house-price-prediction

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1 Pipeline for predicting house prices

This is a simple example of how to: take a modest dataset, distill the feature set through exploratory data analysis, and then scale down features and train a variety of regression models via a pipeline. In the end, I select the random forest regression model, which typically yields very good results, and apply a grid search to tune model parameters, before predicting prices.

1.1 Imports

In [171]:
```
import sklearn.datasets as datasets

import re
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

from pandas.plotting import scatter_matrix
import seaborn as sns

from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score, KFold
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LinearRegression, Lasso, ElasticNet
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR

from sklearn.pipeline import Pipeline

from sklearn.externals import joblib
```

```
from sklearn.metrics import mean_squared_error

# We want to make sure all numbers display in a consistent manner
pd.options.display.float_format = '{:.5f}'.format
```

1.2 Loading in data

In this case we are using the standard sklearn dataset called 'Boston House Prices', which contains features about houses (e.g. location, age, number of rooms, basement area), where the median values of the properties are the target values.

1.2.1 Boston House Prices dataset

Notes Data Set Characteristics:

```
:Number of Instances: 506

:Number of Attributes: 13 numeric/categorical predictive

:Median Value (attribute 14) is usually the target

:Attribute Information (in order):
    - 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
```

```
In [194]: # Load dataset
          data = datasets.load_boston()
          # Extract feature names, predictors and targets from sklearn dictionary
          names = data.feature_names
          predictors = data.data
          targets = data.target
          # Concatenate predictors and targets for easier processing later on. Let's also name
          df = pd.concat([pd.DataFrame(predictors, columns=names), pd.DataFrame(targets, colum
```

1.3 Inspecting data

We have everything in one table with all columns labelled, as intended.

```
In [195]: df.head()
```

```
Out[195]:      CRIM       ZN   INDUS    CHAS     NOX      RM      AGE     DIS     RAD  \
          0 0.00632 18.00000 2.31000 0.00000 0.53800 6.57500 65.20000 4.09000 1.00000
          1 0.02731  0.00000 7.07000 0.00000 0.46900 6.42100 78.90000 4.96710 2.00000
          2 0.02729  0.00000 7.07000 0.00000 0.46900 7.18500 61.10000 4.96710 2.00000
          3 0.03237  0.00000 2.18000 0.00000 0.45800 6.99800 45.80000 6.06220 3.00000
          4 0.06905  0.00000 2.18000 0.00000 0.45800 7.14700 54.20000 6.06220 3.00000

                TAX  PTRATIO         B   LSTAT     MEDV
          0 296.00000 15.30000 396.90000 4.98000 24.00000
          1 242.00000 17.80000 396.90000 9.14000 21.60000
          2 242.00000 17.80000 392.83000 4.03000 34.70000
          3 222.00000 18.70000 394.63000 2.94000 33.40000
          4 222.00000 18.70000 396.90000 5.33000 36.20000
```

Lets confirm what type of values we have (should all be floating values).

```
In [196]: df.dtypes.value_counts()
```

```
Out[196]: float64    14
          dtype: int64
```

Lets summarize each attribute. From a glance we could expect some of the data to be quite skewed.

