LES FACULTÉS
DE L'UNIVERSITÉ
CATHOLIQUE DE LILLE

Foundations

WELCOME ON BOARD !

Baptiste Mokas

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LES FACULTÉS
DE L'UNIVERSITÉ
CATHOLIQUE DE LILLE

WHY ?

Part 1 : Contextualization

1.1 Introduction

- Presentation of the speaker.
- Connection to the master's program. Announcement of the session's objectives.

1.2 Theoretical Importance of the Course

- Presentation of the reasons why the course is essential in the program.

1.3. Practical Applications

- Concrete examples of course applications in the real world.
- Presentation of a case study or a fictional scenario related to the course content.
- Reminder of the career opportunities the course can provide.
- Presentation of the tools ecosystems

1.4 Networking and Opportunities

Highlight professional networking opportunities related to the course, such as conferences, internships, industry events, etc. Encourage students to explore these opportunities to enhance their academic experience.

Part 2 : Story Line & Timeline

2.1 Presentation of the Storyline

2.2 Presentation of the Timeline

2.3 Questionnaire on Prior Knowledge

- Distribute a quick questionnaire to assess students' knowledge and skills in the course's subject matter.
- Analyze the responses to tailor the teaching accordingly.

Part 3 : Methodology

3.1 Learning Methodology

- Explain the teaching method you will use in the course (e.g., lectures, group work, case studies, individual projects).
- Discuss available educational resources, such as recommended readings, videos, websites, etc. Present expectations regarding class participation and attendance.
- Explain how student feedback will be considered to improve the course over time. Encourage students to provide constructive feedback to contribute to the enhancement of teaching.

3.2 Support Resources

- Inform students about available support resources, such as tutoring services, libraries, writing centers, etc.
- Encourage students to seek help in case of academic or personal difficulties.

Part 4: Evaluation and Grading

4.1 Evaluation and Grading

- Detail of the assessment methods that will be used in the course (e.g., exams, assignments, presentations, projects).
- Explain the weighting of each assessment in the final grade. Specify grading criteria and quality expectations.

4.2 Presentation of the Capstone Project Objective

- Encourage students to brainstorm possible solutions and discuss them as a group.

4.3 Frequently Asked Questions (FAQs)

- Invite students to ask questions about course content, assessments, expectations, etc.
- Provide detailed responses to the questions.

WHO I AM ?

Baptiste Mokas (29 yo)

SaaS Founder
@Weeki
The Endless Visual
Workspace

| Researcher
| Data Scientist
| Teacher
| ML Engineer
| Writer
| Music producer
| Phd Student

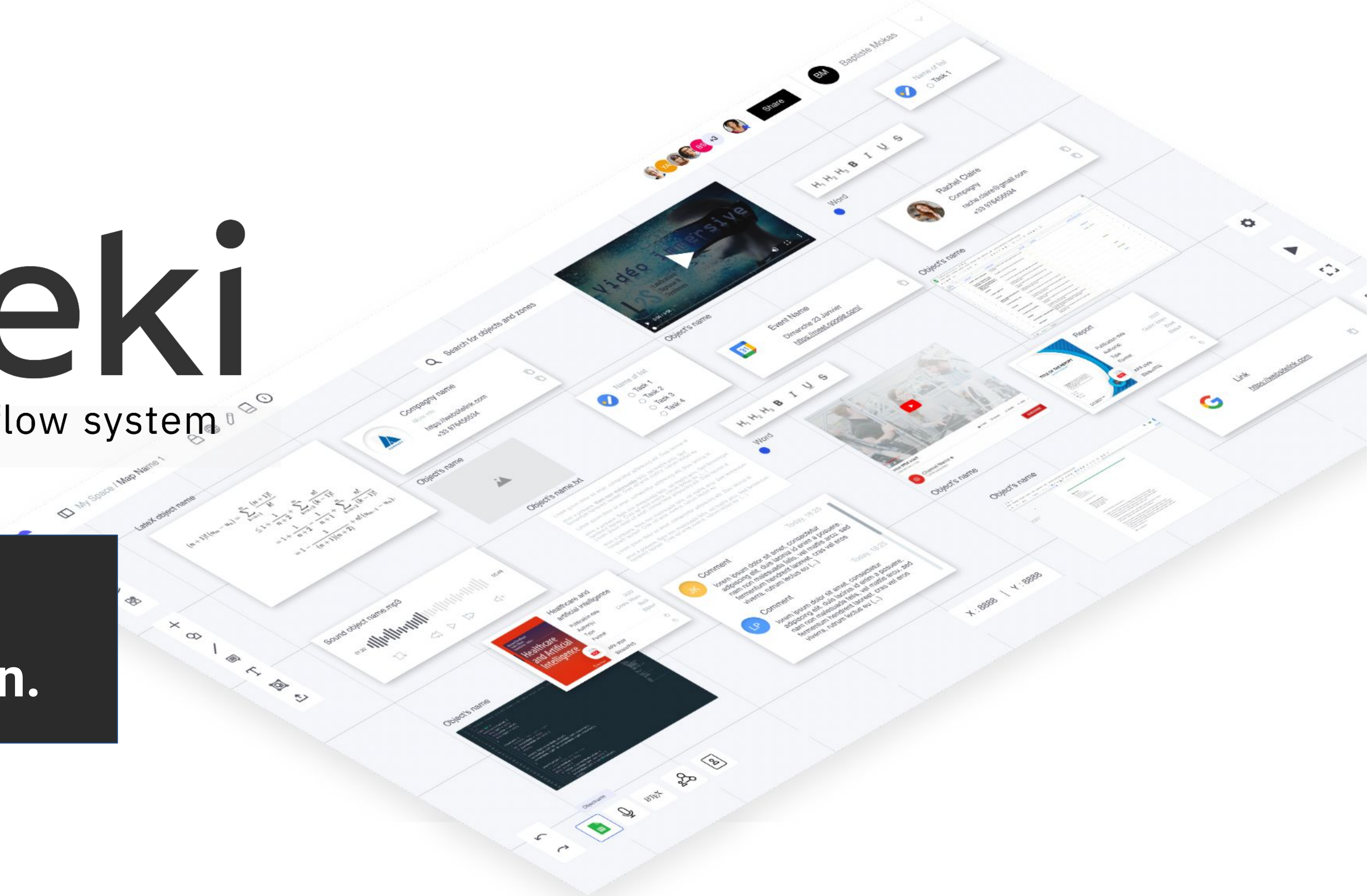
EURATECHNOLOGIES
EUROPE'S STARTUP BUILDER

X

weeki

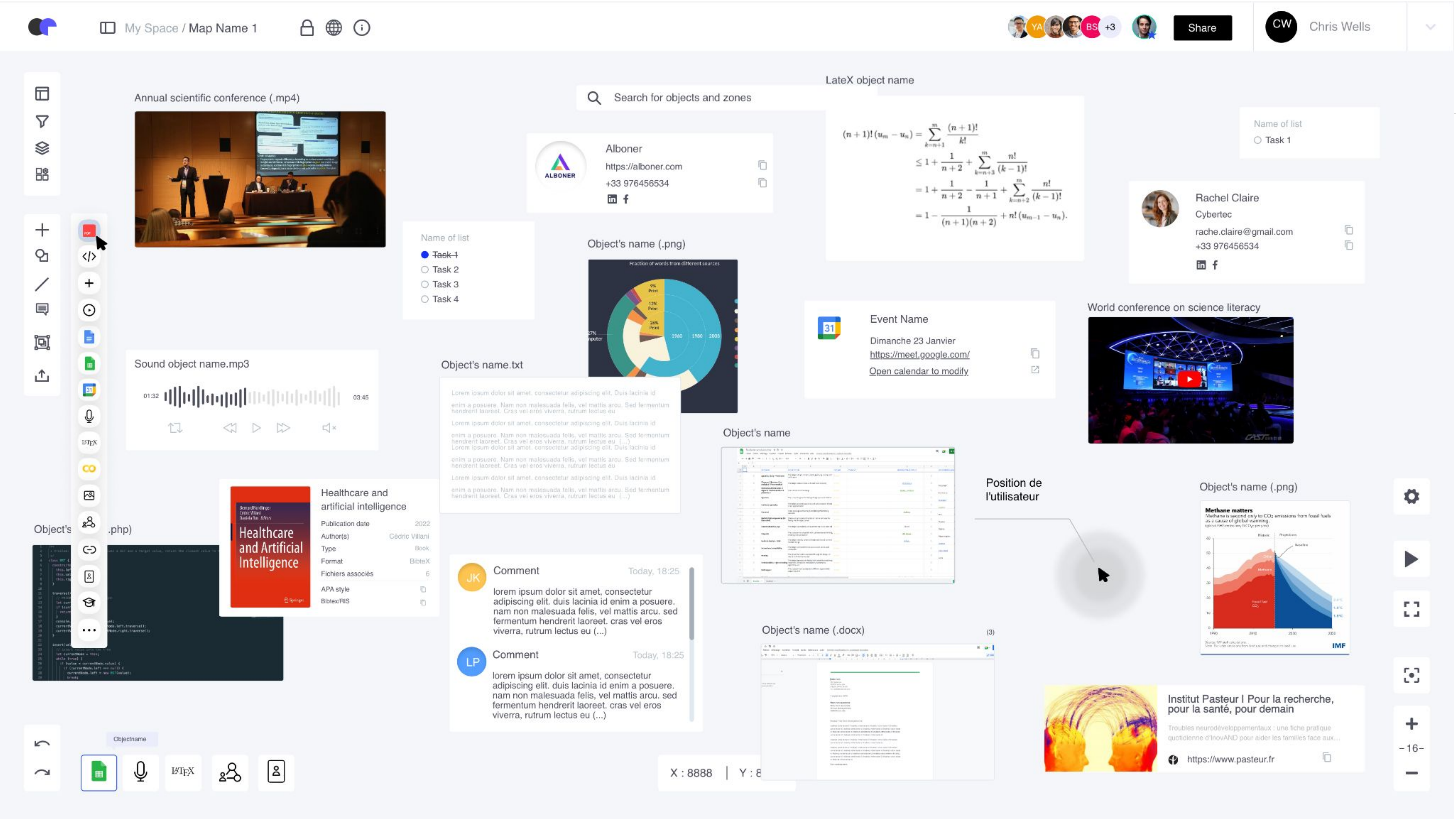
weeki

scientific workflow system



SaaS solution for scientific collaboration.

euratechnologies



My Space / Map Name 1
+3
Share
CW
Chris Wells
Annual scientific conference (.mp4)
Search for objects and zones
LateX object name
Alboner
ALBONER
https://alboner.com
+33 976456534
Name of list
Task 1
Task 2
Task 3
Task 4
Object's name (.png)
Fraction of words from different sources
Name of list
Task 1
Rachel Claire
Cybertec
rache.claire@gmail.com
+33 976456534
Event Name
Dimanche 23 Janvier
https://meet.google.com/
Open calendar to modify
World conference on science literacy
Sound object name.mp3
01:32
03:45
Object's name.txt
Object's name
Healthcare and artificial intelligence
Publication date 2022
Author(s) Cedric Villani
Type Book
Format BibteX
Fichiers associés 6
APA style
Bibtex/RIS
Healthcare and Artificial Intelligence
Position de l'utilisateur
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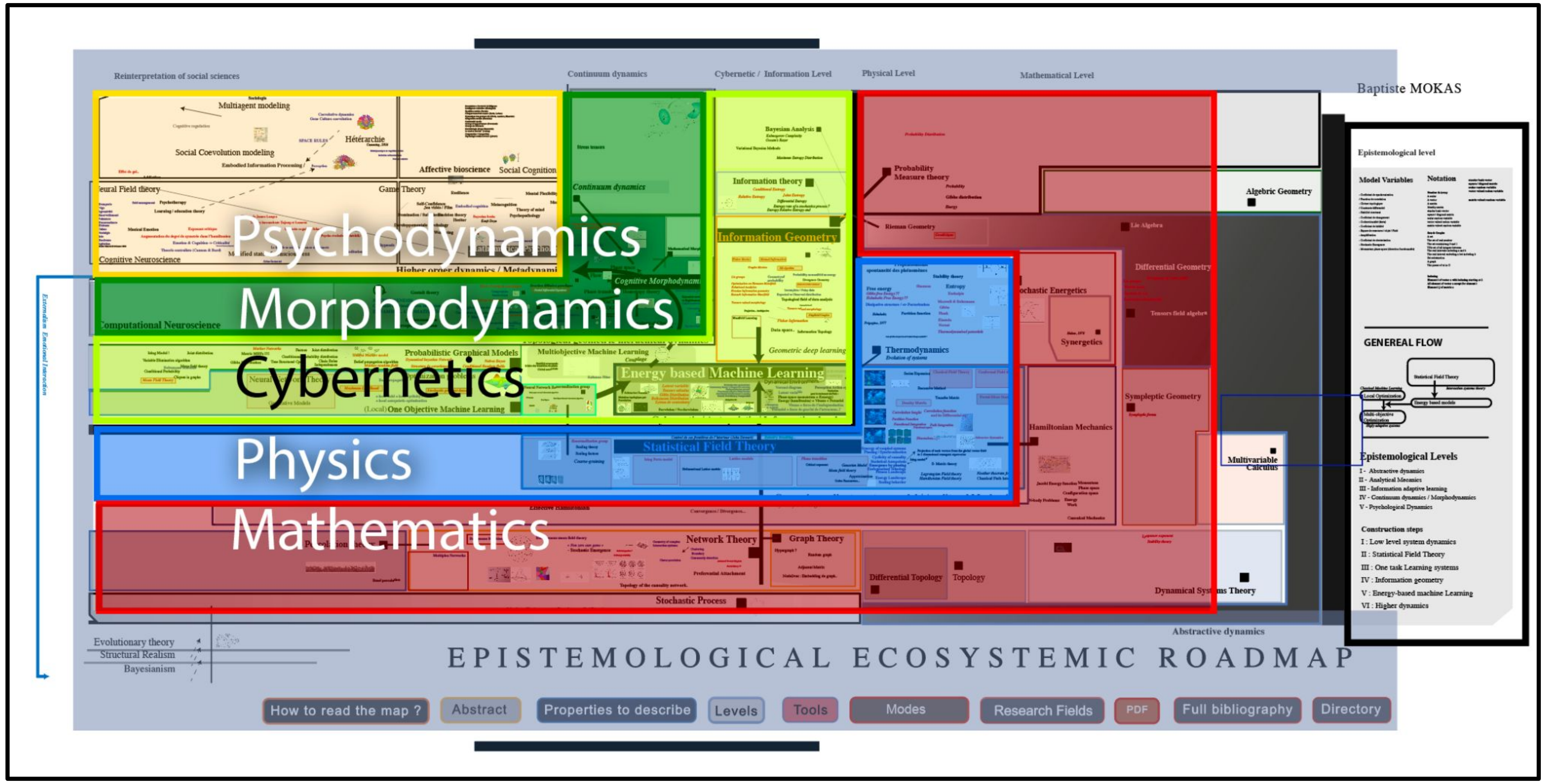
EVERYTHING IS CONNECTED



LINK WITH THE MASTER PROGRAM

Probability & Statistics

Biostatistics

MATIERE		Nom de l'enseignant	TOT Etud	TOT H. Cours	TOT H. TD	TOT H. TP	ECTS
BCC 1 -	**Biosciences**		**36**	**30**	**6**		**7**
B701	Cellular and Molecular Biology of Diseases	**Farouk Allouche**	24	24			**4**
B702	Biostatistics I	Baptiste Mokas	12	6	6		**3**
BCC 2 -	**Data Sciences**		**66**	**18**	**12**		**8**
B703	Bioinformatics I	**Marie-Joe Karam**	30	6		24	**4**
B704	Databases I*	**Nicolas Gouvy**	36	12	12	12	**4**
BCC 3 -	**Communication and Management**		**60**	**12**	**48**		**7**
B705	Project Management*	Olga LAZKO	24	6	18		**3**
B706	Languages	**CLARIFE**	18		18		**2**
B707	Communication Tools / Dataviz*	Xavier Lesaffre	18	6	12		**2**
BCC 4 -	**Probability and Statistics**		**24**	**12**	**12**		**3**
B708	Probability and Statistics	Baptiste Mokas	24	12	12		**3**
BCC 5 -	**Remediation - Elective Course (Cours optionnels)**		**42**	**12**	**12**	**18**	**5**
B709	Basics in Cellular and Molecular Biology	-	42	24	18		**5**
B710	Algorithms*	**Charles Yaacoub**	42	12	12	18	**5**
TOTAL SEMESTRE 1			**228**	**66**	**78**	**18**	**30**

MATIERE		Nom de l'enseignant	TOT Etud	TOT H. Cours	TOT H. TD	TOT H. TP	ECTS
BCC 1 -	**Biosciences**		**48**	**6**	**30**		**5**
B0801	Scientific Method	**Farouk Allouche**	18		18		**2**
B0802	Biostatistics II	Baptiste Mokas	30	6	12	12	**3**
BCC 2 -	**Data Sciences**		**138**	**54**	**36**		**15**
B0803	Bioinformatics II	**Marie-Joe Karam**	30	6	24		**4**
B0804	Object Oriented Programming	Julien Fifani	24	12		12	**3**
B0805	Data Structure and Complexity	Petra Bilane	48	24	12	12	**4**
B0806	Databases II	**Abir Karami**	36	12	12	12	**4**
BCC 3 -	**Communication and Management**		**36**	**18**	**18**		**4**
B0807	Regulations and Laws	Estelle Dourthe	18	18			**2**
B0808	Languages	**CLARIFE**	18		18		**2**
BCC 6 -	**Professionnalization**		**0**	**0**	**0**		**6**
	Parcours recherche option 1		**0**				
B0809	Project in data management in biosciences (Internship)	**Farouk Allouche**	0				**3**
B0810	Thesis (Research Thesis)	**Farouk Allouche**	0				**3**
	Parcours professionnalisant Option 2		**0**				
B0811	Project in data management in biosciences (Apprenticeship)	**Farouk Allouche**	0				**3**
B0812	Report	**Farouk Allouche**	0				**3**
TOTAL SEMESTRE 2			**222**	**78**	**84**	**0**	**30**

MATIERE		TOT Etud	TOT H. Cours	TOT D. TD	TOT H. TP	ECTS
BCC 1 -	**Biosciences**	**42**	**24**	**18**	**0**	**5**
B0901	Introduction to translational research and clinical trials	24	12	12		**3**
B0902	Advances in Biosciences - Seminars I	18	12	6		**2**
BCC 2 -	**Data Sciences**	**108**	**48**	**24**	**36**	**13**
B0903	Applied Biotechnologies I	18	6	12		**3**
B0904	Operational tools for data management in biosciences	36	12	12	12	**4**
B0905	Introduction to AI & Machine Learning	48	24		24	**4**
B0906	Mechanisms of Data protection	12	6	6		**2**
BCC 3 -	**Management and Communication**	**78**	**48**	**30**	**0**	**12**
B0907	Innovation Management	24	12	12		**3**
B0908	European Environment and Policies in life sciences and public health	18	18			**3**
B0909	Responsible Research and Innovation	18	18			**3**
B0910	Languages	18		18		**3**
TOTAL SEMESTRE 3		**228**	**120**	**72**	**36**	**30**

WHY IT'S IMPORTANT ?

CREATE / DEVELOP A NEW THINKING PARADIGM !

1 - Understanding the theory / foundations of the discipline

The primary goals of this course are to provide students with a comprehensive understanding of the probability theory and statistics, by getting overview of foundations and theories.

2 - Understanding the quantitative ontologial nature of our world

Students will be able to know the ontological mathematical nature of systems, especially biological systems, and will be able to handle every possible mathematical tools and theories to extract knowledge from them, from the real world.

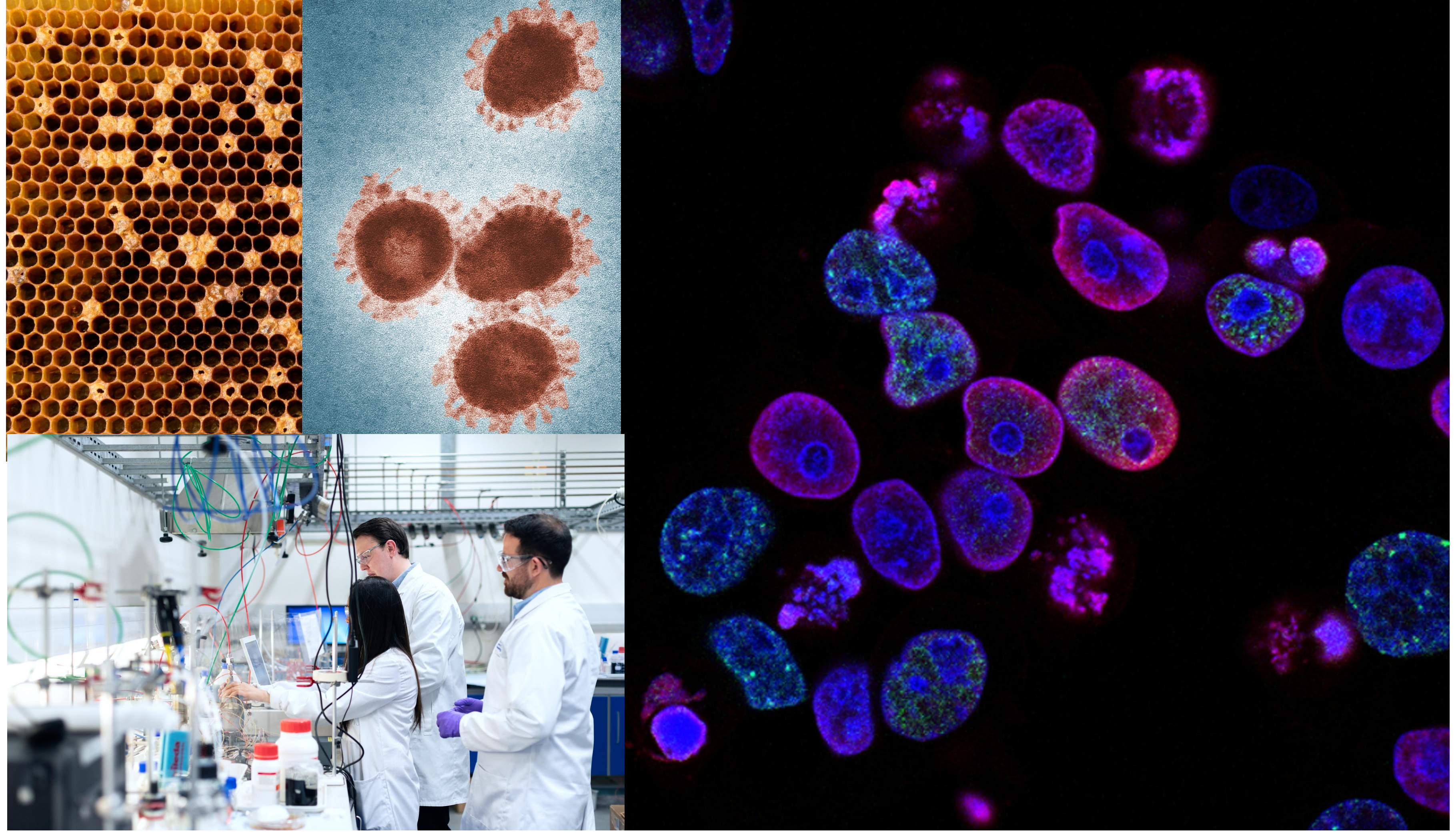
REAL WORLD APPLICATIONS

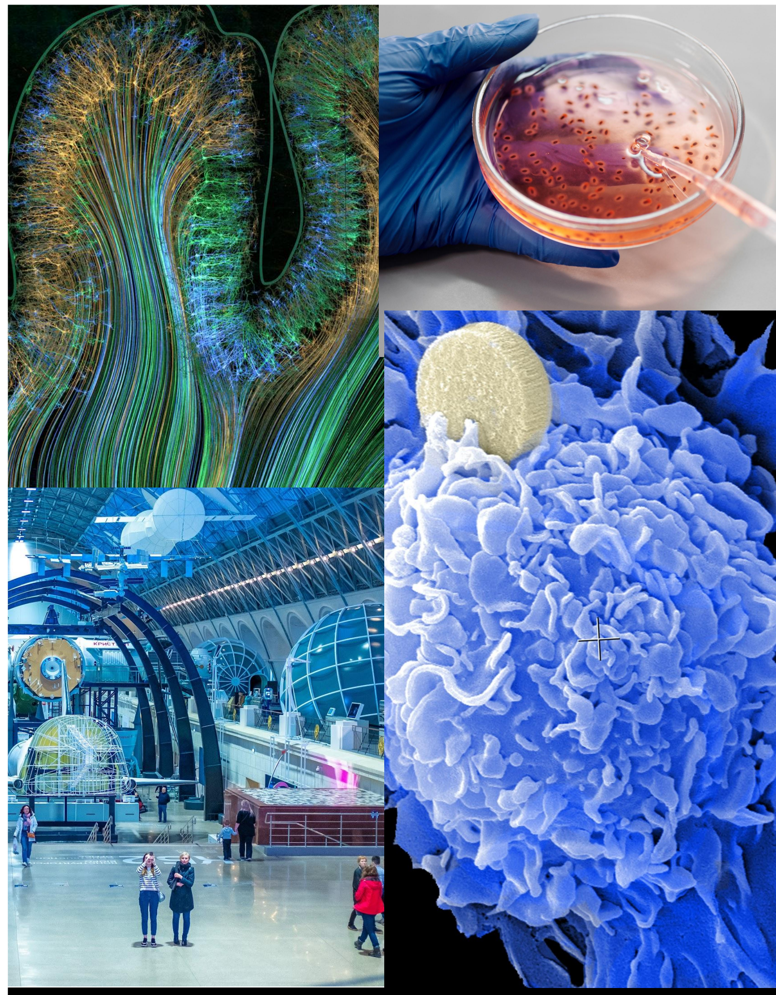
3 - Being autonomous in the journey of experimental design and statistical modelization

By the end of this course, students should be equipped with the knowledge and skills necessary to analyze and interpret complex data, make informed decisions, and apply statistical methods in various real-world scenarios.

