



Review of pipelines using sklearn



Pipeline Review

- Takes a list of named 2-tuples (name, pipeline_step) as input
- Tuples can contain any arbitrary scikit-learn compatible estimator or transformer object
- Pipeline implements fit/predict methods
- Can be used as input estimator into grid/randomized search and cross val score methods



Scikit-learn pipeline example

```
In [1]: import pandas as pd
   ...: from sklearn.ensemble import RandomForestRegressor
   ...: import numpy as np
   ...: from sklearn.preprocessing import StandardScaler
   ...: from sklearn.pipeline import Pipeline
   ...: from sklearn.model selection import cross val score
In [2]: names = ["crime","zone","industry","charles",
   ...: "no", "rooms", "age", "distance",
   ...: "radial","tax","pupil","aam","lower","med price"]
In [3]: data = pd.read csv("boston housing.csv",names=names)
In [4]: X, y = data.iloc[:,:-1], data.iloc[:,-1]
In [5]: rf_pipeline = Pipeline[("st_scaler",
   ...: StandardScaler()),
   ...: ("rf model", RandomForestRegressor())]
In [6]: scores = cross val score(rf pipeline, X, y,
   ...: scoring="neg mean squared error",cv=10)
```



Scikit-learn pipeline example

```
In [7]: final_avg_rmse = np.mean(np.sqrt(np.abs(scores)))
In [8]: print("Final RMSE:", final_avg_rmse)
Final RMSE: 4.54530686529
```



Preprocessing I: LabelEncoder and OneHotEncoder

- LabelEncoder: Converts a categorical column of strings into integers
- OneHotEncoder: Takes the column of integers and encodes them as dummy variables
- Cannot be done within a pipeline



Preprocessing II: DictVectorizer

- Traditionally used in text processing
- Converts lists of feature mappings into vectors
- Need to convert DataFrame into a list of dictionary entries
- Explore the scikit-learn documentation





Let's build pipelines!





Incorporating xgboost into pipelines



Scikit-Learn Pipeline Example With XGBoost

```
In [1]: import pandas as pd
   ...: import xgboost as xgb
   ...: import numpy as np
   ...: from sklearn.preprocessing import StandardScaler
   ...: from sklearn.pipeline import Pipeline
   ...: from sklearn.model selection import cross val score
In [2]: names = ["crime","zone","industry","charles","no",
   ...: "rooms", "age", "distance", "radial", "tax",
   ...: "pupil", "aam", "lower", "med price"]
In [3]: data = pd.read csv("boston housing.csv", names=names)
In [4]: X, y = data.iloc[:,:-1], data.iloc[:,-1]
In [5]: xgb pipeline = Pipeline[("st scaler",
   ...: StandardScaler()),
   ...: ("xgb_model",xgb.XGBRegressor())]
In [6]: scores = cross val score(xgb pipeline, X, y,
   ...:scoring="neg mean squared error",cv=10)
In [7]: final avg rmse = np.mean(np.sqrt(np.abs(scores)))
In [8]: print("Final XGB RMSE:", final avg rmse)
Final RMSE: 4.02719593323
```



Additional Components Introduced For Pipelines

- sklearn_pandas:
 - DataFrameMapper Interoperability between pandas and scikit-learn
 - CategoricalImputer Allow for imputation of categorical variables before conversion to integers
- sklearn.preprocessing:
 - Imputer Native imputation of numerical columns in scikit-learn
- sklearn.pipeline:
 - FeatureUnion combine multiple pipelines of features into a single pipeline of features





Let's practice!





Tuning xgboost hyperparameters in a pipeline



Tuning XGBoost hyperparameters in a Pipeline

```
In [1]: import pandas as pd
   ...: import xgboost as xgb
   ...: import numpy as np
   ...: from sklearn.preprocessing import StandardScaler
   ...: from sklearn.pipeline import Pipeline
   ...: from sklearn.model selection import RandomizedSearchCV
In [2]: names = ["crime","zone","industry","charles","no",
   ...: "rooms", "age", "distance", "radial", "tax",
   ...: "pupil", "aam", "lower", "med price"]
In [3]: data = pd.read csv("boston housing.csv", names=names)
In [4]: X, y = data.iloc[:,:-1], data.iloc[:,-1]
In [5]: xgb pipeline = Pipeline[("st scaler",
   ...: StandardScaler()), ("xgb model",xgb.XGBRegressor())]
In [6]: gbm param grid = {
       'xgb_model__subsample': np.arange(.05, 1, .05),
   ...: 'xgb model max depth': np.arange(3,20,1),
        'xgb model colsample bytree': np.arange(.1,1.05,.05) }
   . . . :
In [7]: randomized neg mse = RandomizedSearchCV(estimator=xgb pipeline,
   ...: param distributions=gbm param grid, n iter=10,
   ...: scoring='neg mean squared error', cv=\overline{4})
In [8]: randomized neg mse.fit(X, y)
```



Tuning XGBoost hyperparameters in a Pipeline II





Let's finish this up!





Final Thoughts



What We Have Covered And You Have Learned

- Using XGBoost for classification tasks
- Using XGBoost for regression tasks
- Tuning XGBoost's most important hyperparameters
- Incorporating XGBoost into sklearn pipelines



What We Have Not Covered (And How You Can Proceed)

- Using XGBoost for ranking/recommendation problems (Netflix/Amazon problem)
- Using more sophisticated hyperparameter tuning strategies for tuning XGBoost models (Bayesian Optimization)
- Using XGBoost as part of an ensemble of other models for regression/classification





Congratulations!