Reddit News Headlines and Stock Market Performance

In the current financial market, predicting daily stock prices using daily news as input is clearly a very complex task. Moreover, the market is very volatile because it is a result of multiple factors that change continuously.

Our research questions are centered around using reddit data to predict the Dow Jones stock average in two different ways, using text word count and using text sentiment of reddit headlines.

Our research questions are:

- 1. Can the text content of reddit daily news headlines be used to predict past stock prices?
- 2. Can the sentiment of reddit daily news headlines be used to predict past stock prices?

Load and Clean Data

Begin by loading and formating the data.

Dataset includes the top 25 most viewed news stories from reddit for a day and the Dow Jones stock performance over this time.

Out[172]:

	Date	Label	Top1	Top2	Top3	Top4	Top5	Top6	
0	2008- 08-08	0	b"Georgia 'downs two Russian warplanes' as cou	b'BREAKING: Musharraf to be impeached.'	b'Russia Today: Columns of troops roll into So	b'Russian tanks are moving towards the capital	b"Afghan children raped with 'impunity,' U.N	b'150 Russian tanks have entered South Ossetia	b"Br (
1	2008- 08-11	1	b'Why wont America and Nato help us? If they w	b'Bush puts foot down on Georgian conflict'	b"Jewish Georgian minister: Thanks to Israeli	b'Georgian army flees in disarray as Russians 	b"Olympic opening ceremony fireworks 'faked'"	b'What were the Mossad with fraudulent New Zea	b ang sale
2	2008- 08-12	0	b'Remember that adorable 9- year-old who sang a	b"Russia 'ends Georgia operation'"	b"If we had no sexual harassment we would hav	b"Al-Qa'eda is losing support in Iraq because	b'Ceasefire in Georgia: Putin Outmaneuvers the	b'Why Microsoft and Intel tried to kill the XO	b': The G V th
3	2008- 08-13	0	b' U.S. refuses Israel weapons to attack Iran:	b"When the president ordered to attack Tskhinv	b' Israel clears troops who killed Reuters cam	b'Britain\'s policy of being tough on drugs is	b'Body of 14 year old found in trunk; Latest (b'China has moved 10 *million* quake survivors	ann Or Ge In
4	2008- 08-14	1	b'All the experts admit that we should legalis	b'War in South Osetia - 89 pictures made by a	b'Swedish wrestler Ara Abrahamian throws away	b'Russia exaggerated the death toll in South O	b'Missile That Killed 9 Inside Pakistan May Ha	b"Rushdie Condemns Random House's Refusal to P	b e

5 rows × 27 columns

Merge the Dow Jones and the top news from reddit together. Also create a copy of the DF in order to use for sentiment analysis later.

Out[177]:

	Date	Label	Top1	Top2	Top3	Top4	Top5	Top6	
1988	2008- 08-08	0	b"Georgia 'downs two Russian warplanes' as cou	b'BREAKING: Musharraf to be impeached.'	b'Russia Today: Columns of troops roll into So	b'Russian tanks are moving towards the capital	b"Afghan children raped with 'impunity,' U.N	b'150 Russian tanks have entered South Ossetia	b"E
1987	2008- 08-11	1	b'Why wont America and Nato help us? If they w	b'Bush puts foot down on Georgian conflict'	b"Jewish Georgian minister: Thanks to Israeli	b'Georgian army flees in disarray as Russians	b"Olympic opening ceremony fireworks 'faked'"	b'What were the Mossad with fraudulent New Zea	anį sa
1986	2008- 08-12	0	b'Remember that adorable 9- year-old who sang a	b"Russia 'ends Georgia operation'"	b"'If we had no sexual harassment we would hav	b"Al- Qa'eda is losing support in Iraq because	b'Ceasefire in Georgia: Putin Outmaneuvers the	b'Why Microsoft and Intel tried to kill the XO	b The (

3 rows × 33 columns

Merge all 25 top headlines together

Optionally delete other extra columns of data [2:27]]

