83_sklearn_pipeline

May 5, 2024

0.1 Let's redefine a model

[ ]:
```
# Let's import some packages

from dataidea.packages import * # imports np, pd, plt, etc
from sklearn.neighbors import KNeighborsRegressor
```

[ ]:
```
# loading the data set

data = pd.read_csv('../assets/boston.csv')
```

The Boston Housing Dataset

The Boston Housing Dataset is a derived from information collected by the U.S. Census Service concerning housing in the area of Boston MA. The following describes the dataset columns:

- CRIM - per capita crime rate by town
- ZN - proportion of residential land zoned for lots over 25,000 sq.ft.
- INDUS - proportion of non-retail business acres per town.
- CHAS - Charles River dummy variable (1 if tract bounds river; 0 otherwise)
- NOX - nitric oxides concentration (parts per 10 million)
- RM - average number of rooms per dwelling
- AGE - proportion of owner-occupied units built prior to 1940
- DIS - weighted distances to five Boston employment centres
- RAD - index of accessibility to radial highways
- TAX - full-value property-tax rate per $10,000
- PTRATIO - pupil-teacher ratio by town
- B - 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
- LSTAT - % lower status of the population
- MEDV - Median value of owner-occupied homes in $1000's

[ ]:
```
# looking at the top part

data.head()
```

[ ]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296.0
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242.0
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242.0
```

```
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222.0
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222.0

   PTRATIO       B  LSTAT  MEDV
0     15.3  396.90   4.98  24.0
1     17.8  396.90   9.14  21.6
2     17.8  392.83   4.03  34.7
3     18.7  394.63   2.94  33.4
4     18.7  396.90   5.33  36.2
```

0.1.1 Training our first model

In week 4, we learned that to train a model (for supervised machine learning), we needed to have a set of X variables (also called independent, predictor etc), and then, we needed a y variable (also called dependent, outcome, predicted etc).

[ ]:
```
# Selecting our X set and y

X = data.drop('MEDV', axis=1)
y = data.MEDV
```

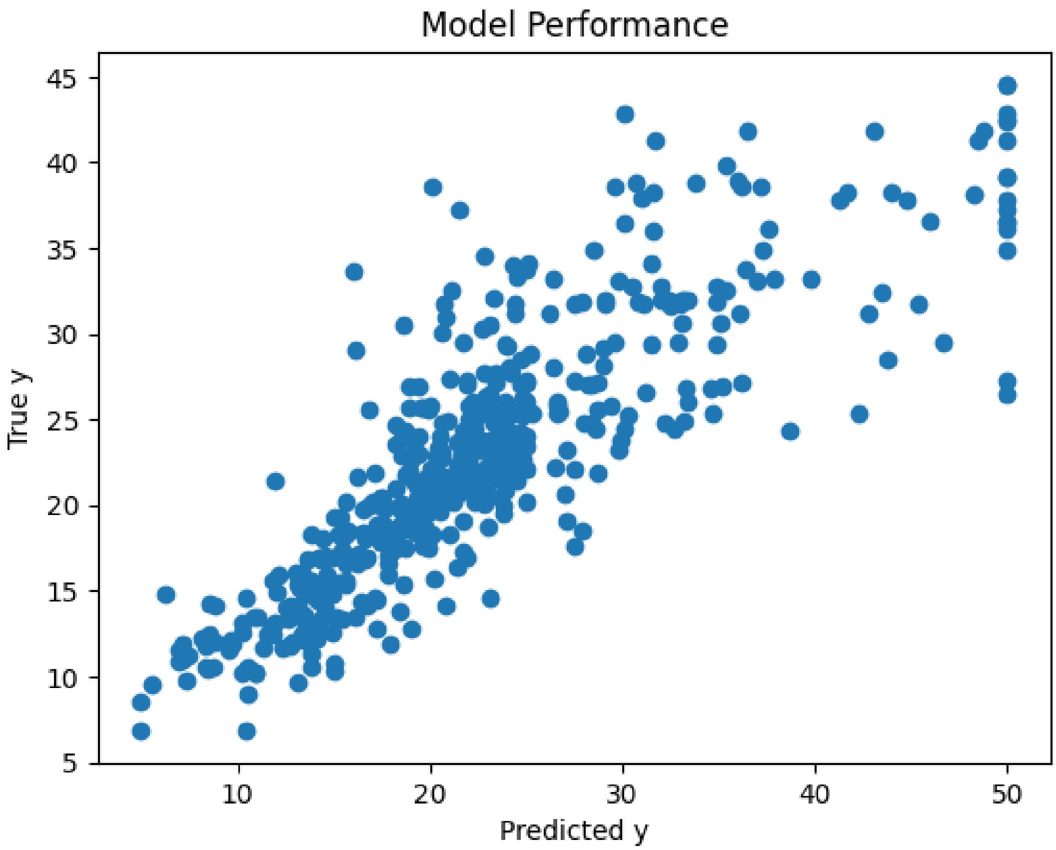
Now we can train the `KNeighborsRegressor` model, this model naturally makes predictions by averaging the values of the 5 neighbors to the point that you want to predict

[ ]:
```
# lets traing the KNeighborsRegressor

