Download data

Data available via scikit-learn

> https://scikit-learn.org/stable/modules/classes.html#module-sklearn.datasets (https://scikit-learn.org/stable/modules/classes.html#module-sklearn.datasets)

In [14]:

```
from sklearn import datasets

##### classifiction (supervised/descrete) #####
wine_bunch = datasets.load_wine()
print(type(wine_bunch))
print(wine_bunch.keys())
# print(wine_bunch.DESCR)

##### regression (supervised/continuous) #####
reg_bunch = datasets.load_boston()
print(reg_bunch.keys())


##### clustering (unsupervised/descrete) ####
#radmon generated data
# gene expression
##### dimensionality reduction (unuspervised/continuous) #####
#https://idyll.pub/post/dimensionality-reduction-293e465c2a3443e8941b016d/
#gene expression
```

```
<class 'sklearn.utils.Bunch'>
dict_keys(['data', 'target', 'target_names', 'DESCR', 'feature_names'])
.. _wine_dataset:

Wine recognition dataset
------------------------

**Data Set Characteristics:**

    :Number of Instances: 178 (50 in each of three classes)
    :Number of Attributes: 13 numeric, predictive attributes and the class
    :Attribute Information:
            - Alcohol
            - Malic acid
            - Ash
            - Alcalinity of ash
            - Magnesium
            - Total phenols
            - Flavanoids
            - Nonflavanoid phenols
            - Proanthocyanins
            - Color intensity
            - Hue
            - OD280/OD315 of diluted wines
            - Proline

    - class:
            - class_0
            - class_1
            - class_2

    :Summary Statistics:

    ============================= ==== ===== ======= =====
                                   Min   Max   Mean     SD
    ============================= ==== ===== ======= =====
    Alcohol:                      11.0  14.8    13.0   0.8
    Malic Acid:                   0.74  5.80    2.34  1.12
    Ash:                          1.36  3.23    2.36  0.27
    Alcalinity of Ash:            10.6  30.0    19.5   3.3
    Magnesium:                    70.0 162.0    99.7  14.3
    Total Phenols:                0.98  3.88    2.29  0.63
    Flavanoids:                   0.34  5.08    2.03  1.00
    Nonflavanoid Phenols:         0.13  0.66    0.36  0.12
    Proanthocyanins:              0.41  3.58    1.59  0.57
    Colour Intensity:              1.3  13.0     5.1   2.3
    Hue:                          0.48  1.71    0.96  0.23
    OD280/OD315 of diluted wines: 1.27  4.00    2.61  0.71
    Proline:                       278  1680     746   315
    ============================= ==== ===== ======= =====

    :Missing Attribute Values: None
    :Class Distribution: class_0 (59), class_1 (71), class_2 (48)
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988
```

```
This is a copy of UCI ML Wine recognition datasets.
https://archive.ics.uci.edu/ml/machine-learning-databases/wine/wine.data

The data is the results of a chemical analysis of wines grown in the same
region in Italy by three different cultivators. There are thirteen different
measurements taken for different constituents found in the three types of
wine.

Original Owners:

Forina, M. et al, PARVUS -
An Extendible Package for Data Exploration, Classification and Correlation.
Institute of Pharmaceutical and Food Analysis and Technologies,
Via Brigata Salerno, 16147 Genoa, Italy.

Citation:

Lichman, M. (2013). UCI Machine Learning Repository
[https://archive.ics.uci.edu/ml]. Irvine, CA: University of California,
School of Information and Computer Science.

.. topic:: References

  (1) S. Aeberhard, D. Coomans and O. de Vel,
  Comparison of Classifiers in High Dimensional Settings,
  Tech. Rep. no. 92-02, (1992), Dept. of Computer Science and Dept. of
  Mathematics and Statistics, James Cook University of North Queensland.
  (Also submitted to Technometrics).

  The data was used with many others for comparing various
  classifiers. The classes are separable, though only RDA
  has achieved 100% correct classification.
  (RDA : 100%, QDA 99.4%, LDA 98.9%, 1NN 96.1% (z-transformed data))
  (All results using the leave-one-out technique)

  (2) S. Aeberhard, D. Coomans and O. de Vel,
  "THE CLASSIFICATION PERFORMANCE OF RDA"
  Tech. Rep. no. 92-01, (1992), Dept. of Computer Science and Dept. of
  Mathematics and Statistics, James Cook University of North Queensland.
  (Also submitted to Journal of Chemometrics).

dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

Pandas overview

In [16]:
```
import pandas as pd
import numpy as np
wine = pd.DataFrame(wine_bunch.data, columns=wine_bunch.feature_names)
display(wine)

