proposal

April 7, 2017

1 Capstone Project for Machine Learning Nano Degree

1.1 Overview

Project aims to explore multiple concepts around machine learning methodologies and apply them to classify a financial data set into a tradable or a non tradable node. Once learned, the model can then infer a node or a set of nodes as a possible trade signal or not.

1.1.1 Problem Domain

Use machine learning methedologies like deep learning to generate trade signals. Data given has some characteristics that get fed into the model. The model then outputs a binary state expressing a trade or not.

1.1.2 Project Origin

Traders look at financial data mostly technical analysis data and decide to enter a trade, or not, based on certain characteristics of data. For e.g. they look at moving averages of multiple time frames and make a decision based on which moving average is above or below than the other. The idea here is to not focus on a single characteristics like Open price, 8 day moving average etc… but looking at all the input charactersitics at every node / row and learn the model by adjusting weights to match the provided labels. If output of model is close to the label, model increases weights on the parts of network that caused the closeness and reduces weights on the others.

1.1.3 Data Sets and Input Data

Input data for this project is a series of timeseries nodes with High, Open, Close, Low and Volume as columns for each sample row of input. These sample rows also contain values of these columns when a trade had happenned and when only a quote was published. The reqid tells us whether the row is from a trade or a quote.

There are three files that data is loaded from.

reqids.cvs

reqid,symbol,quotetype
1001,AAPL,BID_ASK
1002,CLZ16,BID_ASK
1003,AAPL,TRADES
1003,CLZ16,TRADES

- Reqids is the id of the request node like 1001 is id for Apple AAPL for all non trade quotes. There are four reqids chosen for this project.
- Symbol is the market symbol of the record. There are two symbols in this dataset.
- APPL : Apple Inc.
- CLZ16: Crude Oil Future for December 2016.
- Quote Type column tells whether sample row is a trade or a simple quote.

header.csv

ReqId, Date, Open, High, Low, Close, Volume, Count, WAP, HasGaps

- ReqId: Determines symbol of record and whether it was a trade or a quote. see reqid section above for details.
- Date: Date and Time of record.
- Open: Open price for the time period of the record for the symbol.
- High: High price for the time period of the record for the symbol.
- Low: Lowest price for the time period of the record for the symbol.
- Close: Close price for the time period of the record for the symbol.
- Volume: Total volume of contracts tradeed.
- Count: Number of quotes. Ignored for this project.
- WAP: weighted average price for the period of the record. Ignored for this project
- HasGaps: Indicator specifying if price jumped in that time period of the record. Ignored for this project.

data.csv

- About 22K+ records for both symbols in the order of the header.

1.2 Problem Statement

Generate a trade signal by classifying a record with a binary signal where true or 1 indicating make a trade and 0 not to trade. Learn the model using dataset of 22K+ records with four major factors, high, low, close and open prices. Project is allowed to create more factors / features if needed. Goal of a project is to evaluate certain models and suggest the optimal model. Suggestion should also report further modifications needed to improve model. Model selection should be based on not only the performance on the given dataset but also on future needs of scaling the model to a larger dataset.

1.3 Metrics

Models are evaluated based on accuracy as the metric. The model that provides the best accuracy consistently over the test data set should be chosen. Considerations of scaling up in terms of data input should also be considered. Cost is a good to have as a factor to chose but is not a mandatory requirement to chose optimal model.

1.4 Strategy

Implement few model of different behavior and evaluate them side by side. Implementation will involve deep learning methods and simple classification models. Strategy will

```
1 begin with simple net with two hidden layers
2 add cnn to 1
3 add rnn to 2
4 run the enire set with SVM
```

Strategy will then compare structure, loss, accuracy and weight distribution for each.

1.5 Data Exploration

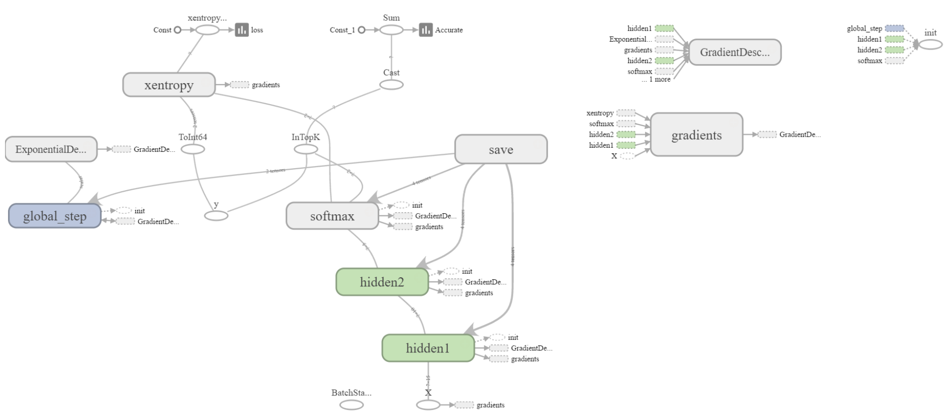
1.5.1 Descriptive Statistics

1.5.2 Characteristics and Anomalies

1.6 Input Space

1.7 Algorithms and Techniques

1.7.1 Simple Net

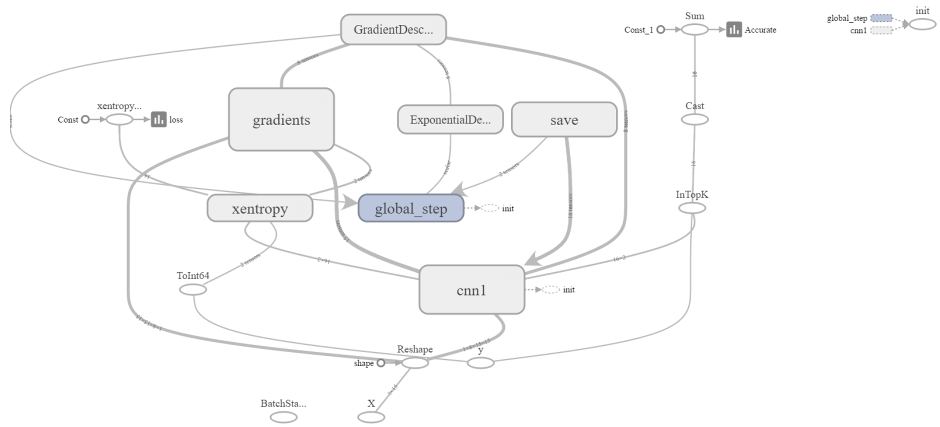


Simple Net with Two Hidden Layers

- This net is a simple neural net with two hidden layers of 10 and 5 neural nodes respectively.
- Input is a 120 * 15 batch that gets fed into a 10 unit layer and then the output of the 10 unit layer gets fed into a 5 unit layer. Finally, output of the 5 unit layer is fed into a softmax layer that outputs two classes, yes or no. Yes (1) meaning it is a trade and no (0) meaning no trade.
- The diagram shows the execution graph followed by this net

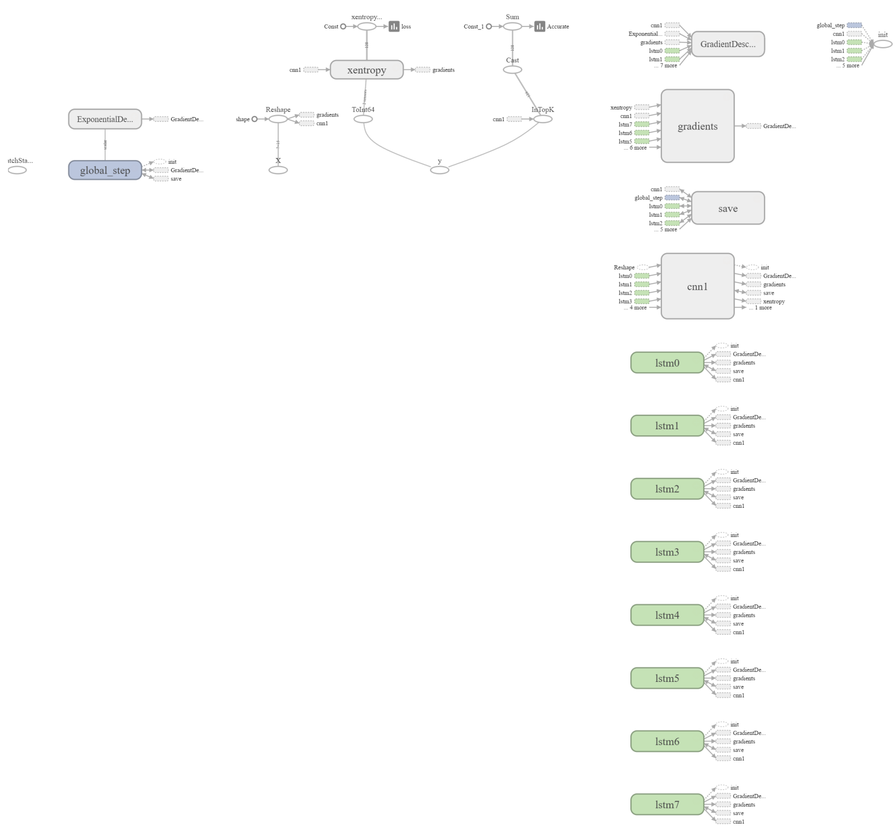
1.7.2 CNN + Dropout

- This net is a convolution net that takes the same input as the simple net and reshapes the input to match 15 @ 8/15 convolution net. There are 15 matrices of 8,15 size.



CNN Net with dropout attached to simple net

- Idea behind this configuration is that we need to look at 8 rows or 15 original features at one time. We do this 15 times.
- We also add a pooling layer with stride 2,2 and filter 2,2 that will reduce the output to 15 @ 4,4
- This output reshaped to 16,15 would then be forwarded to the simple net. ### RNN



- This net is a combination of CNN and RNN net.
- Convolution net as descibed above.
- This output reshaped to 16,15 would then be forwarded to the rnn of shape 16,15 and a time step of 8.
- Output of this rnn is 128,15 (16*8, 15) which is forwarded to the simple net.

1.8 Load Data

There are three files to load headers.csv which indicates column headers. used for dataframe column names reqids.csv which tells symbols and whether it is a trade record or a quote data.csv which is the real data and will need some wrangling

In [1]:
```
import numpy as np
import tensorflow as tf
import pandas as pd
import re
import numpy.core.defchararray as npc
from IPython.display import display
import matplotlib
from matplotlib import pyplot as plt
%matplotlib inline
from tensorflow import summary

DATA_FILE="data.csv"
HEADER_FILE="header.csv"
REQIDS_FILE="reqids.csv"

print("loading header")
header = pd.read_csv(HEADER_FILE)
header.columns = [s.strip() for s in header.columns.values]
h = header.columns.values
print("loading dataset")
raw_data = pd.read_csv(DATA_FILE, names=h, dtype = {'Date': str, 'ReqId': r
       , 'Close' : np.float64, 'High' : np.float64, 'Low' : np.float64, '\
print("loading reqids")
reqids = pd.read_csv(REQIDS_FILE)
```

```
loading header
loading dataset
loading reqids
```

1.9 Preprocess

- Some clean up is required before this data can be used for training.
- Some additional features must be added to this original data set for better learning and avoid overfitting.

- Some original features must be deleted as they are redundant for training.

Cleanup * Rows have a indication record showing end of quote or trade record. These must be cleaned up * Additional features are added

- Short Term Exponential Moving Average: ShortEMA. This is a 5 or 8 period average. We chose 5.
- Long Term Exponential Moving Average: LongEMA. This is a 21 day moving average.
- Bollinger Band: BBAUpper, BBALower. Upper and Lower bands are 2 Standard Deviations away from a 21 Day Exponential Moving Average
- Last Minimum: Last lowest price on a 21 period window
- Last Maximum: Last highest price on a 21 period window
- Remove first 21 rows as the largest additional feature calculated is a 21 period calculation which means first 20 rows will not have valid values for this calculated feature. This will deteriorate training or make it impossible to learn.

In [2]:
```
print(pd.__name__, pd.__version__)
import pandas.core
from pandas.core import window
from pandas.core.window import EWM

def preprocess_raw_data(raw_data, reqids):
    dcol = raw_data['Date']
    dcolf = dcol.str.match("finished-")
    raw_data_wo_finish = raw_data[~dcolf]
    rownum = raw_data_wo_finish.shape[0]
    raw_data_wo_finish['Date'] = pd.DatetimeIndex(pd.to_datetime(raw_data_w
    raw_data_wo_finish['ReqId'] = raw_data_wo_finish['ReqId'].astype(int)
    raw_data_wo_finish['Open'] = raw_data_wo_finish['Open'].astype(float)
    raw_data_wo_finish['High'] = raw_data_wo_finish['High'].astype(float)
    raw_data_wo_finish['Low'] = raw_data_wo_finish['Low'].astype(float)
    raw_data_wo_finish['Close'] = raw_data_wo_finish['Close'].astype(float)
    raw_data_wo_finish = pd.merge(raw_data_wo_finish, reqids, on=['ReqId'])
    raw_data_wo_finish = pd.get_dummies(data = raw_data_wo_finish, columns
    del raw_data_wo_finish['Volume']
    del raw_data_wo_finish['HasGaps']
    del raw_data_wo_finish['WAP']
    del raw_data_wo_finish['Count']
    del raw_data_wo_finish['ReqId']
    ### lets add more features
    ### 5 period moving average MA
    ### 21 period moving average with bollinger bands bb
    ### 21 period min
    ### 21 period max
    ### TODO:
    ### these periods could be parameterized to describe and evaluate model
    raw_data_wo_finish['ShortEMA'] = np.round(raw_data_wo_finish['Close'].e
    raw_data_wo_finish['LongEMA']  = np.round(raw_data_wo_finish['Close'].e
```

```
            raw_data_wo_finish['BBAUpper'] = np.round(2 * raw_data_wo_finish['Close
            raw_data_wo_finish['BBALower'] = np.round(raw_data_wo_finish['Close'] -
            raw_data_wo_finish['LastMin']  = np.round(raw_data_wo_finish['Close'].r
            raw_data_wo_finish['LastMax']  = np.round(raw_data_wo_finish['Close'].r
            ### remove first 20 rows
            raw_data_wo_finish = raw_data_wo_finish.loc[20:,:]
            raw_data_wo_finish = raw_data_wo_finish.reset_index()
            print(raw_data_wo_finish.head())
            return raw_data_wo_finish

        data = preprocess_raw_data(raw_data, reqids)
        data.head()
        print("post process describe")
        display(data.describe())

        print("reqids ...")
        display(reqids)
```

```
pandas 0.19.2


d:\anaconda3\lib\site-packages\ipykernel\__main__.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
d:\anaconda3\lib\site-packages\ipykernel\__main__.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
d:\anaconda3\lib\site-packages\ipykernel\__main__.py:13: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
d:\anaconda3\lib\site-packages\ipykernel\__main__.py:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
d:\anaconda3\lib\site-packages\ipykernel\__main__.py:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
d:\anaconda3\lib\site-packages\ipykernel\__main__.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i


   index                Date   Open   High    Low  Close  QuoteType_BID_ASK  \
0     20 2016-11-03 17:20:00  44.68  44.69  44.67  44.69                  1
1     21 2016-11-03 17:21:00  44.69  44.73  44.68  44.70                  1
2     22 2016-11-03 17:22:00  44.71  44.73  44.71  44.73                  1
3     23 2016-11-03 17:23:00  44.72  44.74  44.71  44.73                  1
4     24 2016-11-03 17:24:00  44.72  44.74  44.71  44.73                  1

   QuoteType_TRADES  Symbol_AAPL  Symbol_CLZ16  ShortEMA  LongEMA  BBAUpper  \
0                 0            0             1    44.689   44.675    44.741
1                 0            0             1    44.693   44.678    44.751
2                 0            0             1    44.705   44.683    44.788
3                 0            0             1    44.713   44.688    44.792
4                 0            0             1    44.719   44.692    44.795

   BBALower  LastMin  LastMax
0    44.639    44.60    44.70
1    44.649    44.60    44.70
2    44.672    44.60    44.73
3    44.668    44.60    44.73
4    44.665    44.63    44.73
post process describe


              index          Open          High           Low         Close  \
count  20476.000000  20476.000000  20476.000000  20476.000000  20476.000000
mean   10257.500000     87.949620     88.088826     87.907819     88.062044
std     5911.056392     30.875283     30.838791     30.891753     30.831320
min       20.000000      1.000000     43.140000      0.010000     43.110000
25%     5138.750000     44.930000     44.960000     44.910000     44.940000
50%    10257.500000    109.300000    109.400000    109.260000    109.400000
75%    15376.250000    110.310000    110.390000    110.270000    110.370000
max    20495.000000    111.950000    130.250000    111.950000    119.000000

       QuoteType_BID_ASK  QuoteType_TRADES   Symbol_AAPL  Symbol_CLZ16  \
count       20476.000000      20476.000000  20476.000000  20476.000000
mean            0.561438          0.438562      0.444716      0.555284
std             0.496223          0.496223      0.496946      0.496946
min             0.000000          0.000000      0.000000      0.000000
25%             0.000000          0.000000      0.000000      0.000000
50%             1.000000          0.000000      0.000000      1.000000
75%             1.000000          1.000000      1.000000      1.000000
max             1.000000          1.000000      1.000000      1.000000
```

```
           ShortEMA       LongEMA      BBAUpper      BBALower       LastMin  \
count  20476.000000  20476.000000  20476.000000  20476.000000  20476.000000
mean      88.055896     88.031303     88.347929     87.776160     87.893586
std       30.829414     30.824813     31.033311     30.780286     30.828215
min       43.184000     43.344000     43.454000     42.663000     43.110000
25%       44.940000     44.940000     45.059000     44.860000     44.880000
50%      109.400000    109.395000    109.637000    109.040500    109.220000
75%      110.355250    110.349000    110.449000    110.164250    110.240000
max      114.009000    113.656000    177.471000    112.997000    114.010000

            LastMax
count  20476.000000
mean      88.174035
std       30.860927
min       43.400000
25%       45.010000
50%      109.500000
75%      110.410000
max      119.000000


reqids ...


   ReqId Symbol QuoteType
0   1001   AAPL   BID_ASK
1   1002  CLZ16   BID_ASK
2   1003   AAPL    TRADES
3   1003  CLZ16    TRADES
```

