ISLR Ch.4 Exercise

MSSP MA679

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4.7.6 Suppose we collect data for a group of students in a statistics class with variables X_1 = hours studied, X_2 = undergrad GPA, and Y = receive an A. We fit a logistic regression and produce estimated coefficient, β_0 = –6, β_1 = 0.05, β_2 = 1.

part a

Since β_0 = –6, β_1 = 0.05, β_2 = 1, X_1 = 40, X_2 = 3.5

$$p(X) = \frac{\exp(\beta_0+\beta_1 X_1+\beta_2 X_2)}{1+\exp(\beta_0+\beta_1 X_1+\beta_2 X_2)}$$

$$= \frac{\exp(-6+0.05*40+3.5)}{1+\exp(-6+0.05*40+3.5)} = 37.75\%$$

part b

$$p(X) = 0.5 = \frac{\exp(-6+0.05X_1+3.5)}{1+\exp(-6+0.05X_1+3.5)}$$

We obtain $X_1 = 50$

4.7.8 Suppose that we take a data set, divide it into equally-sized training and test sets, and then try out two different classification procedures. First we use logistic regression and get an error rate of 20 % on the training data and 30 % on the test data. Next we use 1-nearest neigh- bors (i.e. K = 1) and get an average error rate (averaged over both test and training data sets) of 18%. Based on these results, which method should we prefer to use for classification of new observations? Why?

Using KNN(K=1), the training error rate would be 0% becuase the result would always be the training point itself. Since the averaged error rate over both test and training data sets, we obtain test error rate as 18%*2-0% = 36%. Thus, logistic regression provides us a better test error rate.

4.7.9 This problem has to do with *odds*.

part a. On average, what fraction of people with an odds of 0.37 of defaulting on their credit card payment will in fact default?

$\frac{P(X)}{1-P(X)} = 0.37$

We obtain, $P(X) = 0.27$

part b. Suppose that an individual has a 16% chance of defaulting on her credit card payment. What are the odds that she will de- fault?

$\frac{P(X)}{1-P(X)} = \frac{0.16}{1-0.16} = 0.19$

4.7.10

part a

In [1]:

```python
import numpy as np
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import math
from sklearn.preprocessing import scale
import sklearn.linear_model as skl_lm
from sklearn.metrics import mean_squared_error, r2_score
import statsmodels.formula.api as smf
from numpy import corrcoef
from pandas.plotting import scatter_matrix
from statsmodels.stats.outliers_influence import OLSInfluence
from statsmodels.graphics.regressionplots import plot_leverage_resid2
import seaborn as sns
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis as QDA
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import scale
from scipy import stats
from sklearn.datasets import load_boston


wk = pd.read_csv('Weekly.csv')
print( "There are", wk.shape[0], "rows and ", wk.shape[1], "columns in Weekly dataset." )
wk.head()
```

```
There are 1089 rows and  9 columns in Weekly dataset.
```

Out[1]:

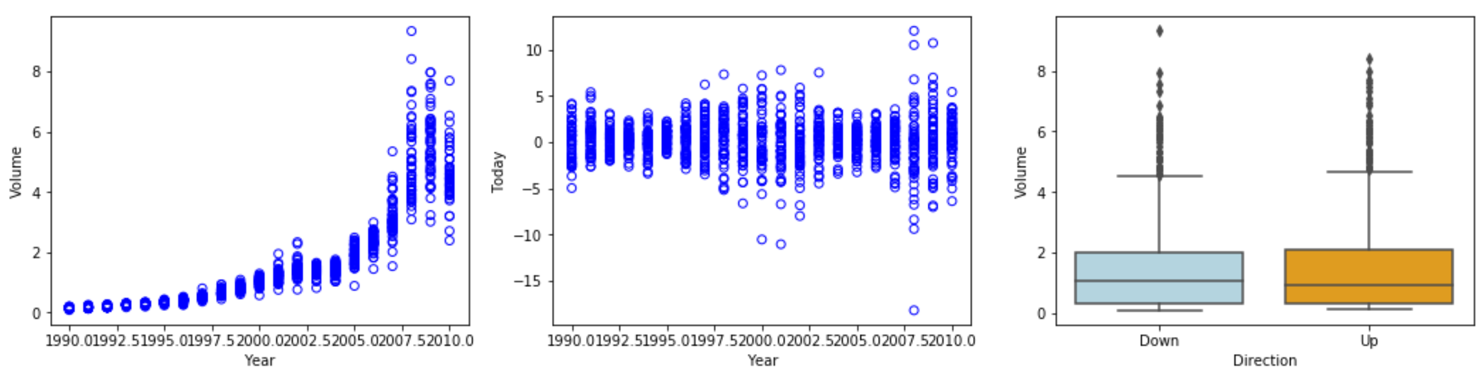
	Year	Lag1	Lag2	Lag3	Lag4	Lag5	Volume	Today	Direction
0	1990	0.816	1.572	-3.936	-0.229	-3.484	0.154976	-0.270	Down
1	1990	-0.270	0.816	1.572	-3.936	-0.229	0.148574	-2.576	Down
2	1990	-2.576	-0.270	0.816	1.572	-3.936	0.159837	3.514	Up
3	1990	3.514	-2.576	-0.270	0.816	1.572	0.161630	0.712	Up
4	1990	0.712	3.514	-2.576	-0.270	0.816	0.153728	1.178	Up

