Yicheng_Wang_FinalProject_LSTM

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1 Using News to Predict Stock Movements

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2 Abstract

Using machine learning techniques - LSTM model, I will predict the direction of next market-residualized returns from news data about news articles/alerts published about assets, such as article details, sentiment, and other commentary. Then, I will use this direction to trade by building a long short portfolio that long the predicted positive return stocks and short the predicted negative return stocks rolling in the test period.

Note: this project uses data that can only be used internally in Kaggle, so it cannot run locally.

Source: https://www.kaggle.com/c/two-sigma-financial-news

3 Data

```
In [1]: from kaggle.competitions import twosigmanews
        # You can only call make_env() once, so don't lose it!
        env = twosigmanews.make_env()
```

```
Loading the data... This could take a minute.
Done!
```

```
In [4]: import numpy as np
        import pandas as pd
        import talib
        import time
        from datetime import datetime

        import matplotlib.pyplot as plt
        import plotly.offline as py
        py.init_notebook_mode(connected=True)
```

```
import plotly.graph_objs as go
import plotly.tools as tls

from wordcloud import WordCloud
from nltk.corpus import stopwords
stop = set(stopwords.words('english'))
%matplotlib inline
```

```
In [6]: # DataFrames contain all market and news data from February 2007 to December 2016
        (market_train_df, news_train_df) = env.get_training_data()
```

```
In [7]: market_train_df['date_market'] = market_train_df.time.dt.date  # time to date
        news_train_df['date_news'] = news_train_df.time.dt.date  # time to date
```

```
In [8]: sp500 = pd.read_csv("../input/sp500/data.csv", index_col=0, parse_dates=True)
```

4 Exploratory Data Analysis

4.1 Market Data

4.1.1 Technical indicators

```
In [9]: # momentum indicators: MACD, RSI, MOM
        market_train_df['macd'] = market_train_df.groupby(
            ['assetCode']).apply(lambda x: talib.MACD(x['close'])[0]
                                ).reset_index().set_index('level_1')[0]
        market_train_df['rsi'] = market_train_df.groupby(
            ['assetCode']).apply(lambda x: talib.RSI(x['close'])
                                ).reset_index().set_index('level_1')[0]
        market_train_df['mom'] = market_train_df.groupby(
            ['assetCode']).apply(lambda x: talib.MOM(x['close'])
                                ).reset_index().set_index('level_1')[0]
        # volume indicator: OBV
        market_train_df['obv'] = market_train_df.groupby(
            ['assetCode']).apply(lambda x: talib.OBV(x['close'], x['volume'])
                                ).reset_index().set_index('level_1')[0]
```

```
In [10]: # standard deviations, sum of volumes
         market_train_df['close_std10'] = market_train_df.groupby(
             ['assetName'])['close'].rolling(10).std().reset_index().set_index('level_1')['clos
         market_train_df['volume_sum10'] = market_train_df.groupby(
             ['assetName'])['volume'].rolling(10).sum().reset_index().set_index('level_1')['vol
```

```
In [11]: print('{} samples, {} assets, and {} features in the training news dataset.'.format(
             market_train_df.shape[0], len(market_train_df['assetName'].unique()),
             market_train_df.shape[1]))
```

```
4072956 samples, 3511 assets, and 23 features in the training news dataset.
```

```
In [12]: market_train_df.columns
```

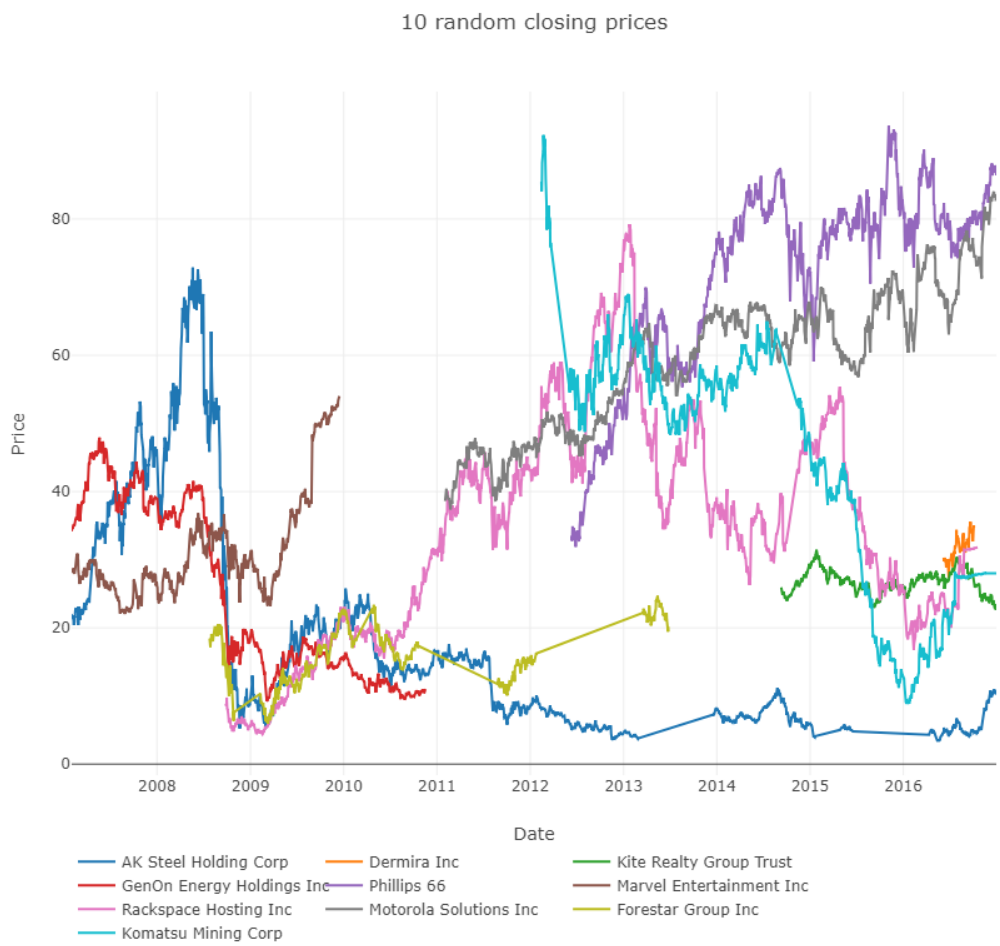
```
Out[12]: Index(['time', 'assetCode', 'assetName', 'volume', 'close', 'open',
                'returnsClosePrevRaw1', 'returnsOpenPrevRaw1',
                'returnsClosePrevMktres1', 'returnsOpenPrevMktres1',
                'returnsClosePrevRaw10', 'returnsOpenPrevRaw10',
                'returnsClosePrevMktres10', 'returnsOpenPrevMktres10',
                'returnsOpenNextMktres10', 'universe', 'date_market', 'macd', 'rsi',
                'mom', 'obv', 'close_std10', 'volume_sum10'],
               dtype='object')
```

4.1.2 Visualization

```
In [ ]: data = []
        for stk in np.random.choice(market_train_df['assetName'].unique(), 10):
            stk_df = market_train_df[(market_train_df['assetName'] == stk)]

            data.append(go.Scatter(
                                    x = stk_df['time'].dt.strftime(date_format='%Y-%m-%d').values,
                                    y = stk_df['close'].values,
                                    name = stk)
                       )

        layout = go.Layout(dict(title = "10 random closing prices",
                                xaxis = dict(title = 'Date'),
                                yaxis = dict(title = 'Price'),
                               ),
                           legend=dict(orientation="h")
                          )

        py.iplot(dict(data=data, layout=layout))
```

```
In [2]: from IPython.display import Image
        Image(filename = "newplot3.png", width=800, height=800)
```

```
Out[2]:
```

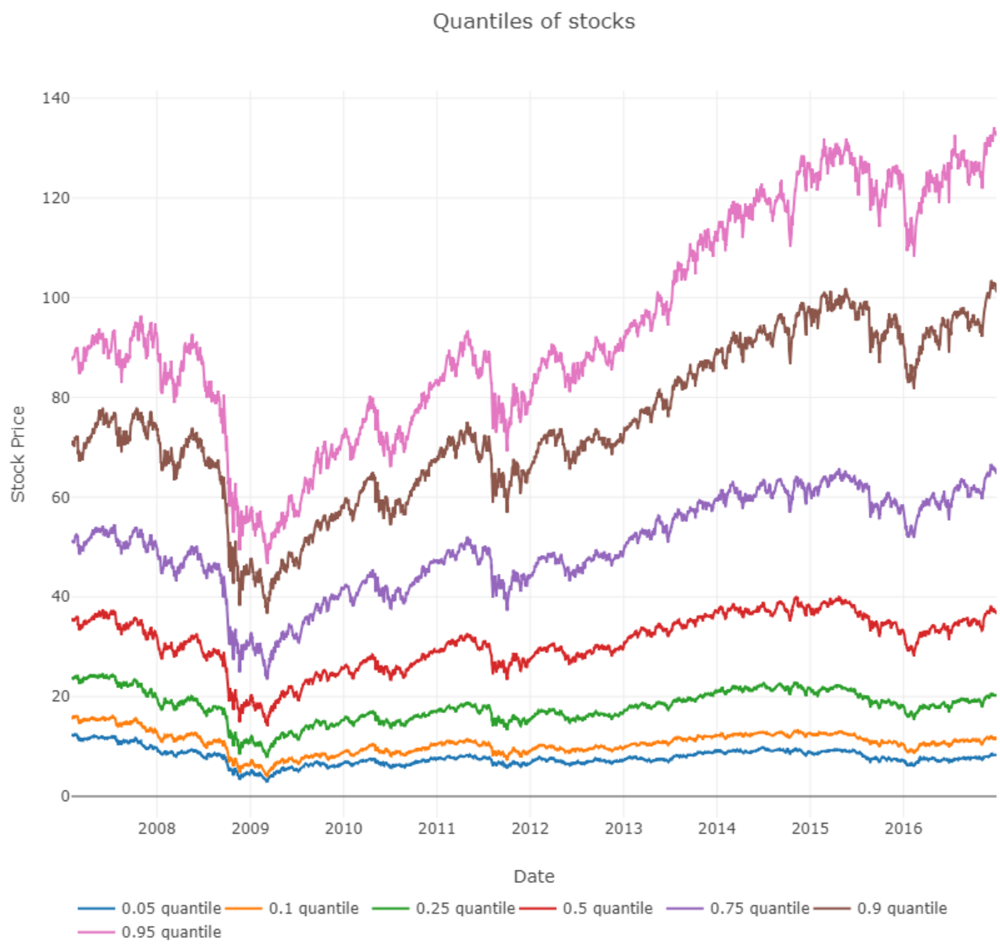



```
In [ ]: data = []
        for i in [0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95]:
            price_df = market_train_df.groupby('time')['close'].quantile(i).reset_index()

            data.append(go.Scatter(
                x = price_df['time'].dt.strftime(date_format='%Y-%m-%d').values,
                y = price_df['close'].values,
                name = f'{i} quantile'
            ))

        layout = go.Layout(dict(title = "Quantiles of stocks",
                                xaxis = dict(title = 'Date'),
                                yaxis = dict(title = 'Stock Price'),
                                   ),
                               legend=dict(orientation="h")
                              )
```

```
        py.iplot(dict(data=data, layout=layout))
```

```
In [30]: Image(filename = "newplot2.png", width=800, height=800)
```

