An Overview of AI, Cybernetics, & Dynamic Systems

Systems Sciences Foundations

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Outline

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AI: Definitions and Main Goals

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

- **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:**
  - *Deep Learning, Decision Tree, Overfitting.*

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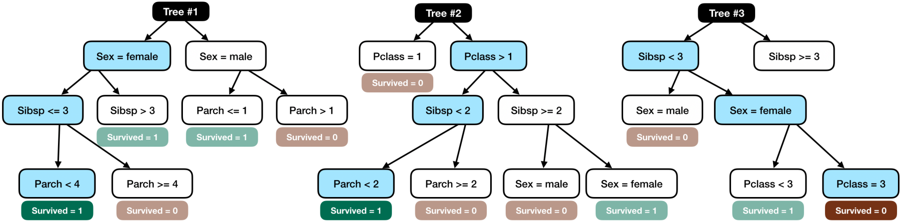
Case Study: Titanic in Kaggle

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



Tree #1 votes **Survived = 1**

Tree #2 votes **Survived = 1**

Tree #3 votes **Survived = 0**

→ **Random forest predicts** **Survived = 1**

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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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?
5. What do you anticipate as the next big leap or challenge in AI, and why?

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Did you know?

- **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.

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Cybernetics: Definitions and History

- **Cybernetics:** Study of communication and control in `living beings` and `machines`.
- **Norbert Wiener (1948):** Formalized the term, focusing on feedback systems.
- **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, less adaptive*).
  - Closed-loop: Uses sensors or feedback signals (*PID control, fuzzy logic*).
- **Homeostasis:**
  - Maintaining internal stability via continuous regulation (e.g., *thermostats*).

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Study Case: Thermostat System

Relation with AI

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

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Definitions and System Characteristics

- **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.

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

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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.
  - Understanding stable vs. unstable dynamics.
- **Problem-Solving Approaches:**
  - Control theory to manipulate system trajectories (e.g., feedback, adaptive control).
  - Reinforcement Learning for autonomous agents adjusting actions dynamically.

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Case Study: Lotka—Volterra model

Case Study: SIR model

Case Study: Bank — Event-Based Simulation

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?
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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.

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1. Basic Concepts of Artificial Intelligence
2. Basic Concepts of Cybernetics
3. Introduction to Dynamic Systems

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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`.

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Thanks!

Questions?

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

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