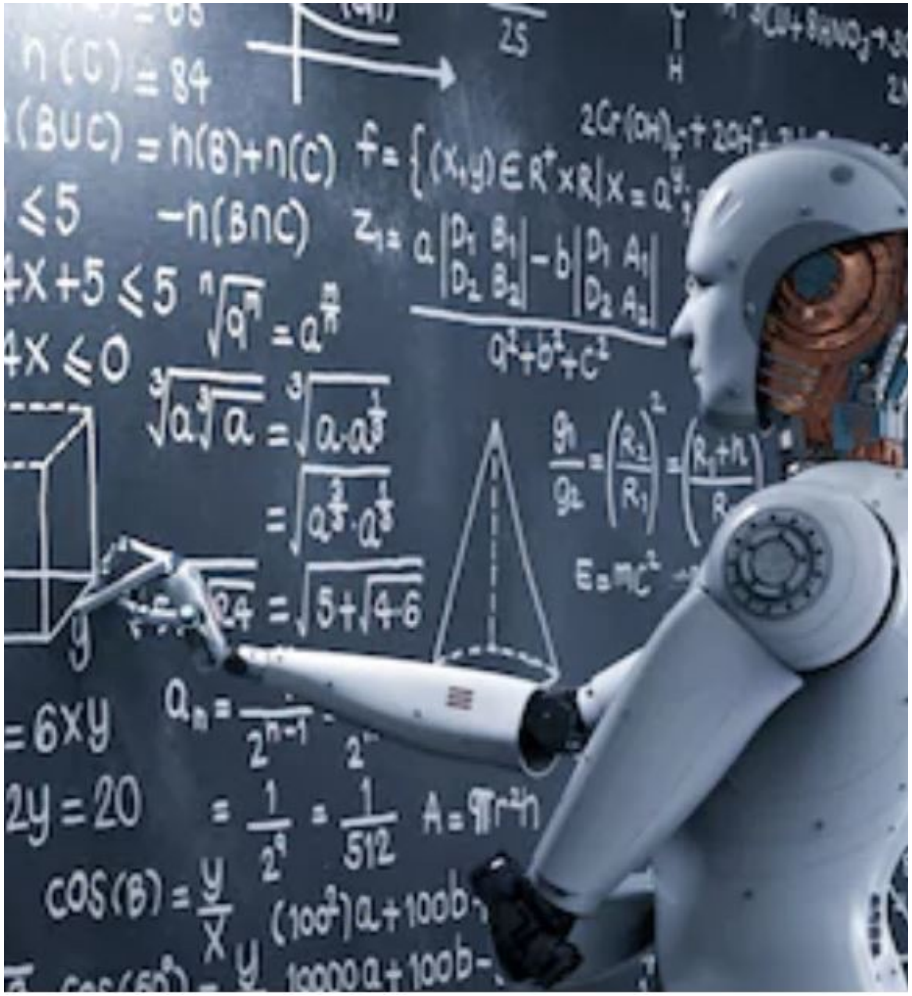
Imperial College London

Summer 2022

MRes: **Machine Learning and Big Data in the Physical Sciences**



Pre-course: Statistics in Python

Nicholas Wardle

Imperial College London

Statistics in Python

In the MLBD MRes taught module "Statistical Methods for Experimental Physics ", we use python heavily. In this precourse material, we will introduce the basic tools in python that we use for statistics. Some of these are also covered in the "Scientific Python" precourse, but here we'll focus on statistics use cases.

The most common packages we'll need are `matplotlib`, `numpy` and `scipy`.

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

You can also find the interactive version of this short course in https://github.com/ImperialCollegeLondon/MResMLBDinPhysicalSciences/tree/main/PreCourse/Statistics/StatisticsInPython.ipynb

Random variables

Random variables are a central concept in probability and statistics. We will only deal with two types of random variables, discrete and continuous.

In python, we can use the `numpy.random` variable for generating random discrete and continuous variables.

for *discrete* variables, we might have a set (or infinite set) of discrete outcomes for some event. For example, the event could be a dice roll, where the discrete outcomes are 1,2,3,4,5 or 6. We can randomly generate rolls using the `numpy.random.choice` method.

```
dice_roll_outcomes = ['1','2','3','4','5','6']
random_roll = numpy.random.choice(dice_roll_outcomes)
print(random_roll)
```

```
2
```

We can also generate random *continuous* variables using python with the `numpy.random.uniform` method. By default, this will generate a random number between 0 and 1, but we can also provide a minimum and maximum value to change that range.

```
minimum=-1
maximum=3
random_continuous = numpy.random.uniform(minimum,maximum)
print(random_continuous)
```

```
0.08054280536967395
```

Probability distributions

In the above cells, the probability that a particular outcome occurs is independent on that outcome. We also want to look at random variables that are distributed such that different outcomes have different probabilities -- i.e we want to use probability distributions.

the `scipy.stats` package has lots of different probability distributions we can access. Below are some examples of common probability distributions. We'll use the notation that x is our random variable and $f(x; \theta)$ is the probability distribution, where θ are the parameters of that distribution.

