assignment2

March 29, 2023

0.1 MET CS677 Data Science with Python - Assignment 2

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Built with Python 3.10.6

[1]:
```
!python --version
```

```
Python 3.10.6
```

[2]:
```
# This enables SVG graphics inline (only use with static plots (non-Bokeh))
%config InlineBackend.figure_formats = {'svg',}
```

[3]:
```
%%javascript
MathJax.Hub.Config({
    tex2jax: {
        inlineMath: [['$','$'], ['\\(','\\)']],
        processEscapes: true
    },
    tex: {
        packages: {'[+]': ['require']},
    },
});
```

```
<IPython.core.display.Javascript object>
```

[4]:
```
import operator
import numpy as np
import pandas as pd

from assignment2 import (
    add_true_labels,
    buy_and_hold,
    buy_from_prediction,
    get_labels,
    linechart,
    get_both_up_days,
    get_training_tables,
    get_testing_tables,
    get_years,
```

```python
    get_statistics,
    float_to_percentage,
    predict_next_day,
    w_prediction_accuracy,
    question_1_3,
    question_1_4,
    read_stocks,
    prediction_accuracy,
    show_table,
    show_tables,
    compute_ensemble,
    style_df,
)
from constants import (
    SONY_TICKER,
    SPY_TICKER,
    DATE_KEY,
    TRUE_LABEL_KEY,
    ENSEMBLE_ORACLE_KEY,
    W_ORACLE,
    BUY_AND_HOLD_KEY,
    ENSEMBLE_KEY
)
from utils import (
    compute_probability,
    mean,
    resources,
)
from typing import cast
from pandas import DataFrame, Series
from IPython.display import Latex
from pandas.io.formats.style import Styler
from pandas._config import config # noqa
from pandas._config.config import is_bool, OptionError # noqa

# Global pandas options.
pd.set_option('display.max_rows', 10)

# TODO Don't have time.
pd.set_option('mode.chained_assignment', None)

# Columns to drop for visual export.
drop_cols = [
    "Week_Number",
    "Year_Week",
    "Short_MA",
    "Long_MA",
```

```python
    "Adj Close",
]

print(f"Resources directory is located at {resources}.")
```

```
Resources directory is located at
/home/alan/src/bu/cs677/assignment2/assignment2/resources.
```

[5]:
```python
# Read the stock data files into pandas dataframes.
sony_dataframe, spy_dataframe = cast(tuple[DataFrame, DataFrame], read_stocks())

sony_dataframe = sony_dataframe.drop(columns=drop_cols)
spy_dataframe = spy_dataframe.drop(columns=drop_cols)

# Set the date column to be datetime objects instead of string.
sony_dataframe[DATE_KEY] = pd.to_datetime(sony_dataframe[DATE_KEY])
spy_dataframe[DATE_KEY] = pd.to_datetime(spy_dataframe[DATE_KEY])

# Create pandas stylers for each data set.
sony_table: Styler = style_df(data=sony_dataframe, caption="SONY Stock␣
 ↪Dataset", color=False)
spy_table: Styler = style_df(data=spy_dataframe, caption="S&P-500 Stock␣
 ↪Dataset", color=False)
```

[6]:
```python
# Assignment description.
Latex(
    r'In many data science applications, you want to identify patterns, labels␣
 ↪or classes based on available data. In this assignment we will focus on␣
 ↪discovering patterns in your past stock behavior.'
    "\n"
    r'To each trading day $i$ you will assign a "trading" label "+" or "-"␣
 ↪depending whether the corresponding daily return for that day $r_i \ge{0}$␣
 ↪or $r_i <{0}$. We will call these "true" labels and we compute these for all␣
 ↪days in all 5 years.'
    "\n"
    r'We will use years 1, 2, and 3 as training years and we will use years 4␣
 ↪and 5 as testing years. For each day in years 4 and 5, we will predict a␣
 ↪label based on some patterns that we observe in training years. We will call␣
 ↪these "predicted" labels. We know the "true" labels for years 4 and 5 and we␣
 ↪compute "predicted" labels for years 4 and 5. Therefore, we can analyze how␣
 ↪good are our predictions for all labels, "+" labels only and "-" labels only␣
 ↪in years 4 and 5.'
)
```

[6]: In many data science applications, you want to identify patterns, labels or classes based on available data. In this assignment we will focus on discovering patterns in your past stock behavior. To each trading day i you will assign a ”trading” label ”+” or ”-” depending whether the corresponding

daily return for that day $r_i \geq 0$ or $r_i < 0$. We will call these "true" labels and we compute these for all days in all 5 years. We will use years 1, 2, and 3 as training years and we will use years 4 and 5 as testing years. For each day in years 4 and 5, we will predict a label based on some patterns that we observe in training years. We will call these "predicted" labels. We know the "true" labels for years 4 and 5 and we compute "predicted" labels for years 4 and 5. Therefore, we can analyze how good are our predictions for all labels, "+" labels only and "-" labels only in years 4 and 5.

[7]:
```
Latex(r'$\textbf{Question 1: }$ You have a csv table of daily returns for your␣
↪stock and for S\&P-500 ("SPY" ticker).')
```

[7]:

Question 1: You have a csv table of daily returns for your stock and for S&P-500 ("SPY" ticker).

