Backtesting a Random Forest

MGMT 767 / BUSI 449: Data-Driven Investments: Equity

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Overview of Backtesting

- The goal is to illustrate the process of evaluating a model for combining characteristics to predict stock returns.
- A model has parameters (coefficients) that must be estimated from past data.
- It may also have hyperparameters that should be tuned from past data (more later).
- If we wanted to apply a model today, we would use all past data to estimate the parameters. Then look at today's characteristic values and run them through the model to predict returns.

- To evaluate how a model would have worked in the past, we should recreate this at each past portfolio revision date:
    - Estimate the parameters based on the data prior to that date.
    - Look at the characteristic values at that date and run them through the model to predict returns.
    - Form a portfolio based on the predictions.
    - Calculate the return of the portfolio up to the next portfolio revision date.
    - Rinse and repeat.

Examples of models

- Linear regression
- Penalized linear regression (LASSO, ridge regression, elastic net)
- Random forests
- Boosted trees
- Neural networks

Introduction to Random Forests

Random forest

- From your data set, generate random "pseudo data sets" by bootstrapping.
    - Randomly choose rows from the original set with replacement until you have as many rows as in the original.
    - Do this, say, 100 times, to create 100 pseudo data sets.
- Fit a decision tree (more coming) to each pseudo data sets.
- Average the predictions from the 100 decision trees.

Decision tree example

- Generate some simple random data: predictors x_1 and x_2 and outcome y
- Fit a decision tree to predict y from x_1 and x_2.

In [2]:

```
import numpy as np
import pandas as pd

np.random.seed(0)
x1 = np.random.normal(size=100)
x2 = np.random.normal(size=100)
e = np.random.normal(size=100)
y = 2*x1 + 3*x2 + e
df = pd.DataFrame(
    dict(x1=x1, x2=x2, y=y)
)
```

In [3]:

```
df
```

Out[3]:

```
          x1         x2         y
 0  1.764052   1.883151   8.808375
 1  0.400157  -1.347759  -3.482342
 2  0.978738  -1.270485  -0.754319
 3  2.240893   0.969397   8.045240
 4  1.867558  -1.173123   0.855877
...      ...        ...        ...
95  0.706573  -0.171546   2.035399
96  0.010500   0.771791   2.434097
97  1.785870   0.823504   6.625207
98  0.126912   2.163236   6.344083
99  0.401989   1.336528   5.183618

100 rows × 3 columns
```

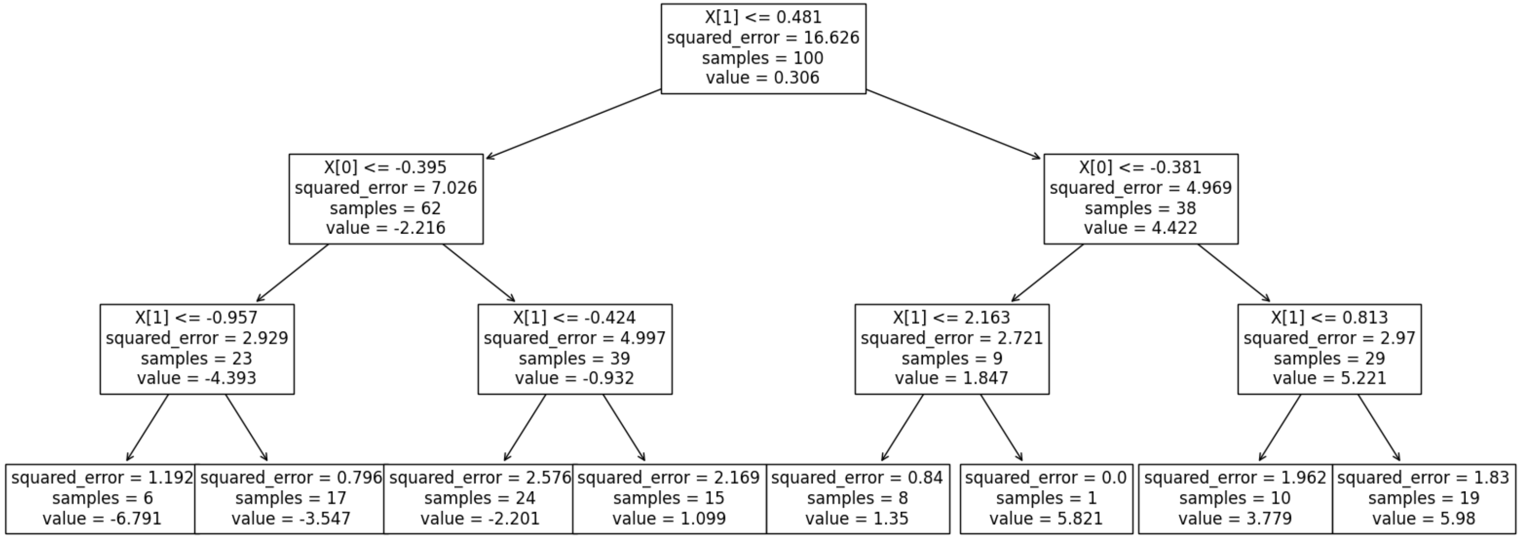
Fit and view a decision tree

```
In [4]: from sklearn.tree import DecisionTreeRegressor, plot_tree
        tree = DecisionTreeRegressor(max_depth=3)
        tree.fit(X=df[["x1", "x2"]], y=df.y)
```

```
Out[4]: ▾ DecisionTreeRegressor
        DecisionTreeRegressor(max_depth=3)
```

