Predict Stock Market with ML

January 2, 2025

1 Predict The Stock Market With ML

We'll going to use S&P 500 and predict tomorrow's index price using 20 years of historical data. We will also backtesting if this is accurate prediction. After that we'll improve the model by adding predictors.

[1]:
```
pip install yfinance
```

```
Requirement already satisfied: yfinance in /opt/conda/lib/python3.11/site-
packages (0.2.51)
Requirement already satisfied: pandas>=1.3.0 in /opt/conda/lib/python3.11/site-
packages (from yfinance) (2.1.3)
Requirement already satisfied: numpy>=1.16.5 in /opt/conda/lib/python3.11/site-
packages (from yfinance) (1.24.4)
Requirement already satisfied: requests>=2.31 in /opt/conda/lib/python3.11/site-
packages (from yfinance) (2.31.0)
Requirement already satisfied: multitasking>=0.0.7 in
/opt/conda/lib/python3.11/site-packages (from yfinance) (0.0.11)
Requirement already satisfied: lxml>=4.9.1 in /opt/conda/lib/python3.11/site-
packages (from yfinance) (5.2.2)
Requirement already satisfied: platformdirs>=2.0.0 in
/opt/conda/lib/python3.11/site-packages (from yfinance) (4.1.0)
Requirement already satisfied: pytz>=2022.5 in /opt/conda/lib/python3.11/site-
packages (from yfinance) (2023.3.post1)
Requirement already satisfied: frozendict>=2.3.4 in
/opt/conda/lib/python3.11/site-packages (from yfinance) (2.4.6)
Requirement already satisfied: peewee>=3.16.2 in /opt/conda/lib/python3.11/site-
packages (from yfinance) (3.17.8)
Requirement already satisfied: beautifulsoup4>=4.11.1 in
/opt/conda/lib/python3.11/site-packages (from yfinance) (4.12.2)
Requirement already satisfied: html5lib>=1.1 in /opt/conda/lib/python3.11/site-
packages (from yfinance) (1.1)
Requirement already satisfied: soupsieve>1.2 in /opt/conda/lib/python3.11/site-
packages (from beautifulsoup4>=4.11.1->yfinance) (2.5)
Requirement already satisfied: six>=1.9 in /opt/conda/lib/python3.11/site-
packages (from html5lib>=1.1->yfinance) (1.16.0)
Requirement already satisfied: webencodings in /opt/conda/lib/python3.11/site-
packages (from html5lib>=1.1->yfinance) (0.5.1)
```

```
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.11/site-packages (from pandas>=1.3.0->yfinance) (2.8.2)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.11/site-
packages (from pandas>=1.3.0->yfinance) (2023.3)
Requirement already satisfied: charset-normalizer<4,>=2 in
/opt/conda/lib/python3.11/site-packages (from requests>=2.31->yfinance) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.11/site-
packages (from requests>=2.31->yfinance) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/opt/conda/lib/python3.11/site-packages (from requests>=2.31->yfinance) (2.1.0)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.11/site-packages (from requests>=2.31->yfinance)
(2023.11.17)
Note: you may need to restart the kernel to use updated packages.
```

[2]:

```python
# Import
import yfinance as yf
import pandas as pd
```

[3]:

```python
sp500 = yf.Ticker("^GSPC") # Download the Price History from Ticker class
sp500 = sp500.history(period = "max")
```

