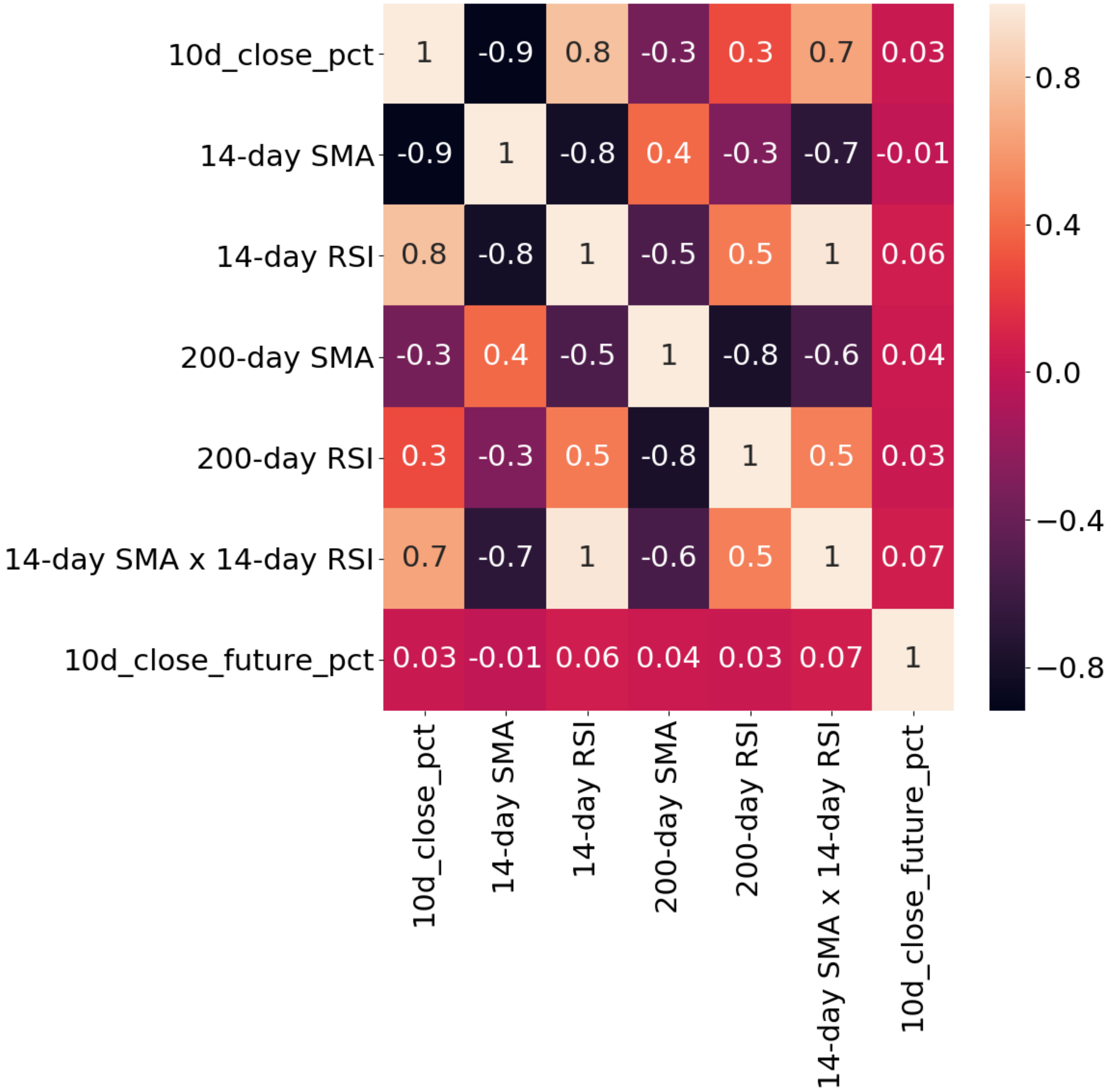
Engineering features

MACHINE LEARNING FOR FINANCE IN PYTHON

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']
```

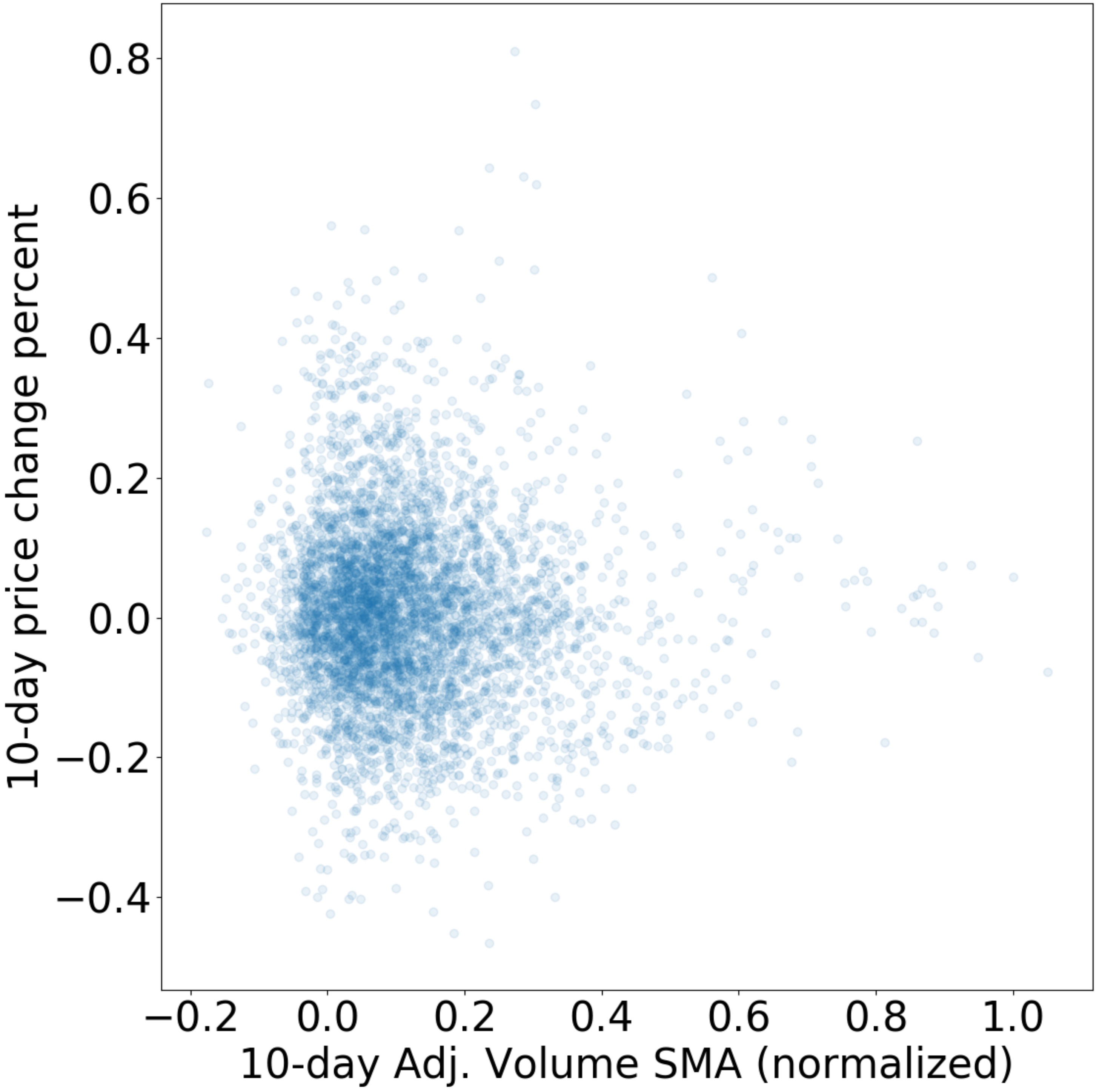
Some models that don't require manually creating interaction features:

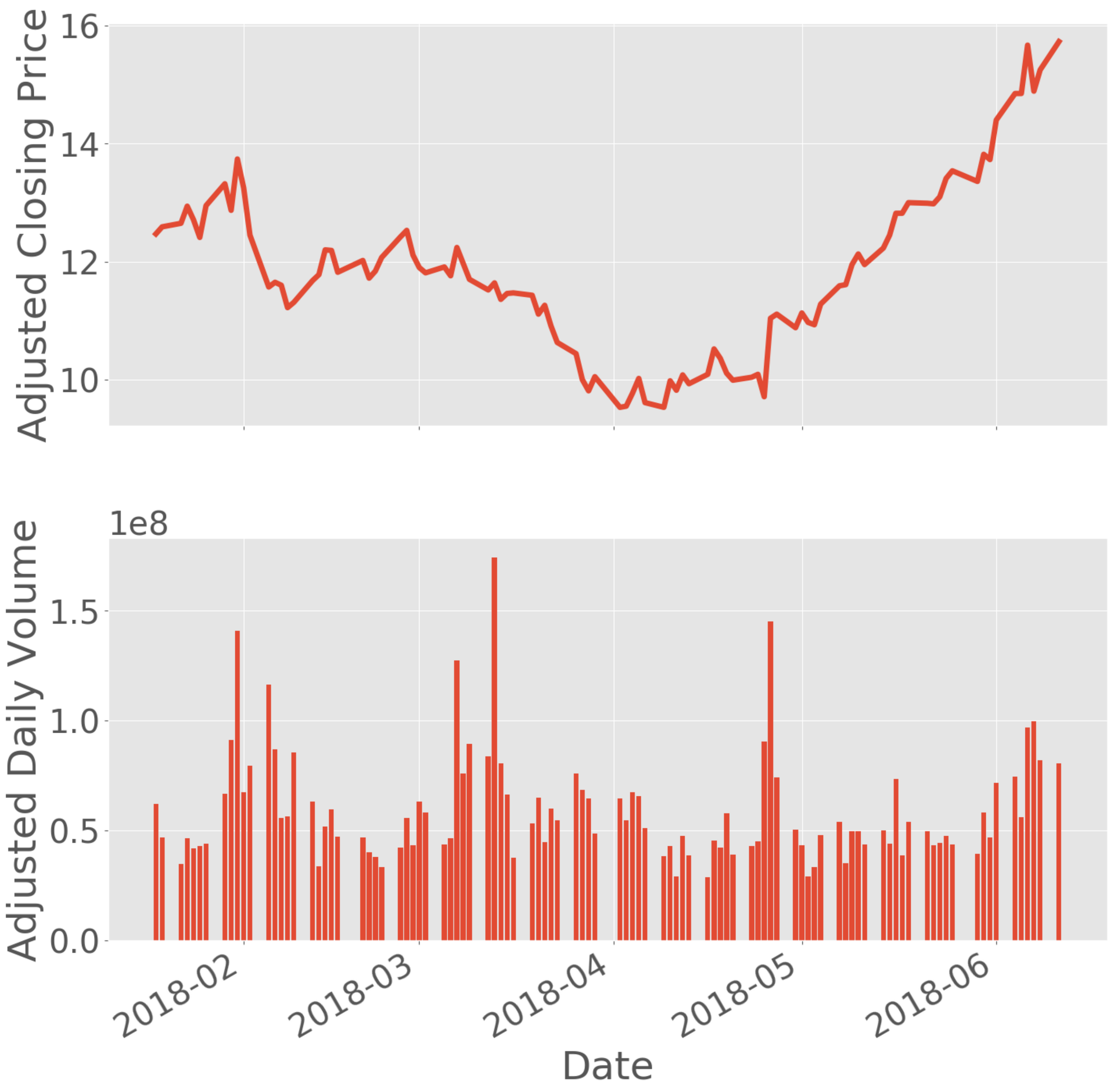
Decision-tree-based models

- Random forests
- Gradient boosting

Others

- neural networks

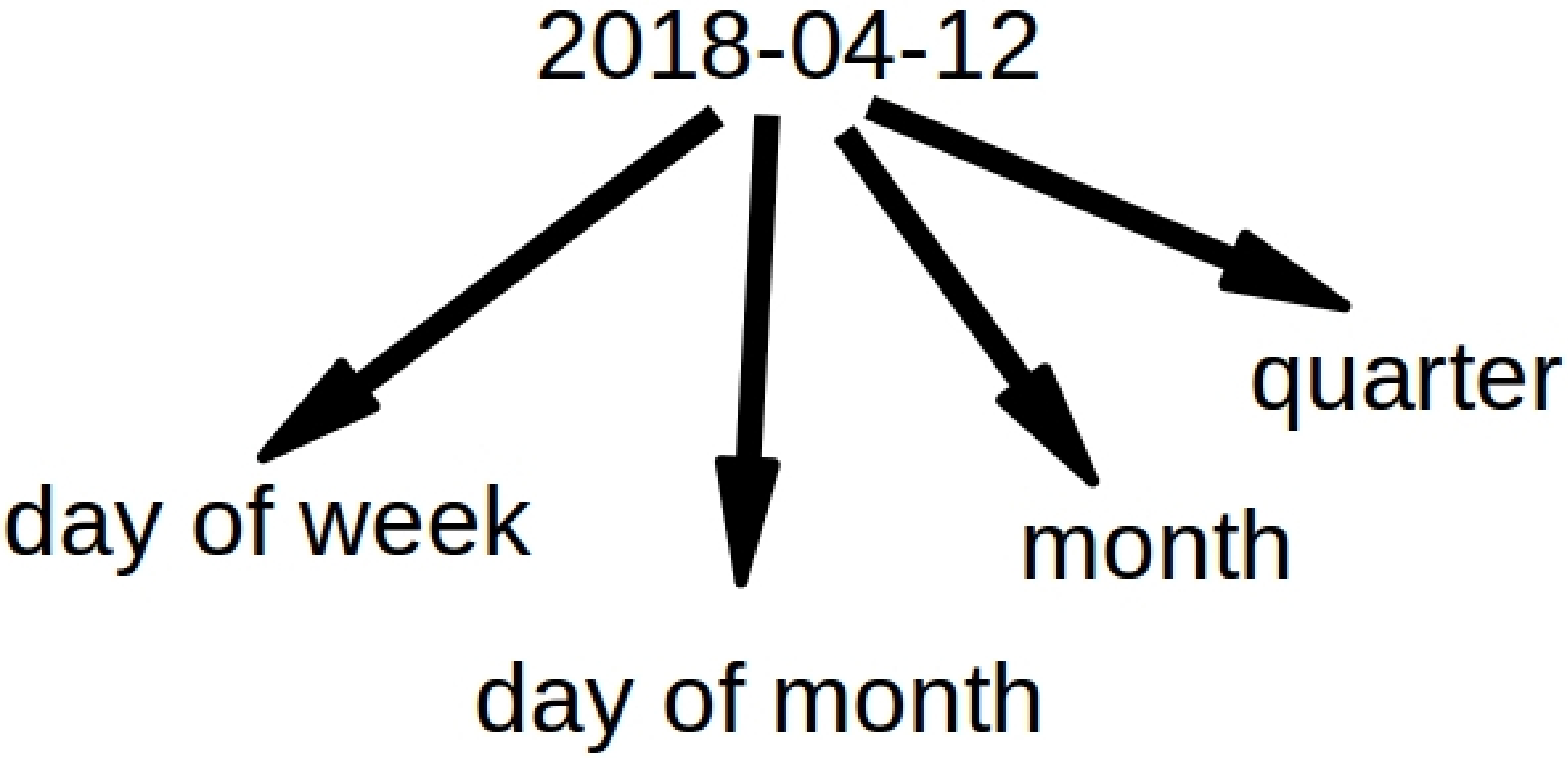

