An Overview of AI, Cybernetics, & Dynamic Systems

Systems Sciences Foundations

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Outline

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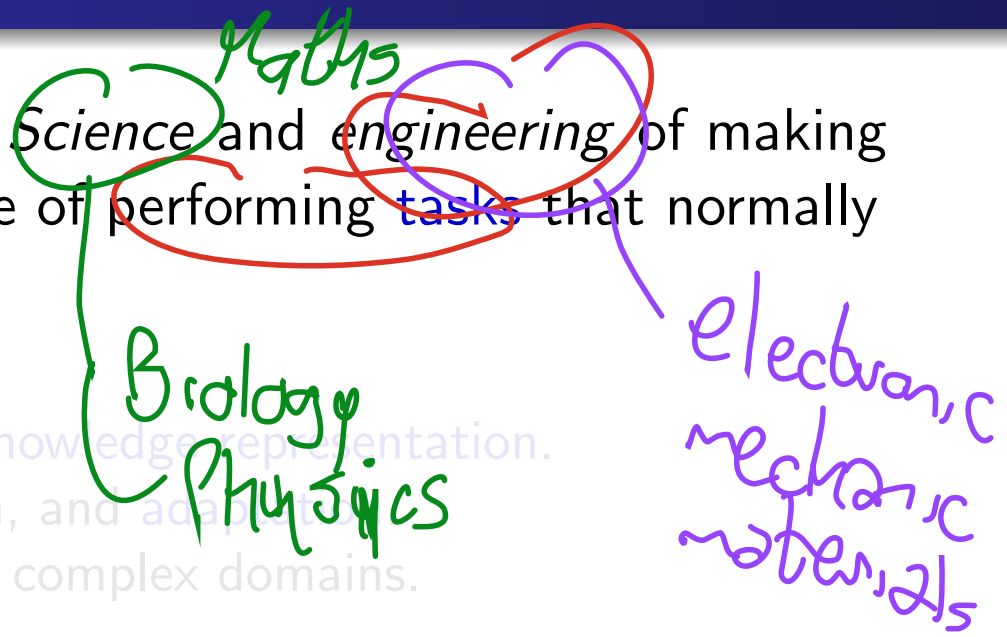
AI: Definitions and Main Goals

- **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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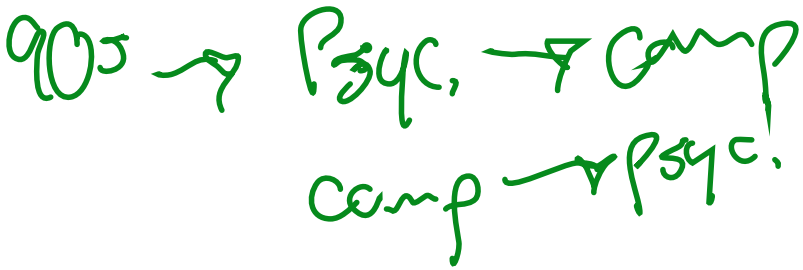
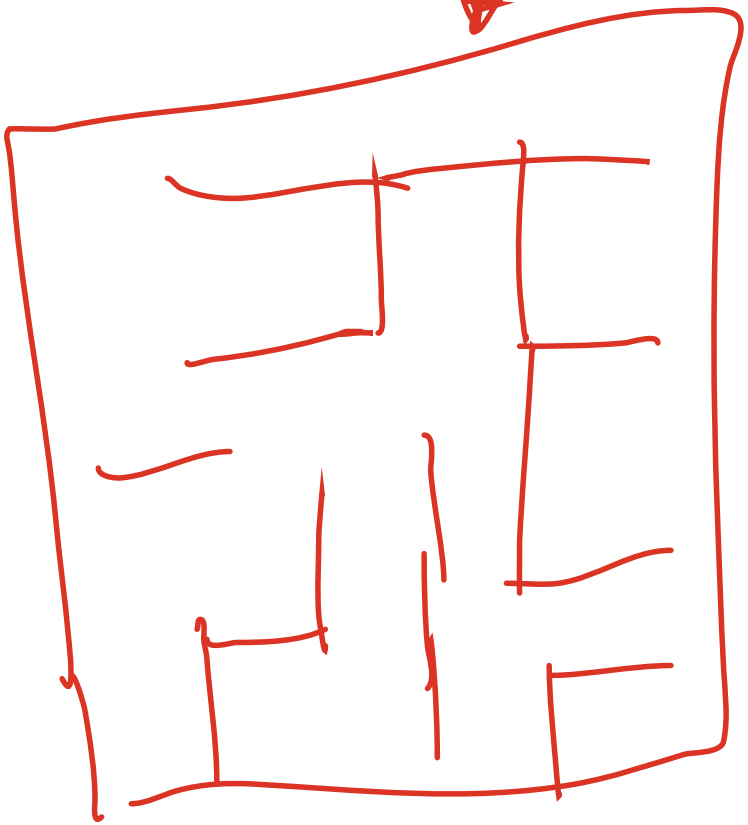


AI Types and Learning Paradigms I

Symbolic vs. Subsymbolic AI:

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



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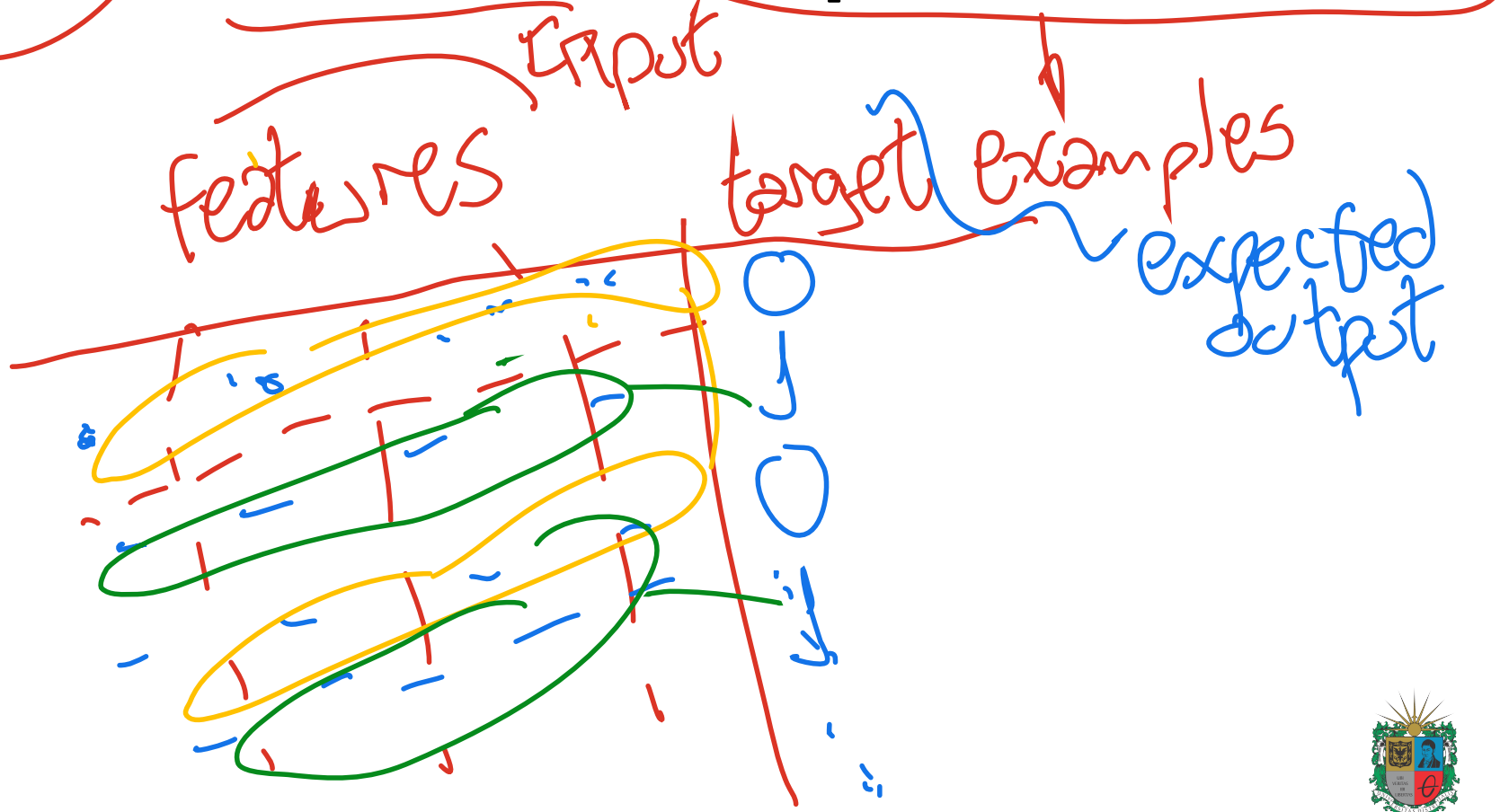

