Week 02 - Boston Housing Example

This example loads the Boston Housing data example and performs regression in Python.

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In [3]:
```
import pandas as pd
from sklearn.linear_model import LinearRegression, Ridge
from sklearn import metrics
```

Prepare the Data

In [5]:
```
dfBoston = pd.read_excel(r'W2 - Boston Housing.xlsx')
```

In [7]:
```
dfBoston.head(5)
```

Out[7]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	TAX	PTRATIO	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	296	15.3	561.120
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	242	17.8	505.008
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	242	17.8	811.286
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	222	18.7	780.892
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	222	18.7	846.356

In [9]:
```
dfBoston.describe()
```

Out[9]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.00
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	408.23
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	168.53
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	187.00
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	279.00
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	330.00
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	666.00
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	711.00

Check for missing/null values

In [12]:
```
dfBoston.isnull().sum()
```

Out[12]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
TAX        0
PTRATIO    0
MEDV       0
dtype: int64
```

Check datatypes for regression

In [14]:
```
dfBoston.dtypes
```

Out[14]:
```
CRIM       float64
ZN         float64
INDUS      float64
CHAS         int64
NOX        float64
RM         float64
AGE        float64
DIS        float64
TAX          int64
PTRATIO    float64
MEDV       float64
dtype: object
```

Split the data into X and y:

In [23]:
```
y = dfBoston['MEDV']
X = dfBoston.drop(columns=['MEDV'])
```

Prepare the Regressions

Specify Hyperparameters

Normally we would calibrate the regularization parameter using a grid-search or cross-validation; however, for simplicity we are just using λ = 10.0.

In [44]:
```
regLambda = 10.0 # Note that lambda is a protected word in python
```

Given hyperparameters, initialize the models - no hyperparameters for classical linear regression.

In [45]:
```
classicLR = LinearRegression()
ridgeLR = Ridge(alpha = regLambda)
```

Fit the models

In [24]:
```
model_CLR = classicLR.fit(X, y)
```

In [46]:
```
model_RLR = ridgeLR.fit(X, y)
```

Build predictions (in-sample)

In [47]:
```
yp = model_CLR.predict(X)
ypr = model_RLR.predict(X)
```

Simple performance metrics

We are not using a validation/holdout set this week. Typically cross-validation or train/validate/test splits would apply when evaluating machine learning models.

In [48]:
```
print("Classical: ")
print("R2:   %10.3f" % metrics.r2_score(y, yp))
print("RMSE: %10.4f" % metrics.mean_squared_error(y, yp) ** 0.5)
print("")
print("Ridge:")
print("R2:   %10.3f" % metrics.r2_score(y, ypr))
print("RMSE: %10.4f" % metrics.mean_squared_error(y, ypr) ** 0.5)
```

```
Classical: 
R2:        0.737
RMSE:   105.7196

Ridge:
R2:        0.728
RMSE:   107.5038
```

Output intercepts and coefficients for comparison

In [49]:
```
#  Simple vs. Regularized (Ridge)
cols= len(X.columns)
coeffs = [model_CLR.coef_, model_RLR.coef_]

