



CHALMERS
UNIVERSITY OF TECHNOLOGY



UNIVERSITY OF GOTHENBURG

MODULE 2: REGRESSION AND CLASSIFICATION

DAT405, 2019-2020, READING PERIOD 1

Core data science tasks

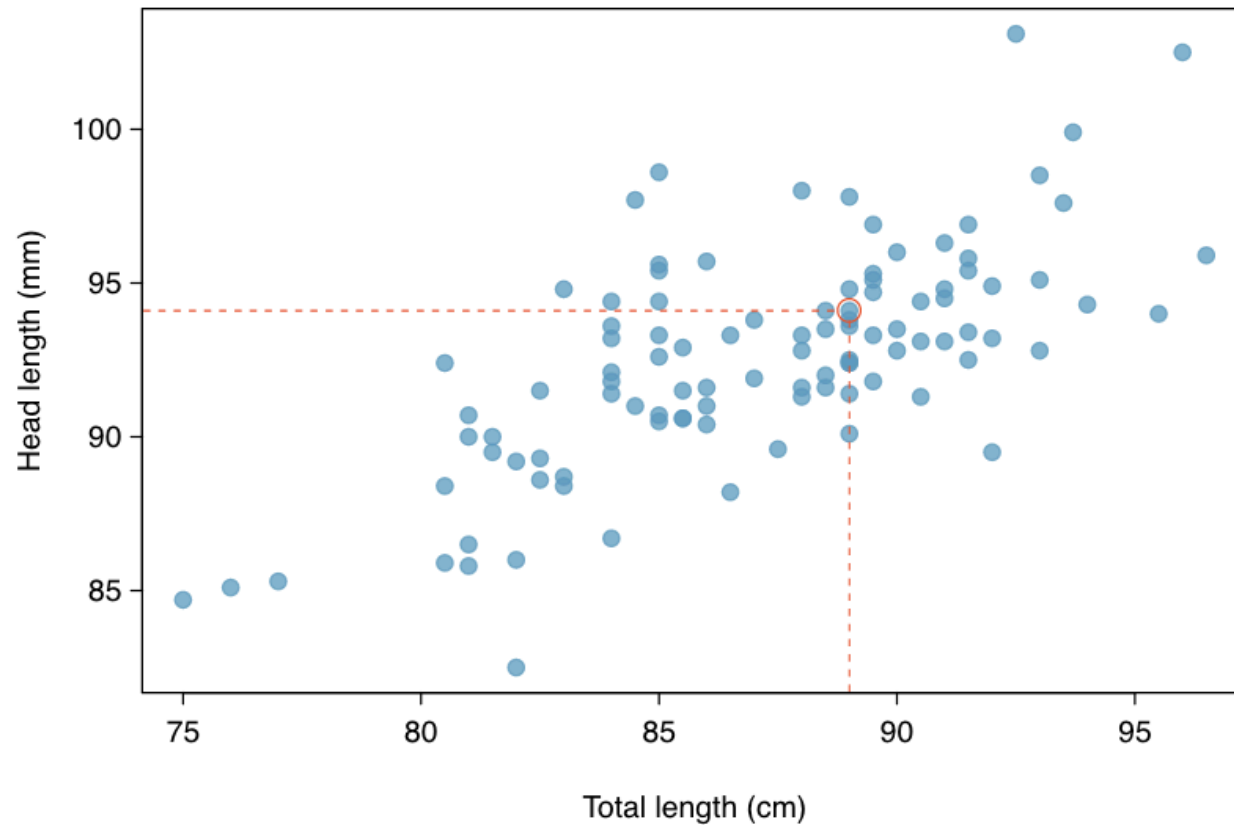
- Regression
 - Predicting a numerical quantity
- Classification
 - Assigning a label from a discrete set of possibilities
- Clustering
 - Grouping items by similarity



REGRESSION

- Predicting a numerical quantity

Brushtail possums (n=104)



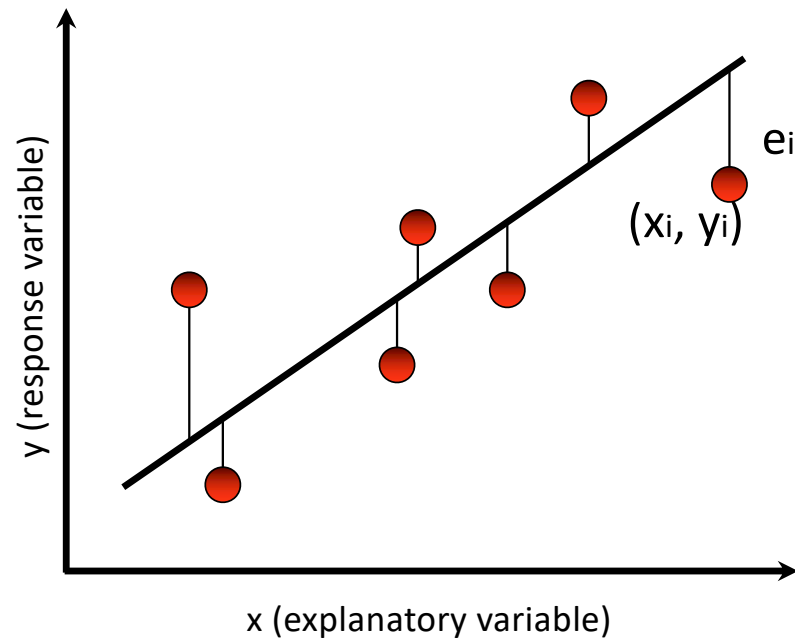
Goal:
Express one
variable as a
function of
other(s)

<https://courses.lumenlearning.com/odessa-introstats1-1/chapter/line-fitting-residuals-and-correlation/>

Linear regression

- “Linear regression is a bread-and-butter modeling technique that should serve as your baseline approach to building data-driven models.”
- “These models are typically easy to build, straightforward to interpret, and often do quite well in practice.”
- “With enough skill and toil, more advanced machine learning techniques might yield better performance, but the possible payoff is often not worth the effort.”
- “Build your linear regression models first, then decide whether it is worth working harder to achieve better results.”