Sort the columns by date

```
In [218]: 1 merged_data = merged_data.sort_values(by="Date")
2 #merged_data.head(2)
```

Hide ipython warning messages

```
In [183]:
            1 %%javascript
            2 (function(on) {
            3 const e=$( "<a>Setup failed</a>" );
            4 const ns="js jupyter suppress warnings";
            5 var cssrules=$("#"+ns);
            6 if(!cssrules.length) cssrules = $("<style id='"+ns+"' type='text/css'>div.ou
            7 e.click(function() {
            8
                   var s='Showing';
            9
                   cssrules.empty()
                   if(on) {
           10
           11
                       s='Hiding';
                       cssrules.append("div.output_stderr, div[data-mime-type*='.stderr'] {
           12
           13
                   e.text(s+' warnings (click to toggle)');
           14
           15
                   on=!on;
           16 }).click();
           17 $(element).append(e);
           18 })(true);
```

Hiding warnings (click to toggle)

Preprocessing the code

1 Next clean the data to make the machine learning models more effective.

Use regex to remove stopwords and to lemmatize all of the top 25 headlines.

```
In [184]:
            1 import regex as re
            2 from nltk.corpus import stopwords
            3
              from nltk.stem import WordNetLemmatizer
            5
              def prepro_text(target_text):
            6
                   # if b'/b"
                   target_text = re.sub(r"^b[\'\"]", '', target_text)
            7
                   target_text = re.sub(r"[^\w\s]", '', target_text)
            8
            9
                   target_text = target_text.lower().strip()
           10
                   target_text = target_text.split()
                   target_text = ' '.join([x for x in target_text if x not in stopwords.wor
           11
           12
                   return target text
```

Out[185]:

	Date	Label	top25_headlines	Top1	Top2	Top3	Top4	T
1988	2008- 08-08	0	georgia downs two russian warplanes countries	b"Georgia 'downs two Russian warplanes' as cou	b'BREAKING: Musharraf to be impeached.'	b'Russia Today: Columns of troops roll into So	b'Russian tanks are moving towards the capital	b"Afg children ra with 'impu U.1
1987	2008- 08-11	1	wont america nato help us wont help us help ir	b'Why wont America and Nato help us? If they w	b'Bush puts foot down on Georgian conflict'	b"Jewish Georgian minister: Thanks to Israeli	b'Georgian army flees in disarray as Russians 	b"Olyr ope ceren firew 'fak
1986	2008- 08-12	0	remember adorable 9yearold sang opening ceremo	b'Remember that adorable 9- year-old who sang a	b"Russia 'ends Georgia operation'"	b"If we had no sexual harassment we would hav	b"Al-Qa'eda is losing support in Iraq because	b'Ceasefil Georgia: F Outmaneu tl
1985	2008- 08-13	0	us refuses israel weapons attack iran report b	b' U.S. refuses Israel weapons to attack Iran:	b"When the president ordered to attack Tskhinv	b' Israel clears troops who killed Reuters cam	b'Britain\'s policy of being tough on drugs is	b'Body c year old fc in trunk; La
1984	2008- 08-14	1	experts admit legalise drugs bwar south osetia	b'All the experts admit that we should legalis	b'War in South Osetia - 89 pictures made by a	b'Swedish wrestler Ara Abrahamian throws away	b'Russia exaggerated the death toll in South O	b'Missile [·] Killed 9 In Pakistan I

5 rows × 34 columns

Run Model for TFIDF and Embeddings

Import train test split. Use the top 25 headlines combined together as the X variable.

The Y variable is a binary label which shows whether or not the stock market went up or down.

Import the count vectorizer and tensorflow.

module https://tfhub.dev/google/universal-sentence-encoder/4 (https://tfhub.de v/google/universal-sentence-encoder/4) loaded

Import the Tfidf vectorizer.

