# Tuning a CART's hyperparameters

MACHINE LEARNING WITH TREE-BASED MODELS IN PYTHON

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# Hyperparameters

Machine learning model:

- **parameters:** learned from data
  - CART example: split-point of a node, split-feature of a node, ...
- **hyperparameters:** not learned from data, set prior to training
  - CART example: `max_depth` , `min_samples_leaf` , splitting criterion ...

# What is hyperparameter tuning?

- **Problem:** search for a set of optimal hyperparameters for a learning algorithm.
- **Solution:** find a set of optimal hyperparameters that results in an optimal model.
- **Optimal model:** yields an optimal **score.**
- **Score:** in sklearn defaults to accuracy (classification) and $R^2$ (regression).
- Cross validation is used to estimate the generalization performance.

# Why tune hyperparameters?

- In `sklearn`, a model's default hyperparameters are not optimal for all problems.
- Hyperparameters should be tuned to obtain the best model performance.

# Approaches to hyperparameter tuning

- Grid Search
- Random Search
- Bayesian Optimization
- Genetic Algorithms
- ....

# Grid search cross validation

- Manually set a grid of discrete hyperparameter values.
- Set a metric for scoring model performance.
- Search exhaustively through the grid.
- For each set of hyperparameters, evaluate each model's CV score.
- The optimal hyperparameters are those of the model achieving the best CV score.

# Grid search cross validation: example

- Hyperparameters grids:
  - `max_depth` = {2,3,4},
  - `min_samples_leaf` = {0.05, 0.1}
- hyperparameter space = { (2,0.05) , (2,0.1) , (3,0.05), ... }
- CV scores = { $score_{(2,0.05)}$ , ... }
- optimal hyperparameters = set of hyperparameters corresponding to the best CV score.

# Inspecting the hyperparameters of a CART in sklearn

```
# Import DecisionTreeClassifier
from sklearn.tree import DecisionTreeClassifier

# Set seed to 1 for reproducibility
SEED = 1

# Instantiate a DecisionTreeClassifier 'dt'
dt = DecisionTreeClassifier(random_state=SEED)
```

# Inspecting the hyperparameters of a CART in sklearn

```python
# Print out 'dt's hyperparameters
print(dt.get_params())
```

```
{'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': False,
 'random_state': 1,
 'splitter': 'best'}
```

```python
# Import GridSearchCV
from sklearn.model_selection import GridSearchCV
# Define the grid of hyperparameters 'params_dt'
params_dt = {
             'max_depth': [3, 4,5, 6],
             'min_samples_leaf': [0.04, 0.06, 0.08],
             'max_features': [0.2, 0.4,0.6, 0.8]
            }
# Instantiate a 10-fold CV grid search object 'grid_dt'
grid_dt = GridSearchCV(estimator=dt,
                       param_grid=params_dt,
                       scoring='accuracy',
                       cv=10,
                       n_jobs=-1)
# Fit 'grid_dt' to the training data
grid_dt.fit(X_train, y_train)
```

# Extracting the best hyperparameters

```
# Extract best hyperparameters from 'grid_dt'
best_hyperparams = grid_dt.best_params_
print('Best hyerparameters:\n', best_hyperparams)
```

```
Best hyerparameters:
  {'max_depth': 3, 'max_features': 0.4, 'min_samples_leaf': 0.06}
```

```
# Extract best CV score from 'grid_dt'
best_CV_score = grid_dt.best_score_
print('Best CV accuracy'.format(best_CV_score))
```

```
Best CV accuracy: 0.938
```

# Extracting the best estimator

```
# Extract best model from 'grid_dt'
best_model = grid_dt.best_estimator_

# Evaluate test set accuracy
test_acc = best_model.score(X_test,y_test)

# Print test set accuracy
print("Test set accuracy of best model: {:.3f}".format(test_acc))
```

```
Test set accuracy of best model: 0.947
```

# Let's practice!

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# Tuning an RF's Hyperparameters

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# Random Forests Hyperparameters

- CART hyperparameters
- number of estimators
- bootstrap
- ....

# Tuning is expensive

Hyperparameter tuning:

- computationally expensive,
- sometimes leads to very slight improvement,

Weight the impact of tuning on the whole project.

# Inspecting RF Hyperparameters in sklearn

```
# Import RandomForestRegressor
from sklearn.ensemble import RandomForestRegressor

# Set seed for reproducibility
SEED = 1

# Instantiate a random forests regressor 'rf'
rf = RandomForestRegressor(random_state= SEED)
```

```python
# Inspect rf' s hyperparameters
rf.get_params()
```

```
{'bootstrap': True,
 'criterion': 'mse',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 10,
 'n_jobs': -1,
 'oob_score': False,
 'random_state': 1,
 'verbose': 0,
 'warm_start': False}
```

```python
# Basic imports
from sklearn.metrics import mean_squared_error as MSE
from sklearn.model_selection import GridSearchCV
# Define a grid of hyperparameter 'params_rf'
params_rf = {
              'n_estimators': [300, 400, 500],
              'max_depth': [4, 6, 8],
              'min_samples_leaf': [0.1, 0.2],
              'max_features': ['log2', 'sqrt']
             }
# Instantiate 'grid_rf'
grid_rf = GridSearchCV(estimator=rf,
                       param_grid=params_rf,
                       cv=3,
                       scoring='neg_mean_squared_error',
                       verbose=1,
                       n_jobs=-1)
```

# Searching for the best hyperparameters

```
# Fit 'grid_rf' to the training set
grid_rf.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   10.0s
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed:   24.3s finished
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=4,
           max_features='log2', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=0.1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=400, n_jobs=1,
           oob_score=False, random_state=1, verbose=0, warm_start=False)
```

# Extracting the best hyperparameters

```python
# Extract the best hyperparameters from 'grid_rf'
best_hyperparams = grid_rf.best_params_

print('Best hyperparameters:\n', best_hyperparams)
```

```
Best hyperparameters:
         {'max_depth': 4,
          'max_features': 'log2',
          'min_samples_leaf': 0.1,
          'n_estimators': 400}
```

# Evaluating the best model performance

```python
# Extract the best model from 'grid_rf'
best_model = grid_rf.best_estimator_
# Predict the test set labels
y_pred = best_model.predict(X_test)
# Evaluate the test set RMSE
rmse_test = MSE(y_test, y_pred)**(1/2)
# Print the test set RMSE
print('Test set RMSE of rf: {:.2f}'.format(rmse_test))
```

```
Test set RMSE of rf: 3.89
```

# Let's practice!

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# Congratulations!

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# How far you have come

- **Chapter 1:** Decision-Tree Learning
- **Chapter 2:** Generalization Error, Cross-Validation, Ensembling
- **Chapter 3:** Bagging and Random Forests
- **Chapter 4:** AdaBoost and Gradient-Boosting
- **Chapter 5:** Model Tuning

# Thank you!

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