Least squares linear regression



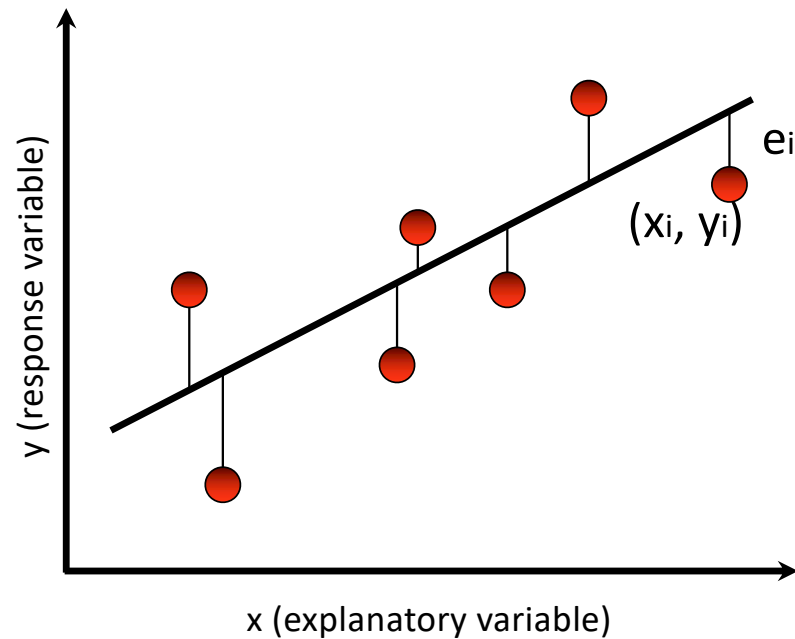
Data (x_i, y_i) $i=1, \dots, n$

Model (Fit): $y = b_1 x + b_0$

Residuals: $e_i = y_i - (b_1 x_i + b_0)$

Data = Fit + Residual

Least squares linear regression



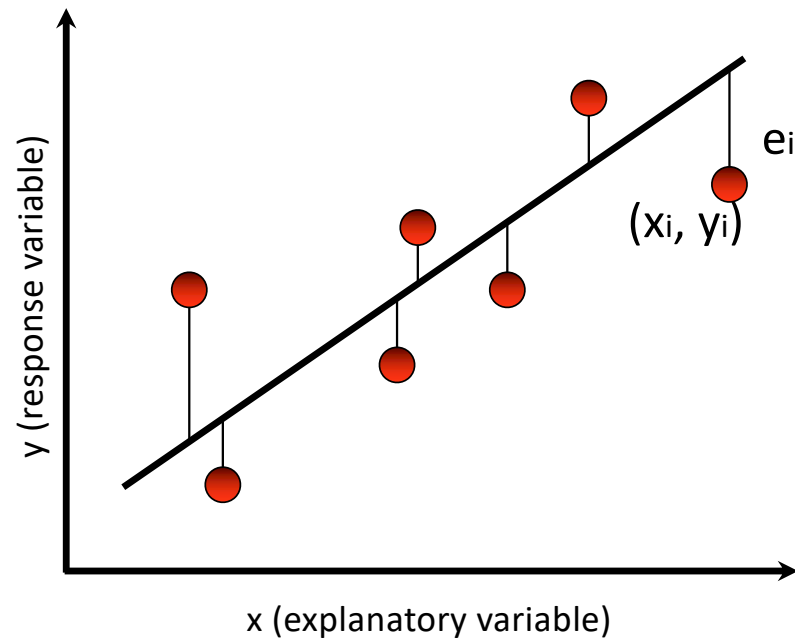
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Data $(x_i, y_i) \ i=1, \dots, n$

Model (Fit): $y = b_1 x + b_0$

Residuals: $e_i = y_i - (b_1 x_i + b_0)$

Data = Fit + Residual

Least squares criterion:

$$\min_{b_0, b_1} \sum_{i=1}^n e_i^2 =$$
$$\min_{b_0, b_1} \sum_{i=1}^n (y_i - (b_1 x_i + b_0))^2$$

Linear regression

- Regression line is useful for visualisation
- A method for forecasting
- Residual error of a regression line is the difference between the predicted and actual values
- Seeks to find the line $y = f(x)$ which minimises the sum of the squared errors over all training points
- An optimisation problem

Goal: a linear model

Predict head length y (the independent variable) from total length x

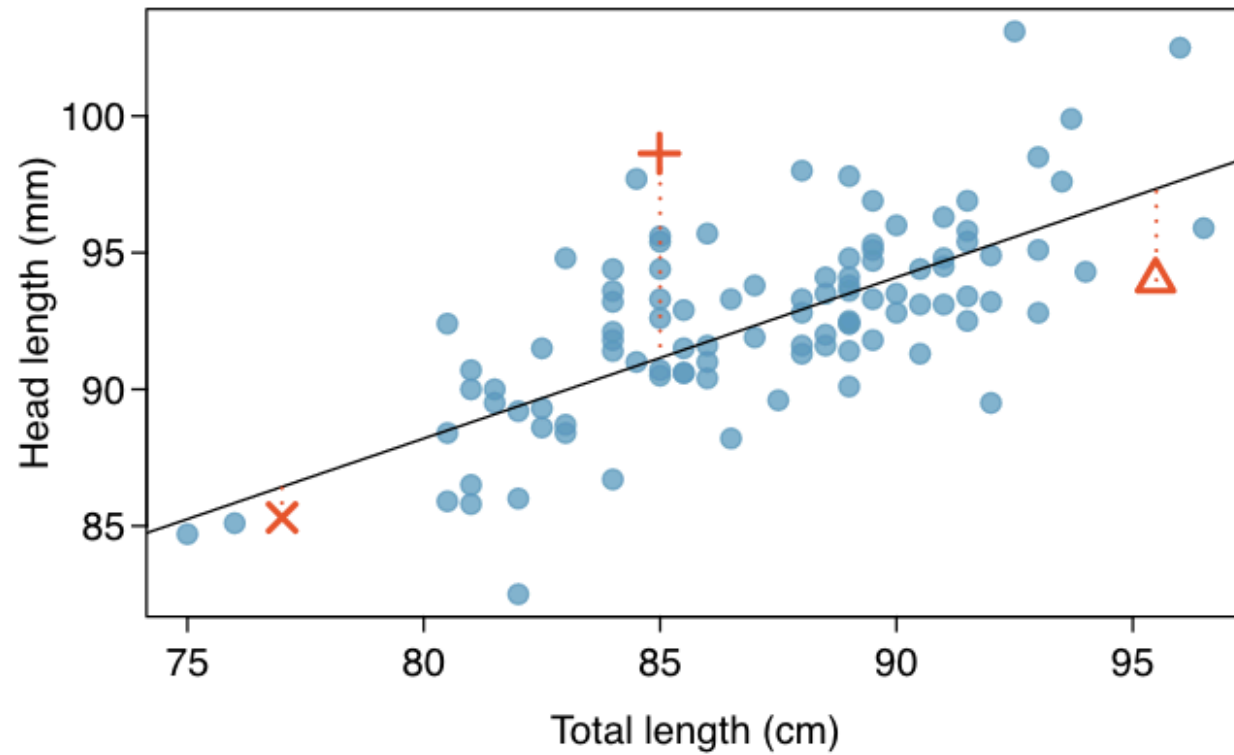
$$y = f(x) + r$$

where $f()$ is some function and r the residual.