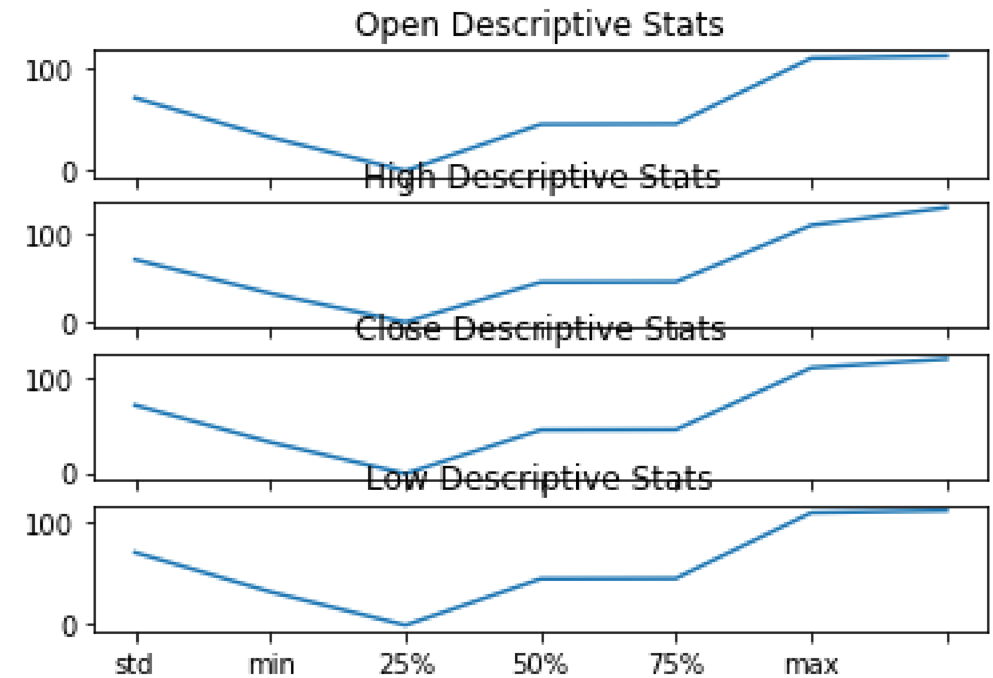
1.10 Raw Data

1.10.1 Describe

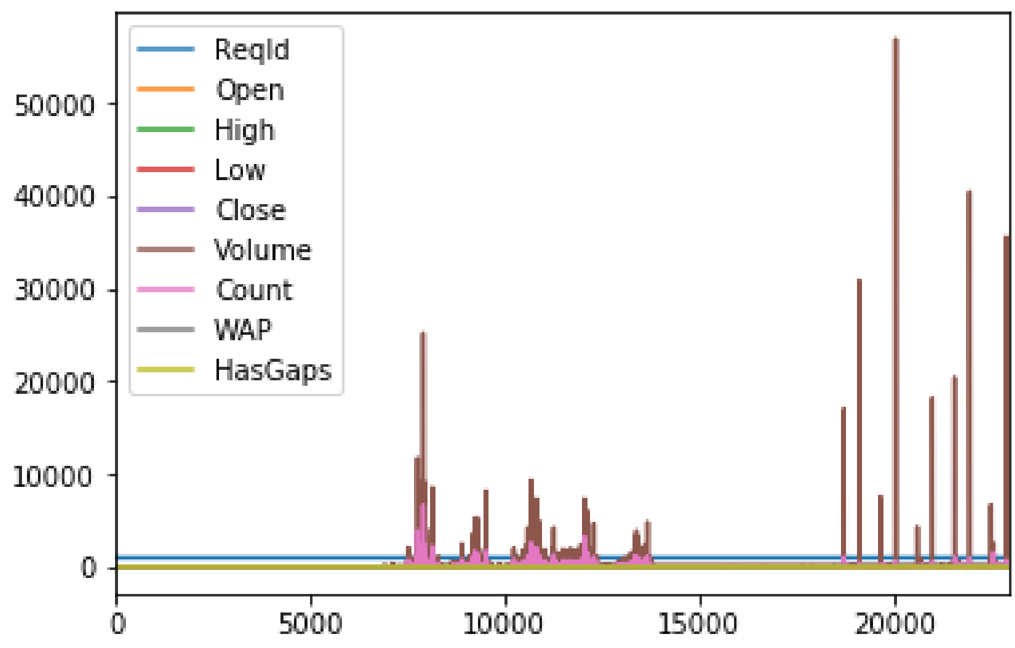
```
In [3]: raw_describe = raw_data.describe()
        display(raw_describe)
        plt.figure(1)
        fig, axs = plt.subplots(4, sharex=True)
        raw_data.plot()

        xcoord = np.arange(7)
        xcoord_labels = ['mean', 'std', 'min', '25%', '50%', '75%', 'max']
        raw_describe_open = raw_data.describe()['Open'][1:,]
        axs[0].plot(xcoord, raw_describe_open[:])
        axs[0].set_title("Open Descriptive Stats")
        axs[0].set_xticklabels(xcoord_labels)

        raw_describe_high = raw_data.describe()['High'][1:,]
```

```
    axs[1].plot(xcoord, raw_describe_high[:])
    axs[1].set_title("High Descriptive Stats")

    raw_describe_close = raw_data.describe()['Close'][1:,]
    axs[2].plot(xcoord, raw_describe_close[:])
    axs[2].set_title("Close Descriptive Stats")

    raw_describe_low = raw_data.describe()['Low'][1:,]
    axs[3].plot(xcoord, raw_describe_low[:])
    axs[3].set_title("Low Descriptive Stats")

    plt.show()
```

```
              ReqId          Open          High           Low         Close  \
count  22910.000000  22910.000000  22910.000000  22910.000000  22910.000000
mean    1002.596945     70.568454     70.694167     70.530062     70.668991
std        1.116314     31.943321     31.969677     31.947299     31.960129
min     1001.000000     -1.000000     -1.000000     -1.000000     -1.000000
25%     1002.000000     44.730000     44.750000     44.710000     44.730000
50%     1002.000000     45.090000     45.110000     45.070000     45.090000
75%     1004.000000    109.770000    109.850000    109.720000    109.820000
max     1004.000000    111.950000    130.250000    111.950000    119.000000

             Volume         Count           WAP  HasGaps
count  22910.000000  22910.000000  22910.000000  22910.0
mean     134.365212     45.905194     34.518787      0.0
std      741.080166    137.766111     42.205519      0.0
min       -1.000000     -1.000000     -1.000000      0.0
25%       -1.000000     -1.000000     -1.000000      0.0
50%       -1.000000     -1.000000     -1.000000      0.0
75%       78.000000     39.000000     45.078000      0.0
max    56940.000000   6667.000000    111.950000      0.0


<matplotlib.figure.Figure at 0x25ba849d0b8>
```



Open Descriptive Stats
High Descriptive Stats
Close Descriptive Stats
Low Descriptive Stats
100
0
std
min
25%
50%
75%
max



ReqId
Open
High
Low
Close
Volume
Count
WAP
HasGaps
50000
40000
30000
20000
10000
0
5000
15000
20000

1.10.2 Analysis

We are dealing with Crude Oil and Apple. Crude oil trading in 40+ prices and Apple in 100+ prices. This is already a wider range than required to learn a model. Automatically, Apple prices will carry more weight as they will effect the learning gradient more than Crude oil.

This is what is shown in the charts above. Notice how high some histogram goes and vary from 0 to 50,000. That is a very biased data to train.

In the descriptive charts above we can see how min of open is lower to 30 and max of open is higher to 100. That is a very spread out data. Spread out data is unsuitable for training. Similar arguments can be made for other columns.

1.11 Pre Processed Data

1.11.1 Describe

```
In [4]: display(data.describe())
        data.plot()
        plt.figure(2)
        fig, axs = plt.subplots(4, sharex=True)

        data_describe_open = data.describe()['Open'][1:,]
        axs[0].plot(xcoord, data_describe_open[:])
        axs[0].set_title("Open Descriptive Stats")
        axs[0].set_xticklabels(xcoord_labels)

        data_describe_high = data.describe()['High'][1:,]
        axs[1].plot(xcoord, data_describe_high[:])
        axs[1].set_title("High Descriptive Stats")

        data_describe_close = data.describe()['Close'][1:,]
        axs[2].plot(xcoord, data_describe_close[:])
        axs[2].set_title("Close Descriptive Stats")

        data_describe_low = data.describe()['Low'][1:,]
        axs[3].plot(xcoord, data_describe_low[:])
        axs[3].set_title("Low Descriptive Stats")

        bbdata = data.loc[:,['Close', 'BBAUpper', 'BBALower', 'ShortEMA', 'LongEMA'
        bbdata = bbdata[-50:]
        bbdata.plot()

        bbdata2 = data.loc[:,['Close', 'BBAUpper', 'BBALower', 'ShortEMA', 'LongEMA
        bbdata2 = bbdata2.loc[0:50,:]
        bbdata2.plot()

        plt.show()
```

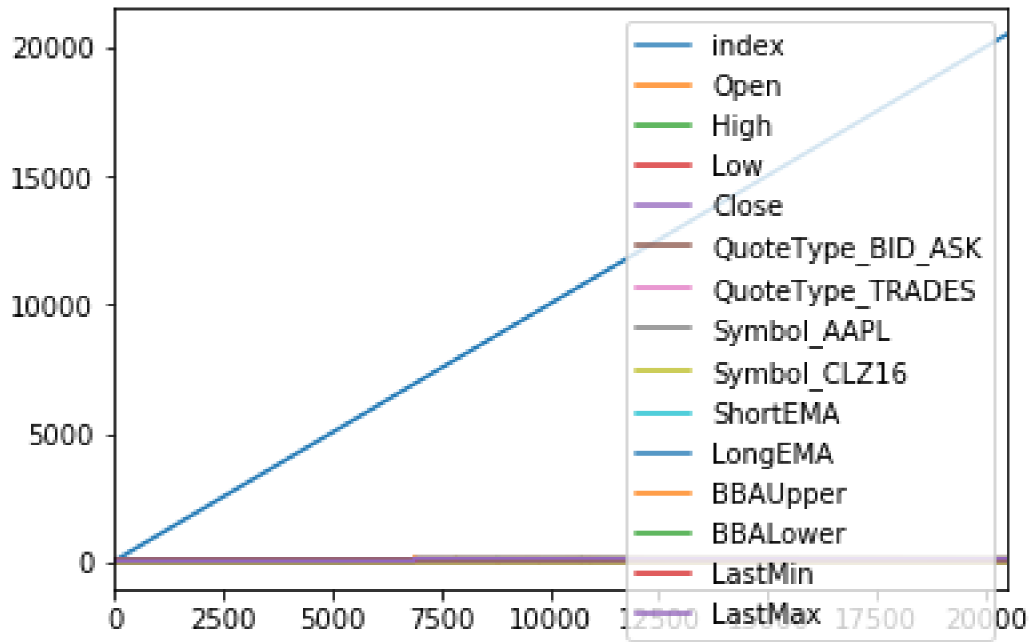
```
              index          Open          High           Low         Close  \
count  20476.000000  20476.000000  20476.000000  20476.000000  20476.000000
```

mean	10257.500000	87.949620	88.088826	87.907819	88.062044
std	5911.056392	30.875283	30.838791	30.891753	30.831320
min	20.000000	1.000000	43.140000	0.010000	43.110000
25%	5138.750000	44.930000	44.960000	44.910000	44.940000
50%	10257.500000	109.300000	109.400000	109.260000	109.400000
75%	15376.250000	110.310000	110.390000	110.270000	110.370000
max	20495.000000	111.950000	130.250000	111.950000	119.000000

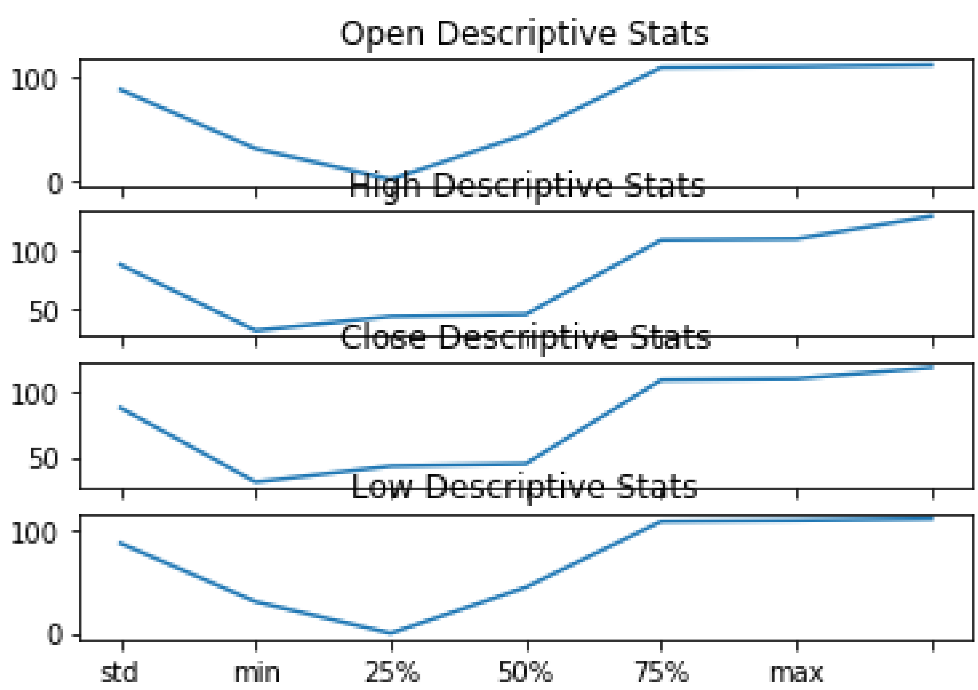
	QuoteType_BID_ASK	QuoteType_TRADES	Symbol_AAPL	Symbol_CLZ16	\
count	20476.000000	20476.000000	20476.000000	20476.000000	
mean	0.561438	0.438562	0.444716	0.555284	
std	0.496223	0.496223	0.496946	0.496946	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	1.000000	
75%	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	