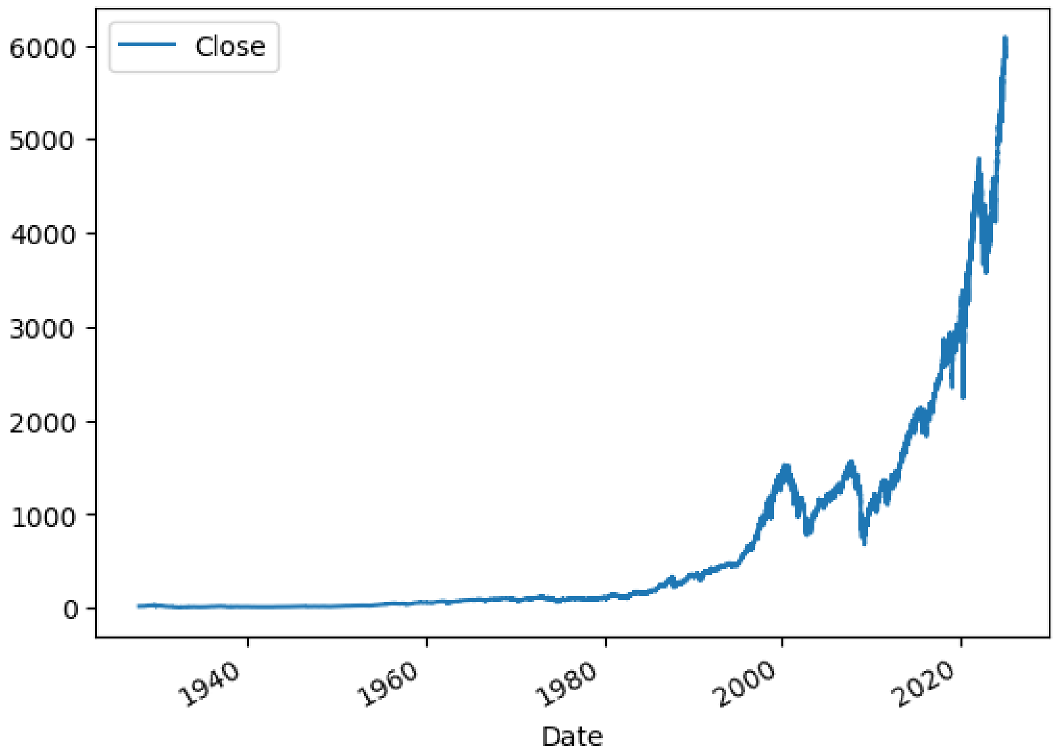
[4]:

```python
#sp500.index
```

[5]:

```python
sp500.plot.line(y="Close", use_index = True)
```

[5]: <Axes: xlabel='Date'>



[6]:
```
#We are not going to use Dividends and Stock in this practice
del sp500["Dividends"]
del sp500["Stock Splits"]
```

[7]:
```
#Shifting  -1 for every close of that day
sp500["Tomorrow"] = sp500["Close"].shift(-1)
```

[8]:
```
# If 1 then it going up and 0 or down
sp500["Target"] = (sp500["Tomorrow"] > sp500["Close"]).astype(int)
```

[9]:
```
#sp500
```

[10]:
```
sp500 = sp500.loc["1990-01-01":].copy()
```

1.0.1 Training an Initial Machine Learning Model

[11]:
```
# Simple ML Model. It help as a initial model since it's hard to be overfit␣
↪than other models
from sklearn.ensemble import RandomForestClassifier
```

[12]:
```
# Randomzation as 1 and split for 100 to avoid overfit, start with small # of␣
↪estimators
```

```
model = RandomForestClassifier(n_estimators = 200, min_samples_split = 100,␣
 ↪random_state = 1)

# We can't use cross validation. Why? Time series nature of data (train works␣
 ↪well but real world would be horrible)
train = sp500.iloc[:-100]
test = sp500.iloc[-100:]

# We aren't going to use Tomorrow or Target since if we use that will cause␣
 ↪overfit since it's already know the results
predictors = ["Close", "Volume", "Open", "High", "Low"]

model.fit(train[predictors], train["Target"])
```

[12]:
```
RandomForestClassifier(min_samples_split=100, n_estimators=200, random_state=1)
```

[13]:
```
# Verify the precision. How precise that we predict goes up actually stock␣
 ↪price go up.
from sklearn.metrics import precision_score

preds = model.predict(test[predictors]) #array
```

[14]:
```
preds = pd.Series(preds, index = test.index)

precision_score(test["Target"],preds)
```