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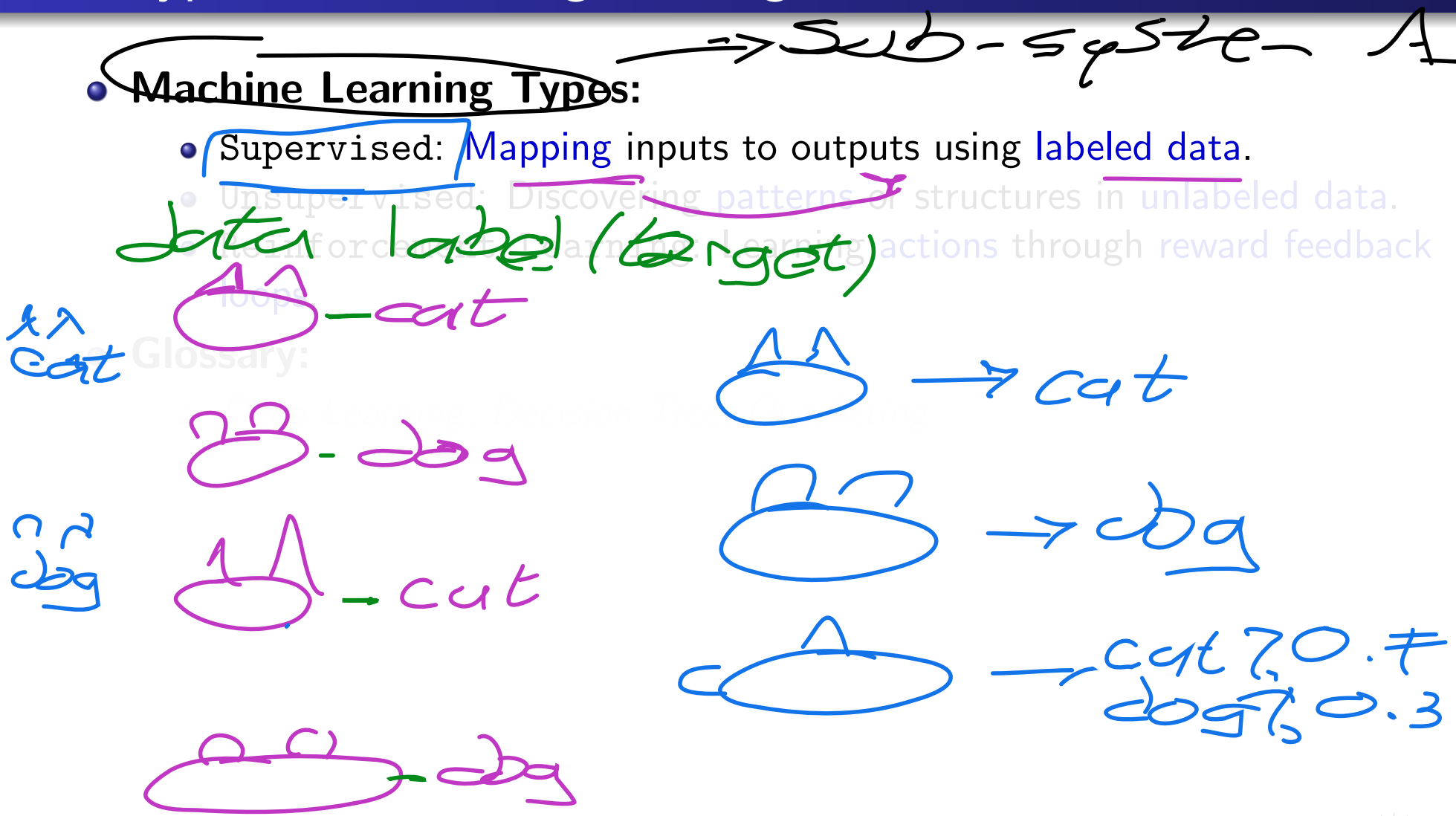

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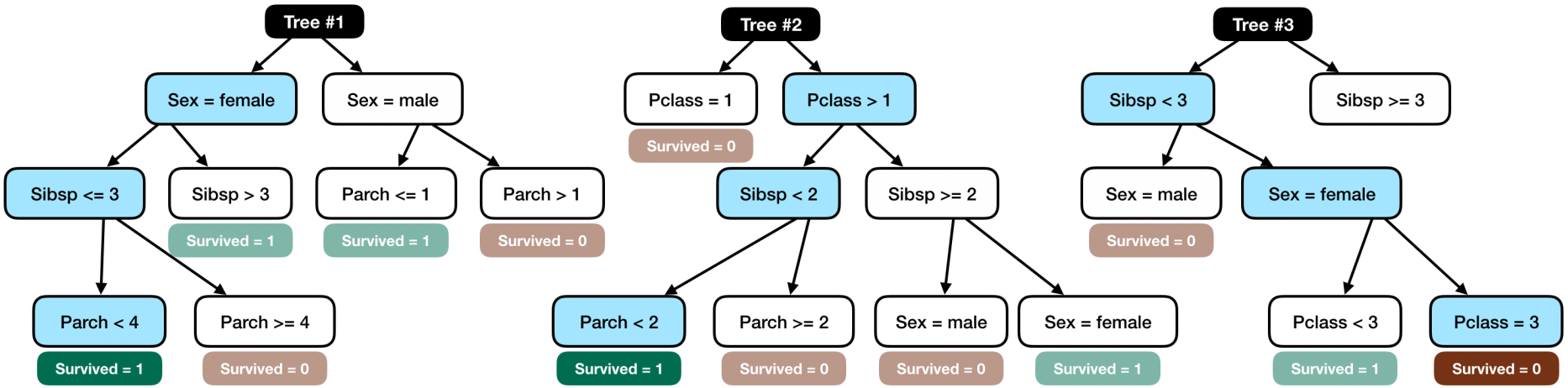
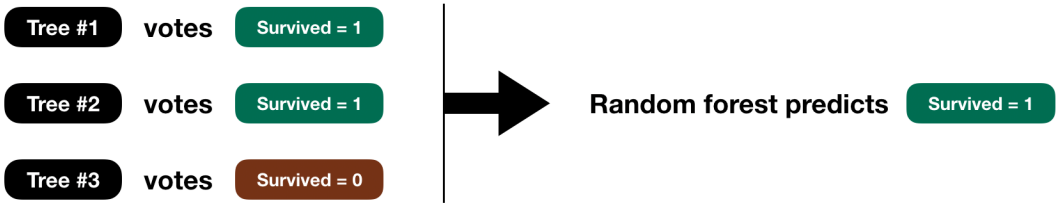
Case Study: Titanic in Kaggle

