Assignment 3

In this assignment, you'll explore linear regression and logistic regression, the perceptron, and support vector machines: popular approaches which share a similar form of producing output in the form of a weighted combination of attributes, but with very different approaches to learning the underyling model. The assignment explores two of the general data mining tasks: regression and classification, and takes a closer look at multiclass classification with these techniques.

Similar to previous assignments, you're expected to respond to each question with your answer in a Markdown cell and clearly labeled code supporting your answer in a code cell. When you submit the assignment, you should upload the two notebooks (`.ipynb` files) corresponding to your solutions and also generate a PDF of each notebook that includes the answers, code, and all intermediate output. In total, you will submit four files: two notebooks and two PDFs generated from those notebooks. This assignment is due on 2/16/16 at 11:59pm.

Part 1: Linear and Logistic Regression, Perceptrons (40 points)

We'll start by looking at a simple example of linear regression. As with many of the other data mining algorithms we've encountered, we'll be using the implementation available in the `linear_model` module of scikit-learn. Now would be a good time to go read the documentation (http://scikit-learn.org/stable/modules/linear_model.html) on linear models and refresh your memory on the high-level ideas. Once you've done that, we'll go through a simple example.

In [15]:
```
## Preliminaries

#Show plots in the notebook
%matplotlib inline

from sklearn import datasets, preprocessing, cross_validation, feature_
from sklearn import linear_model, svm, metrics, ensemble
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import urllib2

# Helper functions
def folds_to_split(data,targets,train,test):
    data_tr = pd.DataFrame(data).iloc[train]
    data_te = pd.DataFrame(data).iloc[test]
    labels_tr = pd.DataFrame(targets).iloc[train]
    labels_te = pd.DataFrame(targets).iloc[test]
    return [data_tr, data_te, labels_tr, labels_te]
```

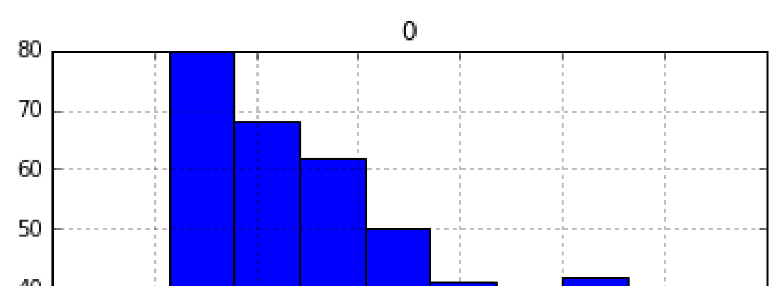
Linear Regression on the Diabetes Dataset

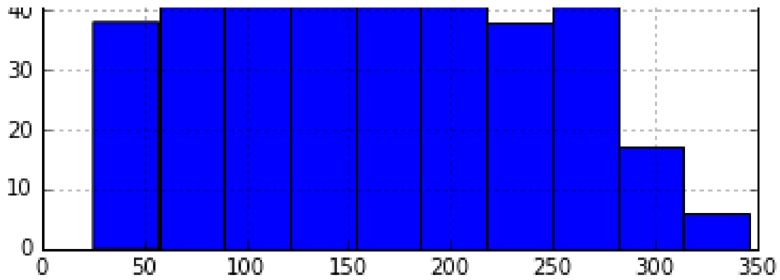
The first dataset we'll explore is the Diabetes dataset (http://scikit-learn.org/stable/modules/generated/sklearn.datasets.load_diabetes.html#sklearn.datasets.load one of the pre-packaged datasets available in scikit-learn. There aren't too many details about t dataset out there, but the common description is that it contains 10 physiological variables (age weight, blood pressure) for 442 patients, and the target is an indication of disease progression a year. Like any good data miners, let's poke around and check out the data before we get starte

