Predict the S&P500 💸

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Introduction 📈

Welcome to this machine learning project with **Python**!

In this project, we will be predicting the stock market using Machine Learning. Specifically, we will be trying to predict when the stock S&P500 Index price will increase in value.

To begin, we will download data on the S&P500 Index prior to cleaning the data and then using it to train a machine learning model. Finally, we will do back-testing to assess the performance of our model, and aim to improve this performance with additional predictors.

S&P500 📈

The Standard and Poor's 500, or simply the S&P 500, is a stock market index tracking the stock performance of **500 large companies** listed on stock exchanges in the United States. It is one of the most commonly followed equity indices.

TECHNOLOGY
SOFTWARE - INFRASTRUCTURE
MSFT -1.21%
ADBE -0.10%
ORCL -0.34%
SEMICONDUCTORS
INTC +0.81%
AVGO +0.14%
TXN +0.89%
NVDA +0.91%
QCOM +0.34%
MU +1.84%
AMD +5.97%
INFORMATION TEC
SOFTWARE -
ACN -0.23%
IBM +0.24%
CRM -0.26%
FIS
INTU
NOW
FISV
CONSUMER ELECTRONICS
AAPL +0.63%
COMMUNICAT
SEMICOND
ELECT
CSCO +0.33%
LRCX
APH
TEL
COMPUTER
FINANCIAL
CREDIT SERVICES
V
MA +0.22%
PYPL
AXP
COF
INSURANCE - DIVERSIFIED
BRK-B -0.19%
FINANCIAL DA
SPGI
CME
ICE
MCO
MSCI
BANKS - REGION
ASSET MAN
INSURANC
USB
PNC
BLK
BK
CB
PGR
TFC
STT
ALL
CAPITAL MARKET
INSURANCE
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SCHW
AON
MET
AFL
BANKS - DIVERSIFIED
JPM -1.02%
BAC -0.16%
WFC -0.80%
C
COMMUNICATION SERVICES
INTERNET CONTENT & INFOR
ENTERTAINMENT
GOOGL +0.18%
DIS
CMCSA -0.19%
NFLX +1.78%
CHTR +0.59%
TELECOM SERVICES
FB +0.08%
VZ +0.58%
T
ATVI
EA
HEALTHCARE
DRUG MANUFACTURERS - GENERAL
JNJ
PFE -0.10%
LLY +0.27%
BMY
ABBV
MRK -0.93%
AMGN
GILD
AGN
BIIB
HEALTHCARE PLANS
UNH -0.30%
CVS +0.85%
CI
HUM
ANTM
CNC
DIAGNOSTICS & RESEARCH
TMO
DHR
A
IQV
LH
MEDICAL INSTRU
DRUG MA
BDX
BAX
ZTS
MEDICAL DEVICES
ABT
MDT -0.77%
BSX
EW
SYK
ISRG
BIOTECHNOLOGY
VRTX
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MEDICAL
HEALTH I
CONSUMER CYCLICAL
INTERNET RETAIL
AMZN +1.48%
HOME IMPROVEM
FOOTWEA
SPECIAL
APPAR
HD
LOW
NKE
ORLY
TJX
ROST
TRAVEL
BKNG
LVS
GM
F
RESTAURANTS
MCD
SBUX
LODGI
PACKA
MAR
APPAR
INDUSTRIALS
SPECIALTY INDUSTRIAL
RAILROADS
INTEGRA
HON
GE
ITW
UNP
CSX
UPS
MMM
ROP
CMI
ETN
TT
EMR
PH
IR
AME
NSC
FDX
FARM & HEA
STAFFIN
CAT
DE
ADP
AEROSPACE & DEFENSE
SPECIAL
WASTE
LMT
BA
NOC
GD
RTX
LHX
WM
CONSUL
JCI
ENERGY
OIL & GAS INTEGRATED
OIL & GA
OIL & G
XOM +1.68%
CVX
COP
EOG
PSX
CONSUMER DEFENSIVE
DISCOUNT STORES
HOUSEHOLD & P
WMT +0.10%
PG +0.10%
COST
TGT
DG
EL
KMB
CL
BEVERAGES -
PACKAGED
TOBACCO
KO
KHC
GIS
PM -0.14%
HRL
K
SJM
MO
CONFE
BEVERA
PEP -0.23%
MDLZ
STZ
SYY
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KR
REAL ESTATE
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PLD
PSA
DLR
EQIX
EQR
AVB
SPG
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UTILITIES - REGULATE
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XEL
ED
EIX
PEG
DUK
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FE
BASIC MATERIALS
SPECIALTY CHE
CHEMI
LIN
ECL
SHW
APD
NEM
Use mouse wheel to zoom in and out. Drag zoomed map to pan it. Double-click a ticker to display detailed information in a new window.
Hover mouse cursor over a ticker to see its main competitors in a stacked view with a 3-month history graph.
-3%
-2%
-1%
0%
+1%
+2%
+3%

Downloading & Cleaning Data 📈

Downloading S&P500 Price Data 📈

We will be using the **yfinance** package in *Python*. Importing this package calls the **Yahoo Finance API** to download daily stock and index prices.