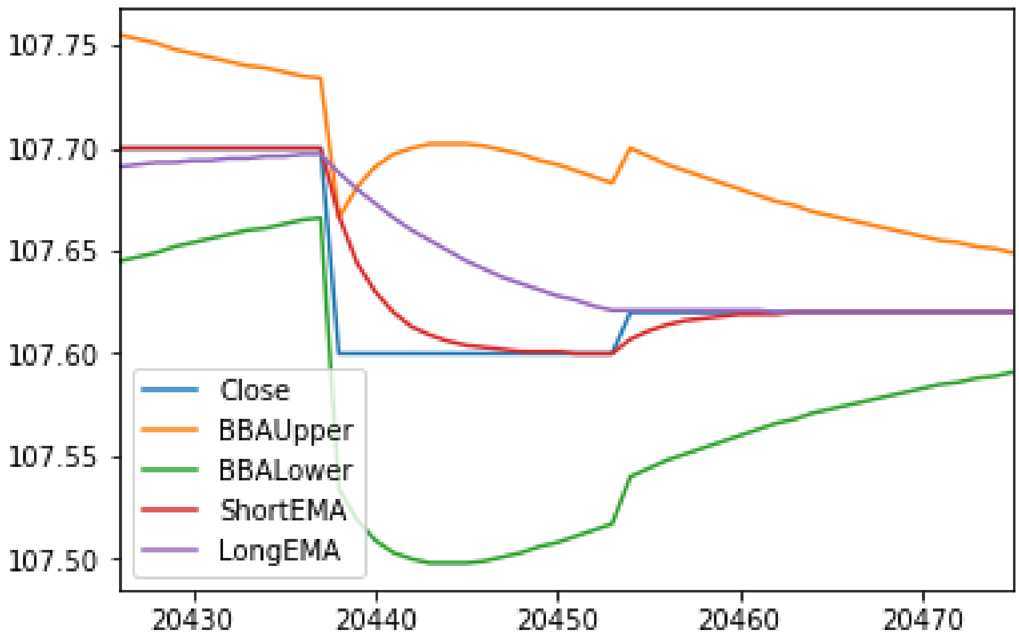
	ShortEMA	LongEMA	BBAUpper	BBALower	LastMin	\
count	20476.000000	20476.000000	20476.000000	20476.000000	20476.000000	
mean	88.055896	88.031303	88.347929	87.776160	87.893586	
std	30.829414	30.824813	31.033311	30.780286	30.828215	
min	43.184000	43.344000	43.454000	42.663000	43.110000	
25%	44.940000	44.940000	45.059000	44.860000	44.880000	
50%	109.400000	109.395000	109.637000	109.040500	109.220000	
75%	110.355250	110.349000	110.449000	110.164250	110.240000	
max	114.009000	113.656000	177.471000	112.997000	114.010000	

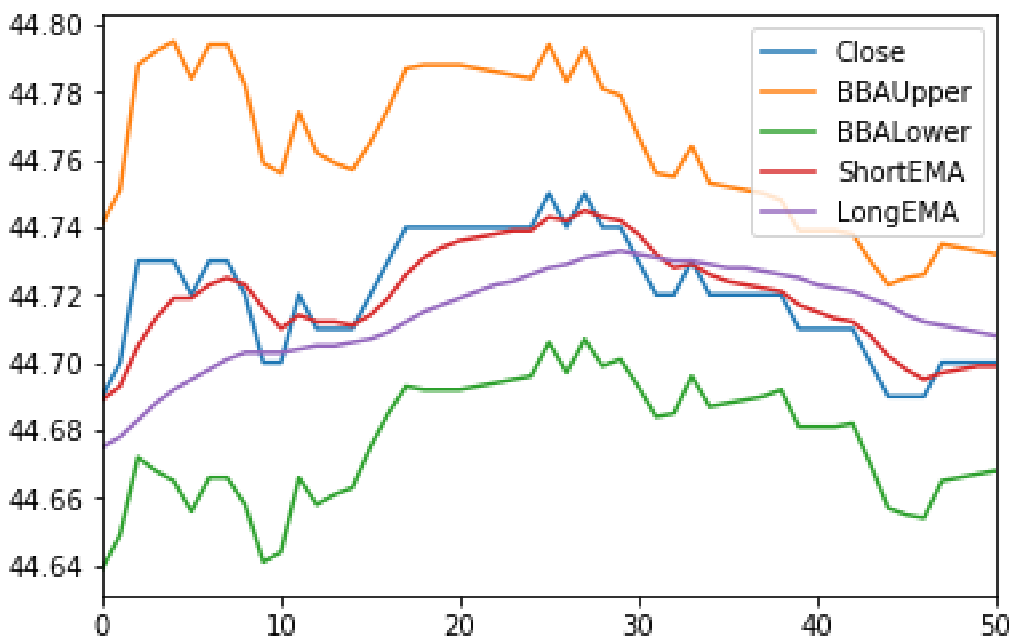
	LastMax
count	20476.000000
mean	88.174035
std	30.860927
min	43.400000
25%	45.010000
50%	109.500000
75%	110.410000
max	119.000000




```
<matplotlib.figure.Figure at 0x25bab3f70b8>
```







1.11.2 Analysis

After adding more features we see that the bias in data still exists. The lower two charts show additional features per symbol. As we can see, data for each symbol is still very variable. This calls for standardizing data.

1.12 Standardize and Filter Outliers

1.12.1 Prepare Training Set

- Generate Labels
- We decide how many periods to look ahead at each node for each symbol.
- Then we calculate the farthest the price of the symbol within the symbol's look ahead period.
- If the price move is more than look ahead range for that symbol, label the record 1

In [5]:
```
from sklearn import preprocessing
training_data = data[:]
del training_data['Date']
### generate labels
HYPER_PERIODS_LOOK_AHEAD = 10
HYPER_RANGE_LOOK_AHEAD_CL = .10
HYPER_RANGE_LOOK_AHEAD_AAPL = .5

def generate_labels(training_data, lookahead, range_cl, range_aapl):
    end = training_data.shape[0]

    #print('end: ', end)
    labels = np.zeros((end, 1))
    for begin in np.arange(end):
        if begin % 5000 == 0:
            print('progress...', begin, ' records')
        #print("begin:", begin)
        close = training_data.iloc[begin, 3]
        #print('close at begin:', close)
        look_ahead_begin = begin + 1
        look_ahead_end = (look_ahead_begin + HYPER_PERIODS_LOOK_AHEAD) % en
        #print('look_ahead_end: ', look_ahead_end)
        look_ahead_data = training_data.loc[look_ahead_begin:look_ahead_enc
        for rownum in range(look_ahead_begin,look_ahead_end):
            #print('rownum: ', rownum)
            row = look_ahead_data.loc[rownum,:]
            #print('got row: ', row)
            max_price = np.max(row)
            #print('maxprice: ', max_price)
            if row['Symbol_CLZ16'] == 1:
                if np.abs(close - max_price) >= HYPER_RANGE_LOOK_AHEAD_CL:
                    #print('range in CL: ', np.abs(close - max_price), ' Cl
                    labels[begin] = 1
                #else:
                #    labels[begin][1] = 1
            elif row['Symbol_AAPL'] == 1:
                if np.abs(close - max_price) >= HYPER_RANGE_LOOK_AHEAD_AAPI
                    #print('range in AAPL: ', np.abs(close - max_price), '
```

```
                    labels[begin] = 1
                #else:
                #    labels[begin][1] = 1


        print('found ', np.sum(labels), 'possible trades')
        with tf.name_scope("labels"):
            summary.scalar("LookAheadPeriod", lookahead)
            summary.scalar("RangeCL", range_cl)
            summary.scalar("RangeAAPL", range_aapl)
            summary.scalar("PotentialTrades", np.sum(labels))
        return labels



    training_labels = generate_labels(training_data, HYPER_PERIODS_LOOK_AHEAD,
                                      HYPER_RANGE_LOOK_AHEAD_AAPL )
    standardized_data = preprocessing.scale(training_data)
    print('data is standardized and ready to train')
```

```
progress... 0  records
progress... 5000  records
progress... 10000  records
progress... 15000  records
progress... 20000  records
found  6507.0 possible trades
data is standardized and ready to train
```

1.13 Split DataSet into Train, CrossValidation and Test

Split 60/20/20 into train, validation and test data set

```
In [6]: ### lets take a peek at our data
        print(standardized_data[-5:])
        total_rows, total_cols = standardized_data.shape[0], standardized_data.shap
        print('TotalRows: ', total_rows, ' TotalCols: ', total_cols)
        print('Training Data Columns: ', training_data.columns.values)
```

```
[[ 1.73128951  0.63710706  0.63334685  0.63812054  0.63436899 -1.13144959
   1.13144959 -0.89491872  0.89491872  0.63460765  0.63550022  0.62215542
   0.64357179  0.63924867  0.63013142]
 [ 1.73145868  0.63710706  0.63334685  0.63812054  0.63436899 -1.13144959
   1.13144959  1.11741992 -1.11741992  0.63460765  0.63550022  0.6221232
   0.64360428  0.63924867  0.63013142]
 [ 1.73162786  0.63710706  0.63334685  0.63812054  0.63436899 -1.13144959
   1.13144959 -0.89491872  0.89491872  0.63460765  0.63550022  0.62205875
   0.64366926  0.63924867  0.63013142]
 [ 1.73179704  0.63710706  0.63334685  0.63812054  0.63436899 -1.13144959
```

```
   1.13144959  1.11741992 -1.11741992  0.63460765  0.63550022  0.62202653
   0.64370175  0.63989744  0.63013142]
 [ 1.73196622  0.63710706  0.63334685  0.63812054  0.63436899 -1.13144959
   1.13144959 -0.89491872  0.89491872  0.63460765  0.63550022  0.62196208
   0.64376673  0.63989744  0.63013142]]
TotalRows:  20476  TotalCols:  15
Training Data Columns:  ['index' 'Open' 'High' 'Low' 'Close' 'QuoteType_BID_ASK' 'Q
 'Symbol_AAPL' 'Symbol_CLZ16' 'ShortEMA' 'LongEMA' 'BBAUpper' 'BBALower'
 'LastMin' 'LastMax']
```

```
In [7]: train_len = int(0.6 * total_rows)
        validate_len = int(0.2 * total_rows)
        test_len = int(0.2 * total_rows)

        std_train_data = standardized_data[0:train_len]
        std_train_label = training_labels[0:train_len, 0]
        print("Train positives: ", np.sum(std_train_label))
        std_validate_data = standardized_data[train_len+1:train_len + 1 + validate_
        std_validate_label = training_labels[train_len+1:train_len + 1 + validate_l
        print("Validate positives: ", np.sum(std_validate_label))
        test_start = train_len + validate_len + 1
        std_test_data = standardized_data[test_start:test_start + test_len]
        std_test_label = training_labels[validate_len+1:validate_len + 1 + test_len
        print("Test positives: ", np.sum(std_test_label))
        print('training len: ', train_len, ', validate len: ', validate_len, ', \
        test len: ', test_len, ', total rows: ', total_rows)
        print('training shape: ', std_train_data.shape, std_train_label.shape)
        print('validation shape: ', std_validate_data.shape, std_validate_label.sha
        print('test shape: ', std_test_data.shape, std_test_label.shape)
```

```
Train positives:  3555.0
Validate positives:  888.0
Test positives:  1556.0
training len:  12285 , validate len:  4095 , test len:  4095 , total rows:  20476
training shape:  (12285, 15) (12285,)
validation shape:  (4095, 15) (4095,)
test shape:  (4095, 15) (4095,)
```

1.14 Prepare for Training

```
In [8]: import math

        np.random.seed(40)

        def build_training_feed(batch_size, dataset, labels):
            data_rows = dataset.shape[0]
```

```
    label_rows = labels.shape[0]
    if dataset.shape[0] < batch_size:
        raise("data ", data_rows, " needs more than batch_size ", batch_siz
    if data_rows != label_rows:
        raise("data and labels must be of same size: ", data_rows, label_ro

    random_index_start = np.random.choice(np.arange(data_rows - batch_size)
    tf.summary.scalar("RandomIndexStart", random_index_start)
    random_index_end = random_index_start + batch_size

    return {X: dataset[random_index_start: random_index_end], y: \
            labels[random_index_start: random_index_end], batch_start_index

HYPER_BATCH_SIZE = 120
HYPER_LEARNING_RATE = 0.1

def build_training_set_placeholders(batch_size, input_features):
    ### input
    X = tf.placeholder(tf.float32, shape=(None, input_features), name = "X'
    y = tf.placeholder(tf.int32, shape=(None), name = "y")
    return X, y

def build_simple_net(X, input_features, num_hidden1, num_hidden2):

    ### hidden1
    with tf.name_scope("hidden1"):
        h1w = tf.Variable(tf.truncated_normal([input_features, num_hidden1]
                          stddev = 1.0 / math.sqrt(float(input_features))),
        h1b = tf.Variable(tf.zeros(num_hidden1), name="biases")
        hidden1 = tf.nn.relu(tf.matmul(X, h1w) + h1b)
        tf.summary.histogram("weights", h1w)
        tf.summary.histogram("biases", h1b)

    with tf.name_scope("hidden2"):
        h2w = tf.Variable(tf.truncated_normal([num_hidden1, num_hidden2],\
                                               stddev = 1.0 / math.sqrt(float
        h2b = tf.Variable(tf.zeros(num_hidden2), name = "biases")
        hidden2 = tf.nn.relu(tf.matmul(hidden1, h2w) + h2b)
        tf.summary.histogram("weights", h2w)
        tf.summary.histogram("biases", h2b)

    with tf.name_scope("softmax"):
        smw = tf.Variable(tf.truncated_normal([num_hidden2, 2], \
                          stddev = 1.0 / math.sqrt(float(num_hidden2))), na
        smb = tf.Variable(tf.zeros(2), name = "biases")
        logits = tf.matmul(hidden2, smw) + smb
        tf.summary.histogram("weights", smw)
        tf.summary.histogram("biases", smb)
```

```
    with tf.name_scope("building"):
        tf.summary.scalar("InputFeatures", input_features)
        tf.summary.scalar("Hidden1",num_hidden1)
        tf.summary.scalar("Hidden2", num_hidden2)

    return logits

def build_loss(logits, labels):
    labels = tf.to_int64(labels)
    cross_entropy = tf.nn.sparse_softmax_cross_entropy_with_logits(logits=l
                , labels = labels, name = "xentropy")
    tf.summary.histogram("xentropy", cross_entropy)
    loss = tf.reduce_mean(cross_entropy, name="xentropy_mean")
    tf.summary.scalar("loss", loss)
    return loss

def build_train(loss, learning_rate):
    optimizer = tf.train.GradientDescentOptimizer(learning_rate)
    tf.summary.scalar("LearningRate", learning_rate)
    train_op = optimizer.minimize(loss, global_step = global_step)
    tf.summary.scalar("GlobalStep", global_step)
    return train_op

def build_eval(logits, labels):
    correct = tf.nn.in_top_k(logits, labels, 1)
    accurate = tf.reduce_sum(tf.cast(correct, tf.int32))
    tf.summary.scalar("Accurate", accurate)
    return accurate
```