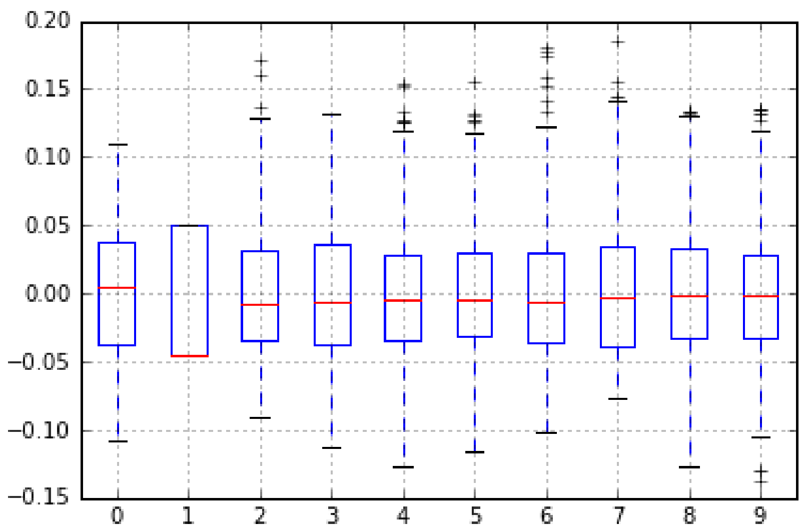
In [16]:
```
# Load the data
diabetes = datasets.load_diabetes();
# Put it into pandas DataFrames
diabetes_data_df = pd.DataFrame(diabetes.data);
diabetes_target_df = pd.DataFrame(diabetes.target)

# How many attributes and records are there?
print diabetes_data_df.shape

# What are the descriptive statistics?
print diabetes_data_df.describe()
# How are the labels distributed?
diabetes_target_df.hist()

# How are the attributes distributed?
plt.figure()
axes = diabetes_data_df.boxplot()
```

```
(442, 10)
                  0             1             2             3  
4  \
count  4.420000e+02  4.420000e+02  4.420000e+02  4.420000e+02  4.420
000e+02
mean  -3.634285e-16  1.308343e-16 -8.045349e-16  1.281655e-16 -8.835
316e-17
std    4.761905e-02  4.761905e-02  4.761905e-02  4.761905e-02  4.761
905e-02
min   -1.072256e-01 -4.464164e-02 -9.027530e-02 -1.123996e-01 -1.267
807e-01
25%   -3.729927e-02 -4.464164e-02 -3.422907e-02 -3.665645e-02 -3.424
784e-02
50%    5.383060e-03 -4.464164e-02 -7.283766e-03 -5.670611e-03 -4.320
866e-03
75%    3.807591e-02  5.068012e-02  3.124802e-02  3.564384e-02  2.835
801e-02
max    1.107267e-01  5.068012e-02  1.705552e-01  1.320442e-01  1.539
137e-01

                  5             6             7             8  
9  
count  4.420000e+02  4.420000e+02  4.420000e+02  4.420000e+02  4.420
000e+02
mean   1.327024e-16 -4.574646e-16  3.777301e-16 -3.830854e-16 -3.412
882e-16
std    4.761905e-02  4.761905e-02  4.761905e-02  4.761905e-02  4.761
905e-02
min   -1.156131e-01 -1.023071e-01 -7.639450e-02 -1.260974e-01 -1.377
672e-01
25%   -3.035840e-02 -3.511716e-02 -3.949338e-02 -3.324879e-02 -3.317
903e-02
50%   -3.819065e-03 -6.584468e-03 -2.592262e-03 -1.947634e-03 -1.077
698e-03
75%    2.984439e-02  2.931150e-02  3.430886e-02  3.243323e-02  2.791
705e-02
max    1.987880e-01  1.811791e-01  1.852344e-01  1.335990e-01  1.356
118e-01
```

```
/Users/viktorjankov/anaconda/lib/python2.7/site-packages/ipykernel/_
_main__.py:17: FutureWarning: 
The default value for 'return_type' will change to 'axes' in a futur
e release.
 To use the future behavior now, set return_type='axes'.
 To keep the previous behavior and silence this warning, set return_
type='dict'.
```







Notice anything interesting about the data? The attributes have been normalized - each has a similar mean and standard deviation. Now let's train our first regression model.

In [17]:
```
# First we'll do a simple train-test split:
[dbt_tr_data, dbt_te_data,
 dbt_tr_target, dbt_te_target] = cross_validation.train_test_split(diab

# Create the LinearRegression classifier
lr = linear_model.LinearRegression()

# Learn the linear regression model
lr.fit(dbt_tr_data, dbt_tr_target)

# Print out the coefficient of determination (R^2)
print "R^2:\t",lr.score(dbt_te_data,dbt_te_target)

# Peek at the predictions
dbt_te_predict = lr.predict(dbt_te_data)
print dbt_te_predict

# And also the mean squared error:
print "MSE:\t", metrics.mean_squared_error(dbt_te_target, dbt_te_predic

# Which attributes were important to this prediction? We can find out b
print lr.coef_
```

```
R^2:    0.533716155537
[ 124.87699265  241.04779116  239.55002222  262.61331893  245.760759
35
  215.38130957   98.25024738  167.10341193   86.15467868  149.231306
48
  139.44688429  121.07843815  145.93392542  113.89242688  137.000019
59
  106.07596308  188.8720697   151.64642212  147.17548161  193.976209
2
  193.24395545  123.38347892  244.93128416  221.35017651   73.231771
37
  175.0689274   270.81318019   76.43093304  147.64128689  106.932261
73
   72.18329933  246.22062792  155.49372733  132.93631466  122.141629
7
   70.14373998  182.1432308   259.16039335  119.69523429  217.322246
65
  156.87184212  209.45289148  152.68147644   97.91484124   99.479911
66
   60.35999351  163.47427462  175.63241326  165.73475646  120.171374
96
  143.1380446    65.50402188  161.25927147  165.59617116  127.563187
62
  145.47983532  119.2772516   140.89228502  138.44957973  234.270316
41
   70.42410076  219.75216763   96.49453974  169.97467564   75.491765
72
  141.43569069  146.08650475   97.22882088  235.72934302  115.606263
81
  140.86586191   83.8398695   226.79822353  232.14151232  153.569348
61
   85.00662969  185.94162205  100.59978839   80.74525585  160.501532
47
  136.07622533  111.57342257  150.66490274  181.52512021  203.544638
09
  205.67406873  142.71143086  127.42691032  139.56003045  151.354371
13
  242.54261548  206.12199133  145.09312121  120.10821335  248.910441
86
  177.46641126  145.28356072   79.89910472  155.73208421  113.432393
24
  162.18337986   99.99524699  191.84896583  154.24943403  166.819089
55
  104.90171597  220.98892005  134.51002344   38.0086503   203.293999
74
  181.12997599]
MSE:    2919.42264017
[  11.18121228 -219.22917848  492.74550531  360.62854712 -880.756963
56
  560.47207888  138.68964051  208.07342467  723.26859805   47.007418
34]
```