knn_model = KNeighborsRegressor() # instanciate the model class
knn_model.fit(X, y) # train the model on X, y
score = knn_model.score(X, y) # obtain the model score on X, y
predicted_y = knn_model.predict(X) # make predictions on X

print('score:', score)
```

```
score: 0.716098217736928
```

Now lets go ahead and try to visualize the performance of the model. The scatter plot is of true labels against predicted labels. Do you think the model is doing well?

[ ]:
```
# looking at the performance

plt.scatter(y, predicted_y)
plt.title('Model Performance')
plt.xlabel('Predicted y')
plt.ylabel('True y')
plt.show()
```



0.2 Some feature selection.

Feature selection is a process where you automatically select those features in your data that contribute most to the prediction variable or output in which you are interested.

In week 7 we learned that having irrelevant features in your data can decrease the accuracy of many models. In the code below, we try to find out the best features that best contribute to the outcome variable

[ ]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_regression # score function for ANOVA␣
↪with continuous outcome
```

[ ]:
```
# lets do some feature selection using ANOVA

data_num = data.drop(['CHAS','RAD'], axis=1) # dropping categorical
X = data_num.drop("MEDV", axis=1)
y = data_num.MEDV

# using SelectKBest
test_reg = SelectKBest(score_func=f_regression, k=6)
```

```
fit_boston = test_reg.fit(X, y)
indexes = fit_boston.get_support(indices=True)

print(fit_boston.scores_)
print(indexes)
```

```
[ 89.48611476  75.2576423  153.95488314 112.59148028 471.84673988
  83.47745922  33.57957033 141.76135658 175.10554288  63.05422911
 601.61787111]
[ 2  3  4  7  8 10]
```

From above, we can see from above that the best features for now are those in indexes `[ 2  3  4  7  8 10]` in the `num_data` dataset. Lets find them in the `data` and add on our categorical ones to set up our new X set

[ ]:
```
# redifining the X set

new_X = data[['INDUS', 'NOX', 'RM', 'TAX', 'PTRATIO', 'LSTAT', 'CHAS','RAD']]
```

0.2.1 Training our second model

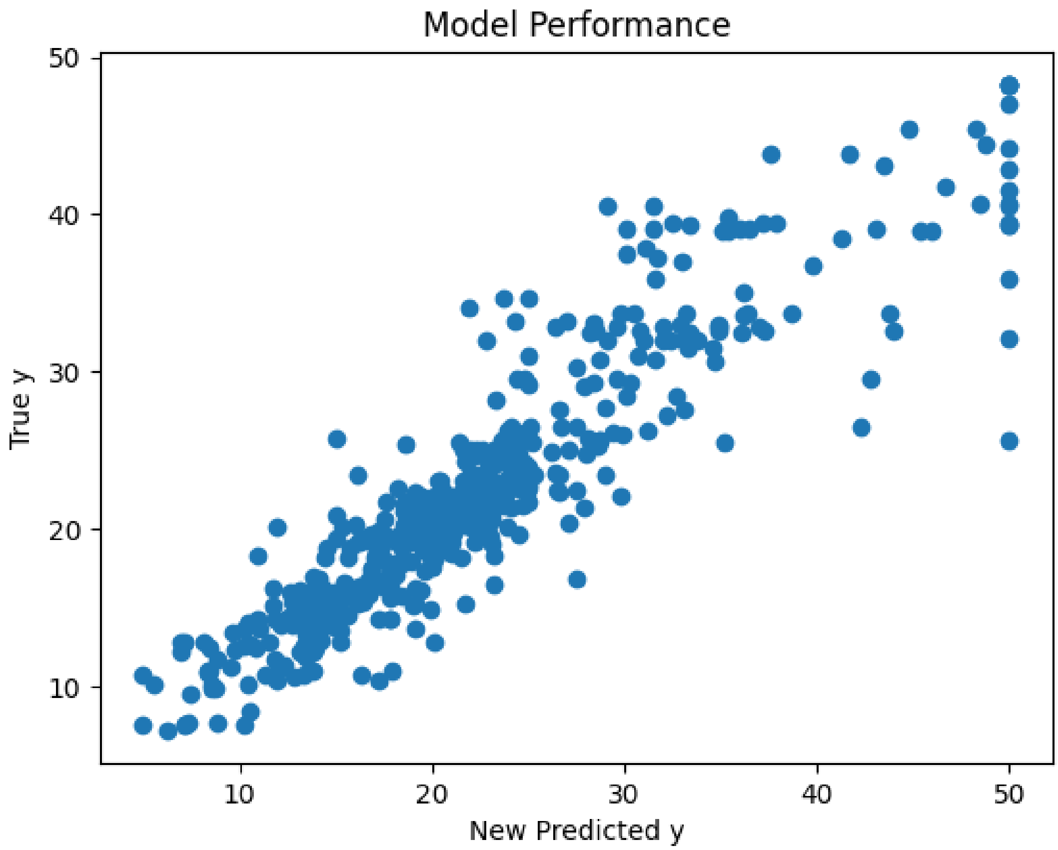
Now that we have selected out the features, X that we thing best contribute to the outcome, let's retrain our machine learning model and see if we are gonna get better results