Out[30]:

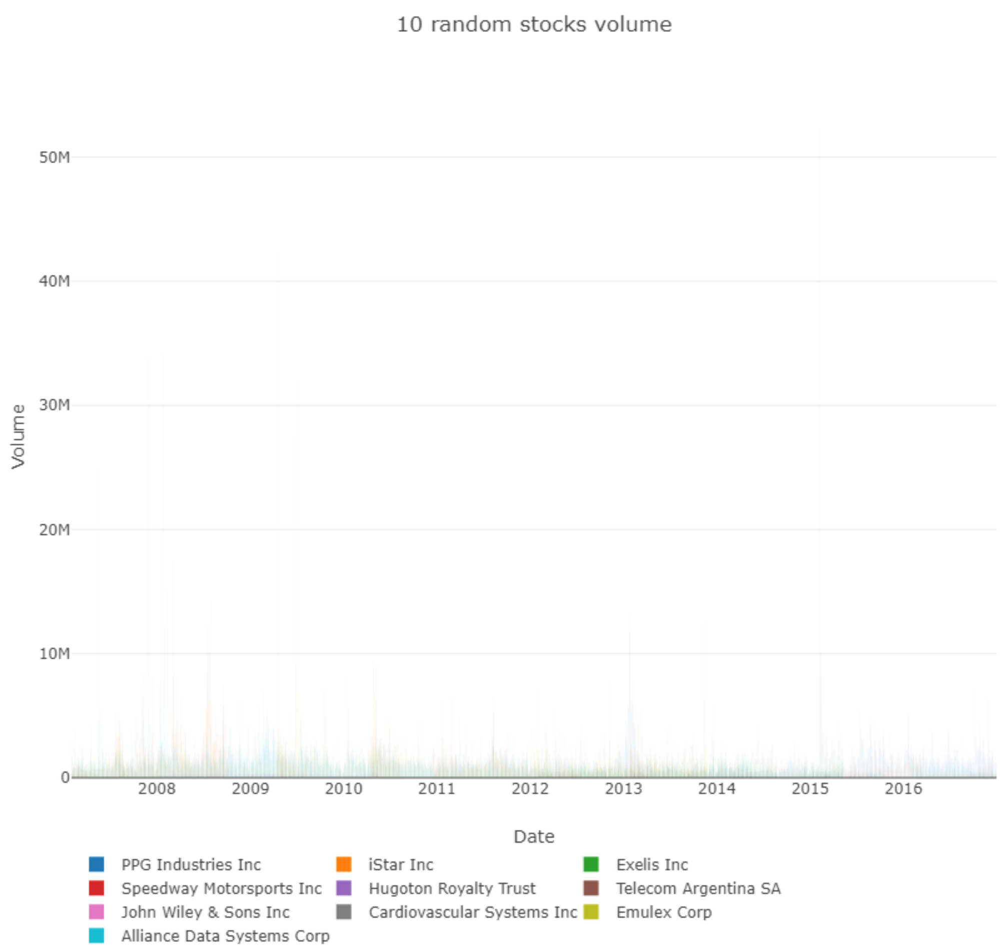



```
In [ ]: data = []
        for stk in np.random.choice(market_train_df['assetName'].unique(), 10):
            stk_df = market_train_df[(market_train_df['assetName'] == stk)]

            data.append(go.Bar(
                                        x = stk_df['time'].dt.strftime(date_format='%Y-%m-%d').values,
                                        y = stk_df['volume'].values,
                                        name = stk)
                           )
```

```
    layout = go.Layout(dict(title = "10 random stocks volume",
                            xaxis = dict(title = 'Date'),
                            yaxis = dict(title = 'Volume'),
                           ),
                       legend=dict(orientation="h")
                      )

    py.iplot(dict(data=data, layout=layout))
    del data
```

In [29]: `Image(filename = "newplot1.png", width=800, height=800)`

Out[29]:



We get some extremely high stock activities in 2008-2009 and 2015.

In [16]: `market_train_df.describe()`

```
Out[16]:              volume         close      ...      close_std10   volume_sum10
         count  4.072956e+06  4.072956e+06      ...     4.041732e+06   4.041732e+06
         mean   2.665312e+06  3.971241e+01      ...     1.146128e+00   2.674124e+07
         std    7.687606e+06  4.228822e+01      ...     2.454329e+00   7.034922e+07
         min    0.000000e+00  7.000000e-02      ...     0.000000e+00   1.020000e+04
         25%    4.657968e+05  1.725000e+01      ...     3.620313e-01   5.246970e+06
         50%    9.821000e+05  3.030000e+01      ...     6.570380e-01   1.056597e+07
         75%    2.403165e+06  4.986000e+01      ...     1.181694e+00   2.496402e+07
         max    1.226791e+09  1.578130e+03      ...     3.909133e+02   6.663201e+09

         [8 rows x 19 columns]
```

4.2 News Data

```
In [17]: print('{} samples, {} assets, and {} features in the training news dataset.'.format(
             news_train_df.shape[0], len(news_train_df['assetName'].unique()), news_train_df.sh
```

```
9328750 samples, 8902 assets, and 36 features in the training news dataset.
```

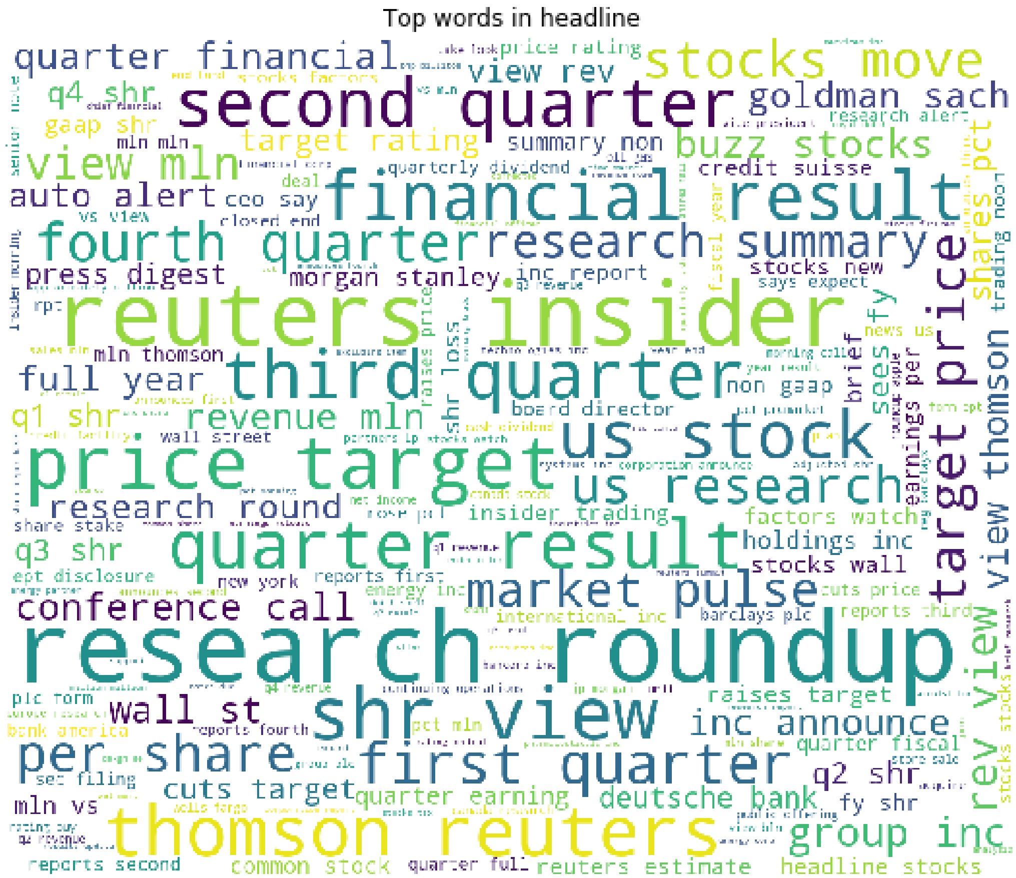
```
In [18]: news_train_df.drop(['sourceTimestamp', 'firstCreated', 'sourceId',
                              'provider', 'takeSequence', 'subjects',
                             'audiences'], axis=1, inplace=True)
```

```
In [19]: # transform to asset codes to only first one
         news_train_df['assetCodes'] = news_train_df['assetCodes'].map(lambda x: list(eval(x))
```

4.2.1 Headline

headline(object) - the item's headline
headlineTag(object) - the Thomson Reuters headline tag for the news item

```
In [20]: text = ' '.join(np.random.choice(news_train_df['headline'].str.lower().values, 100000
         wordcloud = WordCloud(max_font_size=None, stopwords=stop, background_color='white',
                               width=1200, height=1000).generate(text)
         plt.figure(figsize=(12, 8))
         plt.imshow(wordcloud)
         plt.title('Top words in headline')
         plt.axis("off")
         plt.show()
         del text, wordcloud
```