Hopefully you can see the similarities between how to build a LinearRegression model (http://sc learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html#sklearn.linear_ and the previous assignment on DecisionTrees. The big difference is that the predictions are no values (much like the training targets). One consequence is that we can't use the same metrics classification. One metric that we've discussed (and that linear regression attempts to minimize squared error (https://en.wikipedia.org/wiki/Mean_squared_error) or MSE. If you understand ho leap to the default metric that regression reports (via the `.score()` function) -- the coefficient c (https://en.wikipedia.org/wiki/Coefficient_of_determination) (R^2) -- shouldn't be too hard to un the R^2 metric and make sure you understand what it measures.

The above example used a simple train-test split, but we can be more confident of our conclusi validation. Let's use cross-validation to experiment with the same dataset and take a look at the example provides you with some tricks that you might have missed in the last assignment, so u below and learning to use it should be helpful

In [18]:

```
foldnum = 0
fold_results = pd.DataFrame()
for train, test in cross_validation.KFold(len(diabetes.data), n_folds=1
    foldnum+=1
    [dbt_tr_data, dbt_te_data,
     dbt_tr_target, dbt_te_target] = folds_to_split(diabetes.data,diabe

    lr = linear_model.LinearRegression()
    lr.fit(dbt_tr_data, dbt_tr_target)
    # We could print out our results
    print "Fold %d\t\t R^2 metric = %03.3f \t\t MSE = %03.1f " % (foldn
                                                                  lr.sc
                                                                  metri

                                                                 )
    # But a nicer way to store them is in a DataFrame
    fold_results.loc[foldnum, 'R^2'] = lr.score(dbt_te_data, dbt_te_tar
    fold_results.loc[foldnum, 'MSE'] = metrics.mean_squared_error(dbt_t

    # By the way, if you were searching over parameters in an inner for
    # you could store those in your results DataFrame just as easily, f
    # for param in params.keys():
    #     for paramVal in params[param]:
    #         paramDict={};
    #         paramDict[param]=paramVal
    #         dtree = tree.DecisionTreeClassifier(random_state=20160121,
    #         dtree.fit(mushroom_train,mushroom_train_labels)
    #         fold_results.loc[foldnum,'%s=%s' % (param, paramVal)]=dtre

#Now let's look at the results:
print fold_results
#And compute the mean error across folds:
print fold_results.mean()
```

```
Fold 1          R^2 metric = 0.556          MSE = 2533.8
Fold 2          R^2 metric = 0.231          MSE = 2870.8
Fold 3          R^2 metric = 0.354          MSE = 3512.7
Fold 4          R^2 metric = 0.622          MSE = 2759.2
Fold 5          R^2 metric = 0.266          MSE = 3555.7
Fold 6          R^2 metric = 0.618          MSE = 2900.4
Fold 7          R^2 metric = 0.418          MSE = 3696.3
Fold 8          R^2 metric = 0.435          MSE = 2282.3
Fold 9          R^2 metric = 0.434          MSE = 4122.9
Fold 10         R^2 metric = 0.686          MSE = 1769.7
         R^2          MSE
1   0.556144  2533.848109
2   0.230561  2870.767711
3   0.353578  3512.723509
4   0.621905  2759.227129
5   0.265876  3555.677943
6   0.618193  2900.380412
7   0.418159  3696.281878
8   0.435152  2282.279598
9   0.434370  4122.939981
10  0.685685  1769.684057
R^2       0.461962
MSE    3000.381033
dtype: float64
```

Question 1: Linear Regression, Ridge Regressio Lasso (20 points)

Now it's your turn to perform a linear regression experiment! Use the [Boston Housing Prices Da (http://scikit-learn.org/stable/modules/generated/sklearn.datasets.load_boston.html#sklearn.datasets.load_b](http://scikit-learn.org/stable/modules/generated/sklearn.datasets.load_boston.html#sklearn.datasets.load_b) built into scikit-learn to better understand regression. You can load it with `datasets.load_bo` and use the `.DESCR` field to learn more about the dataset.

1. Perform exploratory data analysis on the Boston Housing data.

   - From your exploratory data analysis, what do you notice about the attribute values?
   - Which parameter to the `LinearRegression` model could you use to deal with this issue?
   - Perform 10-fold cross-validation (with `shuffle=True` and `random_state=2016020` with a `LinearRegression` model that uses the parameter identified above. Report th average coefficient of determination and mean squared error metric on the test set (averaged across folds).
2. Two very popular options in Linear Regression are the [Lasso method (https://en.wikipedia.org/wiki/Lasso_(statistics))](https://en.wikipedia.org/wiki/Lasso_(statistics)) and [Ridge Regression (https://en.wikipedia.org/wiki/Tikhonov_regularization)](https://en.wikipedia.org/wiki/Tikhonov_regularization). These are implemented in the [Lassc (http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html#sklearn.linear_model.](http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html#sklearn.linear_model.)

and Ridge (http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Ridge.html#sklearn.linear_model. models in sklearn.

