EXTREME GRADIENT BOOSTING WITH XGBOOST

Why tune your model?

Sergey Fogelson

Untuned Model Example

```
In [1]: import pandas as pd
In [2]: import xgboost as xgb
In [3]: import numpy as np
In [4]: housing_data = pd.read_csv("ames_housing_trimmed_processed.csv")
In [5]: X,y = housing_data[housing_data.columns.tolist()[:-1]],
        housing_data[housing_data.columns.tolist()[-1]]
In [6]: housing_dmatrix = xgb.DMatrix(data=X,label=y)

In [7]: untuned_params={"objective":"reg:linear"}

In [8]: untuned_cv_results_rmse = xgb.cv(dtrain=housing_dmatrix,
        params=untuned_params,nfold=4,
        metrics="rmse",as_pandas=True,seed=123)

In [9]: print("Untuned rmse: %f" %((untuned_cv_results_rmse["test-rmse-mean
Untuned rmse: 34624.229980
```

Tuned Model Example

```
In [1]: import pandas as pd
In [2]: import xgboost as xgb
In [3]: import numpy as np
In [4]: housing_data = pd.read_csv("ames_housing_trimmed_processed.csv")
In [5]: X,y = housing_data[housing_data.columns.tolist()[:-1]],
   ...: housing_data[housing_data.columns.tolist()[-1]]
In [6]: housing_dmatrix = xgb.DMatrix(data=X,label=y)

In [7]: tuned_params = {"objective":"reg:linear",'colsample_bytree': 0.3,
   ...: 'learning_rate': 0.1, 'max_depth': 5}

In [8]: tuned_cv_results_rmse = xgb.cv(dtrain=housing_dmatrix,
   ...: params=tuned_params, nfold=4, num_boost_round=200, metrics="rmse",
   ...: as_pandas=True, seed=123)

In [9]: print("Tuned rmse: %f" %((tuned_cv_results_rmse["test-rmse-mean"])
   ...: .tail(1)))
Tuned rmse: 29812.683594
```

EXTREME GRADIENT BOOSTING WITH XGBOOST

Let's tune some models!

EXTREME GRADIENT BOOSTING WITH XGBOOST

Tunable parameters in XGBoost

Sergey Fogelson
VP of Analytics, Viacom

Common tree tunable parameters

- **learning rate:** learning rate/eta
- **gamma:** min loss reduction to create new tree split
- **lambda:** L2 reg on leaf weights
- **alpha:** L1 reg on leaf weights
- **max_depth:** max depth per tree
- **subsample:** % samples used per tree
- **colsample_bytree:** % features used per tree

Linear tunable parameters

- **lambda:** L2 reg on weights
- **alpha:** L1 reg on weights
- **lambda_bias:** L2 reg term on bias

- You can also tune the number of estimators used for both base model types!

EXTREME GRADIENT BOOSTING WITH XGBOOST

Let's get to some tuning!

EXTREME GRADIENT BOOSTING WITH XGBOOST

Review of Grid Search and Random Search

Sergey Fogelson
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Grid Search: Review

- Search exhaustively over a given set of hyperparameters, once per set of hyperparameters
- Number of models = number of distinct values per hyperparameter multiplied across each hyperparameter
- Pick final model hyperparameter values that give best cross-validated evaluation metric value

Grid Search: Example

```
In [1]: import pandas as pd
In [2]: import xgboost as xgb
In [3]: import numpy as np
In [4]: from sklearn.model_selection import GridSearchCV

In [5]: housing_data = pd.read_csv("ames_housing_trimmed_processed.csv")
In [6]: X, y = housing_data[housing_data.columns.tolist()[:-1]],
   ...: housing_data[housing_data.columns.tolist()[-1]
In [7]: housing_dmatrix = xgb.DMatrix(data=X,label=y)

In [8]: gbm_param_grid = {
   ...: 'learning_rate': [0.01,0.1,0.5,0.9],
   ...: 'n_estimators': [200],
   ...: 'subsample': [0.3, 0.5, 0.9]}

In [9]: gbm = xgb.XGBRegressor()
In [10]: grid_mse = GridSearchCV(estimator=gbm,
    ...: param_grid=gbm_param_grid,
    ...: scoring='neg_mean_squared_error', cv=4, verbose=1)
In [11]: grid_mse.fit(X, y)
```

Random Search: Review

- Create a (possibly infinite) range of hyperparameter values per hyperparameter that you would like to search over
- Set the number of iterations you would like for the random search to continue
- During each iteration, randomly draw a value in the range of specified values for each hyperparameter searched over and train/evaluate a model with those hyperparameters
- After you've reached the maximum number of iterations, select the hyperparameter configuration with the best evaluated score

Random Search: Example

```
In [1]: import pandas as pd
In [2]: import xgboost as xgb
In [3]: import numpy as np
In [4]: from sklearn.model_selection import RandomizedSearchCV
In [5]: housing_data = pd.read_csv("ames_housing_trimmed_processed.csv")
In [6]: X,y = housing_data[housing_data.columns.tolist()[:-1]],
   ...: housing_data[housing_data.columns.tolist()[-1]]
In [7]: housing_dmatrix = xgb.DMatrix(data=X,label=y)

In [8]: gbm_param_grid = {
   ...: 'learning_rate': np.arange(0.05,1.05,.05),
   ...: 'n_estimators': [200],
   ...: 'subsample': np.arange(0.05,1.05,.05)}

In [9]: gbm = xgb.XGBRegressor()
In [10]: randomized_mse = RandomizedSearchCV(estimator=gbm,
    ...: param_distributions=gbm_param_grid, n_iter=25,
    ...: scoring='neg_mean_squared_error', cv=4, verbose=1)
In [11]: randomized_mse.fit(X, y)
```

EXTREME GRADIENT BOOSTING WITH XGBOOST

Let's practice!

EXTREME GRADIENT BOOSTING WITH XGBOOST

Limits of Grid Search and Random Search

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Grid Search and Random Search Limitations

- Grid Search
  - Number of models you must build with every additional new parameter grows very quickly
- Random Search
  - Parameter space to explore can be massive
  - Randomly jumping throughout the space looking for a "best" result becomes a waiting game

EXTREME GRADIENT BOOSTING WITH XGBOOST

Let's practice!