[8]:
```
# Display tables with the original csv datasets.
show_tables([sony_table, spy_table])
```

	Date	Year	Month	Day	Weekday	Open	High	Low	Close
0	2016-01-04 00:00:00	2016	1	4	Monday	24.450000	24.800000	24.310000	24.730000
1	2016-01-05 00:00:00	2016	1	5	Tuesday	24.910000	25.720000	24.910000	25.470000
2	2016-01-06 00:00:00	2016	1	6	Wednesday	25.470000	25.470000	23.270000	23.630000
3	2016-01-07 00:00:00	2016	1	7	Thursday	23.520000	23.650000	23.170000	23.270000
4	2016-01-08 00:00:00	2016	1	8	Friday	23.820000	23.910000	23.000000	23.000000

	Date	Year	Month	Day	Weekday	Open	High	Low	Clos
0	2016-01-04 00:00:00	2016	1	4	Monday	200.490000	201.030000	198.590000	201.0200
1	2016-01-05 00:00:00	2016	1	5	Tuesday	201.400000	201.900000	200.050000	201.3600
2	2016-01-06 00:00:00	2016	1	6	Wednesday	198.340000	200.060000	197.600000	198.8200
3	2016-01-07 00:00:00	2016	1	7	Thursday	195.330000	197.440000	193.590000	194.0500
4	2016-01-08 00:00:00	2016	1	8	Friday	195.190000	195.850000	191.580000	191.9200

[9]:
```
table_1: Styler = style_df(
    data=DataFrame(
        {
            "Date": ["1/2/2015", "1/3/2015", "1/6/2015", ". . .", ". . .", "12/
↪30/2019", "12/31/2019"],
            ". . .": [". . .", ". . .", ". . .", ". . .", ". . .", ". . .", ". .
↪ ."],
            "Return": ["0.015", "-0.01", "0.0.2", ". . .", ". . .", "0", "-0.
↪03"]
        }
    ),
    caption="Table 1: Initial data",
    color=False
)
```

[10]:
```
display(
    Latex(
```

```
        r' 1. For each file, read them into a pandas frame and add a column␣
 ↪"True Label". In that column, for each day (row) $i$ with daily return $r_i␣
 ↪\ge{0}$ you assign a "+" label ("up day"). For each day $i$ with daily␣
 ↪return $r_i <{0}$ you assign "-" ("down days"). You do this for every day␣
 ↪for all 5 years for both tickers.'
        "\n"
        r'For example, if your initial dataframe were:'
    )
)
show_table(table_1, max_rows=10)
Latex(
    r'you will add an additional column "True Label" and have data as shown in␣
 ↪Table 2.'
    "\n"
    r'Your daily "true labels" sequence is $+,-,+,...,+,-$.'
)
```

1. For each file, read them into a pandas frame and add a column "True Label". In that column, for each day (row) i with daily return $r_i \geq 0$ you assign a "+" label ("up day"). For each day i with daily return $r_i < 0$ you assign "-" ("down days"). You do this for every day for all 5 years for both tickers. For example, if your initial dataframe were:

	Date	. . .	Return
0	1/2/2015	. . .	0.015
1	1/3/2015	. . .	-0.01
2	1/6/2015	. . .	0.0.2
3	. . .	. . .	. . .
4	. . .	. . .	. . .
5	12/30/2019	. . .	0
6	12/31/2019	. . .	-0.03

[10]:

you will add an additional column "True Label" and have data as shown in Table 2. Your daily "true labels" sequence is $+, -, +, ..., +, -$.

[11]:

```
table_2: DataFrame = table_1.data.copy()
table_2[TRUE_LABEL_KEY] = ["+", "-", "+", ". . .", ". . .", "+", "-"]
table_2: Styler = Styler(data=table_2, caption="Table 2: Adding True Labels")
show_table(table_2, max_rows=10)
```

	Date	. . .	Return	True Label
0	1/2/2015	. . .	0.015	+
1	1/3/2015	. . .	-0.01	-
2	1/6/2015	. . .	0.0.2	+
3	. . .	. . .	. . .	. . .
4	. . .	. . .	. . .	. . .
5	12/30/2019	. . .	0	+
6	12/31/2019	. . .	-0.03	-

[12]:
```
# Add 'True Label' column based upon the daily return.
add_true_labels(sony_dataframe)
add_true_labels(spy_dataframe)

# Display the updated tables with the styled 'True Labels' column.
show_tables([sony_table, spy_table])
```

	Date	Year	Month	Day	Weekday	Open	High	Low	Close
0	2016-01-04 00:00:00	2016	1	4	Monday	24.450000	24.800000	24.310000	24.730000
1	2016-01-05 00:00:00	2016	1	5	Tuesday	24.910000	25.720000	24.910000	25.470000
2	2016-01-06 00:00:00	2016	1	6	Wednesday	25.470000	25.470000	23.270000	23.630000
3	2016-01-07 00:00:00	2016	1	7	Thursday	23.520000	23.650000	23.170000	23.270000
4	2016-01-08 00:00:00	2016	1	8	Friday	23.820000	23.910000	23.000000	23.000000