- What *one word* captures what Lasso and Ridge do? (It's in the first sentence of both Wikipedia articles and sklearn documentation pages)
- Perform 10-fold CV with normal `LinearRegression`, `Lasso`, and `Ridge`. Compare tl attribute weights (`coef_`) of each of these methods. What do you observe?
- Report the average R^2 and MSE for each method on the test set across folds. How d these variants of linear regression perform?

Hint: If you'd like to understand Ridge Regression better, you might want to look at this exa (http://scikit-learn.org/stable/auto_examples/linear_model/plot_ols_ridge_variance.html)

Answers 1:

1.

a) From the exploratory data analysis, we noticed that the range of the values is huge, which is not good. For example, most of the attributes have a value below 100, while the 9th and 11th attribute have values in the hundreds. Betewen 300 and 700 for the 9th attribute [TAX] and around 400 for the 11th attribute [B]
b) To deal with this issue, we'll use the normalize=True parameter to the LinearRegression model
c) Averages:
R^2 0.713643
MSE 23.657502

2.

a) Regularization. Both Lasso and Ridge regression are used for regularization to prevent overfitting
b) Looking at the attribute weights, we see several differences between the different models. First, Lasso gets completly rid of most features, by settings the weights of 0. It only keeps 2 or 3 features in most cases as the only relevant once to predict the median house price
The Ridge regression model on the other hand, keeps most features, but we can notice that the weights are slightly different to the weights of the original linear regresion (i.e there are only small changes to the weights).

c)
Averages:
Linear Regression:
R^2 0.713643
MSE 23.657502

Lasso Regularization:
R^2 0.580869
MSE 35.198977

Ridge Regression:
R^2 0.708486
MSE 24.133678

TTest for LinearRegression vs RidgeRegression
Ttest_relResult(statistic=1.2154248843325626, pvalue=0.25512413165702003)

TTest for Lasso vs RidgeRegression
Ttest_relResult(statistic=-9.4005571317290304, pvalue=5.9711873467613727e-06)

TTest for LinearRegression vs Lasso
Ttest_relResult(statistic=8.7799598190605064, pvalue=1.0449626130453215e-05)

The Lasso regression model performs significantly worse than the linear regression and the ridge regression model. This means that the model is not overfitted, and most features are relevant to predicting the median house prices. So when Lasso gets rid of some features, the model performs worse.
The Ridge regression performs slightly worse than the regular linear regression, but according to the ttest, this difference is not significant.

In [19]:
```
# Load the data
boston = datasets.load_boston();

# Brief description of the data
print boston.DESCR
```

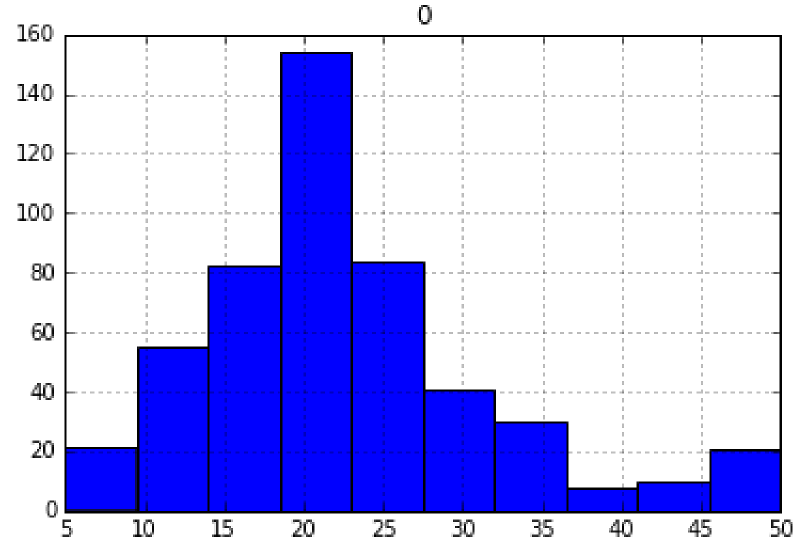
```
Boston House Prices dataset

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 ove
r 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 millio
n)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to
1940
        - DIS      weighted distances to five Boston employment cent
res
        - 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 b
lacks 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.
http://archive.ics.uci.edu/ml/datasets/Housing (http://archive.ics.u
ci.edu/ml/datasets/Housing)


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

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hed
onic
prices and the demand for clean air', J. Environ. Economics & Manage
ment,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression di
agnostics
...', Wiley, 1980.   N.B. Various transformations are used in the ta
ble on
```

