "document", "title"]
    data =  {
    "Inputs": {

            "input1":
            {
                "ColumnNames": ["Col1", "Col2", "Col3"],
                "Values": [ datalist  ]
            },        },
        "GlobalParameters": { }
    }


    body = str.encode(json.dumps(data))

    headers = {'Content-Type':'application/json', 'Authorization':('Bearer '+ api_key)}

    req = urllib2.Request(url, body, headers)

    try:
        response = urllib2.urlopen(req)

        # If you are using Python 3+, replace urllib2 with urllib.request in the above code:
        # req = urllib.request.Request(url, body, headers)
        # response = urllib.request.urlopen(req)

        result = response.read()
        #print(result)
        y = json.loads(result)
        return(y["Results"]["output1"]["value"]["Values"] )

    except urllib2.HTTPError, error:
        print("The request failed with status code: " + str(error.code))

        # Print the headers - they include the requert ID and the timestamp, which are useful for debugging the failure
```

```
: #this function is used to send multiple requests to the web service with one invocation.
def sendbulkrequest(datalist, url, api_key):
    #datalist is a list ["class", "document", "title"]
    data =  {
        "Inputs": {

                "input1":
                {
                    "ColumnNames": ["Col1", "Col2", "Col3"],
                    "Values":  datalist
                },        },
            "GlobalParameters": { }
    }

    body = str.encode(json.dumps(data))
    headers = {'Content-Type':'application/json', 'Authorization':('Bearer '+ api_key)}

    req = urllib2.Request(url, body, headers)

    try:
        response = urllib2.urlopen(req)

        # If you are using Python 3+, replace urllib2 with urllib.request in the above code:
        # req = urllib.request.Request(url, body, headers)
        # response = urllib.request.urlopen(req)

        result = response.read()
        y = json.loads(result)
        return(y["Results"]["output1"]["value"]["Values"] )
    except urllib2.HTTPError, error:
        print("The request failed with status code: " + str(error.code))

        # Print the headers - they include the requert ID and the timestamp, which are useful for debugging the failure
        print(error.info())

        return json.loads(error.read())
```

```
        return json.loads(error.read())
```

```
def read_azure_blob(subj, base):
    #base is the url for the azure blob store
    docpath =base+ "/"+subj+".csv"
    response = urllib2.urlopen(docpath)
    data = csv.reader(response)
    biglist =  []
    for row in data:
        biglist.append(row)
    return biglist
```

```
#first read the test data file arxivnophy
base = "https://scimldata.blob.core.windows.net/arxiv"
nophytable = read_azure_blob('arxivnophy', base)
```

next test it with the first entry in the table with the three way.

```
x = sendrequest(nophytable[0], url[2], api_key[2])
print x
```

```
[[u"'compsci'", u"'compsci'", u"'compsci'"]]
```

```
len(x)
```

```
1
```

```
multx = sendbulkrequest(nophytable, url[2], api_key[2])
```

Let's see how well the three way does if we ask if either the first or second choice is correct.

```
correct = {"'compsci'": 0, "'finance'": 0, "'bio'": 0, "'math'": 0}
num = {"'compsci'": 0, "'finance'": 0, "'bio'": 0, "'math'": 0}
```

5]:
```
correct = {"'compsci'": 0, "'finance'": 0, "'bio'": 0, "'math'": 0}
num = {"'compsci'": 0, "'finance'": 0, "'bio'": 0, "'math'": 0}
for i in range(len(multx)):
    x = multx[i]
    key = x[0]
    num[key] = num[key]+1.0
    if (key==x[1]) or (key==x[2]):
        correct[key] = correct[key] +1.0
    #else:
for key in correct:
    correct[key] = 100.0*correct[key]/num[key]
print num
print correct
```

```
{"'bio'": 316.0, "'finance'": 232.0, "'compsci'": 648.0, "'math'": 742.0}
{"'bio'": 65.82278481012658, "'finance'": 60.3448275862069, "'compsci'": 72.37654320987654, "'math'": 88.27493261455525}
```

2]:
```
def make_confusion_table(multx):
    tble = {"'compsci'":{"'compsci'": 0, "'finance'": 0, "'bio'": 0,  "'math'": 0},
            "'finance'":{"'compsci'": 0, "'finance'": 0, "'bio'": 0, "'math'": 0},
            "'bio'":{"'compsci'": 0, "'finance'": 0, "'bio'": 0,  "'math'": 0},
            "'math'":{"'compsci'": 0, "'finance'": 0, "'bio'": 0, "'math'": 0}}
    predicted = []
    tclass = []
    for e in multx:
        x = e[0]
        tclass.extend([x])
        sc = e[1]
        predicted.extend([sc])
    for i in range(0, len(tclass)):
        if tclass[i] == 'none':
            print "found none"
        else:
           tble[predicted[i]][tclass[i]] = tble[predicted[i]][tclass[i]] +1
    names = ["'bio'", "'compsci'", "'finance'", "'math'"]
    for x in names:
        total = 0
        for y in names:
            total = total + tble[y][x]
        print "total for " +x +"= "+str(total)
        for y in names:
            tble[y][x] = 100.0*tble[y][x]/(1.0*total)
    df = pd.DataFrame(tble, columns=[ "'bio'", "'compsci'", "'finance'", "'math'"])
    return df
```

```
df = make_confusion_table(multx)
df
```

```
total for 'bio'= 316
total for 'compsci'= 648
total for 'finance'= 232
total for 'math'= 742
```

	'bio'	'compsci'	'finance'	'math'
'bio'	50.316456	20.886076	0.949367	27.848101
'compsci'	4.938272	62.654321	1.543210	30.864198
'finance'	5.603448	9.913793	47.844828	36.637931
'math'	3.908356	13.477089	2.291105	80.323450

```
#next do the confusion matrix for the neural net classifer
multx2 = sendbulkrequest(nophytable, url[0], api_key[0])
```

```
df = make_confusion_table(multx2)
df
```

```
total for 'bio'= 316
total for 'compsci'= 648
total for 'finance'= 232
total for 'math'= 742
```

	'bio'	'compsci'	'finance'	'math'
'bio'	51.265823	19.936709	4.746835	24.050633
'compsci'	10.493827	57.716049	4.320988	27.469136
'finance'	6.465517	17.241379	50.431034	25.862069
'math'	6.469003	16.037736	5.525606	71.967655

The code below assumes that the test file is store in Azure blob store as a csv file. It uses the three way classifier and the neural net classifier and the logistic regression classifier to compare the confusion matrix of each.

```
total for 'math'= 742
```

	'bio'	'compsci'	'finance'	'math'
'bio'	51.265823	19.936709	4.746835	24.050633
'compsci'	10.493827	57.716049	4.320988	27.469136
'finance'	6.465517	17.241379	50.431034	25.862069
'math'	6.469003	16.037736	5.525606	71.967655

```
# now for the logistic regression service
multx3 = sendbulkrequest(nophytable, url[1], api_key[1])
```

