Better Predicting the Stock Market

By: Lauren Esser

PROBLEM STATEMENT

Can we use News Headlines to better predict when the S&P 500 will rise?

Business Value

By creating a model that gives a high success rate of stock market predictions we can invest our money wisely to make good profits.

Data

Stock Market: www.kibot.com/free_historical_data.aspx

Stock Market data comes from kibot.com which provides free historical intraday data on the S&P 500 dating back to September 2009.

News: https://www.kaggle.com/rmisra/news-category-dataset

News dataset contains around 200k news headlines from 2012 to 2018 obtained from the Huffington Post.

THE OSEMN PROCESS

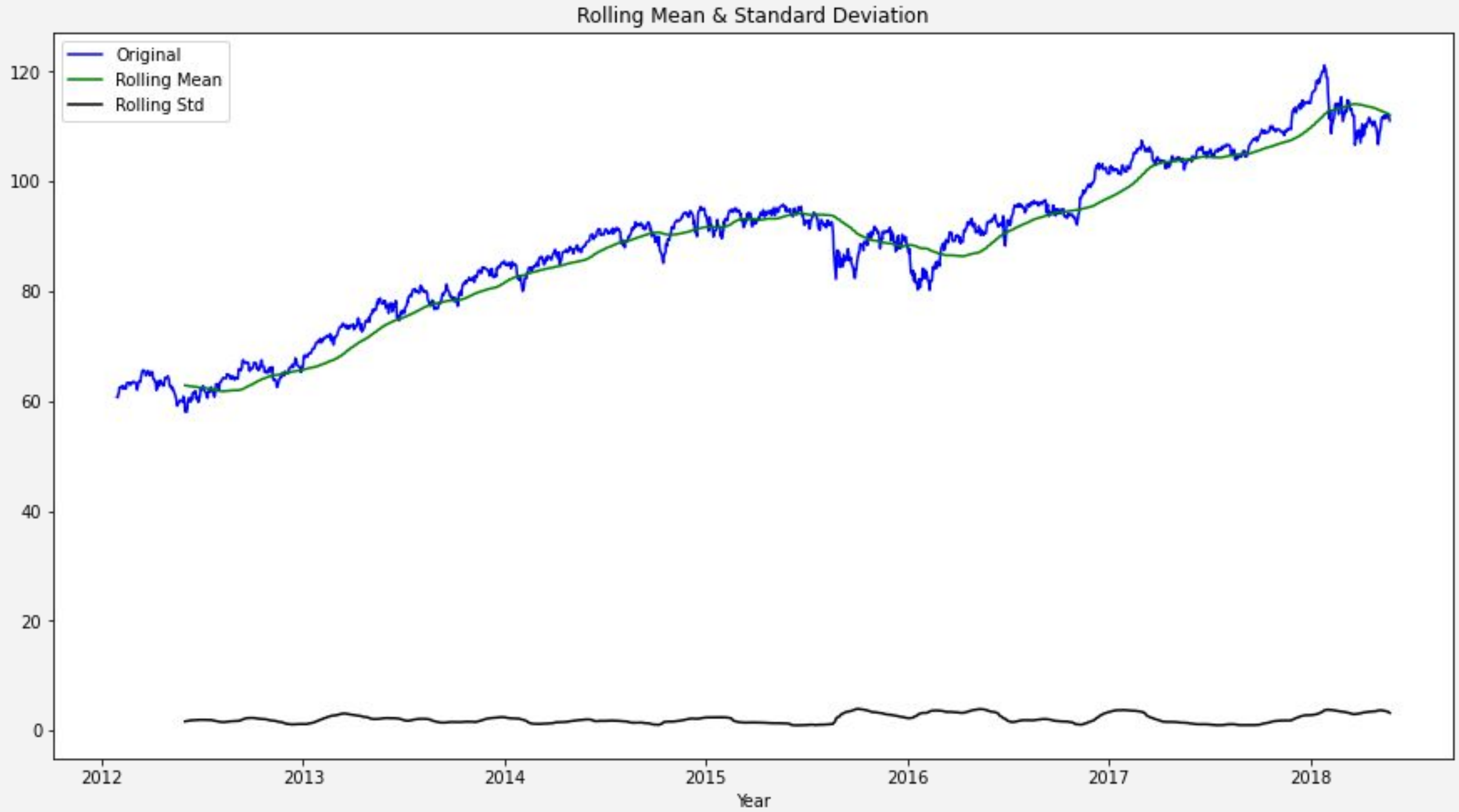
OBTAIN - Data was obtained on Huffington Post News Headlines and the S&P 500

