bitcoin-analysis-lstm

September 29, 2021

[1]:
```
import tensorflow as tf
import numpy as np
import pandas as pd
from datetime import datetime, timedelta
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

[2]:
```
df = pd.read_csv('sentiment-bitcoin.csv')
df = df.rename(columns = {'Unnamed: 0': 'timestamp'})
df.head()
```

[2]:
```
             timestamp  Polarity  Sensitivity  Tweet_vol     Open     High  \
0  2018-07-11 20:00:00  0.102657     0.216148     4354.0  6342.97  6354.19
1  2018-07-11 21:00:00  0.098004     0.218612     4432.0  6352.99  6370.00
2  2018-07-11 22:00:00  0.096688     0.231342     3980.0  6350.85  6378.47
3  2018-07-11 23:00:00  0.103997     0.217739     3830.0  6362.36  6381.25
4  2018-07-12 00:00:00  0.094383     0.195256     3998.0  6369.49  6381.25

       Low  Volume_BTC  Volume_Dollar  Close_Price
0  6291.00      986.73     6231532.37      6350.00
1  6345.76      126.46      804221.55      6356.48
2  6345.00      259.10     1646353.87      6361.93
3  6356.74       81.54      519278.69      6368.78
4  6361.83      124.55      793560.22      6380.00
```

0.1 Simple metrics study

[3]:
```
df['Polarity'].describe()
```

[3]:
```
count    294.000000
mean       0.099534
std        0.012114
min        0.051695
25%        0.091489
50%        0.099198
75%        0.106649
```

```
max        0.135088
Name: Polarity, dtype: float64
```

[4]:
```
df['Sensitivity'].describe()
```

[4]:
```
count    294.000000
mean       0.214141
std        0.014940
min        0.174330
25%        0.203450
50%        0.214756
75%        0.223910
max        0.271796
Name: Sensitivity, dtype: float64
```

[5]:
```
df['Tweet_vol'].describe()
```

[5]:
```
count      294.000000
mean      4691.119048
std       1048.922706
min       2998.000000
25%       3878.750000
50%       4452.000000
75%       5429.750000
max      10452.000000
Name: Tweet_vol, dtype: float64
```

[6]:
```
df['Close_Price'].describe()
```

[6]:
```
count     294.000000
mean     6920.150000
std       565.424866
min      6149.110000
25%      6283.497500
50%      7281.975000
75%      7424.560000
max      7750.090000
Name: Close_Price, dtype: float64
```

0.2 Detecting outliers / sudden spikes in our close prices

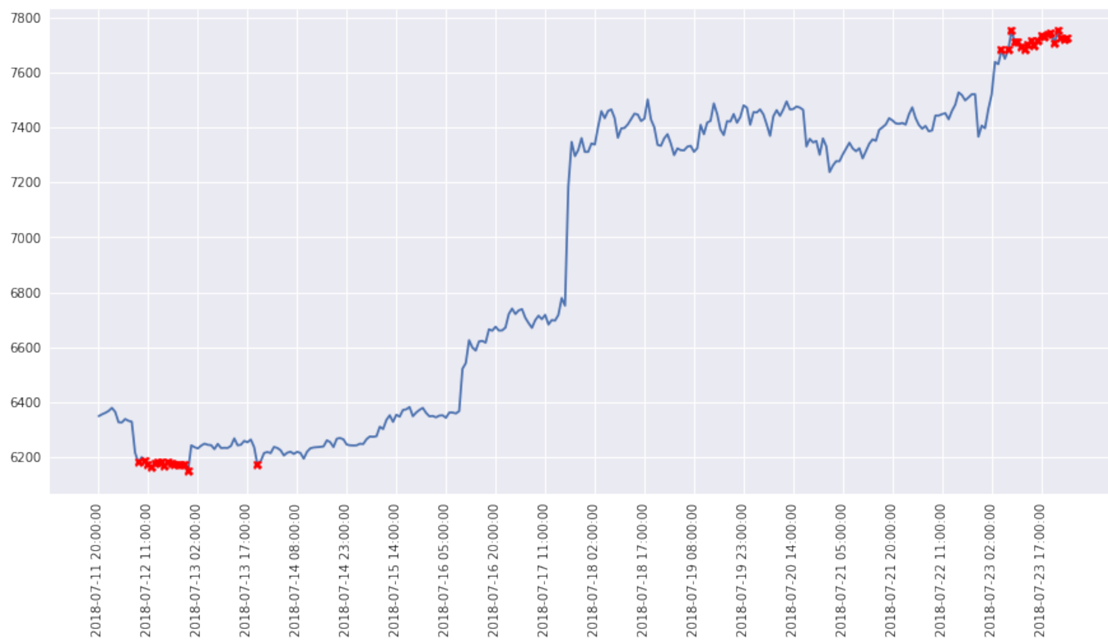
[7]:
```
def detect(signal, treshold = 2.0):
    detected = []
    for i in range(len(signal)):
        if np.abs(signal[i]) > treshold:
            detected.append(i)
    return detected
```

[8]:
```
signal = np.copy(df['Close_Price'].values)
std_signal = (signal - np.mean(signal)) / np.std(signal)
s = pd.Series(std_signal)
s.describe(percentiles = [0.25, 0.5, 0.75, 0.95])
```

[8]:
```
count    2.940000e+02
mean     2.223467e-15
std      1.001705e+00
min     -1.365972e+00
25%     -1.127892e+00
50%      6.410081e-01
75%      8.936113e-01
95%      1.375160e+00
max      1.470319e+00
dtype: float64
```

[9]:
```
outliers = detect(std_signal, 1.3)
```

[10]:
```
plt.figure(figsize = (15, 7))
plt.plot(np.arange(len(signal)), signal)
plt.plot(
    np.arange(len(signal)),
    signal,
    'X',
    label = 'outliers',
    markevery = outliers,
    c = 'r',
)
plt.xticks(
    np.arange(len(signal))[::15], df['timestamp'][::15], rotation = 'vertical'
)
plt.show()
```



[11]:

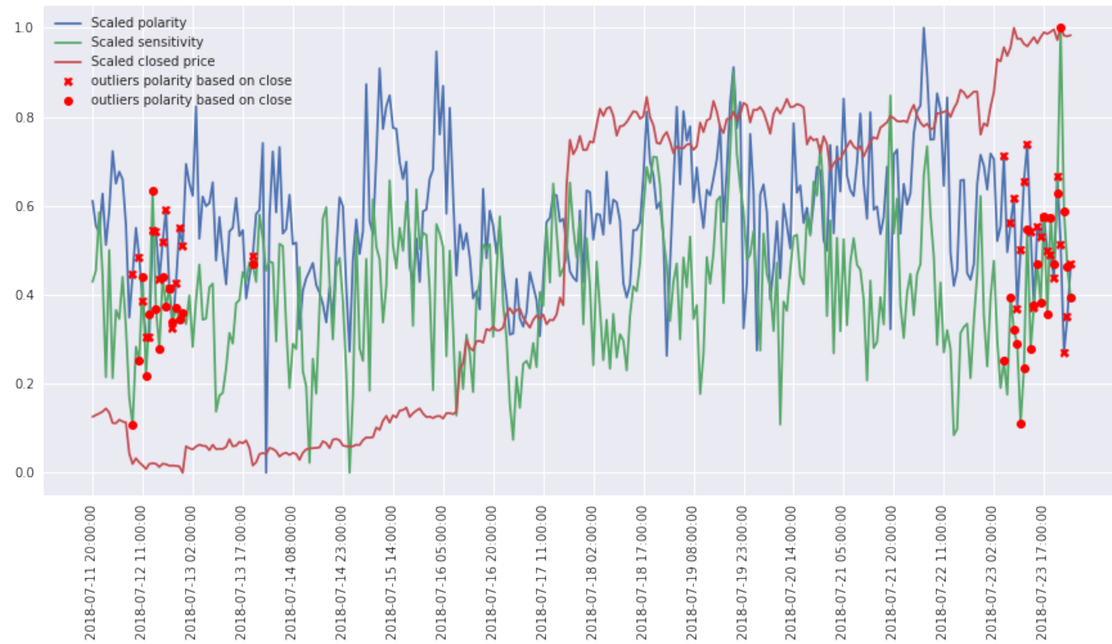
```
from sklearn.preprocessing import MinMaxScaler