1.15 Lets Build Training Cycle

In [10]:
```
import os

with tf.Graph().as_default():
    ## global step
    batch_start_index = tf.placeholder(tf.int32, shape=(1), name="BatchSta
    global_step = tf.Variable(0, name="global_step", trainable=False)
    print("Global Step", global_step)
    learning_rate = tf.train.exponential_decay(HYPER_LEARNING_RATE, global
            HYPER_BATCH_SIZE, 0.95, staircase=True)
    print("Learning Rate", learning_rate)
    tf.summary.scalar("GlobalStep", global_step)
    tf.summary.scalar("LearningRate", learning_rate)

    input_features = std_train_data.shape[1]
    print("input_features %d" % (input_features))
    X, y = build_training_set_placeholders(HYPER_BATCH_SIZE, input_feature
```

```
print("X", X)
print("y", y)


print("validation data ", std_validate_data.shape, " validation label
print("test data ", std_test_data.shape, " test label ", std_test_labe

logits = build_simple_net(X, input_features, 10, 5)
print("logits", logits)
loss = build_loss(logits, y)
print("loss", loss)
trop = build_train(loss, learning_rate)
print("Training Op", trop)
accurate = build_eval(logits, y)
print("Accuracy", accurate)
print("Initializing Global Variables")
init = tf.global_variables_initializer()
print("Creating Saver")
saver = tf.train.Saver()
print("Creating Session")
sess = tf.Session()
print("Creating Summary Writer")
summary_writer = tf.summary.FileWriter("d:\\temp\\simple", sess.graph)
print("Running Init")
sess.run(init)
num_steps = 20000
tf.summary.scalar("NumberOfSteps", num_steps)
summary = tf.summary.merge_all()
for step in np.arange(num_steps):
    feed_dict = build_training_feed(HYPER_BATCH_SIZE, std_train_data,
    op, step_loss = sess.run([trop, loss], feed_dict = feed_dict)
    if step % 100 == 0:
        #print('step %d has loss %f ' % (step, step_loss) )
        summary_str = sess.run(summary, feed_dict = feed_dict)
        summary_writer.add_summary(summary_str, step)
        summary_writer.flush()

    if (step + 1) % 1000 == 0 or (step + 1) == num_steps:
        checkpoint_file = os.path.join("D:\\temp\\simple", 'modelsimpl
        saver.save(sess, checkpoint_file, global_step=step)
        prediction = sess.run(accurate, feed_dict = feed_dict)
        train_accuracy = tf.cast(prediction, tf.float32) / HYPER_BATCH
        valid_feed_dict = build_training_feed(HYPER_BATCH_SIZE, std_va
        valid_prediction = accurate.eval(session = sess, feed_dict = v
        print("Train Prediction %0.2f Validation Prediction %0.2f" %
        valid_accuracy = tf.cast(valid_prediction, tf.float32) / HYPER
        print("Train Accuracy at step %d is %0.2f and Validate accurac
               (step, sess.run(train_accuracy)\
```

```
                        , sess.run(valid_accuracy), sess.run(batch_start_index, fe

            total_test_accuracy = 0
            for test_steps in range(test_len):
                test_feed_dict = build_training_feed(HYPER_BATCH_SIZE, std_test_da
                test_prediction = sess.run(accurate, feed_dict = test_feed_dict)
                test_accuracy = tf.cast(test_prediction, tf.float32) / HYPER_BATCH
                total_test_accuracy += sess.run(test_accuracy)

            print("Test Accuracy %0.2f" % (total_test_accuracy / test_len))
```

```
Global Step Tensor("global_step/read:0", shape=(), dtype=int32)
Learning Rate Tensor("ExponentialDecay:0", shape=(), dtype=float32)
input_features 15
X Tensor("X:0", shape=(?, 15), dtype=float32)
y Tensor("y:0", dtype=int32)
validation data  (4095, 15)  validation label  (4095,)
test data  (4095, 15)  test label  (4095,)
logits Tensor("softmax/add:0", shape=(?, 2), dtype=float32)
loss Tensor("xentropy_mean:0", shape=(), dtype=float32)
Training Op name: "GradientDescent"
op: "AssignAdd"
input: "global_step"
input: "GradientDescent/value"
attr {
  key: "T"
  value {
    type: DT_INT32
  }
}
attr {
  key: "_class"
  value {
    list {
      s: "loc:@global_step"
    }
  }
}
attr {
  key: "use_locking"
  value {
    b: false
  }
}
```

```
Accuracy Tensor("Sum:0", shape=(), dtype=int32)
Initializing Global Variables
Creating Saver
Creating Session
Creating Summary Writer
Running Init
```

```
d:\anaconda3\lib\site-packages\ipykernel\__main__.py:17: VisibleDeprecationWarning:
```

```
Train Prediction 120.00 Validation Prediction 111.00
Train Accuracy at step 999 is 1.00 and Validate accuracy is 0.93 batch start 2784
Train Prediction 89.00 Validation Prediction 110.00
Train Accuracy at step 1999 is 0.74 and Validate accuracy is 0.92 batch start 1910
Train Prediction 112.00 Validation Prediction 33.00
Train Accuracy at step 2999 is 0.93 and Validate accuracy is 0.28 batch start 9107
Train Prediction 104.00 Validation Prediction 100.00
Train Accuracy at step 3999 is 0.87 and Validate accuracy is 0.83 batch start 2020
Train Prediction 59.00 Validation Prediction 90.00
Train Accuracy at step 4999 is 0.49 and Validate accuracy is 0.75 batch start 7982
Train Prediction 120.00 Validation Prediction 109.00
Train Accuracy at step 5999 is 1.00 and Validate accuracy is 0.91 batch start 8890
Train Prediction 64.00 Validation Prediction 111.00
Train Accuracy at step 6999 is 0.53 and Validate accuracy is 0.93 batch start 1086
Train Prediction 119.00 Validation Prediction 109.00
Train Accuracy at step 7999 is 0.99 and Validate accuracy is 0.91 batch start 9424
Train Prediction 86.00 Validation Prediction 111.00
Train Accuracy at step 8999 is 0.72 and Validate accuracy is 0.93 batch start 1159
Train Prediction 120.00 Validation Prediction 97.00
Train Accuracy at step 9999 is 1.00 and Validate accuracy is 0.81 batch start 3041
Train Prediction 94.00 Validation Prediction 100.00
Train Accuracy at step 10999 is 0.78 and Validate accuracy is 0.83 batch start 132
Train Prediction 120.00 Validation Prediction 120.00
Train Accuracy at step 11999 is 1.00 and Validate accuracy is 1.00 batch start 769
Train Prediction 25.00 Validation Prediction 100.00
Train Accuracy at step 12999 is 0.21 and Validate accuracy is 0.83 batch start 119
Train Prediction 91.00 Validation Prediction 38.00
Train Accuracy at step 13999 is 0.76 and Validate accuracy is 0.32 batch start 590
Train Prediction 120.00 Validation Prediction 109.00
Train Accuracy at step 14999 is 1.00 and Validate accuracy is 0.91 batch start 759
Train Prediction 120.00 Validation Prediction 75.00
Train Accuracy at step 15999 is 1.00 and Validate accuracy is 0.62 batch start 898
Train Prediction 87.00 Validation Prediction 115.00
Train Accuracy at step 16999 is 0.73 and Validate accuracy is 0.96 batch start 101
Train Prediction 48.00 Validation Prediction 34.00
Train Accuracy at step 17999 is 0.40 and Validate accuracy is 0.28 batch start 632
Train Prediction 120.00 Validation Prediction 120.00
```

```
Train Accuracy at step 18999 is 1.00 and Validate accuracy is 1.00 batch start 8832
Train Prediction 115.00 Validation Prediction 57.00
Train Accuracy at step 19999 is 0.96 and Validate accuracy is 0.47 batch start 1428
Test Accuracy 0.62
```

1.15.1 Model Results

Train and Validation accuracy converges and Test Accuracy 61%. The model is far from spectacular but is still worth using. Anything that can give you more than 50% consistently is a good model to start with.

Train Accuracy at step 999 is 1.00 and Validate accuracy is 0.93 batch start 2784
Train Accuracy at step 1999 is 0.74 and Validate accuracy is 0.92 batch start 1910
Train Accuracy at step 2999 is 0.93 and Validate accuracy is 0.28 batch start 9107
Train Accuracy at step 3999 is 0.87 and Validate accuracy is 0.83 batch start 2020
Train Accuracy at step 4999 is 0.49 and Validate accuracy is 0.75 batch start 7982
Train Accuracy at step 5999 is 1.00 and Validate accuracy is 0.91 batch start 8890
Train Accuracy at step 6999 is 0.53 and Validate accuracy is 0.93 batch start 10866
Train Accuracy at step 7999 is 0.99 and Validate accuracy is 0.91 batch start 9424
Train Accuracy at step 8999 is 0.72 and Validate accuracy is 0.93 batch start 11598
Train Accuracy at step 9999 is 1.00 and Validate accuracy is 0.81 batch start 3041
Train Accuracy at step 10999 is 0.78 and Validate accuracy is 0.83 batch start 1329
Train Accuracy at step 11999 is 1.00 and Validate accuracy is 1.00 batch start 7698
Train Accuracy at step 12999 is 0.21 and Validate accuracy is 0.83 batch start 11994
Train Accuracy at step 13999 is 0.76 and Validate accuracy is 0.32 batch start 5906
Train Accuracy at step 14999 is 1.00 and Validate accuracy is 0.91 batch start 7591
Train Accuracy at step 15999 is 1.00 and Validate accuracy is 0.62 batch start 8989
Train Accuracy at step 16999 is 0.73 and Validate accuracy is 0.96 batch start 10167
Train Accuracy at step 17999 is 0.40 and Validate accuracy is 0.28 batch start 6325
Train Accuracy at step 18999 is 1.00 and Validate accuracy is 1.00 batch start 8832
Train Accuracy at step 19999 is 0.96 and Validate accuracy is 0.47 batch start 1428
Test Accuracy 0.62

1.15.2 Add CNN + Dropout Re Evaluate

In [9]:
```
from tensorflow.contrib.layers import flatten
import os

def build_cnn_net(CX, input_features, num_hidden1, num_hidden2):

    #### cnn1
    with tf.name_scope("cnn1"):
        #### read one sampple at a time, 8 rows (short term data) and 8 col
        #### map features 15. 15 convolutions of 1*8*8
        print("input to cnn network: ", CX)
        cnnw1 = tf.Variable(tf.truncated_normal(shape=(1, 8, 15, 15),\
                                                stddev = 1.0 / math.sqrt(64.
                                , name = "weights")
```

```
print("cnn1 weights: ", cnnw1)
cnnb1 = tf.Variable(tf.zeros(15))
print("cnn1 biases: ", cnnb1)
conv1 = tf.nn.conv2d(CX, cnnw1, strides=[1,1,1,1], padding='VALID')
print("cnn with stride 1: ", conv1)
conv1 = tf.nn.relu(conv1)
print("cnn after relu: ", conv1)
conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2,
print("conv1 after pool:", conv1)
### 1, 8, 15, 15 will turn into 1, 4, 4, 15 due to 1, 2, 2, 1 pooli
RX = tf.reshape(conv1, shape=[-1,15])
print("RX after flatten: ", RX)
### hidden1
with tf.name_scope("hidden1"):
    h1w = tf.Variable(tf.truncated_normal([input_features, num_hidd
                  stddev = 1.0 / math.sqrt(float(input_features))),
    h1b = tf.Variable(tf.zeros(num_hidden1), name="biases")
    hidden1 = tf.nn.relu(tf.matmul(RX, h1w) + h1b)
    tf.summary.histogram("weights", h1w)
    tf.summary.histogram("biases", h1b)

with tf.name_scope("hidden2"):
    h2w = tf.Variable(tf.truncated_normal([num_hidden1, num_hidden2
                                           stddev = 1.0 / math.sqrt(float
    h2b = tf.Variable(tf.zeros(num_hidden2), name = "biases")
    hidden2 = tf.nn.relu(tf.matmul(hidden1, h2w) + h2b)
    tf.summary.histogram("weights", h2w)
    tf.summary.histogram("biases", h2b)

with tf.name_scope("dropout"):
    hidden2 = tf.nn.dropout(hidden2, 0.75)
    print("hidden2 after dropout: ", hidden2)

with tf.name_scope("softmax"):
    smw = tf.Variable(tf.truncated_normal([num_hidden2, 2], \
                  stddev = 1.0 / math.sqrt(float(num_hidden2))), na
    smb = tf.Variable(tf.zeros(2), name = "biases")
    logits = tf.matmul(hidden2, smw) + smb
    tf.summary.histogram("weights", smw)
    tf.summary.histogram("biases", smb)

with tf.name_scope("building"):
    tf.summary.scalar("InputFeatures", input_features)
    tf.summary.scalar("Hidden1",num_hidden1)
    tf.summary.scalar("Hidden2", num_hidden2)

return logits
```

```python
def build_cnn_feed(batch_size, training_data, training_labels):
    feed_dict = build_training_feed(batch_size, training_data, training_lab
    feed_dict[y] = feed_dict[y][0:16]
    return feed_dict

with tf.Graph().as_default():
    # global step
    batch_start_index = tf.placeholder(tf.int32, shape=(1), name="BatchSta
    global_step = tf.Variable(0, name="global_step", trainable=False)
    print("Global Step", global_step)
    learning_rate = tf.train.exponential_decay(HYPER_LEARNING_RATE, global_
            HYPER_BATCH_SIZE, 0.95, staircase=True)
    print("Learning Rate", learning_rate)
    tf.summary.scalar("GlobalStep", global_step)
    tf.summary.scalar("LearningRate", learning_rate)

    input_features = std_train_data.shape[1]
    print("input_features %d" % (input_features))
    X, y = build_training_set_placeholders(HYPER_BATCH_SIZE, input_features
    print("X", X)
    print("y", y)

    CX = tf.reshape(X, [1, 8, 15, 15])
    print("CX: ", CX)
    print("validation data ", std_validate_data.shape, " validation label "
    print("test data ", std_test_data.shape, " test label ", std_test_label
    logits = build_cnn_net(CX, input_features, 10, 15)
    print("CNN Logits: ", logits)
    loss = build_loss(logits, y)
    print("CNN Loss: ", loss)
    trop = build_train(loss, learning_rate)
    print("CNN Training Op: ", trop)
    accuracy = build_eval(logits, y)
    print("CNN Accuracy: ", accuracy)
    init = tf.global_variables_initializer()
    print("CNN Init: ", init)
    saver = tf.train.Saver()
    print("CNN Saver: ", saver)
    sess = tf.Session()
    print("CNN Session: ", sess)
    sw = tf.summary.FileWriter("d:\\temp\\cnn", sess.graph)
    print("Summary Writer: ", sw)
    sess.run(init)
    print("sesson init run complete")
    num_steps = 20000
    tf.summary.scalar("NumberOfSteps", num_steps)
    summary = tf.summary.merge_all()
    for step in np.arange(num_steps):
```

```
                feed_dict = build_cnn_feed(HYPER_BATCH_SIZE, std_train_data, std_tr
                op, step_loss = sess.run([trop, loss], feed_dict = feed_dict)
                if step % 100 == 0:
                    summary_str = sess.run(summary, feed_dict = feed_dict)
                    sw.add_summary(summary_str, step)
                    sw.flush()
                if (step + 1) % 1000 == 0 or (step + 1) == num_steps:
                    checkpoint_file = os.path.join("D:\\temp\\cnn", "modelcnn.ckpt'
                    saver.save(sess, checkpoint_file, global_step=step)
                    prediction = sess.run(accuracy, feed_dict=feed_dict)
                    train_accuracy = tf.cast(prediction, tf.float32) / 16
                    valid_feed_dict = build_cnn_feed(HYPER_BATCH_SIZE, std_validate
                    valid_prediction = accuracy.eval(session = sess, feed_dict = va
                    print("Train Prediction %0.2f Validation Prediction %0.2f" % (p
                    valid_accuracy = tf.cast(valid_prediction, tf.float32) / 16
                    print("Train Accuracy at step %d is %0.2f and Validate accuracy
                          (step, sess.run(train_accuracy)\
                        , sess.run(valid_accuracy), sess.run(batch_start_index, fee

            total_test_accuracy = 0
            for test_steps in range(test_len):
                test_feed_dict = build_cnn_feed(HYPER_BATCH_SIZE, std_test_data, st
                test_prediction = sess.run(accuracy, feed_dict = test_feed_dict)
                test_accuracy = tf.cast(test_prediction, tf.float32) / 16
                total_test_accuracy += sess.run(test_accuracy)

            print("Test Accuracy %0.2f" % (total_test_accuracy / test_len))
```

```
Global Step Tensor("global_step/read:0", shape=(), dtype=int32)
Learning Rate Tensor("ExponentialDecay:0", shape=(), dtype=float32)
input_features 15
X Tensor("X:0", shape=(?, 15), dtype=float32)
y Tensor("y:0", dtype=int32)
CX:  Tensor("Reshape:0", shape=(1, 8, 15, 15), dtype=float32)
validation data  (4095, 15)  validation label  (4095,)
test data  (4095, 15)  test label  (4095,)
input to cnn network:  Tensor("Reshape:0", shape=(1, 8, 15, 15), dtype=float32)
cnn1 weights:  Tensor("cnn1/weights/read:0", shape=(1, 8, 15, 15), dtype=float32)
cnn1 biases:  Tensor("cnn1/Variable/read:0", shape=(15,), dtype=float32)
cnn with stride 1:  Tensor("cnn1/add:0", shape=(1, 8, 8, 15), dtype=float32)
cnn after relu:  Tensor("cnn1/Relu:0", shape=(1, 8, 8, 15), dtype=float32)
conv1 after pool: Tensor("cnn1/MaxPool:0", shape=(1, 4, 4, 15), dtype=float32)
RX after flatten:  Tensor("cnn1/Reshape:0", shape=(16, 15), dtype=float32)
hidden2 after dropout:  Tensor("cnn1/dropout/dropout/mul:0", shape=(16, 15), dtype=
CNN Logits:  Tensor("cnn1/softmax/add:0", shape=(16, 2), dtype=float32)
CNN Loss:  Tensor("xentropy_mean:0", shape=(), dtype=float32)
CNN Training Op:  name: "GradientDescent"
op: "AssignAdd"
```

```
input: "global_step"
input: "GradientDescent/value"
attr {
  key: "T"
  value {
    type: DT_INT32
  }
}
attr {
  key: "_class"
  value {
    list {
      s: "loc:@global_step"
    }
  }
}
attr {
  key: "use_locking"
  value {
    b: false
  }
}

CNN Accuracy:  Tensor("Sum:0", shape=(), dtype=int32)
CNN Init:  name: "init"
op: "NoOp"
input: "^global_step/Assign"
input: "^cnn1/weights/Assign"
input: "^cnn1/Variable/Assign"
input: "^cnn1/hidden1/weights/Assign"
input: "^cnn1/hidden1/biases/Assign"
input: "^cnn1/hidden2/weights/Assign"
input: "^cnn1/hidden2/biases/Assign"
input: "^cnn1/softmax/weights/Assign"
input: "^cnn1/softmax/biases/Assign"

CNN Saver:  <tensorflow.python.training.saver.Saver object at 0x000002429B896E10>
CNN Session:  <tensorflow.python.client.session.Session object at 0x000002429B92BCE
Summary Writer:  <tensorflow.python.summary.writer.writer.FileWriter object at 0x00
sesson init run complete


d:\anaconda3\lib\site-packages\ipykernel\__main__.py:17: VisibleDeprecationWarning:


Train Prediction 16.00 Validation Prediction 16.00
Train Accuracy at step 999 is 1.00 and Validate accuracy is 1.00 batch start 8353
Train Prediction 16.00 Validation Prediction 16.00
```

```
Train Accuracy at step 1999 is 1.00 and Validate accuracy is 1.00 batch start 9204
Train Prediction 14.00 Validation Prediction 16.00
Train Accuracy at step 2999 is 0.88 and Validate accuracy is 1.00 batch start 6699
Train Prediction 16.00 Validation Prediction 12.00
Train Accuracy at step 3999 is 1.00 and Validate accuracy is 0.75 batch start 7472
Train Prediction 5.00 Validation Prediction 12.00
Train Accuracy at step 4999 is 0.31 and Validate accuracy is 0.75 batch start 1177
Train Prediction 16.00 Validation Prediction 16.00
Train Accuracy at step 5999 is 1.00 and Validate accuracy is 1.00 batch start 239
Train Prediction 7.00 Validation Prediction 16.00
Train Accuracy at step 6999 is 0.44 and Validate accuracy is 1.00 batch start 11697
Train Prediction 9.00 Validation Prediction 16.00
Train Accuracy at step 7999 is 0.56 and Validate accuracy is 1.00 batch start 5949
Train Prediction 16.00 Validation Prediction 7.00
Train Accuracy at step 8999 is 1.00 and Validate accuracy is 0.44 batch start 8407
Train Prediction 16.00 Validation Prediction 16.00
Train Accuracy at step 9999 is 1.00 and Validate accuracy is 1.00 batch start 5600
Train Prediction 14.00 Validation Prediction 0.00
Train Accuracy at step 10999 is 0.88 and Validate accuracy is 0.00 batch start 3374
Train Prediction 4.00 Validation Prediction 16.00
Train Accuracy at step 11999 is 0.25 and Validate accuracy is 1.00 batch start 3844
Train Prediction 0.00 Validation Prediction 1.00
Train Accuracy at step 12999 is 0.00 and Validate accuracy is 0.06 batch start 9756
Train Prediction 16.00 Validation Prediction 16.00
Train Accuracy at step 13999 is 1.00 and Validate accuracy is 1.00 batch start 9569
Train Prediction 6.00 Validation Prediction 12.00
Train Accuracy at step 14999 is 0.38 and Validate accuracy is 0.75 batch start 6864
Train Prediction 16.00 Validation Prediction 16.00
Train Accuracy at step 15999 is 1.00 and Validate accuracy is 1.00 batch start 2862
Train Prediction 1.00 Validation Prediction 14.00
Train Accuracy at step 16999 is 0.06 and Validate accuracy is 0.88 batch start 4326
Train Prediction 16.00 Validation Prediction 16.00
Train Accuracy at step 17999 is 1.00 and Validate accuracy is 1.00 batch start 9267
Train Prediction 16.00 Validation Prediction 16.00
Train Accuracy at step 18999 is 1.00 and Validate accuracy is 1.00 batch start 1039
Train Prediction 16.00 Validation Prediction 10.00
Train Accuracy at step 19999 is 1.00 and Validate accuracy is 0.62 batch start 1025
Test Accuracy 0.60
```

