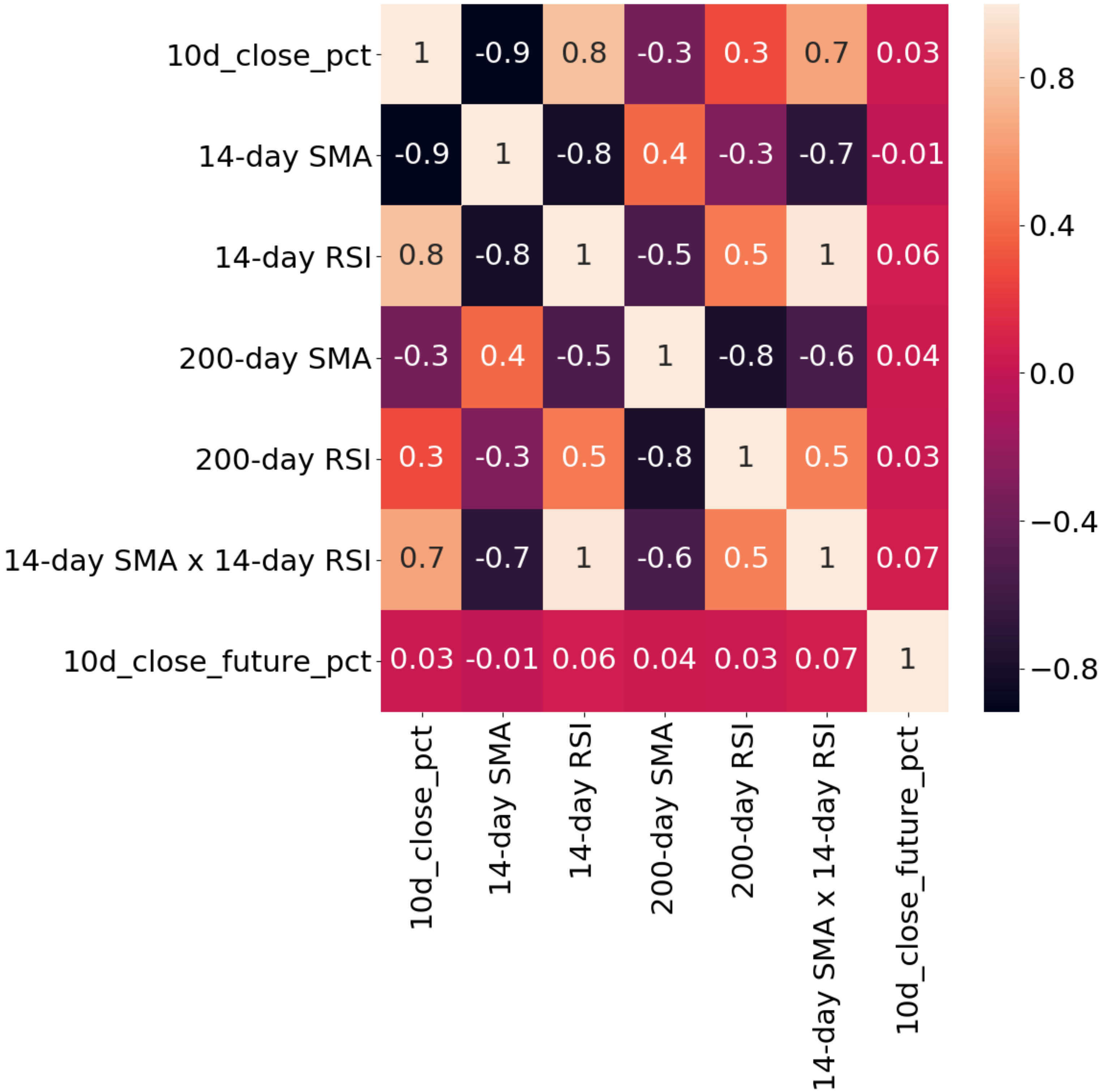
MACHINE LEARNING FOR FINANCE IN PYTHON

Engineering features

Nathan George
Data Science Professor


10d_close_pct
14-day SMA
14-day RSI
200-day SMA
200-day RSI
14-day SMA x 14-day RSI
10d_close_future_pct
1 -0.9 0.8 -0.3 0.3 0.7 0.03
-0.9 1 -0.8 0.4 -0.3 -0.7 -0.01
0.8 -0.8 1 -0.5 0.5 1 0.06
-0.3 0.4 -0.5 1 -0.8 -0.6 0.04
0.3 -0.3 0.5 -0.8 1 0.5 0.03
0.7 -0.7 1 -0.6 0.5 1 0.07
0.03 -0.01 0.06 0.04 0.03 0.07 1
0.8
0.4
0.0
−0.4
−0.8

One problem with linear models

```
# add non-linear interaction term for a linear model
SMAxRSI = amd_df['14-day SMA'] * amd_df['14-day RSI']
```

Some models that don't require manually creating interaction features:

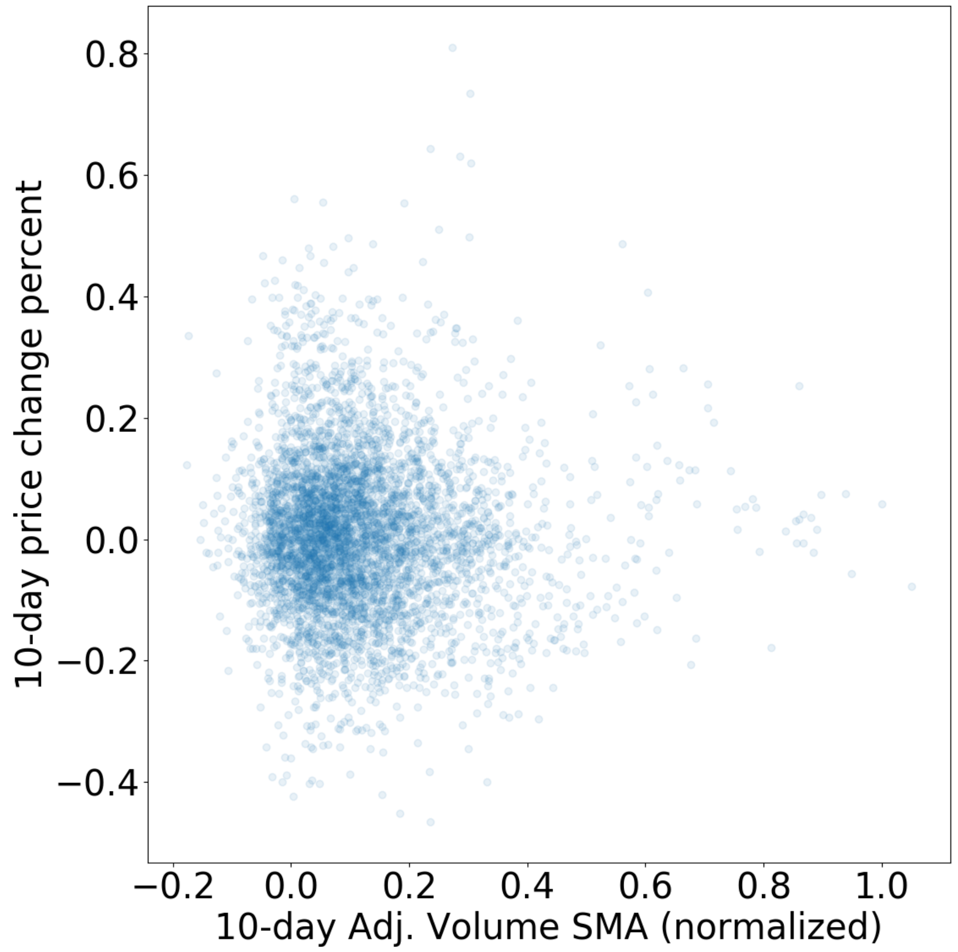
Decision-tree-based models

- Random forests
- Gradient boosting

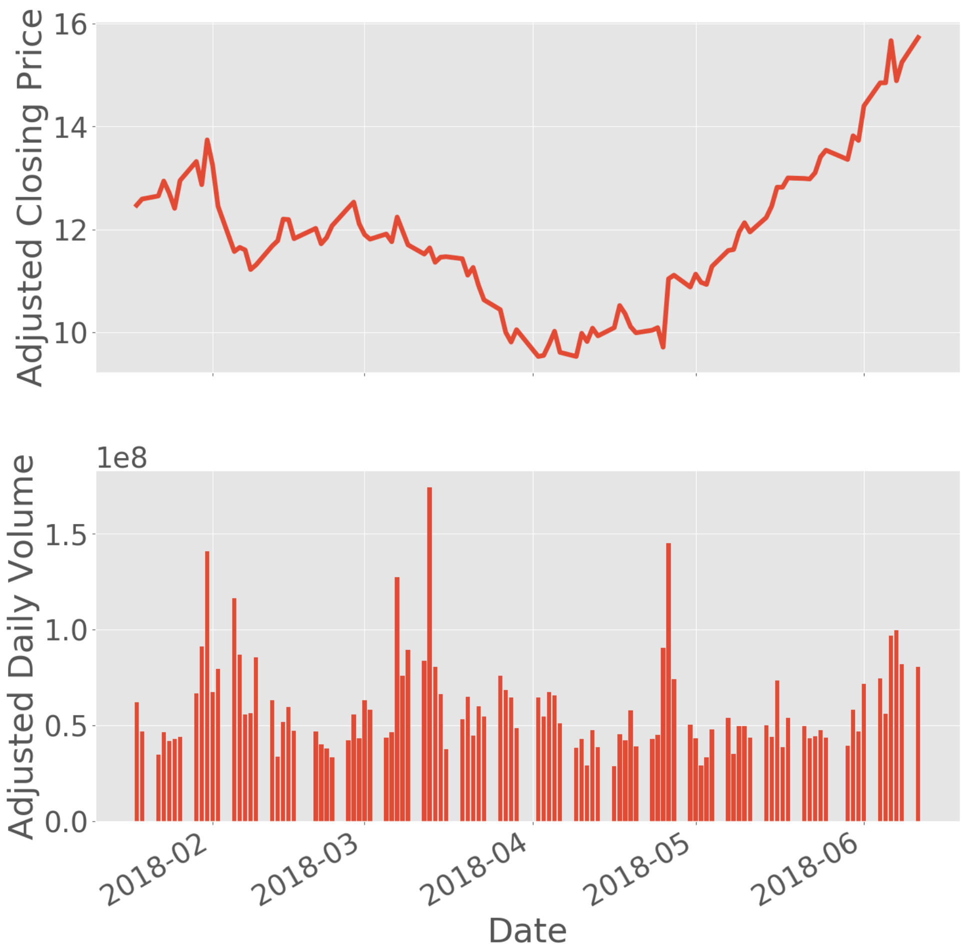
Others

- neural networks

Feature engineering



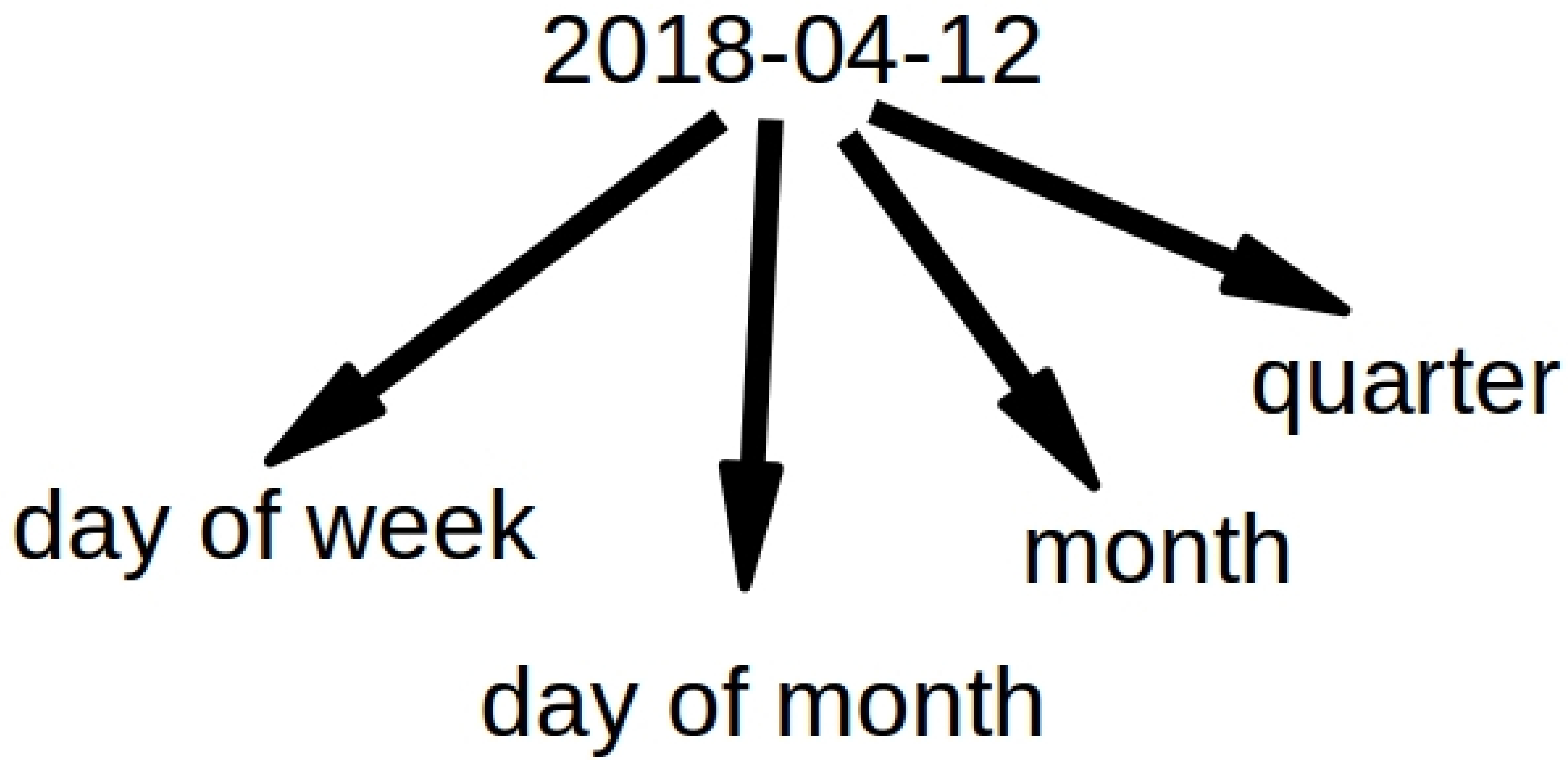
Volume


Adjusted Closing Price
16
14
12
10
1e8
Adjusted Daily Volume
1.5
1.0
0.5
0.0
2018-02
2018-03
2018-04
2018-05
2018-06
Date

Volume features

```
amd_df['Adj_Volume_1d_change'] = amd_df['Adj_Volume'].pct_change()

one_day_change = amd_df['Adj_Volume_1d_change'].values
amd_df['Adj_Volume_1d_change_SMA'] = talib.SMA(one_day_change,
                                               timeperiod=10)
```

Datetime feature engineering

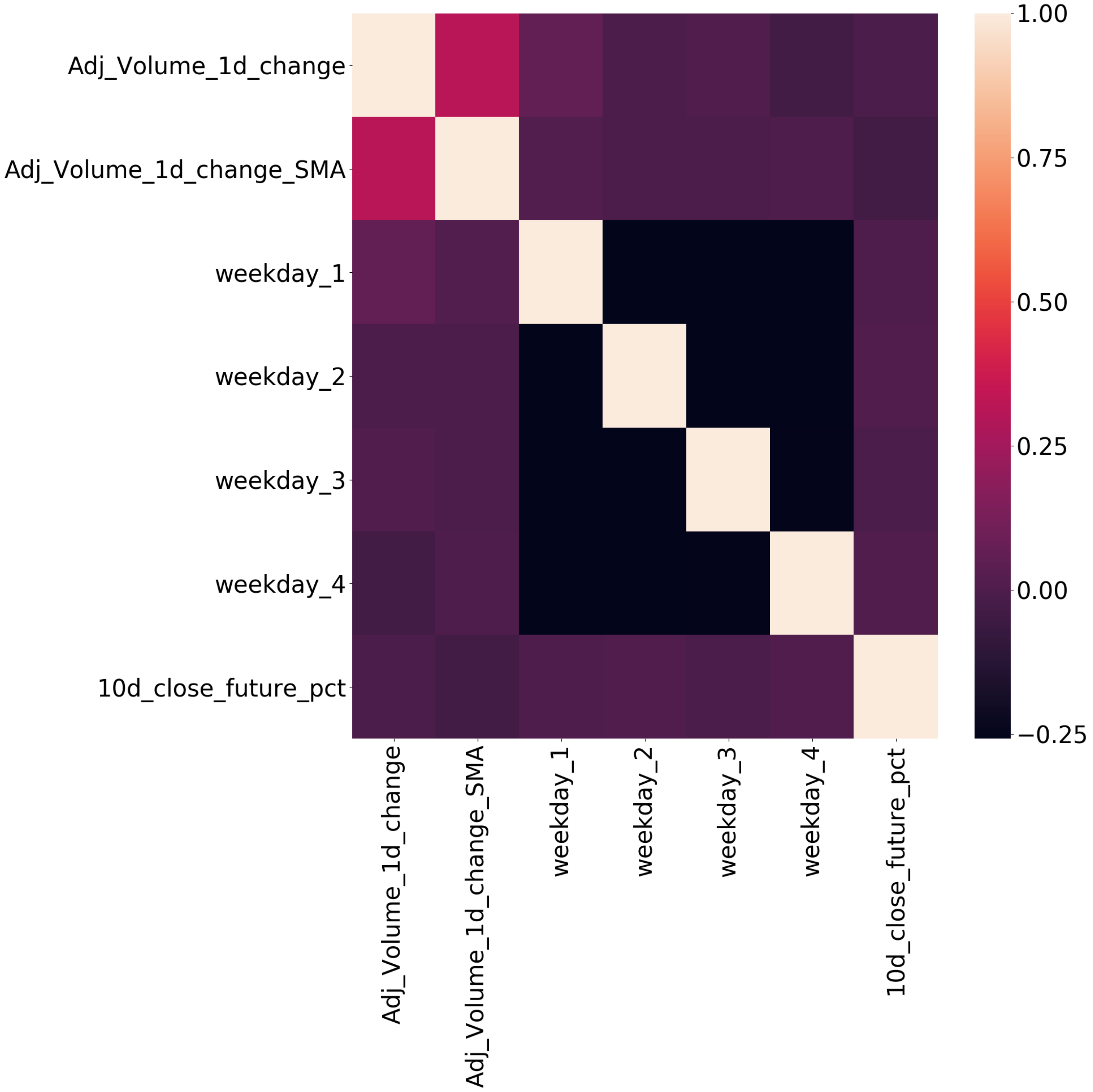


Extracting the day of week

```
print(amd_df.index.dayofweek)

Int64Index([2, 3, 4, 0, 1, 2, 3, 4, 0, 1,
            ...
            1, 2, 3, 4, 0, 1, 2, 3, 4, 0],
           dtype='int64', name='Date', length=4807)
```

Dummies

```
days_of_week = pd.get_dummies(amd_df.index.dayofweek,
                              prefix='weekday',
                              drop_first=True)

print(days_of_week.head())

            weekday_1  weekday_2  weekday_3  weekday_4
Date
2018-04-10          1          0          0          0
2018-04-11          0          1          0          0
2018-04-12          0          0          1          0
2018-04-13          0          0          0          1
2018-04-16          0          0          0          0
```


Adj_Volume_1d_change
Adj_Volume_1d_change_SMA
weekday_1
weekday_2
weekday_3
weekday_4
10d_close_future_pct
1.00
0.75
0.50
0.25
0.00
−0.25

MACHINE LEARNING FOR FINANCE IN PYTHON

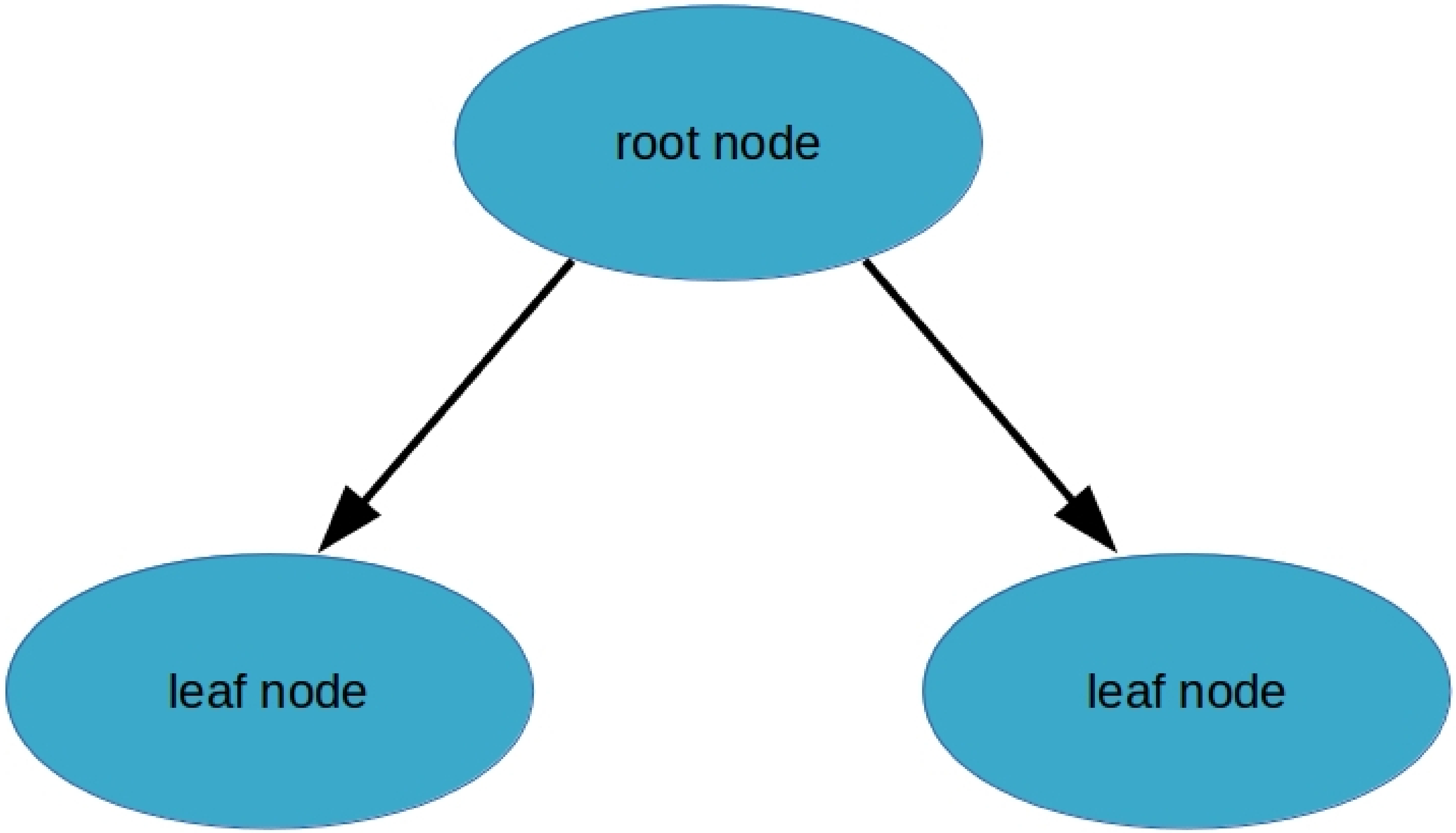
Engineer some features!

