In [346…

```
import pandas as pd
import numpy as np
import tensorflow as tf
import seaborn as sns
import datetime
from datetime import timedelta
import math
import requests
import plotly as py
import plotly.express as px
from plotly.subplots import make_subplots
import plotly.graph_objects as go
import matplotlib.pyplot as plt


import sklearn as sk
import sklearn.preprocessing
from sklearn import metrics
from matplotlib.pyplot import figure

from sklearn.preprocessing import  (StandardScaler, MinMaxScaler, LabelBinarizer)
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn import linear_model
from sklearn.linear_model import LinearRegression, LogisticRegression
import xgboost as xgb
from sklearn.metrics import *
# from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn import tree
from sklearn import decomposition
from sklearn.pipeline import Pipeline
from sklearn.metrics import r2_score


import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM, Bidirectional

import plotly
import chart_studio
import plotly.express as px
```

Creating DataFrame

In [347…

```
#manipulatable variables
numDaysBack = str(365*5) #for daily you can go back multiple years worth, for daily you can only go back 90 day
myInterval = 'daily' # options are daily or hourly
theCoins = ['ethereum'] #can add more than one coin if you like
window_length = 14
mycom = 0.4
lower_macd_ema = 12
upper_macd_ema = 26
trigger_macd_ema = 9


def df_builder_clean(days, interval, coins):
    #manipulatable variables
    numDaysBack = days #for daily you can go back multiple years worth, for daily you can only go back 90 days
    myInterval = interval # options are daily or hourly
    theCoins = coins

    #builds initial dataframe with ethereum as first market but just to log the dates we are working with
    geckoReq = 'https://api.coingecko.com/api/v3/coins/ethereum/market_chart?vs_currency=usd&days='+numDaysBack
    r = requests.get(geckoReq).json()
    ts = r['prices'][0][0]
    ts = ts/1000
    HistPricesList = []
    for i in range(len(r['prices'])):
        currentUnix = r['prices'][i][0]
        price = r['prices'][i][1]
        currentUnix = currentUnix/1000
#         currentTS = datetime.datetime.fromtimestamp(currentUnix).strftime("%d-%m-%Y %H:%M:%S") #adding dd-mm-
        currentTS = datetime.datetime.fromtimestamp(currentUnix).strftime("%m-%d-%Y") #just the date mm-dd-yyyy
        HistPricesList.append([currentTS])
    global df
    df = pd.DataFrame(HistPricesList, columns = ['date'])


    #looping through each coin and adding in all data points and input variables
    for coin in theCoins:
        price_data(coin)
#         add_ewm(coin, mycom)
#         add_rsi(coin, window_length)
#         add_macd(coin, lower_macd_ema, upper_macd_ema, trigger_macd_ema)
        print('just added: ', coin)
    df['date'] = pd.to_datetime(df['date'])
    df = df.set_index('date')
#     print('r')
#     display(r)
    return df


def price_data(coin):
    global df
    # geckoReq = 'https://api.coingecko.com/api/v3/coins/ethereum/market_chart?vs_currency=usd&days=60&interva
    geckoReq = 'https://api.coingecko.com/api/v3/coins/'+coin+'/market_chart?vs_currency=usd&days='+numDaysBack

    r = requests.get(geckoReq).json()
    ts = r['prices'][0][0]
    # print(ts)
    ts = ts/1000
    print(datetime.datetime.fromtimestamp(ts).strftime("%m-%d-%Y"))
    # print('prices length',len(r['prices']))
    HistPricesList = []
    for i in range(len(r['prices'])):
        currentUnix = r['prices'][i][0]
        price = r['prices'][i][1]
        volume = r['total_volumes'][i][1]
        currentUnix = currentUnix/1000
        currentTS = datetime.datetime.fromtimestamp(currentUnix).strftime("%m-%d-%Y")
    #     print('price: ', price, 'TS: ', currentTS)
        HistPricesList.append([currentTS, price, volume])
    #     currentUnix = currentTS
#         print(HistPricesList)
    dfCoin = pd.DataFrame(HistPricesList, columns = ['date', coin, coin+'_volume'])
#     print('dfCoin')
#     display(dfCoin)
    df = pd.merge(df, dfCoin[coin], left_on = df['date'], right_on=dfCoin['date']).drop(['key_0'], axis = 1)
    df = pd.merge(df, dfCoin[coin+'_volume'], left_on = df['date'], right_on=dfCoin['date']).drop(['key_0'], ax

def add_ewm(coin, mycom):
    df[coin+'_ewm'] = df[coin].ewm(com=mycom).mean()

def add_rsi(coin, window_length):
    global df
    df['diff'] = df[coin].diff(1)
    df['gain'] = df['diff'].clip(lower=0).round(2)
    df['loss'] = df['diff'].clip(upper=0).abs().round(2)

    # Get initial Averages
    df['avg_gain'] = df['gain'].rolling(window=window_length, min_periods=window_length).mean()[:window_length+
    df['avg_loss'] = df['loss'].rolling(window=window_length, min_periods=window_length).mean()[:window_length+

    # Get WMS averages
    # Average Gains
    for i, row in enumerate(df['avg_gain'].iloc[window_length+1:]):
        df['avg_gain'].iloc[i + window_length + 1] =\
            (df['avg_gain'].iloc[i + window_length] *
             (window_length - 1) +
             df['gain'].iloc[i + window_length + 1])\
            / window_length
    # Average Losses
    for i, row in enumerate(df['avg_loss'].iloc[window_length+1:]):
        df['avg_loss'].iloc[i + window_length + 1] =\
            (df['avg_loss'].iloc[i + window_length] *
             (window_length - 1) +
             df['loss'].iloc[i + window_length + 1])\
            / window_length

    df['rs'] = df['avg_gain'] / df['avg_loss']

    df['rsi'] = 100 - (100 / (1.0 + df['rs']))
    df = pd.DataFrame(df)
    df = df.drop(['gain', 'loss', 'avg_loss', 'avg_gain', 'rs'], axis = 1)

    #renaming diff and rsi columns
    dict = {'diff': coin+'_diff',
        'rsi': coin+'_rsi'}
    df.rename(columns=dict,
              inplace=True)

def add_macd(coin, lower_macd_ema, upper_macd_ema, trigger_macd_ema):
    global df
    #get ema for lower
    k = df[coin].ewm(span=lower_macd_ema, adjust = False, min_periods = lower_macd_ema).mean()

    #get ema for upper
    d = df[coin].ewm(span=upper_macd_ema, adjust=False, min_periods=upper_macd_ema).mean()

    macd = k-d

    # Get the 9-Day EMA of the MACD for the Trigger line
    macd_s = macd.ewm(span=trigger_macd_ema, adjust=False, min_periods=trigger_macd_ema).mean()
    # Calculate the difference between the MACD - Trigger for the Convergence/Divergence value
    macd_h = macd - macd_s
    # Add all of our new values for the MACD to the dataframe
    df['macd'] = df.index.map(macd)
    df['macd_h'] = df.index.map(macd_h)
    df['macd_s'] = df.index.map(macd_s)



mydf = pd.DataFrame(df_builder_clean(numDaysBack, myInterval, theCoins))
display(mydf)
```

```
08-18-2017
just added:  ethereum
```

