A Python Companion to ISLR

Naresh Gurbuxani

May 15, 2019

Contents

1 Introduction

Figure 1 shows graphs of Wage versus three variables.

Figure 2 shows boxplots of previous days' percentage changes in S&P 500 grouped according to today's change `Up` or `Down`.

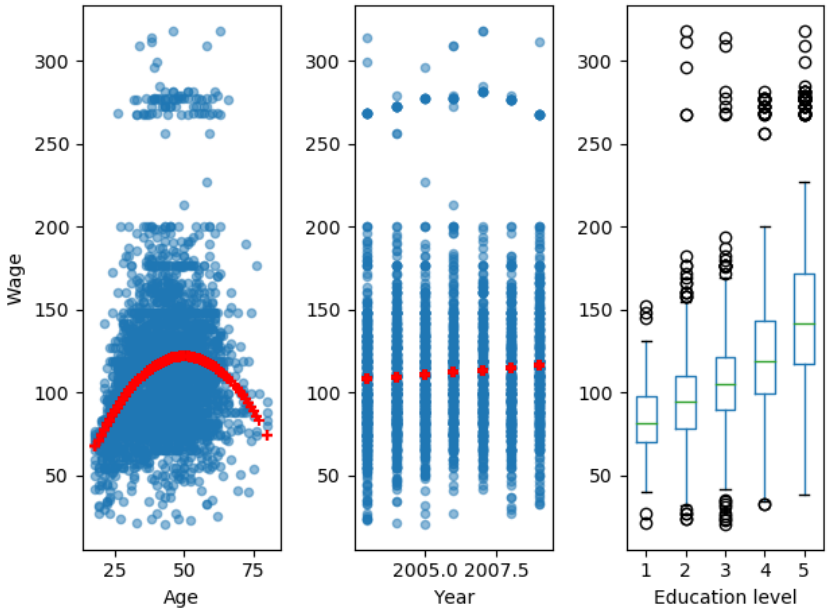

Figure 1: `Wage` data, which contains income survey information for males from the central Atlantic region of the United States. Left: `wage` as a function of `age`. On average, `wage` increases with `age` until about 60 years of age, at which point it begins to decline. Center: `wage` as a function of `year`. There is a slow but steady increase of approximately $10,000 in the average `wage` between 2003 and 2009. Right: Boxplots displaying `wage` as a function of `education`, with 1 indicating the lowest level (no highschool diploma) and 5 the highest level (an advanced graduate degree). On average, `wage` increases with the level of `education`.

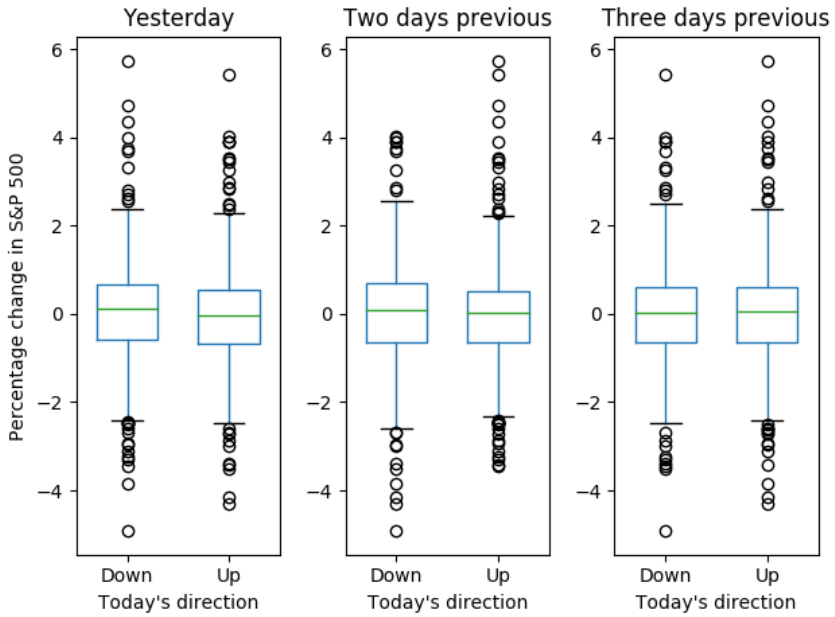

Figure 2: Left: Boxplots of the previous day's percentage change in the S&P 500 index for the days for which the market increased or decreased, obtained from the `Smarket` data. Center and Right: Same as left panel, but the percentage changes for two and three days previous are shown.

2 Statistical Learning

2.1 What is Statistical Learning?

Figure 3 shows scatter plots of `sales` versus `TV`, `radio`, and `newspaper` advertising. In each panel, the figure also includes an OLS regression line.