THE HUFFINGTON POST

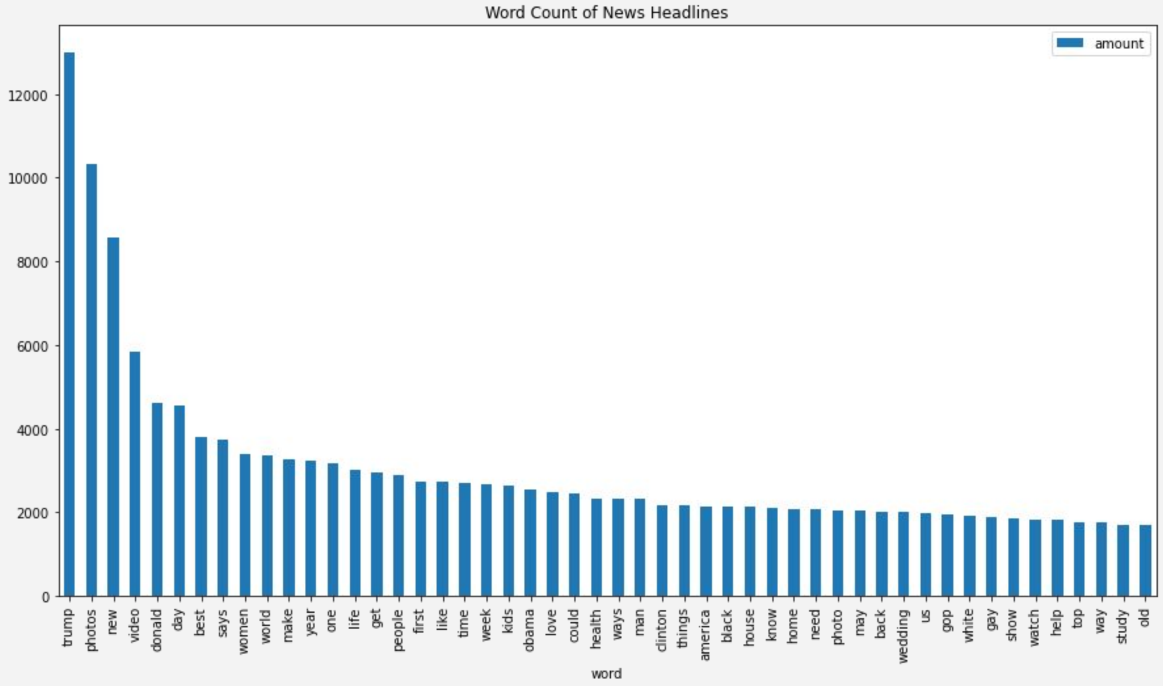
STANDARD &POOR'S 500

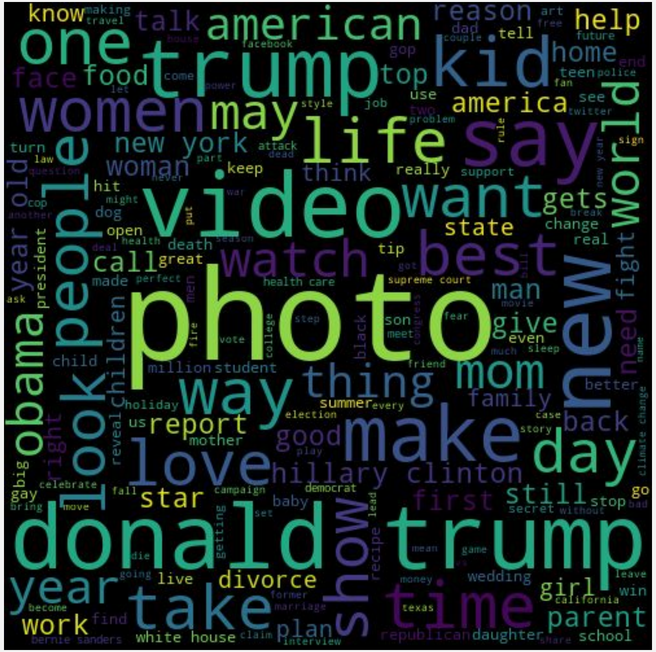
SCRUB - Index converted to datetime, checked for nulls, and identified stop words, punctuation, and tokenizing in news dataset.

EXPLORE STOCKS - took a look at line plots, rolling statistics, dickey-fuller, density plots, and transformations.



EXPLORE NEWS - took a look headline by genre and year, as well as the top recurring words.





MODEL 1: Stocks Time Series

```
#plug in optimal parameter values
arima_model = sm.tsa.statespace.SARIMAX(X_train,
                                        order = (2,1,2),
                                        seasonal_order = (1,1,2,12),
                                        enforce_stationarity=False,
                                        enforce_invertibility=False)


#fit model
output = arima_model.fit()

display(output.summary())
```