Create a function to run the model with either TFIDF or embedding.

```
In [242]:
            1 from sklearn.feature extraction.text import TfidfVectorizer
               # return the vectors
            2
            3
               def text vector(target method='tfidf', \
                                target list train=X train.to list(),\
            4
            5
                               target_list_test = X_test.to_list(),\
            6
                               max features=None):
                   .....
            7
            8
                   type: target method: string - ("tfidf", "embedding")
            9
                   rtype: list of vectors
           10
           11
           12
           13
                   if target_method == "embedding":
           14
                       use x train = []
           15
                       use x test = []
                       use_x_train = use(target_list_train)
           16
           17
                       use x test = use(target list test)
           18
                       return use_x_train, use_x_test
           19
                   if target method == "tfidf":
           20
                       vectorizer = TfidfVectorizer(max features=max features)
           21
           22
                       tfidf_train = vectorizer.fit_transform(target_list_train)
           23
                       tfidf test = vectorizer.transform(target list test)
                       tfidf scaler = MaxAbsScaler()
           24
                       tfidf x train = tfidf scaler.fit transform(tfidf train)
           25
                       tfidf_x_test = tfidf_scaler.transform(tfidf_test)
           26
           27
                       return tfidf x train, tfidf x test
```

TFIDF Logistic Regression

```
In [243]:
              %%time
            1
            2
            3
              tfidf x train, tfidf x test = text vector("tfidf", X train, X test)
            4
            5 import pandas as pd
            6 import numpy as np
            7 | from sklearn.linear model import LogisticRegression
            8
               from sklearn.metrics import accuracy_score, confusion_matrix
            9
           10 logmodel = LogisticRegression()
           11
              logmodel.fit(tfidf_x_train, y_train)
           12
              predictions = logmodel.predict(tfidf x test)
           13
           14 #print(accuracy_score(y_test, predictions))
           15
           16 | accuracy tfidf = accuracy score(y test, predictions)
              percentage = "{:.2%}".format(accuracy tfidf)
           17
           18
              print("accuracy percentage is", percentage)
           19
           20
```

accuracy percentage is 51.51% Wall time: 1.18 s

We got an accuracy below 50% for the TFIDF logistic regression.

Embeddings Logistic Regression

```
In [244]:
               %%time
            1
            2
            3
              # embedding
              embedding x train, embedding x test = text vector("embedding")
            5
              import pandas as pd
            7 import numpy as np
            8 | from sklearn.linear model import LogisticRegression
            9
              from sklearn.metrics import accuracy_score, confusion_matrix
           10
           11
              logmodel = LogisticRegression()
           12
              logmodel.fit(embedding x train, y train)
           13
           14 | predictions = logmodel.predict(embedding x test)
           15
              #print(accuracy_score(y_test, predictions))
           16
           17 | accuracy_embeddings = accuracy_score(y_test, predictions)
              percentage = "{:.2%}".format(accuracy embeddings)
           18
              print("accuracy percentage is", percentage)
           19
           20
           21
```

```
accuracy percentage is 51.01% Wall time: 3.17 s
```

We got a slightly better accuracy with embeddings and logistic regression.

MLP classfier

accuracy percentage is 47.99%

Text related to stock

Filter the dataset for stock related keywords

Now we want to look at the performance of our models based on only stock related keywords.

Used the column with the top 25 headlines to get the new dataframe with stock related keywords only.

The new dataframe has 553 rows compared to close to 2,000 for the original column.

```
In [226]:
               stock related keywords = "stock|market|feds|bond|bonds|stocks|bull|bear"
            1
            2
            3
               import numpy as np
            4
            5
               temp df = merged data.copy()
            6
            7
               merged data keywords = temp df[['top25 headlines', 'Label']]
            8
            9
               merged_data_keywords['Label'] = merged_data_keywords['Label'].astype(str)
           10
           11
               mask = np.column stack([merged data keywords[col].str.contains(stock related
               stock_keyword = merged_data_keywords.loc[mask.any(axis=1)]
           12
           13
               stock_keyword['Label'] = stock_keyword['Label'].astype(int)
           14
           15
           16
               #stock keyword
```

Train test split for stock keyword dataframe.

