An Overview of AI, Cybernetics, & Dynamic Systems

Systems Sciences Foundations

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Xerox

Outline

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AI: Definitions and Main Goals

Maths

- **Artificial Intelligence (AI):** *Science* and *engineering* of making **intelligent machines** capable of performing tasks that normally require human intelligence.

Biology
Physics

electronic
mechanic
materials

- **Main Goals:**
  - Automate reasoning and knowledge representation.
  - Enable learning, perception, and adaptation.
  - Achieve problem-solving in complex domains.
- **Scope:**
  - Broad field spanning subtopics like `machine learning`, `robotics`, and `cognitive modeling`.

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AI
O

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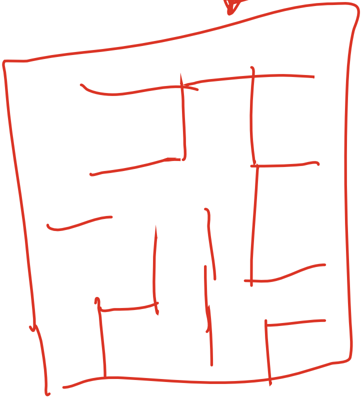
90s → Psyc, → Comp
Comp → Psyc.

AI Types and Learning Paradigms I

Symbolic vs. Subsymbolic AI:

- *Symbolic (GOFAI)*: Knowledge-based systems with logical rules.
- *Subsymbolic*: Neural networks that learn patterns from data.



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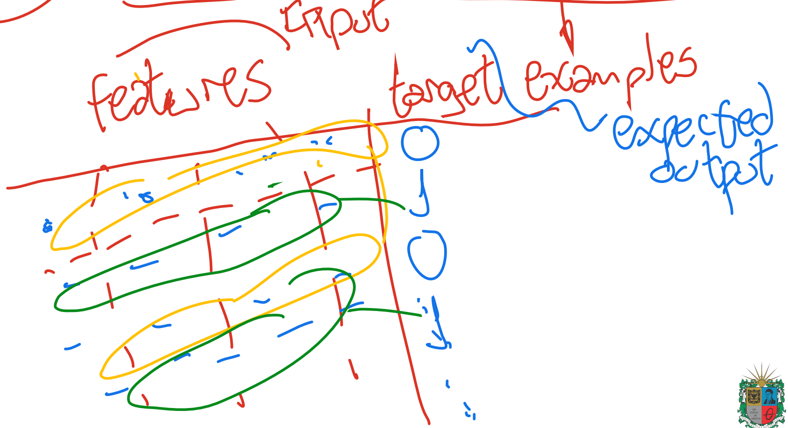

AI Types and Learning Paradigms II

→ Sub-system AI

- **Machine Learning Types:**
  - Supervised: Mapping inputs to outputs using labeled data.
  - Unsupervised: Discovering patterns or structures in unlabeled data.
  - Reinforcement Learning: Learning actions through reward feedback loops.
- **Glossary:**

data label (target)

cat

- cat

- dog

dog

- cut

- dog

→ cat

→ dog

→ cat ? 0.7
dog ? 0.3

AI Types and Learning Paradigms II

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  - *Deep Learning, Decision Tree, Overfitting.*

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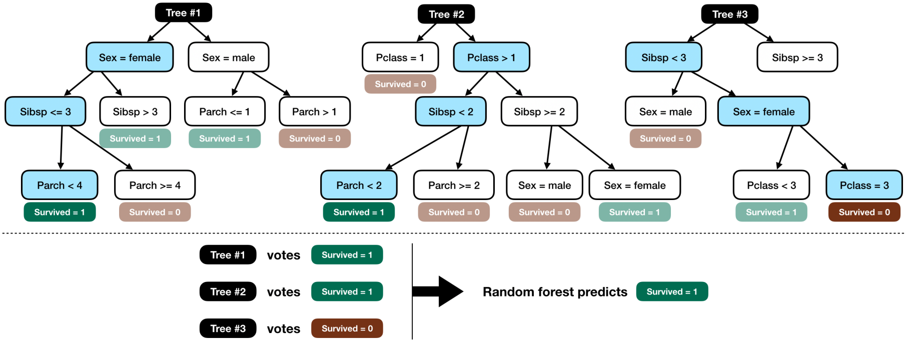
Case Study: Titanic in Kaggle

Did the passenger survive?

PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
893	3	Wilkes, Mrs. James (Ellen Needs)	female	47	1	0	363272	7		S



Psychological Foundations of AI

- **Human Cognition and Behavior:**
  - Inspired AI research in learning, perception, and problem solving.
- **Learning Theories:**
  - *Behaviorism:* Learning as conditioning.
  - *Constructivism:* Building mental models through experience.
- **Implications for AI:**
  - Cognitive architectures simulate attention, memory, and reasoning.
  - Ethical and social concerns about mind-like systems.

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Discussion

1. What key differences separate symbolic (GOFAI) from subsymbolic (neural networks) approaches, and when might each be more suitable?
2. How do supervised, unsupervised, and reinforcement learning each handle data differently, and can you suggest real-world examples for each?
3. In what ways could insights from psychology inform the design of more human-like AI systems?
4. Which ethical concerns should developers keep in mind as AI becomes increasingly integrated into society?
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output

Supervised → label

Unsupervised → Pattern

Reinforcement learning

strategy → optimization

Semi-supervised

→ target classes

million

→ supervised

500 Human

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control + feedback

Cognitive / kids

learning paradigms

Neuro ?

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- Data exposure
- Privacy

→ deep voice
deepfake

misinformation

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2017 → 2021

+ papers →

+ patents → hardware

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Did you know?

OpenAI

- **AI in Art:**
  - AI-generated art is gaining popularity, with tools like DALL-E and Midjourney.
  - AI in music composition is also on the rise, with systems like OpenAI's MuseNet.
- **AI in Healthcare:**
  - AI is revolutionizing diagnostics, drug discovery, and personalized medicine.
  - AI systems can analyze medical images, predict patient outcomes, and assist in treatment planning.

high quality → deepfake

copyright → Picasso

art student

5 years

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synt.

musicians

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images + data

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Patient → Eastfeld

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Google Healtcare → Source

AWS Medical AI

Outline

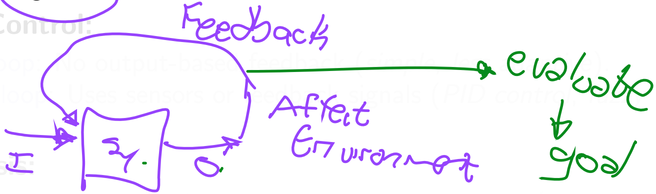
Cybernetics: Definitions and History

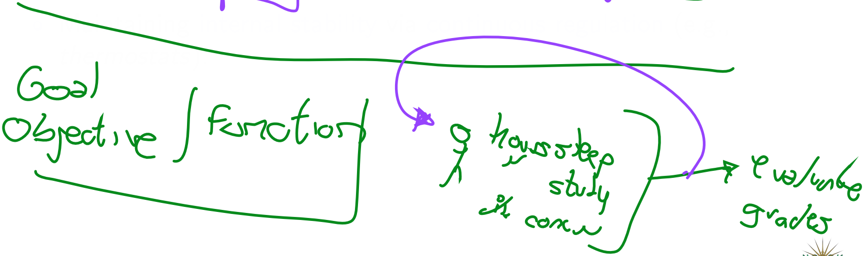
1 2

- **Cybernetics:** Study of communication and control in living beings and machines. environment
- **Norbert Wiener (1948):** Formalized the term, focusing on feedback systems. Termostato
- **Applications:**
  - Robotics, AI, management science, social systems analysis.

Control Mechanisms in Cybernetics

- **Feedback Loops:** *Adjust* system behavior based on comparing `outputs to goals`.
- Types of Control:
  - Open-loop: No output-based feedback (simple, ...).
  - Closed-loop: Uses sensors or feedback signals (*PID control*, ... *logic*).
- Homeostasis:





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  - Maintaining internal stability via continuous regulation (e.g., *thermostats*).

