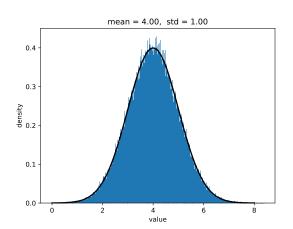
Machine learning II, unsupervised learning and agents: overview of mathematical tools

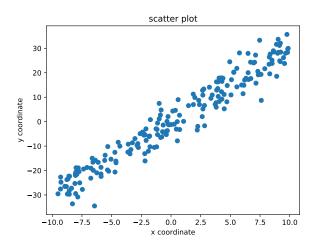


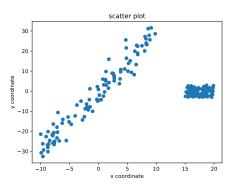
Probabilities and statistics

Optimization

Probabilities and statistics

To have a solid understanding of modern machine learning, it is necessary to be familiar with elementary probabilities and statistics.





We want to analyse how the data are **distributed**. For instance the x coordinate, the y coordinate.

- ► (informal definition) A random variable is a quantity that can take several values, with some randomness.
- ▶ https://en.wikipedia.org/wiki/Random_variable

- ▶ A random variable is a quantity that can take several values
- ► For instance :
 - ▶ the result of a dice throw



Figure - Dice

- ► A random variable is a quantity that can take several values
- For instance :
 - ▶ the result of a dice throw
 - waiting time with RATP



Figure – Some metro station

- ► A random variable is a quantity that can take several values
- ► For instance :
 - ▶ the result of a dice throw
 - waiting time with RATP
 - weather



Figure - Weather in November

- ▶ A random variable is a quantity that can take several values
- For instance :
 - the result of a dice throw
 - waiting time with RATP
 - weather
 - number of cars taking the periphérique at the same time

Why are random variables important?

- most datasets encountered in machine learning can be considered as sampled from random variables.
- this is important for theoretical studies, and hence for applications: a better theoretical understanding of a problem allows to choose the best algorithm to solve it.
- theoretical results are sometimes precise in the sense that they allow to estimate the order of magnitude of the statistical error (e.g. the prediction error) as a function of d (dimension of the samples) and n (number of samples)
- ▶ a subdomain of machine learning is "statistical learning"

► Some random variables are continuous, others discrete

- ► Some are continuous, others discrete
- continuous : weather, RATP

- Some are continuous, others discrete
- continuous : weather, RATP
- ▶ discrete : dice (6 possibilities), number of cars (> 10000)

- ▶ A random variable is linked to a **probability distribution**.
- ▶ It quantifies the probability of observing one outcome.

- ► A random variable is linked to a **probability distribution**, which is a function *P*
- ▶ It quantifies the probability of observing one outcome.
- ► For a discrete variable : each possible outcome is associated with a number between 0 and 1

- ► For a dice game, the possible outcomes are in the set $\{1, 2, 3, 4, 5, 6\}$
- ► For a dice game : P(1) = ? P(2) = ? P(3) = ? P(4) = ? P(5) = ? P(6) = ?

- ▶ For a dice game, the possible outcomes are in the set $\{1, 2, 3, 4, 5, 6\}$
- ► For a dice game : $P(1) = \frac{1}{6}$, $P(2) = \frac{1}{6}$, $P(3) = \frac{1}{6}$, $P(4) = \frac{1}{6}$, $P(5) = \frac{1}{6}$, $P(6) = \frac{1}{6}$
- This is called a uniform distribution

 Periphérique : probably a time-dependent very complicated distribution

Continuous variables

- ▶ The situation is different for continuous random variables.
- ► The distribution is given by a **probability density function**. Informally, the probably of being between x and x + dx is p(x)dx.
- https://en.wikipedia.org/wiki/Probability_density_ function
- ▶ Not that some variables are neither discrete nor continuous.