0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
10-day price change percent
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
10-day Adj. Volume SMA (normalized)


16
14
12
10
Adjusted Closing Price
1e8
1.5
1.0
0.5
0.0
Adjusted Daily Volume
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

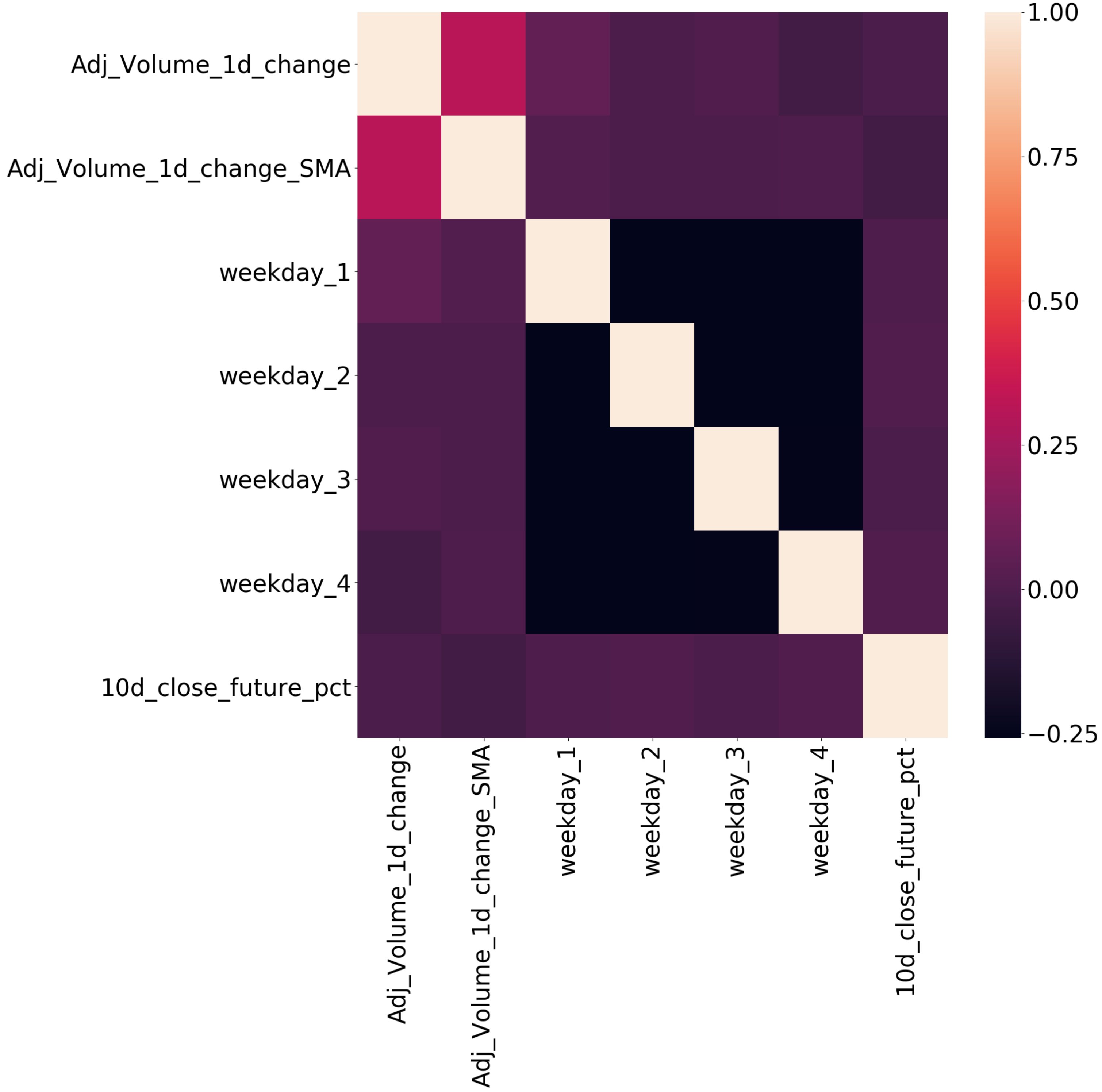
```
print(amd_df.index.dayofweek)
```

```
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

Engineer some features!