print ("%8s" % "VAR", "%9s" % "SIMPLE", "%9s" % "RIDGE", "%9s" % "Delta")
print ("%8s" % "CONSTANT", "%9.4f" % model_CLR.intercept_, "%9.4f" % model_RLR.inte
rcept_, "%9.4f" % (model_CLR.intercept_ - model_RLR.intercept_))
for i in range(0,cols):
    print("%8s" % X.columns[i], "%9.4f" % coeffs[0][i], "%9.4f" % coeffs[1][i], "%
9.4f" % (coeffs[0][i] - coeffs[1][i]))
```

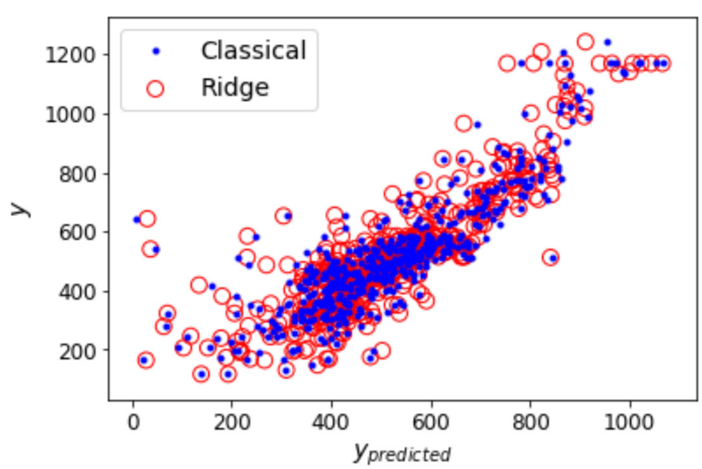
```
     VAR    SIMPLE     RIDGE     Delta
CONSTANT  460.8067  287.9152  172.8914
    CRIM   -2.9659   -3.0527    0.0868
      ZN    0.6512    0.7459   -0.0947
   INDUS   -1.8057   -3.3139    1.5083
    CHAS   49.9448   36.7983   13.1466
     NOX -388.1702  -54.2600 -333.9102
      RM  150.8887  147.7418    3.1469
     AGE   -1.2088   -1.5286    0.3198
     DIS  -32.8275  -28.1377   -4.6898
     TAX   -0.0966   -0.1630    0.0664
 PTRATIO  -21.9390  -18.9238   -3.0152
```

Plots and visualizations

In [50]:
```
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
```

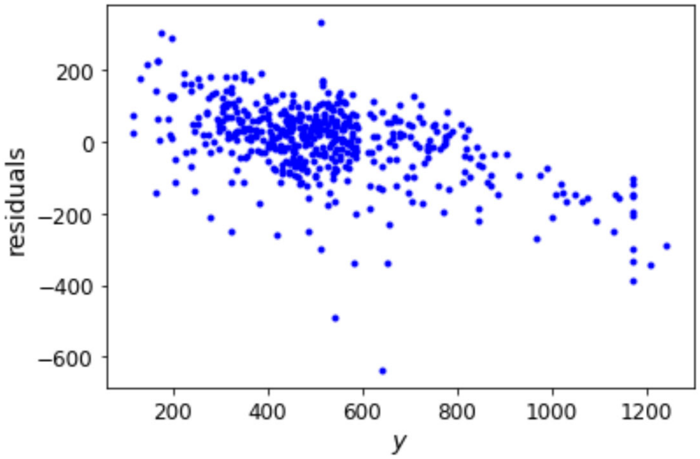
Plot Y vs. Prediction using Classical and Ridge

In [64]:
```
plt.plot(yp, y, "b.", label="Classical")
plt.scatter(ypr, y, s=80, facecolors='none', edgecolors='r', label="Ridge")
plt.xlabel("$y_{predicted}$")
plt.ylabel("$y$")
plt.legend(loc="upper left", fontsize=14)
plt.show()
```

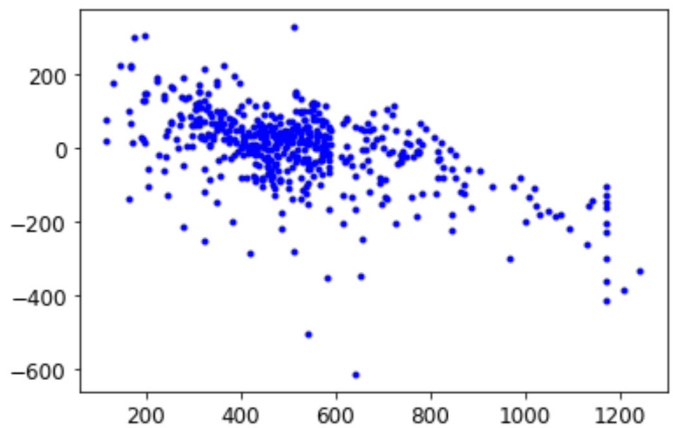


Plot residuals for classical and ridge

In [60]:
```
plt.plot(y, (yp - y), "b.")
plt.xlabel("$y$")
plt.ylabel("residuals")
plt.show()
```



In [63]:
```
plt.plot(y,(ypr-y), "b.")
plt.show()
```



End of Notebook!