

# Backtesting Random Forest II

MGMT 638: Data-Driven Investments: Equity

Kerry Back, Rice University



# Outline

Follow same procedure as in 06a-random\_forest\_backtest except

- Multiply all features by mktvol
  - So twice as many features: original plus original\*mktvol
- Use percentile (rank from 0 to 100) of return instead of (return - median) as target
- Use maxdepth=4 instead of maxdepth=3



Read data



```
In [49]: import pandas as pd

url = "https://www.dropbox.com/scl/fi/hjpebns5qv0nzh1ucl4tr/data-2023-11-13.c
df = pd.read_csv(url)
df.head()
```

```
Out[49]:
```

	<b>ticker</b>	<b>date</b>	<b>marketcap</b>	<b>pb</b>	<b>ret</b>	<b>mom</b>	<b>volume</b>	<b>volatility</b>
<b>0</b>	AACC	2011-01-14	188.3	1.4	-0.014634	-0.184615	2.078000e+04	0.071498
<b>1</b>	AAI	2011-01-14	1012.1	2.0	0.002677	0.438224	2.775580e+06	0.128450
<b>2</b>	AAIC	2011-01-14	189.3	1.0	-0.010119	0.684547	3.466000e+04	0.048505
<b>3</b>	AAON	2011-01-14	479.4	4.2	0.007778	0.528685	2.817291e+05	0.044912
<b>4</b>	AATC	2011-01-14	63.3	1.4	-0.013960	0.008216	6.800000e+03	0.049756

Define model and target



```
In [50]: from sklearn.ensemble import RandomForestRegressor
forest = RandomForestRegressor(max_depth=4)

df["target"] = df.groupby("date", group_keys=False).ret.apply(
    lambda x: x.rank(pct=True)
)
```

Define predictors (features)



```
In [51]: features = [  
    "marketcap",  
    "pb",  
    "mom",  
    "volume",  
    "volatility",  
    "roe",  
    "accruals",  
    "agr"  
]  
features.sort()
```



```
In [52]: for x in features:
          df[x+"_vol"] = df[x]*df.mktvol

          features += [x+"_vol" for x in features]
```

## Define training dates and training windows

- For this example, I am going to train once per year using the prior three years of data.
- Obviously, other choices are possible.
- The reason for not using all past data is to capture any changes in the market.



```
In [53]: dates = list(df.date.unique())
         dates.sort()
         train_dates = dates[156::52] # once per year starting after three years

         past_dates = {} # dates on which to train for each training date
         future_dates = {} # dates for which to predict for each training date
         for date in train_dates:
             past_dates[date] = dates[(dates.index(date)-156):dates.index(date)]
             if date < train_dates[-1]:
                 future_dates[date] = dates[dates.index(date):(dates.index(date)+52)]
             else:
                 future_dates[date] = dates[dates.index(date):]
```



Run the loop



```
In [54]: new_data = None
for date in train_dates:
    past = past_dates[date]
    past = df[df.date.isin(past)]
    future = future_dates[date]
    future = df[df.date.isin(future)]
    forest.fit(X=past[features], y=past.target)
    predictions = forest.predict(X=future[features])
    predictions = pd.DataFrame(predictions)
    predictions.columns = ["predict"]
    for col in ["ticker", "date"]:
        predictions[col] = future[col].to_list()
    new_data = pd.concat((new_data, predictions))

df = df.merge(new_data, on=["ticker", "date"], how="inner")
```

In [55]: `df.tail()`

Out[55]:

	<b>ticker</b>	<b>date</b>	<b>marketcap</b>	<b>pb</b>	<b>ret</b>	<b>mom</b>	<b>volume</b>	<b>volatility</b>
<b>1010370</b>	ZNTL	2023-11-10	1262.5	2.4	-0.449664	-0.174662	743655.8	0.086553
<b>1010371</b>	ZUMZ	2023-11-10	335.0	0.9	-0.069190	-0.245402	201904.4	0.053633
<b>1010372</b>	ZUO	2023-11-10	1088.9	9.7	0.018065	0.080163	662494.2	0.070317
<b>1010373</b>	ZYME	2023-11-10	504.0	1.1	-0.018843	-0.215539	435386.8	0.062766
<b>1010374</b>	ZYXI	2023-11-10	310.4	5.3	-0.023484	-0.356304	379338.0	0.066363

5 rows × 23 columns

Form portfolios and compute returns



```
In [56]: df["rnk_long"] = df.groupby("date", group_keys=False).predict.rank(
        ascending=False,
        method="first"
    )
df["rnk_short"] = df.groupby("date", group_keys=False).predict.rank(
    ascending=True,
    method="first"
)
longs = df[df.rnk_long<=44]
shorts = df[df.rnk_short<=44]
```



```
In [57]: long_ret = longs.groupby("date").ret.mean()
short_ret = shorts.groupby("date").ret.mean()
print(f"mean annualized long return is {52*long_ret.mean():.2%}")
print(f"mean annualized short return is {52*short_ret.mean():.2%}")
```

```
mean annualized long return is 21.60%
mean annualized short return is -27.99%
```

Try sector-neutral strategy



```
In [58]: df["rnk_long"] = df.groupby(["date", "sector"], group_keys=False).predict.rank(
        ascending=False,
        method="first"
    )
df["rnk_short"] = df.groupby(["date", "sector"], group_keys=False).predict.rank(
        ascending=True,
        method="first"
    )
longs = df[df.rnk_long <= 4]
shorts = df[df.rnk_short <= 4]
```

```
In [59]: long_neutral_ret = longs.groupby("date").ret.mean()  
short_neutral_ret = shorts.groupby("date").ret.mean()  
print(f"mean annualized long sector-neutral return is {52*long_neutral_ret.me  
print(f"mean annualized short sector-neutral return is {52*short_neutral_ret.i
```

```
mean annualized long sector-neutral return is 20.04%  
mean annualized short sector-neutral return is -17.89%
```



Plot long-minus-short returns



```
In [60]: lms = long_ret - short_ret
lms_neutral = long_neutral_ret - short_neutral_ret

lms.index = pd.to_datetime(lms.index)
lms_neutral.index = pd.to_datetime(lms_neutral.index)

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("whitegrid")

(1+lms).cumprod().plot(logy=True, label="long minus short")
(1+lms_neutral).cumprod().plot(logy=True, label="neutral long minus short")
plt.legend()
plt.show()
```