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discret

continue → more adaptive + insights

Δ s seg
Δ J seg
Δ J min

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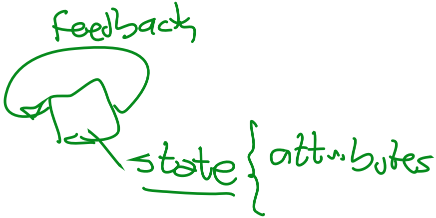
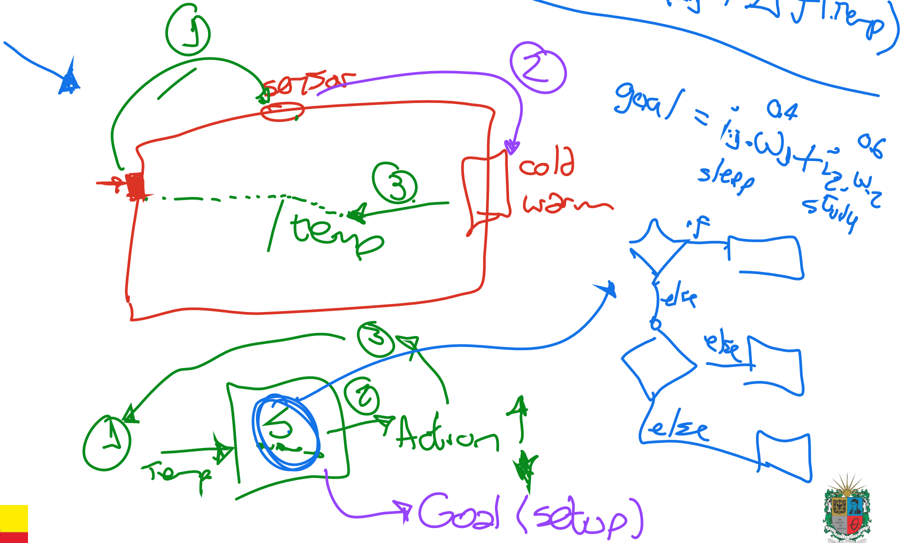


Study Case: Thermostat System

$$n.\ t_i = t_{i-1} + \Delta f(\text{temp})$$

$$\text{goal} = i_1 \cdot w_1 + i_2 \cdot w_2$$



Relation with AI

50's (40's)

- **Cybernetics + AI:**
  - Early *AI research* leveraged cybernetic principles of feedback and adaptation.
  - **Reinforcement Learning** is a prime example of a feedback-driven method.

Adaptation → No ≠ smart

girafe

- **Self-Regulatory Systems:**

LaMark

Aptitude

- **Interdisciplinary Insights:**

endemic

Darwin → mutation

random

Evolution

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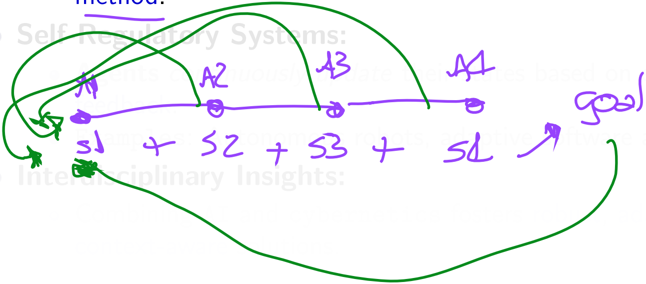

- **Self-Regulatory Systems:**
  - Agents continuously update their states based on environmental feedback.
  - Examples: Autonomous robots, adaptive software agents.
- **Interdisciplinary Insights:**
  - Combining AI and cybernetics fosters robust, adaptive, and context-aware solutions.

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System
+
Decision
Making
Process

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→ health
→ transport & logistics
→ education

Discussion

1. How do feedback loops in cybernetics enhance the adaptability of AI systems?

Data → Adjust Behavior → Complete Goal

2. Can you provide examples of real-world applications where cybernetics and AI intersect?
3. What are the ethical implications of creating self-regulating systems in society?
4. How can we ensure that AI systems maintain a balance between autonomy and human oversight?
5. What future trends do you foresee in the integration of cybernetics and AI?

