

# Hyper parameter tuning

video

github

Note Random Search CV -> chose randomly from all the parameter , instent of trying all the possible combination like gride search cv

value of scoring

- For classification metrics
  - Accuracy: scoring='accuracy'
  - Precision: scoring='precision'
  - Recall: scoring='recall'
  - F1 Score: scoring='f1'
- For Regression metrics
  - Mean Absolute Error (MAE): scoring='neg\_mean\_absolute\_error'
  - Mean Squared Error (MSE): scoring='neg\_mean\_squared\_error'
  - R^2 Score: scoring='r2'
  - Root Mean Squared Error (RMSE): Need to create custom scoring function for it
  - Adjusted R^2 Score: Need to create custom scoring function for it
- code for custom Root Mean Squared Error (RMSE) and Adjusted R^2 Score:

```
from sklearn.metrics import make_scorer, r2_score, mean_squared_error
import numpy as np

# Custom RMSE scorer
def rmse(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))

# Custom Adjusted R^2 scorer
def adjusted_r2(y_true, y_pred, n, p):
    r2 = r2_score(y_true, y_pred)
    adj_r2 = 1 - (1 - r2) * ((n - 1) / (n - p - 1))
    return adj_r2

# Create custom scorers
rmse_scorer = make_scorer(rmse, greater_is_better=False) # We want to minimize rmse, hence greater_is_better=False
adj_r2_scorer = make_scorer(adjusted_r2, greater_is_better=True) # We want to maximize adjusted r2, hence greater_is_better=True

from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression

# Define model
model = LinearRegression()

# Parameter grid
param_grid = {
    'fit_intercept': [True, False],
    'normalize': [True, False]
}

# GridSearchCV with custom scoring
grid_search_rmse = GridSearchCV(model, param_grid, cv=5, scoring=rmse_scorer)
grid_search_adj_r2 = GridSearchCV(model, param_grid, cv=5, scoring=adj_r2_scorer)

# Fit GridSearchCV
grid_search_rmse.fit(X_train, y_train)
grid_search_adj_r2.fit(X_train, y_train)

# Best RMSE
best_rmse = -grid_search_rmse.best_score_ # negate to get positive value
print(f"Best RMSE: {best_rmse:.4f}")

# Best Adjusted R^2
best_adj_r2 = grid_search_adj_r2.best_score_
print(f"Best Adjusted R^2: {best_adj_r2:.4f}")
```

code

- GridSearchCV
  - # Number of trees in random forest  
n\_estimators = [20,60,100,120]
  - # Number of features to consider at every split  
max\_features = [0.2,0.6,1.0]
  - # Maximum number of levels in tree  
max\_depth = [2,8,None]
  - # Number of samples  
max\_samples = [0.5,0.75,1.0]
  - param\_grid = {'n\_estimators': n\_estimators,  
 'max\_features': max\_features,  
 'max\_depth': max\_depth,  
 'max\_samples': max\_samples  
 }
  - rf = RandomForestClassifier()
  - from sklearn.model\_selection import GridSearchCV
  - rf\_grid = GridSearchCV(estimator = rf,  
 param\_grid = param\_grid,  
 cv = 5,  
 scoring='accuracy'  
 verbose=2,  
 n\_jobs = -1)
  - rf\_grid.fit(X\_train,y\_train)
  - rf\_grid.best\_params\_
  - rf\_grid.best\_score\_
- RandomSearchCV
  - # Number of trees in random forest  
n\_estimators = [20,60,100,120]
  - # Number of features to consider at every split  
max\_features = [0.2,0.6,1.0]
  - # Maximum number of levels in tree  
max\_depth = [2,8,None]
  - # Number of samples  
max\_samples = [0.5,0.75,1.0]
  - # Bootstrap samples  
bootstrap = [True,False]
  - # Minimum number of samples required to split a node  
min\_samples\_split = [2, 5]
  - # Minimum number of samples required at each leaf node  
min\_samples\_leaf = [1, 2]
  - param\_grid = {'n\_estimators': n\_estimators,  
 'max\_features': max\_features,  
 'max\_depth': max\_depth,  
 'max\_samples': max\_samples,  
 'bootstrap': bootstrap,  
 'min\_samples\_split': min\_samples\_split,  
 'min\_samples\_leaf': min\_samples\_leaf  
 }
  - from sklearn.model\_selection import RandomizedSearchCV
  - rf\_grid = RandomizedSearchCV(estimator = rf,  
 param\_distributions = param\_grid,  
 cv = 5,  
 scoring='accuracy'  
 verbose=2,  
 n\_jobs = -1)
  - rf\_grid.fit(X\_train,y\_train)
  - rf\_grid.best\_params\_
  - rf\_grid.best\_score\_