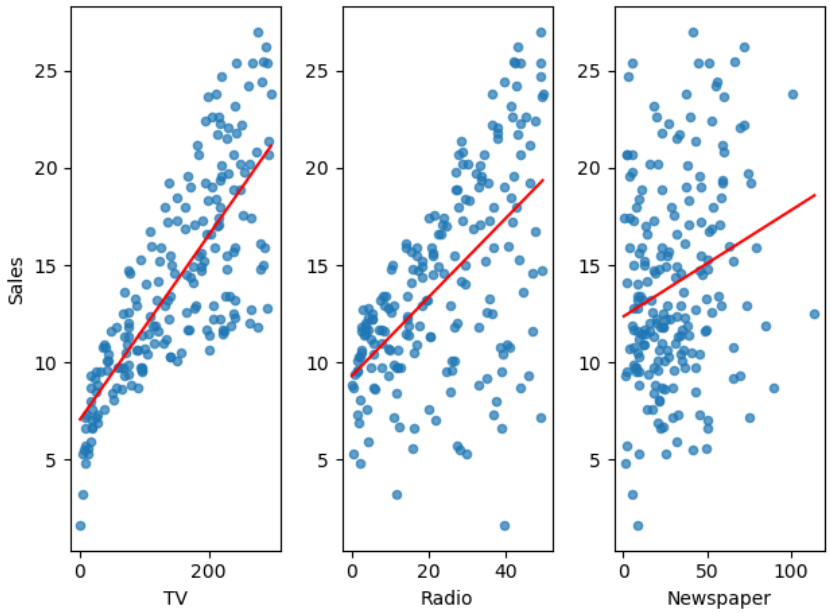

Figure 3: The `Advertising` data set. The plot displays `sales`, in thousands of units, as a function of `TV`, `radio`, and `newspaper` budgets, in thousands of dollars, for 200 different markets. In each plot we show the simple least squares fit of `sales` to that variable. In other words, each red line represents a simple model that can be used to predict `sales` using `TV`, `radio`, and `newspaper`, respectively.

Figure 4 is a plot of `Income` versus `Years of Education` from the Income data set. In the left panel, the "true" function (given by blue line) is actually my guess.

Figure 5 is a plot of `Income` versus `Years of Education` and `Seniority` from the `Income` data set. Since the book does not provide the true values of `Income`, "true" values shown in the plot are actually third order polynomial fit.

Figure 6 shows an example of the parametric approach applied to the

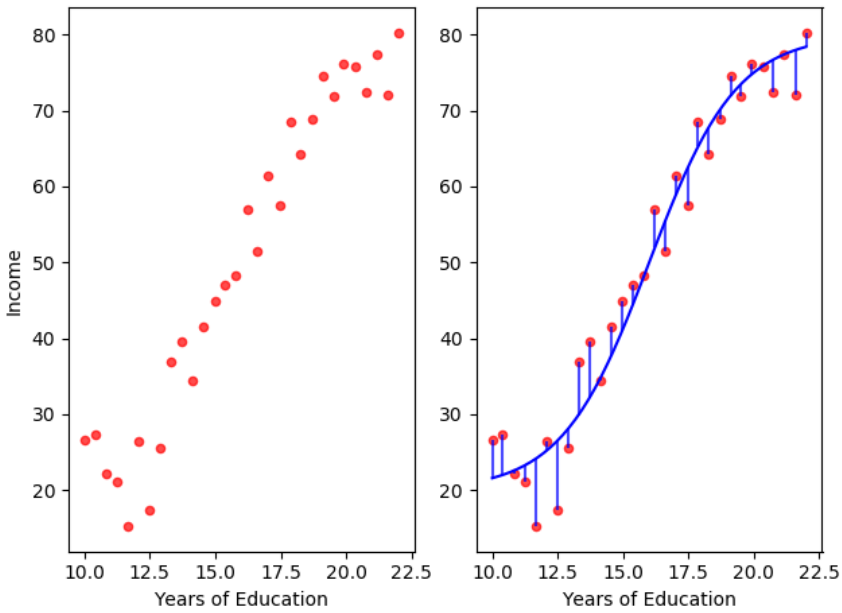

Figure 4: The `Income` data set. Left: The red dots are the observed values of `income` (in tens of thousands of dollars) and `years of education` for 30 individuals. Right: The blue curve represents the true underlying relationship between `income` and `years of education`, which is generally unknown (but is known in this case because the data are simulated). The vertical lines represent the error associated with each observation. Note that some of the errors are positive (when an observation lies above the blue curve) and some are negative (when an observation lies below the curve). Overall, these errors have approximately mean zero.