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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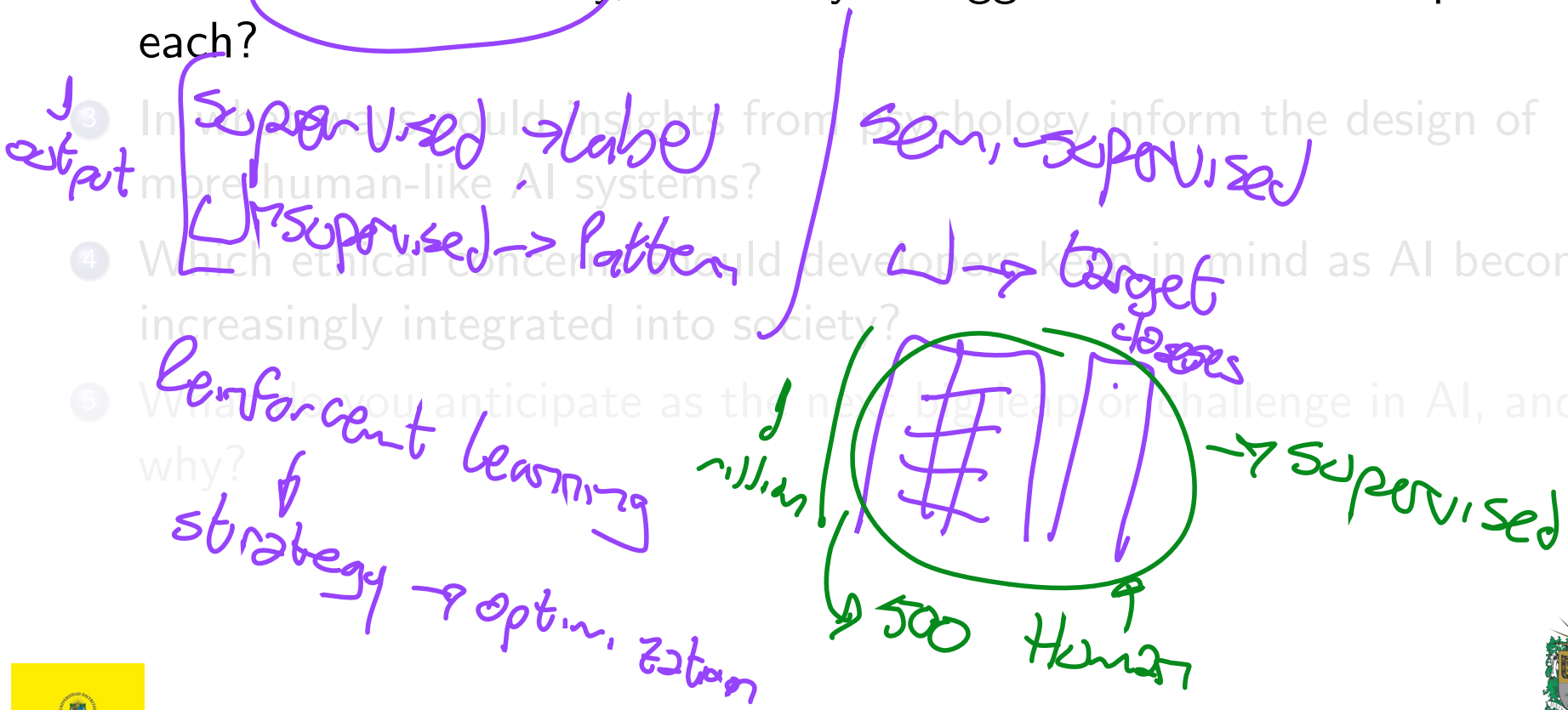

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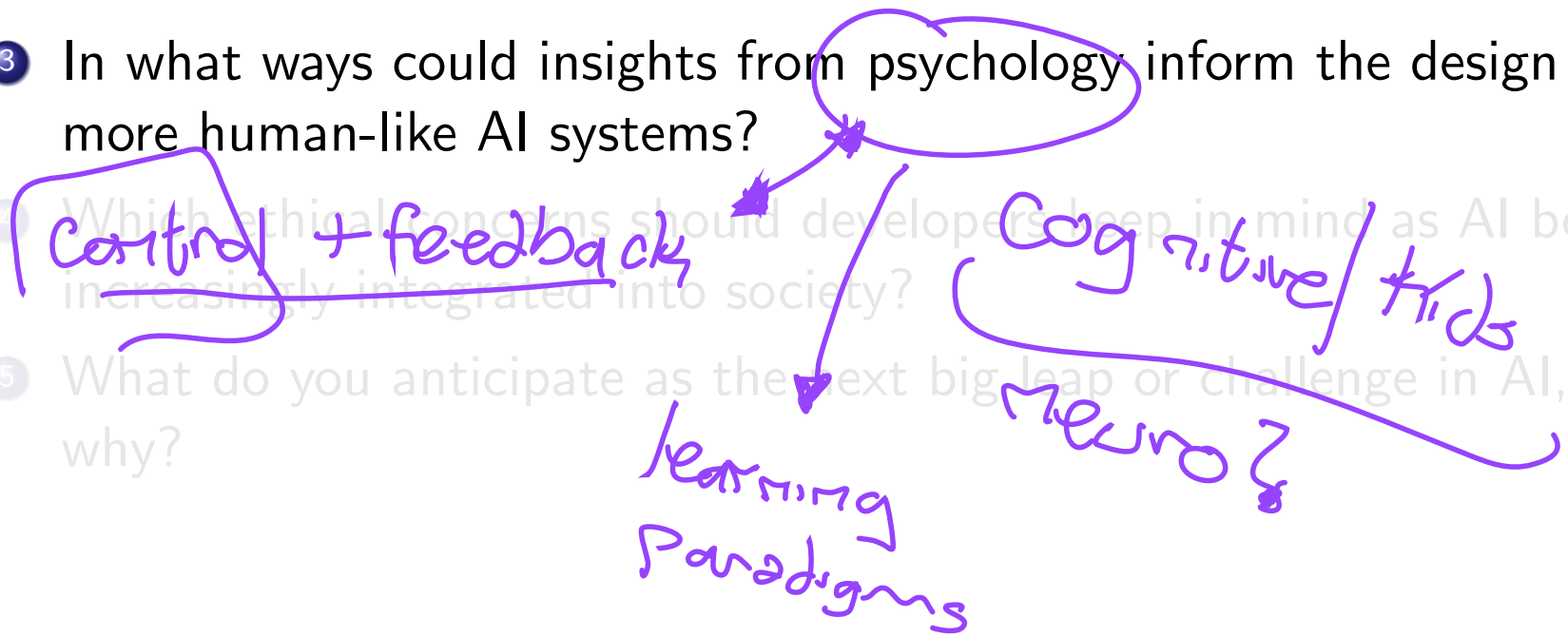