Uniform discrete

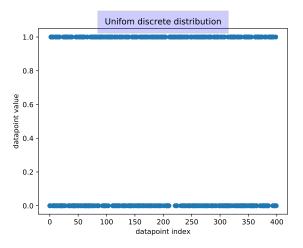


Figure – Uniform discrete distribution with 2 values

Uniform discrete

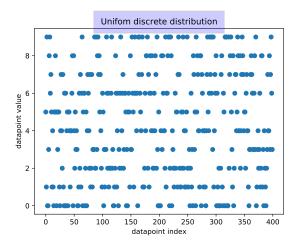


Figure – Uniform discrete distribution with 10 values

Bernoulli

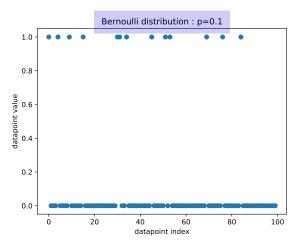


Figure - Bernoulli distribution

Bernoulli p

- With probability p, X = 1
- ▶ With probability 1 p, X = 0

Bernoulli

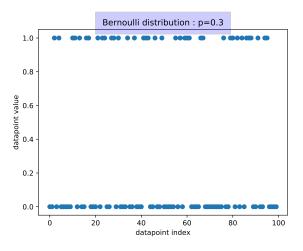


Figure - Bernoulli Distribution

Bernoulli

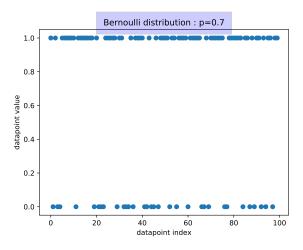


Figure - Bernoulli Distribution

Uniform continuous

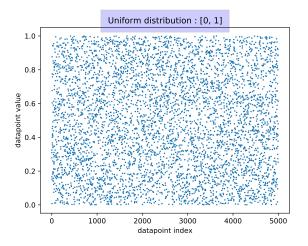


Figure – Uniform continuous distribution

Uniform continuous

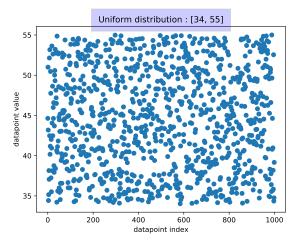


Figure – Uniform continuous distribution

Uniform continuous

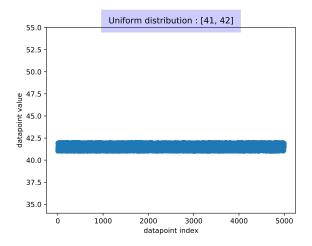


Figure – Uniform continuous distribution

Normal

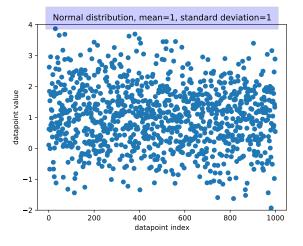


Figure – Normal distribution

Normal

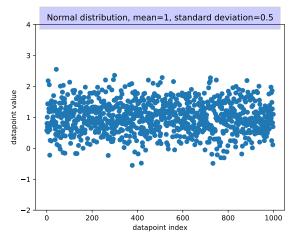


Figure – Normal distribution

Normal

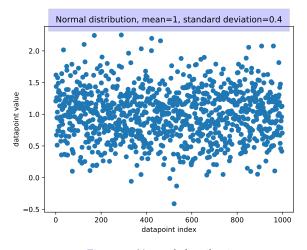


Figure – Normal distribution

White noise

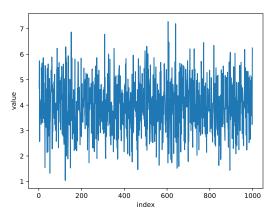


Figure – White noise

Histograms

Histograms are an alternative representation of the results of a (one-dimensional) random variable.