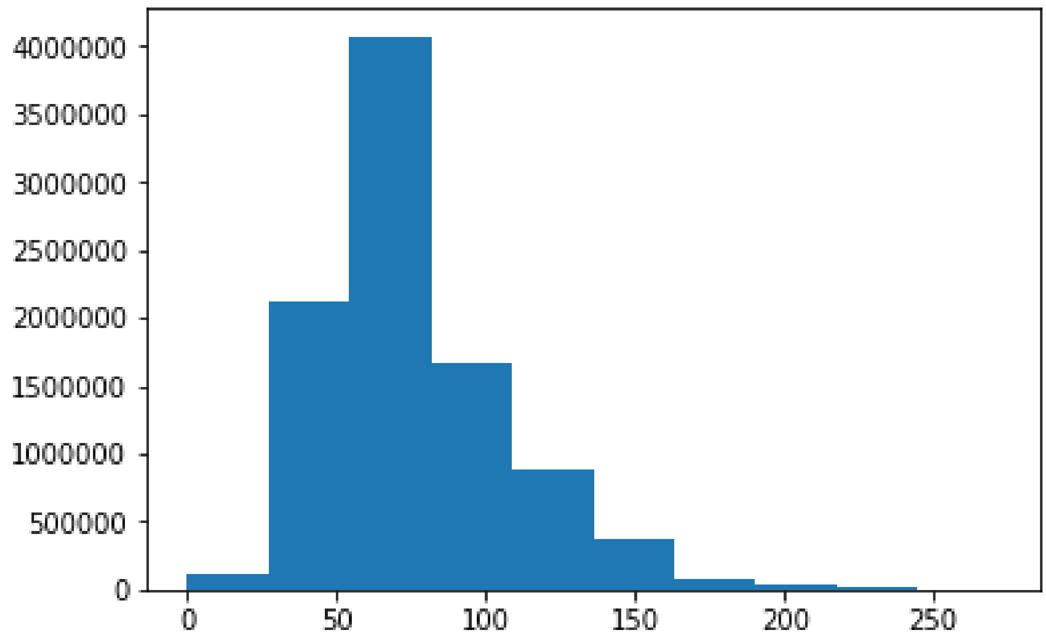


Top occurring words are 'reuters' (since news data are from thomson reuters), 'research', 'roundup', 'financial', 'result', 'quarter', 'target', 'view' ... showing these news are reporting facts and giving views about the company.

```
In [21]: # length of headline: integer
         news_train_df['headline_length'] = np.vectorize(len)(news_train_df['headline'])
```

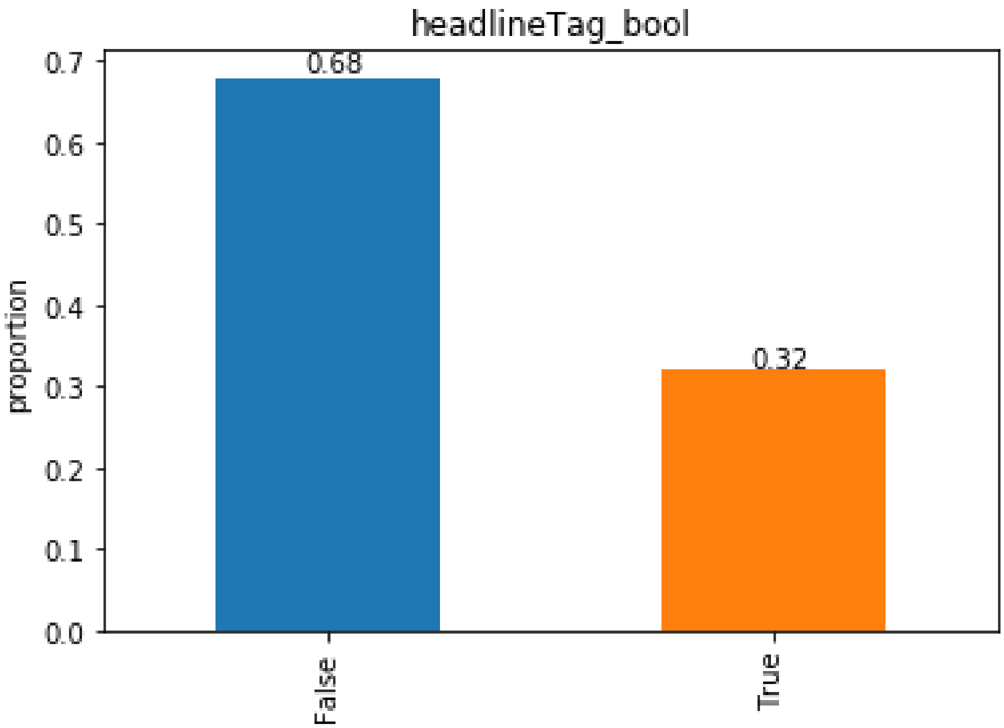
```
In [22]: plt.hist(news_train_df['headline_length'])
```

```
Out[22]: (array([1.046720e+05, 2.116444e+06, 4.071293e+06, 1.672903e+06,
                 8.783550e+05, 3.717980e+05, 7.174800e+04, 2.569700e+04,
                 1.461800e+04, 1.222000e+03]),
          array([  0. ,  27.2,  54.4,  81.6, 108.8, 136. , 163.2, 190.4, 217.6,
                 244.8, 272. ]),
          <a list of 10 Patch objects>)
```



Most headlines have length about 50-100 words.

```
In [23]: # headline tag: string -> categorical
         tag_label = {k: v for v, k in enumerate(news_train_df['headlineTag'].unique())}
         news_train_df['headlineTag'] = news_train_df['headlineTag'].map(tag_label)
         del tag_label

In [24]: # if there is headline tag: boolean
         news_train_df['headlineTag_bool'] = (news_train_df['headlineTag'] > 0)

In [25]: def plot_class_hist(prob_list):
             ax = prob_list.plot('bar')
             ax.set_title(prob_list.name)
             ax.set_ylabel('proportion')
             for p in ax.patches:
                 ax.annotate(str(round(p.get_height(),3)), (p.get_x() + 0.2, p.get_height() * 
             plt.show()

In [26]: headlineTag_bool = news_train_df['headlineTag_bool'].value_counts() / len(news_train_
         plot_class_hist(headlineTag_bool)
         del headlineTag_bool
```



A larger proportion of the news don't have headline tags.

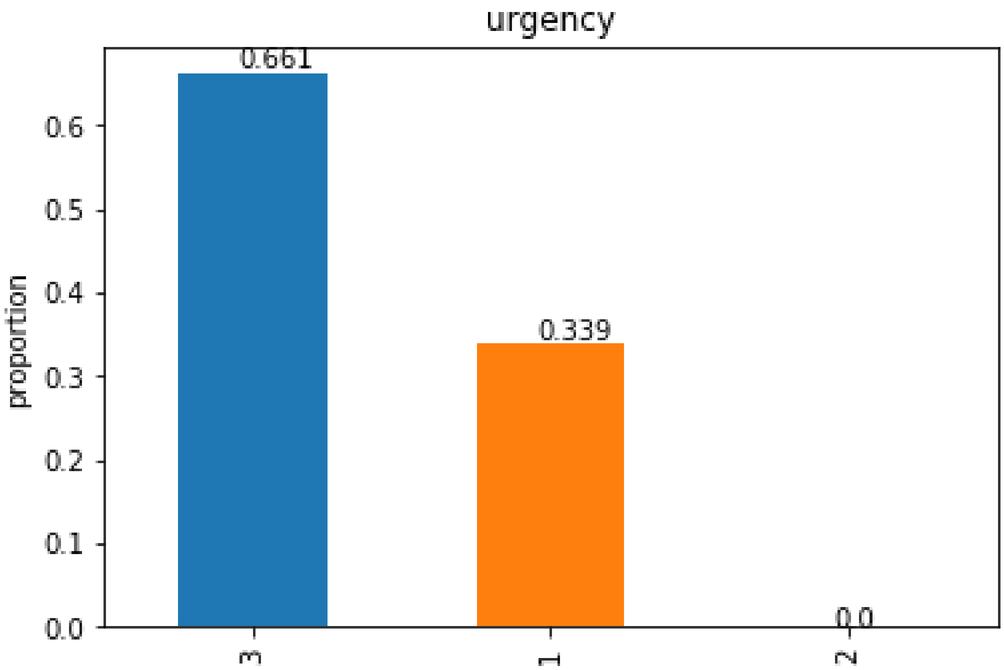
4.2.2 Urgency

urgency(int8) - differentiates story types (1: alert, 3: article)

firstMentionSentence(int16) - the first sentence, starting with the headline, in which the scored asset is mentioned.
1: headline
2: first sentence of the story body
3: second sentence of the body, etc
0: the asset being scored was not found in the news item's headline or body text. As a result, the entire news item's text (headline + body) will be used to determine the sentiment score.

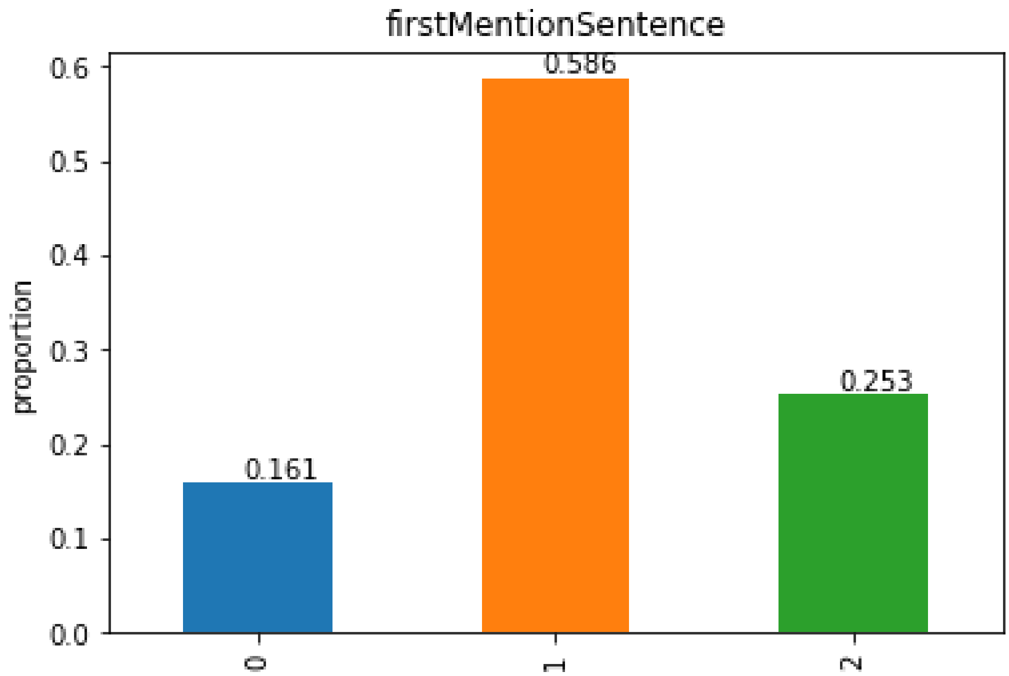
relevance(float32) - a decimal number indicating the relevance of the news item to the asset. It ranges from 0 to 1. If the asset is mentioned in the headline, the relevance is set to 1. When the item is an alert (urgency == 1), relevance should be gauged by firstMentionSentence instead.

```
In [27]: # 3 levels of news urgency: categorical
         urgency = news_train_df['urgency'].value_counts() / len(news_train_df)
         plot_class_hist(urgency)
         del urgency
```