	Date	Year	Month	Day	Weekday	Open	High	Low	Clos
0	2016-01-04 00:00:00	2016	1	4	Monday	200.490000	201.030000	198.590000	201.0200
1	2016-01-05 00:00:00	2016	1	5	Tuesday	201.400000	201.900000	200.050000	201.3600
2	2016-01-06 00:00:00	2016	1	6	Wednesday	198.340000	200.060000	197.600000	198.8200
3	2016-01-07 00:00:00	2016	1	7	Thursday	195.330000	197.440000	193.590000	194.0500
4	2016-01-08 00:00:00	2016	1	8	Friday	195.190000	195.850000	191.580000	191.9200

[13]:
```
# Get a list of all the years in the dataset.
sony_years, spy_years = cast(
    tuple[list[int], list[int]], get_years(sony_dataframe, spy_dataframe)
)

# Separate data into training and testing data based upon the years.
# Create training dataset from years 1, 2, and 3.
sony_training_table, spy_training_table = cast(
    tuple[DataFrame, DataFrame],
    get_training_tables((sony_dataframe, sony_years), (spy_dataframe,␣
↪spy_years)),
)

# Create testing dataset from years 4 and 5.
sony_testing_table, spy_testing_table = cast(
    tuple[DataFrame, DataFrame],
    get_testing_tables((sony_dataframe, sony_years), (spy_dataframe,␣
↪spy_years)),
)

# Get the 'up days' for the training datasets.
sony_training_up_days, spy_training_up_days = cast(
    tuple[DataFrame, DataFrame],
    get_both_up_days(sony_training_table, spy_training_table),
)

# Get arrays of the training labels.
```

```
sony_training_labels: np.ndarray = get_labels(sony_training_table)
spy_training_labels: np.ndarray = get_labels(spy_training_table)
```

[14]:
```
Latex(
    r' 2. Take years 1, 2, and 3. Let $L$ be the number of trading days.␣
 ↪Assuming 250 trading days per year, $L$ will contain about 750 days. Let␣
 ↪$L^-$ be all trading days with "-" labels and let $L^+$ be all trading days␣
 ↪with "+" labels. Assuming that all days are independent of each other and␣
 ↪that the ration of "up" and "down" days remains the same in the future,␣
 ↪compute the default probability $p^*$ that the next day is a "up" day.'
)
```

[14]:

2. Take years 1, 2, and 3. Let L be the number of trading days. Assuming 250 trading days per year, L will contain about 750 days. Let L^- be all trading days with "-" labels and let L^+ be all trading days with "+" labels. Assuming that all days are independent of each other and that the ration of "up" and "down" days remains the same in the future, compute the default probability p^* that the next day is a "up" day.

[15]:
```
# Compute the default probability that the next day is an 'up' day.
sony_default_probability: float = compute_probability(
    len(sony_training_up_days), len(sony_training_table)
)

spy_default_probability: float = compute_probability(
    len(spy_training_up_days), len(spy_training_table)
)
```

[16]:
```
Latex(
    r' 3. Take years 1, 2, and 3. What is the probability that after seeing $k$␣
 ↪consecutive "down days", the next day is an "up day"? For example, if $k =␣
 ↪3$, what is the probability of seeing "$-,-,-,+$" as opposed to seeing␣
 ↪"$-,-,-,-$". Compute this for $k = 1,2,3$.'
)
```

[16]:

3. Take years 1, 2, and 3. What is the probability that after seeing k consecutive "down days", the next day is an "up day"? For example, if $k = 3$, what is the probability of seeing "$-,-,-,+$" as opposed to seeing "$-,-,-,-$". Compute this for $k = 1, 2, 3$.

[17]:
```
# k values for questions 1.3 and question 1.4.
k_list: list[int] = [1, 2, 3]

print("Question 1.3 with SONY dataset:")
question_1_3(k_list, sony_training_labels)

print("Question 1.3 with S&P-500 dataset:")
question_1_3(k_list, spy_training_labels)
```

```
Question 1.3 with SONY dataset:
```

```
Probability for k = 1: 0.5521126760563381
Probability for k = 2: 0.5408805031446541
Probability for k = 3: 0.547945205479452


Question 1.3 with S&P-500 dataset:
Probability for k = 1: 0.5952380952380952
Probability for k = 2: 0.5955882352941176
Probability for k = 3: 0.6363636363636364
```

[18]:
```
Latex(
    r' 4. Take years 1, 2, and 3. What is the probability that after seeing $k$␣
 ↪consecutive "up days", the next day is still an "up day"? For example, if $k␣
 ↪= 3$, what is the probability of seeing "$+,+,+,+$" as opposed to seeing␣
 ↪"$+,+,+,-$"? Compute this for $k = 1,2,3$.'
)
```

[18]:

4. Take years 1, 2, and 3. What is the probability that after seeing k consecutive ”up days”, the next day is still an ”up day”? For example, if $k = 3$, what is the probability of seeing ”$+, +, +, +$” as opposed to seeing ”$+, +, +, -$”? Compute this for $k = 1, 2, 3$.