```
df = make_confusion_table(multx3)
df
```

```
total for 'bio'= 316
total for 'compsci'= 648
total for 'finance'= 232
total for 'math'= 742
```

	'bio'	'compsci'	'finance'	'math'
'bio'	54.113924	23.417722	0.316456	22.151899
'compsci'	6.172840	65.740741	1.234568	26.851852
'finance'	5.172414	9.913793	43.534483	41.379310
'math'	3.504043	14.555256	2.021563	79.919137

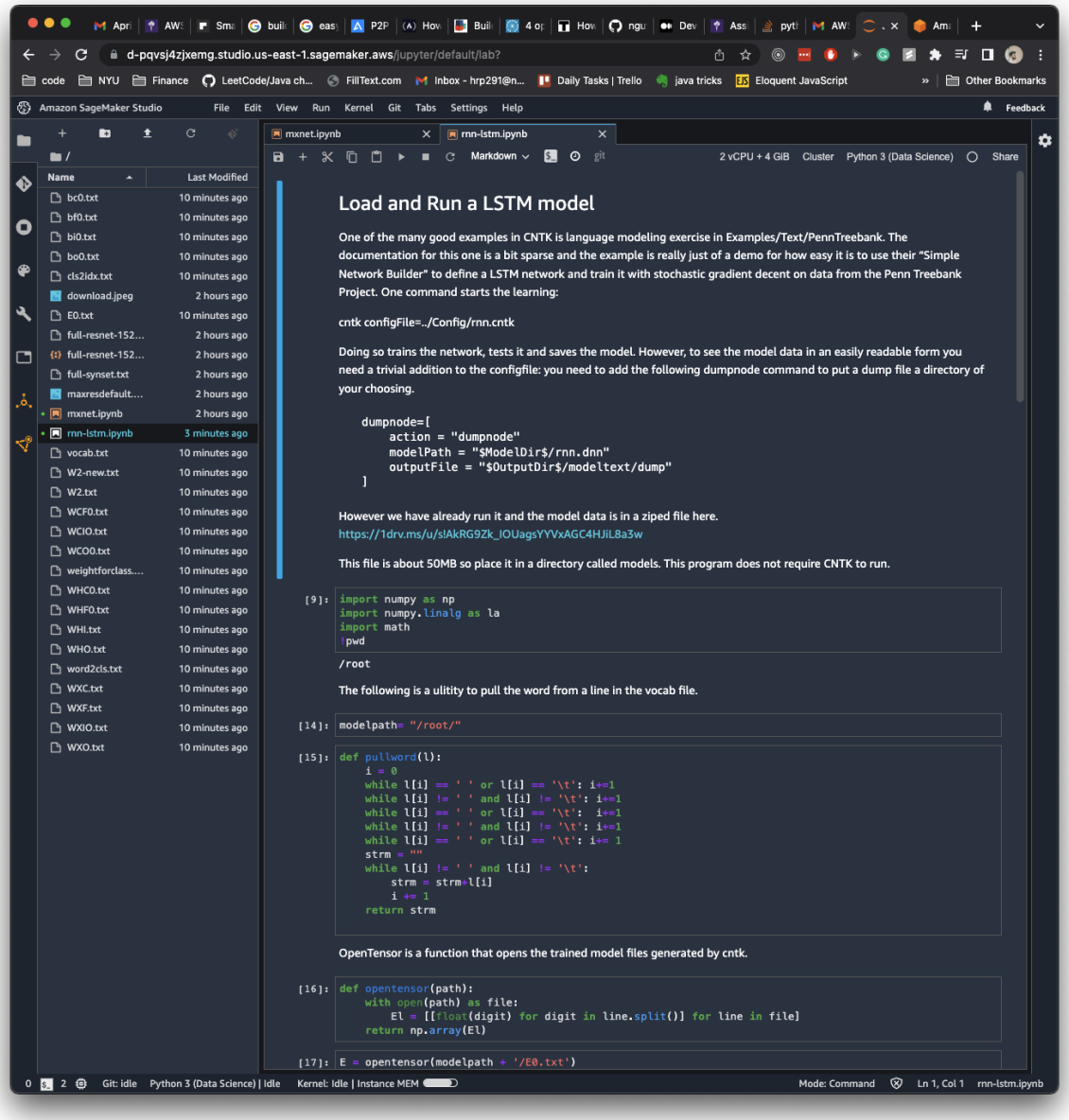
as we can see, all three are rather poor. the three way is only slightly better.

PART 3

Get familiar with Machine Learning using Amazon ML; execute and document the following exercise

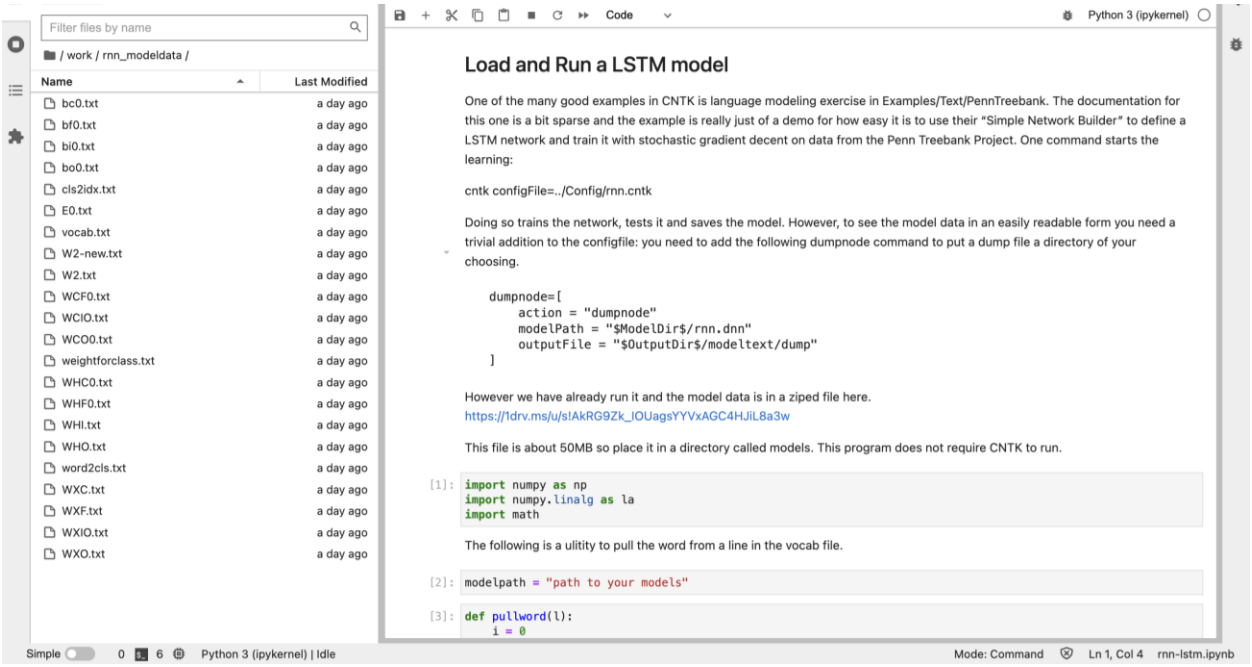
Running the notebook on the amazon sagemaker service

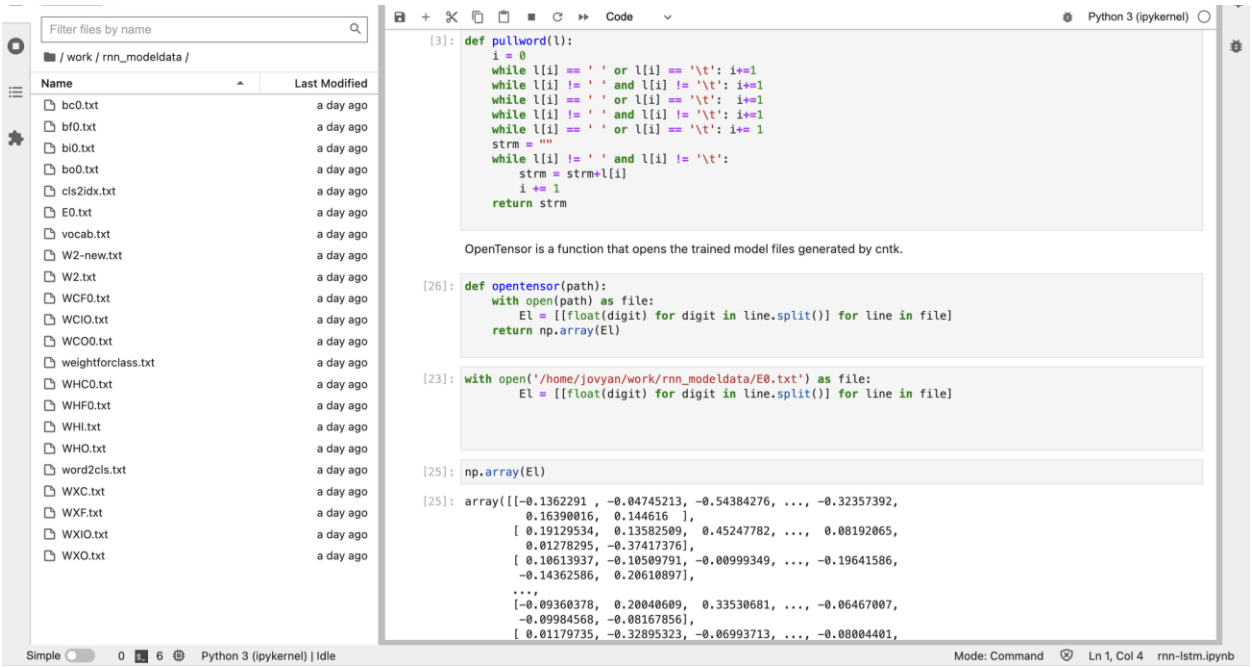
The documentation for this one is a bit sparse and the example is really just of a demo for how easy it is to use their “Simple Network Builder” to define a LSTM network and train it with stochastic gradient decent on data from the Penn Treebank Project. One command starts the learning:

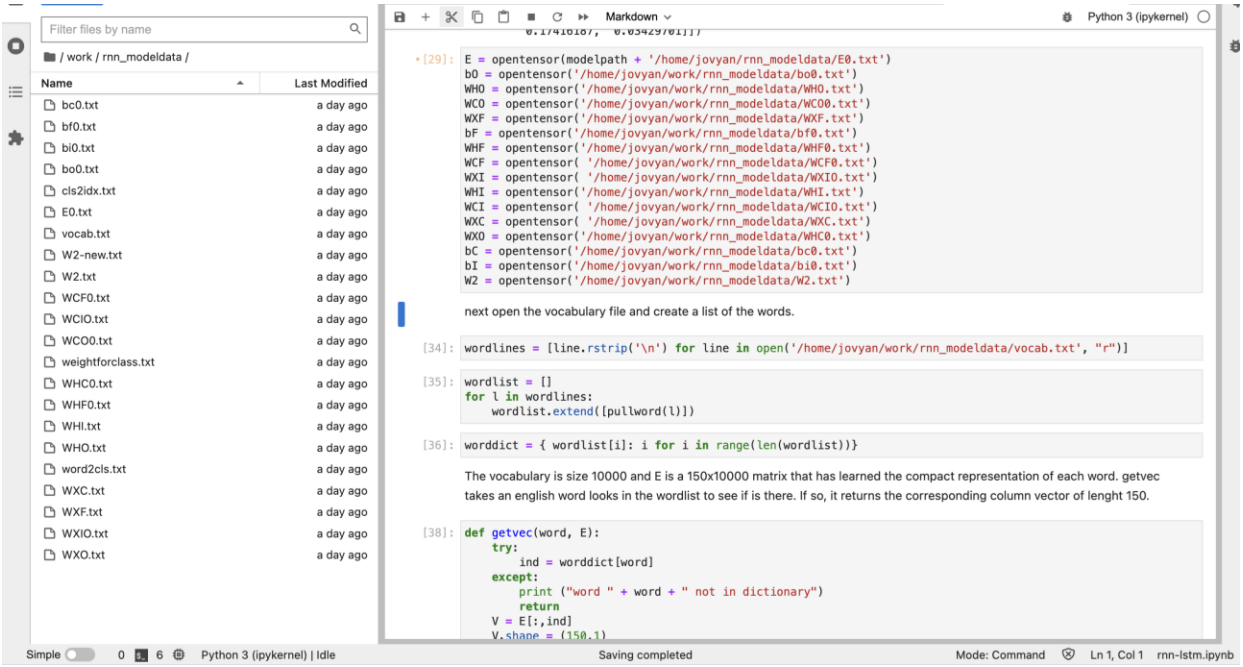


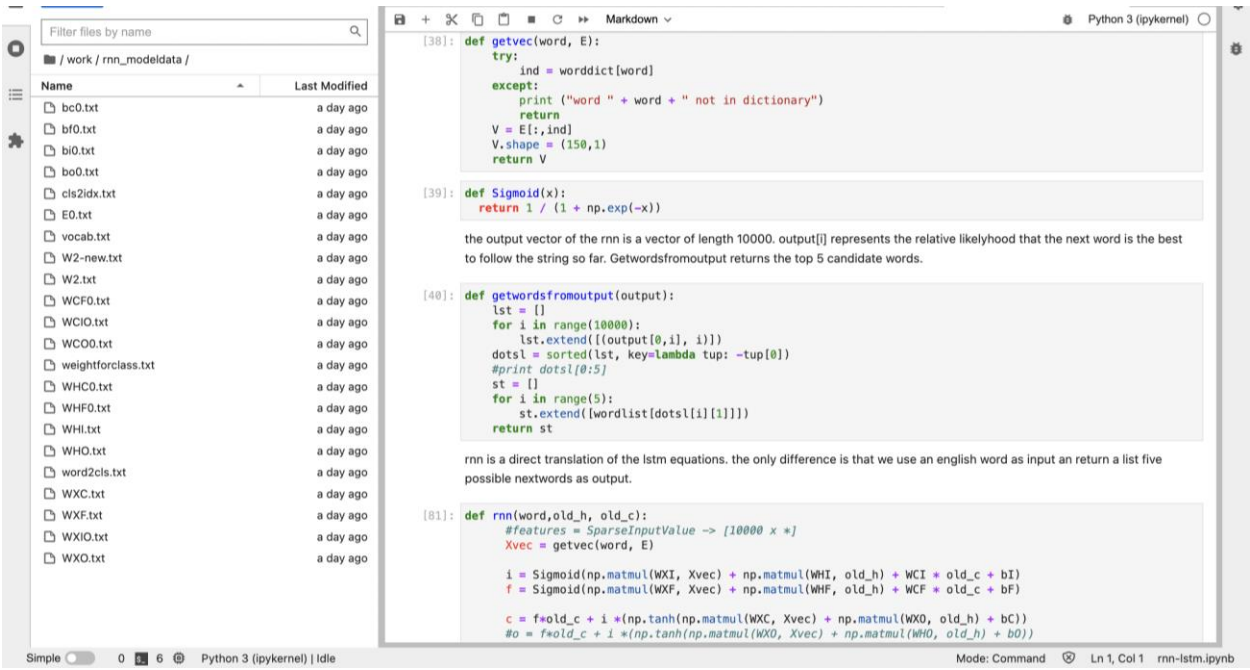
Doing so trains the network, tests it and saves the model. However, to see the model data in an easily readable form you need a trivial addition to the configfile: you need to add the following dumpnode command to put a dump file a directory of your choosing.

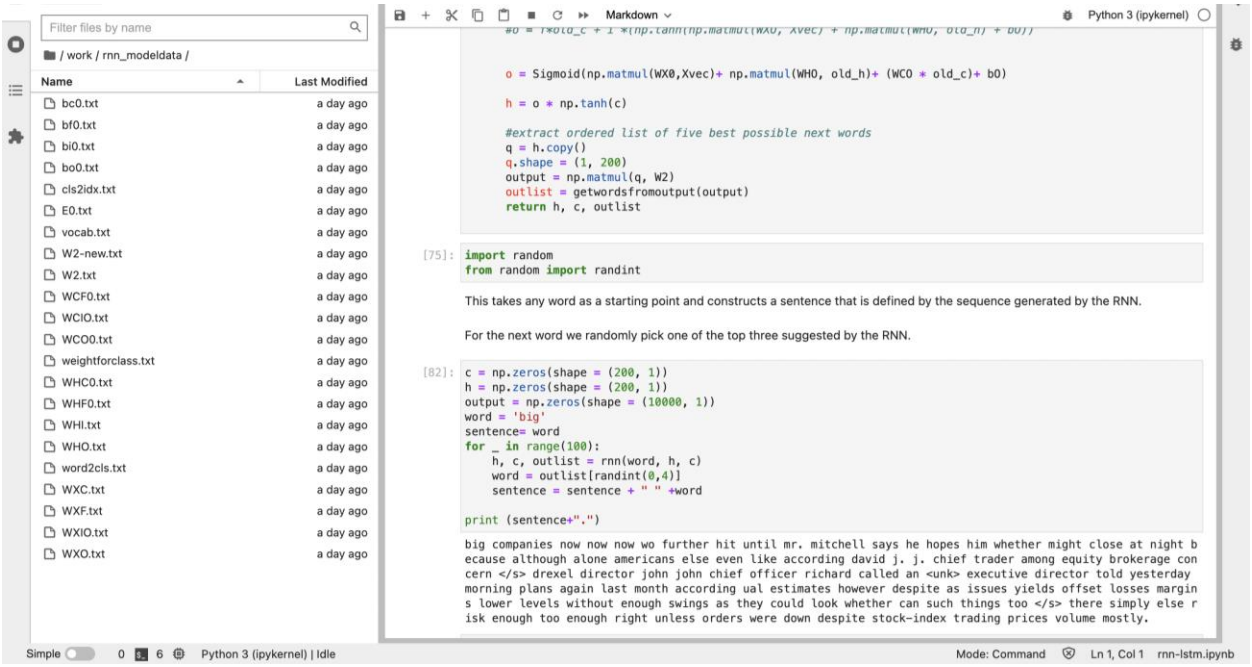
the output vector of the rnn is a vector of length 10000. output[i] represents the relative likelyhood that the next word is the best to follow the string so far. Getwordsfromoutput returns the top 5 candidate words.



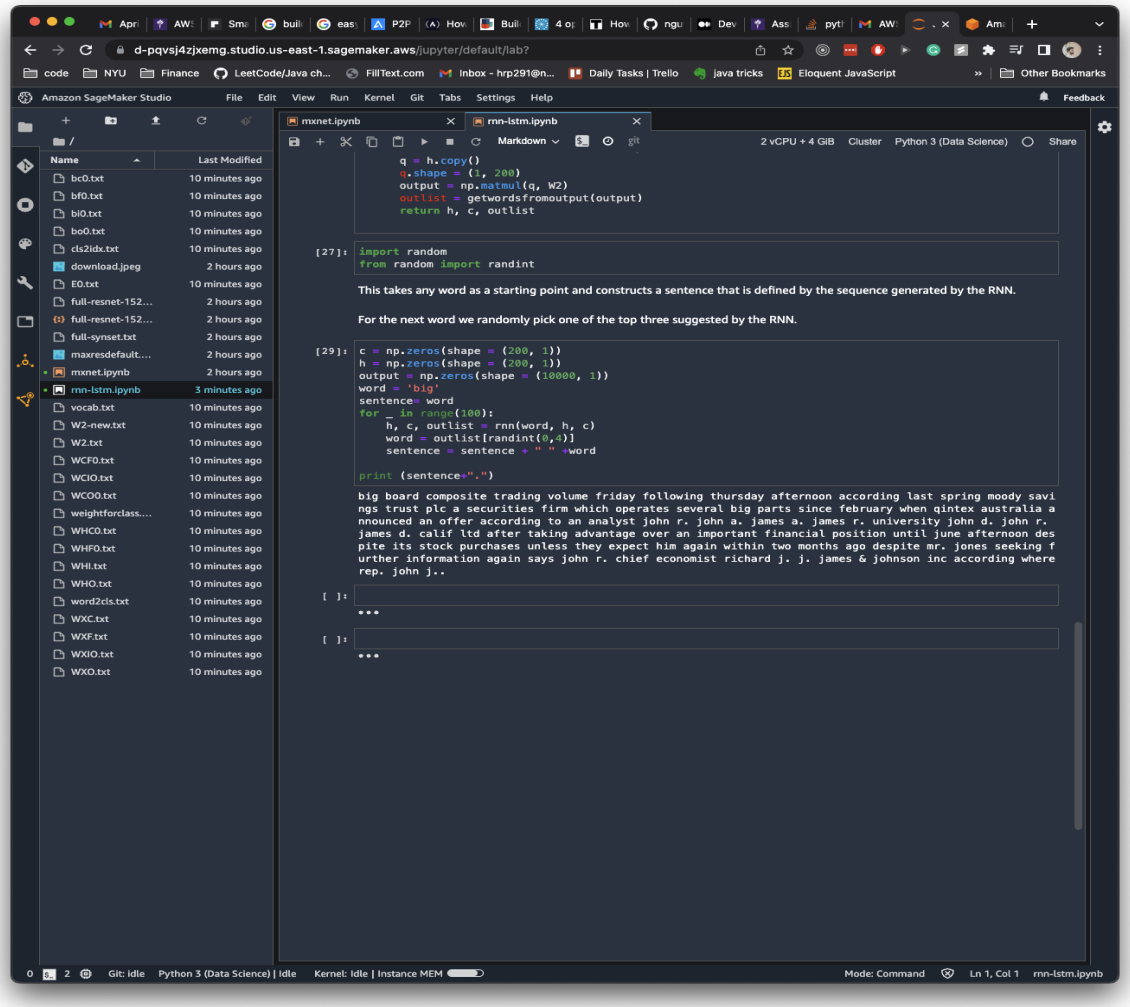



Filter files by name
/ work / rnn_modeldata /
Name
Last Modified
bc0.txt a day ago
bf0.txt a day ago
bi0.txt a day ago
bo0.txt a day ago
cls2idx.txt a day ago
E0.txt a day ago
vocab.txt a day ago
W2-new.txt a day ago
W2.txt a day ago
WCF0.txt a day ago
WCIO.txt a day ago
WCO0.txt a day ago
weightforclass.txt a day ago
WHC0.txt a day ago
WHF0.txt a day ago
WHI.txt a day ago
WHO.txt a day ago
word2cls.txt a day ago
WXC.txt a day ago
WXF.txt a day ago
WXIO.txt a day ago
WXO.txt a day ago
Markdown
Python 3 (ipykernel)
[29]:
E = opentensor(modelpath + '/home/jovyan/rnn_modeldata/E0.txt')
bO = opentensor('/home/jovyan/work/rnn_modeldata/bo0.txt')
WHO = opentensor('/home/jovyan/work/rnn_modeldata/WHO.txt')
WCO = opentensor('/home/jovyan/work/rnn_modeldata/WCO0.txt')
WXF = opentensor('/home/jovyan/work/rnn_modeldata/WXF.txt')
bF = opentensor('/home/jovyan/work/rnn_modeldata/bf0.txt')
WHF = opentensor('/home/jovyan/work/rnn_modeldata/WHF0.txt')
WCF = opentensor('/home/jovyan/work/rnn_modeldata/WCF0.txt')
WXI = opentensor('/home/jovyan/work/rnn_modeldata/WXIO.txt')
WHI = opentensor('/home/jovyan/work/rnn_modeldata/WHI.txt')
WCI = opentensor('/home/jovyan/work/rnn_modeldata/WCIO.txt')
WXC = opentensor('/home/jovyan/work/rnn_modeldata/WXC.txt')
WXO = opentensor('/home/jovyan/work/rnn_modeldata/WHC0.txt')
bC = opentensor('/home/jovyan/work/rnn_modeldata/bc0.txt')
bI = opentensor('/home/jovyan/work/rnn_modeldata/bi0.txt')
W2 = opentensor('/home/jovyan/work/rnn_modeldata/W2.txt')
next open the vocabulary file and create a list of the words.
[34]:
wordlines = [line.rstrip('\n') for line in open('/home/jovyan/work/rnn_modeldata/vocab.txt', "r")]
[35]:
wordlist = []
for l in wordlines:
wordlist.extend([pullword(l)])
[36]:
worddict = { wordlist[i]: i for i in range(len(wordlist))}
The vocabulary is size 10000 and E is a 150x10000 matrix that has learned the compact representation of each word. getvec takes an english word looks in the wordlist to see if is there. If so, it returns the corresponding column vector of lenght 150.
[38]:
def getvec(word, E):
try:
ind = worddict[word]
except:
print ("word " + word + " not in dictionary")
return
V = E[:,ind]
V.shape = (150,1)
Simple
0
6
Python 3 (ipykernel) | Idle
Saving completed
Mode: Command
Ln 1, Col 1
rnn-lstm.ipynb


Filter files by name
/ work / rnn_modeldata /
Name
Last Modified