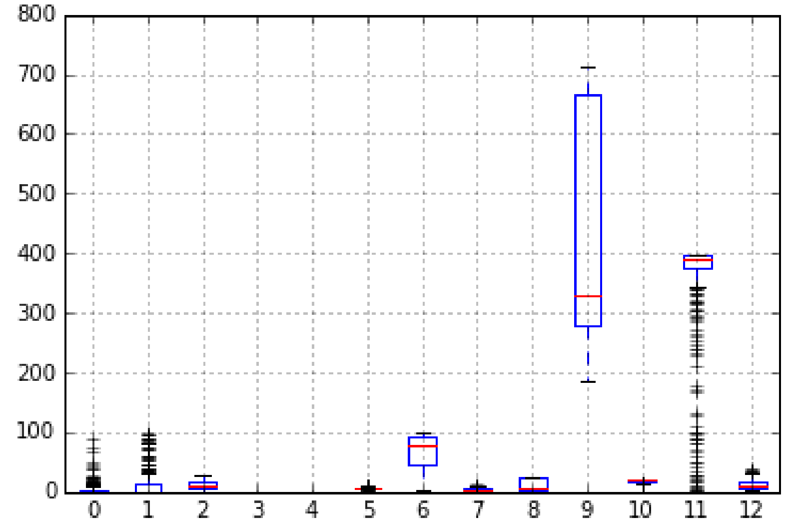
```
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning p
apers that address regression
problems.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Inf
luential Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Lea
rning. In Proceedings on the Tenth International Conference of Machi
ne Learning, 236-243, University of Massachusetts, Amherst. Morgan K
aufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
(http://archive.ics.uci.edu/ml/datasets/Housing))
```

In [20]:
```
# Part 1a) Explore the dataset
# Put it into pandas DataFrames
boston_data_df = pd.DataFrame(boston.data);
boston_target_df = pd.DataFrame(boston.target)

# How many attributes and records are there?
print boston_data_df.shape

# What are the descriptive statistics?
print boston_data_df.describe()

# How are the labels distributed?
boston_target_df.hist()

# How are the attributes distributed?
plt.figure()
axes = boston_data_df.boxplot()
```

```
(506, 13)
                0           1           2           3           4  
5  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  5
06.000000   
mean     3.593761   11.363636   11.136779    0.069170    0.554695    
6.284634   
std      8.596783   23.322453    6.860353    0.253994    0.115878    
0.702617   
min      0.006320    0.000000    0.460000    0.000000    0.385000    
3.561000   
25%      0.082045    0.000000    5.190000    0.000000    0.449000    
5.885500   
50%      0.256510    0.000000    9.690000    0.000000    0.538000    
6.208500   
75%      3.647423   12.500000   18.100000    0.000000    0.624000    
6.623500   
max     88.976200  100.000000   27.740000    1.000000    0.871000    
8.780000   

                6           7           8           9          10  
11  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  5
06.000000   
mean    68.574901    3.795043    9.549407  408.237154   18.455534  3
56.674032   
std     28.148861    2.105710    8.707259  168.537116    2.164946    
91.294864   
min      2.900000    1.129600    1.000000  187.000000   12.600000    
0.320000   
25%     45.025000    2.100175    4.000000  279.000000   17.400000  3
75.377500   
50%     77.500000    3.207450    5.000000  330.000000   19.050000  3
91.440000   
75%     94.075000    5.188425   24.000000  666.000000   20.200000  3
96.225000   
max    100.000000   12.126500   24.000000  711.000000   22.000000  3
96.900000   

               12  
count  506.000000  
mean    12.653063  
std      7.141062  
min      1.730000  
25%      6.950000  
50%     11.360000  
75%     16.955000  
max     37.970000  

/Users/viktorjankov/anaconda/lib/python2.7/site-packages/ipykernel/_
_main__.py:17: FutureWarning: 
The default value for 'return_type' will change to 'axes' in a futur
e release.
 To use the future behavior now, set return_type='axes'.
```

```
To keep the previous behavior and silence this warning, set return_
type='dict'.
```





In [21]:
```
# Part 1b) Cross Validation
foldnum = 0
fold_results = pd.DataFrame()
for train, test in cross_validation.KFold(len(boston.data), n_folds=10,
    foldnum+=1
    [boston_tr_data, boston_te_data,
     boston_tr_target, boston_te_target] = folds_to_split(boston.data,b

    lr = linear_model.LinearRegression(normalize=True)
    lr.fit(boston_tr_data, boston_tr_target)

    # But a nicer way to store them is in a DataFrame
    fold_results.loc[foldnum, 'R^2'] = lr.score(boston_te_data, boston_
    fold_results.loc[foldnum, 'MSE'] = metrics.mean_squared_error(bosto

#Now let's look at the results:
print fold_results
#And compute the mean error across folds:
print fold_results.mean()
```

```
         R^2        MSE
1   0.717454  23.926098
2   0.620171  34.779133
3   0.783767  18.841212
4   0.556936  30.379589
5   0.769709  16.603228
6   0.693492  22.287915
7   0.828865  19.256283
8   0.631266  33.237697
9   0.796774  16.961117
10  0.737993  20.302751
R^2     0.713643
MSE    23.657502
dtype: float64
```