[19]:
```
# Question 1.4 results for each dataset.
print("Question 1.4 with SONY dataset:")
question_1_4(k_list, sony_training_labels)

print("Question 1.4 with S&P-500 dataset:")
question_1_4(k_list, spy_training_labels)
```

```
Question 1.4 with SONY dataset:
Probability for k = 1: 0.507537688442211
Probability for k = 2: 0.5
Probability for k = 3: 0.46534653465346537


Question 1.4 with S&P-500 dataset:
Probability for k = 1: 0.5203836930455635
Probability for k = 2: 0.5023041474654378
Probability for k = 3: 0.46788990825688076
```

[20]:
```
Latex(
    r'$\textbf{Predicting Labels: }$    We will now describe a procedure to␣
 ↪predict labels for each day in years 4 and 5 from the "true" labels in␣
 ↪training years 1, 2, and 3.'
    "\n"
```

```
    r'For each day $d$ in year 4 and 5, we look at the pattern of last $W$ true␣
↪labels (including this day $d$). By looking at the frequency of this pattern␣
↪and the true label for the next day in the training set, we will predict␣
↪label for $d + 1$. Here $W$ is the $\textbf{hyperparameter}$ that we will␣
↪choose based upon our prediction accuracy.'
    "\n"
    r'Suppose $W = 3$. You look at a particular day $d$ and suppose that the␣
↪sequence of last $W$ labels is $s = "-,+,-"$. We want to predict the label␣
↪for the next day $d + 1$. To do this, we count the number of sequences of␣
↪length $W + 1$ in the training set where the first $W$ labels coincide with␣
↪$s$. In other words, we count the number $N^-(s)$ of sequences "$s,+$". If␣
↪$N^+(s) \ge{N^-(s)}$, then the next day is assigned "+". If $N^+(s) <␣
↪N^-(s)$, then the next day is assigned "-". In the unlikely event that␣
↪$N^+(s) = N^-(s) = 0$, we will assign a label based upon the default␣
↪probability $p*$ that we computed in the previous question.'
)
```

[20]:

Predicting Labels: We will now describe a procedure to predict labels for each day in years 4 and 5 from the "true" labels in training years 1, 2, and 3. For each day d in year 4 and 5, we look at the pattern of last W true labels (including this day d). By looking at the frequency of this pattern and the true label for the next day in the training set, we will predict label for $d+1$. Here W is the **hyperparameter** that we will choose based upon our prediction accuracy. Suppose $W = 3$. You look at a particular day d and suppose that the sequence of last W labels is $s = "-,+,-"$. We want to predict the label for the next day $d+1$. To do this, we count the number of sequences of length $W+1$ in the training set where the first W labels coincide with s. In other words, we count the number $N^-(s)$ of sequences "$s,+$". If $N^+(s) \geq N^-(s)$, then the next day is assigned "+". If $N^+(s) < N^-(s)$, then the next day is assigned "-". In the unlikely event that $N^+(s) = N^-(s) = 0$, we will assign a label based upon the default probability $p*$ that we computed in the previous question.

[21]:

```
Latex(r'$\textbf{Question 2: }$')
```

[21]:

Question 2:

[22]:

```
Latex(
    r' 1. For $W = 2, 3, 4$, compute predicted labels for each day in year $4$␣
↪and $5$ based on true labels in years $1, 2$, and $3$ only'
    "\n"
    r'Perform this for your ticker and for "SPY".'
)
```

[22]:

1. For $W = 2, 3, 4$, compute predicted labels for each day in year 4 and 5 based on true labels in years $1, 2$, and 3 only Perform this for your ticker and for "SPY".

[23]:

```
# Get arrays of the testing labels.
sony_testing_labels: np.ndarray = get_labels(sony_testing_table)
spy_testing_labels: np.ndarray = get_labels(spy_testing_table)
```

[24]:
```python
# W values for questions 2.
w_list: list[int] = [2, 3, 4]

# For W = 2, 3, 4: Predict the next day and add it to the testing table.
for w in w_list:
    # SONY dataset predictions.
    sony_testing_table[f"W{w}"] = predict_next_day(
        df=sony_testing_table,
        training_labels=sony_testing_labels,
        window_size=w,
        default_probability=sony_default_probability,
    )

    # S&P-500 dataset predictions.
    spy_testing_table[f"W{w}"] = predict_next_day(
        df=spy_testing_table,
        training_labels=spy_testing_labels,
        window_size=w,
        default_probability=spy_default_probability,
    )

show_tables([sony_testing_table, spy_testing_table])
```

	Date	Year	Month	Day	Weekday	Open	High	Low	Close
0	2019-01-02 00:00:00	2019	1	2	Wednesday	47.570000	48.980000	47.400000	48.720000
1	2019-01-03 00:00:00	2019	1	3	Thursday	48.230000	48.280000	46.890000	47.020000
2	2019-01-04 00:00:00	2019	1	4	Friday	48.120000	49.550000	48.020000	49.210000
3	2019-01-07 00:00:00	2019	1	7	Monday	49.460000	50.310000	49.430000	49.720000
4	2019-01-08 00:00:00	2019	1	8	Tuesday	50.150000	50.260000	49.410000	49.890000

	Date	Year	Month	Day	Weekday	Open	High	Low	Clos
0	2019-01-02 00:00:00	2019	1	2	Wednesday	245.980000	251.210000	245.950000	250.18000
1	2019-01-03 00:00:00	2019	1	3	Thursday	248.230000	248.570000	243.670000	244.21000
2	2019-01-04 00:00:00	2019	1	4	Friday	247.590000	253.110000	247.170000	252.39000
3	2019-01-07 00:00:00	2019	1	7	Monday	252.690000	255.950000	251.690000	254.38000
4	2019-01-08 00:00:00	2019	1	8	Tuesday	256.820000	257.310000	254.000000	256.77000

[25]:
```python
Latex(
    r' 2. For each $W = 2, 3, 4$, compute the accuracy - what percentage of␣
↪true labels (both positive and negative) have you predicted correctly for␣
↪the last two years.'
)
```

[25]:

2. For each $W = 2, 3, 4$, compute the accuracy - what percentage of true labels (both positive and negative) have you predicted correctly for the last two years.