1.15.3 Model Results

Adding CNN and dropouts didn't make an impact on accuracy but it did help converging Training and Validation evaluations. This is also a gain in the whole process as adding CNN and dropouts will reduce training time.

Train Accuracy at step 999 is 1.00 and Validate accuracy is 1.00 batch start 8353
Train Accuracy at step 1999 is 1.00 and Validate accuracy is 1.00 batch start 9204

Train Accuracy at step 2999 is 0.88 and Validate accuracy is 1.00 batch start 6699
Train Accuracy at step 3999 is 1.00 and Validate accuracy is 0.75 batch start 7472
Train Accuracy at step 4999 is 0.31 and Validate accuracy is 0.75 batch start 1177
Train Accuracy at step 5999 is 1.00 and Validate accuracy is 1.00 batch start 239
Train Accuracy at step 6999 is 0.44 and Validate accuracy is 1.00 batch start 11697
Train Accuracy at step 7999 is 0.56 and Validate accuracy is 1.00 batch start 5949
Train Accuracy at step 8999 is 1.00 and Validate accuracy is 0.44 batch start 8407
Train Accuracy at step 9999 is 1.00 and Validate accuracy is 1.00 batch start 5600
Train Accuracy at step 10999 is 0.88 and Validate accuracy is 0.00 batch start 3374
Train Accuracy at step 11999 is 0.25 and Validate accuracy is 1.00 batch start 3844
Train Accuracy at step 12999 is 0.00 and Validate accuracy is 0.06 batch start 9756
Train Accuracy at step 13999 is 1.00 and Validate accuracy is 1.00 batch start 9569
Train Accuracy at step 14999 is 0.38 and Validate accuracy is 0.75 batch start 6864
Train Accuracy at step 15999 is 1.00 and Validate accuracy is 1.00 batch start 2862
Train Accuracy at step 16999 is 0.06 and Validate accuracy is 0.88 batch start 4326
Train Accuracy at step 17999 is 1.00 and Validate accuracy is 1.00 batch start 9267
Train Accuracy at step 18999 is 1.00 and Validate accuracy is 1.00 batch start 10390
Train Accuracy at step 19999 is 1.00 and Validate accuracy is 0.62 batch start 10258
Test Accuracy 0.60 ## Now Lets Add RNN and Reevaluate

```
In [9]: print(tf.__version__)
        from tensorflow.contrib.layers import flatten
        import os
        import math

        def build_rnn_net(CX, input_features, num_hidden1, num_hidden2):

            #### cnn1
            with tf.name_scope("cnn1"):
                #### read one sampple at a time, 8 rows (short term data) and 8 co
                #### map features 15. 15 convolutions of 1*8*8
                print("input to cnn network: ", CX)
                cnnw1 = tf.Variable(tf.truncated_normal(shape=(1, 8, 15, 15),\
                                                        stddev = 1.0 / math.sqrt(64.
                                    , name = "weights")
                print("cnn1 weights: ", cnnw1)
                cnnb1 = tf.Variable(tf.zeros(15))
                print("cnn1 biases: ", cnnb1)
                conv1 = tf.nn.conv2d(CX, cnnw1, strides=[1,1,1,1], padding='VALID')
                print("cnn with stride 1: ", conv1)
                conv1 = tf.nn.relu(conv1)
                print("cnn after relu: ", conv1)
                conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2,
                print("conv1 after pool:", conv1)
                ### 1, 8, 15, 15 will turn into 1, 4, 4, 15 due to 1, 2, 2, 1 pooli

                RNX = tf.reshape(conv1, shape=[16, 15])
                rnxshape = RNX.get_shape().as_list()
```

```
print("RNX for RNN: ", RNX, " with shape: ", rnxshape)
cell = tf.nn.rnn_cell.BasicLSTMCell(rnxshape[1], forget_bias=1.0, s
print("LSTM Cell: ", cell)
print("LSTM State Size: ", cell.state_size)
print("LSTM Output Size: ", cell.output_size)
### gather all outputs from rnn steps and create a layer

outputs = []
initial_state = cell.zero_state(16, tf.float32)
print("LSTM Initial State: ", initial_state)
state = initial_state
for step in np.arange(8):
    with tf.variable_scope("lstm" + str(step)):
        (cell_output, state) = cell(RNX, state)
        print("Cell Output: ", cell_output, ", state: ", state)
        outputs.append(cell_output)

output = tf.reshape(tf.concat(values=outputs, concat_dim=1), shape=
print("Output after collecting all step outputs from LSTM: ", outpu
### hidden1
with tf.name_scope("hidden1"):
    h1w = tf.Variable(tf.truncated_normal([input_features, num_hidd
                  stddev = 1.0 / math.sqrt(float(input_features))),
    h1b = tf.Variable(tf.zeros(num_hidden1), name="biases")
    hidden1 = tf.nn.relu(tf.matmul(output, h1w) + h1b)
    tf.summary.histogram("weights", h1w)
    tf.summary.histogram("biases", h1b)

with tf.name_scope("hidden2"):
    h2w = tf.Variable(tf.truncated_normal([num_hidden1, num_hidden2
                                    stddev = 1.0 / math.sqrt(float
    h2b = tf.Variable(tf.zeros(num_hidden2), name = "biases")
    hidden2 = tf.nn.relu(tf.matmul(hidden1, h2w) + h2b)
    tf.summary.histogram("weights", h2w)
    tf.summary.histogram("biases", h2b)

with tf.name_scope("dropout"):
    hidden2 = tf.nn.dropout(hidden2, 0.75)
    print("hidden2 after dropout: ", hidden2)

with tf.name_scope("softmax"):
    smw = tf.Variable(tf.truncated_normal([num_hidden2, 2], \
                  stddev = 1.0 / math.sqrt(float(num_hidden2))), na
    smb = tf.Variable(tf.zeros(2), name = "biases")
    logits = tf.matmul(hidden2, smw) + smb
    tf.summary.histogram("weights", smw)
    tf.summary.histogram("biases", smb)
```

```
            with tf.name_scope("building"):
                tf.summary.scalar("InputFeatures", input_features)
                tf.summary.scalar("Hidden1",num_hidden1)
                tf.summary.scalar("Hidden2", num_hidden2)

            return logits

    def build_rnn_feed(batch_size, training_data, training_labels, labels_size)
        #print("batch_size: ", batch_size, " , labels_size: ", labels_size)
        data_rows = training_data.shape[0]
        label_rows = training_labels.shape[0]

        if data_rows < batch_size:
            raise("data ", data_rows, " needs more than batch_size ", batch_siz
        if label_rows < labels_size:
            raise("lables ", label_rows, " needs more than labels_size ", label

        cap_size = np.max([batch_size, labels_size])

        random_index_start = np.random.choice(np.arange(data_rows - cap_size),
        tf.summary.scalar("RandomIndexStart", random_index_start)
        random_index_end = random_index_start + batch_size

        random_index_validate_end = random_index_start + labels_size

        return {X: training_data[random_index_start: random_index_end], y: \
                training_labels[random_index_start: random_index_validate_end],
```

```
0.12.0-rc1
```

```
In [11]: with tf.Graph().as_default():
             # global step
             batch_start_index = tf.placeholder(tf.int32, shape=(1), name="BatchSta
             global_step = tf.Variable(0, name="global_step", trainable=False)
             print("Global Step", global_step)
             learning_rate = tf.train.exponential_decay(HYPER_LEARNING_RATE, global
                     HYPER_BATCH_SIZE, 0.95, staircase=True)
             print("Learning Rate", learning_rate)
             tf.summary.scalar("GlobalStep", global_step)
             tf.summary.scalar("LearningRate", learning_rate)

             input_features = std_train_data.shape[1]
             print("input_features %d" % (input_features))
             X, y = build_training_set_placeholders(HYPER_BATCH_SIZE, input_feature
             print("X", X)
             print("y", y)
```

```
CX = tf.reshape(X, [1, 8, 15, 15])
print("CX: ", CX)
print("validation data ", std_validate_data.shape, " validation label
print("test data ", std_test_data.shape, " test label ", std_test_labe
logits = build_rnn_net(CX, input_features, 10, 15)
print("RNN Logits: ", logits)
loss = build_loss(logits, y)
print("RNN Loss: ", loss)
trop = build_train(loss, learning_rate)
print("RNN Training Op: ", trop)
accuracy = build_eval(logits, y)
print("RNN Accuracy: ", accuracy)
init = tf.global_variables_initializer()
print("RNN Init: ", init)
saver = tf.train.Saver()
print("RNN Saver: ", saver)
sess = tf.Session()
print("RNN Session: ", sess)
sw = tf.summary.FileWriter("d:\\temp\\rnn", sess.graph)
print("Summary Writer: ", sw)
sess.run(init)
print("sesson init run complete")
num_steps = 20000
tf.summary.scalar("NumberOfSteps", num_steps)
summary = tf.summary.merge_all()
for step in np.arange(num_steps):
    feed_dict = build_rnn_feed(HYPER_BATCH_SIZE, std_train_data, std_t
    op, step_loss = sess.run([trop, loss], feed_dict = feed_dict)
    if step % 100 == 0:
        summary_str = sess.run(summary, feed_dict = feed_dict)
        sw.add_summary(summary_str, step)
        sw.flush()
    if (step + 1) % 1000 == 0 or (step + 1) == num_steps:
        checkpoint_file = os.path.join("D:\\temp\\rnn", "modelrnn.ckpt
        saver.save(sess, checkpoint_file, global_step=step)
        prediction = sess.run(accuracy, feed_dict=feed_dict)
        train_accuracy = tf.cast(prediction, tf.float32) / 128
        valid_feed_dict = build_rnn_feed(HYPER_BATCH_SIZE, std_validat
        valid_prediction = accuracy.eval(session = sess, feed_dict = v
        print("Train Prediction %0.2f Validation Prediction %0.2f" % (
        valid_accuracy = tf.cast(valid_prediction, tf.float32) / 128
        print("Train Accuracy at step %d is %0.2f and Validate accurac
              (step, sess.run(train_accuracy)\
            , sess.run(valid_accuracy), sess.run(batch_start_index, fe

total_test_accuracy = 0
for test_steps in range(test_len):
    test_feed_dict = build_rnn_feed(HYPER_BATCH_SIZE, std_test_data, s
```

```
                test_prediction = sess.run(accuracy, feed_dict = test_feed_dict)
                test_accuracy = tf.cast(test_prediction, tf.float32) / 128
                total_test_accuracy += sess.run(test_accuracy)

            print("Test Accuracy %0.2f" % (total_test_accuracy / test_len))
```

```
0.12.0-rc1
Global Step Tensor("global_step/read:0", shape=(), dtype=int32)
Learning Rate Tensor("ExponentialDecay:0", shape=(), dtype=float32)
input_features 15
X Tensor("X:0", shape=(?, 15), dtype=float32)
y Tensor("y:0", dtype=int32)
CX:  Tensor("Reshape:0", shape=(1, 8, 15, 15), dtype=float32)
validation data  (4095, 15)  validation label  (4095,)
test data  (4095, 15)  test label  (4095,)
input to cnn network:  Tensor("Reshape:0", shape=(1, 8, 15, 15), dtype=float32)
cnn1 weights:  Tensor("cnn1/weights/read:0", shape=(1, 8, 15, 15), dtype=float32)
cnn1 biases:  Tensor("cnn1/Variable/read:0", shape=(15,), dtype=float32)
cnn with stride 1:  Tensor("cnn1/add:0", shape=(1, 8, 8, 15), dtype=float32)
cnn after relu:  Tensor("cnn1/Relu:0", shape=(1, 8, 8, 15), dtype=float32)
conv1 after pool: Tensor("cnn1/MaxPool:0", shape=(1, 4, 4, 15), dtype=float32)
RNX for RNN:  Tensor("cnn1/Reshape:0", shape=(16, 15), dtype=float32)  with shape:
LSTM Cell:  <tensorflow.python.ops.rnn_cell.BasicLSTMCell object at 0x0000024289172
LSTM State Size:  LSTMStateTuple(c=15, h=15)
LSTM Output Size:  15
LSTM Initial State:  LSTMStateTuple(c=<tf.Tensor 'cnn1/zeros_1:0' shape=(16, 15) dt
Cell Output:  Tensor("cnn1/lstm0/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm1/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm2/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm3/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm4/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm5/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm6/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm7/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Output after collecting all step outputs from LSTM:  Tensor("cnn1/Reshape_1:0", sha
hidden2 after dropout:  Tensor("cnn1/dropout/dropout/mul:0", shape=(128, 15), dtype
RNN Logits:  Tensor("cnn1/softmax/add:0", shape=(128, 2), dtype=float32)
RNN Loss:  Tensor("xentropy_mean:0", shape=(), dtype=float32)
RNN Training Op:  name: "GradientDescent"
op: "AssignAdd"
input: "global_step"
input: "GradientDescent/value"
attr {
  key: "T"
  value {
    type: DT_INT32
  }
}
```

```
attr {
  key: "_class"
  value {
    list {
      s: "loc:@global_step"
    }
  }
}
attr {
  key: "use_locking"
  value {
    b: false
  }
}

RNN Accuracy:  Tensor("Sum:0", shape=(), dtype=int32)
RNN Init:  name: "init"
op: "NoOp"
input: "^global_step/Assign"
input: "^cnn1/weights/Assign"
input: "^cnn1/Variable/Assign"
input: "^lstm0/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm0/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm1/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm1/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm2/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm2/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm3/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm3/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm4/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm4/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm5/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm5/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm6/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm6/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm7/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm7/BasicLSTMCell/Linear/Bias/Assign"
input: "^cnn1/hidden1/weights/Assign"
input: "^cnn1/hidden1/biases/Assign"
input: "^cnn1/hidden2/weights/Assign"
input: "^cnn1/hidden2/biases/Assign"
input: "^cnn1/softmax/weights/Assign"
input: "^cnn1/softmax/biases/Assign"

RNN Saver:  <tensorflow.python.training.saver.Saver object at 0x0000024289D12E80>
RNN Session:  <tensorflow.python.client.session.Session object at 0x0000024289163AC
Summary Writer:  <tensorflow.python.summary.writer.writer.FileWriter object at 0x00
sesson init run complete
```

```
d:\anaconda3\lib\site-packages\ipykernel\__main__.py:98: VisibleDeprecationWarning:


Train Prediction 82.00 Validation Prediction 91.00
Train Accuracy at step 999 is 0.64 and Validate accuracy is 0.71 batch start 6227
Train Prediction 126.00 Validation Prediction 128.00
Train Accuracy at step 1999 is 0.98 and Validate accuracy is 1.00 batch start 1410
Train Prediction 38.00 Validation Prediction 108.00
Train Accuracy at step 2999 is 0.30 and Validate accuracy is 0.84 batch start 9663
Train Prediction 101.00 Validation Prediction 97.00
Train Accuracy at step 3999 is 0.79 and Validate accuracy is 0.76 batch start 7141
Train Prediction 122.00 Validation Prediction 105.00
Train Accuracy at step 4999 is 0.95 and Validate accuracy is 0.82 batch start 3336
Train Prediction 106.00 Validation Prediction 128.00
Train Accuracy at step 5999 is 0.83 and Validate accuracy is 1.00 batch start 2022
Train Prediction 120.00 Validation Prediction 36.00
Train Accuracy at step 6999 is 0.94 and Validate accuracy is 0.28 batch start 10468
Train Prediction 128.00 Validation Prediction 93.00
Train Accuracy at step 7999 is 1.00 and Validate accuracy is 0.73 batch start 8478
Train Prediction 42.00 Validation Prediction 119.00
Train Accuracy at step 8999 is 0.33 and Validate accuracy is 0.93 batch start 11977
Train Prediction 45.00 Validation Prediction 74.00
Train Accuracy at step 9999 is 0.35 and Validate accuracy is 0.58 batch start 9936
Train Prediction 97.00 Validation Prediction 112.00
Train Accuracy at step 10999 is 0.76 and Validate accuracy is 0.88 batch start 1163
Train Prediction 42.00 Validation Prediction 59.00
Train Accuracy at step 11999 is 0.33 and Validate accuracy is 0.46 batch start 4707
Train Prediction 88.00 Validation Prediction 63.00
Train Accuracy at step 12999 is 0.69 and Validate accuracy is 0.49 batch start 1066
Train Prediction 58.00 Validation Prediction 67.00
Train Accuracy at step 13999 is 0.45 and Validate accuracy is 0.52 batch start 1195
Train Prediction 52.00 Validation Prediction 36.00
Train Accuracy at step 14999 is 0.41 and Validate accuracy is 0.28 batch start 1002
Train Prediction 100.00 Validation Prediction 50.00
Train Accuracy at step 15999 is 0.78 and Validate accuracy is 0.39 batch start 6953
Train Prediction 128.00 Validation Prediction 46.00
Train Accuracy at step 16999 is 1.00 and Validate accuracy is 0.36 batch start 8839
Train Prediction 97.00 Validation Prediction 43.00
Train Accuracy at step 17999 is 0.76 and Validate accuracy is 0.34 batch start 2422
Train Prediction 32.00 Validation Prediction 36.00
Train Accuracy at step 18999 is 0.25 and Validate accuracy is 0.28 batch start 9684
Train Prediction 64.00 Validation Prediction 128.00
Train Accuracy at step 19999 is 0.50 and Validate accuracy is 1.00 batch start 6128
Test Accuracy 0.62
```