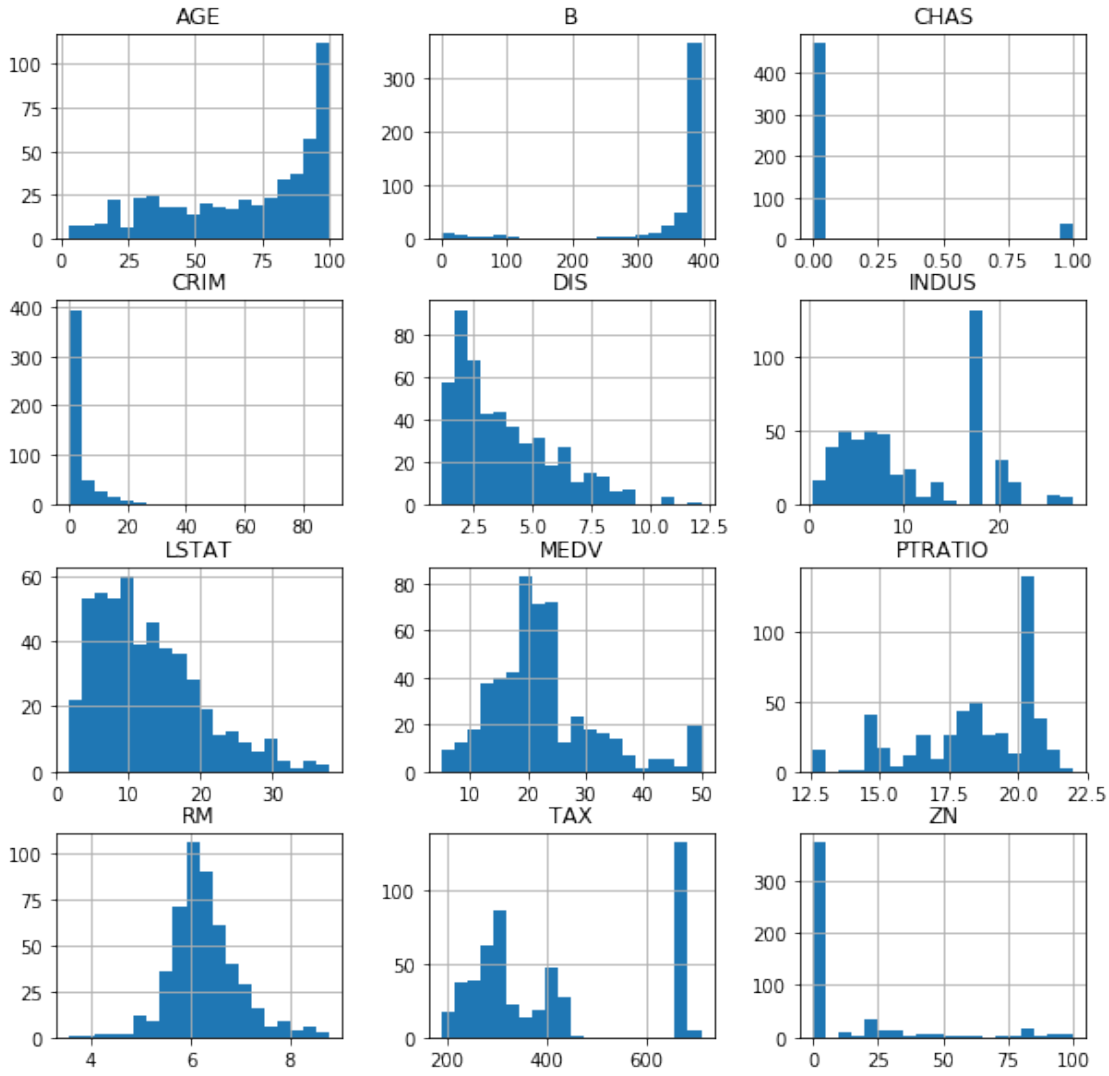
```
In [197]: df.describe()
```

```
Out[197]:             CRIM        ZN      INDUS      CHAS       NOX        RM       AGE  \
          count 506.00000 506.00000 506.00000 506.00000 506.00000 506.00000 506.00000
          mean    3.59376  11.36364  11.13678   0.06917   0.55470   6.28463  68.57490
          std     8.59678  23.32245   6.86035   0.25399   0.11588   0.70262  28.14886
          min     0.00632   0.00000   0.46000   0.00000   0.38500   3.56100   2.90000
          25%     0.08204   0.00000   5.19000   0.00000   0.44900   5.88550  45.02500
          50%     0.25651   0.00000   9.69000   0.00000   0.53800   6.20850  77.50000
          75%     3.64742  12.50000  18.10000   0.00000   0.62400   6.62350  94.07500
          max    88.97620 100.00000  27.74000   1.00000   0.87100   8.78000 100.00000

                      DIS       RAD       TAX   PTRATIO         B     LSTAT      MEDV
          count 506.00000 506.00000 506.00000 506.00000 506.00000 506.00000 506.00000
          mean    3.79504   9.54941 408.23715  18.45553 356.67403  12.65306  22.53281
          std     2.10571   8.70726 168.53712   2.16495  91.29486   7.14106   9.19710
          min     1.12960   1.00000 187.00000  12.60000   0.32000   1.73000   5.00000
          25%     2.10018   4.00000 279.00000  17.40000 375.37750   6.95000  17.02500
          50%     3.20745   5.00000 330.00000  19.05000 391.44000  11.36000  21.20000
          75%     5.18843  24.00000 666.00000  20.20000 396.22500  16.95500  25.00000
          max    12.12650  24.00000 711.00000  22.00000 396.90000  37.97000  50.00000
```

We can also plot histograms for each column to get a clear idea of the shape of the data. It might be a good idea to redistribute some of the data. I will skip over it for now.

```
In [208]: df.hist(figsize=(10, 10), bins=20)
          plt.show()
```



We need to make sure we don't have any Nan values in our dataset, otherwise the ML algorithms will fail.

```
In [198]: df.isna().sum()

Out[198]: CRIM       0
          ZN         0
          INDUS      0
          CHAS       0
```