Let's take for example the *Poisson* distribution, which has one parameter λ.

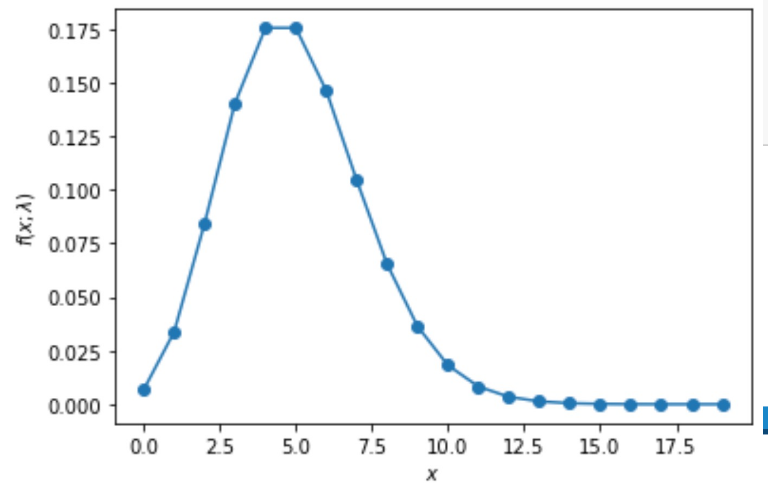
$$f(x; \lambda) = \frac{\lambda^x}{x!} e^{-\lambda}$$

The Poisson distribution is for discrete random variables and x will be a random integer between 0 and +infinity. In scipy we can use the `stats.poisson` module.

We can plot the distribution using the `.pmf` (for discrete random variables) which stands for "probability mass function". Note that the `pmf` function has the calling pattern `.pmf(x,param1,param2,...)`.

```
lamb = 5
x = range(0,20)

plt.plot(x,stats.poisson.pmf(x,lamb),marker="o")
plt.xlabel("$x$")
plt.ylabel("$f(x;\lambda)$")
plt.show()
```



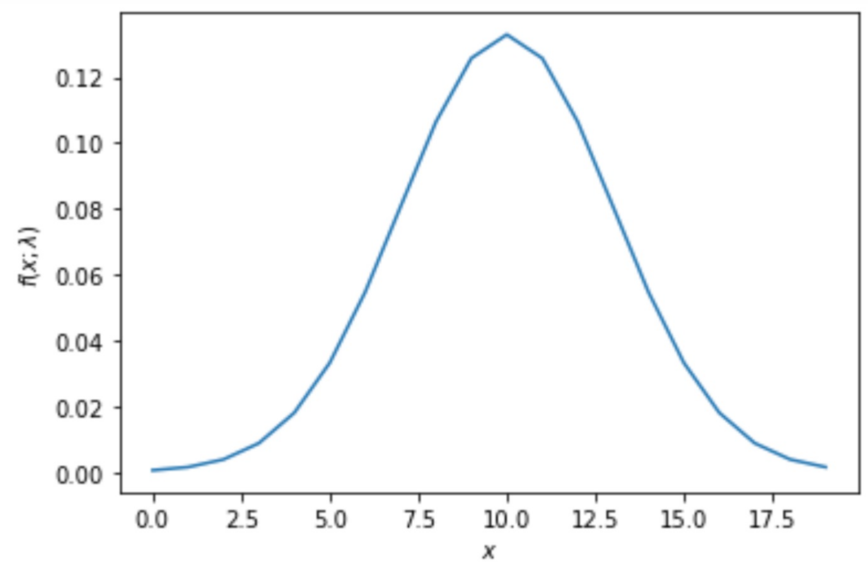
Imperial College London

We can do the same thing for continuous random variables. For example, the Gaussian distribution has two parameters μ, and σ. In scipy, a Gaussian is called a *normal* distribution (`stats.norm`)

In this case we need to use the `.pdf` function - which stands for "probability density function" to plot the distribution.

```
mu = 10
sigma = 3
x = range(0,20)

plt.plot(x,stats.norm.pdf(x,mu,sigma))
plt.xlabel("$x$")
plt.ylabel("$f(x;\lambda)$")
plt.show()
```



We can use these modules to *generate* random variables that are distributed according to some probability distribution. For example, lets generate 100 discrete random variables that are distributed according to a Poisson distribution with parameter $\lambda = 4$. We will use the `.rvs` method for it.

