Machine Learning

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Machine Learning is making the computer learn from studying data and statistics.

Machine Learning is a step into the direction of artificial intelligence (AI).

Machine Learning is a program that analyses data and learns to predict the outcome.

Where To Start?

In this tutorial we will go back to mathematics and study statistics, and how to calculate important numbers based on data sets.

We will also learn how to use various Python modules to get the answers we need.

And we will learn how to make functions that are able to predict the outcome based on what we have learned.

Data Set

In the mind of a computer, a data set is any collection of data. It can be anything from an array to a complete database.

Example of an array:

```
[99,86,87,88,111,86,103,87,94,78,77,85,86]
```

Example of a database:

Carname	Color	Age	Speed	AutoPass

BMW	red	5	99	Y
Volvo	black	7	86	Y
VW	gray	8	87	N
VW	white	7	88	Y
Ford	white	2	111	Y
VW	white	17	86	Y
Tesla	red	2	103	Y
BMW	black	9	87	Y
Volvo	gray	4	94	N
Ford	white	11	78	N
Toyota	gray	12	77	N
VW	white	9	85	N
Toyota	blue	6	86	Y

By looking at the array, we can guess that the average value is probably around 80 or 90, and we are also able to determine the highest value and the lowest value, but what else can we do?

And by looking at the database we can see that the most popular color is white, and the oldest car is 17 years, but what if we could predict if a car had an AutoPass, just by looking at the other values?

That is what Machine Learning is for! Analyzing data and predict the outcome!

In Machine Learning it is common to work with very large data sets. In this tutorial we will try to make it as easy as possible to understand the different concepts of machine learning, and we will work with small easy-to-understand data sets.

Data Types

To analyze data, it is important to know what type of data we are dealing with.

We can split the data types into three main categories:

- **Numerical**
- **Categorical**
- **Ordinal**

Numerical data are numbers, and can be split into two numerical categories:

- Discrete Data
  - numbers that are limited to integers. Example: The number of cars passing by.
- Continuous Data
  - numbers that are of infinite value. Example: The price of an item, or the size of an item

Categorical data are values that cannot be measured up against each other. Example: a color value, or any yes/no values.

Ordinal data are like categorical data, but can be measured up against each other. Example: school grades where A is better than B and so on.

By knowing the data type of your data source, you will be able to know what technique to use when analyzing them.

You will learn more about statistics and analyzing data in the next chapters.

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Machine Learning - Mean Median Mode

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Mean, Median, and Mode

What can we learn from looking at a group of numbers?

In Machine Learning (and in mathematics) there are often three values that interests us:

- **Mean** - The average value
- **Median** - The mid point value
- **Mode** - The most common value

Example: We have registered the speed of 13 cars:

```
speed = [99,86,87,88,111,86,103,87,94,78,77,85,86]
```

What is the average, the middle, or the most common speed value?

Mean

The mean value is the average value.

To calculate the mean, find the sum of all values, and dived the sum by the number of values:

```
(99+86+87+88+111+86+103+87+94+78+77+85+86) / 13 = 89.77
```

The NumPy module has a method for this:

Example

Use the NumPy `mean()` method to find the average speed:

```
import numpy

speed = [99,86,87,88,111,86,103,87,94,78,77,85,86]

x = numpy.mean(speed)

print(x)
```

Run example »

Median

The median value is the value in the middle, after you have sorted all the values:

77, 78, 85, 86, 86, 86, 87, 87, 88, 94, 99, 103, 111

It is important that the numbers are sorted before you can find the median.

The NumPy module has a method for this:

Example

Use the NumPy `median()` method to find the middle value:

```
import numpy

speed = [99,86,87,88,111,86,103,87,94,78,77,85,86]

x = numpy.median(speed)
```

```
print(x)
```

Run example »

If there are two numbers in the middle, divide the sum of those numbers by two.

77, 78, 85, 86, 86, 86, 87, 87, 94, 98, 99, 103

(86 + 87) / 2 = 86.5

Example

Using the NumPy module:

```
import numpy

speed = [99,86,87,88,86,103,87,94,78,77,85,86]

x = numpy.median(speed)

print(x)
```

Run example »

Mode

The Mode value is the value that appears the most number of times:

99, 86, 87, 88, 111, 86, 103, 87, 94, 78, 77, 85, 86 = 86

The SciPy module has a method for this:

Example

Use the SciPy `mode()` method to find the number that appears the most:

```
from scipy import stats

speed = [99,86,87,88,111,86,103,87,94,78,77,85,86]

x = stats.mode(speed)

print(x)
```

Run example »

Chapter Summary

The Mean, Median, and Mode are techniques that are often used in Machine Learning, so it is important to understand the concept behind them.

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Machine Learning - Standard Deviation

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What is Standard Deviation?

Standard deviation is a number that describes how spread out the values are.

A low standard deviation means that most of the numbers are close to the mean (average) value.

A high standard deviation means that the values are spread out over a wider range.

Example: This time we have registered the speed of 7 cars:

```
speed = [86,87,88,86,87,85,86]
```

The standard deviation is:

```
0.9
```

Meaning that most of the values are within the range of 0.9 from the mean value, which is 86.4.

Let us do the same with a selection of numbers with a wider range:

```
speed = [32,111,138,28,59,77,97]
```

The standard deviation is:

```
37.85
```

Meaning that most of the values are within the range of 37.85 from the mean value, which is 77.4.

As you can see, a higher standard deviation indicates that the values are spread out over a wider range.

The NumPy module has a method to calculate the standard deviation:

Example

Use the NumPy `std()` method to find the standard deviation:

```
import numpy

speed = [86,87,88,86,87,85,86]

x = numpy.std(speed)

print(x)
```

Run example »

Example

```
import numpy

speed = [32,111,138,28,59,77,97]

x = numpy.std(speed)

print(x)
```

Run example »

Variance

Variance is another number that indicates how spread out the values are.

In fact, if you take the square root of the variance, you get the standard variation!

Or the other way around, if you multiply the standard deviation by itself, you get the variance!

To calculate the variance you have to do as follows:

1. Find the mean:

```
(32+111+138+28+59+77+97) / 7 = 77.4
```

2. For each value: find the difference from the mean:

```
 32 - 77.4 = -45.4
111 - 77.4 =  33.6
138 - 77.4 =  60.6
 28 - 77.4 = -49.4
 59 - 77.4 = -18.4
 77 - 77.4 = - 0.4
 97 - 77.4 =  19.6
```

3. For each difference: find the square value:

```
(-45.4)^2 = 2061.16
 (33.6)^2 = 1128.96
 (60.6)^2 = 3672.36
(-49.4)^2 = 2440.36
(-18.4)^2 =  338.56
(- 0.4)^2 =    0.16
 (19.6)^2 =  384.16
```

4. The variance is the average number of these squared differences:

(2061.16+1128.96+3672.36+2440.36+338.56+0.16+384.16) / 7 = 1432.2

Luckily, NumPy has a method to calculate the variance:

Example

Use the NumPy `var()` method to find the variance:

```
import numpy

speed = [32,111,138,28,59,77,97]

x = numpy.var(speed)

print(x)
```

Run example »

Standard Deviation

As we have learned, the formula to find the standard deviation is the square root of the variance:

√1432.25 = 37.85

Or, as in the example from before, use the NumPy to calculate the standard deviation:

Example

Use the NumPy `std()` method to find the standard deviation:

```
import numpy

speed = [32,111,138,28,59,77,97]

x = numpy.std(speed)

print(x)
```

Run example »

Symbols

Standard Deviation is often represented by the symbol Sigma: σ

Variance is often represented by the symbol Sigma Square: σ^2

Chapter Summary

The Standard Deviation and Variance are terms that are often used in Machine Learning, so it is important to understand how to get them, and the concept behind them.

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Machine Learning - Percentiles

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What are Percentiles?

Percentiles are used in statistics to give you a number that describes the value that a given percent of the values are lower than.

Example: Let's say we have an array of the ages of all the people that lives in a street.

```
ages = [5,31,43,48,50,41,7,11,15,39,80,82,32,2,8,6,25,36,27,61,31]
```

What is the 75. percentile? The answer is 43, meaning that 75% of the people are 43 or younger.

The NumPy module has a method for finding the specified percentile:

Example

Use the NumPy `percentile()` method to find the percentiles:

```
import numpy

ages = [5,31,43,48,50,41,7,11,15,39,80,82,32,2,8,6,25,36,27,61,31]

x = numpy.percentile(ages, 75)

print(x)
```

Run example »

Example

What is the age that 90% of the people are younger than?

```
import numpy

ages = [5,31,43,48,50,41,7,11,15,39,80,82,32,2,8,6,25,36,27,61,31]

x = numpy.percentile(ages, 90)

print(x)
```

Run example »

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Machine Learning - Data Distribution

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Data Distribution

Earlier in this tutorial we have worked with very small amounts of data in our examples, just to understand the different concepts.

In the real world, the data sets are much bigger, but it can be difficult to gather real world data, at least at an early stage of a project.

How Can we Get Big Data Sets?

To create big data sets for testing, we use the Python module NumPy, which comes with a number of methods to create random data sets, of any size.

Example

Create an array containing 250 random floats between 0 and 5:

```
import numpy

x = numpy.random.uniform(0.0, 5.0, 250)

print(x)
```

Run example »

Histogram

To visualize the data set we can draw a histogram with the data we collected.

We will use the Python module Matplotlib to draw a histogram:

Example

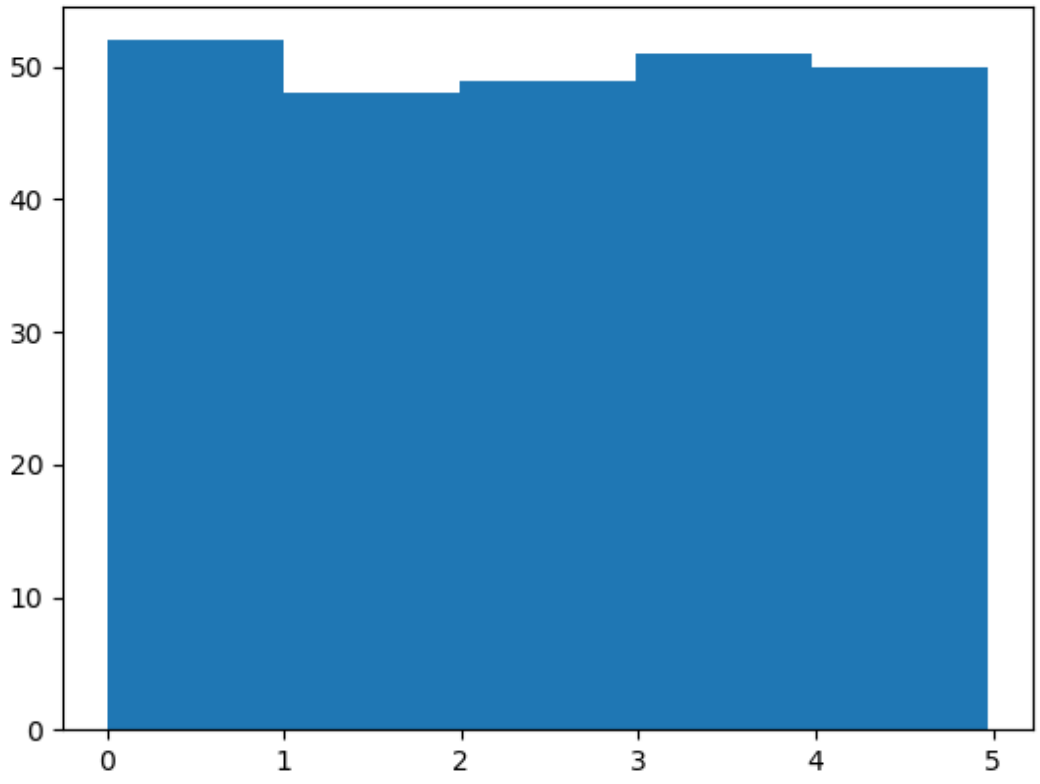
Draw a histogram:

```
import numpy
import matplotlib.pyplot as plt

x = numpy.random.uniform(0.0, 5.0, 250)

plt.hist(x, 5)
plt.show()
```

Result:



Run example »

Histogram Explained

We use the array from the example above to draw a histogram with 5 bars.

The first bar represents how many values in the array are between 0 and 1.

The second bar represents how many values are between 1 and 2.

Etc.

Which gives us this result:

- 52 values are between 0 and 1
- 48 values are between 1 and 2
- 49 values are between 2 and 3
- 51 values are between 3 and 4
- 50 values are between 4 and 5

Note: The array values are random numbers and will not show the exact same result on your computer.

Big Data Distributions

An array containing 250 values is not considered very big, but now you know how to create a random set of values, and by changing the parameters, you can create the data set as big as you want.