Simplest case:

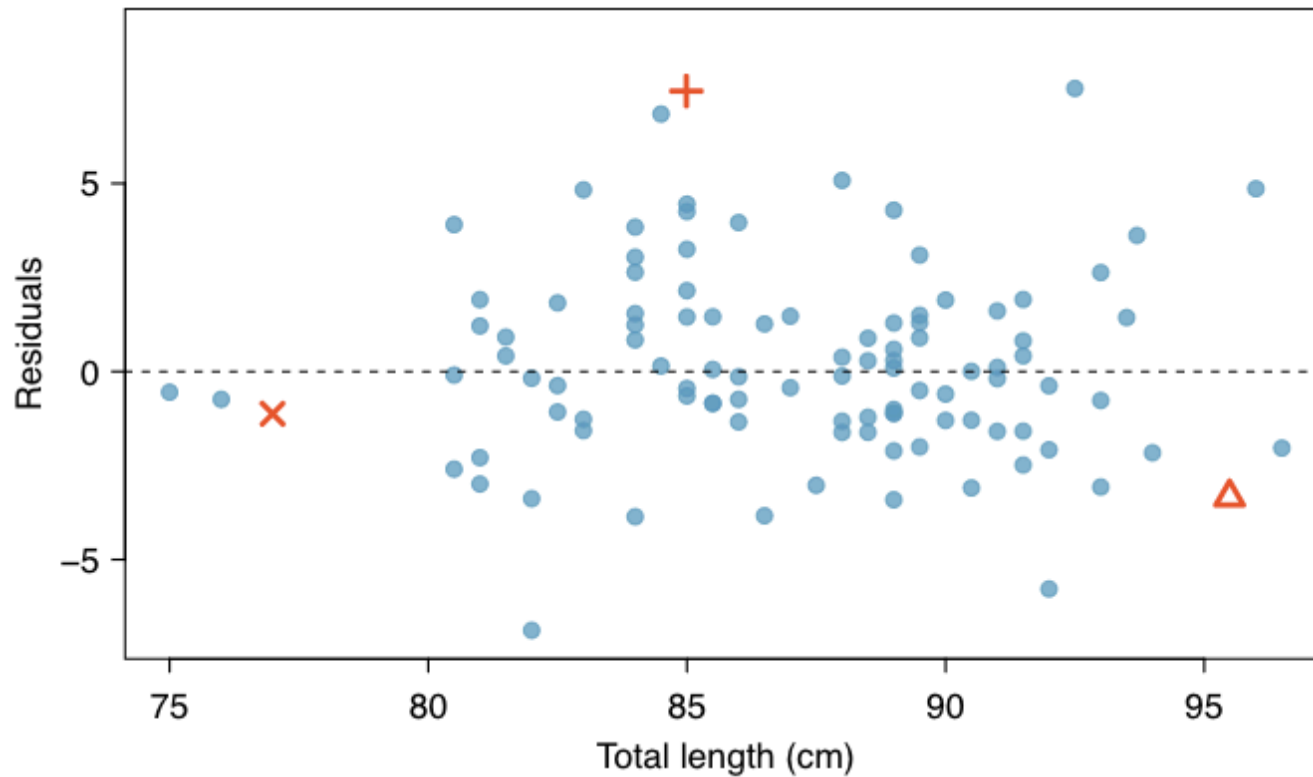
$f()$ is linear, that is $f(x) = a x + b$

A linear model



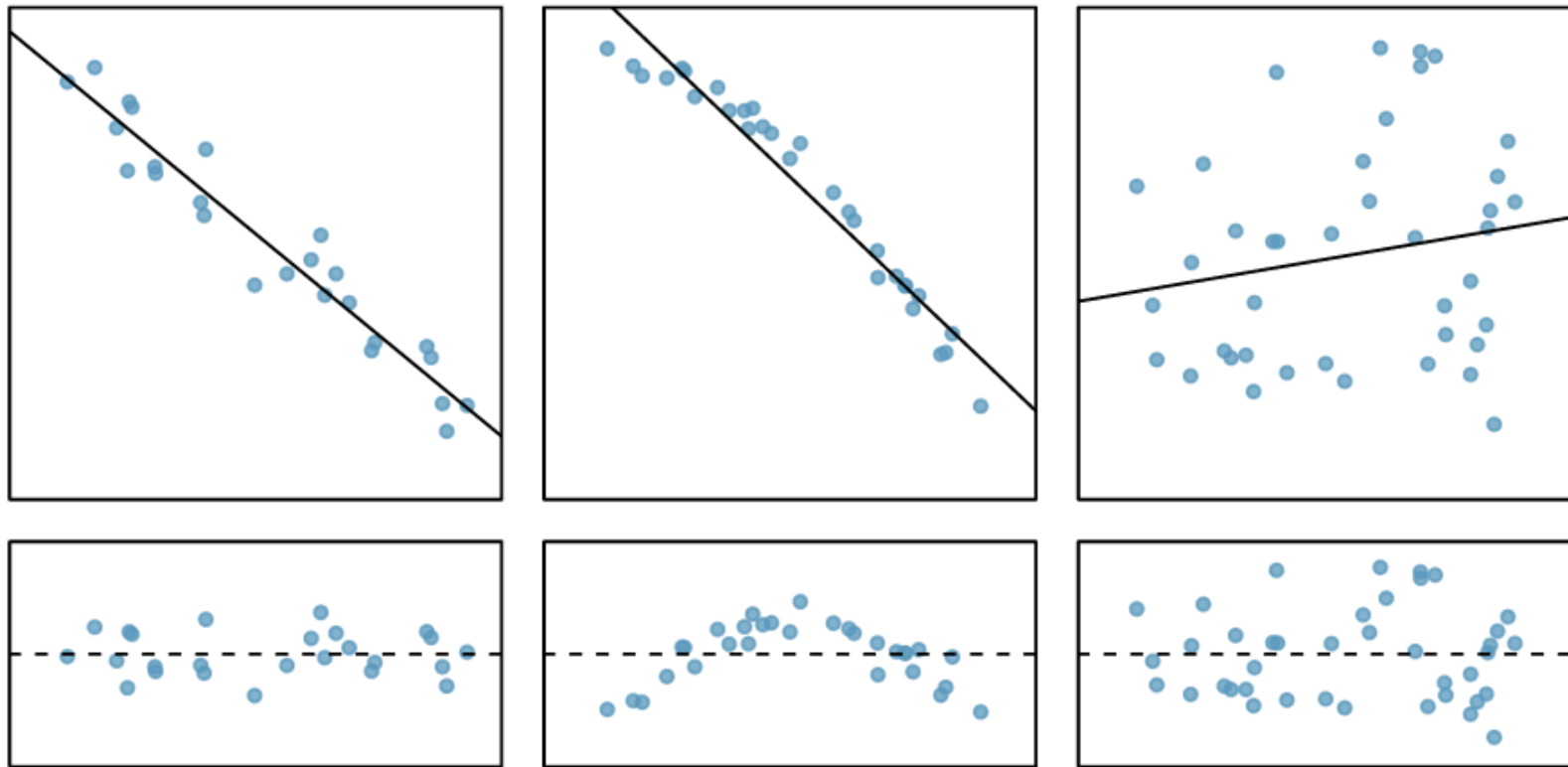
<https://courses.lumenlearning.com/odessa-introstats1-1/chapter/line-fitting-residuals-and-correlation/>