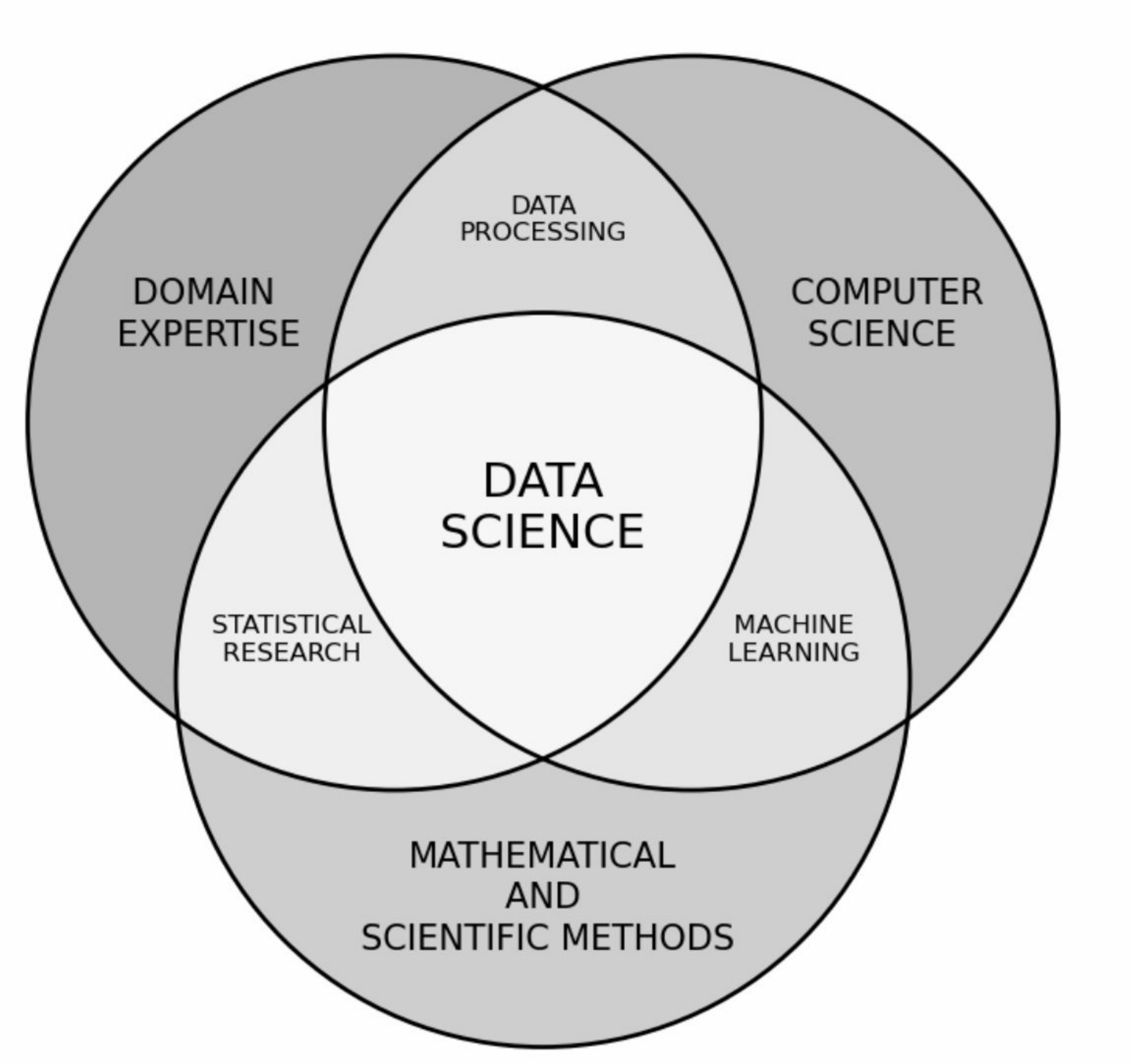
We will understand that the real world is complex and that we can use different tools to handle this complexity. The ultimate purpose will be to create the ability to choose the best tools depending on the nature of the data (experimental design, linearity, parametric, or not)

MATHS
+
COMPLEX ADAPTIVE SYSTEMS
+
BIOLOGY
=
❤️

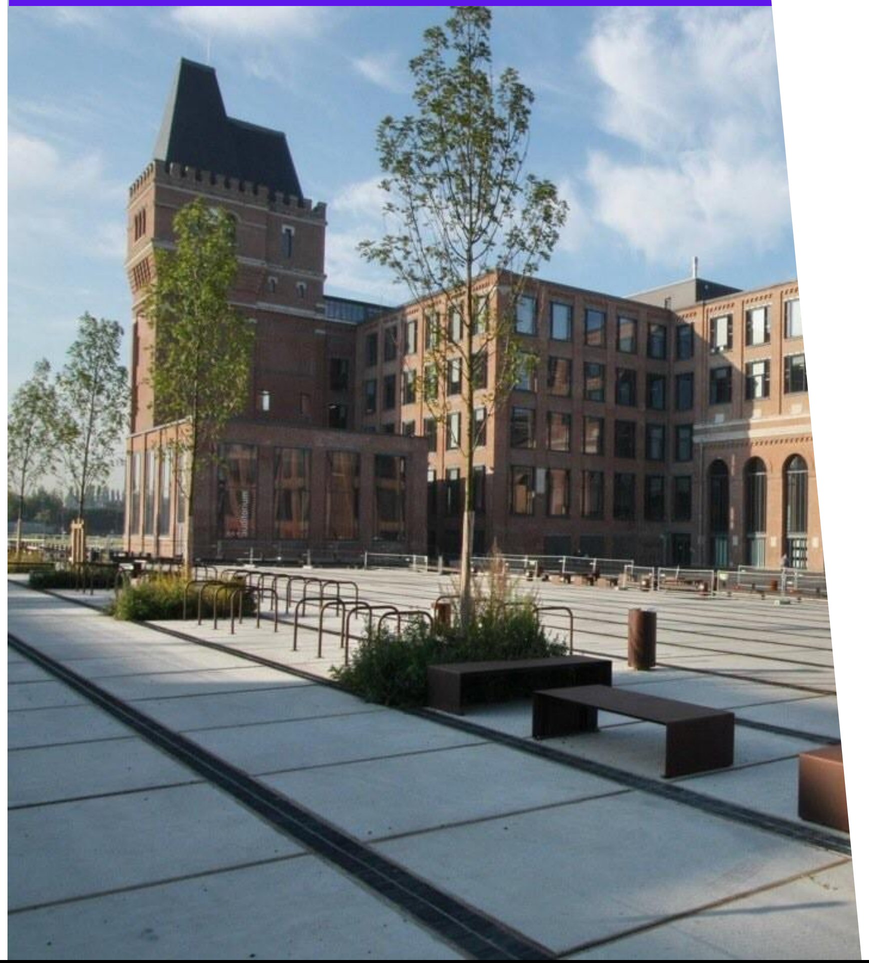


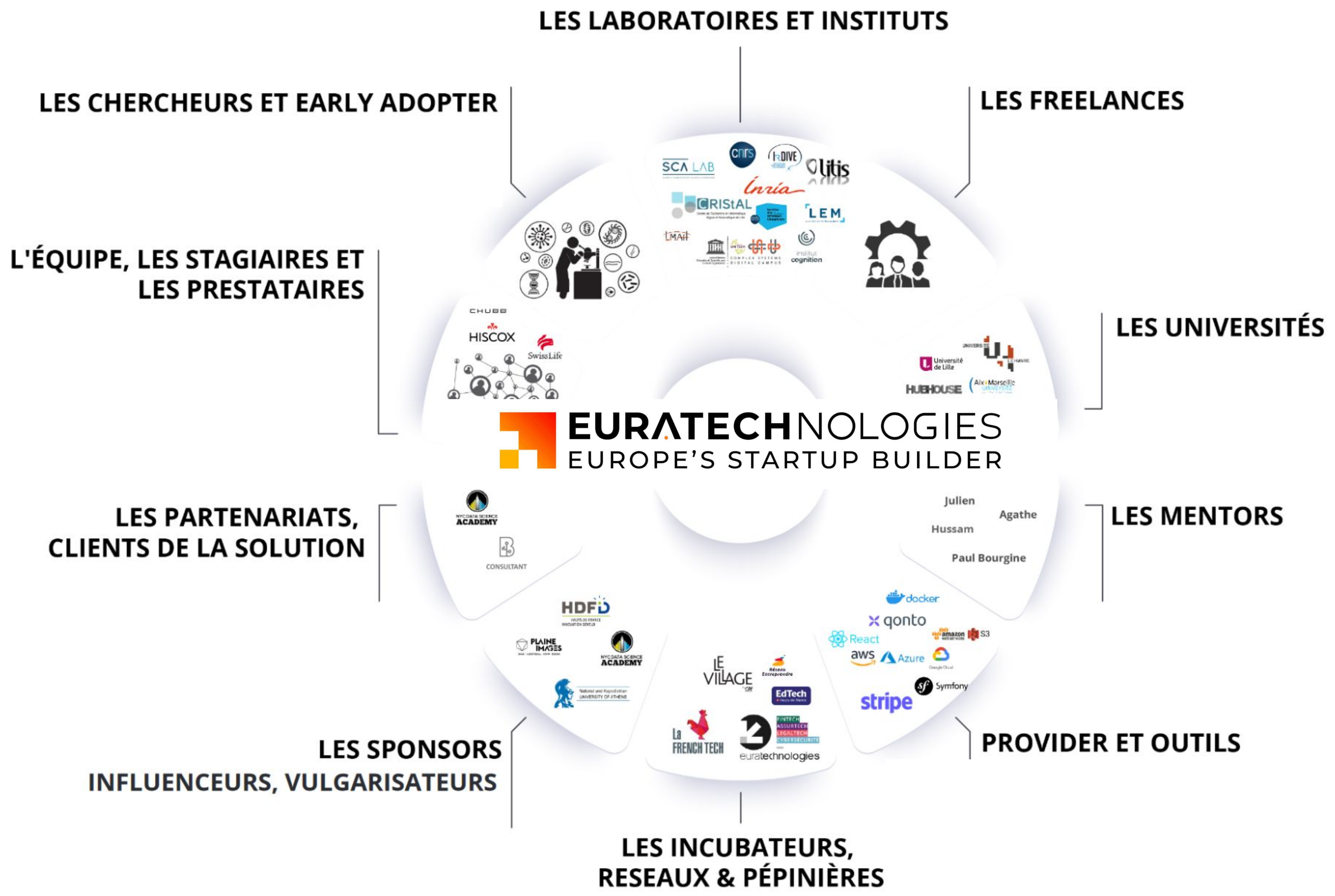


SUPERCHARGE YOUR CAREER !



A network of synergies





1 THEORETICAL LEARNING

- Presentation of slides using a video projector
- Schematization on the board

2 ACTIVE LEARNING

- Group exercise (TD)
- Debate
- Collective problem exploration
- Code demonstrations (R / Python)

3 APPLICATIONS

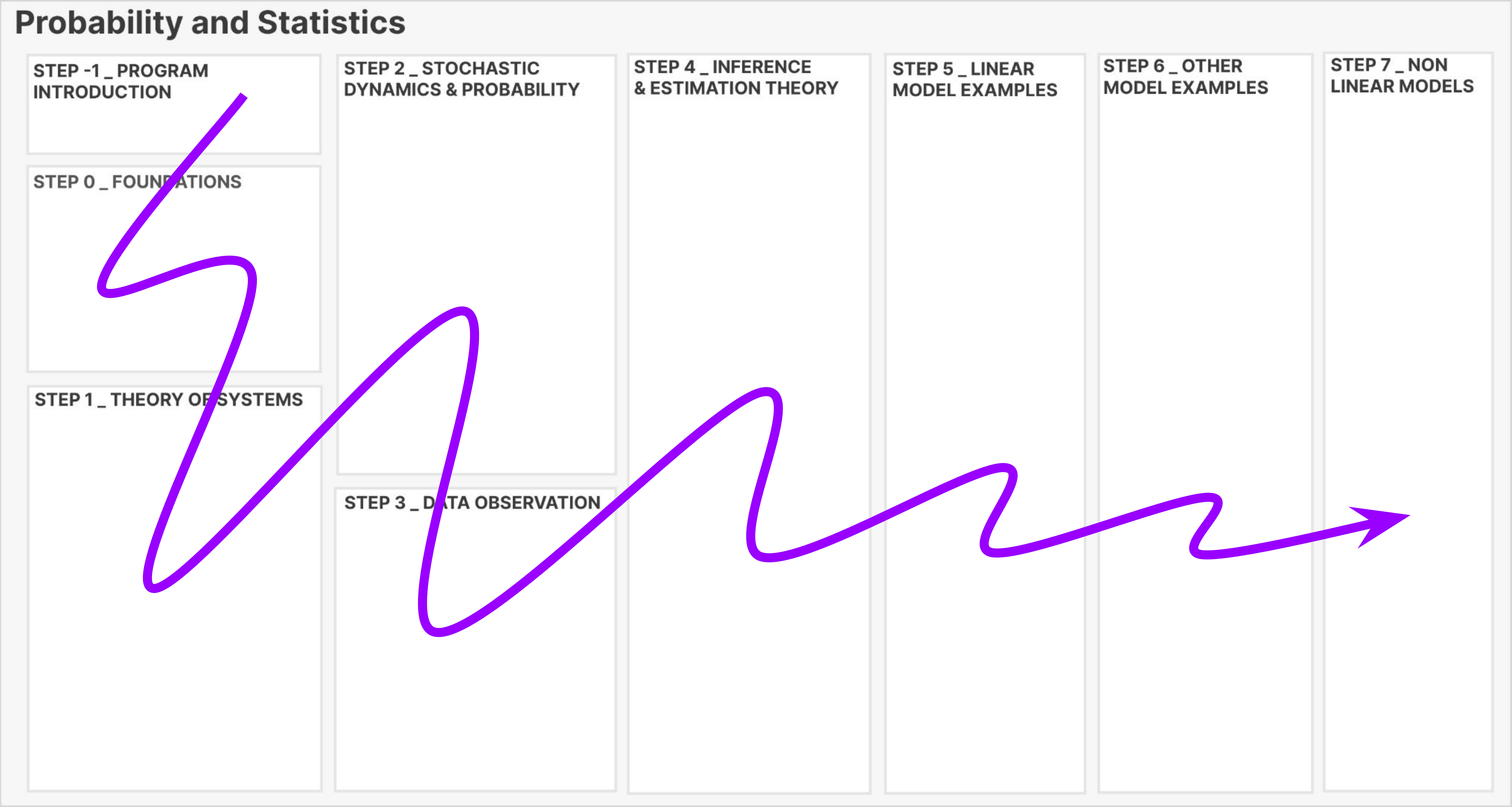
- A capstone project by groups at the middle of the semester

OUR STORY LINE

Probability and Statistics

STEP -1 _ PROGRAM INTRODUCTION STEP 0 _ FOUNDATIONS STEP 1 _ THEORY OF SYSTEMS	STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY STEP 3 _ DATA OBSERVATION	STEP 4 _ INFERENCE & ESTIMATION THEORY	STEP 5 _ LINEAR MODEL EXAMPLES	STEP 6 _ OTHER MODEL EXAMPLES	STEP 7 _ NON LINEAR MODELS

OUR STORY LINE



OUR STORY LINE

Probability and Statistics

STEP -1 _ PROGRAM INTRODUCTION

STEP 0 _ FOUNDATIONS

WHAT IS KNOWLEDGE ?

STEP 1 _ THEORY OF SYSTEMS

WHAT IS THE VERY NATURE OF REALITY ?

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

WHAT CAN WE KNOW ABOUT RANDOMNESS ?

STEP 3 _ DATA OBSERVATION

WHAT TO DO WITH MY DATA ?

STEP 4 _ INFERENCE & ESTIMATION THEORY

HOW TO “PROOVE” SOMETHING ?

STEP 5 _ LINEAR MODEL EXAMPLES

STEP 6 _ OTHER MODEL EXAMPLES

STEP 7 _ NON LINEAR MODELS

HOW TO MODEL REALITY SO I CAN PREDICT DYNAMICS ?

OUR STORY LINE

Probability and Statistics

STEP -1 _ PROGRAM INTRODUCTION
- -1 - PROGRAM INTRODUCTION

STEP 0 _ FOUNDATIONS
- 0.1 - ELEMENTS OF CALCULUS & TOOLS
- 0.2 - EPISTEMOLOGY & THEORY OF KNOWLEDGE

STEP 1 _ THEORY OF SYSTEMS
- 1.1 - DYNAMICAL SYSTEMS
- 1.2 - COMPLEX ADAPTIVE SYSTEMS

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY
- 2.1 - MEASURE THEORY
- 2.2 - PROBABILITY THEORY
- 2.3 - USUAL PROBABILITY DISTRIBUTIONS
- 2.4 - ASYMPTOTIC STATISTICS
- 2.5 - STOCHASTIC PROCESS & TIME SERIES
- 2.6 - INFORMATION GEOMETRY

STEP 3 _ DATA OBSERVATION
- 3.1 - DESCRIPTIVE STATISTICS & DATAVIZUALISATION
- 3.2 - EXPLORATORY DATA ANALYSIS

STEP 4 _ INFERENCE & ESTIMATION THEORY
- 4.1 - PARAMETERS ESTIMATIONS & LEARNING
- 4.2 - EXPERIMENTAL DESIGN & HYPOTHESIS TESTING
- 4.4 - DECISION TREES & MODEL SELECTION
- 4.5 - BAYESIAN INFERENCES

STEP 5 _ LINEAR MODEL EXAMPLES
- 5.1 - SIMPLE LINEAR REGRESSION
- 5.2 - MULTIPLE LINEAR REGRESSION
- 5.3 - OTHER REGRESSIONS MODELS

STEP 6 _ OTHER MODEL EXAMPLES
- 6.1 - USUAL UNIVARIATE TESTING
- 6.2 - USUAL MULTIVARIATE TESTING
- 6.3 - NON PARAMETRIC STATISTICS

STEP 7 _ NON LINEAR MODELS
- 7.1 - PROBABILISTIC GRAPHICAL MODELS
- 7.2 - PERCOLATION THEORY
- 7.3 - SPATIAL STATISTICS
- 7.4 - EXTREM VALUE THEORY
- 7.5 - AGENT BASED MODELING
- 7.6 - NETWORK DYNAMICS

OUR STORY LINE

PROGRAM INTRODUCTION

STEP 0 _ FOUNDATIONS

0.1 - ELEMENTS OF CALCULUS

0.2 - EPISTEMOLOGY & THEORY OF KNOWLEDGE

STEP 1 _ THEORY OF SYSTEMS

1.1 - DYNAMICAL SYSTEMS

1.2 - COMPLEX ADAPTIVE SYSTEMS

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

2.1 - MEASURE THEORY

2.2 - PROBABILITY THEORY

2.3 - USUAL PROBABILITY DISTRIBUTIONS

2.4 - ASYMPTOTIC STATISTICS

2.5 - STOCHASTIC PROCESS & TIME SERIES

2.6 - INFORMATION GEOMETRY

STEP 3 _ DATA OBSERVATION

3.1 - DESCRIPTIVE STATISTICS

3.2 - EXPLORATORY DATA ANALYSIS

STEP 4 _ INFERENCE & ESTIMATION THEORY

4.1 - PARAMETERS ESTIMATIONS

4.2 - EXPERIMENTAL DESIGN & HYPOTHESIS TESTING

4.3 - STATISTICAL SAMPLING METHODS

4.4 - DECISION TREE & MODELS SELECTION

4.5 - BAYESIAN INFERENCES

STEP 5 _ LINEAR MODELS EXAMPLES

5.1 - SIMPLE LINEAR REGRESSION

5.2 - MULTIPLE LINEAR REGRESSION

5.3 - OTHER REGRESSION MODELS

STEP 6 _ OTHER CLASSIC MODEL EXAMPLES

6.1 - USUAL UNIVARIATE TESTING

6.2 - USUAL MULTIVARIATE TESTING

6.3 - NON PARAMETRIC STATISTICS

STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.1 - PROBABILISTIC GRAPHICAL MODELS

7.2 - PERCOLATION THEORY

7.3 - SPATIAL STATISTICS

7.4 - EXTREME VALUE THEORY

7.5 - AGENT-BASED MODELING

7.6 - NETWORK DYNAMICS

OUR STORY LINE

PROGRAM INTRODUCTION

What are the basics you should never forget ?

STEP 0 _ FOUNDATIONS
- 0.1 - ELEMENTS OF CALCULUS
- 0.2 - EPISTEMOLOGY & THEORY OF KNOWLEDGE

What is the nature of the phenomenon you are observing?

STEP 1 _ THEORY OF SYSTEMS
- 1.1 - DYNAMICAL SYSTEMS
- 1.2 - COMPLEX ADAPTIVE SYSTEMS

What are the theoretical mathematical foundation you need to know ?

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY
- 2.1 - MEASURE THEORY
- 2.2 - PROBABILITY THEORY
- 2.3 - USUAL PROBABILITY DISTRIBUTIONS
- 2.4 - ASYMPTOTIC STATISTICS
- 2.5 - STOCHASTIC PROCESS & TIME SERIES
- 2.6 - INFORMATION GEOMETRY

Before any models, how can you describe your data ?

STEP 3 _ DATA OBSERVATION
- 3.1 - DESCRIPTIVE STATISTICS
- 3.2 - EXPLORATORY DATA ANALYSIS

How you can tell that your data can help you to understand our world ?

STEP 4 _ INFERENCE & ESTIMATION THEORY
- 4.1 - PARAMETERS ESTIMATIONS

Which method should you choose ?

- 4.2 - EXPERIMENTAL DESIGN & HYPOTHESIS TESTING
- 4.3 - STATISTICAL SAMPLING METHODS
- 4.4 - DECISION TREE & MODELS SELECTION
- 4.5 - BAYESIAN INFERENCES

Which models should I know?

STEP 5 _ LINEAR / REGRESSION MODELS EXAMPLES
- 5.1 - SIMPLE LINEAR REGRESSION
- 5.2 - MULTIPLE LINEAR REGRESSION
- 5.3 - OTHER REGRESSION MODELS

STEP 6 _ OTHER CLASSIC MODEL EXAMPLES
- 6.1 - USUAL UNIVARIATE TESTING
- 6.2 - USUAL MULTIVARIATE TESTING
- 6.3 - NON PARAMETRIC STATISTICS

How to go further ?

STEP 7 _ NON-LINEAR MODELS EXAMPLES
- 7.1 - PROBABILISTIC GRAPHICAL MODELS
- 7.2 - PERCOLATION THEORY
- 7.3 - SPATIAL STATISTICS
- 7.4 - EXTREME VALUE THEORY
- 7.5 - AGENT-BASED MODELING
- 7.6 - NETWORK DYNAMICS

THE TIMELINE
OF THE FIRST SEMESTER

PROBABILITY & STATISTICS

CM1	Course 1 (4h) 27/09 13h à 17h	CM - PROGRAM INTRODUCTION			
CM2	Course 2 (4h) 29/09 13h à 17h	CM - EPISTEMOLOGY and THEORY OF KNOWLEDGE + CM - CALCULUS		CM - COMPLEX ADAPTIVE SYSTEMS + CM - DYNAMICAL SYSTEMS	
CM3	Course 1 (4h) 6/10 13h à 17h	CM - MEASURE THEORY	CM - PROBABILITY THEORY		CM - USUAL PROBABILITY DISTRIBUTIONS
CM4	Course 1 (4h) 13/10 13h à 17h	CM - PARAMETERS ESTIMATIONS	CM - DESIGN & TESTING	CM - STATISTICAL SAMPLING METHODS	CM - DECISION TREE & MODELS SELECTION
CM5	Course 1 (4h) 18/10 13h à 17h	CM - STOCHASTIC PROCESS & TIME SERIES		TD - CAPSTONE PROJECT & EXERCICES	
CM6	Course 1 (4h) 27/10 13h à 17h	CM - ASYMPTOTIC STATISTICS	CM - BAYESIAN INFERENCE	CM - INFORMATION GEOMETRY	TD - CAPSTONE PROJECT & EXERCICES

BIOSTATISTICS

CM7	Course 1 (4h) 10/11 13h à 17h	CM - DESCRIPTIVE STATISTICS	CM - SIMPLE LINEAR REGRESSION	CM - MULTIPLE LINEAR REGRESSION	
CM8	Course 1 (4h) 15/11 13h à 17h	CM - USUAL UNIVARIATE TESTING		TD - CAPSTONE PROJECT & EXERCICES	
CM9	Course 1 (4h) 24/11 13h à 17h	CM - USUAL MULTIVARIATE TESTING		TD - CAPSTONE PROJECT & EXERCICES	

THE TIMELINE OF THE FIRST SEMESTER

BIOSTATISTICS

CM10	Cours 11	CM - OTHER REGRESSION METHODS	TD - CAPSTONE PROJECT & EXERCICES
CM11	Cours 12	CM - EXPLORATORY DATA ANALYSIS	TD - CAPSTONE PROJECT & EXERCICES
CM12	Cours 12	CM - NON PARAMETRIC STATISTICS	TD - CAPSTONE PROJECT & EXERCICES
CM13	Cours 13	CM - PROBABILISTIC GRAPHICAL MODELS	TD - CAPSTONE PROJECT & EXERCICES
CM14	Cours 14	CM - PERCOLATION THEORY	TD - CAPSTONE PROJECT & EXERCICES
CM15	Cours 15	CM - SPATIAL STATISTICS	TD - CAPSTONE PROJECT & EXERCICES
CM16	Cours 16	CM - AGENT BASED MODELING	TD - CAPSTONE PROJECT & EXERCICES
CM17	Cours 17	CM - NETWORK DYNAMICS	

WHAT ABOUT YOU ?

PRESENTATION & SELF ASSESSMENT QUESTIONNAIRE

First name / Last name :

Email :

My future dream job :

Why I did choose to be here :

What is my level in statistics and probability (bachelor's degree, master's degree, nothing?) :

Your analysis scale

Not at all	Rather not	Moderately	Rather yes	Absolutely
☐	☐	☐	☐	☐

STEP 0 - FOUNDATIONS

0.1 - ELEMENTS OF CALCULUS & TOOLS

🇺🇸	🇫🇷	I know this concept well	I think I can use it I need it for my projects
Affine function	Fonction affine	☐☐☐☐☐	☐☐☐☐☐
Differentiation under the integral sign theorem	Théorème de dérivation sous le signe d'intégrale	☐☐☐☐☐	☐☐☐☐☐
Young's theorem	Théorème de Young	☐☐☐☐☐	☐☐☐☐☐
Convex function	Fonction convexe	☐☐☐☐☐	☐☐☐☐☐
Exponential function	Fonction exponentielle	☐☐☐☐☐	☐☐☐☐☐
Function	Fonction	☐☐☐☐☐	☐☐☐☐☐
Hyperbolic function	Fonction hyperbolique	☐☐☐☐☐	☐☐☐☐☐
Linear form	Forme linéaire	☐☐☐☐☐	☐☐☐☐☐
Chain rule theorem	Théorème de la règle de la chaîne	☐☐☐☐☐	☐☐☐☐☐
Parseval's theorem	Théorème de Parseval	☐☐☐☐☐	☐☐☐☐☐
Continuous function	Fonction continue	☐☐☐☐☐	☐☐☐☐☐
Linear function	Fonction linéaire	☐☐☐☐☐	☐☐☐☐☐
Polynomial function	Fonction polynomiale	☐☐☐☐☐	☐☐☐☐☐
Transpose	Transposée	☐☐☐☐☐	☐☐☐☐☐
Stone-Weierstrass theorem	Théorème de Stone-Weierstrass	☐☐☐☐☐	☐☐☐☐☐
Taylor's formula	Formule de Taylor	☐☐☐☐☐	☐☐☐☐☐
Differentiable function	Fonction dérivable	☐☐☐☐☐	☐☐☐☐☐
Derived function (or Derivative)	Fonction dérivée	☐☐☐☐☐	☐☐☐☐☐
Antiderivative (or Indefinite integral)	Fonction primitive	☐☐☐☐☐	☐☐☐☐☐
Inverse function	Fonction réciproque	☐☐☐☐☐	☐☐☐☐☐
Quadratic form	Forme quadratique	☐☐☐☐☐	☐☐☐☐☐
Polynomial function (Répété)	Fonction polynomiale	☐☐☐☐☐	☐☐☐☐☐

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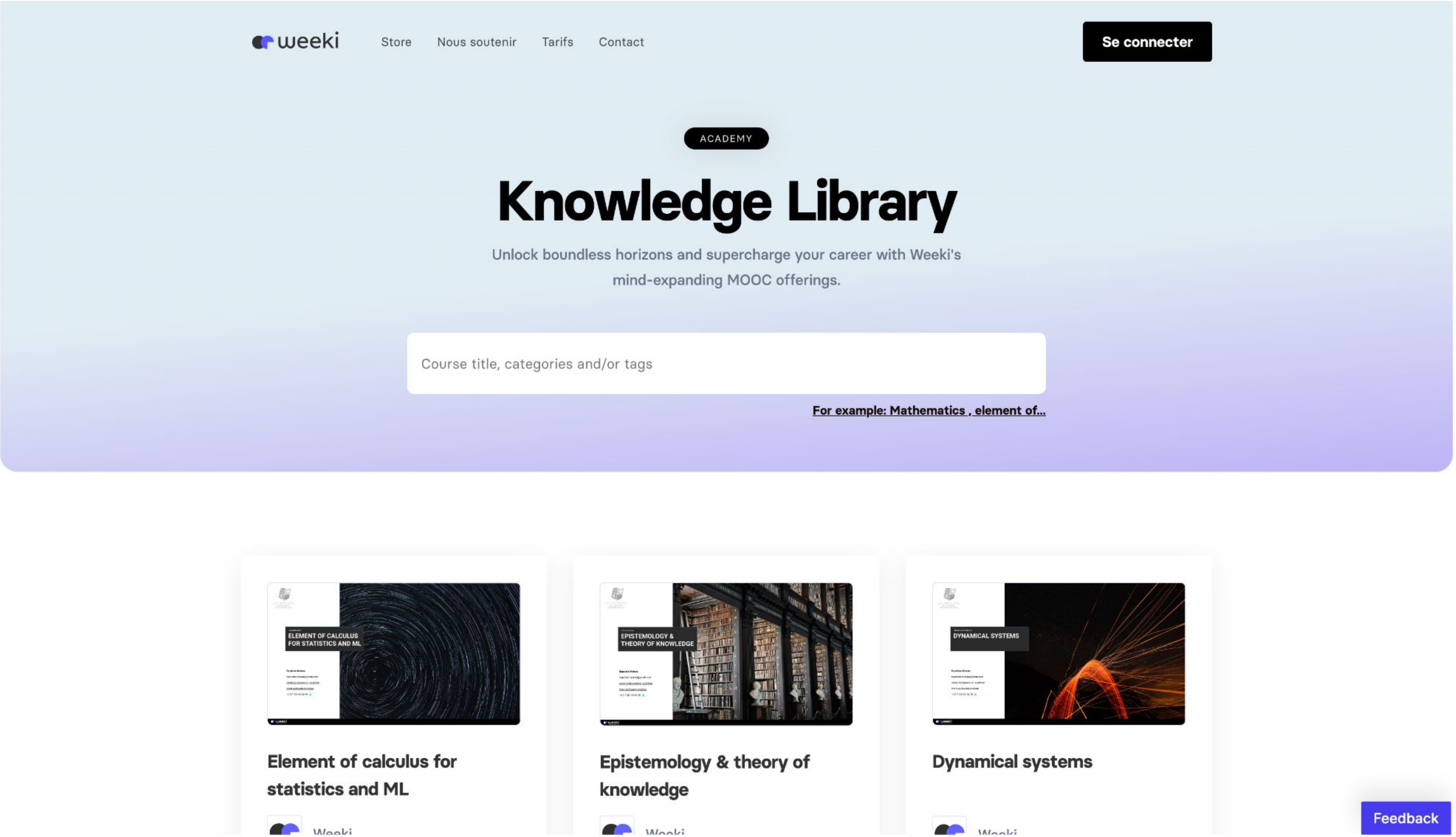
SUPPORT RESOURCES ON "WEEKI.IO"



50% / CAPSTONE PROJECT

Evaluation criteria :

- ❏ Research Methodology
- ❏ Data Collection Quality
- ❏ Exploratory Data Analysis (EDA)
- ❏ Modeling and Algorithms
- ❏ Data Preprocessing
- ❏ Performance Evaluation
- ❏ Results Interpretation
- ❏ Communication Skills
- ❏ Innovation
- ❏ Project Management

Deliverables :
You can create a Jupiter notebook via google collab or write a pdf document based on the classic structure of a scientific article.

To send by email at baptiste@weeki.io

50% / END-OF-SEMESTER KNOWLEDGE AND SKILLS QUESTIONNAIRE (EXAM)

Evaluation criteria :

- ❏ Understanding of the theory :
  10 questions about theoretical knowledge
- ❏ Understanding of the tools :
  10 questions about the ability to use tools (R & Python)
- ❏ Understanding of mathématical models :
  10 questions on the ability to go deep into a model and make calculations

Deliverables :
Fill out a questionnaire of 30 questions

STRUCTURE OF THE CAPSTONE PROJECT

1. Introduction:
- Contextualize the project.
- State the research problem or objectives.
- Justify the significance of the topic.