In [1]:

```
import yfinance as yf
```

After importing the yfinance package, we are going to initialise a Ticker class which will allow us to download price history for a single symbol. For the S&P500 Index, the symbol of **GSPC**.

In [2]:

```
sp500 = yf.Ticker("^GSPC")
```

Now, we are going to query the historical prices using the **.history( )** method. Passing the argument **period="max"** to this method will query data from when the index was first created. Doing this gives us pandas data frame.

In [3]:

```python
sp500 = sp500.history(period="max")

# Display data frame
sp500
```

Out[3]:

Date	Open	High	Low	Close	Volume	Dividends	Sto Spl
1950-01-03 00:00:00-05:00	16.660000	16.660000	16.660000	16.660000	1260000	0	
1950-01-04 00:00:00-05:00	16.850000	16.850000	16.850000	16.850000	1890000	0	
1950-01-05 00:00:00-05:00	16.930000	16.930000	16.930000	16.930000	2550000	0	
1950-01-06 00:00:00-05:00	16.980000	16.980000	16.980000	16.980000	2010000	0	
1950-01-09 00:00:00-05:00	17.080000	17.080000	17.080000	17.080000	2520000	0	
...	...	...	...	...	...	...	
2023-02-17 00:00:00-05:00	4077.389893	4081.510010	4047.949951	4079.090088	4045480000	0	
2023-02-21 00:00:00-05:00	4052.350098	4052.350098	3995.189941	3997.340088	4121590000	0	
2023-02-22 00:00:00-05:00	4001.830078	4017.370117	3976.899902	3991.050049	4079320000	0	
2023-02-23 00:00:00-05:00	4018.600098	4028.300049	3969.189941	4012.320068	3952940000	0	
2023-02-24 00:00:00-05:00	3973.239990	3978.250000	3943.080078	3970.040039	3877700000	0	

18406 rows × 7 columns

In the above data frame, each row represents a single trading day. The columns that we will be using to train our initial model are:

- **Open** - Opening price
- **High** - Highest price during the day
- **Low** - Lowest price during the day
- **Close** - Closing price
- **Volume** - Total volume of trades that day

The remaining two columns will not be used and will be dropped later on.

The **Date** column on the left is the index column. Inspecting this index column reveals that we have a **DateTimeIndex**:

```
In [4]:  # Inspect data frame index
         sp500.index
```

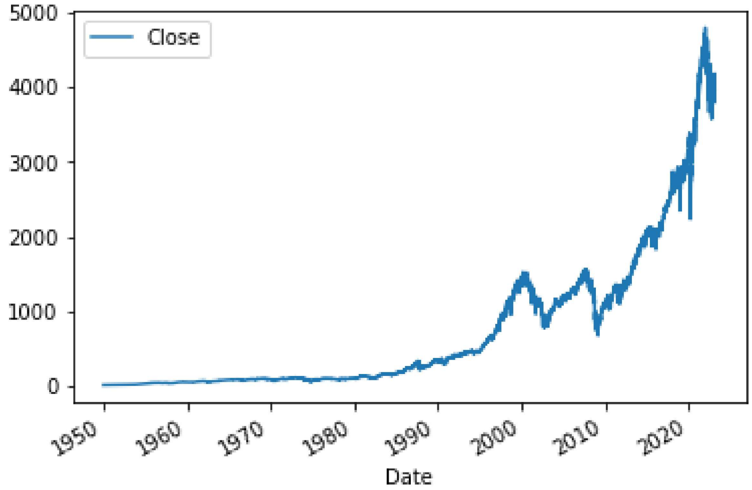
```
Out[4]: DatetimeIndex(['1950-01-03 00:00:00-05:00', '1950-01-04 00:00:00-05:00',
                       '1950-01-05 00:00:00-05:00', '1950-01-06 00:00:00-05:00',
                       '1950-01-09 00:00:00-05:00', '1950-01-10 00:00:00-05:00',
                       '1950-01-11 00:00:00-05:00', '1950-01-12 00:00:00-05:00',
                       '1950-01-13 00:00:00-05:00', '1950-01-16 00:00:00-05:00',
                       ...
                       '2023-02-10 00:00:00-05:00', '2023-02-13 00:00:00-05:00',
                       '2023-02-14 00:00:00-05:00', '2023-02-15 00:00:00-05:00',
                       '2023-02-16 00:00:00-05:00', '2023-02-17 00:00:00-05:00',
                       '2023-02-21 00:00:00-05:00', '2023-02-22 00:00:00-05:00',
                       '2023-02-23 00:00:00-05:00', '2023-02-24 00:00:00-05:0
        0'],
                      dtype='datetime64[ns, America/New_York]', name='Date', len
        gth=18406, freq=None)
```

Cleaning and Visualising the Stock Market Data 📈

First, we will plot the closing price (**Close**) against the index (**Date**) to visualise the historical trend of the index.

