

# Advanced aspects in multi-criteria decision-making: coping with uncertainty using Probability Theory

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Decision-making challenges in a changing world: an international  
overview on academic and professional environments

UNIVERSITÀ DEGLI STUDI DI PALERMO

# Part I

## An Introduction to Probability Theory

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# Random Variables

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- 3 Pick randomly an apple. Which is its weight?  
If  $X$  denotes the weight, then  $0 < X < \infty$ .

# Classification of random variables

## Discrete

- Toss a coin 20 times. How many heads?
- Toss a coin until a head appears. How many tosses?
- How many visitors has a web page in a day?
- ...

The value of the random variable “jumps”.

## Continuous

- The weight of an apple.
- The time of a flight travel.
- The height of a citizen of a given country.
- ...

The value of the random variable “flows”.



# Discrete random variables

Let  $X$  be a discrete random variable with values  $x_1, x_2, \dots$

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It's clear that  $X = 0, 1, 2$ .

- $X = 0$ . No heads  $\rightarrow$  Tail-Tail.  $\text{pr}(X = 0) = (1 - p)^2$ .
- $X = 1$ . One head  $\rightarrow$  Tail-Head or Head-Tail.  $\text{pr}(X = 1) = 2p(1 - p)$ .
- $X = 2$ . Two heads  $\rightarrow$  Head-Head.  $\text{pr}(X = 2) = p^2$ .

## Example 1

Toss a coin  $n$  times.

$p = \text{pr}(\text{Head})$ .

If  $X$  is the number of heads, then

$$\text{pr}(X = k) = ?$$

## Example 2

There are  $n$  persons in a room.

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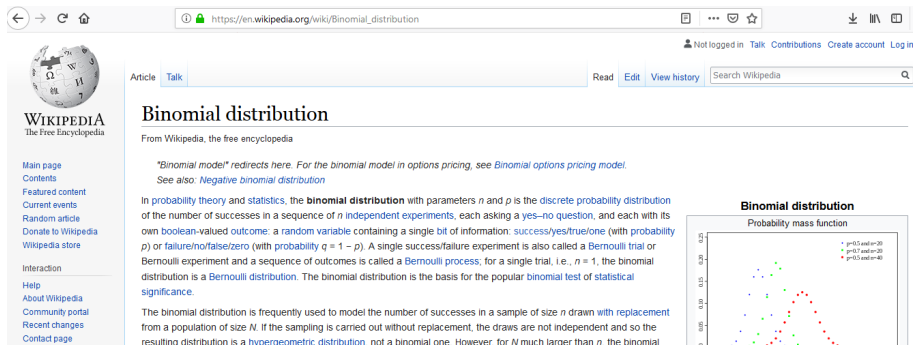
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These problems are exactly the same!

# What is a probability distribution?

- There are **few** different models.
- Useful for a wide range of problems.
- No necessity of deducing formulas.
- For example, the two previous problems can be modelled by the “binomial distribution”.



The screenshot shows the Wikipedia page for the Binomial distribution. The page title is "Binomial distribution". The text describes it as a discrete probability distribution of the number of successes in a sequence of  $n$  independent experiments, each asking a yes–no question. It mentions parameters  $n$  and  $p$ , and the outcome being a random variable containing a single bit of information: success/yes/true/one (with probability  $p$ ) or failure/no/false/zero (with probability  $q = 1 - p$ ). It also notes that a single success/failure experiment is also called a Bernoulli trial or Bernoulli experiment and a sequence of outcomes is called a Bernoulli process. For a single trial, i.e.,  $n = 1$ , the binomial distribution is a Bernoulli distribution. The binomial distribution is the basis for the popular binomial test of statistical significance.