minmax = MinMaxScaler().fit(df[['Polarity', 'Sensitivity', 'Close_Price']])
scaled = minmax.transform(df[['Polarity', 'Sensitivity', 'Close_Price']])
```

[12]:

```
plt.figure(figsize = (15, 7))
plt.plot(np.arange(len(signal)), scaled[:, 0], label = 'Scaled polarity')
plt.plot(np.arange(len(signal)), scaled[:, 1], label = 'Scaled sensitivity')
plt.plot(np.arange(len(signal)), scaled[:, 2], label = 'Scaled closed price')
plt.plot(
    np.arange(len(signal)),
    scaled[:, 0],
    'X',
    label = 'outliers polarity based on close',
    markevery = outliers,
    c = 'r',
)
plt.plot(
    np.arange(len(signal)),
    scaled[:, 1],
    'o',
    label = 'outliers polarity based on close',
    markevery = outliers,
    c = 'r',
)
plt.xticks(
```

```
    np.arange(len(signal))[::15], df['timestamp'][::15], rotation = 'vertical'
)
plt.legend()
plt.show()
```



Doesnt show much from trending, how about covariance correlation?

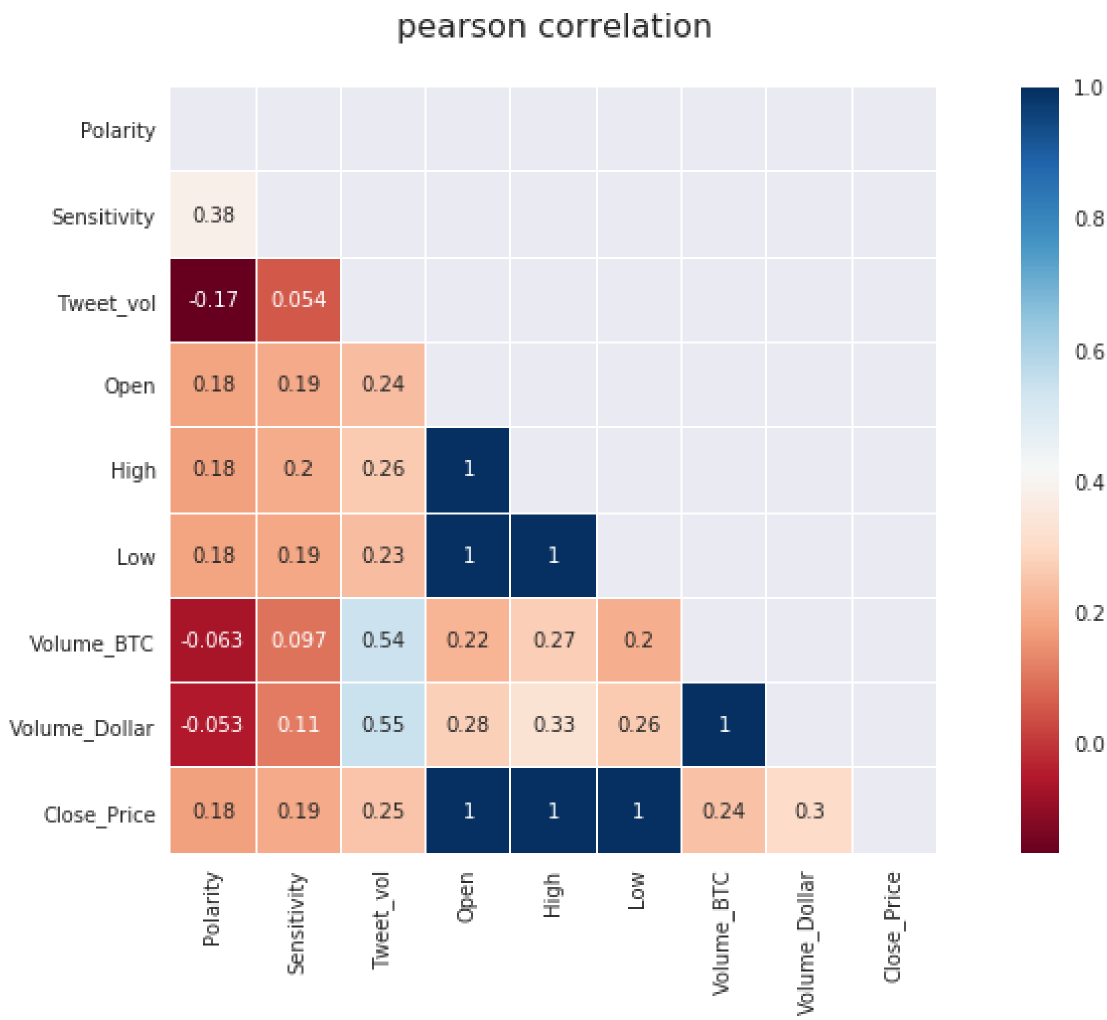
0.3 Pearson correlation

[13]:
```
colormap = plt.cm.RdBu
plt.figure(figsize = (15, 7))
plt.title('pearson correlation', y = 1.05, size = 16)