[ ]:
```
knn_model = KNeighborsRegressor()
knn_model.fit(new_X, y)
new_score = knn_model.score(new_X, y)
new_predicted_y = knn_model.predict(new_X)

print('Feature selected score:', new_score)
```

```
Feature selected score: 0.8324963639640872
```

The model seems to score better with a significant increment in accuracy from `0.71` to `0.83`. As like last time, let us try to visualize the difference in performance

[ ]:
```
plt.scatter(y, new_predicted_y)
plt.title('Model Performance')
plt.xlabel('New Predicted y')
plt.ylabel('True y')
plt.show()
```



I do not know about you, but as for me, I notice a meaningful improvement in the predictions made from the model considering this scatter plot

0.3 Scaling the data

In week 7, we learned some advantages of scaling our data like:

- preventing dominance by features with larger scales
- faster convergence in optimization algorithms
- reduce the impact of outliers

In the next section, we will use the sklearn `StandardScaler` to rescale our data, read more about it in the sklearn documentation

[ ]:
```
# importing the StandardScaler

from sklearn.preprocessing import StandardScaler
```

[ ]:
```
scaler = StandardScaler() # instanciating the StandardScaler
standardized_data_num = scaler.fit_transform(
    data[['INDUS', 'NOX', 'RM', 'TAX', 'PTRATIO', 'LSTAT']]
    ) # rescaline numeric features
```

```
standardized_data_num_df = pd.DataFrame(
    standardized_data_num,
    columns=['INDUS', 'NOX', 'RM', 'TAX', 'PTRATIO', 'LSTAT']
    ) # converting the standardized to dataframe
```

[ ]:
```
from sklearn.preprocessing import OneHotEncoder
```

[ ]:
```
one_hot_encoder = OneHotEncoder()
encoded_data_cat = one_hot_encoder.fit_transform(data[['CHAS', 'RAD']])
encoded_data_cat_array = encoded_data_cat.toarray()
# Get feature names
feature_names = one_hot_encoder.get_feature_names_out(['CHAS', 'RAD'])

encoded_data_cat_df = pd.DataFrame(
    data=encoded_data_cat_array,
    columns=feature_names
)
```

Let us add that to the new X and form a standardized new X set

[ ]:
```
standardized_new_X = pd.concat(
    [standardized_data_num_df, encoded_data_cat_df],
    axis=1
    )
```

0.3.1 Training our third model

Now that we have the *right* features selected and standardized, let us train a new model and see if it is gonna beat the first models

[ ]:
```
knn_model = KNeighborsRegressor()
knn_model.fit(standardized_new_X, y)
new_stardard_score = knn_model.score(standardized_new_X, y)
new_predicted_y = knn_model.predict(standardized_new_X)

print('Standardized score:', new_stardard_score)
```

```
Standardized score: 0.8734524530397529
```

This new models appears to do better than the earlier ones with an improvement in score from `0.83` to `0.87`. Do you think this is now a good model?

0.4 The Pipeline

It turns out the above efforts to improve the performance of the model add extra steps to pass before you can have a *good* model. But what about if we can put together the transformers into on object we do most of that stuff.