The binomial distribution is frequently used to model the number of successes in a sample of size  $n$  drawn with replacement from a population of size  $N$ . If the sampling is carried out without replacement, the draws are not independent and so the resulting distribution is a hypergeometric distribution, not a binomial one. However, for  $N$  much larger than  $n$ , the binomial

On the right side of the page, there is a graph titled "Binomial distribution" with the subtitle "Probability mass function". The graph shows three discrete probability distributions for different values of  $n$  and  $p$ :

- $p=0.5$  and  $n=20$  (blue dots)
- $p=0.7$  and  $n=20$  (green dots)
- $p=0.5$  and  $n=40$  (red dots)

The x-axis represents the number of successes (0 to 40), and the y-axis represents the probability mass function (0.0 to 0.25).

# Continuous random variables

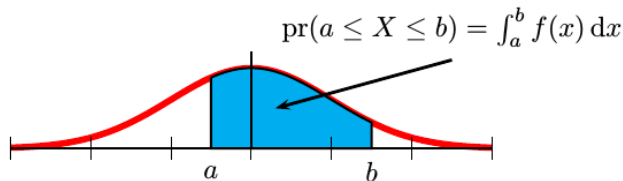
Let  $X$  be a continuous random variable.

$X$  is determined by fixing  $f : \mathbb{R} \rightarrow \mathbb{R}$  such that

$$\text{pr}(a \leq X \leq b) = \int_a^b f(x) \, dx.$$

This function  $f$  is said to be the **density function** of  $X$ .

In most situations, no necessity of computing any integral, since there are **few** models, and the integrals are very easy or are tabulated.





## Examples

- If we toss a fair coin many times, then the proportion of heads tends to  $1/2$ .
- If I weight many apples, and I compute the mean, then this mean tends to a concrete value.

These examples show the **law of large numbers**.

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Let  $X$  be a random variable. We perform the random experiment many times obtaining  $X_1, \dots, X_n$  and let  $\bar{X}_n = (X_1 + \dots + X_n)/n$ . Intuitively,  $\bar{X}_n$  will tend to a number. **Which? How can it be computed?**

# Expectation

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## Definition of the **expectation**

Let  $X$  be a random variable. The expectation of  $X$  is defined as

- If  $X$  is discrete,  $\mathbb{E}(X) = \sum_i x_i \text{pr}(X = x_i)$ .
- If  $X$  is continuous,  $\mathbb{E}(X) = \int_{-\infty}^{\infty} xf(x) dx$ .

# Law of large numbers

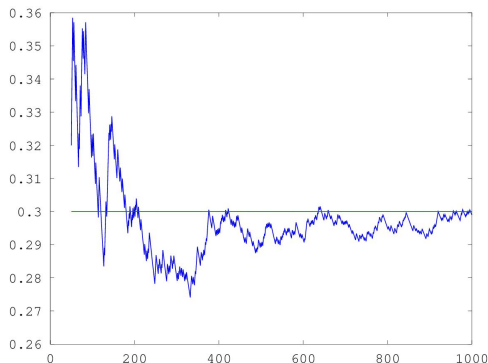
If  $X_1, X_2, X_3, \dots$  are independent random variables with the same distribution and  $\mu$  is the common expectation, then for all  $\varepsilon > 0$ , one has

$$\lim_{n \rightarrow \infty} \text{pr} \left( \left| \frac{X_1 + \dots + X_n}{n} - \mu \right| < \varepsilon \right) = 1.$$

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$$p = 0.3.$$

$$\text{pr}(X_i = 1) = p.$$

$$\text{pr}(X_i = 0) = 1 - p.$$

$$\mathbb{E}(X_i) = p.$$

$$(X_1 + \dots + X_n)/n \simeq \mathbb{E}(X_i).$$

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Let  $X_1$  be a continuous uniform random variable defined in  $[0, 1]$ .

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Which random variable has a larger variance?



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Which random variable has a larger variance?  $X_2$ .

# Properties of the expectation and variance

Let  $X$  and  $Y$  be two random variables and  $k \in \mathbb{R}$ .

## Expectation

- $\mathbb{E}(X + Y) = \mathbb{E}(X) + \mathbb{E}(Y)$ .
- $\mathbb{E}(kX) = k\mathbb{E}(X)$ .