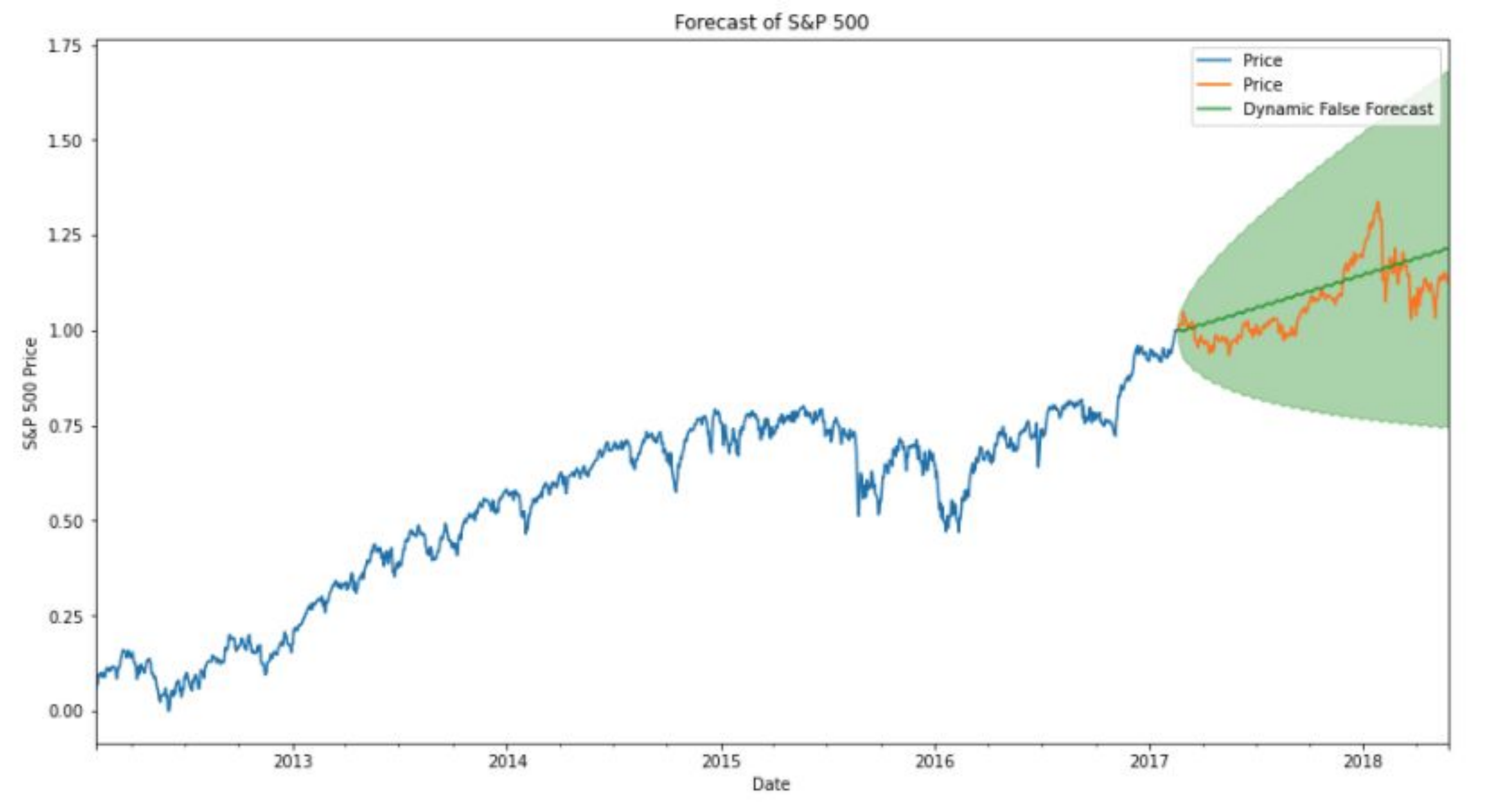
Statespace Model Results

Dep. Variable:	Price	**No. Observations:**	1320
Model:	SARIMAX(2, 1, 2)x(1, 1, 2, 12)	**Log Likelihood**	3600.164
Date:	Tue, 01 Dec 2020	**AIC**	-7184.327
Time:	16:47:01	**BIC**	-7143.090
Sample:	01-30-2012 - 02-17-2017	**HQIC**	-7168.843
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.8463	1.272	0.665	0.506	-1.648	3.340
ar.L2	-0.0281	1.052	-0.027	0.979	-2.090	2.034
ma.L1	-1.2201	1.351	-0.903	0.367	-3.869	1.429
ma.L2	0.0417	1.535	0.027	0.978	-2.968	3.051
ar.S.L12	-0.6949	0.283	-2.459	0.014	-1.249	-0.141
ma.S.L12	-0.3230	0.294	-1.100	0.271	-0.898	0.253
ma.S.L24	-0.6730	0.294	-2.288	0.022	-1.250	-0.097
sigma2	0.0001	5.03e-05	2.883	0.004	4.65e-05	0.000

Ljung-Box (Q):	38.05	**Jarque-Bera (JB):**	376.23
Prob(Q):	0.56	**Prob(JB):**	0.00
Heteroskedasticity (H):	2.26	**Skew:**	-0.43
Prob(H) (two-sided):	0.00	**Kurtosis:**	5.51

Results from Neural Network model in Appendix A



Forecast of S&P 500
S&P 500 Price
Date
Price
Price
Dynamic False Forecast
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2013
2014
2015
2016
2017
2018

MODEL 2: NLP USING STOCK DATA: 53% Accuracy

```
model = Sequential()
model.add(Embedding(max_words, 300)) #can change 100 for how many datapts
model.add(LSTM(64, activation = 'relu', return_sequences=True,
               kernel_regularizer=regularizers.l1(0.001)))

model.add(Dropout(0.3))
model.add(LSTM(32, activation = 'relu', return_sequences=False,
               kernel_regularizer=regularizers.l1(0.001)))
model.add(Dropout(0.5))
model.add(Dense(32, activation = 'relu', kernel_regularizer=regularizers.l1(0.001)))
model.add(Dense(1, activation = 'sigmoid'))

model.compile(optimizer= optimizers.Adam(), loss = 'binary_crossentropy',
              metrics = ['acc', precision, recall])

#display(model.summary())
history = model.fit(X_train_padded, y_train, batch_size = 32, epochs = 8,
                    callbacks = callback, validation_split = .1,
                    class_weight = class_weight)
```

Visualizations in Appendix B

MODEL 3: Using News Headlines to better predict the stock market


```
final_model = Sequential()

final_model.add(LSTM(64, activation = 'relu', input_shape = input_shape,
                     return_sequences = True))
#final_model.add(Dropout(0.5))
final_model.add(LSTM(32, activation = 'relu', return_sequences = False))
final_model.add(Dense(1, activation = 'relu'))

final_model.compile(optimizer = optimizers.Nadam(), loss = 'mse',
                    metrics = ['mse'])

display(final_model.summary())
history = final_model.fit(generator, epochs = 20)
```