In [5]:

```python
import matplotlib.pyplot as plt
plt.figure(figsize=(20, 8))
plot_tree(tree, fontsize=12)
plt.show()
```



X[1] <= 0.481
squared_error = 16.626
samples = 100
value = 0.306

X[0] <= -0.395
squared_error = 7.026
samples = 62
value = -2.216

X[0] <= -0.381
squared_error = 4.969
samples = 38
value = 4.422

X[1] <= -0.957
squared_error = 2.929
samples = 23
value = -4.393

X[1] <= -0.424
squared_error = 4.997
samples = 39
value = -0.932

X[1] <= 2.163
squared_error = 2.721
samples = 9
value = 1.847

X[1] <= 0.813
squared_error = 2.97
samples = 29
value = 5.221

squared_error = 1.192
samples = 6
value = -6.791

squared_error = 0.796
samples = 17
value = -3.547

squared_error = 2.576
samples = 24
value = -2.201

squared_error = 2.169
samples = 15
value = 1.099

squared_error = 0.84
samples = 8
value = 1.35

squared_error = 0.0
samples = 1
value = 5.821

squared_error = 1.962
samples = 10
value = 3.779

squared_error = 1.83
samples = 19
value = 5.98

Fit a random forest and view goodness of fit

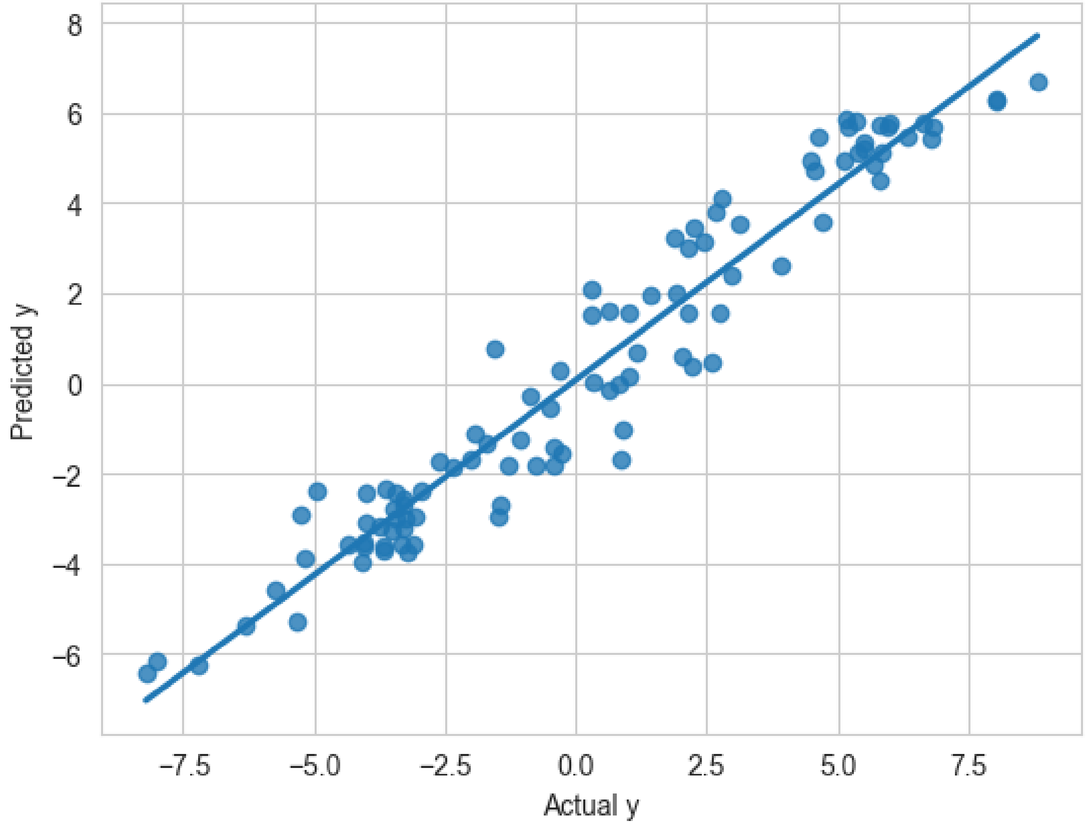
In [6]:

```
from sklearn.ensemble import RandomForestRegressor
forest = RandomForestRegressor(max_depth=3)
forest.fit(X=df[["x1", "x2"]], y=df.y)
predict = forest.predict(X=df[["x1", "x2"]])
```