Example

Create an array with 100000 random numbers, and display them using a histogram with 100 bars:

```
import numpy
import matplotlib.pyplot as plt

x = numpy.random.uniform(0.0, 5.0, 100000)

plt.hist(x, 100)
plt.show()
```

Run example »

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Machine Learning - Normal Data Distribution

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Normal Data Distribution

In the previous chapter we learned how to create a completely random array, of a given size, and between two given values.

In this chapter we will learn how to create an array where the values are concentrated around a given value.

In probability theory this kind of data distribution is known as the *normal data distribution*, or the *Gaussian data distribution*, after the mathematician Carl Friedrich Gauss who came up with the formula of this data distribution.

Example

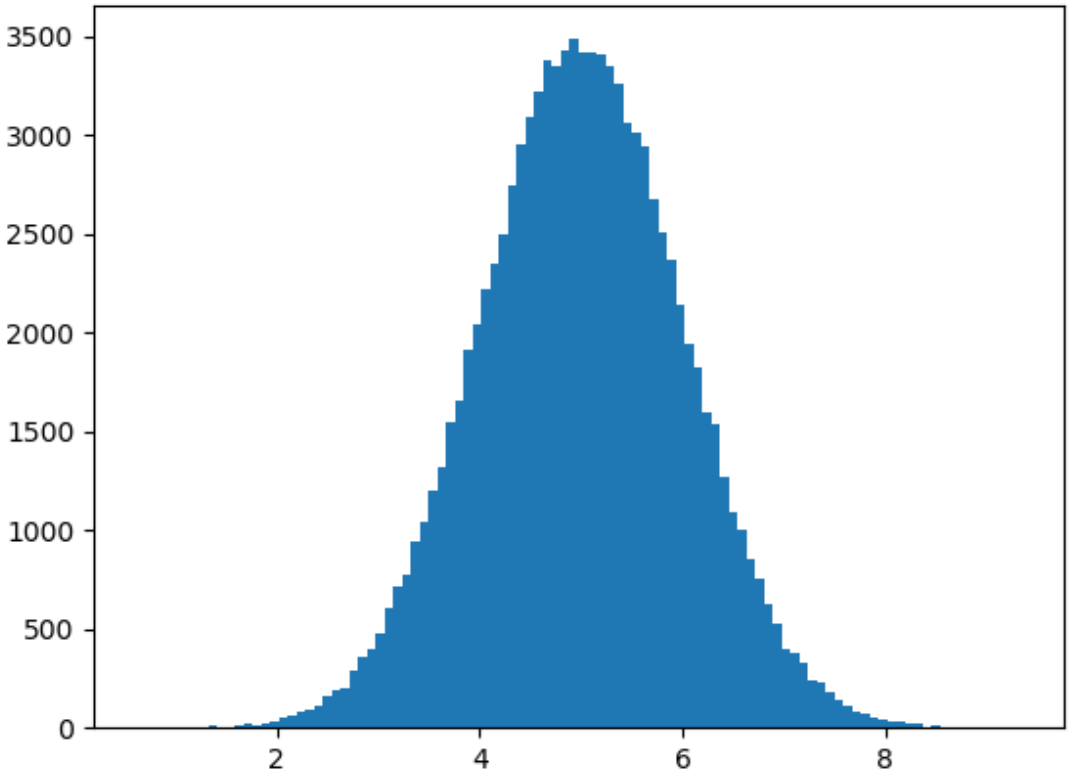
A typical normal data distribution:

```
import numpy
import matplotlib.pyplot as plt

x = numpy.random.normal(5.0, 1.0, 100000)

plt.hist(x, 100)
plt.show()
```

Result:



Run example »

Note: A normal distribution graph is also known as the *bell curve* because of it's characteristic shape of a bell.

Histogram Explained

We use the array from the `numpy.random.normal()` method, with 100000 values, to draw a histogram with 100 bars.

We specify that the mean value is 5.0, and the standard deviation is 1.0.

Meaning that the values should be concentrated around 5.0, and rarely further away than 1.0 from the mean.

And as you can see from the histogram, most values are between 4.0 and 6.0, with a top at approximately 5.0.

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Machine Learning - Scatter Plot

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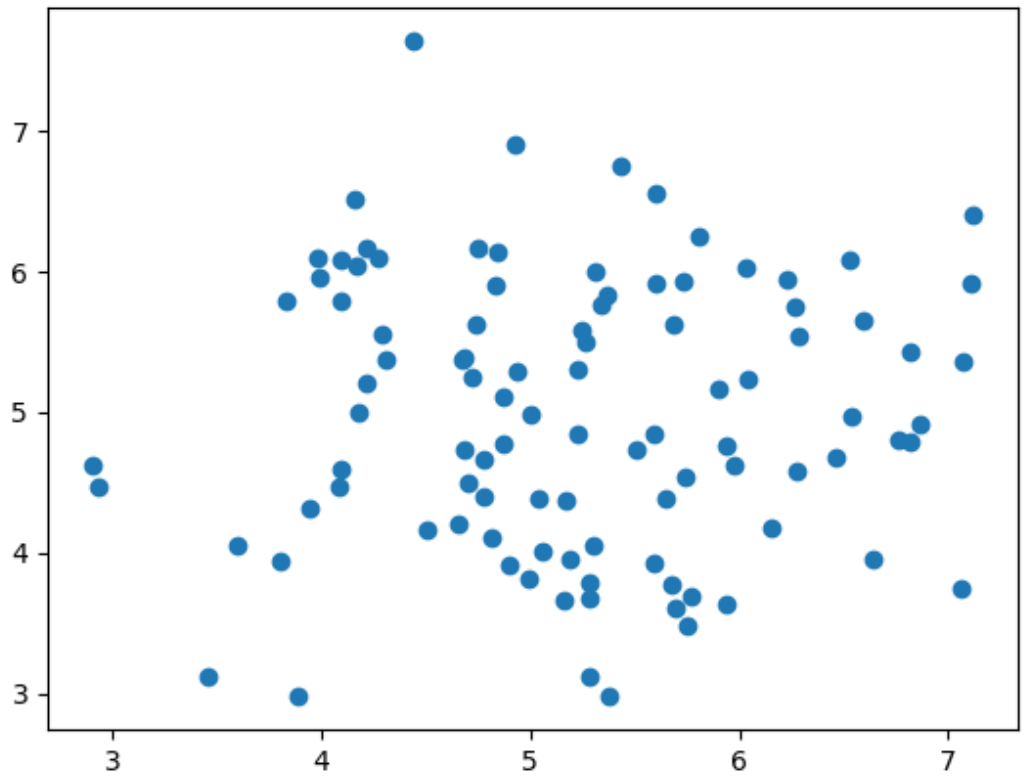
Scatter Plot

A scatter plot is diagram where each value in the data set is represented by a dot.



The Matplotlib module has a method for drawing scatter plots, it needs two arrays of the same length, one for the values of the x-axis, and one for the values of the y-axis:

```
y = [5,7,8,7,2,17,2,9,4,11,12,9,6]

x = [99,86,87,88,111,86,103,87,94,78,77,85,86]
```

The `x` array represents the age of each car.

The `y` array represents the speed of each car.

Example

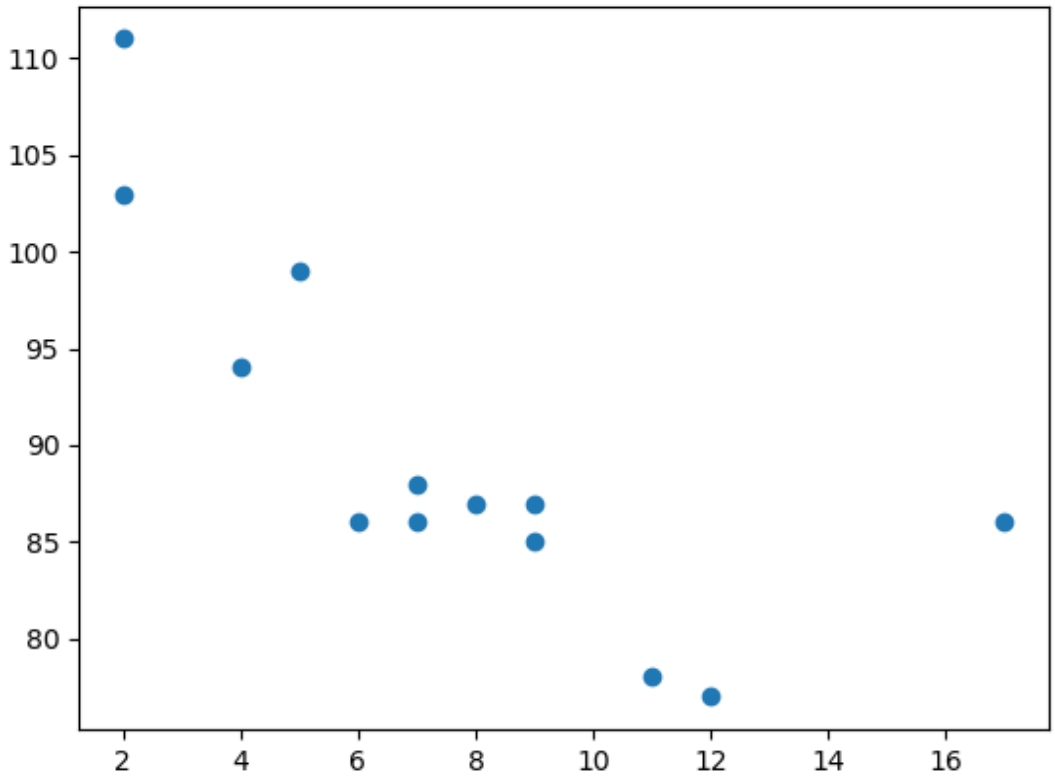
Use the `scatter()` method to draw a scatter plot diagram:

```
import matplotlib.pyplot as plt

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

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

Result:



Run example »

Scatter Plot Explained

The x-axis represents ages, and the y-axis represents speeds.

What we can read from the diagram is that the two fastest cars were both 2 years old, and the slowest car was 12 years old.

Note: It seems that the newer the car, the faster it drives, but that could be a coincidence, after all we only registered 13 cars.

Random Data Distributions

In Machine Learning the data sets can contain thousands-, or even millions, of values.

You might not have real world data when you are testing an algorithm, you might have to use randomly generated values.

As we have learned in the previous chapter, the NumPy module can help us with that!

Let us create two arrays that are both filled with 1000 random numbers from a normal data distribution.

The first array will have the mean set to 5.0 with a standard deviation of 1.0.

The second array will have the mean set to 10.0 with a standard deviation of 2.0:

Example

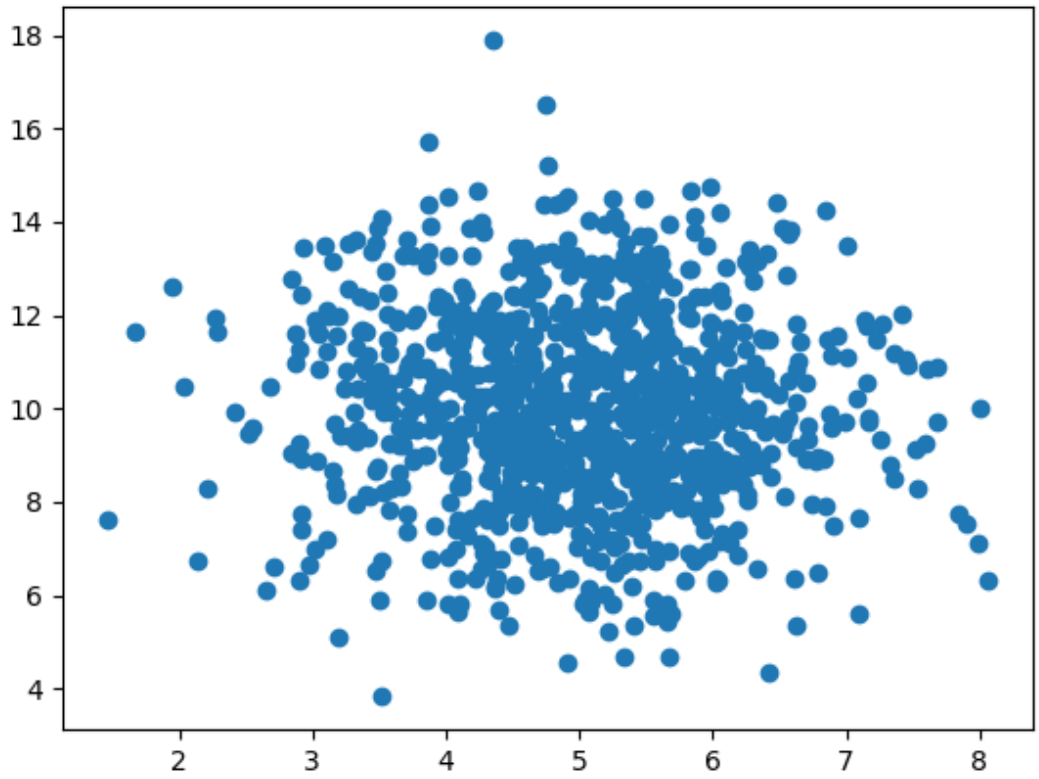
A scatter plot with 1000 dots:

```
import numpy
import matplotlib.pyplot as plt

x = numpy.random.normal(5.0, 1.0, 1000)
y = numpy.random.normal(10.0, 2.0, 1000)
```

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

Result:



Run example »

Scatter Plot Explained

We can see that the dots are concentrated around the value 5 on the x-axis, and 10 on the y-axis.

We can also see that the spread is wider on the y-axis than on the x-axis.

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Machine Learning - Linear Regression

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Regression

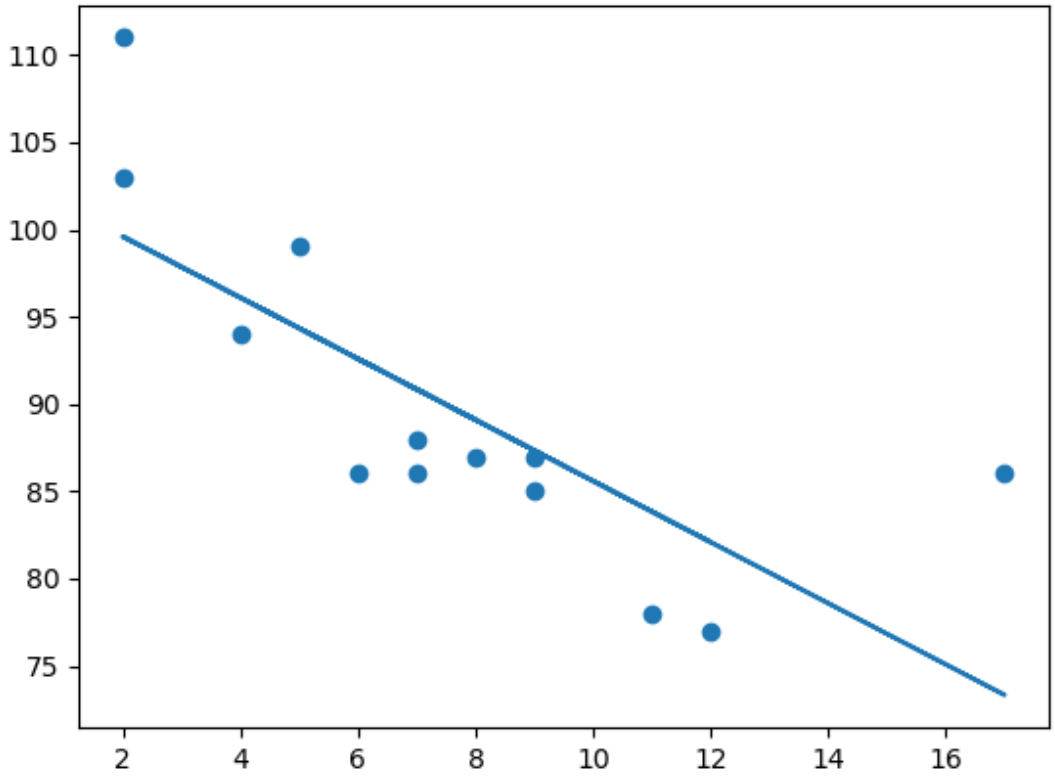
The term regression is used when you try to find the relationship between variables.

In Machine Learning, and in statistical modeling, that relationship is used to predict the outcome of future events.

Linear Regression

Linear regression uses the relationship between the data-points to draw a straight line through all them.

This line can be used to predict future values.



In Machine Learning, predicting the future is very important.

How Does it Work?

Python has methods for finding a relationship between data-points and to draw a line of linear regression. We will show you how to use these methods instead of going through the mathematic formula.

In the example below, the x-axis represents age, and the y-axis represents speed. We have registered the age and speed of 13 cars as they were passing a tollbooth. Let us see if the data we collected could be used in a linear regression:

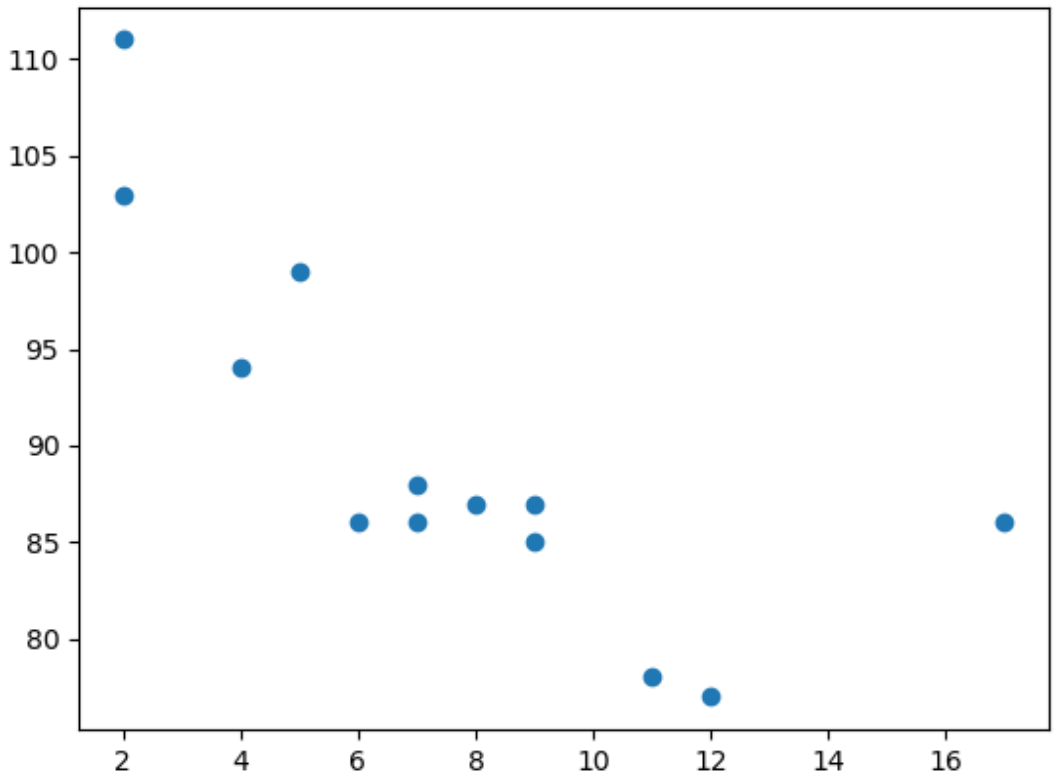
Example

Start by drawing a scatter plot:

```
import matplotlib.pyplot as plt

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
```

```
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

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

Result:



Run example »

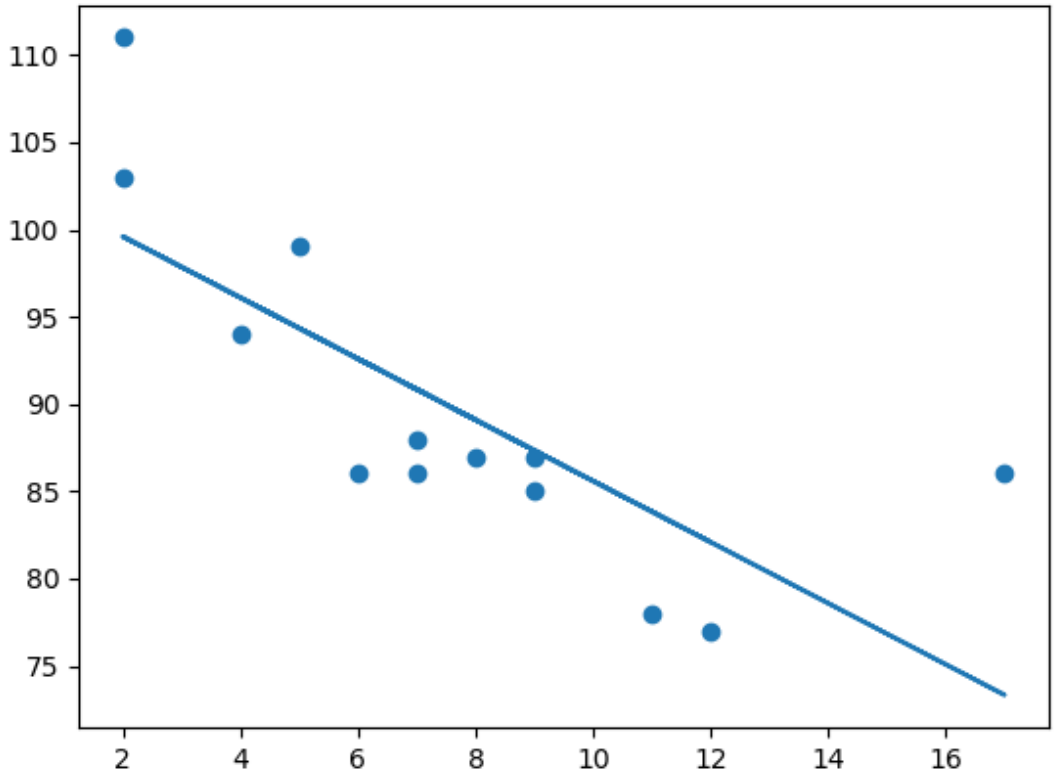
Example

Import `scipy` and draw the line of Linear Regression:

```
import matplotlib.pyplot as plt
from scipy import stats

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]
```

```
slope, intercept, r, p, std_err = stats.linregress(x, y)

def myfunc(x):
  return slope * x + intercept

mymodel = list(map(myfunc, x))

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

Result:



Run example »

Example Explained

Import the modules you need:

```
import matplotlib.pyplot as plt
from scipy import stats
```

Create the arrays that represents the values of the x and y axis:

```
x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]
```

Execute a method that returns some important key values of Linear Regression:

```
slope, intercept, r, p, std_err = stats.linregress(x, y)
```

Create a function that uses the `slope` and `intercept` values to return a new value. This new value represents where on the y-axis the corresponding x value will be placed:

```
def myfunc(x):
  return slope * x + intercept
```

Run each value of the x array through the function. This will result in a new array with new values for the y-axis:

```
mymodel = list(map(myfunc, x))
```

Draw the original scatter plot:

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

Draw the line of linear regression:

```
plt.plot(x, mymodel)
```

Display the diagram:

```
plt.show()
```

R-Squared

It is important to know how well the relationship between the values of the x-axis and the values of the y-axis is, if there are no relationship the linear regression can not be used to predict anything.

The relationship is measured with a value called the r-squared.

The r-squared value ranges from 0 to 1, where 0 means no relationship, and 1 means 100% related.

Python and the Scipy module will computed this value for you, all you have to do is feed it with the x and y values:

Example

How well does my data fit in a linear regression?

```
from scipy import stats

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

slope, intercept, r, p, std_err = stats.linregress(x, y)

print(r)
```

Run example »

Note: The result -076 shows that there are a relationship, not perfect, but it indicates that we could use linear regression in future predictions.

Predict Future Values

Now we can use the information we have gathered to predict future values.

Example: Let us try to predict the speed of a 10 years old car.

To do so, we need the same `myfunc()` function from the example above:

```
def myfunc(x):
  return slope * x + intercept
```

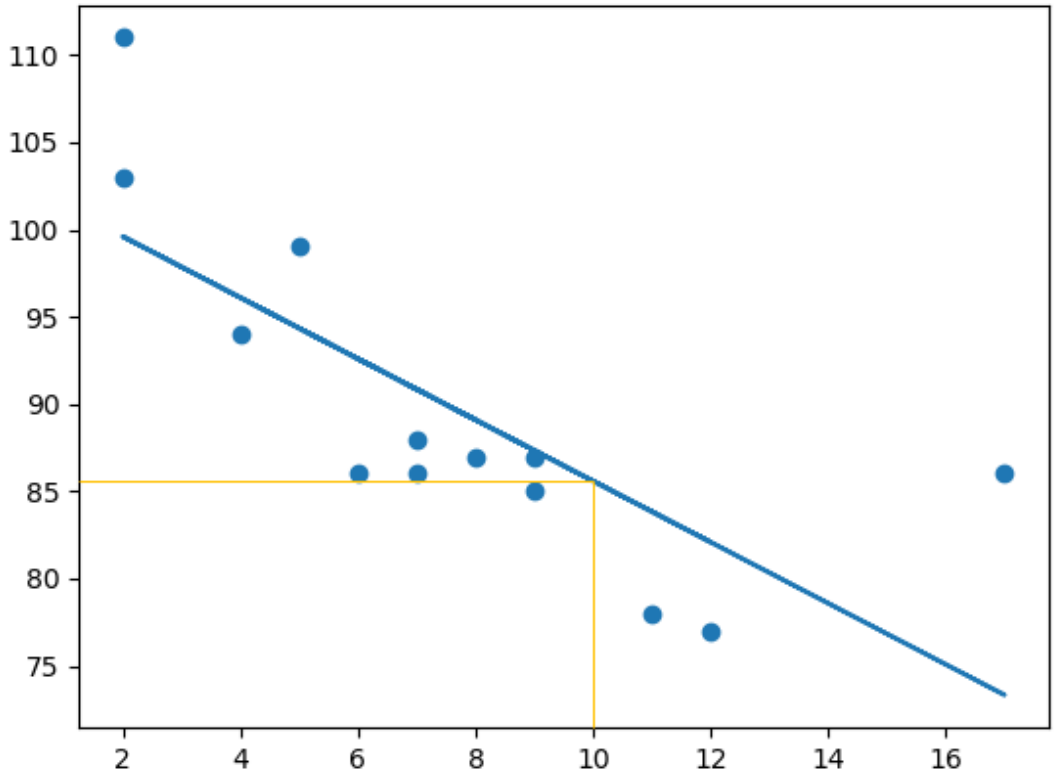
Example

Predict the speed of a 10 years old car:

```
from scipy import stats

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

slope, intercept, r, p, std_err = stats.linregress(x, y)

def myfunc(x):
  return slope * x + intercept

speed = myfunc(10)

print(speed)
```

Run example »

The example predicted a speed at 85.6, which we also could read from the diagram:



Bad Fit?

Let us create an example where linear regression would not be the best method to predict future values.

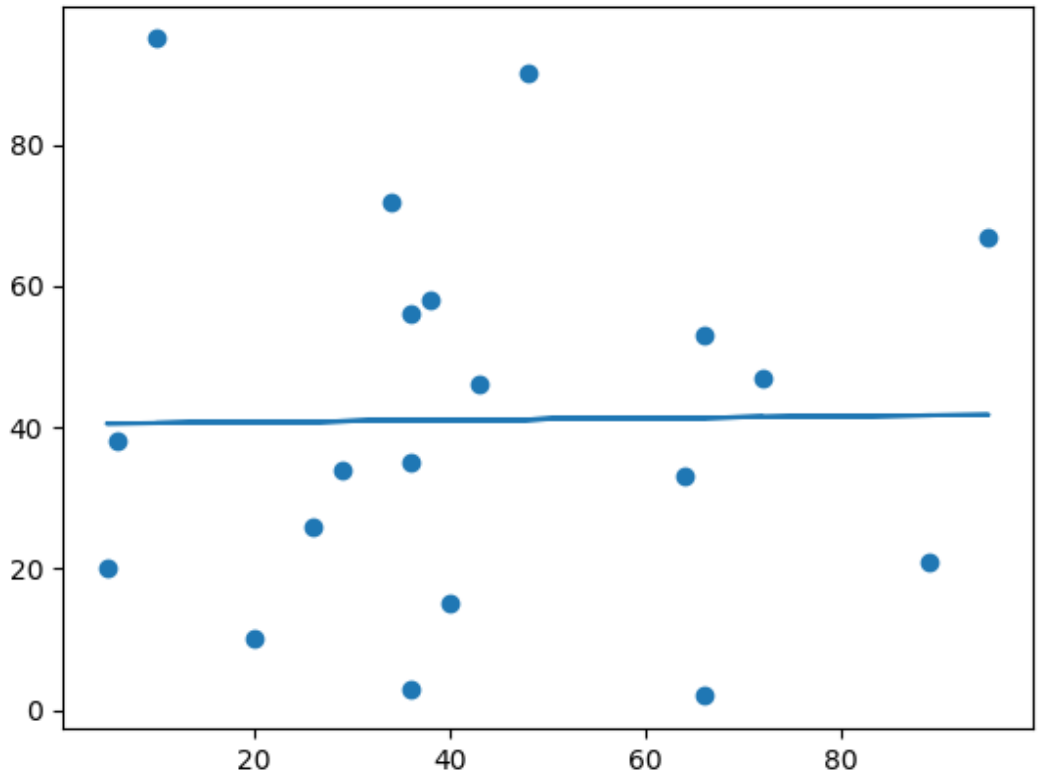
Example

These values for the x- and y-axis should result in a very bad fit for linear regression:

```
import matplotlib.pyplot as plt
from scipy import stats

x = [89,43,36,36,95,10,66,34,38,20,26,29,48,64,6,5,36,66,72,40]
y = [21,46,3,35,67,95,53,72,58,10,26,34,90,33,38,20,56,2,47,15]

slope, intercept, r, p, std_err = stats.linregress(x, y)

def myfunc(x):
  return slope * x + intercept
```

```
mymodel = list(map(myfunc, x))

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

Result:



Run example »

And the r-squared value?

Example

You should get a very low r-squared value.

```
import numpy
from scipy import stats
```

```
x = [89,43,36,36,95,10,66,34,38,20,26,29,48,64,6,5,36,66,72,40]
y = [21,46,3,35,67,95,53,72,58,10,26,34,90,33,38,20,56,2,47,15]

slope, intercept, r, p, std_err = stats.linregress(x, y)

print(r)
```

Run example »

The result: 0.013 indicates a very bad relationship, and tells us that this data set is not suitable for linear regression.

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Machine Learning - Polynomial Regression

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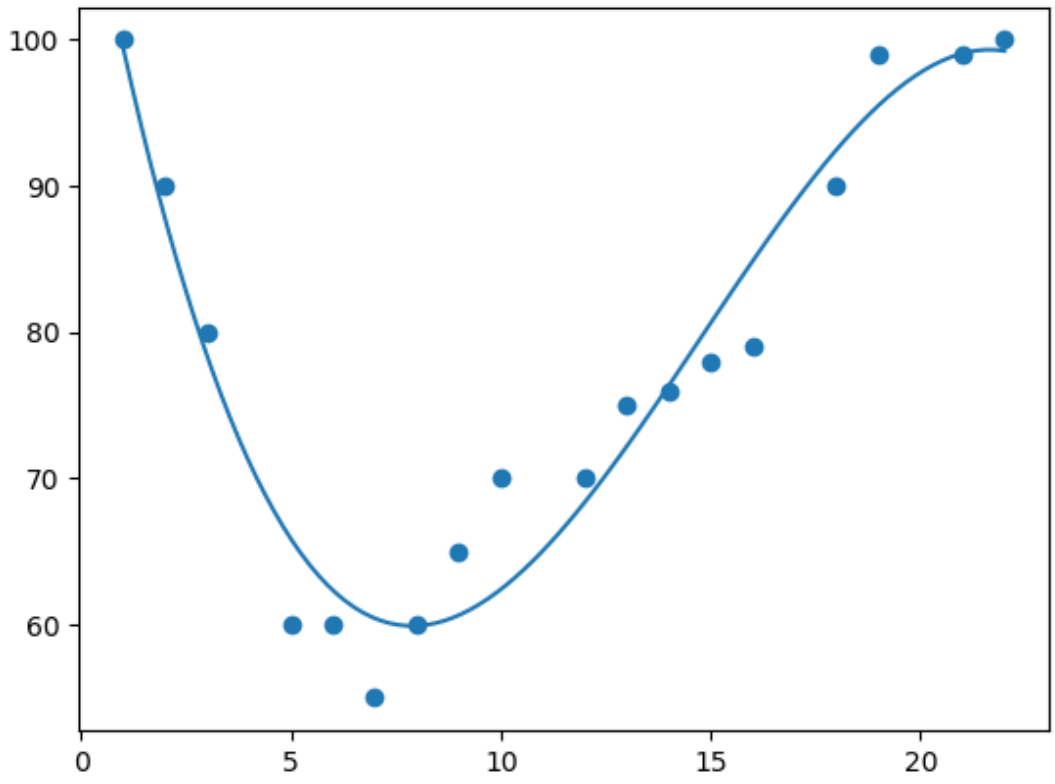
Polynomial Regression

If your data points clearly will not fit a linear regression (a straight line through all data points), it might be ideal for polynomial regression.

Polynomial regression, like linear regression, uses the relationship between the variables x and y to find the best way to draw a line through the data points.



How Does it Work?

Python has methods for finding a relationship between data-points and to draw a line of polynomial regression. We will show you how to use these methods instead of going through the mathematic formula.

In the example below, we have registered 18 cars as they were passing a certain tollbooth.

We have registered the car's speed, and the time of day (hour) the passing occurred.

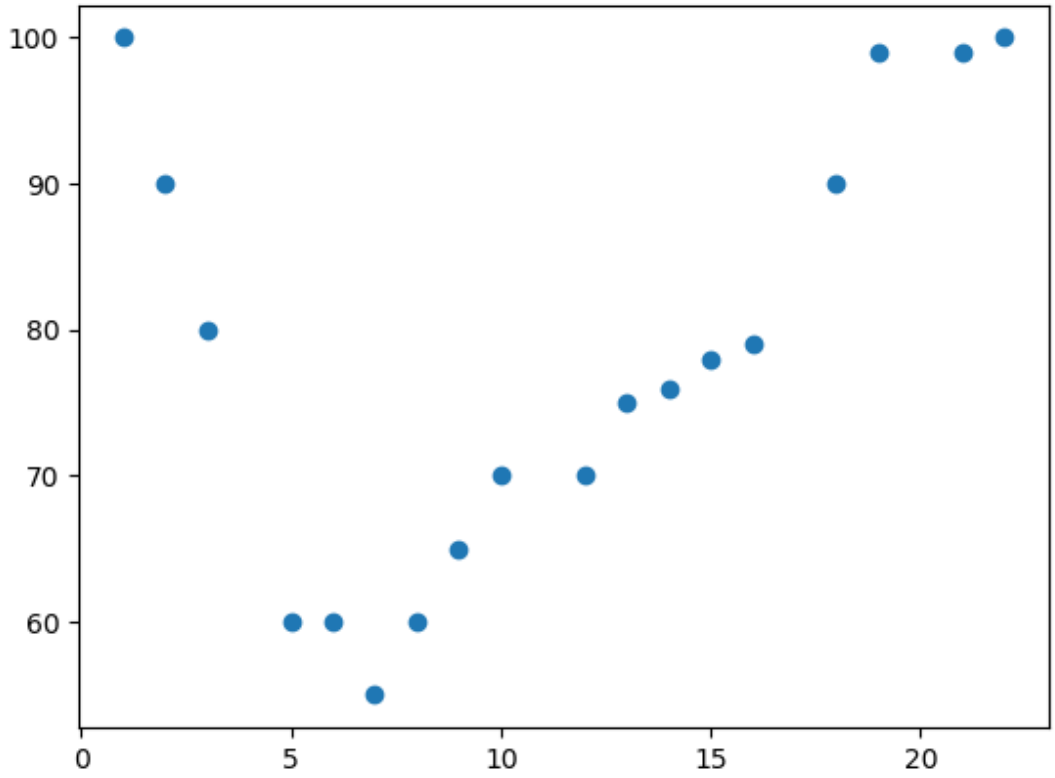
The x-axis represents the hours of the day and the y-axis represents the speed:

Example

Start by drawing a scatter plot:

```
import matplotlib.pyplot as plt

x = [1,2,3,5,6,7,8,9,10,12,13,14,15,16,18,19,21,22]
y = [100,90,80,60,60,55,60,65,70,70,75,76,78,79,90,99,99,100]

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

Result:



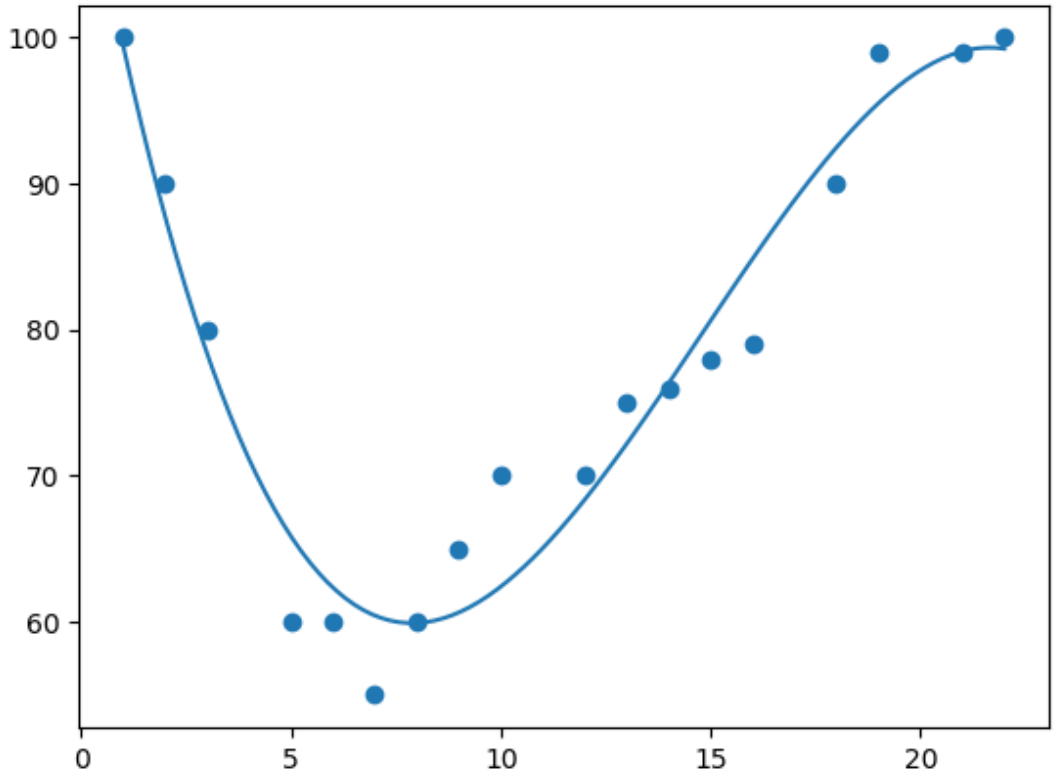
Run example »

Example

Import `numpy` and `matplotlib` then draw the line of Polynomial Regression:

```
import numpy
import matplotlib.pyplot as plt

x = [1,2,3,5,6,7,8,9,10,12,13,14,15,16,18,19,21,22]
y = [100,90,80,60,60,55,60,65,70,70,75,76,78,79,90,99,99,100]

mymodel = numpy.poly1d(numpy.polyfit(x, y, 3))

myline = numpy.linspace(1, 22, 100)

plt.scatter(x, y)
plt.plot(myline, mymodel(myline))
plt.show()
```

Result:



Run example »

Example Explained

Import the modules you need:

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

Create the arrays that represents the values of the x and y axis:

```
x = [1,2,3,5,6,7,8,9,10,12,13,14,15,16,18,19,21,22]
y = [100,90,80,60,60,55,60,65,70,70,75,76,78,79,90,99,99,100]
```

NumPy has a method that lets us make a polynomial model:

```
mymodel = numpy.poly1d(numpy.polyfit(x, y, 3))
```

Then specify how the line will display, we start at position 1, and end at position 22:

```
myline = numpy.linspace(1, 22, 100)
```

Draw the original scatter plot:

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

Draw the line of polynomial regression:

```
plt.plot(myline, mymodel(myline))
```

Display the diagram:

```
plt.show()
```

R-Squared

It is important to know how well the relationship between the values of the x- and y-axis is, if there are no relationship the polynomial regression can not be used to predict anything.

The relationship is measured with a value called the r-squared.

The r-squared value ranges from 0 to 1, where 0 means no relationship, and 1 means 100% related.

Python and the Sklearn module will computed this value for you, all you have to do is feed it with the x and y arrays:

Example

How well does my data fit in a polynomial regression?

```
import numpy
from sklearn.metrics import r2_score

x = [1,2,3,5,6,7,8,9,10,12,13,14,15,16,18,19,21,22]
y = [100,90,80,60,60,55,60,65,70,70,75,76,78,79,90,99,99,100]

mymodel = numpy.poly1d(numpy.polyfit(x, y, 3))

print(r2_score(y, mymodel(x)))
```

Run example »

Note: The result 0.94 shows that there is a very good relationship, and we can use polynomial regression in future predictions.

Predict Future Values

Now we can use the information we have gathered to predict future values.

Example: Let us try to predict the speed of a car that passes the tollbooth at around 17 P.M:

To do so, we need the same `mymodel` array from the example above:

```
mymodel = numpy.poly1d(numpy.polyfit(x, y, 3))
```

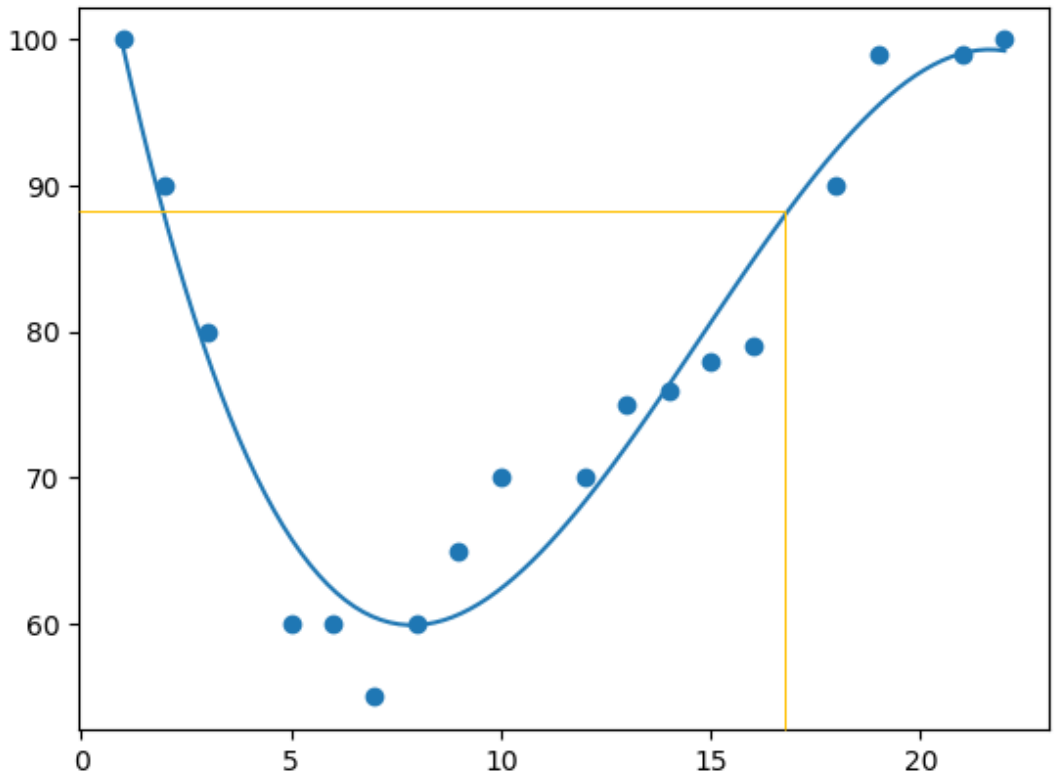
Example

Predict the speed of a car passing at 17 P.M:

```
import numpy
from sklearn.metrics import r2_score

x = [1,2,3,5,6,7,8,9,10,12,13,14,15,16,18,19,21,22]
y = [100,90,80,60,60,55,60,65,70,70,75,76,78,79,90,99,99,100]

mymodel = numpy.poly1d(numpy.polyfit(x, y, 3))

speed = mymodel(17)
print(speed)
```

Run example »

The example predicted a speed to be 88.87, which we also could read from the diagram:



Bad Fit?

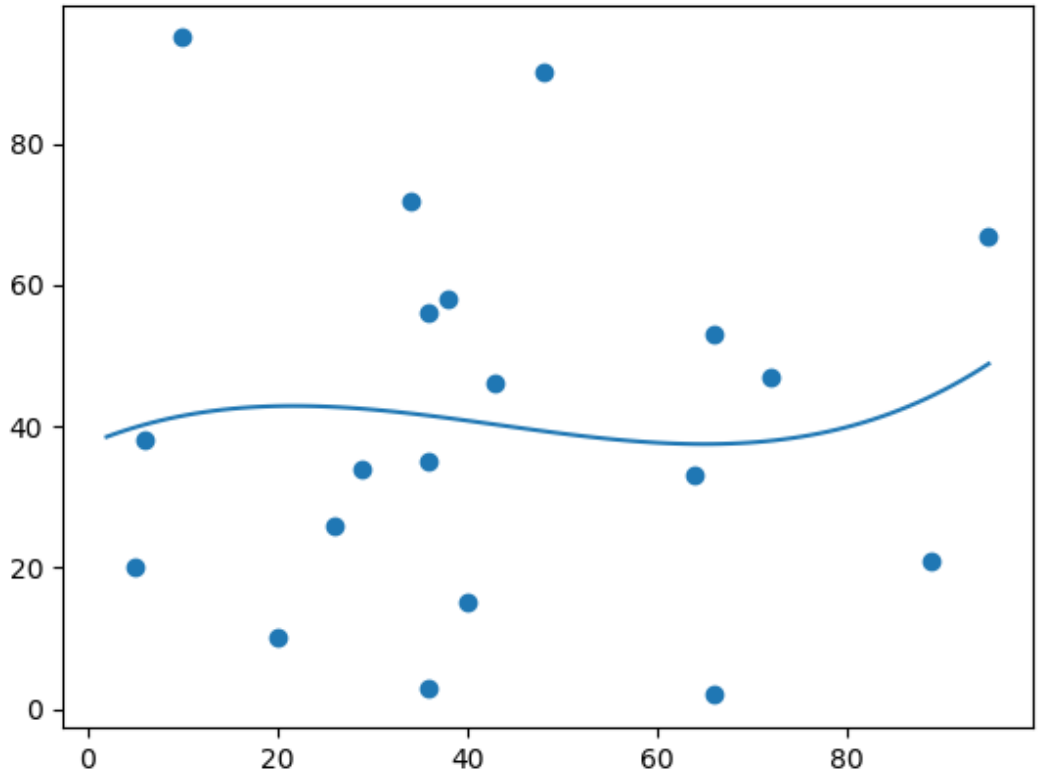
Let us create an example where polynomial regression would not be the best method to predict future values.

Example

These values for the x- and y-axis should result in a very bad fit for polynomial regression:

```
import numpy
import matplotlib.pyplot as plt

x = [89,43,36,36,95,10,66,34,38,20,26,29,48,64,6,5,36,66,72,40]
y = [21,46,3,35,67,95,53,72,58,10,26,34,90,33,38,20,56,2,47,15]

mymodel = numpy.poly1d(numpy.polyfit(x, y, 3))

myline = numpy.linspace(2, 95, 100)

plt.scatter(x, y)
plt.plot(myline, mymodel(myline))
plt.show()
```

Result:



Run example »

And the r-squared value?

Example

You should get a very low r-squared value.

```
import numpy
from sklearn.metrics import r2_score

x = [89,43,36,36,95,10,66,34,38,20,26,29,48,64,6,5,36,66,72,40]
y = [21,46,3,35,67,95,53,72,58,10,26,34,90,33,38,20,56,2,47,15]

mymodel = numpy.poly1d(numpy.polyfit(x, y, 3))

print(r2_score(y, mymodel(x)))
```

Run example »

The result: 0.00995 indicates a very bad relationship, and tells us that this data set is not suitable for polynomial regression.

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Machine Learning - Multiple Regression

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Multiple Regression

Multiple regression is like linear regression, but with more than one independent value, meaning that we try to predict a value based on **two or more** variables.

Take a look at the data set below, it contains some information about cars.

Car	Model	Volume	Weight	CO2
Toyota	Aygo	1000	790	99
Mitsubishi	Space Star	1200	1160	95
Skoda	Citigo	1000	929	95
Fiat	500	900	865	90
Mini	Cooper	1500	1140	105
VW	Up!	1000	929	105
Skoda	Fabia	1400	1109	90
Mercedes	A-Class	1500	1365	92
Ford	Fiesta	1500	1112	98
Audi	A1	1600	1150	99
Hyundai	I20	1100	980	99

We can predict the CO2 emission of a car based on the size of the engine, but with multiple regression we can throw in more variables, like the weight of the car, to make the prediction more accurate.

How Does it Work?

In Python we have modules that will do the work for us. Start by importing the Pandas module.

```
import Pandas
```

The Pandas module allows us to read csv files and return a DataFrame object.

```
df = pandas.read_csv("cars.csv")
```

Then make a list of the independent values and call this variable `X`.

Put the dependent values in a variable called `y`.