In [22]:

```
# Part 2 Using Lasso and Ridge Regression

from scipy import stats

foldnum = 0
lr_fold_results = pd.DataFrame()
lasso_fold_results = pd.DataFrame()
ridge_fold_results = pd.DataFrame()

for train, test in cross_validation.KFold(len(boston.data), n_folds=10,
    foldnum+=1
    [boston_tr_data, boston_te_data,
     boston_tr_target, boston_te_target] = folds_to_split(boston.data,b

    lr = linear_model.LinearRegression(normalize=True)
    lr.fit(boston_tr_data, boston_tr_target)

    lasso = linear_model.Lasso(alpha=0.1, normalize=True, random_state=
    lasso.fit(boston_tr_data, boston_tr_target)

    ridge = linear_model.Ridge(alpha=0.1, normalize=True, random_state=
    ridge.fit(boston_tr_data, boston_tr_target)

    # But a nicer way to store them is in a DataFrame
    lr_fold_results.loc[foldnum, 'R^2'] = lr.score(boston_te_data, bost
    lr_fold_results.loc[foldnum, 'MSE'] = metrics.mean_squared_error(bo

    lasso_fold_results.loc[foldnum, 'R^2'] = lasso.score(boston_te_data
    lasso_fold_results.loc[foldnum, 'MSE'] = metrics.mean_squared_error

    ridge_fold_results.loc[foldnum, 'R^2'] = ridge.score(boston_te_data
    ridge_fold_results.loc[foldnum, 'MSE'] = metrics.mean_squared_error

#Now let's look at the results:
print "TTest for LinearRegression vs RidgeRegression"
print stats.ttest_rel(lr_fold_results['R^2'].values, ridge_fold_results
print "\n"

print "TTest for Lasso vs RidgeRegression"
print stats.ttest_rel(lasso_fold_results['R^2'].values, ridge_fold_resu
print "\n"

print "TTest for LinearRegression vs Lasso"
print stats.ttest_rel(lr_fold_results['R^2'].values, lasso_fold_results
print "\n"


#And compute the mean error across folds:
print "Linear Regression:"
print lr_fold_results.mean()
print "\n"

print "Lasso Regularization:"
print lasso_fold_results.mean()
```

```
print lasso_fold_results.mean()
print "\n"

print "Ridge Regression: "
print ridge_fold_results.mean()
```

```
TTest for LinearRegression vs RidgeRegression
Ttest_relResult(statistic=1.2154248843325628, pvalue=0.2551241316570
2003)


TTest for Lasso vs RidgeRegression
Ttest_relResult(statistic=-9.4005571317290268, pvalue=5.971187346761
393e-06)


TTest for LinearRegression vs Lasso
Ttest_relResult(statistic=8.7799598190605046, pvalue=1.0449626130453
218e-05)


Linear Regression:
R^2     0.713643
MSE    23.657502
dtype: float64


Lasso Regularization:
R^2     0.580869
MSE    35.198977
dtype: float64


Ridge Regression:
R^2     0.708486
MSE    24.133678
dtype: float64
```

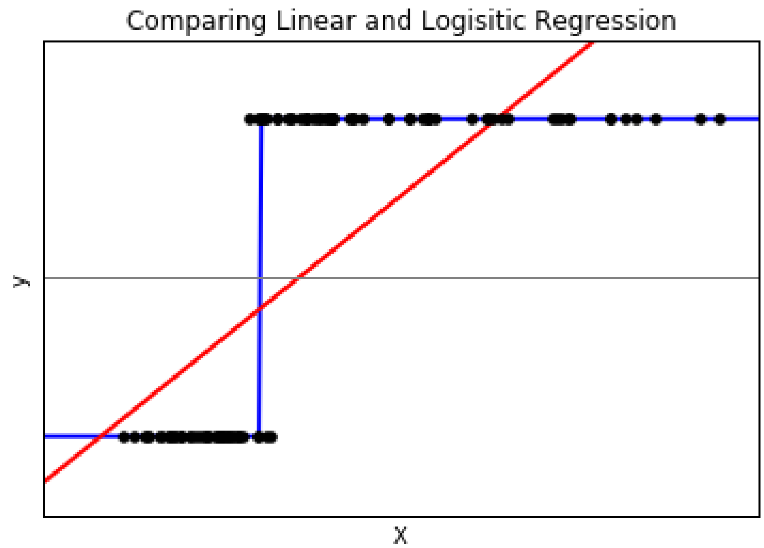
Logistic Regression

Now let's look at a different application for regression algorithms: classification. As we learned in class, regression algorithm can be adapted to a binary classification fairly simply. Instead of predicting some continuous value, we predict the class. So, for example, instead of predicting the diabetes condition of a patient we would predict whether or not a patient has diabetes by having the label be 1 when the patient has diabetes and 0 when the patient does not have diabetes.

In this setting the regression algorithm tries to learn some combination of features to get 0 for the negative instance and 1 for the positive instances. Of course, linear regression algorithms produce continuous values, not just 1s and 0s, so we have to convert the continuous values into 1s and 0s. Usually this is done by rounding values above 0.5 to 1 and the remaining values to 0 (using, for example, the numpy [round (http://docs.scipy.org/doc/numpy-1.10.0/reference/generated/numpy.round_.html)](http://docs.scipy.org/doc/numpy-1.10.0/reference/generated/numpy.round_.html) function).