Residual plot



<https://courses.lumenlearning.com/odessa-introstats1-1/chapter/line-fitting-residuals-and-correlation/>

Sample data and residual plots



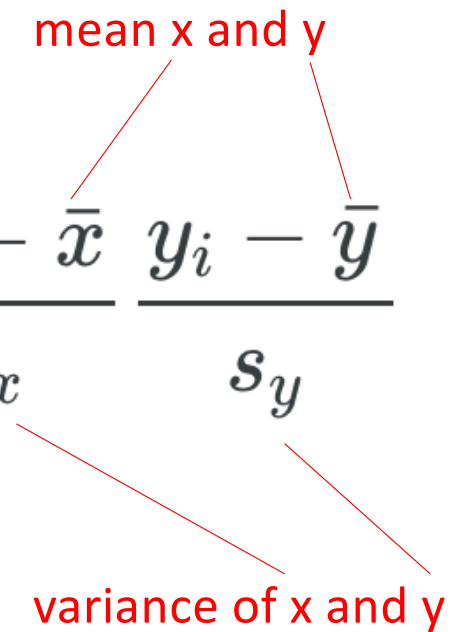
<https://courses.lumenlearning.com/odessa-introstats1-1/chapter/line-fitting-residuals-and-correlation/>

Correlation

$$R = \frac{1}{n - 1} \sum_{i=1}^n \frac{x_i - \bar{x}}{s_x} \frac{y_i - \bar{y}}{s_y}$$