```
X = df[['Weight', 'Volume']]
y = df['CO2']
```

Tip: It is common to name the list of independent values with a upper case X, and the list of dependent values with a lower case y.

We will use some methods from the sklearn module, so we will have to import that module as well:

```
from sklearn import linear_model
```

From the sklearn module we will use the `LinearRegression()` method to create a linear regression object.

This object has a method called `fit()` that takes the independent and dependent values as parameters and fills the regression object with data that describes the relationship:

```
regr = linear_model.LinearRegression()
regr.fit(X, y)
```

Now we have a regression object that are ready to predict CO2 values based on a car's weight and volume:

```
#predict the CO2 emission of a car where the weight is 2300g, and the volume is 1300ccm:
predictedCO2 = regr.predict([[2300, 1300]])
```

Example

See the whole example in action:

```
import pandas
from sklearn import linear_model

df = pandas.read_csv("cars.csv")

X = df[['Weight', 'Volume']]
y = df['CO2']

regr = linear_model.LinearRegression()
regr.fit(X, y)

#predict the CO2 emission of a car where the weight is 2300g, and the volume is
1300ccm:
predictedCO2 = regr.predict([[2300, 1300]])

print(predictedCO2)
```

Result:

```
[107.2087328]
```

Run example »

We have predicted that a car with 1.3 liter engine, and a weight of 2.3 kg, will release approximately 107 grams of CO2 for every kilometer it drives.

Coefficient

The coefficient is a factor that describes the relationship with an unknown variable.

Example: if `x` is a variable, then `2x` is `x` two times. `x` is the unknown variable, and the number `2` is the coefficient.

In this case, we can ask for the coefficient value of weight against CO2, and for volume against CO2. The answer(s) we get tells us what would happen if we increase, or decrease, one of the independent values.

Example

Print the coefficient values of the regression object:

```
import pandas
from sklearn import linear_model

df = pandas.read_csv("cars.csv")

X = df[['Weight', 'Volume']]
y = df['CO2']

regr = linear_model.LinearRegression()
regr.fit(X, y)

print(regr.coef_)
```

Result:

```
[0.00755095 0.00780526]
```

Run example »

Result Explained

The result array represents the coefficient values of weight and value.

Weight: 0.00755095
Volume: 0.00780526

These values tells us that if the weight increases by 1g, the CO2 emission increases by 0.00755095g.

And if the engine size (Volume) increases by 1 ccm, the CO2 emission increases by 0.00780526 g.

I think that is a fair guess, but let test it!

We have already predicted that if a car with a 1300ccm engine weighs 2300g, the CO2 emission will be approximately 107g.

What if we increase the weight with 1000g?

Example

Copy the example from before, but change the weight from 2300 to 3300:

```
import pandas
from sklearn import linear_model

df = pandas.read_csv("cars.csv")

X = df[['Weight', 'Volume']]
y = df['CO2']

regr = linear_model.LinearRegression()
regr.fit(X, y)

predictedCO2 = regr.predict([[3300, 1300]])

print(predictedCO2)
```

Result:

```
[114.75968007]
```

Run example »

We have predicted that a car with 1.3 liter engine, and a weight of 3.3 kg, will release approximately 115 grams of CO2 for every kilometer it drives.

Which shows that the coefficient of 0.00755095 is correct:

107.2087328 + (1000 * 0.00755095) = 114.75968

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Machine Learning - Scale

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Scale Features

When your data has different values, and even different measurement units, it can be difficult to compare them. What is kilograms compared to meters? Or altitude compared to time?

The answer to this problem is scaling. We can scale data into new values that are easier to compare.

Take a look at the table below, it is the same data set that we used in the multiple regression chapter, but this time the **volume** column contains values in *liters* instead of *ccm* (1.0 instead of 1000).

Car	Model	Volume	Weight	CO2
Toyota	Aygo	1.0	790	99
Mitsubishi	Space Star	1.2	1160	95
Skoda	Citigo	1.0	929	95
Fiat	500	0.9	865	90
Mini	Cooper	1.5	1140	105
VW	Up!	1.0	929	105
Skoda	Fabia	1.4	1109	90
Mercedes	A-Class	1.5	1365	92
Ford	Fiesta	1.5	1112	98
Audi	A1	1.6	1150	99
Hyundai	I20	1.1	980	99
Suzuki	Swift	1.3	990	101

It can be difficult to compare the volume 1.0 with the weight 790, but if we scale them both into comparable values, we can easily see how much one value is compared to the other.

There are different methods for scaling data, in this tutorial we will use a method called standardization.

The standardization method uses this formula:

`z = (x - u) / s`

Where `z` is the new value, `x` is the original value, `u` is the mean and `s` is the standard deviation.

If you take the **weight** column from the data set above, the first value is 790, and the scaled value will be:

`(790 - 1292.23) / 238.74 = -2.1`

If you take the **volume** column from the data set above, the first value is 1.0, and the scaled value will be:

`(1.0 - 1.61) / 0.38 = -1.59`

Now you can compare -2.1 with -1.59 instead of comparing 790 with 1.0.

You do not have to do this manually, the Python sklearn module has a method called `StandardScaler()` which returns a Scaler object with methods for transforming data sets.

Example

Scale all values in the Weight and Volume columns:

```
import pandas
from sklearn import linear_model
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()

df = pandas.read_csv("cars2.csv")

X = df[['Weight', 'Volume']]

scaledX = scale.fit_transform(X)

print(scaledX)
```

Result:

Note that the first two values are -2.1 and -1.59, which corresponds to our calculations:

```
[[-2.10389253 -1.59336644]
 [-0.55407235 -1.07190106]
 [-1.52166278 -1.59336644]
 [-1.78973979 -1.85409913]
 [-0.63784641 -0.28970299]
 [-1.52166278 -1.59336644]
 [-0.76769621 -0.55043568]
 [ 0.3046118  -0.28970299]
 [-0.7551301  -0.28970299]
 [-0.59595938 -0.0289703 ]
 [-1.30803892 -1.33263375]
 [-1.26615189 -0.81116837]
 [-0.7551301  -1.59336644]
 [-0.16871166 -0.0289703 ]
 [ 0.14125238 -0.0289703 ]
 [ 0.15800719 -0.0289703 ]
 [ 0.3046118  -0.0289703 ]
 [-0.05142797  1.53542584]
 [-0.72580918 -0.0289703 ]
 [ 0.14962979  1.01396046]
 [ 1.2219378  -0.0289703 ]
 [ 0.5685001   1.01396046]
 [ 0.3046118   1.27469315]
 [ 0.51404696 -0.0289703 ]
 [ 0.51404696  1.01396046]
 [ 0.72348212 -0.28970299]
 [ 0.8281997   1.01396046]
 [ 1.81254495  1.01396046]
 [ 0.96642691 -0.0289703 ]
 [ 1.72877089  1.01396046]
 [ 1.30990057  1.27469315]
 [ 1.90050772  1.01396046]
 [-0.23991961 -0.0289703 ]
 [ 0.40932938 -0.0289703 ]
 [ 0.47215993 -0.0289703 ]
 [ 0.4302729   2.31762392]]
```

Run example »

Predict CO2 Values

The task in the Multiple Regression chapter was to predict the CO2 emission from a car when you only knew its weight and volume.

When the data set is scaled, you will have to use the scale when you predict values:

Example

Predict the CO2 emission from a 1.3 liter car that weighs 2300 kilograms:

```
import pandas
from sklearn import linear_model
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()

df = pandas.read_csv("cars2.csv")

X = df[['Weight', 'Volume']]
y = df['CO2']

scaledX = scale.fit_transform(X)

regr = linear_model.LinearRegression()
regr.fit(scaledX, y)

scaled = scale.transform([[2300, 1.3]])

predictedCO2 = regr.predict([scaled[0]])
print(predictedCO2)
```

Result:

```
[107.2087328]
```

Run example »

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Machine Learning - Train/Test

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Evaluate Your Model

In Machine Learning we create models to predict the outcome of certain events, like in the previous chapter where we predicted the CO2 emission of a car when we knew the weight and engine size.

To measure if the model is good enough, we can use a method called Train/Test.

What is Train/Test

Train/Test is a method to measure the accuracy of your model.

It is called Train/Test because you split the the data set into two sets: a training set and a testing set.

80% for training, and 20% for testing.

You *train* the model using the training set.

You *test* the model using the testing set.

Train the model means *create* the model.

Test the model means test the accuracy of the model.

Start With a Data Set

Start with a data set you want to test.

Our data set illustrates 100 customers in a shop, and their shopping habits.

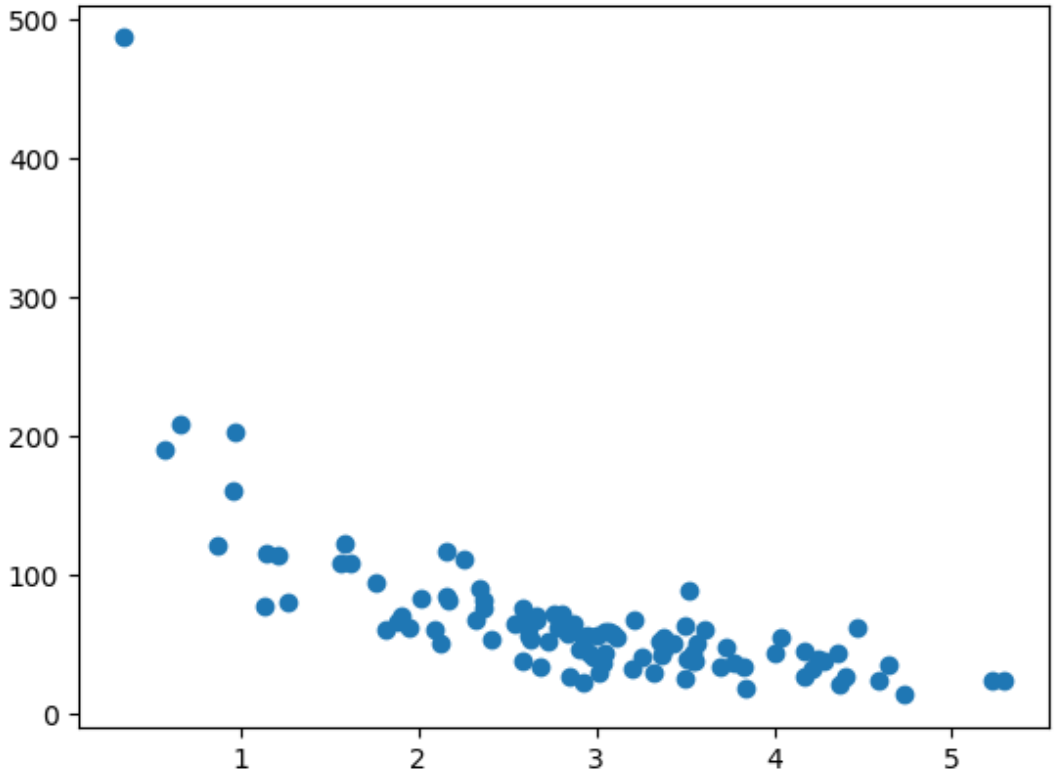
Example

```
import numpy
import matplotlib.pyplot as plt
numpy.random.seed(2)

x = numpy.random.normal(3, 1, 100)
y = numpy.random.normal(150, 40, 100) / x

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

Result:

The x axis represents the number of minutes before making a purchase.

The y axis represents the amount of money spent on the purchase.



Run example »

Split Into Train/Test

The *training* set should be a random selection of 80% of the original data.

The *testing* set should be the remaining 20%.

```
train_x = x[:80]
train_y = y[:80]

test_x = x[80:]
test_y = y[80:]
```

Display the Training Set

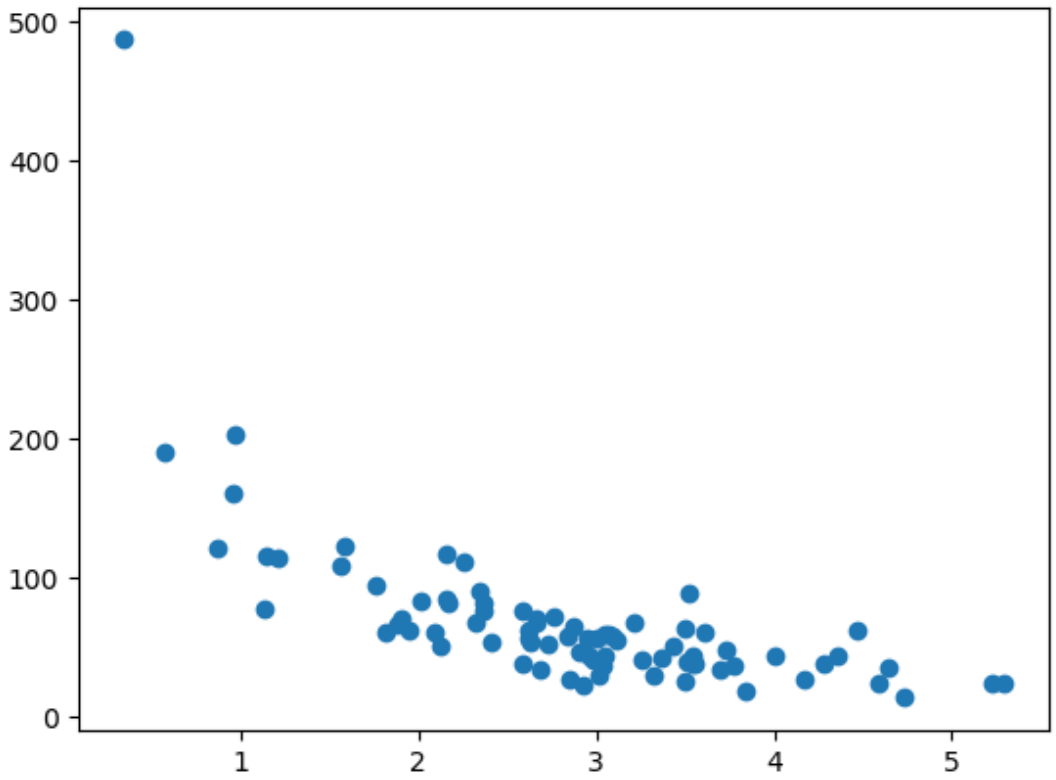
Display the same scatter plot with the training set:

Example

```
plt.scatter(train_x, train_y)
plt.show()
```

Result:

It looks like the original data set, so it seems to be a fair selection:



Run example »