In [5]:

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



It can be observed that the trend is near-exponential, with very rapid price increased in the 2000s and 2010s.

Now, we will delete the **Dividends** and **Stock Splits** columns, as we will not be using them.

In [6]:

```
del sp500["Dividends"]
del sp500["Stock Splits"]
```

In [7]:
```
sp500
```

Out[7]:

	Open	High	Low	Close	Volume
Date					
1950-01-03 00:00:00-05:00	16.660000	16.660000	16.660000	16.660000	1260000
1950-01-04 00:00:00-05:00	16.850000	16.850000	16.850000	16.850000	1890000
1950-01-05 00:00:00-05:00	16.930000	16.930000	16.930000	16.930000	2550000
1950-01-06 00:00:00-05:00	16.980000	16.980000	16.980000	16.980000	2010000
1950-01-09 00:00:00-05:00	17.080000	17.080000	17.080000	17.080000	2520000
...	...	...	...	...	...
2023-02-17 00:00:00-05:00	4077.389893	4081.510010	4047.949951	4079.090088	4045480000
2023-02-21 00:00:00-05:00	4052.350098	4052.350098	3995.189941	3997.340088	4121590000
2023-02-22 00:00:00-05:00	4001.830078	4017.370117	3976.899902	3991.050049	4079320000
2023-02-23 00:00:00-05:00	4018.600098	4028.300049	3969.189941	4012.320068	3952940000
2023-02-24 00:00:00-05:00	3973.239990	3978.250000	3943.080078	3970.040039	3877700000

18406 rows × 5 columns

Create Target for Machine Learning 📈

We need a variable that we will be predicting using our model. In machine learning applications, this is called the **target**, whereas predictors are often referred to as **features** of the data set.

The target variable will indicate whether or not the SP500 Index price will increase or decrease after a day of trading. We will do this by creating a column called **Tomorrow**; we will create this by using the **.shift( )** method to *shift* the **Close** prices back one day. Ideally, we want to know if we buy S&P500 stock on day 1 if the price of that stock will increase on day 2.

In [8]:

```
sp500["Tomorrow"] = sp500["Close"].shift(-1)

# Display data frame
sp500
```

Out[8]:

	Open	High	Low	Close	Volume	Tomorrow
Date						
1950-01-03 00:00:00-05:00	16.660000	16.660000	16.660000	16.660000	1260000	16.850000
1950-01-04 00:00:00-05:00	16.850000	16.850000	16.850000	16.850000	1890000	16.930000
1950-01-05 00:00:00-05:00	16.930000	16.930000	16.930000	16.930000	2550000	16.980000
1950-01-06 00:00:00-05:00	16.980000	16.980000	16.980000	16.980000	2010000	17.080000
1950-01-09 00:00:00-05:00	17.080000	17.080000	17.080000	17.080000	2520000	17.030001
...	...	...	...	...	...	...
2023-02-17 00:00:00-05:00	4077.389893	4081.510010	4047.949951	4079.090088	4045480000	3997.340088
2023-02-21 00:00:00-05:00	4052.350098	4052.350098	3995.189941	3997.340088	4121590000	3991.050049
2023-02-22 00:00:00-05:00	4001.830078	4017.370117	3976.899902	3991.050049	4079320000	4012.320068
2023-02-23 00:00:00-05:00	4018.600098	4028.300049	3969.189941	4012.320068	3952940000	3970.040039
2023-02-24 00:00:00-05:00	3973.239990	3978.250000	3943.080078	3970.040039	3877700000	NaN

18406 rows × 6 columns

To create our **Target** variable, we need to compare the closing price on one day with the closing price on the following day. In our **Target** column, a price rise will be indicated by a 1, otherwise 0.