In [2]:

```
fig, (ax11,ax22,ax33) = plt.subplots(1,3,figsize=(18,4))



#  Volume vs. Year
ax11.scatter(wk.Year.values, wk.Volume.values, facecolors='none', edgecolors='
b' )
ax11.set_xlabel('Year')
ax11.set_ylabel('Volume')

# Today vs. Year
ax22.scatter(wk.Year.values, wk.Today.values, facecolors='none', edgecolors='b
' )
ax22.set_xlabel('Year')
ax22.set_ylabel('Today')


# Plot Lag1 vs Today's return
c_palette = {'Down':'lightblue', 'Up':'orange'}
sns.boxplot('Direction', 'Volume', data=wk, orient='v', ax=ax33, palette=c_pal
ette)
```

Out[2]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x101e01ac8>
```

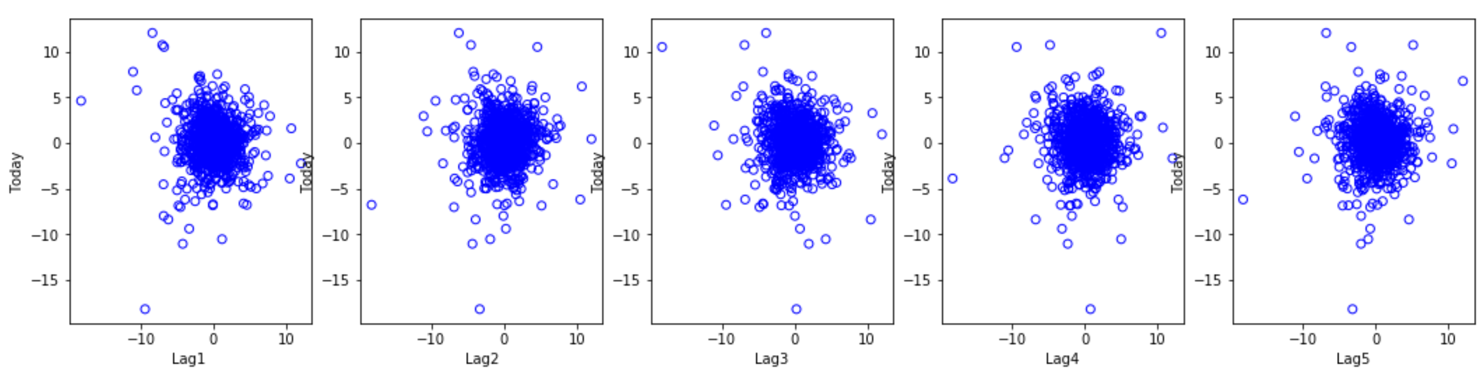


In [3]:

```
fig, (ax1,ax2,ax3,ax4,ax5) = plt.subplots(1,5,figsize=(18,4))


# Plot Lag1 vs Today
ax1.scatter(wk.Lag1.values, wk.Today.values, facecolors='none', edgecolors='b'
)
ax1.set_xlabel('Lag1 ')
ax1.set_ylabel('Today')

# Plot Lag2 vs Today
ax2.scatter(wk.Lag2.values, wk.Today.values, facecolors='none', edgecolors='b'
)
ax2.set_xlabel('Lag2')
ax2.set_ylabel('Today')


# Plot Lag3 vs Today
ax3.scatter(wk.Lag3.values, wk.Today.values, facecolors='none', edgecolors='b'
)
ax3.set_xlabel('Lag3')
ax3.set_ylabel('Today')

# Plot Lag4 vs Today
ax4.scatter(wk.Lag4.values, wk.Today.values, facecolors='none', edgecolors='b'
)
ax4.set_xlabel('Lag4')
ax4.set_ylabel('Today')


# Plot Lag5 vs Today
ax5.scatter(wk.Lag5.values, wk.Today.values, facecolors='none', edgecolors='b'
)
ax5.set_xlabel('Lag5')
ax5.set_ylabel('Today')
```

Out[3]:

```
Text(0, 0.5, 'Today')
```



Positive relationship between Volume and Year. No obvious correlation between Today and Lags, Year and Today.

part b

In [4]:

```
pred = sm.add_constant(wk[wk.columns[1:7]])
dirc = np.array([1 if el=='Up' else 0 for el in wk.Direction.values])

glm1 = sm.Logit(dirc,pred)
glm1results=glm1.fit()
print(glm1results.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.682441
         Iterations 4
                           Logit Regression Results
==================================================================
============
Dep. Variable:                      y   No. Observations:
1089
Model:                          Logit   Df Residuals:
1082
Method:                           MLE   Df Model:
6
Date:                Thu, 07 Feb 2019   Pseudo R-squ.:
0.006580
Time:                        21:27:08   Log-Likelihood:
-743.18
converged:                       True   LL-Null:
-748.10
                                        LLR p-value:
0.1313
==================================================================
============
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------
------------
const          0.2669      0.086      3.106      0.002       0.098
0.435
Lag1          -0.0413      0.026     -1.563      0.118      -0.093
0.010
Lag2           0.0584      0.027      2.175      0.030       0.006
0.111
Lag3          -0.0161      0.027     -0.602      0.547      -0.068
0.036
Lag4          -0.0278      0.026     -1.050      0.294      -0.080
0.024
Lag5          -0.0145      0.026     -0.549      0.583      -0.066
0.037
Volume        -0.0227      0.037     -0.616      0.538      -0.095
0.050
==================================================================
============
```

Only Lag2 has a 95% confidence interval containing zero

part c

In [5]:

```
dirc_predicted = glm1results.predict(pred)
dirc_predicted= np.array(dirc_predicted > 0.5, dtype=float)
Ctable = np.histogram2d(dirc_predicted, dirc, bins=2)[0]
print(pd.DataFrame(Ctable, ['Down', 'Up'], ['Down', 'Up']))
print('\n')
print('Error Rate =', 1-(Ctable[0,0]+Ctable[1,1])/np.sum(Ctable))
```

```
       Down     Up
Down   54.0   48.0
Up    430.0  557.0


Error Rate = 0.43893480257116624
```

percision = $\frac{557}{430+557} = 56\%$

type one error (false positive rate) = $\frac{430}{430+54} = 89\%$

type two error (false negative rate) = $\frac{48}{557+48} = 8\%$

sensitivity = 1 - 8% = 92%

The model has a very high false positive rate.

part d

In [6]:

```
predTest = sm.add_constant(wk[wk.Year > 2008].Lag2)
dircTest = np.array([1 if el=='Up' else 0 for el in wk[wk.Year > 2008].Directi
on])

predTrain = sm.add_constant(wk[wk.Year <= 2008].Lag2)
dircTrain = np.array([1 if el=='Up' else 0 for el in wk[wk.Year <= 2008].Direc
tion])

glmTrain = sm.Logit(dircTrain,predTrain)
glmTrainresults=glmTrain.fit()
print(glmTrainresults.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.685555
         Iterations 4
                           Logit Regression Results
==================================================================
============
Dep. Variable:                      y   No. Observations:
985
Model:                          Logit   Df Residuals:
983
Method:                           MLE   Df Model:
1
Date:                Thu, 07 Feb 2019   Pseudo R-squ.:
0.003076
Time:                        21:27:08   Log-Likelihood:
-675.27
converged:                       True   LL-Null:
-677.35
                                        LLR p-value:
0.04123
==================================================================
============
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------
------------
const          0.2033      0.064      3.162      0.002      0.077
0.329
Lag2           0.0581      0.029      2.024      0.043      0.002
0.114
==================================================================
============
```

In [7]:

```
dircTrain_predicted = glmTrainresults.predict(predTest)
dircTrain_predicted= np.array(dircTrain_predicted > 0.5, dtype=float)
CtableTrain = np.histogram2d(dircTrain_predicted, dircTest, bins=2)[0]
print(pd.DataFrame(CtableTrain, ['Down', 'Up'], ['Down', 'Up']))
print('\n')
print('Error Rate =', 1-(CtableTrain[0,0]+CtableTrain[1,1])/np.sum(CtableTrain
))
```

```
      Down    Up
Down   9.0   5.0
Up    34.0  56.0


Error Rate = 0.375
```

The error rate has decreased, but the type one error is still large.

part e

In [8]:

```
LDAClf = LDA(solver='lsqr', store_covariance=True)

PredLDA_train = wk[wk.Year <= 2008].Lag2.values
PredLDA_train = PredLDA_train.reshape((len(PredLDA_train),1))

PredLDA_test = wk[wk.Year > 2008].Lag2.values
PredLDA_test = PredLDA_test.reshape((len(PredLDA_test),1))

LDAClf.fit(PredLDA_train, dircTrain)
print('Priors = ', LDAClf.priors_ )
print('Class Means = ', LDAClf.means_[0], LDAClf.means_[1])
print('Coeffecients = ', LDAClf.coef_)
print('\n')
```

```
Priors =  [0.44771574 0.55228426]
Class Means =  [-0.03568254] [0.26036581]
Coeffecients =  [[0.05780187]]
```

In [9]:

```
dircTrainLDA_predicted = LDAClf.predict(PredLDA_test)
dircTrainLDA_predicted= np.array(dircTrainLDA_predicted > 0.5, dtype=float)

CtableLDATrain = np.histogram2d(dircTrainLDA_predicted, dircTest, bins=2)[0]
print('CONFUSION MATRIX')
print(pd.DataFrame(CtableLDATrain, ['Down', 'Up'], ['Down', 'Up']))
print('\n')
print('Error Rate =', 1-(CtableLDATrain[0,0]+CtableLDATrain[1,1])/np.sum(Ctabl
eLDATrain))
```

```
CONFUSION MATRIX
      Down    Up
Down   9.0   5.0
Up    34.0  56.0


Error Rate = 0.375
```

The result of LDA is the same as the result of logistic regression

part f

In [10]:

```
QDAClf = QDA( store_covariance=True)

PredQDA_train = wk[wk.Year <= 2008].Lag2.values
PredQDA_train = PredQDA_train.reshape((len(PredQDA_train),1))

PredQDA_test = wk[wk.Year > 2008].Lag2.values
PredQDA_test = PredQDA_test.reshape((len(PredQDA_test),1))

