Backtesting a Random Forest

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

Kerry Back and Kevin Crotty, Rice University

Overview of Backtesting

- We want to evaluate a model for combining characteristics to predict stock returns.
- A model has parameters (coefficients) that must be estimated from past data. It must be "trained."
- 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 (train the model) 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.

Once we've computed historical returns from training and applying the model in this way, we need to evaluate them.

- Average return
- Sharpe ratio
- CAPM alpha
- Factor model attribution and alpha
- Maximum drawdown

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]:

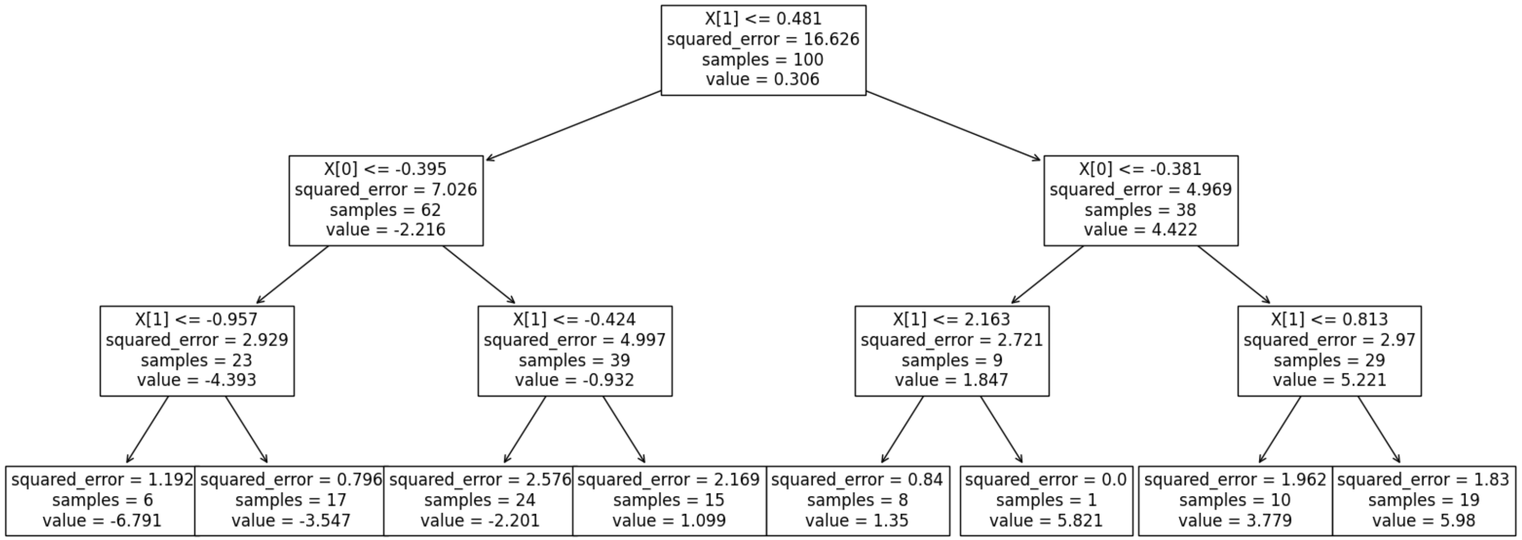
```
from sklearn.tree import DecisionTreeRegressor, plot_tree
tree = DecisionTreeRegressor(max_depth=3)
tree.fit(X=df[["x1", "x2"]], y=df.y)
```

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()
```



Fit a random forest and view goodness of fit

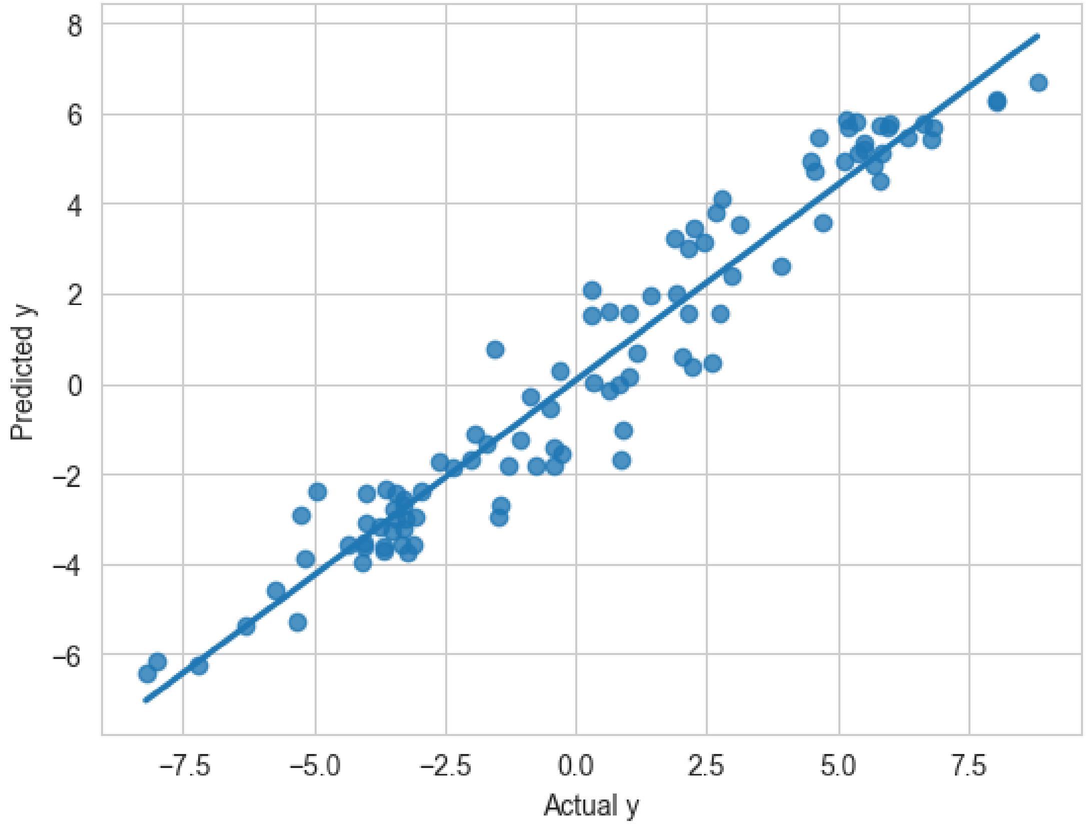
In [6]:

```
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]:

```
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]:
```
df2.head()
```

Out[12]:

	ticker	date	pb	marketcap	lastupdated	close	ret	mom
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]:

```
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()
```