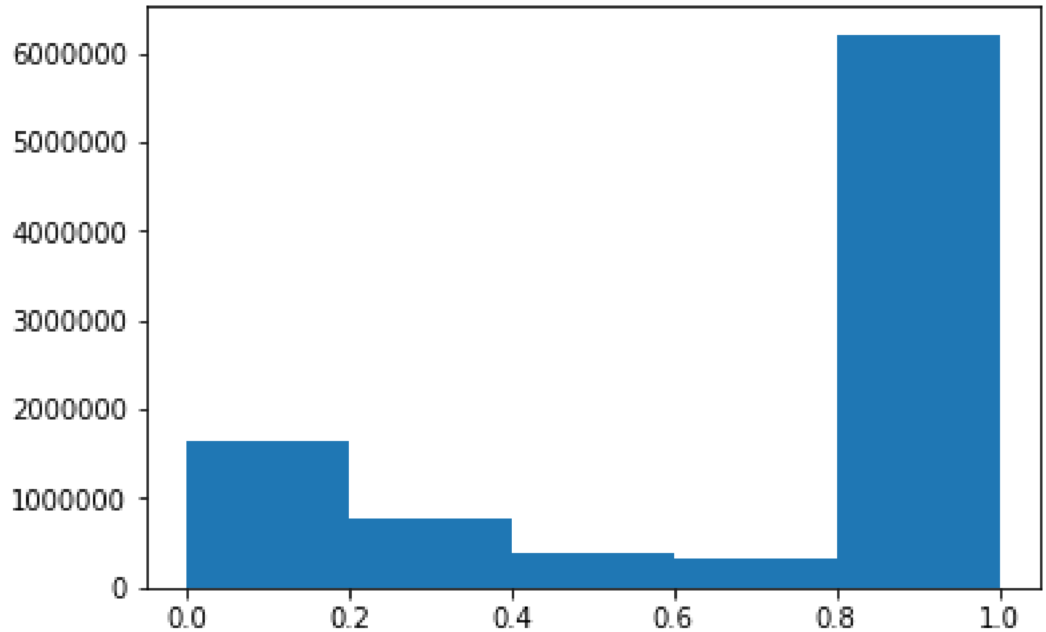
34% of news are alerts.

```
In [28]: # position of first mentioning of company name: int
         firstMentionSentence = pd.Series([
             len(news_train_df[news_train_df['firstMentionSentence'] ==0]) / len(news_train_df
             len(news_train_df[news_train_df['firstMentionSentence'] ==1]) / len(news_train_df
             len(news_train_df[news_train_df['firstMentionSentence'] >=2]) / len(news_train_df
             name = 'firstMentionSentence')
         plot_class_hist(firstMentionSentence)
         del firstMentionSentence
```



16% of news have company name in the headline, 59% are in the first sentence, while the rest are in the following sentences.

```
In [29]: # float
         plt.hist(news_train_df['relevance'], bins=5)

Out[29]: (array([1646521.,  775002.,  389218.,  311429., 6206580.]),
          array([0.0012584 , 0.20100673, 0.40075505, 0.6005034 , 0.80025166,
                 1.        ], dtype=float32),
          <a list of 5 Patch objects>)
```



A great proportion of news are very urgent, while there are still a good proportion are very little relevent to the company itself.

4.2.3 bodySize

bodySize(int32) - the size of the current version of the story body in characters
companyCount(int8) - the number of companies explicitly listed in the news item in the subjects field
sentenceCount(int16) - the total number of sentences in the news item. Can be used in conjunction with firstMentionSentence to determine the relative position of the first mention in the item.
wordCount(int32) - the total number of lexical tokens (words and punctuation) in the news item

```
In [30]: news_train_df['word_per_sentence'] = news_train_df['wordCount'] / news_train_df['sente
```

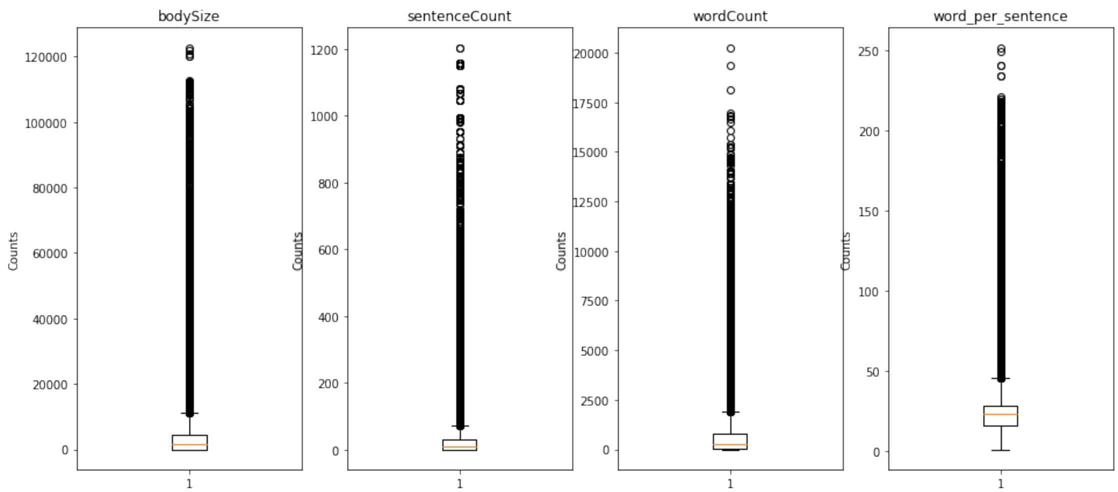
```
In [31]: # integers
         news_train_df[['bodySize', 'companyCount', 'sentenceCount', 'wordCount',
                        'word_per_sentence']].describe()
```

```
Out[31]:            bodySize        ...         word_per_sentence
         count   9.328750e+06       ...              9.328750e+06
         mean    3.768918e+03       ...              2.315733e+01
         std     7.475653e+03       ...              9.928620e+00
         min     0.000000e+00       ...              1.000000e+00
         25%     0.000000e+00       ...              1.620000e+01
         50%     1.571000e+03       ...              2.308333e+01
         75%     4.504000e+03       ...              2.785714e+01
         max     1.227700e+05       ...              2.516923e+02
```

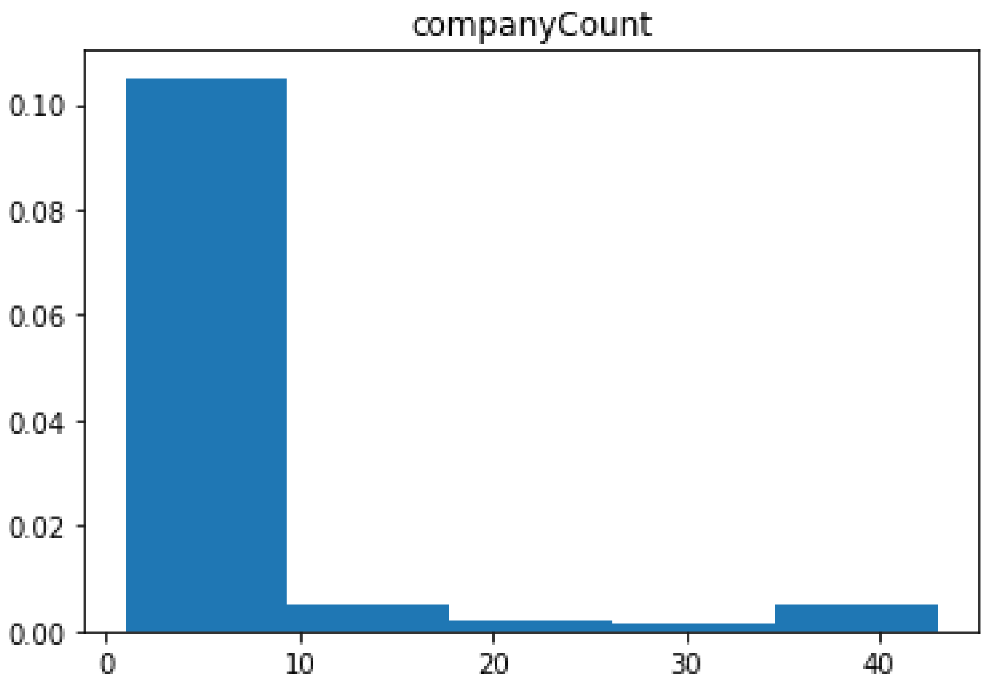
```
[8 rows x 5 columns]
```

On average company name occurs 5 times in the news, with a average size of 580 words.

```
In [32]: fig, ax = plt.subplots(1,4, figsize=(16,7))
         i = 0
         for n in ['bodySize', 'sentenceCount', 'wordCount', 'word_per_sentence']:
             ax[i].boxplot(news_train_df[n])
             ax[i].set_title(n)
             ax[i].set_ylabel('Counts')
             i += 1
```




```
In [33]: plt.title('companyCount')
         plt.hist(news_train_df['companyCount'], bins=5, density=True)

Out[33]: (array([0.10498829, 0.00521244, 0.00203631, 0.00165101, 0.00515956]),
          array([ 1. ,  9.4, 17.8, 26.2, 34.6, 43. ]),
          <a list of 5 Patch objects>)
```



