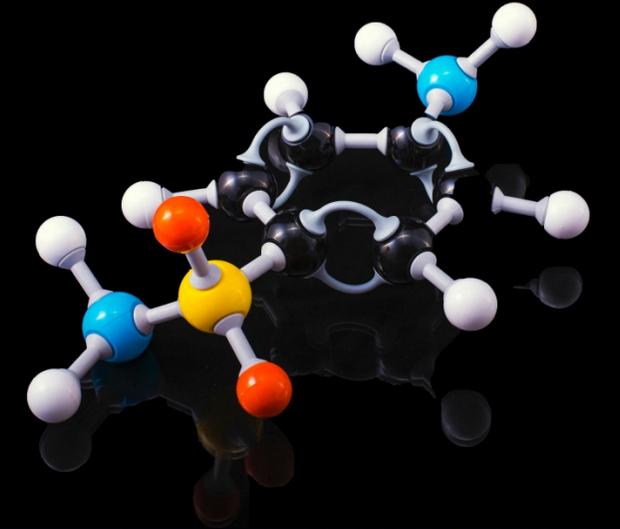




LES FACULTÉS
DE L'UNIVERSITÉ
CATHOLIQUE DE LILLE



Theory Of Systems

NETWORK DYNAMICS

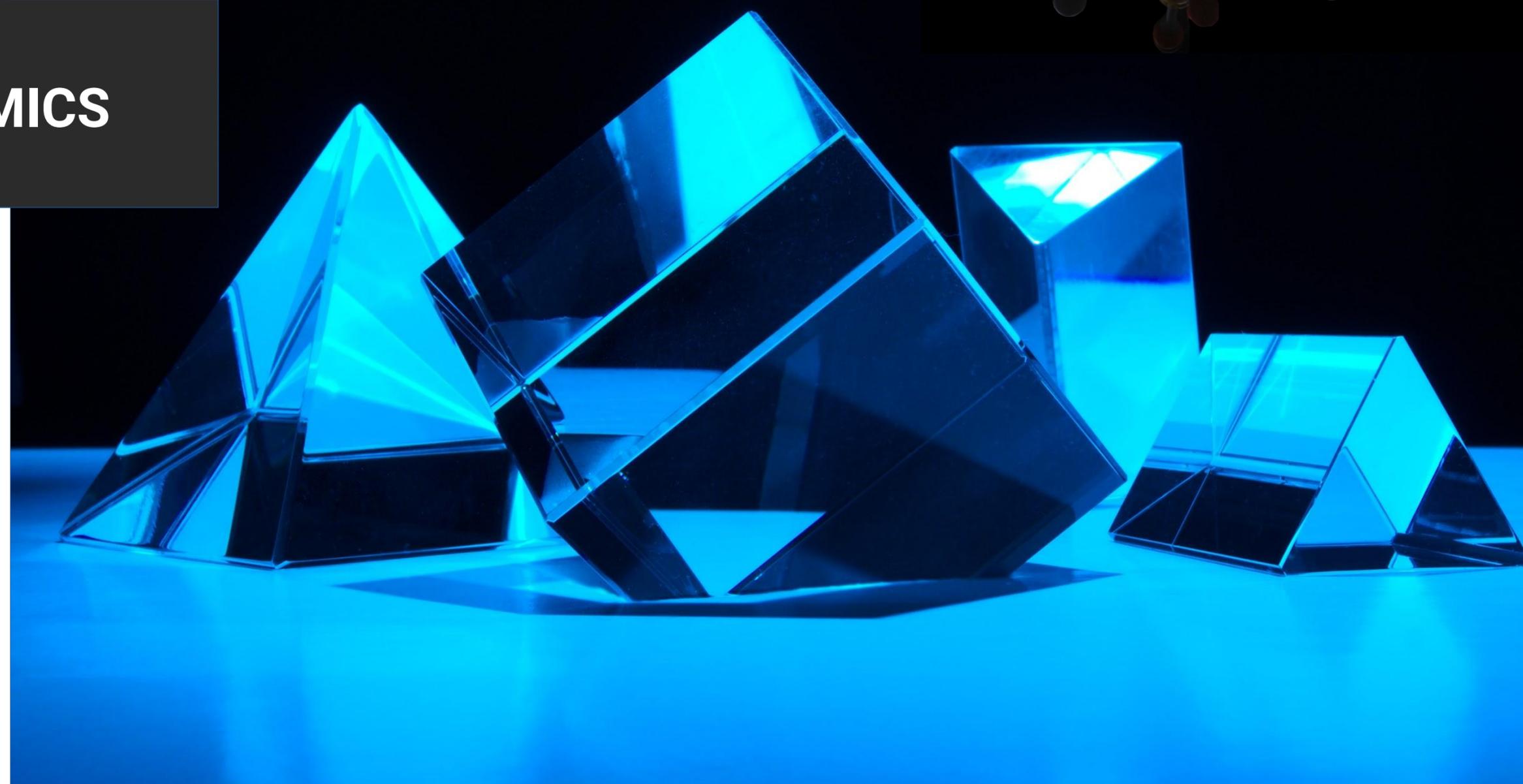
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OLD VERSION