date	ethereum	ethereum_volume
2017-08-18	296.622090	5.537022e+08
2017-08-19	295.171577	3.428230e+08
2017-08-20	322.201220	1.743910e+09
2017-08-21	312.174471	8.983443e+08
2017-08-22	316.788920	4.664746e+08
...	...	...
2022-08-16	1896.031277	1.412055e+10
2022-08-16	1880.600101	1.424023e+10
2022-08-16	1880.600101	1.412055e+10
2022-08-16	1896.031277	1.424023e+10
2022-08-16	1896.031277	1.412055e+10

1832 rows × 2 columns

In [348…

```
mydf.dropna(inplace=True)
# myCols = ['ethereum', 'ethereum_volume', 'ethereum_ewm', 'ethereum_rsi', 'macd', 'macd_h', 'macd_s', 'ethere
```

In [349…

```
my_data = mydf

###Need to add this att night when API adds same day values
display(my_data.tail(6))
my_data.drop(my_data.tail(6).index,
        inplace = True)


display(my_data)
```

date	ethereum	ethereum_volume
2022-08-16	1896.031277	1.424023e+10
2022-08-16	1896.031277	1.412055e+10
2022-08-16	1880.600101	1.424023e+10
2022-08-16	1880.600101	1.412055e+10
2022-08-16	1896.031277	1.424023e+10
2022-08-16	1896.031277	1.412055e+10

date	ethereum	ethereum_volume
2017-08-18	296.622090	5.537022e+08
2017-08-19	295.171577	3.428230e+08
2017-08-20	322.201220	1.743910e+09
2017-08-21	312.174471	8.983443e+08
2017-08-22	316.788920	4.664746e+08
...	...	...
2022-08-11	1881.427405	2.183707e+10
2022-08-12	1959.330925	1.584926e+10
2022-08-13	1982.411828	1.481675e+10
2022-08-14	1936.701164	1.217221e+10
2022-08-15	1908.277642	1.831087e+10