1.15.4 Model Results

Adding RNN also could not increase accuracy of model.

Train Accuracy at step 999 is 0.64 and Validate accuracy is 0.71 batch start 6227
Train Accuracy at step 1999 is 0.98 and Validate accuracy is 1.00 batch start 1410
Train Accuracy at step 2999 is 0.30 and Validate accuracy is 0.84 batch start 9663
Train Accuracy at step 3999 is 0.79 and Validate accuracy is 0.76 batch start 7141
Train Accuracy at step 4999 is 0.95 and Validate accuracy is 0.82 batch start 3336
Train Accuracy at step 5999 is 0.83 and Validate accuracy is 1.00 batch start 2022
Train Accuracy at step 6999 is 0.94 and Validate accuracy is 0.28 batch start 10468
Train Accuracy at step 7999 is 1.00 and Validate accuracy is 0.73 batch start 8478
Train Accuracy at step 8999 is 0.33 and Validate accuracy is 0.93 batch start 11977
Train Accuracy at step 9999 is 0.35 and Validate accuracy is 0.58 batch start 9936
Train Accuracy at step 10999 is 0.76 and Validate accuracy is 0.88 batch start 1163
Train Accuracy at step 11999 is 0.33 and Validate accuracy is 0.46 batch start 4707
Train Accuracy at step 12999 is 0.69 and Validate accuracy is 0.49 batch start 10668
Train Accuracy at step 13999 is 0.45 and Validate accuracy is 0.52 batch start 11956
Train Accuracy at step 14999 is 0.41 and Validate accuracy is 0.28 batch start 10026
Train Accuracy at step 15999 is 0.78 and Validate accuracy is 0.39 batch start 6953
Train Accuracy at step 16999 is 1.00 and Validate accuracy is 0.36 batch start 8839
Train Accuracy at step 17999 is 0.76 and Validate accuracy is 0.34 batch start 2422
Train Accuracy at step 18999 is 0.25 and Validate accuracy is 0.28 batch start 9684
Train Accuracy at step 19999 is 0.50 and Validate accuracy is 1.00 batch start 6128
Test Accuracy 0.62

1.16 Run a simple SVM

```
In [10]: import sklearn
         from sklearn.svm import SVC
         model = SVC()
         model.fit(std_train_data, std_train_label)
         s = model.score(std_test_data, std_test_label)
         print("accuracy score : " , s)
```

```
accuracy score :  0.620024420024
```

1.16.1 Model Results

accuracy score : 0.620024420024

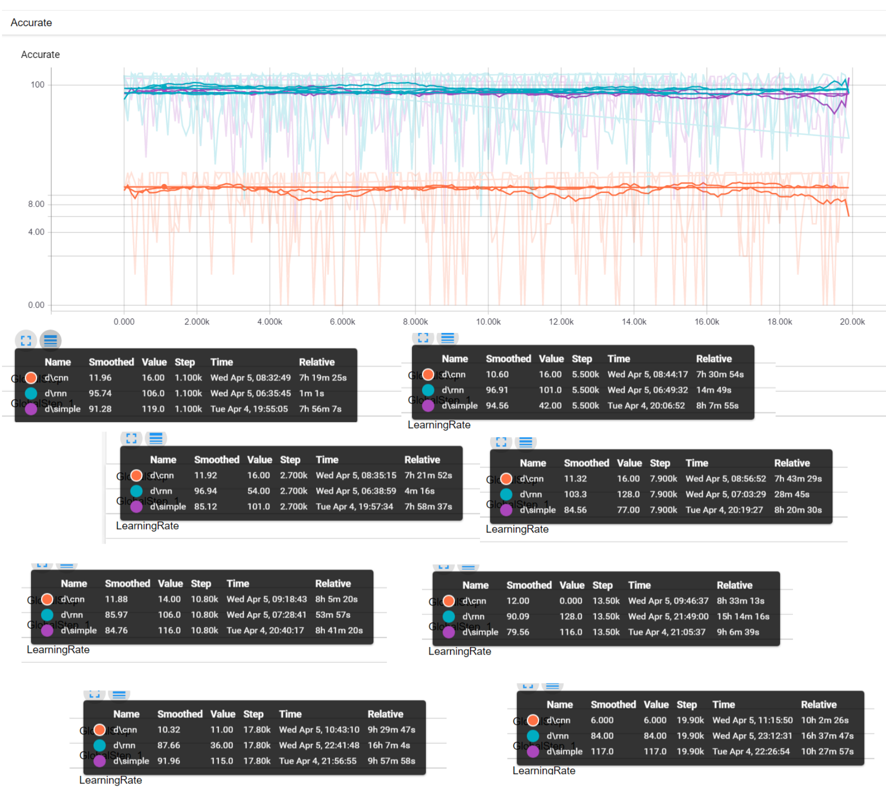
we are running the same accuracy as deep learning. At this level of data set complexity, deep learning isn't adding any benefit to accuracy.

1.17 Side By Side Comparison

1.17.1 Acuracy

comparison	simple	cnn	rnn	remarks
speed of training	moderate	quick	quick	rnn gets to consistent training accuracy really quick
consistency	moderate	highest	high	cnn gives consistent acccuracy from very early cycles of training
time to train	high	high	moderate	rnn takes the lowest time to train and comes to max accuracy the fastest

comparison	simple	cnn	rnn	remarks
cost of training	moderate	low	high	rnn is repetitive and takes a lot of calculations to calculate loss gradients

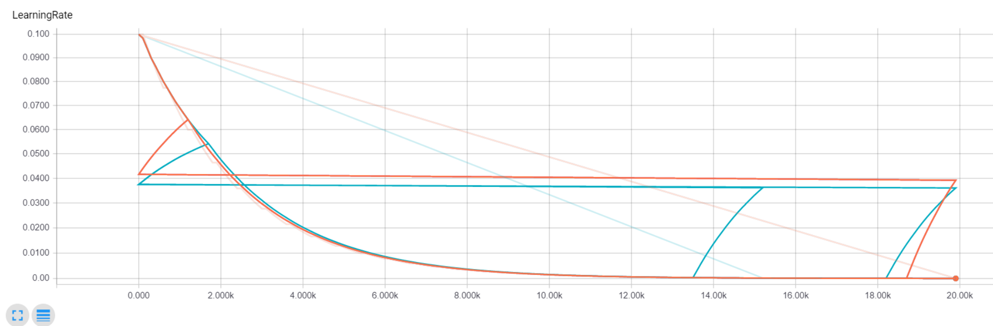


accuracy comparison

Conclusion

In terms of *accuracy*, simple and rnn are the best suited models. They both give high accuracies and come with pros and cons. Rnn runs into high accuracy early on training.

1.17.2 Learning Rate

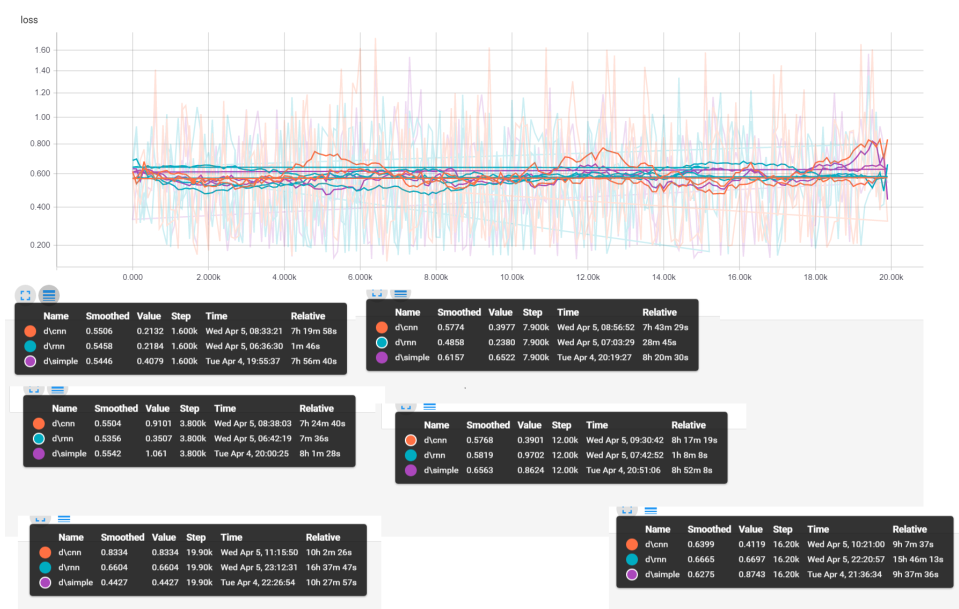


learning rate

Conclusion

Learning rate stabilizes around 8K training cycle in all three models. Simple and RNN are consistent with values where as CNN stabilizes this rate early on around 2K cycle.