In [7]:

```
import seaborn as sns
sns.set_style("whitegrid")

sns.regplot(x=df.y, y=predict, ci=None)
plt.xlabel("Actual y")
plt.ylabel("Predicted y")
plt.show()
```



Data for Backtesting Example

In [9]:

```python
df = pd.read_csv("02_data.csv", index_col=["ticker", "date"])
"""
df = pd.read_csv(
    "https://www.dropbox.com/s/km8tb71md3a5m1r/02_data.csv?dl=1",
    index_col=["ticker", "date"]
)
"""
df.head()
```

Out[9]:

		pb	marketcap	lastupdated	close	ret	mom
ticker	**date**						
AA	**2019-08-23**	0.7	3436.5	2019-08-19	18.52	-0.015660	-0.434685
	2019-08-30	0.7	3382.7	2019-08-27	18.23	-0.058148	-0.451343
	2019-09-06	0.7	3186.0	2019-09-04	17.17	0.025635	-0.472985
	2019-09-13	0.7	3267.7	2019-09-09	17.61	0.281083	-0.535282
	2019-12-06	0.8	3793.1	2019-12-02	20.44	-0.033275	-0.359533

Relative predictors and returns

- To control for variation over time in levels of predictors, use deviations from medians.
- We want to predict relative performance (which stocks will do better than others), so use deviation from median return as the target.

In [9]:

```python
for col in ["mom", "pb", "ret"]:
    df[col+"_adjusted"] = df.groupby("date", group_keys=False)[col].apply(
        lambda x: x - x.median()
    )
```

Backtest Random Forest

Overview

- max_depth is a hyperparameter that we could "tune," but today just try max_depth=2
- For speed, train only once per year.
- Use trained model to make predictions weekly.
- Pick best 50 stocks each week and hold equally weighted until end of week.
- Repeat until end of year.
- Then retrain and repeat.
- First, make some changes to the dataframe (put date and ticker in columns, add year, and sort).

In [10]:

```
df = df.reset_index()
df["date"] = pd.to_datetime(df.date)
df["year"] = df.date.map(lambda x: x.year)
df = df.sort_values(by=["date", "ticker"])
```

In [11]:

```
df2 = None
forest = RandomForestRegressor(max_depth=2)

for year in range(2014, 2024):
    print(year)
    start = df[df.year == year].date.min()
    past = df[df.date < start]
    future = df[df.year == year].copy()
    forest.fit(X=past[["mom_adjusted", "pb_adjusted"]], y=past["ret_adjusted"
    future["predict"] = forest.predict(X=future[["mom_adjusted", "pb_adjusted
    df2 = pd.concat((df2, future))
```

```
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
```