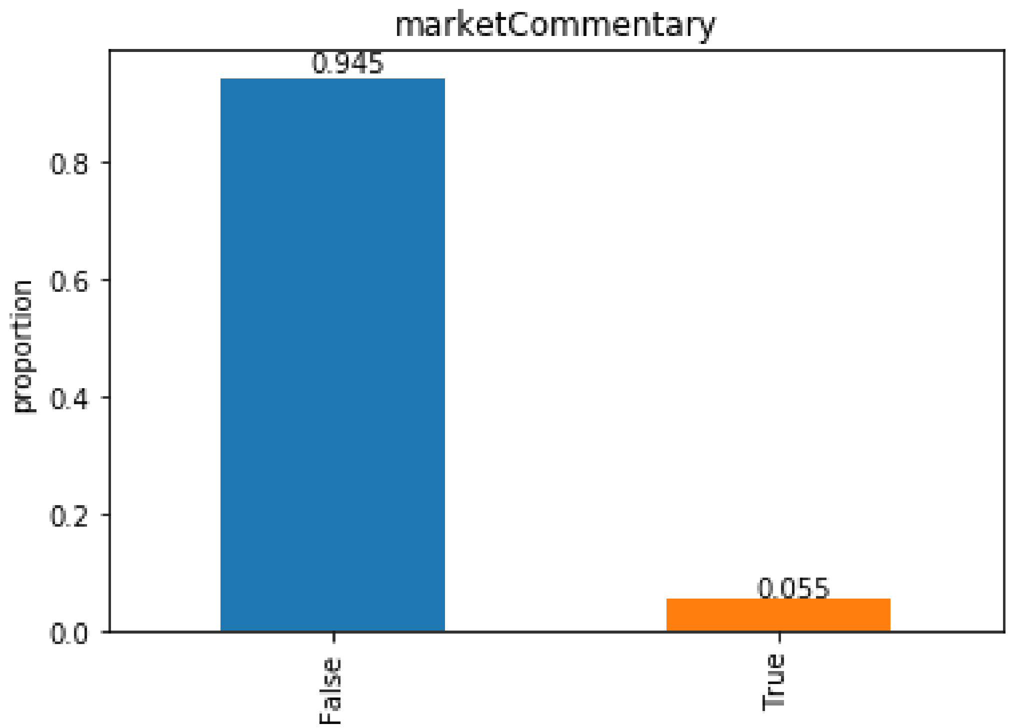
4.2.4 SentimentClass

marketCommentary(bool) - boolean indicator that the item is discussing general market conditions, such as "After the Bell" summaries.

sentimentClass(int8) - indicates the predominant sentiment class for this news item with respect to the asset. The indicated class is the one with the highest probability.
sentimentNegative(float32) - probability that the sentiment of the news item was negative for the asset
sentimentNeutral(float32) - probability that the sentiment of the news item was neutral for the asset
sentimentPositive(float32) - probability that the sentiment of the news item was positive for the asset

sentimentWordCount(int32) - the number of lexical tokens in the sections of the item text that are deemed relevant to the asset. This can be used in conjunction with wordCount to determine the proportion of the news item discussing the asset.

```
In [34]: # boolean
         plot_class_hist(news_train_df['marketCommentary'].value_counts() / len(news_train_df)
```



Most(94.5%) of news didn't give market commentary about the company.

In [35]:
```
news_train_df.loc[:,'sentimentClass':'sentimentPositive'].head()
```

Out[35]:
```
   sentimentClass        ...          sentimentPositive
0              -1        ...                   0.079934
1              -1        ...                   0.054064
2              -1        ...                   0.254280
3              -1        ...                   0.084368
4              -1        ...                   0.091366

[5 rows x 4 columns]
```

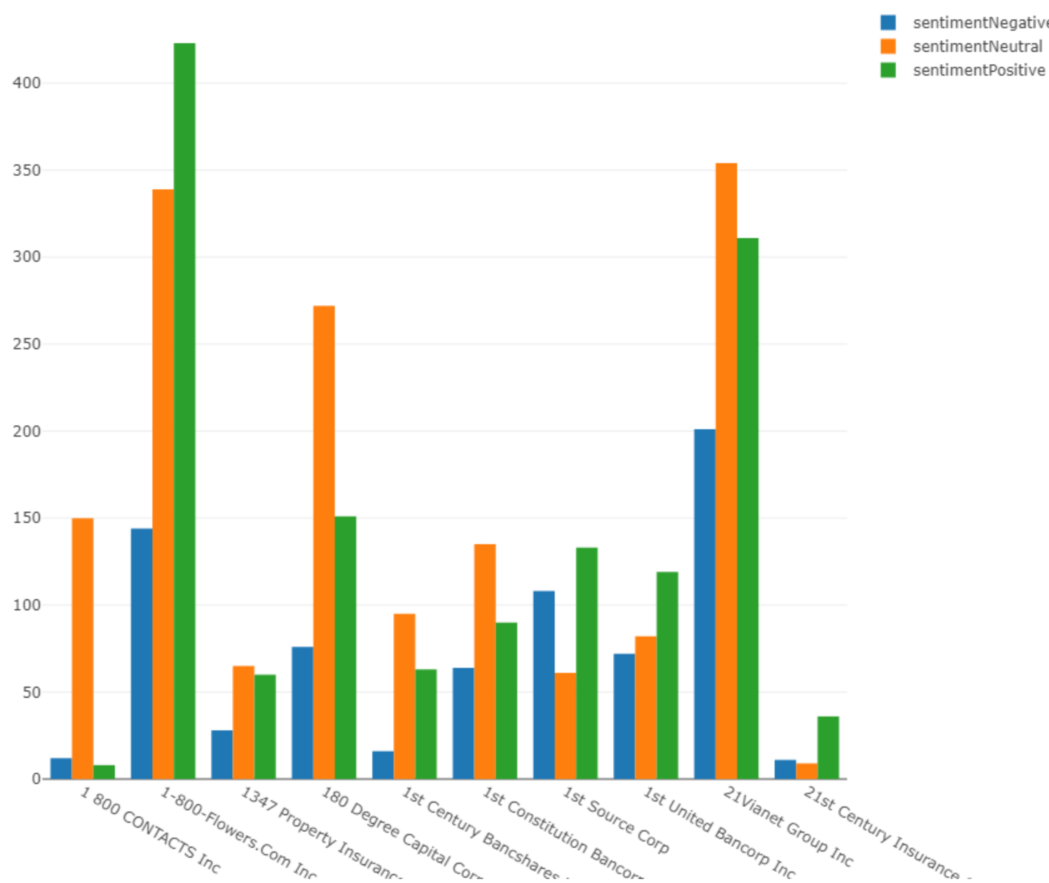
In [36]:
```
news_sentiment = news_train_df.groupby(
    ["assetName"]).apply(
    lambda x: x['sentimentClass'].value_counts())
# news_sentiment = news_sentiment.set_index(['assetName','level_1'])
news_sentiment = news_sentiment.unstack(level=-1)
```

In [ ]:
```
trace0 = go.Bar(
    x=news_sentiment.index[:10],
    y=news_sentiment.iloc[:,0][:10],
    name='sentimentNegative',
)
trace1 = go.Bar(
```

```
    x=news_sentiment.index[:10],
    y=news_sentiment.iloc[:,1][:10],
    name='sentimentNeutral',
)
trace2 = go.Bar(
    x=news_sentiment.index[:10],
    y=news_sentiment.iloc[:,2][:10],
    name='sentimentPositive',
)

data = [trace0, trace1, trace2]

py.iplot(dict(data=data))
del news_sentiment
```

In [3]:
```
Image(filename = "newplot4.png", width=800, height=800)
```

Out[3]:



```
In [38]: for i, j in zip([-1, 0, 1], ['negative', 'neutral', 'positive']):
             df_sentiment = news_train_df.loc[news_train_df['sentimentClass'] == i, 'assetName
             print('Top mentioned companies for {} sentiment are:'.format(j))
             print(df_sentiment.value_counts().head(5))
             print('')
```

```
Top mentioned companies for negative sentiment are:
Citigroup Inc              30823
JPMorgan Chase & Co        29129
Bank of America Corp       28197
Apple Inc                  26702
Goldman Sachs Group Inc    25044
Name: assetName, dtype: int64

Top mentioned companies for neutral sentiment are:
Barclays PLC         24898
HSBC Holdings PLC    23191
Deutsche Bank AG     20702
BHP Billiton PLC     18019
Rio Tinto PLC        16782
Name: assetName, dtype: int64

Top mentioned companies for positive sentiment are:
Barclays PLC              22855
Apple Inc                 22770
General Electric Co       20055
Royal Dutch Shell PLC     18206
Citigroup Inc             18025
Name: assetName, dtype: int64
```

4.2.5 noveltyCount

noveltyCount12H(int16) - The 12 hour novelty of the content within a news item on a particular asset. It is calculated by comparing it with the asset-specific text over a cache of previous news items that contain the asset.
noveltyCount24H(int16) - same as above, but for 24 hours
noveltyCount3D(int16) - same as above, but for 3 days
noveltyCount5D(int16) - same as above, but for 5 days
noveltyCount7D(int16) - same as above, but for 7 days

```
In [39]: news_train_df.loc[:,'noveltyCount12H':'noveltyCount7D'].describe()
```

```
Out[39]:        noveltyCount12H       ...        noveltyCount7D
         count     9.328750e+06       ...          9.328750e+06
         mean      1.385130e+00       ...          3.170360e+00
         std       8.220864e+00       ...          1.657174e+01
         min       0.000000e+00       ...          0.000000e+00
```

```
25%        0.000000e+00       ...          0.000000e+00
50%        0.000000e+00       ...          0.000000e+00
75%        2.000000e+00       ...          2.000000e+00
max        5.000000e+02       ...          5.000000e+02

[8 rows x 5 columns]
```

4.2.6 VolumeCounts

volumeCounts12H(int16) - the 12 hour volume of news for each asset. A cache of previous news items is maintained and the number of news items that mention the asset within each of five historical periods is calculated.
volumeCounts24H(int16) - same as above, but for 24 hours
volumeCounts3D(int16) - same as above, but for 3 days
volumeCounts5D(int16) - same as above, but for 5 days
volumeCounts7D(int16) - same as above, but for 7 days

```
In [40]: news_train_df.loc[:,'volumeCounts12H':'volumeCounts7D'].head()
```

```
Out[40]:    volumeCounts12H       ...         volumeCounts7D
         0                0       ...                      7
         1                1       ...                      3
         2                0       ...                     17
         3                0       ...                     15
         4                0       ...                      0

         [5 rows x 5 columns]
```

```
In [41]: news_train_df.loc[:,'volumeCounts12H':'volumeCounts7D'].describe()
```

```
Out[41]:        volumeCounts12H       ...         volumeCounts7D
         count     9.328750e+06       ...           9.328750e+06
         mean      8.522672e+00       ...           4.050544e+01
         std       2.930322e+01       ...           8.948574e+01
         min       0.000000e+00       ...           0.000000e+00
         25%       1.000000e+00       ...           4.000000e+00
         50%       4.000000e+00       ...           1.300000e+01
         75%       9.000000e+00       ...           4.100000e+01
         max       2.564000e+03       ...           2.974000e+03

         [8 rows x 5 columns]
```