2. Literature Review *(optional)*
- Present relevant prior work.
- Discuss methods and findings from similar research.

3. Methodology:
- Provide a detailed description of the research approach.
- Explain the tools, techniques, and algorithms used.
- Justify methodological choices.

4. Data Collection and Preprocessing:
- Describe data sources and collection protocols.
- Explain data cleaning and preprocessing steps.

5. Exploratory Data Analysis (EDA) *(optional)*
- Present EDA results using graphs and descriptive statistics.
- Identify significant trends or anomalies.

6. Modeling and Experimentation:
- Present data science models employed.
- Detail experiments, model parameters, and evaluation methods.

7. Results and Discussion:
- Present the obtained results, including model performance.
- Interpret results in relation to initial objectives.
- Discuss implications of findings.

8. Conclusion:
- Summarize key conclusions.
- Highlight project contributions.
- Suggest directions for future work.

9. References:
- List all references cited in the project (min 5)

Appendices (if necessary):
- Include additional details, source code, extra graphs, etc.

FAQ TIME

OUR STORY LINE

Probability and Statistics

STEP -1 _ PROGRAM INTRODUCTION

STEP 0 _ FOUNDATIONS

WHAT IS KNOWLEDGE ?

STEP 1 _ THEORY OF SYSTEMS

WHAT IS THE VERY NATURE OF REALITY ?

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

WHAT CAN WE KNOW ABOUT RANDOMNESS ?

STEP 3 _ DATA OBSERVATION

WHAT TO DO WITH MY DATA ?

STEP 4 _ INFERENCE & ESTIMATION THEORY

HOW TO “PROOVE” SOMETHING ?

STEP 5 _ LINEAR MODEL EXAMPLES

STEP 6 _ OTHER MODEL EXAMPLES

STEP 7 _ NON LINEAR MODELS

HOW TO MODEL REALITY SO I CAN PREDICT DYNAMICS ?

What are the basics you should never forget ?

STEP 0 _ FOUNDATIONS

0.1 - ELEMENTS OF CALCULUS

Description:

This course covers fundamental concepts of **calculus, such as differentiation and integration,** as well as essential mathematical tools like **linear algebra and optimization techniques**.

Significance:

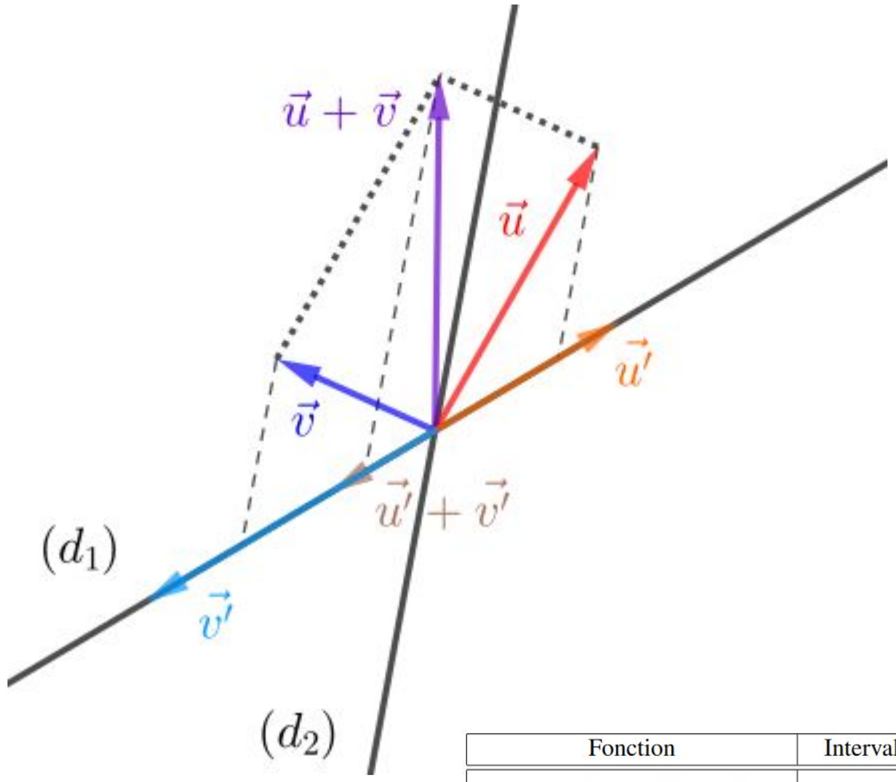
Calculus provides the **mathematical foundation for modeling and understanding the rates of change in biological systems**. Linear algebra and optimization are crucial for solving complex equations and optimizing system behavior.

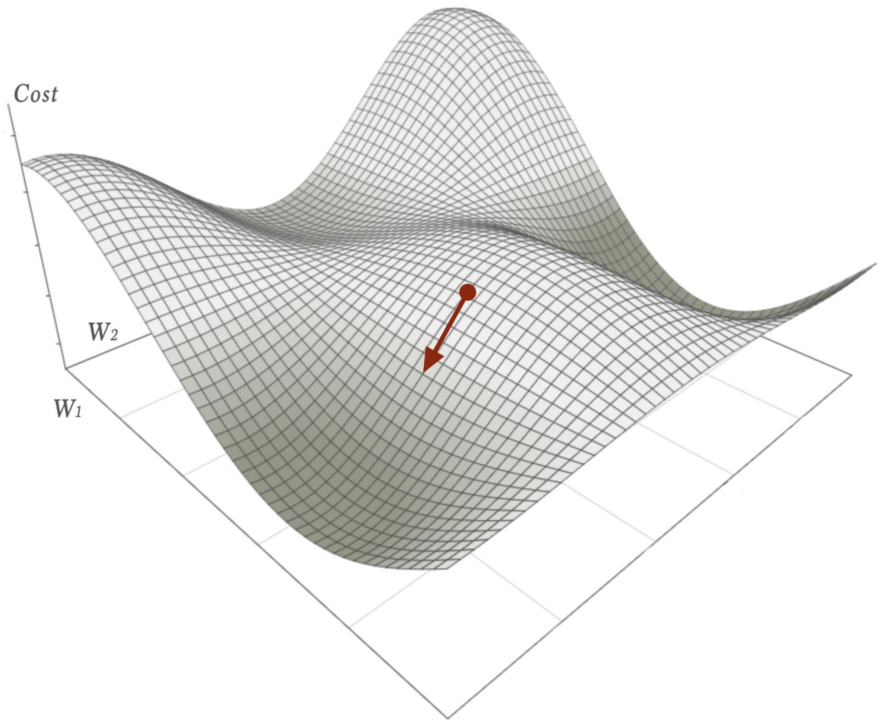
Applications in Biology:

Calculus is used to model population growth, enzyme kinetics, and the dynamics of biochemical reactions.

Reference:

"Mathematical Models in the Applied Sciences" by A.C. Fowler





Fonction	Intervalle d'int
$(x-a)^n, n \in \mathbb{N}, a \in \mathbb{R}$	$\mathbb{R}$
$\frac{1}{x-a}, a \in \mathbb{R}$	$]-\infty; a[$ OU]
$\frac{1}{(x-a)^n}, a \in \mathbb{R}, n \geq 2$	$]-\infty; a[$ OU]
$\cos(ax), a \in \mathbb{R}\backslash\{0\}$	$\mathbb{R}$
$\sin(ax), a \in \mathbb{R}\backslash\{0\}$	$\mathbb{R}$
$\tan(x)$	$]k\pi - \frac{\pi}{2}; k\pi +$
$\ln(x)$	$\mathbb{R}^{+,*}$
$e^{ax}, a \in \mathbb{R}\backslash\{0\}$	$\mathbb{R}$
$(x-a)^\alpha, a \in \mathbb{R}, \alpha \in \mathbb{R}\backslash\{-1\}$	$]a; +\infty$
$a^x, a > 0$	$\mathbb{R}$
$\frac{1}{x^2+1}$	$\mathbb{R}$
$\sqrt{x-a}, a \in \mathbb{R}$	$]a; +\infty$
$\frac{1}{\sqrt{x-a}}, a \in \mathbb{R}$	$]a; +\infty$
$\frac{1}{\sqrt{1-x^2}}$	$]-1; 1$

What are the basics you should never forget ?

STEP 0 _ FOUNDATIONS

0.2 - EPISTEMOLOGY & THEORY OF KNOWLEDGE

Description:

This course explores the epistemological underpinnings of **scientific knowledge and theories**, including discussions on how we gain knowledge and the nature of scientific inquiry.

Significance:

Understanding the philosophy of science is essential for **critically evaluating scientific models and theories**, which is crucial in modeling complex adaptive systems.

Applications in Biology:

Epistemology helps biologists question assumptions and design experiments that lead to **robust and reliable biological models**.

Reference:

"Scientific Knowledge: A Sociological Analysis" by Barry Barnes

STEP 1 _ THEORY OF SYSTEMS

General Description:

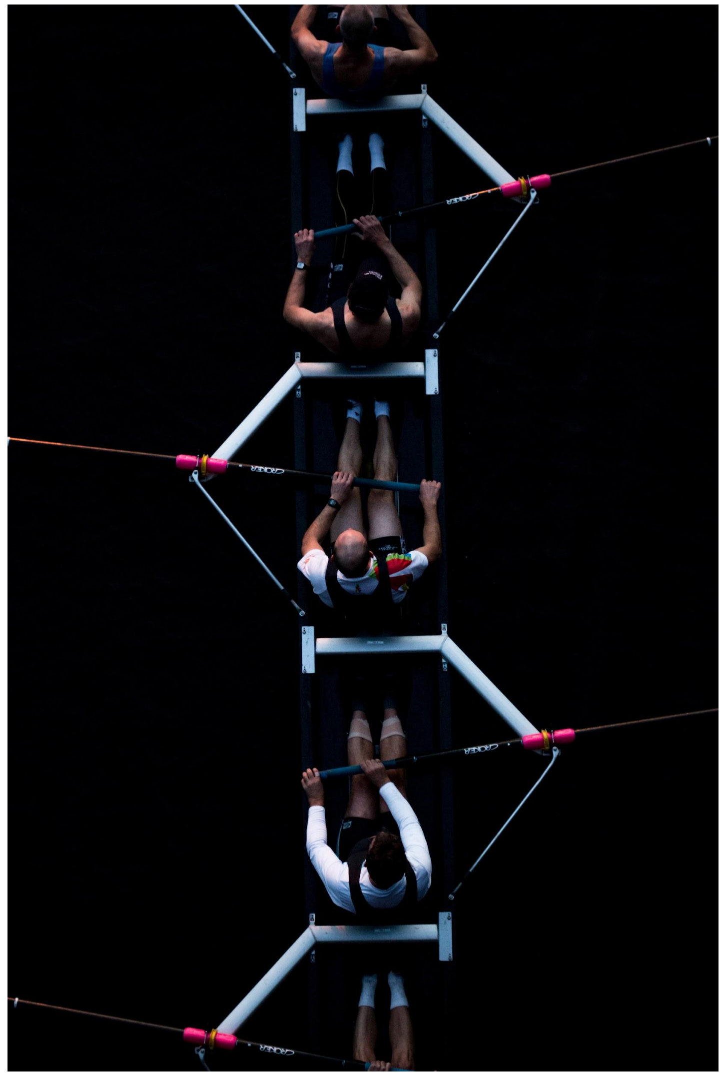
The Theory of Systems step introduces students to the **theoretical framework for understanding systems**, including dynamic and complex adaptive systems.

Significance:

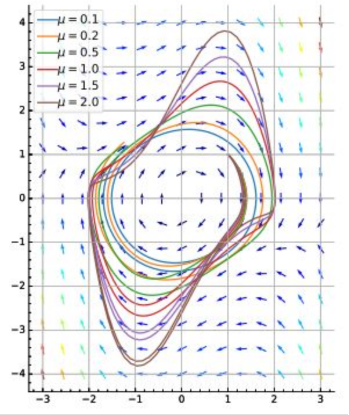
It lays the groundwork for students to grasp **the core principles that underlie the modeling of complex biological systems**.

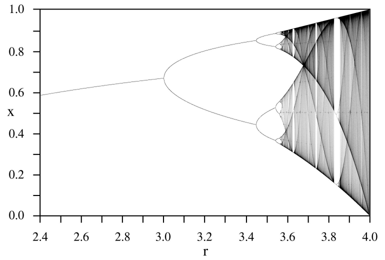
Applications in Biology:

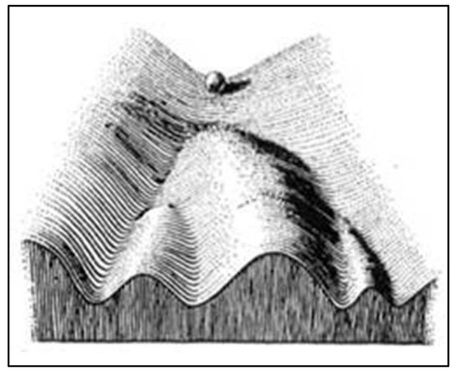
The theoretical foundations from this step are applied when modeling ecological systems, cellular signaling networks, and population dynamics in biology.

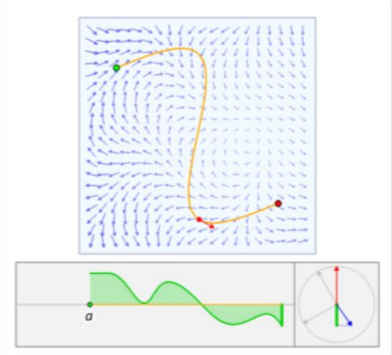


OUR STORY LINE









STEP 1 _ THEORY OF SYSTEMS

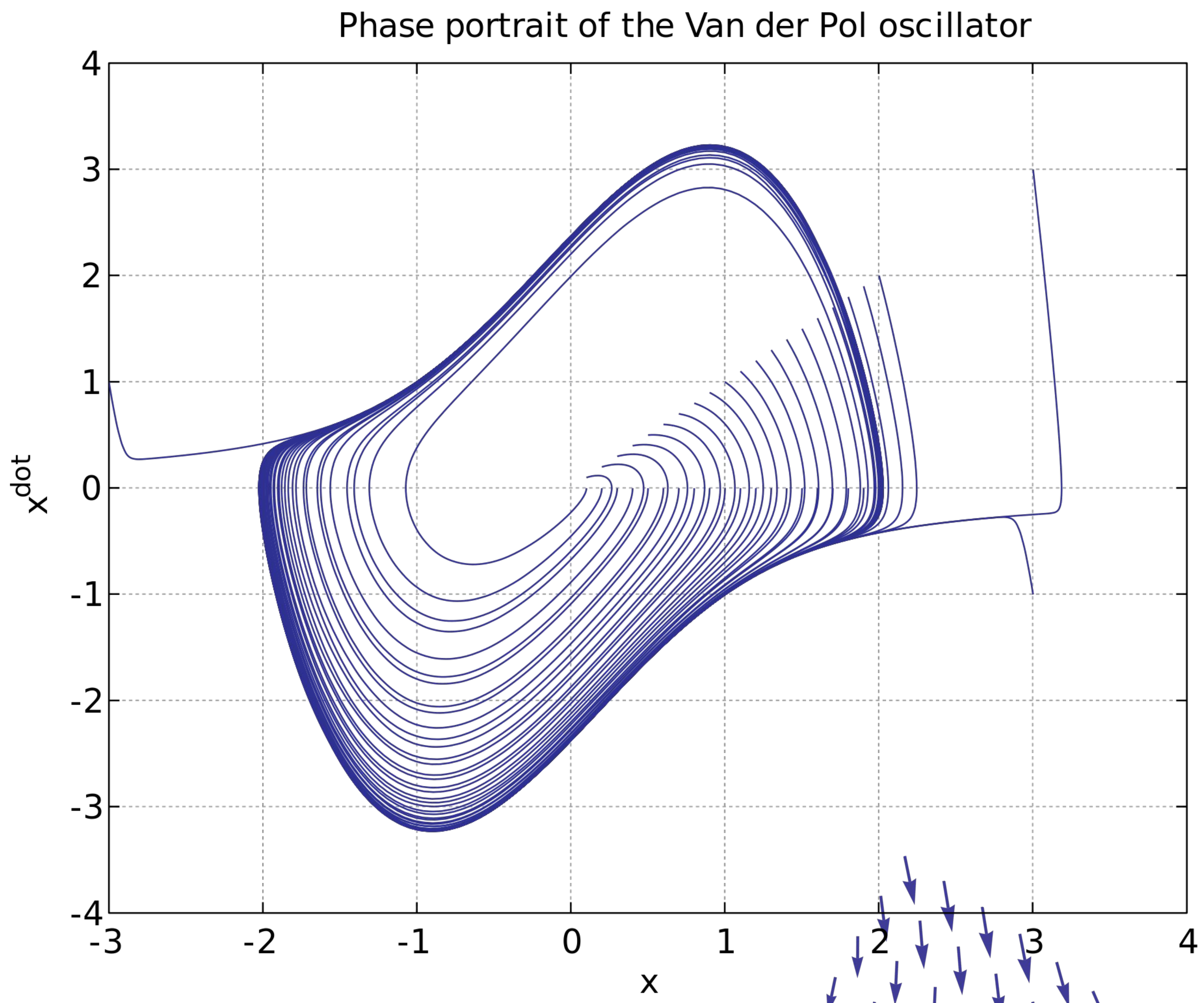
1.1 - DYNAMICAL SYSTEMS

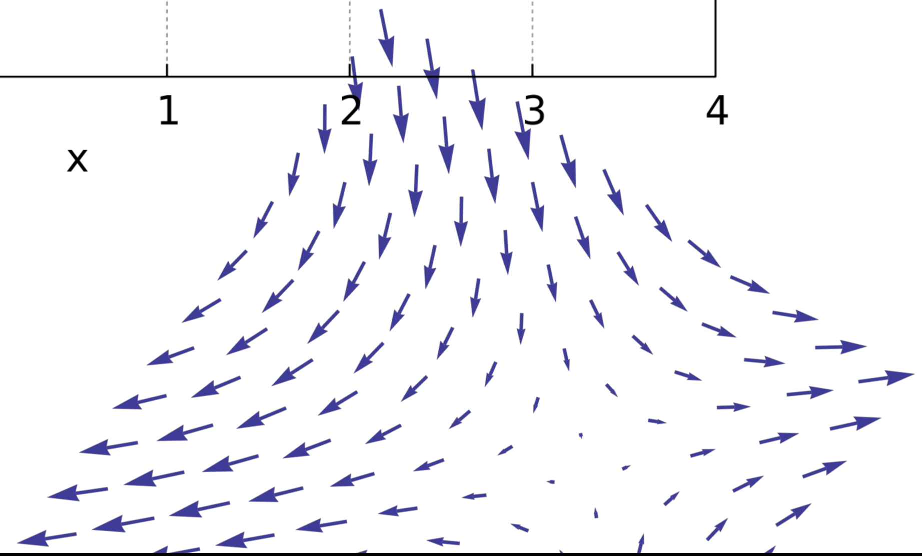
Description:
This course focuses on **dynamical systems theory**, which examines how systems change over time through differential equations and state-space representations.

Significance:
Dynamical systems theory is vital for modeling the **time-dependent behavior of biological systems**, including population dynamics and neural networks.

Applications in Biology:
It's applied to study ecological systems, epidemiology, and neural firing patterns.

Reference:
"Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry, and Engineering" by Steven H. Strogatz

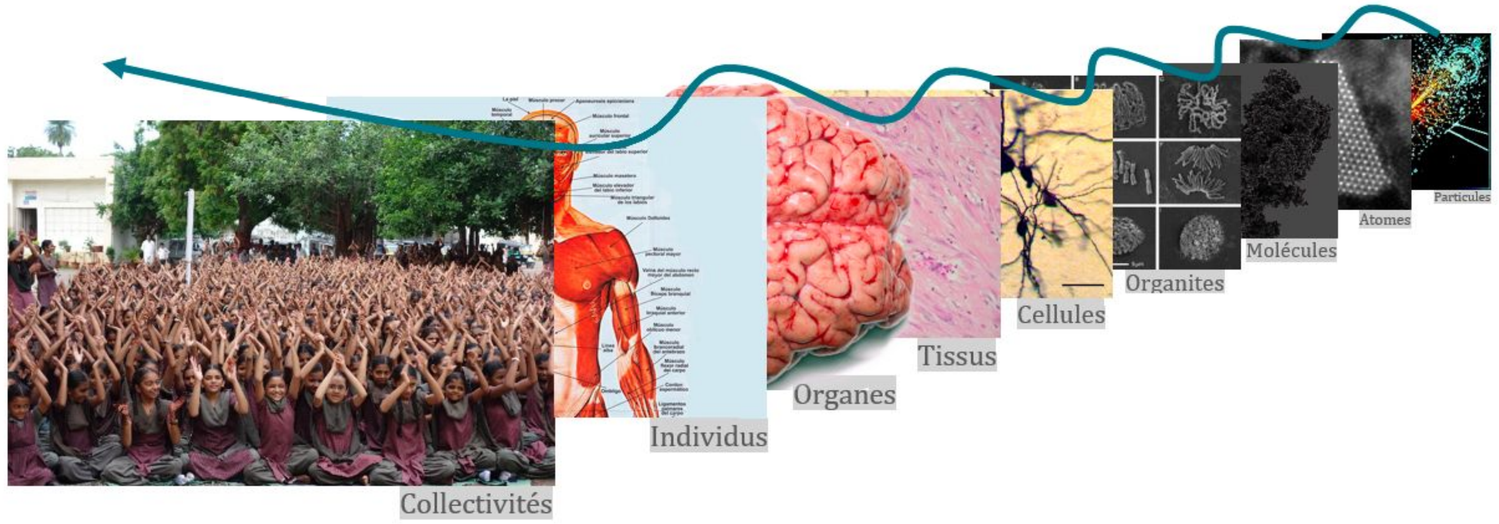




OUR STORY LINE

STEP 1 _ THEORY OF SYSTEMS

1.2 - COMPLEX ADAPTIVE SYSTEMS



Description:
This course delves into complex adaptive systems, which are **systems with many interacting components that adapt to their environment**.

Significance:
Complex adaptive systems theory is critical for **modeling biological systems like ecosystems**, immune systems, and social networks, which exhibit emergent behaviors.

Applications in Biology:
It's used to model the behavior of ant colonies, the immune response to infections, and the spread of diseases in populations.

Reference:
"Complex Adaptive Systems: An Introduction to Computational Models of Social Life" by John H. Miller and Scott E. Page

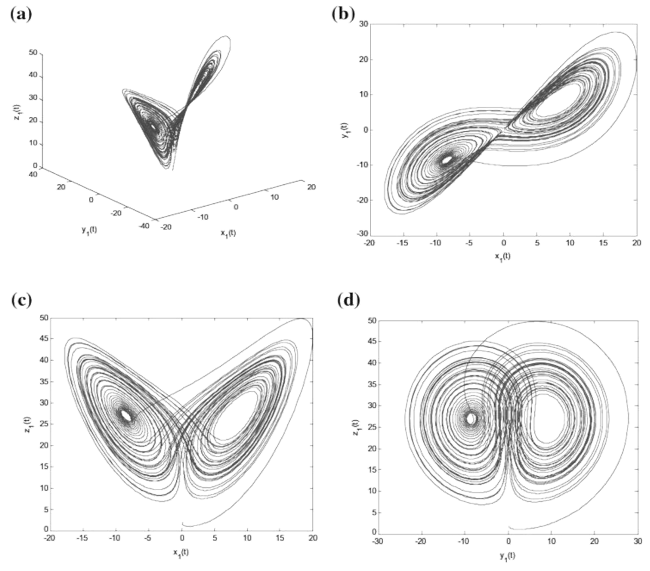


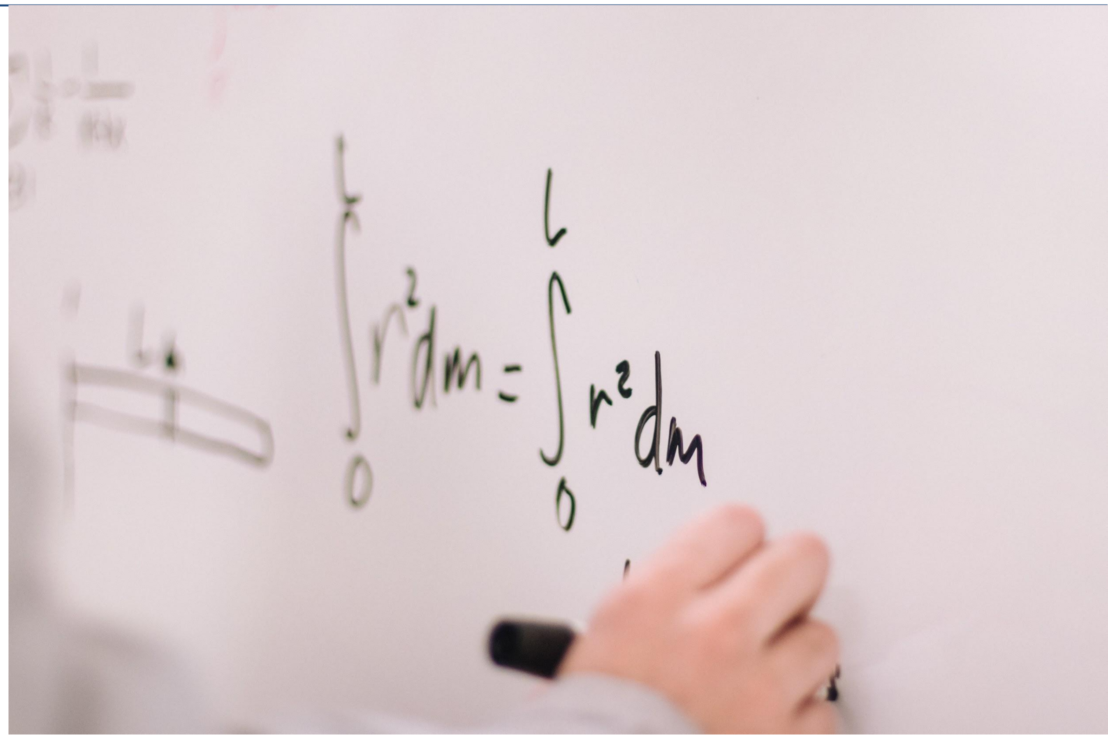
Fig. 1 Phase portraits of the Lorenz system at $q = 0.993$: **a** $x_1 - y_1 - z_1$ space, **b** $x_1 - y_1$ plane, **c** $x_1 - z_1$ plane, **d** $y_1 - z_1$ plane

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

General Description:
This step focuses on stochastic dynamics and probability theory, crucial for **modeling systems with inherent uncertainty**.

Significance:
Stochastic dynamics and probability are fundamental for **representing randomness and variability in biological systems**.

Applications in Biology:
They are used to model genetic mutations, population variability, and the spread of diseases in biology.



STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

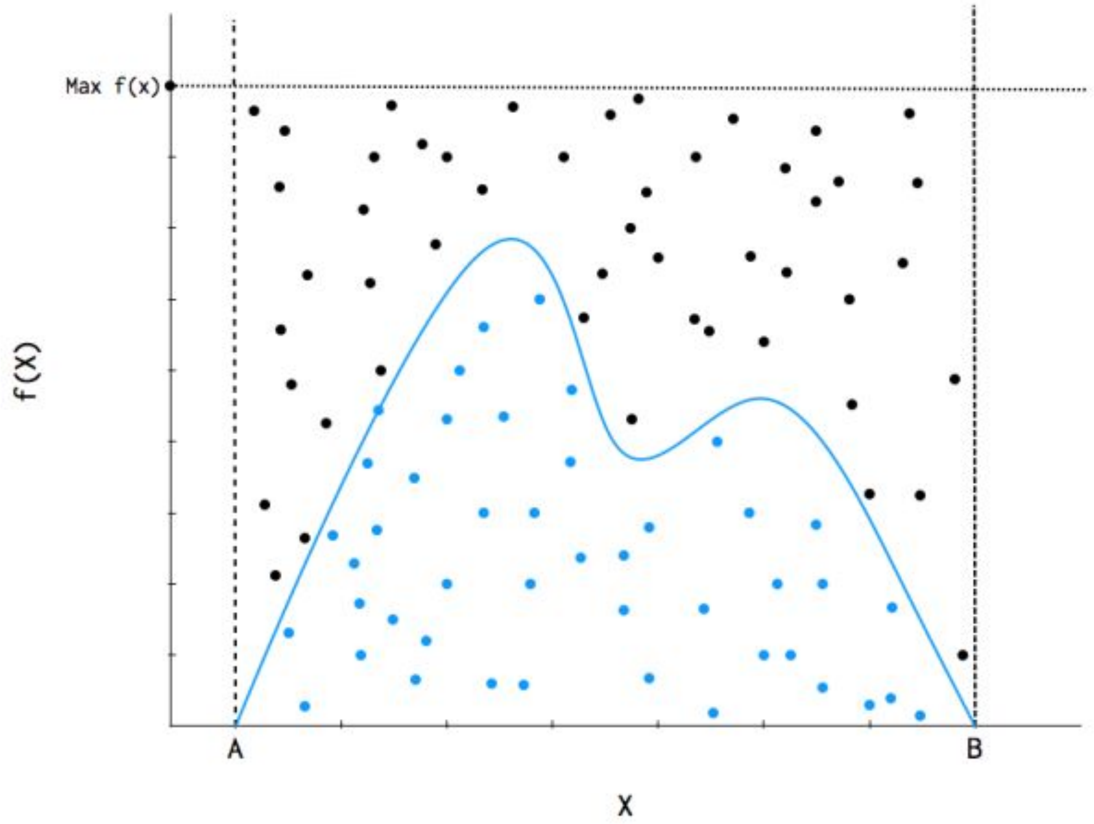
2.1 - MEASURE THEORY

Description:
This course covers measure theory, a branch of mathematics dealing with the construction and **properties of measures, which are used to study probabilistic phenomena**.