[26]:
```python
w_accuracy_keys: list[str] = [f"W{w}*" for w in w_list]
```

```python
# Compute the prediction accuracy for SONY.
w_prediction_accuracy(sony_testing_table, w_list)
sony_accuracies = {key: sony_testing_table.attrs[key] for key in␣
↪w_accuracy_keys}

# Compute the prediction accuracy for S&P-500.
w_prediction_accuracy(spy_testing_table, w_list)
spy_accuracies = {key: spy_testing_table.attrs[key] for key in w_accuracy_keys}

print("SONY prediction accuracies: ")
for accuracy, value in sony_accuracies.items():
    print(f"{accuracy}: {value}")

print("S&P-500 prediction accuracies: ")
for accuracy, value in spy_accuracies.items():
    print(f"{accuracy}: {value}")
```

```
SONY prediction accuracies:
W2*: 0.5657370517928287
W3*: 0.5708582834331337
W4*: 0.586
S&P-500 prediction accuracies:
W2*: 0.5856573705179283
W3*: 0.590818363273453
W4*: 0.606
```

[27]:
```python
Latex(
    r' 3. Which $W^*$ value gave you the highest accuracy for your stock and␣
↪which $W^*$ value gave you the highest accuracy for S\&P-500?'
)
```

[27]: 3. Which W^* value gave you the highest accuracy for your stock and which W^* value gave you the highest accuracy for S&P-500?

[28]:
```python
# Get the highest accuracy value for SONY.
sony_highest_accuracy: tuple[str, float] = \
    max(sony_accuracies.items(), key=operator.itemgetter(1))
print(
    f"SONY highest accuracy is {sony_highest_accuracy[0]} with an accuracy of "
    f"{sony_highest_accuracy[1]}."
)

# Get the highest accuracy value for S&P-500.
spy_highest_accuracy: tuple[str, float] = \
    max(spy_accuracies.items(), key=operator.itemgetter(1))
print(
```

```
    f"S&P-500 highest accuracy is {spy_highest_accuracy[0]} with an accuracy of␣
↪"
    f"{spy_highest_accuracy[1]}."
)
```

```
SONY highest accuracy is W4* with an accuracy of 0.586.
S&P-500 highest accuracy is W4* with an accuracy of 0.606.
```

[29]:
```
Latex(
    r'$\textbf{Question 3: }$ One of the most powerful methods to (potentially)␣
↪improve predictions is to combine predictions by some "averaging". This is␣
↪called $\textit{ensemble learning}$. Let us consider the following procedure:
↪ for every day $d$, you 3 predicted labels: for $W = 2$, $W = 3$, and $W =␣
↪4$. Let us compute an "ensemble" label for day $d$ by taking the majority of␣
↪your labels for that day. For example, if your predicted labels were "-",␣
↪"-", and "+", then we would take "-" as the ensemble label for day $d$ (the␣
↪majority of the three labels is "-"). If, on the other hand, your predicted␣
↪labels were "-", "+", and "+", then we would take "+" as the ensemble label␣
↪for day $d$ (the majority of the predicted labels is "+"). Compute such␣
↪ensemble labels and answer the following:'
)
```

[29]:
Question 3: One of the most powerful methods to (potentially) improve predictions is to combine predictions by some "averaging". This is called *ensemble learning*. Let us consider the following procedure: for every day d, you 3 predicted labels: for $W = 2$, $W = 3$, and $W = 4$. Let us compute an "ensemble" label for day d by taking the majority of your labels for that day. For example, if your predicted labels were "-", "-", and "+", then we would take "-" as the ensemble label for day d (the majority of the three labels is "-"). If, on the other hand, your predicted labels were "-", "+", and "+", then we would take "+" as the ensemble label for day d (the majority of the predicted labels is "+"). Compute such ensemble labels and answer the following:

[30]:
```
Latex(
    r' 1. Compute ensemble labels for year 4 and 5 for both your stock and␣
↪S\&P-500.'
)
```

[30]:
1. Compute ensemble labels for year 4 and 5 for both your stock and S&P-500.

[31]:
```
w_cols: list[str] = ["W2", "W3", "W4"]

# Compute ensemble labels for year 4 and 5 of SONY.
compute_ensemble(sony_testing_table, w_cols)
sony_ensemble_row: Series = sony_testing_table[ENSEMBLE_KEY].transpose()
print(sony_ensemble_row)

# Compute ensemble labels for year 4 and 5 of S&P-500.
compute_ensemble(spy_testing_table, w_cols)
```

```
spy_ensemble_row: Series = spy_testing_table[ENSEMBLE_KEY].transpose()
print(spy_ensemble_row)
```

```
0      NaN
1      NaN
2      NaN
3      NaN
4        +
      …
499      +
500      -
501      +
502      +
503      +
Name: Ensemble, Length: 504, dtype: object
0      NaN
1      NaN
2      NaN
3      NaN
4        +
      …
499      +
500      -
501      +
502      +
503      +
Name: Ensemble, Length: 504, dtype: object
```

[32]:
```
Latex(
    r' 2. For both S\&P-500 and your ticker, what percentage of labels in year␣
 ↪$4$ and $5$ do you compute correctly by using ensemble?'
)
```

[32]:

2. For both S&P-500 and your ticker, what percentage of labels in year 4 and 5 do you compute correctly by using ensemble?