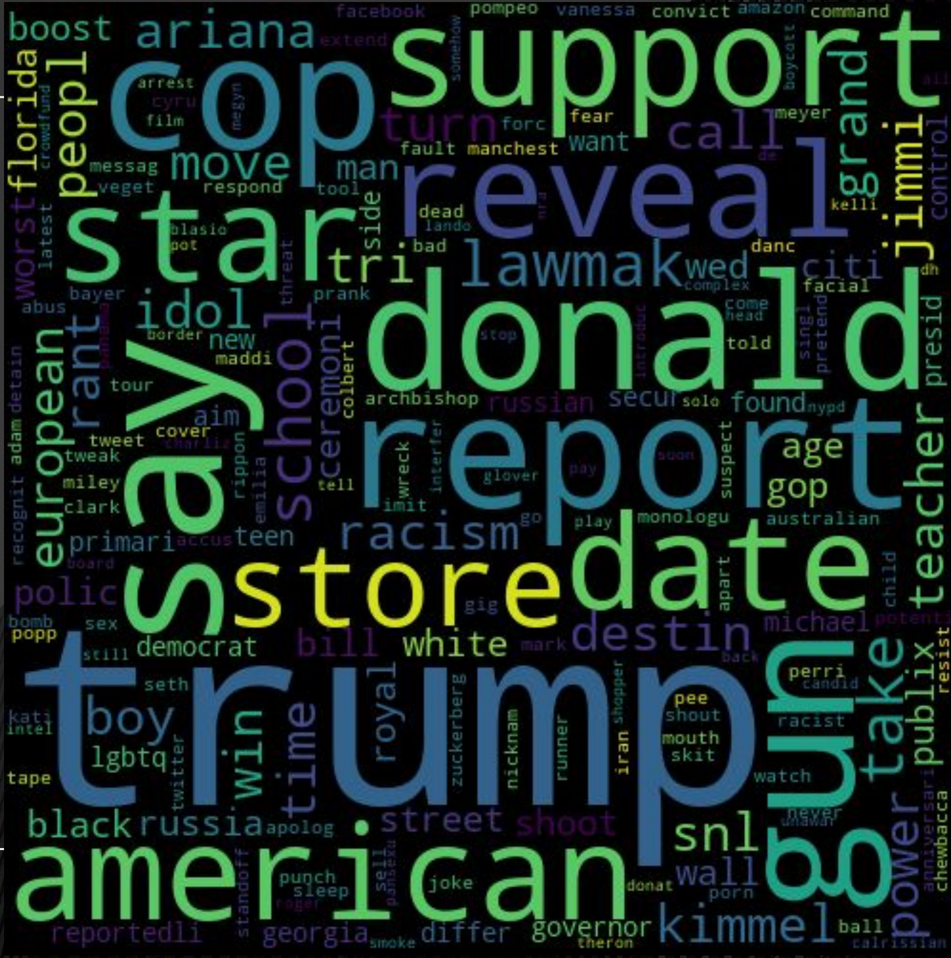
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_3 (LSTM)                (None, 50, 64)            17152
_________________________________________________________________
lstm_4 (LSTM)                (None, 32)                12416
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 33
=================================================================
Total params: 29,601
Trainable params: 29,601
Non-trainable params: 0
_________________________________________________________________
```

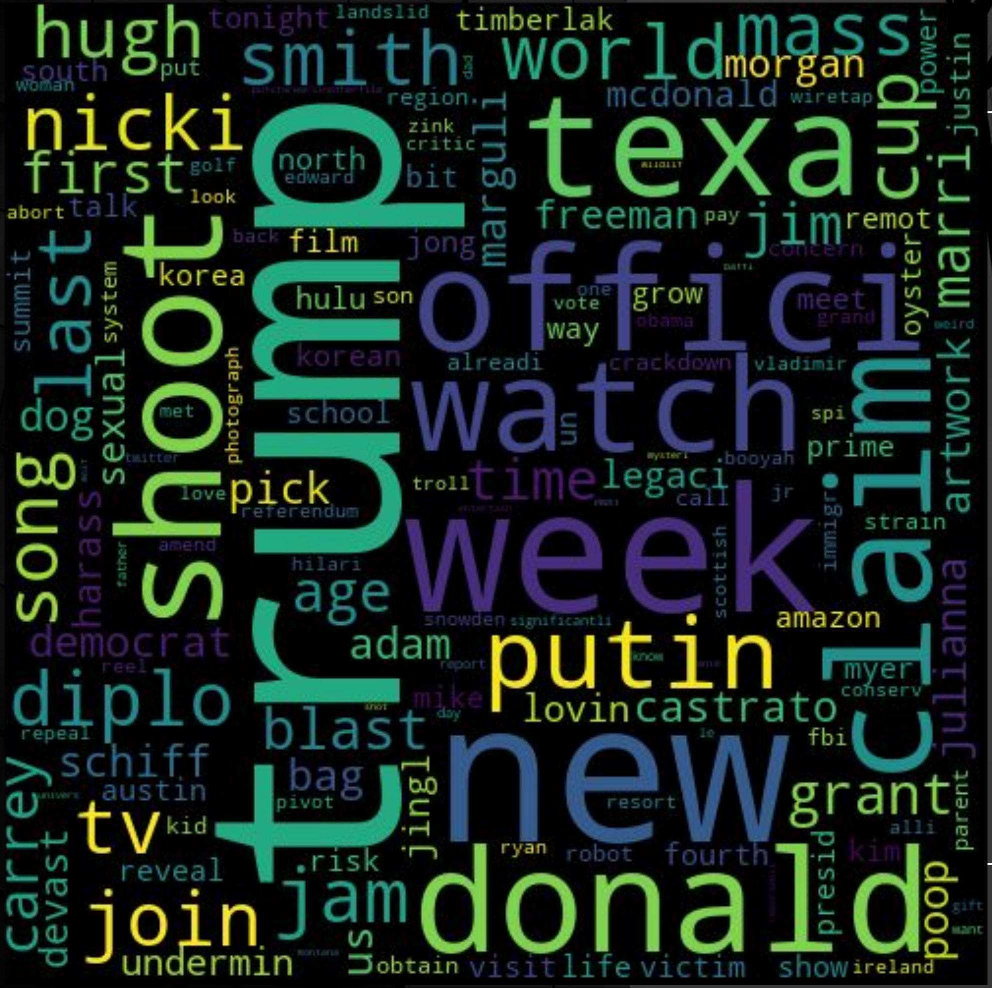
MY RECOMMENDATIONS

1. Look at positive word list