Significance:
Measure theory is **foundational for understanding probability distributions and stochastic processes**, which are essential for modeling uncertainty in biological systems.

Applications in Biology:
Measure theory is applied to study the randomness of genetic mutations, variation in gene expression, and modeling biochemical reactions under uncertainty.

Reference:
"Real Analysis: Measure Theory, Integration, and Hilbert Spaces" by Elias M. Stein and Rami Shakarchi



STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

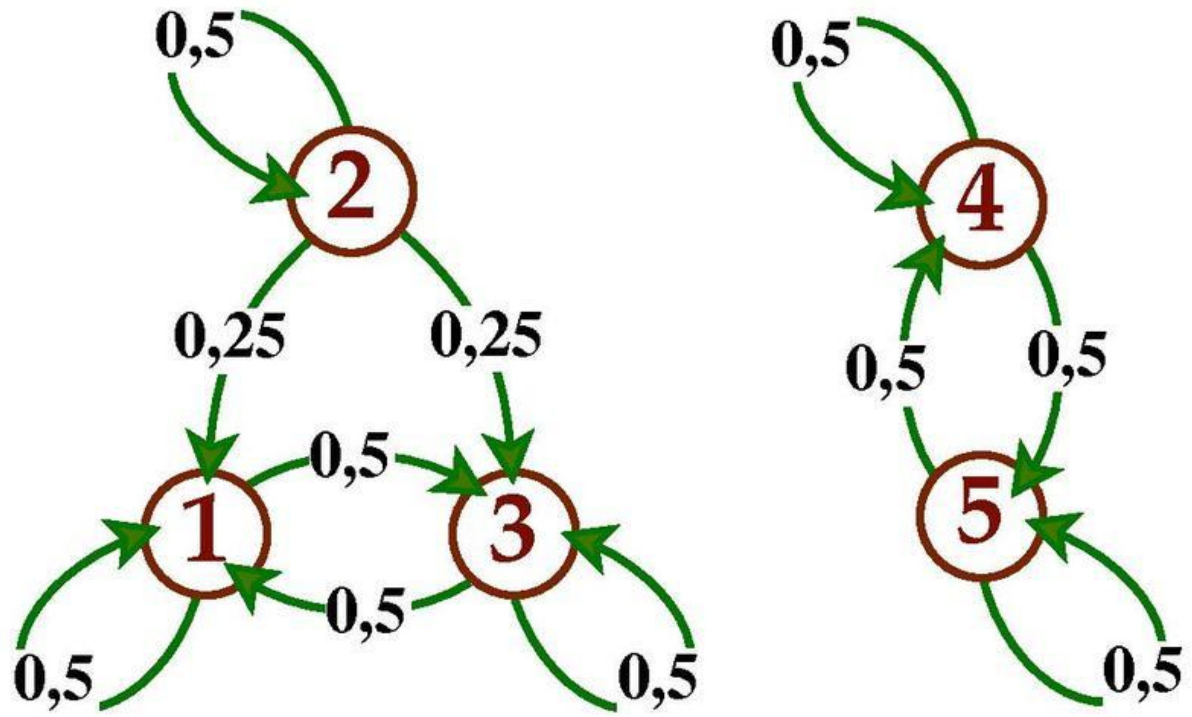
2.2 - PROBABILITY THEORY

Description:
This course explores the principles and methods of probability theory, including concepts like **random variables**, **probability distributions**, and conditional probability.

Significance:
Probability theory is a key component for **modeling the uncertainty and variability inherent in biological systems**.

Applications in Biology:
Probability theory is used everywhere !

Reference:
"Stochastic Processes in Physics and Chemistry"
N.G. Van Kampen



STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

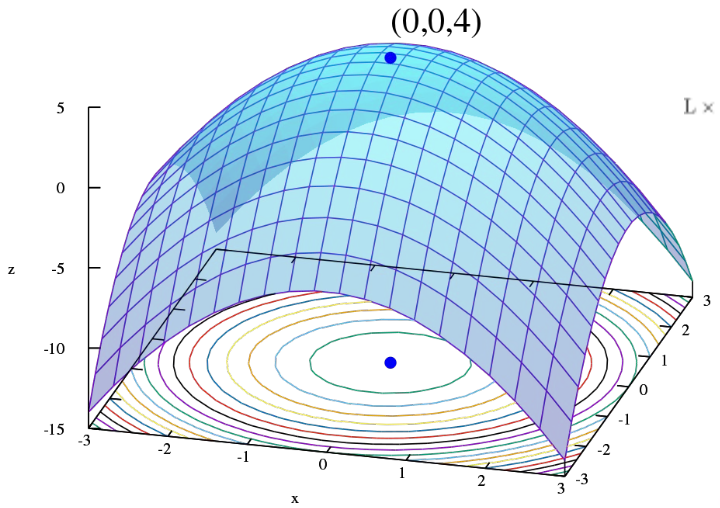
2.3 - USUAL PROBABILITY DISTRIBUTIONS

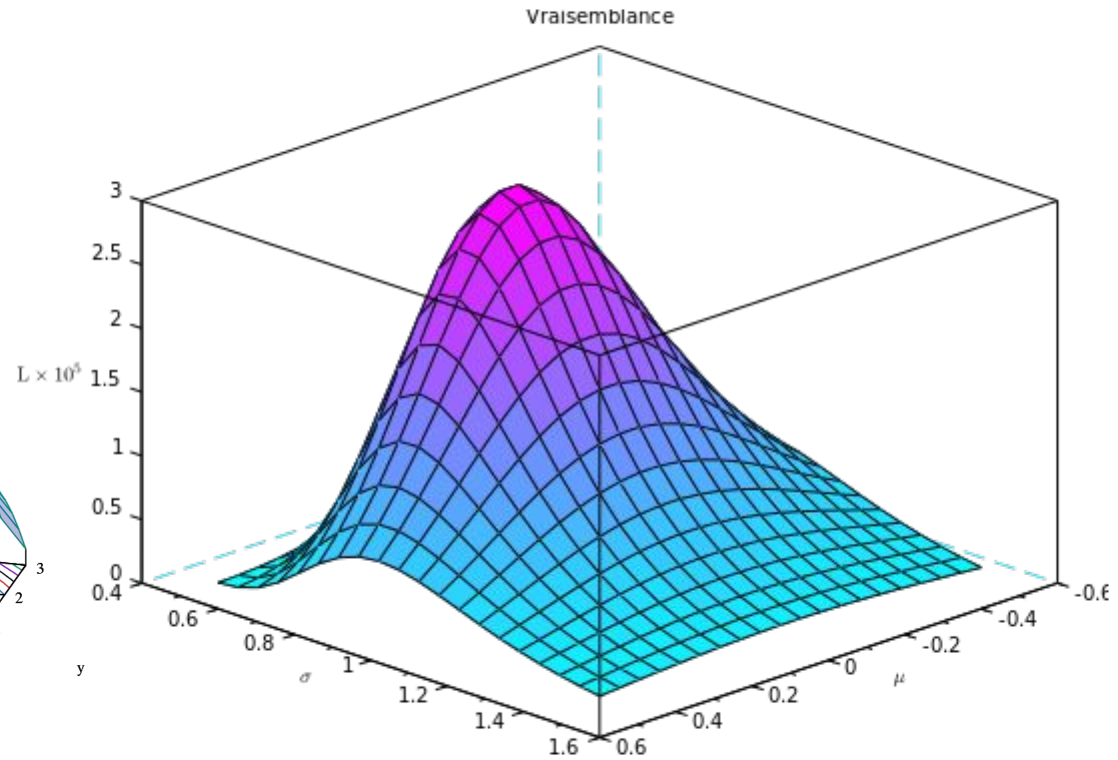
Description:
This course covers common probability distributions such as the **Gaussian, Poisson, and binomial distributions** and their properties.

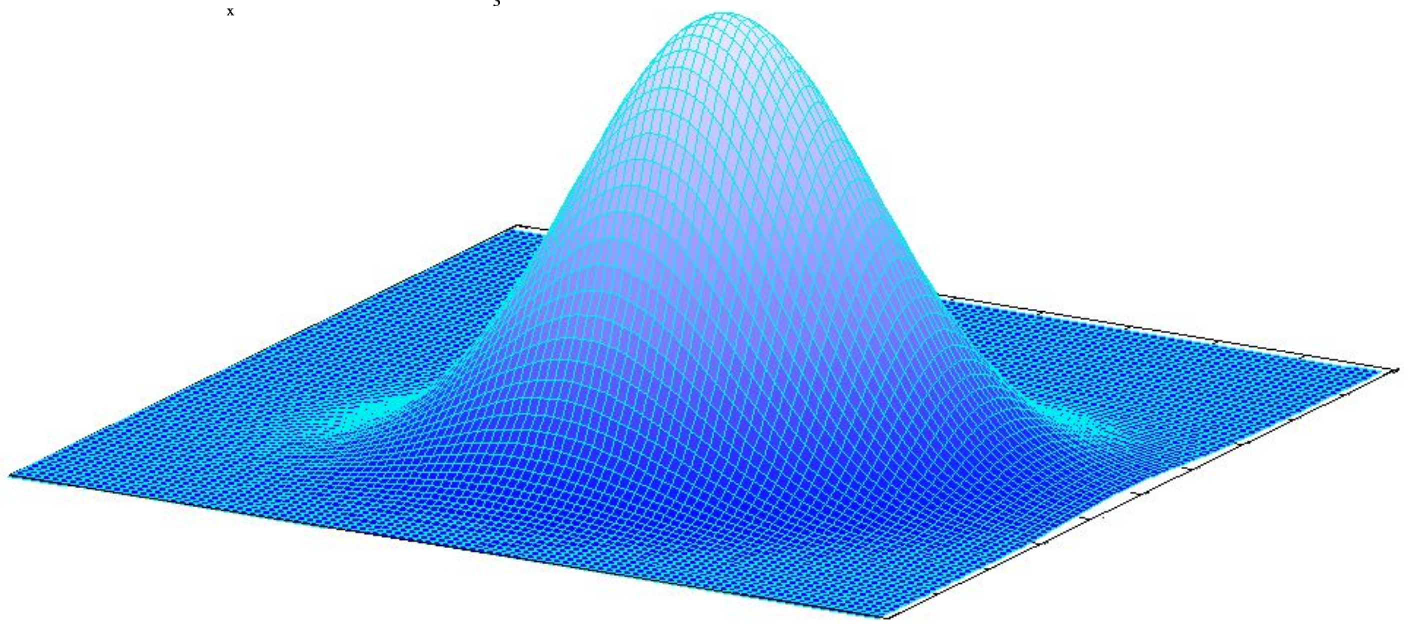
Significance:
Understanding these distributions is crucial for **modeling random events and data** in biology.

Applications in Biology:
Gaussian distributions are used to model measurement errors in experiments, Poisson distributions describe count data (e.g., cell division events), and binomial distributions are used in genetics.

Reference:
"Probability and Statistics" by Morris H. DeGroot and Mark J. Schervish







STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

2.4 - ASYMPTOTIC STATISTICS

Description:

This course deals with the **behavior of statistical estimators and tests as sample sizes grow to infinity**.

Significance:

Asymptotic statistics is important for understanding the **limits and reliability of statistical methods in the context of large biological datasets**.

Applications in Biology:

It's applied in genomics to analyze large-scale gene expression data, where sample sizes can be substantial.

Reference:

"Large Sample Techniques for Statistics" by Lehmann, E. L., and Casella, G.

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

2.5 - STOCHASTIC PROCESS & TIME SERIES

Description:

This course explores **stochastic processes, which are collections of random variables evolving over time**, and time series analysis, focusing on **data collected sequentially in time**.

Significance:

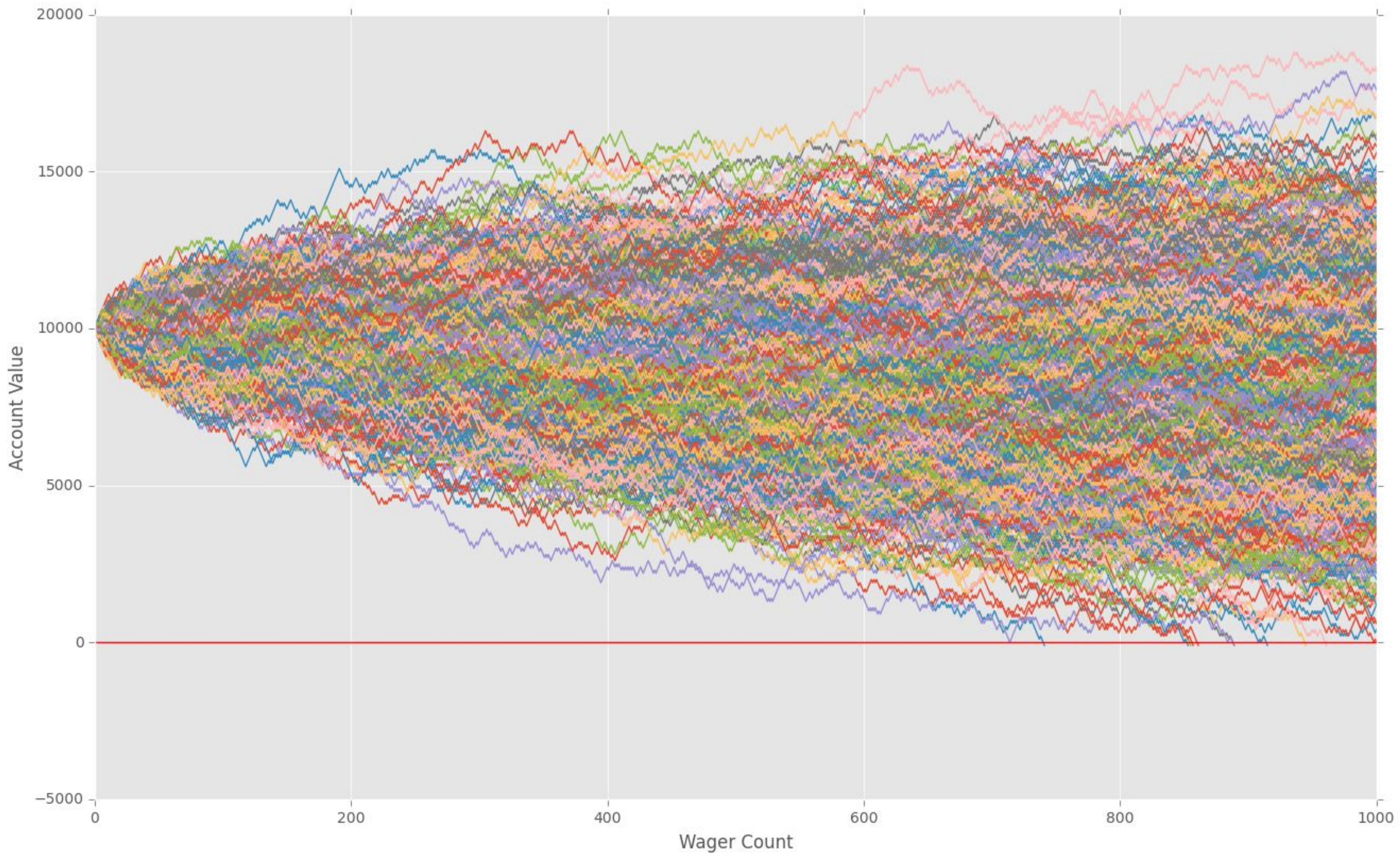
Stochastic processes are used to **model dynamic biological systems with random components**, and time series analysis helps **identify patterns** and trends.

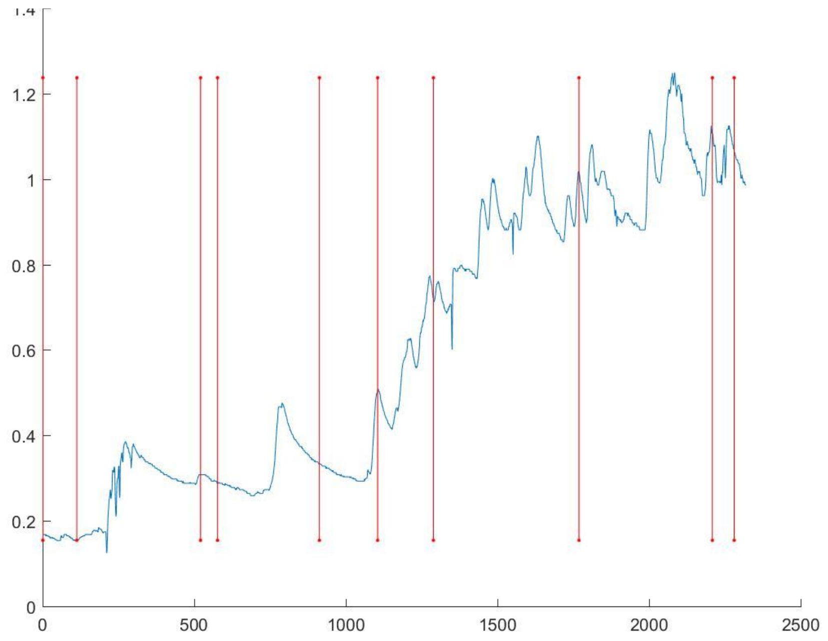
Applications in Biology:

It's applied to model gene expression time series, analyze ecological data, and study neuronal firing patterns.

Reference:

"Time Series Analysis and Its Applications: With R Examples" by Robert H. Shumway and David S. Stoffer

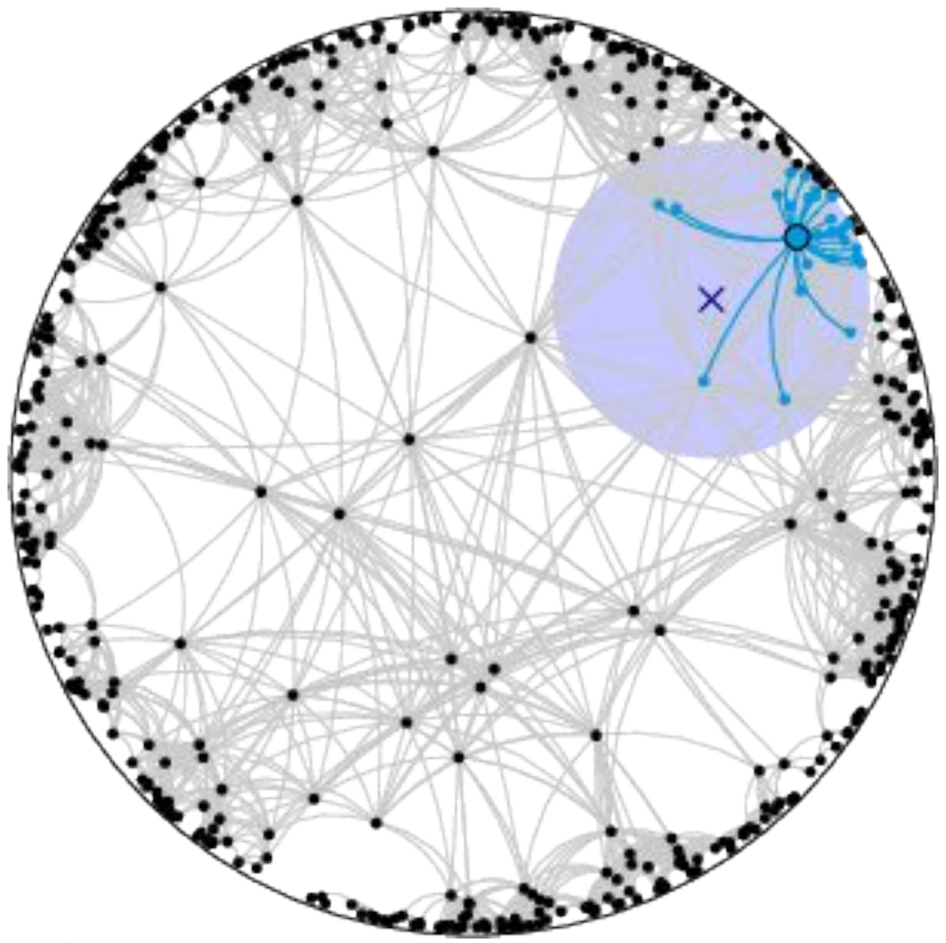




OUR STORY LINE

STEP 2 _ STOCHASTIC DYNAMICS & PROBABILITY

2.6 - INFORMATION GEOMETRY



Description:

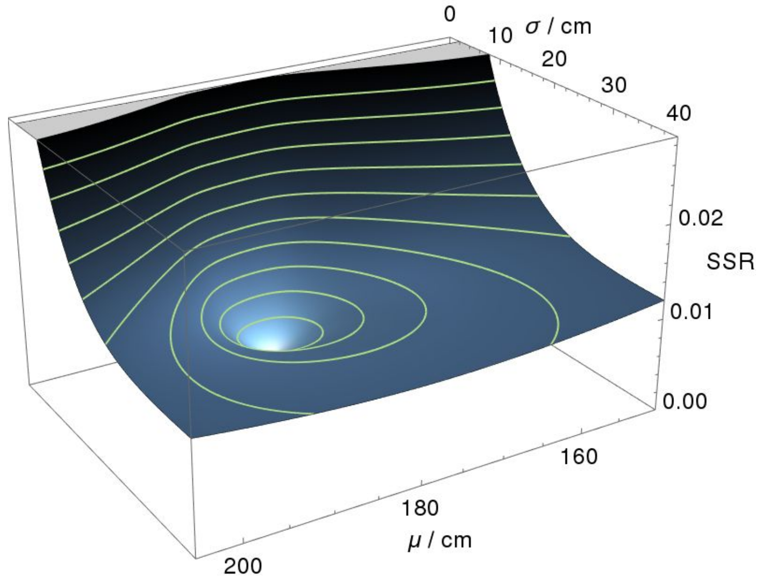
This course delves into information geometry, a field that **applies differential geometry to probability theory and information theory**.

Significance:

Information geometry is valuable for understanding the **geometric structure of probability distributions**, which is useful in complex biological data analysis.

Applications in Biology:

It's used in phylogenetic tree construction, analyzing **high-dimensional biological data**, and modeling molecular evolution.



Reference:

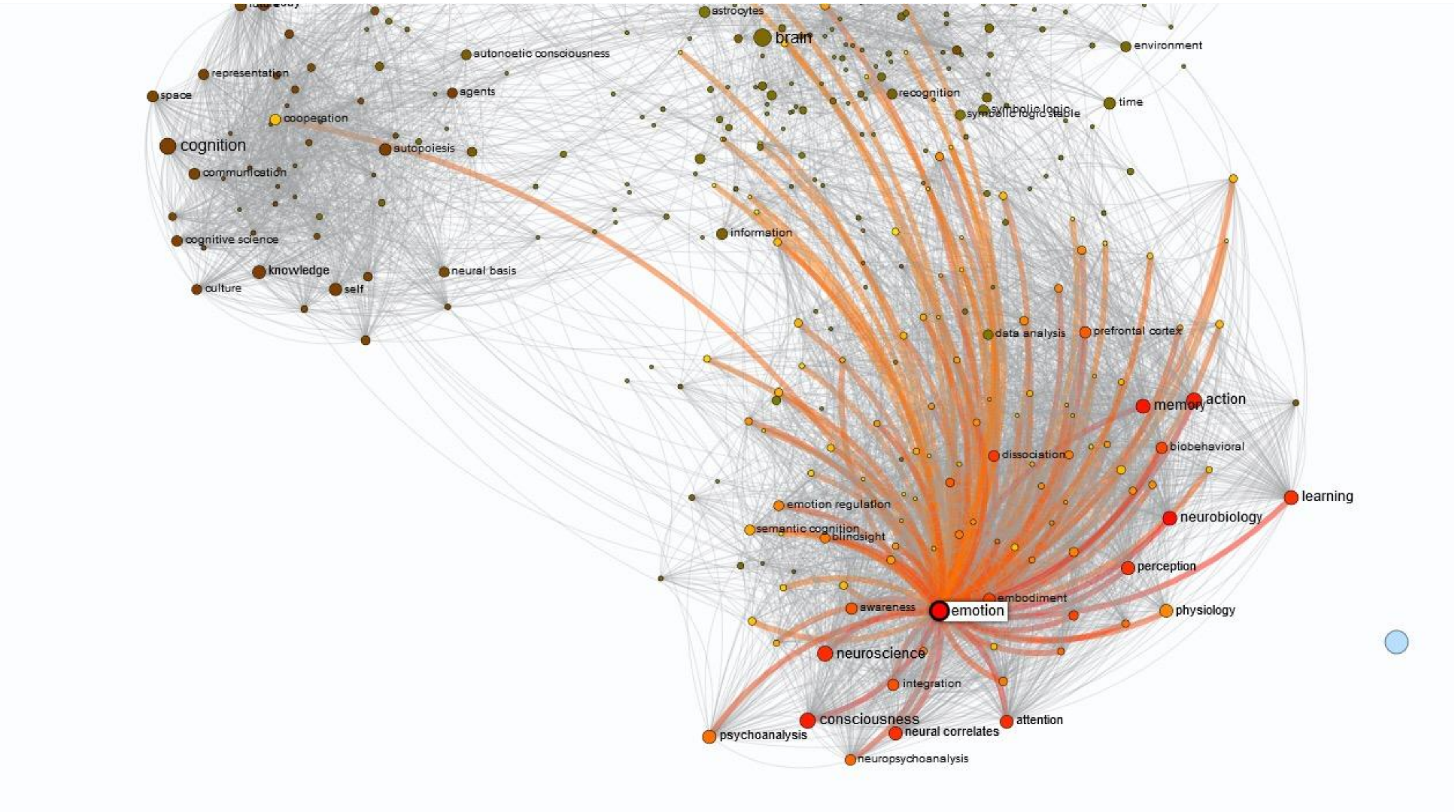
"Information Geometry and Its Applications" by Shun-ichi Amari and Hiroshi Nagaoka

STEP 3 _ DATA OBSERVATION & DATA VISUALIZATION

General Description:
Data Observation covers **statistical techniques for observing, summarizing, and exploring data.**

Significance:
These skills are vital for **gathering insights from biological data, understanding patterns, and identifying variables of interest**.

Applications in Biology:
Data observation techniques are applied to analyze gene expression data, ecological surveys, and clinical trial outcomes in biology.



STEP 3 _ DATA OBSERVATION

3.1 - DESCRIPTIVE STATISTICS & DATA VISUALIZATION

Description:

This course covers descriptive statistics, which involve **summarizing and presenting data using measures of central tendency, variability, and graphical representations**.

Significance:

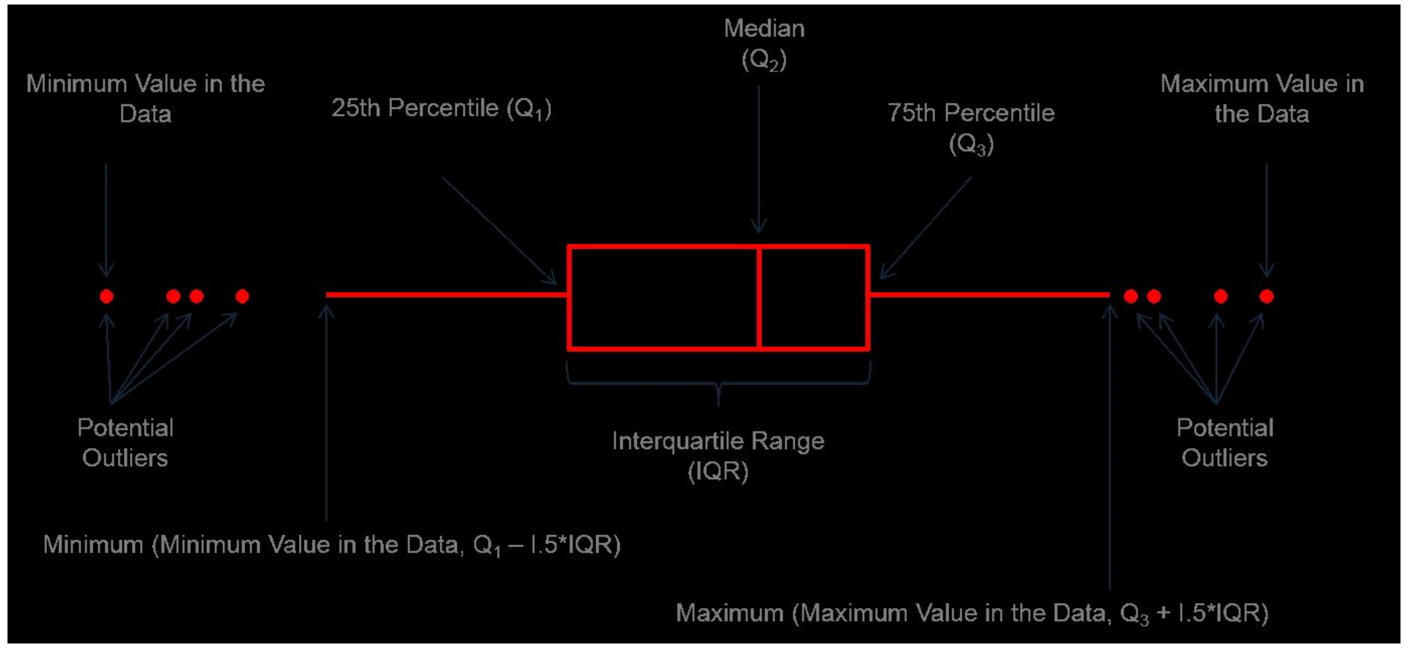
Descriptive statistics are **essential for understanding the characteristics and patterns in biological data**.