QDAClf.fit(PredQDA_train, dircTrain)


print('Priors = ', QDAClf.priors_ )
print('Class Means = ', QDAClf.means_[0], QDAClf.means_[1])
print('Coeffecients = ', QDAClf.covariance_)
print('\n')
```

```
Priors =  [0.44771574 0.55228426]
Class Means =  [-0.03568254] [0.26036581]
Coeffecients =  [array([[4.83781758]]), array([[5.37073888]])]
```

In [11]:

```
dircTrainQDA_predicted = QDAClf.predict(PredQDA_test)
dircTrainQDA_predicted= np.array(dircTrainQDA_predicted > 0.5, dtype=float)

CtableQDATrain = np.histogram2d(dircTrainQDA_predicted, dircTest, bins=2)[0]
print('CONFUSION MATRIX')
print(pd.DataFrame(CtableLDATrain, ['Down', 'Up'], ['Down', 'Up']))
print('\n')
print('Error Rate =', 1-(CtableQDATrain[0,0]+CtableQDATrain[1,1])/np.sum(Ctabl
eQDATrain))
```

```
CONFUSION MATRIX
      Down    Up
Down   9.0   5.0
Up    34.0  56.0


Error Rate = 0.41346153846153844
```

In this exercise, we only have one predictor, but quadratic decision boundary requires multiple predictors. Thus, the model does not fit very well with QDA classifier.

part g

In [12]:

```
KNNClf = KNeighborsClassifier(n_neighbors=1)

PredKNN_train = wk[wk.Year <= 2008].Lag2.values
PredKNN_train = PredKNN_train.reshape((len(PredKNN_train),1))

PredKNN_test = wk[wk.Year > 2008].Lag2.values
PredKNN_test = PredKNN_test.reshape((len(PredKNN_test),1))


KNNClf.fit(PredKNN_train, dircTrain)

dircTrainKNN_predicted = KNNClf.predict(PredKNN_test)



CtableKNN = np.histogram2d(dircTrainKNN_predicted, dircTest , bins=2)[0]
print(pd.DataFrame(CtableKNN, ['Down', 'Up'], ['Down', 'Up']))
print('')
print('Error Rate =', 1-(CtableKNN[0,0]+CtableKNN[1,1])/np.sum(CtableKNN))
```

```
      Down    Up
Down  21.0  31.0
Up    22.0  30.0

Error Rate = 0.5096153846153846
```

part h

Comparing error rate, logistic model or LDA models work best.

part i

In [13]:

```
pred3 = wk.columns[1:4]
dirc3 = np.array([1 if el=='Up' else 0 for el in wk.Direction.values])

pred3Test = sm.add_constant(wk[wk.Year > 2008][pred3])
dirc3Test = np.array([1 if el=='Up' else 0 for el in wk[wk.Year > 2008].Direct
ion])

pred3Train = sm.add_constant(wk[wk.Year <= 2008][pred3])
dirc3Train = np.array([1 if el=='Up' else 0 for el in wk[wk.Year <= 2008].Dire
ction])

glm3Train = sm.Logit(dirc3Train,pred3Train)
glm3Trainresults=glm3Train.fit()



dirc3Train_predicted = glm3Trainresults.predict(pred3Test)
dirc3Train_predicted= np.array(dirc3Train_predicted > 0.5, dtype=float)
Ctable3Train = np.histogram2d(dirc3Train_predicted, dirc3Test, bins=2)[0]
print(pd.DataFrame(Ctable3Train, ['Down', 'Up'], ['Down', 'Up']))
print('\n')
print('Error Rate =', 1-(Ctable3Train[0,0]+Ctable3Train[1,1])/np.sum(Ctable3Tr
ain))
```

```
Optimization terminated successfully.
         Current function value: 0.683687
         Iterations 4
      Down    Up
Down   8.0   9.0
Up    35.0  52.0


Error Rate = 0.42307692307692313
```

In [14]:

```
wk['Lag1xLag2'] = pd.Series(wk.Lag1*wk.Lag2, index=wk.index)
pred2 = ['Lag1', 'Lag2', 'Lag1xLag2']


pred2Test = sm.add_constant(wk[wk.Year > 2008][pred2])
dirc2Test = np.array([1 if el=='Up' else 0 for el in wk[wk.Year > 2008].Direct
ion])

pred2Train = sm.add_constant(wk[wk.Year <= 2008][pred2])
dirc2Train = np.array([1 if el=='Up' else 0 for el in wk[wk.Year <= 2008].Dire
ction])

glm2Train = sm.Logit(dirc2Train,pred2Train)
glm2Trainresults=glm2Train.fit()


dirc2Train_predicted = glm2Trainresults.predict(pred2Test)
dirc2Train_predicted= np.array(dirc2Train_predicted > 0.5, dtype=float)
Ctable2Train = np.histogram2d(dirc2Train_predicted, dirc2Test, bins=2)[0]
print(pd.DataFrame(Ctable3Train, ['Down', 'Up'], ['Down', 'Up']))
print('\n')
print('Error Rate =', 1-(Ctable2Train[0,0]+Ctable2Train[1,1])/np.sum(Ctable2Tr
ain))
```

```
Optimization terminated successfully.
         Current function value: 0.683701
         Iterations 4
      Down    Up
Down   8.0   9.0
Up    35.0  52.0