mask = np.zeros_like(df.corr())
mask[np.triu_indices_from(mask)] = True

sns.heatmap(
    df.corr(),
    mask = mask,
    linewidths = 0.1,
    vmax = 1.0,
    square = True,
    cmap = colormap,
    linecolor = 'white',
    annot = True,
)
```

```
plt.show()
```



[14]:
```
def df_shift(df, lag = 0, start = 1, skip = 1, rejected_columns = []):
    df = df.copy()
    if not lag:
        return df
    cols = {}
    for i in range(start, lag + 1, skip):
        for x in list(df.columns):
            if x not in rejected_columns:
                if not x in cols:
                    cols[x] = ['{}_{}'.format(x, i)]
                else:
                    cols[x].append('{}_{}'.format(x, i))
    for k, v in cols.items():
```

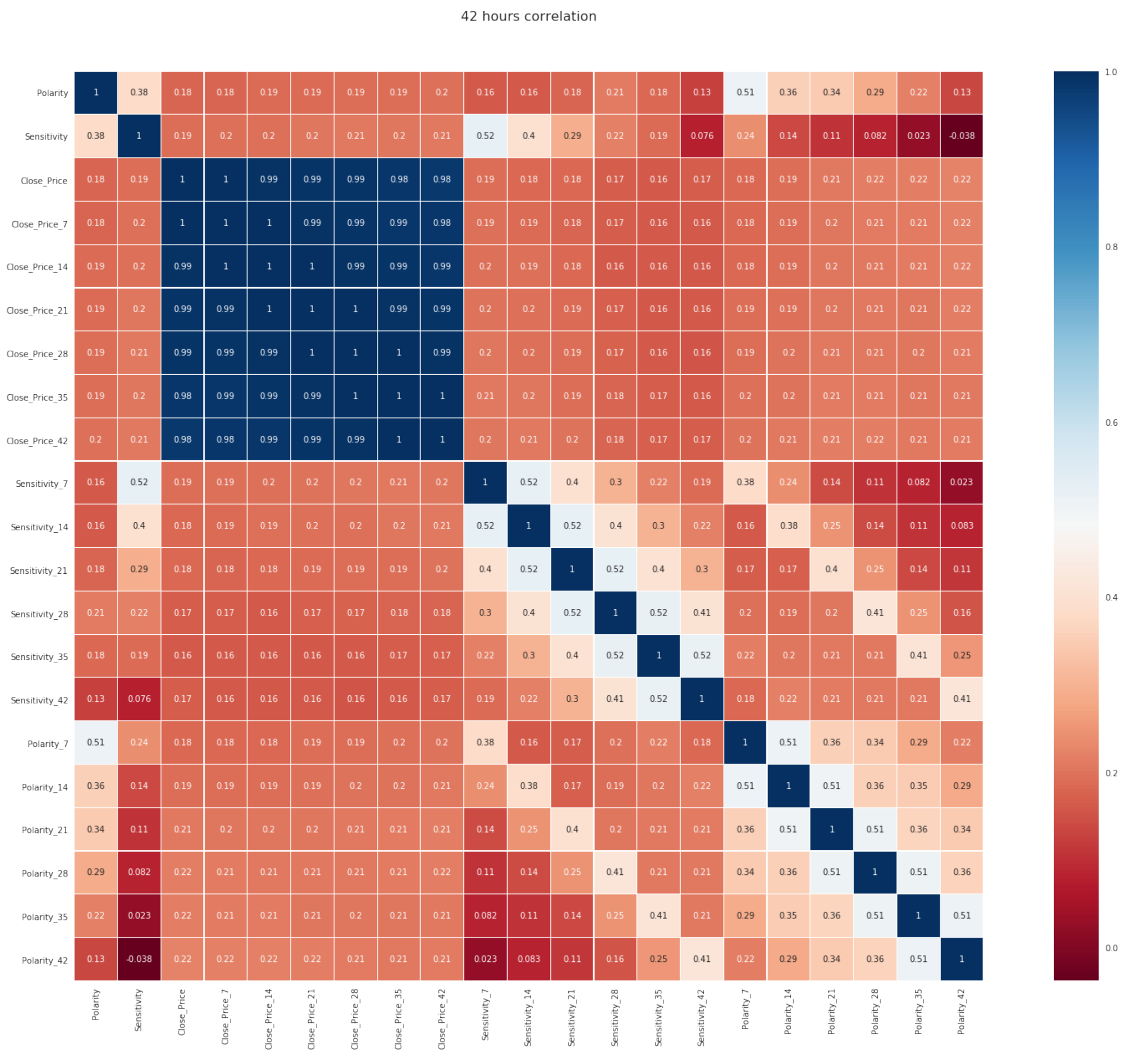
```
        columns = v
        dfn = pd.DataFrame(data = None, columns = columns, index = df.index)
        i = 1
        for c in columns:
            dfn[c] = df[k].shift(periods = i)
            i += 1
        df = pd.concat([df, dfn], axis = 1, join_axes = [df.index])
    return df
```

[15]:
```
df_new = df_shift(df, lag = 42, start = 7, skip = 7)
df_new.shape
```

[15]: (294, 70)

[16]:
```
colormap = plt.cm.RdBu
plt.figure(figsize = (30, 20))
ax = plt.subplot(111)
plt.title('42 hours correlation', y = 1.05, size = 16)
selected_column = [
    col
    for col in list(df_new)
    if any([k in col for k in ['Polarity', 'Sensitivity', 'Close']])
]