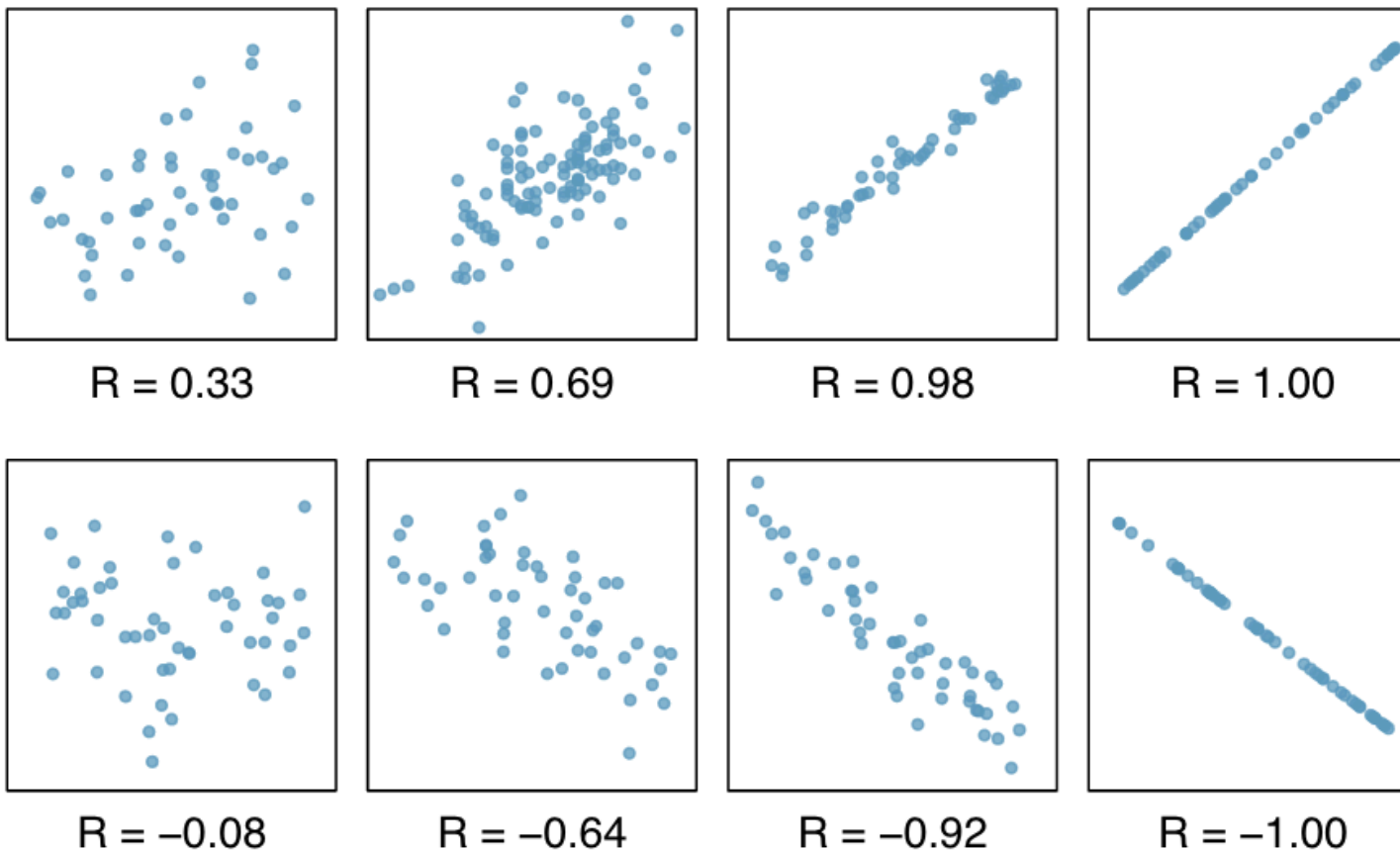
mean x and y

variance of x and y

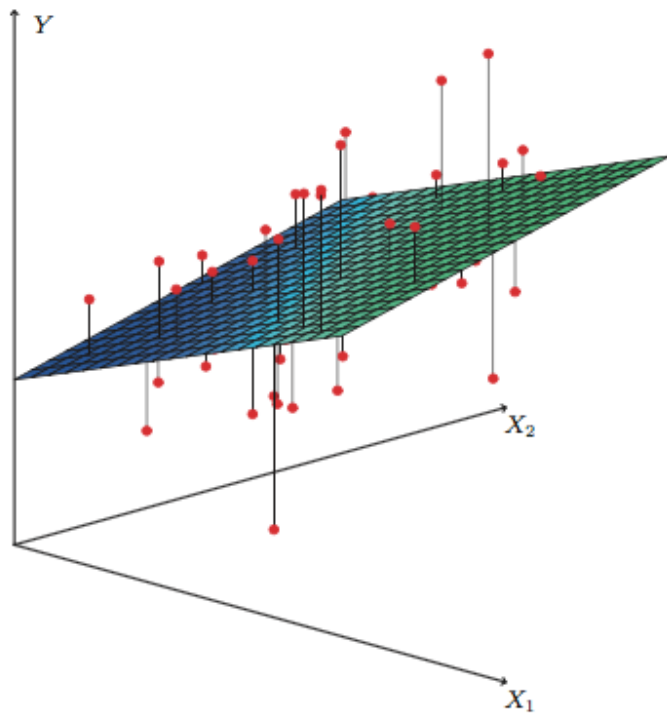


Quantifies the strength of a linear trend

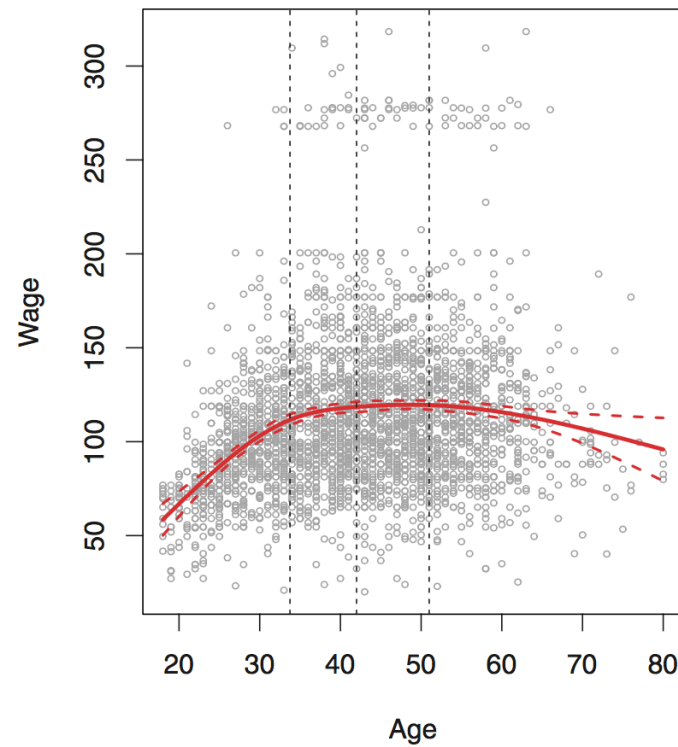
Scatter plots and correlations



Regression problems



Multi-dimensional data



Non-linear

From Intro to Statistical Learning.

Linear regression in python

`sklearn.linear_model.LinearRegression()`

scikit-learn documentation:

- https://scikit-learn.org/stable/modules/linear_model.html
- https://scikit-learn.org/stable/auto_examples/linear_model/plot_ols.html
- https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

Python Data Science Handbook

- <https://jakevdp.github.io/PythonDataScienceHandbook/05.06-linear-regression.html>

Generating an array of random numbers

- Random values in the range [0,1)
- Construct and initialise a pseudo-random number generator

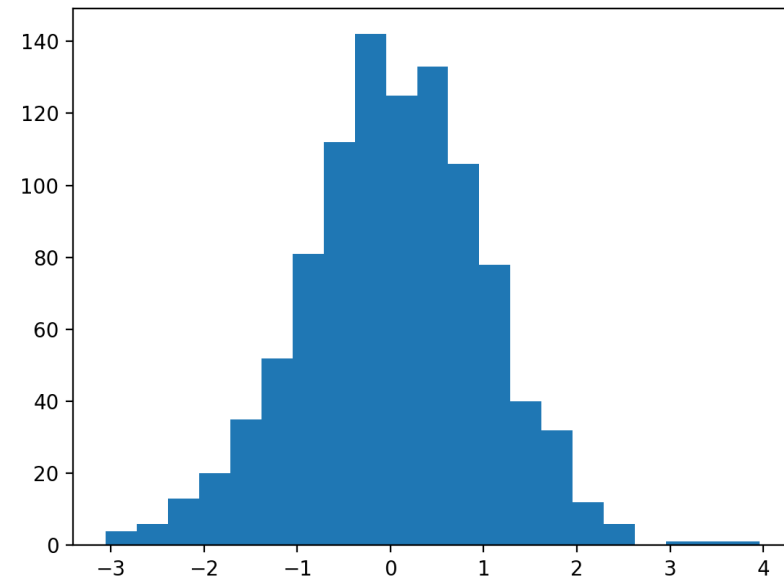
```
>>> import numpy as np
>>> rng = np.random.RandomState(1)
>>> rng.rand(10)
array([4.17022005e-01, 7.20324493e-01, 1.14374817e-04, 3.02332573e-01,
        1.46755891e-01, 9.23385948e-02, 1.86260211e-01, 3.45560727e-01,
        3.96767474e-01, 5.38816734e-01])
>>>
```