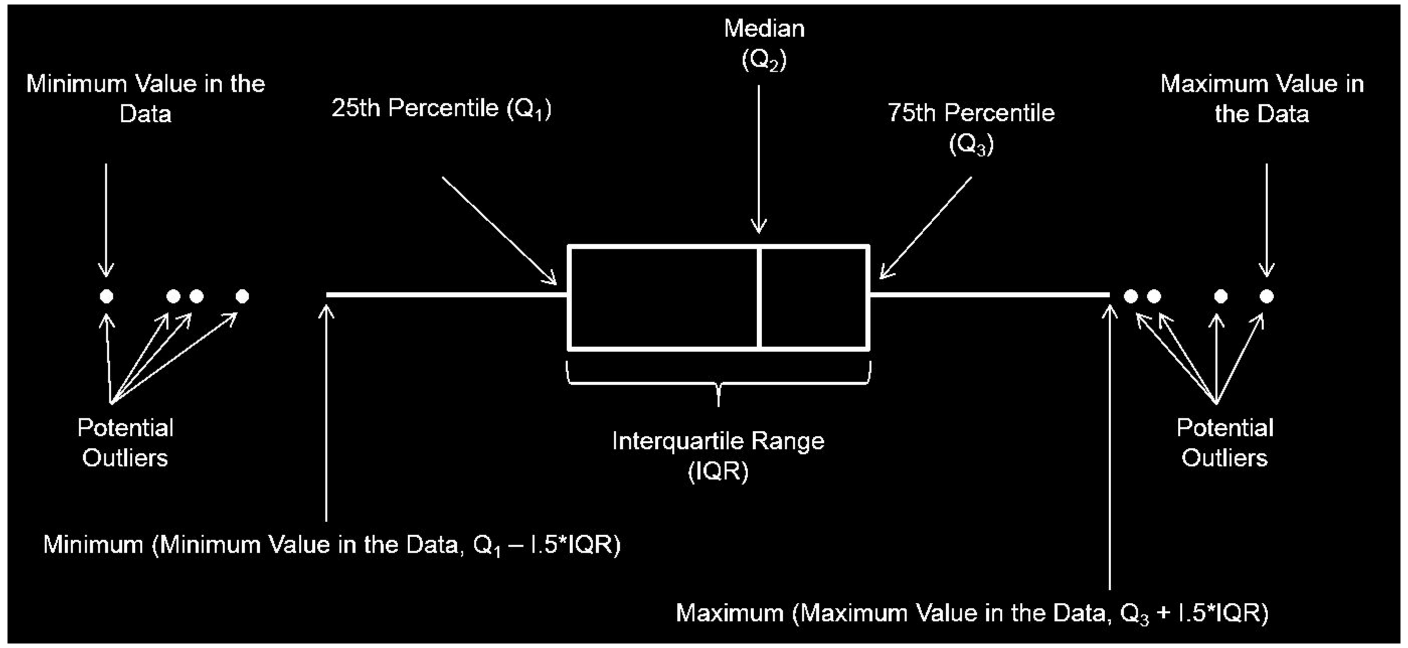
Applications in Biology:

Descriptive statistics are used to summarize features of gene expression data, describe the distribution of species in ecological surveys, and analyze clinical trial outcomes.

Reference:

"Introduction to the Practice of Statistics" by David S. Moore, George P. McCabe, and Bruce A. Craig

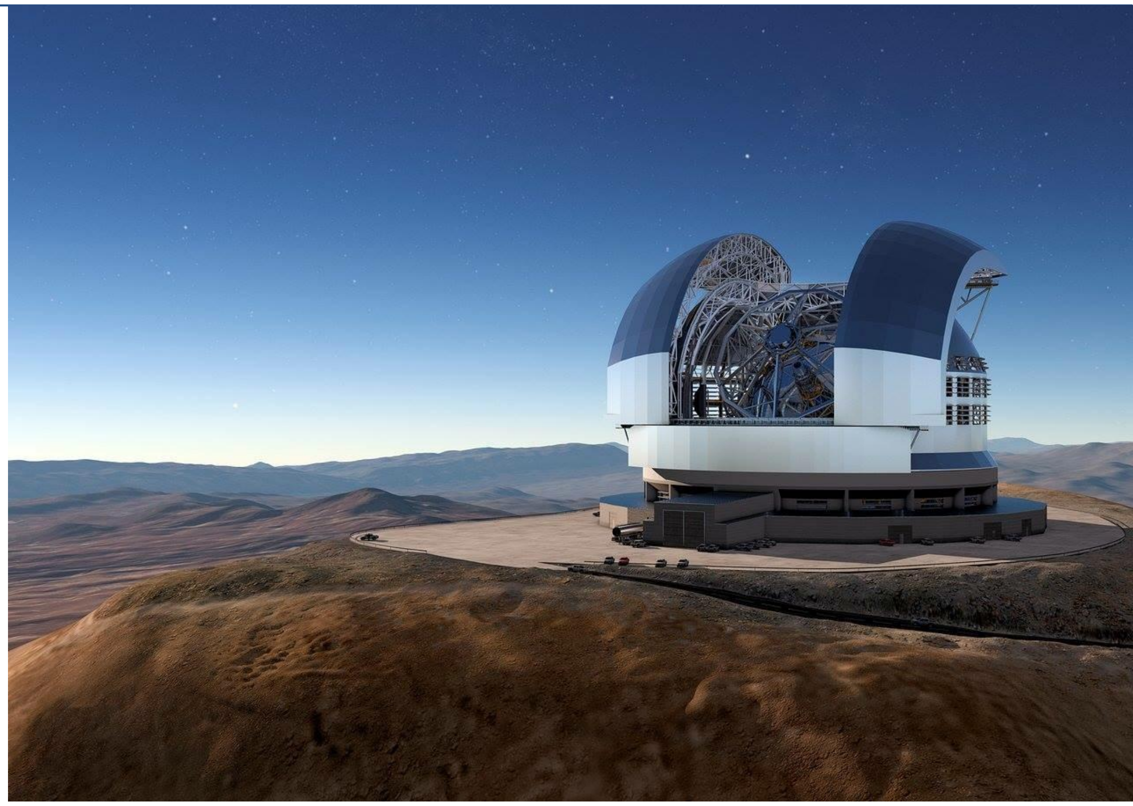


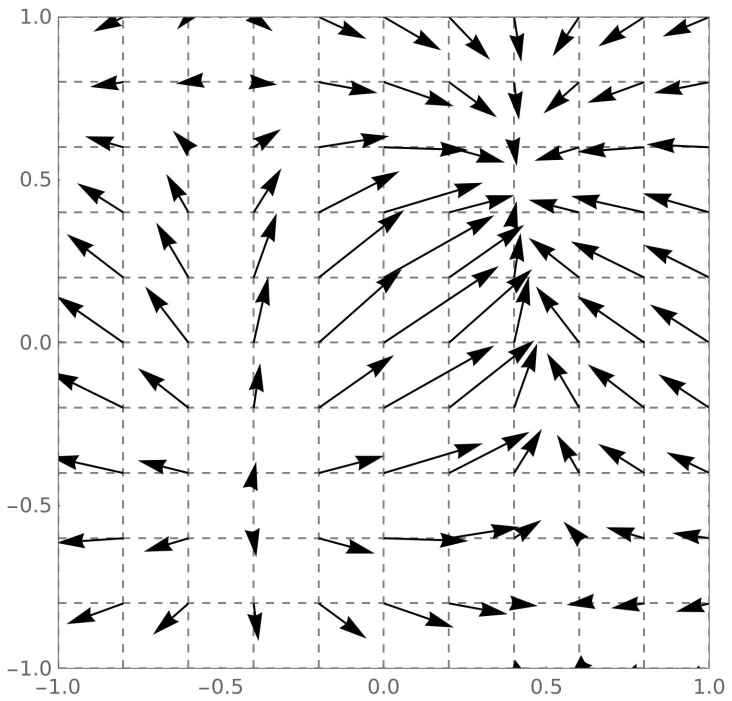


OUR STORY LINE

STEP 3 _ DATA OBSERVATION

3.2 - EXPLORATORY DATA ANALYSIS



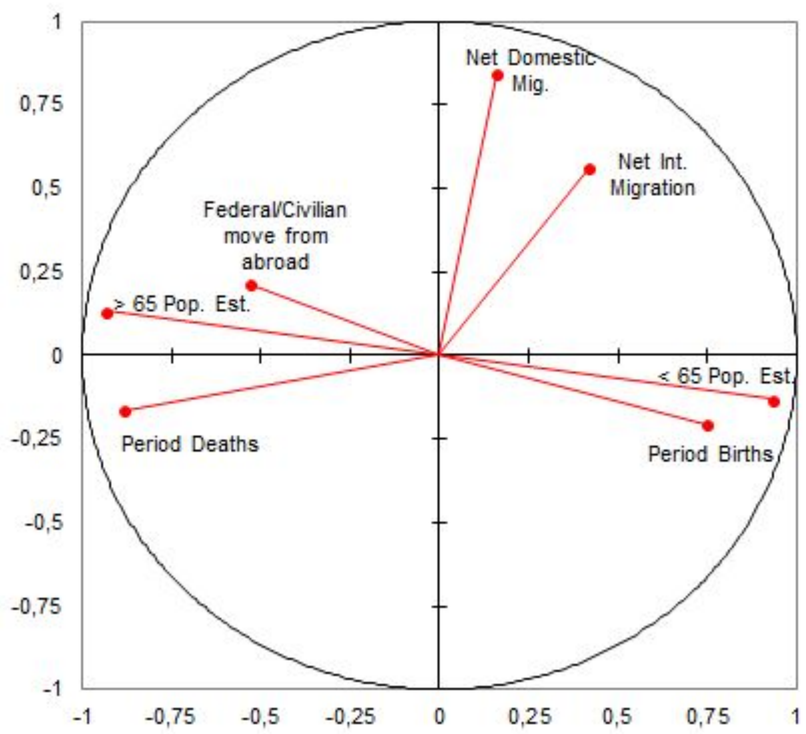


Description:
This course focuses on exploratory data analysis (EDA), **a process of visually and statistically exploring datasets to uncover patterns, anomalies, and relationships**.

Significance:
EDA is a crucial step in understanding complex biological data and **identifying potential variables** for modeling.

Applications in Biology:
EDA is applied in genomics to visualize gene expression profiles, identify biomarkers, and discover associations between genetic variants and diseases.

Reference:
"Exploratory Data Analysis" by John W. Tukey

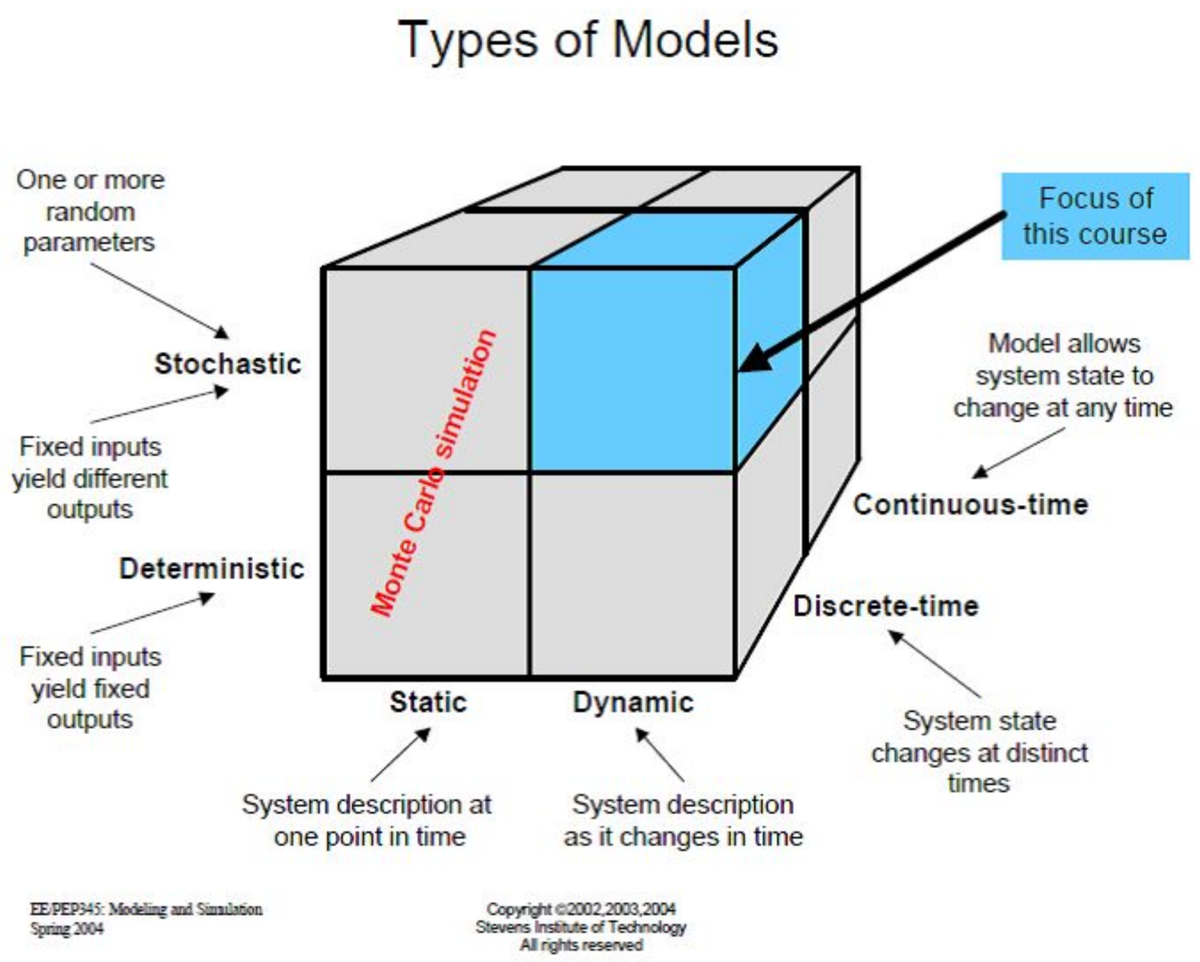


STEP 4 _ INFERENCE & ESTIMATION THEORY

General Description:
Inference and Estimation Theory teaches students how to **make predictions and draw conclusions from data**.

Significance:
These techniques **enable you to make informed decisions and draw meaningful insights from biological data**.

Applications in Biology:
Inference and estimation are used in epidemiology, genetics, and clinical studies to make predictions and draw conclusions about disease prevalence, genetic associations, and treatment effectiveness.



OUR STORY LINE

STEP 4 _ INFERENCE & ESTIMATION THEORY

4.1 - PARAMETERS ESTIMATIONS

Description:

This course deals with **methods for estimating population parameters from sample data**, including **point estimates** and **confidence intervals**.

Significance:

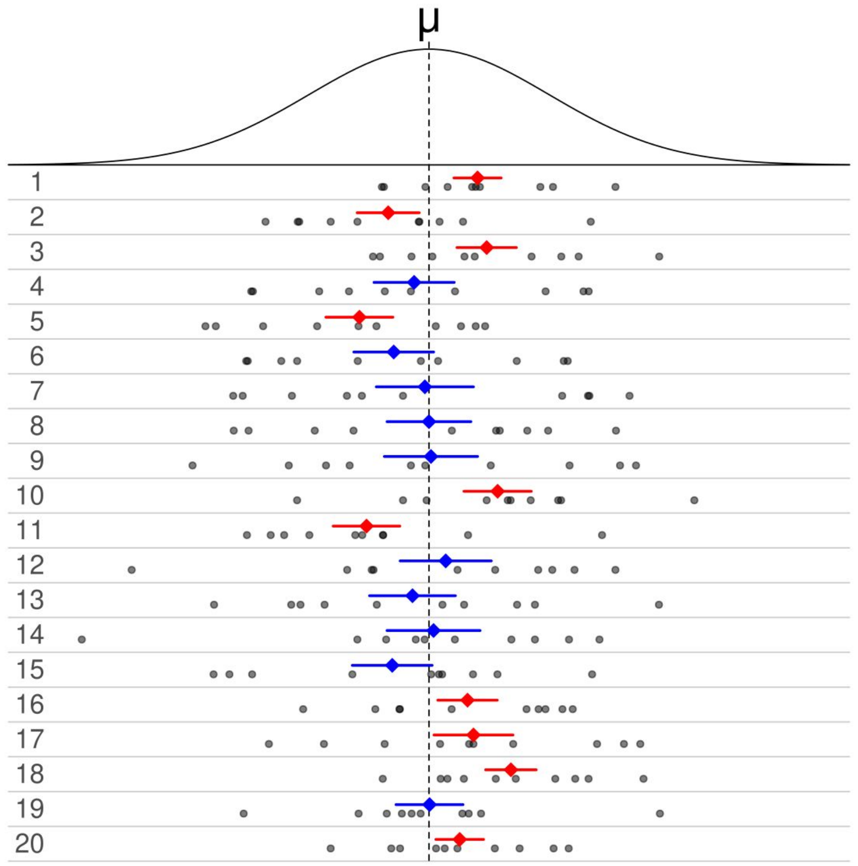
Parameter estimation is **fundamental for making inferences about biological populations from limited data**.

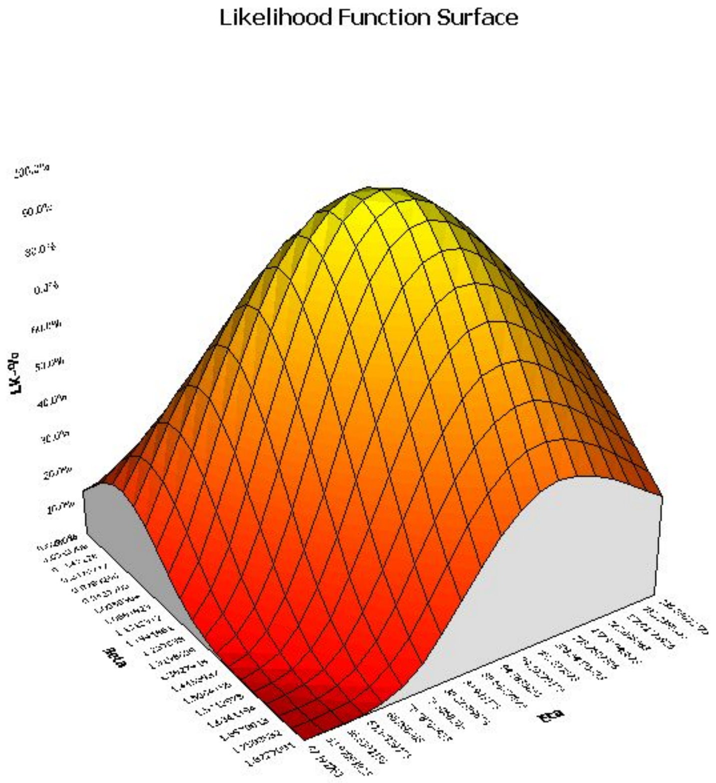
Applications in Biology:

It's used to estimate parameters in population growth models, calculate genetic diversity metrics, and determine drug dosage levels.

Reference:

"Statistical Inference" by George Casella and Roger L. Berger





STEP 4 _ INFERENCE & ESTIMATION THEORY

4.2 - EXPERIMENTAL DESIGN & HYPOTHESIS TESTING

Description:

This course covers experimental design principles and **hypothesis testing methods for evaluating scientific hypotheses**.

Significance:

Proper experimental design and hypothesis testing are critical for **conducting rigorous biological experiments and making informed decisions**.

Applications in Biology:

It's applied in clinical trials to test the effectiveness of new drugs, assess the impact of environmental factors on ecosystems, and evaluate the significance of genetic mutations.

Reference:

"Design and Analysis of Experiments" by Douglas C. Montgomery

STEP 4 _ INFERENCE & ESTIMATION THEORY

4.3 - STATISTICAL SAMPLING METHODS

Description:

This course explores various **sampling methods used to collect representative data from populations**.

Significance:

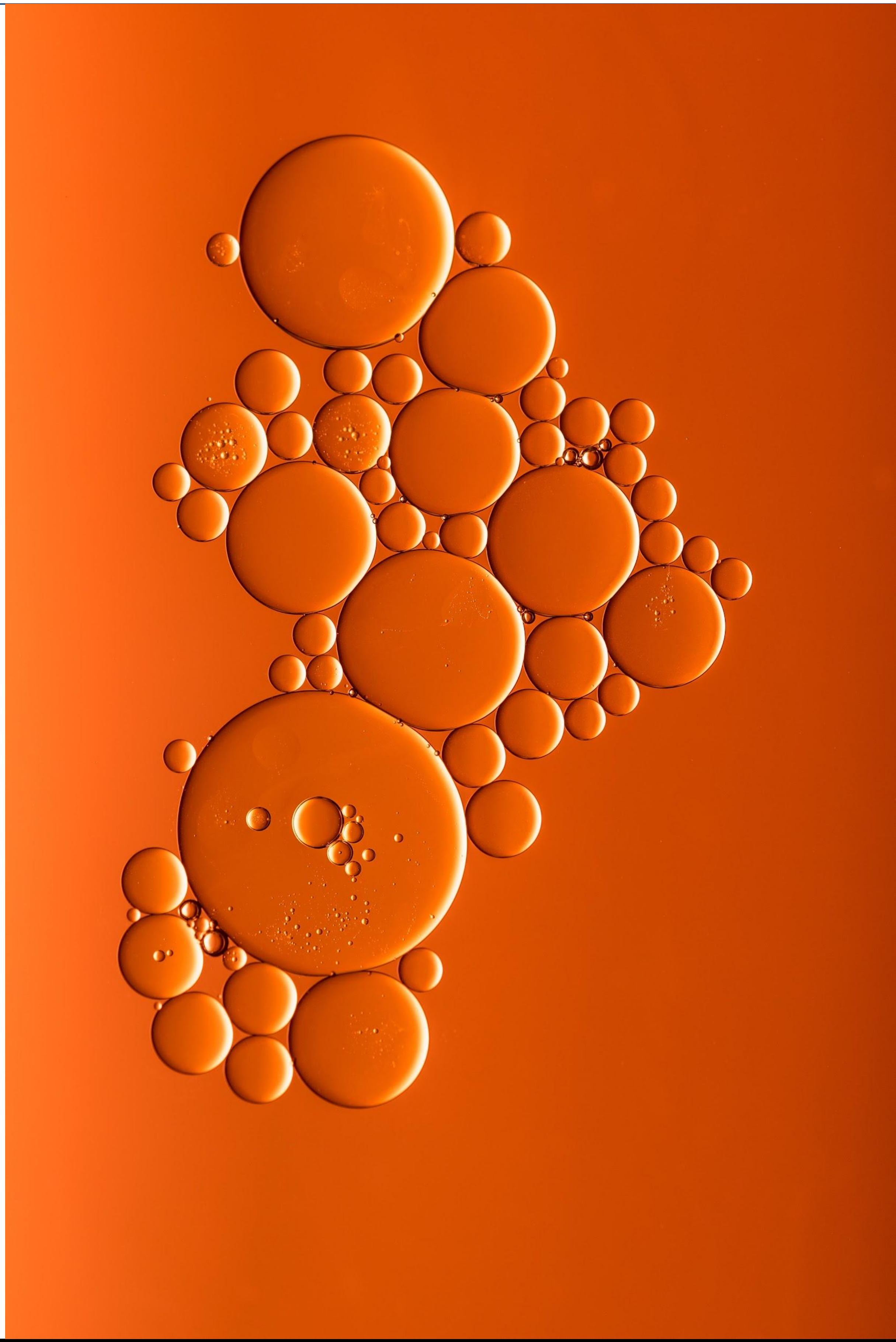
Sampling methods are essential in biology for **selecting study subjects, collecting data, and ensuring the generalizability of results**.

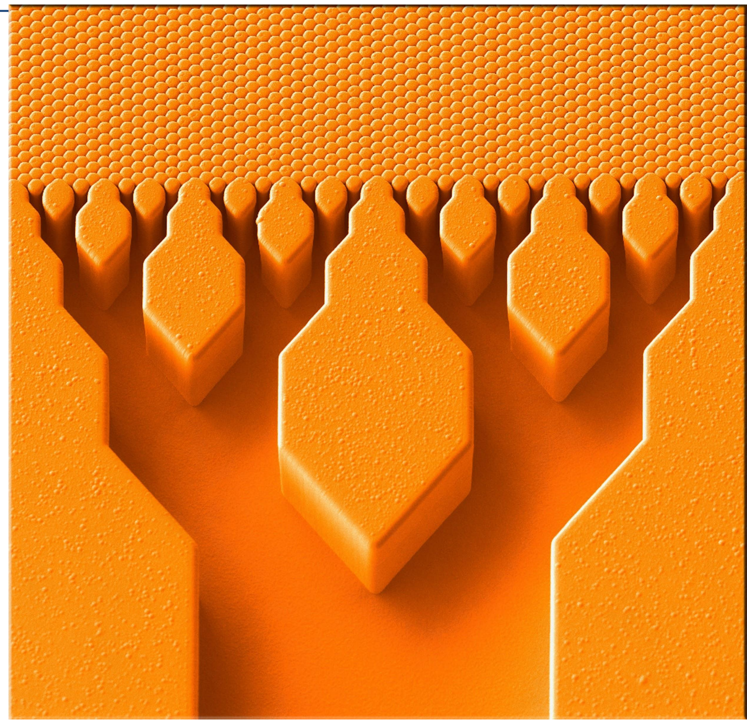
Applications in Biology:

Sampling methods are used in ecological surveys, biodiversity assessments, and clinical studies.

Reference:

"Sampling Techniques" by William G. Cochran





STEP 4 _ INFERENCE & ESTIMATION THEORY

4.4 - DECISION TREE & MODELS SELECTION

Description:

This course discusses **decision tree diagrams** and **model selection techniques** to choose the best model for a given dataset.

Significance:

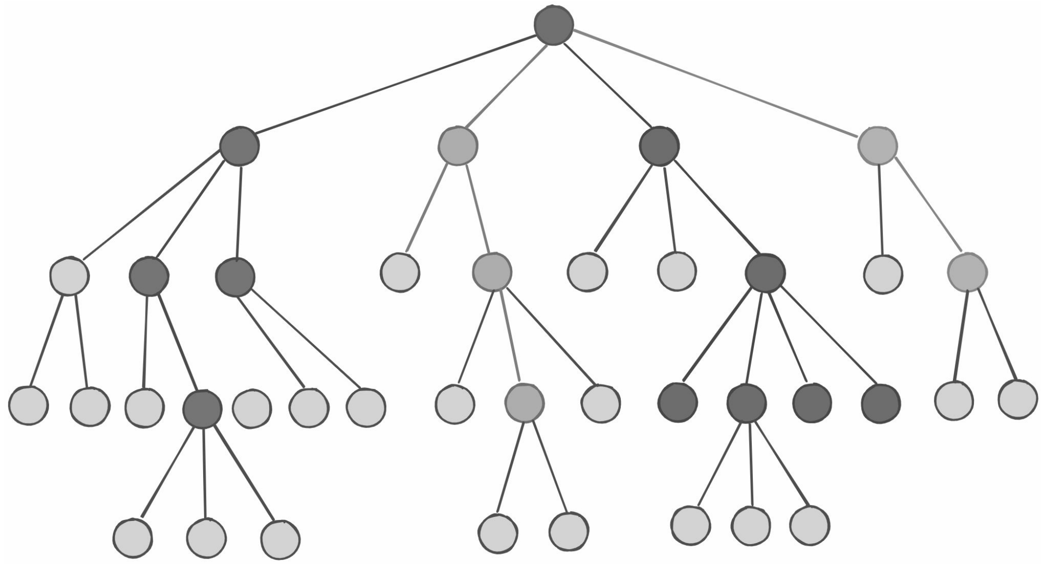
A global view of the **decision tree you have to go through is necessary to choose the right model** !

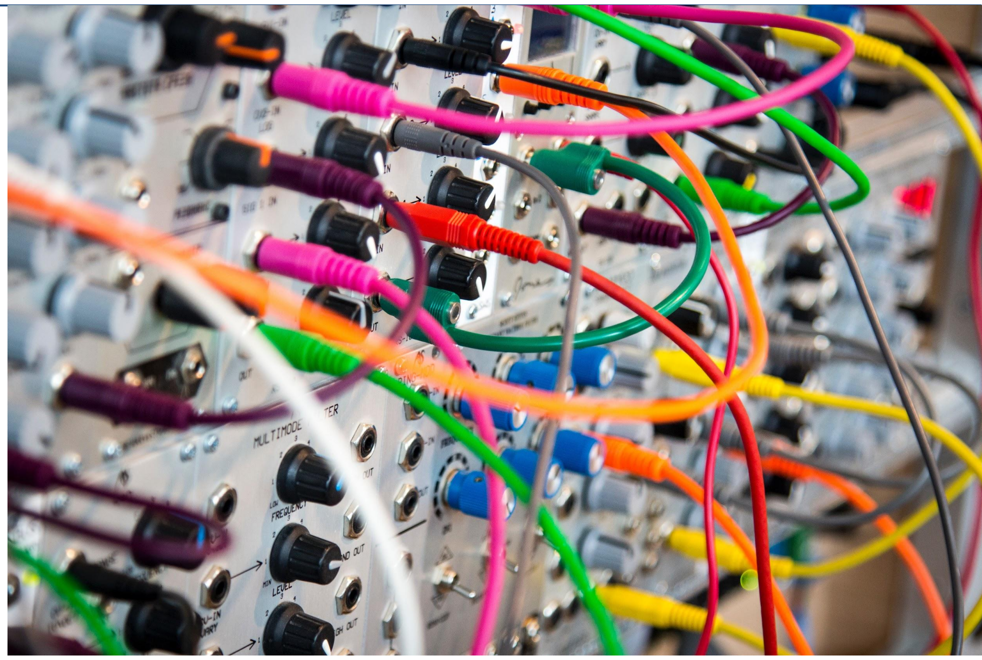
Applications in Biology:

Application for every experiment !