1824 rows × 2 columns

LSTM Univariate Forecasting with Train-Val-Test Split and 3 day sliding window

In [350…

```
#
import datetime

def str_to_datetime(s):
  split = s.split('-')
  year, month, day = int(split[0]), int(split[1]), int(split[2])
  return datetime.datetime(year=year, month=month, day=day)

datetime_object = str_to_datetime('2017-08-16')
datetime_object
```

Out[350…

```
datetime.datetime(2017, 8, 16, 0, 0)
```

In [351…

```
my_data = df
#df.rename(columns={"date": "Date"})
df = df.rename(columns={"ethereum": "Close","date": "Date"})
#df = df.drop(columns = 'ethereum_volume')
df
```

Out[351…

date	Close	ethereum_volume
2017-08-18	296.622090	5.537022e+08
2017-08-19	295.171577	3.428230e+08
2017-08-20	322.201220	1.743910e+09
2017-08-21	312.174471	8.983443e+08
2017-08-22	316.788920	4.664746e+08
...	...	...
2022-08-16	1896.031277	1.412055e+10
2022-08-16	1880.600101	1.424023e+10
2022-08-16	1880.600101	1.412055e+10
2022-08-16	1896.031277	1.424023e+10
2022-08-16	1896.031277	1.412055e+10

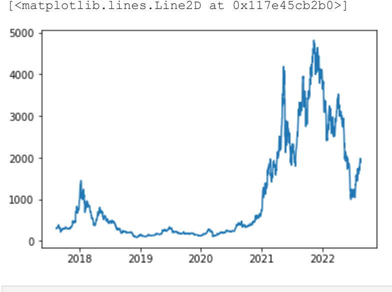
1832 rows × 2 columns

In [352…

```
#Plotting the close price over specified time (5 years)
plt.plot(df.index, df['Close'])

plt.xlabel('Date')
plt.ylabel('ETH Price in $')
```

Out[352…

```
[&lt;matplotlib.lines.Line2D at 0x117e45cb2b0&gt;]
```



In [353…

```
'''Function to create sliding window using 3 previous days as window length'''

def create_sliding_window(dataframe, first_date_str, last_date_str, n=3):
  first_date = str_to_datetime(first_date_str)
  last_date  = str_to_datetime(last_date_str)

  target_date = first_date

  dates = []
  X, Y = [], []

  last_time = False
  while True:
    df_subset = dataframe.loc[:target_date].tail(n+1)

    if len(df_subset) != n+1:
      print(f'Error: Window of size {n} is too large for date {target_date}')
      return

    values = df_subset['Close'].to_numpy()
    x, y = values[:-1], values[-1]

    dates.append(target_date)
    X.append(x)
    Y.append(y)

    next_week = dataframe.loc[target_date:target_date+datetime.timedelta(days=7)]
    next_datetime_str = str(next_week.head(2).tail(1).index.values[0])
    next_date_str = next_datetime_str.split('T')[0]
    year_month_day = next_date_str.split('-')
    year, month, day = year_month_day
    next_date = datetime.datetime(day=int(day), month=int(month), year=int(year))

    if last_time:
      break

    target_date = next_date

    if target_date == last_date:
      last_time = True

  ret_df = pd.DataFrame({})
  ret_df['Target Date'] = dates
#creating target- i dates for 3 previous dates in our case
  X = np.array(X)
  for i in range(0, n):
    X[:, i]
    ret_df[f'Target-{n-i}'] = X[:, i]
#Target is the oucome variable
  ret_df['Target'] = Y

  return ret_df
# Start day first time around: '2017-08-19'
# Start day second time around: '2021-08-16'
sliding_window_df = create_sliding_window(df,
                                '2017-08-22',
                                '2022-08-15',
                                          n=3)
sliding_window_df
```