Run With TFIDF

```
In [236]:
            1
               tfidf_x_train, tfidf_x_test = text_vector("tfidf", \
            2
                                                          X train,\
                                                          X_test
            3
            4
In [233]:
               from sklearn.linear model import LogisticRegression
            2
               logmodel = LogisticRegression()
            3
               logmodel.fit(tfidf x train,y train)
            4
               predictions = logmodel.predict(tfidf_x_test)
            5
              accuracy stock tfidf = accuracy score(y test, predictions)
            7
               percentage = "{:.2%}".format(accuracy_stock_tfidf)
               print("accuracy percentage is", percentage)
```

accuracy percentage is 54.55%

Run with MLP

```
In [237]: 1  from sklearn.neural_network import MLPClassifier
    from sklearn.datasets import make_classification

4  clf = MLPClassifier(max_iter = 300).fit(tfidf_x_train, y_train)
    predictions = clf.predict(tfidf_x_test)

6     accuracy_score(y_test, predictions)

8     accuracy_score(y_test, predictions)

9     accuracy_stock_mlp = accuracy_score(y_test, predictions)
    percentage = "{:.2%}".format(accuracy_stock_mlp)
    print("accuracy_percentage is", percentage)
```

accuracy percentage is 56.06%

Sentiment Analysis

Next we will move on to our second research question:

Can the sentiment of reddit daily news headlines be used to predict past stock prices?

Write function to get the sentiment using vader and textblob.

```
In [198]:
            1 #uses textblob to get the sentiment scores of the column
               import nltk
            3 | nltk.download('vader_lexicon')
            4 from textblob import TextBlob
            5 import nltk
            6 | from nltk.sentiment import SentimentIntensityAnalyzer
               from nltk.sentiment import vader
            7
               sia = vader.SentimentIntensityAnalyzer()
            9
               def text_sent(target_method, target_list_text):
           10
           11
           12
           13
                   rtype: list of entiment scores
           14
           15
                   if target method == 'blob':
           16
                       blob_list = []
           17
                       for title in target_list_text:
           18
                           blob = TextBlob(title)
                           blob_list.append(blob.sentiment.polarity)
           19
           20
           21
                       return blob_list
           22
           23
                   if target method == 'NLTK':
           24
                       NLTK_list = []
           25
           26
                       for title in target list text:
           27
                           sia polarity = sia.polarity scores(title)
                           NLTK_list.append(sia_polarity['compound'])
           28
           29
                       return NLTK list
```

Get the average sentiment for blob and Vader

```
In [199]:
            1
               # Average sentiment for column by blob
            2
            3
               column list blob = []
            4
            5
               for i in range(1,23):
            6
                   #print(i,'i is')
            7
                   i str = str(i)
            8
                   Topic = ('Top'+i str) # 'Top' + 1 = 'Top1'
                   Topic_sent_blob = (Topic + '_sent_' 'blob')
            9
                   topic_list = text_sent("blob",merged_data_sent[Topic])
           10
           11
                   merged data sent[Topic sent blob] = topic list
           12
                   column_list_blob.append(Topic_sent_blob)
           13
           14
           15
               merged data sent sum blob = merged data sent[column list blob].sum(axis=1)
           16
               merged_data_sent["average_blob_sent"] = merged_data_sent_sum_blob / 22
           17
           18
           19
               # Average sentiment by column for NLTK
           20
           21
           22
               column_list_nltk = []
           23
           24
               for i in range(1,23):
           25
                   i str = str(i)
                   Topic = ('Top'+i_str)
           26
                   Topic_sent_nltk = (Topic + '_sent_' 'NLTK')
           27
                   topic_list = text_sent("NLTK",merged_data_sent[Topic])
           28
           29
                   merged data sent[Topic sent nltk] = topic list
           30
                   column list nltk.append(Topic sent nltk)
           31
           32
               merged data sent sum nltk = merged data sent[column list nltk].sum(axis=1)
               merged_data_sent["average_nltk_sent"] = merged_data_sent_sum_nltk / 22
           33
           34
           35
```

```
In [200]: 1 #merged_data_sent['Top23']
```