MACHINE LEARNING FOR FINANCE IN PYTHON

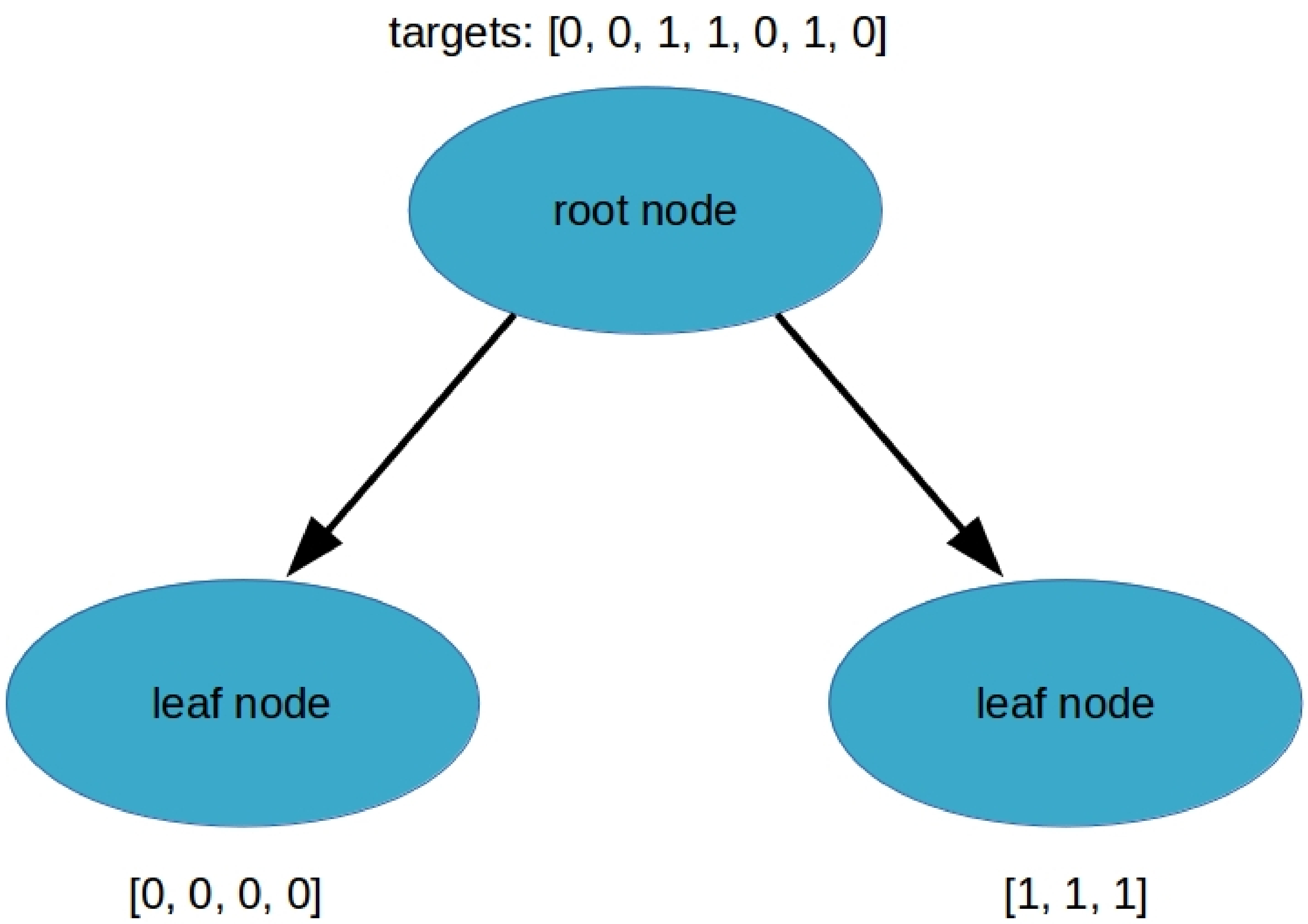
Decision Trees

Nathan George
Data Science Professsor

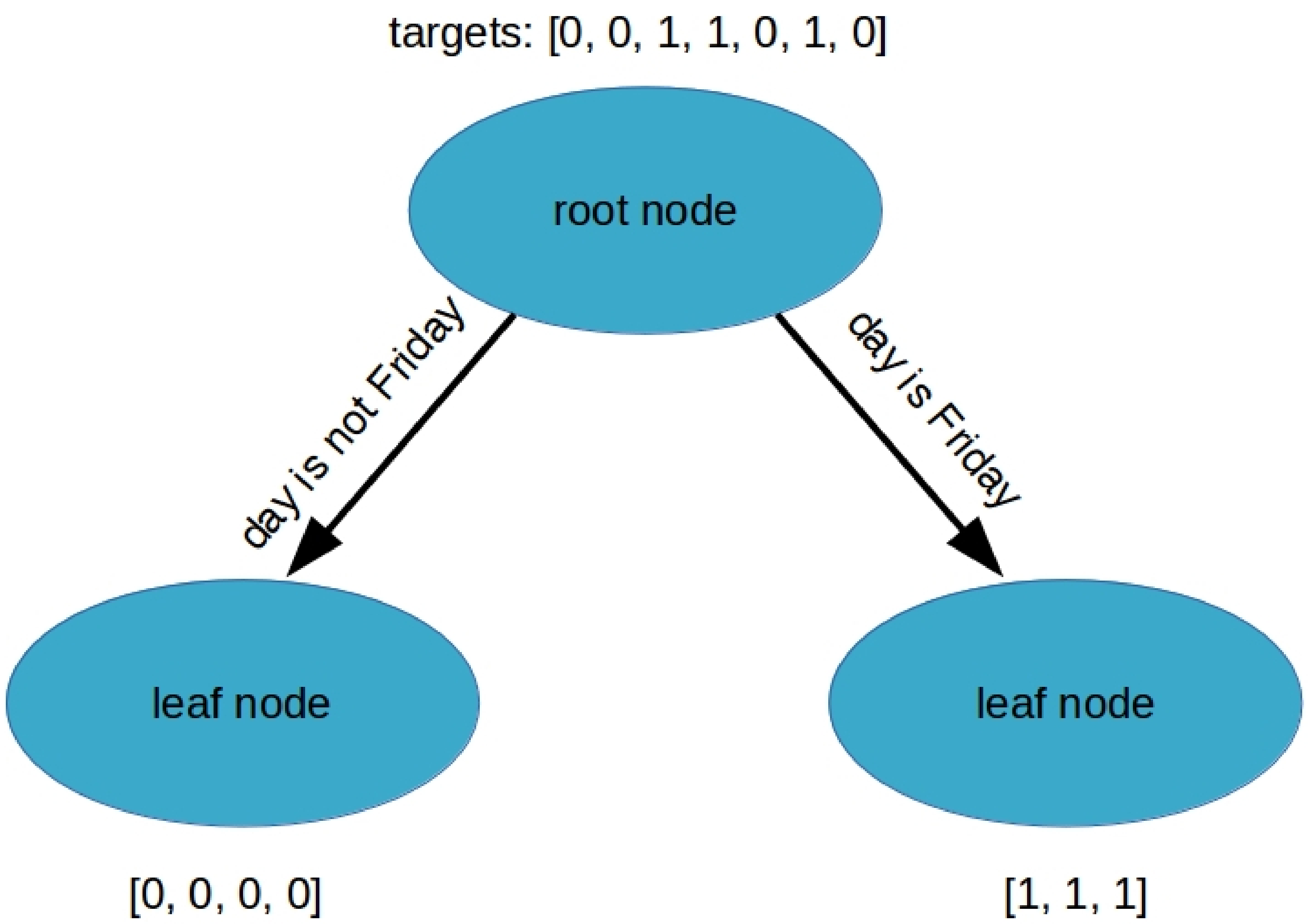
Decision trees



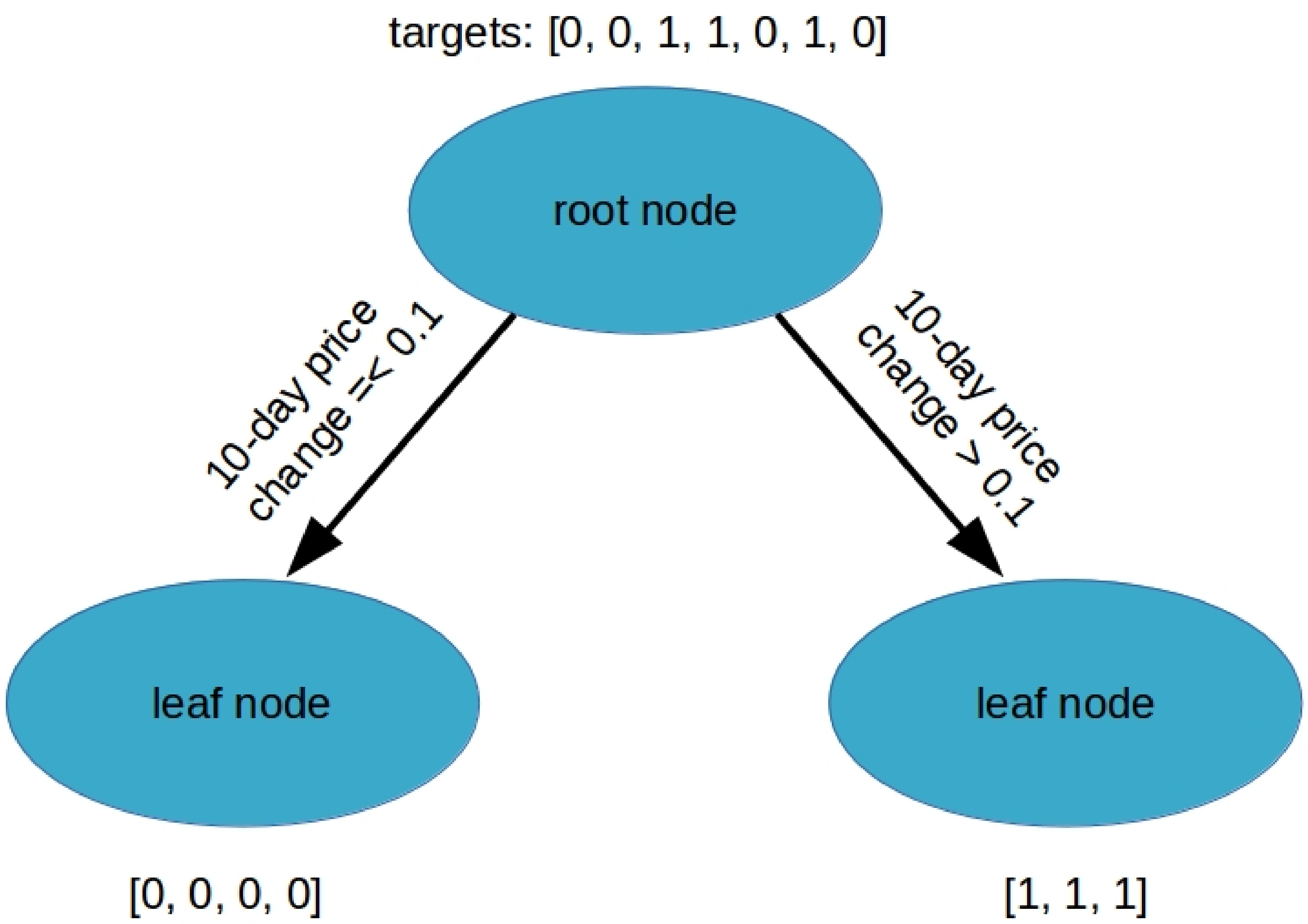
Decision trees