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- Data exposure
- Privacy

→ deep voice, deepfake / misinformation

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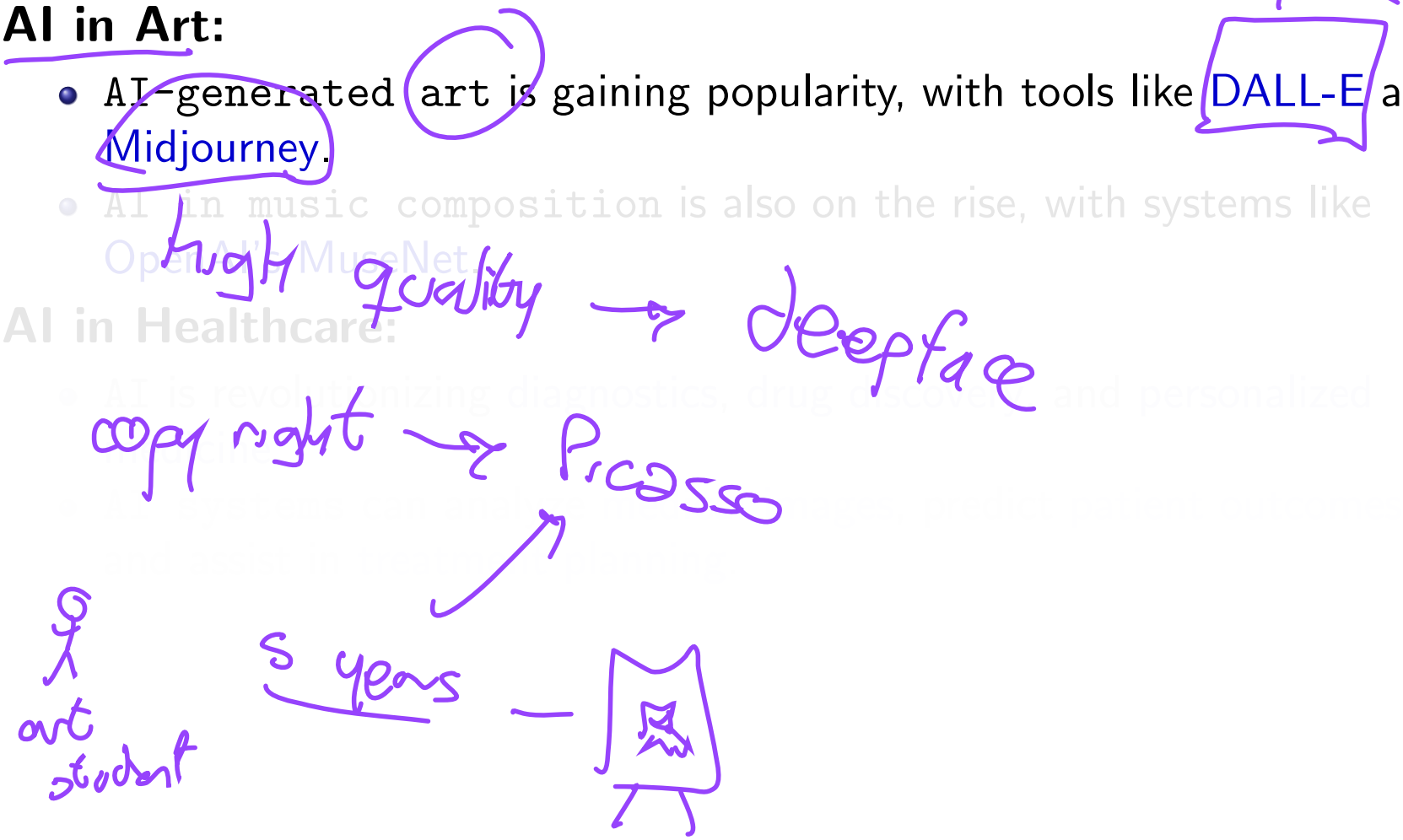
  - AI-generated art is gaining popularity, with tools like DALL-E and Midjourney.
  - AI in music composition is also on the rise, with systems like OpenAI's MuseNet.
- **AI in Healthcare:**
  - AI is revolutionizing diagnostics, drug discovery, and personalized medicine.
  - AI systems can analyze medical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



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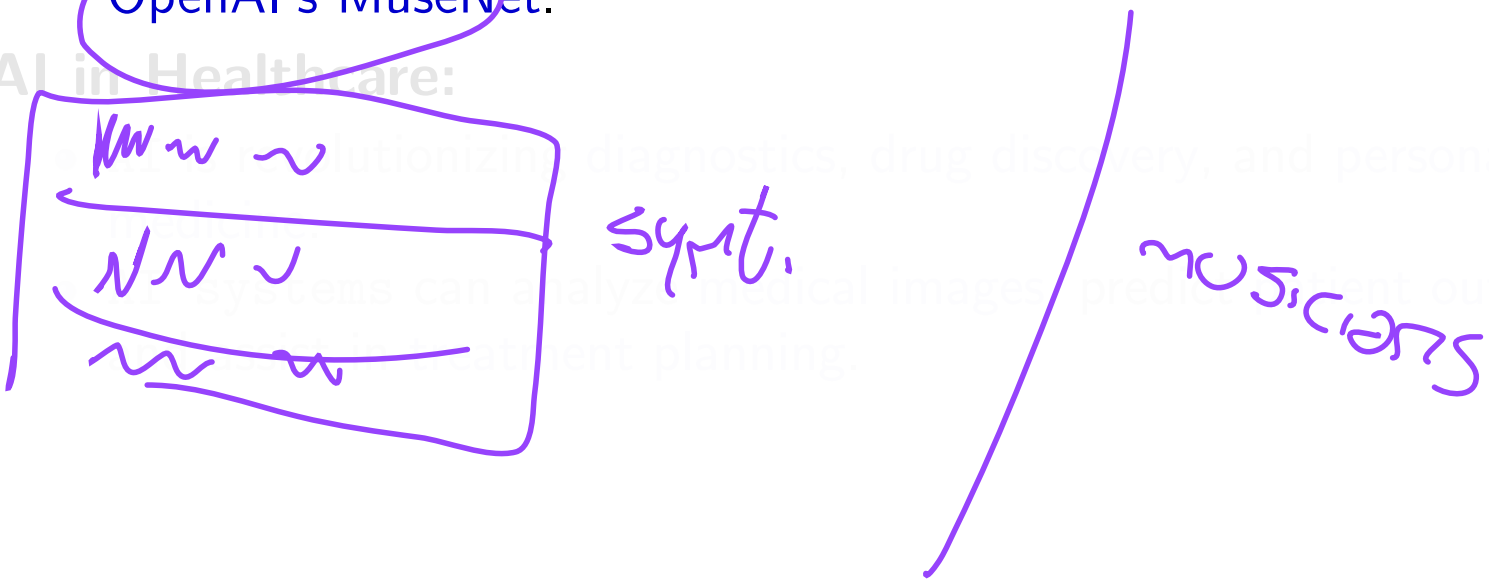

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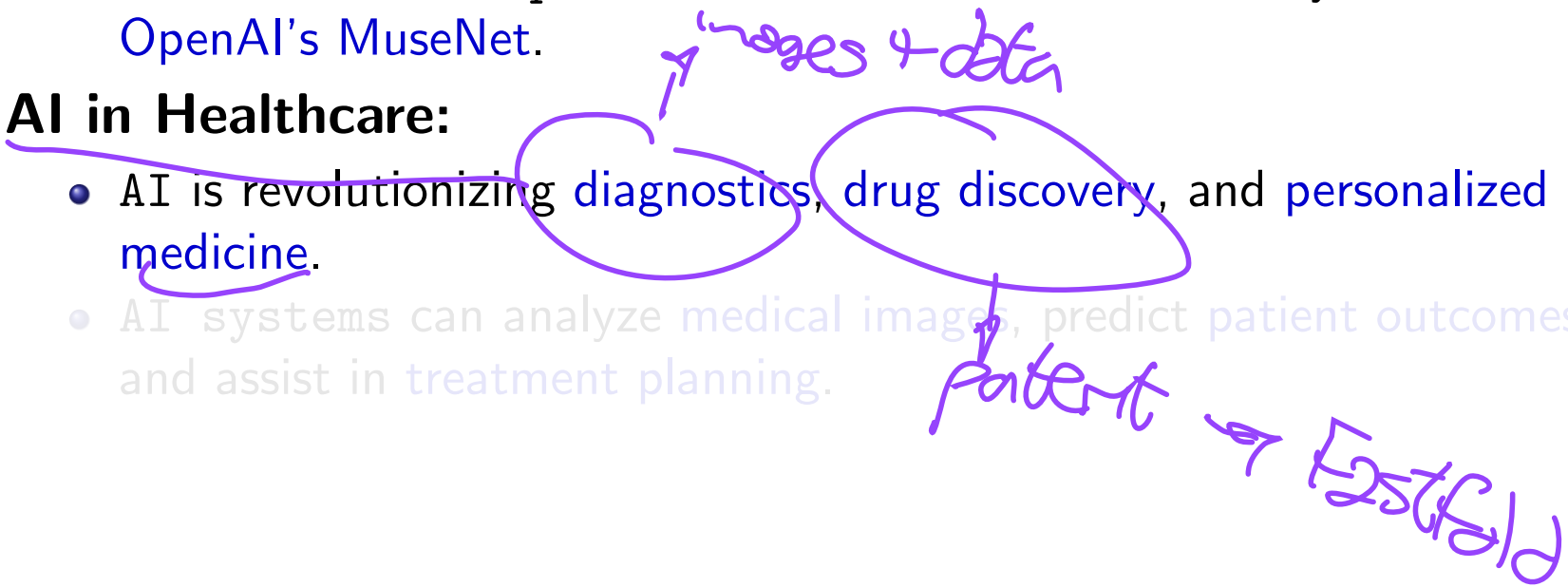