# # play with these functions #
# print(list(wine))
# print(wine.proline)
# print(wine.iloc[10:20,])
# # print(wine.iloc[10:20,['ash','magnesium']])  # error bec iloc but col name
instead of index
# print(wine.iloc[10:20,0:3])
# print(wine.loc[10:20,['ash','magnesium']])
```

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflava
0	14.23	1.71	2.43	15.6	127.0	2.80	3.06	
1	13.20	1.78	2.14	11.2	100.0	2.65	2.76	
2	13.16	2.36	2.67	18.6	101.0	2.80	3.24	
3	14.37	1.95	2.50	16.8	113.0	3.85	3.49	
4	13.24	2.59	2.87	21.0	118.0	2.80	2.69	
5	14.20	1.76	2.45	15.2	112.0	3.27	3.39	
6	14.39	1.87	2.45	14.6	96.0	2.50	2.52	
7	14.06	2.15	2.61	17.6	121.0	2.60	2.51	
8	14.83	1.64	2.17	14.0	97.0	2.80	2.98	
9	13.86	1.35	2.27	16.0	98.0	2.98	3.15	
10	14.10	2.16	2.30	18.0	105.0	2.95	3.32	
11	14.12	1.48	2.32	16.8	95.0	2.20	2.43	
12	13.75	1.73	2.41	16.0	89.0	2.60	2.76	
13	14.75	1.73	2.39	11.4	91.0	3.10	3.69	
14	14.38	1.87	2.38	12.0	102.0	3.30	3.64	
15	13.63	1.81	2.70	17.2	112.0	2.85	2.91	
16	14.30	1.92	2.72	20.0	120.0	2.80	3.14	
17	13.83	1.57	2.62	20.0	115.0	2.95	3.40	
18	14.19	1.59	2.48	16.5	108.0	3.30	3.93	
19	13.64	3.10	2.56	15.2	116.0	2.70	3.03	
20	14.06	1.63	2.28	16.0	126.0	3.00	3.17	
21	12.93	3.80	2.65	18.6	102.0	2.41	2.41	
22	13.71	1.86	2.36	16.6	101.0	2.61	2.88	
23	12.85	1.60	2.52	17.8	95.0	2.48	2.37	
24	13.50	1.81	2.61	20.0	96.0	2.53	2.61	
25	13.05	2.05	3.22	25.0	124.0	2.63	2.68	
26	13.39	1.77	2.62	16.1	93.0	2.85	2.94	
27	13.30	1.72	2.14	17.0	94.0	2.40	2.19	
28	13.87	1.90	2.80	19.4	107.0	2.95	2.97	
29	14.02	1.68	2.21	16.0	96.0	2.65	2.33	
...	...	...	...	...	...	...	...	
148	13.32	3.24	2.38	21.5	92.0	1.93	0.76	
149	13.08	3.90	2.36	21.5	113.0	1.41	1.39	
150	13.50	3.12	2.62	24.0	123.0	1.40	1.57	
151	12.79	2.67	2.48	22.0	112.0	1.48	1.36	

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflava
152	13.11	1.90	2.75	25.5	116.0	2.20	1.28	
153	13.23	3.30	2.28	18.5	98.0	1.80	0.83	
154	12.58	1.29	2.10	20.0	103.0	1.48	0.58	
155	13.17	5.19	2.32	22.0	93.0	1.74	0.63	
156	13.84	4.12	2.38	19.5	89.0	1.80	0.83	
157	12.45	3.03	2.64	27.0	97.0	1.90	0.58	
158	14.34	1.68	2.70	25.0	98.0	2.80	1.31	
159	13.48	1.67	2.64	22.5	89.0	2.60	1.10	
160	12.36	3.83	2.38	21.0	88.0	2.30	0.92	
161	13.69	3.26	2.54	20.0	107.0	1.83	0.56	
162	12.85	3.27	2.58	22.0	106.0	1.65	0.60	
163	12.96	3.45	2.35	18.5	106.0	1.39	0.70	
164	13.78	2.76	2.30	22.0	90.0	1.35	0.68	
165	13.73	4.36	2.26	22.5	88.0	1.28	0.47	
166	13.45	3.70	2.60	23.0	111.0	1.70	0.92	
167	12.82	3.37	2.30	19.5	88.0	1.48	0.66	
168	13.58	2.58	2.69	24.5	105.0	1.55	0.84	
169	13.40	4.60	2.86	25.0	112.0	1.98	0.96	
170	12.20	3.03	2.32	19.0	96.0	1.25	0.49	
171	12.77	2.39	2.28	19.5	86.0	1.39	0.51	
172	14.16	2.51	2.48	20.0	91.0	1.68	0.70	
173	13.71	5.65	2.45	20.5	95.0	1.68	0.61	
174	13.40	3.91	2.48	23.0	102.0	1.80	0.75	
175	13.27	4.28	2.26	20.0	120.0	1.59	0.69	
176	13.17	2.59	2.37	20.0	120.0	1.65	0.68	
177	14.13	4.10	2.74	24.5	96.0	2.05	0.76	

178 rows × 13 columns

```
['alcohol', 'malic_acid', 'ash', 'alcalinity_of_ash', 'magnesium', 'total_phe
nols', 'flavanoids', 'nonflavanoid_phenols', 'proanthocyanins', 'color_intens
ity', 'hue', 'od280/od315_of_diluted_wines', 'proline']
0      1065.0
1      1050.0
2      1185.0
3      1480.0
4       735.0
5      1450.0
6      1290.0
7      1295.0
8      1045.0
9      1045.0
10     1510.0
11     1280.0
12     1320.0
13     1150.0
14     1547.0
15     1310.0
16     1280.0
17     1130.0
18     1680.0
19      845.0
20      780.0
21      770.0
22     1035.0
23     1015.0
24      845.0
25      830.0
26     1195.0
27     1285.0
28      915.0
29     1035.0
        ...
148     650.0
149     550.0
150     500.0
151     480.0
152     425.0
153     675.0
154     640.0
155     725.0
156     480.0
157     880.0
158     660.0
159     620.0
160     520.0
161     680.0
162     570.0
163     675.0
164     615.0
165     520.0
166     695.0
167     685.0
168     750.0
169     630.0
170     510.0
```

```
171     470.0
172     660.0
173     740.0
174     750.0
175     835.0
176     840.0
177     560.0
Name: proline, Length: 178, dtype: float64
    alcohol  malic_acid   ash  alcalinity_of_ash  magnesium  total_phenols  \
10    14.10        2.16  2.30               18.0      105.0           2.95
11    14.12        1.48  2.32               16.8       95.0           2.20
12    13.75        1.73  2.41               16.0       89.0           2.60
13    14.75        1.73  2.39               11.4       91.0           3.10
14    14.38        1.87  2.38               12.0      102.0           3.30
15    13.63        1.81  2.70               17.2      112.0           2.85
16    14.30        1.92  2.72               20.0      120.0           2.80
17    13.83        1.57  2.62               20.0      115.0           2.95
18    14.19        1.59  2.48               16.5      108.0           3.30
19    13.64        3.10  2.56               15.2      116.0           2.70

    flavanoids  nonflavanoid_phenols  proanthocyanins  color_intensity   hue
\
10        3.32                  0.22             2.38             5.75  1.25
11        2.43                  0.26             1.57             5.00  1.17
12        2.76                  0.29             1.81             5.60  1.15
13        3.69                  0.43             2.81             5.40  1.25
14        3.64                  0.29             2.96             7.50  1.20
15        2.91                  0.30             1.46             7.30  1.28
16        3.14                  0.33             1.97             6.20  1.07
17        3.40                  0.40             1.72             6.60  1.13
18        3.93                  0.32             1.86             8.70  1.23
19        3.03                  0.17             1.66             5.10  0.96

    od280/od315_of_diluted_wines  proline
10                          3.17   1510.0
11                          2.82   1280.0
12                          2.90   1320.0
13                          2.73   1150.0
14                          3.00   1547.0
15                          2.88   1310.0
16                          2.65   1280.0
17                          2.57   1130.0
18                          2.82   1680.0
19                          3.36    845.0
    alcohol  malic_acid   ash
10    14.10        2.16  2.30
11    14.12        1.48  2.32
12    13.75        1.73  2.41
13    14.75        1.73  2.39
14    14.38        1.87  2.38
15    13.63        1.81  2.70
16    14.30        1.92  2.72
17    13.83        1.57  2.62
18    14.19        1.59  2.48
19    13.64        3.10  2.56
     ash  magnesium
10  2.30      105.0
```

```
11  2.32       95.0
12  2.41       89.0
13  2.39       91.0
14  2.38      102.0
15  2.70      112.0
16  2.72      120.0
17  2.62      115.0
18  2.48      108.0
19  2.56      116.0
20  2.28      126.0
```

wineX is Pandas DataFrame (bacuase we made it a DF earlier)

wineY is ndaray

In [19]:
```
wineX = wine
wineY = wine_bunch.target

print(wineX.shape,wineY.shape)
print(type(wineX))
print(type(wineY))
```

```
(178, 13) (178,)
<class 'pandas.core.frame.DataFrame'>
<class 'numpy.ndarray'>
```

Supervised classification

Test / train split

In [32]:
```
# random sampling
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(wineX, wineY, test_size=0.
2, random_state=42)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
print(type(X_train))
print(type(X_test))
print(type(y_train))
print(type(y_test))
```