Error Rate = 0.42307692307692313
```

Using multiple lags or interaction of lags does not help.

In [15]:

```
KNN20Clf = KNeighborsClassifier(n_neighbors=20)

PredKNN20_train = wk[wk.Year <= 2008].Lag2.values
PredKNN20_train = PredKNN20_train.reshape((len(PredKNN20_train),1))

PredKNN20_test = wk[wk.Year > 2008].Lag2.values
PredKNN20_test = PredKNN20_test.reshape((len(PredKNN20_test),1))


KNN20Clf.fit(PredKNN20_train, dircTrain)

dircTrainKNN20_predicted = KNN20Clf.predict(PredKNN20_test)



CtableKNN20 = np.histogram2d(dircTrainKNN20_predicted, dircTest , bins=2)[0]
print(pd.DataFrame(CtableKNN20, ['Down', 'Up'], ['Down', 'Up']))
print('')
print('Error Rate =', 1-(CtableKNN20[0,0]+CtableKNN20[1,1])/np.sum(CtableKNN20
))
```

```
      Down    Up
Down  23.0  22.0
Up    20.0  39.0

Error Rate = 0.40384615384615385
```

Increasing K decreases error rate.

4.7.11

part a

In [16]:

```
at = pd.read_csv('Auto.csv')
print( "There are", at.shape[0], "rows and ", at.shape[1], "columns in Auto da
taset." )
at['MPG01'] = at.mpg > at.mpg.median()
at.head()
```

```
There are 392 rows and  9 columns in Auto dataset.
```

Out[16]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino

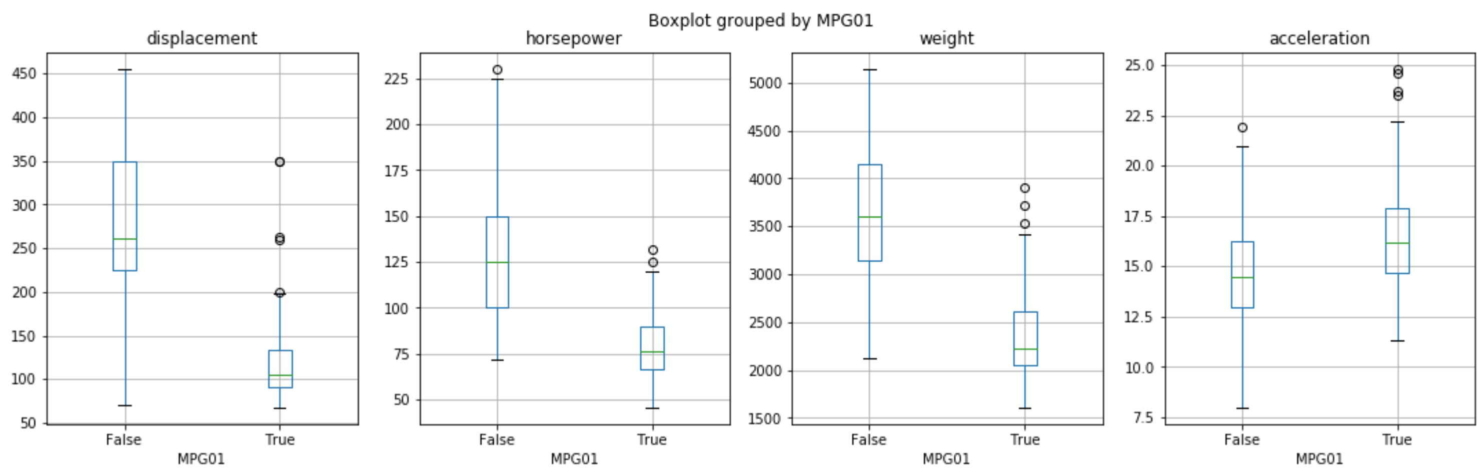
part b

In [17]:

```
fig, ( ax2, ax3,ax4,ax5) = plt.subplots(1,4, figsize=(18,5))

at.boxplot(['displacement'], by='MPG01', ax=ax2)
at.boxplot(['horsepower'], by='MPG01', ax=ax3)
at.boxplot(['weight'],by='MPG01',ax=ax4)
at.boxplot(['acceleration'], by='MPG01', ax=ax5)
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1c1709b2b0>
```



part c

In [18]:

```
n_samples = 250
rows_sample = np.random.choice([True, False], n_samples)
atTrain = at.loc[rows_sample]
atTest = at.loc[~rows_sample]
```

In [19]:

```
predictors = ['displacement','horsepower', 'weight', 'acceleration']
pred_train =  atTrain[predictors].values
mpg_train = atTrain['MPG01'].values

pred_test = atTest[predictors].values
mpg_test = atTest['MPG01'].values

LDA_clf = LDA(solver='lsqr',store_covariance=True)
LDA_clf.fit(pred_train,mpg_train)

print('Class Priors =', LDA_clf.priors_)
print('Class Means =', LDA_clf.means_[0], LDA_clf.means_[1])
print('Coeffecients =', LDA_clf.coef_)


mpg_predicted = LDA_clf.predict(pred_test)
print('The error rate of the LDA model is ',np.mean(mpg_predicted!=mpg_test))
```