sns.heatmap(
    df_new[selected_column].corr(),
    ax = ax,
    linewidths = 0.1,
    vmax = 1.0,
    square = True,
    cmap = colormap,
    linecolor = 'white',
    annot = True,
)
plt.show()
```



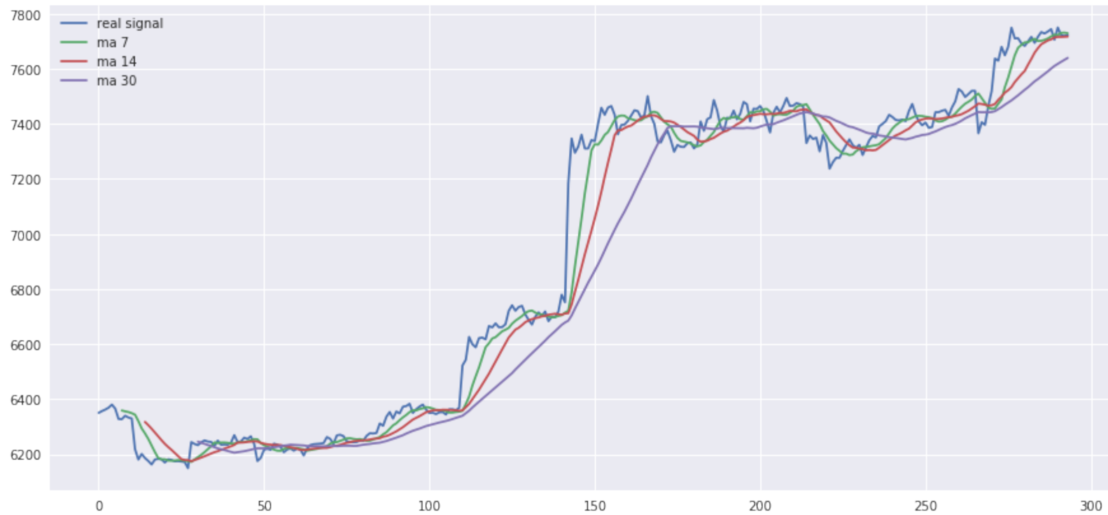
0.4 How about we check trends from moving average? i chose 7, 14, 30 hours

I think i had too much playing daily trending data

[17]:
```
def moving_average(signal, period):
    buffer = [np.nan] * period
    for i in range(period, len(signal)):
        buffer.append(signal[i - period : i].mean())
    return buffer
```

[18]:
```
signal = np.copy(df['Close_Price'].values)
ma_7 = moving_average(signal, 7)
ma_14 = moving_average(signal, 14)
ma_30 = moving_average(signal, 30)
```

[19]:
```
plt.figure(figsize = (15, 7))
plt.plot(np.arange(len(signal)), signal, label = 'real signal')
plt.plot(np.arange(len(signal)), ma_7, label = 'ma 7')
plt.plot(np.arange(len(signal)), ma_14, label = 'ma 14')
plt.plot(np.arange(len(signal)), ma_30, label = 'ma 30')
plt.legend()
plt.show()
```



Trends gonna increase anyway!

0.5 Now deep learning LSTM

[20]:
```
num_layers = 1
learning_rate = 0.005
size_layer = 128
timestamp = 5
epoch = 500
dropout_rate = 0.6
```

[21]:
```
dates = pd.to_datetime(df.iloc[:, 0]).tolist()
```

[22]:
```
class Model:
    def __init__(
        self, learning_rate, num_layers, size, size_layer, forget_bias = 0.8
    ):
        def lstm_cell(size_layer):
            return tf.nn.rnn_cell.LSTMCell(size_layer, state_is_tuple = False)