MACHINE LEARNING FOR FINANCE IN PYTHON

Decision Trees

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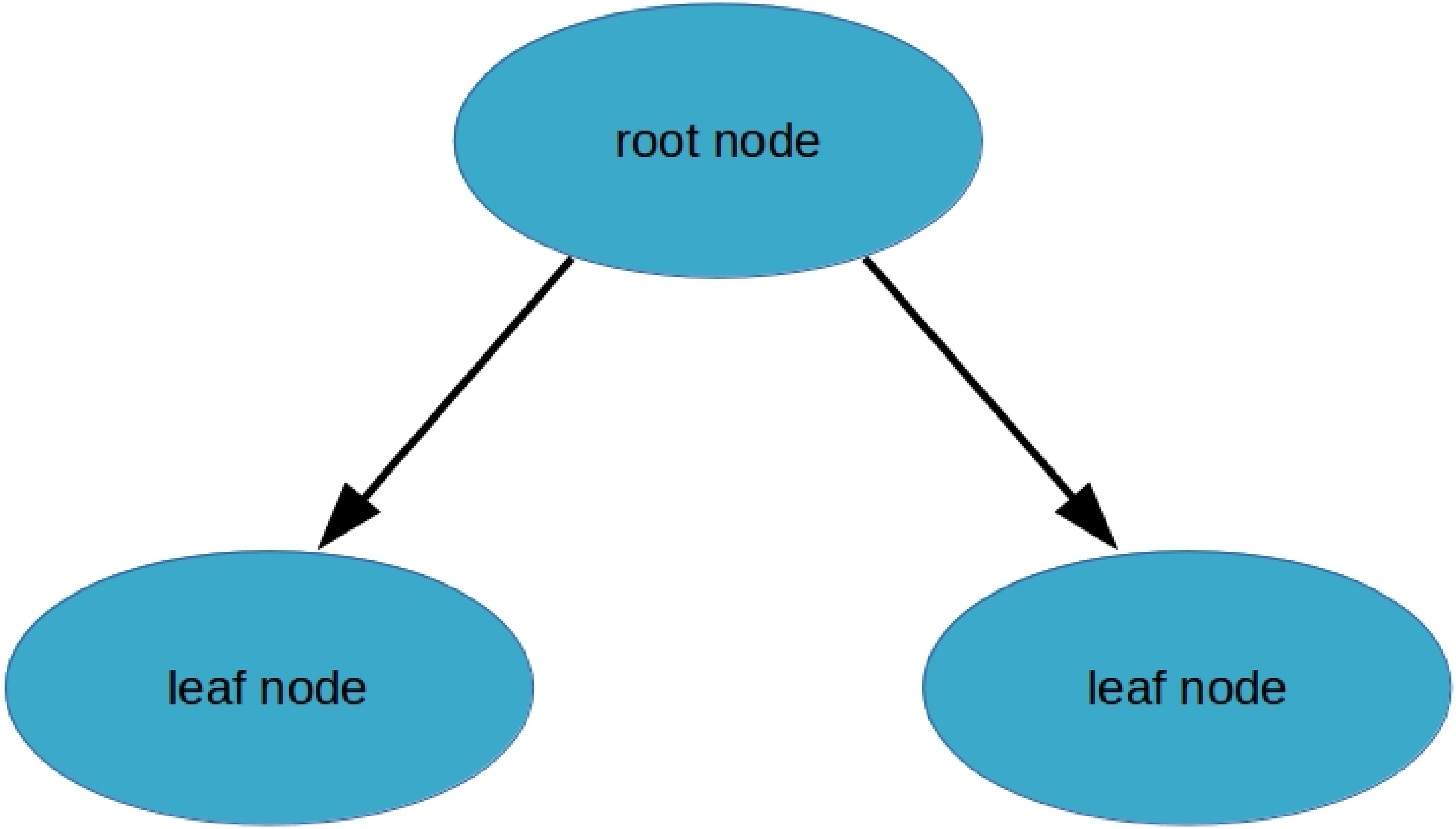
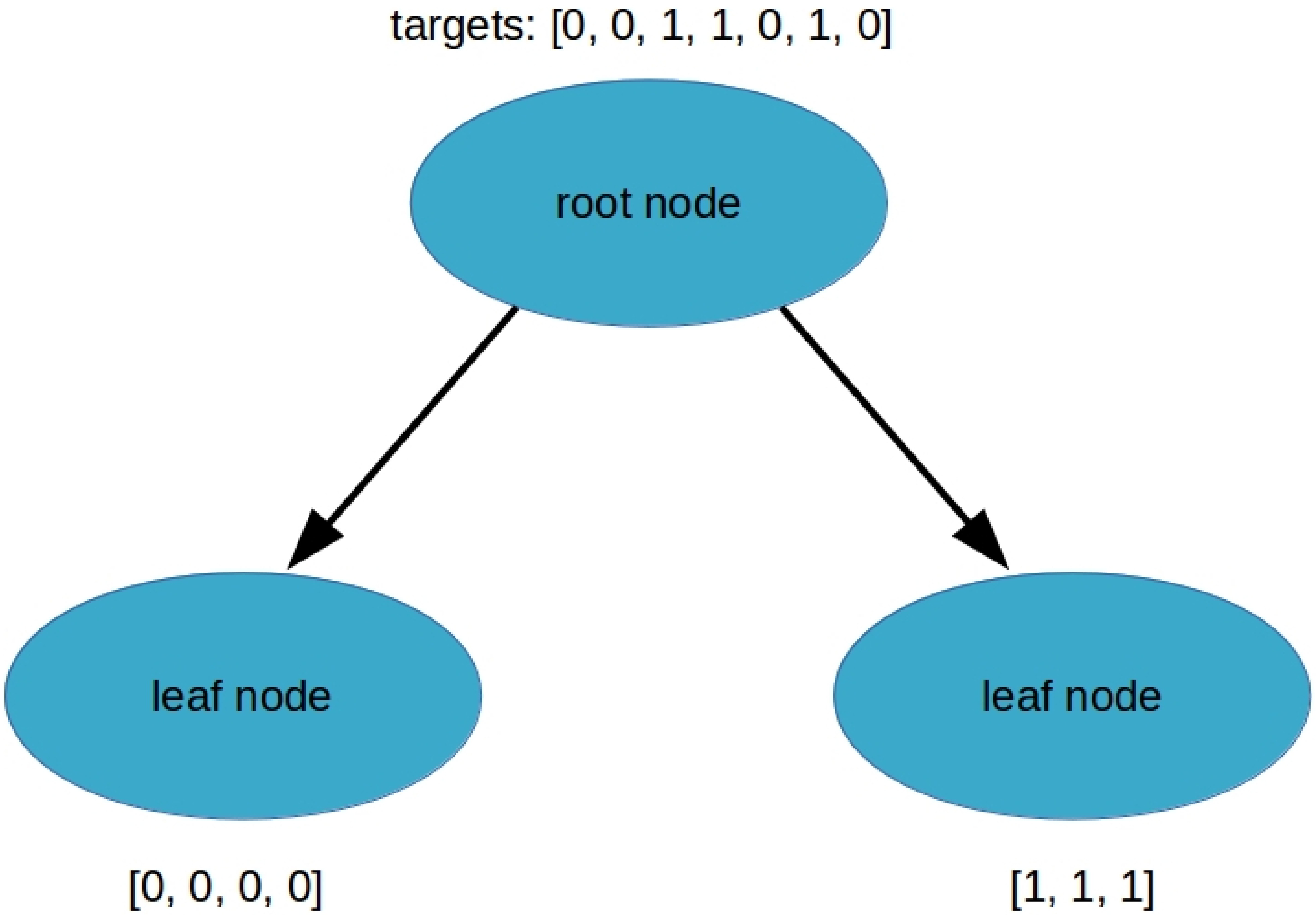
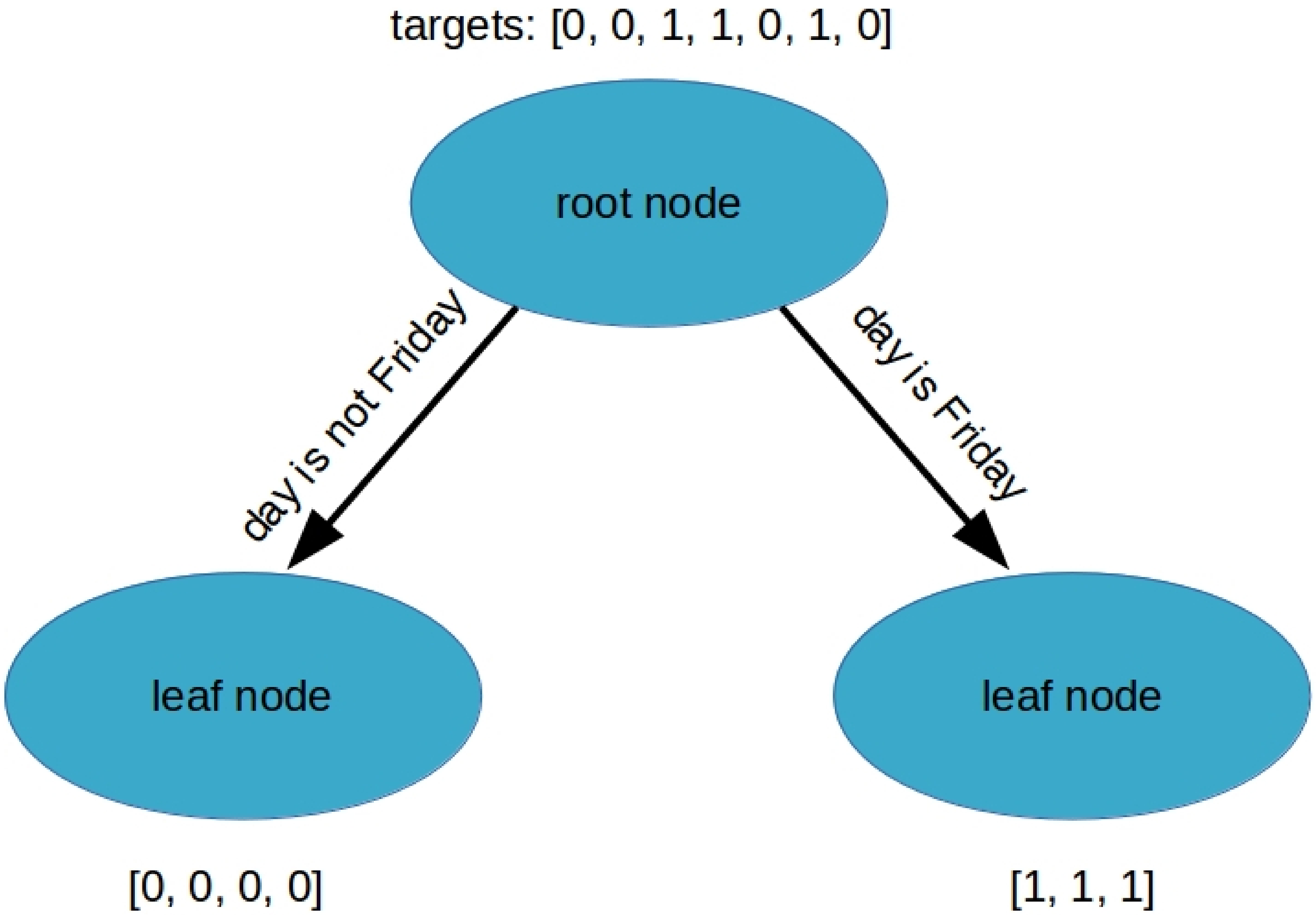
Decision trees