[33]:
```
# Compute ensemble labels for year 4 and 5 of S&P-500.
compute_ensemble(spy_testing_table, w_cols)
spy_ensemble_row: Series = spy_testing_table[ENSEMBLE_KEY].transpose()
print(spy_ensemble_row)

# Compute the accuracy of the ensemble column for SONY.
prediction_accuracy(sony_testing_table, ENSEMBLE_KEY)
sony_ensemble_accuracy: float = sony_testing_table.attrs[f'{ENSEMBLE_KEY}*']
print(f"Ensemble accuracy for SONY:␣
 ↪{float_to_percentage(sony_ensemble_accuracy)}")
```

```
# Compute the accuracy of the ensemble column for S&P-500.
prediction_accuracy(spy_testing_table, ENSEMBLE_KEY)
spy_ensemble_accuracy: float = spy_testing_table.attrs[f'{ENSEMBLE_KEY}*']
print(
    f"Ensemble accuracy for S&P-500: ␣
↪{float_to_percentage(spy_ensemble_accuracy)}"
)
```

```
0      NaN
1      NaN
2      NaN
3      NaN
4        +
      …
499      +
500      -
501      +
502      +
503      +
Name: Ensemble, Length: 504, dtype: object
Ensemble accuracy for SONY: 58.40%
Ensemble accuracy for S&P-500: 59.00%
```

[34]:
```
Latex(
    r' 3. Did you improve your accuracy on predicting "-" labels by using␣
↪ensemble compared to $W = 2, 3, 4$?'
)
```

[34]:
3. Did you improve your accuracy on predicting "-" labels by using ensemble compared to $W = 2, 3, 4$?

[35]:
```
w_negative_keys: list[str] = [f"W{w}-*" for w in w_list]

# Compute the prediction accuracy for negatives in SONY.
w_prediction_accuracy(sony_testing_table, w_list, ('-',))
sony_negative_accuracies = {
    key: sony_testing_table.attrs[key] for key in w_negative_keys
}
prediction_accuracy(sony_testing_table, ENSEMBLE_KEY, ('-',))

# Compare '-' accuracies.
sony_ensemble_negative_accuracy: float = \
    sony_testing_table.attrs[f"{ENSEMBLE_KEY}-*"]
sony_w_negative_accuracy: float = mean(list(sony_negative_accuracies.values()))

print(f"SONY Ensemble accuracy for '-': {sony_ensemble_negative_accuracy}")
print(f"SONY W accuracy for '-': {sony_w_negative_accuracy}")
```

```python
if sony_ensemble_negative_accuracy >= sony_w_negative_accuracy:
    print("Ensemble for SONY had better accuracy than W for negative '-'.")
else:
    print("W for SONY had better accuracy than Ensemble for negative '-'.")
```

```
SONY Ensemble accuracy for '-': 0.106
SONY W accuracy for '-': 0.1131114716118891
W for SONY had better accuracy than Ensemble for negative '-'.
```

[36]:
```python
Latex(
    r' 4. Did you improve your accuracy on predicting "+" labels by using␣
↪ensemble compared to $W = 2, 3, 4$?'
)
```

[36]:

4. Did you improve your accuracy on predicting "+" labels by using ensemble compared to $W = 2, 3, 4$?

[37]:
```python
w_positive_keys: list[str] = [f"W{w}+*" for w in w_list]

# Compute the prediction accuracy for positives in SONY.
w_prediction_accuracy(sony_testing_table, w_list, ('+',))
sony_positive_accuracies = {
    key: sony_testing_table.attrs[key] for key in w_positive_keys
}
prediction_accuracy(sony_testing_table, ENSEMBLE_KEY, ('+',))

# Compare '+' accuracies.
sony_ensemble_positive_accuracy: float = \
    sony_testing_table.attrs[f"{ENSEMBLE_KEY}+*"]
sony_w_positive_accuracy: float = mean(list(sony_positive_accuracies.values()))

print(f"SONY Ensemble accuracy for '+': {sony_ensemble_positive_accuracy}")
print(f"SONY W accuracy for '+': {sony_w_positive_accuracy}")
if sony_ensemble_positive_accuracy >= sony_w_positive_accuracy:
    print("Ensemble for SONY had better accuracy than W for positive '+'.")
else:
    print("W for SONY had better accuracy than Ensemble for positive '+'.")
```

```
SONY Ensemble accuracy for '+': 0.478
SONY W accuracy for '+': 0.4610869734634317
Ensemble for SONY had better accuracy than W for positive '+'.
```

[38]:
```python
Latex(
    r'$\textbf{Question 4: }$ For $W = 2, 3, 4$ and ensemble, compute the␣
↪following (both for your ticker and "SPY") statistics based upon years $4$␣
↪and $5$:'
)
```