Create a DF with just the average blob sent and the average nltk sent. Get the average sent for each day

average NLTK sent is -0.21 average Blob sent is 0.01

Out[201]:

	average_nltk_sent	average_blob_sent	Label
1988	-0.318659	-0.048722	0
1987	-0.114414	0.030705	1
1986	-0.264577	-0.041955	0
1985	-0.131123	0.005201	0
1984	-0.157518	0.054723	1
4	-0.150886	-0.007135	0
3	-0.003755	0.036262	1
2	-0.282536	0.034246	1
1	-0.214800	0.020274	1
0	-0.297809	0.025758	1

1989 rows × 3 columns

Check if positive sentiment for the day is related to a rise in stock prices.

If the Dow Jones went up and the sentiment was postive mark as "correct". If the Dow Jones went up and sentiment was down mark as incorrect.

If the Dow Jones went down and the sentiment was postive mark as "incorrect". If the Dow Jones went down and sentiment was down marka as incorrect.

Do this for both vader and blob.

```
In [202]:
             1
               nltk correct = []
             2
               blob correct = []
             3
             4
             5
               for average_nltk_sent, average_blob_sent, Label in label_sent_df.itertuples(
             6
                    if average_nltk_sent <0:</pre>
             7
                        if Label == 0:
             8
                             correct = 1
             9
                             nltk correct.append(1)
            10
                        else:
            11
                             correct = 0
            12
                            nltk_correct.append(0)
            13
                    else:
            14
                    #if average nltk sent > 0:
                        if Label == 1:
            15
            16
                             correct = 1
            17
                            nltk correct.append(1)
            18
                        else:
            19
                             correct = 0
            20
                            nltk correct.append(0)
            21
            22
                    if average_blob_sent <0:</pre>
            23
                        if Label == 0:
            24
                             correct = 1
            25
                            blob_correct.append(1)
            26
                        else:
                             correct = 0
            27
            28
                            blob_correct.append(0)
            29
                    else:
            30
                    #if average_nltk_sent > 0:
            31
                        if Label == 1:
            32
                             correct = 1
            33
                            blob correct.append(1)
            34
                        else:
            35
                             correct = 0
            36
                            blob_correct.append(0)
            37
               label_sent_df['nltk_correct_score'] = nltk_correct
            38
               label sent df['blob correct score'] = blob correct
            39
            40
            41
            42
               #label sent df
            43
            44
```

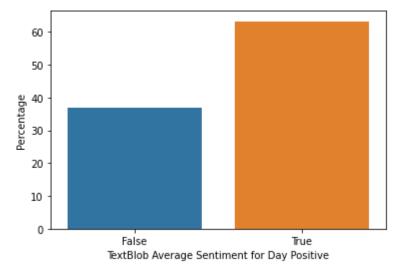
Insert extra columns in DF showing if the blob or vader sent was negative or postive