Out[353…

	Target Date	Target-3	Target-2	Target-1	Target
0	2017-08-22	295.171577	322.201220	312.174471	316.788920
1	2017-08-23	322.201220	312.174471	316.788920	321.785298
2	2017-08-24	312.174471	316.788920	321.785298	329.025281
3	2017-08-25	316.788920	321.785298	329.025281	329.865783
4	2017-08-26	321.785298	329.025281	329.865783	343.341337
...	...	...	...	...	...
1815	2022-08-11	1775.701356	1698.966129	1852.878555	1881.427405
1816	2022-08-12	1698.966129	1852.878555	1881.427405	1959.330925
1817	2022-08-13	1852.878555	1881.427405	1959.330925	1982.411828
1818	2022-08-14	1881.427405	1959.330925	1982.411828	1936.701164
1819	2022-08-15	1959.330925	1982.411828	1936.701164	1908.277642

1820 rows × 5 columns

In [354…

```
'''this function takes sliding window df, output is date, 3d matrix X of 3 day windowed dates, and the target c
Used to convert df into np array to feed into the lstm model'''
def sliding_window_df_to_date_X_y(windowed_dataframe):
  df_as_np = windowed_dataframe.to_numpy()
#take in first column as dates
  dates = df_as_np[:, 0]
#takes middle 3 cols as middle 3d matrix
  middle_matrix = df_as_np[:, 1:-1]
  X = middle_matrix.reshape((len(dates), middle_matrix.shape[1], 1))
# y is target column
  Y = df_as_np[:, -1]

  return dates, X.astype(np.float32), Y.astype(np.float32)

dates, X, y = sliding_window_df_to_date_X_y(sliding_window_df)

dates.shape, X.shape, y.shape
```

Out[354…

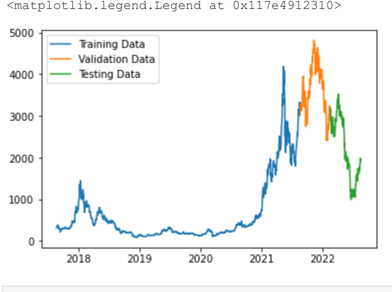
```
((1820,), (1820, 3, 1), (1820,))
```

In [355…

```
#split data into train-test validation 80-10-10%
q_80 = int(len(dates) * .8)
q_90 = int(len(dates) * .9)

#training = first  80% of data
dates_train, X_train, y_train = dates[:q_80], X[:q_80], y[:q_80]
#validation to get data between 80-90%
dates_val, X_val, y_val = dates[q_80:q_90], X[q_80:q_90], y[q_80:q_90]
#test data is 90-100%
dates_test, X_test, y_test = dates[q_90:], X[q_90:], y[q_90:]

plt.plot(dates_train, y_train)
plt.plot(dates_val, y_val)
plt.plot(dates_test, y_test)
plt.xlabel('Date')
plt.ylabel('ETH Price in $')
plt.legend(['Training Data', 'Validation Data', 'Testing Data'])
```

Out[355…

```
&lt;matplotlib.legend.Legend at 0x117e4912310&gt;
```



In [356…

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import layers
#best model is full 5 year with LSTM 200 , dense layers 80, learning rate .001

#rectified linear activation function or ReLU for short is a piecewise linear function that will output the inp
#if it is positive, otherwise, it will output zero. It has become the default activation function for many type
#because a model that uses it is easier to train and often achieves better performance.
model = Sequential([layers.Input((3, 1)),                          #3 for 3 days in past and 1 for target
                    layers.LSTM(200),
                    layers.Dense(80, activation='relu'),
                    layers.Dense(80, activation='relu'),
                    layers.Dense(1)])
#default linear output, ideal for univariate outcomes
model.summary()
#####Dannys Model implementation

# model = keras.Sequential()
# model.add(keras.layers.LSTM(100, return_sequences=True, input_shape=(3, 1)))
# model.add(keras.layers.LSTM(100, return_sequences=False))
# model.add(keras.layers.Dense(25))
# model.add(keras.layers.Dense(1))
# model.summary()


######

model.compile(loss='mse',                                          #we are looking to minimize MSE
              optimizer=Adam(learning_rate=0.001),
              metrics=['mean_absolute_error'])               #tells us the average of how much we are off by in


model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=13)