2. Avoid words on negative list
3. Make your model more specific
4. Follow same path

01

POSITIVE WORDS LIST



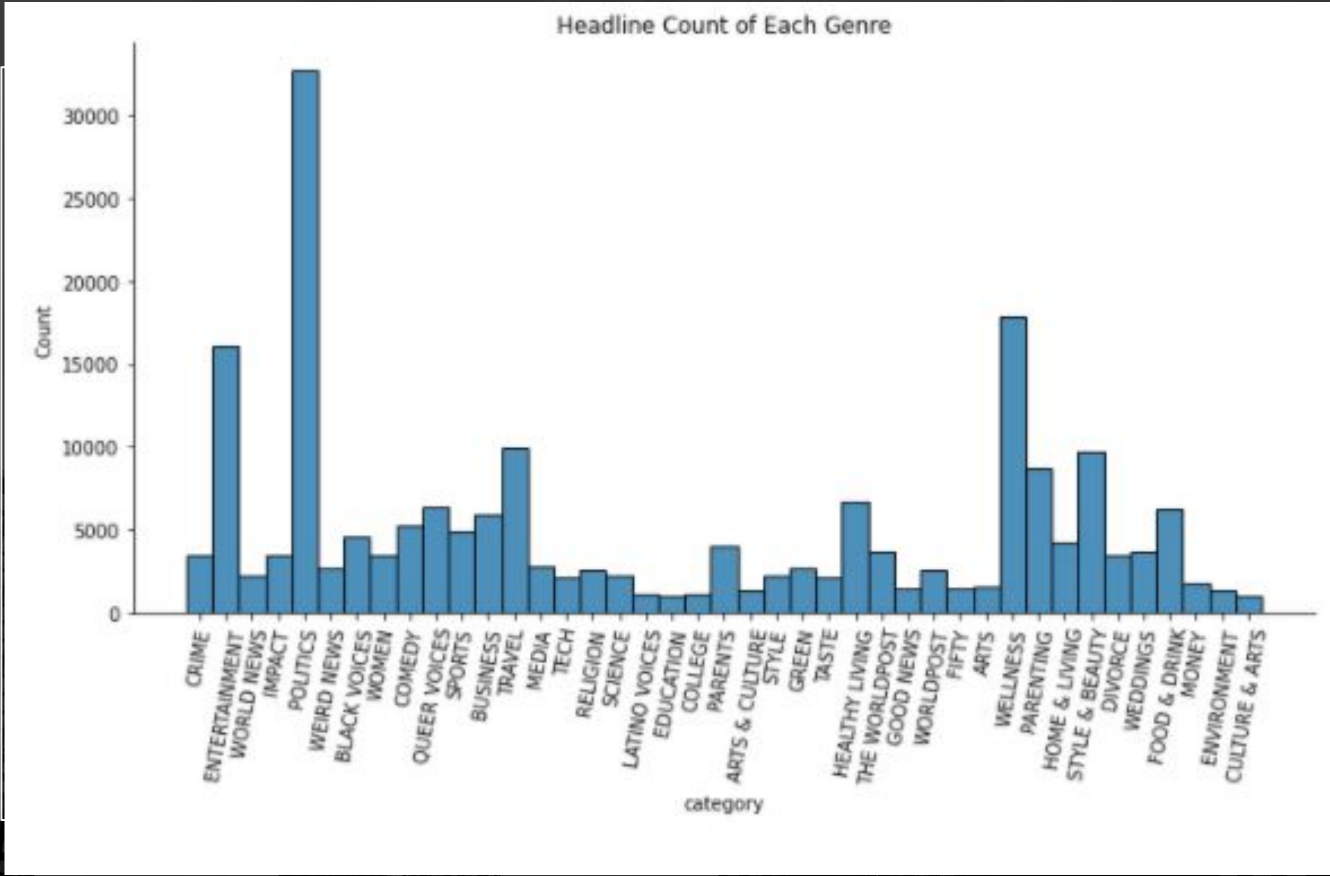


NEGATIVE WORDS LIST

02

03

SAME MODEL, MORE SPECIFIC HEADLINES

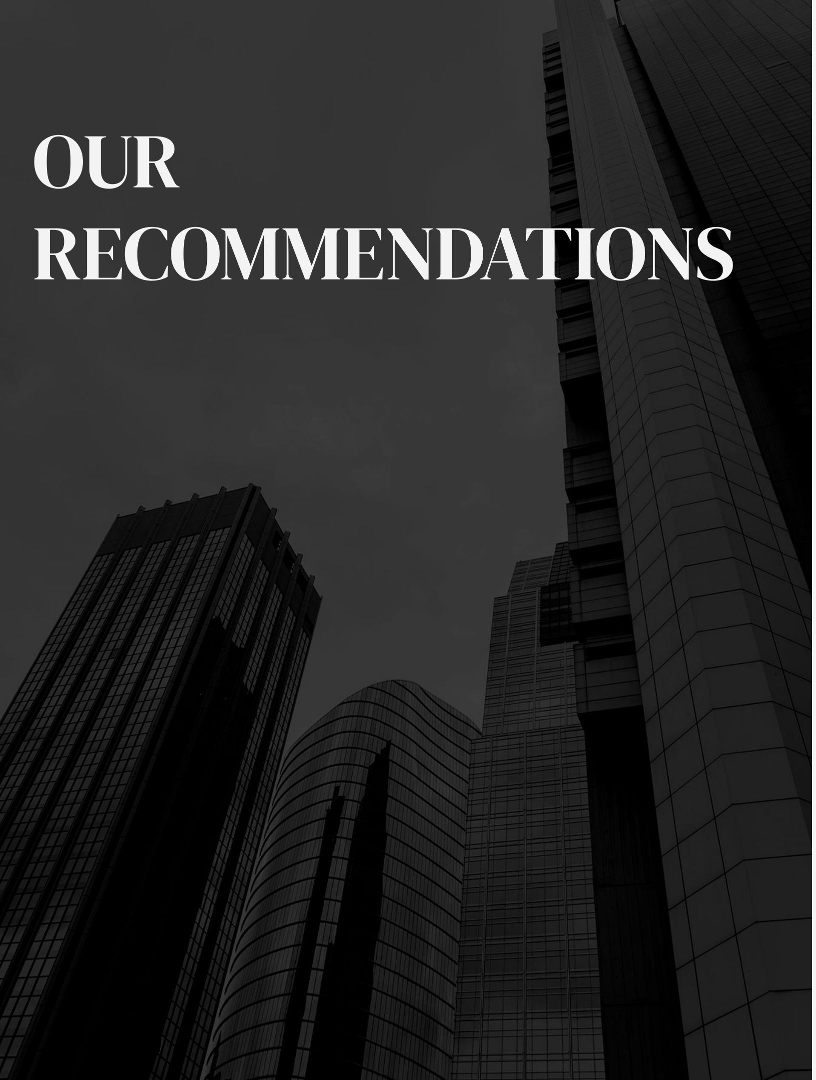


1. Build a simple Time Series Model

2. Create a NLP Model to see what words cause the stock to increase or decrease

3. Build a Time Series Model to see which news headlines better predict the market.

OUR RECOMMENDATIONS



1. Look at positive word list
2. Avoid words on negative list
3. Make your model more specific
4. Follow same path

FUTURE WORK