## Variance

- If  $X$  and  $Y$  are independent,  $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$ .
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## Example – Mean

Let  $X_1, \dots, X_n$  independent random variables with  $\mathbb{E}(X_i) = \mu$  and  $\text{Var}(X_i) = \sigma^2$ .

$$\mathbb{E}\left(\frac{X_1 + \dots + X_n}{n}\right) = \mu, \quad \text{Var}\left(\frac{X_1 + \dots + X_n}{n}\right) = \frac{\sigma^2}{n}$$

# The meaning of the variance

## Chebyshev's inequality

If  $X$  is an **arbitrary** random variable, then

$$\text{pr}(|X - \mathbb{E}(X)| \geq c) \leq \frac{\text{Var}(X)}{c^2}.$$

**The smaller  $\text{Var}(X)$  is, the more concentrated is  $X$  respect its expectation.**



Чебышёв

# The normal distribution

## Definition of the **normal distribution**

It is a continuous distribution whose density function is

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right).$$

The expectation is  $\mu$  and the variance is  $\sigma^2$ .

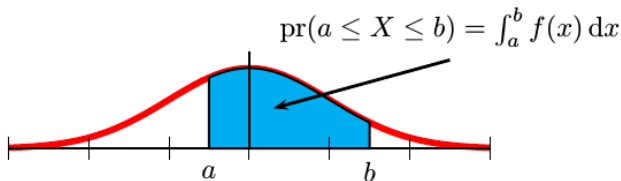
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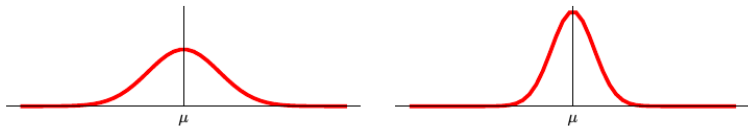
The expectation is  $\mu$  and the variance is  $\sigma^2$ .



The definite integral of  $f$  is **always** computed by means of tables or a software.

# Properties of the normal distribution

- The normal distribution is symmetric respect its expectation.
- It is very concentrated around the expectation.
- For large numbers, the probability is negligible.



The variance of the left distribution is larger than the variance of the right distribution.

# Usefulness and meaning of the normal distribution

The normal distribution is ubiquitous. It appears in

- The height of adult male (and female) humans.
- The intelligent quotient.
- The weight of a concrete variety of apples.
- The time of a flight between two airports.
- The temperature at 1st May in a given city.
- The errors of measurements (Gauss).
- ...



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In fact, normal distribution approximates very well. Remember that its density function is defined for all  $x \in \mathbb{R}$ , but for an interval  $I$  far from the expectation, then  $\text{pr}(X \in I) \simeq 0$ .

**Meaning of the normal distribution. The central limit theorem**

Under certain (fairly common) conditions, the mean of many random variables will have an approximately normal distribution.

# Part II

## An Introduction to AHP

# What is the Analyty Hierarchy Process?

Decision making is becoming increasingly complex due to the large number of alternatives and multiple conflicting goals.

The Analytic Hierarchy Process (AHP) has been accepted as a leading multiattribute decision-aiding model.

Decisions arise in every type of application including

- Planning
- Economy
- Resource allocation
- Medical management
- Emergency situations
- ...

# Pairwise comparisons

I want to submit a manuscript to one of the following two journals:

- Journal of Superb Mathematics
- International Bulletin of Excellent Theorems

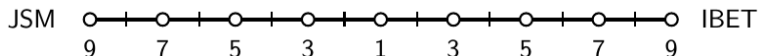
What can I do?

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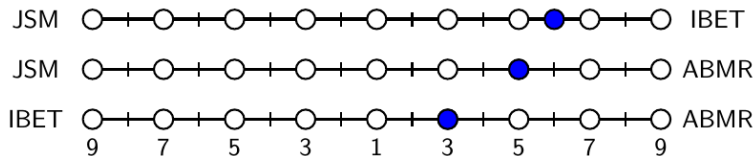
What can I do?