bc0.txt a day ago
bf0.txt a day ago
bi0.txt a day ago
bo0.txt a day ago
cls2idx.txt a day ago
E0.txt a day ago
vocab.txt a day ago
W2-new.txt a day ago
W2.txt a day ago
WCF0.txt a day ago
WCIO.txt a day ago
WCO0.txt a day ago
weightforclass.txt a day ago
WHC0.txt a day ago
WHF0.txt a day ago
WHI.txt a day ago
WHO.txt a day ago
word2cls.txt a day ago
WXC.txt a day ago
WXF.txt a day ago
WXIO.txt a day ago
WXO.txt a day ago
Markdown
Python 3 (ipykernel)
[38]:
def getvec(word, E):
try:
ind = worddict[word]
except:
print ("word " + word + " not in dictionary")
return
V = E[:,ind]
V.shape = (150,1)
return V
[39]:
def Sigmoid(x):
return 1 / (1 + np.exp(-x))
the output vector of the rnn is a vector of length 10000. output[i] represents the relative likelyhood that the next word is the best to follow the string so far. Getwordsfromoutput returns the top 5 candidate words.
[40]:
def getwordsfromoutput(output):
lst = []
for i in range(10000):
lst.extend([[output[0,i], i]])
dotsl = sorted(lst, key=lambda tup: -tup[0])
#print dotsl[0:5]
st = []
for i in range(5):
st.extend([wordlist[dotsl[i][1]]])
return st
rnn is a direct translation of the lstm equations. the only difference is that we use an english word as input an return a list five possible nextwords as output.
[81]:
def rnn(word,old_h, old_c):
#features = SparseInputValue -> [10000 x *]
Xvec = getvec(word, E)
i = Sigmoid(np.matmul(WXI, Xvec) + np.matmul(WHI, old_h) + WCI * old_c + bI)
f = Sigmoid(np.matmul(WXF, Xvec) + np.matmul(WHF, old_h) + WCF * old_c + bF)
c = f*old_c + i *(np.tanh(np.matmul(WXC, Xvec) + np.matmul(WXO, old_h) + bC))
#o = f*old_c + i *(np.tanh(np.matmul(WXO, Xvec) + np.matmul(WHO, old_h) + bO))
Simple
0
6
Python 3 (ipykernel) | Idle
Mode: Command
Ln 1, Col 1
rnn-lstm.ipynb



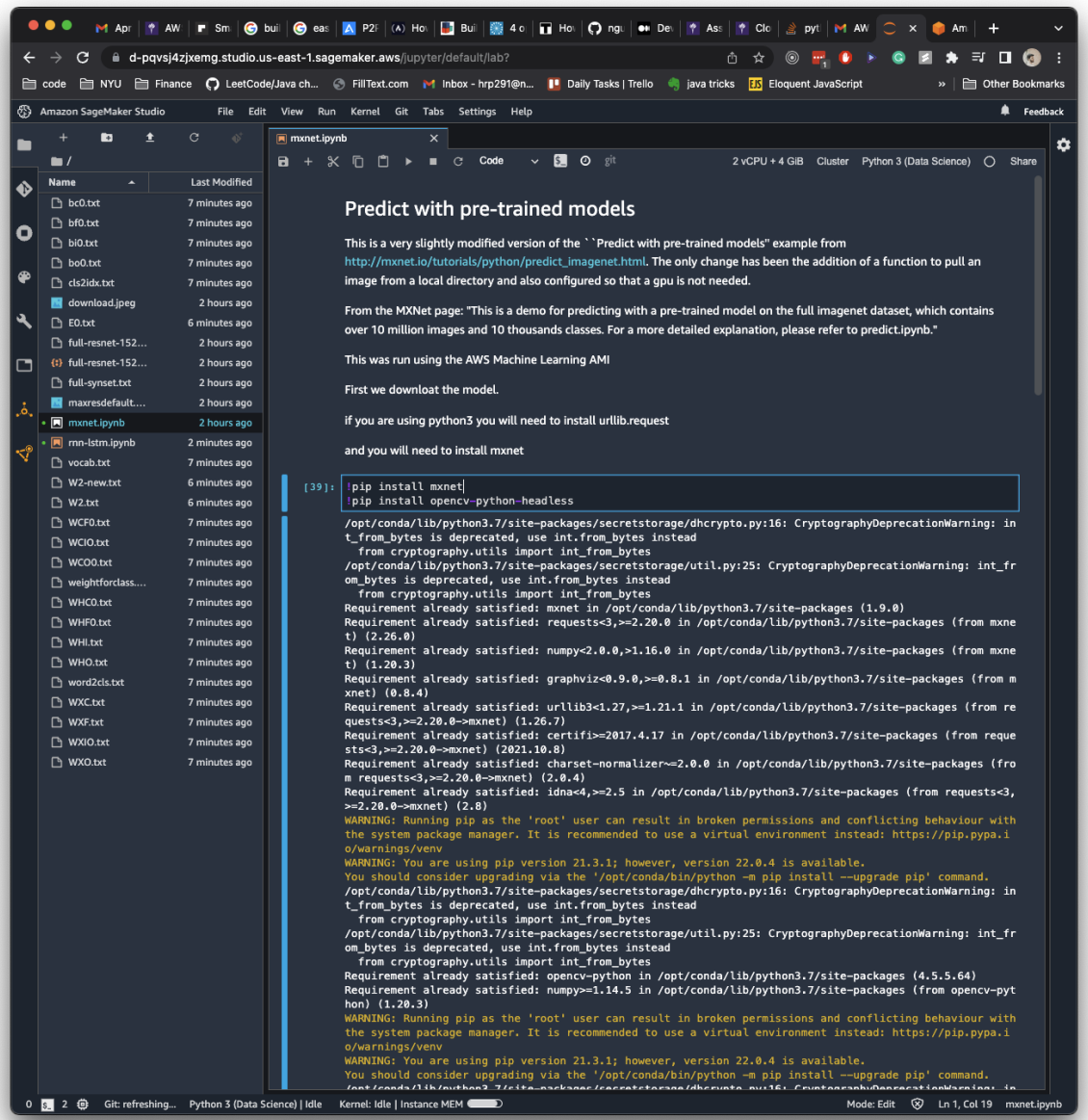
This takes any word as a starting point and constructs a sentence that is defined by the sequence generated by the RNN.
For the next word we randomly pick one of the top three suggested by the RNN.



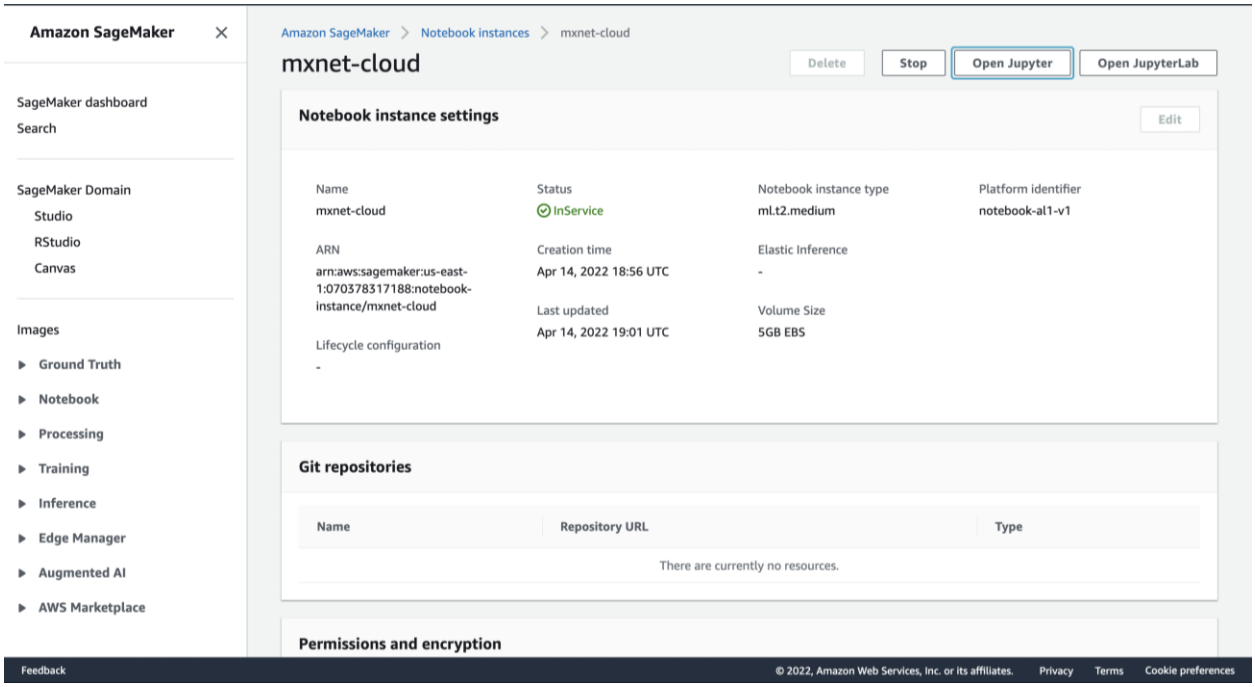
PART 4

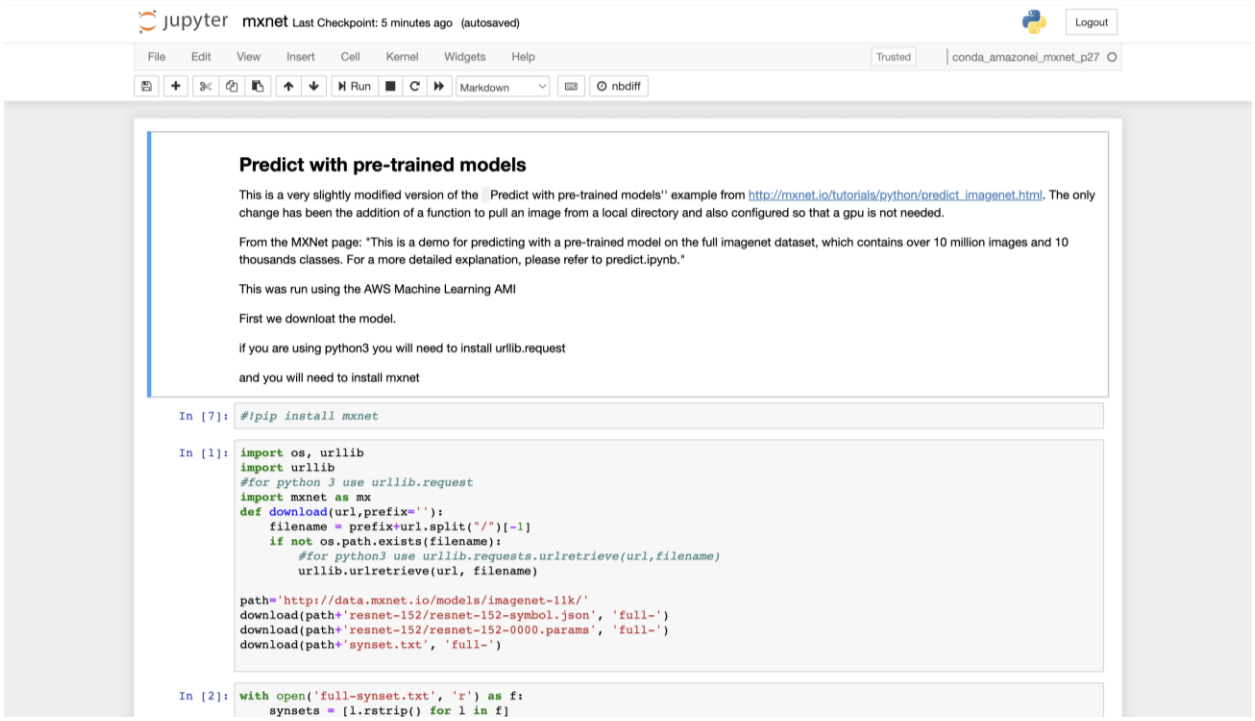
Experiment with Deep Learning using Amazon's preferred Deep Learning toolkit MXNet; execute and document the following exercise

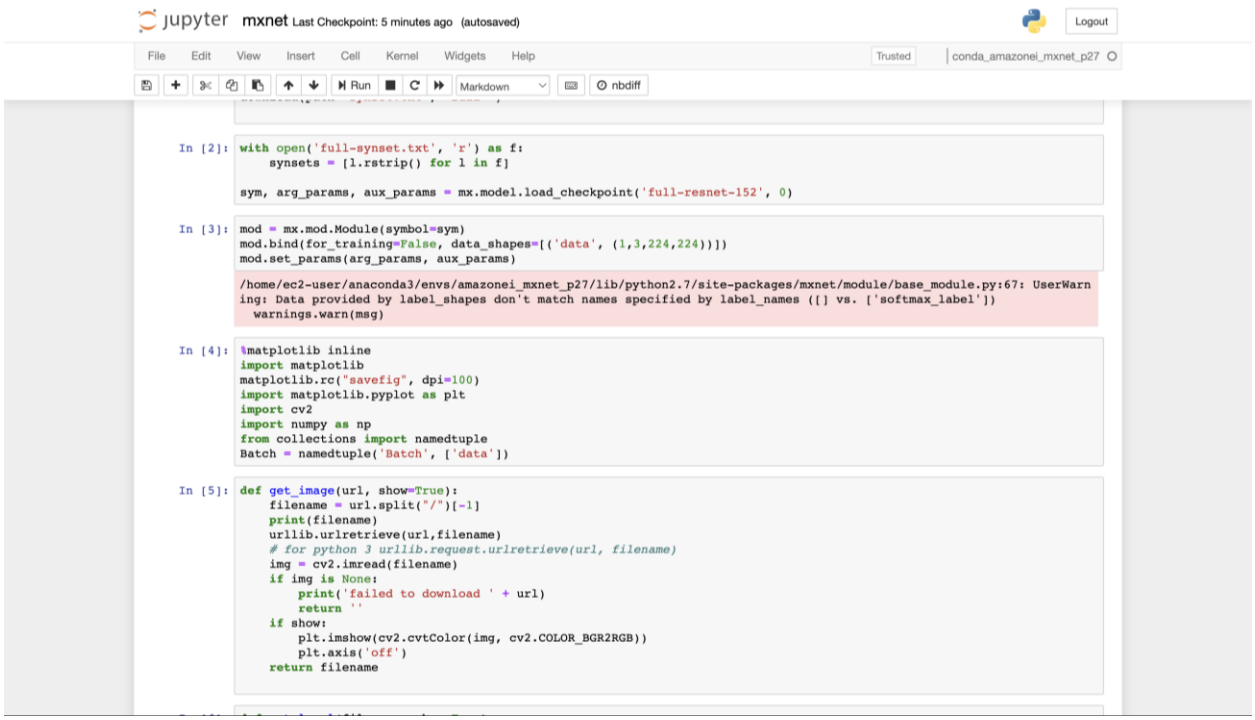
The only change has been the addition of a function to pull an image from a local directory and also configured so that a gpu is not needed.
From the MXNet page: "This is a demo for predicting with a pre-trained model on the full imagenet dataset, which contains over 10 million images and 10 thousands classes. For a more detailed explanation, please refer to predict.ipynb."
This was run using the AWS Machine Learning AMI

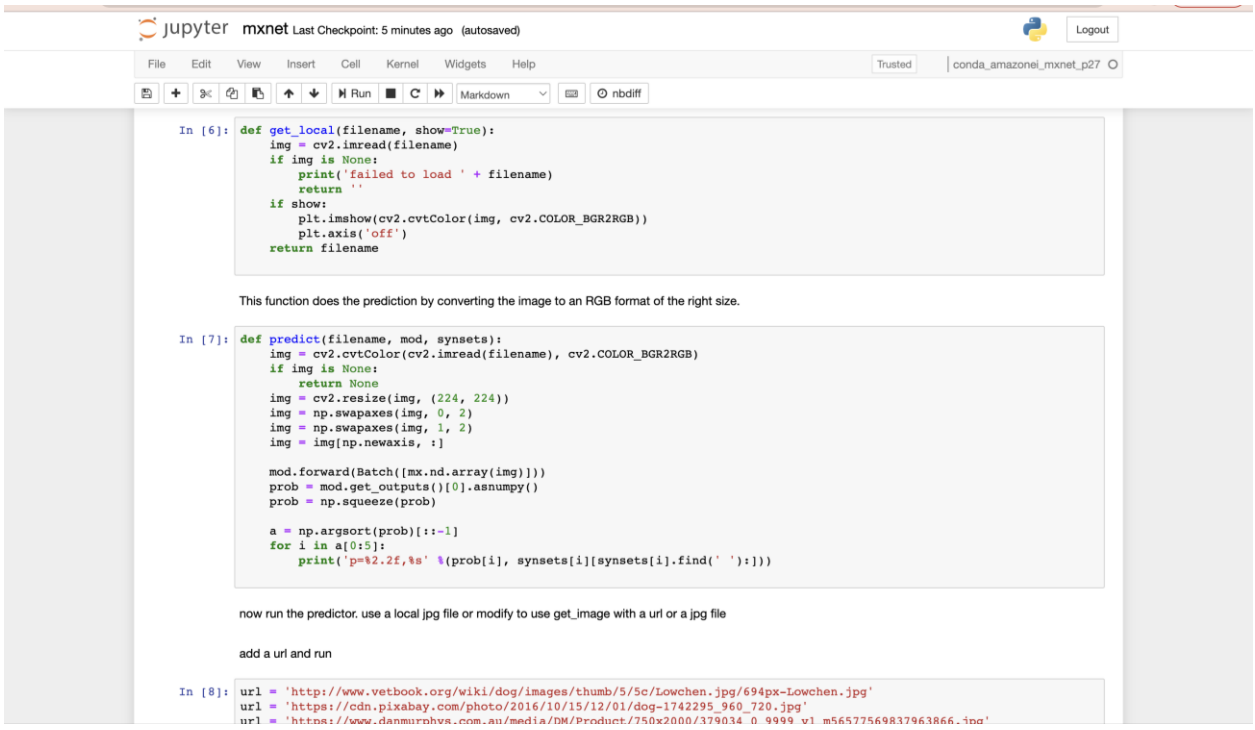


This function does the prediction by converting the image to an RGB format of the right size.









now run the predictor. use a local jpg file or modify to use get_image with a url or a jpg file
add a url and run

jupyter **mxnet** Last Checkpoint: 6 minutes ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help

Trusted | conda_amazonei_mxnet_p27

Run | Markdown | nbdiff

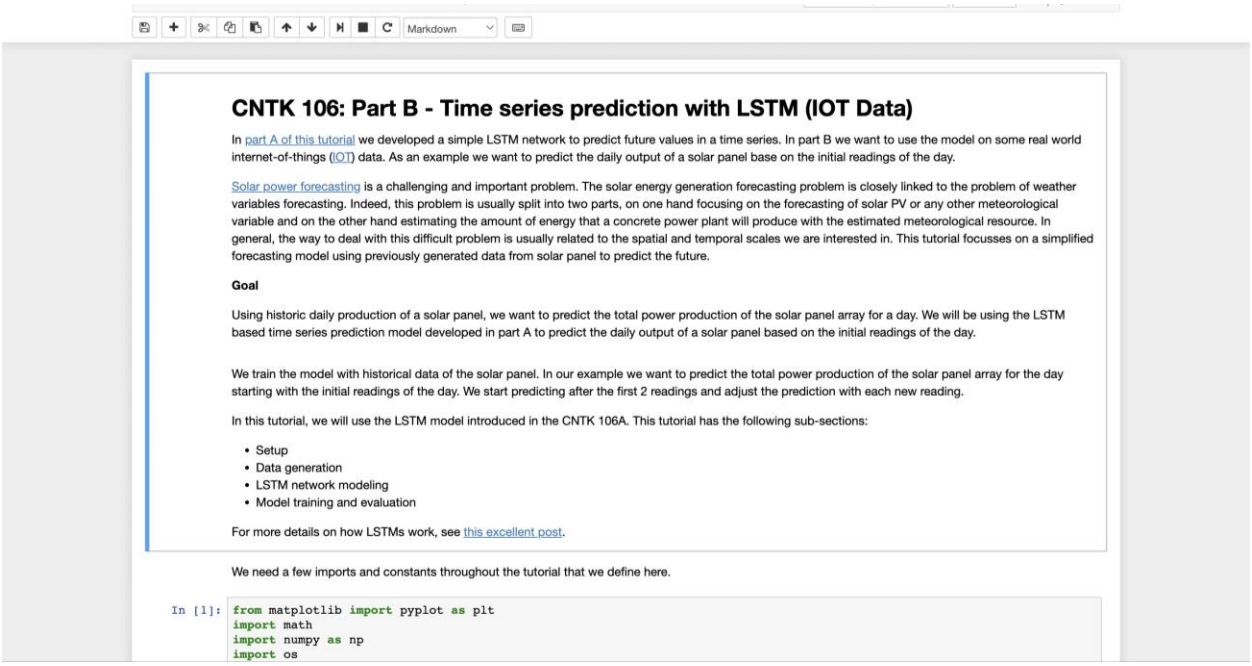
In [8]:
```
url = 'http://www.vetbook.org/wiki/dog/images/thumb/5/5c/Lowchen.jpg/694px-Lowchen.jpg'
url = 'https://cdn.pixabay.com/photo/2016/10/15/12/01/dog-1742295_960_720.jpg'
url = 'https://www.danmurphys.com.au/media/DM/Product/750x2000/379034_0_9999_v1_m56577569837963866.jpg'
url = 'https://img-new.cgtrader.com/items/20608/heineken_beer_bottle_3d_model_fbx_lwo_lw_lws_obj_max_lxo_79aea18d-613b-
url = 'https://upload.wikimedia.org/wikipedia/commons/thumb/1/16/Official_Portrait_of_President_Reagan_1981.jpg/1200px-
url = 'http://3.bp.blogspot.com/-wRi2GBtO-Yk/T3cYy2VIgRI/AAAAAAAAB-8/Z9X6Jjc1P34/s1600/great-blue-heron.jpg'
url = 'http://assets.nydailynews.com/polopoly_fs/1.2773122.1472670685!/img/httpImage/image.jpg_gen/derivatives/article_
url = 'http://il.ytimg.com/vi/UxUBDJlsnjI/maxresdefault.jpg'
file = get_image(url)
predict(file, mod, synsets)
```