#best performence 81 for 5 year dataset
```

```
Model: "sequential_12"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_12 (LSTM)              (None, 200)               161600

 dense_36 (Dense)            (None, 80)                16080

 dense_37 (Dense)            (None, 80)                6480

 dense_38 (Dense)            (None, 1)                 81

=================================================================
Total params: 184,241
Trainable params: 184,241
Non-trainable params: 0
_________________________________________________________________
Epoch 1/13
46/46 [==============================] - 2s 14ms/step - loss: 907510.1250 - mean_absolute_error: 596.9955 - val
_loss: 13142629.0000 - val_mean_absolute_error: 3575.3301
Epoch 2/13
46/46 [==============================] - 0s 6ms/step - loss: 674827.4375 - mean_absolute_error: 460.7157 - val_
loss: 9505243.0000 - val_mean_absolute_error: 3024.2346
Epoch 3/13
46/46 [==============================] - 0s 5ms/step - loss: 281691.3438 - mean_absolute_error: 238.9135 - val_
loss: 4185924.2500 - val_mean_absolute_error: 1956.1639
Epoch 4/13
46/46 [==============================] - 0s 5ms/step - loss: 44461.6797 - mean_absolute_error: 68.2895 - val_lo
ss: 1498647.2500 - val_mean_absolute_error: 1078.1969
Epoch 5/13
46/46 [==============================] - 0s 5ms/step - loss: 23647.6758 - mean_absolute_error: 53.9253 - val_lo
ss: 1526048.3750 - val_mean_absolute_error: 1103.2618
Epoch 6/13
46/46 [==============================] - 0s 5ms/step - loss: 17900.8223 - mean_absolute_error: 45.4817 - val_lo
ss: 741587.8750 - val_mean_absolute_error: 721.6210
Epoch 7/13
46/46 [==============================] - 0s 6ms/step - loss: 13010.6523 - mean_absolute_error: 44.6935 - val_lo
ss: 741313.5625 - val_mean_absolute_error: 717.1180
Epoch 8/13
46/46 [==============================] - 0s 6ms/step - loss: 11432.8779 - mean_absolute_error: 40.0447 - val_lo
ss: 697089.4375 - val_mean_absolute_error: 682.3502
Epoch 9/13
46/46 [==============================] - 0s 6ms/step - loss: 12158.1416 - mean_absolute_error: 43.0863 - val_lo
ss: 666023.3750 - val_mean_absolute_error: 654.3730
Epoch 10/13
46/46 [==============================] - 0s 6ms/step - loss: 13832.5225 - mean_absolute_error: 48.2737 - val_lo
ss: 1188815.7500 - val_mean_absolute_error: 946.7506
Epoch 11/13
46/46 [==============================] - 0s 7ms/step - loss: 20247.9160 - mean_absolute_error: 59.8973 - val_lo
ss: 1322668.8750 - val_mean_absolute_error: 1013.5662
Epoch 12/13
46/46 [==============================] - 0s 6ms/step - loss: 14006.0957 - mean_absolute_error: 46.5204 - val_lo
ss: 704963.1875 - val_mean_absolute_error: 708.4948
Epoch 13/13
46/46 [==============================] - 0s 6ms/step - loss: 8619.7461 - mean_absolute_error: 38.2299 - val_los
s: 333955.5312 - val_mean_absolute_error: 436.9828
```

Out[356…

```
&lt;keras.callbacks.History at 0x117e48b29a0&gt;
```

In [357…

```
#Prediction on the training set
train_predictions = model.predict(X_train).flatten()

plt.plot(dates_train, train_predictions)
plt.plot(dates_train, y_train)
plt.xlabel('Date')
plt.ylabel('ETH Price in $')
plt.legend(['Training Predictions', 'Training Observations'])
```

```
46/46 [==============================] - 0s 2ms/step
```

Out[357…

```
&lt;matplotlib.legend.Legend at 0x117e8054970&gt;
```

In [358…

```
#plotly graph of train set

fig = px.line(x=dates_train, y=[y_train, train_predictions],labels={'wide_variable_0':'Train Predictions', 'wid

fig.update_layout(
    title="Training Set Predictions (Red) vs Actual (Blue)",
    xaxis_title="Date",
    yaxis_title="Price ($)",
    font=dict(
        family="Arial, monospace",
        size=18,
        color="Black"
    )
)

fig.update_layout(legend_title_text = "Plots")
fig.update_traces(showlegend=False)
fig.show()
```

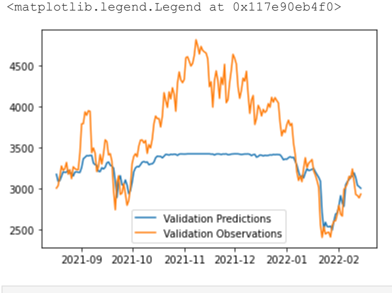
In [359…