```
(142, 13) (142,)
(36, 13) (36,)
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

Repeat the split, but in the context of K-fold validation

In [33]:
```
# k-fold
from sklearn.model_selection import KFold
kf = KFold(n_splits=5,random_state=42, shuffle=True)
kf.get_n_splits(wineX)
print(kf)
for train_index, test_index in kf.split(wineX):
    X_train, X_test = wineX.iloc[train_index], wineX.iloc[test_index]
    y_train, y_test = wineY[train_index], wineY[test_index]
    print(X_train.shape, y_train.shape)
    print(X_test.shape, y_test.shape)
# NOTE: wineX is a dataframe, wineY is a ndarray (syntax is different line 7 a
nd 8)
print(type(X_train))
print(type(X_test))
print(type(y_train))
print(type(y_test))
```

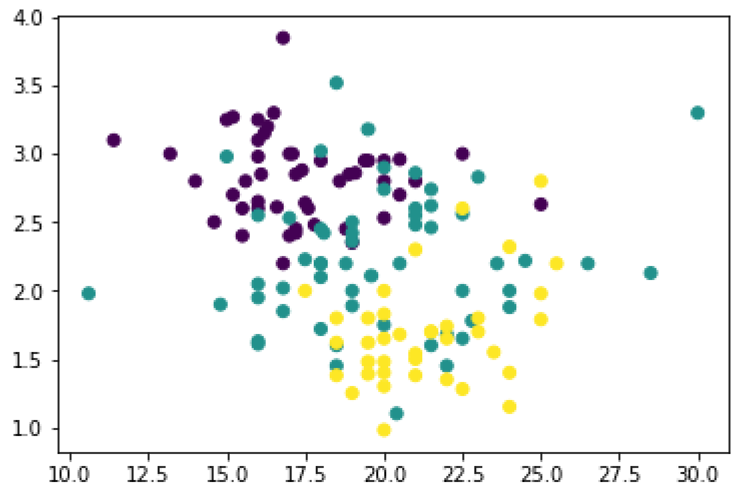
```
KFold(n_splits=5, random_state=42, shuffle=True)
(142, 13) (142,)
(36, 13) (36,)
(142, 13) (142,)
(36, 13) (36,)
(142, 13) (142,)
(36, 13) (36,)
(143, 13) (143,)
(35, 13) (35,)
(143, 13) (143,)
(35, 13) (35,)
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
```

KNN classification

Visualize the data

In [34]:
```
%matplotlib inline
# K Nearest Neighbors
import matplotlib.pyplot as plt
print(list(X_train))
plt.scatter(X_train['alcalinity_of_ash'], X_train['total_phenols'],c=y_train)
plt.show()
# CHANGE which features that you are plotting
# Can only visualize on 2 dimensions but algorithm will cluster on all dimensi
ons
```

```
['alcohol', 'malic_acid', 'ash', 'alcalinity_of_ash', 'magnesium', 'total_phe
nols', 'flavanoids', 'nonflavanoid_phenols', 'proanthocyanins', 'color_intens
ity', 'hue', 'od280/od315_of_diluted_wines', 'proline']
```

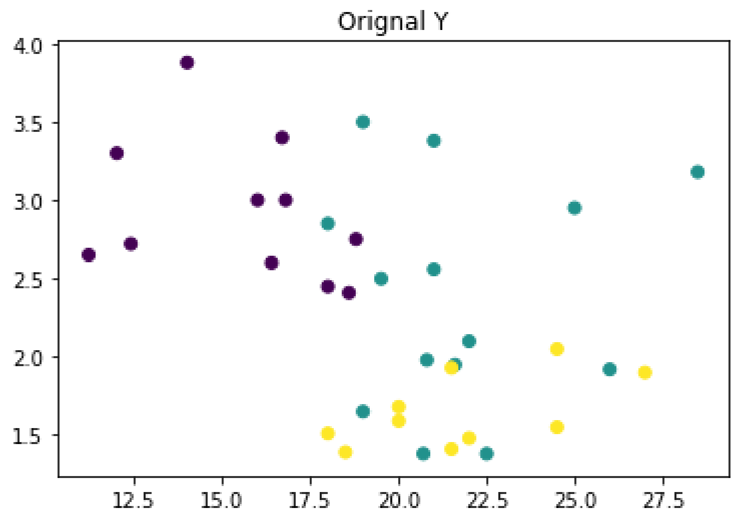


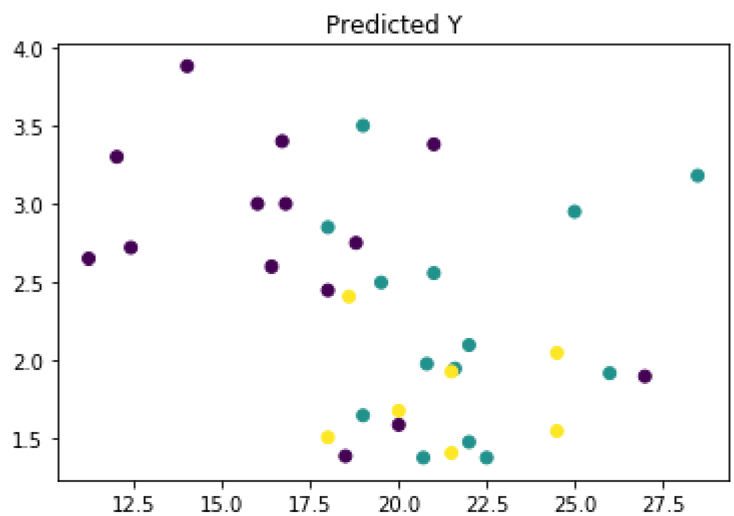
In [30]:
```
from sklearn.neighbors import KNeighborsClassifier
neigh = KNeighborsClassifier(n_neighbors=3, leaf_size=10)
neigh.fit(X_train, y_train)
print(neigh)
# print(neigh.predict(X_test))
# print(neigh.predict_proba(X_test))
# # TEST SCORE
# print(neigh.score(X_test,y_test))
# # TRAINING SCORE
# print(neigh.score(X_train,y_train))
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=10, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=3, p=2,
                     weights='uniform')
[0 0 0 2 0 0 0 0 0 0 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 2 2 2 1 0 0 2 2 0 2]
[[1.         0.         0.        ]
 [1.         0.         0.        ]
 [0.66666667 0.33333333 0.        ]
 [0.         0.33333333 0.66666667]
 [1.         0.         0.        ]
 [1.         0.         0.        ]
 [1.         0.         0.        ]
 [1.         0.         0.        ]
 [1.         0.         0.        ]
 [1.         0.         0.        ]
 [1.         0.         0.        ]
 [0.         0.66666667 0.33333333]
 [0.         0.66666667 0.33333333]
 [0.66666667 0.33333333 0.        ]
 [0.         0.66666667 0.33333333]
 [0.         0.66666667 0.33333333]
 [0.         1.         0.        ]
 [0.         0.66666667 0.33333333]
 [0.         1.         0.        ]
 [0.         0.66666667 0.33333333]
 [0.         1.         0.        ]
 [0.         0.66666667 0.33333333]
 [0.         1.         0.        ]
 [0.         1.         0.        ]
 [0.         0.66666667 0.33333333]
 [0.         0.33333333 0.66666667]
 [0.         0.33333333 0.66666667]
 [0.         0.33333333 0.66666667]
 [0.         0.66666667 0.33333333]
 [0.66666667 0.33333333 0.        ]
 [0.33333333 0.33333333 0.33333333]
 [0.         0.33333333 0.66666667]
 [0.         0.33333333 0.66666667]
 [0.66666667 0.         0.33333333]
 [0.         0.33333333 0.66666667]]
0.8285714285714286
0.8671328671328671
```