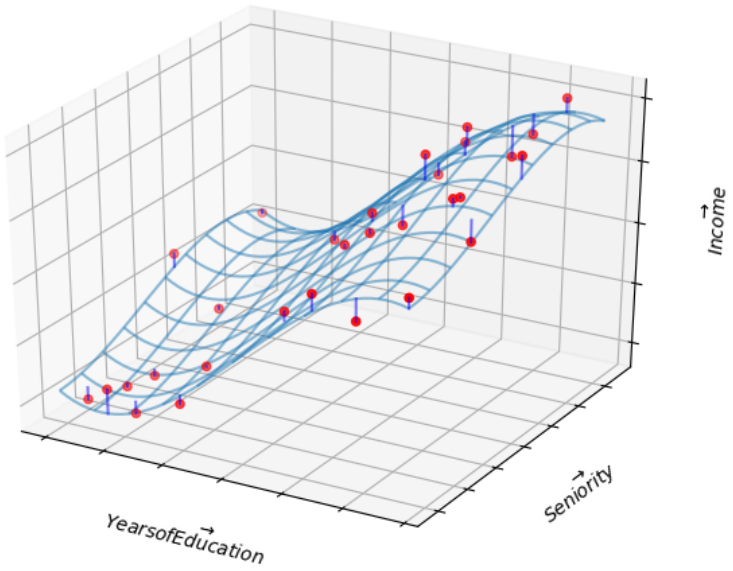

Figure 5: The plot displays `income` as a function of `years of education` and `seniority` in the `Income` data set. The blue surface represents the true underlying relationship between `income` and `years of education` and `seniority`, which is known since the data are simulated. The red dots indicate the observed values of these quantities for 30 individuals.

`Income` data from previous figure.

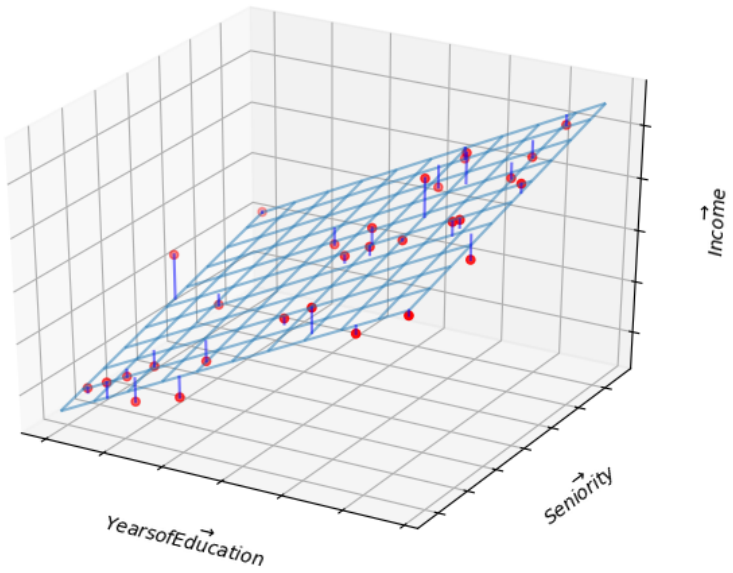

Figure 6: A linear model fit by least squares to the `Income` data from figure 5. The observations are shown in red, and the blue plane indicates the least squares fit to the data.

Figure 7 provides an illustration of the trade-off between flexibility and interpretability for some of the methods covered in this book.

Figure 8 provides a simple illustration of the clustering problem.

2.2 Assessing Model Accuracy

Figure 9 illustrates the tradeoff between training MSE and test MSE. We select a "true function" whose shape is similar to that shown in the book. In the left panel, the orange, blue, and green curves illustrate three possible estimates for f given by the black curve. The orange line is the linear regression fit, which is relatively inflexible. The blue and green curves were produced using *smoothing splines* from `UnivariateSpline` function in `scipy` package. We obtain different levels of flexibility by varying the parameter `s`, which affects the number of knots.

For the right panel, we have chosen polynomial fits. The degree of polynomial represents the level of flexibility. This is because the function

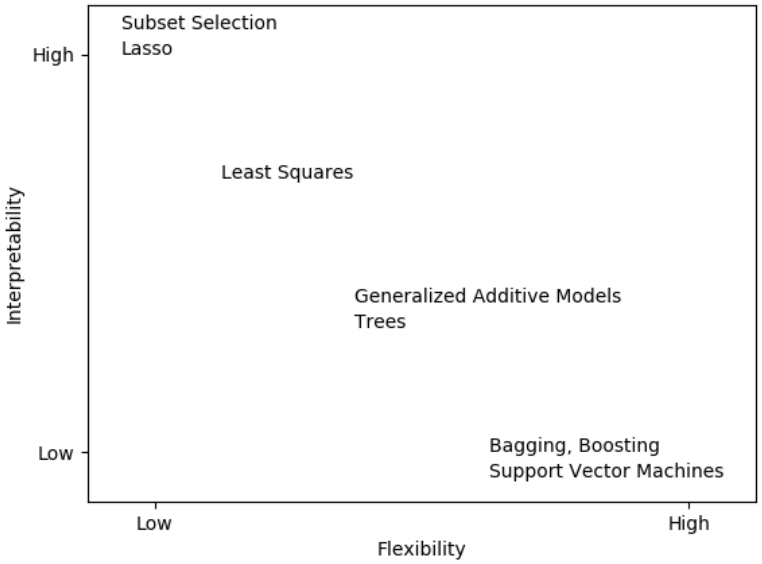

Figure 7: A representation of the tradeoff between flexibility and interpretability, using different statistical learning methods. In general, as the flexibility of a method increases, its interpretability decreases.