Reference:

"Introduction to Data Mining" by Pang-Ning Tan, Michael Steinbach, and Vipin Kumar





STEP 4 _ INFERENCE & ESTIMATION THEORY

4.5 - BAYESIAN INFERENCES

Description:

This course introduces **Bayesian inference, a statistical framework that incorporates prior knowledge to update beliefs based on observed data**.

$$P(B_J \mid A) = \frac{P(A \mid B_J)\,P(B_J)}{\sum_{i=1}^{n} P(A \mid B_i)\,P(B_i)}$$

Calcworkshop.com

Significance:

Bayesian inference is powerful for modeling **complex systems with limited data** and incorporating expert knowledge.

Applications in Biology:

Bayesian methods are used in phylogenetics, protein structure prediction, and personalized medicine.

Reference:

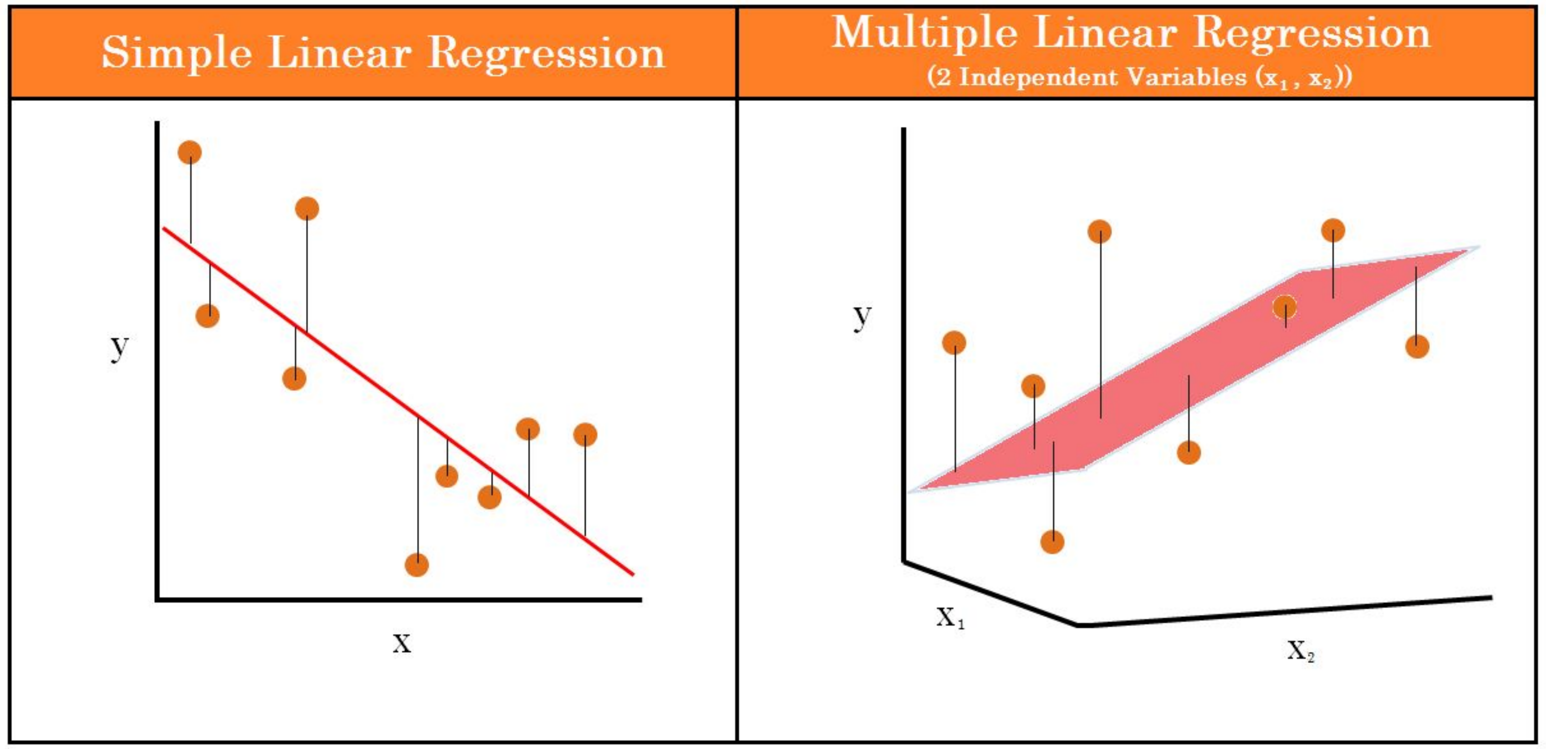
"Bayesian Data Analysis" by Andrew Gelman, John B. Carlin, Hal S. Stern, et al.

STEP 5 _ LINEAR / REGRESSION MODELS EXAMPLES

General Description:
Linear Models Examples **introduce you to linear regression and other linear modeling techniques**.

Significance:
These models help students **understand and predict relationships between variables in biological systems**.

Applications in Biology:
Linear models are used in genomics, pharmacokinetics, and ecological studies to predict outcomes based on linear relationships between variables.



STEP 5 _ LINEAR MODELS EXAMPLES

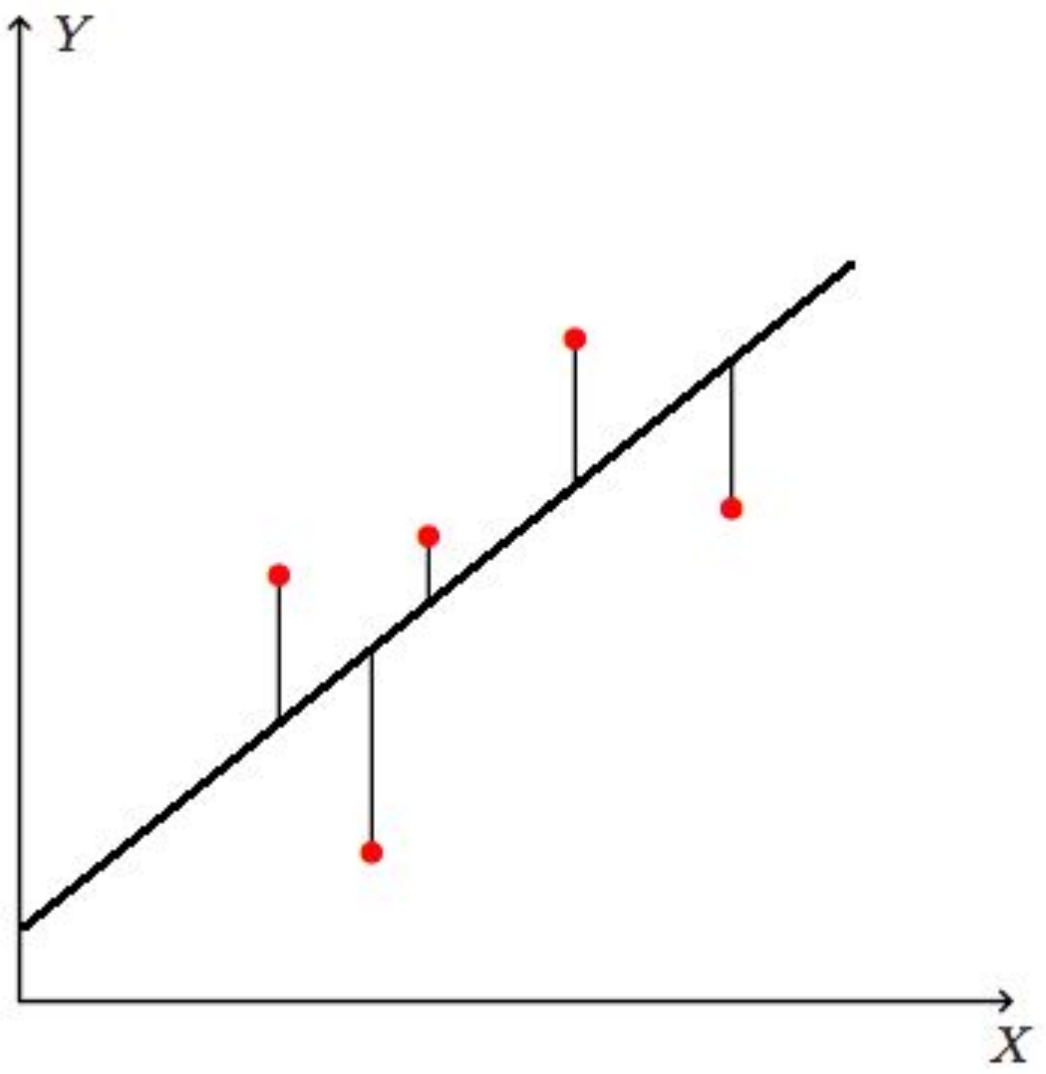
5.1 - SIMPLE LINEAR REGRESSION

Description:
This course covers simple linear regression, a statistical technique for **modeling the relationship between two variables using a linear equation**.

Significance:
Simple linear regression is **the foundation for understanding how one variable influences another**, which is important in biological modeling.

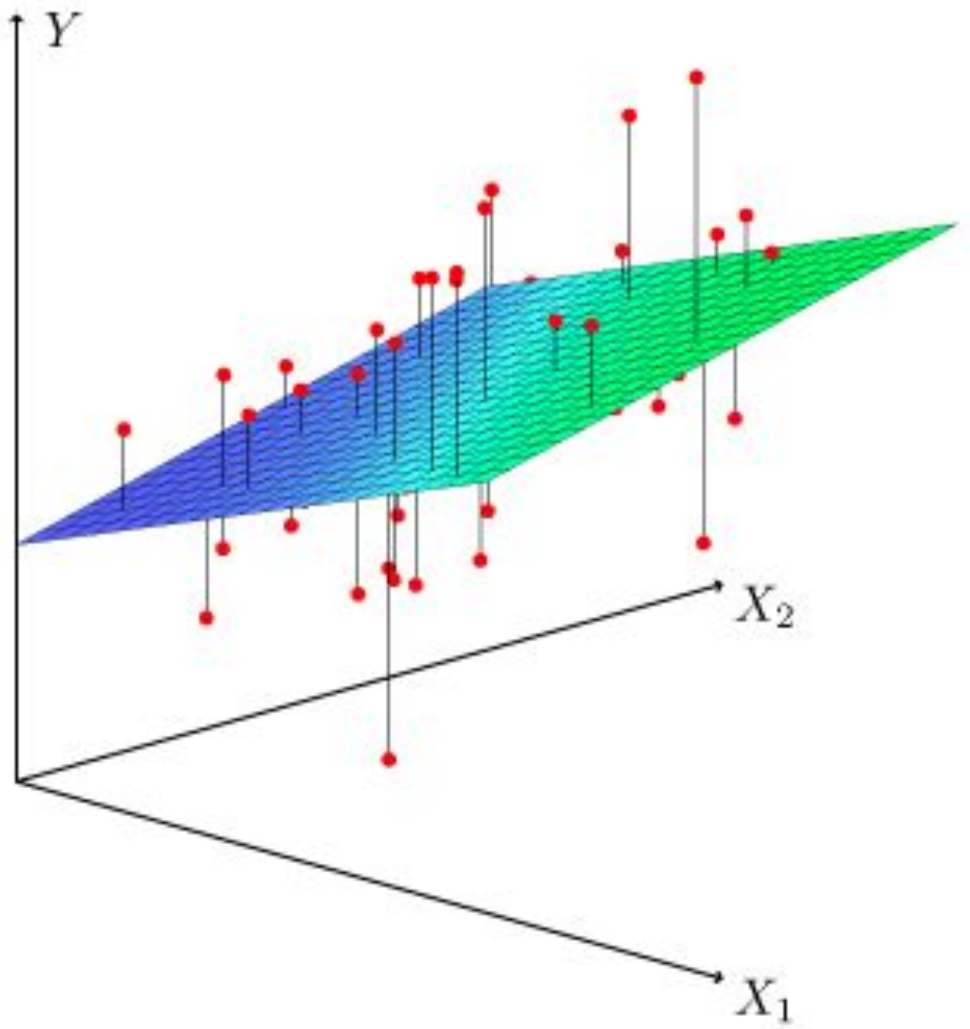
Applications in Biology:
It's used to study the relationship between age and disease risk, body size and metabolic rate, and other linear associations in biological data.

Reference:
"Linear Regression Analysis" by George A. F. Seber and Alan J. Lee



STEP 5 _ LINEAR MODELS EXAMPLES

5.2 - MULTIPLE LINEAR REGRESSION



Description:

This course **extends linear regression to multiple independent variables**, allowing for more complex modeling.

Significance:

Multiple linear regression is crucial for **modeling biological systems with multiple influencing factors**.

Applications in Biology:

It's applied to predict species abundance based on environmental variables, study the influence of multiple genes on a phenotype, and assess the impact of multiple drugs on a disease.

Reference:

"Applied Linear Regression" by Sanford Weisberg

OUR STORY LINE

STEP 5 _ LINEAR MODELS EXAMPLES

5.3 - OTHER REGRESSION MODELS

Description:

This course explores **other regression techniques beyond linear regression, such as logistic regression, Poisson regression, and non-linear regression**.

Significance:

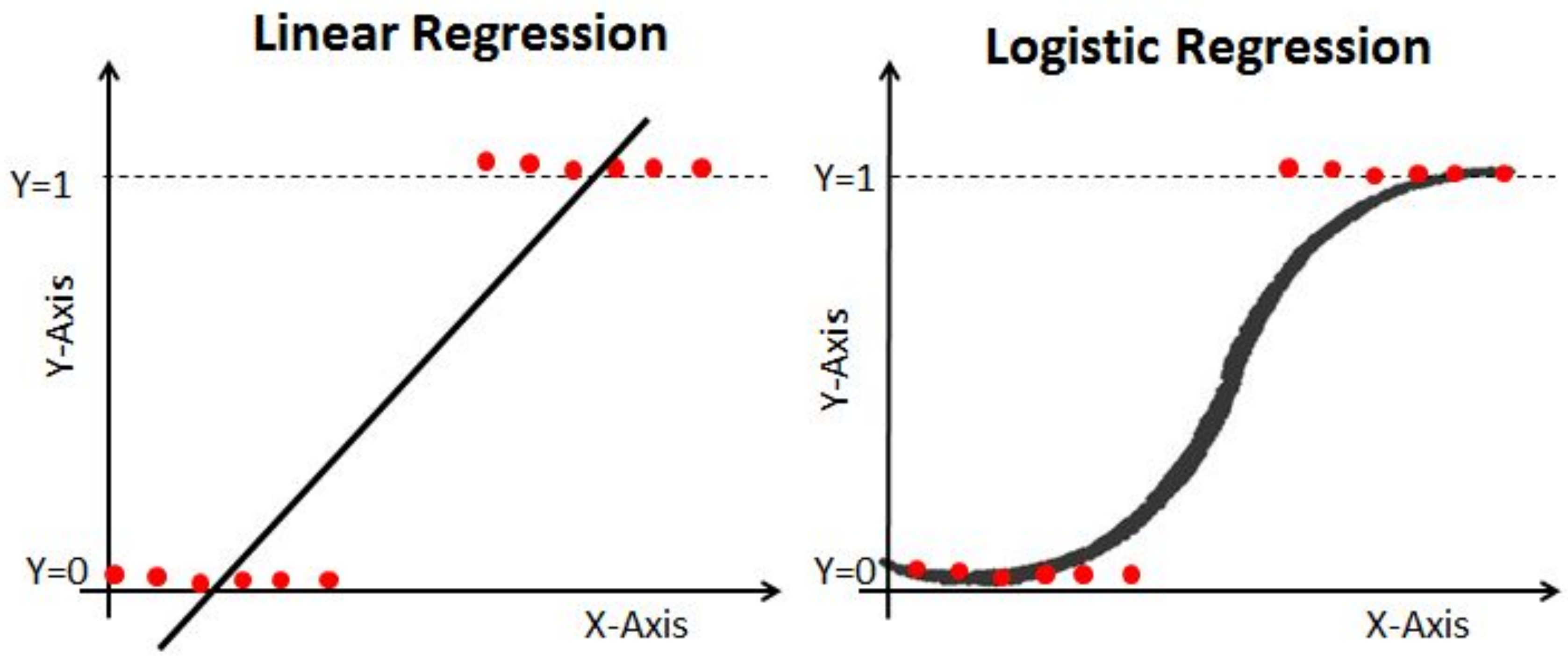
Different regression methods are useful for **capturing various relationships in biological data**.

Applications in Biology:

Logistic regression is used for binary outcomes like disease presence/absence, Poisson regression models count data like gene expression, and non-linear regression is applied in modeling enzyme kinetics.

Reference:

"Regression Models for Data Science in R" by Brian Caffo, Garrett M. Fitzmaurice, and Jeffrey D. Leek



STEP 6 _ OTHER CLASSIC MODEL EXAMPLES

General Description:
This step covers classic **statistical models beyond linear regression**.

Significance:
These models provide students with a broader toolkit for modeling various aspects of complex biological systems.

Applications in Biology:
Classic models are used in the analysis of clinical trials, ecological niche modeling, and identifying associations in genetics.

STEP 6 _ OTHER CLASSIC MODEL EXAMPLES

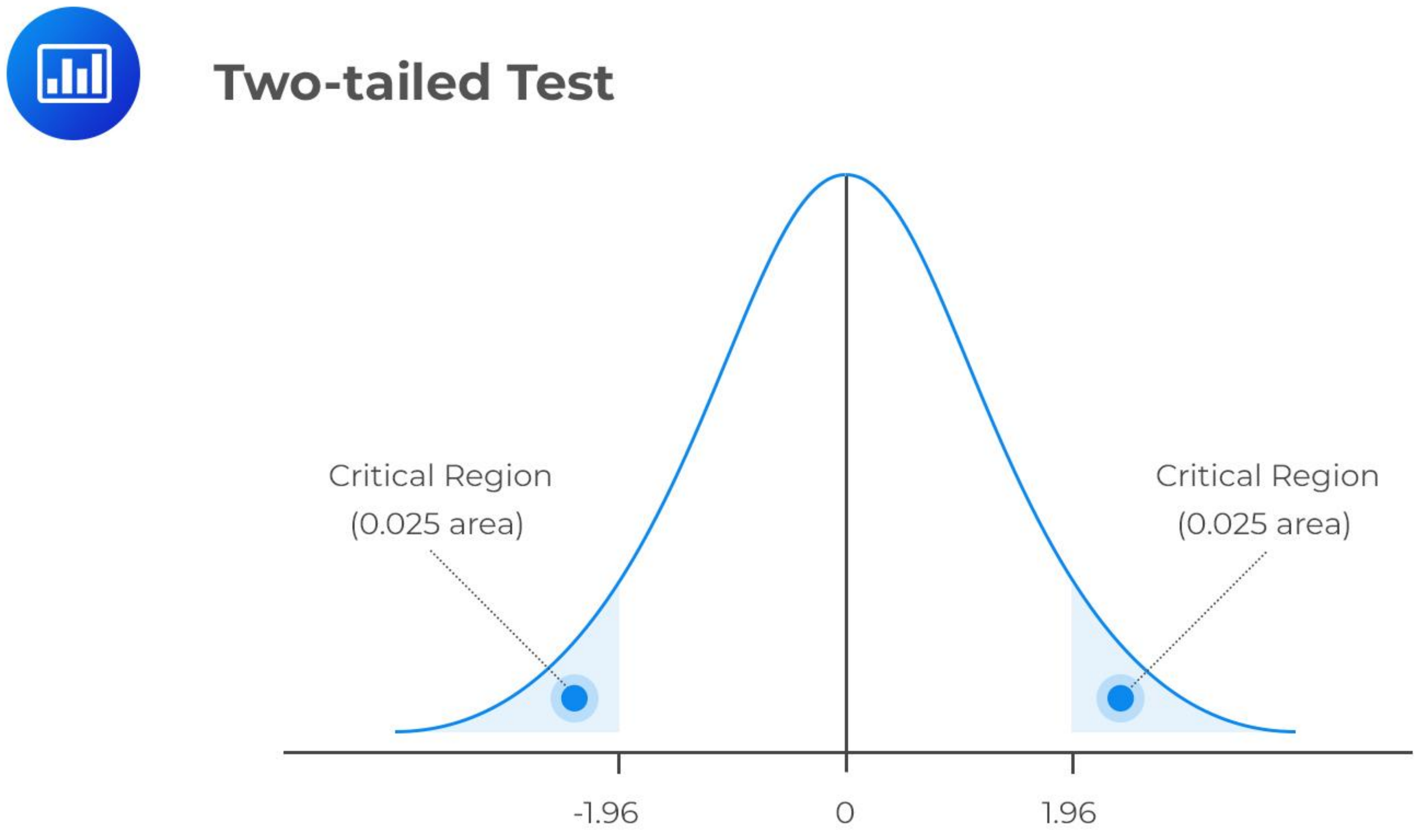
6.1 - USUAL UNIVARIATE TESTING

Description:
This course covers **classic univariate statistical tests such as t-tests, ANOVA, and chi-squared tests.**

Significance:
Univariate tests **help identify significant differences or associations** between variables in biological experiments.

Applications in Biology:
t-tests are used to compare means of two groups in clinical trials, ANOVA is applied to analyze variations in gene expression under different conditions, and chi-squared tests assess associations in genetics.

Reference:
"Statistical Methods for the Social Sciences" by Alan Agresti and Barbara Finlay



STEP 6 _ OTHER CLASSIC MODEL EXAMPLES

6.2 - USUAL MULTIVARIATE TESTING

Description:

This course explores **multivariate statistical techniques for analyzing data with multiple dependent and independent variables**.

Significance:

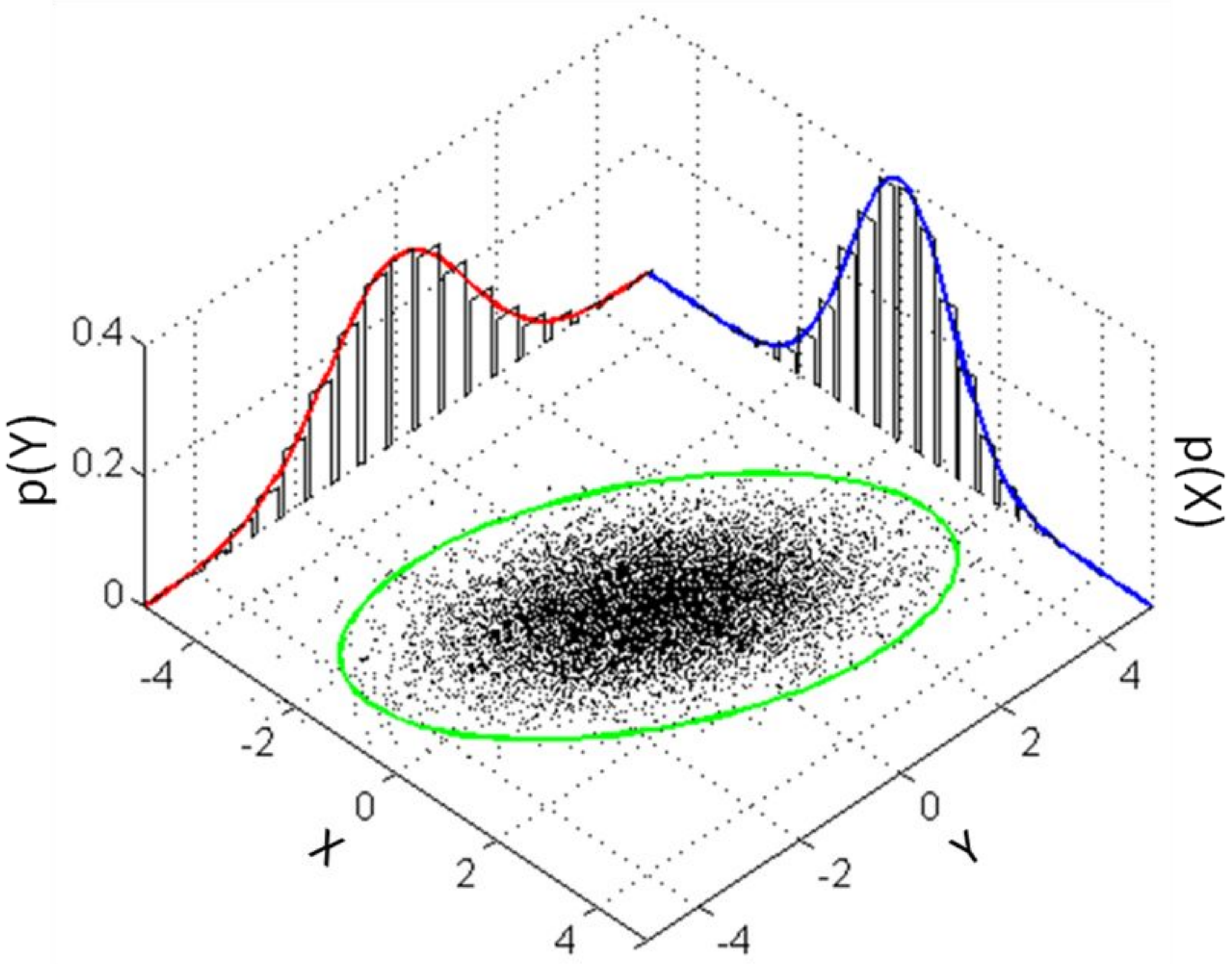
Multivariate testing is essential **for understanding complex relationships in biological datasets**.

Applications in Biology:

Multivariate analysis is used in ecology to assess the impact of **multiple environmental factors** on species diversity, in genomics to identify gene clusters with similar expression patterns, and in epidemiology to analyze the combined effects of multiple risk factors.

Reference:

"Multivariate Data Analysis" by Joseph F. Hair Jr., William C. Black, Barry J. Babin, and Rolph E. Anderson



STEP 6 _ OTHER CLASSIC MODEL EXAMPLES

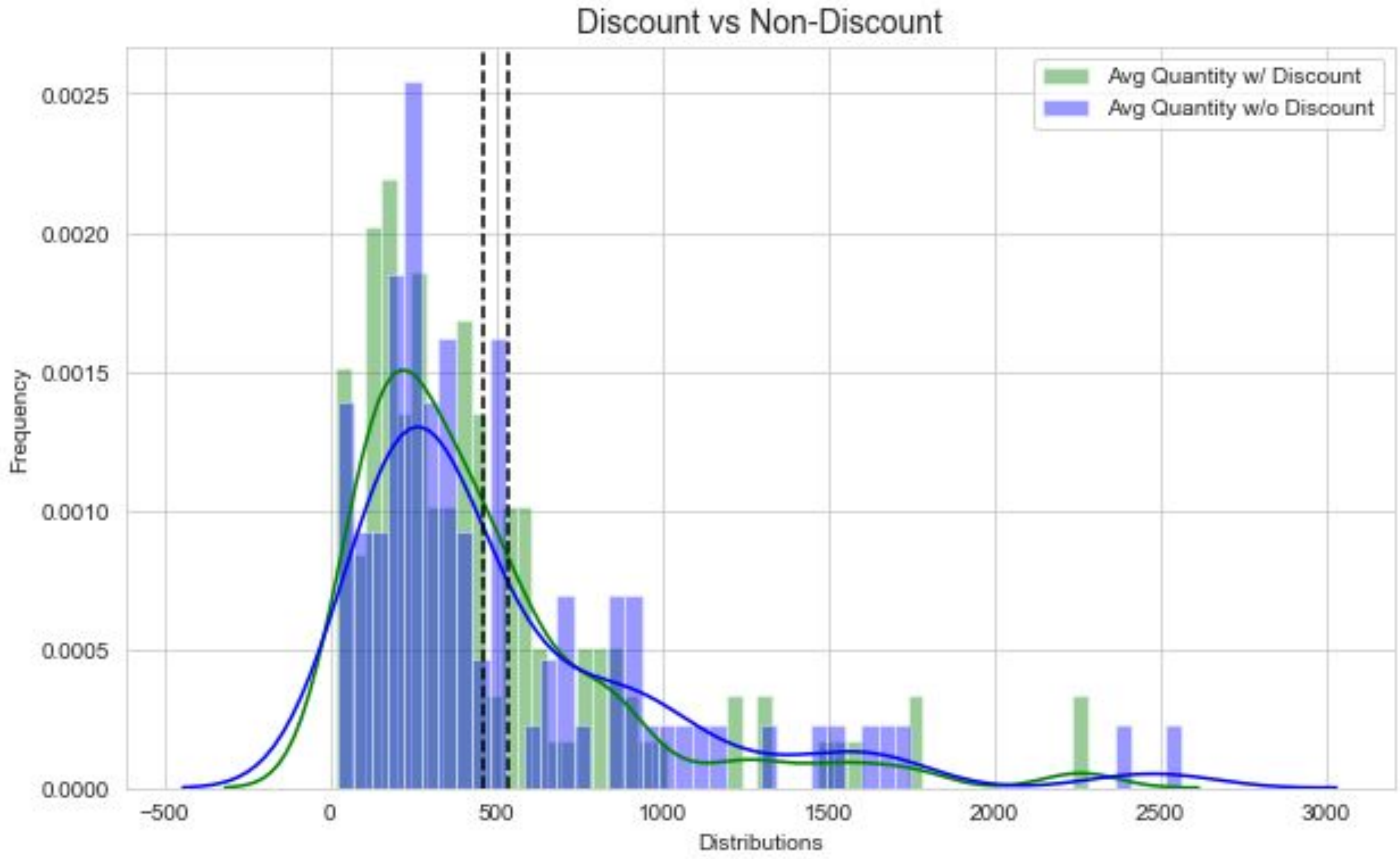
6.3 - NON PARAMETRIC STATISTICS

Description:
This course introduces non-parametric statistics, **which do not assume a specific data distribution and are suitable for non-normally distributed data**.