The sklearn `Pipeline` allows you to sequentially apply a list of transformers to preprocess the data and, if desired, conclude the sequence with a final predictor for predictive modeling.

Intermediate steps of the pipeline must be 'transforms', that is, they must implement fit and transform methods. The final estimator only needs to implement fit.

Let us build a model that puts together transformation and modelling steps into one `pipeline` object

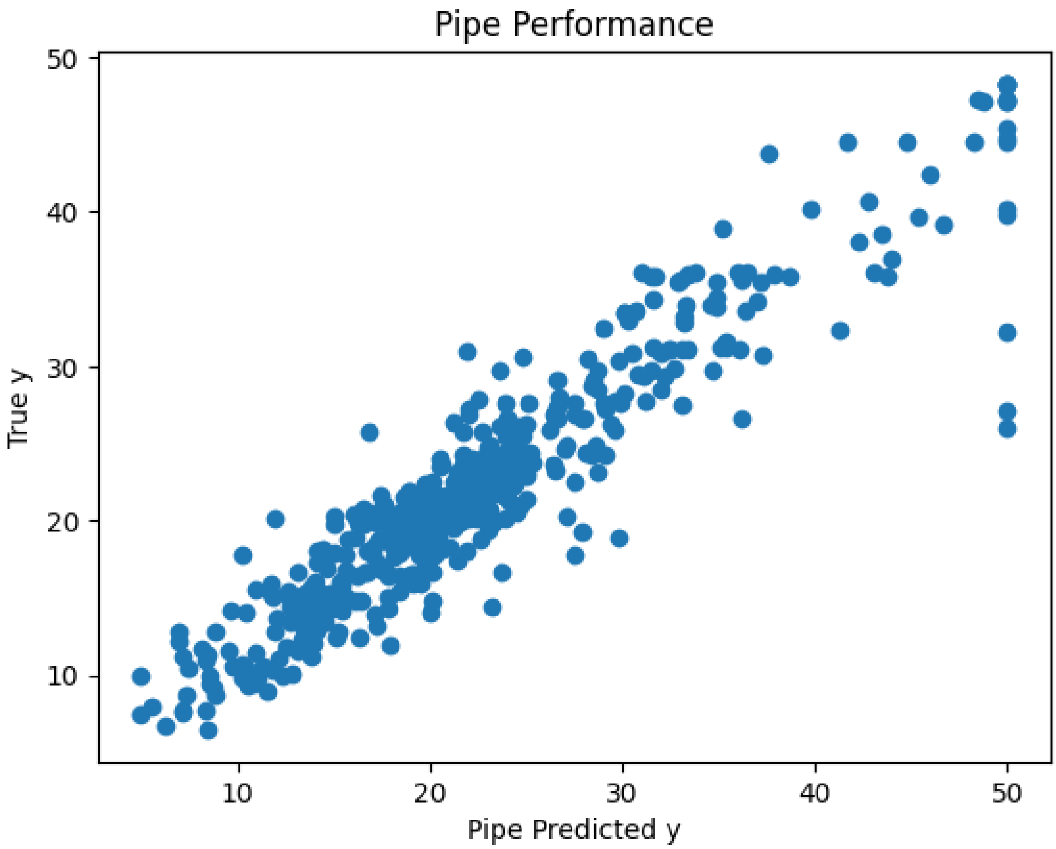
[ ]:
```
# lets import the Pipeline from sklearn

from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
```

[ ]:
```
numeric_cols = ['INDUS', 'NOX', 'RM', 'TAX', 'PTRATIO', 'LSTAT']
categorical_cols = ['CHAS', 'RAD']
```

[ ]:
```
# Preprocessing steps
numeric_transformer = StandardScaler()
categorical_transformer = OneHotEncoder()

# Combine preprocessing steps
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])

# Pipeline
pipe = Pipeline([
    ('preprocessor', preprocessor),
    ('model', KNeighborsRegressor())
])

# Fit the pipeline
pipe.fit(new_X, y)

# Score the pipeline
pipe_score = pipe.score(new_X, y)

# Predict using the pipeline
pipe_predicted_y = pipe.predict(new_X)

print('Pipe Score:', pipe_score)
```

```
Pipe Score: 0.8734524530397529
```

[ ]:
```
plt.scatter(y, pipe_predicted_y)
plt.title('Pipe Performance')
plt.xlabel('Pipe Predicted y')
plt.ylabel('True y')
plt.show()
```



We can observe that the model still gets the same good score, but now all the transformation steps, both on numeric and categorical variables are in a single pipeline object together with the model.