In [9]:

```
sp500["Target"] = (sp500["Tomorrow"] > sp500["Close"]).astype(int)
sp500
```

Out[9]:

	Open	High	Low	Close	Volume	Tomorrow	T
Date							
1950-01-03 00:00:00-05:00	16.660000	16.660000	16.660000	16.660000	1260000	16.850000	
1950-01-04 00:00:00-05:00	16.850000	16.850000	16.850000	16.850000	1890000	16.930000	
1950-01-05 00:00:00-05:00	16.930000	16.930000	16.930000	16.930000	2550000	16.980000	
1950-01-06 00:00:00-05:00	16.980000	16.980000	16.980000	16.980000	2010000	17.080000	
1950-01-09 00:00:00-05:00	17.080000	17.080000	17.080000	17.080000	2520000	17.030001	
...	...	...	...	...	...	...	
2023-02-17 00:00:00-05:00	4077.389893	4081.510010	4047.949951	4079.090088	4045480000	3997.340088	
2023-02-21 00:00:00-05:00	4052.350098	4052.350098	3995.189941	3997.340088	4121590000	3991.050049	
2023-02-22 00:00:00-05:00	4001.830078	4017.370117	3976.899902	3991.050049	4079320000	4012.320068	
2023-02-23 00:00:00-05:00	4018.600098	4028.300049	3969.189941	4012.320068	3952940000	3970.040039	
2023-02-24 00:00:00-05:00	3973.239990	3978.250000	3943.080078	3970.040039	3877700000	NaN	

18406 rows × 7 columns

Typically, the more data the better, when it comes to training machine learning algorithms. However, with financial market data there is a risk that some of the economic/ market fundamentals may have shifted since records began, rendering earlier data less useful in training a model to make future predictions.

For example, the 1980s saw the breakthrough of **free-market economic policies** including financial and environmental deregulation, increased free trade, and the watering-down of antitrust enforcement.

To insure against the risk that changing fundamentals may affect our model's predictive accuracy, we will drop observations prior to 1990.

In [10]:

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

The **.copy( )** method was used as sometimes an error can arise if assigning back to a subsetted data frame.

In [11]:

```
sp500
```

Out[11]:

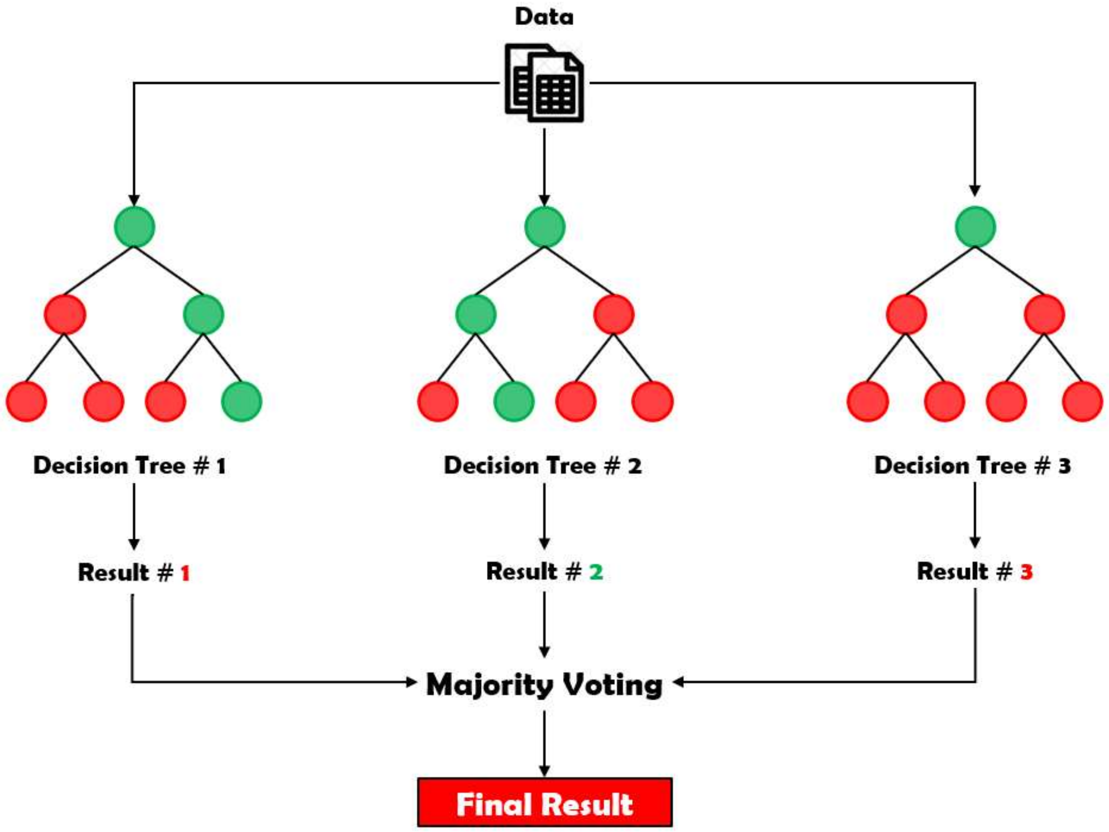
	Open	High	Low	Close	Volume	Tomorrow	T
Date							
1990-01-02 00:00:00-05:00	353.399994	359.690002	351.980011	359.690002	162070000	358.760010	
1990-01-03 00:00:00-05:00	359.690002	360.589996	357.890015	358.760010	192330000	355.670013	
1990-01-04 00:00:00-05:00	358.760010	358.760010	352.890015	355.670013	177000000	352.200012	
1990-01-05 00:00:00-05:00	355.670013	355.670013	351.350006	352.200012	158530000	353.790009	
1990-01-08 00:00:00-05:00	352.200012	354.239990	350.540009	353.790009	140110000	349.619995	
...	...	...	...	...	...	...	
2023-02-17 00:00:00-05:00	4077.389893	4081.510010	4047.949951	4079.090088	4045480000	3997.340088	
2023-02-21 00:00:00-05:00	4052.350098	4052.350098	3995.189941	3997.340088	4121590000	3991.050049	
2023-02-22 00:00:00-05:00	4001.830078	4017.370117	3976.899902	3991.050049	4079320000	4012.320068	
2023-02-23 00:00:00-05:00	4018.600098	4028.300049	3969.189941	4012.320068	3952940000	3970.040039	
2023-02-24 00:00:00-05:00	3973.239990	3978.250000	3943.080078	3970.040039	3877700000	NaN	