Note that the calling pattern is `.rvs(param1,param2,...,size=n)`)

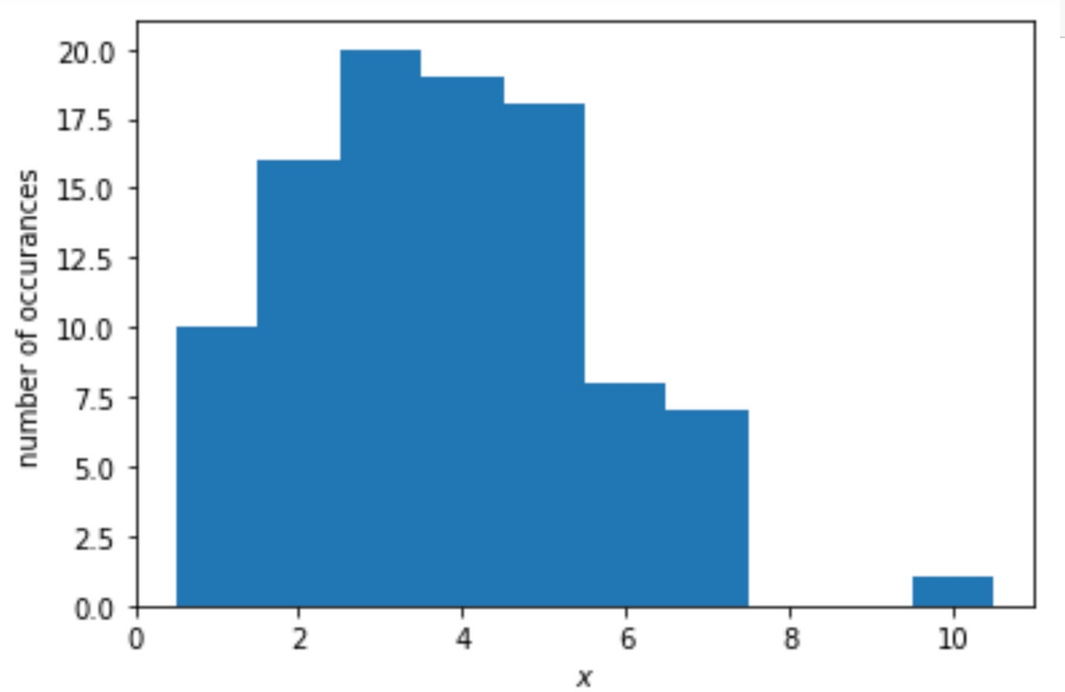
```
discrete_random = stats.poisson.rvs(4,size=100)
print(discrete_random)
```

```
[ 4  4  3  6  5  5  1  3  2  1  2  2  3  7  5  4  3  4  3  5  3  1  5  4
  5  3  2  3  5  3  7  3  1  4  6  3  5  2  3  6 10  2  2  5  2  4  6  7
  4  4  2  5  7  2  1  3  4  0  4  2  4  5  4  1  3  6  3  7  7  3  2  4
  1  6  5  5  4  7  1  6  2  3  5  1  6  2  1  2  3  4  2  5  4  4  4  5
  3  5  5  3]
```

Imperial College London

We can plot these as a *histogram* to see how the random variables are distributed.

```
plt.hist(discrete_random,bins=10,range=(0.5,10.5))
plt.xlabel("$x$")
plt.ylabel("number of occurances")
plt.show()
```



You can find a list of the probability distributions available in scipy.stats at

https://docs.scipy.org/doc/scipy/reference/tutorial/stats/discrete.html

and

https://docs.scipy.org/doc/scipy/reference/tutorial/stats/continuous.html

Imperial College London

Moments

We often want to calculate moments of distributions of samples of random variables. In python, we can do this very quickly using the `numpy` package.

Let's calculate the mean and standard deviation for a sample of random numbers that are generated from a Gaussian distribution with parameters $\mu = 0, \sigma = 4$.

```
random_variables = stats.norm.rvs(0,4,1000)

print("mean=",numpy.mean(random_variables))
print("standard deviation=",numpy.std(random_variables))
```

```
mean= 0.05190728612751064
standard deviation= 4.03126327986501
```

You will see that the mean is quite close to μ and the standard deviation is close to σ. There is a good reason for this that you'll learn in your statistics lectures!