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Google Healthcare → source

AWS medical AI

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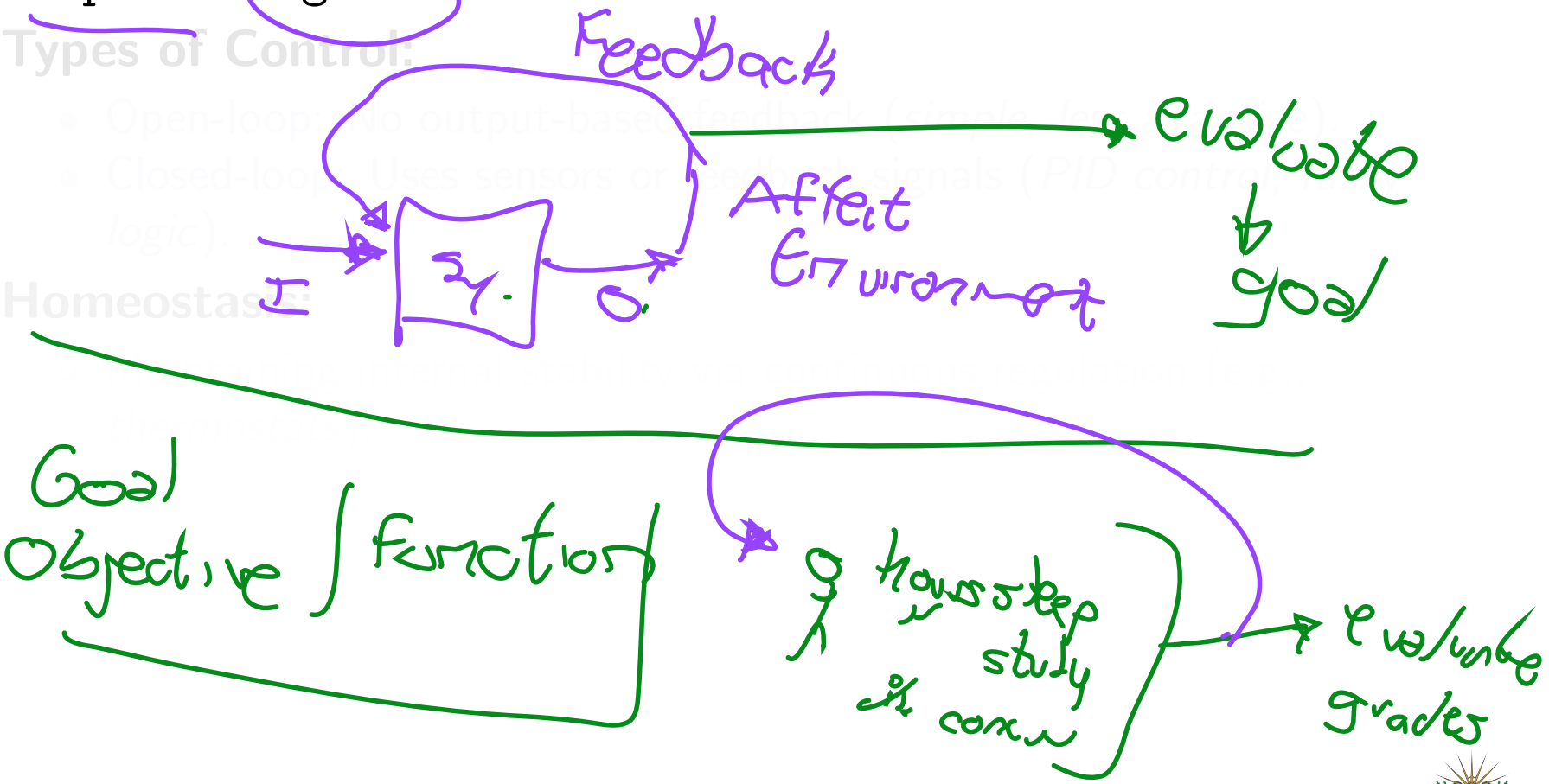
Cybernetics: Definitions and History

- **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.



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- **Types of Control:**
  - Open-loop: No output-based feedback (*simple, less adaptive*).
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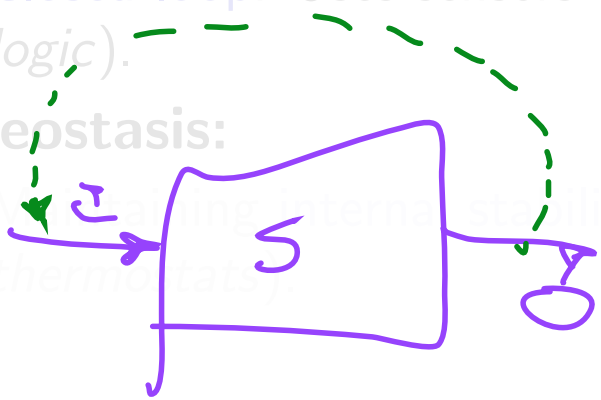
- **Homeostasis:**
  - Maintaining internal stability via continuous regulation (e.g., *thermostats*).