```
#prediction on the validation set
val_predictions = model.predict(X_val).flatten()

plt.plot(dates_val, val_predictions)
plt.plot(dates_val, y_val)
plt.xlabel('Date')
plt.ylabel('ETH Price in $')
plt.legend(['Validation Predictions', 'Validation Observations'])
```

```
6/6 [==============================] - 0s 7ms/step
```

Out[359…

```
&lt;matplotlib.legend.Legend at 0x117e90eb4f0&gt;
```



In [360…

```
#plotly graph of val set


fig = px.line(x=dates_val, y=[y_val, val_predictions],labels={'wide_variable_0':'Validation Predictions', 'wide

fig.update_layout(
    title="Validation Set Predictions (Red) vs Actual (Blue)",
    xaxis_title="Date",
    yaxis_title="Price ($)",
    font=dict(
        family="Arial, monospace",
        size=18,
        color="Black"
    )
)

fig.update_layout(legend_title_text = "Plots")
fig.update_traces(showlegend=False)
fig.show()
```

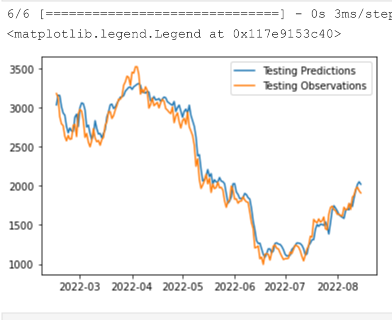
In [361…

```
#Prediction on testing set
test_predictions = model.predict(X_test).flatten()

plt.plot(dates_test, test_predictions)
plt.plot(dates_test, y_test)
plt.xlabel('Date')
plt.ylabel('ETH Price in $')
plt.legend(['Testing Predictions', 'Testing Observations'])

#seems to predict downfalls better than upticks
```

```
6/6 [==============================] - 0s 3ms/step
```

Out[361…

```
&lt;matplotlib.legend.Legend at 0x117e9153c40&gt;
```



In [362…

```
#plotly graph of test set


fig = px.line(x=dates_test, y=[y_test, test_predictions],labels={'wide_variable_0':'Test Predictions', 'wide_va

fig.update_layout(
    title="Test Set Predictions (Red) vs Actual (Blue)",
    xaxis_title="Date",
    yaxis_title="Price ($)",
    font=dict(
        family="Arial, monospace",
        size=18,
        color="Black"
    )
)

fig.update_layout(legend_title_text = "Plots")
fig.update_traces(showlegend=False)
fig.show()
```

In [363…

```
from sklearn.metrics import r2_score

print('R2_score for Training Set: ', r2_score(y_train, train_predictions))
print('R2_score for Validation Set: ', r2_score(y_val, val_predictions))
print('R2_score for Test Set: ', r2_score(y_test, test_predictions))
```

```
R2_score for Training Set:  0.9896533080152631
R2_score for Validation Set:  0.07083109590160397
R2_score for Test Set:  0.9698724359608772
```

In [364…

```
rmse_train = np.sqrt(np.mean(train_predictions - y_train)**2)
rmse_val = np.sqrt(np.mean(val_predictions - y_val)**2)
rmse_test = np.sqrt(np.mean(test_predictions - y_test)**2)
print('RMSE for Training Set: ',rmse_train)
print('RMSE for Validation Set: ',rmse_val)
print('RMSE for Testing Set: ',rmse_test)
```

```
RMSE for Training Set:  7.104269504547119
RMSE for Validation Set:  383.6580810546875
RMSE for Testing Set:  52.23227310180664
```

In [365…

```
#combined prediction on train/val/testing
plt.plot(dates_train, train_predictions)
plt.plot(dates_train, y_train)
plt.plot(dates_val, val_predictions)
plt.plot(dates_val, y_val)
plt.plot(dates_test, test_predictions)
plt.plot(dates_test, y_test)
plt.legend(['Training Predictions',
            'Training Observations',
            'Validation Predictions',
            'Validation Observations',
            'Testing Predictions',
            'Testing Observations'])
```

Out[365…

```
&lt;matplotlib.legend.Legend at 0x117e9198b20&gt;
```

Perhaps LSTM models are not great for extrapolation of data. It does not deal with data outside of its range well. The information from the training data does not help predict the latter values with a volatile increases accuratley.

In [366…