Random numbers from the “standard normal” distribution

```
import matplotlib.pyplot as plt
import numpy as np

rng = np.random.RandomState(1)

plt.hist(rng.randn(1000), bins=21)
plt.show()
```



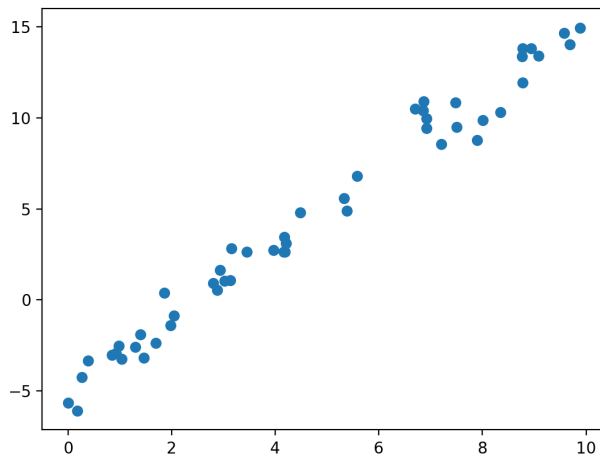
Scatter data about a line with slope 2 and intercept -5

```
import matplotlib.pyplot as plt
import numpy as np
```

```
rng = np.random.RandomState(1)
x = 10 * rng.rand(50)
y = 2 * x - 5 + rng.randn(50)
```

```
print("x is ", x)
print("y is ", y)
```

```
plt.scatter(x, y)
plt.show()
```



```
$ python plot50.py
```

```
x is [4.17022005e+00 7.20324493e+00 1.14374817e-03 3.02332573e+00
```

```
1.46755891e+00 9.23385948e-01 1.86260211e+00 3.45560727e+00
```

```
3.96767474e+00 5.38816734e+00 4.19194514e+00 6.85219500e+00
```

```
2.04452250e+00 8.78117436e+00 2.73875932e-01 6.70467510e+00
```

```
4.17304802e+00 5.58689828e+00 1.40386939e+00 1.98101489e+00
```

```
8.00744569e+00 9.68261576e+00 3.13424178e+00 6.92322616e+00
```

```
8.76389152e+00 8.94606664e+00 8.50442114e-01 3.90547832e-01
```

```
1.69830420e+00 8.78142503e+00 9.83468338e-01 4.21107625e+00
```

```
9.57889530e+00 5.33165285e+00 6.91877114e+00 3.15515631e+00
```

```
6.86500928e+00 8.34625672e+00 1.82882773e-01 7.50144315e+00
```

```
9.88861089e+00 7.48165654e+00 2.80443992e+00 7.89279328e+00
```

```
1.03226007e+00 4.47893526e+00 9.08595503e+00 2.93614148e+00
```

```
2.87775339e+00 1.30028572e+00]
```

```
y is [ 2.65326739  8.56128423 -5.66895863  1.03398685 -3.18219253 -
```

```
2.91881241
```

```
0.3850064  2.6532587  2.74351393  4.88870572  2.63673199 10.39684461
```

```
-0.86014725 11.92535308 -4.26133265 10.50960534  3.466255  6.79099968
```

```
-1.89209091 -1.39022006  9.87237318 14.01588879  1.05958933  9.4330755
```

```
13.36676646 13.82323535 -3.01352845 -3.33376317 -2.35778955 13.81571822
```

```
-2.5201335  3.12405966 14.64630875  5.58773399  9.96917167  2.83012944
```

```
10.91559396 10.2960171 -6.07834826  9.49842044 14.93725885 10.83948201
```

```
0.92451479  8.76338535 -3.24168388  4.78584517 13.4020048  1.63429415
```

```
0.53317863 -2.60018663]
```

numpy.linspace() and numpy.newaxis

```
>>> import numpy
>>> values = numpy.linspace(0, 1, 5)
>>> values
array([0.   , 0.25, 0.5  , 0.75, 1.   ])
>>> numpy.shape(values)
(5,)
>>> values[:, numpy.newaxis]
array([[0.   ],
       [0.25],
       [0.5  ],
       [0.75],
       [1.   ]])
>>> numpy.shape(values[:, numpy.newaxis])
(5, 1)
>>>
```

- Return evenly spaced numbers over a specified interval.

Least squares linear regression

```
import matplotlib.pyplot as plt
import numpy as np

rng = np.random.RandomState(1)
x = 10 * rng.rand(50)
y = 2 * x - 5 + rng.randn(50)
plt.scatter(x, y)

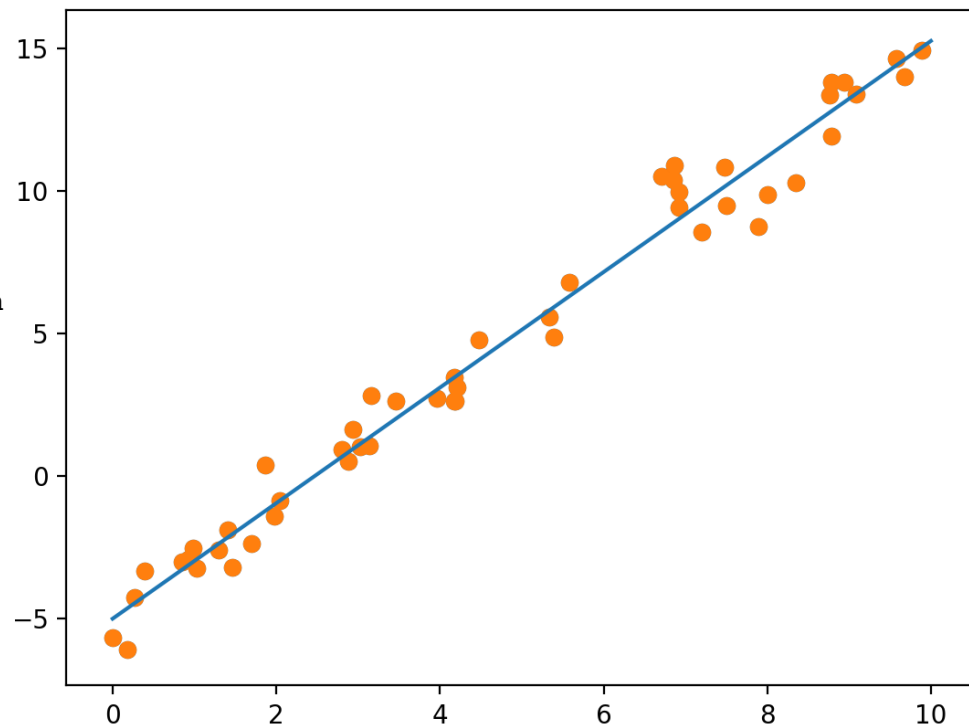
from sklearn.linear_model import LinearRegression
model = LinearRegression()

model.fit(x[:, np.newaxis], y)

xfit = np.linspace(0, 10, 1000)
yfit = model.predict(xfit[:, np.newaxis])

plt.scatter(x, y)
plt.plot(xfit, yfit);

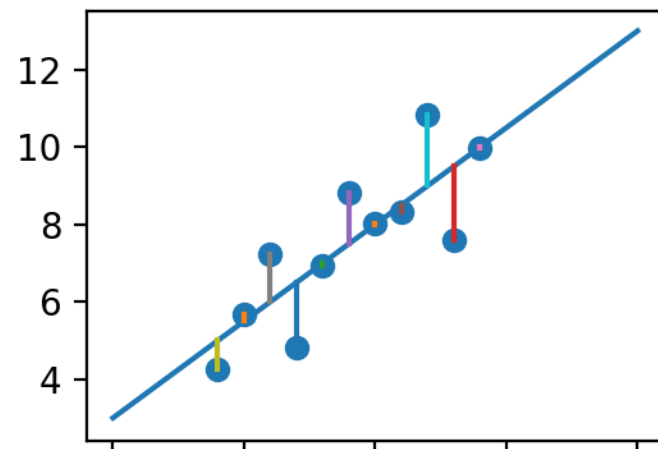
plt.show()
```