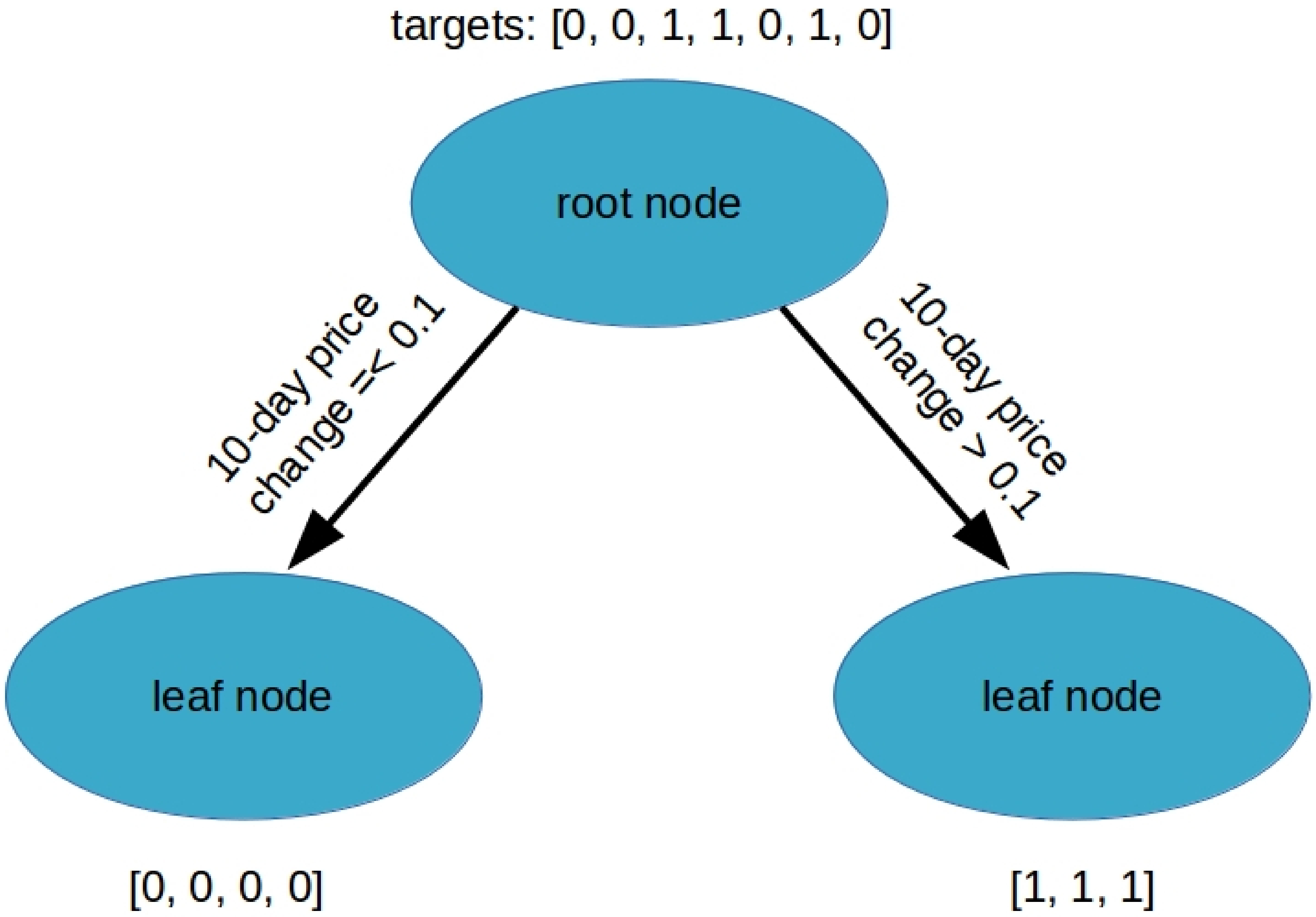
Decision trees



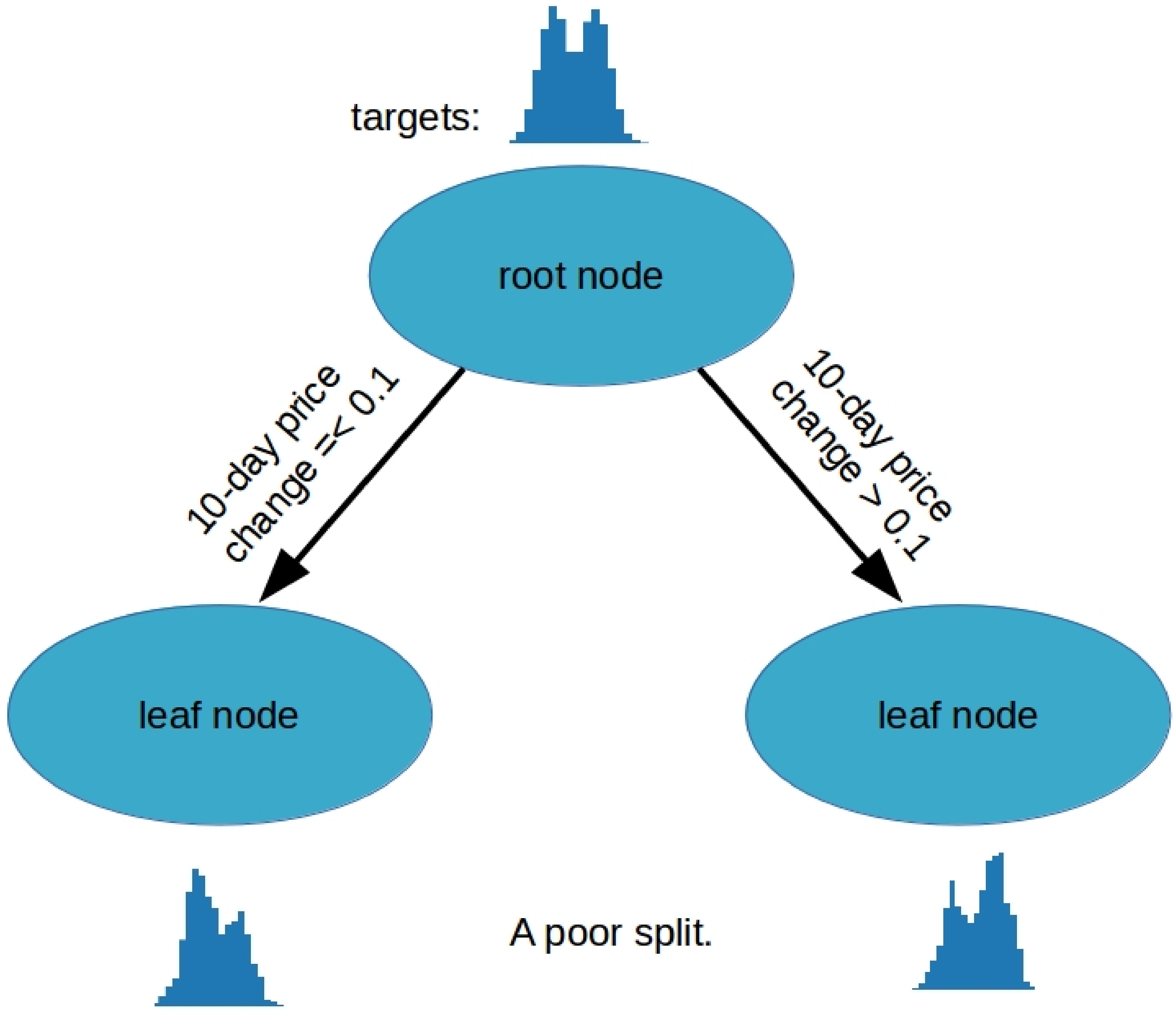
Decision tree splits



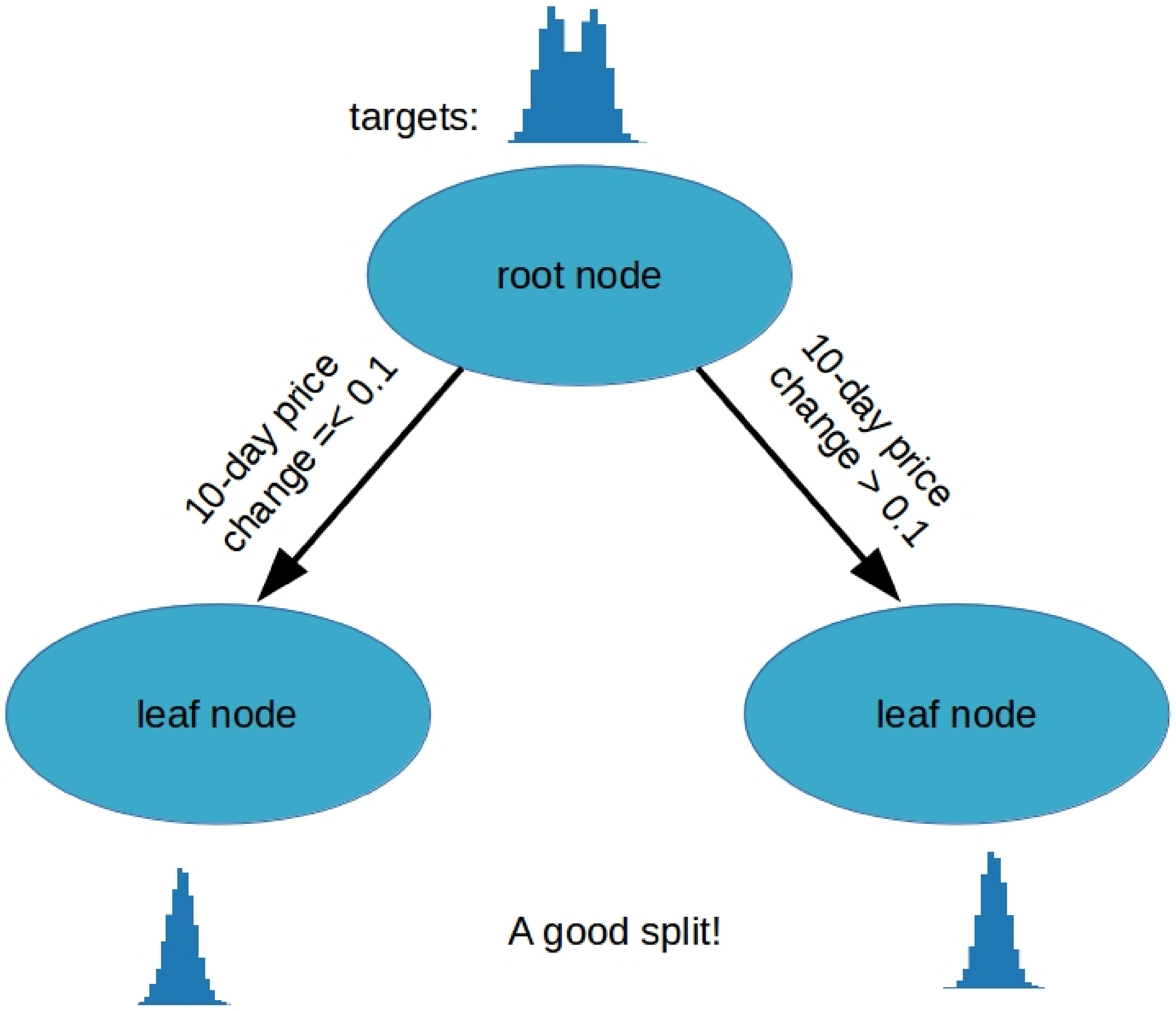
Decision tree splits