Fais moi une structure de cours en 4 parties (part 1, 2 ...4) chacune comportant 3 à 4 sous parties (1.1, 1.2, ...), avec un point pour chaque sous-partie, sur la dynamique des réseaux des systèmes complexes. Il faut que tu sois sur des éléments purement sur la théorie des réseaux sans parler directement de la théorie des systèmes complexes. Le cours est en anglais

Part 5: Network Dynamics

5.1 Introduction to Network Theory

- Basics of Graph Theory
- Complex Networks in Various Fields

5.2 Modeling Dynamic Networks

- Time-Dependent Networks
- Dynamic Network Models

5.3 Synchronization in Networks

- Synchronization Phenomena in Coupled Oscillators
- Kuramoto Model

5.4 Network Resilience and Robustness

- Robustness Analysis in Dynamic Networks
- Cascading Failures

5.5 Complex Contagion and Epidemics

- Epidemic Spreading on Networks
- Threshold Models and Complex Contagion

5.6 Applications of Network Dynamics

- Social Networks and Information Diffusion
- Brain Connectivity and Functional Networks

5.7 Ongoing Research and Challenges in Network Dynamics

- Current Research Trends in Network Science
- Open Problems and Future Directions

Part 1: Mathematical Foundations

1.1 Set Theory and Relations

- Introduction to Sets
- Set Operations (Union, Intersection, Complement)
- Relations and Functions

1.2 Linear Algebra

- Vector Spaces and Subspaces
- Matrix Operations (Addition, Multiplication)
- Determinants and Inverses

1.3 Calculus

- Limits and Continuity
- Derivatives (Single and Multivariable)
- Integrals (Definite and Indefinite)

Part 2: Probability and Statistics

2.1 Probability Theory

- Sample Spaces and Events
- Probability Distributions (Discrete and Continuous)
- Conditional Probability and Bayes' Theorem

2.2 Statistical Inference

- Hypothesis Testing
- Confidence Intervals
- Maximum Likelihood Estimation

2.3 Random Variables

- Expected Value and Variance
- Central Limit Theorem
- Probability Density Functions

Part 3: Optimization and Numerical Methods

3.1 Optimization Theory

- Types of Optimization Problems (Linear, Non-linear)
- Gradient Descent
- Constrained Optimization

3.2 Numerical Methods

- Root-Finding Algorithms (Newton-Raphson, Bisection)
- Numerical Integration (Simpson's Rule, Trapezoidal Rule)
- Linear Programming

3.3 Differential Equations

- First-Order Differential Equations
- Second-Order Differential Equations
- Systems of Differential Equations