1. Separate News Headlines by Category to see which Category impacts the S&P 500 more.
2. Test different Headline Sources (ex. Wall Street Journal, New York Times, ESPN etc.) to see if one news source has a greater impact than others.
3. Test if categorical papers impact categorical stocks. Ex. sports headlines impacting sports company stocks.
4. Try different model types. Ex. PDArima model for initial time series model.

Thank you for your time and consideration!

QUESTIONS?

Feel free to e-mail me at Lauren.Esser02@gmail.com or reach out via LinkedIn

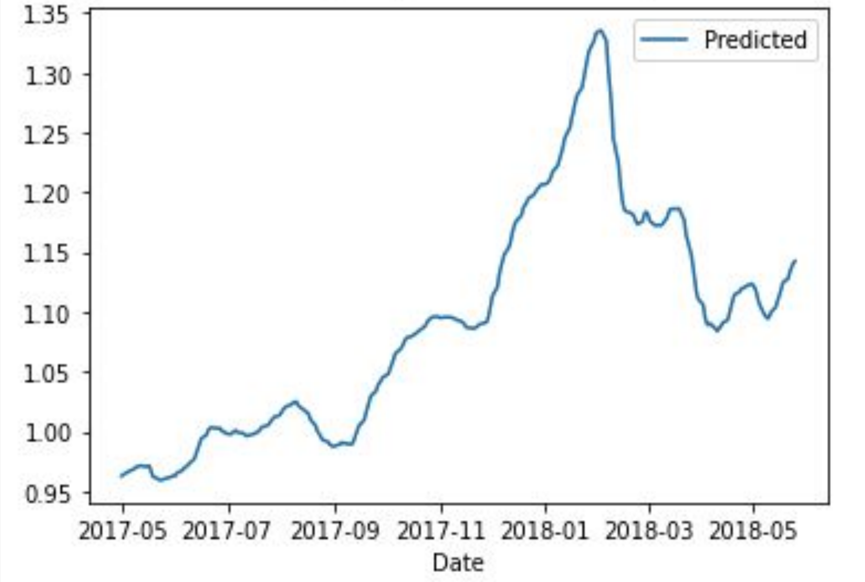
APPENDIX A1:

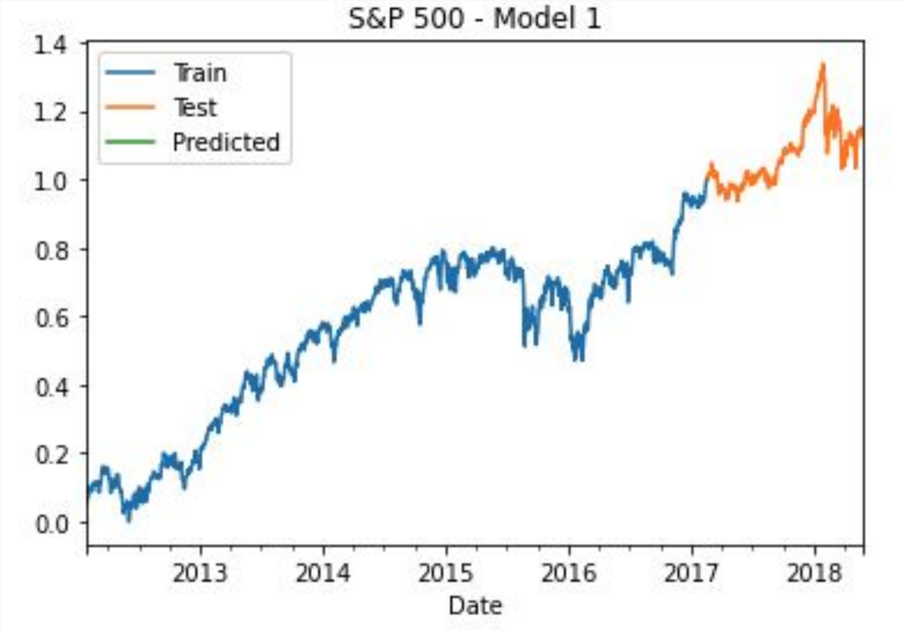
Neural Network Stocks Time Series