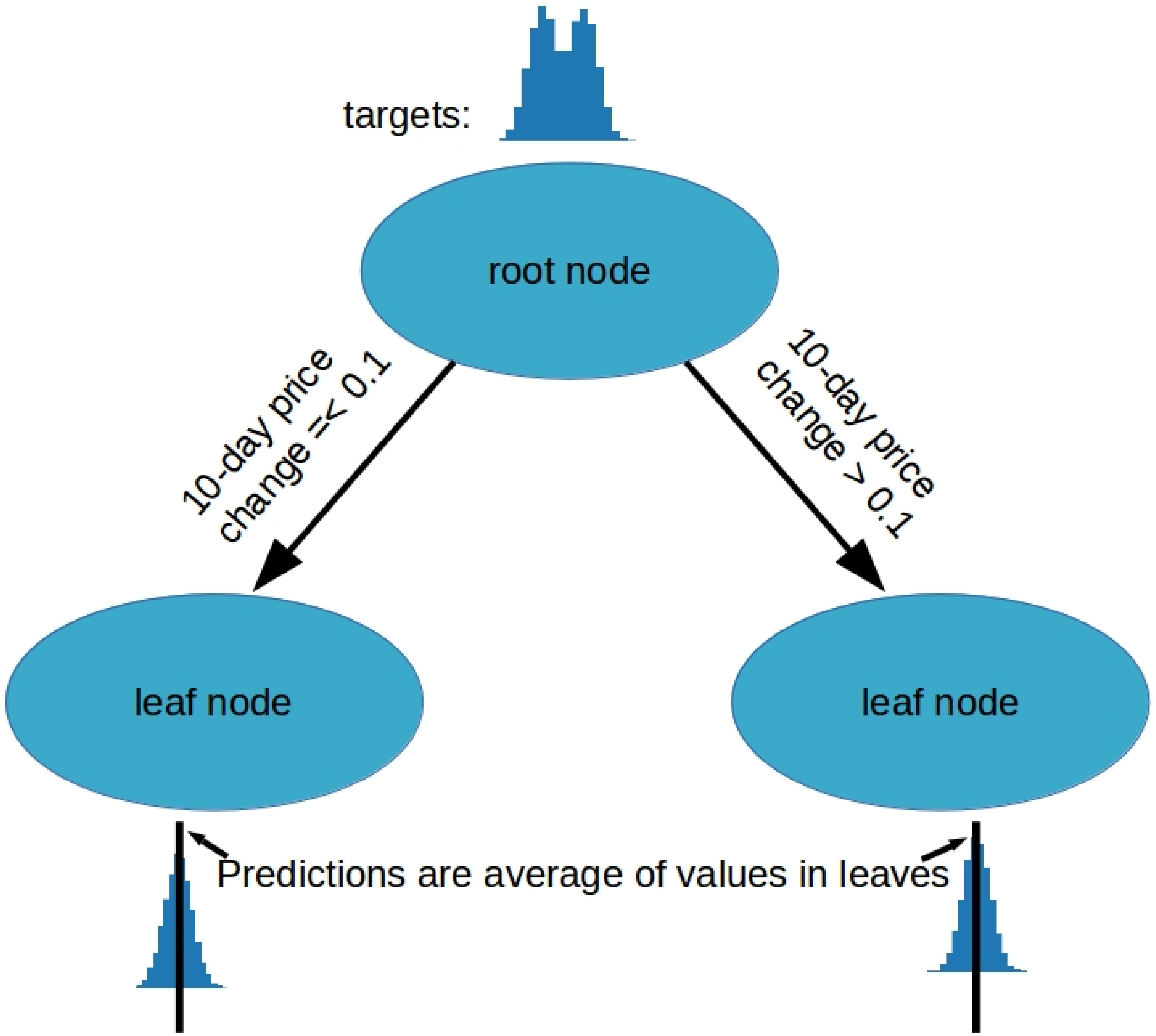
Bad tree


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!

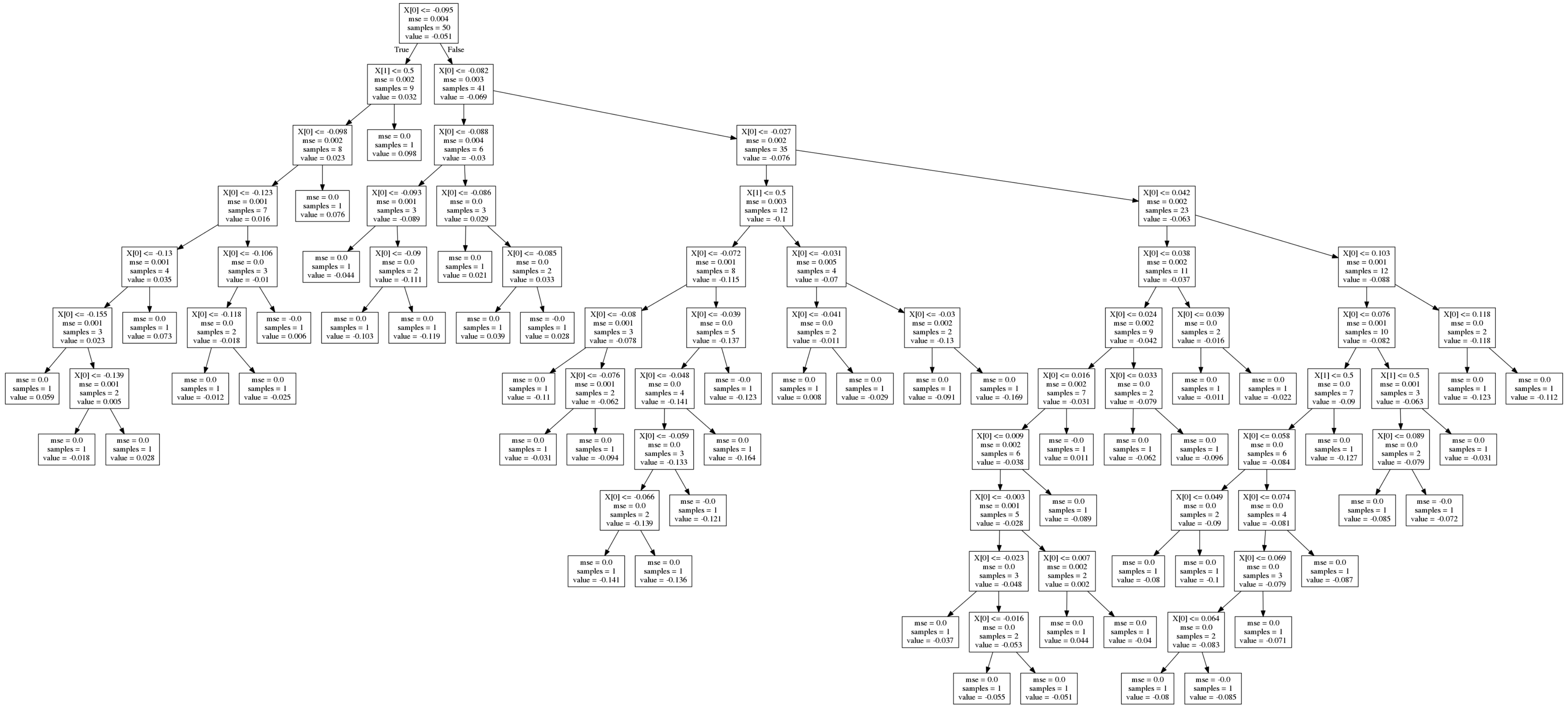
Decision tree regression



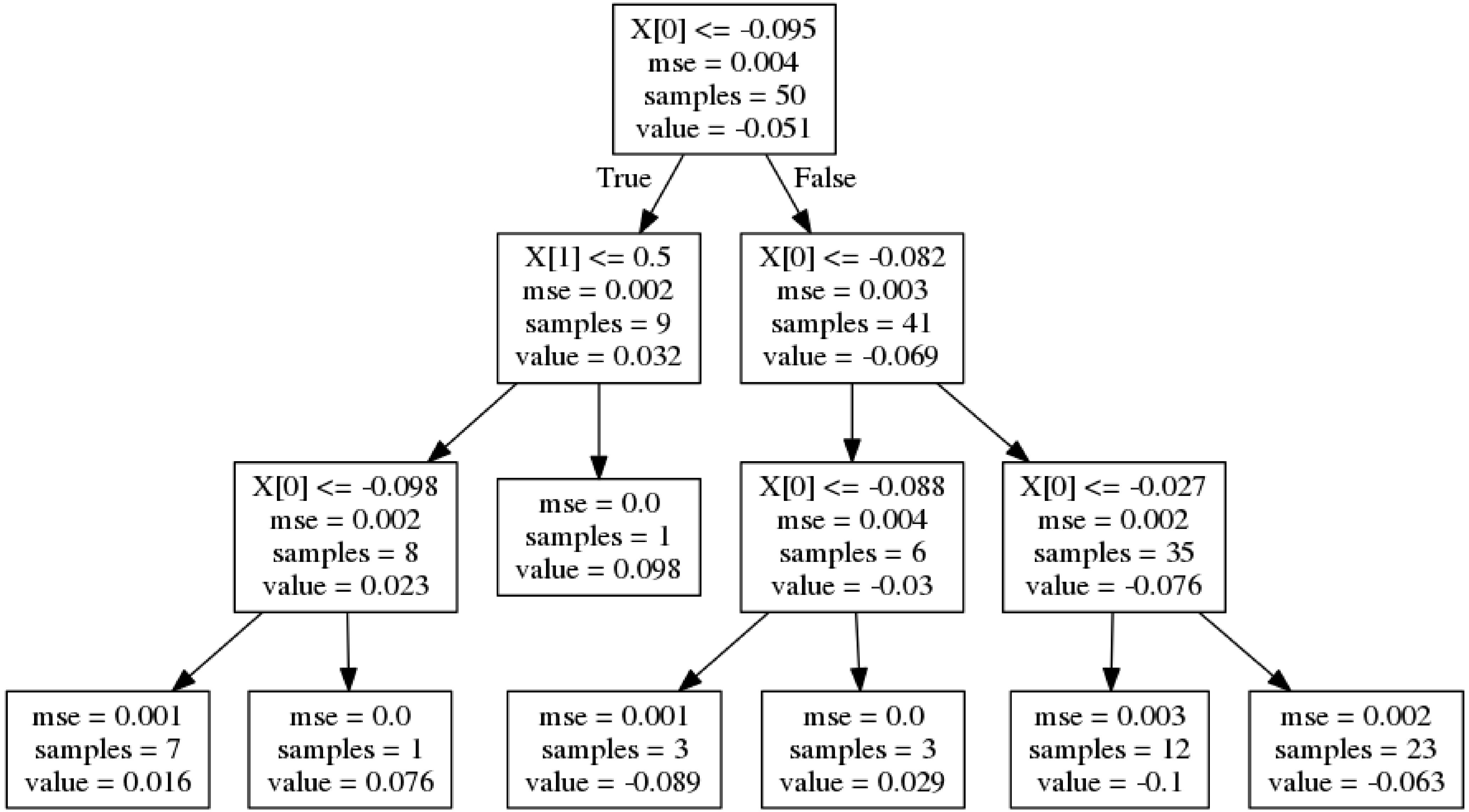