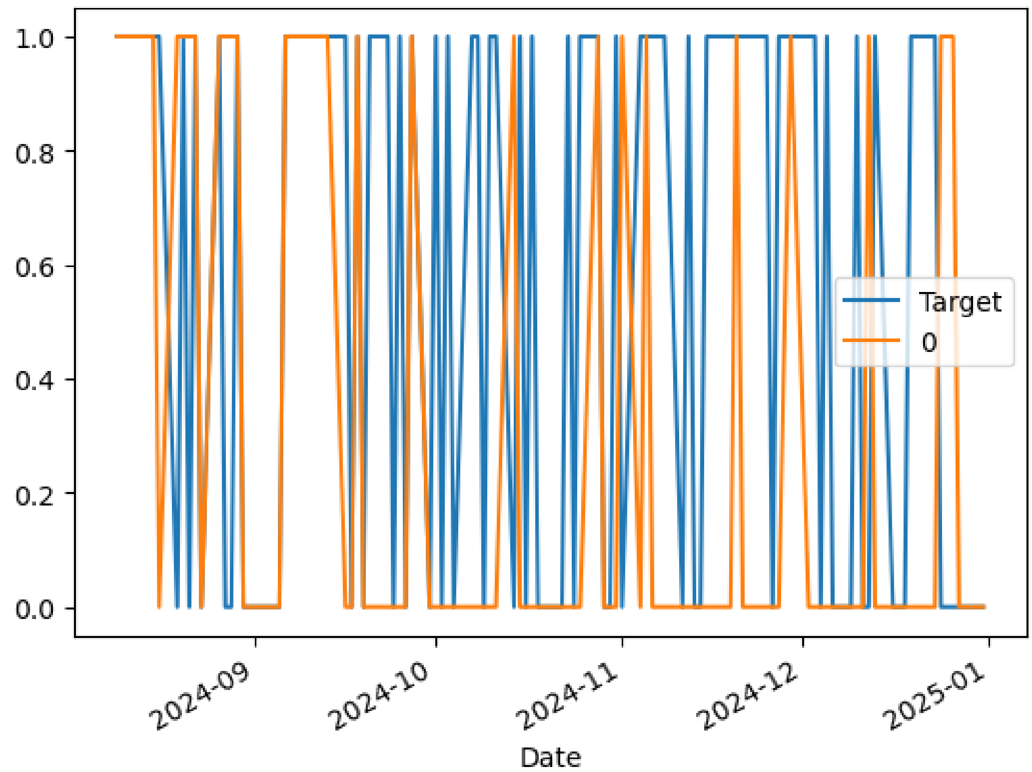
[14]:
```
0.7
```

We got precision as 70% which is good but we could make it better

[15]:
```
# Plot prediction
combined = pd.concat([test["Target"], preds], axis = 1) #axis = 1 so each test␣
 ↪output will be as a column

combined.plot()
```

[15]:
```
<Axes: xlabel='Date'>
```



1.0.2 Backtesting

[16]:
```
# Similar as above but instead using train predictor as well.
def predict(train, test, predictors, model):
    model.fit(train[predictors], train["Target"])
    preds = model.predict(test[predictors])
    preds = pd.Series(preds, index=test.index, name="Predictions") #Named the␣
↪series as Predictions
    combined = pd.concat([test["Target"], preds], axis = 1)
    return combined
```

[17]:
```
# Training

#Training for 10 years where each business day is 250 days per year. 25000 days␣
↪for 10 years
def backtest(data, model, predictors, start = 2500, step = 250):
    all_predictions = []

    for i in range(start, data.shape[0], step): #data.shape[0] -> # of rows
        train = data.iloc[0:i].copy()
        test = data.iloc[i:(i+step)].copy()
```

```
        predictions = predict(train, test, predictors, model)
        all_predictions.append(predictions)

    return pd.concat(all_predictions)
```

[18]:
```
#Call Back test
predictions = backtest(sp500, model, predictors)

predictions["Predictions"].value_counts()
```

[18]:
```
Predictions
0    3628
1    2689
Name: count, dtype: int64
```

[19]:
```
precision_score(predictions["Target"], predictions["Predictions"])
```

[19]:
```
0.5273335812569728
```

1.0.3 Benchmark

[20]:
```
predictions["Target"].value_counts() / predictions.shape[0]
```

[20]:
```
Target
1    0.535856
0    0.464144
Name: count, dtype: float64
```

Based on the Benchmark, 52.8% precision make it little worse than natural percentage of the days that stockmarket goes up.