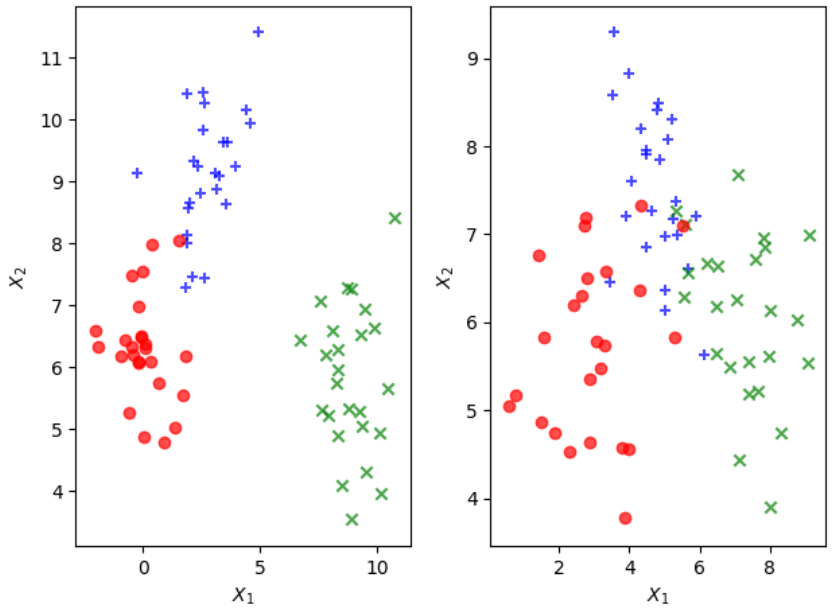

Figure 8: A clustering data set involving three groups. Each group is shown using a different colored symbol. Left: The three groups are well-separated. In this setting, a clustering approach should successfully identify the three groups. Right: There is some overlap among the groups. Now the clustering taks is more challenging.

`UnivariateSpline` does not more than five degrees of freedom.

When we repeat the simulations for figure 9, we see considerable variation in the right panel MSE plots. But the overall conclusion remains the same.

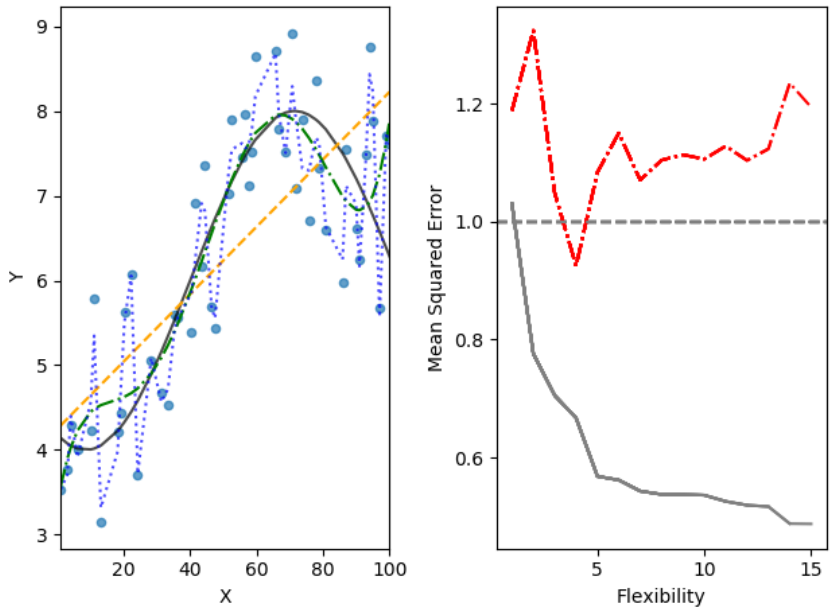

Figure 9: Left: Data simulated from f, shown in black. Three estimates of f are shown: the linear regression line (orange curve), and two smoothing spline fits (blue and green curves). Right: Training MSE (grey curve), test MSE (red curve), and minimum possible test MSE over all methods (dashed grey line).

Figure 10 provides another example in which the true f is approximately linear.

Figure 11 displays an example in which f is highly non-linear. The training and test MSE curves still exhibit the same general patterns.

Figure 12 displays the relationship between bias, variance, and test MSE. This relationship is referred to as *bias-variance trade-off*. When simulations are repeated, we see considerable variation in different graphs, especially for MSE lines. But overall shape remains the same.

Figure 13 provides an example using a simulated data set in two-dimensional space consisting of predictors X_1 and X_2.