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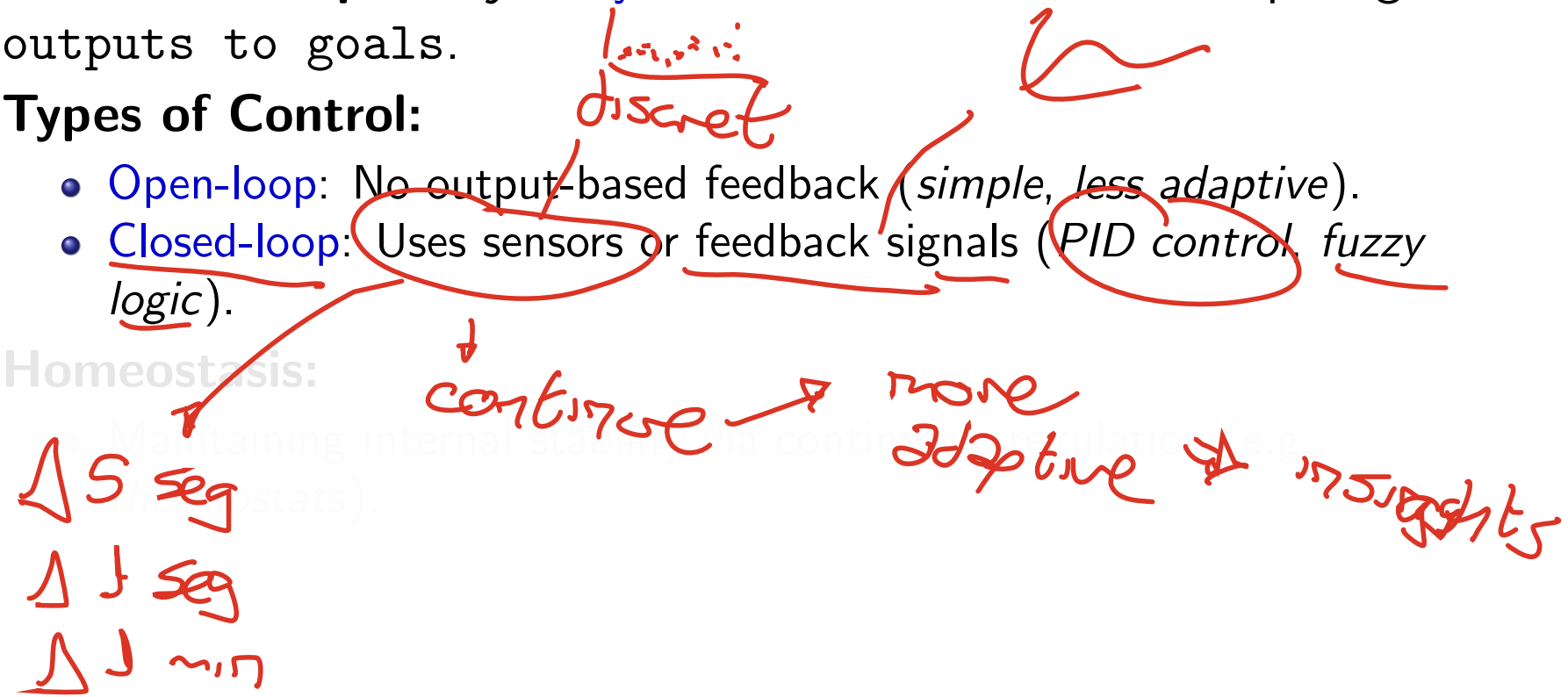

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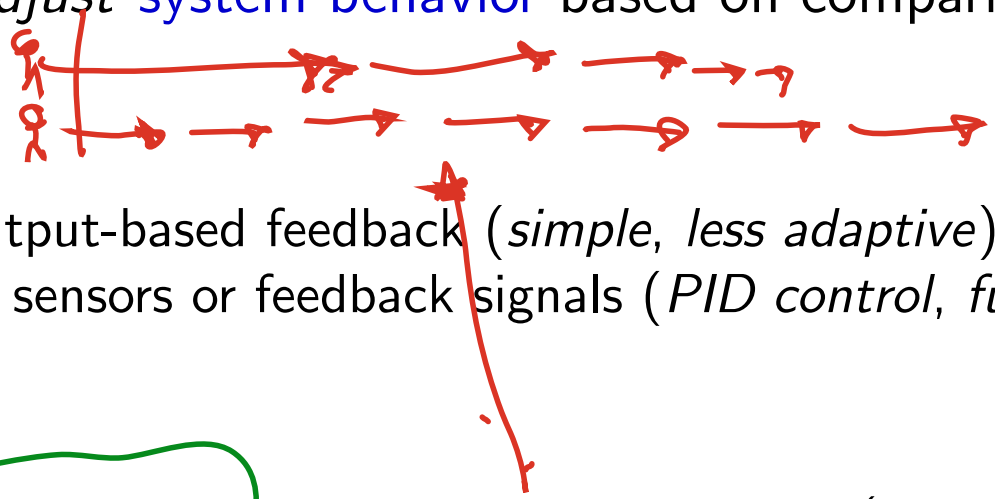

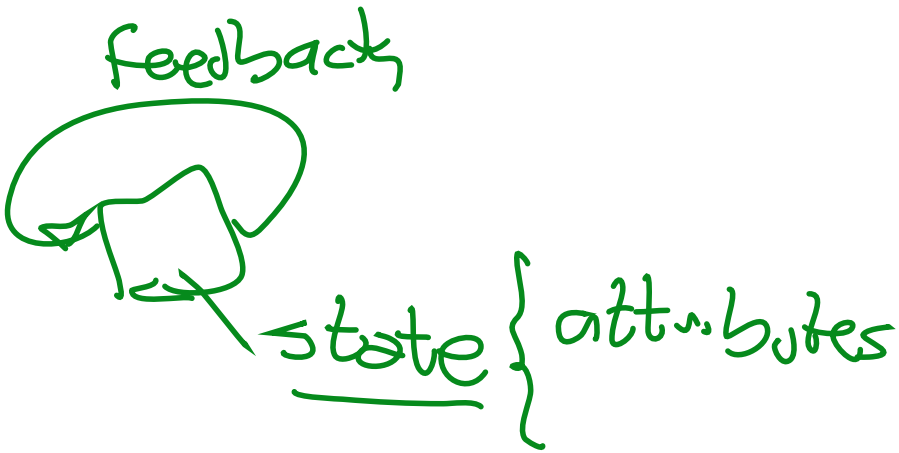

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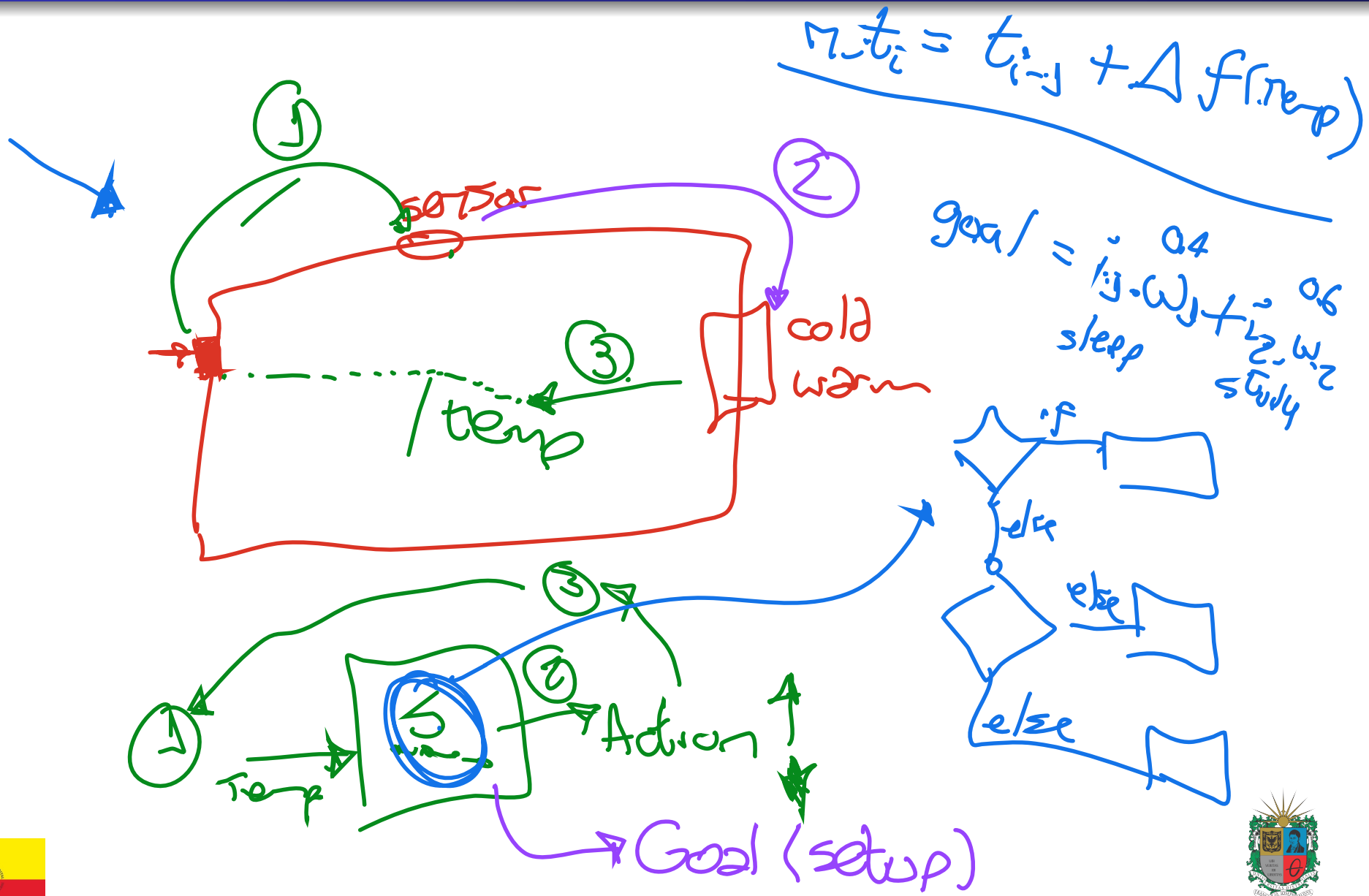
Study Case: Thermostat System