```
Class Priors = [0.63636364 0.36363636]
Class Means = [ 287.94047619  134.3452381  3693.60714286   14.3333
3333] [ 104.54166667   78.29166667 2223.5625       16.55416667]
Coeffecients = [[-0.04946214  0.04704727 -0.00146785 -0.30826663]]
The error rate of the LDA model is  0.13559322033898305
```

part d

In [20]:

```
QDA_clf = QDA()
QDA_clf.fit(pred_train,mpg_train)

print('Class Priors =', QDA_clf.priors_)
print('Class Means =', QDA_clf.means_[0], QDA_clf.means_[1])

mpgqda_predicted = QDA_clf.predict(pred_test)
print('The error rate of the QDA model is ',np.mean(mpgqda_predicted!=mpg_test
))
```

```
Class Priors = [0.63636364 0.36363636]
Class Means = [ 287.94047619  134.3452381  3693.60714286   14.3333
3333] [ 104.54166667   78.29166667 2223.5625       16.55416667]
The error rate of the QDA model is  0.1016949152542373
```

part e

In [21]:

```
pred_train = sm.add_constant(atTrain[predictors])
pred_test = sm.add_constant(atTest[predictors])


glm11 = sm.Logit(mpg_train,pred_train)
glm11results = glm11.fit()
print(glm11results.summary())
print(' Correlations  ' , atTrain[predictors].corr())

glmtest_predictions = glm11results.predict(pred_test)
mpgglm_predicted = np.array(glmtest_predictions > 0.5, dtype=bool)
print('The error rate of the logistic model is ',np.mean(mpgglm_predicted!=mpg
_test))
```

```
Optimization terminated successfully.
         Current function value: 0.144763
         Iterations 10
                           Logit Regression Results
==================================================================
============
Dep. Variable:                      y   No. Observations:
132
Model:                          Logit   Df Residuals:
127
Method:                           MLE   Df Model:
4
Date:                Thu, 07 Feb 2019   Pseudo R-squ.:
0.7791
Time:                        21:27:09   Log-Likelihood:
-19.109
converged:                       True   LL-Null:
-86.524
                                        LLR p-value:
3.608e-28
==================================================================
==============
                   coef    std err          z      P>|z|      [0.0
25      0.975]
------------------------------------------------------------------
--------------
const           31.8350     10.455      3.045      0.002      11.3
44      52.326
displacement    -0.0519      0.018     -2.877      0.004      -0.0
87      -0.017
horsepower      -0.1283      0.057     -2.267      0.023      -0.2
39      -0.017
weight           0.0003      0.002      0.157      0.875      -0.0
04       0.004
acceleration    -0.8361      0.357     -2.344      0.019      -1.5
35      -0.137
==================================================================
==============

Possibly complete quasi-separation: A fraction 0.35 of observation
s can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identif
ied.
 Correlations                displacement  horsepower    weight
acceleration
displacement      1.000000    0.916261  0.950644     -0.696084
horsepower        0.916261    1.000000  0.887532     -0.801366
weight            0.950644    0.887532  1.000000     -0.604177
acceleration     -0.696084   -0.801366 -0.604177      1.000000
The error rate of the logistic model is  0.09322033898305085
```

part g

In [22]:

```
pred_train =  atTrain[predictors].values
mpg_train = atTrain['MPG01'].values

pred_test = atTest[predictors].values
mpg_test = atTest['MPG01'].values


train_error_rate = np.zeros(10)
test_error_rate = np.zeros(10)
K = np.arange(1,11)

for i, j in enumerate(K):
    # Construct a KNN classifier and fit
    knn = KNeighborsClassifier(n_neighbors=j)
    knn.fit(pred_train,mpg_train)

    # use the model on the training data to get training error rate
    y_train_predicted = knn.predict(pred_train)
    # compute the training error rate for this k-value
    train_error_rate[i] = np.mean(y_train_predicted!=mpg_train)

    # Use the model on the held out test data
    mpg_test_predicted = knn.predict(pred_test)
    # compute the error rate for this k-value
    test_error_rate[i] = np.mean(mpg_test_predicted!=mpg_test)

print('The test error rate for k = 1 - 10 are: ', test_error_rate)
```

```
The test error rate for k = 1 - 10 are:  [0.13559322 0.11016949 0.
07627119 0.09322034 0.09322034 0.11016949
 0.09322034 0.07627119 0.07627119 0.06779661]
```

4.7.12

part a

part b

In [23]:

```
def power():
    """ print 2**3 """
    print(2**3)

power()
```

8

In [24]:

```
def power2(x,a):
    """ print x to the power of a """
    print(x**a)

power2(3,8)
```

```
6561
```

part c

In [25]:

```
power2(10,3)
power2(8,17)
power2(131,3)
```

```
1000
2251799813685248
2248091
```

part d

In [26]:

```
def power3(x,a):
    """ return x raised to the power of a """
    return(x**a)
```

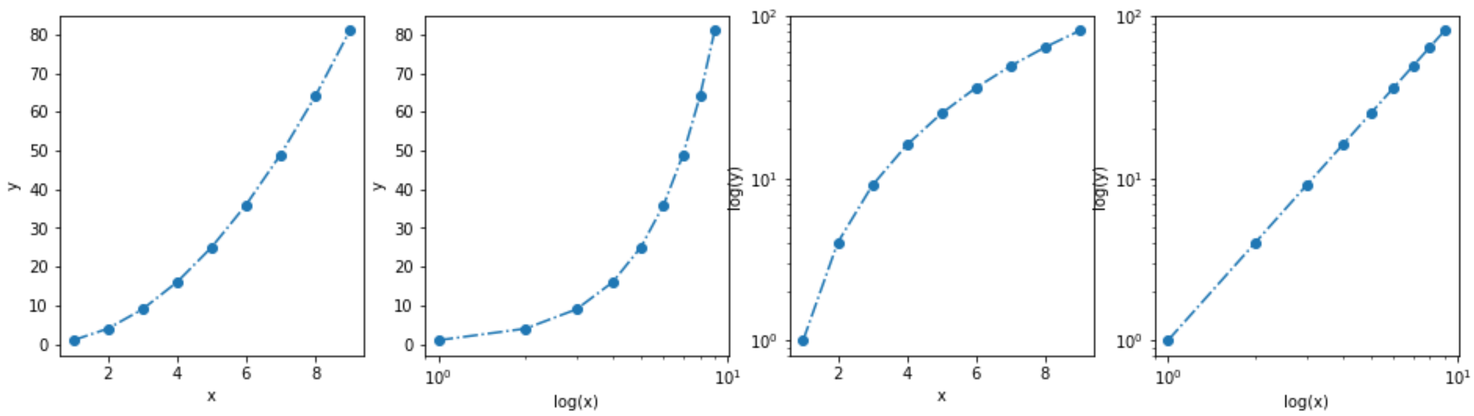
part e

In [27]:

```
x = np.arange(1,10)
y = power3(x,2)

fig, (ax1,ax2,ax3,ax4) = plt.subplots(1,4, figsize=(16,4))

ax1.plot(x,y,linestyle='-.', marker='o')
ax1.set_xlabel('x')
ax1.set_ylabel('y')

ax2.semilogx(x,y, linestyle='-.', marker='o')
ax2.set_xlabel('log(x)')
ax2.set_ylabel('y')

ax3.semilogy(x,y, linestyle='-.', marker='o')
ax3.set_xlabel('x')
ax3.set_ylabel('log(y)')

ax4.loglog(x,y, linestyle='-.', marker='o')
ax4.set_xlabel('log(x)')
ax4.set_ylabel('log(y)')
```

Out[27]:

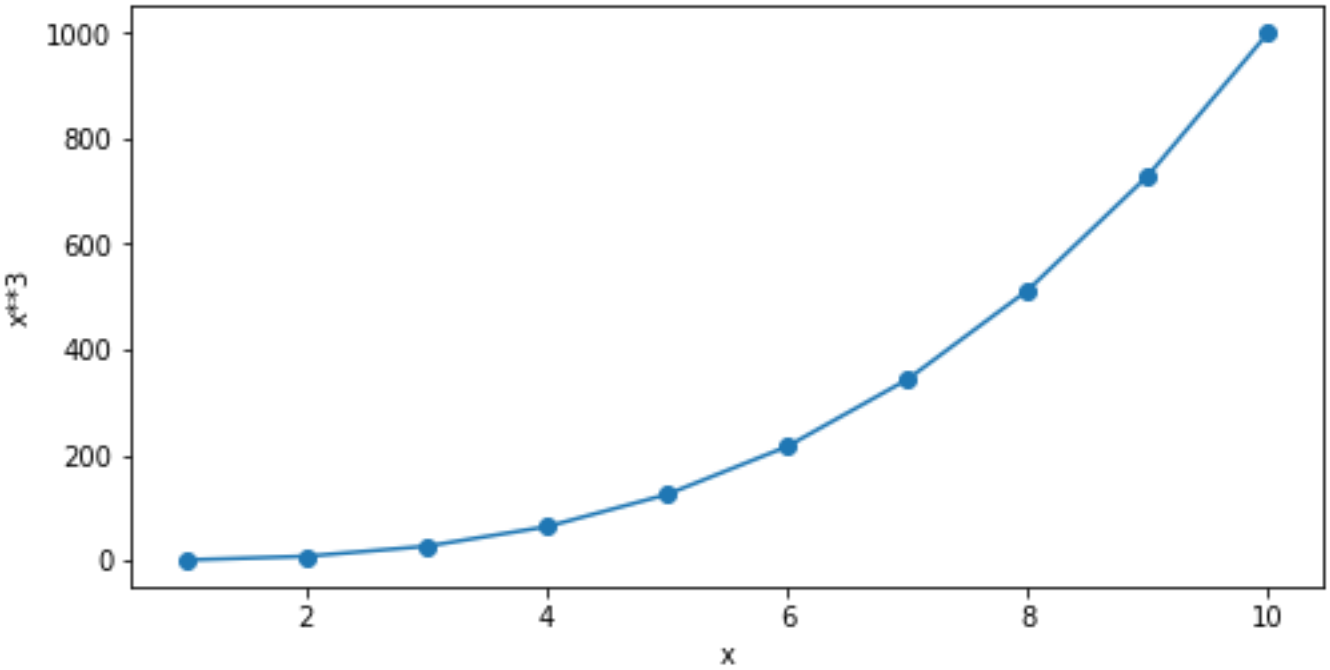
```
Text(0, 0.5, 'log(y)')
```



part f

In [28]:

```
def plot_power(x,a):
    """Plots x vs x**a """
    y = x**a

    fig, ax = plt.subplots(figsize=(8,4))
    ax.plot(x,y, linestyle = '-', marker = 'o')
    ax.set_xlabel('x')
    ax.set_ylabel('x**'+str(a))
plot_power(np.arange(1,11),3)
```



4.7.13

In [29]:

```
BOS = load_boston()
predictors = BOS.data
response = BOS.target
boston_data = np.column_stack([predictors,response])
col_names = np.append(BOS.feature_names, 'MEDV')
BOS = pd.DataFrame(boston_data, columns = col_names)
BOS['CRIM01'] = pd.Series(BOS.CRIM > BOS.CRIM.median(), index=BOS.index)
BOS.head()
```

Out[29]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90

In [30]:

```
rows = np.random.choice([True, False], 500)
BOS_train = BOS.loc[rows]
BOS_test = BOS.loc[~rows]

predictors = ['NOX', 'AGE', 'PTRATIO', 'LSTAT', 'MEDV']
PRED_train = sm.add_constant(BOS_train[predictors])
PRED_test = sm.add_constant(BOS_test[predictors])

CRIM_train = BOS_train.CRIM01.values
CRIM_test = BOS_test.CRIM01.values

glm13 = sm.Logit(CRIM_train, PRED_train)
glm13results = glm13.fit()
print(glm13results.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.251645
         Iterations 9
                           Logit Regression Results
==================================================================
============
Dep. Variable:                      y   No. Observations:
240
Model:                          Logit   Df Residuals:
234
Method:                           MLE   Df Model:
5
Date:                Thu, 07 Feb 2019   Pseudo R-squ.:
0.6347
Time:                        21:27:10   Log-Likelihood:
-60.395
converged:                       True   LL-Null:
-165.35
                                        LLR p-value:
2.160e-43
==================================================================
============
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------
------------
const        -36.3639      6.337     -5.738      0.000     -48.785
-23.943
NOX           46.6091      7.688      6.063      0.000      31.542
61.676
AGE           -0.0040      0.013     -0.297      0.767      -0.030
0.022
PTRATIO        0.4618      0.162      2.843      0.004       0.143
0.780
LSTAT         -0.0642      0.056     -1.146      0.252      -0.174
0.046
MEDV           0.1551      0.054      2.882      0.004       0.050
0.261
==================================================================
============
```

In [31]:

```
CRIM_predicted = glm13results.predict(PRED_test) > 0.5
print('The error rate of the logistic model is ',np.mean(CRIM_predicted!=CRIM_
test))
```

```
The error rate of the logistic model is  0.1346153846153846
```

In [32]:

```
PRED_train = BOS_train[predictors].values
PRED_test = BOS_test[predictors].values

CRIM_train = BOS_train.CRIM01.values
CRIM_test = BOS_test.CRIM01.values

LDA_clf = LDA(solver='lsqr',store_covariance=True)
LDA_clf.fit(PRED_train,CRIM_train)

print('Class Priors =', LDA_clf.priors_)
print('Class Means =', LDA_clf.means_[0], LDA_clf.means_[1])
print('Coeffecients =', LDA_clf.coef_)

LDACRIM_predicted = LDA_clf.predict(PRED_test)
print('The error rate of the LDA model is ',np.mean(LDACRIM_predicted!=CRIM_te
st))
```

```
Class Priors = [0.54583333 0.45416667]
Class Means = [ 0.47119008 51.55801527 17.94961832  9.64664122 24.
33282443] [ 0.63705505 85.3587156  18.89816514 15.60963303 20.9293
578 ]
Coeffecients = [[3.27552082e+01 7.36628035e-03 4.25451811e-01 2.61
434203e-02
  1.27459137e-01]]
The error rate of the LDA model is  0.16923076923076924
```

In [33]:

```
train_error_rate = np.zeros(10)
test_error_rate = np.zeros(10)
K = np.arange(1,11)

for i, j in enumerate(K):
    # Construct a KNN classifier and fit
    knn = KNeighborsClassifier(n_neighbors=j)
    knn.fit(PRED_train,CRIM_train)

    # use the model on the training data to get training error rate
    CRIM_train_predicted = knn.predict(PRED_train)
    # compute the training error rate for this k-value
    train_error_rate[i] = np.mean(CRIM_train_predicted!=CRIM_train)

    # Use the model on the held out test data
    CRIM_test_predicted = knn.predict(PRED_test)
    # compute the error rate for this k-value
    test_error_rate[i] = np.mean(CRIM_test_predicted!=CRIM_test)

print('The test error rate for k = 1 - 10 are: ', test_error_rate)

print('The train error rate for k = 1 - 10 are: ', train_error_rate)
```

```
The test error rate for k = 1 - 10 are:  [0.28846154 0.35384615 0.
21923077 0.23461538 0.20384615 0.21538462
 0.19230769 0.21923077 0.2        0.22692308]
The train error rate for k = 1 - 10 are:  [0.         0.14583333 0
.14583333 0.19166667 0.175      0.18333333
 0.16666667 0.1875     0.19583333 0.2       ]
```

In [ ]:

```

```