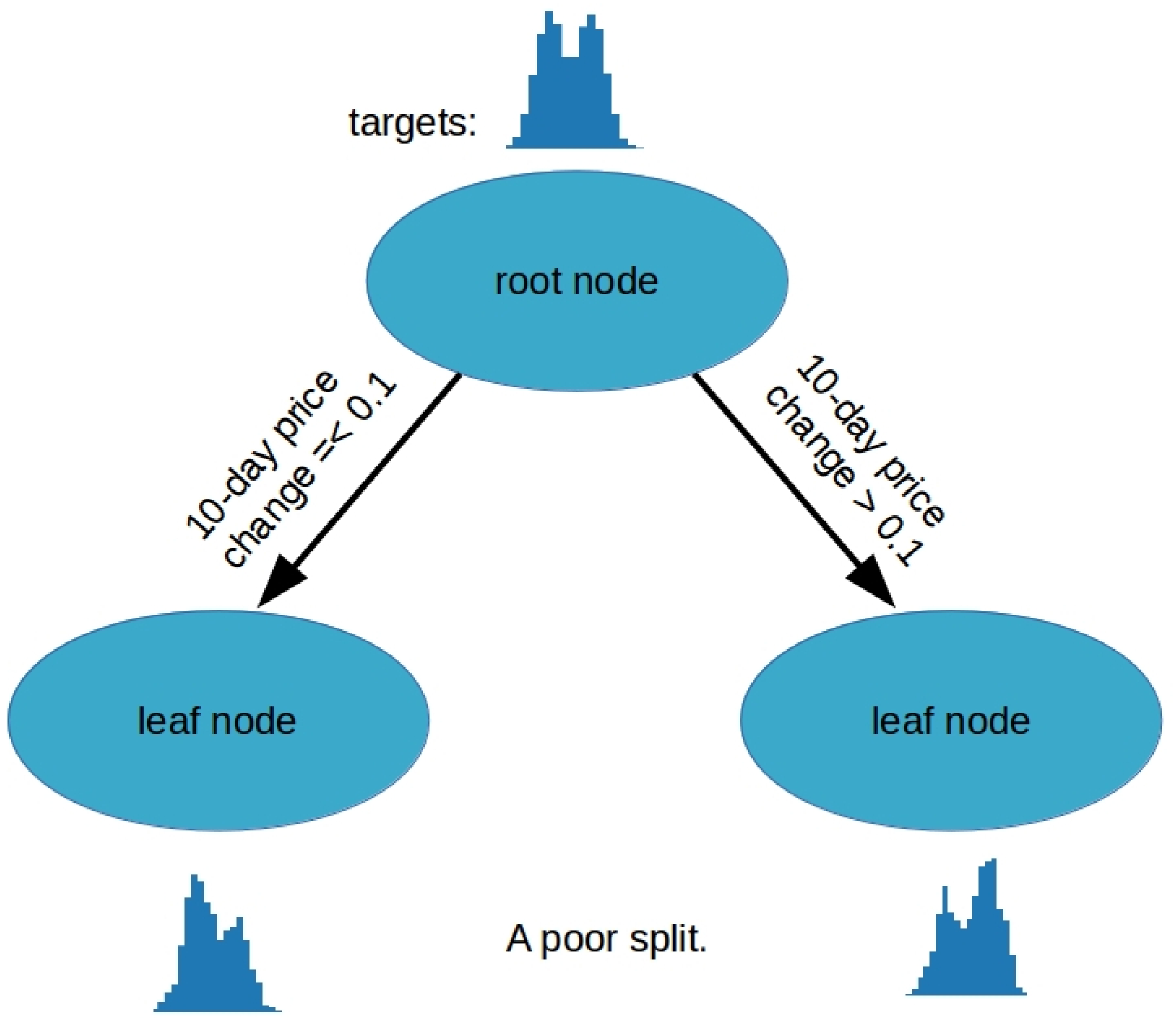
Decision tree splits



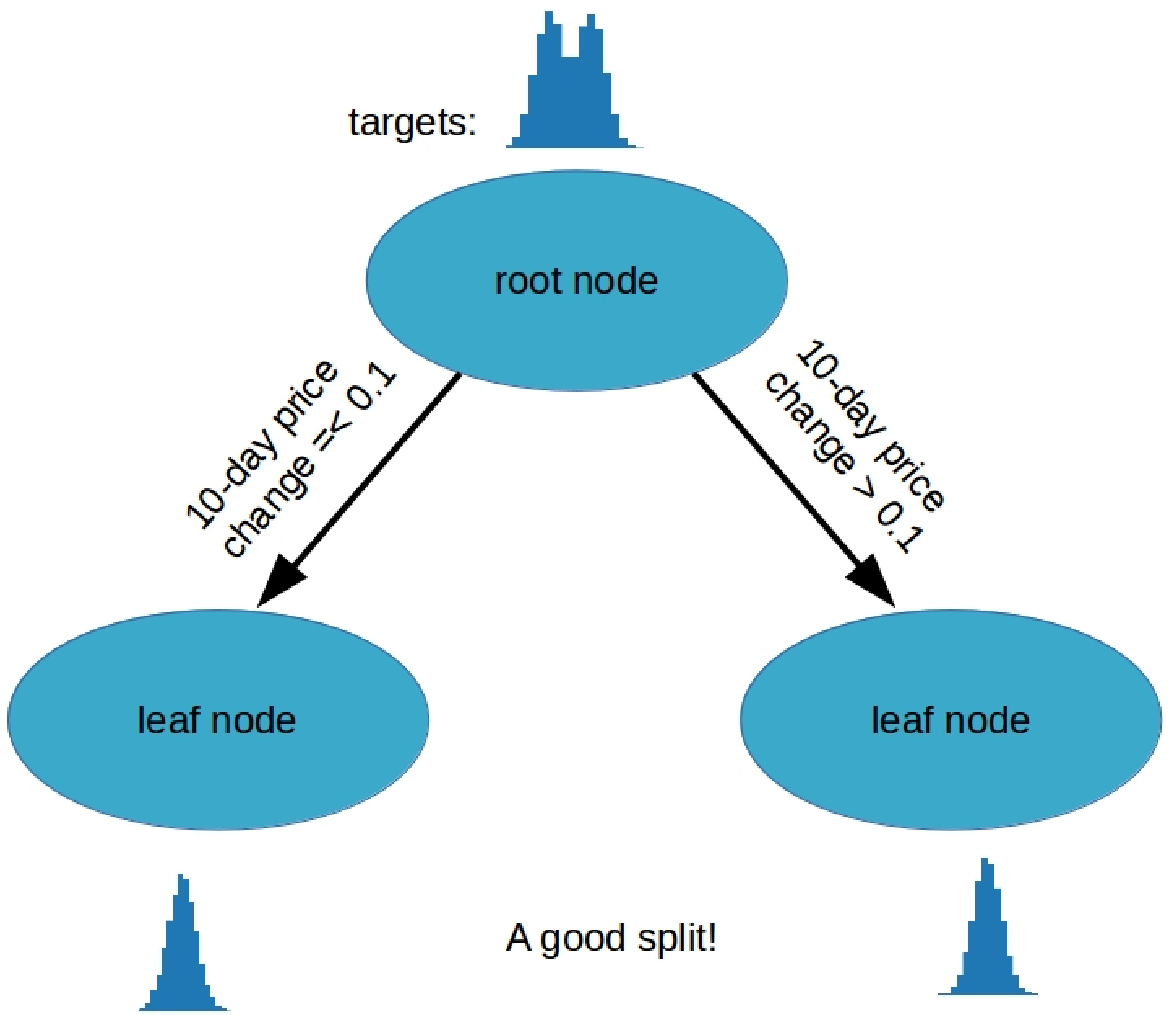
Decision tree splits



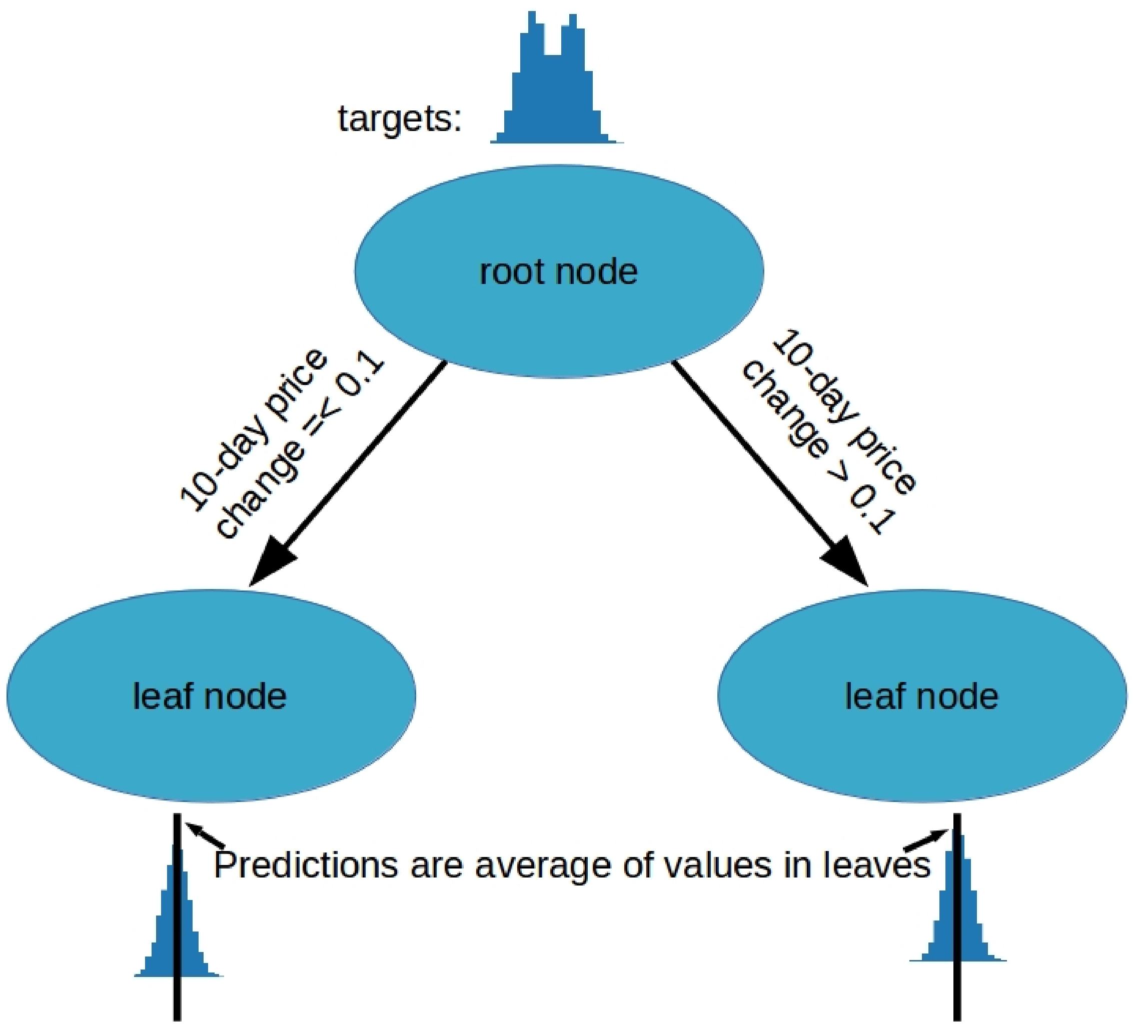
Bad tree


targets:
root node
10-day price change =< 0.1
10-day price change > 0.1
leaf node
leaf node
A poor split.