In [35]:
```
print(list(X_train))
y_pred = neigh.predict(X_test)

#PLOT RESULTS
plt.title("Orignal Y")
plt.scatter(X_test['alcalinity_of_ash'], X_test['total_phenols'],c=y_test)
plt.show()
plt.title("Predicted Y")
plt.scatter(X_test['alcalinity_of_ash'], X_test['total_phenols'],c=y_pred)
plt.show()
```

```
['alcohol', 'malic_acid', 'ash', 'alcalinity_of_ash', 'magnesium', 'total_phe
nols', 'flavanoids', 'nonflavanoid_phenols', 'proanthocyanins', 'color_intens
ity', 'hue', 'od280/od315_of_diluted_wines', 'proline']
```





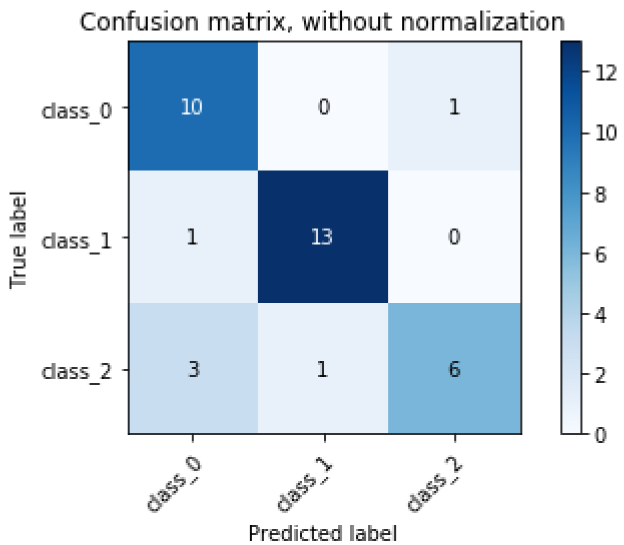
Visualizing the results

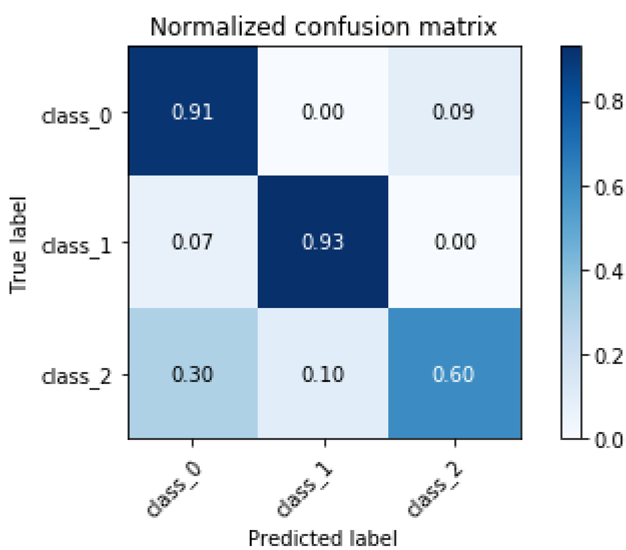
TRY ON DIFFERENT SPLIT!!

In [39]:
```
# run cell below plotting function heading first before running this cell (out of order)

from sklearn.metrics import confusion_matrix
from sklearn.utils.multiclass import unique_labels

class_names = wine_bunch.target_names

plot_confusion_matrix(y_test, y_pred, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plot_confusion_matrix(y_test, y_pred, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')
```

```
Confusion matrix, without normalization
[[10  0  1]
 [ 1 13  0]
 [ 3  1  6]]
Normalized confusion matrix
[[0.90909091 0.         0.09090909]
 [0.07142857 0.92857143 0.        ]
 [0.3        0.1        0.6       ]]
```

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2e629aa20>





Plotting function

Refernce:

[https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html#sphx-glr-auto-examples-model-selection-plot-confusion-matrix-py (https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html#sphx-glr-auto-examples-model-selection-plot-confusion-matrix-py)](https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html#sphx-glr-auto-examples-model-selection-plot-confusion-matrix-py)

In [38]:
```python
def plot_confusion_matrix(y_true, y_pred, classes,
                          normalize=False,
                          title=None,
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if not title:
        if normalize:
            title = 'Normalized confusion matrix'
        else:
            title = 'Confusion matrix, without normalization'

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    # Only use the labels that appear in the data
    classes = classes[unique_labels(y_true, y_pred)]
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # We want to show all ticks...
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # ... and label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')

    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")

    # Loop over data dimensions and create text annotations.
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    return ax
```

Excercise 1 (30minutes)

In [61]:
```
# 1. Perform K-fold KNN cross validation on the wine data
# 2. Modify KNN hyper parameters and see how it effects the results

# #pseudo code:
# create k-folds
# for each split:
#     train KNN
#     predict for the split
#     see the score

# k-fold
from sklearn.model_selection import KFold
kf = KFold(n_splits=6,random_state=42, shuffle=True)
kf.get_n_splits(wineX)
print(kf)

for train_index, test_index in kf.split(wineX):
    X_train, X_test = wineX.iloc[train_index], wineX.iloc[test_index]
    y_train, y_test = wineY[train_index], wineY[test_index]
    print(X_train.shape, y_train.shape)
    print(X_test.shape, y_test.shape)
    neigh = KNeighborsClassifier(n_neighbors=3, leaf_size=10)
    neigh.fit(X_train, y_train)
#     print(neigh)
#     print(neigh.predict(X_test))
#     print(neigh.predict_proba(X_test))
    # TEST SCORE
    print("TEST score {:f}".format(neigh.score(X_test,y_test)))
    # TRAINING SCORE
    print("TRAINING score {:f}".format(neigh.score(X_train,y_train)))
```

```
KFold(n_splits=6, random_state=42, shuffle=True)
(148, 13) (148,)
(30, 13) (30,)
TEST score 0.766667
TRAINING score 0.864865
(148, 13) (148,)
(30, 13) (30,)
TEST score 0.766667
TRAINING score 0.858108
(148, 13) (148,)
(30, 13) (30,)
TEST score 0.600000
TRAINING score 0.864865
(148, 13) (148,)
(30, 13) (30,)
TEST score 0.700000
TRAINING score 0.864865
(149, 13) (149,)
(29, 13) (29,)
TEST score 0.551724
TRAINING score 0.872483
(149, 13) (149,)
(29, 13) (29,)
TEST score 0.827586
TRAINING score 0.879195
```