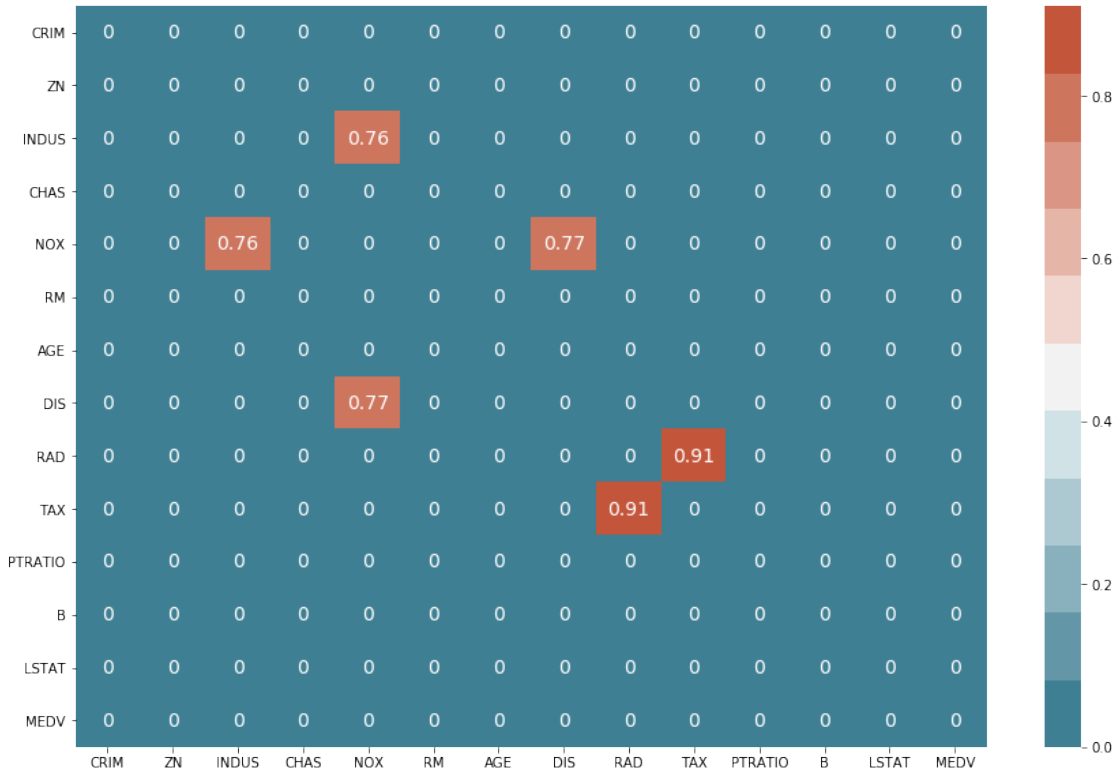
```
NOX         0
RM          0
AGE         0
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT       0
MEDV        0
dtype: int64
```

Now lets see if we can find strong correlations between columns.

```
In [199]: df_corr = df.corr().abs()
          filter = (df_corr == 1) | (df_corr < 0.75)
          df_corr[filter] = 0
          df_corr

          f, ax = plt.subplots(figsize=(15, 10))
          sns.heatmap(df_corr, annot=True, annot_kws={'size': 14},
                      cmap=sns.diverging_palette(220, 20, n=11))
```

```
Out[199]: <matplotlib.axes._subplots.AxesSubplot at 0x1a16ec5da0>
```



1.4 Dimensionality reduction

From the previous plot, we were able to ascertain that the 'NOX' and the 'RAD' columns are strongly correlated with other columns. Therefore, lets go ahead a drop them from our dataframe.

```
In [200]: cols_corr_manual = ['NOX', 'RAD']
          df = df.drop(columns=cols_corr_manual)
          df.head()
```

Out[200]:

	CRIM	ZN	INDUS	CHAS	RM	AGE	DIS	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.00000	2.31000	0.00000	6.57500	65.20000	4.09000	296.00000	15.30000	396.90000	4.98000	24.00000
1	0.02731	0.00000	7.07000	0.00000	6.42100	78.90000	4.96710	242.00000	17.80000	396.90000	9.14000	21.60000
2	0.02729	0.00000	7.07000	0.00000	7.18500	61.10000	4.96710	242.00000	17.80000	392.83000	4.03000	34.70000
3	0.03237	0.00000	2.18000	0.00000	6.99800	45.80000	6.06220	222.00000	18.70000	394.63000	2.94000	33.40000
4	0.06905	0.00000	2.18000	0.00000	7.14700	54.20000	6.06220	222.00000	18.70000	396.90000	5.33000	36.20000