5 Data Preparation

calculate sum or average factor values for stocks by day
combine market and news dataframes

```
In [42]: # prepare news dataframe
         news_df = news_train_df.groupby(['assetCodes', 'date_news'], as_index=False).agg({
```

```
        'urgency': 'mean',  # (1,2,3) average urgency of all news in that day
        'bodySize': 'sum',  # total body size for all news in that day for the asset
        'companyCount': 'sum',
        'headlineTag': 'sum',
        'marketCommentary': 'mean',  # (0-1) more market commentary in that day, closer t
        'sentenceCount': 'sum',
        'wordCount': 'sum',
        'firstMentionSentence': 'mean',
        'relevance': 'mean',
        'sentimentNegative': 'mean',
        'sentimentNeutral': 'mean',
        'sentimentPositive': 'mean',
        'sentimentWordCount': 'sum',
        'headline_length': 'sum',
        'noveltyCount12H': 'mean',
        'noveltyCount24H': 'mean',
        'noveltyCount3D': 'mean',
        'noveltyCount5D': 'mean',
        'noveltyCount7D': 'mean',
        'volumeCounts12H': 'mean',
        'volumeCounts24H': 'mean',
        'volumeCounts3D': 'mean',
        'volumeCounts5D': 'mean',
        'volumeCounts7D': 'mean'
    })
```

In [43]:
```
def max_sentiment(x):
    if x['sentimentNegative'] > x['sentimentNeutral'] and x['sentimentNegative'] > x[
        return -1
    if x['sentimentPositive'] > x['sentimentNeutral'] and x['sentimentPositive'] > x[
        return 1
    else:
        return 0
```

In [44]:
```
news_df['word_per_sentence'] = news_df['wordCount'] / news_df['sentenceCount']
news_df['sentimentWordProportion'] = news_df[
    'sentimentWordCount'] / news_df['wordCount']
news_df['sentimentClass'] = news_df.apply(max_sentiment, axis=1)
```

In [45]:
```
# Combine data frames
df = pd.merge(market_train_df, news_df, how='left', left_on=['date_market', 'assetCode
              right_on=['date_news', 'assetCodes'])
df.dropna(axis=0, inplace=True)
df.drop(['date_news'], axis=1, inplace=True)
df.rename(columns={'date_market': 'date'}, inplace=True)
```

In [46]:
```
# binary value for y values
df['label'] = df.returnsOpenNextMktres10.map(lambda x: 0 if x < 0 else 1)
```

5.1 Handling Numerical and Categorical Variables

one hot encode categorical variable sentimentClass: -1, 0, 1
normalize numerical variables

In [47]:
```
encode_col = ['sentimentClass']
scale_col = ['volume', 'returnsClosePrevRaw1',
       'returnsOpenPrevRaw1', 'returnsClosePrevMktres1',
       'returnsOpenPrevMktres1', 'returnsClosePrevRaw10',
       'returnsOpenPrevRaw10', 'returnsClosePrevMktres10',
       'returnsOpenPrevMktres10', 'marketCommentary', 'relevance',
       'macd', 'rsi', 'mom', 'obv', 'close_std10',
       'volume_sum10', 'urgency', 'bodySize', 'companyCount',
       'headlineTag', 'sentenceCount', 'wordCount',
       'firstMentionSentence', 'sentimentWordCount',
       'headline_length', 'noveltyCount12H', 'noveltyCount24H',
       'noveltyCount3D', 'noveltyCount5D', 'noveltyCount7D', 'volumeCounts12H',
       'volumeCounts24H', 'volumeCounts3D', 'volumeCounts5D', 'volumeCounts7D',
       'word_per_sentence', 'sentimentWordProportion']
y_col = ['returnsOpenNextMktres10']
```

In [48]:
```
def encode_categorical(df, cat_cols):
    print('encoding categorical columns... Done')

    cat_encoded_df = pd.get_dummies(df[cat_cols[0]], prefix=cat_cols[0])
    return cat_encoded_df
```

In [49]:
```
from sklearn.preprocessing import StandardScaler

def scale_numerical(df, num_cols):
    print('scaling numerical columns... Done')

    scaler = StandardScaler()  # with mean 0 and variance 1
    df[num_cols] = scaler.fit_transform(df[num_cols])
```

In [50]:
```
cat_encoded_df = encode_categorical(df, encode_col)
cat_col = cat_encoded_df.columns
df = pd.concat([df, cat_encoded_df], axis=1)
scale_numerical(df, scale_col)
```

```
encoding categorical columns... Done
scaling numerical columns... Done


/opt/conda/lib/python3.6/site-packages/sklearn/preprocessing/data.py:625: DataConversionWarning

Data with input dtype float32, float64 were all converted to float64 by StandardScaler.

/opt/conda/lib/python3.6/site-packages/sklearn/base.py:462: DataConversionWarning:
```

```
Data with input dtype float32, float64 were all converted to float64 by StandardScaler.
```

```
In [51]: cat_col = list(cat_col)
         X_col = cat_col + scale_col
```

5.2 Split Train, Valid, Test datasets

Train & validation set: February 2007 to December 2015
Test set for trading: Jan 2016 to December 2016 (1 year)

```
In [52]: split_date = '2015-12-31 22:00:00+0000'
         train_set = df.loc[df['time'] <= split_date]
         test_set = df.loc[df['time'] > split_date]
         print('Splitting into training and testing ...Done')
```

```
Splitting into training and testing ...Done
```

```
In [53]: sp500 = sp500.loc[split_date:,:]
         sp500['return'] = sp500['S&P 500'].pct_change()
```

```
In [54]: split_date = '2015-03-02 22:00:00+0000'
         train_nn = train_set.loc[train_set.time < split_date, :]
         val_nn = train_set.loc[train_set.time >= split_date, :]
         print('Splitting into training and validation ...Done')
```

```
Splitting into training and validation ...Done
```

6 LSTM Network Modeling

6.1 LSTM

Long short-term memory (LSTM) units are units of a recurrent neural network (RNN). A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell.

LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with the exploding and vanishing gradient problems that can be encountered when training traditional RNNs. Relative insensitivity to gap length is an advantage of LSTM over RNNs, hidden Markov models and other sequence learning methods in numerous applications

6.2 Setting up Model

6.2.1 Input

(time window, feature) = (10, 41) for each stock for each day

6.2.2 Output

probability of positive 10-day residual return for each stock for each day

6.2.3 Speed up process

1. Normalize input (X)

2. Initialize weight, uses activation 'relu'

3. Using mini-batch gradient descent: 32, 64, 128...

4. Using 'adam' optimizer

5. Using batch normalization before activation
6. Uses early stopping

6.2.4 Hyperparameters

- batch size: 32(default), 64(compare)

- hidden units/layers: > 3 layers, [64, 16, 1] (default) seems reasonable with a starting 41 features, [128, 64, 16, 1] for comparison

- time window size: only use 10(default) because of memory issue

- epoch: 5 and early stop if not improving after 2 epoches, I tried 10 epoches and don't see improvements after first two epoches most of time
- loss: binary crossentropy, to classify positive or negative 10-day residual returns

Source: https://medium.com/machine-learning-bites/deeplearning-series-deep-neural-networks-tuning-and-optimization-39250ff7786d

```
In [55]: def load_data(data, window, data_name):
             print('Loading {} data for model, window length: {}'.format(data_name, window))

             X, y, d, r, u = [], [], [], [], []
             index_record = np.array([])
             groupby_obj = data.groupby(['assetCode'], sort=False)

             for _, data in groupby_obj:

                 data = data.sort_values(by=['date'])
                 num_sequences = data.shape[0] - window
```

```
            if num_sequences > 0:
                for seq in range(num_sequences):
                    index_record = np.append(index_record, data.index.values[seq+window-1]
                    # window days of X to predict one y
                    X.append(data[X_col].iloc[seq:seq+window].values)  # X: 2d arrays
                    y.append(data.label.iloc[seq+window-1])  # y binary: one point
                    d.append(data.date.iloc[seq+window-1])  # date
                    r.append(data.returnsOpenNextMktres10.iloc[seq+window-1])  # returns
                    u.append(data.universe.iloc[seq+window-1])  # universe

        # 1 feature
        X, y, d, r, u = np.array(X), np.array(y), np.array(d), np.array(r), np.array(u)

        print('                            ...Done')
        return X, y, d, r, u, index_record
```