Regression trees

```
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

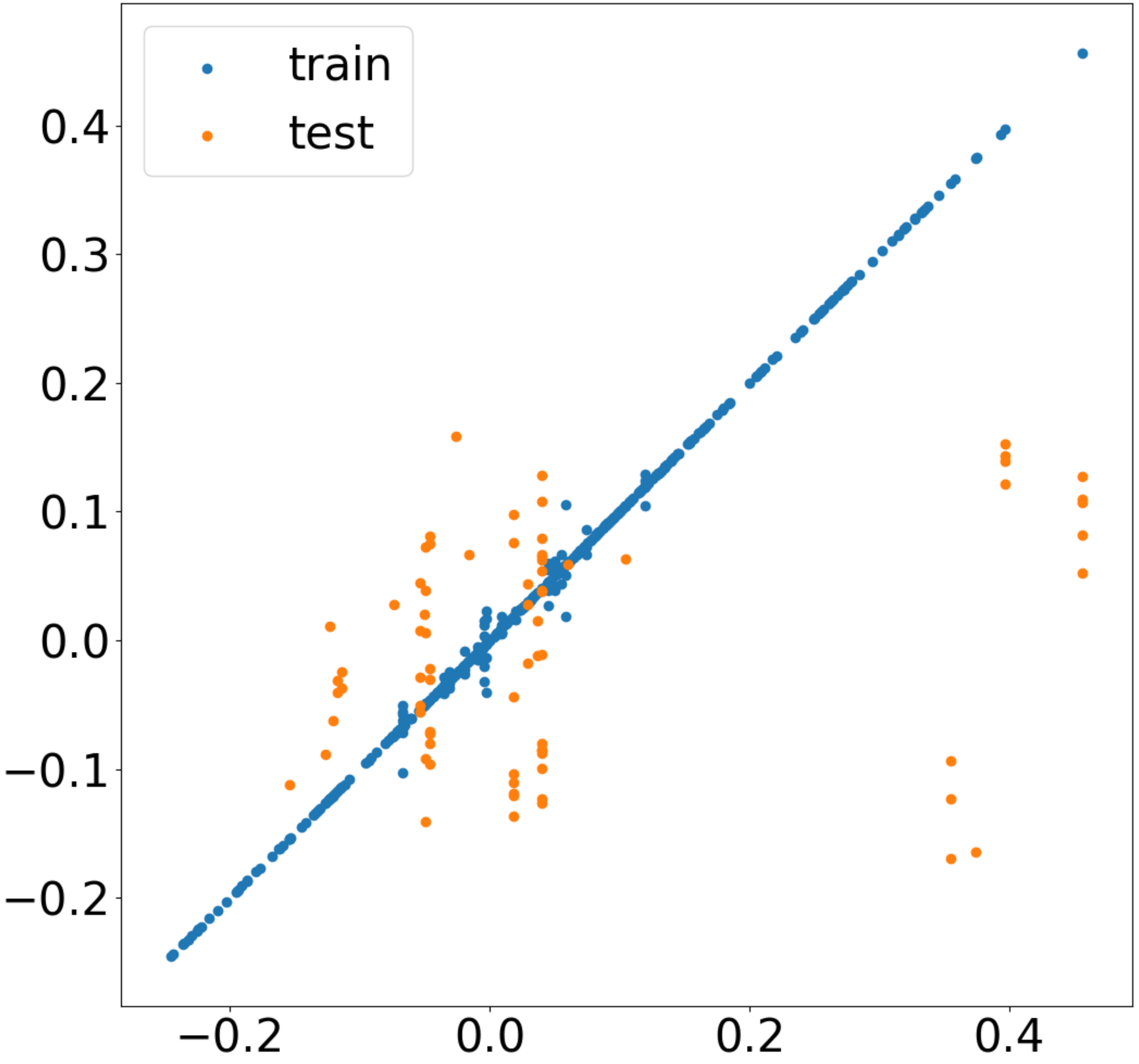


Evaluate model

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