[38]:

Question 4: For $W = 2, 3, 4$ and ensemble, compute the following (both for your ticker and "SPY") statistics based upon years 4 and 5:

[39]:

```
Latex(
    r' 1. TP - true positives (your predicted label is "+" and true label is␣
 ↪"+".'
    "\n"
    r' 2. FP - false positives (your predicted label is "+" but true label is␣
 ↪"-".'
    "\n"
    r' 3. TN - true negatives (your predicted label is "-" but true label is␣
 ↪"-".'
    "\n"
    r' 4. FN - false negatives (your predicted label is "-" but true label is␣
 ↪"+".'
    "\n"
    r' 5. TNR = TP/(TP + FN) - true positive rate. This is the fraction of␣
 ↪positive labels that you predicted correctly. This is also called␣
 ↪sensitivity, recall, or hit rate.'
    "\n"
    r' 6. TNR = TN/(TN + FP) - true negative rate. This is the fraction of␣
 ↪negative labels that you predicted correctly. This is also called␣
 ↪specificity or selectivity.'
)
```

[39]:

1. TP - true positives (your predicted label is "+" and true label is "+". 2. FP - false positives (your predicted label is "+" but true label is "-". 3. TN - true negatives (your predicted label is "-" but true label is "-". 4. FN - false negatives (your predicted label is "-" but true label is "+". 5. TNR = TP/(TP + FN) - true positive rate. This is the fraction of positive labels that you predicted correctly. This is also called sensitivity, recall, or hit rate. 6. TNR = TN/(TN + FP) - true negative rate. This is the fraction of negative labels that you predicted correctly. This is also called specificity or selectivity.

[40]:

```
Latex(
    r' 7. Summarize your findings in the table below.'
)
```

[40]:

7. Summarize your findings in the table below.

[41]:

```
w_keys: list[str] = ["W2", "W3", "W4", ENSEMBLE_KEY]

# Get statistics for all W labels in S&P-500 stock data table.
spy_statistics_table: DataFrame = DataFrame([
    get_statistics(
        df=spy_testing_table,
        column=w_key,
        accuracy=spy_testing_table.attrs[f"{w_key}*"],
```

```
        ticker=SPY_TICKER
    )
    for w_key in w_keys
])

# Get statistics for all W labels in SONY stock data table.
sony_statistics_table: DataFrame = DataFrame([
    get_statistics(
        df=sony_testing_table,
        column=w_key,
        accuracy=sony_testing_table.attrs[f"{w_key}*"],
        ticker=SONY_TICKER
    )
    for w_key in w_keys
])

# Build the prediction results statistics table.
statistics_table: DataFrame = pd.concat(
    [spy_statistics_table, sony_statistics_table]
).reset_index(drop=True)
```

[42]:
```
show_table(Styler(data=statistics_table, caption="Table 3: Prediction Results␣
↪for W = 1, 2, 3 and ensemble"), max_rows=20)
```

	W	ticker	TP	FP	TN	FN	accuracy	TPR	TNR
0	W2	SPY	294	208	0	0	0.585657	1.000000	0.000000
1	W3	SPY	271	183	25	22	0.590818	0.924915	0.120192
2	W4	SPY	212	117	91	80	0.606000	0.726027	0.437500
3	Ensemble	SPY	270	183	25	22	0.590000	0.924658	0.120192
4	W2	SONY	216	152	68	66	0.565737	0.765957	0.309091
5	W3	SONY	255	189	31	26	0.570858	0.907473	0.140909
6	W4	SONY	222	149	71	58	0.586000	0.792857	0.322727
7	Ensemble	SONY	239	167	53	41	0.584000	0.853571	0.240909

[43]:
```
Latex(
    r' 8. Discuss your findings.'
)
```

[43]: 8. Discuss your findings.

[44]:
```
Latex(
    r' Discussion: After viewing an overview of each prediction method, it␣
↪stands out that W4 has the highest accuracy, but is very close to ensemble.␣
↪Also, the ensemble recall is very high for both. W3 also has high recall for␣
↪each and the recall starts to dip going into W4, so that is an interesting␣
↪observation.'
)
```

[44]:

Discussion: After viewing an overview of each prediction method, it stands out that W4 has the highest accuracy, but is very close to ensemble. Also, the ensemble recall is very high for both. W3 also has high recall for each and the recall starts to dip going into W4, so that is an interesting observation.

[45]:

```
Latex(
    rf'$\textbf{{Question 5: }}$ At the beginning of year $4$, you start with␣
 ↪\$100 dollars and trade for 2 years based upon predicted labels.'
)
```

[45]:

Question 5: At the beginning of year 4, you start with \$100 dollars and trade for 2 years based upon predicted labels.

