

Tree Strategy HW1 Q1, Q2

January 21, 2024

0.1 Imports

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.metrics import accuracy_score, confusion_matrix
pd.set_option('use_inf_as_na', True)
from collections import Counter
```

```
/var/folders/sp/wlr6xm2979l8vx6kjh2z1dk00000gn/T/ipykernel_58828/2166773765.py:6
: FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
pd.set_option('use_inf_as_na', True)
```

0.2 Loading the Data Set (you need to put in the file where you have stored the data)

```
[2]: raw_data = pd.read_pickle('dataset.pkl')

[4]: raw_data = raw_data.drop([x for x in raw_data.columns if 'fqtr' in x],axis=1)
```

0.3 Restricting to Companies with Market Cap > 1 Billion

```
[5]: data = raw_data[raw_data['market_cap'] > 1000.0]
```

0.4 The Total Number of Companies w/ Market Cap > 1 Billion that appear during our time horizon

```
[6]: len(data.index.get_level_values(1).unique())
```

```
[6]: 4076
```

0.5 Filling in Missing Values

```
[8]: data = data.copy()
data.replace([np.inf, -np.inf], np.nan, inplace=True)
data = data.fillna(method='ffill')
```

```
/var/folders/sp/wlr6xm2979l8vx6kjh2z1dk00000gn/T/ipykernel_58828/970161762.py:3:
FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a
future version. Use obj.ffill() or obj.bfill() instead.
    data = data.fillna(method='ffill')
```

```
[9]: data = data.fillna(0)
```

```
[10]: data['pred_rel_return']
```

```
[10]: date      ticker
2000-02-09  CSC0    -0.025923
           ROP      0.066175
2000-02-10  CMOS     0.241345
2000-02-11  DELL     0.306035
2000-02-15  VAL      0.043852
           ...
2018-12-21  NKE      -0.100100
           SAFM      -0.100100
           SCHL      -0.100100
           WBA       -0.100100
2018-12-24  KMX      -0.100100
Name: pred_rel_return, Length: 111468, dtype: float64
```

0.6 HW Question 1

Inserting a column in the dataset where entries are 1 if stock outperforms SPY in the earnings period, and -1 otherwise:

```
[11]: # function to return appropriate values based on performance
def f_1(x):
    if x > 0:
        return 1
    else:
        return -1
```

```
[12]: # apply the function to the column of relative returns
data = data.copy()
data['rel_performance_1'] = data['pred_rel_return'].apply(f_1)
```

This is the column of labels next to the original relative returns:

```
[13]: data[['pred_rel_return', 'rel_performance_1']]
```

```
[13]:
```

date	ticker	pred_rel_return	rel_performance_1
2000-02-09	CSCO	-0.025923	-1
	ROP	0.066175	1
2000-02-10	CMOS	0.241345	1
2000-02-11	DELL	0.306035	1
2000-02-15	VAL	0.043852	1
...	
2018-12-21	NKE	-0.100100	-1
	SAFM	-0.100100	-1
	SCHL	-0.100100	-1
	WBA	-0.100100	-1
2018-12-24	KMX	-0.100100	-1

[111468 rows x 4 columns]

Thus we can observe that the labels for the stocks whose relative returns are positive (i.e. indicating it outperformed the SPY) have label 1 (e.g CMOS has label 1). Otherwise if they are negative or zero, the label is -1 (e.g. NKE has label -1).

0.7 HW Question 2

Inserting a column in the dataset where entries are:

- 2 if the stock return is more than 5% higher than the SPY return
- 1 if it is between 1% and 5% higher than the SPY return
- 0 if it is between -1% and 1% relative to the SPY return
- -1 if it is between -1% and -5% relative to the SPY return

```
[14]: # function to return appropriate values based on performance as detailed above
def f_2(x):
    if x > 0.05:
        return 2
    elif x > 0.01:
        return 1
    elif x > -0.01:
        return 0
    elif x > -0.05:
        return -1
```

```
[15]: # apply the function to the column of relative returns
data = data.copy()
data['rel_performance_2'] = data['pred_rel_return'].apply(f_2)
```

This is the column of labels next to the original relative returns:

```
[16]: data[['pred_rel_return', 'rel_performance_2']]
```

```
[16]:
```

		pred_rel_return	rel_performance_2
date	ticker		
2000-02-09	CSCO	-0.025923	-1.0
	ROP	0.066175	2.0
2000-02-10	CMOS	0.241345	2.0
2000-02-11	DELL	0.306035	2.0
2000-02-15	VAL	0.043852	1.0
...	
2018-12-21	NKE	-0.100100	NaN
	SAFM	-0.100100	NaN
	SCHL	-0.100100	NaN
	WBA	-0.100100	NaN
2018-12-24	KMX	-0.100100	NaN

[111468 rows x 2 columns]

Thus we can observe that the labels were applied correctly:

- CMOS had a relative return of 0.24135 (i.e. ~ 24.1% higher than the SPY) so its label is 2
- VAL had a relative return of 0.043852 (i.e. ~ 4.3% higher than the SPY) so its label is 1
- CSCO had a relative return of -0.025923 (i.e. ~ -2.5% relative to the SPY) so its label is -1
- NKE had a relative return of -0.100100 (i.e. ~ -10% relative to the SPY) so its label is NaN (as we have not assigned a label for those stocks with relative performance less than 5% compared to the SPY).

```
[17]: # Find those stocks whose relative performance 2 label is 0
data[['pred_rel_return', 'rel_performance_2']].loc[data['rel_performance_2'] == 0]
```

```
[17]:
```

		pred_rel_return	rel_performance_2
date	ticker		
2000-02-24	MDT	0.005511	0.0
	ORTL	0.005511	0.0
2000-03-08	DDS	-0.004425	0.0
2000-04-13	DJ	-0.009937	0.0
2000-04-14	CYN	-0.003053	0.0
...	
2018-09-20	CPRT	-0.004948	0.0
2018-09-27	KMX	-0.008830	0.0
2018-10-01	MTN	0.004993	0.0
2018-10-02	CALM	0.004993	0.0
	KMG	0.004993	0.0

[7647 rows x 2 columns]

It remains to check that if we can observe that the label 0 was applied correctly:

- MDT had a relative return of 0.005511 (i.e. ~ 0.55% higher than the SPY) so its label is 0 as this is between -1% and 1%

Thus all labels have been applied appropriately.