Significance:
Non-parametric statistics are valuable **when biological data deviate from standard distribution assumptions**.

Applications in Biology:
Non-parametric tests are used in **analyzing ranked data in experiments, comparing distributions of gene expression, and studying non-Gaussian ecological data.**

Reference:
"Nonparametric Statistics for the Behavioral Sciences" by Sidney Siegel and N. John Castellan Jr



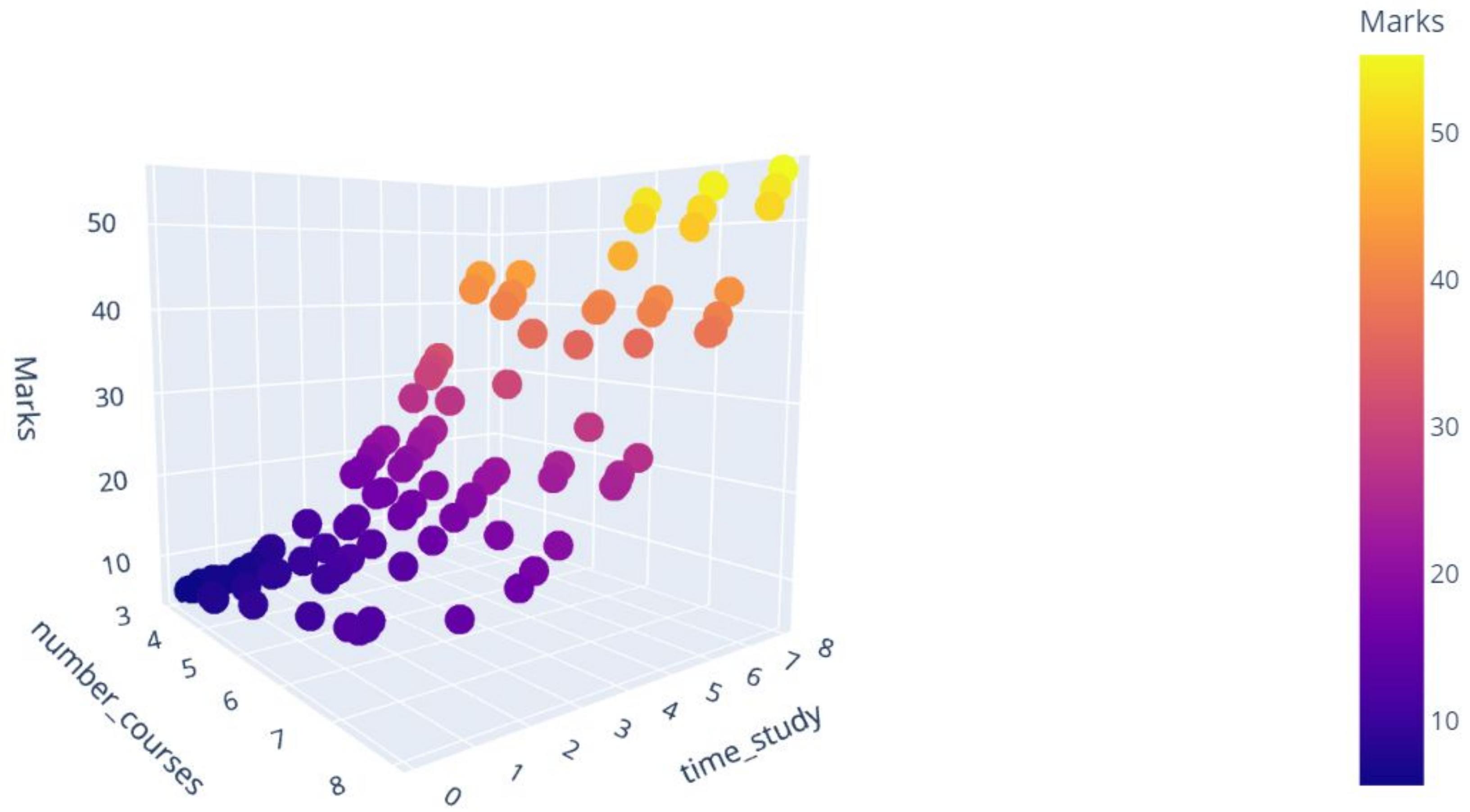
STEP 7 _ NON-LINEAR MODELS EXAMPLES

General Description:
Non-Linear Models Examples introduce you to probabilistic graphical models, percolation theory, spatial statistics, extreme value theory, agent-based modeling, and network dynamics.

Nonlinear statistical models are used to **model complex relationships between variables in data, where the relationship between the variables cannot be adequately represented by a simple linear relationship**.

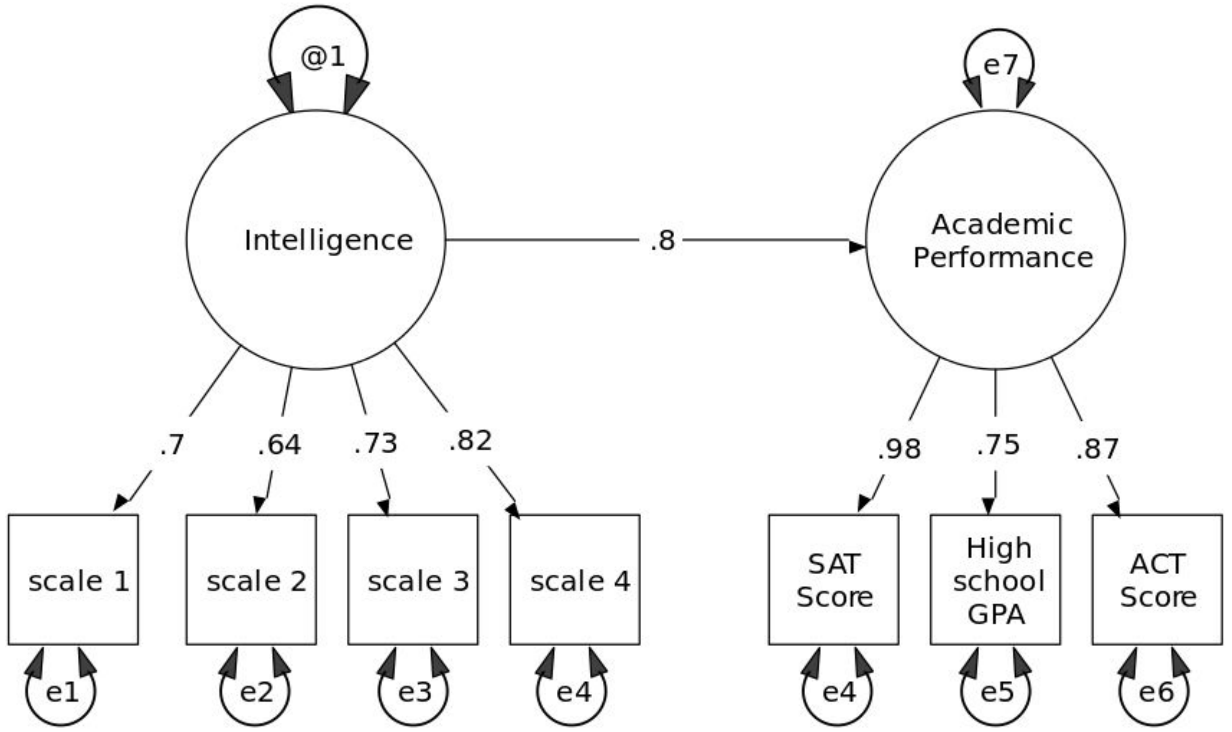
Significance:
These models allow students to **represent complex, non-linear interactions** and behaviors in biological systems.

Applications in Biology:
They are applied in modeling gene regulatory networks, disease spread, ecological patterns, rare event prediction, simulation of complex ecological systems, and network analysis of biological interactions.



STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.1 - PROBABILISTIC GRAPHICAL MODELS



Description:

This course explores probabilistic graphical models (PGMs), **a framework for modeling complex probabilistic relationships among variables using graphs**.

Significance:

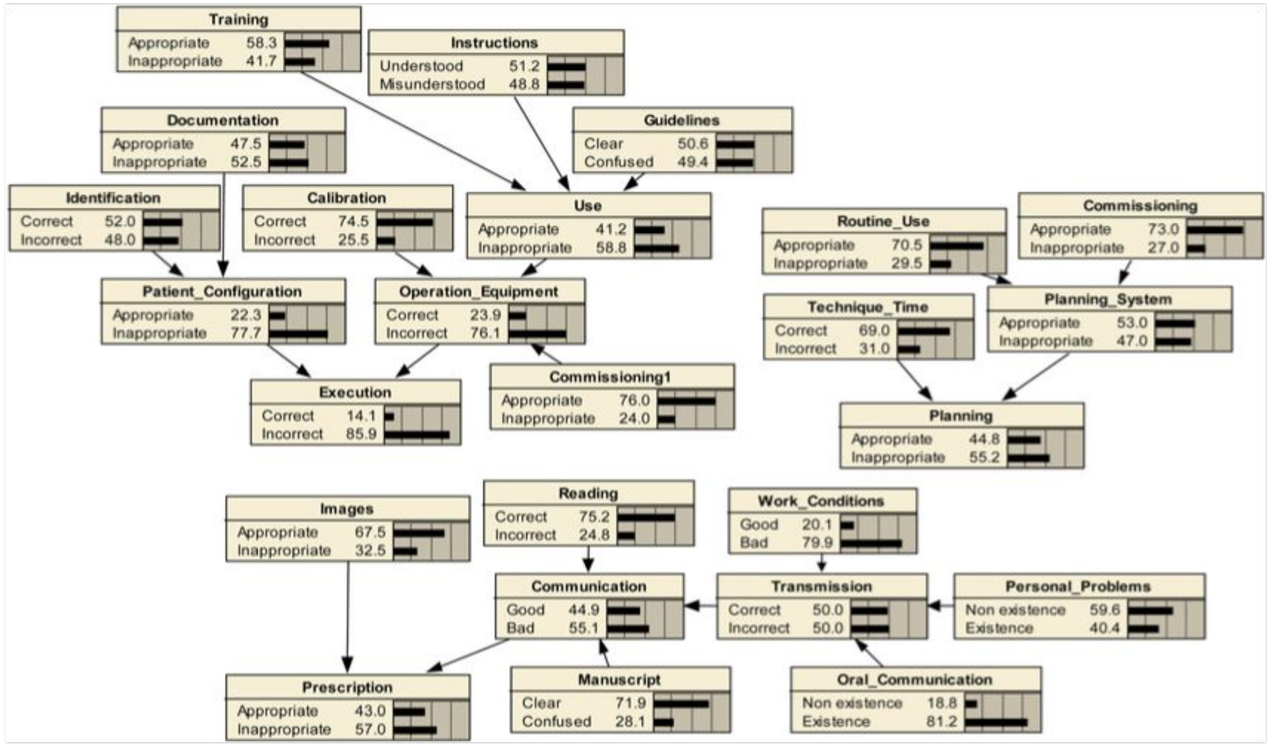
PGMs are essential for **modeling intricate dependencies and uncertainties in biological systems**.

Applications in Biology:

PGMs are used in gene regulatory network modeling, protein-protein interaction prediction, and Bayesian networks for disease diagnosis.

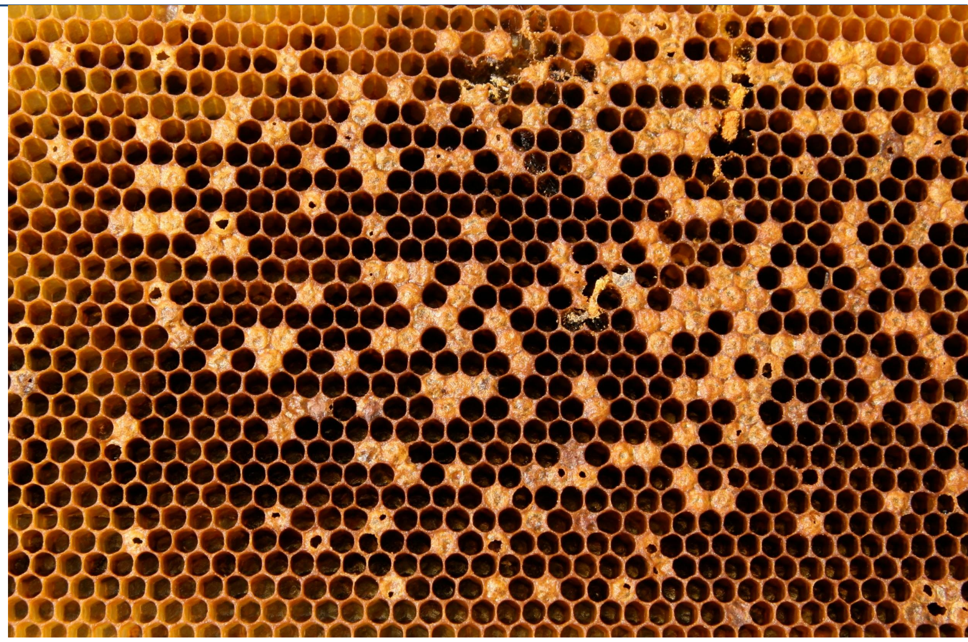
Reference:

"Probabilistic Graphical Models: Principles and Techniques" by Daphne Koller and Nir Friedman



STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.2 - PERCOLATION THEORY



Description:

This course covers percolation theory, which **studies the behavior of connected clusters in random networks**.

Significance:

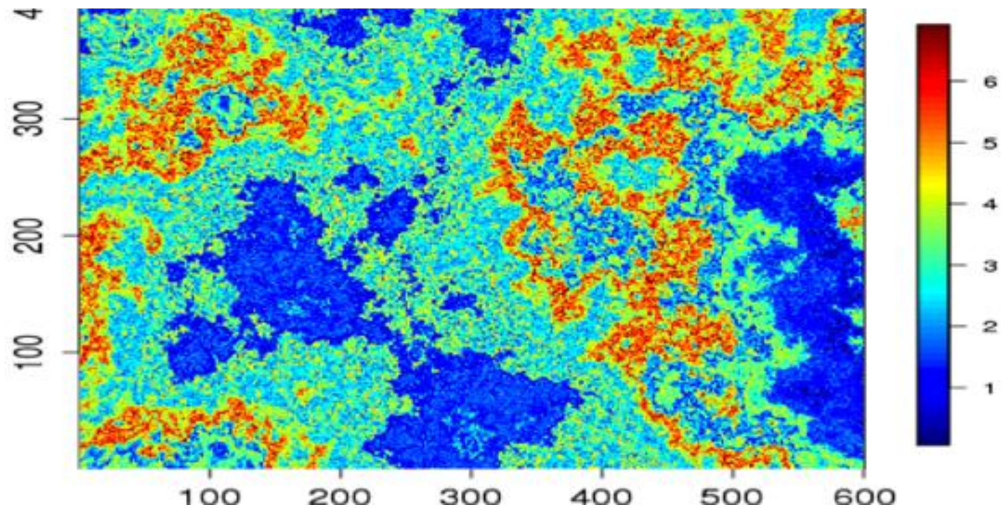
Percolation theory is valuable for **understanding network connectivity and robustness in biological networks**.

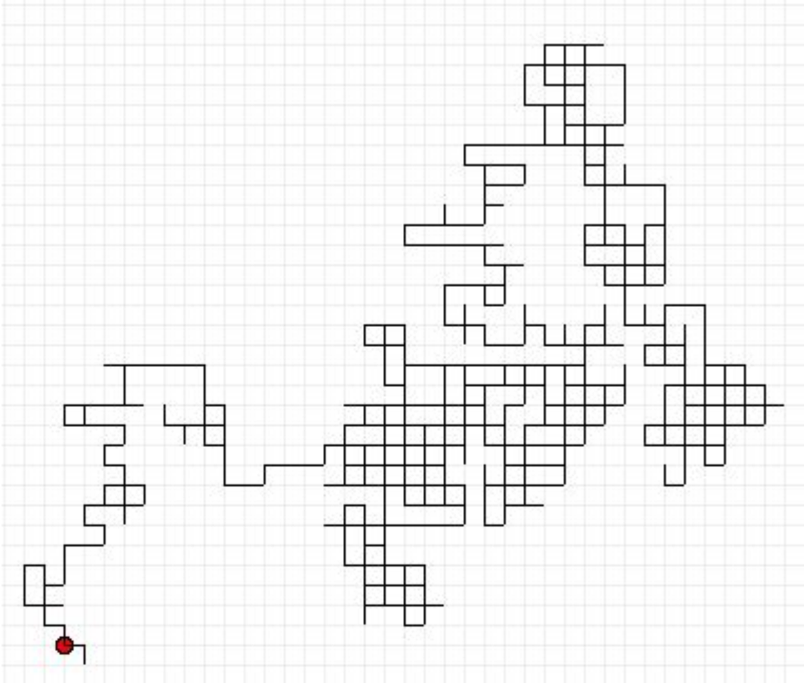
Applications in Biology:

It's applied to study the spread of infectious diseases in contact networks and the percolation of water through soil in ecology.

Reference:

"Percolation" by Geoffrey Grimmett





STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.3 - SPATIAL STATISTICS

Description:

This course focuses on spatial statistics, which deal with **data distributed in space, addressing issues like spatial autocorrelation and spatial modeling**.

Significance:

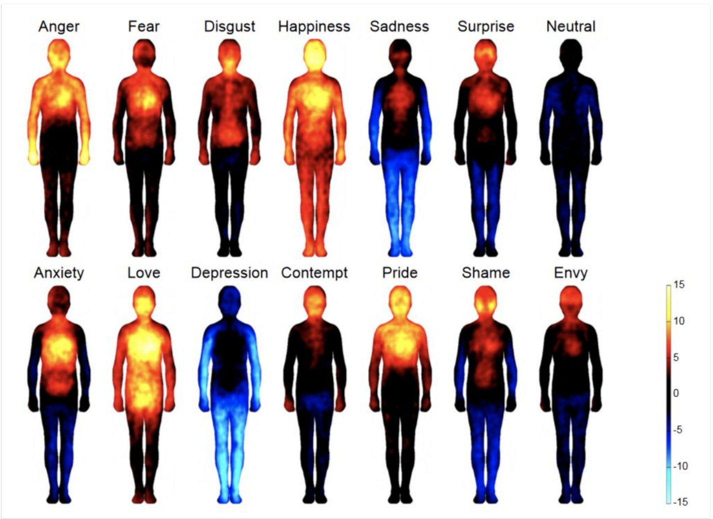
Spatial statistics are **crucial for analyzing spatial patterns and processes in ecological and epidemiological studies**.

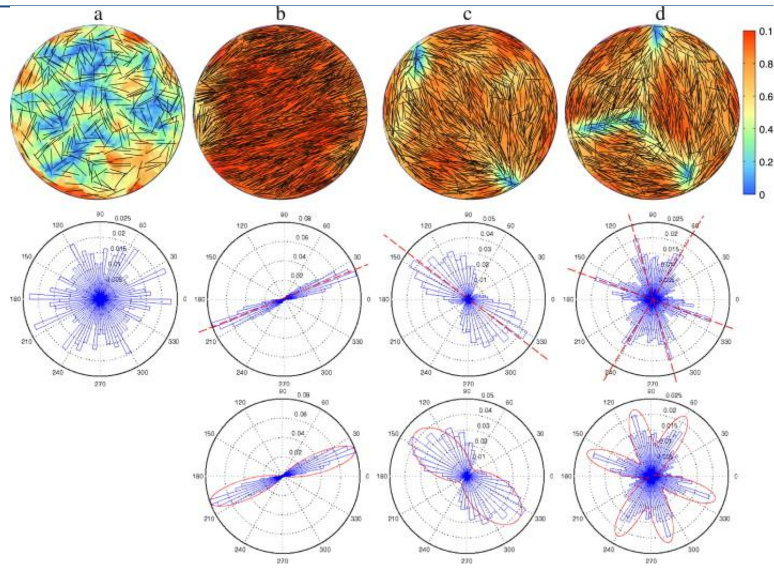
Applications in Biology:

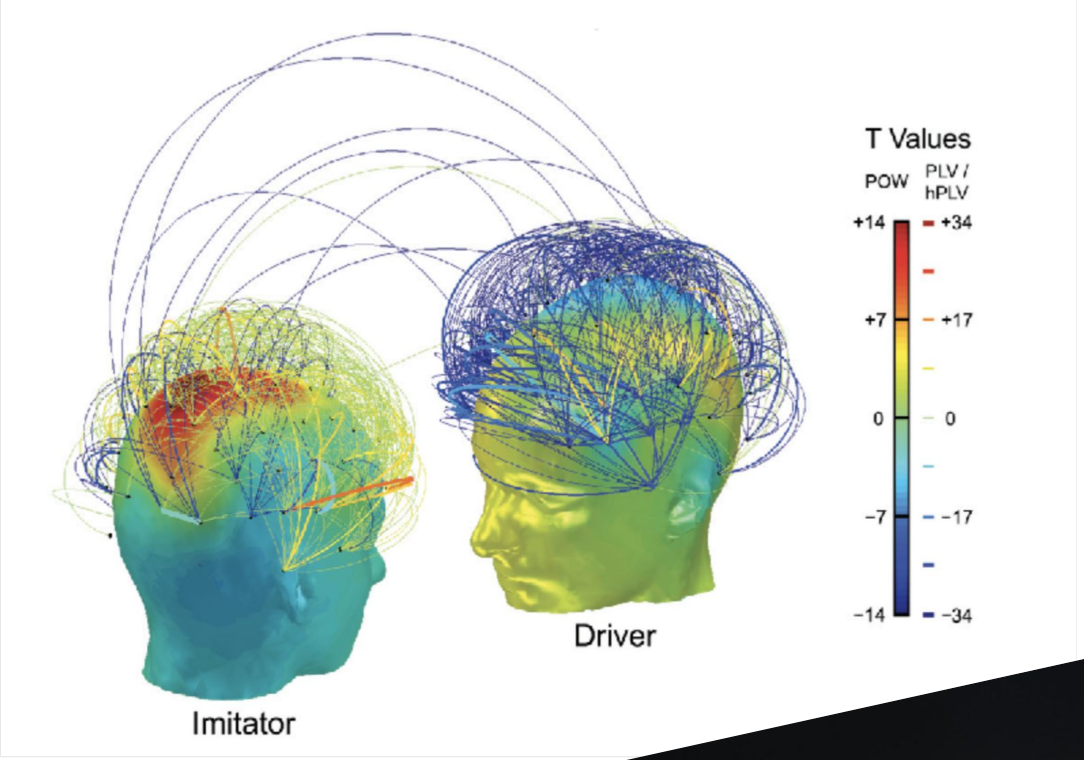
Spatial statistics are used in habitat suitability modeling, disease cluster detection, and analyzing geographic variation in genetic diversity.

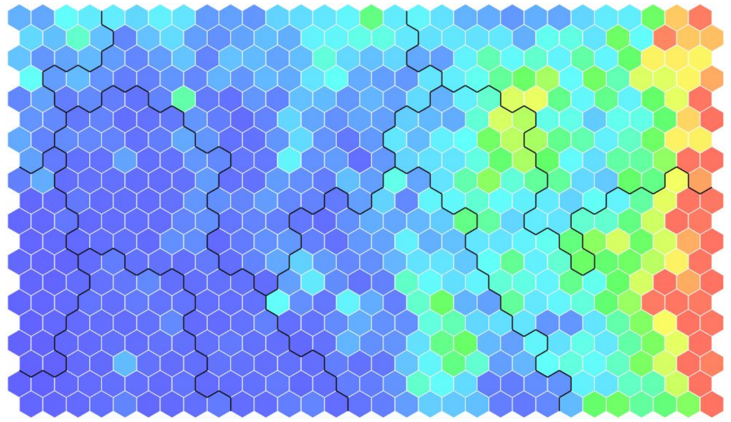
Reference:

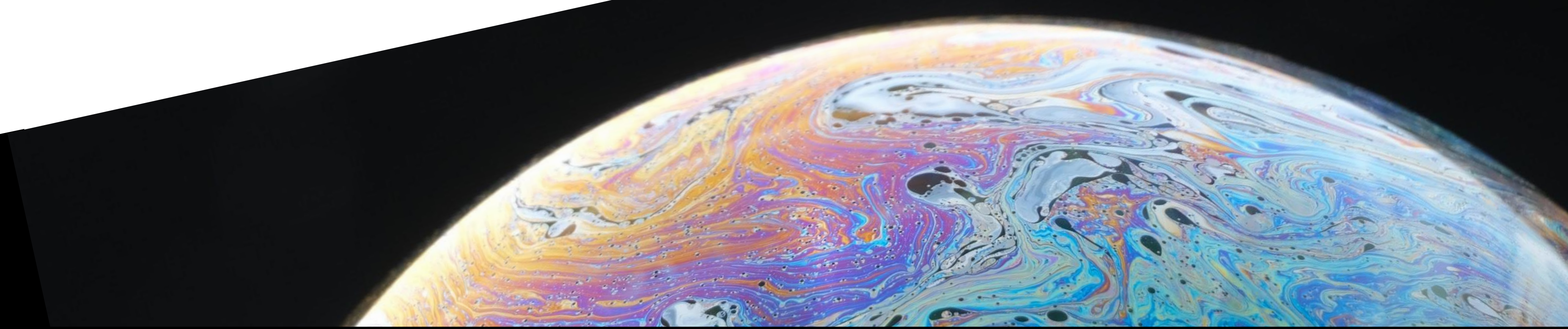
"Spatial Statistics and Geostatistics: Theory and Applications for Geographic Information Science and Technology" by Xavier Emery and Gérard Biau











STEP 7 _ NON-LINEAR MODELS EXAMPLES

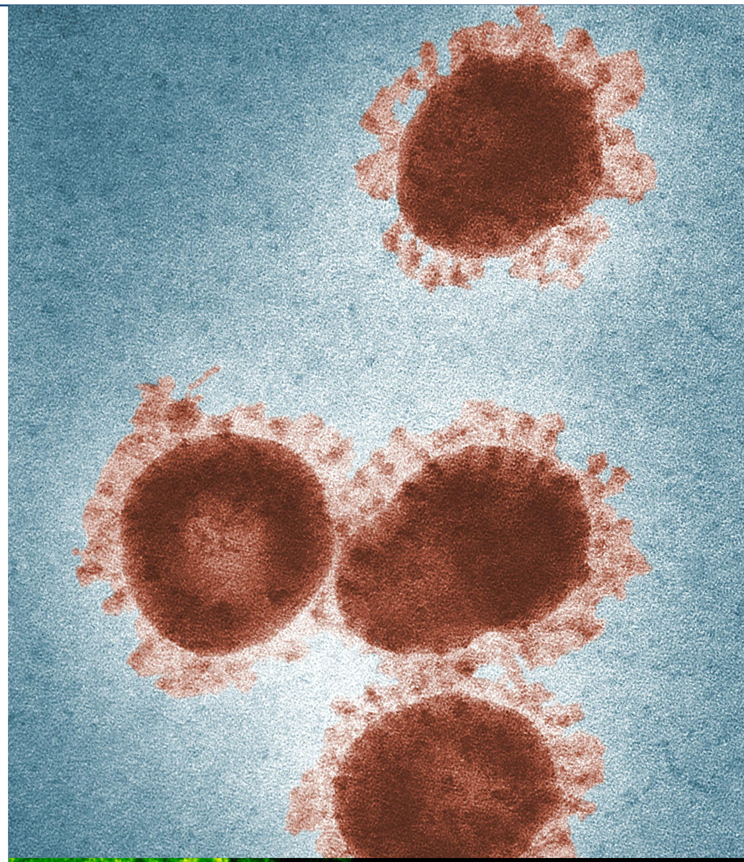
7.4 - EXTREME VALUE THEORY

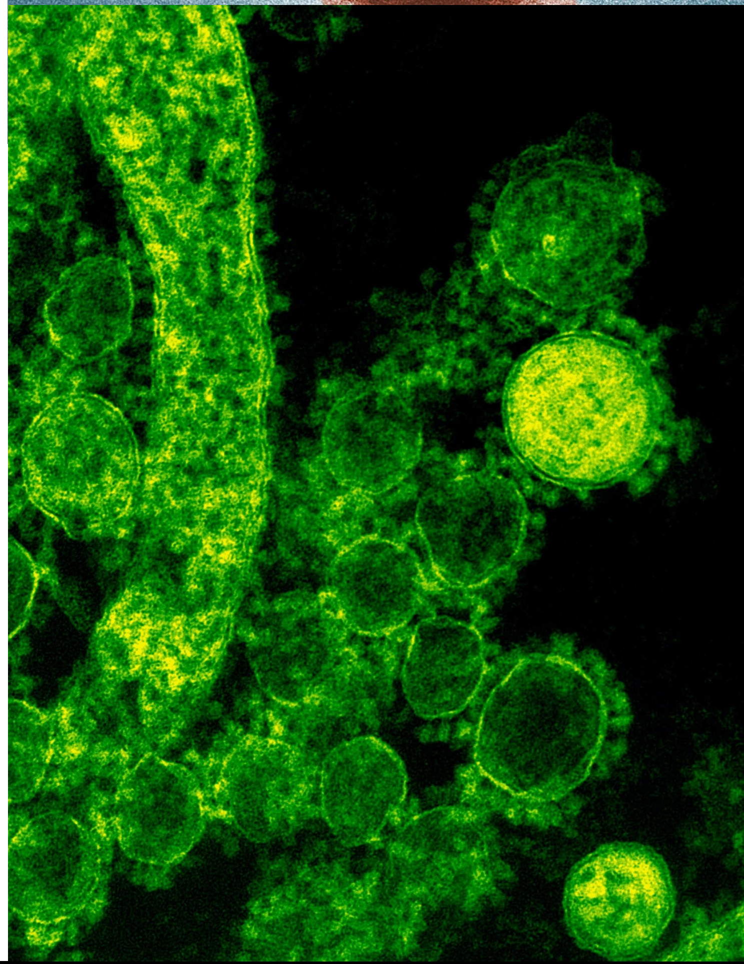
Description:
This course explores extreme value theory, which deals with **the modeling of rare and extreme events**.