```
0.6662215501032416
-0.08917300191734268
```

```python
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

Grow some trees!

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Random forests

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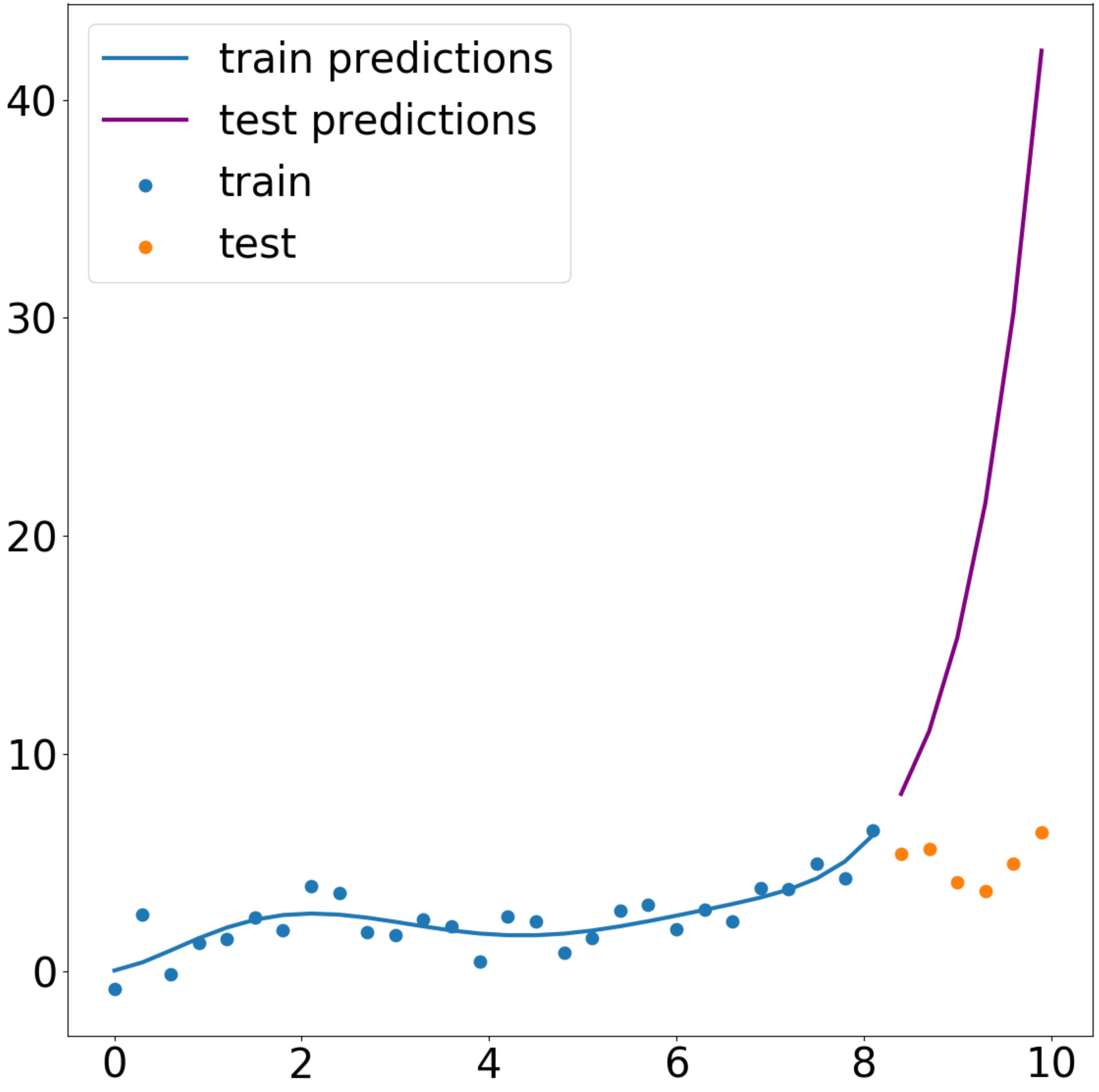
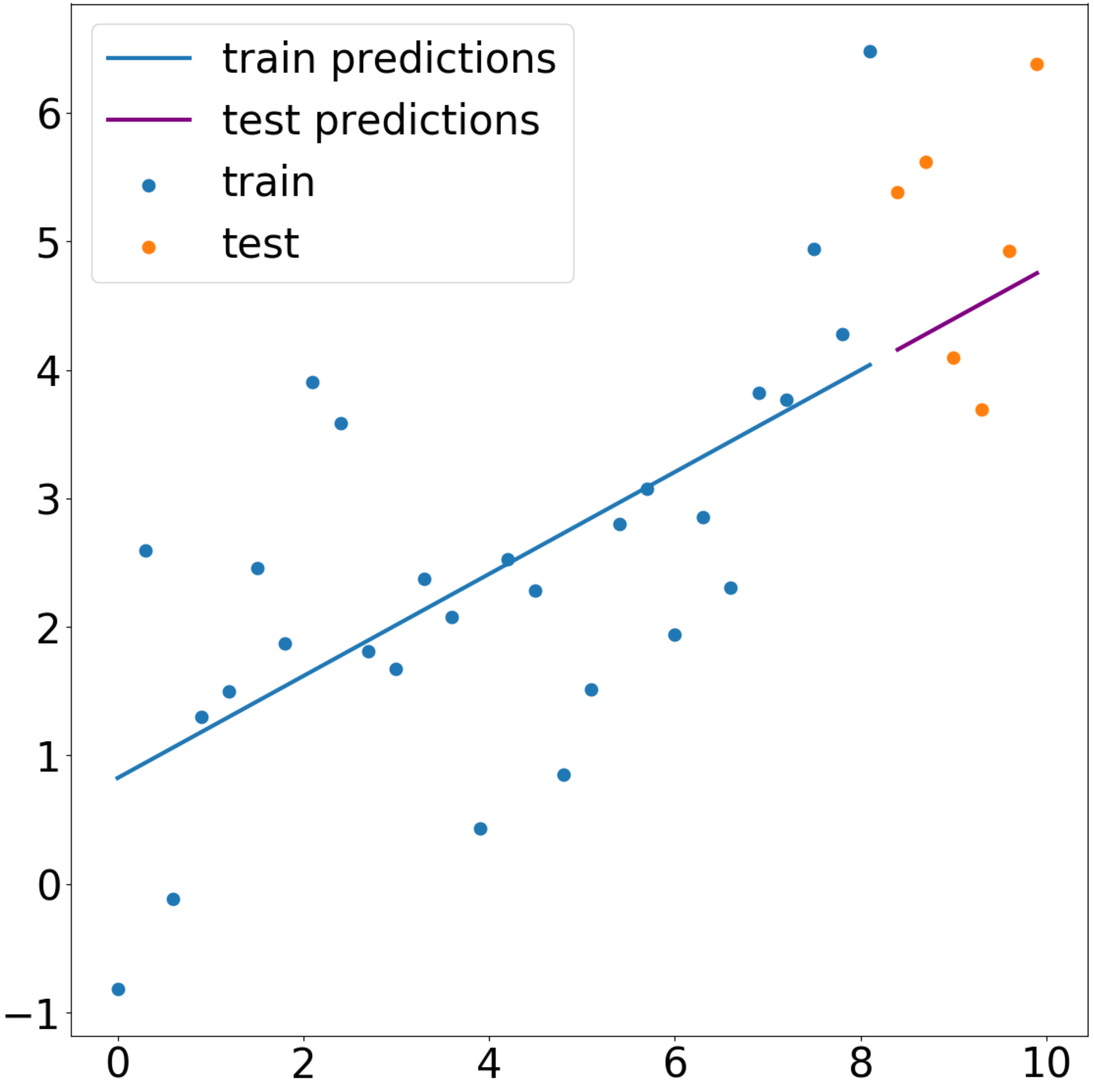
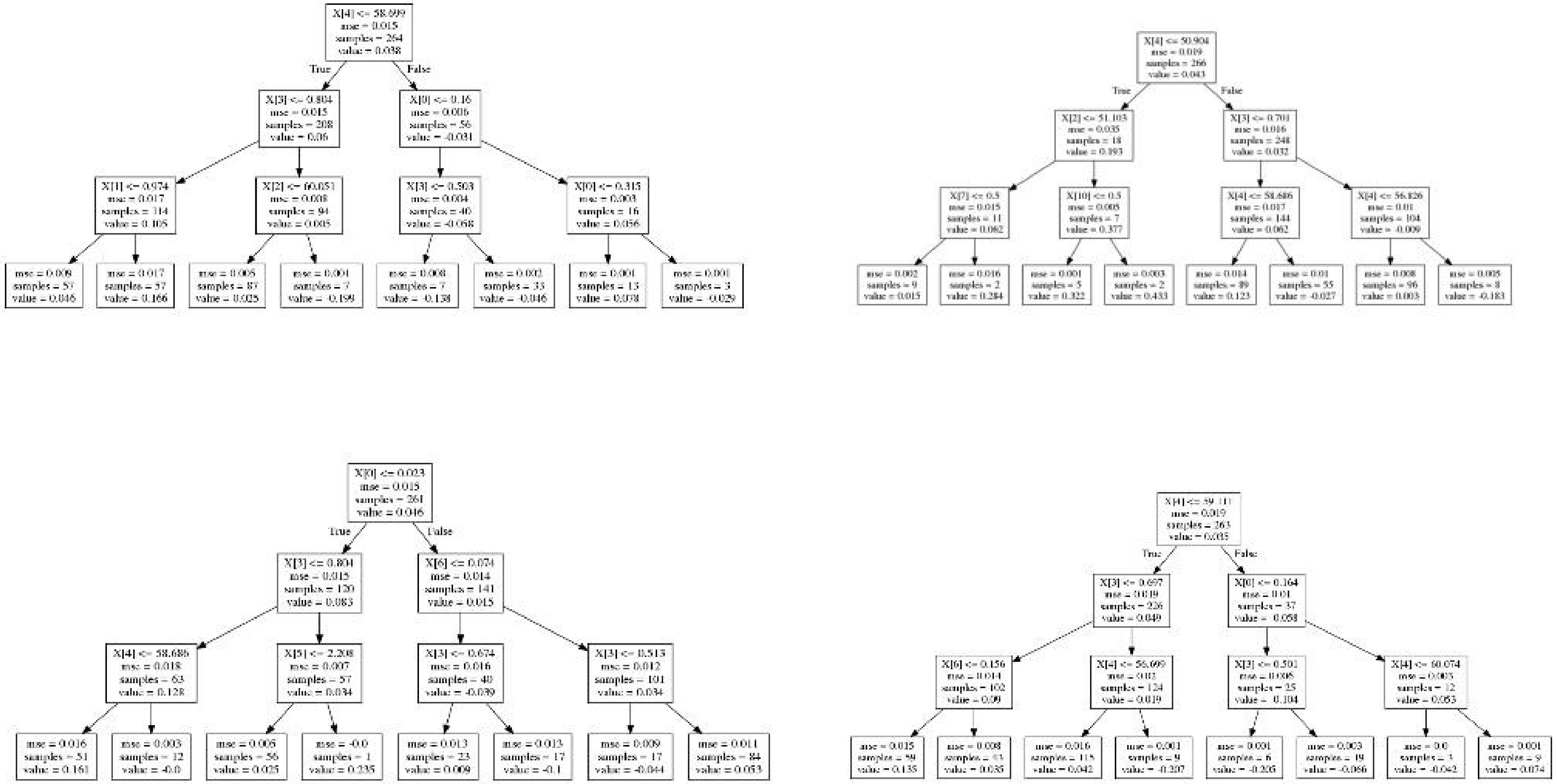
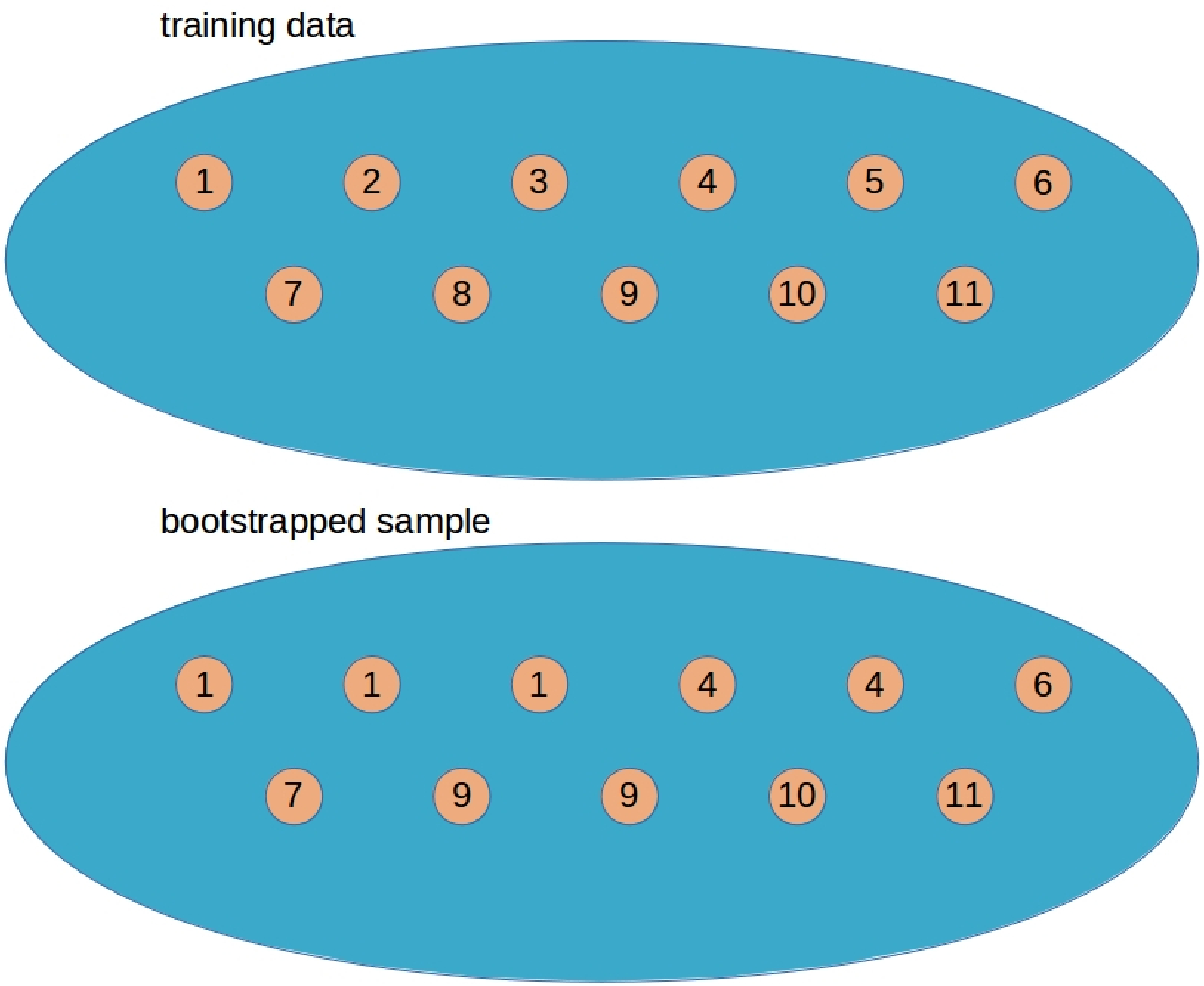