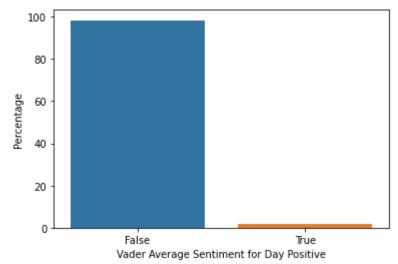
```
In [203]:
            1
               import numpy as np
            2
            3
               average blob sent pos = []
               for x in label sent df['average blob sent']:
            4
            5
                   if x > 0:
            6
                        average_blob_sent_pos.append(1)
            7
                   else:
            8
                        average blob sent pos.append(0)
            9
               label_sent_df['average_blob_sent_pos'] = average_blob_sent_pos
           10
           11
               average_nltk_sent_pos = []
           12
           13
               for x in label_sent_df['average_nltk_sent']:
                   if x > 0:
           14
           15
                        average nltk sent pos.append(1)
           16
                   else:
           17
                        average nltk sent pos.append(0)
           18
           19
               label_sent_df['average_nltk_sent_pos'] = average_nltk_sent_pos
           20
           21
           22
               label_sent_df['nltk_equals_blob_pos'] = (label_sent_df['average_nltk_sent_po
           23
           24
               #label_sent_df
           25
           26
```

Create plots based of the amount of postives days for both vader and blob sent.

Also compare how many of the vader sentiment matching the blob sentiment.

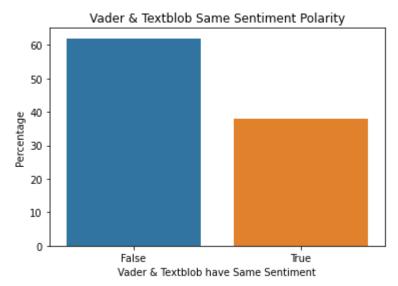
Vader VS Textblob Average Daily Sentiment





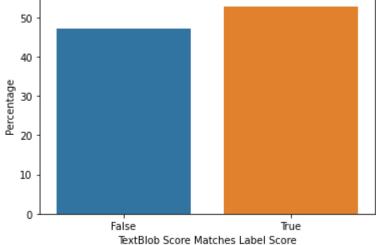
While Textblob only had 39% of days with an average sentiment score, Vader had over 90% of

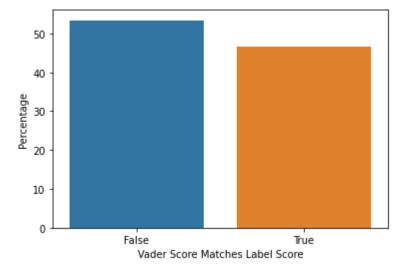
days with a negative sentiment score.



Unsuprisingly, Vader and Textblob only match on polarity (neg and neg or pos and pos) around 40% of the time

Vader and Texblob Match with Dow Jones





Textblob does a slightly better job of matching the Dow Jones average, however both Textblob and Vader match right around 50% of the time.

Sentiment With Decision Tree and Logistic Regression Models

Logistic Regression Model

Perform a logistic regression model using sentiment to predict if stocks went up or down.

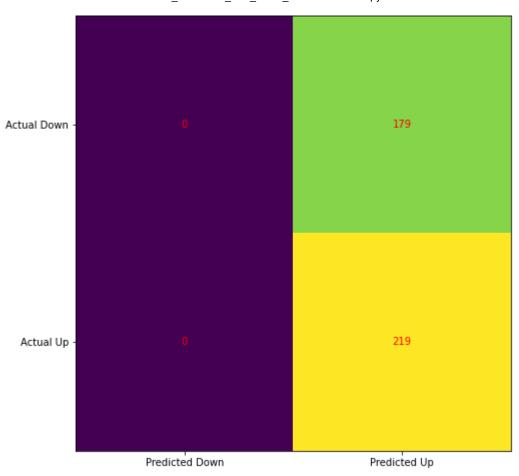
Use text blob and NLTK as the X and the Dow Jones label of whether Dow Jones went down or up as the y.