Supervised regression

Test / train split

In [72]:
```
##### regression (supervised/continuous) #####
reg_bunch = datasets.load_boston()
print(reg_bunch.keys())
print(reg_bunch.data)

# random sampling
from sklearn import preprocessing
reg_bunch.data = preprocessing.scale(reg_bunch.data)
print(reg_bunch.DESCR)
regX = pd.DataFrame(reg_bunch.data, columns=reg_bunch.feature_names)
regY = reg_bunch.target
print("regX sample: \n", regX.iloc[0:10])
print("regY sample: \n", regY[0:10])

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(regX, regY, test_size=0.2,
random_state=42)
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
[[6.3200e-03 1.8000e+01 2.3100e+00 ... 1.5300e+01 3.9690e+02 4.9800e+00]
 [2.7310e-02 0.0000e+00 7.0700e+00 ... 1.7800e+01 3.9690e+02 9.1400e+00]
 [2.7290e-02 0.0000e+00 7.0700e+00 ... 1.7800e+01 3.9283e+02 4.0300e+00]
 ...
 [6.0760e-02 0.0000e+00 1.1930e+01 ... 2.1000e+01 3.9690e+02 5.6400e+00]
 [1.0959e-01 0.0000e+00 1.1930e+01 ... 2.1000e+01 3.9345e+02 6.4800e+00]
 [4.7410e-02 0.0000e+00 1.1930e+01 ... 2.1000e+01 3.9690e+02 7.8800e+00]]
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (a
ttribute 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

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at Carneg
ie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers tha
```

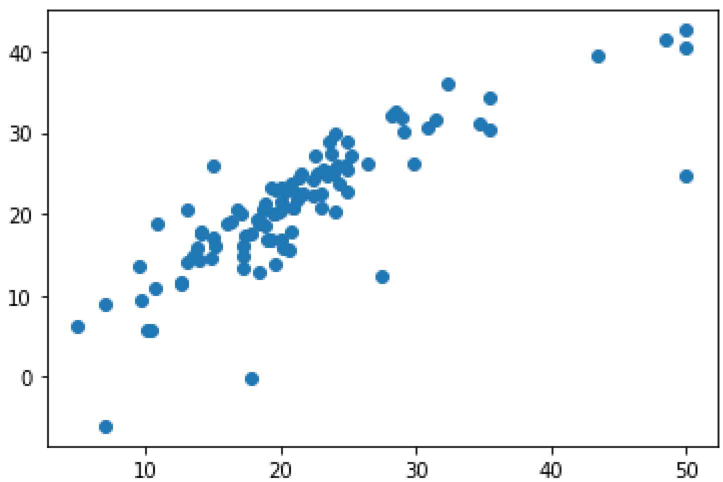
```
t address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential
Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In
Proceedings on the Tenth International Conference of Machine Learning, 236-24
3, University of Massachusetts, Amherst. Morgan Kaufmann.

regX sample:
       CRIM        ZN     INDUS      CHAS       NOX        RM       AGE  \
0 -0.419782  0.284830 -1.287909 -0.272599 -0.144217  0.413672 -0.120013
1 -0.417339 -0.487722 -0.593381 -0.272599 -0.740262  0.194274  0.367166
2 -0.417342 -0.487722 -0.593381 -0.272599 -0.740262  1.282714 -0.265812
3 -0.416750 -0.487722 -1.306878 -0.272599 -0.835284  1.016303 -0.809889
4 -0.412482 -0.487722 -1.306878 -0.272599 -0.835284  1.228577 -0.511180
5 -0.417044 -0.487722 -1.306878 -0.272599 -0.835284  0.207096 -0.351157
6 -0.410243  0.048772 -0.476654 -0.272599 -0.265154 -0.388411 -0.070229
7 -0.403696  0.048772 -0.476654 -0.272599 -0.265154 -0.160466  0.978808
8 -0.395935  0.048772 -0.476654 -0.272599 -0.265154 -0.931206  1.117494
9 -0.400729  0.048772 -0.476654 -0.272599 -0.265154 -0.399808  0.616090

        DIS       RAD       TAX   PTRATIO         B     LSTAT
0  0.140214 -0.982843 -0.666608 -1.459000  0.441052 -1.075562
1  0.557160 -0.867883 -0.987329 -0.303094  0.441052 -0.492439
2  0.557160 -0.867883 -0.987329 -0.303094  0.396427 -1.208727
3  1.077737 -0.752922 -1.106115  0.113032  0.416163 -1.361517
4  1.077737 -0.752922 -1.106115  0.113032  0.441052 -1.026501
5  1.077737 -0.752922 -1.106115  0.113032  0.410571 -1.043322
6  0.839244 -0.523001 -0.577519 -1.505237  0.426798 -0.031268
7  1.024638 -0.523001 -0.577519 -1.505237  0.441052  0.910700
8  1.087196 -0.523001 -0.577519 -1.505237  0.328448  2.421774
9  1.329635 -0.523001 -0.577519 -1.505237  0.329325  0.623344
regY sample:
 [24.  21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9]
(404, 13) (404,)
(102, 13) (102,)
```