        rnn_cells = tf.nn.rnn_cell.MultiRNNCell(
```

```
            [lstm_cell(size_layer) for _ in range(num_layers)],
            state_is_tuple = False,
        )
        self.X = tf.placeholder(tf.float32, (None, None, size))
        self.Y = tf.placeholder(tf.float32, (None, size))
        drop = tf.contrib.rnn.DropoutWrapper(
            rnn_cells, output_keep_prob = forget_bias
        )
        self.hidden_layer = tf.placeholder(
            tf.float32, (None, num_layers * 2 * size_layer)
        )
        self.outputs, self.last_state = tf.nn.dynamic_rnn(
            drop, self.X, initial_state = self.hidden_layer, dtype = tf.float32
        )
        self.logits = tf.layers.dense(
            self.outputs[-1],
            size,
            kernel_initializer = tf.glorot_uniform_initializer(),
        )
        self.cost = tf.reduce_mean(tf.square(self.Y - self.logits))
        self.optimizer = tf.train.AdamOptimizer(learning_rate).minimize(
            self.cost
        )
```

[23]:
```
minmax = MinMaxScaler().fit(
    df[['Polarity', 'Sensitivity', 'Tweet_vol', 'Close_Price']].astype(
        'float32'
    )
)
df_scaled = minmax.transform(
    df[['Polarity', 'Sensitivity', 'Tweet_vol', 'Close_Price']].astype(
        'float32'
    )
)
df_scaled = pd.DataFrame(df_scaled)
df_scaled.head()
```

[23]:

	0	1	2	3
0	0.611105	0.429055	0.181916	0.125479
1	0.555312	0.454335	0.192380	0.129527
2	0.539534	0.584944	0.131741	0.132931
3	0.627175	0.445375	0.111618	0.137210
4	0.511893	0.214693	0.134156	0.144218

[24]:
```
tf.reset_default_graph()
modelnn = Model(
    learning_rate, num_layers, df_scaled.shape[1], size_layer, dropout_rate
```

```
)
sess = tf.InteractiveSession()
sess.run(tf.global_variables_initializer())
```

```
WARNING:tensorflow:<tensorflow.python.ops.rnn_cell_impl.LSTMCell object at
0x7fda6e020828>: Using a concatenated state is slower and will soon be
deprecated.  Use state_is_tuple=True.
```

We need to scale our data between 0 - 1 or any scaled you wanted, but must not less than -1 and more than 1, because LSTM is using tanh function, squashing high values can caused gradient vanishing later

[25]:
```
for i in range(epoch):
    init_value = np.zeros((1, num_layers * 2 * size_layer))
    total_loss = 0
    for k in range(0, (df_scaled.shape[0] // timestamp) * timestamp, timestamp):
        batch_x = np.expand_dims(
            df_scaled.iloc[k : k + timestamp].values, axis = 0
        )
        batch_y = df_scaled.iloc[k + 1 : k + timestamp + 1].values
        last_state, _, loss = sess.run(
            [modelnn.last_state, modelnn.optimizer, modelnn.cost],
            feed_dict = {
                modelnn.X: batch_x,
                modelnn.Y: batch_y,
                modelnn.hidden_layer: init_value,
            },
        )
        init_value = last_state
        total_loss += loss
    total_loss /= df.shape[0] // timestamp
    if (i + 1) % 100 == 0:
        print('epoch:', i + 1, 'avg loss:', total_loss)
```

```
epoch: 100 avg loss: 0.009472558752569402
epoch: 200 avg loss: 0.007681161466311535
epoch: 300 avg loss: 0.006072720400346765
epoch: 400 avg loss: 0.005432833451777697
epoch: 500 avg loss: 0.0048205173004354385
```

[29]:
```
def predict_future(future_count, df, dates, indices = {}):
    date_ori = dates[:]
    cp_df = df.copy()
    output_predict = np.zeros((cp_df.shape[0] + future_count, cp_df.shape[1]))
    output_predict[0] = cp_df.iloc[0]
    upper_b = (cp_df.shape[0] // timestamp) * timestamp
    init_value = np.zeros((1, num_layers * 2 * size_layer))
    for k in range(0, (df.shape[0] // timestamp) * timestamp, timestamp):
```