Texblob

```
In [210]:
            1 from sklearn.model_selection import train_test_split
              import matplotlib.pyplot as plt
            3 import numpy as np
            4 from sklearn.linear model import LogisticRegression
              from sklearn.metrics import classification_report, confusion_matrix
            7
              model = LogisticRegression(solver='liblinear')
            8
            9
              X = merged_data_sent[['average_blob_sent']]
           10
           11
              y = merged_data_sent['Label']
           12
           13
           14 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
In [211]:
              from sklearn.linear model import LogisticRegression
               logmodel = LogisticRegression()
            3
              logmodel.fit(X_train,y_train)
               predictions blob = logmodel.predict(X test)
            4
            5
            6
              from sklearn.metrics import classification_report
            7
               print(classification_report(y_test,predictions_blob))
            8
            9
               cm = confusion_matrix(y_test, predictions_blob)
           10
           fig, ax = plt.subplots(figsize=(8, 8))
           12
              ax.imshow(cm)
           13 ax.grid(False)
           14 | ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted Down', 'Predicted Up'))
           15 | ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual Down', 'Actual Up'))
           16 ax.set_ylim(1.5, -0.5)
              for i in range(2):
           17
           18
                   for j in range(2):
           19
                       ax.text(j, i, cm[i, j], ha='center', va='center', color='red')
           20
              plt.show()
```

	precision	recall	f1-score	support
0 1	0.00 0.55	0.00 1.00	0.00 0.71	179 219
accuracy macro avg weighted avg	0.28 0.30	0.50 0.55	0.55 0.35 0.39	398 398 398

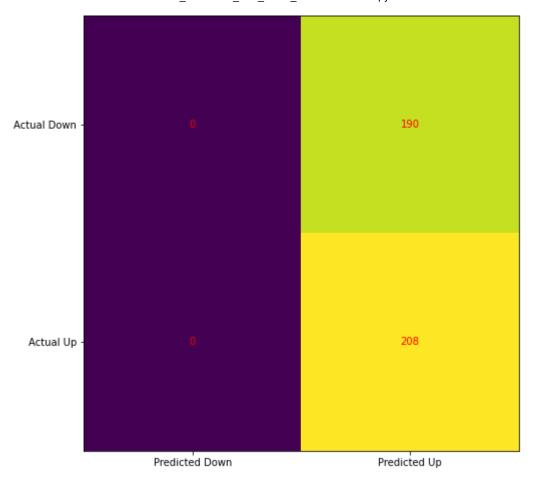


Vader

```
In [212]:
               #need to split into blob and NLTK and not combine together.
            2
            3
            4
              from sklearn.model_selection import train_test_split
              import matplotlib.pyplot as plt
            7
              import numpy as np
              from sklearn.linear_model import LogisticRegression
            8
            9
               from sklearn.metrics import classification_report, confusion_matrix
           10
               model = LogisticRegression(solver='liblinear', random_state=0)
           11
           12
           13
              X = merged_data_sent[['average_nltk_sent']]
           14
           15
              y = merged_data_sent['Label']
           16
           17
           18
              X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
In [213]:
               from sklearn.linear model import LogisticRegression
               logmodel = LogisticRegression()
            3
               logmodel.fit(X_train,y_train)
            4
               predictions_nltk = logmodel.predict(X_test)
            5
            6
            7
               from sklearn.metrics import classification report
               print(classification_report(y_test,predictions_nltk))
            9
               cm = confusion_matrix(y_test, predictions_nltk)
           10
           11
           12
              fig, ax = plt.subplots(figsize=(8, 8))
           13 ax.imshow(cm)
              ax.grid(False)
           15 | ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted Down', 'Predicted Up'))
           16 | ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual Down', 'Actual Up'))
               ax.set ylim(1.5, -0.5)
           17
           18
              for i in range(2):
           19
                   for j in range(2):
                       ax.text(j, i, cm[i, j], ha='center', va='center', color='red')
           20
           21
               plt.show()
```

support	f1-score	recall	precision	
190	0.00	0.00	0.00	0
208	0.69	1.00	0.52	1
398	0.52			accuracy
398	0.34	0.50	0.26	macro avg
398	0.36	0.52	0.27	weighted avg



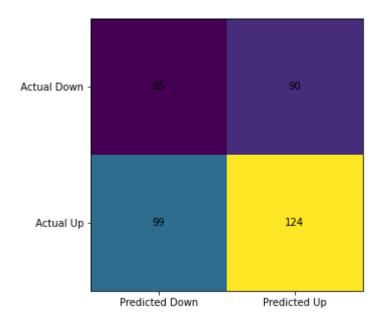
The vader logistic regression model was slightly more accurate than the textblob.

