LSTM on Amazon Fine Food Reviews

In [5]:

```
import sqlite3

import gensim
%matplotlib inline
import pandas as pd
import numpy as np
import sqlite3
import re
import nltk
import matplotlib.pyplot as plt
from  nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
import seaborn as sn
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn import preprocessing
from sklearn.metrics import accuracy_score,f1_score,log_loss
import warnings
warnings.filterwarnings('ignore')
# LSTM for sequence classification in the IMDB dataset
import numpy
from keras.datasets import imdb
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers.embeddings import Embedding
from keras.preprocessing import sequence
# fix random seed for reproducibility
numpy.random.seed(7)
```

```
Using TensorFlow backend.
```

In [6]:

```
#loading data
con = sqlite3.connect(r'/content/drive/My Drive/database.sqlite')
data = pd.read_sql_query('select * from REVIEWS where Score!=3',con)
data.head()
```

Out[6]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Medicine
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy

In [7]:

```
def change_labels(x):
    if x > 3:
        return 1
    return 0
temp_score = data['Score']
temp_score = temp_score.map(change_labels)
data['Score'] =  temp_score
data['Score'].head()
```

Out[7]:

```
0    1
1    0
2    1
3    0
4    1
Name: Score, dtype: int64
```

In [8]:

```
#data cleanising
print('Number of data points before removing duplicates',data.shape[0])
sorted_data=data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort',
na_position='last')
clean_data=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first',
inplace=False)
print('Number of data points after removing duplicates',clean_data.shape[0])
```

```
Number of data points before removing duplicates 525814
Number of data points after removing duplicates 364173
```

In [9]:

```
clean_data=clean_data[clean_data['HelpfulnessNumerator']<=clean_data['HelpfulnessDenominator']]
print('Now the Number of data points are',clean_data.shape[0])
```

```
Now the Number of data points are 364171
```

In [0]:

```
#to remove HTML Tags
def clean_html(x):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', x)
    return cleantext
#  to remove unwanted charecteres like '!',',' etc.

def cleansen(x):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',x)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
stemmer = nltk.stem.SnowballStemmer('english')
```

In [11]:

```
import datetime

str1=' '
final_string=[]
```

```
final_string=[]

s=''
start_time = datetime.datetime.now()
for sent in clean_data['Text'].values:
    filtered_sentence=[]
    sent=clean_html(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleansen(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                # if(cleaned_words.lower() not in stop_words):
                    s=(stemmer.stem(cleaned_words.lower()))
                    filtered_sentence.append(s)
                # else:
                 #    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = " ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

    final_string.append(str1)
clean_data['CleanedText']=final_string
print('Total time taken to clean the reviews',datetime.datetime.now()-start_time)
```

```
Total time taken to clean the reviews 0:07:53.717293
```

In [0]:

```
clean_data=clean_data.head(100000)
```

In [0]:

```
words = pd.DataFrame()
vocaby = pd.DataFrame()
```

In [0]:

```
#replacing words with frequency of thier occurances
vocab_words = []
for sent in clean_data['CleanedText'].values:
  for words in sent.split():
    vocab_words.append(words)
```

In [0]:

```
vocab_length = np.array(vocab_words).shape[0]
```

In [0]:

```
vocaby['words']=vocab_words
```

In [17]:

```
vocaby.head()
```

Out[17]:

	words
0	this
1	witti
2	littl
3	book
4	make

In [0]:

In [18]:

```
top_words=5000

Words=vocaby['words'].value_counts().head(top_words)#reutrns a dictionary wth key as word and valu
e as count
```

In [19]:

```
print(len(Words))
Words
```

```
5000
```

Out[19]:

```
the             303098
and             218562
this            111739
for              92786
that             69652
have             61774
with             60071
you              57547
but              55865
are              53597
was              50386
not              50161
they             48631
like             41457
these            39569
tast             39441
them             37411
tea              35349
good             33012
use              32383
love             31112
product          30953
one              30654
flavor           30266
great            30043
veri             28606
it               28270
just             27810
can              27569
tri              26525
                 ...
gingeri             36
brace               36
bend                36
smother             36
uti                 36
perish              36
unclear             36
huh                 36
mileag              36
salmonella          36
patio               36
artisan             36
limp                36
structur            36
nap                 36
sunni               36
peruvian            36
port                36
boysenberri         36
quirki              36
southwest           36
physician           36
slipperi            35
cooper              35
pho                 35
ravioli             35
boson               35
strengthen          35
adher               35
```

```
lasagn             35
Name: words, Length: 5000, dtype: int64
```