Regression

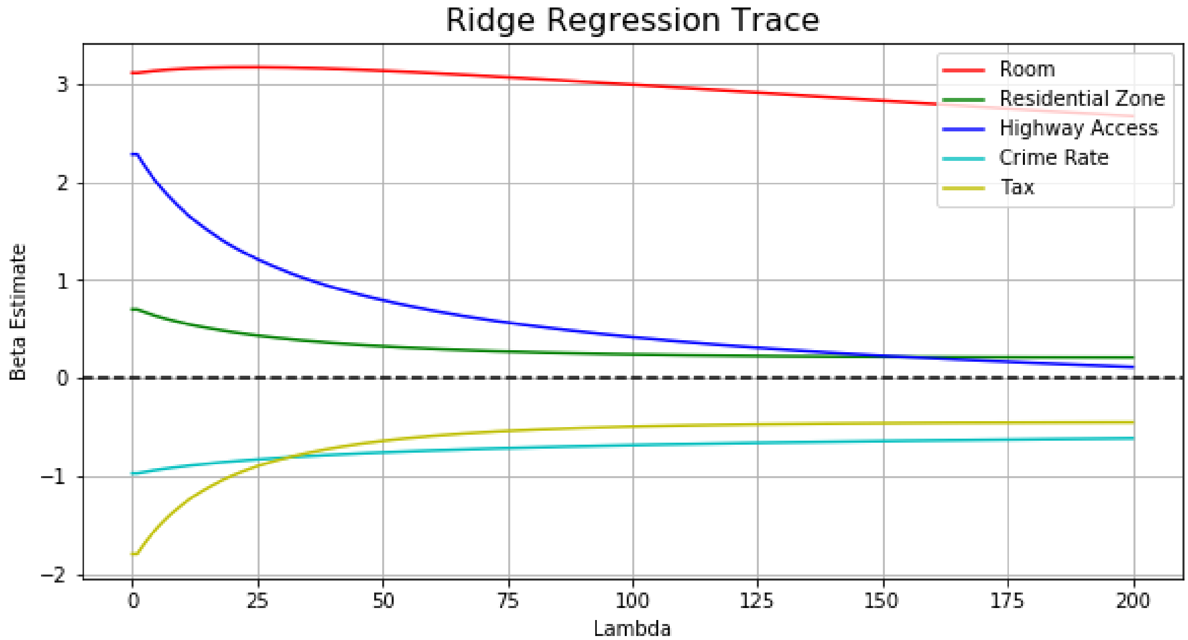
[https://scikit-learn.org/stable/modules/linear_model.html (https://scikit-learn.org/stable/modules/linear_model.html)](https://scikit-learn.org/stable/modules/linear_model.html)

In [92]:
```
##### linear regression ########
from sklearn import linear_model

reg = linear_model.LinearRegression()
reg.fit(X_train, y_train)
print(reg.coef_)
y_pred = reg.predict(X_test)
print("LR Train score: {:f}".format(reg.score(X_train,y_train)))
print("LR Test score: {:f}".format(reg.score(X_test,y_test)))
plt.scatter(y_test, y_pred)
plt.show()
```

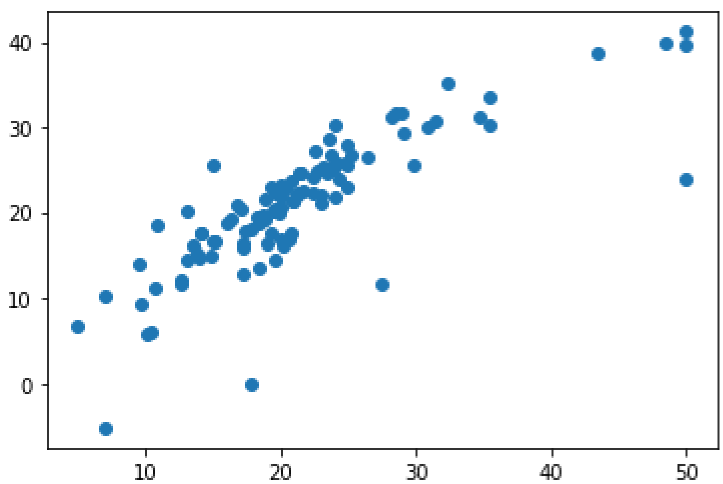
```
[-0.97149423  0.70155562  0.27675212  0.70653152 -1.99143043  3.11571836
 -0.17706021 -3.04577065  2.28278471 -1.79260468 -1.97995351  1.12649864
 -3.62814937]
LR Train score: 0.750886
LR Test score: 0.668759
```



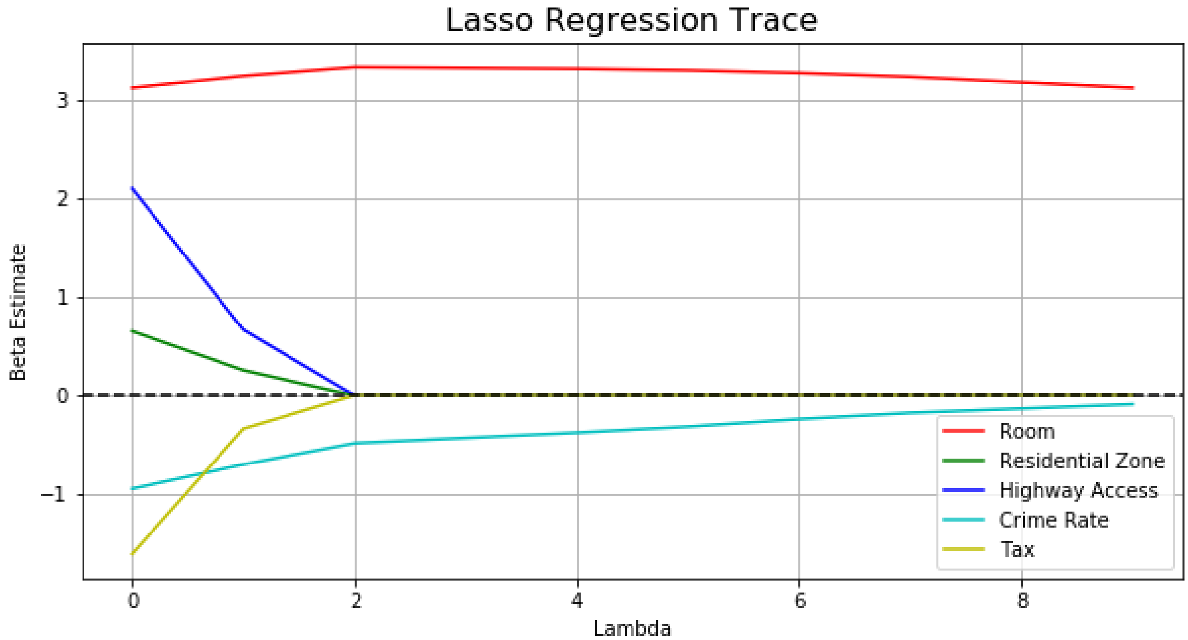
In [93]:
```
#### RIDGE regression  ######
from sklearn.linear_model import Ridge

def find_alpha():
    # adopted from: https://towardsdatascience.com/ridge-regression-for-better
-usage-2f19b3a202db
    ridge_reg = Ridge(alpha=0)
    ridge_reg.fit(X_train, y_train)
    ridge_df = pd.DataFrame({'variable': reg_bunch.feature_names, 'estimate':
ridge_reg.coef_})
    ridge_train_pred = []
    ridge_test_pred = []
    # iterate lambdas

    # iterate lambdas
    for alpha in np.arange(0, 200, 1):
        # training
        ridge_reg = Ridge(alpha=alpha)
        ridge_reg.fit(X_train, y_train)
        var_name = 'estimate' + str(alpha)
        ridge_df[var_name] = ridge_reg.coef_
        # prediction
        ridge_train_pred.append(ridge_reg.predict(X_train))
        ridge_test_pred.append(ridge_reg.predict(X_test))

    # organize dataframe
    ridge_df = ridge_df.set_index('variable').T.rename_axis('estimate').rename
_axis(1).reset_index()
    # plot betas by lambda
    fig, ax = plt.subplots(figsize=(10, 5))
    ax.plot(ridge_df.RM, 'r', ridge_df.ZN, 'g', ridge_df.RAD, 'b', ridge_df.CR
IM, 'c', ridge_df.TAX, 'y')
    ax.axhline(y=0, color='black', linestyle='--')
    ax.set_xlabel("Lambda")
    ax.set_ylabel("Beta Estimate")
    ax.set_title("Ridge Regression Trace", fontsize=16)
    ax.legend(labels=['Room','Residential Zone','Highway Access','Crime Rate',
'Tax'])
    ax.grid(True)
    plt.show()

# Rooms is the features that has the most significance
find_alpha()

ridge = Ridge(alpha=20.0)
ridge.fit(X_train, y_train)
print(ridge.coef_)
y_pred = ridge.predict(X_test)
print("RIDGE Train score: {:f}".format(ridge.score(X_train,y_train)))
print("RIDGE Test score: {:f}".format(ridge.score(X_test,y_test)))
plt.scatter(y_test, y_pred)
plt.show()
```