Relation with AI

- **Cybernetics + AI:**
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  - **Reinforcement Learning** is a prime example of a feedback-driven method.
- **Self-Regulatory Systems:**
  - Agents *continuously* update their ... based on environmental feedback.
- **Interdisciplinary Insights:**

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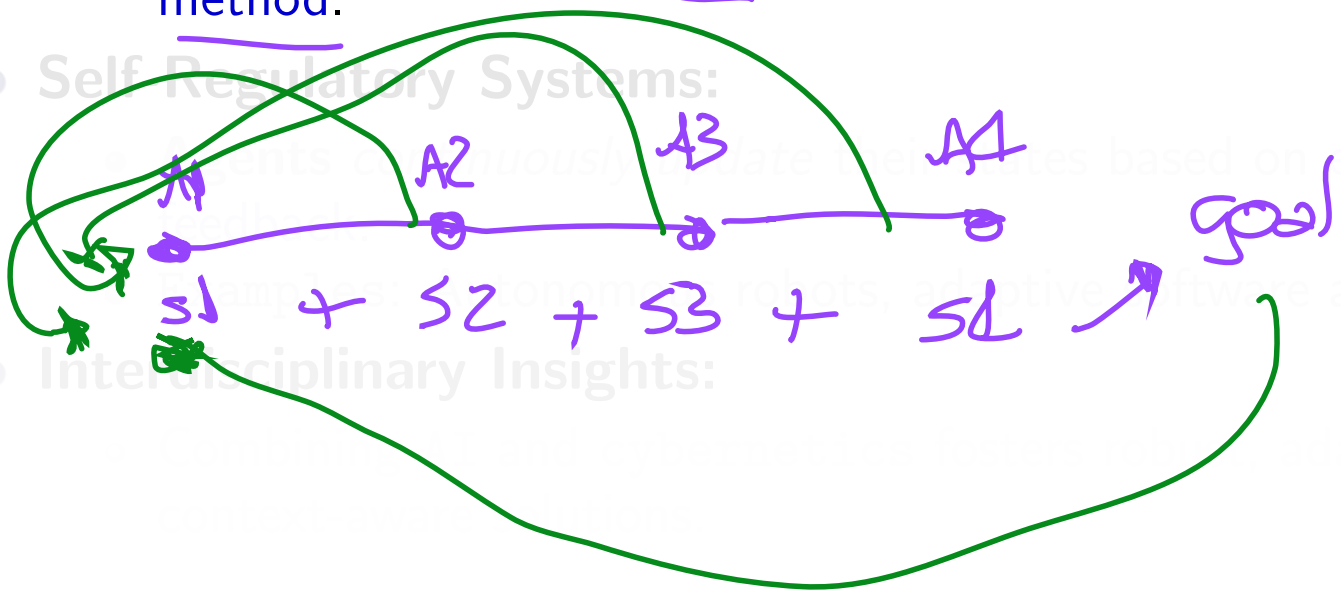

- **Self-Regulatory Systems:**
  - Agents continuously update their actions based on environmental feedback.
  - Examples: thermostats, robots, adaptive software agents.
- **Interdisciplinary Insights:**
  - Contributions from fields like psychology, sociology, and communication theory.

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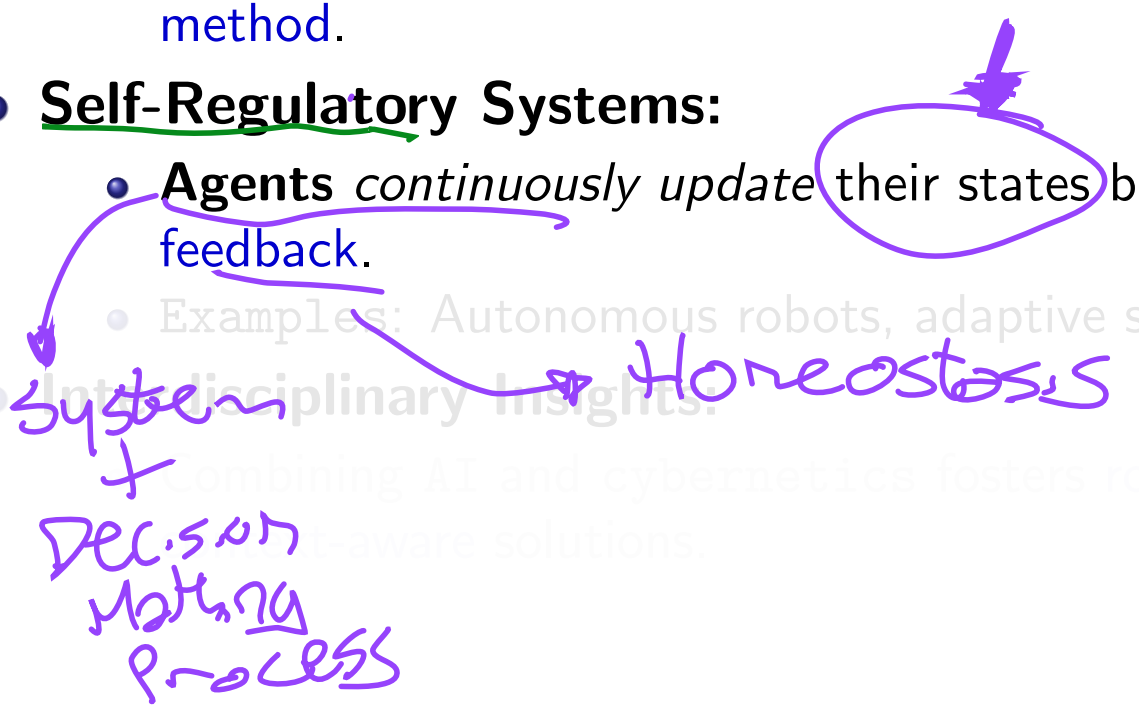

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→ healthy
→ transport & logistics
→ education