Part 4: Graph Theory and Network Dynamics

4.1 Graph Theory Basics

- Graphs and Graph Representations
- Graph Connectivity
- Graph Algorithms (BFS, DFS)

4.2 Network Dynamics

- Dynamic Systems on Networks
- Epidemic Models (SIR, SEIR)
- Information Flow and Diffusion

KEYWORDS (NEW)

Dynamiques déterministes

Modélisation causale

KEYWORDS

- Theory of Systems: Network Dynamics
- Intellectual Adventure
- Mathematics
- Networks
- Data-Driven Insights
- Discovery
- Complex Systems
- Theoretical Knowledge
- Intellectual Awakening
- Mathematical Foundations
- Dynamics of Networks and Systems
- George Polya
- Problem-Solving Strategies
- Paul Erdős
- Graph Theory
- Network Structures
- Real-World Applications
- Practical Implications
- Network Analysts
- Social Networks
- Communication Systems
- Transportation Networks
- Data Scientists
- Disease Spread Modeling
- Information Flow
- Complex Systems Dynamics
- Healthcare Professionals
- Engineers
- Researchers
- Business Analysts
- Interconnected World
- Skillset
- Analyze
- Model
- Optimize
- Decode Network Behaviors
- Predict System Responses
- Critical Nodes of Influence
- Analytical Mindset
- Problem-Solving
- Data-Driven Era
- Groundbreaking Research
- Innovative Solutions
- Data-Driven Decisions
- Learning Community
- Weeki Team
- Compass
- Enroll
- Exploration
- Vibrant Learning Community
- Knowledge
- Data-Driven Insights.

In the context of the course on Systems Theory and Agent-Based Modeling, one relevant use case is simulating the spread of diseases in a population. This use case touches upon various aspects of the course, including Agent-Based Modeling (ABM), mathematical foundations for systems theory, and its application in computational epidemiology.

Description:

In this use case, we'll create an Agent-Based Model to simulate the spread of a contagious disease within a population. The model will consider individual agents (representing people) who can move, interact with each other, and make decisions regarding their health and contact with others.

Key Components:

1. **Agents:** Each agent represents an individual in the population. Agents have attributes such as age, health status, and infection status.
2. **Agent Interactions:** Agents can interact with each other, potentially leading to the transmission of the disease. These interactions can occur within a certain radius of each agent.
3. **Agent Decision-Making:** Agents make decisions based on their health status and the risk of infection. For example, a healthy agent may decide to maintain social distance or wear a mask in crowded places.
4. **Emergent Properties:** The spread of the disease within the population will exhibit emergent properties, such as the overall infection rate and patterns of disease transmission.
5. **Dynamical Systems:** Differential equations and mathematical modeling will be used to describe the dynamics of disease transmission, including the infection rate, recovery rate, and the impact of interventions.
6. **Validation and Calibration:** The model will be validated and calibrated using real-world data to ensure that it accurately represents the dynamics of the specific disease being simulated.

Here's a Python code example (Agent-Based Model):

```
1 import random
2
3 # Define agent attributes
4 class Agent:
5     def __init__(self, health_status):
6         self.health_status = health_status
7         self.infected = False
8
9     def interact(self, other_agent):
10        # Define rules for agent interactions and disease transmission
11        if self.infected and not other_agent.infected:
12            if random.random() < transmission_probability:
13                other_agent.infected = True
14
15 # Create a population of agents
16 population = [Agent("healthy") for _ in range(population_size)]
17 patient_zero = random.choice(population)
18 patient_zero.infected = True
19
20 # Simulate agent interactions and disease spread over time
21 for day in range(simulation_duration):
22     for agent in population:
23         if agent.infected:
24             # Define agent's actions when infected
25             # For example, they may interact with nearby agents
26             nearby_agents = [other_agent for other_agent in population if distance(agent, other_agent) < interaction_radius]
27             for other_agent in nearby_agents:
28                 agent.interact(other_agent)
29
30 # Analyze and visualize the results
31 # Calculate infection rates, plot graphs, etc.
```

This use case demonstrates how Systems Theory and Agent-Based Modeling can be applied to simulate and analyze the spread of diseases, helping researchers and policymakers understand and develop strategies for disease control and prevention.