1.17.3 Loss



loss

Conclusion

RNN stabilizes early and shows lowest losses. Simple shows lower losses during training than RNN but is more volatile. CNN jumps with average higher losses and gets worse in later runs. Best runs occurs around 8K where learning rate stabilizes as well.

1.17.4 Distributions

cnn distributions

CNN Distribution on CNN and RNN runs   Conclusion
See how RNN weights and Biases on the CNN layer changes and converges better than CNN only runs. This tells us that RNN is learning better than CNN. *possibly too little data for CNN to adjust weights and biases*

- Notice that weights start from a normal distribution and shows less signs of vanishing gradient as these weights are evenly spread out.

Hidden Distribution on Simple runs   Conclusion
weights and biases converges quickly and remain the same after wards.

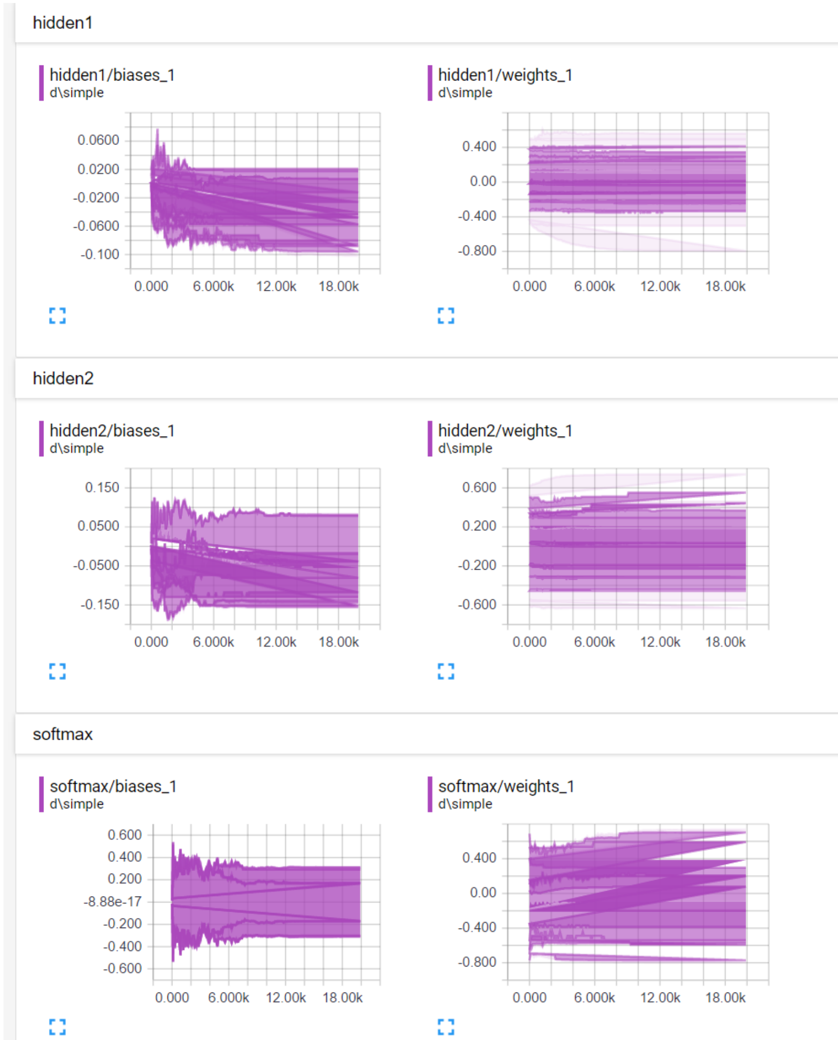
- Notice that weights start from a normal distribution and shows less signs of vanishing gradient as these weights are evenly spread out.

Xentropy Distribution   Conclusion
Notice how cnn has the lowest average of entropy but is highly volatile. Next lowest is Simple but also fluctuates. Rnn carries entropy towards a higher average and fluctuates less than others. This means RNN learns more and is consistently making progress.

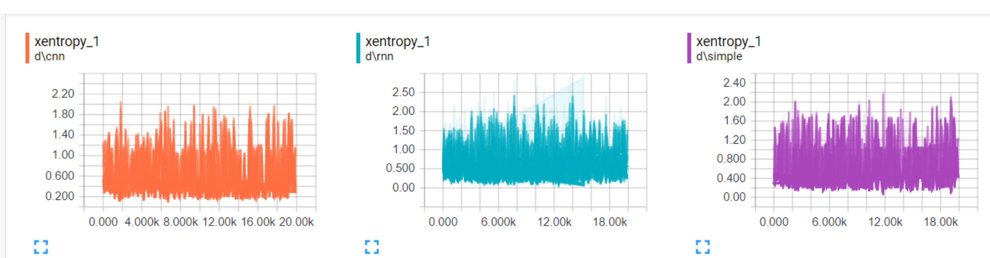
1.17.5 Histograms

CNN Layers on CNN and RNN Runs   Conclusion
RNN is more evenly spread out indicating a continuous learning. We expect that because unlike image data which is similar in local areas, financial data is more spread out.

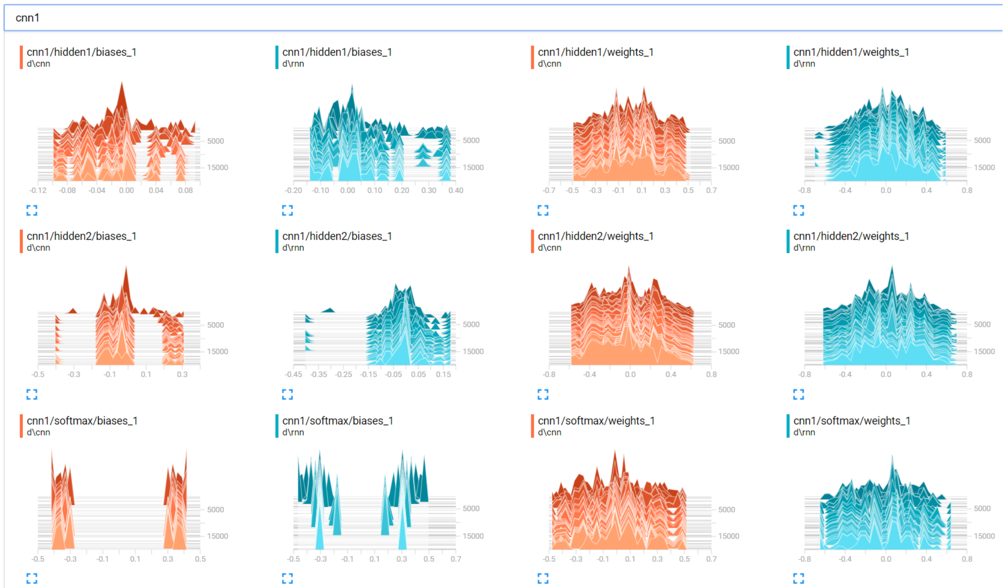
Hidden Layers on Simple Runs   Conclusion
Well spread out and softmax converges with little spikes. Model has nothing else to learn.



simple distribution



xentropy distribution



cnn hist

Entropy Conclusion
Notice how RNN has very little to no information to gain in later runs. Model learns quickly and remains there.

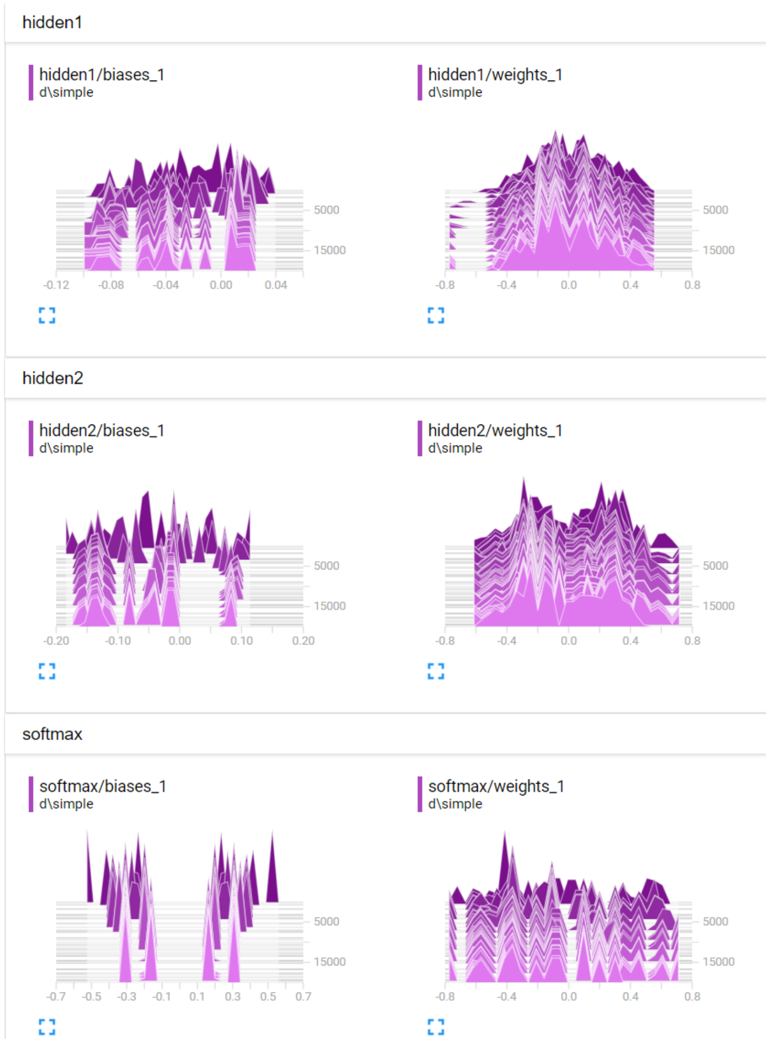
1.18 Model Selection

- After comparing all factors for all four models i.e. SVM, Simple Neural Net, CNN and RNN we conclude that **RNN** is the best approach to take. Reasons for this selection is stated as below
- Quickly Learns which is the same as SVM
- Returns the same accuracy as SVM
- Could be scaled to larger data sets more easily than SVM.
- In the light of above item and being aligned to the problem statement of chosing a model to be scalable in future, we suggest RNN to be the model to use for this project.

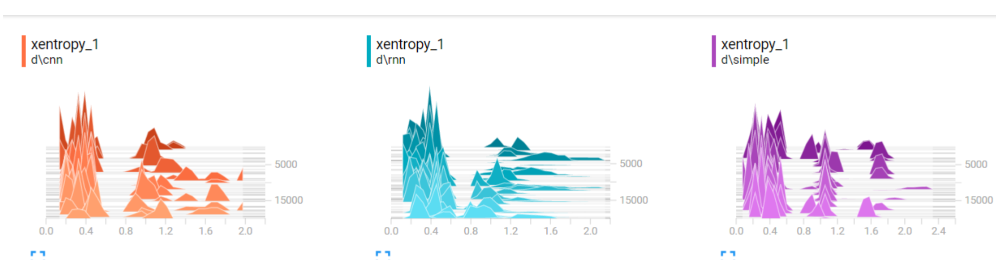
1.19 Find Optimal Training Epochs

- Save model at every 100 cycle in a different checkpoint.
- Store the checkpoint information
- Retrieve model from each checkpoint
- Run evaluation on 100 rows of test set
- Pick the one with best results
- List out the results for that pick

```
In [11]: import os
         base_checkpoint_path = "D:\\temp\\rnnopt"
         checkpoints = np.arange(100, 8100, 100)
         checkpoint_files = {}
```