In [0]:

```
#fuction to replace words with counts
def text_count(row):
    count = []
    for w in row['CleanedText'].split():
        if w in Words:
            count.append(Words[w])
        else:
            count.append(0)
    return count
```

In [0]:

```
clean_data['countvectorize'] = clean_data.apply(lambda row: text_count(row),axis=1)
```

In [21]:

```
clean_data['countvectorize']
```

Out[21]:

```
138706    [111739, 0, 13380, 688, 24074, 2237, 198, 122,...
138688    [776, 3246, 39569, 0, 688, 218562, 1327, 30309...
138689    [111739, 1143, 8356, 92786, 884, 959, 9892, 53...
138690    [111739, 30043, 13380, 688, 3246, 21441, 7107,...
138691    [111739, 688, 0, 16507, 303098, 5326, 303098, ...
138693    [122, 0, 688, 69652, 935, 303098, 0, 1122, 120...
138694    [2008, 249, 2681, 2485, 4419, 11450, 3246, 223...
138695    [1605, 111739, 688, 25097, 336, 218562, 6725, ...
138696    [28270, 30043, 688, 60071, 284, 78, 1189, 463,...
138697    [111739, 688, 4387, 7783, 218562, 50386, 3246,...
138687    [22615, 303098, 617, 753, 307, 218562, 81, 142...
138698    [303098, 5492, 89, 252, 3451, 303098, 689, 798...
138700    [30043, 688, 6646, 1111, 4053, 988, 3585, 1812...
138701    [12903, 6555, 31112, 4631, 5229, 218562, 6490,...
138702    [111739, 688, 50386, 8879, 683, 3422, 92786, 1...
138703    [11721, 5133, 1854, 788, 111739, 688, 3528, 25...
138704    [111739, 688, 4856, 245, 157, 988, 80, 25730, ...
138705    [442, 713, 935, 303098, 32383, 4631, 5229, 600...
138707    [1854, 31112, 25730, 303098, 15418, 0, 688, 10...
138708    [111739, 30654, 303098, 14212, 884, 688, 6406,...
138709    [127, 1402, 122, 202, 413, 25730, 581, 0, 0, 3...
138699    [463, 884, 688, 6952, 1501, 3246, 23141, 50386...
138686    [28606, 317, 0, 218562, 0, 303098, 78, 53597, ...
138692    [4631, 5229, 60071, 6490, 0, 0, 0, 0, 0, 0, 76...
138680    [111739, 6651, 13380, 688, 31112, 11721, 2936,...
138677    [25730, 884, 31112, 111739, 688, 9711, 0, 6725...
138678    [30654, 0, 417, 111739, 688, 1095, 7940, 3246,...
138685    [111739, 122, 1854, 218562, 7783, 688, 3246, 1...
138684    [111739, 89, 1527, 18386, 3153, 8012, 13258, 5...
138679    [9004, 1185, 3289, 303098, 0, 0, 310, 30654, 3...
                                ...
124657    [111739, 35349, 21441, 28606, 568, 692, 30266,...
124656    [1812, 3570, 111739, 50161, 2170, 330, 692, 30...
124655    [27810, 9134, 111739, 692, 35349, 92786, 30309...
124654    [39441, 28606, 1269, 55865, 13482, 681, 12544,...
124653    [688, 1405, 4293, 111739, 35349, 252, 303098, ...
124651    [6646, 1069, 1408, 303098, 692, 30266, 218562,...
124650    [7107, 3115, 1315, 692, 30266, 6068, 50161, 46...
204536    [0, 5870, 1916, 1521, 5305, 35349, 1584, 21856...
398831    [8144, 35349, 218562, 5870, 155, 16078, 21441,...
398830    [12903, 8072, 303098, 358, 111739, 5305, 35349...
398829    [7393, 111739, 2056, 9799, 2499, 218562, 24074...
277086    [111739, 8144, 35349, 69652, 50161, 1744, 9726...
277094    [27810, 9134, 12544, 111739, 35349, 279, 21856...
```

```
277093    [31112, 111739, 35349, 28270, 303, 1059, 6392,...
277092    [92786, 5626, 7368, 218562, 1266, 26525, 11173...
277091    [5251, 8303, 3926, 7501, 2641, 1584, 5305, 353...
277088    [111739, 35349, 627, 32383, 24074, 3201, 35349...
277089    [3554, 778, 0, 35349, 6621, 1454, 111739, 816,...
277087    [4073, 0, 1911, 35349, 5251, 61774, 14525, 191...
277090    [1055, 0, 303098, 14212, 9225, 35349, 303098, ...
242       [15418, 8072, 111739, 30953, 21420, 2888, 5895...
252       [31112, 111739, 9077, 39441, 14525, 11305, 218...
251       [15418, 31112, 111739, 9077, 218562, 28270, 14...
250       [111739, 9077, 28606, 33012, 32383, 111739, 18...
249       [16078, 32383, 1159, 9077, 6367, 5674, 13380, ...
248       [111739, 8144, 9077, 21441, 3946, 3115, 2150, ...
247       [28270, 27810, 9077, 303098, 1159, 28270, 3026...
246       [32383, 17946, 111739, 9077, 92786, 11721, 501...
245       [30953, 1947, 691, 12936, 3454, 2681, 3173, 30...
244       [31112, 111739, 9077, 14612, 22615, 0, 9077, 2...
Name: countvectorize, Length: 100000, dtype: object
```