- 1 Equal importance.
- 3 Moderate importance of one over another.
- 5 Strong importance.
- 7 Very strong importance.
- 9 Extreme importance.

# Reciprocal matrices

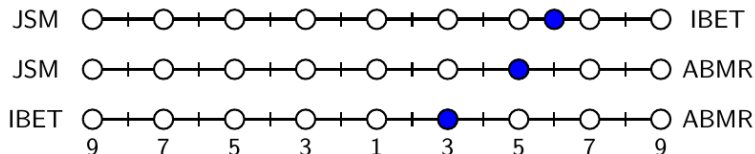
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	JSM	IBET	ABMR
JSM	1	1/6	1/5
IBET	6	1	1/3
ABMR	5	3	1

# Reciprocal matrices

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$$\begin{bmatrix} 1 & 1/6 & 1/5 \\ 6 & 1 & 1/3 \\ 5 & 3 & 1 \end{bmatrix}.$$

## Definition of **reciprocal matrices**

A square matrix  $(a_{ij})_{i,j=1}^n$  is **reciprocal** when  $a_{ij} > 0$  and  $a_{ij} = 1/a_{ji}$  for all  $i, j \in \{1, \dots, n\}$ .

# Consistent matrices

	JSM	IBET	ABMR
JSM	1	1/6	1/5
IBET	6	1	1/3
ABMR	5	3	1

- I prefer ABMR 3 times over IBET.
- I prefer IBET 6 times over JSM.
- I prefer ABMR 5 times over JSM.

This is not “rational”. I had to prefer ABMR  $3 \times 6$  times over JSM!

$$3 \times 6 \neq 5.$$

## Definition of **consistent matrices**

A matrix  $A = (a_{ij})_{i,j=1}^n \in \mathbb{R}_{n,n}$  is **consistent** when  $a_{ij} > 0$  and  $a_{ij}a_{jk} = a_{ik}$  for all  $i, j, k \in \{1, \dots, n\}$ .



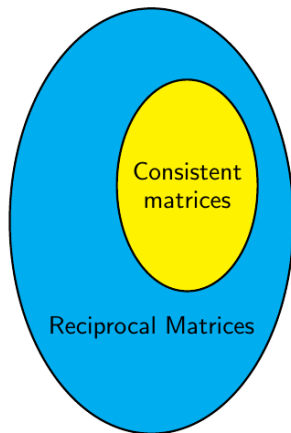
# Reciprocal and consistent matrices

Any consistent matrix is a reciprocal matrix.

However, if  $A$  is a reciprocal matrix, it may happen that  $A$  is not consistent.

$$A = \begin{bmatrix} 1 & a & b \\ 1/a & 1 & c \\ 1/b & 1/c & 1 \end{bmatrix}$$

is reciprocal, but if  $ac \neq b$ , then  $A$  is not consistent.



# The priority vector. Example

We start from the preferences (it's not usual).

Imagine that

- 50% of the days, I prefer tea.
- 40% of the days, I prefer milk.
- 10% of the days, I prefer coffee.

The normalised priority vector is  $(0.5, 0.4, 0.1)$ .

I prefer milk 4 times than coffee, tea 5 times than coffee, tea  $5/4$  times than milk.

$$A = \begin{array}{c} \text{tea} \\ \text{milk} \\ \text{coffee} \end{array} \begin{array}{ccc} \text{tea} & \text{milk} & \text{coffee} \\ \left[ \begin{array}{ccc} 1 & 5/4 & 5 \\ 4/5 & 1 & 4 \\ 1/5 & 1/4 & 1 \end{array} \right] \end{array} \text{ is consistent (and therefore, reciprocal).}$$

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The entry  $(i, j)$  of  $A$  is  $v_i/v_j$ , being  $(v_1, v_2, v_3)$  the priority vector.