```
maxresdefault.jpg
p=0.19, garbage truck, dustcart
p=0.11, blacktop, blacktopping
p=0.09, garbage man, garbageman, garbage collector, garbage carter, garbage hauler, refuse collector, dustman
p=0.05, harvester, reaper
p=0.04, broadcaster, spreader
```

In [ ]:

PART 5

The Tutorials/ and Examples/ folders contain a variety of example configurations for CNTK networks using the Python API, C# and Brain Script. The examples are structured by topic into Image, Language Understanding, Speech, and so forth. To get started with CNTK we recommend the tutorials



Markdown

CNTK 106: Part B - Time series prediction with LSTM (IOT Data)

In part A of this tutorial we developed a simple LSTM network to predict future values in a time series. In part B we want to use the model on some real world internet-of-things (IOT) data. As an example we want to predict the daily output of a solar panel base on the initial readings of the day.

Solar power forecasting is a challenging and important problem. The solar energy generation forecasting problem is closely linked to the problem of weather variables forecasting. Indeed, this problem is usually split into two parts, on one hand focusing on the forecasting of solar PV or any other meteorological variable and on the other hand estimating the amount of energy that a concrete power plant will produce with the estimated meteorological resource. In general, the way to deal with this difficult problem is usually related to the spatial and temporal scales we are interested in. This tutorial focusses on a simplified forecasting model using previously generated data from solar panel to predict the future.

Goal

Using historic daily production of a solar panel, we want to predict the total power production of the solar panel array for a day. We will be using the LSTM based time series prediction model developed in part A to predict the daily output of a solar panel based on the initial readings of the day.

We train the model with historical data of the solar panel. In our example we want to predict the total power production of the solar panel array for the day starting with the initial readings of the day. We start predicting after the first 2 readings and adjust the prediction with each new reading.

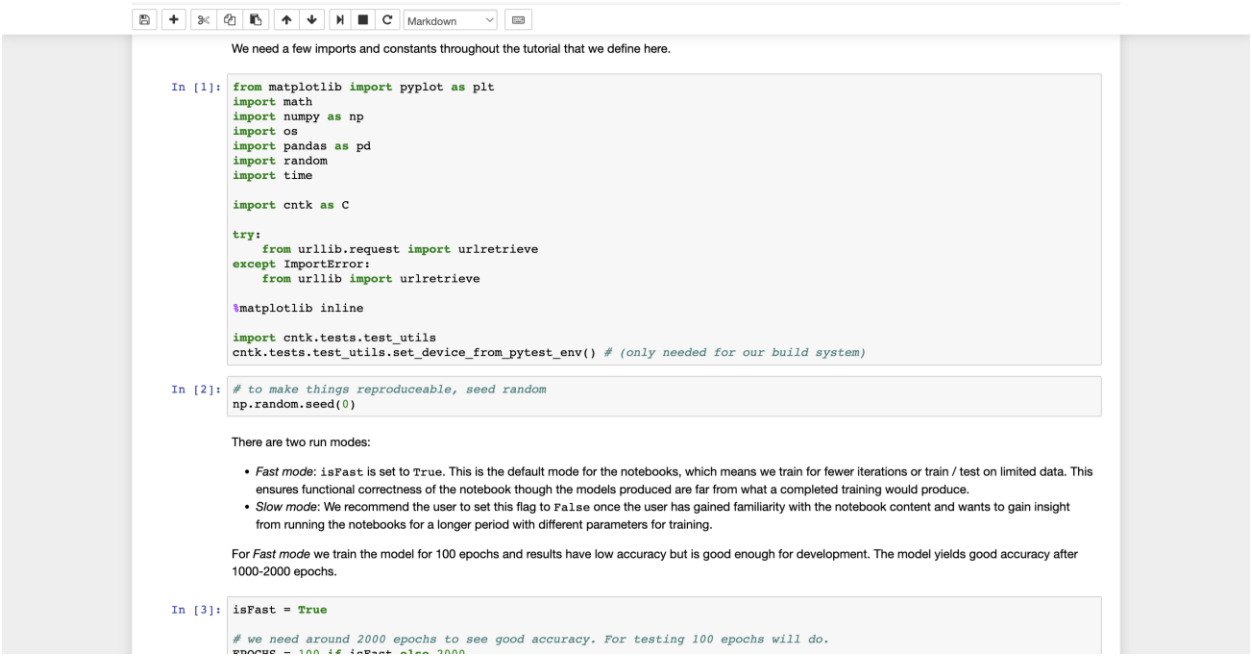
In this tutorial, we will use the LSTM model introduced in the CNTK 106A. This tutorial has the following sub-sections:

- Setup
- Data generation
- LSTM network modeling
- Model training and evaluation

For more details on how LSTMs work, see this excellent post.

We need a few imports and constants throughout the tutorial that we define here.

In [1]:
```
from matplotlib import pyplot as plt
import math
import numpy as np
import os
```



Markdown

We need a few imports and constants throughout the tutorial that we define here.

In [1]:
```
from matplotlib import pyplot as plt
import math
import numpy as np
import os
import pandas as pd
import random
import time