In [0]:

```
# Split data into train and test
x_train, x_test, y_train, y_test = train_test_split(clean_data['countvectorize'].values,
                                                    clean_data['Score'],
                                                    test_size=0.3,
                                                    shuffle=False,
                                                    random_state=0)
```

In [23]:

```
print("Total number words present in first review:\n",len(x_train[1]))
print()
print("List of word indexes present in first review:\n", x_train[1])
print()
```

```
Total number words present in first review:
 40

List of word indexes present in first review:
 [776, 3246, 39569, 0, 688, 218562, 1327, 303098, 15418, 0, 617, 69652, 117, 37411, 218562, 31112,
37411, 2237, 31112, 37411, 14611, 4754, 1322, 303098, 5895, 1246, 1989, 303098, 0, 5674, 3386, 68,
218562, 6852, 7883, 3028, 7393, 303098, 253, 4147]
```

In [24]:

```
max_review_length = 500
x_train = sequence.pad_sequences(x_train, maxlen=max_review_length)
x_test = sequence.pad_sequences(x_test, maxlen=max_review_length)

print("Total number words present in first review after padding:\n",len(x_train[1]))
print()
print("List of word indexes present in first review padding:\n", x_train[1])
print()
```

```
Total number words present in first review after padding:
 500

List of word indexes present in first review padding:
 [     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      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      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      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      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
      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      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      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      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
    776   3246  39569      0    688 218562   1327 303098  15418      0
    617  69652    117  37411 218562  31112  37411   2237  31112  37411
  14611   4754   1322 303098   5895   1246   1989 303098      0   5674
   3386     68 218562   6852   7883   3028   7393 303098    253   4147]
```

In [0]:

```python
from keras.layers import BatchNormalization, Dense, Dropout, Flatten, LSTM
from keras.layers.embeddings import Embedding
from keras.regularizers import L1L2
# Batch size
batch_size = 192

# Number of time whole data is trained
epochs = 5

# Embedding vector size
embedding_vecor_length = 32

# Bias regularizer value - we will use elasticnet
reg = L1L2(0.01, 0.01)

# Plot train and cross validation loss
def plot_train_cv_loss(trained_model, epochs, colors=['b']):
    fig, ax = plt.subplots(1,1)
    ax.set_xlabel('epoch')
    ax.set_ylabel('Categorical Crossentropy Loss')
    x_axis_values = list(range(1,6))

    validation_loss = trained_model.history['val_loss']
    train_loss = trained_model.history['loss']

    ax.plot(x_axis_values, validation_loss, 'b', label="Validation Loss")
    ax.plot(x_axis_values, train_loss, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

Model 1 with 1 Lstm layer

In [26]:

```
# Instantiate sequntial model
model = Sequential()

# Add Embedding Layer
model.add(Embedding(vocab_length, embedding_vecor_length, input_length=max_review_length))

# Add batch normalization
model.add(BatchNormalization())

# Add dropout
model.add(Dropout(0.20))

# Add LSTM Layer
model.add(LSTM(100))

# Add dropout
model.add(Dropout(0.20))

# Add Dense Layer
model.add(Dense(1, activation='sigmoid'))

# Summary of the model
print("Model Summary: \n")
model.summary()
print()
print()

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Run the model
trained_model = model.fit(x_train, np.array(y_train), batch_size = batch_size, epochs = epochs, ver
bose=1, validation_data=(x_test, y_test))
```

```
Model Summary:

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 500, 32)           183078368
_________________________________________________________________
batch_normalization_1 (Batch (None, 500, 32)           128
_________________________________________________________________
dropout_1 (Dropout)          (None, 500, 32)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 100)               53200
_________________________________________________________________
dropout_2 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101
=================================================================
Total params: 183,131,797
Trainable params: 183,131,733
Non-trainable params: 64
_________________________________________________________________


Train on 70000 samples, validate on 30000 samples
Epoch 1/5
70000/70000 [==============================] - 1556s 22ms/step - loss: 0.2713 - acc: 0.8913 - val_
loss: 0.2345 - val_acc: 0.8968
Epoch 2/5
70000/70000 [==============================] - 1536s 22ms/step - loss: 0.1969 - acc: 0.9212 - val_
loss: 0.1942 - val_acc: 0.9248
Epoch 3/5
70000/70000 [==============================] - 1540s 22ms/step - loss: 0.1680 - acc: 0.9338 - val_
loss: 0.1822 - val_acc: 0.9287
Epoch 4/5
70000/70000 [==============================] - 1541s 22ms/step - loss: 0.1512 - acc: 0.9410 - val_
loss: 0.1729 - val_acc: 0.9336
Epoch 5/5
70000/70000 [==============================] - 1580s 23ms/step - loss: 0.1370 - acc: 0.9470 - val_
loss: 0.1724 - val_acc: 0.9333
```

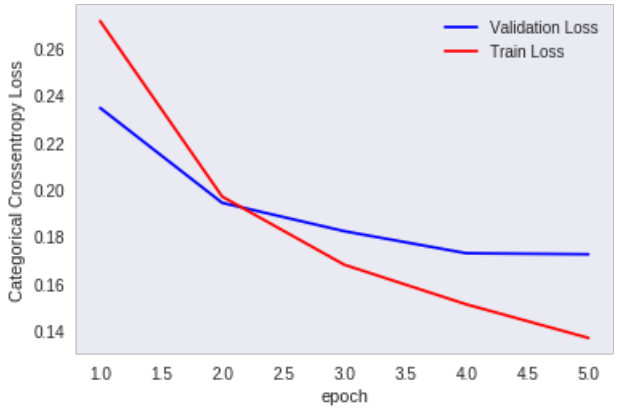
In [27]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test accuracy: {0:.2f}%'.format(score[1]*100))
```

```
Test accuracy: 93.33%
```