In particular, any column is a multiple of the priority vector.

# The priority vector (consistent matrices)

## Theorem

*A matrix  $A = (a_{ij}) \in \mathbb{R}_{n,n}$  is consistent if and only if exists  $\mathbf{v} = (v_1, \dots, v_n) \in \mathbb{R}^n$  such that  $v_i > 0$  and  $a_{ij} = v_i/v_j$  for all  $i, j$ .*

## Definition of the **priority vector**

This (normalised) vector  $\mathbf{v}$  is important: It tells us how to rank the alternatives. It is called the **priority vector**.

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## Theorem

If  $A \in \mathbb{R}_{n,n}$  is consistent and  $\mathbf{v}$  is a priority vector, then  $A\mathbf{v} = n\mathbf{v}$ .

## Definition of an **eigenvalue** and **eigenvector**

Given a square matrix  $A$ , we say that  $\lambda \in \mathbb{C}$  is an **eigenvalue** of  $A$  if exists a nonzero vector  $\mathbf{v}$  such that  $A\mathbf{v} = \lambda\mathbf{v}$ . The vector  $\mathbf{v}$  is called an **eigenvector**.

# Inconsistency of reciprocal matrices

T. Saaty proposed a measure of the inconsistency of a reciprocal matrix.

## Theorem (Saaty, 1970)

Let  $A \in \mathbb{R}_{n,n}$  be reciprocal. Let

$$\rho(A) := \max\{|\lambda| : \lambda \text{ is an eigenvalue of } A\}.$$

The following statements hold:

- $\rho(A) \leq n$ .
- $\rho(A) = n$  if and only if  $A$  is consistent.

Saaty proposed to define that the inconsistency of a reciprocal matrix is acceptable if  $n - \rho(A)$  is “small” in a precise sense that it is omitted here.

# The priority vector (reciprocal matrices)

Let  $A \in \mathbb{R}_{n,n}$  be reciprocal and assume that its consistency is acceptable.

The *Perron theorem* (1907) asserts that a real square matrix with positive entries has a unique largest real eigenvalue and that the corresponding eigenvector (unique up to a scalar multiple) can be chosen to have strictly positive components.

## Definition of the **priority vector**

We define the priority vector of a reciprocal matrix as the eigenvector given by the Perron theorem.

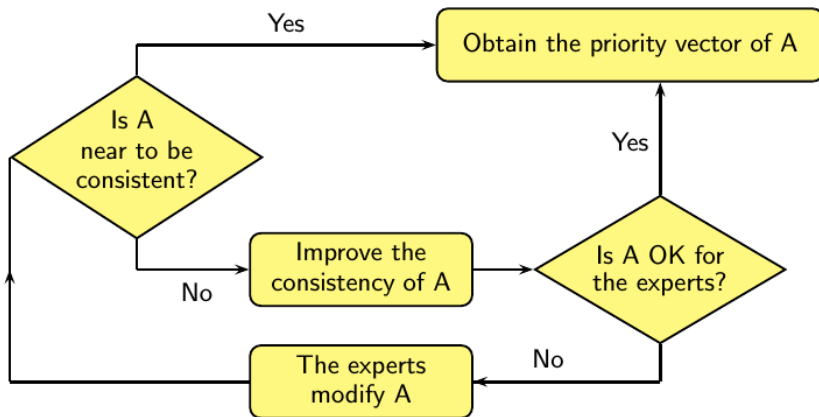
# A flowchart in AHP theory

**First step:** The expert build a reciprocal matrix  $A$ .



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# Modifying a reciprocal matrix to improve its consistency

Given a reciprocal matrix  $A$  whose consistency is not acceptable, we must find another reciprocal matrix  $B$  such that

$A \simeq B$       and      the consistency of  $B$  is acceptable.