import cntk as C

try:
    from urllib.request import urlretrieve
except ImportError:
    from urllib import urlretrieve

%matplotlib inline

import cntk.tests.test_utils
cntk.tests.test_utils.set_device_from_pytest_env() # (only needed for our build system)
```

In [2]:
```
# to make things reproduceable, seed random
np.random.seed(0)
```

There are two run modes:

- *Fast mode*: `isFast` is set to `True`. This is the default mode for the notebooks, which means we train for fewer iterations or train / test on limited data. This ensures functional correctness of the notebook though the models produced are far from what a completed training would produce.
- *Slow mode*: We recommend the user to set this flag to `False` once the user has gained familiarity with the notebook content and wants to gain insight from running the notebooks for a longer period with different parameters for training.

For *Fast mode* we train the model for 100 epochs and results have low accuracy but is good enough for development. The model yields good accuracy after 1000-2000 epochs.

In [3]:
```
isFast = True

# we need around 2000 epochs to see good accuracy. For testing 100 epochs will do.
```

from running the notebooks for a longer period with different parameters for training.

For *Fast mode* we train the model for 100 epochs and results have low accuracy but is good enough for development. The model yields good accuracy after 1000-2000 epochs.

In [3]:
```
isFast = True

# we need around 2000 epochs to see good accuracy. For testing 100 epochs will do.
EPOCHS = 100 if isFast else 2000
```

Data generation

Our solar panel, emits two measures at every 30 min interval:

- `solar.current` is the current production in Watt
- `solar.total` is the total produced for the day so far in Watt/hour

Our prediction approach involves starting with the first 2 initial readings of the day. Based on these readings we start predicting and adjust the prediction with each new reading. The training data we are going to use comes as a csv file and has the following format:

```
time,solar.current,solar.total
7am,6.3,1.7
7:30am,44.3,11.4
...
```

The training dataset we use contains data captured for 3 years and can be found here. The dataset is not pre-processed: it is raw data and contains smaller gaps and errors (like a panel failed to report).

Pre-processing

Most of the code in this example is related to data preparation. Thankfully the pandas library make this easy.

`generate_solar_data()` function performs the following tasks:

- read raw data into a pandas dataframe,

The training dataset we use contains data captured for 3 years and can be found here. The dataset is not pre-processed: it is raw data and contains smaller gaps and errors (like a panel failed to report).

Pre-processing

Most of the code in this example is related to data preparation. Thankfully the pandas library make this easy.

`generate_solar_data()` function performs the following tasks:

- read raw data into a pandas dataframe,
- normalize the data,
- groups by day and
- append the columns "solar.current.max" and "solar.total.max", and
- generates the sequences for each day.

Sequence generation: All sequences are concatenated into a single list of sequences. There is *no more notion of timestamp* in our train input and **only** the sequences matter.

Note if we have less than 8 datapoints for a day we skip over the day assuming something is missing in the raw data. If we get more than 14 data points in a day we truncate the readings.

Training / Testing / Validation data preparation

We start by reading the csv file for use with CNTK. The raw data is sorted by time and we should randomize it before splitting into training, validation and test datasets but this would make it impractical to visualize results in the tutorial. Hence, we split the dataset in the following manner: pick in sequence, 8 values for training, 1 for validation and 1 for test until there is no more data. This will spread training, validation and test datasets across the full timeline while preserving time order.

In [4]:
```
def generate_solar_data(input_url, time_steps, normalize=1, val_size=0.1, test_size=0.1):
    """
    generate sequences to feed to rnn based on data frame with solar panel data
    the csv has the format: time ,solar.current, solar.total
     (solar.current is the current output in Watt, solar.total is the total production
      for the day so far in Watt hours)
    """
    # try to find the data file local. If it doesn't exists download it.
    cache_path = os.path.join("data", "iot")
```

Markdown

In [4]:
```
def generate_solar_data(input_url, time_steps, normalize=1, val_size=0.1, test_size=0.1):
    """
    generate sequences to feed to rnn based on data frame with solar panel data
    the csv has the format: time ,solar.current, solar.total
     (solar.current is the current output in Watt, solar.total is the total production
      for the day so far in Watt hours)
    """
    # try to find the data file local. If it doesn't exists download it.
    cache_path = os.path.join("data", "iot")
    cache_file = os.path.join(cache_path, "solar.csv")
    if not os.path.exists(cache_path):
        os.makedirs(cache_path)
    if not os.path.exists(cache_file):
        urlretrieve(input_url, cache_file)
        print("downloaded data successfully from ", input_url)
    else:
        print("using cache for ", input_url)

    df = pd.read_csv(cache_file, index_col="time", parse_dates=['time'], dtype=np.float32)

    df["date"] = df.index.date

    # normalize data
    df['solar.current'] /= normalize
    df['solar.total'] /= normalize

    # group by day, find the max for a day and add a new column .max
    grouped = df.groupby(df.index.date).max()
    grouped.columns = ["solar.current.max", "solar.total.max", "date"]