Figure 14 displays the KNN decision boundary, using $K = 10$, when

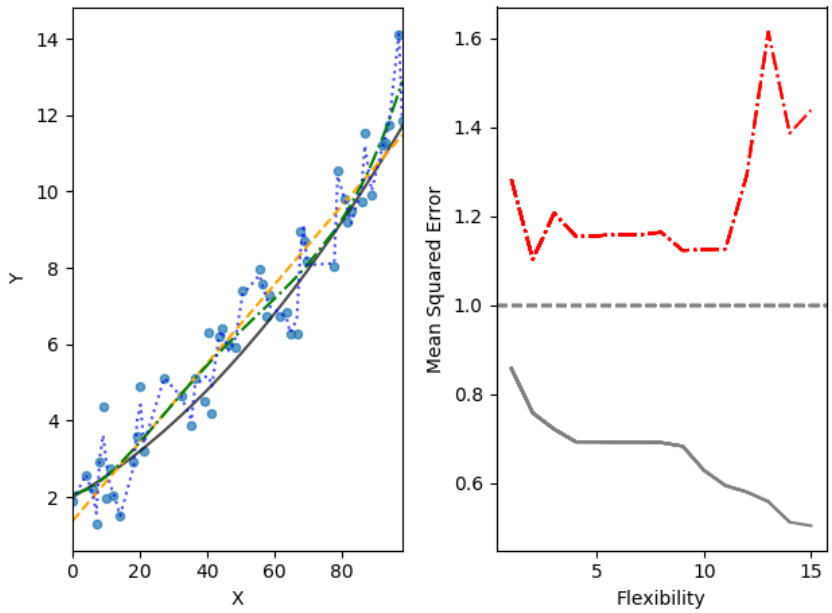

Figure 10: Details are as in figure 9 using a different true f that is much closer to linear. In this setting, linear regression provides a very good fit to the data.

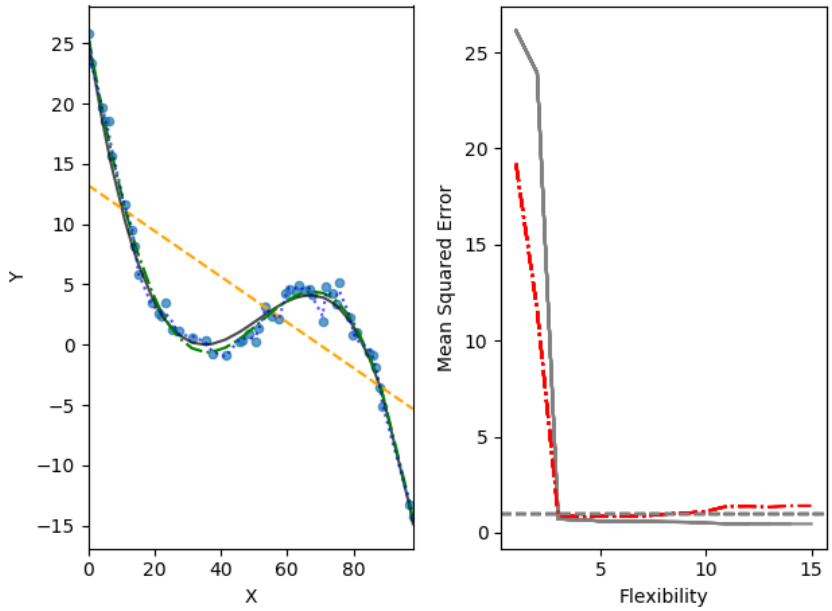

Figure 11: Details are as in figure 9, using a different f that is far from linear. In this setting, linear regression provides a very poor fit to the data.

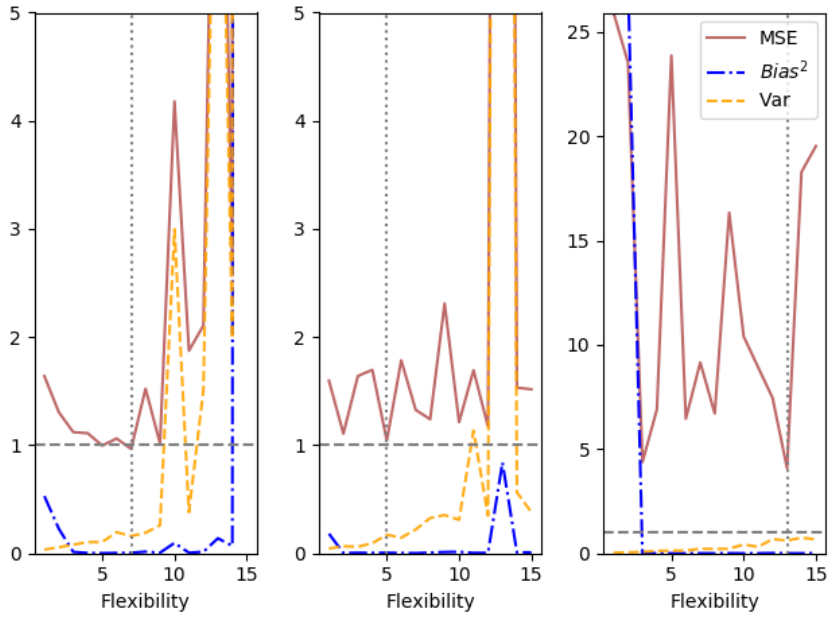

Figure 12: Squared bias (blue curve), variance (orange curve), $Var(\epsilon)$ (dashed line), and test MSE (red curve) for the three data sets in figures 9 - 11. The vertical dotted line indicates the flexibility level corresponding to the smallest test MSE.