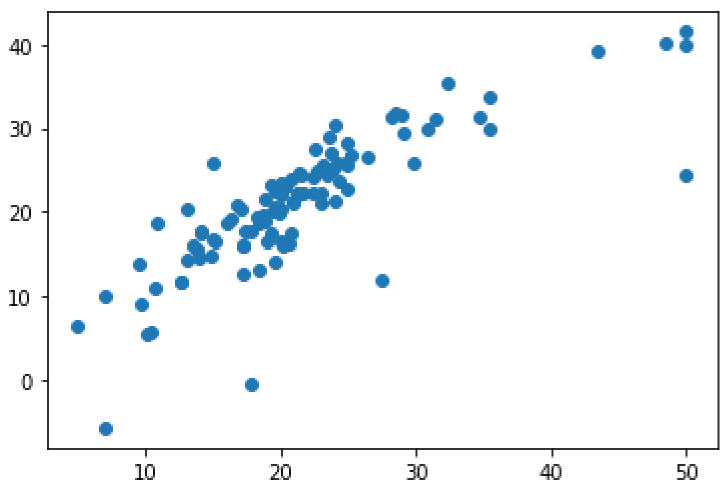

```
[-0.84416652  0.46198062 -0.03418626  0.75114482 -1.53723325  3.17316115
 -0.1880602  -2.48151078  1.31849282 -0.97365431 -1.83807721  1.08177436
 -3.40377171]
RIDGE Train score: 0.747905
RIDGE Test score: 0.663563
```



In [94]:
```
#### LASSO regression  ######
from sklearn import linear_model

def find_alpha():
    ridge_reg = linear_model.Lasso(alpha=0.01)
    ridge_reg.fit(X_train, y_train)
    ridge_df = pd.DataFrame({'variable': reg_bunch.feature_names, 'estimate':
ridge_reg.coef_})
    ridge_train_pred = []
    ridge_test_pred = []
    # iterate lambdas

    # iterate lambdas
    for alpha in np.arange(0.1, 1,0.1):
        # training
        ridge_reg = linear_model.Lasso(alpha=alpha)
        ridge_reg.fit(X_train, y_train)
        var_name = 'estimate' + str(alpha)
        ridge_df[var_name] = ridge_reg.coef_
        # prediction
        ridge_train_pred.append(ridge_reg.predict(X_train))
        ridge_test_pred.append(ridge_reg.predict(X_test))

    # organize dataframe
    ridge_df = ridge_df.set_index('variable').T.rename_axis('estimate').rename
_axis(1).reset_index()
    # plot betas by lambda
    fig, ax = plt.subplots(figsize=(10, 5))
    ax.plot(ridge_df.RM, 'r', ridge_df.ZN, 'g', ridge_df.RAD, 'b', ridge_df.CR
IM, 'c', ridge_df.TAX, 'y')
    ax.axhline(y=0, color='black', linestyle='--')
    ax.set_xlabel("Lambda")
    ax.set_ylabel("Beta Estimate")
    ax.set_title("Lasso Regression Trace", fontsize=16)
    ax.legend(labels=['Room','Residential Zone','Highway Access','Crime Rate',
'Tax'])
    ax.grid(True)
    plt.show()

find_alpha()

lasso = linear_model.Lasso(alpha=0.05)
lasso.fit(X_train, y_train)
print(lasso.coef_)
y_pred = lasso.predict(X_test)
print("LASSO Train score: {:f}".format(lasso.score(X_train,y_train)))
print("LASSO Test score: {:f}".format(lasso.score(X_test,y_test)))

plt.scatter(y_test, y_pred)
plt.show()
```



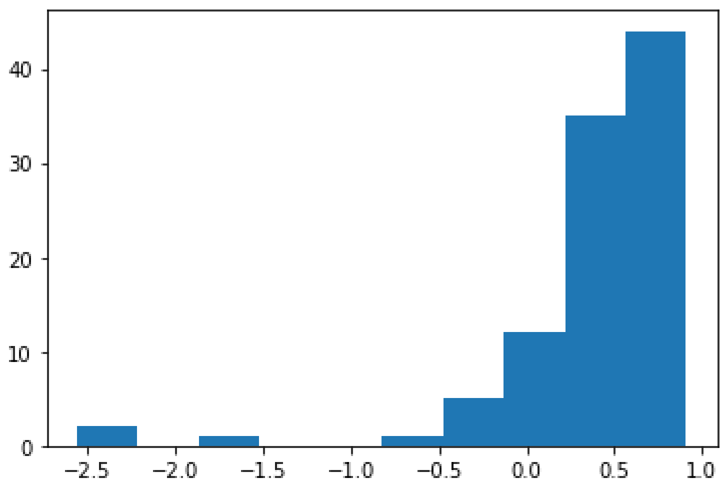

```
[-0.83796934  0.46704064  0.          0.70483741 -1.74067035  3.16378634
 -0.06698043 -2.67152839  1.42785917 -0.98008334 -1.90529396  1.07252204
 -3.62223499]
LASSO Train score: 0.749226
LASSO Test score: 0.662584
```