However, there's still something messy about this setting. Linear regression wants to predict continuous values and we're conscripting it to produce 1s and 0s. What if we had a regression algorithm that, by design, predicted 1s and 0s? This is exactly what logistic regression does. Let's look at an example of the difference, taken from the [scikit-learn documentation (http://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic.html)](http://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic.html)

In [23]:
```
# Code source: Gael Varoquaux
# License: BSD 3 clause

# this is our test set, it's just a straight line with some
# Gaussian noise
xmin, xmax = -5, 5
n_samples = 100
np.random.seed(0)
X = np.random.normal(size=n_samples)
y = (X > 0).astype(np.float)
X[X > 0] *= 4
X += .3 * np.random.normal(size=n_samples)

X = X[:, np.newaxis]

#Learn a Linear Regression model
lr = linear_model.LinearRegression()
lr.fit(X, y)

# Learn a Logistic Regression model
lgr = linear_model.LogisticRegression(C=1e5)
lgr.fit(X, y)

# Plot the training data (as black dots)
plt.scatter(X.ravel(), y, color='black', zorder=20)

#Create some test data
X_test = np.linspace(-5, 10, 300).reshape(300,1)

# Plot the predictions of the logistic regression model (blue line)
plt.plot(X_test, lgr.predict(X_test), color='blue', linewidth=2)

# Plot the prediction of the linear regresion model (red line)
plt.plot(X_test, lr.predict(X_test), color='red', linewidth=2)

# Make the plot prettier
plt.axhline(.5, color='.5')
plt.ylabel('y')
plt.xlabel('X')
plt.xticks(())
plt.yticks(())
plt.ylim(-.25, 1.25)
plt.xlim(-4, 10)
plt.title('Comparing Linear and Logisitic Regression')
plt.show()
```



The black dots in the plot above are the training data. The linear regression model fits that training data with the line shown in red. The logistic regression model fits the same training data with the line shown in blue. As you can see, the logistic regression model is a much closer fit to the binary training data than the linear regression model.

Now let's explore logistic regression with a different data set. The [Adult dataset (http://archive.ics.uci.edu/ml/datasets/Adult)](http://archive.ics.uci.edu/ml/datasets/Adult) consists of 14 attributes from census data and tries to predict whether an individual has an income exceeding $50K. I've covered some of the basic steps to get the data loaded, but you can explore the original data `census_orig` (which has readable, nominal attributes) and the transformed data `census_data` and `census_labels` to get a better understanding of the dataset.

In [24]:
```
census_data = urllib2.urlopen("http://archive.ics.uci.edu/ml/machine-le
census_orig = pd.read_csv(census_data, quotechar='"', skipinitialspace=
                              names=['Age','WorkClass', 'FnlWgt', 'Edu
                                     'Occupation', 'Relationship', 'Ra
                                     'CapitalGain', 'CapitalLoss', 'Ho
                                     'NativeCountry', 'Label'],
                              na_values="?", index_col=False)

census_orig = census_orig.dropna()

# Convert labels from strings to boolean
label_encoder = preprocessing.LabelEncoder()
census_labels = pd.DataFrame(label_encoder.fit_transform(census_orig.il

# Convert nominal attributes to encoded versions
attr_encoder = feature_extraction.DictVectorizer(sparse=False)
census_data = pd.DataFrame(attr_encoder.fit_transform(census_orig.iloc[
census_data.columns = attr_encoder.get_feature_names()
```

Question 2: Logistic Regression (20 points)

1. Learn linear and logistic regression classifiers for the census data. Perform 10-fold cross-validation (with `shuffle=True` and `random_state=20160202`) and report the mean accuracy of each classifier. Remember, you have to transform the linear regression result to get a classification.
2. One of the important aspects data mining is data normalization. Use the `StandardScaler` to normalize your data. Now re-run the same 10-fold experiment for both classifiers. What changed?
3. The Lasso and Ridge methods above are also part of logistic regression, although you must specify them slightly differently. You can specify the parameter `penalty='l1'` or `penalty='l2'` to specify Lasso or Ridge, respectively. The importance of regularization can be specified using the parameter C. Perform 10-fold CV with the L1 and L2 penalties and C=[0.1, 10]. Report the results of each combination (for a total of 4) averaged across folds.

Note: if this were a real experiment, you would want to do your parameter search with a validation set.

Answers 2:

1.

Linear Regression Mean Accuracy 0.833996
Logistic Regression Accuracy 0.790465

2.

The accuracies changed between the two models. Now with the data normalized, the Logistic Regression performs better than the Linear Regression, whereas in the original, non-standardized data, the reverse was true. It's worthy to note that the accuracy of the Logistic Regression improved significanlty ~5%