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We **need** a distance in the set of reciprocal matrices! A classical measure is the following:

## Definition of the **Frobenius norm**

If  $A = (a_{ij})$  and  $B = (b_{ij})$  are matrices, then

$$\|A - B\|_F = \sum_{i,j} (a_{ij} - b_{ij})^2.$$

# The Frobenius norm is not suitable in AHP

## Example

$$A_1 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, \quad B_1 = \begin{bmatrix} 1 & 2 \\ 1/2 & 1 \end{bmatrix}, \quad A_2 = \begin{bmatrix} 1 & 8 \\ 1/8 & 1 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 1 & 9 \\ 1/9 & 1 \end{bmatrix}$$

- Matrix  $A_1$  reflects the two criteria are equivalent, while  $B_1$  reflects that the 1st criterion is twice more important than the 2nd criterion.
- The importance of the criteria in  $A_2$  and  $B_2$  are very close.
- Thus, in an intuitive point of view, the distance between  $A_1$  and  $B_1$  must be much greater than the distance between  $A_2$  and  $B_2$ .

$$\|A_1 - B_1\|_F \simeq 1.118, \quad \|A_2 - B_2\|_F \simeq 1.001.$$

## Another distance

We define the following distance in the set of  $n \times n$  reciprocal matrices:

### Definition

$$d(A, B) = \|L(A) - L(B)\|_F,$$

where  $L(A)$  is a  $n \times n$  matrix whose  $(i, j)$  entry is  $\log(a_{ij})$ .

### Example

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$$d(A_1, B_1) \simeq 0.9803, \quad d(A_2, B_2) \simeq 0.1666.$$

Also we need the mapping  $E : M_{n,n} \rightarrow M_{n,n}$  given by  $(E(A))_{ij} = \exp(a_{ij})$ .

- ① The expert builds a reciprocal  $n \times n$  matrix  $A$ .
- ② We compute  $B = L(A)$ , i.e.,  $b_{ij} = \log(a_{ij})$ .
- ③ Compute

$$M = \frac{1}{n} \left[ (BU_n) - (BU_n)^T \right],$$

where “ $T$ ” means the transposition and  $U_n$  is the  $n \times n$  matrix all of whose components are 1.

- ④ Compute  $X_A = E(M)$ , i.e.,  $x_{ij} = \exp(m_{ij})$ .



# Linearisation process

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This process is based on the next result

## Theorem

*If  $A$  is reciprocal and  $X_A$  is computed as before, then  $X_A$  is consistent and  $d(A, X_A) = \min\{d(A, C) : C \text{ is consistent}\}$ .*

**Caution!** It's possible that this matrix  $X_A$  doesn't reflect the requirements of the expert. In this, case, a feedback process must be performed (modifying  $X_A$ ).

# Linearisation process (bis)

- ① The expert builds a reciprocal  $n \times n$  matrix  $A$ .
- ② We compute  $B = L(A)$ , i.e.,  $b_{ij} = \log(a_{ij})$ .
- ③ Compute

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- ④ Compute  $X_A = E(M)$ , i.e.,  $x_{ij} = \exp(m_{ij})$ .
- ⑤ A priority vector of  $X_A$  is  $\mathbf{v} = (v_1, \dots, v_n)$ , where

$$v_i = \sqrt[n]{a_{i1} \cdots a_{in}}.$$

# Part III

## AHP and Probability Theory

# Probability judgements

I want to buy a car and I can choose from A, B, C.

I prefer A twice B  $\rightarrow \begin{bmatrix} 1 & 2 & \\ 1/2 & 1 & \\ & & 1 \end{bmatrix}$ . The value of 2 is **exact**.

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I prefer A twice B, but I am not sure about the exact preference  $\rightarrow$

$$\begin{bmatrix} 1 & a_{12} & \\ 1/a_{12} & 1 & \\ & & 1 \end{bmatrix}.$$

$a_{12}$  is a **random variable**.