8352 rows × 7 columns

Training Initial Model 📈

Random Forest 📈

A random forest model works by training individual decision trees with randomised parameters prior to averaging the results from those decision trees (see below). Random forests are resistant to over-fitting, they also tend to run relatively quickly, and they can pick up non-linearities in the data. For example, the opening price is not linearly correlated with **Target**.



Initialise Random Forest Class 📈

When initialising our model, we will set the following parameters:

- **n_estimators** - Number of Decision Trees used in forest
- **min_samples_split** - Specifies minimum number of samples required to split an internal node (prevents over-fitting)
- **random_state** - Sets seed

In [12]:

```
from sklearn.ensemble import RandomForestClassifier

# Initialise model
model = RandomForestClassifier(n_estimators=100, min_samples_split=100, ra
```

Split Data: Train & Test 📈

We will now split our data into **training** and **testing** sets. As we are using time-series data, **cross-validation (CV)** will NOT be used. Using CV on time series data may lead to great training results but pretty terrible testing results; this is because CV does not take the time-series nature of the data into account, and thus could result in using *future* data to predict *past* data. This is referred to as **leakage**.

For example, if I wanted to predict whether the price would increase from - for example - the 1st February 2008 to the 2nd February 2008, it would help me if I knew that the price on the 3rd February 2008 was greater than on the 1st. If that was the case, I would assign a greater probability to the price *increasing* on the 2nd than to it decreasing. In the real-world, we do not have the privilege of seeing into the future, so it makes no sense to train our model as if it will have this ability, either.

To split the data, we will put all but the last 100 rows of the data into the training set.

In [13]:

```
train = sp500.iloc[:-100]
test = sp500.iloc[-100:]
```

Predictors 📈

Now, we will create a list of the predictors that we will use to train our model.

In [14]:

```
predictors = ["Close", "Volume", "Open", "High", "Low"]
```

Fit the Model 📈

In [15]:

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

Out[15]:

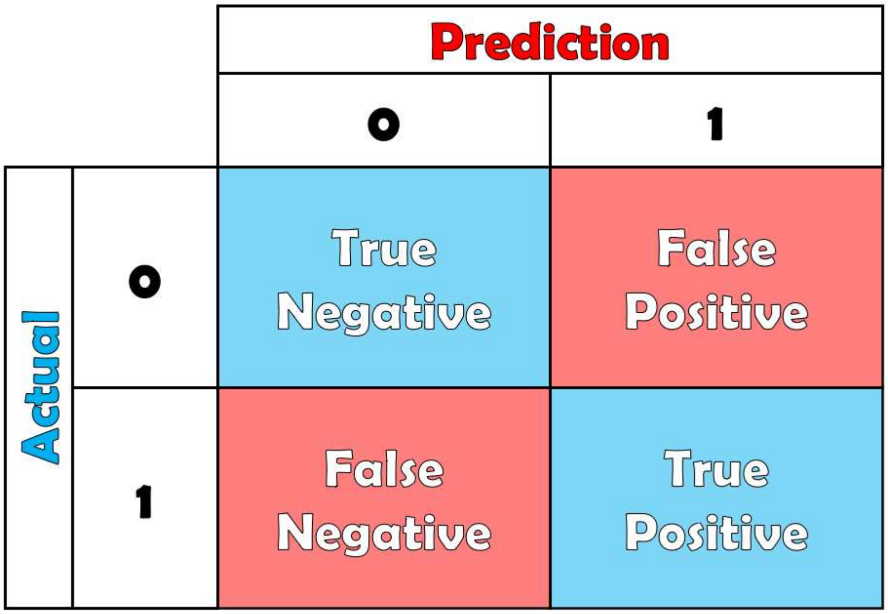
```
RandomForestClassifier(min_samples_split=100, random_state=1)
```

Performance 📈

To assess the performance of our model, we will use the **precision** metric. The precision is the proportion of **True Positives (TP)** relative to the sum of True Positives *and* False Positives:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

In this use-case, it represents the proportion of time that the index price went up *given that* we predicted it to go up.