In [56]:
```
from keras.models import Sequential
from keras.layers import Dense, BatchNormalization, LSTM, Activation
from keras.losses import binary_crossentropy

def build_model(layers, X_train):
    model = Sequential()

    # first layer
    model.add(BatchNormalization())
    model.add(LSTM(
        input_shape=(X_train.shape[1], X_train.shape[2]),  # first layer need input sh
        output_dim=layers[0],
        activation='relu',
        return_sequences=True))  # must return TRUE for input of next layer of LSTM

    for i in range(1, len(layers)-2):
        model.add(LSTM(
            output_dim = layers[i],  # output dimension
            activation='relu',
            return_sequences=True))  # must return TRUE for input of next layer of LS

    # second last layer
    model.add(LSTM(
        output_dim = layers[-2],  # output dimension
        activation='relu',
        return_sequences=False))

    # last layer
    model.add(Dense(
        output_dim=layers[-1],
        activation="sigmoid"))
```

```
        start = time.time()
        model.compile(optimizer='adam',loss=binary_crossentropy, metrics=['accuracy'])
        print("Model Compilation Time : ", time.time() - start)
        return model
```

```
Using TensorFlow backend.
```

```
In [57]: from keras.callbacks import EarlyStopping, ModelCheckpoint
         X_train, y_train, X_test, y_test = None, None, None, None
         data_loaded = False

         def run_model(layers=[64, 16, 1], epoch=5, batch=64, window=10):
             global X_train, y_train, X_test, y_test, data_loaded

             start = datetime.now()
             if len(layers) < 3:
                 print('>>> ERROR: at least 3 layers!!! Your layers: {}'.format(layers))
                 return

             print('>>> START RUNNING ...')
             print('>>> Building model, layers: {}'.format(layers))
             if not data_loaded:
                 data_loaded = True
                 X_train, y_train, _, _, _, _ = load_data(train_nn, window, 'train')
                 X_test, y_test, _, _, _, _ = load_data(val_nn, window, 'validation')
             lstm_model = build_model(layers, X_train)

             # fit on difference hyperparameter values
             print('>>> Fitting model, epoch: {}, batch size: {}'.format(epoch, batch))
             check_point = ModelCheckpoint('model.hdf5',verbose=True, save_best_only=True)
             early_stop = EarlyStopping(patience=2,verbose=True)
             lstm_model.fit(
                 X_train,
                 y_train,
                 epochs=epoch,
                 batch_size=batch,
                 validation_data=(X_test, y_test),
                 callbacks=[early_stop, check_point])

             # model prediction
             print('>>> Doing prediction ...')
             X_pred, y_pred, d_pred, r_pred, u_pred, index_pred = load_data(test_set, window,
             lstm_model.load_weights('model.hdf5')
             # store result: assetCode, date,
             pred_result = test_set.loc[index_pred, ['assetCode', 'date']]
             # > 0.5, predicted positive return, < 0.5, predicted negative return
```

```
        pred_result['pred_r'] = np.array([lstm_model.predict(
            X.reshape(1,X_pred.shape[1],X_pred.shape[2]))[0][0] for X in X_pred])
        pred_result['pred_y'] = (pred_result['pred_r'] * 2 - 1 > 0).astype(int)
        pred_result['actual_r'] = r_pred
        pred_result['actual_y'] = y_pred
        # whether the stock is tradable on that day
        pred_result['universe'] = u_pred

        print(lstm_model.summary())

        print(">>> Model Running Time : ", datetime.now() - start)
        print('*********************** Finished!!! ***********************')
        return pred_result
```

```
In [58]: result1 = run_model()
         result2 = run_model(layers=[64, 16, 1], epoch=5, batch=128)
         result3 = run_model(layers=[128, 64, 16, 1], epoch=5, batch=64)
```

```
>>> START RUNNING ...
>>> Building model, layers: [64, 16, 1]
Loading train data for model, window length: 10
                            ...Done
Loading validation data for model, window length: 10
                            ...Done
Model Compilation Time :  0.017302274703979492
>>> Fitting model, epoch: 5, batch size: 64


/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:14: UserWarning:

Update your `LSTM` call to the Keras 2 API: `LSTM(input_shape=(10, 41), activation="relu", retu

/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:26: UserWarning:

Update your `LSTM` call to the Keras 2 API: `LSTM(activation="relu", return_sequences=False, un

/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:31: UserWarning:

Update your `Dense` call to the Keras 2 API: `Dense(activation="sigmoid", units=1)`



Train on 621221 samples, validate on 63043 samples
Epoch 1/5
621221/621221 [==============================] - 152s 244us/step - loss: 0.6852 - acc: 0.5518 -

Epoch 00001: val_loss improved from inf to 0.69248, saving model to model.hdf5
Epoch 2/5
621221/621221 [==============================] - 150s 241us/step - loss: 0.6815 - acc: 0.5608 -
```

```
Epoch 00002: val_loss did not improve from 0.69248
Epoch 3/5
621221/621221 [==============================] - 155s 250us/step - loss: 0.6788 - acc: 0.5659 -

Epoch 00003: val_loss did not improve from 0.69248
Epoch 00003: early stopping
>>> Doing prediction ...
Loading test data for model, window length: 10
                            ...Done
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization_1 (Batch (None, 10, 41)            164
_________________________________________________________________
lstm_1 (LSTM)                (None, 10, 64)            27136
_________________________________________________________________
lstm_2 (LSTM)                (None, 16)                5184
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 17
=================================================================
Total params: 32,501
Trainable params: 32,419
Non-trainable params: 82
_________________________________________________________________
None
>>> Model Running Time :  0:24:32.301228
************************ Finished!!! ************************
>>> START RUNNING ...
>>> Building model, layers: [64, 16, 1]
Model Compilation Time :  0.016728639602661133
>>> Fitting model, epoch: 5, batch size: 128
Train on 621221 samples, validate on 63043 samples
Epoch 1/5
621221/621221 [==============================] - 99s 160us/step - loss: 0.6853 - acc: 0.5520 -

Epoch 00001: val_loss improved from inf to 0.68881, saving model to model.hdf5
Epoch 2/5
621221/621221 [==============================] - 95s 153us/step - loss: 0.6818 - acc: 0.5600 -

Epoch 00002: val_loss did not improve from 0.68881
Epoch 3/5
621221/621221 [==============================] - 94s 152us/step - loss: 0.6792 - acc: 0.5654 -

Epoch 00003: val_loss did not improve from 0.68881
Epoch 00003: early stopping
>>> Doing prediction ...
Loading test data for model, window length: 10
```

```
                            ...Done
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
batch_normalization_2 (Batch (None, 10, 41)            164       
_________________________________________________________________
lstm_3 (LSTM)                (None, 10, 64)            27136     
_________________________________________________________________
lstm_4 (LSTM)                (None, 16)                5184      
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 17        
=================================================================
Total params: 32,501
Trainable params: 32,419
Non-trainable params: 82
_________________________________________________________________
None
>>> Model Running Time :  0:08:48.876253
*********************** Finished!!! ***********************
>>> START RUNNING ...
>>> Building model, layers: [128, 64, 16, 1]
Model Compilation Time :  0.01616525650024414
>>> Fitting model, epoch: 5, batch size: 64


/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:14: UserWarning:

Update your `LSTM` call to the Keras 2 API: `LSTM(input_shape=(10, 41), activation="relu", retu

/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:20: UserWarning:

Update your `LSTM` call to the Keras 2 API: `LSTM(activation="relu", return_sequences=True, uni



Train on 621221 samples, validate on 63043 samples
Epoch 1/5
621221/621221 [==============================] - 275s 443us/step - loss: 0.6856 - acc: 0.5513 -

Epoch 00001: val_loss improved from inf to 0.69634, saving model to model.hdf5
Epoch 2/5
621221/621221 [==============================] - 284s 457us/step - loss: 0.6816 - acc: 0.5597 -

Epoch 00002: val_loss did not improve from 0.69634
Epoch 3/5
621221/621221 [==============================] - 285s 459us/step - loss: 0.6778 - acc: 0.5689 -

Epoch 00003: val_loss did not improve from 0.69634
```

```
Epoch 00003: early stopping
>>> Doing prediction ...
Loading test data for model, window length: 10
                            ...Done
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization_3 (Batch (None, 10, 41)            164
_________________________________________________________________
lstm_5 (LSTM)                (None, 10, 128)           87040
_________________________________________________________________
lstm_6 (LSTM)                (None, 10, 64)            49408
_________________________________________________________________
lstm_7 (LSTM)                (None, 16)                5184
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 17
=================================================================
Total params: 141,813
Trainable params: 141,731
Non-trainable params: 82
_________________________________________________________________
None
>>> Model Running Time :  0:19:26.068177
************************ Finished!!! ************************
```

```
In [59]: result1.to_csv('../input/result1.csv')
         result2.to_csv('../input/result2.csv')
         result3.to_csv('../input/result3.csv')
```

7 Performance Analysis

Construct portfolio that long stocks with positive predicted return and short stocks with negative predicted return with initial capital 10,000,000 in total. Then, portfolio is compared with SP500 index performance.

```
In [60]: from sklearn.metrics import roc_curve, auc, classification_report, confusion_matrix, a

         def performance_result(result, capital = 10000000., rebalance=1):

             'define function to calculate maximum drawdown'
             def MaxDrawdown(Ret_Cum):
                 # ret_cum also can be portfolio position series
                 ContVal = np.zeros(np.size(Ret_Cum))
                 MaxDD = np.zeros(np.size(Ret_Cum))
                 for i in range(np.size(Ret_Cum)):
                     if i == 0:
                         if Ret_Cum[i] < 0:
```

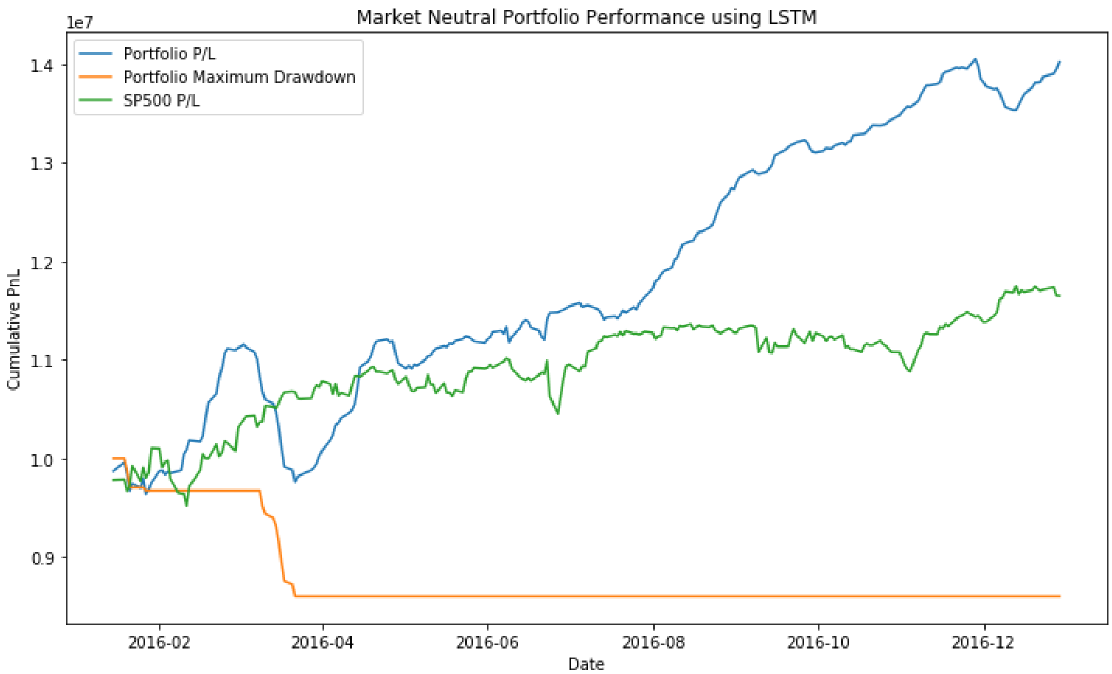
```
                ContVal[i] = Ret_Cum[i]
            else:
                ContVal[i] = 0
        else:
            ContVal[i] = Ret_Cum[i] - np.max(Ret_Cum[0:(i+1)])
        MaxDD[i] = np.min(ContVal[0:(i+1)])
    return MaxDD

' confusion matrix '
def plot_confusion(conmat):
    confusion = pd.DataFrame(conmat, index=['negative', 'positive'],
                             columns=['predicted negative', 'predicted positive'])
    print(confusion)
print('>>> Confusion Matrix')
result_conf = confusion_matrix(result['actual_y'], result['pred_y'])
plot_confusion(result_conf)

# classification report
print('\n>>> Classfication Report')
print(classification_report(result['pred_y'], result['actual_y']))

# manipulate data
result_df = result[result['universe'] == 1]
result_df_pred = result_df[['assetCode', 'date', 'pred_y']]
result_df_pred.set_index(['assetCode', 'date'], inplace=True)
result_df_pred = result_df_pred.unstack(level=0)
result_df_pred.columns = result_df_pred.columns.get_level_values(1)
result_df_ret = result_df[['assetCode', 'date', 'actual_r']]
result_df_ret.set_index(['assetCode', 'date'], inplace=True)
result_df_ret = result_df_ret.unstack(level=0)
result_df_ret.columns = result_df_ret.columns.get_level_values(1)

# resample data by business day
if len(result_df_pred) > rebalance > 1:
    result_df_pred = result_df_pred.resample(str(rebalance)+'B',
                                             convention='start').asfreq()
    result_df_ret = result_df_ret.resample(str(rebalance)+'B',
                                           convention='start').sum()

# get long short portfolio
result_df_pred_short = 1 - result_df_pred
long = result_df_pred.sum(axis=1) / (result_df_pred.sum(axis=1)
                                     + result_df_pred_short.sum(axis=1))
long_df = result_df_pred * result_df_ret.values  # df
short = 1 - long
short_df = result_df_pred_short * result_df_ret.values

# get portfolio cumpnl & maximum drawdown
```

```
            port_ret = long * long_df.mean(axis=1) + short * short_df.mean(axis=1)
            port_cumpnl = capital * (1+port_ret.cumsum())
            maxDD = MaxDrawdown(port_cumpnl.values) + capital

            # sp500 returns & cumpnl
            sp500_ret = sp500.loc[port_ret.index, :]
            sp500_cumret = sp500_ret['return'].cumsum()
            sp500_cumpnl = capital * (1 + sp500_cumret)

            plt.figure(figsize=(12,7))
            plt.title("Market Neutral Portfolio Performance using LSTM")
            plt.xlabel("Date")
            plt.ylabel("Cumulative PnL")
            plt.plot(port_cumpnl, label="Portfolio P/L")
            plt.plot(pd.Series(maxDD, index=port_ret.index), label="Portfolio Maximum Drawdow
            plt.plot(sp500_cumpnl, label = "SP500 P/L")
            plt.legend()

            sp500_mean = round(sp500_ret['return'].mean(), 4)
            sp500_std = round(sp500_ret['return'].std(), 4)
            sharpe = round(sp500_mean / sp500_std, 3)
            print('>>> For SP500:')
            print('Mean daily return: {}, Total return: {}, Daily return volatility {}, Sharpe
                    sp500_mean, round(sp500_cumret[-1], 3), sp500_std*100, sharpe))

            port_mean = round(port_ret.mean(), 4)
            port_std = round(port_ret.std(), 4)
            sharpe = round(port_mean / port_std, 3)
            print('\n>>> For my portfolio:')
            print('Mean daily return: {}, Total return: {}, Daily return volatility {}, Sharpe
                    port_mean, round(port_ret.cumsum()[-1], 3),
                    port_std, sharpe, maxDD[-1]))
```

```
In [61]: performance_result(result1)
```

```
>>> Confusion Matrix
          predicted negative  predicted positive
negative               11312               23805
positive                9484               27935

>>> Classfication Report
              precision    recall  f1-score   support

           0       0.32      0.54      0.40     20796
           1       0.75      0.54      0.63     51740

   micro avg       0.54      0.54      0.54     72536
```