    # merge continuous readings and daily max values into a single frame
    df_merged = pd.merge(df, grouped, right_index=True, on="date")
    df_merged = df_merged[["solar.current", "solar.total",
                           "solar.current.max", "solar.total.max"]]
    # we group by day so we can process a day at a time.
    grouped = df_merged.groupby(df_merged.index.date)
    per_day = []
    for _, group in grouped:
        per_day.append(group)

    # split the dataset into train, validatation and test sets on day boundaries
```

jupyter CNTK_106B_LSTM_Timeseries_with_IOT_Data (unsaved changes)

Logout

File Edit View Insert Cell Kernel Widgets Help

Not Trusted | Python 3

Markdown

```
    df_merged = df_merged[["solar.current", "solar.total",
                           "solar.current.max", "solar.total.max"]]
    # we group by day so we can process a day at a time.
    grouped = df_merged.groupby(df_merged.index.date)
    per_day = []
    for _, group in grouped:
        per_day.append(group)

    # split the dataset into train, validatation and test sets on day boundaries
    val_size = int(len(per_day) * val_size)
    test_size = int(len(per_day) * test_size)
    next_val = 0
    next_test = 0

    result_x = {"train": [], "val": [], "test": []}
    result_y = {"train": [], "val": [], "test": []}

    # generate sequences a day at a time
    for i, day in enumerate(per_day):
        # if we have less than 8 datapoints for a day we skip over the
        # day assuming something is missing in the raw data
        total = day["solar.total"].values
        if len(total) < 8:
            continue
        if i >= next_val:
            current_set = "val"
            next_val = i + int(len(per_day) / val_size)
        elif i >= next_test:
            current_set = "test"
            next_test = i + int(len(per_day) / test_size)
        else:
            current_set = "train"
        max_total_for_day = np.array(day["solar.total.max"].values[0])
        for j in range(2, len(total)):
            result_x[current_set].append(total[0:j])
            result_y[current_set].append([max_total_for_day])
            if j >= time_steps:
                break
    # make result_y a numpy array
    for ds in ["train", "val", "test"]:
        result_y[ds] = np.array(result_y[ds])
    return result_x, result_y
```

Data caching

For routine testing we would like to cache the data locally when available. If it is not available from the cache locations we shall download.

In [5]:
```
# We keep upto 14 inputs from a day
TIMESTEPS = 14

# 20000 is the maximum total output in our dataset. We normalize all values with
# this so our inputs are between 0.0 and 1.0 range.
NORMALIZE = 20000

X, Y = generate_solar_data("https://www.cntk.ai/jup/dat/solar.csv",
                           TIMESTEPS, normalize=NORMALIZE)
```

```
using cache for  https://www.cntk.ai/jup/dat/solar.csv
```

Utility for data fetching

`next_batch()` yields the next batch for training. We use variable size sequences supported by CNTK and batches are a list of numpy arrays where the numpy arrays have variable length.

A standard practice is to shuffle batches with each epoch. We don't do this here because we want to be able to graph the data that is easily interpretable.

In [6]:
```
# process batches of 10 days
BATCH_SIZE = TIMESTEPS * 10

def next_batch(x, y, ds):
    """get the next batch for training"""

    def as_batch(data, start, count):
        return data[start:start + count]

    for i in range(0, len(x[ds]), BATCH_SIZE):
        yield as_batch(X[ds], i, BATCH_SIZE), as_batch(Y[ds], i, BATCH_SIZE)
```

Understand the data format

You can now see the sequence we are going to feed to the LSTM. Note if we have less than 8 datapoints for a day we skip over the day assuming something is missing in the raw data. If we get more than 14 data points in a day we truncate the readings.

In [7]:
```
X['train'][0:3]
```

Out[7]:
```
[array([ 0.       ,  0.0006985], dtype=float32),
 array([ 0.       ,  0.0006985,  0.0033175], dtype=float32),
 array([ 0.       ,  0.0006985,  0.0033175,  0.010375 ], dtype=float32)]
```

In [8]:
```
Y['train'][0:3]
```

Out[8]:
```
array([[ 0.23899999],
       [ 0.23899999],
       [ 0.23899999]], dtype=float32)
```

Model Creation (LSTM network)

Corresponding to the maximum possible 14 data points in the input sequence, we model our network with 14 LSTM cells, 1 cell for each data point we take during the day. Since the input sequences can be between 8 and 14 data points per sequence, we take the advantage of CNTK support for variable sequences as input to a LSTM so we can feed our sequences as-is with no additional need for padding.

The output of the neural network is the total output for the day and each sequence for a given day has the same total output.

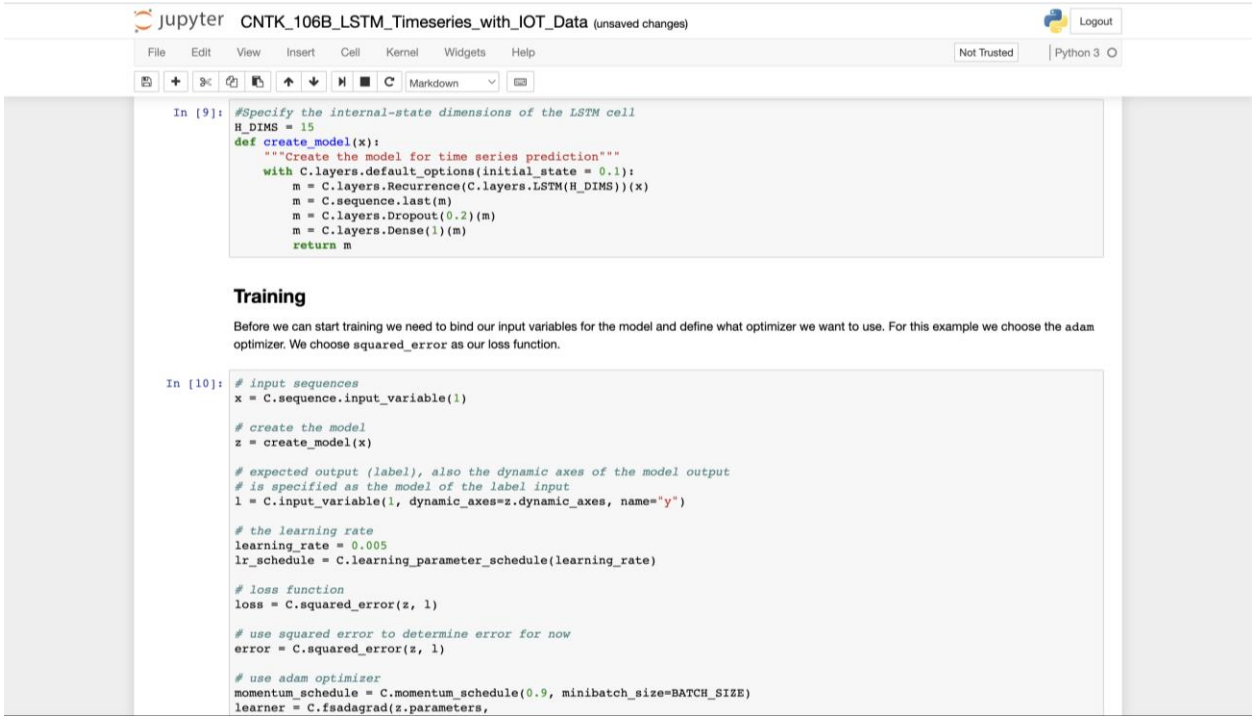
For example:

```
1.7,11.4 -> 10300
1.7,11.4,67.5 -> 10300
1.7,11.4,67.5,250.5 ... -> 10300
1.7,11.4,67.5,250.5,573.5 -> 10300
```

The outputs from the LSTMs are fed into a dense layer and we randomly dropout 20% of the values to not overfit the model to the training set. The output of the dense layer becomes the prediction our model generates.

Notice: We lost the timestamp altogether; in our model only the sequences of readings matter.

Our LSTM model has the following design:

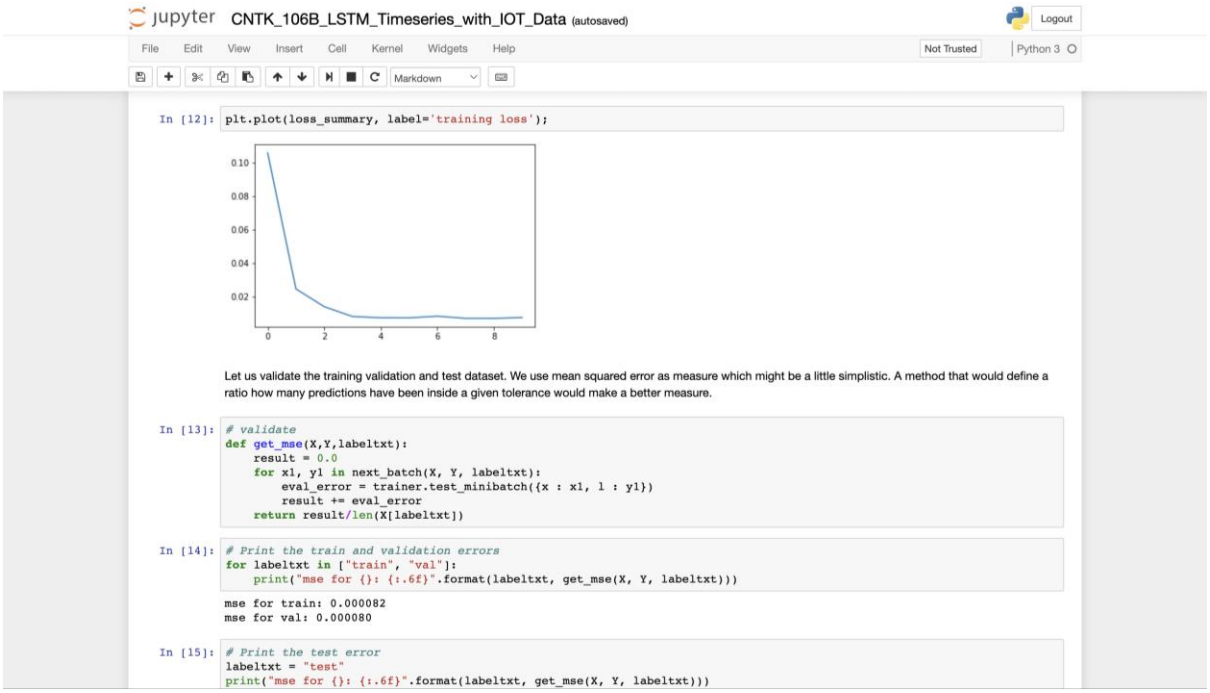


In this tutorial we will walk through several complete CNTK examples, showing

- how to describe a network in our network-description language BrainScript;
- how to set the learning parameters; and
- how to read in, and write out, data

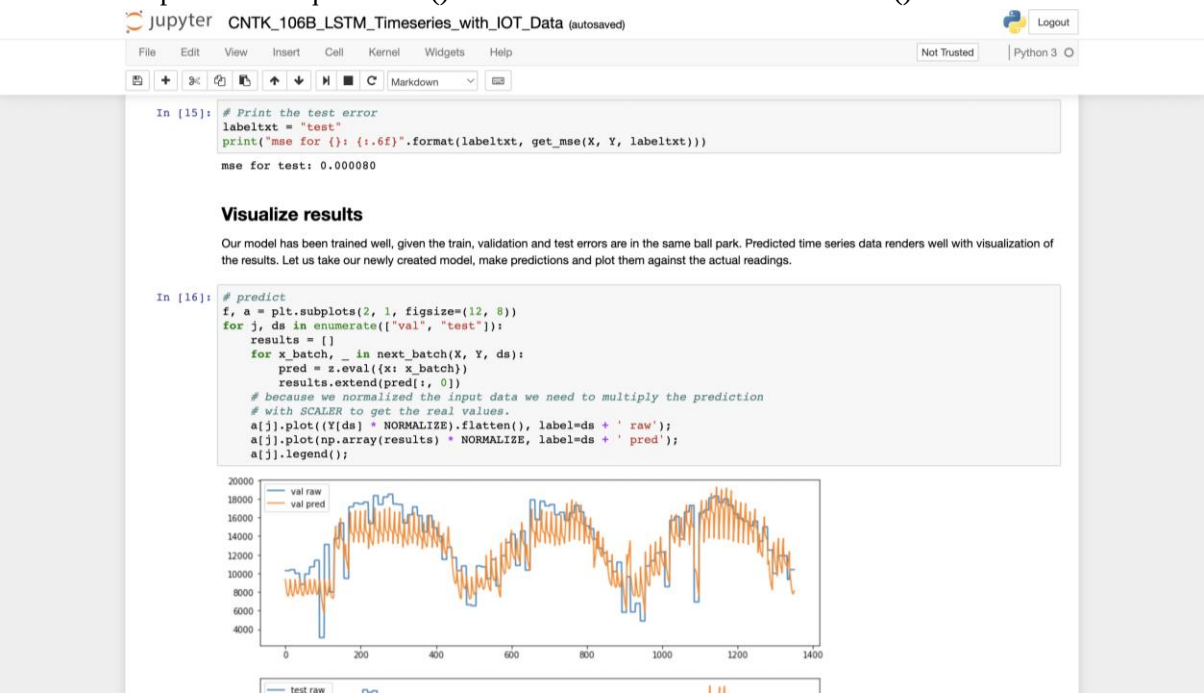
Logistic regression is a simple model for performing binary classification. Given some real-valued d-dimensional example x = (x1 ... xd)', we want to output one of two labels: 0 or 1, true or false, spam or not-spam, etc. So, we want to learn a function y = f(x; w, b) where y is in {0, 1} and w = (w1 ... wd) and b are parameters that we will learn that describe the relationship between x and y.

Without CNTK, we need to choose an optimization procedure and solve the derivatives of a cost function with respect to the parameters we want to learn. Seeing logistic regression as a probabilistic model, we can maximize the likelihood of the data. This turns out to be the same as minimizing the cross-entropy cost function, which for logistic regression is also known as the 'logistic loss function'.



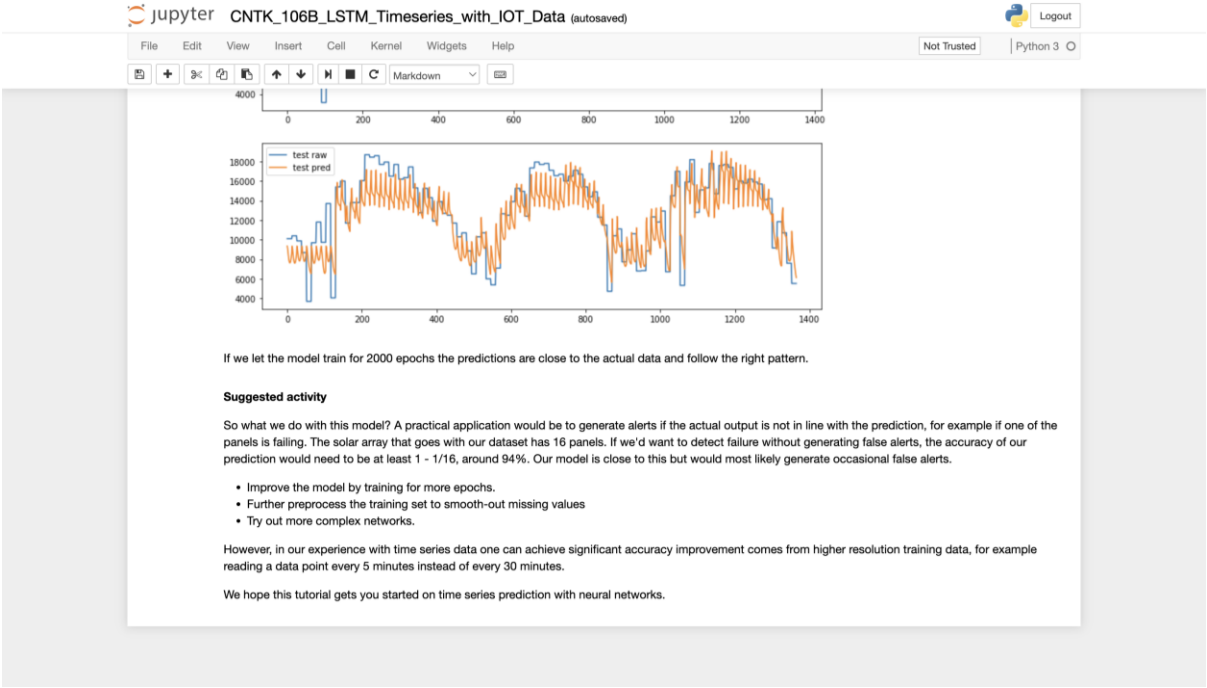
the label dimension is now 3 instead of 1;

- we take out the Sigmoid() node;
- we replace the Logistic() learning criterion by CrossEntropyWithSoftmax() which will add the softmax layer and use cross entropy as the objective function; and
- we replaced the SquareError() evaluation node with ErrorPrediction().



The softmax function is a generalization of the logistic function. It maps a vector of real values to a probability distribution. It is widely used for multi-class classification problems. In this context, if we

are trying to predict the class of an instance out of K possible classes, the model would compute a K-dimensional vector whose components represent the confidence scores for each class.



If we let the model train for 2000 epochs the predictions are close to the actual data and follow the right pattern.

Suggested activity

So what we do with this model? A practical application would be to generate alerts if the actual output is not in line with the prediction, for example if one of the panels is failing. The solar array that goes with our dataset has 16 panels. If we'd want to detect failure without generating false alerts, the accuracy of our prediction would need to be at least 1 - 1/16, around 94%. Our model is close to this but would most likely generate occasional false alerts.

- Improve the model by training for more epochs.
- Further preprocess the training set to smooth-out missing values
- Try out more complex networks.

However, in our experience with time series data one can achieve significant accuracy improvement comes from higher resolution training data, for example reading a data point every 5 minutes instead of every 30 minutes.

We hope this tutorial gets you started on time series prediction with neural networks.

PART 6

Get familiar with Deep Learning using TensorFlow; execute and document the following exercise

The data consists csv file of a GRE exam score in the range 0 to 800, a grade point average in the range 0 to 4.0 and the rank of the student's undergrad institution in the range 4 to 1 (top). The Admission Decision in binary.

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Run Code nbdiff

A very simple Tensorflow Logistic Regression example.

we will build a logistic regression model of some (fake) graduate school admissions decisions. The data consists csv file of a GRE exam score in the range 0 to 800, a grade point average in the range 0 to 4.0 and the rank of the student's undergrad institution in the range 4 to 1 (top). The Admission Decision in binary.

There are six columns in the data. Ignore column 0. the GRE, GPA and school rank are in columns 1 through 3. Column 4 is an admission decision that is only based on the rank of the school: only students with a rank 1 school get in and others not. Column 5 contains a more interesting (but still silly) admission model where you get in if your GRE score is 800 or your rank is 1. in the example below we use the former model. It is easy for the system to learn it perfectly.

The csv file is called dat.csv and it is here https://1drv.ms/u/s!AkRG9Zk_IOUag5lX1xzlv7rP9T5FFg

In [1]:
```
import tensorflow as tf
import numpy as np
import csv
```