```
#making future predictions
from copy import deepcopy

# recursive_predictions = []
# #predictions for last 20% of data using training Data
# recursive_dates = np.concatenate([dates_val, dates_test])


# #loop through recursive dates and make predictions

# for target_date in recursive_dates:
#   last_window = deepcopy(X_train[-1])
#   next_prediction = model.predict(np.array([last_window])).flatten()
#   recursive_predictions.append(next_prediction) #add predictions to list
#   last_window[-1] = next_prediction


#3 day window
recursive_predictions = []
recursive_dates = dates_test[-7:]
last_window  = X_test[-7]

for target_date in recursive_dates:
    print(last_window)
    next_prediction = model.predict(np.array([last_window])).flatten()
    recursive_predictions.append(next_prediction)
    new_window = list(last_window[1:])
    new_window.append(next_prediction)
    new_window = np.array(new_window)
    last_window = new_window
```

```
[[1693.2966]
 [1699.0065]
 [1775.7014]]
1/1 [==============================] - 0s 14ms/step
[[1699.0065]
 [1775.7014]
 [1769.9469]]
1/1 [==============================] - 0s 18ms/step
[[1775.7014]
 [1769.9469]
 [1802.3805]]
1/1 [==============================] - 0s 15ms/step
[[1769.9469]
 [1802.3805]
 [1831.1313]]
1/1 [==============================] - 0s 18ms/step
[[1802.3805]
 [1831.1313]
 [1874.2806]]
1/1 [==============================] - 0s 15ms/step
[[1831.1313]
 [1874.2806]
 [1926.7195]]
1/1 [==============================] - 0s 16ms/step
[[1874.2806]
 [1926.7195]
 [1987.3724]]
1/1 [==============================] - 0s 16ms/step
```

In [367…

```
mpl_fig = plt.figure()

plt.plot(dates_train, train_predictions)
plt.plot(dates_train, y_train)
plt.plot(dates_val, val_predictions)
plt.plot(dates_val, y_val)
plt.plot(dates_test, test_predictions)
plt.plot(dates_test, y_test)
plt.plot(recursive_dates, recursive_predictions)
plt.legend(['Training Predictions',
            'Training Observations',
            'Validation Predictions',
            'Validation Observations',
            'Testing Predictions',
            'Testing Observations',
            'Recursive Predictions'])
```

Out[367… <matplotlib.legend.Legend at 0x117e92f2850>

In [368…

```
recursive_predictions[0:]
```

Out[368…

```
[array([1769.9469], dtype=float32),
 array([1802.3805], dtype=float32),
 array([1831.1313], dtype=float32),
 array([1874.2806], dtype=float32),
 array([1926.7195], dtype=float32),
 array([1987.3724], dtype=float32),
 array([2049.384], dtype=float32)]
```

In [369…

```
#actual values of last 7 day price
y_test.tolist
print(y_test[-7:])
```

```
[1698.9662 1852.8785 1881.4274 1959.3309 1982.4119 1936.7012 1908.2776]
```

In [374…

```
##recursively predicted values of last 7 day price
# my1 = [1769.9469,1802.3805,1831.1313,1874.2806,1926.7195,1987.3724,2049.384]
# my1
```

Out[374… [1769.9469, 1802.3805, 1831.1313, 1874.2806, 1926.7195, 1987.3724, 2049.384]

In [370…

```
# pd.DataFrame(y_test)
data = mydf.filter(['ethereum'])
data = data.tail(len(y_test))
data['Predictions'] = test_predictions
display(data)
validation = data
```

	ethereum	Predictions
date		
2022-02-15	3179.300207	3033.818115
2022-02-16	3128.640781	3158.602783
2022-02-17	2881.613122	3152.917480
2022-02-18	2792.303848	3012.685303
2022-02-19	2768.971652	2930.754639
...	...	...
2022-08-11	1881.427405	1846.740601
2022-08-12	1959.330925	1940.652954
2022-08-13	1982.411828	2016.360474
2022-08-14	1936.701164	2051.524902
2022-08-15	1908.277642	2019.810425

182 rows × 2 columns

In [371…