1.0.4 Adding Additional Predictors

By adding more predictors check that whether the accuracy goes up or not.

[21]:
```
horizons = [2, 5, 60, 250, 1000] #last 2 days, 5 days, 3 months, etc.

#By checking for each span ratio, how long it goes up in that spans to help␣
 ↪better prediction (hypothesis).
new_predictors = []

for horizon in horizons:
    rolling_avg = sp500.rolling(horizon).mean() # rolling() provide window␣
 ↪(days span) calculation

    ratio_column = f"Close_Ratio_{horizon}" # create column name for each span
    sp500[ratio_column] = sp500["Close"] / rolling_avg["Close"]
```

```
    trend_column = f"Trend_{horizon}"
    sp500[trend_column] = sp500.shift(1).rolling(horizon).sum()["Target"] # It␣
↪will calculate the past days of the Target number so if 0 0 0 1 1 then would␣
↪be for last 5 days there are 2 days that goes up

    new_predictors += [ratio_column, trend_column]
```

[22]:
```
sp500 # There would be lot of NaN since if they can't find the enough days␣
↪prior to the data, it will automatically become NaN
```

[22]:
```
                                  Open         High          Low        Close  \
Date
1990-01-02 00:00:00-05:00   353.399994   359.690002   351.980011   359.690002
1990-01-03 00:00:00-05:00   359.690002   360.589996   357.890015   358.760010
1990-01-04 00:00:00-05:00   358.760010   358.760010   352.890015   355.670013
1990-01-05 00:00:00-05:00   355.670013   355.670013   351.350006   352.200012
1990-01-08 00:00:00-05:00   352.200012   354.239990   350.540009   353.790009
…                                    …            …            …            …
2024-12-24 00:00:00-05:00  5984.629883  6040.100098  5981.439941  6040.040039
2024-12-26 00:00:00-05:00  6024.970215  6049.750000  6007.370117  6037.589844
2024-12-27 00:00:00-05:00  6006.169922  6006.169922  5932.950195  5970.839844
2024-12-30 00:00:00-05:00  5920.669922  5940.790039  5869.160156  5906.939941
2024-12-31 00:00:00-05:00  5919.740234  5929.740234  5868.859863  5881.629883

                               Volume     Tomorrow  Target  Close_Ratio_2  \
Date
1990-01-02 00:00:00-05:00   162070000   358.760010       0            NaN
1990-01-03 00:00:00-05:00   192330000   355.670013       0       0.998706
1990-01-04 00:00:00-05:00   177000000   352.200012       0       0.995675
1990-01-05 00:00:00-05:00   158530000   353.790009       1       0.995098
1990-01-08 00:00:00-05:00   140110000   349.619995       0       1.002252
…                                   …            …     …              …
2024-12-24 00:00:00-05:00  1757720000  6037.589844       0       1.005491
2024-12-26 00:00:00-05:00  2904530000  5970.839844       0       0.999797
2024-12-27 00:00:00-05:00  3159610000  5906.939941       0       0.994441
2024-12-30 00:00:00-05:00  3433250000  5881.629883       0       0.994620
2024-12-31 00:00:00-05:00  3128350000          NaN       0       0.997853

                           Trend_2  Close_Ratio_5  Trend_5  Close_Ratio_60  \
Date
1990-01-02 00:00:00-05:00      NaN            NaN      NaN             NaN
1990-01-03 00:00:00-05:00      NaN            NaN      NaN             NaN
1990-01-04 00:00:00-05:00      0.0            NaN      NaN             NaN
1990-01-05 00:00:00-05:00      0.0            NaN      NaN             NaN
1990-01-08 00:00:00-05:00      1.0       0.993731      NaN             NaN
…                                …              …        …               …
```

```
2024-12-24 00:00:00-05:00       2.0        1.017383       3.0          1.023002
2024-12-26 00:00:00-05:00       1.0        1.011334       3.0          1.021639
2024-12-27 00:00:00-05:00       0.0        0.996689       3.0          1.009600
2024-12-30 00:00:00-05:00       0.0        0.986810       2.0          0.998213
2024-12-31 00:00:00-05:00       0.0        0.985626       1.0          0.993570

                           Trend_60  Close_Ratio_250  Trend_250  \
Date
1990-01-02 00:00:00-05:00       NaN              NaN        NaN
1990-01-03 00:00:00-05:00       NaN              NaN        NaN
1990-01-04 00:00:00-05:00       NaN              NaN        NaN
1990-01-05 00:00:00-05:00       NaN              NaN        NaN
1990-01-08 00:00:00-05:00       NaN              NaN        NaN
…                               …                …          …
2024-12-24 00:00:00-05:00      35.0         1.115492      144.0
2024-12-26 00:00:00-05:00      35.0         1.114008      143.0
2024-12-27 00:00:00-05:00      34.0         1.100716      143.0
2024-12-30 00:00:00-05:00      34.0         1.088002      143.0
2024-12-31 00:00:00-05:00      33.0         1.082402      143.0

                           Close_Ratio_1000  Trend_1000
Date
1990-01-02 00:00:00-05:00               NaN         NaN
1990-01-03 00:00:00-05:00               NaN         NaN
1990-01-04 00:00:00-05:00               NaN         NaN
1990-01-05 00:00:00-05:00               NaN         NaN
1990-01-08 00:00:00-05:00               NaN         NaN
…                                       …          …
2024-12-24 00:00:00-05:00          1.337188       531.0
2024-12-26 00:00:00-05:00          1.335962       530.0
2024-12-27 00:00:00-05:00          1.320543       529.0
2024-12-30 00:00:00-05:00          1.305803       528.0
2024-12-31 00:00:00-05:00          1.299617       527.0

[8817 rows x 17 columns]
```