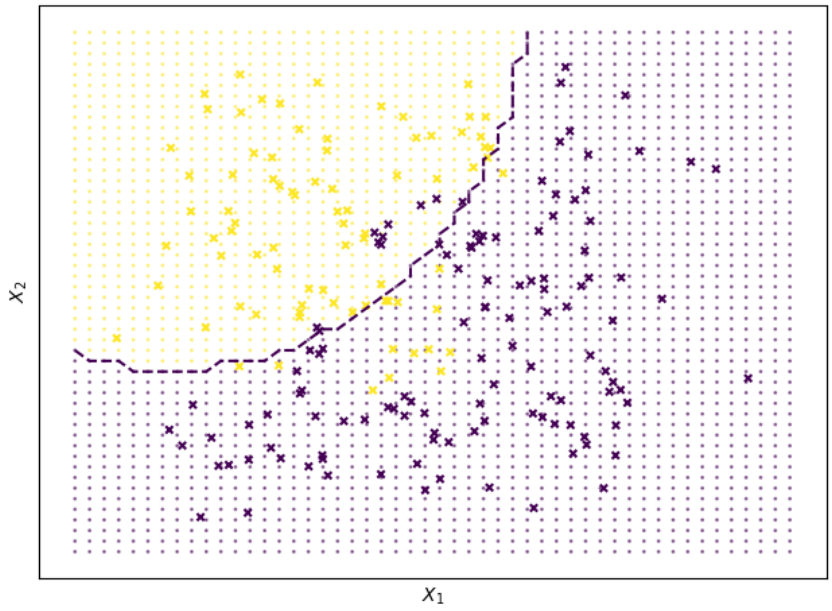

Figure 13: A simulated data set consisting of 200 observations in two groups, indicated in blue and orange. The dashed line represents the Bayes decision boundary. The orange background grid indicates the region in which a test observation will be assigned to the orange class, and blue background grid indicates the region in which a test observation will be assigned to the blue class.

applied to the simulated data set from figure 13. Even though the true distribution is not known by the KNN classifier, the KNN decision making boundary is very close to that of the Bayes classifier.

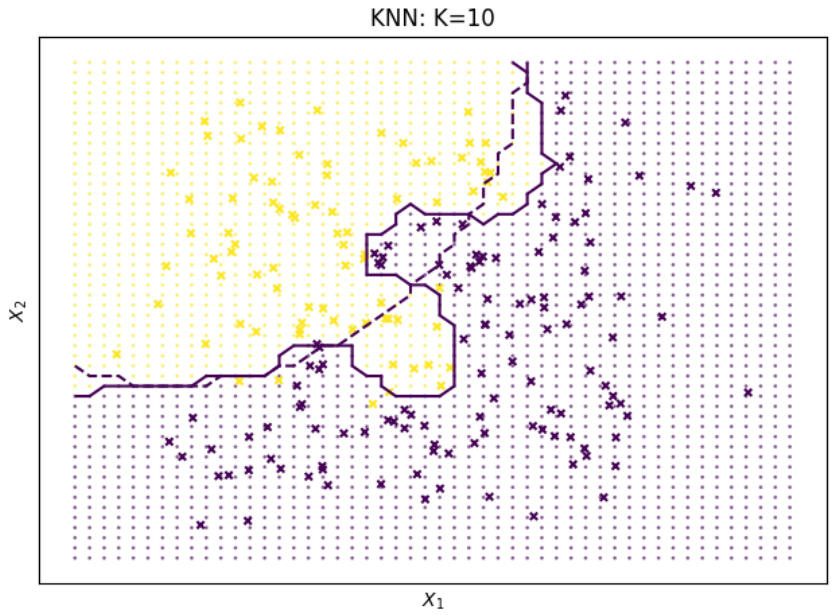

Figure 14: The firm line indicates the KNN decision boundary on the data from figure 13, using $K = 10$. The Bayes decision boundary is shown as a dashed line. The KNN and Bayes decision boundaries are very similar.

In figure 16 we have plotted the KNN test and training errors as a function of $\frac{1}{K}$. As $\frac{1}{K}$ increases, the method becomes more flexible. As in the regression setting, the training error rate consistently declines as the flexibility increases. However, the test error exhibits the characteristic U-shape, declining at first (with a minimum at approximately $K = 10$) before increasing again when the method becomes excessively flexible and overfits.