Good tree


targets:
root node
10-day price change =< 0.1
10-day price change > 0.1
leaf node
leaf node
A good split!

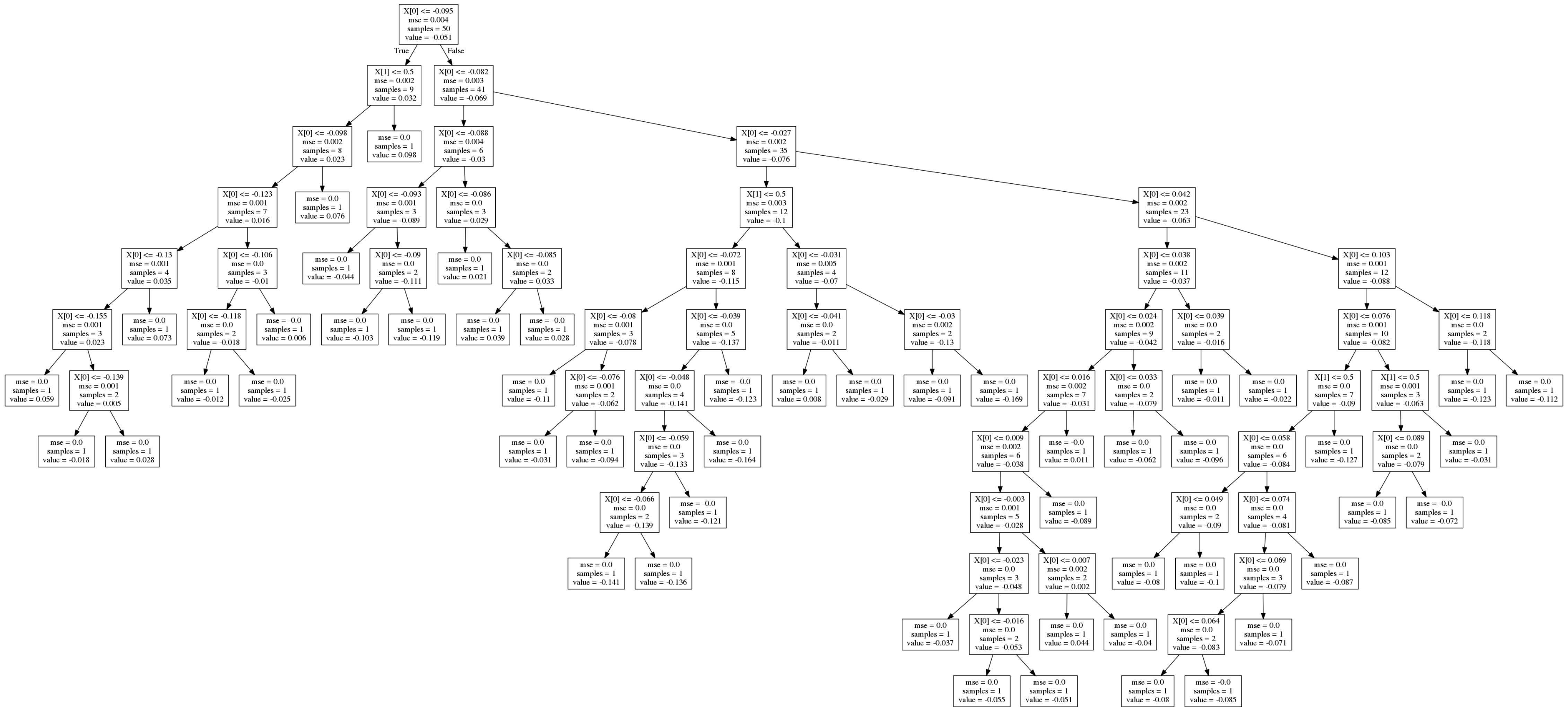
Decision tree regression



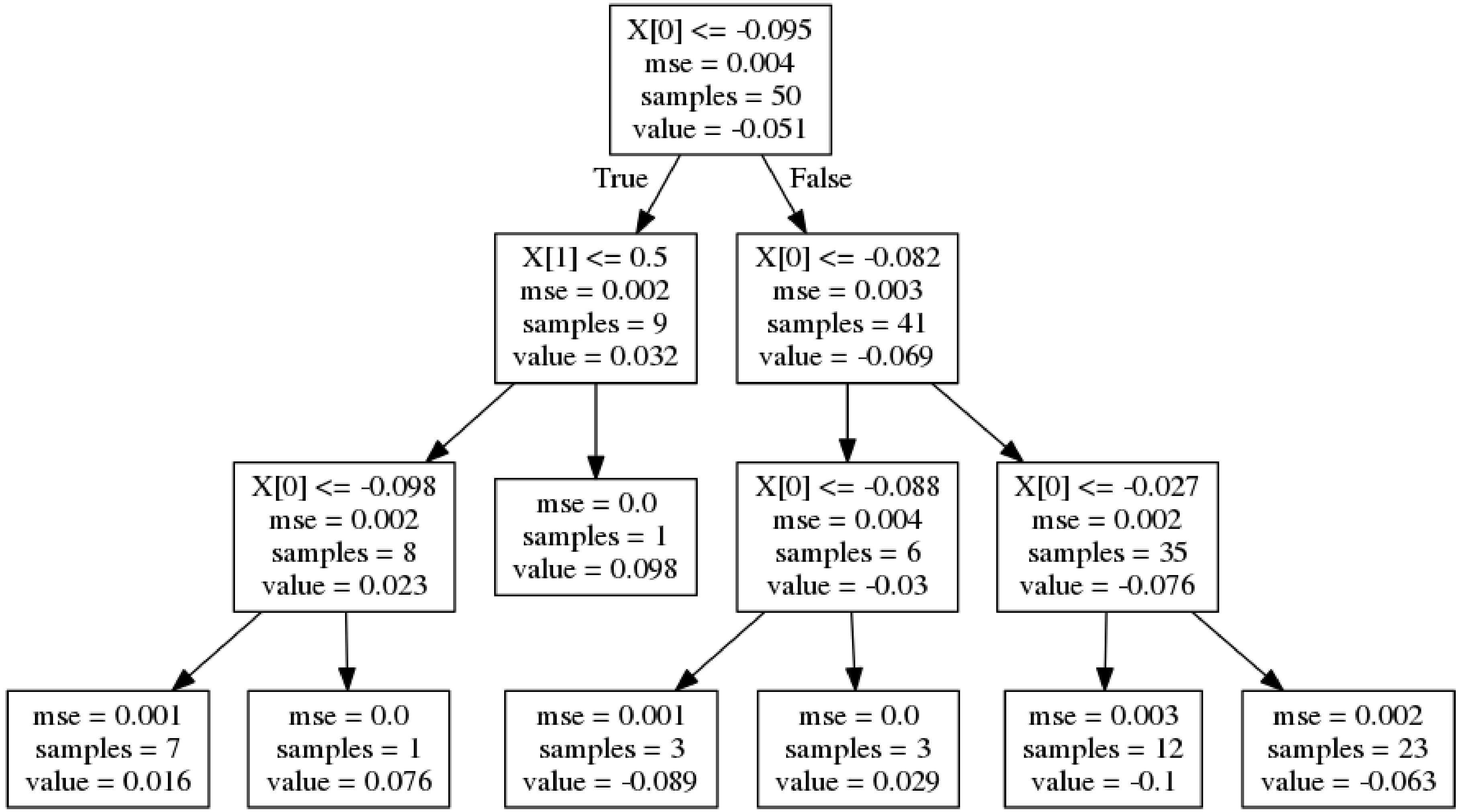
Regression trees

```
from sklearn.tree import DecisionTreeRegressor

decision_tree = DecisionTreeRegressor(max_depth=5)

decision_tree.fit(train_features, train_targets)
```

Decision tree hyperparameters



Max depth of 3

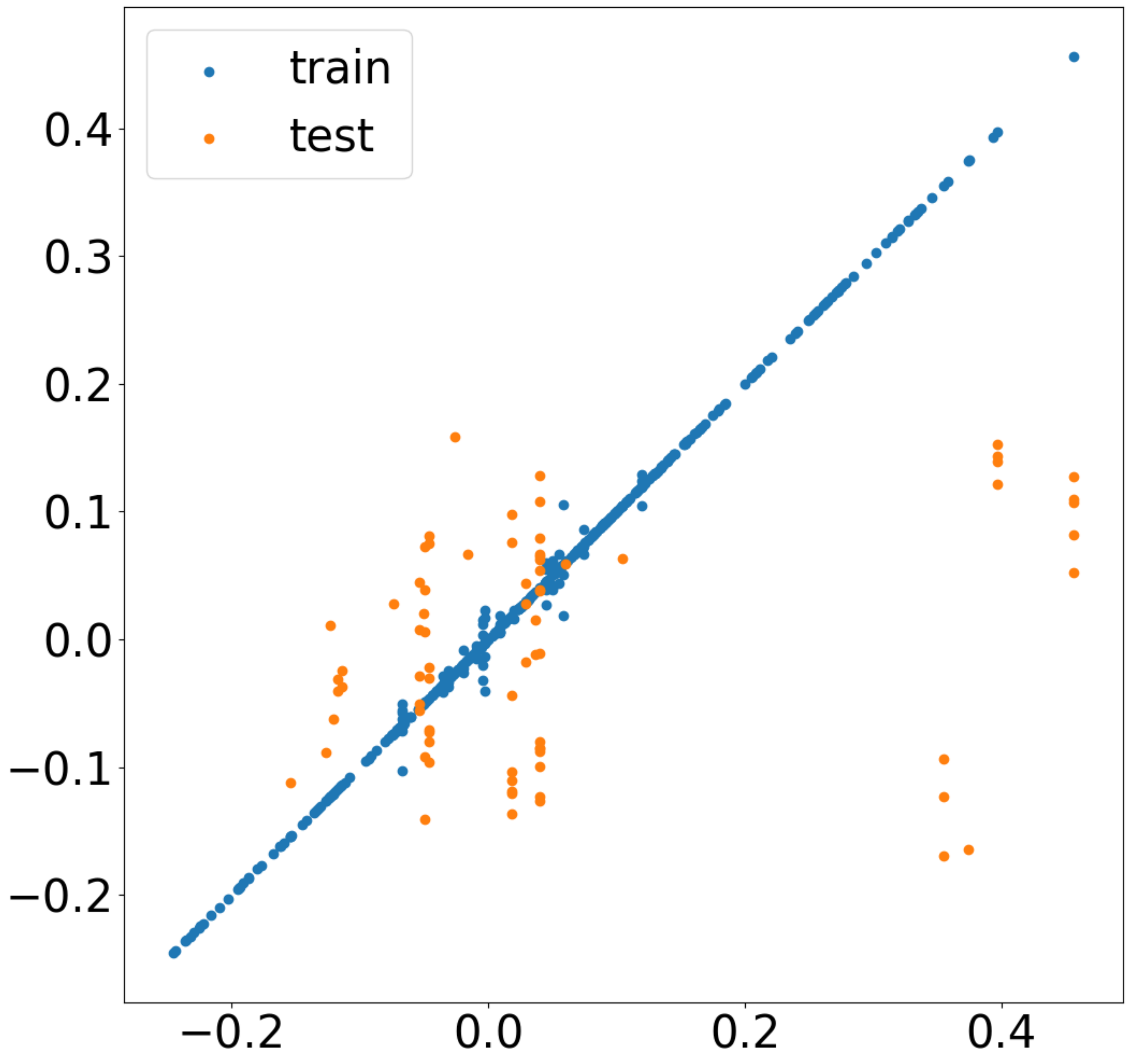


Evaluate model

```
print(decision_tree.score(train_features, train_targets))
print(decision_tree.score(test_features, test_targets))
```

```
0.6662215501032416
-0.08917300191734268
```

```
train_predictions = decision_tree.predict(train_features)
test_predictions = decision_tree.predict(test_features)
plt.scatter(train_predictions, train_targets, label='train')
plt.scatter(test_predictions, test_targets, label='test')
plt.legend()
plt.show()
```