- Halmos, P. R. (1960). Naive Set Theory. Springer.
- Strang, G. (2006). Linear Algebra and Its Applications. Cengage Learning.
- Stewart, J. (2015). Calculus: Early Transcendentals. Cengage Learning.
- Ross, S. M. (2014). Introduction to Probability and Statistics for Engineers and Scientists. Academic Press.
- Casella, G., & Berger, R. L. (2001). Statistical Inference. Duxbury Press.
- Papoulis, A., & Pillai, S. U. (2002). Probability, Random Variables, and Stochastic Processes. McGraw-Hill.
- Boyd, S., & Vandenberghe, L. (2004). Convex Optimization. Cambridge University Press.
- Press, W. H., Teukolsky, S. A., Vetterling, W. T., & Flannery, B. P. (2007). Numerical Recipes: The Art of Scientific Computing. Cambridge University Press.
- Zill, D. G., & Wright, W. S. (2012). Differential Equations with Boundary-Value Problems. Cengage Learning.
- Diestel, R. (2017). Graph Theory. Springer.
- Newman, M. (2018). Networks. Oxford University Press.
- Pastor-Satorras, R., Castellano, C., Van Mieghem, P., & Vespignani, A. (2015). Epidemic Processes in Complex Networks. Reviews of Modern Physics, 87(3), 925-979.
- Wasserman, S., & Faust, K. (1994). Social Network Analysis: Methods and Applications. Cambridge University Press.
- Luenberger, D. G. (2003). Linear and Nonlinear Programming. Springer.
- Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer.
- Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., & Hwang, D. U. (2006). Complex Networks: Structure and Dynamics. Physics Reports, 424(4-5), 175-308.
- Easley, D., & Kleinberg, J. (2010). Networks, Crowds, and Markets: Reasoning About a Highly Connected World. Cambridge University Press.
- Leskovec, J., Rajaraman, A., & Ullman, J. D. (2014). Mining of Massive Datasets. Cambridge University Press.
- Albert, R., & Barabási, A. L. (2002). Statistical Mechanics of Complex Networks. Reviews of Modern Physics, 74(1), 47-97.
- Barzel, B., & Barabási, A. L. (2013). Universality in Network Dynamics. Nature Physics, 9(10), 673-681.

TEXTE DE DESCRIPTION DU COURS

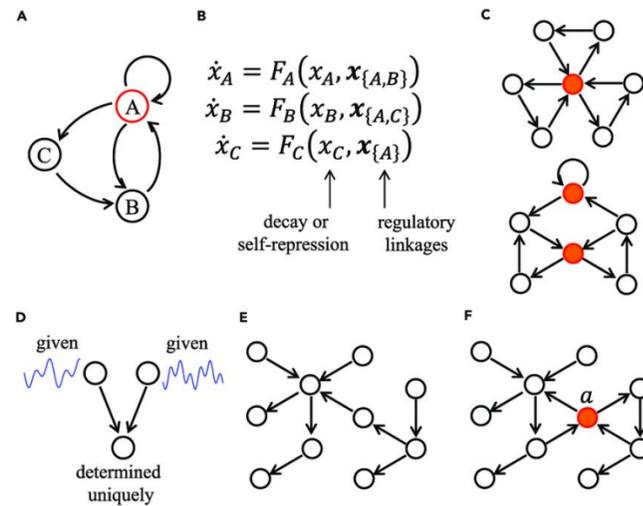
Let's embark on an intellectual adventure through the captivating realm of "Theory of Systems: Network Dynamics." Imagine being drawn into a narrative where the intricate web of mathematics, networks, and data-driven insights awaits your exploration. Picture yourself standing at the crossroads of discovery, fueled by curiosity and the desire to unravel the secrets of complex systems. This course promises not just theoretical knowledge but a journey of intellectual awakening, where you'll harness the power of mathematical foundations to understand and master the dynamics of networks and systems.