		Prediction	
		0	1
Actual	0	True Negative	False Positive
	1	False Negative	True Positive

In [16]:

```python
# Import precision metric
from sklearn.metrics import precision_score
```

Now, we generate predictions using our predictors.

In [17]:

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

This generates an array of predictions. This is not wholly useful, so we will convert this into a pandas **Series**.

In [18]:

```python
# Display predictions
preds
```

Out[18]:

```
array([0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1,
       1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1,
       0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0,
       1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1])
```

In [19]:

```python
import pandas as pd

# Convert to Series
preds = pd.Series(preds, index=test.index)

# Display Series
preds
```

Out[19]:

```
Date
2022-10-03 00:00:00-04:00    0
2022-10-04 00:00:00-04:00    1
2022-10-05 00:00:00-04:00    1
2022-10-06 00:00:00-04:00    1
2022-10-07 00:00:00-04:00    1
                            ..
2023-02-17 00:00:00-05:00    1
2023-02-21 00:00:00-05:00    1
2023-02-22 00:00:00-05:00    1
2023-02-23 00:00:00-05:00    1
2023-02-24 00:00:00-05:00    1
Length: 100, dtype: int32
```

Finally, we will calculate the **precision score** by comparing whether the index price actual increased with our predictions.

In [20]:

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

Out[20]:

```
0.34328358208955223
```

This means that when we predicted that the index would increase, we were correct 34.3% of the time. This is not very good.

Plot Predictions vs Actuals 📈

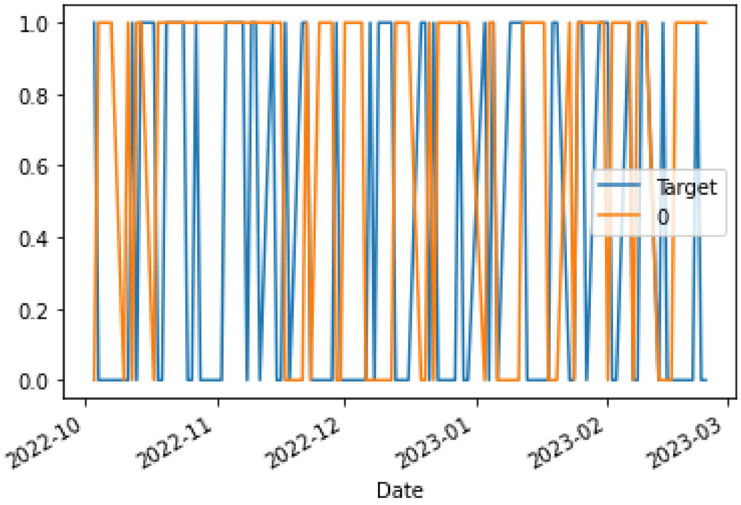
To plot our predictions, we will combine them with our actual values using the **.concat( )** method. Setting the *axis* parameter to 1 means that both inputs will be treated as columns.

In [21]:

```python
combined = pd.concat([test["Target"], preds], axis=1)
```

In [22]:

```
combined.plot();
```



We can see above that when we predicted the index price to increase, it mostly went down. Not good!

Building a Back-testing System 📈

Currently, we are only testing against the last 100 days of index data. We want to be testing against across multiple years of data to see how the algorithm performs in different periods.

To achieve this, we will be performing **back-testing**. To set up back-testing, we start by creating a prediction function that will contain all of the steps that we have just performed, and then a back-test function that will nest our prediction function.

Prediction Function 📈

In [23]:

```
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")
    combined = pd.concat([test["Target"], preds], axis=1)
    return combined
```

Back-test function 📈

We will now create a back-test function. This function will take - among others - two arguments: **start** and **step**.

When we train our model, we will want a certain amount of data to train the initial model. In each trading year, there are approximately **250** trading days (as trades do not occur on the weekend). So, a **start** value of 2500 equates to taking around 10 years worth of data to train the initial model.

The **step** argument allows us to train more models using data from a subsequent time period. For example, suppose that we set **start** to 2500, we will train our initial model using the first 10 years of data and predict prices for the 11th year; with a step size of **250**, we will train our next model using approximately 11 years of data, and then predict the 12th year prices, and so on.