train
test
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.2
0.0
0.2
0.4

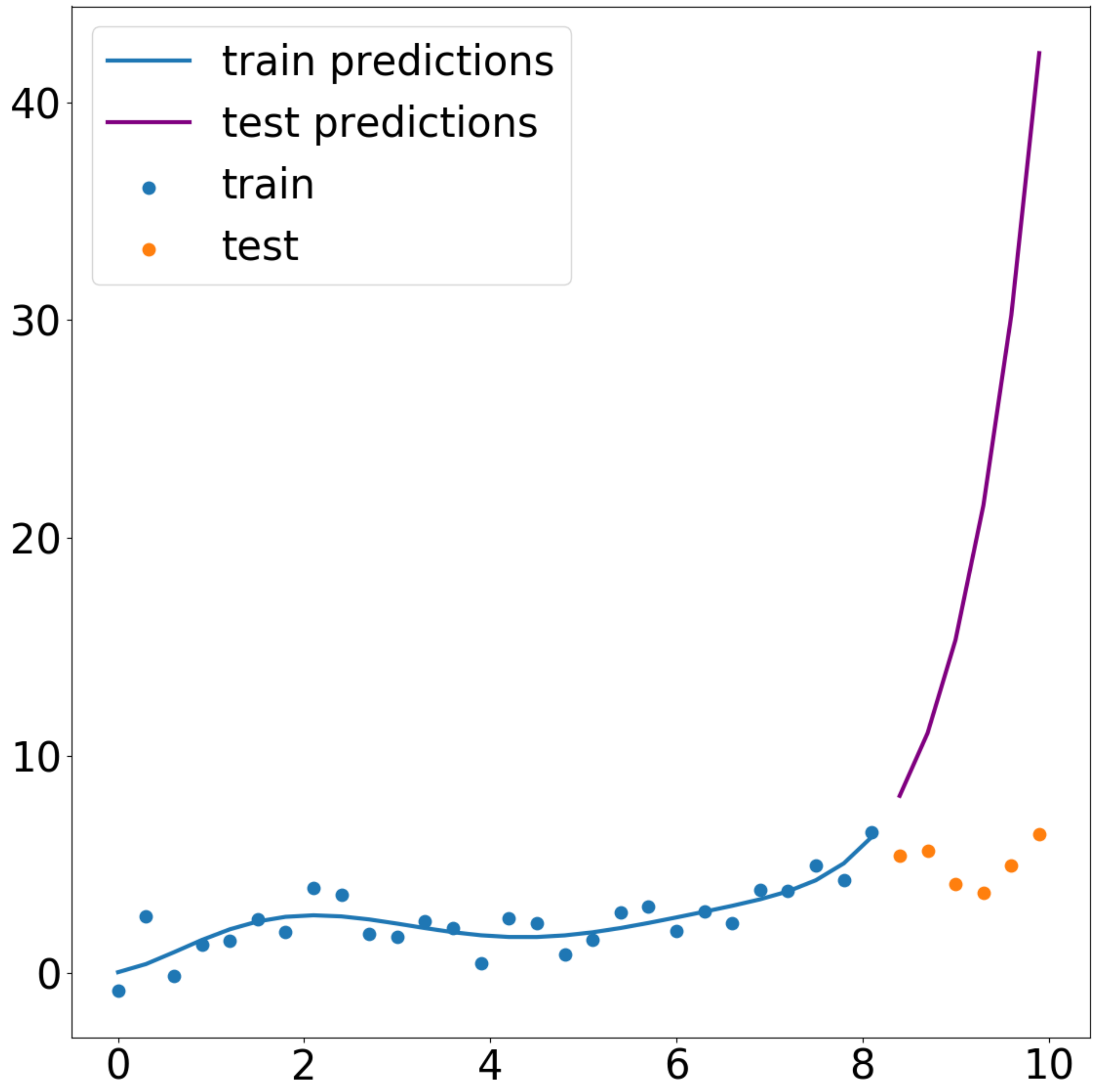
MACHINE LEARNING FOR FINANCE IN PYTHON

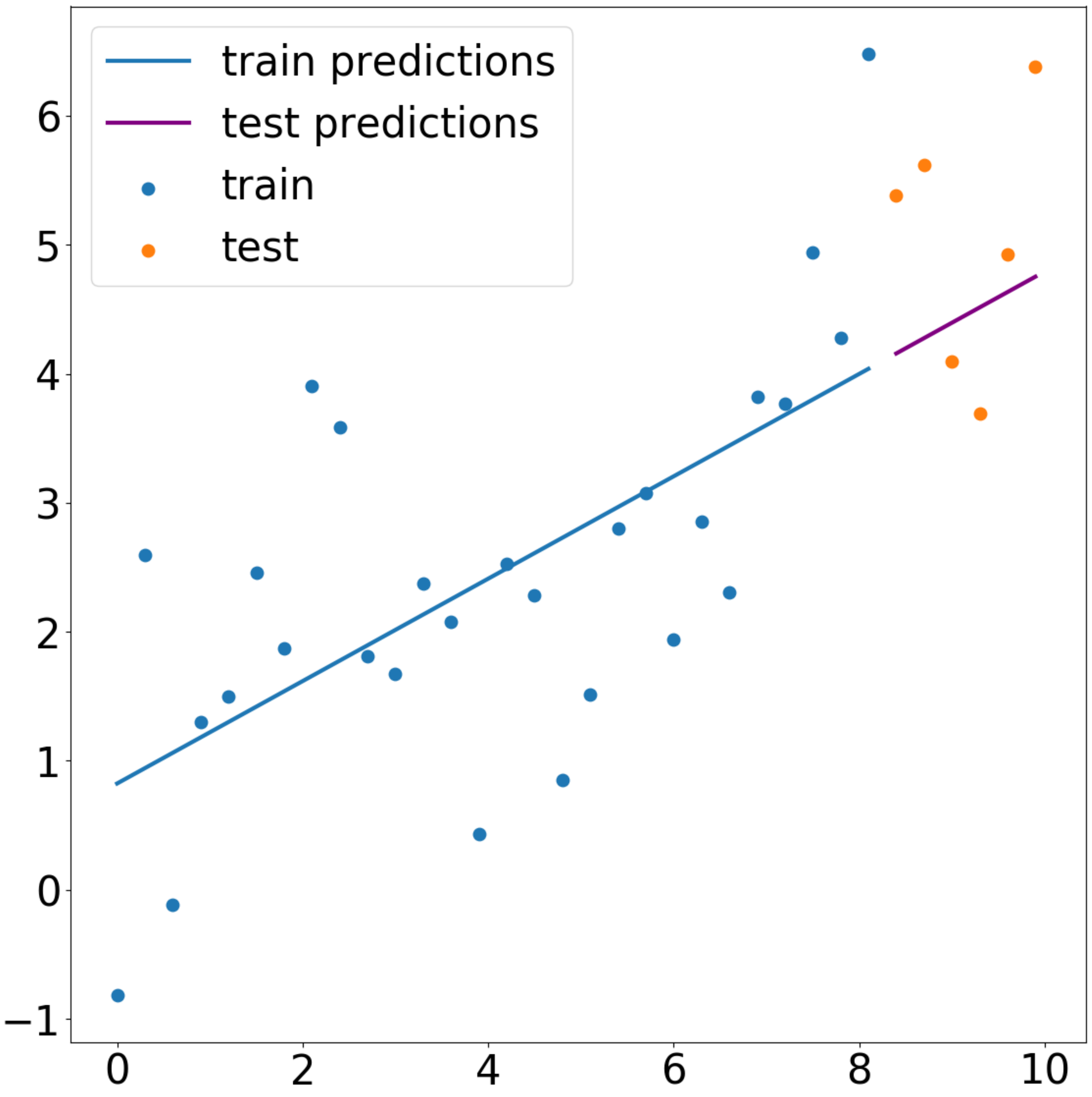
Grow some trees!