Significance:
Extreme value theory is vital for understanding **extreme events in biological systems, such as rare disease outbreaks** or extreme weather events.

Applications in Biology:
It's applied in epidemiology to estimate the risk of rare diseases, in ecology to assess the impact of extreme environmental conditions, and in genetics to study rare genetic mutations.

Reference:
"An Introduction to Statistical Modeling of Extreme Values" by Stuart Coles





STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.5 - AGENT-BASED MODELING

Description:

This course introduces agent-based modeling, a **computational approach to modeling complex systems by simulating individual agents and their interactions**.

Significance:

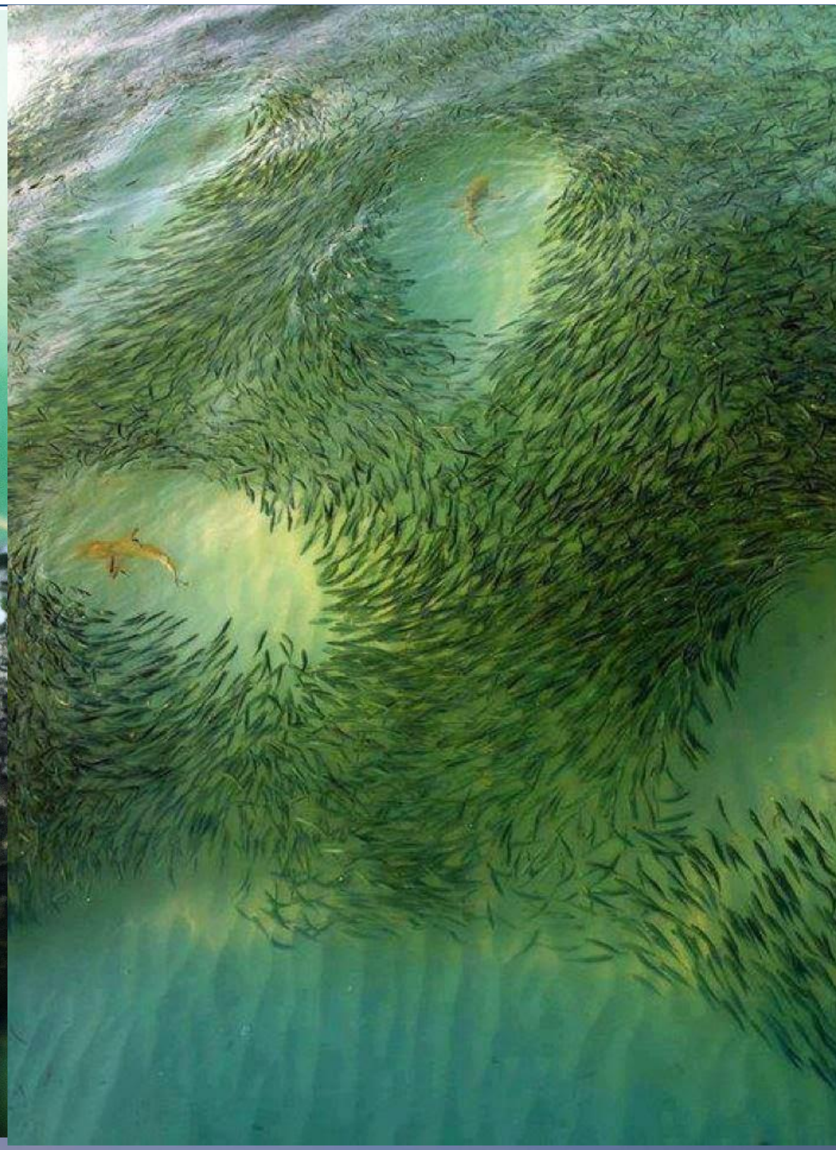
Agent-based modeling is valuable for **studying emergent phenomena** and **interactions in biological systems**.

Applications in Biology:

Agent-based models are used to simulate the behavior of organisms in ecosystems, study disease spread in populations, and model social interactions in animal groups.

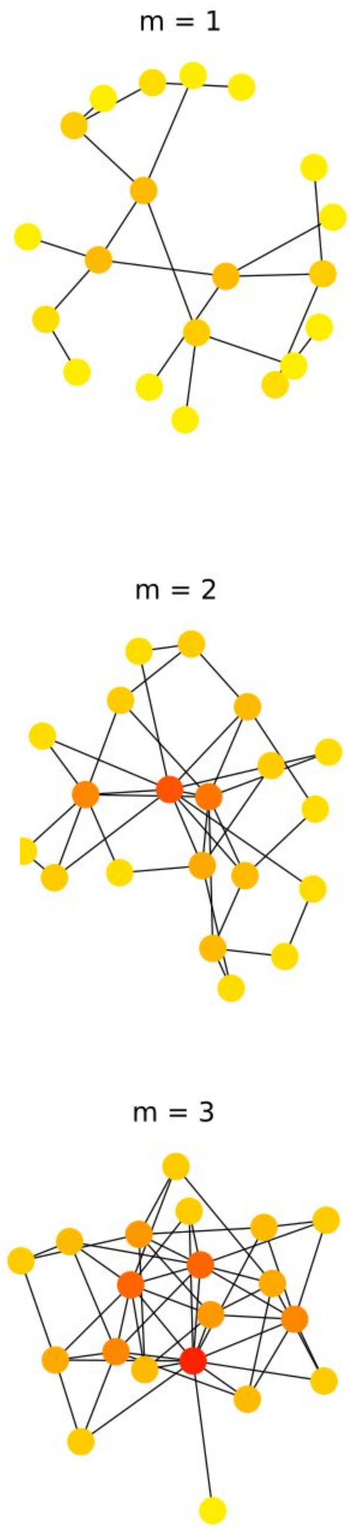
Reference:

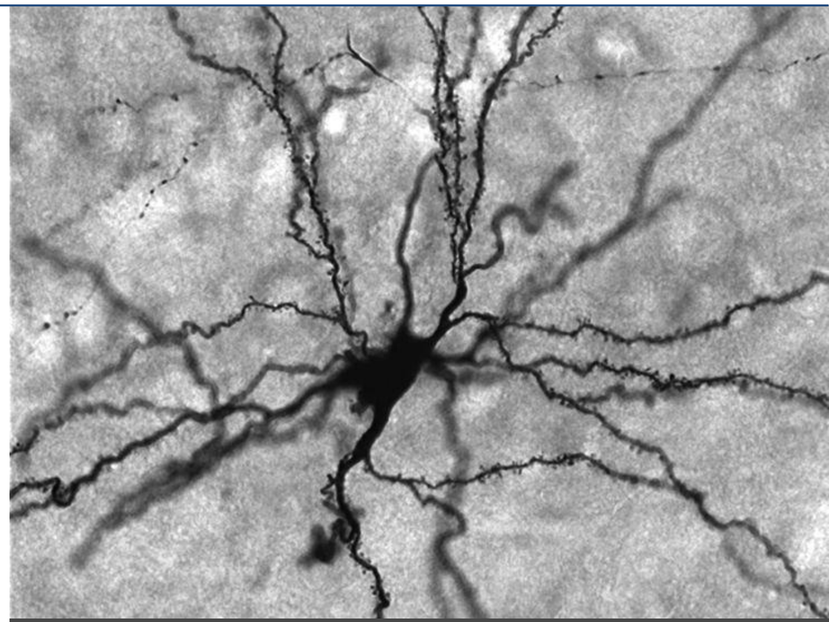
"Agent-Based and Individual-Based Modeling: A Practical Introduction" by Steven F. Railsback and Volker Grimm

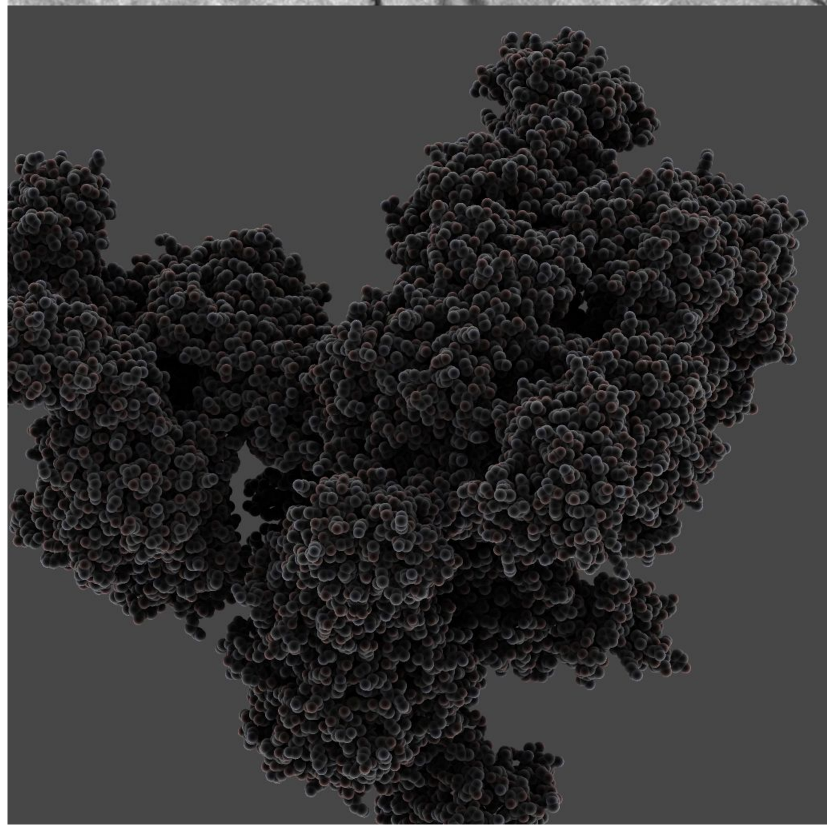


STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.6 - NETWORK DYNAMICS







Description:

This course focuses on **network dynamics, which explores how complex systems evolve and behave over networks**.

Significance:

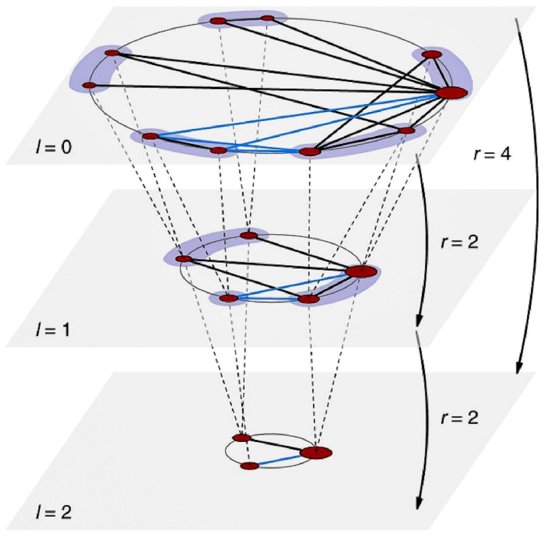
Network dynamics is crucial for **modeling the spread of information, diseases, or influence in biological networks**.

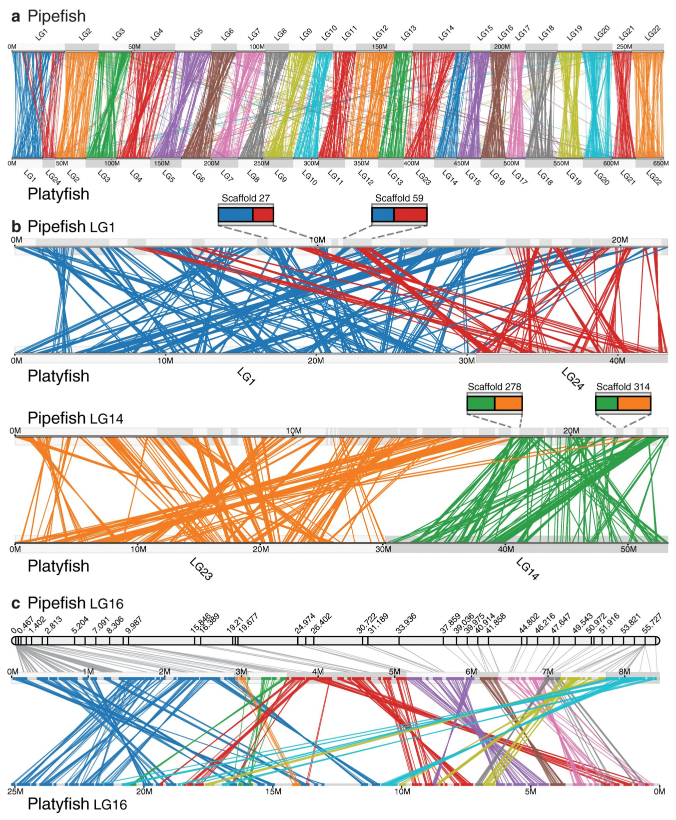
Applications in Biology:

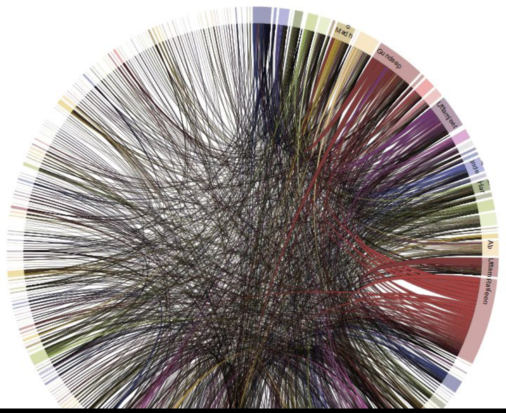
It's applied in analyzing protein-protein interaction networks, studying disease transmission in contact networks, and understanding ecological food webs.

Reference:

"Networks: An Introduction" by Mark Newman

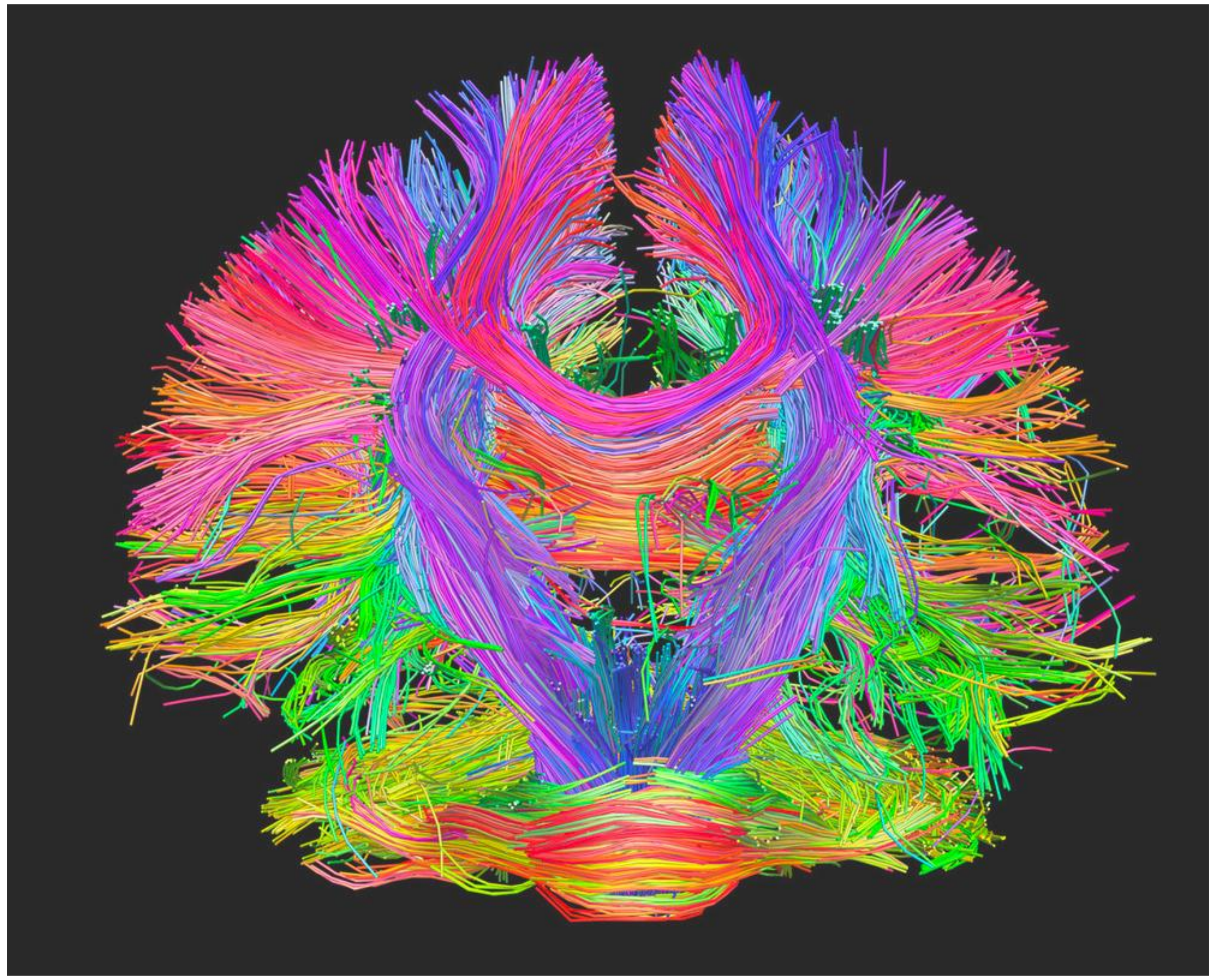


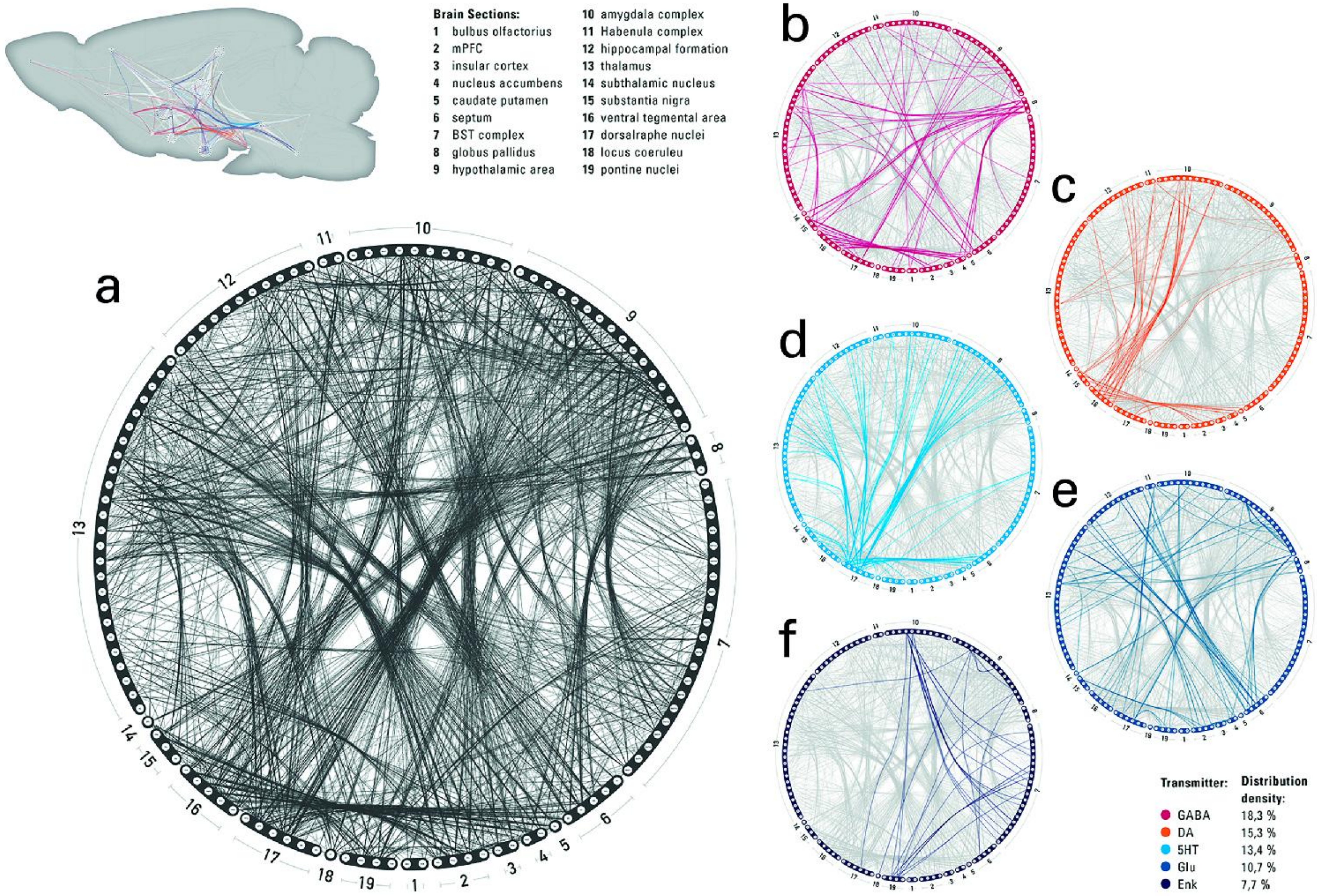




STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.6 - NETWORK DYNAMICS

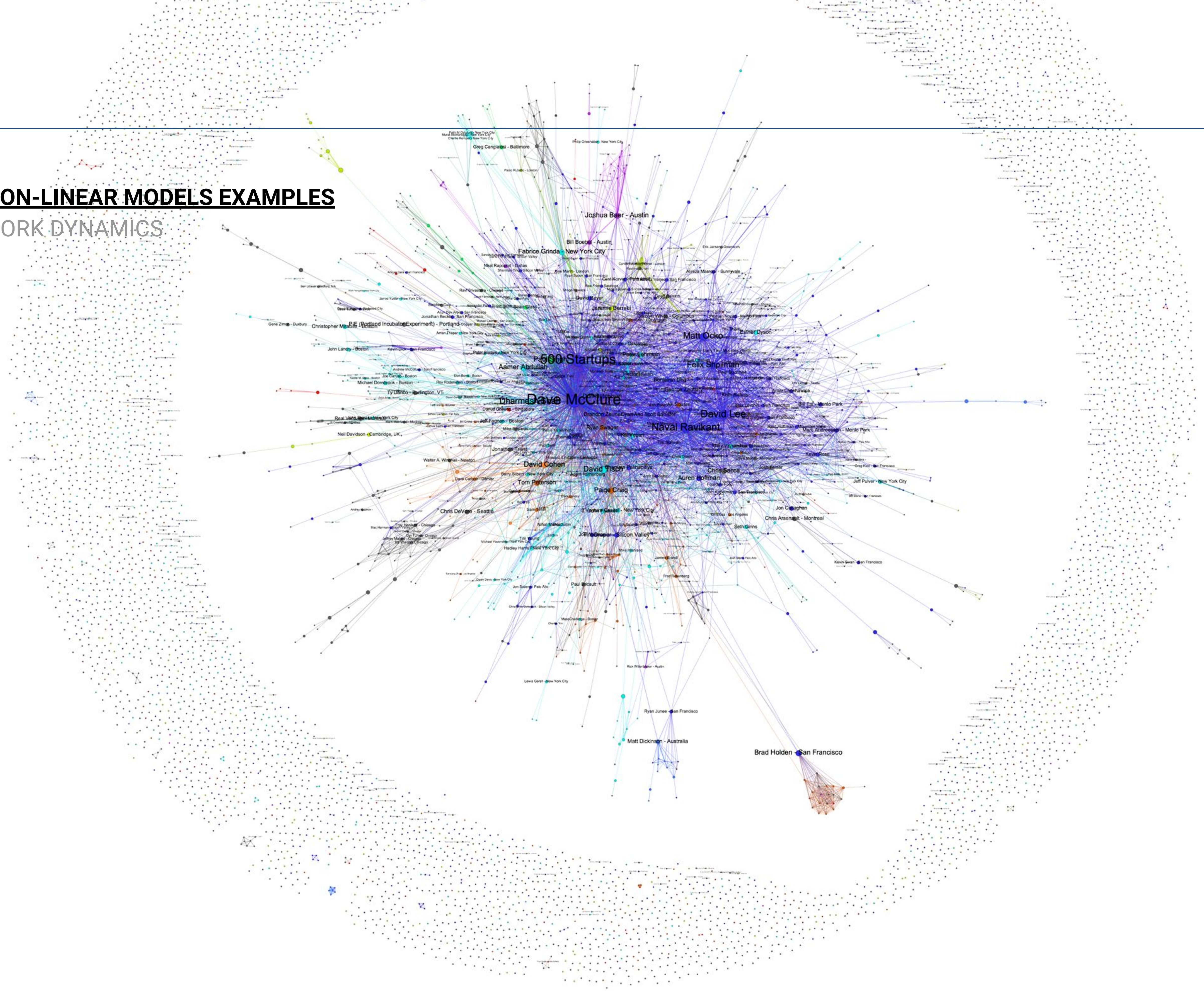




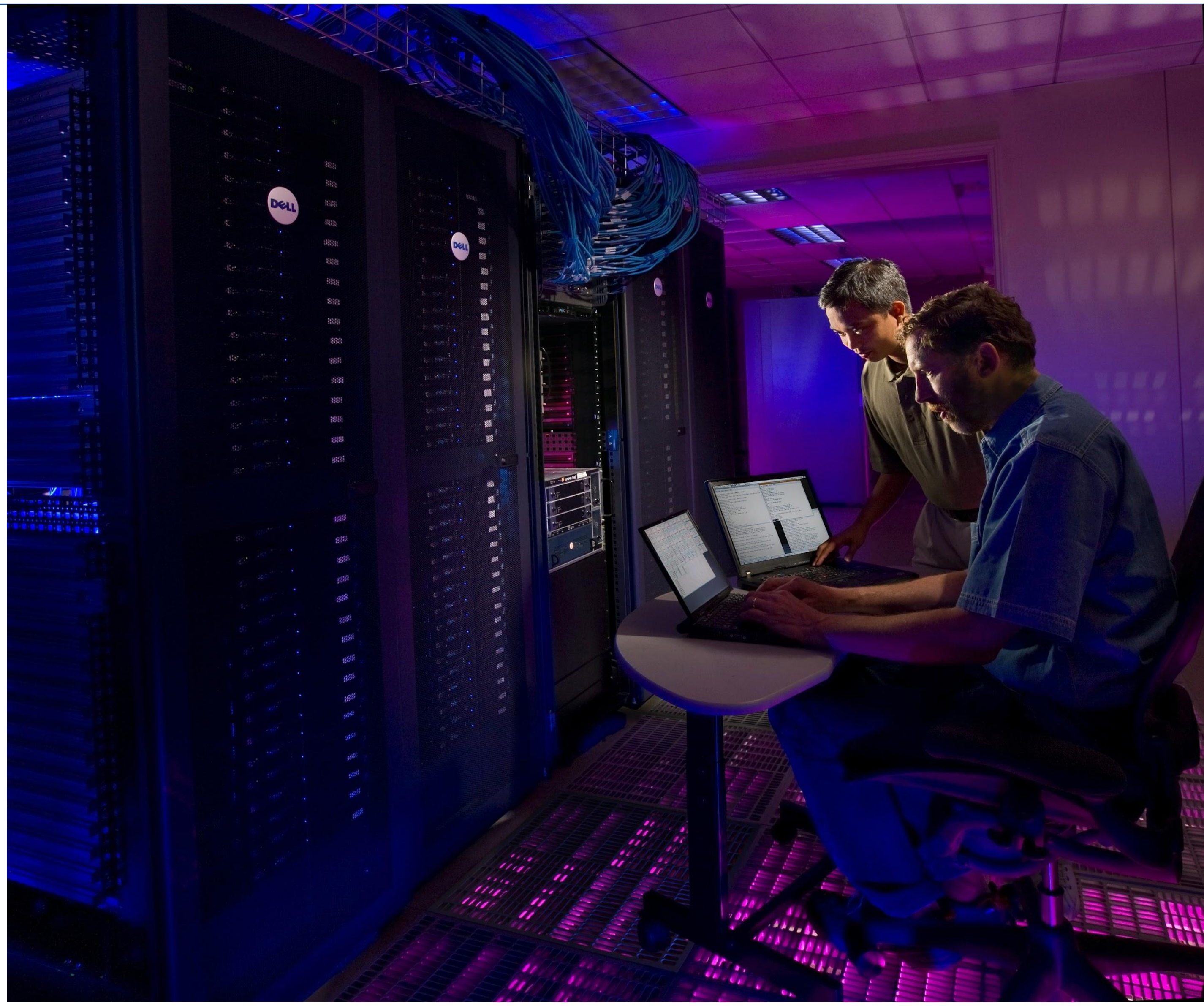
OUR STORY LINE

STEP 7 _ NON-LINEAR MODELS EXAMPLES

7.6 - NETWORK DYNAMICS



STEP 8 _ COMPUTATIONAL METHODS & MACHINE LEARNING



General Description:
This step covers **computational methods and machine learning techniques, which are essential for analyzing complex biological data**.

Significance:
Computational methods and machine learning empower students to **handle large-scale biological datasets and build predictive models**.

Applications in Biology:
Machine learning is used in genomics for gene prediction, drug discovery, and disease classification, while computational methods are applied in systems biology for modeling complex biological processes.

Check with colleagues !