By doing this, we will generate predictions for a lot of different years which will hopefully provide us with greater confidence in our model.

Our **back-test function** includes:

1. Create list of data frames where each data frame will contain predictions for a single year
2. Loop through data year-by-year
3. Split training and testing data
4. Generate predictions
5. Append list of data frames
6. Concatenate all predictions together

In [24]:

```
def backtest(data, model, predictors, start=2500, step=250):

    # (1) - Create list of prediction data frames
    all_predictions = []

    # (2) - Loop through data
    for i in range(start, data.shape[0], step):

        # (3) - Split into training and testing sets
        train = data.iloc[0:i].copy()
        test = data.iloc[i:(i+step)].copy()

        # (4) - Generate predictions
        predictions = predict(train, test, predictors, model)

        # (5) - Append list
        all_predictions.append(predictions)

    # (6) - Concatenate predictions
    return pd.concat(all_predictions)
```

In [25]:

```
predictions = backtest(sp500, model, predictors)
```

Using the **.value_counts( )** method, we can see how many days we predicted the index price would go up versus how many times we predicted it would go down.

In [26]:

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

Out[26]:

	Predictions
0	3401
1	2451

Now, we can look at our **precision score**.

In [27]:

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

Out[27]:

```
0.5275397796817626
```

We have a score of 52.8% which, while not fantastic, is a significant improvement on 34.3%. As a bench-mark, we can assess this against the number of days that the market actually increased in price.

In [28]:

```
prop = predictions["Target"].value_counts() / predictions.shape[0]
prop.to_frame().rename(columns={"Target":"Proportion"})
```

Out[28]:

	Proportion
1	0.533664
0	0.466336

In the days that we looked at, the S&P500 actually increased in price 53.4% of days, and went down in price 46.6% of days.

Unfortunately, this suggests that should our strategy just be to randomly buy stock at in one day and selling in the next, we may have been marginally better-off than using our algorithm.

Adding Predictors to Model 📈

We will now add predictors to our model to try and improve its precision score.

We will create some **rolling averages**. These can be useful as they incorporate the performance of the index in time periods prior to the day you are want to predict. To do this, we will create a list called **horizons** which will give us rolling averages across different *time horizons* of prior trading days to that which we are looking to predict.

We will loop through each time horizon in our list using a *for loop*. This will:

1. Create **new_predictors** list
2. Loop through each time horizon in our list
3. Create a rolling average for each time horizon
4. Create closed ratios and add these to our data frame
5. Create a trend column for the last x days when the price actually went up
6. Add these new columns to our **new_predictors** list

In [29]:

```
# Horizons - 2 prior trading days, 5 prior trading days, so on
horizons = [2,5,60,250,1000]

# (1) - Create new predictors list
new_predictors = []

# (2) - Loop through each time horizon
for horizon in horizons:

    # (3) - Create rolling average
    rolling_averages = sp500.rolling(horizon).mean()

    # (4) - Create closed ratios
    ratio_column = f"Close_Ratio_{horizon}"
    sp500[ratio_column] = sp500["Close"] / rolling_averages["Close"]

    # (5) - Create price trends
    trend_column = f"Trend_{horizon}"
    sp500[trend_column] = sp500.shift(1).rolling(horizon).sum()["Target"]

    # (6) - Add new predictors to list
    new_predictors+= [ratio_column, trend_column]
```

In [30]:

```
# See missing values
sp500.head()
```

Out[30]:

	Open	High	Low	Close	Volume	Tomorrow	Target
Date							
1990-01-02 00:00:00-05:00	353.399994	359.690002	351.980011	359.690002	162070000	358.760010	0
1990-01-03 00:00:00-05:00	359.690002	360.589996	357.890015	358.760010	192330000	355.670013	0
1990-01-04 00:00:00-05:00	358.760010	358.760010	352.890015	355.670013	177000000	352.200012	0
1990-01-05 00:00:00-05:00	355.670013	355.670013	351.350006	352.200012	158530000	353.790009	1
1990-01-08 00:00:00-05:00	352.200012	354.239990	350.540009	353.790009	140110000	349.619995	0

As we are not able to create a rolling average for some entries, it will generate missing values for those entries, as you can see above. Let's drop these missing values, as machine learning algorithms do not process them very well.

```
In [31]: sp500 = sp500.dropna(subset=sp500.columns[sp500.columns != "Tomorrow"])
```

```
In [32]: sp500.head(5)
```

Out[32]:

Date	Open	High	Low	Close	Volume	Tomorrow	Target
1993-12-14 00:00:00-05:00	465.730011	466.119995	462.459991	463.059998	275050000	461.839996	0
1993-12-15 00:00:00-05:00	463.059998	463.690002	461.839996	461.839996	331770000	463.339996	1
1993-12-16 00:00:00-05:00	461.859985	463.980011	461.859985	463.339996	284620000	466.380005	1
1993-12-17 00:00:00-05:00	463.339996	466.380005	463.339996	466.380005	363750000	465.850006	0
1993-12-20 00:00:00-05:00	466.380005	466.899994	465.529999	465.850006	255900000	465.299988	0

Improving Model 📈

We will improve our model initially by updating some of our parameters. To do this, we will increase the number of Decision Trees to 200 (**n_estimators**) while also reducing the minimum number of samples required to split a node to 50 (**min_samples_split**).

```
In [33]: model = RandomForestClassifier(n_estimators=200, min_samples_split=50, ra
```

We will also be a little bit more sophisticated in terms of how the model defines the index increasing in price. To elaborate, we had previously been using the **model.predict( )** method to predict when the index price increased. This returns a value of 1 if $p \geq 0.5$ that the index will increase in price, 0 otherwise.

Instead, we will use the **model.predict_proba( )** method. This will return a probability that the price will increase. We want to extract this probability and then apply a custom threshhold to the predicted probabilities. This will return a value of 1 (i.e. a prediction that the index value increased) if the predicted probability is $p \geq 0.6$, 0 otherwise.

In [34]:

```python
def predict(train, test, predictors, model):
    model.fit(train[predictors], train["Target"])

    # Extract probability that the price will increase from second column
    preds = model.predict_proba(test[predictors])[:,1]

    # Set custom threshold
    preds[preds >=.6] = 1
    preds[preds <.6] = 0


    preds = pd.Series(preds, index=test.index, name="Predictions")
    combined = pd.concat([test["Target"], preds], axis=1)
    return combined
```

To train this model, we will only be using the **new predictors**. This is because the other variables are absolute numbers, and hence do not really tell us much about future price movements. For example, if the opening price is 463.059998, this does not tell us anything about whether the index price will increase or decrease.

In [35]:

```python
predictions = backtest(sp500, model, new_predictors)
```

After training our model, we can once again see how many trading days we predicted that the index price would increase in versus the number of trading days that we predicted it would decrease.

In [36]:

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

Out[36]:

	Predictions
0.0	4039
1.0	813

It can be noted that the number of times we predicted that the market would increase is lower than in our prior model. This would suggest we would be making trades (buying and selling) on fewer days, but on those days that we did trade, we would be *more confident* that we would have correctly predicted the price movement of the index.

Performance of Improved Model 📈

In [37]:

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

Out[37]:

```
0.5694956949569495
```

Our **precision** has increased to 56.9% which is a marked improvement.

In [38]:

```
prop = predictions["Target"].value_counts() / predictions.shape[0]
prop.to_frame().rename(columns={"Target":"Proportion"})
```

Out[38]:

	Proportion
1	0.543693
0	0.456307

We can see that the proportion of times that the index actually increased in value was 54.4% of the time, hence our precision is marginally greater than our bench-mark, thus the model may be useful.

Conclusion 📈

In this project, we downloaded stock price data from the S&P500 Index using the **yfinance** API. After this, we cleaned the data and created a simple visualisation to see its historical trend. We then filtered out data from the year 1990 onwards, to avoid fundamental shifts in markets that may affect our predictions.

Next, we built our initial machine learning model and assessed its predictive performance using the **precision**. This was not very good at only 34.3%. In fact, it would have led to a worse performance than simply randomly trading. Bad news!

We then created a **back-test** function to measure to measure our accuracy over longer periods of time. This improved our model's performance considerably.

Finally, we sought to improve our model by enriching our predictors. We achieved this with rolling averages and trends, and increasing the threshold our model used to denote a price change as positive or negative. This would lead to a lower number of days in which we traded, but on those days that we did trade, we would be more confident in our predictions.

Our final performance was 56.9%. Not incredible, but better than our benchmark value of 54.4%.

Suggested Next Steps 📈

One way in which the model could be improved would be to use over-night exchanges. While the S&P500 Index only trades during US market hours, other indices open earlier; it may be an idea to correlate their performances with the S&P500. For example, if an indices that opens earlier than the S&P500 is increasing, will the S&P500 tend to increase also upon opening?

Economic metrics regarding inflation or interest rates could also be incorporated into the model, as these can affect consumer trends and business decisions, and - very importantly - **expectations** of future market prices.

Key components of the S&P500 can also be incorporated into the model. For example, if the tech industry is in a downturn then this may negatively impact upon the S&P500 Index prices several months later.

Alternatively, the resolution can also be increased. This project looks at daily data, but data can be acquired on a more granular level, such as hourly or minite-by-minute data.