MACHINE LEARNING FOR FINANCE IN PYTHON

Random forests

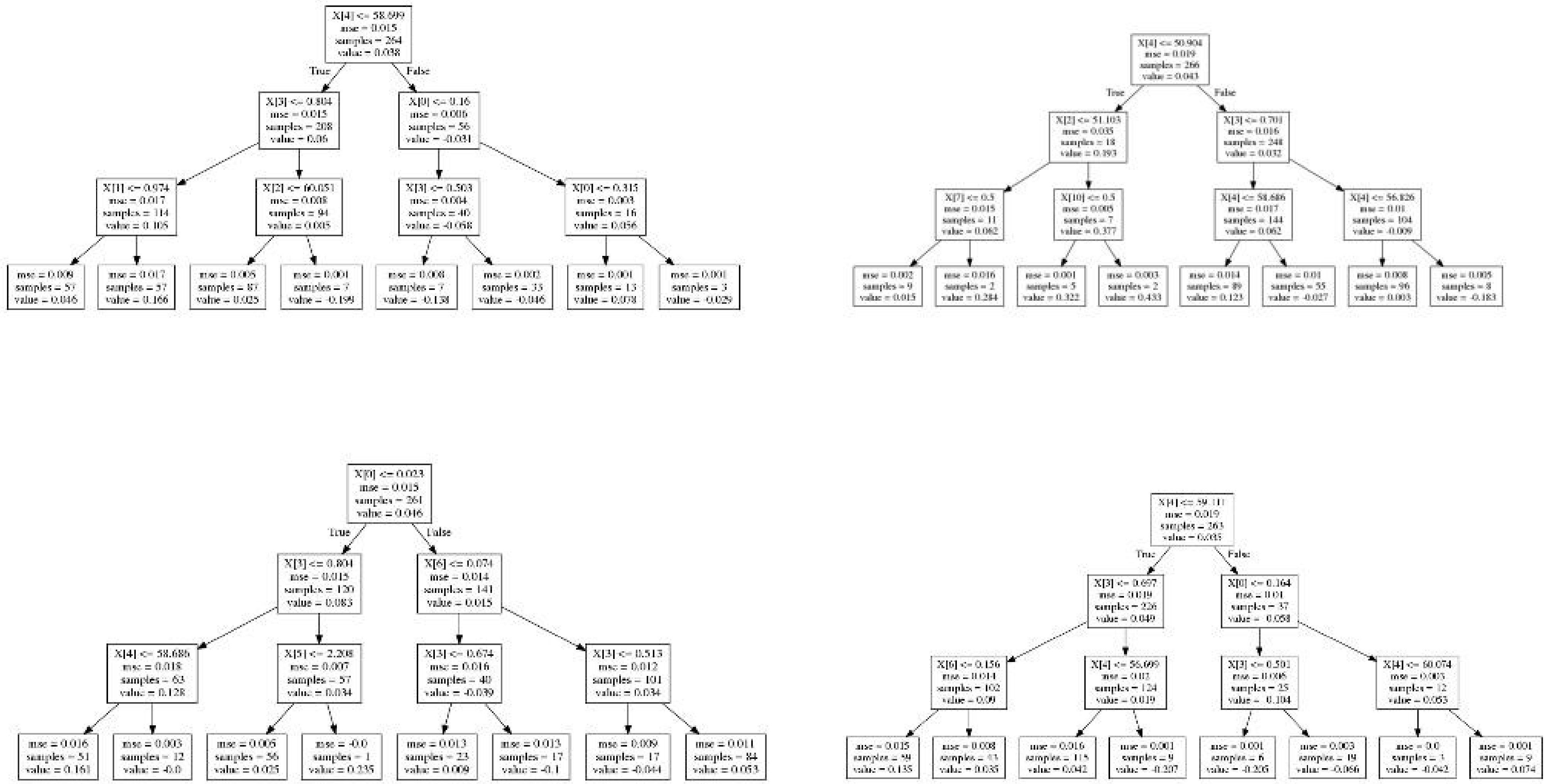
Nathan George
Data Science Professor


train predictions
test predictions
train
test
40
30
20
10
0
0
2
4
6
8
10

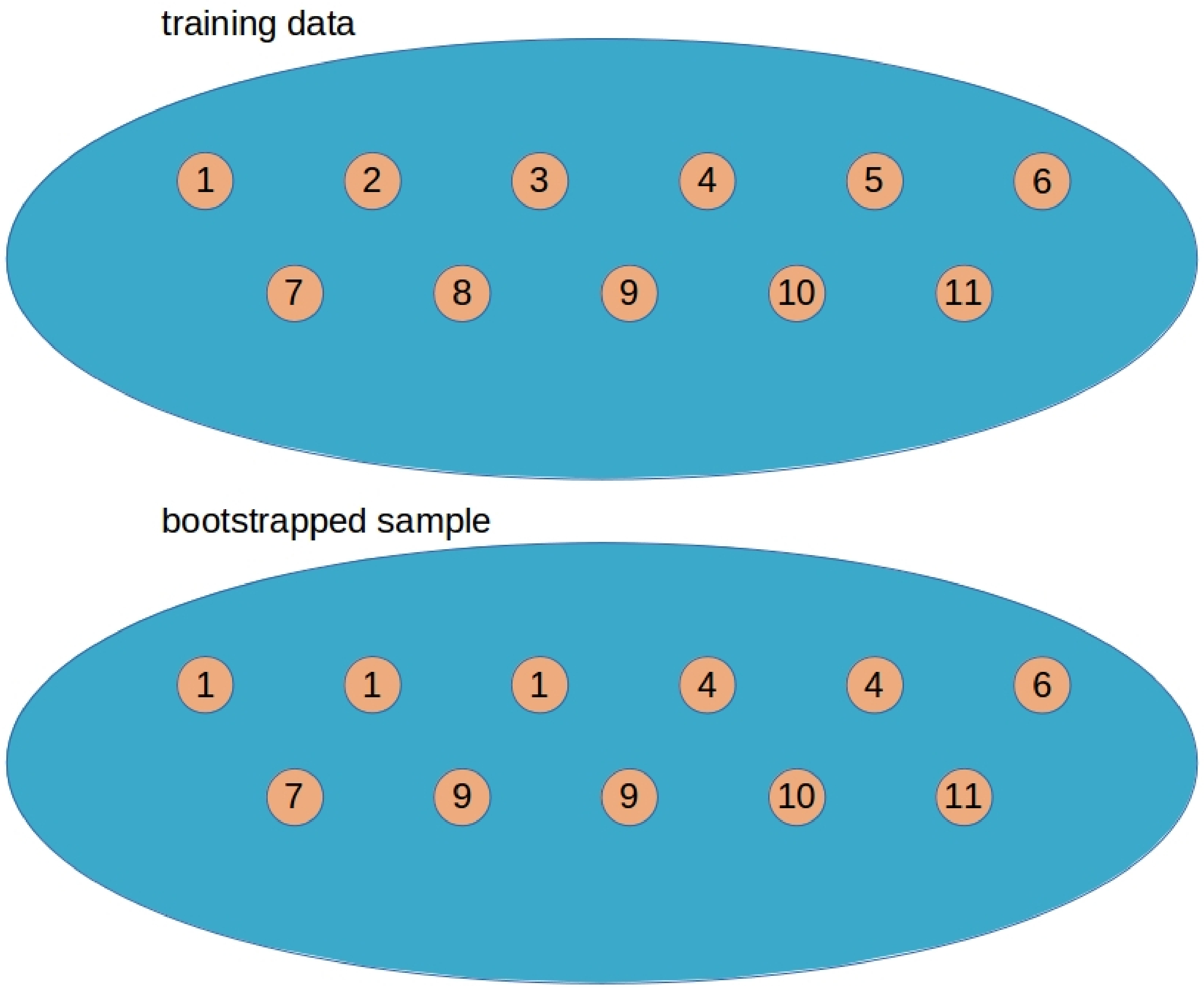


train predictions
test predictions
train
test
6
5
4
3
2
1
0
−1
0
2
4
6
8
10

Random forests



Bootstrap aggregating (bagging)



Feature sampling

Random Forests

- A collection (ensemble) of decision trees
- Bootstrap aggregating (bagging)
- Sample of features at each split

sklearn implementation

```
from sklearn.ensemble import RandomForestRegressor

random_forest = RandomForestRegressor()
random_forest.fit(train_features, train_targets)
print(random_forest.score(train_features, train_targets))
```

Hyperparameters

```
random_forest = RandomForestRegressor(n_estimators=200,
                                      max_depth=5,
                                      max_features=4,
                                      random_state=42)
```

ParameterGrid

```
from sklearn.model_selection import ParameterGrid

grid = {'n_estimators': [200], 'max_depth':[3, 5], 'max_features': [4, 8]}


from pprint import pprint

pprint(list(ParameterGrid(grid)))

[{'max_depth': 3, 'max_features': 4, 'n_estimators': 200},
 {'max_depth': 3, 'max_features': 8, 'n_estimators': 200},
 {'max_depth': 5, 'max_features': 4, 'n_estimators': 200},
 {'max_depth': 5, 'max_features': 8, 'n_estimators': 200}]
```

ParamaterGrid

```
test_scores = []

# loop through the parameter grid, set hyperparameters, save the scores
for g in ParameterGrid(grid):
    rfr.set_params(**g)  # ** is "unpacking" the dictionary
    rfr.fit(train_features, train_targets)
    test_scores.append(rfr.score(test_features, test_targets))

# find best hyperparameters from the test score and print
best_idx = np.argmax(test_scores)
print(test_scores[best_idx])
print(ParameterGrid(grid)[best_idx])
```

```
0.05594252725411142
{'max_depth': 5, 'max_features': 8, 'n_estimators': 200}
```