To fully grasp the significance of this course, we need to draw from the wisdom of prominent mathematicians and scholars who have paved the way for our understanding of systems and networks. Think about luminaries such as George Polya, who made profound contributions to problem-solving strategies, or Paul Erdős, whose work in graph theory laid the groundwork for our comprehension of network structures. These mathematical giants have left an indelible mark on the field, and their contributions serve as a testament to the rich history and importance of the concepts you'll encounter in this course.

Now, let's dive into the real-world applications and practical implications of the "Theory of Systems: Network Dynamics." This knowledge transcends academic boundaries and finds utility in a multitude of fields. Network analysts use these principles to decipher the intricacies of social networks, communication systems, and transportation networks. Data scientists harness these skills to model the spread of diseases, information flow, and the dynamics of complex systems. From healthcare professionals to engineers and from researchers to business analysts, the relevance of this course is far-reaching, making it a must-learn for those who seek to navigate the interconnected world effectively.

Understanding the "Theory of Systems: Network Dynamics" is more than just gaining knowledge; it's about acquiring a skillset that empowers you to analyze, model, and optimize complex systems. In today's data-driven era, the ability to decode network behaviors, predict system responses, and identify critical nodes of influence is indispensable. This course equips you with the tools to unravel the mysteries of network dynamics, fostering an analytical mindset that enhances problem-solving in diverse domains. Moreover, it opens doors to a world where you can contribute to groundbreaking research, innovate solutions, and make data-driven decisions that impact our interconnected society.

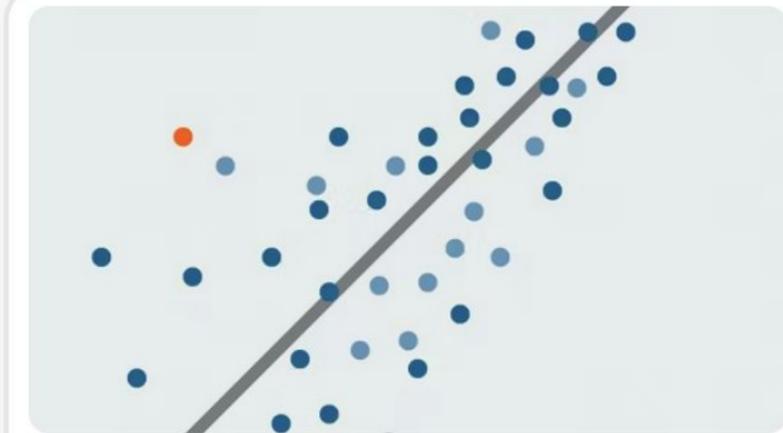
Are you ready to embark on this enlightening journey? Join us in unlocking the potential of the "Theory of Systems: Network Dynamics" and allow mathematics to become your compass in understanding complex systems. Enroll now to commence your exploration and become part of a vibrant learning community. Should you have any questions, seek further guidance, or wish to delve deeper into the subject, don't hesitate to contact the Weeki team. Let's collectively uncover the intricacies of network dynamics and systems, shaping a future that thrives on knowledge and data-driven insights.



Author: Baptiste Mokas, Weeki

Course Name: Simple Linear Regression

#NetworkDynamics
#ComplexSystems
#DataDrivenAnalysis



 Duke University

Linear Regression and Modeling

Compétences que vous acquerez: Probability & Statistics, Regression, Business Analysis, Data Analysis, General Statistics, Statistical Analysis,...

★ 4.8 (1.7k avis)

Débutant · Course · 1 à 4 semaines