Decision Tree Classifier

TextBlob

```
In [215]:
               y_predict_blob = classifier_tree.fit(X_train, y_train).predict(X_test)
            3
               print("Decision Tree Classifier using text blob \n",classification_report(y_
            4
            5
            6
               cm = confusion_matrix(y_test, y_predict_blob)
            8
               fig, ax = plt.subplots(figsize=(5, 5))
            9
               ax.imshow(cm)
               ax.grid(False)
           10
               ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted Down', 'Predicted Up'))
           11
               ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual Down', 'Actual Up'))
           12
               ax.set_ylim(1.5, -0.5)
           13
               for i in range(2):
           14
           15
                   for j in range(2):
           16
                       ax.text(j, i, cm[i, j], ha='center', va='center', color='black')
           17
              plt.show()
```

Decision	Tree	Classifier	using text	blob	
		precision	recall	f1-score	support
	0	0.46	0.49	0.47	175
	1	0.58	0.56	0.57	223
accur	racy			0.53	398
macro	avg	0.52	0.52	0.52	398
weighted	avg	0.53	0.53	0.53	398

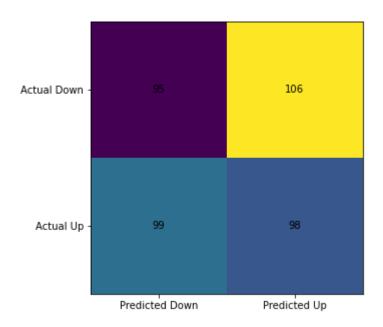


Vader

```
In [217]:
            1
              y_predict_nltk = classifier_tree.fit(X_train, y_train).predict(X_test)
            3
               print("Decision Tree Classifier using NLTK \n", classification_report(y_test
            4
            5
            6
               cm = confusion_matrix(y_test, y_predict_nltk)
            8
              fig, ax = plt.subplots(figsize=(5, 5))
            9
               ax.imshow(cm)
              ax.grid(False)
           10
              ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted Down', 'Predicted Up'))
           11
              ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual Down', 'Actual Up'))
           12
           13
              ax.set_ylim(1.5, -0.5)
              for i in range(2):
           14
           15
                   for j in range(2):
           16
                       ax.text(j, i, cm[i, j], ha='center', va='center', color='black')
           17
              plt.show()
```

Decision Tree Classifier using NLTK

	precision	recall	f1-score	support
0	0.49	0.47	0.48	201
1	0.48	0.50	0.49	197
accuracy			0.48	398
macro avg	0.49	0.49	0.48	398
weighted avg	0.49	0.48	0.48	398



For the decision tree, both vader and textblob had similar accuracy results.

```
In [ ]: 1 In [ ]: 1
```

Overall Conclusions

TFIDF and Embeddings

- In general, our models do not predict the trend of the Dow Jones Industrial Average of each day very well.
- Even though we acheived 51% and 57% accuracy scores, they are still too low to say with any certainty that they are good at predicting the market. With related keywords such as "stock" or "market", we have increased accuracy by over 5% for our logistic regression model.
- We believe that our input variables are not noisy, because we were able to increase our
 accuracy for machine learning models by adding filters and selecting more related variables
 out of the original data sets, such as selecting the texts with the key words, etc.

Sentiment

- Textblob and Vader produced extremely different average sentiment scores.
- Both Textblob and Vader have average accuracies around 53%, with the best average accuracy at 54% and logistic regression with slightly higher accuracies.
- Our decision tree model has a realistic distribution than the logistic regression model as it is a
 lot less skewed.