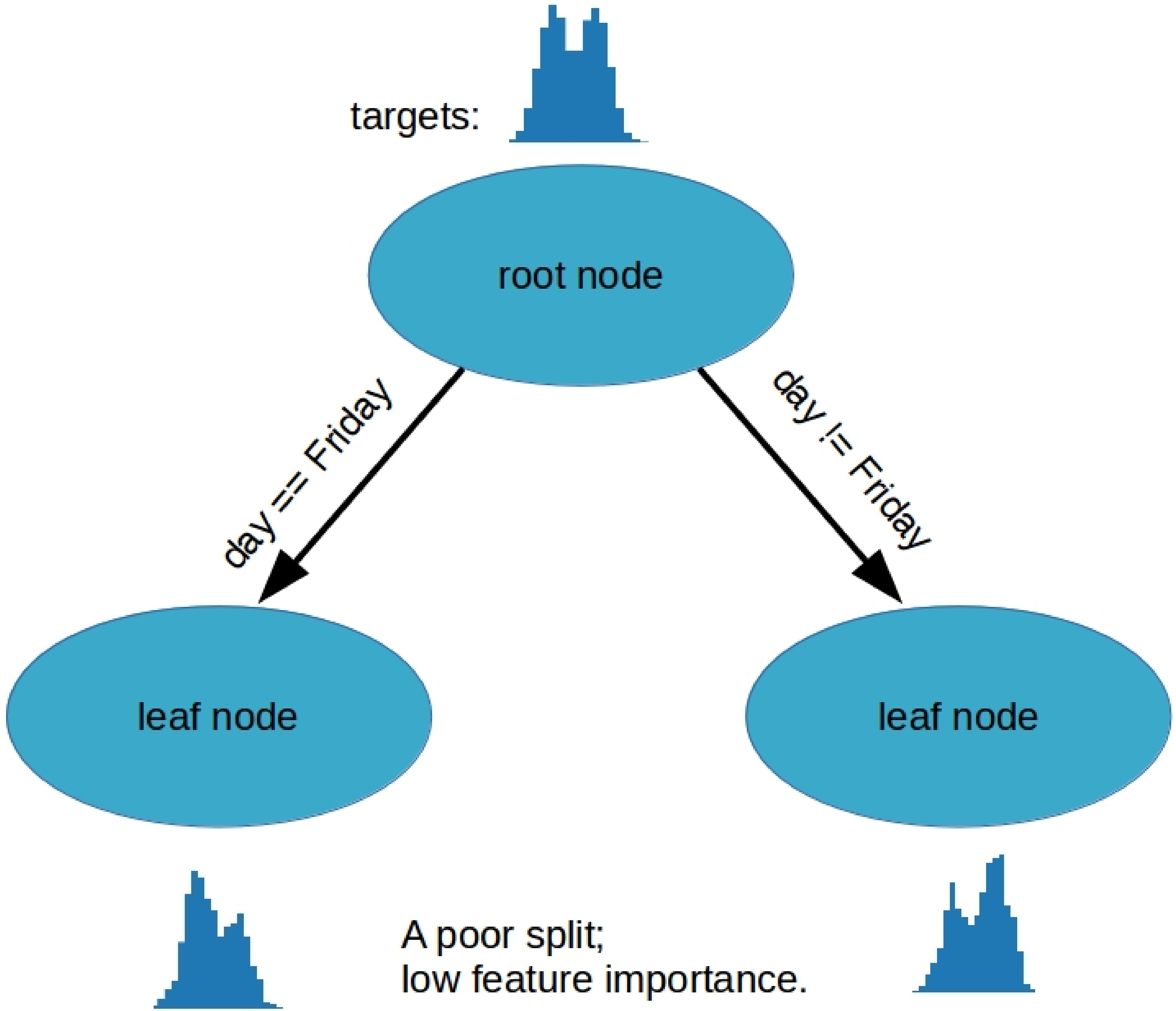
MACHINE LEARNING FOR FINANCE IN PYTHON

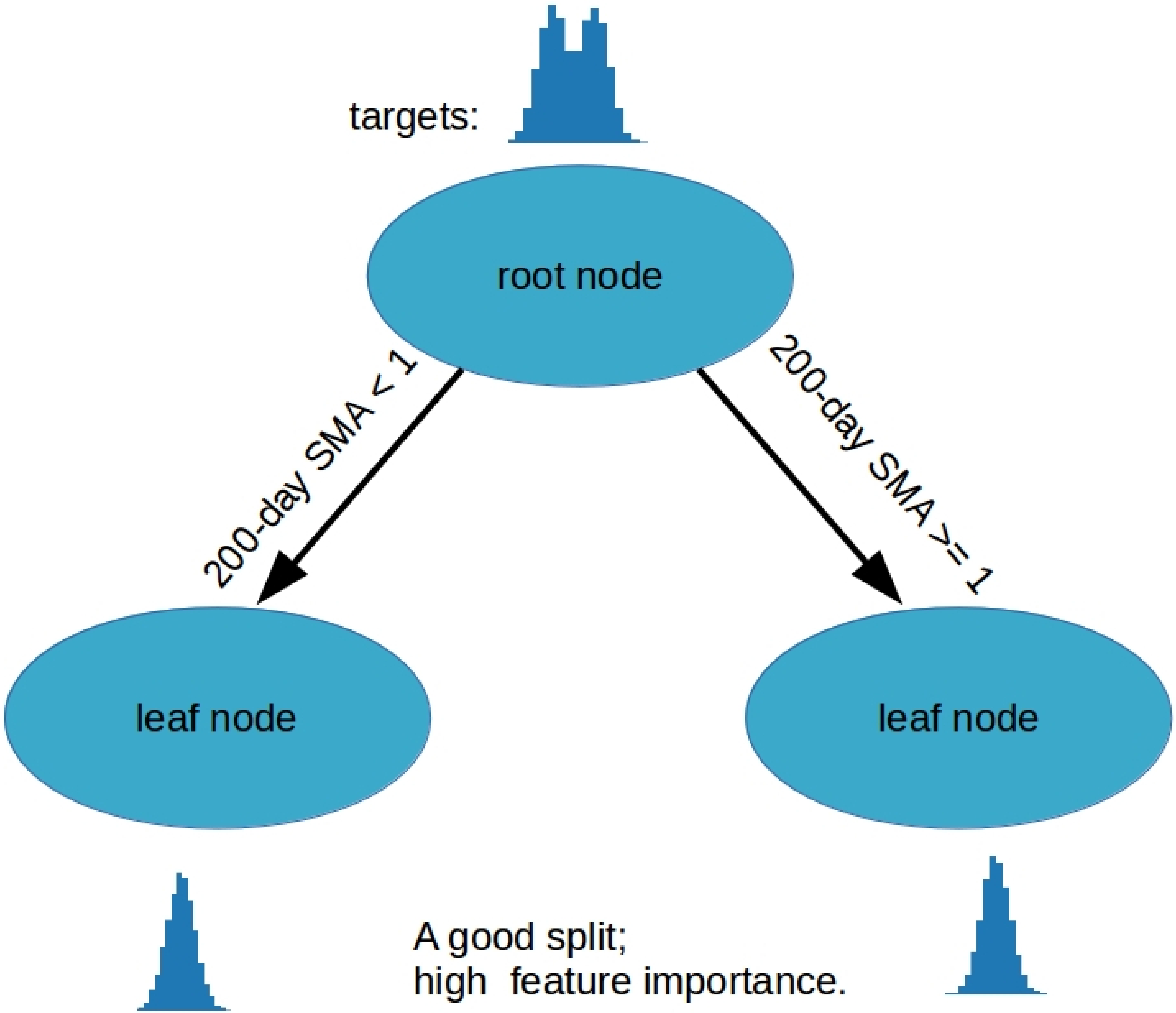
Plant some random forests!

MACHINE LEARNING FOR FINANCE IN PYTHON

Feature importances and gradient boosting

Nathan George
Data Science Professor


targets:
root node
day == Friday
day != Friday
leaf node
leaf node
A poor split;
low feature importance.


targets:
root node
200-day SMA < 1
200-day SMA >= 1
leaf node
leaf node
A good split;
high feature importance.

Extracting feature importances

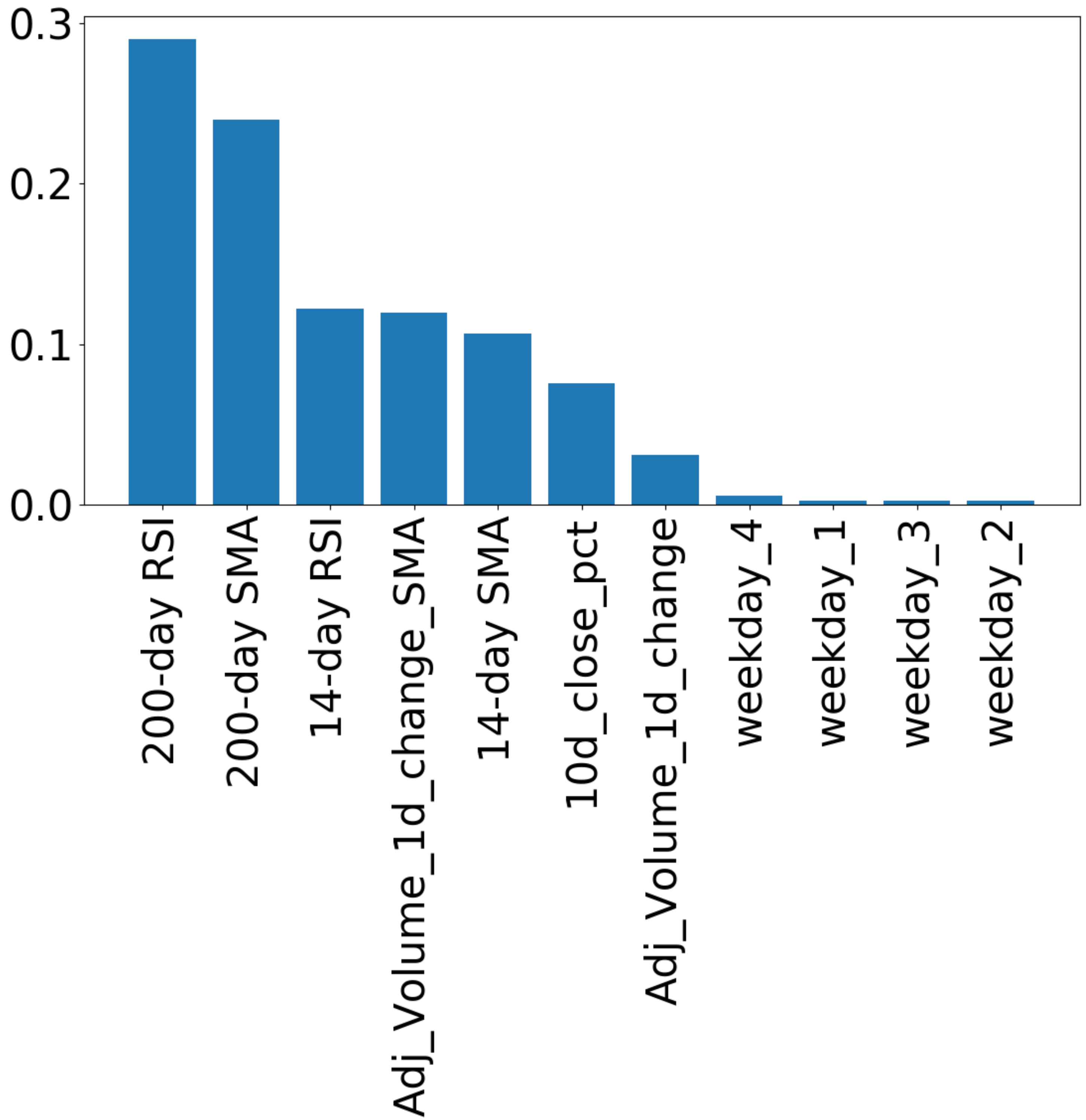
```
from sklearn.ensemble import RandomForestRegressor

random_forest = RandomForestRegressor()
random_forest.fit(train_features, train_targets)

feature_importances = random_forest.feature_importances_

print(feature_importances)
```

```
[0.07586547 0.10697602 0.12215955 0.23969227 0.29010304 0.0314028
 0.11977058 0.00276721 0.00246329 0.0026431  0.00615667]
```

Sorting and plotting

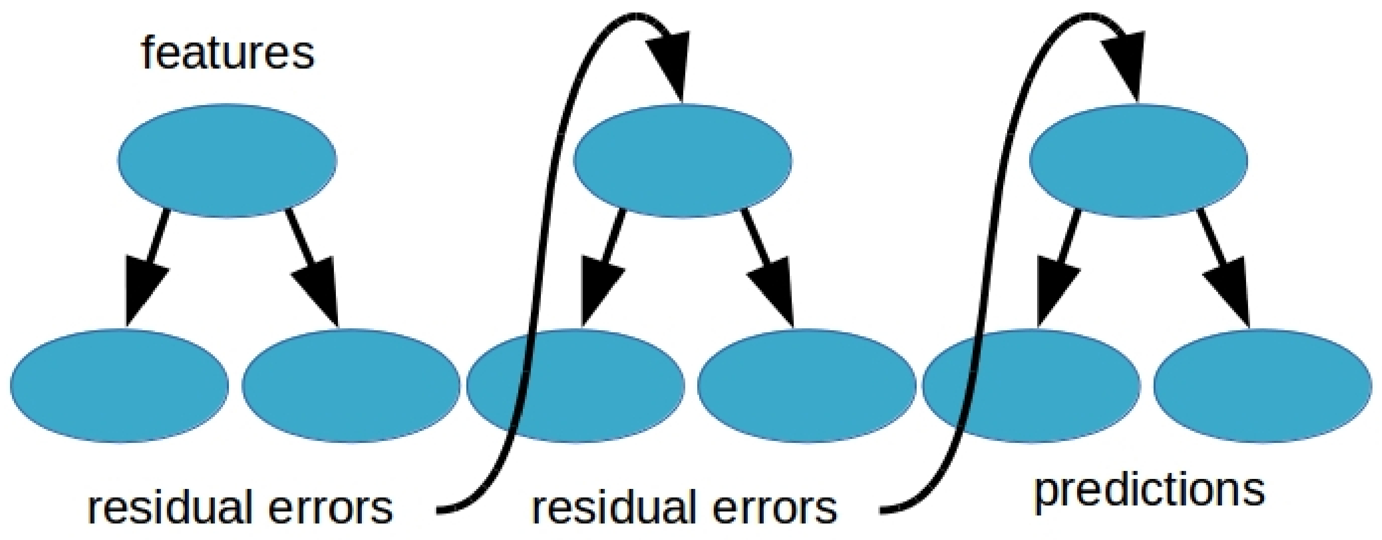
```
# feature importances from random forest model
importances = random_forest.feature_importances_

# index of greatest to least feature importances
sorted_index = np.argsort(importances)[::-1]
```

```
x = range(len(importances))
# create tick labels
labels = np.array(feature_names)[sorted_index]

plt.bar(x, importances[sorted_index], tick_label=labels)

# rotate tick labels to vertical
plt.xticks(rotation=90)
plt.show()
```


0.3
0.2
0.1
0.0
200-day RSI
200-day SMA
14-day RSI
Adj_Volume_1d_change_SMA
14-day SMA
10d_close_pct
Adj_Volume_1d_change
weekday_4
weekday_1
weekday_3
weekday_2

Linear models vs gradient boosting

http://blog.kaggle.com/2017/01/23/a-kaggle-master-explains-gradient-boosting/


features
residual errors
residual errors
predictions

Boosted models

Available boosted models:

- Gradient boosting
- Adaboost

Fitting a gradient boosting model

```
from sklearn.ensemble import GradientBoostingRegressor

gbr = GradientBoostingRegressor(max_features=4,
                                learning_rate=0.01,
                                n_estimators=200,
                                subsample=0.6,
                                random_state=42)

gbr.fit(train_features, train_targets)
```

MACHINE LEARNING FOR FINANCE IN PYTHON

Get boosted!