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1) Alexa - Home assistants

2) Autonomous Car

3) Social Network (Tinder)

algorithm

best recom

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Discussion

JARVIS

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? → learn

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1 limits → Wall-e → control, development

2 Ultron → Humans → Robots

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– Reinforcement Learning Human Feedback

RLHF

– Retraining

Dataset

Trillion

Discussion

→ Militar – Gover – Acad? → houses

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Superhumanism → Super Intelligence

robots → houses

→ 70's Orchestra

LLM → Human

Did you know?

Destilator → LLM (15 billion)

① → ②

SLM ← 1 billion

- **Cybernetic Art:**
  - Artists use cybernetic principles to create **interactive installations**.
  - Examples include responsive sculptures and generative art.
- Cybernetics in Nature:

Van Gogh < Virtual Reality / Augmented Reality

1 2 3 5 6 8 9 12 → 36 → 9 ✓

1 2 3 5 6 8 9 1 → 35 → 8 ✗

Did you know?

hydrogen

- **Cybernetic Art:**
  - Artists use cybernetic principles to create **interactive installations**.
  - Examples include responsive sculptures and generative art.
- **Cybernetics in Nature:**
  - **Natural systems** exhibit cybernetic principles, like *feedback loops* in *ecosystems*.
  - Understanding these systems can inform *sustainable practices*.

metal

80 billions

Data Centers

2%

energy

nuclear

residuals

0.5%

cyber truck

Colombia => energy crisis

100%

millions → energy

lithium

coltan

gold

Outline

Definitions and System Characteristics

temporal → time

- **Dynamic System:**
  - **System** whose state evolves over time based on inputs, initial conditions, and internal feedback.
- **Inputs vs. Outputs:**
  - **Inputs:** Exogenous factors driving system change.
  - **Outputs:** Responses or changes in the observable state.
- **Non-linearity:**
  - Many dynamic systems contain complex interdependencies that are non-linear.

world

12,5

I

O

2 ítoes

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parsimonium

enviro

output

blackbox

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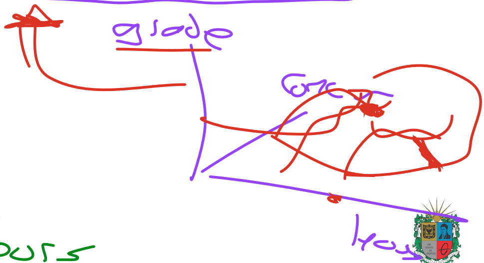


Chaos Theory and Sensitivity

- **Chaos Theory:**
  - Studies how small variations in initial conditions can *lead* to large differences in outcomes.
  - Butterfly Effect exemplifies extreme sensitivity.

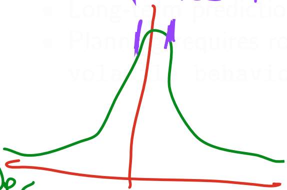
Input

Brazil

USA

- **Implications:**
  - Long-term predictions become *difficult* in chaotic regimes.
  - Planning requires robust control methods to handle uncertainty or volatile behaviors.

rules + random

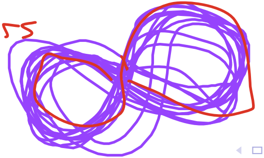


order

disorder

Chaotic Attractors

Lorenz



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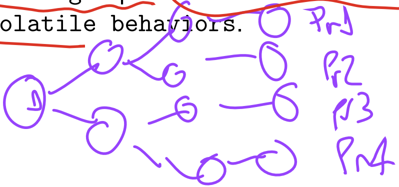
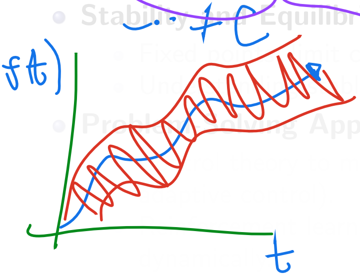
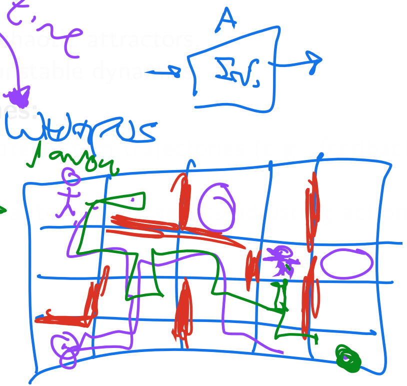