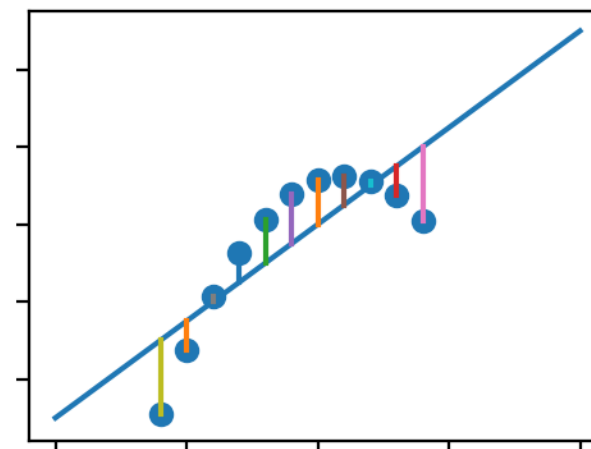
Slope and intercept of the regression line

```
>>> import numpy as np
>>>
>>> rng = np.random.RandomState(1)
>>> x = 10 * rng.rand(50)
>>> y = 2 * x - 5 + rng.randn(50)
>>> from sklearn.linear_model import LinearRegression
>>> model = LinearRegression()
>>>
>>> model.fit(x[:, np.newaxis], y)
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
>>> print(model.intercept_)
-4.998577085553202
>>> print(model.coef_)
[2.02720881]
>>>
```

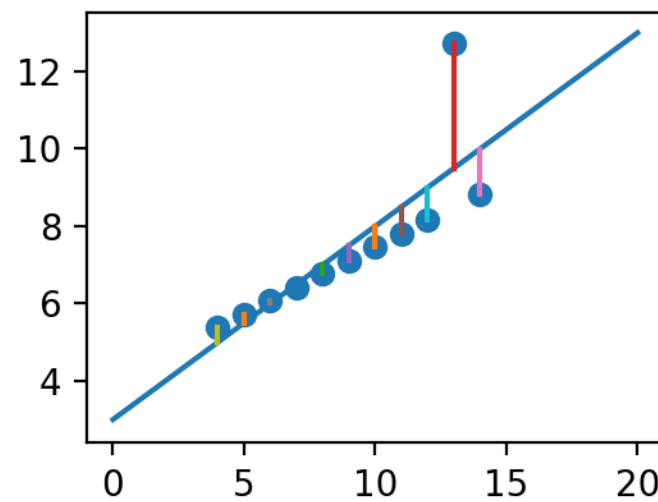
d1.txt



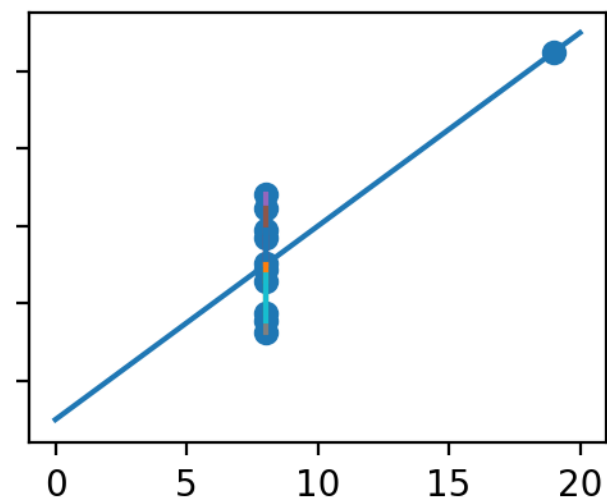
d2.txt



d3.txt



d4.txt




```

import sys
import pandas
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

model = LinearRegression()
fig, axs = plt.subplots(2, 2, sharex = 'all', sharey = 'all')

for i in range(4):
    df = pandas.read_csv(sys.argv[i+1], sep=' ')
    xValues = df['x']
    yValues = df['y']
    model.fit(xValues[:, np.newaxis], yValues)
    xfit = np.linspace(0, 20, 1000)
    yfit = model.predict(xfit[:, np.newaxis])
    axs[ i // 2, i % 2 ].scatter(xValues, yValues)
    axs[ i // 2, i % 2 ].plot(xfit, yfit)
    axs[ i // 2, i % 2 ].set_title(sys.argv[i+1])

    yPredicted = model.predict(xValues[:, np.newaxis])
    for j in range(len(xValues)):
        lineXdata = (xValues[j], xValues[j])
        lineYdata = (yValues[j], yPredicted[j])
        axs[ i // 2, i % 2 ].plot(lineXdata, lineYdata)

# Hide x labels and tick labels for top plots and y ticks for right plots.
for ax in axs.flat:
    ax.label_outer()

plt.show()