train predictions
test predictions
train
test
40
30
20
10
0
0
2
4
6
8
10


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}]
```

ParameterGrid

```
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}
```

Plant some random forests!

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Feature importances and gradient boosting

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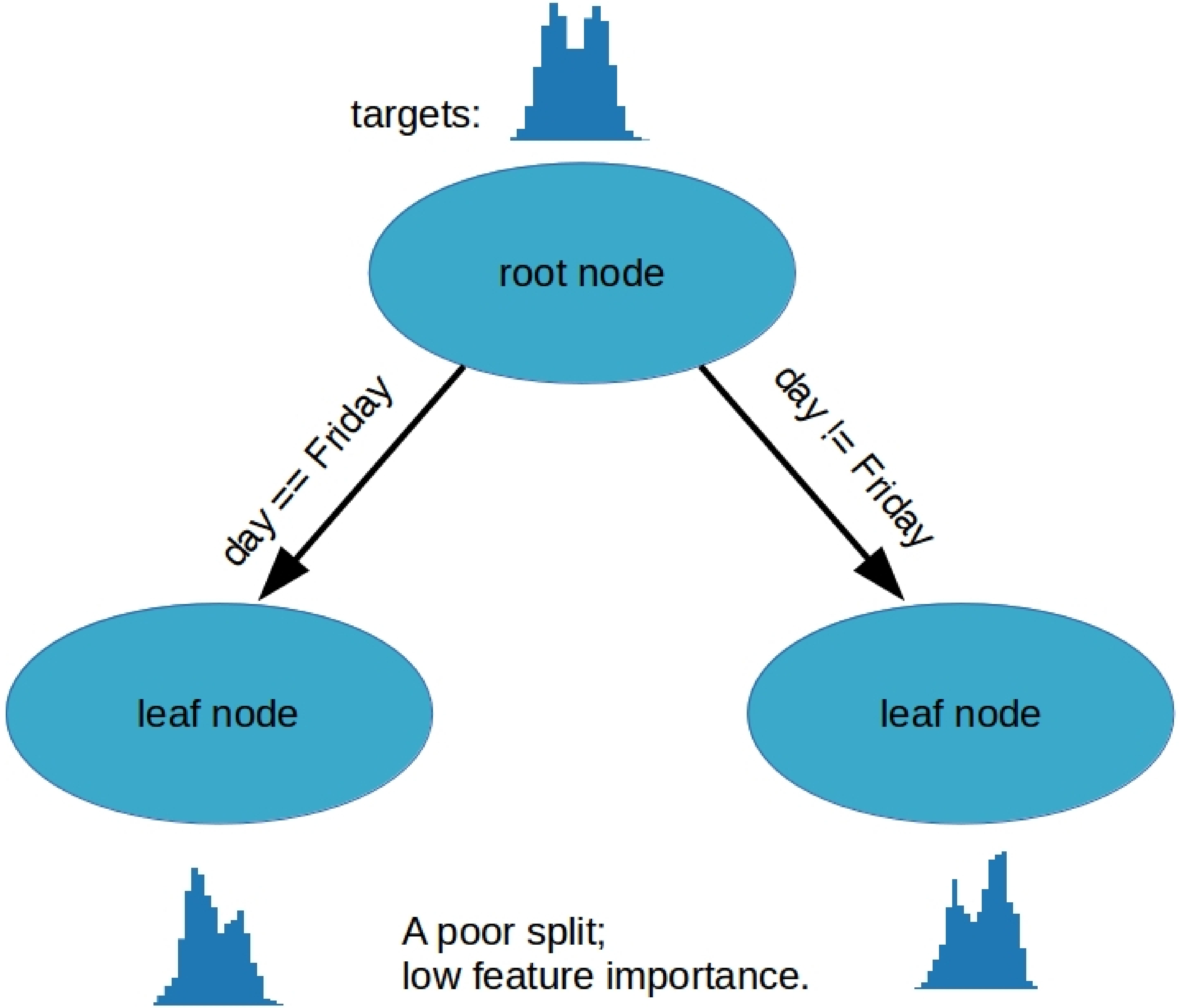
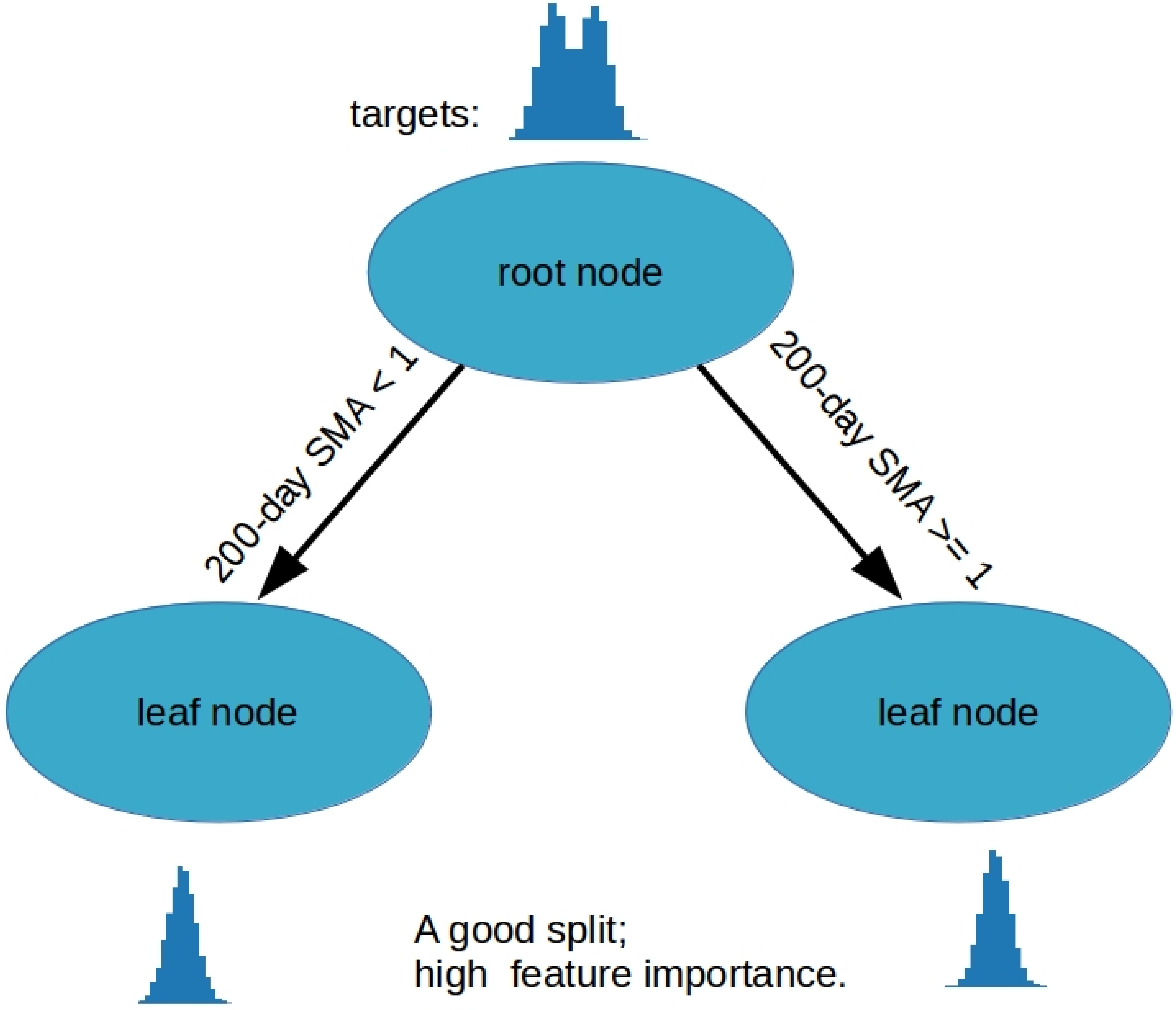

targets:
root node
day == Friday
day != Friday
leaf node
leaf node
A poor split;
low feature importance.


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

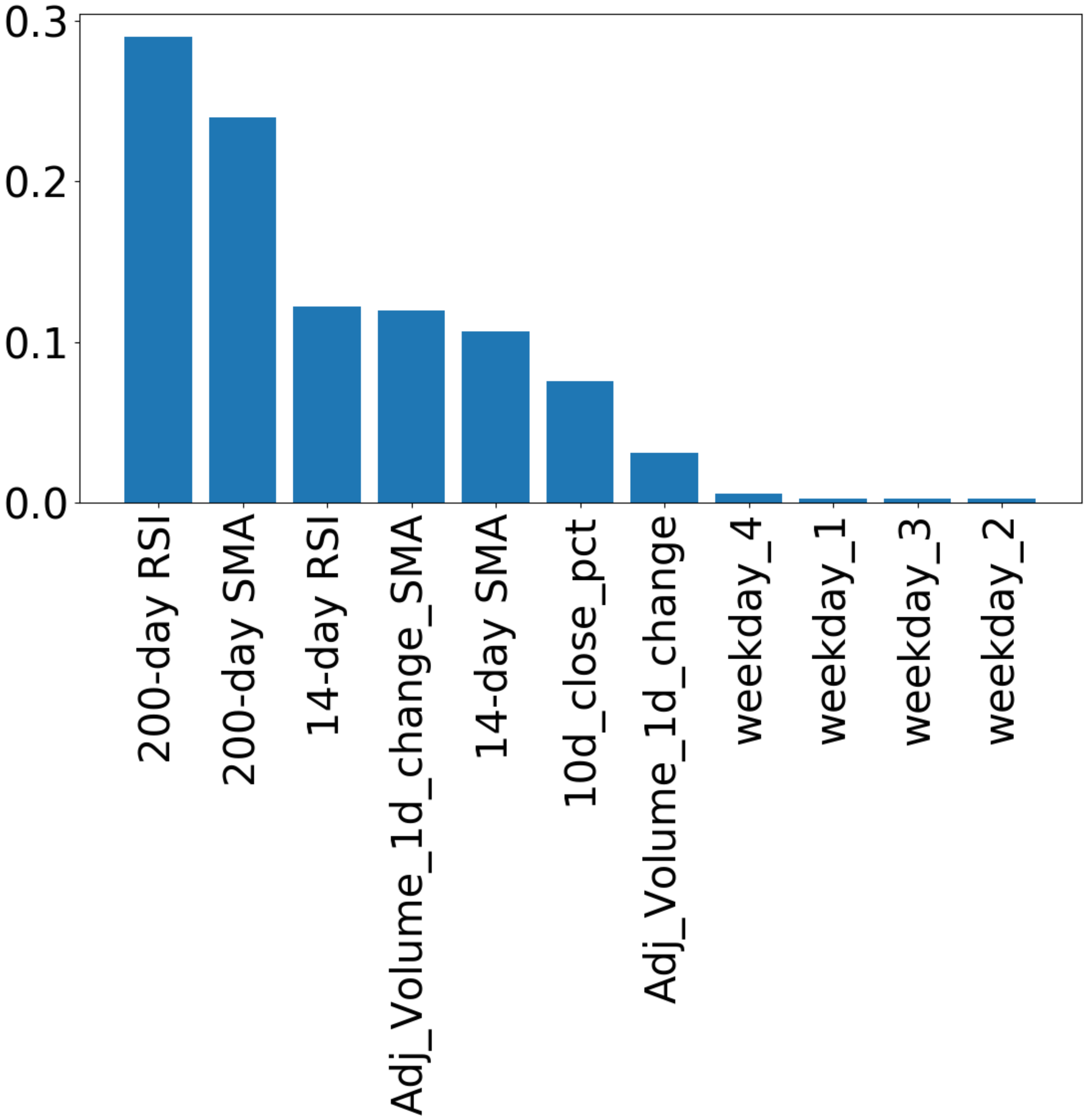
Extracting feature importances

```python
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]
```

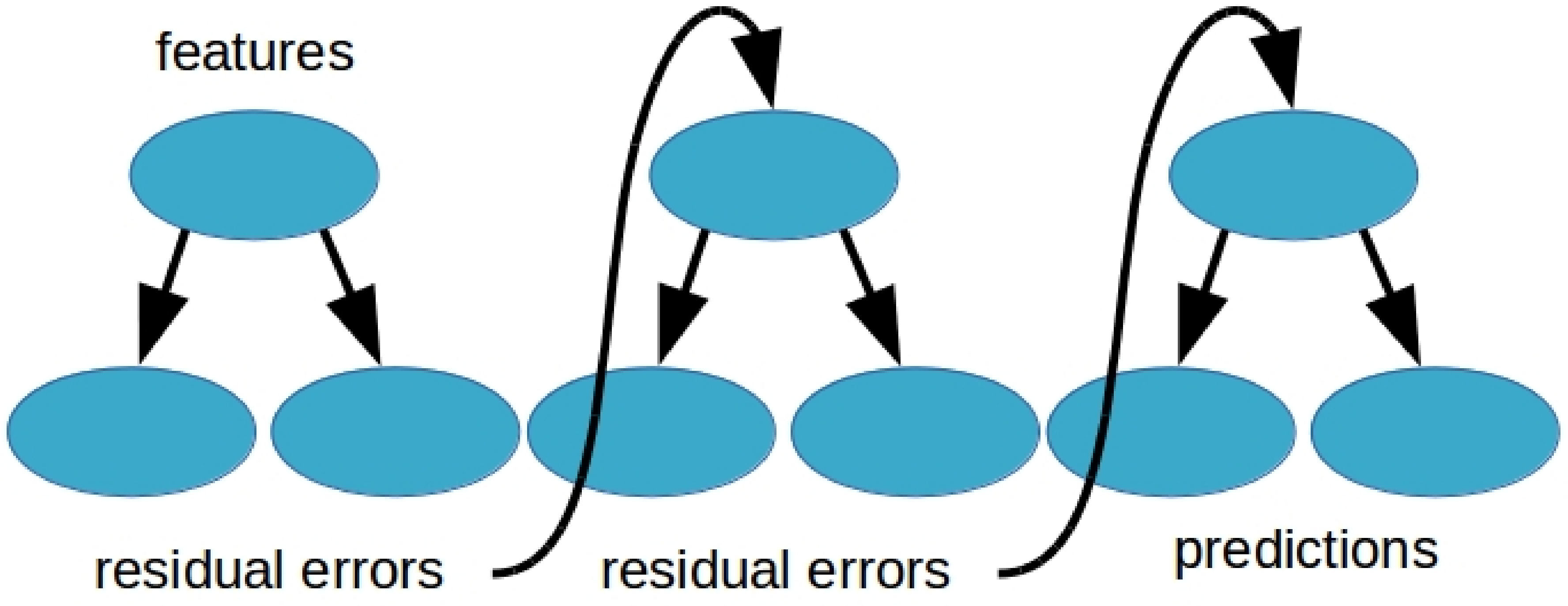
Sorting and plotting

```
# 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)
```

Get boosted!

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