Linear Regression Mean Accuracy 0.833864
Logistic Regression Accuracy 0.848551

3.
Lasso Log Regression
L1 0.1: 0.848087
L1 10: 0.848551

Ridge Log Regression:
L2 0.1: 0.848485
L2 10: 0.848551

In [25]:
```
# Part 1 no normalization
from sklearn.metrics import accuracy_score

#maybe do your EDA here?
foldnum = 0
lr_fold_results = pd.DataFrame()
lgr_fold_results = pd.DataFrame()

for train, test in cross_validation.KFold(len(census_data), n_folds=10,
    foldnum+=1

    [adult_tr_data, adult_te_data,
     adult_tr_target, adult_te_target] = folds_to_split(census_data,cen

    lr = linear_model.LinearRegression()
    lr.fit(adult_tr_data, adult_tr_target)

    prediction = lr.predict(adult_te_data)
    classified_prediction = []
    for value in range(len(prediction)):
        classified_prediction.append(round(prediction[value]))
    adult_te_classified_data = pd.DataFrame(classified_prediction)

    lgr = linear_model.LogisticRegression(C=1e5)
    lgr.fit(adult_tr_data, np.reshape(adult_tr_target.values,[len(adult

    # But a nicer way to store them is in a DataFrame
    lr_fold_results.loc[foldnum, 'LinearReg Mean Accuracy'] = accuracy_
    lgr_fold_results.loc[foldnum, 'LogRegr Accuracy'] = lgr.score(adult

#Now let's look at the results:
print lr_fold_results
#And compute the mean error across folds:
print lr_fold_results.mean()

print lgr_fold_results
print lgr_fold_results.mean()
```

```
    LinearReg Mean Accuracy
1                  0.840570
2                  0.833941
3                  0.834881
4                  0.839523
5                  0.830902
6                  0.831565
7                  0.834218
8                  0.827586
9                  0.832560
10                 0.834218
LinearReg Mean Accuracy    0.833996
dtype: float64
    LogRegr Accuracy
1           0.783560
2           0.790520
3           0.797082
4           0.802056
5           0.781167
6           0.790119
7           0.793103
8           0.783820
9           0.784483
10          0.798740
LogRegr Accuracy    0.790465
dtype: float64
```

In [26]:
```
# Part 2 normalizing the data
from sklearn import preprocessing

sscaler = preprocessing.StandardScaler()
census_data_norm = pd.DataFrame(sscaler.fit_transform(census_data.value

#maybe do your EDA here?
foldnum = 0
lr_fold_results = pd.DataFrame()
lgr_fold_results = pd.DataFrame()

for train, test in cross_validation.KFold(len(census_data_norm), n_fold
    foldnum+=1

    [adult_tr_data, adult_te_data,
     adult_tr_target, adult_te_target] = folds_to_split(census_data_nor

    lr = linear_model.LinearRegression()
    lr.fit(adult_tr_data, adult_tr_target)

    prediction = lr.predict(adult_te_data)
    classified_prediction = []
    for value in range(len(prediction)):
        classified_prediction.append(round(prediction[value]))
    adult_te_classified_data = pd.DataFrame(classified_prediction)

    lgr = linear_model.LogisticRegression(C=1e5)
    lgr.fit(adult_tr_data, np.reshape(adult_tr_target.values,[len(adult

    # But a nicer way to store them is in a DataFrame
    lr_fold_results.loc[foldnum, 'LinearReg Mean Accuracy'] = accuracy_
    lgr_fold_results.loc[foldnum, 'LogRegr Accuracy'] = lgr.score(adult

#Now let's look at the results:
print lr_fold_results
#And compute the mean error across folds:
print lr_fold_results.mean()

print lgr_fold_results
print lgr_fold_results.mean()
```

```
    LinearReg Mean Accuracy
1                  0.842559
2                  0.832615
3                  0.835212
4                  0.839191
5                  0.830570
6                  0.831233
7                  0.832560
8                  0.826260
9                  0.832891
10                 0.835544
LinearReg Mean Accuracy    0.833864
dtype: float64
    LogRegr Accuracy
1           0.857474
2           0.846536
3           0.855106
4           0.852122
5           0.842838
6           0.845159
7           0.852122
8           0.838196
9           0.848806
10          0.847149
LogRegr Accuracy    0.848551
dtype: float64
```

In [27]:
```
# Part 3 Lasso and Ridge using Logistic Regression
foldnum = 0
fold_l1_01_results = pd.DataFrame()
fold_l1_10_results = pd.DataFrame()

fold_l2_01_results = pd.DataFrame()
fold_l2_10_results = pd.DataFrame()


for train, test in cross_validation.KFold(len(census_data_norm), n_fold
    foldnum+=1

    [adult_tr_data, adult_te_data,
     adult_tr_target, adult_te_target] = folds_to_split(census_data_nor

    lgr_l1_01 = linear_model.LogisticRegression(penalty = 'l1', C=0.1)
    lgr_l1_10 = linear_model.LogisticRegression(penalty = 'l1', C=10)
    lgr_l2_01 = linear_model.LogisticRegression(penalty = 'l2', C=0.1)
    lgr_l2_10 = linear_model.LogisticRegression(penalty = 'l2', C=10)

    lgr_l1_01.fit(adult_tr_data, np.reshape(adult_tr_target.values,[len
    lgr_l1_10.fit(adult_tr_data, np.reshape(adult_tr_target.values,[len

    lgr_l2_01.fit(adult_tr_data, np.reshape(adult_tr_target.values,[len
    lgr_l2_10.fit(adult_tr_data, np.reshape(adult_tr_target.values,[len

    # But a nicer way to store them is in a DataFrame
    fold_l1_01_results.loc[foldnum, 'L1 0.1: '] = lgr_l1_01.score(adult
    fold_l1_10_results.loc[foldnum, 'L1 10: '] = lgr_l1_10.score(adult_

    fold_l2_01_results.loc[foldnum, 'L2 0.1: '] = lgr_l2_01.score(adult
    fold_l2_10_results.loc[foldnum, 'L2 10: '] = lgr_l2_10.score(adult_


#And compute the mean error across folds:
print fold_l1_01_results.mean()
print fold_l1_10_results.mean()
print fold_l2_01_results.mean()
print fold_l2_10_results.mean()
```

```
L1 0.1:     0.848087
dtype: float64
L1 10:     0.848551
dtype: float64
L2 0.1:     0.848485
dtype: float64
L2 10:     0.848551
dtype: float64
```