# AHP and probabilistic related concepts

Remember that if  $X$  and  $Y$  are random variables and  $k \in \mathbb{R}$ , then

- $\mathbb{E}(X + Y) = \mathbb{E}(X) + \mathbb{E}(Y)$ ,  $\mathbb{E}(kX) = k\mathbb{E}(X)$ .
- $\text{Var}(kX) = k^2\text{Var}(X)$ .
- If  $X$  and  $Y$  are independent, then  $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$ .

But, in view of the properties of the reciprocal matrices and linearisation process

- If  $A = (a_{ij})$  is reciprocal, then  $a_{ji} = 1/a_{ij}$ .
- The  $i$ th coordinate of the priority vector of the nearest consistent matrix to  $A$  is  $\sqrt[n]{a_{i1} \cdots a_{in}}$ .

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## Definition of the **geometric expectation** and **variance**

Given a positive random variable  $X$ ,

- The **geometric expectation** of  $X$  is  $\mathbb{G}(X) = \exp(\mathbb{E}(\log X))$ .
- The **geometric variance** of  $X$  is  $\text{Var}_g(X) = \text{Var}(\log X)$ .

Let  $X, Y$  be random variables and  $k \in \mathbb{R}$

- $\mathbb{G}(XY) = \mathbb{G}(X)\mathbb{G}(Y)$ ,  $\mathbb{G}(X^k) = \mathbb{G}(X)^k$ .
- $\text{Var}_g(X^k) = k^2 \text{Var}_g(X)$ .
- If  $X$  and  $Y$  are independent, then  $\text{Var}_g(XY) = \text{Var}_g(X)\text{Var}_g(Y)$ .

Which allows to study reciprocal matrices and the linearisation process:

- If  $A = (a_{ij})$  is reciprocal, then  $a_{ji} = 1/a_{ij}$ .
- The  $i$ th coordinate of the priority vector of the nearest consistent matrix to  $A$  is  $\sqrt[n]{a_{i1} \cdots a_{n1}}$ .

# An example

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$a_{12}$  is a random variable such that  $\text{pr}(a_{12} = 1) = \text{pr}(a_{12} = 2) = 1/2$ .

$$\mathbb{E}(a_{12}) = \frac{1+2}{2} = 1.5, \quad \mathbb{E}(a_{21}) = \frac{1+1/2}{2} = 0.75,$$

but

$$a_{21} = \frac{1}{a_{12}}, \quad \mathbb{E}(a_{21}) \neq \frac{1}{\mathbb{E}(a_{12})}.$$

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On the other hand,

$$\mathbb{G}(a_{12}) = \sqrt{1 \cdot 2} = \sqrt{2}, \quad \mathbb{G}(a_{21}) = \sqrt{1 \cdot \frac{1}{2}} = \frac{1}{\sqrt{2}} = \frac{1}{\mathbb{G}(a_{12})}.$$

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In the 2nd situation, the expert's doubts are much smaller than in the 1st situation.

However,  $\text{Var}(a_{12}) = \text{Var}(b_{12})$  — it follows from  $\text{Var}(X + k) = \text{Var}(X)$ , where  $X$  is a random variable and  $k$  is a constant.

In contrast, one has  $\text{Var}_g(a_{12}) = 0.12011$ ,  $\text{Var}_g(b_{12}) = 0.00347$ .

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In view of this property and the linearisation process, it is logical to assume that  $\log(a_{ij})$  follows a normal distribution.

## Example (numerical, Octave)

I have doubts about  $a_{12}$ . I want that  $a_{12}$  is around 2.

Assume that  $X = \log(a_{12})$  follows a normal distribution with mean  $\log(2)$ .

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sigma = 1.5; X = sigma*randn(1,10)+log(2)
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generates 10 numbers randomly, normally distributed with mean  $\log(2)$  and variance  $1.5^2$ .

We obtain 6.7, 0.14, 0.43, 2.3, 0.18, 12.9, 3.1, 1.2, 9.4, 1.5 Too much variance!

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We can choose smaller variances until we accept the randomly numbers.

# Many thanks

These slides are available at

<http://personales.upv.es/jbenitez/investigacion.html>