```

Fitting non-linear functions

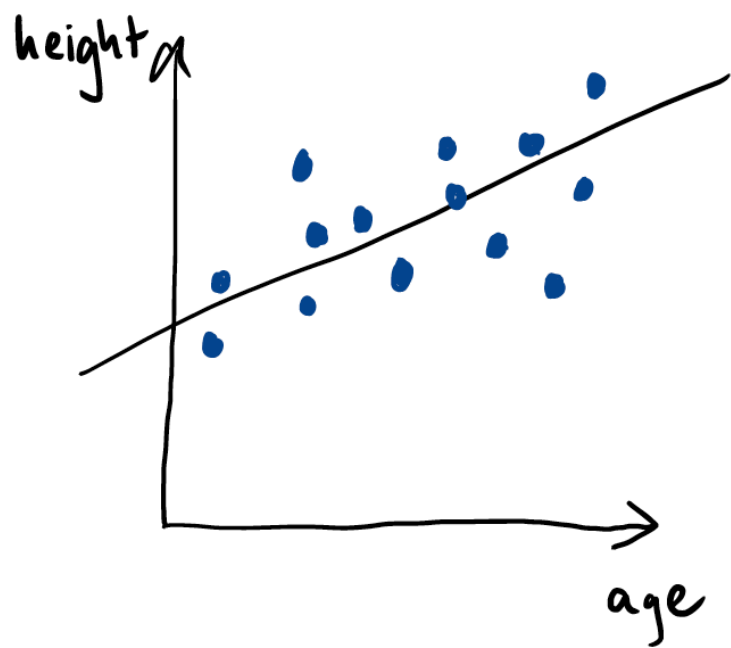
- Could fit quadratics, arbitrary higher order polynomials, exponential and logarithmic curves, etc. instead of straight lines
- Alternatively, we could explicitly include other component variables in our data matrix, e.g. \sqrt{x} , $\log(x)$, x^3 , $1/x$, $\sin(x)$, etc.
- Can then capture a non-linear relationship with a linear model!
- Inconvenient and impractical to explicitly enumerate all possibilities
- Consider using more powerful learning methods, e.g. support vector machines.



CLASSIFICATION

- Assigning a label from a discrete set of possibilities

regression



classification



Iris data set

R. A. Fisher (1936). "The use of multiple measurements in taxonomic problems". Annals of Eugenics. 7 (2): 179–188.

- Petal length
- Petal width
- Sepal length
- Sepal width

50 samples from each of three species

Iris
setosa



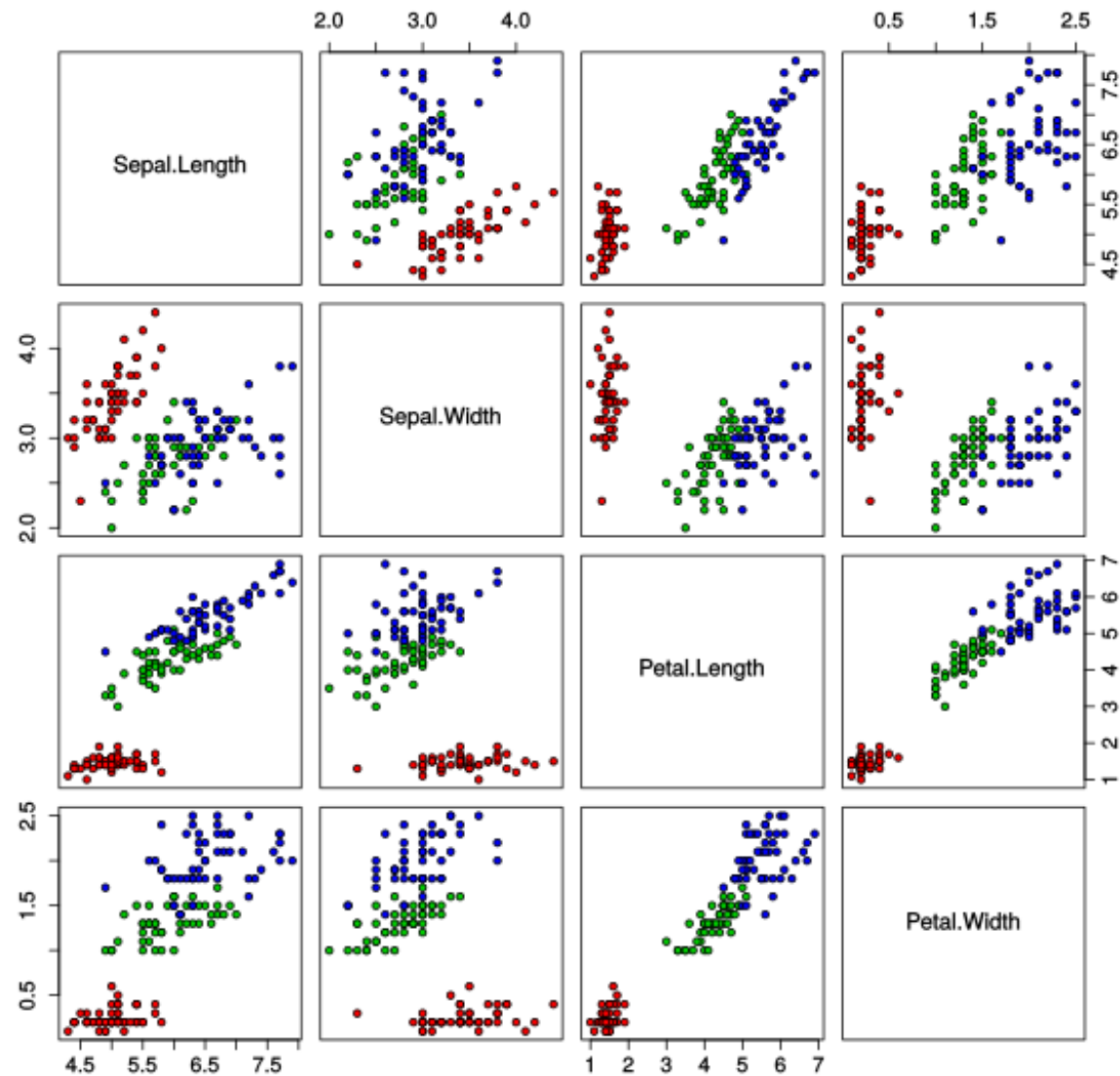
Iris
versicolor



Iris
virginica



Iris Data (red=setosa,green=versicolor,blue=virginica)



https://commons.wikimedia.org/wiki/File:Iris_dataset_scatterplot.svg (User:Nicoguardo)