Dynamic Systems Analysis and Design

- **Modeling Approaches:**
  - Ordinary Differential Equations (ODEs), agent-based models, simulation.
- **Stability and Equilibria:**
  - Fixed points, limit cycles, chaotic attractors.

time





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  - Understanding stable vs. unstable dynamics.
- **Problem-Solving Approaches:**
  - Control theory to manipulate system trajectories (e.g., feedback, adaptive control).
  - Reinforcement le[illegible] agents adjusting actions [illegible] dynamics.

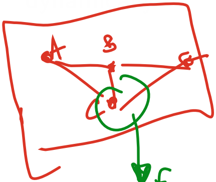
1 2 3

feedback

input

internal

external



fixed

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no time influence

randomness + feedback

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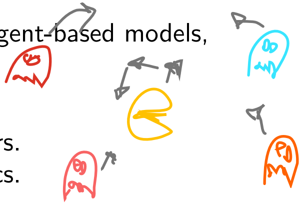

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cybernetics

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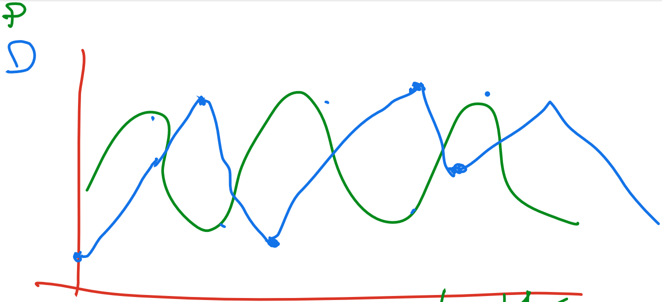
  - Reinforcement learning for autonomous agents adjusting actions dynamically.

Case Study: Lotka—Volterra model



births

$$\frac{dP}{dt} = \alpha x - \beta xy$$

dead by dep.

$$\frac{dD}{dt} = \delta xy - \sigma y$$

death

prey by food

Case Study: SIR model

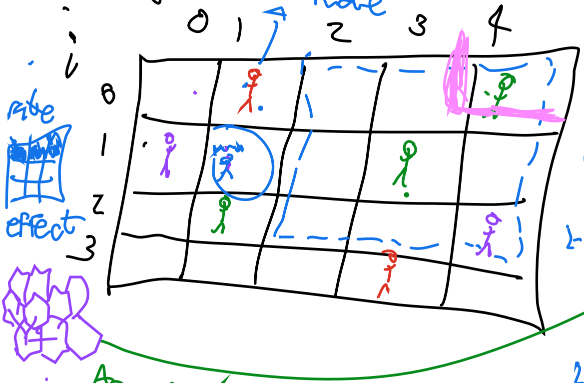
(SARS)

Susceptible - Infected - Recovery

for t in time:

for person in world:

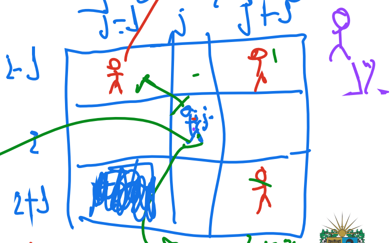
random move



rate 10%

rate

Neighborhood



Agent (Object)

AI (inference)

Chaos - random

rate dis 10% 15%

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Case Study: Bank — Event-Based Simulation

list ← queue.