Uniform discrete

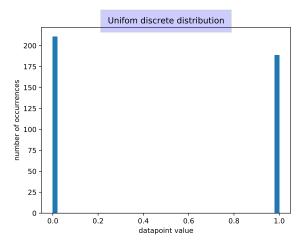


Figure - Historgram 1

Uniform discrete

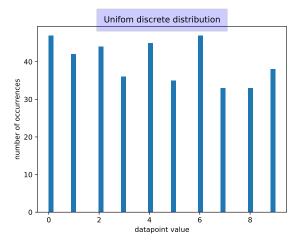


Figure – Historgram 1

Bernoulli

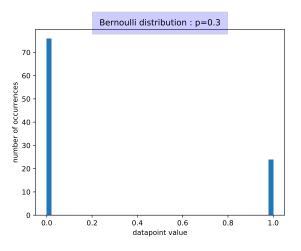


Figure – Historgram 2

Uniform continuous

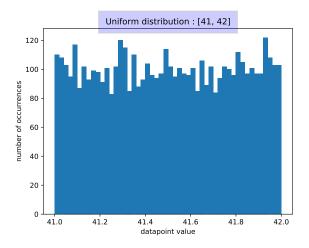


Figure - Historgram 3

Normal

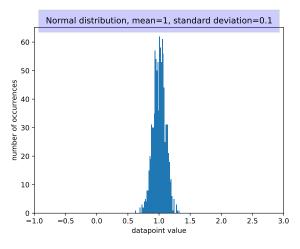


Figure - Historgram 4

Normal

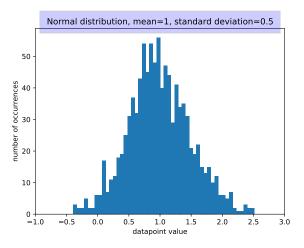


Figure – Historgram 4

cd distributions/
We can use the files analyze_distribution_1.py and
analyze_distribution_2.py to analyze and plot some simple
datasets, stored in csv_files/

Distribution 1

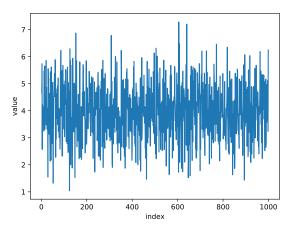


Figure – The data we analyze

histograms

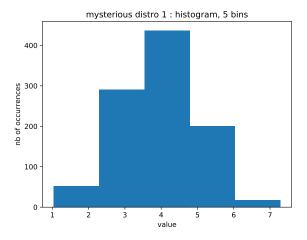
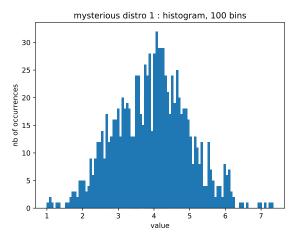


Figure – 5 bins

histograms



 $Figure-100\ bins$

histograms

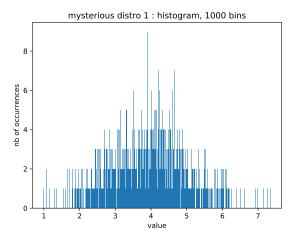


Figure – 1000 bins (too many)

Normal distribution

```
import csv
import numpy as np

file_name = 'mysterious_distro_1.csv'

mean = 4
std_dev = 1
nb_point = 1000

with open('csv_files/' + file_name, 'w') as csvfile:
    filewriter = csv.writer(csvfile, delimiter=',')
    for point in range(1, nb_point):
        random_variable = np.random.normal(loc=mean, scale=std_dev)
        filewriter.writerow([str(point), str(random_variable)])
```

Figure - create_normal.py : Creation of the distribution

Second example

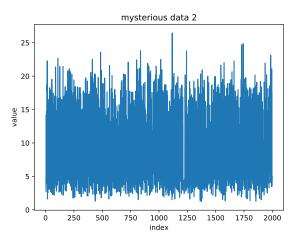


Figure – Second distribution

Fitting

In most cases, it won't be that straightforward to fit a distribution :

- the random variable may be multidimensonial
- need to choose a family of distributions (parametric vs non-parametric)
- an optimization might be needed in order to find good parameters.

Multidimensional vectors

We often consider random variables and data that live in spaces with a higher dimension than 2 (random vectors).

- images
- sensor that receives multimodal information

Correlation

Random vectors with correlated components are common statistical objects.

- In physics, temperature and pressure, measured by some sensores are correlated.
- ▶ In a dataset of customers of a company, some dimensions are likely to be correlted.

To study the statistical relationship between components, we can compute the **covariance** of the two components, or the **correlation**, (normalized covariance (see below)).

https://en.wikipedia.org/wiki/Correlation

Expected value (espérance)

▶ For a discrete random variable X that takes the values x_i with probability p_i :

$$E(X) = \sum_{i=1}^{n} p_i x_i \tag{1}$$

► For a continuous random variable X with density p :

$$E(X) = \int x p(x) dx \tag{2}$$

Note that X may have values in \mathbb{R}^d , with $d \geq 1$.