Display the Testing Set

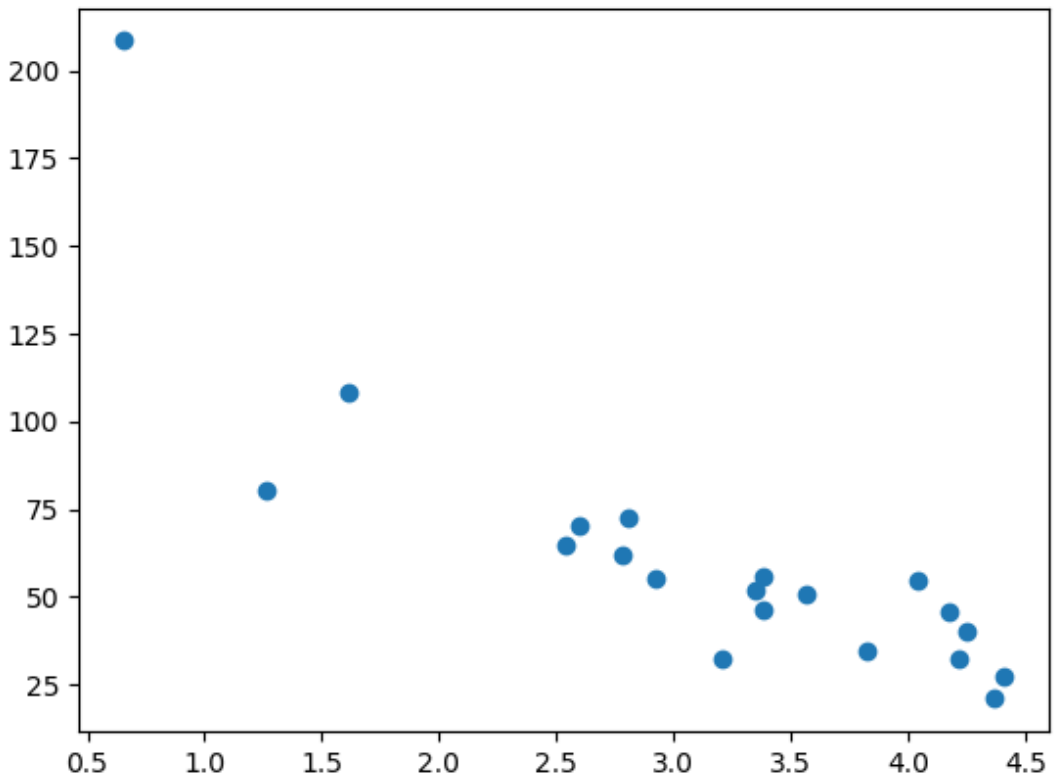
To make sure the testing set is not completely different, we will take a look at the testing set as well.

Example

```
plt.scatter(test_x, test_y)
plt.show()
```

Result:

The testing set also looks like the original data set:



Run example »

Fit the Data Set

What does the data set look like? In my opinion I think the best fit would be a polynomial regression, so let us draw a line of polynomial regression.

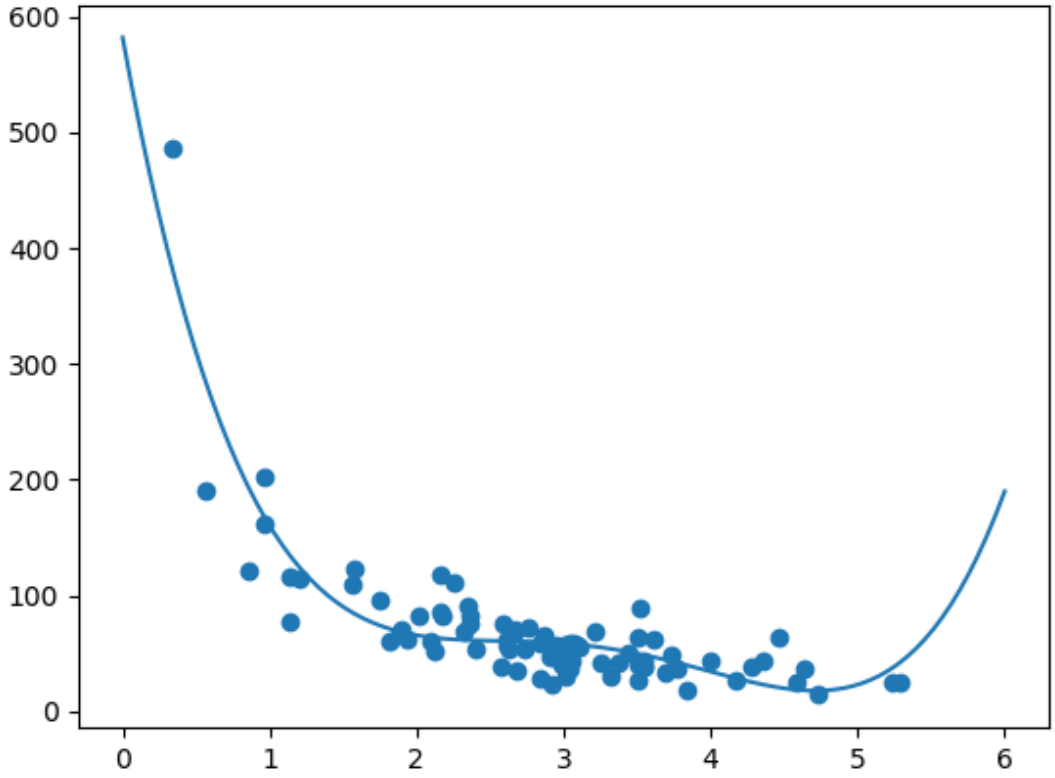
To draw a line through the data points, we use the `plot()` method of the matplotlib module:

Example

Draw a polynomial regression line through the data points:

```
import numpy
import matplotlib.pyplot as plt
numpy.random.seed(2)

x = numpy.random.normal(3, 1, 100)
y = numpy.random.normal(150, 40, 100) / x

train_x = x[:80]
train_y = y[:80]

test_x = x[80:]
test_y = y[80:]

mymodel = numpy.poly1d(numpy.polyfit(train_x, train_y, 4))

myline = numpy.linspace(0, 6, 100)

plt.scatter(train_x, train_y)
plt.plot(myline, mymodel(myline))
plt.show()
```

Result:



Run example »

The result can back my suggestion of the data set fitting a polynomial regression, even though it would give us some weird results if we try to predict values outside of the data set. Example: the line indicates that a customer spending 6 minutes in the shop would make a purchase worth 200. That is probably a sign of overfitting.

But what about the R-squared score? The R-squared score is a good indicator of how well my data set is fitting the model.

R2

Remember R2, also known as R-squared?

It measures the relationship between the x axis and the y axis, and the value ranges from 0 to 1, where 0 means no relationship, and 1 means totally related.

The sklearn module has a method called `rs_score()` that will help us find this relationship.

In this case we would like to measure the relationship between the minutes a customer stays in the shop and how much money they spend.

Example

How well does my training data fit in a polynomial regression?

```
import numpy
from sklearn.metrics import r2_score
numpy.random.seed(2)

x = numpy.random.normal(3, 1, 100)
y = numpy.random.normal(150, 40, 100) / x

train_x = x[:80]
train_y = y[:80]

test_x = x[80:]
test_y = y[80:]

mymodel = numpy.poly1d(numpy.polyfit(train_x, train_y, 4))

r2 = r2_score(train_y, mymodel(train_x))

print(r2)
```

Run example »

Note: The result 0.799 shows that there is a OK relationship.

Bring in the Testing Set

Now we have made a model that is OK, at least when it comes to training data.

Now we want to test the model with the testing data as well, to see if gives us the same result.

Example

Let us find the R2 score when using testing data:

```
import numpy
from sklearn.metrics import r2_score
numpy.random.seed(2)

x = numpy.random.normal(3, 1, 100)
y = numpy.random.normal(150, 40, 100) / x

train_x = x[:80]
train_y = y[:80]

test_x = x[80:]
test_y = y[80:]

mymodel = numpy.poly1d(numpy.polyfit(train_x, train_y, 4))

r2 = r2_score(test_y, mymodel(test_x))

print(r2)
```

Run example »

Note: The result 0.809 shows that the model fits the testing set as well, and we are confident that we can use the model to predict future values.

Predict Values

Now that we have established that our model is OK, we can start predicting new values.

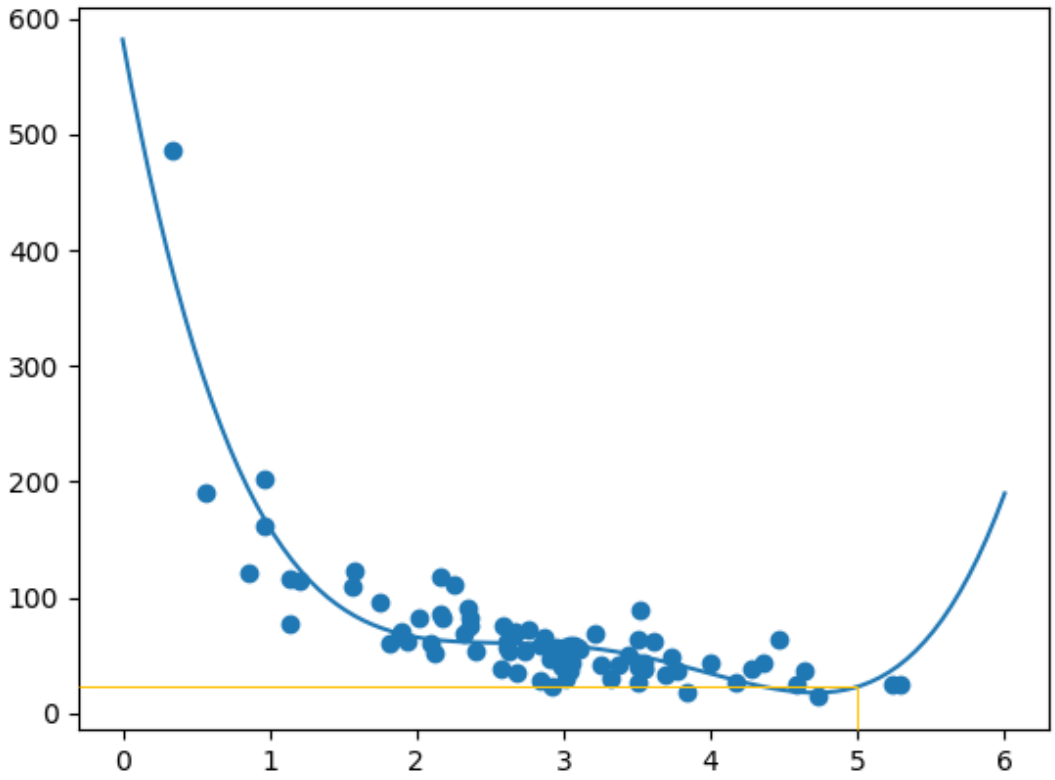
Example

How much money will a buying customer spend, if she or he stays in the shop for 5 minutes?

```
print(mymodel(5))
```

Run example »

The example predicted the customer to spend 22.88 dollars, as seems to correspond to the diagram:



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Machine Learning - Decision Tree

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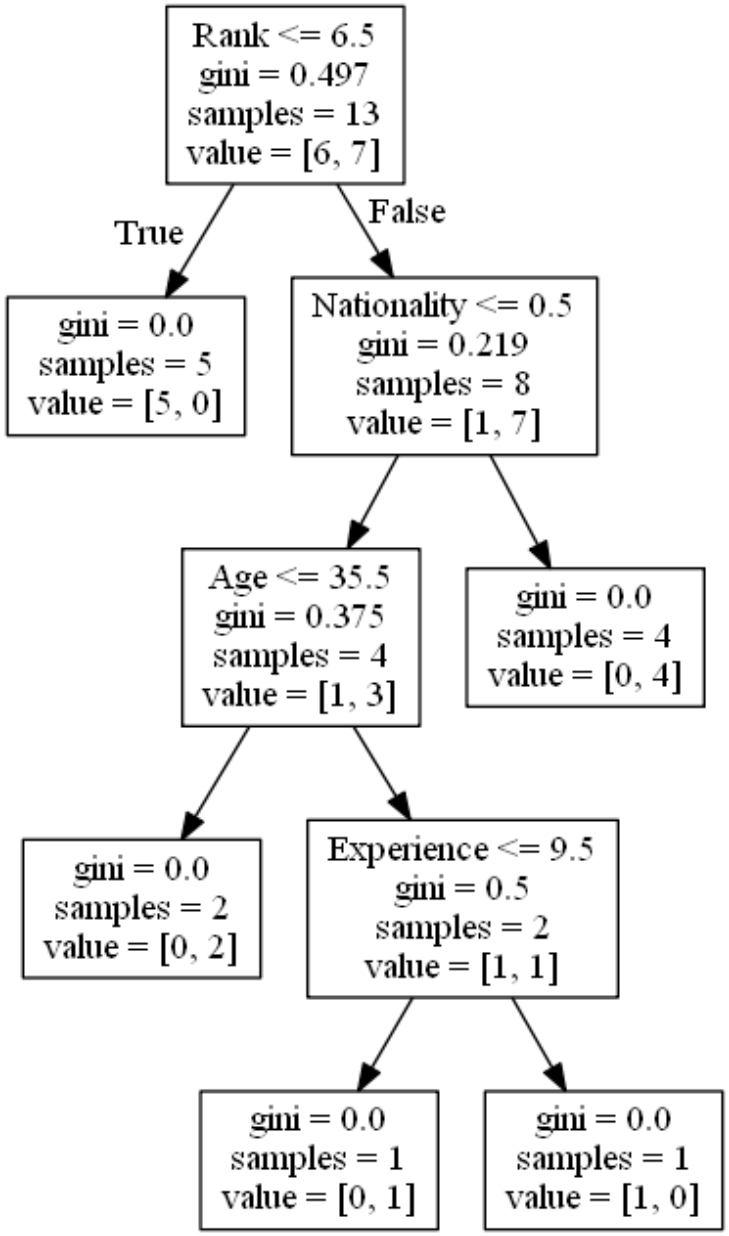


Decision Tree

In this chapter we will show you how to make a "Decision Tree". A Decision Tree is a Flow Chart, and can help you make decisions based on previous experience.