[23]:
```python
# Fixing the NaN issues
sp500 = sp500.dropna()
```

1.0.5 Improving Models

[24]:
```python
model =RandomForestClassifier(n_estimators=200, min_samples_split=50,
 ↪random_state=1)
```

[25]:
```python
# Similar as above but instead find the probability of the prediction
def predict(train, test, predictors, model):
    model.fit(train[predictors], train["Target"])
```

```
    preds = model.predict_proba(test[predictors])[:,1] #predict_proba.
↪Probability the goes up
    preds[preds >= 0.6] = 1
    preds[preds < 0.6] = 0
    # Increase the chance that goes up

    preds = pd.Series(preds, index=test.index, name="Predictions") #Named the
↪series as Predictions
    combined = pd.concat([test["Target"], preds], axis = 1)
    return combined
```

[26]:
```
# Backtest again
predictions = backtest(sp500, model, new_predictors)
```

[27]:
```
predictions["Predictions"].value_counts()
#Why there's lot of 0's?
#A: since we change the threshold to make it more confidence
```

[27]:
```
Predictions
0.0    4463
1.0     853
Name: count, dtype: int64
```

[29]:
```
precision_score(predictions["Target"], predictions["Predictions"])
```

[29]:
```
0.5756154747948418
```

[46]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, f1_score

mae_test = mean_absolute_error(test["Target"],preds)
f1_test = f1_score(test["Target"], preds)

mae_new = mean_absolute_error(predictions["Target"], predictions["Predictions"])
f1_new = f1_score(predictions["Target"], predictions["Predictions"])
```

[50]:
```
print(f"Mean Absolute Error: {mae_test}, F1 Score: {f1_test}")
```

```
Mean Absolute Error: 0.45, F1 Score: 0.48275862068965514
```

[49]:
```
print(f"Mean Absolute Error: {mae_new}, F1 Score: {f1_new}")
```

```
Mean Absolute Error: 0.5212565838976674, F1 Score: 0.2616573407940314
```

1.1 Conclusion

Adding more predictors does not always lead to better performance. In this case, the added predictors likely introduced noise or complexity, outweighing any potential benefits.

[ ]:

```

```