Expected value (espérance)

Exercice 1: Computing an expected value

▶ For a discrete random variable X that takes the values x_i with probability p_i :

$$E(X) = \sum_{i=1}^{n} p_i x_i \tag{3}$$

▶ For a continuous random variable X with density :

$$E(X) = \int x p(x) dx \tag{4}$$

Compute the expected value of the dice game.

Variance

The variance is a measure of the dispersion of a random real variable.

https://en.wikipedia.org/wiki/Variance

$$var(X) = E((X - E(X))^{2})$$
 (5)

Note that we can also define the variance of a multidimensonial random variable (which means a random vector). In that case, it is a matrix.

Covariance

The covariance is a measure of the relationship between the variations of two random variables.

$$cov(X,Y) = E((X - E(X))(Y - E(Y)))$$
 (6)

Correlation

The correlation is the covariance divided by the square roots of the variances.

$$corr(X,Y) = \frac{cov(X,Y)}{\sqrt{Var(X)}\sqrt{Var(Y)}}$$
(7)

Example

The data in csv_files/distribution_3.csv contain samples of a random variable with 5 dimensions (random vector). Some of these dimensions are correlated.

Covariance

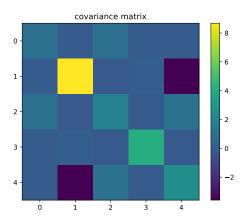


Figure – Covariance matrix of the random vector.

Correlation matrix

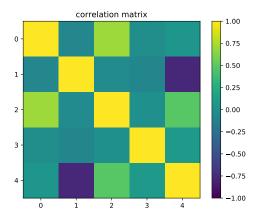


Figure – Correlation matrix for the distribution, note the difference in the scale.

Generation of the data

```
mean 1 = 4
std \overline{\text{dev }} 1 = 1
mean 2 = 15
std \overline{\text{dev }} 2 = 3
mean 3 = -5
std dev 3 = 2
mean noise = 0
noise std dev = 1
nb point = 1000
with open('csv files/' + file name, 'w') as csvfile:
    filewriter = csv.writer(csvfile, delimiter=',')
    for point in range(1, nb point):
        noise = np.random.normal(loc=mean_noise, scale=noise_std_dev)
        random variable 1 = np.random.normal(loc=mean 1, scale=std dev 1)
        random variable 2 = np.random.normal(loc=mean 2, scale=std dev 2)
        random variable 3 = random variable 1 + noise
        random variable 4 = np.random.normal(loc=mean 3, scale=std dev 3)
        random variable 5 = -0.4 * random variable 2 + noise
        filewriter.writerow([str(point),
                               str(random variable 1),
```

Figure - Multidimensional random variable

Exercice 2: Create a one-dimensional dataset with a histogram that looks like this one!

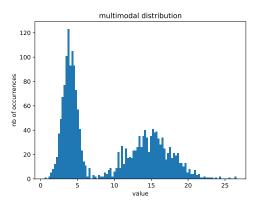


Figure - This distribution has several modes

Minimization of a function

Optimization is another core aspect of machine learning.

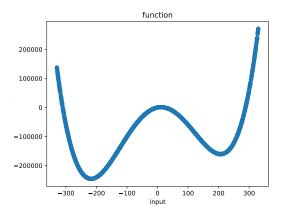


Figure - Loss function

Optimization in machine learning

The loss function typically represents the quality of a set of parameters to solve a problem.

- in supervised learning, typically a measure of the prediction error on the dataset
- ▶ in clustering, typically a distorsion
- in density estimation, a likelihood

Analytic minimization

What is the minimum of the function

$$f: x \to (x-1)^2 + 3.5$$
 (8)

And for what value x is it obtained?

Iterative algotihms

However, in most applications of machine learning, it is not possible to use an analytical solution, either because :

- we do not know the analytical solution
- we know how to compute it, but the computation is too costly for practical use.

Instead, we use **iterative algotihms** (gradient descent, coordinate descent, etc.)

Gradient algorithms

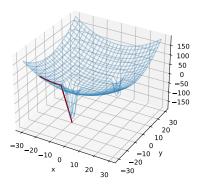


Figure - Optimization trajectory.