```
#define model
model = Sequential()
model.add(LSTM(units = 64, activation = 'relu', input_shape = input_shape))
model.add(Dense(1))

model.compile(optimizer= optimizers.Nadam(), loss = 'mse', metrics = ['mse'])

display(model.summary())
history = model.fit(generator, epochs = 20)
```

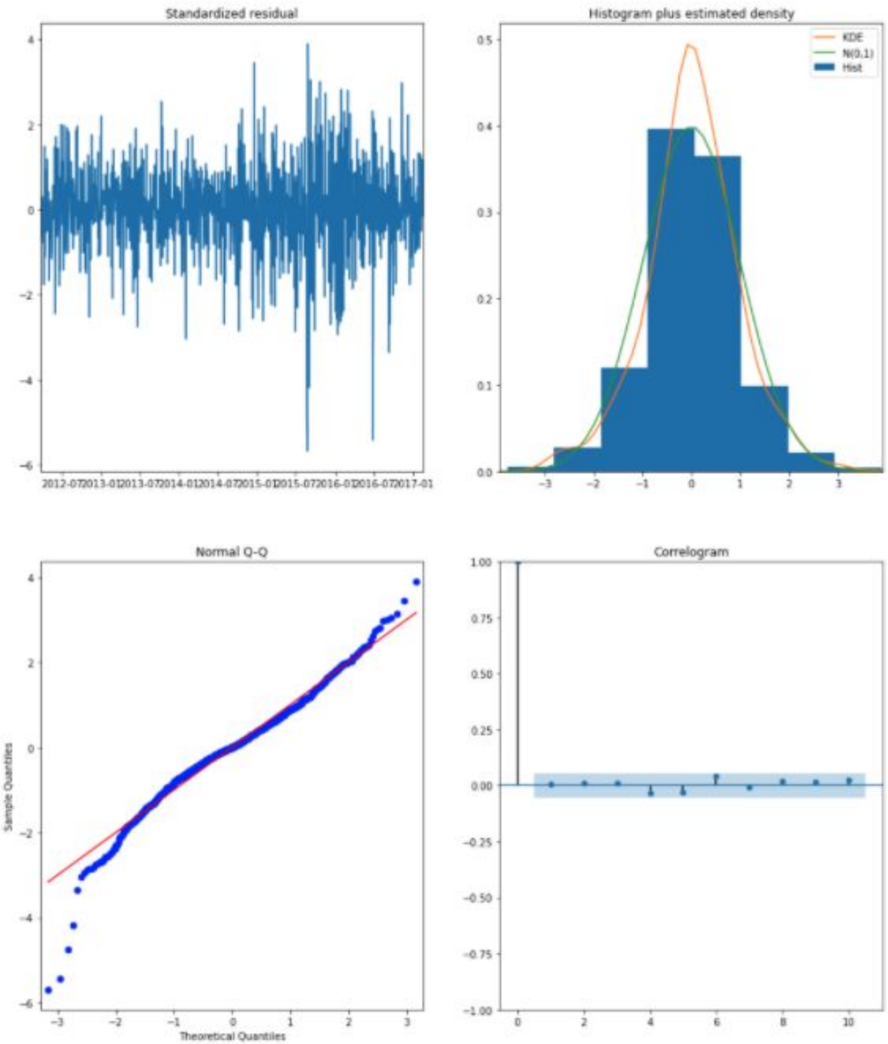
```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 64)                16896
_________________________________________________________________
dense (Dense)                (None, 1)                 65
=================================================================
Total params: 16,961
Trainable params: 16,961
Non-trainable params: 0
```

APPENDIX A2:


Predicted
1.35
1.30
1.25
1.20
1.15
1.10
1.05
1.00
0.95
2017-05
2017-07
2017-09
2017-11
2018-01
2018-03
2018-05
Date


S&P 500 - Model 1
Train
Test
Predicted
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
2013
2014
2015
2016
2017
2018
Date

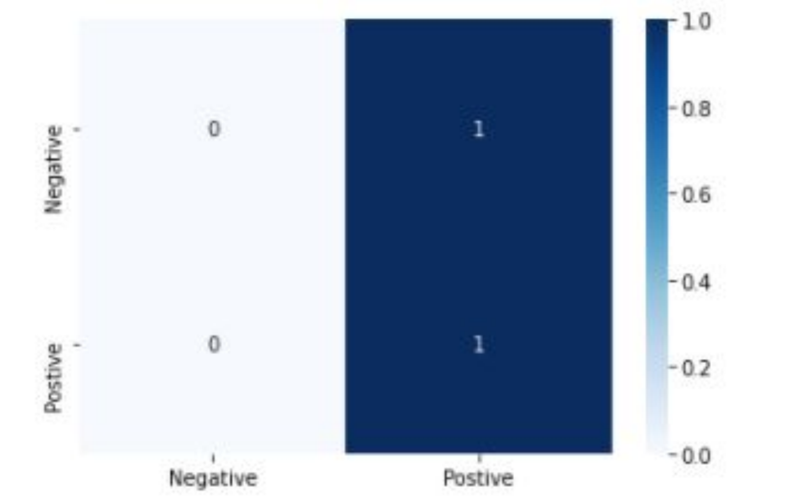
Appendix A3: SARMINA MODEL CHARTS



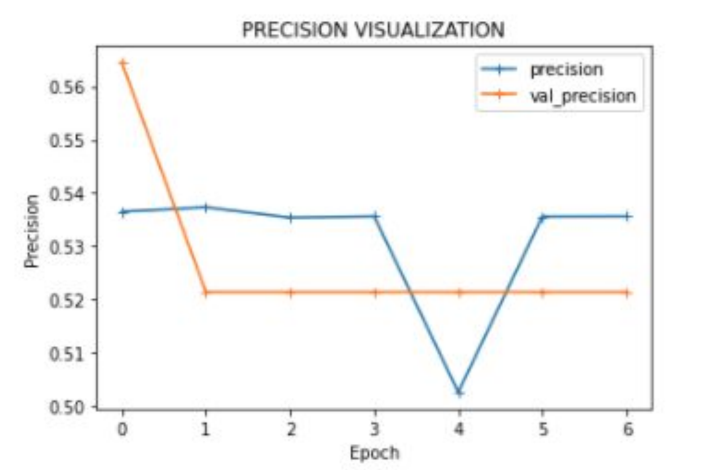
APPENDIX B1

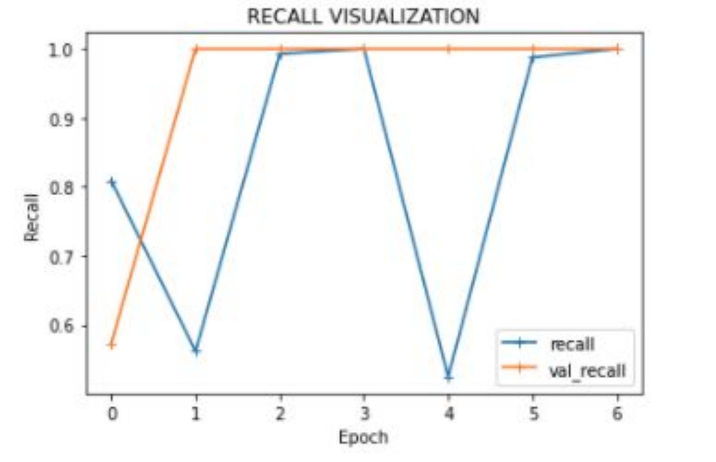
CLASSIFICATION REPORT

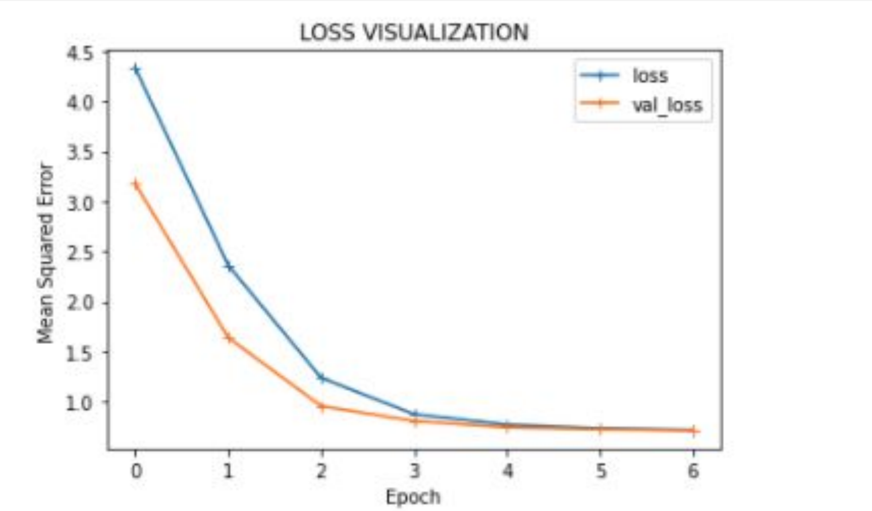
	precision	recall	f1-score	support
Negative	0.00	0.00	0.00	136
Postive	0.53	1.00	0.70	156
accuracy			0.53	292
macro avg	0.27	0.50	0.35	292