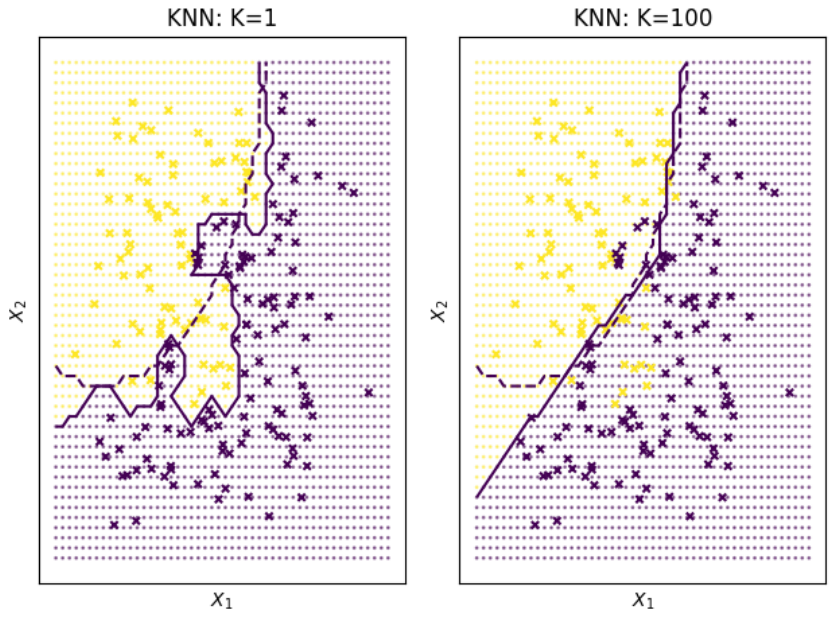

Figure 15: A comparison of the KNN decision boundaries (solid curves) obtained using $K = 1$ and $K = 100$ on the data from figure 13. With $K = 1$, the decision boundary is overly flexible, while with $K = 100$ it is not sufficiently flexible. The Bayes decision boundary is shown as dashed line.

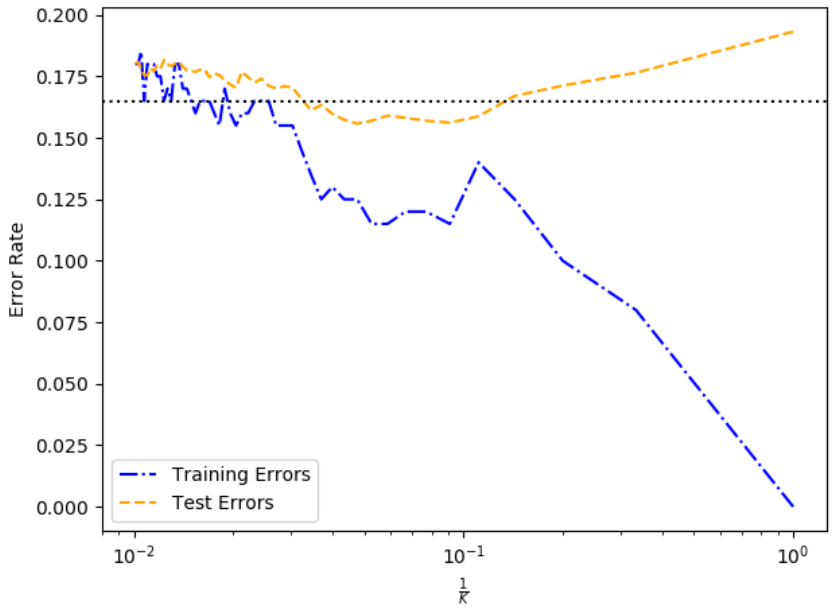

Figure 16: The KNN training error rate (blue, 200 observations) and test error rate (orange, 5,000 observations) on the data from figure 13 as the level of flexibility (assessed using $\frac{1}{K}$) increases, or equivalently as the number of neighbors K decreases. The black dashed line indicates the Bayes error rate.

2.3 Lab: Introduction to Python

2.3.1 Basic Commands

In `Python` a list can be created by enclosing comma-separated elements by square brackets. Length of a list can be obtained using `len` function.

```
x = [1, 3, 2, 5]
print len(x)
y = 3
z = 5
print y + z
```

```
4
8
```

To create an array of numbers, use `array` function in `numpy` library. `numpy` functions can be used to perform element-wise operations on arrays.

```
import numpy as np
x = np.array([[1, 2], [3, 4]])
y = np.array([6, 7, 8, 9]).reshape((2, 2))
print x
print y
print x ** 2
print np.sqrt(y)
```

```
[[1 2]
 [3 4]]
[[6 7]
 [8 9]]
[[ 1  4]
 [ 9 16]]
[[ 2.44948974  2.64575131]
 [ 2.82842712  3.        ]]
```

`numpy.random` has a number of functions to generate random variables that follow a given distribution. Here we create two correlated sets of numbers, `x` and `y`, and use `numpy.corrcoef` to calculate correlation between them.

```
import numpy as np
np.random.seed(911)
x = np.random.normal(size=50)
y = x + np.random.normal(loc=50, scale=0.1, size=50)
print np.corrcoef(x, y)
print np.corrcoef(x, y)[0, 1]
print np.mean(x)
print np.var(y)
print np.std(y) ** 2
```

```
[[ 1.          0.99374931]
 [ 0.99374931  1.        ]]
0.993749313458
-0.0202197243973
0.933062175007
0.933062175007
```

