

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

```
# 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'}
```

```
# 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)
```

```
# 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}
```

```
# 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

```
# 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

```
# 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

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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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