cars

rate = $\mu = 1$, $\sigma = 0.5$ | t

$t=0$

$t=1$ arrive

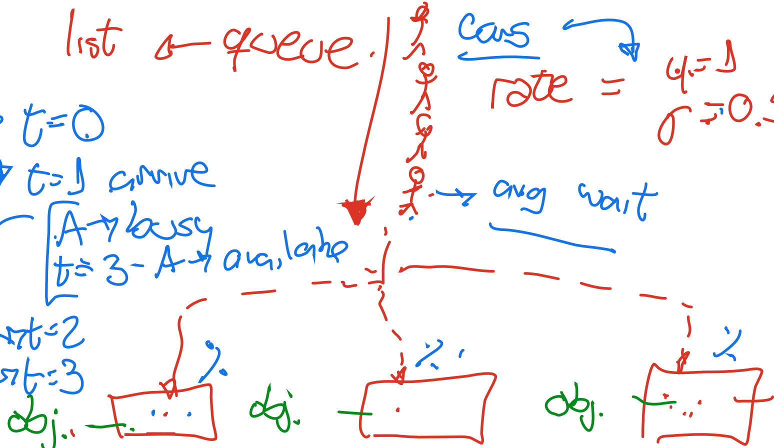
A → busy

$t=3$ - A → available

$t=2$

$t=3$

avg wait



state = idle / busy

random

$C_{?} = 2$ min

$\mu = 3$

$\sigma = 1$

$w = 1-3$ min

list event

Discussion

1. How do chaotic systems challenge our understanding of predictability in dynamic systems?
2. Can you provide examples of real-world systems that exhibit chaotic behavior?
3. What are the advantages and disadvantages of using ODEs versus agent-based models for system analysis?
4. How can we ensure that our models remain relevant and accurate over time?
5. What role does feedback play in the design of effective control systems?

initial conditions

randomness

non-linear

Chaotic Attractors

Discussion

1. How do chaotic systems challenge our understanding of predictability in dynamic systems?
2. Can you provide examples of real-world systems that exhibit chaotic behavior?

Traffic

Nature

⋮

Trading-Economics

Social Behaviors

3. What are the advantages and disadvantages of using ODEs versus agent-based models for system analysis?
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Discussion

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+ complex
reality
hard to build
+ emergent behavior
↳ time → cause & effect

continuous
- random
+ simplicity

predict

Discussion

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+ feedback management → adaptation

modules ← input (transform)

← inference → learning

+ system

tolerant-fault

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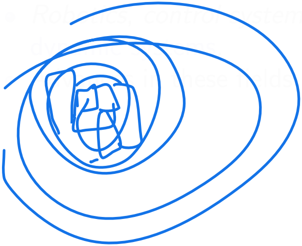
5. What role does feedback play in the design of effective control systems?

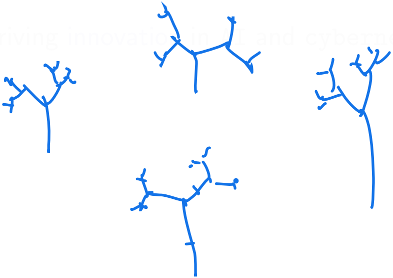
+ regulation → adaptation
+ exploration → problem solving

Did you know?

- **Dynamic Systems in Nature:** chaotic attractors
  - *Ecosystems*, *weather patterns*, and *population dynamics* are all examples of dynamic systems.
  - Understanding these systems can help us predict and manage environmental changes.
- **Dynamic Systems in Technology:**

L-System





Did you know?

- **Dynamic Systems in Nature:**
  - *Ecosystems*, *weather patterns*, and *population dynamics* are all examples of dynamic systems.
  - Understanding these systems can help us predict and manage environmental changes.
- **Dynamic Systems in Technology:**
  - *Robotics*, *control systems*, and *networked systems* are all examples of dynamic systems.
  - Advances in these fields are driving innovation in `AI` and `cybernetics`.

Outline

Conclusion

- **Systems Sciences Foundations** merges `AI`, `cybernetics`, and `dynamic systems`.
- Provides frameworks for `modeling`, `understanding`, and `controlling complex behaviors`.
- Preparatory step for deeper explorations: `advanced ML`, `multi-agent cybernetic architectures`, and `real-world system simulations`.

Real

Outline

Thanks!

Questions?

Repo: *https://github.com/EngAndres/ud-public/tree/main/courses/systems-sciences-foundations*

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