```
        out_logits, last_state = sess.run(
            [modelnn.logits, modelnn.last_state],
            feed_dict = {
                modelnn.X: np.expand_dims(
                    cp_df.iloc[k : k + timestamp], axis = 0
                ),
                modelnn.hidden_layer: init_value,
            },
        )
        init_value = last_state
        output_predict[k + 1 : k + timestamp + 1] = out_logits
    out_logits, last_state = sess.run(
        [modelnn.logits, modelnn.last_state],
        feed_dict = {
            modelnn.X: np.expand_dims(cp_df.iloc[upper_b:], axis = 0),
            modelnn.hidden_layer: init_value,
        },
    )
    init_value = last_state
    output_predict[upper_b + 1 : cp_df.shape[0] + 1] = out_logits
    cp_df.loc[cp_df.shape[0]] = out_logits[-1]
    date_ori.append(date_ori[-1] + timedelta(hours = 1))
    if indices:
        for key, item in indices.items():
            cp_df.iloc[-1, key] = item
    for i in range(future_count - 1):
        out_logits, last_state = sess.run(
            [modelnn.logits, modelnn.last_state],
            feed_dict = {
                modelnn.X: np.expand_dims(cp_df.iloc[-timestamp:], axis = 0),
                modelnn.hidden_layer: init_value,
            },
        )
        init_value = last_state
        output_predict[cp_df.shape[0]] = out_logits[-1]
        cp_df.loc[cp_df.shape[0]] = out_logits[-1]
        date_ori.append(date_ori[-1] + timedelta(hours = 1))
        if indices:
            for key, item in indices.items():
                cp_df.iloc[-1, key] = item
    return {'date_ori': date_ori, 'df': cp_df.values}
```

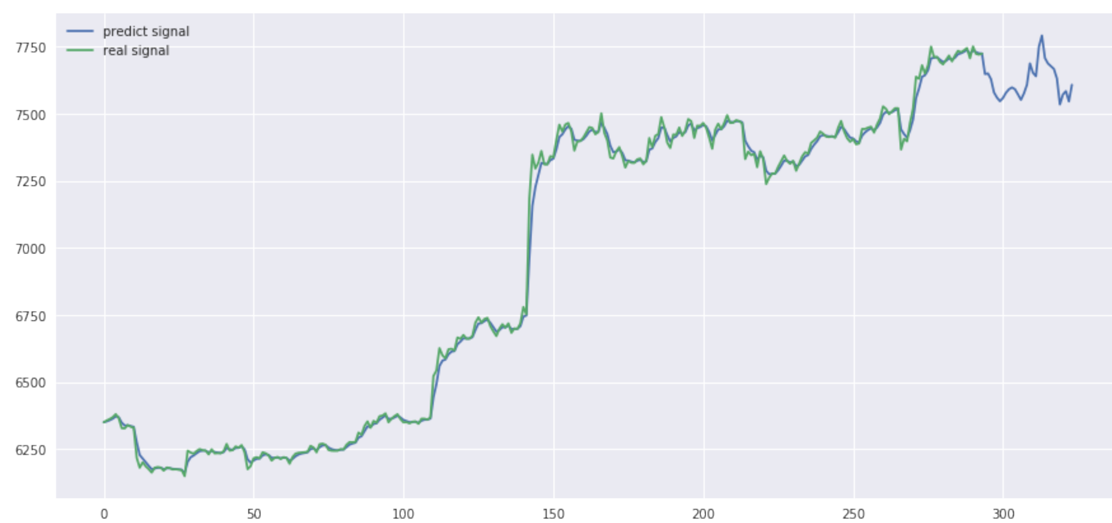
Define some smoothing, using previous value as an anchor

[27]:
```
def anchor(signal, weight):
    buffer = []
    last = signal[0]
```

```
    for i in signal:
        smoothed_val = last * weight + (1 - weight) * i
        buffer.append(smoothed_val)
        last = smoothed_val
    return buffer
```

[30]:
```
predict_30 = predict_future(30, df_scaled, dates)
predict_30['df'] = minmax.inverse_transform(predict_30['df'])
```

[31]:
```
plt.figure(figsize = (15, 7))
plt.plot(
    np.arange(len(predict_30['date_ori'])),
    anchor(predict_30['df'][:, -1], 0.5),
    label = 'predict signal',
)
plt.plot(np.arange(len(signal)), signal, label = 'real signal')
plt.legend()
plt.show()
```



What happen if polarity is double from the max? Polarity is first index

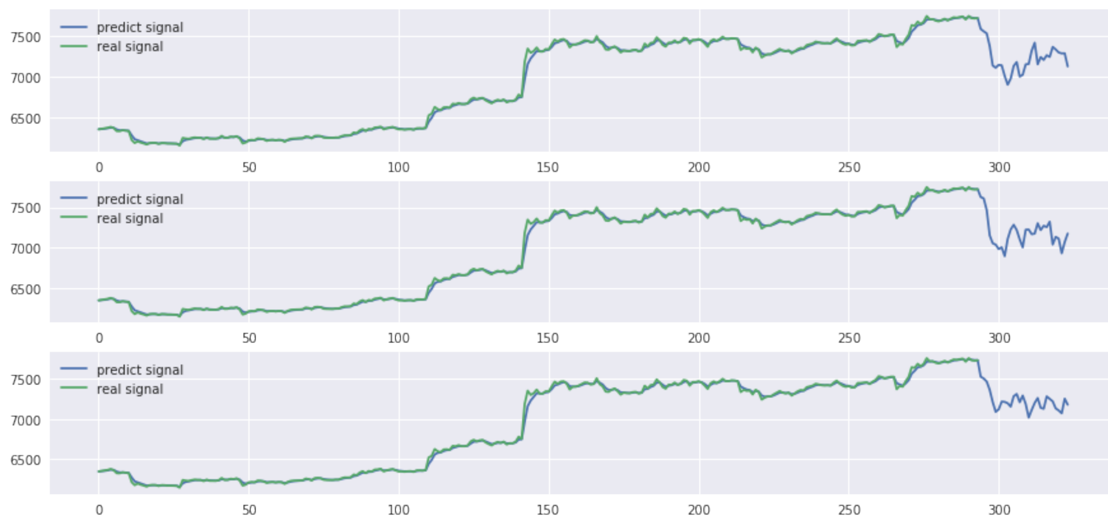
[32]:
```
scaled_polarity = (minmax.data_max_[0] * 2 - minmax.data_min_[0]) / (
    minmax.data_max_[0] - minmax.data_min_[0]
)
scaled_polarity
```

[32]: 2.6198966986921897

[38]:

```
plt.figure(figsize = (15, 7))

for retry in range(3):
    plt.subplot(3, 1, retry + 1)
    predict_30 = predict_future(
        30, df_scaled, dates, indices = {0: scaled_polarity}
    )
    predict_30['df'] = minmax.inverse_transform(predict_30['df'])
    plt.plot(
        np.arange(len(predict_30['date_ori'])),
        anchor(predict_30['df'][:, -1], 0.5),
        label = 'predict signal',
    )
    plt.plot(np.arange(len(signal)), signal, label = 'real signal')
    plt.legend()
plt.show()
```



I retried for 3 times just to study how fitted our model is, if every retry has big trend changes, so we need to retrain again.

What happen if polarity is quadriple from the max? Polarity is first index

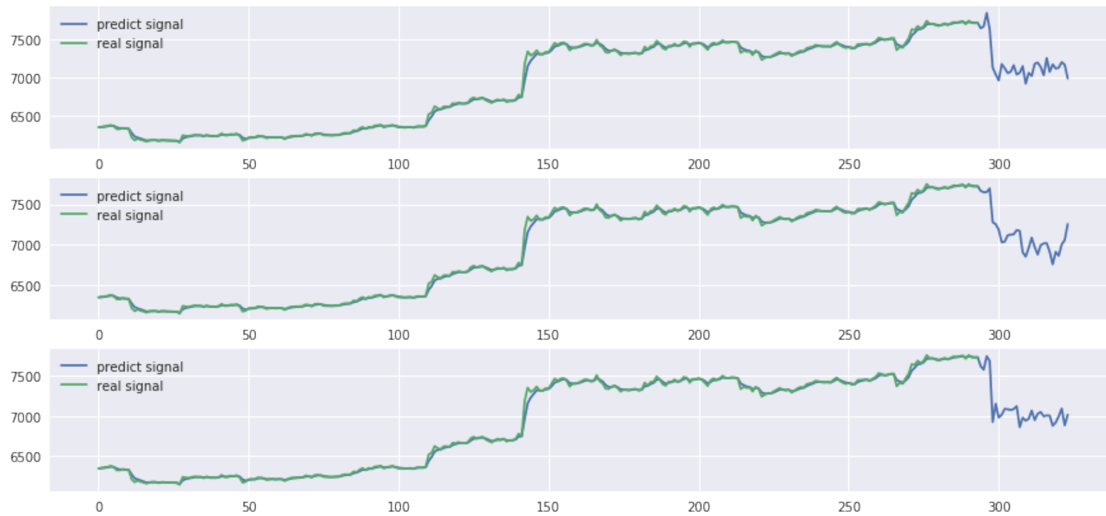
[41]:

```
scaled_polarity = (minmax.data_max_[0] * 4 - minmax.data_min_[0]) / (
    minmax.data_max_[0] - minmax.data_min_[0]
)
scaled_polarity
```

[41]: 5.8596900960765685

```
[42]: plt.figure(figsize = (15, 7))

for retry in range(3):
    plt.subplot(3, 1, retry + 1)
    predict_30 = predict_future(
        30, df_scaled, dates, indices = {0: scaled_polarity}
    )
    predict_30['df'] = minmax.inverse_transform(predict_30['df'])
    plt.plot(
        np.arange(len(predict_30['date_ori'])),
        anchor(predict_30['df'][:, -1], 0.5),
        label = 'predict signal',
    )
    plt.plot(np.arange(len(signal)), signal, label = 'real signal')
    plt.legend()
plt.show()
```



What happen if polarity is quadriple from the min? polarity is first index

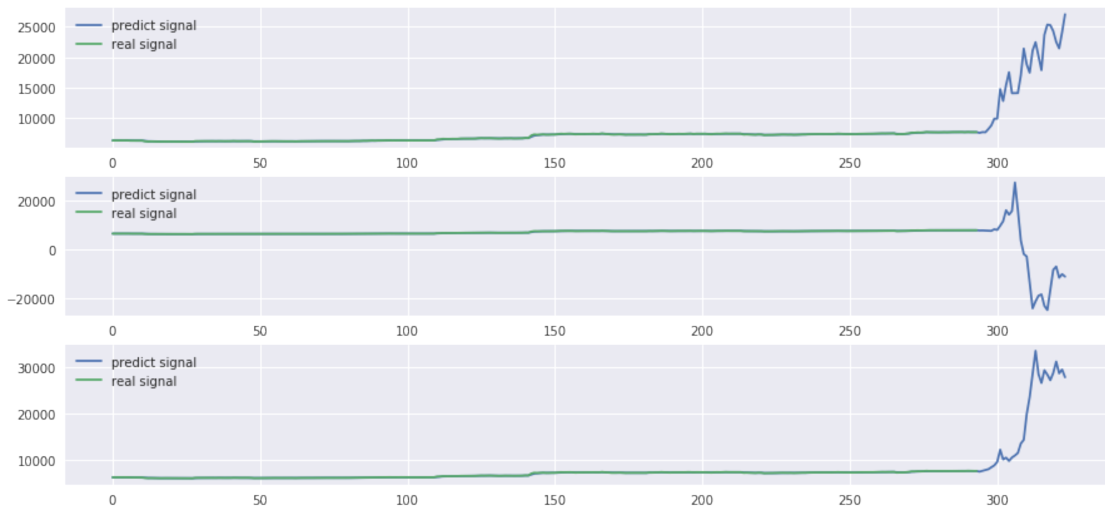
```
[44]: scaled_polarity = (minmax.data_min_[0] / 4 - minmax.data_min_[0]) / (
    minmax.data_max_[0] - minmax.data_min_[0]
)
scaled_polarity
```