```
/home/ec2-user/anaconda3/envs/amazonei_tensorflow2_p27/lib/python2.7/site-packages/OpenSSL/crypto.py:12: CryptographyDeprecationWarning: Python 2 is no longer supported by the Python core team. Support for it is now deprecated in cryptography, and will be removed in the next release.
  from cryptography import x509
```

In [2]:
```
sess=tf.compat.v1.InteractiveSession()
```

In [ ]:
```
#sess = tf.InteractiveSession()
```

In [6]:
```
train_datas = []
train_labels = []
test_datas = []
test_labels = []
i = 0
scale = np.array([[0.01, 1.0, 1.0]])
with open('/home/ec2-user/SageMaker/dat.csv', 'r') as f:
    reader = csv.reader(f)
    for row in reader:
        if i < 300:
```

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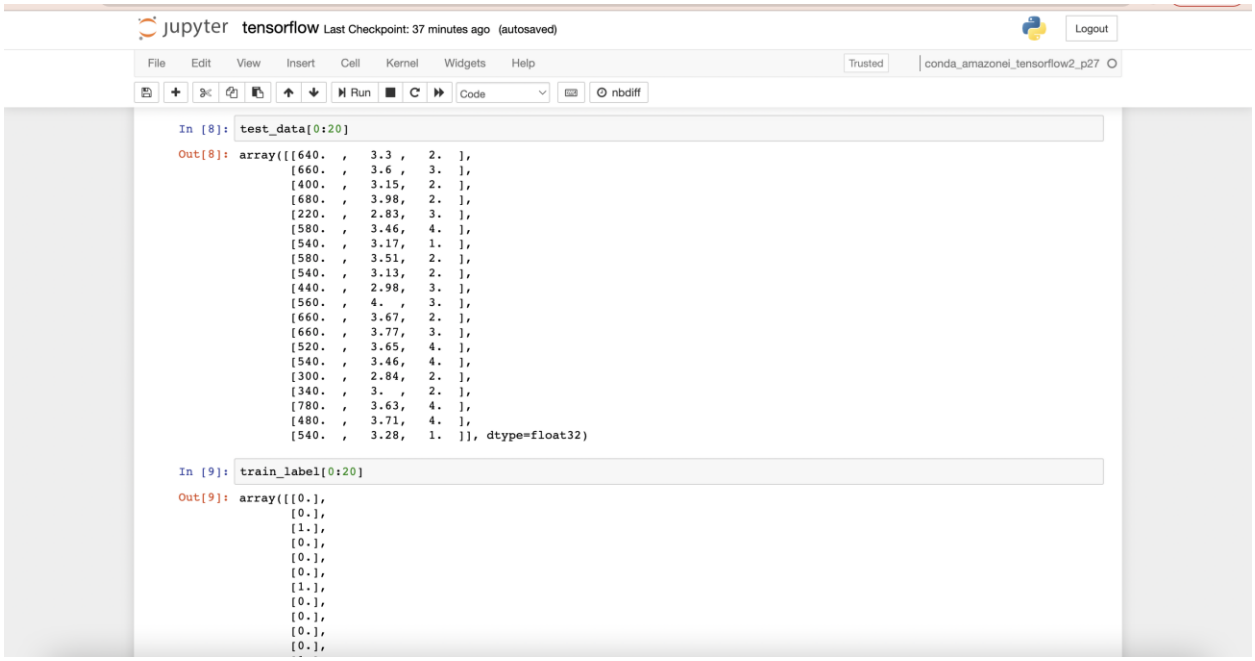
Run Code nbdiff

In [6]:
```
train_datas = []
train_labels = []
test_datas = []
test_labels = []
i = 0
scale = np.array([[0.01, 1.0, 1.0]])
with open('/home/ec2-user/SageMaker/dat.csv', 'r') as f:
    reader = csv.reader(f)
    for row in reader:
        if i < 300:
            train_datas.append([np.float32(x) for x in row[1:4]])
            #print np.float(row[0])
            train_labels.append([np.float32(row[4])])
        else:
            test_datas.append([np.float32(x) for x in row[1:4]])
            test_labels.append([np.float(row[4])])
        i +=1
```

In [7]:
```
test_data  = np.array(test_datas, dtype=np.float32)
test_label = np.array(test_labels, dtype=np.float32)
train_data  = np.array(train_datas, dtype=np.float32)
train_label = np.array(train_labels, dtype=np.float32)
```

In [8]:
```
test_data[0:20]
```

Out[8]:
```
array([[640.  ,   3.3 ,   2.  ],
       [660.  ,   3.6 ,   3.  ],
       [400.  ,   3.15,   2.  ],
       [680.  ,   3.98,   2.  ],
       [220.  ,   2.83,   3.  ],
       [580.  ,   3.46,   4.  ],
       [540.  ,   3.17,   1.  ],
       [580.  ,   3.51,   2.  ],
       [540.  ,   3.13,   2.  ],
       [440.  ,   2.98,   3.  ],
       [560.  ,   4.  ,   3.  ],
       [660.  ,   3.67,   2.  ],
       [660.  ,   3.77,   3.  ],
       [520.  ,   3.65,   4.  ],
       [540.  ,   3.46,   4.  ],
```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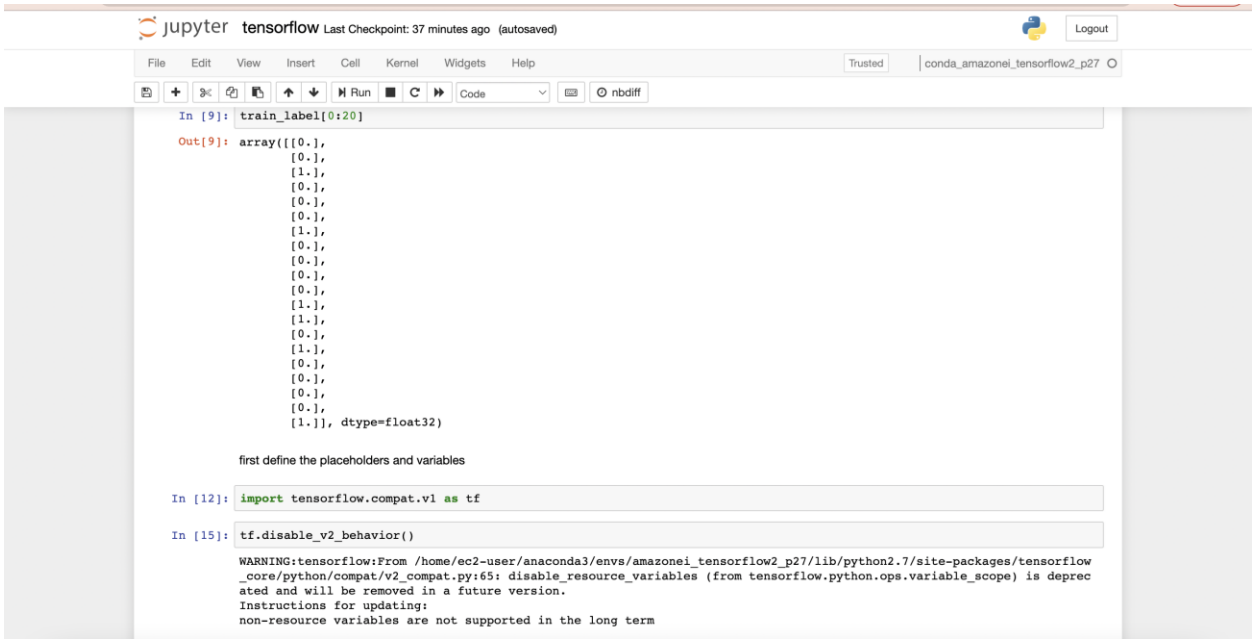
Code
nbdiff
In [8]: test_data[0:20]
Out[8]: array([[640. , 3.3 , 2.],
[660. , 3.6 , 3.],
[400. , 3.15, 2.],
[680. , 3.98, 2.],
[220. , 2.83, 3.],
[580. , 3.46, 4.],
[540. , 3.17, 1.],
[580. , 3.51, 2.],
[540. , 3.13, 2.],
[440. , 2.98, 3.],
[560. , 4. , 3.],
[660. , 3.67, 2.],
[660. , 3.77, 3.],
[520. , 3.65, 4.],
[540. , 3.46, 4.],
[300. , 2.84, 2.],
[340. , 3. , 2.],
[780. , 3.63, 4.],
[480. , 3.71, 4.],
[540. , 3.28, 1.]], dtype=float32)
In [9]: train_label[0:20]
Out[9]: array([[0.],
[0.],
[1.],
[0.],
[0.],
[0.],
[1.],
[0.],
[0.],
[0.],
[0.],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Run
Code
nbdiff
In [9]: train_label[0:20]
Out[9]: array([[0.],
[0.],
[1.],
[0.],
[0.],
[0.],
[1.],
[0.],
[0.],
[0.],
[0.],
[1.],
[1.],
[0.],
[1.],
[0.],
[0.],
[0.],
[0.],
[1.]], dtype=float32)
first define the placeholders and variables
In [12]: import tensorflow.compat.v1 as tf
In [15]: tf.disable_v2_behavior()
WARNING:tensorflow:From /home/ec2-user/anaconda3/envs/amazonei_tensorflow2_p27/lib/python2.7/site-packages/tensorflow
_core/python/compat/v2_compat.py:65: disable_resource_variables (from tensorflow.python.ops.variable_scope) is deprec
ated and will be removed in a future version.
Instructions for updating:
non-resource variables are not supported in the long term

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Run Code nbdiff

In [15]:
```
tf.disable_v2_behavior()
```

```
WARNING:tensorflow:From /home/ec2-user/anaconda3/envs/amazonei_tensorflow2_p27/lib/python2.7/site-packages/tensorflow
_core/python/compat/v2_compat.py:65: disable_resource_variables (from tensorflow.python.ops.variable_scope) is deprec
ated and will be removed in a future version.
Instructions for updating:
non-resource variables are not supported in the long term
```

In [17]:
```
x = tf.placeholder(tf.float32, shape=(None,3))
y = tf.placeholder(tf.float32, shape =(None,1))

# Set model weights
W = tf.Variable(tf.zeros([3, 1]))
b = tf.Variable(tf.zeros([1]))
```

In [18]:
```
training_epochs = 400000
batch_size = 100
display_step = 1000
```

In [19]:
```
pred = tf.sigmoid(tf.matmul(x, W) + b) # Softmax
cost = tf.sqrt(tf.reduce_sum((y - pred)**2/batch_size))

opt = tf.train.AdamOptimizer()
optimizer = opt.minimize(cost)

# Initializing the variables old version is initialize_all_variable.  New version
# has global_variable_initializer.

#init = tf.global_variables_initializer()
init = tf.initialize_all_variables()
```

```
WARNING:tensorflow:From /home/ec2-user/anaconda3/envs/amazonei_tensorflow2_p27/lib/python2.7/site-packages/tensorflow
_core/python/util/tf_should_use.py:198: initialize_all_variables (from tensorflow.python.ops.variables) is deprecated
and will be removed after 2017-03-02.
Instructions for updating:
Use `tf.global_variables_initializer` instead.
```

In [20]:
```
def get_batch2(batch_size, x, y):
    indices = np.random.choice(299, batch_size)
    return x[indices], y[indices]
```

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In [20]:
```
def get_batch2(batch_size, x, y):
    indices = np.random.choice(299, batch_size)
    return x[indices], y[indices]
```

In [21]:
```
sess.run(init)
# Training cycle
for epoch in range(training_epochs):
    avg_cost = 0.
    total_batch = int(len(train_data)/batch_size)
    # Loop over all batches
    for i in range(total_batch):
        batch_xs, batch_ys = get_batch2(batch_size, train_data, train_label)
        # Fit training using batch data
        _, c = sess.run([optimizer, cost], feed_dict={x:batch_xs,y:batch_ys})
        # Compute average loss
        avg_cost += c / total_batch
    # Display logs per epoch step
    if (epoch+1) % display_step == 0:
        print "Epoch:", '%04d' % (epoch+1), "cost=", str(avg_cost)

print "Optimization Finished!"
```

```
Epoch: 383000 cost= nan
Epoch: 384000 cost= nan
Epoch: 385000 cost= nan
Epoch: 386000 cost= nan
Epoch: 387000 cost= nan
Epoch: 388000 cost= nan
Epoch: 389000 cost= nan
Epoch: 390000 cost= nan
Epoch: 391000 cost= nan
Epoch: 392000 cost= nan
Epoch: 393000 cost= nan
Epoch: 394000 cost= nan
Epoch: 395000 cost= nan
Epoch: 396000 cost= nan
Epoch: 397000 cost= nan
Epoch: 398000 cost= nan
```

```
Epoch: 398000 cost= nan
Epoch: 399000 cost= nan
Epoch: 400000 cost= nan
Optimization Finished!
```

define a function in python to compute sigmoid of an array.

In [22]:
```
def sigmoida(z):
    res = np.zeros(len(z))
    for i in range(len(z)):
        y = 1.0/(1.0+np.exp(-z[i]))
        if y > 0.5:
            res[i] = 1
        else:
            res[i] = 0
    return res
```

In [23]:
```
p = sigmoida(pred.eval({x:test_data}))
q = y.eval({y:test_label})
```

how accurate is this. In other words whaat fraction of the cases have p = q.

In [24]:
```
def accurate(p,q):
    total = 0.0
    numones = 0.
    numzeros = 0.
    for i in range(len(p)):
        if p[i] == 0:
            numzeros += 1
        else:
            numones += 1
        if p[i] == q[i]:
            total +=1
    print "accuracy = "+str(total/len(p))
    print 'ratio of 1s ='+str(numones/len(p))
    print 'ratio of 0s ='+str(numzeros/len(p))
```

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In [25]:
```
accurate(p,q)
```

```
accuracy = 0.84
ratio of 1s =0.0
ratio of 0s =1.0
```

In [26]:
```
def softmax(v):
    k = len(v)
    res = np.zeros(k)
    tot = 0.0
    for i in range(k):
        res[i] = np.exp(v[i])
        tot += res[i]
    for i in range(k):
        res[i] = res[i]/tot
    return res
```

In [27]:
```
def sigmoid(x):
    y = 1.0/(1.0+np.exp(-x))
    if y > 0.5:
        return 1
    else:
        return 0
```

if we wish, we may look at the trained W and b arrays.

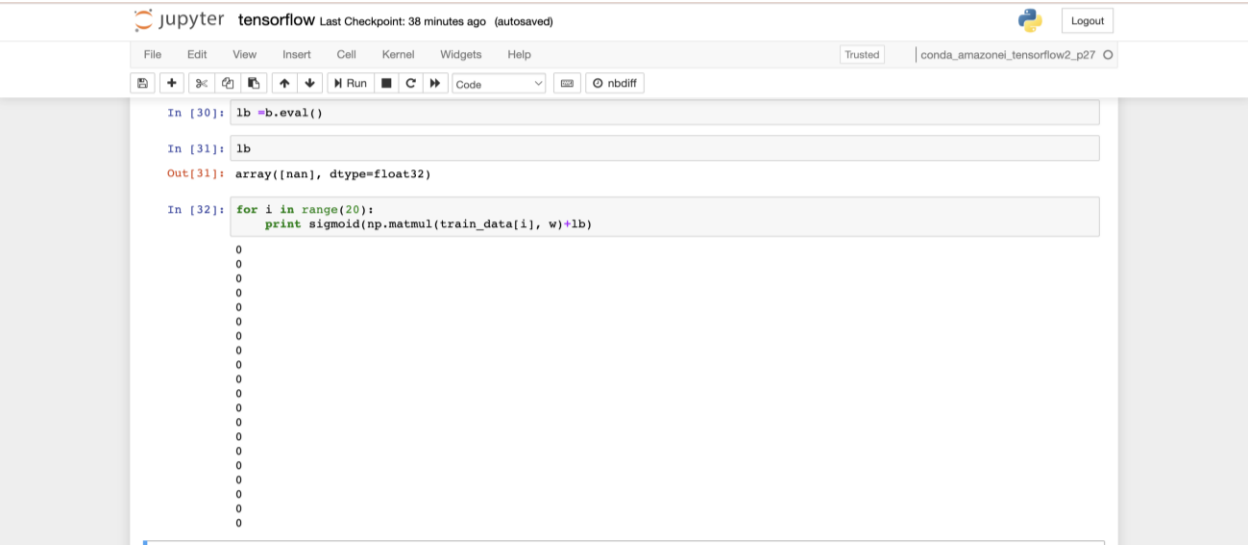
In [28]:
```
w =W.eval()
```

In [29]:
```
w
```

Out[29]:
```
array([[nan],
       [nan],
       [nan]], dtype=float32)
```

In [30]:
```
lb =b.eval()
```

In [31]:
```
lb
```



There are six columns in the data. Ignore column 0. the GRE, GPA and school rank are in columns 1 through 3. Column 4 is an admission decision that is only based on the rank of the school: only students with a rank 1 school get in and others not. Column 5 contains a more interesting (but still silly) admission model where you get in if your GRE score is 800 or your rank is 1. in the example below we use the former model. It is easy for the system to learn it perfectly.