hidden layers



entropy hist

```
best_accuracy = 0
best_accuracy_check_point = ''
```

In [12]:
```
with tf.Graph().as_default():
    # global step
    batch_start_index = tf.placeholder(tf.int32, shape=(1), name="BatchSta
    global_step = tf.Variable(0, name="global_step", trainable=False)
    print("Global Step", global_step)
    learning_rate = tf.train.exponential_decay(HYPER_LEARNING_RATE, global
            HYPER_BATCH_SIZE, 0.95, staircase=True)
    print("Learning Rate", learning_rate)
    tf.summary.scalar("GlobalStep", global_step)
    tf.summary.scalar("LearningRate", learning_rate)

    input_features = std_train_data.shape[1]
    print("input_features %d" % (input_features))
    X, y = build_training_set_placeholders(HYPER_BATCH_SIZE, input_feature
    print("X", X)
    print("y", y)
    CX = tf.reshape(X, [1, 8, 15, 15])
    print("CX: ", CX)
    print("validation data ", std_validate_data.shape, " validation label
    print("test data ", std_test_data.shape, " test label ", std_test_labe
    logits = build_rnn_net(CX, input_features, 10, 15)
    print("RNN Logits: ", logits)
    loss = build_loss(logits, y)
    print("RNN Loss: ", loss)
    trop = build_train(loss, learning_rate)
    print("RNN Training Op: ", trop)
    accuracy = build_eval(logits, y)
    print("RNN Accuracy: ", accuracy)
    init = tf.global_variables_initializer()
    print("RNN Init: ", init)
    saver = tf.train.Saver()
    print("RNN Saver: ", saver)
    sess = tf.Session()
    print("RNN Session: ", sess)
    sw = tf.summary.FileWriter(base_checkpoint_path, sess.graph)
    print("Summary Writer: ", sw)
    sess.run(init)
    print("sesson init run complete")
    num_steps = 8000
    tf.summary.scalar("NumberOfSteps", num_steps)
    summary = tf.summary.merge_all()
    for step in np.arange(num_steps):
        feed_dict = build_rnn_feed(HYPER_BATCH_SIZE, std_train_data, std_t
        op, step_loss = sess.run([trop, loss], feed_dict = feed_dict)
        if step % 100 == 0:
```

```
        print("Running Step: ", str(step))
        summary_str = sess.run(summary, feed_dict = feed_dict)
        sw.add_summary(summary_str, step)
        sw.flush()
        file_name = "modelrnnopt_" + str(step) + ".ckpt"
        checkpoint_file = os.path.join(base_checkpoint_path, file_name
        saver.save(sess, checkpoint_file, global_step=step)
        checkpoint_files[checkpoint_file] = 0
        test_feed_dict = build_rnn_feed(HYPER_BATCH_SIZE, std_test_dat
        ##saver.restore(sess, cp)
        test_prediction = sess.run(accuracy, feed_dict = test_feed_dic
        test_accuracy = tf.cast(test_prediction, tf.float32) / 128
        ta = sess.run(test_accuracy, feed_dict=test_feed_dict)
        print("Test Accuracy: ", str(ta))
        checkpoint_files[checkpoint_file] = ta
        if best_accuracy < ta:
            best_accuracy = ta
            best_accuracy_check_point = checkpoint_file
            print("Running test on checkpoint: ", checkpoint_file, " ,

print("Best Accuracy %0.2f on step %s"% (best_accuracy, best_accuracy_
```

```
Global Step Tensor("global_step/read:0", shape=(), dtype=int32)
Learning Rate Tensor("ExponentialDecay:0", shape=(), dtype=float32)
input_features 15
X Tensor("X:0", shape=(?, 15), dtype=float32)
y Tensor("y:0", dtype=int32)
CX:  Tensor("Reshape:0", shape=(1, 8, 15, 15), dtype=float32)
validation data  (4095, 15)  validation label  (4095,)
test data  (4095, 15)  test label  (4095,)
input to cnn network:  Tensor("Reshape:0", shape=(1, 8, 15, 15), dtype=float32)
cnn1 weights:  Tensor("cnn1/weights/read:0", shape=(1, 8, 15, 15), dtype=float32)
cnn1 biases:  Tensor("cnn1/Variable/read:0", shape=(15,), dtype=float32)
cnn with stride 1:  Tensor("cnn1/add:0", shape=(1, 8, 8, 15), dtype=float32)
cnn after relu:  Tensor("cnn1/Relu:0", shape=(1, 8, 8, 15), dtype=float32)
conv1 after pool: Tensor("cnn1/MaxPool:0", shape=(1, 4, 4, 15), dtype=float32)
RNX for RNN:  Tensor("cnn1/Reshape:0", shape=(16, 15), dtype=float32)  with shape:
LSTM Cell:  <tensorflow.python.ops.rnn_cell.BasicLSTMCell object at 0x0000025BAD74
LSTM State Size:  LSTMStateTuple(c=15, h=15)
LSTM Output Size:  15
LSTM Initial State:  LSTMStateTuple(c=<tf.Tensor 'cnn1/zeros_1:0' shape=(16, 15) dt
Cell Output:  Tensor("cnn1/lstm0/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm1/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm2/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm3/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm4/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm5/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Cell Output:  Tensor("cnn1/lstm6/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
```

```
Cell Output:  Tensor("cnn1/lstm7/BasicLSTMCell/mul_2:0", shape=(16, 15), dtype=floa
Output after collecting all step outputs from LSTM:  Tensor("cnn1/Reshape_1:0", sha
hidden2 after dropout:  Tensor("cnn1/dropout/dropout/mul:0", shape=(128, 15), dtype
RNN Logits:  Tensor("cnn1/softmax/add:0", shape=(128, 2), dtype=float32)
RNN Loss:  Tensor("xentropy_mean:0", shape=(), dtype=float32)
RNN Training Op:  name: "GradientDescent"
op: "AssignAdd"
input: "global_step"
input: "GradientDescent/value"
attr {
  key: "T"
  value {
    type: DT_INT32
  }
}
attr {
  key: "_class"
  value {
    list {
      s: "loc:@global_step"
    }
  }
}
attr {
  key: "use_locking"
  value {
    b: false
  }
}

RNN Accuracy:  Tensor("Sum:0", shape=(), dtype=int32)
RNN Init:  name: "init"
op: "NoOp"
input: "^global_step/Assign"
input: "^cnn1/weights/Assign"
input: "^cnn1/Variable/Assign"
input: "^lstm0/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm0/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm1/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm1/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm2/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm2/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm3/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm3/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm4/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm4/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm5/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm5/BasicLSTMCell/Linear/Bias/Assign"
```

```
input: "^lstm6/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm6/BasicLSTMCell/Linear/Bias/Assign"
input: "^lstm7/BasicLSTMCell/Linear/Matrix/Assign"
input: "^lstm7/BasicLSTMCell/Linear/Bias/Assign"
input: "^cnn1/hidden1/weights/Assign"
input: "^cnn1/hidden1/biases/Assign"
input: "^cnn1/hidden2/weights/Assign"
input: "^cnn1/hidden2/biases/Assign"
input: "^cnn1/softmax/weights/Assign"
input: "^cnn1/softmax/biases/Assign"

RNN Saver:  <tensorflow.python.training.saver.Saver object at 0x0000025BB9D66748>
RNN Session:  <tensorflow.python.client.session.Session object at 0x0000025BB9DB112
Summary Writer:  <tensorflow.python.summary.writer.writer.FileWriter object at 0x00
sesson init run complete
Running Step:  0


d:\anaconda3\lib\site-packages\ipykernel\__main__.py:98: VisibleDeprecationWarning:


Test Accuracy:  1.0
Running test on checkpoint:  D:\temp\rnnopt\modelrnnopt_0.ckpt  , best_accuracy:  1
Running Step:  100
Test Accuracy:  0.226563
Running Step:  200
Test Accuracy:  0.8125
Running Step:  300
Test Accuracy:  0.820313
Running Step:  400
Test Accuracy:  0.96875
Running Step:  500
Test Accuracy:  0.929688
Running Step:  600
Test Accuracy:  0.40625
Running Step:  700
Test Accuracy:  0.34375
Running Step:  800
Test Accuracy:  0.96875
Running Step:  900
Test Accuracy:  0.757813
Running Step:  1000
Test Accuracy:  0.992188
Running Step:  1100
Test Accuracy:  0.679688
Running Step:  1200
Test Accuracy:  0.382813
Running Step:  1300
```

```
Test Accuracy:  0.203125
Running Step:  1400
Test Accuracy:  0.375
Running Step:  1500
Test Accuracy:  0.914063
Running Step:  1600
Test Accuracy:  0.421875
Running Step:  1700
Test Accuracy:  0.359375
Running Step:  1800
Test Accuracy:  0.570313
Running Step:  1900
Test Accuracy:  0.632813
Running Step:  2000
Test Accuracy:  0.421875
Running Step:  2100
Test Accuracy:  0.148438
Running Step:  2200
Test Accuracy:  0.984375
Running Step:  2300
Test Accuracy:  0.789063
Running Step:  2400
Test Accuracy:  1.0
Running Step:  2500
Test Accuracy:  0.8125
Running Step:  2600
Test Accuracy:  0.296875
Running Step:  2700
Test Accuracy:  0.210938
Running Step:  2800
Test Accuracy:  0.96875
Running Step:  2900
Test Accuracy:  0.15625
Running Step:  3000
Test Accuracy:  0.726563
Running Step:  3100
Test Accuracy:  0.15625
Running Step:  3200
Test Accuracy:  0.742188
Running Step:  3300
Test Accuracy:  0.695313
Running Step:  3400
Test Accuracy:  0.289063
Running Step:  3500
Test Accuracy:  0.195313
Running Step:  3600
Test Accuracy:  0.898438
Running Step:  3700
```

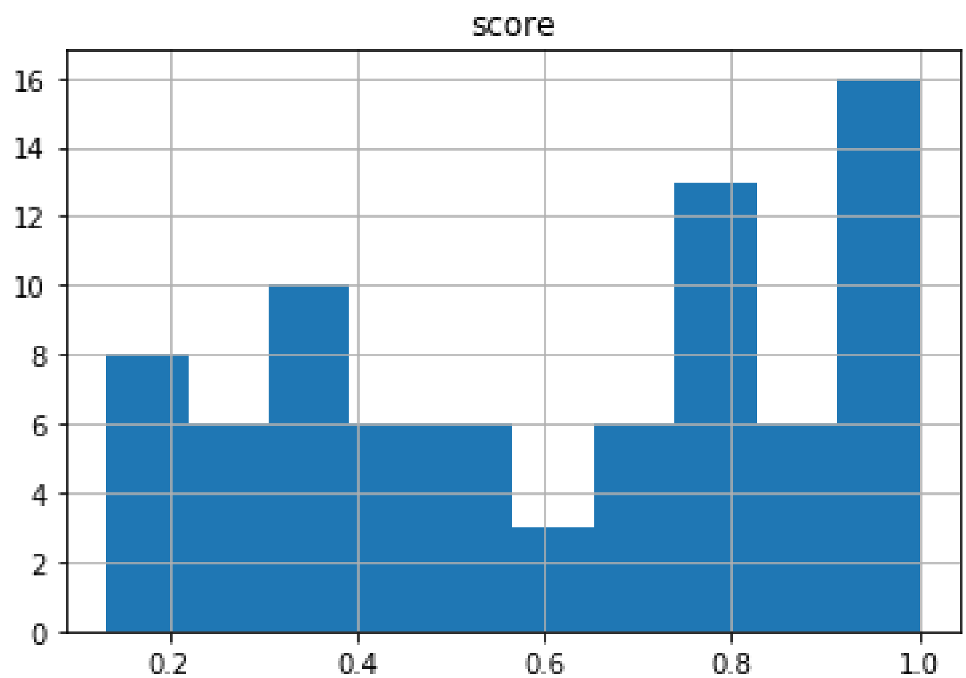
```
Test Accuracy:  0.765625
Running Step:  3800
Test Accuracy:  0.726563
Running Step:  3900
Test Accuracy:  0.5625
Running Step:  4000
Test Accuracy:  0.390625
Running Step:  4100
Test Accuracy:  0.515625
Running Step:  4200
Test Accuracy:  0.515625
Running Step:  4300
Test Accuracy:  0.757813
Running Step:  4400
Test Accuracy:  0.398438
Running Step:  4500
Test Accuracy:  0.742188
Running Step:  4600
Test Accuracy:  0.96875
Running Step:  4700
Test Accuracy:  0.96875
Running Step:  4800
Test Accuracy:  0.757813
Running Step:  4900
Test Accuracy:  0.195313
Running Step:  5000
Test Accuracy:  1.0
Running Step:  5100
Test Accuracy:  1.0
Running Step:  5200
Test Accuracy:  1.0
Running Step:  5300
Test Accuracy:  0.445313
Running Step:  5400
Test Accuracy:  0.265625
Running Step:  5500
Test Accuracy:  0.71875
Running Step:  5600
Test Accuracy:  0.96875
Running Step:  5700
Test Accuracy:  0.84375
Running Step:  5800
Test Accuracy:  1.0
Running Step:  5900
Test Accuracy:  0.132813
Running Step:  6000
Test Accuracy:  0.375
Running Step:  6100
```

```
Test Accuracy:  0.898438
Running Step:  6200
Test Accuracy:  0.75
Running Step:  6300
Test Accuracy:  0.328125
Running Step:  6400
Test Accuracy:  0.382813
Running Step:  6500
Test Accuracy:  0.898438
Running Step:  6600
Test Accuracy:  0.625
Running Step:  6700
Test Accuracy:  0.539063
Running Step:  6800
Test Accuracy:  0.226563
Running Step:  6900
Test Accuracy:  0.898438
Running Step:  7000
Test Accuracy:  0.703125
Running Step:  7100
Test Accuracy:  0.890625
Running Step:  7200
Test Accuracy:  0.453125
Running Step:  7300
Test Accuracy:  0.328125
Running Step:  7400
Test Accuracy:  0.328125
Running Step:  7500
Test Accuracy:  0.5625
Running Step:  7600
Test Accuracy:  0.75
Running Step:  7700
Test Accuracy:  0.546875
Running Step:  7800
Test Accuracy:  0.773438
Running Step:  7900
Test Accuracy:  0.296875
Best Accuracy 1.00 on step D:\temp\rnnopt\modelrnnopt_0.ckpt
```

```
In [33]: scores = pd.DataFrame.from_dict(data=checkpoint_files, orient='index')
         scores.columns = ['score']
         display(scores.head())
         scores.hist()
         scores_90 = scores[scores['score'] >= 0.90]
         display(scores_90.describe())
         display(scores_90)
```

```
                                      score
```

```
D:\temp\rnnopt\modelrnnopt_1300.ckpt  0.203125
D:\temp\rnnopt\modelrnnopt_5800.ckpt  1.000000
D:\temp\rnnopt\modelrnnopt_0.ckpt     1.000000
D:\temp\rnnopt\modelrnnopt_4200.ckpt  0.515625
D:\temp\rnnopt\modelrnnopt_700.ckpt   0.343750


           score
count  16.000000
mean    0.977051
std     0.025906
min     0.914062
25%     0.968750
50%     0.976562
75%     1.000000
max     1.000000


                                         score
D:\temp\rnnopt\modelrnnopt_5800.ckpt  1.000000
D:\temp\rnnopt\modelrnnopt_0.ckpt     1.000000
D:\temp\rnnopt\modelrnnopt_5600.ckpt  0.968750
D:\temp\rnnopt\modelrnnopt_5200.ckpt  1.000000
D:\temp\rnnopt\modelrnnopt_2800.ckpt  0.968750
D:\temp\rnnopt\modelrnnopt_500.ckpt   0.929688
D:\temp\rnnopt\modelrnnopt_2400.ckpt  1.000000
D:\temp\rnnopt\modelrnnopt_5000.ckpt  1.000000
D:\temp\rnnopt\modelrnnopt_2200.ckpt  0.984375
D:\temp\rnnopt\modelrnnopt_4600.ckpt  0.968750
D:\temp\rnnopt\modelrnnopt_800.ckpt   0.968750
D:\temp\rnnopt\modelrnnopt_5100.ckpt  1.000000
D:\temp\rnnopt\modelrnnopt_1500.ckpt  0.914062
D:\temp\rnnopt\modelrnnopt_400.ckpt   0.968750
D:\temp\rnnopt\modelrnnopt_1000.ckpt  0.992188
D:\temp\rnnopt\modelrnnopt_4700.ckpt  0.968750
```



1.20 Analysis of Optimal Config

- Seem to be converging around 5K epoch with 90+ accuracy. If we keep these settings on the model we can expect a more performing model for new test input.

1.21 Reflection

- We started with a problem statement that will take input data with high, low, close and open prices for two market symbols and will develop a machine learning model that will provide consistent results beyond 50% accuracy. With a selection of multiple models, one would be chosen with high accuracy and a possibility of scaling up with more data. Something that can be easier to adjust with more data.
- We looked into data and preprocessed it for training. We added more features to data to get a better learning experience for our deep learning models.
- We selected four models to implement including three deep learning and one a simple classification model. The models were
- SVM for simple classification with rbf kernel. We chose this model becaue it can work with non linear data and is pretty quick and cheap to implement.
- Simple deep learning neural net with two hidden layers. We chose this model to get a better depth of learning that SVM could forget or ignore to accomodate while learning the entire data set at one time. Simple net along with other deep learning models use a stchastic approach which learns batch wise where a batch is a smaller subset of entire data set. This makes learning more efficient and can also learn more features than plain SVM.
- Adding to simple net with two layers, we then added a CNN layer on top of hidden layers. Idea behind CNN layer is to learn a window of weights together instead of one node at a

time which is what happens in a simple neural net. In our case, we tried to learn eight (8) consequitive rows with all fifteen (15) features / columns in the matrix. We started with 15 matrices of 8/15 dimensions on the same input data that we fed Simple net. We then pooled a 2,2 stride on a max basis to reduce the next layer to 15 matrices of 4/4. The output of this layer was then fed into the simple net, thus making it even deeper! As expected this model learnt but came up with multiple optimas. **A difficult** understanding to comprehend why 8/15 turned into 4/4. Also was difficult to come up with a matrix size that could work with the same batch as other models.

- Adding to the depth of CNN, we then inserted a RNN layer between CNN and Simple Net. The window wide weights that we learnt in CNN then added more efficiency into RNN. In our case, we added eight (8) time steps of each cell size of 15 matching our feature columns. __ A difficult__ decision was to chose a proper batch size which is more than column sizes but still under our initial batch size. We chose 16 to make the final output 128/15. This selection also matches our plan to learn 8 rows together. Remember we tried to learn 8 rows together in CNN and now we want to learn 8 rows in sequence in RNN. The output of this layer was then fed into the Simple net, further improving efficiency.
- We then evaluated all these models with pros and cons. We chose RNN model as the best choice fot not only giving us back the same average accuracy as SVM and Simple Net but showing that it learns faster and is more accurate in early learning cycles.
- We then showed the Optimal configuration to use for this model for newer test set. We chose the cycle that returned most accurate scores. In our case it was 5K. We also showed the distribution of scores for this model.
- **Conclusion Note** It was difficult to prepare data for these models as most standard models come pre prepared with initial data. Like images come packed in image format (CNN) and words come packed in embeddings (RNN). Designing this data was a challenging task but was worth the effort. Another challenge was the steep learning curve in using Tensorflow. At the end, it was fruitful as TF gave a lot of tools for visualization. Another challenge was to come up with labels that suited each symbol appropriately. Putting it all together, it was a fun experience learning about all these models and was well worth the time and energy invested.

1.22 Improvements

- More improvements in data preprocessing can improve model behavior. Increased size with more features to learn. Possibly a benchmark index data to add in as a feature like SNP prices etc.. More features and more records to learn will ideally benefit the deep learning models to better perform than our sample size of 20K/15 features. It will help with bias and overfitting.
- Different architectures / layer combinations is due for next phase. Instead of two simple layers of 10/5 we can use multiple layers of wider depth. Same thing for CNN and RNN as well.
- Make this model online by interpretting each record at a time. Doing this can make this model useful in real time or near real time.
- More visualization tools to chose a set of data to train on and test with. That will help chose important features that can add more value to the learning and leave the ones that do not participate much. It can also dive into a specific feature and tell how significant the effect is on the model behavior.