```
[44]: -0.46492252401914214
```

```
[49]: plt.figure(figsize = (15, 7))

for retry in range(3):
    plt.subplot(3, 1, retry + 1)
```

```
    predict_30 = predict_future(
        30, df_scaled, dates, indices = {0: scaled_polarity}
    )
    predict_30['df'] = minmax.inverse_transform(predict_30['df'])
    plt.plot(
        np.arange(len(predict_30['date_ori'])),
        anchor(predict_30['df'][:, -1], 0.5),
        label = 'predict signal',
    )
    plt.plot(np.arange(len(signal)), signal, label = 'real signal')
    plt.legend()
plt.show()
```



The second graph is skewed, but we got 2 graphs represented positive trends

As you can see, the model learnt that, polarity gives negative correlation to the model. If polarity is increase, the trend is decreasing, vice versa

What happen if sentiment volume is double from the max? Volume is third index

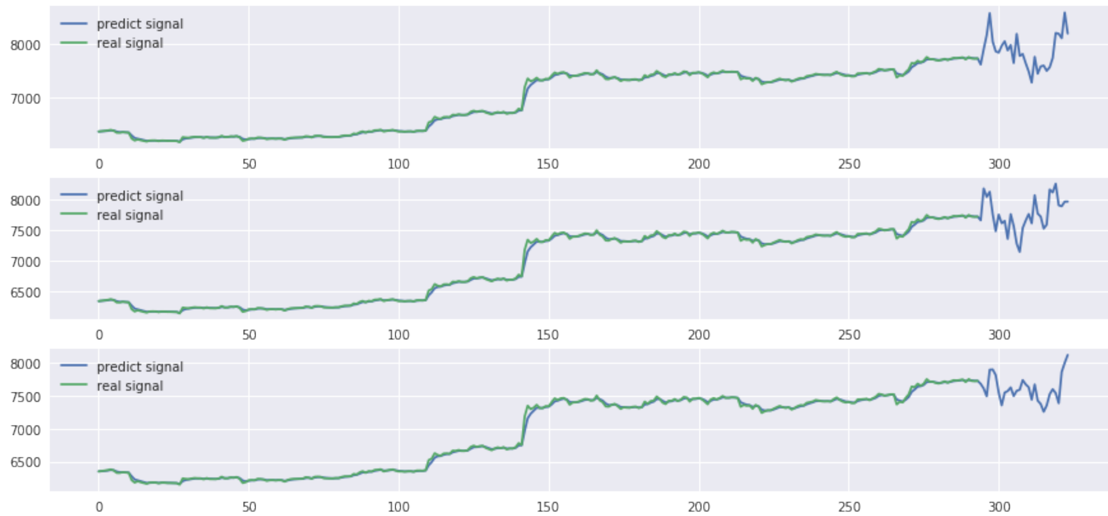
[39]:
```
scaled_volume = (minmax.data_max_[2] * 2 - minmax.data_min_[2]) / (
    minmax.data_max_[2] - minmax.data_min_[2]
)
scaled_volume
```

[39]: 2.4022001609873893

[40]:
```
plt.figure(figsize = (15, 7))

for retry in range(3):
    plt.subplot(3, 1, retry + 1)
```

```
    predict_30 = predict_future(
        30, df_scaled, dates, indices = {2: scaled_volume}
    )
    predict_30['df'] = minmax.inverse_transform(predict_30['df'])
    plt.plot(
        np.arange(len(predict_30['date_ori'])),
        anchor(predict_30['df'][:, -1], 0.5),
        label = 'predict signal',
    )
    plt.plot(np.arange(len(signal)), signal, label = 'real signal')
    plt.legend()
plt.show()
```



What happen if sentiment volume is double from the min? Volume is third index

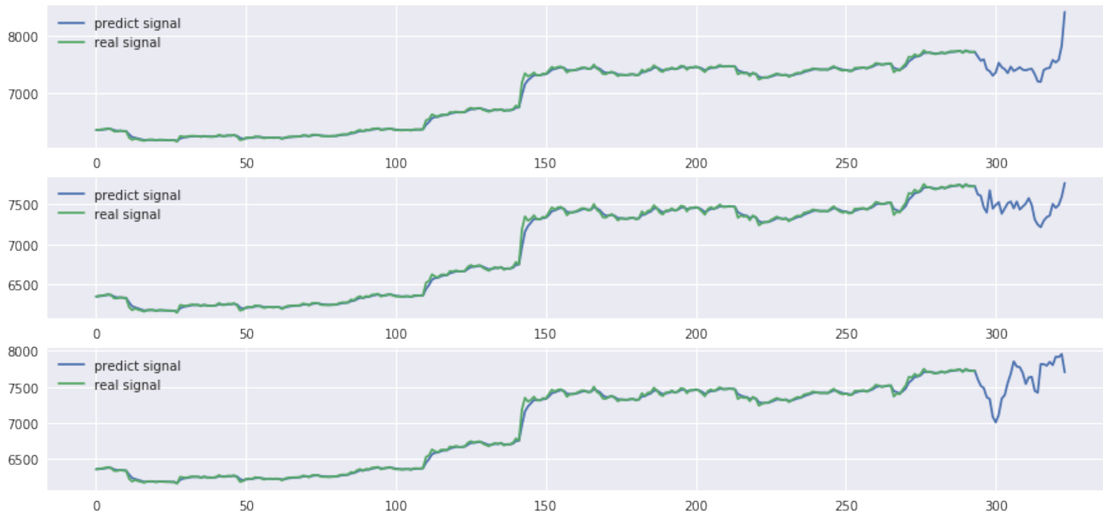
[51]:
```
scaled_volume = (minmax.data_min_[2] / 2 - minmax.data_min_[2]) / (
    minmax.data_max_[2] - minmax.data_min_[2]
)
scaled_volume
```

[51]: -0.20110008049369466

[53]:
```
plt.figure(figsize = (15, 7))

for retry in range(3):
    plt.subplot(3, 1, retry + 1)
    predict_30 = predict_future(
        30, df_scaled, dates, indices = {2: scaled_volume}
    )
    predict_30['df'] = minmax.inverse_transform(predict_30['df'])
```

```
    plt.plot(
        np.arange(len(predict_30['date_ori'])),
        anchor(predict_30['df'][:, -1], 0.5),
        label = 'predict signal',
    )
    plt.plot(np.arange(len(signal)), signal, label = 'real signal')
    plt.legend()
plt.show()
```



As you can see, volume does not brings any impact the learning so much

```
[ ]:
```