In [28]:

```
plot_train_cv_loss(trained_model, epochs)
```



we are getting test accuracy of 93.33 and after 3 epochs model is over fitting

Model 2 with 2 Lstm Layers

In [27]:

```
# Instantiate sequntial model
model = Sequential()

# Add Embedding Layer
model.add(Embedding(vocab_length, embedding_vecor_length, input_length=max_review_length))

# Add batch normalization
model.add(BatchNormalization())

# Add dropout
model.add(Dropout(0.20))

# Add LSTM Layer 1
model.add(LSTM(100,return_sequences=True,bias_regularizer=reg))

# Add dropout
model.add(Dropout(0.20))

# Add LSTM Layer 2
model.add(LSTM(100))

# Add dropout
model.add(Dropout(0.20))




model.add(Dense(1, activation='sigmoid'))
# Summary of the model
print("Model Summary: \n")
model.summary()
print()
print()

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Run the model
trained_model = model.fit(x_train, np.array(y_train), batch_size = batch_size, epochs = epochs, ver
bose=1, validation_data=(x_test, y_test))
```

```
verbose=1, validation_data=(x_test, y_test))
```

Model Summary:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 500, 32)           183078368
_________________________________________________________________
batch_normalization_2 (Batch (None, 500, 32)           128
_________________________________________________________________
dropout_4 (Dropout)          (None, 500, 32)           0
_________________________________________________________________
lstm_3 (LSTM)                (None, 500, 100)          53200
_________________________________________________________________
dropout_5 (Dropout)          (None, 500, 100)          0
_________________________________________________________________
lstm_4 (LSTM)                (None, 100)               80400
_________________________________________________________________
dropout_6 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 101
=================================================================
Total params: 183,212,197
Trainable params: 183,212,133
Non-trainable params: 64
_________________________________________________________________


Train on 70000 samples, validate on 30000 samples
Epoch 1/5
70000/70000 [==============================] - 2799s 40ms/step - loss: 1.7892 - acc: 0.8917 - val_
loss: 1.3410 - val_acc: 0.8957
Epoch 2/5
70000/70000 [==============================] - 2792s 40ms/step - loss: 0.9653 - acc: 0.9208 - val_
loss: 0.6861 - val_acc: 0.9200
Epoch 3/5
70000/70000 [==============================] - 2803s 40ms/step - loss: 0.4603 - acc: 0.9313 - val_
loss: 0.3067 - val_acc: 0.9272
Epoch 4/5
70000/70000 [==============================] - 2776s 40ms/step - loss: 0.1853 - acc: 0.9378 - val_
loss: 0.1831 - val_acc: 0.9296
Epoch 5/5
70000/70000 [==============================] - 2765s 40ms/step - loss: 0.1450 - acc: 0.9434 - val_
loss: 0.1768 - val_acc: 0.9330
```

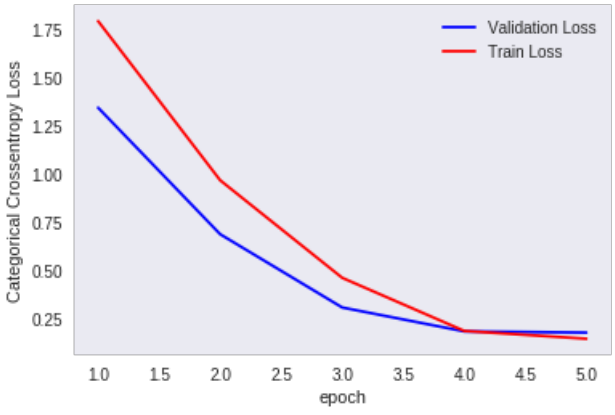
In [28]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test accuracy: {0:.2f}%'.format(score[1]*100))
```

```
Test accuracy: 93.30%
```

In [32]:

```
plot_train_cv_loss(trained_model, epochs)
```



We can see we are getting 93.30 accuracy and after 4 epochs model is not over fitting

In [ ]:

```
Conclusion Table:
```

In [1]:

```
from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["Model", "Train Accuracy", "Test accuracy", "Is Over Fitting"]
x.add_row(["Model1", 94.7, 93.33, 'Yes'])
x.add_row(["Model2", 94.34, 93.30, 'No'])
print(x)
```

```
+--------+----------------+---------------+-----------------+
| Model  | Train Accuracy | Test accuracy | Is Over Fitting |
+--------+----------------+---------------+-----------------+
| Model1 |      94.7      |     93.33     |       Yes       |
| Model2 |     94.34      |      93.3     |        No       |
+--------+----------------+---------------+-----------------+
```

In [ ]:

```

```