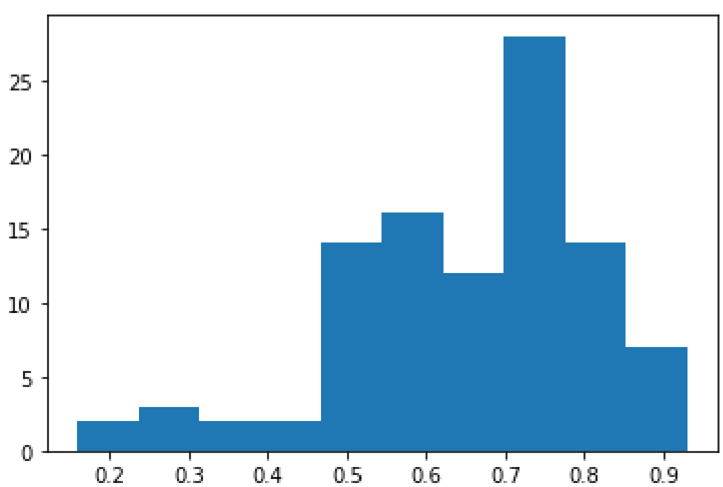
In [97]:
```
from sklearn import linear_model
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error

np.random.seed(101)

#generate dataset (wide datset)
X = np.random.normal(0,1,size=(50, 30))
# will have 10 some high coefficients
coef1 = np.random.uniform(0.5,1,10)
# and 20 low coefficeints
coef2 = np.random.uniform(0.0,0.3,20)
coef = np.concatenate((coef1, coef2), axis=0)
# plt.hist(coef)
# plt.show()
y_dot = X.dot(coef)

# generate response data by adding noise
# why adding noise?
y_response = y_dot + np.random.normal(0,1,50)


lr_train = []
lr_test = []
lr_rmse = []
ridge_train = []
ridge_test = []
ridge_rmse = []
lasso_train = []
lasso_test = []
lasso_rmse = []


for i in range(0,100):
    X_train, X_test, y_train, y_test = train_test_split(X, y_response, test_si
ze=0.2)

    ##### linear regression ########
    reg = linear_model.LinearRegression()
    reg.fit(X_train, y_train)
    y_pred = reg.predict(X_test)
    lr_train.append(reg.score(X_train,y_train))
    lr_test.append(reg.score(X_test,y_test))
    lr_rmse.append(mean_squared_error(y_test, y_pred))


    #### RIDGE regression  ######
    ridge = Ridge(alpha=5.0)
    ridge.fit(X_train, y_train)
    y_pred = ridge.predict(X_test)
    ridge_train.append(ridge.score(X_train,y_train))
    ridge_test.append(ridge.score(X_test,y_test))
    ridge_rmse.append(mean_squared_error(y_test, y_pred))


    #### LASSO regression  ######
```

```
    lasso = linear_model.Lasso(alpha=0.1)
    lasso.fit(X_train, y_train)
    y_pred = lasso.predict(X_test)
    lasso_train.append(lasso.score(X_train,y_train))
    lasso_test.append(lasso.score(X_test,y_test))
    lasso_rmse.append(mean_squared_error(y_test, y_pred))



print('LR train: ',sum(lr_train)/len(lr_train))
print('LR test: ',sum(lr_test)/len(lr_test))
print('LR RMSE: ',sum(lr_rmse)/len(lr_rmse))
print("")
print('Ridge train: ',sum(ridge_train)/len(ridge_train))
print('Ridge test: ',sum(ridge_test)/len(ridge_test))
print('Ridge RMSE: ',sum(ridge_rmse)/len(ridge_rmse))
print("")
print('Lasso train: ',sum(lasso_train)/len(lasso_train))
print('Lasso test: ',sum(lasso_test)/len(lasso_test))
print('Lasso RMSE: ',sum(lasso_rmse)/len(lasso_rmse))



#examine variance and bias
print('\n Hist Plots \n LR test: \n')
plt.hist(lr_test)
plt.show()
print('Ridge test: \n')
plt.hist(ridge_test)
plt.show()
print('Lasso test: \n')
plt.hist(lasso_test)
plt.show()
```

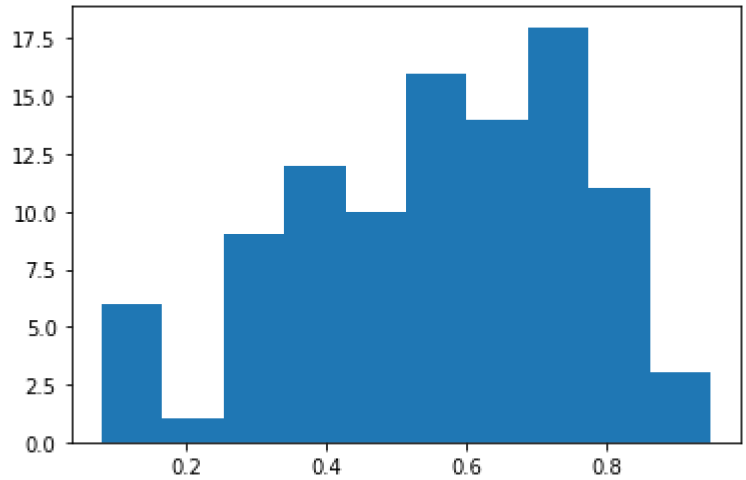
```
LR train:  0.9767790895554215
LR test:  0.3770297714569159
LR RMSE:  3.1986012122242817

Ridge train:  0.9545350496479551
Ridge test:  0.6537684262994671
Ridge RMSE:  2.0192459660320226

Lasso train:  0.917867089365298
Lasso test:  0.5547537632599874
Lasso RMSE:  2.592433720110876

 Hist Plots
 LR test:
```




```
Ridge test:
```




```
Lasso test:
```



ORANGE

Use the script below

https://www.youtube.com/playlist?list=PLmNPvQr9Tf-ZSDLwOzxpvY-HrE0yv-8Fy&disable_polymer=true (https://www.youtube.com/playlist?list=PLmNPvQr9Tf-ZSDLwOzxpvY-HrE0yv-8Fy&disable_polymer=true)

In [ ]:
```
import numpy as np
from Orange.data import Domain, Table

#generate dataset (wide datset)
X = np.random.normal(0,1,size=(50, 30))
# will have 10 some high coefficients
coef1 = np.random.uniform(0.5,1,10)
# and 20 low coefficeints
coef2 = np.random.uniform(0.0,0.3,20)
coef = np.concatenate((coef1, coef2), axis=0)
# plt.hist(coef)
# plt.show()
y_dot = X.dot(coef)
y_response = y_dot + np.random.normal(0,1,50)

y_response = y_response.reshape((y_response.shape[0],1))
all_data = np.append(X, y_response, 1)
out_data = Table(all_data)
```

Excersices

1. Add seed to both Jupyter code and to ORANGE code: np.random.seed(101)
2. Why are the results not the same?
3. Try generating larger data set (50, 30) -> (500, 30). What happens?

Regression Lab

alt text

Data: /data/dow_jones_index/dow_jones_index2.csv

Goal: predict closing price for the last 3 days for each stock. Date is represented as numeric value here, so you need to predict for date > 40700

Classification Lab

alt text

Data: /data/titanic.csv

Goal: Randomly split into train and test and predict "survived" variable