```
moneyStart = 1000
money = moneyStart
eth = money/validation['ethereum'].iloc[1]
validation['buy'] = np.where(validation['ethereum'] > validation['Predictions'], 1, 0)
# validation['sell'] = np.where(validation['ethereum'] < validation['Predictions'], 1, 0)
validation['signal'] = validation['buy'].diff()
validation['money'] = moneyStart
validation = validation.iloc[1:, :]
validation['eth'] = moneyStart/eth
display(validation.head(5))
for index, row in validation.iterrows():
    if row['signal'] == 1:
#         print('buy')
#         print('money: ',  money, 'price: ', row['ethereum'])
        eth = money/row['ethereum']
        validation.loc[index, 'eth'] = eth
        validation.loc[index, 'money'] = money
        row['eth'] = eth
    elif row['signal'] == -1:
#         print('sell')
        money = eth*row['ethereum']
        validation.loc[index, 'eth'] = eth
        validation.loc[index, 'money'] = money
    else:
        validation.loc[index, 'eth'] = eth
        validation.loc[index, 'money'] = money
display(validation)
#     print(moneyStart/row['Close'])
```

```
<ipython-input-371-719820f1c52c>:9: 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: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
```

	ethereum	Predictions	buy	signal	money	eth
date						
2022-02-16	3128.640781	3158.602783	0	-1.0	1000	3128.640781
2022-02-17	2881.613122	3152.917480	0	0.0	1000	3128.640781
2022-02-18	2792.303848	3012.685303	0	0.0	1000	3128.640781
2022-02-19	2768.971652	2930.754639	0	0.0	1000	3128.640781
2022-02-20	2632.491399	2902.815674	0	0.0	1000	3128.640781

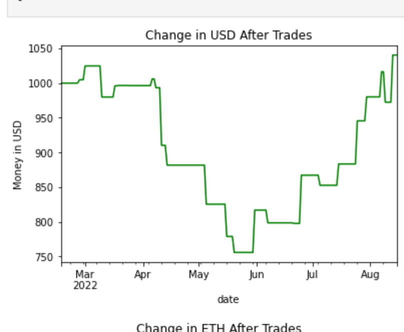
```
C:\Users\YM\anaconda3\lib\site-packages\pandas\core\indexing.py:1720: SettingWithCopyWarning:


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: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
```

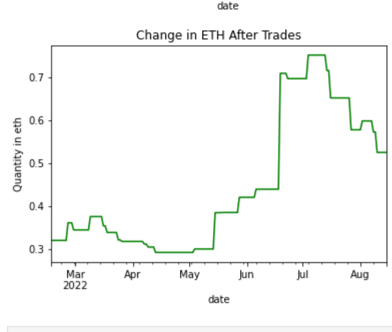
	ethereum	Predictions	buy	signal	money	eth
date						
2022-02-16	3128.640781	3158.602783	0	-1.0	1000.000000	0.319628
2022-02-17	2881.613122	3152.917480	0	0.0	1000.000000	0.319628
2022-02-18	2792.303848	3012.685303	0	0.0	1000.000000	0.319628
2022-02-19	2768.971652	2930.754639	0	0.0	1000.000000	0.319628
2022-02-20	2632.491399	2902.815674	0	0.0	1000.000000	0.319628
...	...	...	...	...	...	...
2022-08-11	1881.427405	1846.740601	1	0.0	972.491444	0.524854
2022-08-12	1959.330925	1940.652954	1	0.0	972.491444	0.524854
2022-08-13	1982.411828	2016.360474	0	-1.0	1040.477551	0.524854
2022-08-14	1936.701164	2051.524902	0	0.0	1040.477551	0.524854
2022-08-15	1908.277642	2019.810425	0	0.0	1040.477551	0.524854

181 rows × 6 columns

In [372…

```
plt.xlabel('Date')
plt.ylabel('Money in USD')
plt.title('Change in USD After Trades')
validation['money'].plot(color='g', label = 'money')
plt.show()
plt.xlabel('Date')
plt.ylabel('Quantity in eth')
plt.title('Change in ETH After Trades')
validation['eth'].plot(color='g', label = 'eth')
plt.show()
```





In [373…

```
validation = validation.drop(columns = ['eth','money'])

plt.figure(figsize = (16, 8))
validation['ethereum'].plot(color='k', label = 'price')
validation['Predictions'].plot(color='b', label='predictions')
plt.plot(validation[validation['signal']==1].index, validation[validation['signal']==1],'^', markersize = 15, c
plt.plot(validation[validation['signal']==-1].index, validation[validation['signal']==-1],'v', markersize = 15,
plt.ylabel('Price in USD')
plt.xlabel('Date')
plt.title('Backtesting', fontsize = 20)
plt.legend()
plt.grid()
plt.show()
```