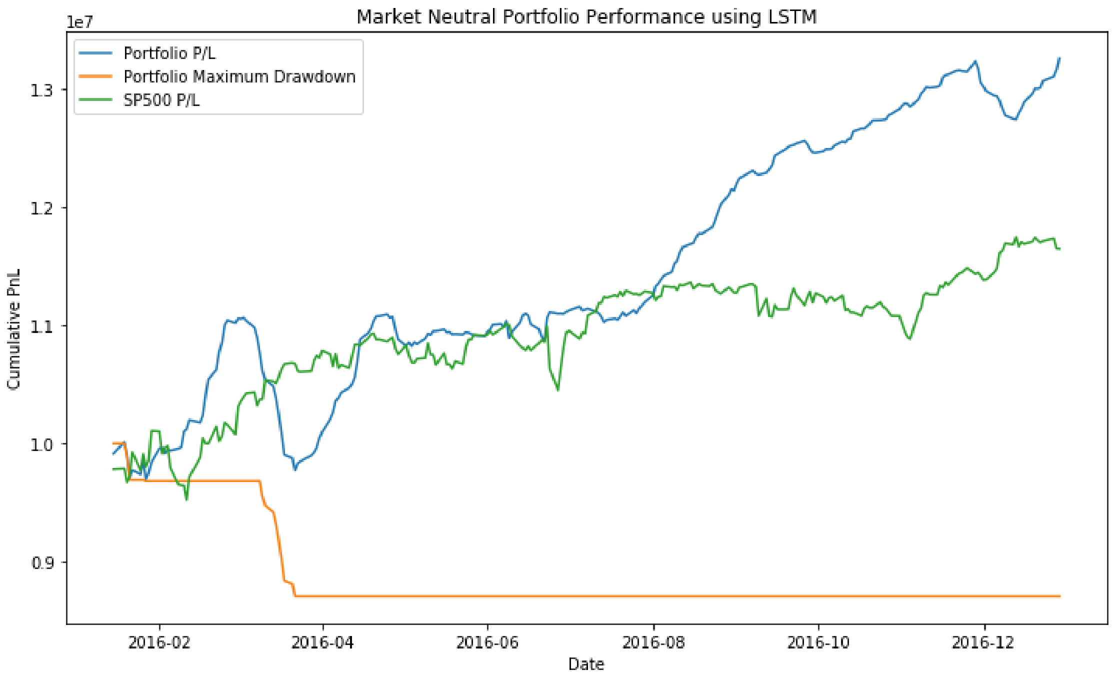
```
   macro avg       0.53      0.54      0.52     72536
weighted avg       0.62      0.54      0.56     72536

>>> For SP500:
Mean daily return: 0.0007, Total return: 0.165, Daily return volatility 0.79, Sharpe ratio: 0.0

>>> For my portfolio:
Mean daily return: 0.0017, Total return: 0.402, Daily return volatility 0.0064, Sharpe ratio: 0
```



In [62]: performance_result(result2)

```
>>> Confusion Matrix
          predicted negative  predicted positive
negative               13878               21239
positive               12128               25291

>>> Classfication Report
              precision    recall  f1-score   support

           0       0.40      0.53      0.45     26006
           1       0.68      0.54      0.60     46530

   micro avg       0.54      0.54      0.54     72536
   macro avg       0.54      0.54      0.53     72536
weighted avg       0.58      0.54      0.55     72536
```

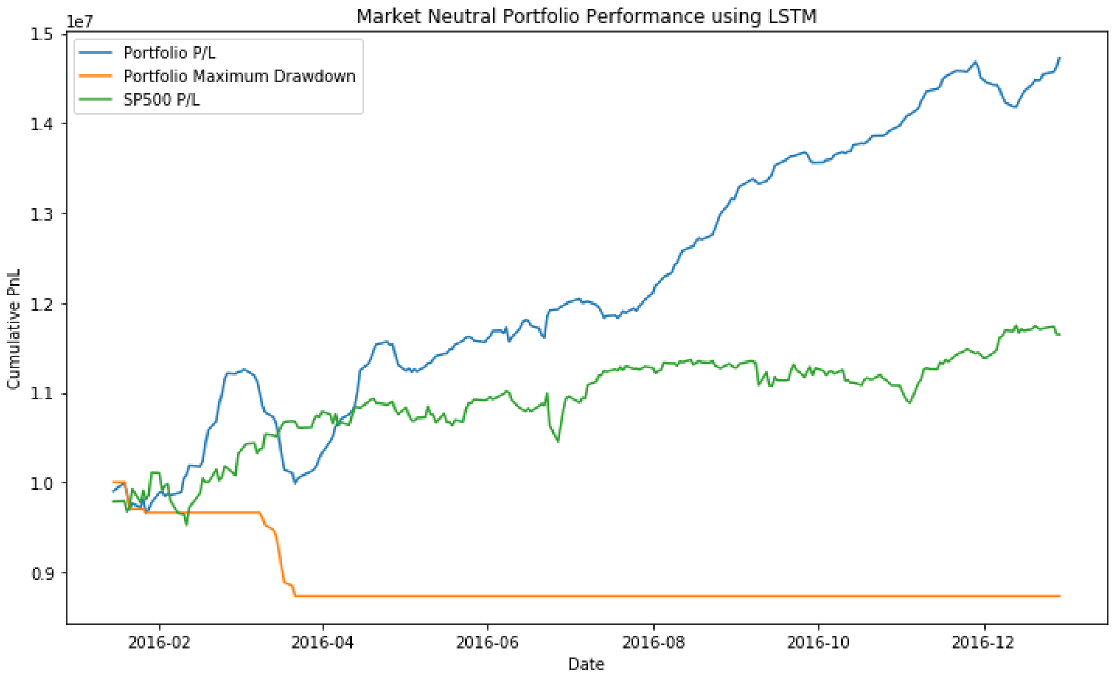
```
>>> For SP500:
Mean daily return: 0.0007, Total return: 0.165, Daily return volatility 0.79, Sharpe ratio: 0.(

>>> For my portfolio:
Mean daily return: 0.0013, Total return: 0.326, Daily return volatility 0.0059, Sharpe ratio: (
```




```
In [63]: performance_result(result3)
```

```
>>> Confusion Matrix
          predicted negative  predicted positive
negative                9496               25621
positive                7817               29602

>>> Classfication Report
              precision    recall  f1-score   support

           0       0.27      0.55      0.36     17313
           1       0.79      0.54      0.64     55223

   micro avg       0.54      0.54      0.54     72536
   macro avg       0.53      0.54      0.50     72536
weighted avg       0.67      0.54      0.57     72536

>>> For SP500:
```

```
Mean daily return: 0.0007, Total return: 0.165, Daily return volatility 0.79, Sharpe ratio: 0.(

>>> For my portfolio:
Mean daily return: 0.002, Total return: 0.472, Daily return volatility 0.0065, Sharpe ratio: 0
```



8 Conclusion

We can see from 3 results with different parameters all using LSTM model that they all perform significantly better than SP500. The best LSTM model with 4 layers produces 0.3 Sharpe ratio and 40% total return over the year 2016. I would say news combined with technical indicators effectively predicts stock returns and earn a good return.

By comparison of models using different parameters, we can see from the results that adding one more layer improves the result a little bit as precision, recall, f1-score, Sharpe ratio all increase. However, if we incerase batch size, the result actually become worse.

For further improvement, I should do a deeper analysis of each news factor and their interactions. Since there are memory and runtime constraint for this project, if those are not issues, I should try LSTM models with different set of hyperparameters and compare. Possibly, I should also try model other than LSTM, such as gradient boosting which is also good for binary classifier. Since for my portfolio, it is rebalanced daily and transaction cost will be a big factor affecting profit, and I didn't subtract transaction cost, I would like to add transaction cost into my calculation for further improvement.