In the example, a person will try to decide if he/she should go to a comedy show or not.

Luckily our example person has registered every time there was a comedy show in town, and registered some information about the comedian, and also registered if he/she went or not.

Age	Experience	Rank	Nationality	Go
36	10	9	UK	NO
42	12	4	USA	NO
23	4	6	N	NO
52	4	4	USA	NO
43	21	8	USA	YES
44	14	5	UK	NO
66	3	7	N	YES
35	14	9	UK	YES
52	13	7	N	YES
35	5	9	N	YES
24	3	5	USA	NO
18	3	7	UK	YES
45	9	9	UK	YES

Now, based on this data set, Python can create a decision tree that can be used to decide if any new shows are worth attending to.

How Does it Work?

First, import the modules you need, and read the dataset with pandas:

Example

Read and print the data set:

```
import pandas
from sklearn import tree
import pydotplus
from sklearn.tree import DecisionTreeClassifier
import matplotlib.pyplot as plt
import matplotlib.image as pltimg

df = pandas.read_csv("shows.csv")

print(df)
```

Run example »

To make a decision tree, all data has to be numerical.

We have to convert the non numerical columns 'Nationality' and 'Go' into numerical values.

Pandas has a `map()` method that takes a dictionary with information on how to convert the values.

```
{'UK': 0, 'USA': 1, 'N': 2}
```

Means convert the values 'UK' to 0, 'USA' to 1, and 'N' to 2.

Example

Change string values into numerical values:

```
d = {'UK': 0, 'USA': 1, 'N': 2}
df['Nationality'] = df['Nationality'].map(d)
d = {'YES': 1, 'NO': 0}
df['Go'] = df['Go'].map(d)

print(df)
```

Run example »

Then we have to separate the *feature* columns from the *target* column.

The feature columns are the columns that we try to predict *from*, and the target column is the column with the values we try to predict.

Example

`X` is the feature columns, `y` is the target column:

```
features = ['Age', 'Experience', 'Rank', 'Nationality']

X = df[features]
y = df['Go']

print(X)
print(y)
```

Run example »

Now we can create the actual decision tree, fit it with our details, and save a .png file on the computer:

Example

Create a Decision Tree, save it as an image, and show the image:

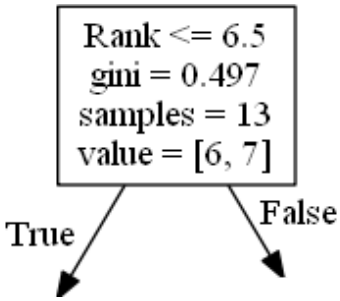
```
dtree = DecisionTreeClassifier()
dtree = dtree.fit(X, y)
data = tree.export_graphviz(dtree, out_file=None, feature_names=features)
graph = pydotplus.graph_from_dot_data(data)
graph.write_png('mydecisiontree.png')

img=pltimg.imread('mydecisiontree.png')
imgplot = plt.imshow(img)
plt.show()
```

Run example »

Result Explained

The decision tree uses your earlier decisions to calculate the odds for you to wanting to go see a comedian or not.

Let us read the different aspects of the decision tree:



Rank

`Rank <= 6.5` means that every comedian with a rank of 6.5 or lower will follow the `True` arrow (to the left), and the rest will follow the `False` arrow (to the right).

`gini = 0.497` refers to the quality of the split, and is always a number between 0.0 and 0.5, where 0.0 would mean all of the samples got the same result, and 0.5 would mean that the split is done exactly in the middle.

`samples = 13` means that there are 13 comedians left at this point in the decision, which is all of them since this is the first step.

`value = [6, 7]` means that of these 13 comedians, 6 will get a "NO", and 7 will get a "GO".

Gini

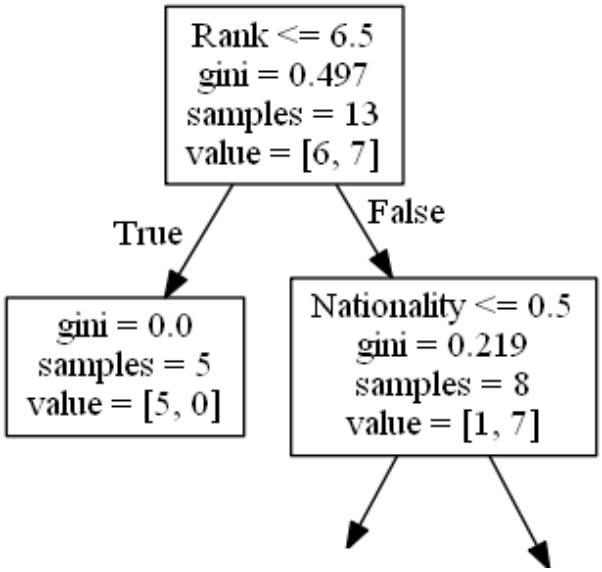
There are many ways to split the samples, we use the GINI method in this tutorial.

The Gini method uses this formula:

$$Gini = 1 - (x/n)^2 \ (y/n)^2$$

Where x is the number of positive answers("GO"), n is the number of samples, and y is the number of negative answers ("NO"), which gives us this calculation:

$$1 - (7 / 13)^2 - (6 / 13)^2 = 0.497$$



The next step contains two boxes, one box for the comedians with a 'Rank' of 6.5 or lower, and one box with the rest.

True - 5 Comedians End Here:

`gini = 0.0` means all of the samples got the same result.

`samples = 5` means that there are 5 comedians left in this branch (5 comedian with a Rank of 6.5 or lower).

`value = [5, 0]` means that 5 will get a "NO" and 0 will get a "GO".

False - 8 Comedians Continue:

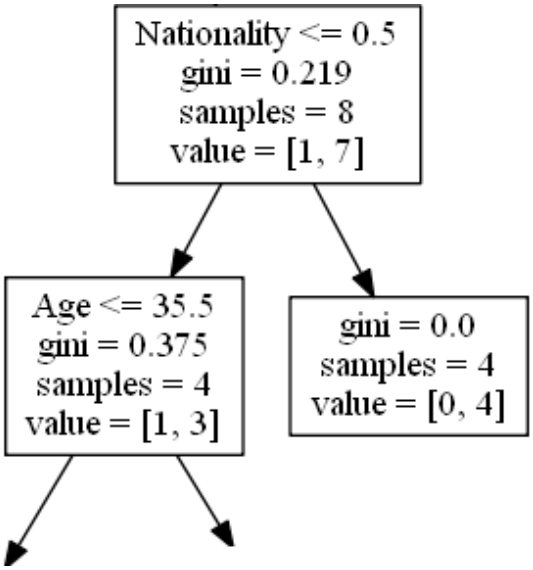
Nationality

`Nationality <= 0.5` means that the comedians with a nationality value of less than 0.5 will follow the arrow to the left (which means everyone from the UK,), and the rest will follow the arrow to the right.

`gini = 0.219` means that about 22% of the samples would go in one direction.

`samples = 8` means that there are 8 comedians left in this branch (8 comedian with a Rank higher than 6.5).

`value = [1, 7]` means that of these 8 comedians, 1 will get a "NO" and 7 will get a "GO".



True - 4 Comedians Continue:

Age

`Age <= 35.5` means that comedians at the age of 35.5 or younger will follow the arrow to the left, and the rest will follow the arrow to the right.

`gini = 0.375` means that about 37,5% of the samples would go in one direction.

`samples = 4` means that there are 4 comedians left in this branch (4 comedians from the UK).

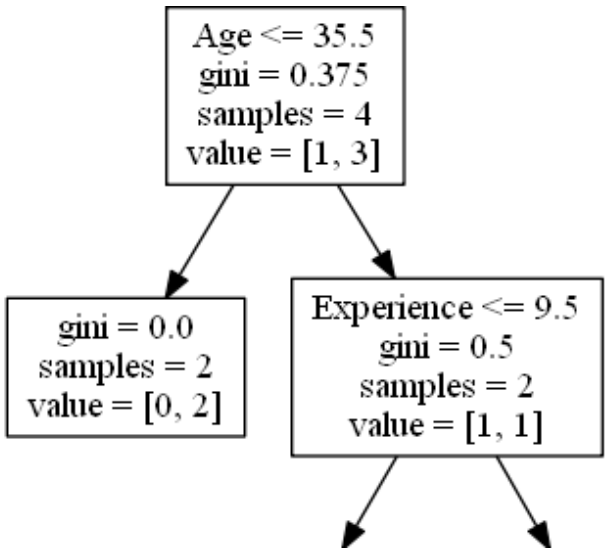
`value = [1, 3]` means that of these 4 comedians, 1 will get a "NO" and 3 will get a "GO".

False - 4 Comedians End Here:

`gini = 0.0` means all of the samples got the same result.

`samples = 4` means that there are 4 comedians left in this branch (4 comedians not from the UK).

`value = [0, 4]` means that of these 4 comedians, 0 will get a "NO" and 4 will get a "GO".



True - 2 Comedians End Here:

`gini = 0.0` means all of the samples got the same result.

`samples = 2` means that there are 2 comedians left in this branch (2 comedians at the age 35.5 or younger).

`value = [0, 2]` means that of these 2 comedians, 0 will get a "NO" and 2 will get a "GO".

False - 2 Comedians Continue:

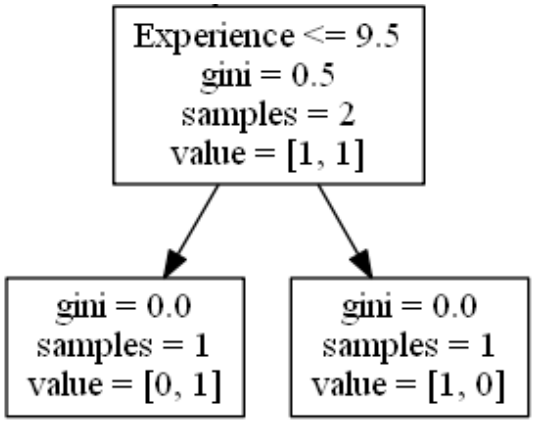
Experience

`Experience <= 9.5` means that comedians with 9.5 years of experience, or more, will follow the arrow to the left, and the rest will follow the arrow to the right.

`gini = 0.5` means that 50% of the samples would go in one direction.

`samples = 2` means that there are 2 comedians left in this branch (2 comedians older than 35.5).

`value = [1, 1]` means that of these 2 comedians, 1 will get a "NO" and 1 will get a "GO".



True - 1 Comedian Ends Here:

`gini = 0.0` means all of the samples got the same result.

`samples = 1` means that there is 1 comedian left in this branch (1 comedian with 9.5 years of experience or less).

`value = [0, 1]` means that 0 will get a "NO" and 1 will get a "GO".

False - 1 Comedian Ends Here:

`gini = 0.0` means all of the samples got the same result.

`samples = 1` means that there is 1 comedians left in this branch (1 comedian with more than 9.5 years of experience).

`value = [1, 0]` means that 1 will get a "NO" and 0 will get a "GO".

Predict Values

We can use the Decision Tree to predict new values.

Example: Should I go see a show starring a 40 years old American comedian, with 10 years of experience, and a comedy ranking of 7?

Example

Use predict() method to predict new values:

```
print(dtree.predict([[40, 10, 7, 1]]))
```

Run example »

Example

What would the answer be if the comedy rank was 6?

```
print(dtree.predict([[40, 10, 6, 1]]))
```

Run example »

Different Results

You will see that the Decision Tree gives you different results if you run it enough times, even if you feed it with the same data.

That is because the Decision Tree does not give us a 100% certain answer. It is based on the probability of an outcome, and the answer will vary.

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