1.5 Setting up train and test datasets

Now we are ready to peel of the last column and assign to the target (y) variable and the rest of the data can be assigned to the predictor (X) variable. After that, we use the sklearn train_test_split function to create train and test datasets for both X and y.

```
In [201]: # Train-set predictors/targets
          X = df.iloc[:, 0:-1]
          y = df.iloc[:, -1]
```

```
In [202]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state
```

1.6 Initialising models, setting up a pipeline, training and predicting

For this part, I would like a list of regression models, then I will create a pipeline that scales the data, reduces feature dimensionality (via PCA) and trains the model, all in one go. We can loop through each model, inserting it into the pipeline, and then finally we can see how the models compare to one another.

```
In [210]: # Lets append tuples to the list that contain both the name of the model and the mod
          # This is what the pipeline expects
          models = []
          models.append( ('LR', LinearRegression()) )
          models.append( ('Lasso', Lasso()) )
          models.append( ('ElasticNet', ElasticNet()) )
          models.append( ('KNN', KNeighborsRegressor()) )
          models.append( ('CART', DecisionTreeRegressor()) )
          models.append( ('SVR', SVR()) )
```

```
In [204]: # Now we can loop through the models and run the pipeline each time
          for name, model in models:
              pipelined_model = Pipeline([('minmax', MinMaxScaler()),
                                          ('pca', PCA(n_components = 3)),
                                          (name, model)])

              # Train model
              pipelined_model.fit(X_train, y_train)

              # Make predictions on the test-set
              y_hat = pipelined_model.predict(X_test)

              # Calculate error
              RMSE = np.sqrt(mean_squared_error(y_test, y_hat))
              print('Model: ', name, ' | RMSE: ', RMSE)
              print('----------------')

              # I also like to save the models each time as a matter of habit
              joblib.dump(pipelined_model, '{}_model.pkl'.format(name))
```

```
Model:  LR  | RMSE:  7.15970109322
----------------
Model:  Lasso  | RMSE:  7.57962692126
----------------
Model:  ElasticNet  | RMSE:  8.1579157098
----------------
Model:  KNN  | RMSE:  6.36588579546
----------------
Model:  CART  | RMSE:  9.45087919969
----------------
Model:  SVR  | RMSE:  7.60464954267
----------------
```

We will now run the pipeline just once with yet another model - the RandomForest regressor - and incorporate a gridsearch to tune the model parameters.

```
In [ ]: # The pipeline as before, but this time the model type is static
        pipelined_model = Pipeline([('minmax', MinMaxScaler()),
                                    ('pca', PCA(n_components = 3)),
                                    ('RF', RandomForestRegressor())])

        grid = {
                'RF__n_estimators': [100, 200, 300, 400, 500],
                'RF__max_depth': [10, 20, 30, 40, 50],
                'RF__min_samples_leaf': [10, 15, 20, 25, 30]
                }
```

```
        # Run cross-validation & discover best combination of params, with 10 folds of cross-v
        grid_search_cv = GridSearchCV(pipelined_model,
                                      grid,
                                      cv=KFold(n_splits=10, random_state=7),
                                      scoring='neg_mean_squared_error',
                                      n_jobs = -1)

        results = grid_search_cv.fit(X_train, y_train)

        print(results.best_score_)
        print(results.best_params_)
```

Now we can create a new instance of the pipeline and pass the 'best_params_' of the gridsearch directly into the regressor.

```
In [205]: pipelined_model = Pipeline([('minmax', MinMaxScaler()),
                                       ('pca', PCA(n_components = 3)),
                                       ('RF', RandomForestRegressor(n_estimators=results.best_params_['RF_
                                                                    max_depth=results.best_params_['RF__ma
                                                                    min_samples_leaf=results.best_params_[

          pipelined_model.fit(X_train, y_train)

          joblib.dump(pipelined_model, 'RF_model.pkl')

Out[205]: ['RF_model.pkl']
```

Once more, we make predictions using the test set.

```
In [206]: # Lets make predictions on the test-set
          y_hat = pipelined_model.predict(X_test)

          # Calc error
          RMSE = np.sqrt(mean_squared_error(y_test, y_hat))
          print('Model: Random forest', ' | ', 'RMSE: ', RMSE)

Model: Random forest  |  RMSE:  6.31066783749
```

Turns out that our RMSE score wins out by a very tight margin. Let's bare in mind that we off by about $6000 US here, because the target values are counted in the 100