weighted avg	0.29	0.53	0.37	292

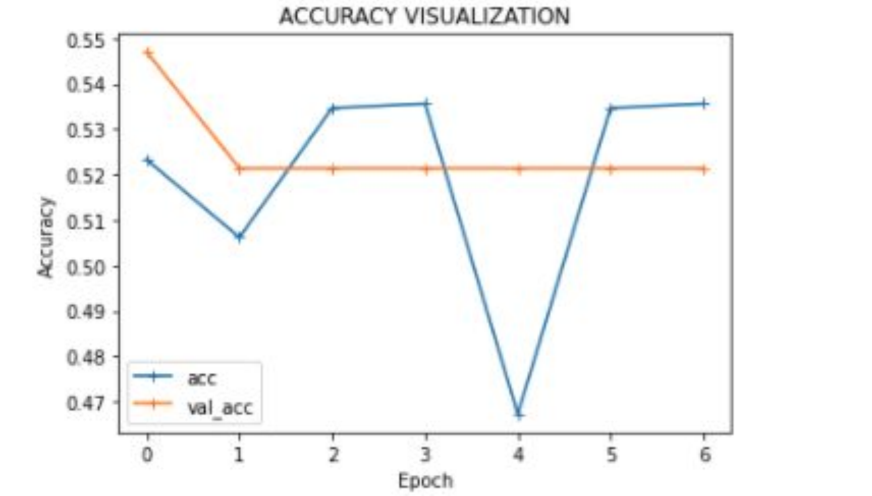


APPENDIX B2


PRECISION VISUALIZATION
Precision
Epoch
precision
val_precision


RECALL VISUALIZATION
Recall
Epoch
recall
val_recall


LOSS VISUALIZATION
Mean Squared Error
Epoch
loss
val_loss


ACCURACY VISUALIZATION
Accuracy
Epoch
acc
val_acc

APPENDIX C: RANDOM FOREST FOR MODEL 2

```
clf = RandomForestClassifier(random_state = 1212, criterion= 'gini',
                             max_depth= 1, min_samples_leaf= 1,
                             min_samples_split= 2 )
clf.fit(X_train_tf, y_train.ravel())
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=1, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=1212,
                       verbose=0, warm_start=False)
```

```
Testing Accuracy for Classifier: 53.42%
------------------------------------------------------------
CLASSIFICATION REPORT
------------------------------------------------------------
              precision    recall  f1-score   support

    Negative       0.00      0.00      0.00       136
    Positive       0.53      1.00      0.70       156

    accuracy                           0.53       292
   macro avg       0.27      0.50      0.35       292
weighted avg       0.29      0.53      0.37       292

------------------------------------------------------------
```