2.3.2 Graphics

`matplotlib` library has a number of functions to plot data in `Python`. It is possible to view graphs on screen or save them in file for inclusion in a document.

```
import numpy as np
import matplotlib               # only if we need to save figure in file
matplotlib.use('Agg')           # only to save figure in file
import matplotlib.pyplot as plt

x = np.random.normal(size=100)
y = np.random.normal(size=100)
plt.plot(x, y)
plt.xlabel('This is x-axis')
plt.ylabel('This is y-axis')
plt.title('Plot of X vs Y')

plt.savefig('xyPlot.png')
```

`numpy` function `linspace` can be used to create a sequence between a start and an end of a given length.

```
import numpy as np
```

```
import matplotlib.pyplot as plt

x = np.linspace(-np.pi, np.pi, num=50)
y = x
xx, yy = np.meshgrid(x, y)
zz = np.cos(yy) / (1 + xx ** 2)

plt.contour(xx, yy, zz)

fig, ax = plt.subplots()
zza = (zz - zz.T) / 2.0
CS = ax.contour(xx, yy, zza)
ax.clabel(CS, inline=1)
```

2.3.3 Indexing Data

To access elements of an array, specify indexes inside square brackets. It is possible to access multiple rows and columns. `shape` method gives number of rows followed by number of columns.

```
import numpy as np

A = np.array(np.arange(1, 17))
A = A.reshape(4, 4, order='F')
print A
print A[1, 2]
print A[(0, 2), (1, 3)]         # does not work
print A[range(0, 3), range(1, 4)]  # does not work
print A[range(0, 2), :]
print A[:, range(0, 2)]
print A.shape
```

```
[[ 1  5  9 13]
 [ 2  6 10 14]
 [ 3  7 11 15]
 [ 4  8 12 16]]
10
[ 5 15]
[ 5 10 15]
[[ 1  5  9 13]
 [ 2  6 10 14]]
```

```
[[1 5]
 [2 6]
 [3 7]
 [4 8]]
(4, 4)
```

2.3.4 Loading Data

`pandas` library provides `read_csv` function to read files with data in rectangular shape.

```
import pandas as pd
Auto = pd.read_csv('data/Auto.csv')
print Auto.head()
print Auto.shape
print Auto.columns
```

```
    mpg  cylinders  displacement horsepower  weight  acceleration  year  \
0  18.0          8         307.0        130    3504          12.0    70
1  15.0          8         350.0        165    3693          11.5    70
2  18.0          8         318.0        150    3436          11.0    70
3  16.0          8         304.0        150    3433          12.0    70
4  17.0          8         302.0        140    3449          10.5    70

   origin                       name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
3       1              amc rebel sst
4       1                ford torino
(397, 9)
Index([u'mpg', u'cylinders', u'displacement', u'horsepower', u'weight',
       u'acceleration', u'year', u'origin', u'name'],
      dtype='object')
```

To load data from an `R` library, use `get_rdataset` function from `statsmodels`. This function seems to work only if the computer is connected to the internet.

```
from statsmodels import datasets
carseats = datasets.get_rdataset('Carseats', package='ISLR').data
print carseats.shape
print carseats.columns
```

```
(400, 11)
Index([u'Sales', u'CompPrice', u'Income', u'Advertising', u'Population',
       u'Price', u'ShelveLoc', u'Age', u'Education', u'Urban', u'US'],
      dtype='object')
```

2.3.5 Additional Graphical and Numerical Summaries

`plot` method can be directly applied to a `pandas` dataframe.

```
import pandas as pd
Auto = pd.read_csv('data/Auto.csv')
Auto.boxplot(column='mpg', by='cylinders', grid=False)
```

`hist` method can be applied to plot a histogram.

```
import pandas as pd
Auto = pd.read_csv('data/Auto.csv')
Auto.hist(column='mpg')
Auto.hist(column='mpg', color='red')
Auto.hist(column='mpg', color='red', bins=15)
```

For pairs plot, use `scatter_matrix` method in `pandas.plotting`.

```
import pandas as pd
from pandas import plotting
Auto = pd.read_csv('data/Auto.csv')
plotting.scatter_matrix(Auto[['mpg', 'displacement', 'horsepower', 'weight',
      'acceleration']])
```

On `pandas` dataframes, `describe` method produces a summary of each variable.

```
import pandas as pd
Auto = pd.read_csv('data/Auto.csv')
print Auto.describe()
```

```
              mpg   cylinders  displacement       weight  acceleration  \
count  397.000000  397.000000    397.000000   397.000000    397.000000
mean    23.515869    5.458438    193.532746  2970.261965     15.555668
std      7.825804    1.701577    104.379583   847.904119      2.749995
min      9.000000    3.000000     68.000000  1613.000000      8.000000
```

25%	17.500000	4.000000	104.000000	2223.000000	13.800000
50%	23.000000	4.000000	146.000000	2800.000000	15.500000
75%	29.000000	8.000000	262.000000	3609.000000	17.100000
max	46.600000	8.000000	455.000000	5140.000000	24.800000

	year	origin
count	397.000000	397.000000
mean	75.994962	1.574307
std	3.690005	0.802549
min	70.000000	1.000000
25%	73.000000	1.000000
50%	76.000000	1.000000
75%	79.000000	2.000000
max	82.000000	3.000000