[46]:

```
Latex(
    r' 1. Take your stock. Plot the growth of your amount for 2 years if you␣
 ↪trade based on the best $W^*$ and on ensemble. On the same graph, plot the␣
 ↪growth of your portfolio for the "buy-and-hold" strategy.'
)
```

[46]:

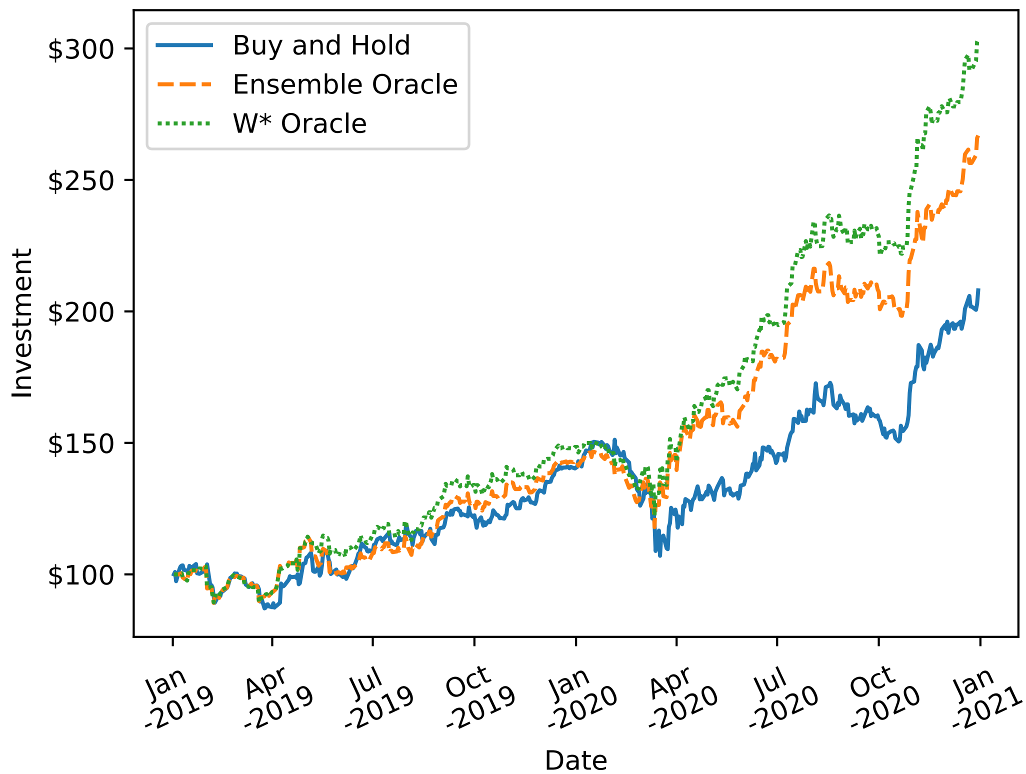
1. Take your stock. Plot the growth of your amount for 2 years if you trade based on the best W^* and on ensemble. On the same graph, plot the growth of your portfolio for the ”buy-and-hold” strategy.

[47]:

```
initial_investment: float = 100.0

# Buy and hold for SONY.
buy_and_hold(sony_testing_table, column=BUY_AND_HOLD_KEY)

# Buy from the predictions made by the ensemble method.
buy_from_prediction(
    sony_testing_table, column=ENSEMBLE_ORACLE_KEY,␣
 ↪prediction_column=ENSEMBLE_KEY
)

# Buy from the predictions made by the best W* method.
buy_from_prediction(
    sony_testing_table, column=W_ORACLE,␣
 ↪prediction_column=sony_highest_accuracy[0].replace('*', '')
)
```

[48]:

```
# Display linechart for SONY.
linechart(sony_testing_table)
```



[49]:
```
Latex(
    r' 2. Examine your chart. Any patterns? (e.g any differences in the year 4␣
 ↪and year 5).'
)
```

[49]: 2. Examine your chart. Any patterns? (e.g any differences in the year 4 and year 5).

[50]:
```
Latex(
    r'After examining the plot for SONY stock, it is clear that the prediction␣
 ↪strategies both had a significant positive impact on the buying strategy␣
 ↪compared to the buy and hold strategy. It seems that having a "W" value that␣
 ↪is higher increases the accuracy and is very close to the ensemble value. I␣
 ↪do notice from the graph itself that there is a big dip early on into 2020,␣
 ↪and a similar looking dip at around the same time in early 2019, so that␣
 ↪could be something to look into as an investor.'
)
```

[50]: After examining the plot for SONY stock, it is clear that the prediction strategies both had a significant positive impact on the buying strategy compared to the buy and hold strategy. It seems that having a "W" value that is higher increases the accuracy and is very close to the ensemble value. I do notice from the graph itself that there is a big early on into 2020, and a similar looking dip at around the same time in early 2019, so that could be something to look into as an

investor.

References

- https://pandas.pydata.org/docs/user_guide/style.html
- https://pandas.pydata.org/docs/user_guide/window.html
- https://pandas.pydata.org/pandas-docs/stable/user_guide/style.html#Optimization
- https://seaborn.pydata.org/generated/seaborn.lineplot.html
- https://matplotlib.org/stable/api/dates_api.html
- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.html
- https://pandas.pydata.org/docs/getting_started/intro_tutorials/03_subset_data.html
- https://pandas.pydata.org/docs/getting_started/intro_tutorials/05_add_columns.html
- https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
- https://ipython.readthedocs.io/en/stable/interactive/magics.html#cell-magics
- https://pandas.pydata.org/docs/getting_started/intro_tutorials/06_calculate_statistics.html
- https://docs.mathjax.org/en/latest/options/index.html#configuring-mathjax