In [12]:

```python
df2.head()
```

Out[12]:

	ticker	date	pb	marketcap	lastupdated	close	ret	mon
811	AAIC	2014-01-03	0.9	455.6	2020-10-26	27.44	-0.018456	0.39596
1136	AAMC	2014-01-03	582.3	2050.2	2023-11-01	902.00	0.025155	8.95157
2357	AAON	2014-01-03	7.4	1202.4	2023-08-17	32.72	-0.031758	1.18059
3080	AAT	2014-01-03	1.9	1269.7	2018-10-18	31.39	0.015607	0.18478
4052	AAWW	2014-01-03	0.8	1011.3	2018-10-18	40.39	0.019064	-0.17234

50 best stocks each week

In [14]:

```python
starting_from_best = df2.groupby(
    "date",
    group_keys=False
).predict.rank(
    ascending=False,
    method="first"
)
best = df2[starting_from_best <= 50]
best_rets = best.groupby("date", group_keys=True).ret.mean()
best_rets.index = pd.to_datetime(best_rets.index)
```

Worst stocks and all stocks

In [15]:

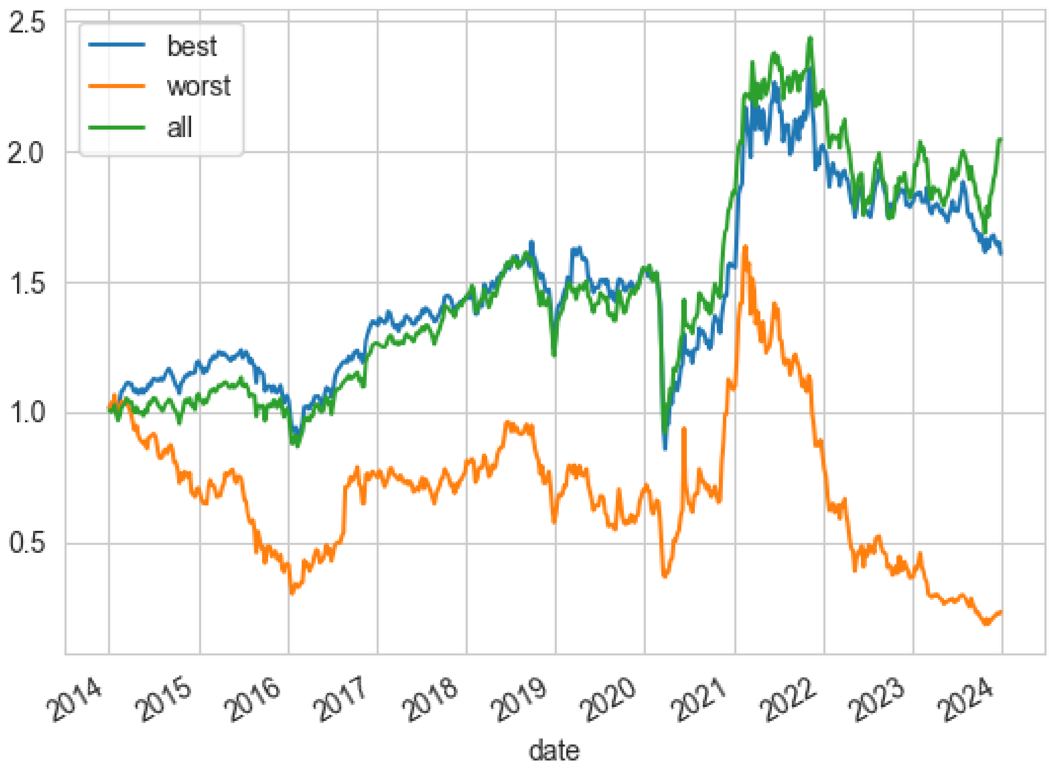
```
starting_from_worst = df2.groupby(
    "date",
    group_keys=False
).predict.rank(
    ascending=True,
    method="first"
)

worst = df2[starting_from_worst <= 50]
worst_rets = worst.groupby("date", group_keys=True).ret.mean()
worst_rets.index = pd.to_datetime(worst_rets.index)

all_rets = df2.groupby("date", group_keys=True).ret.mean()
all_rets.index = pd.to_datetime(all_rets.index)
```

In [16]:

```
(1+best_rets).cumprod().plot(label="best")
(1+worst_rets).cumprod().plot(label="worst")
(1+all_rets).cumprod().plot(label="all")
plt.legend()
plt.show()
```


best
worst
all
date