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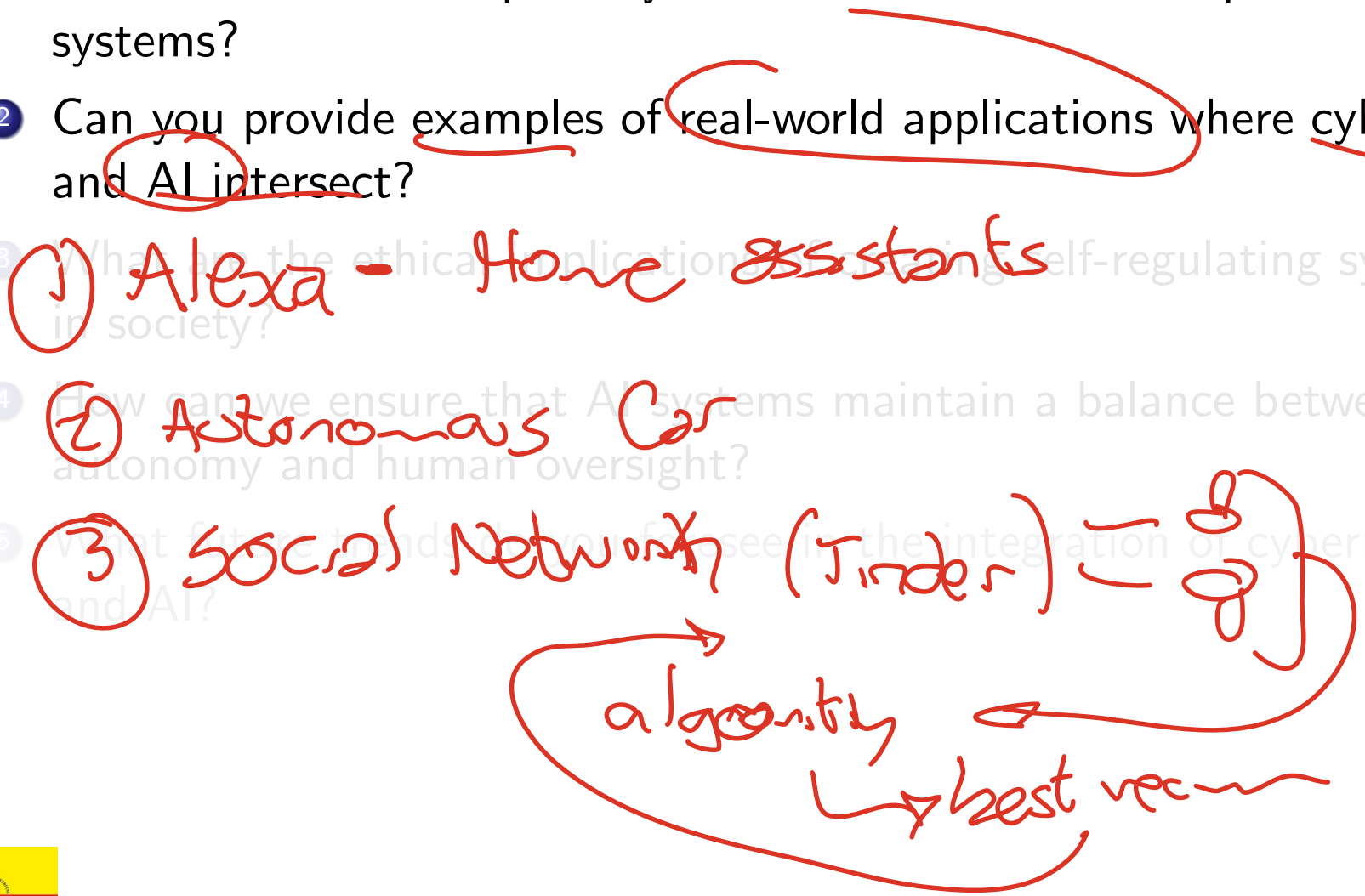

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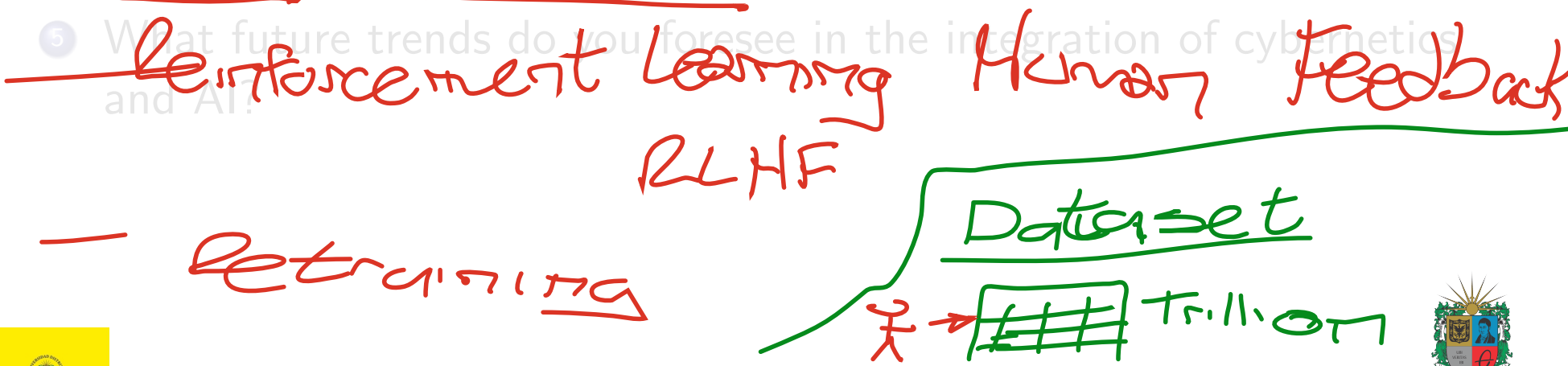

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  - Artists use cybernetic principles to create **interactive installations**.
  - Examples include responsive sculptures and generative art.
- **Cybernetics in Nature:**
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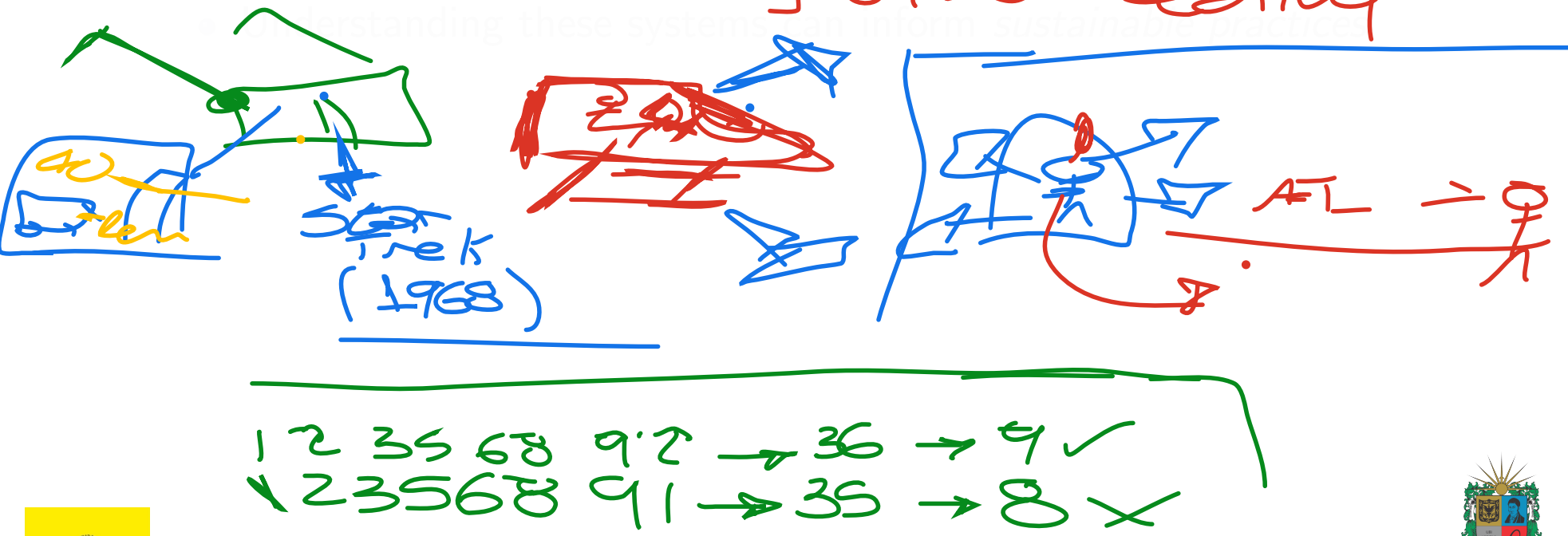
  - Understanding these systems can inform sustainable practices.



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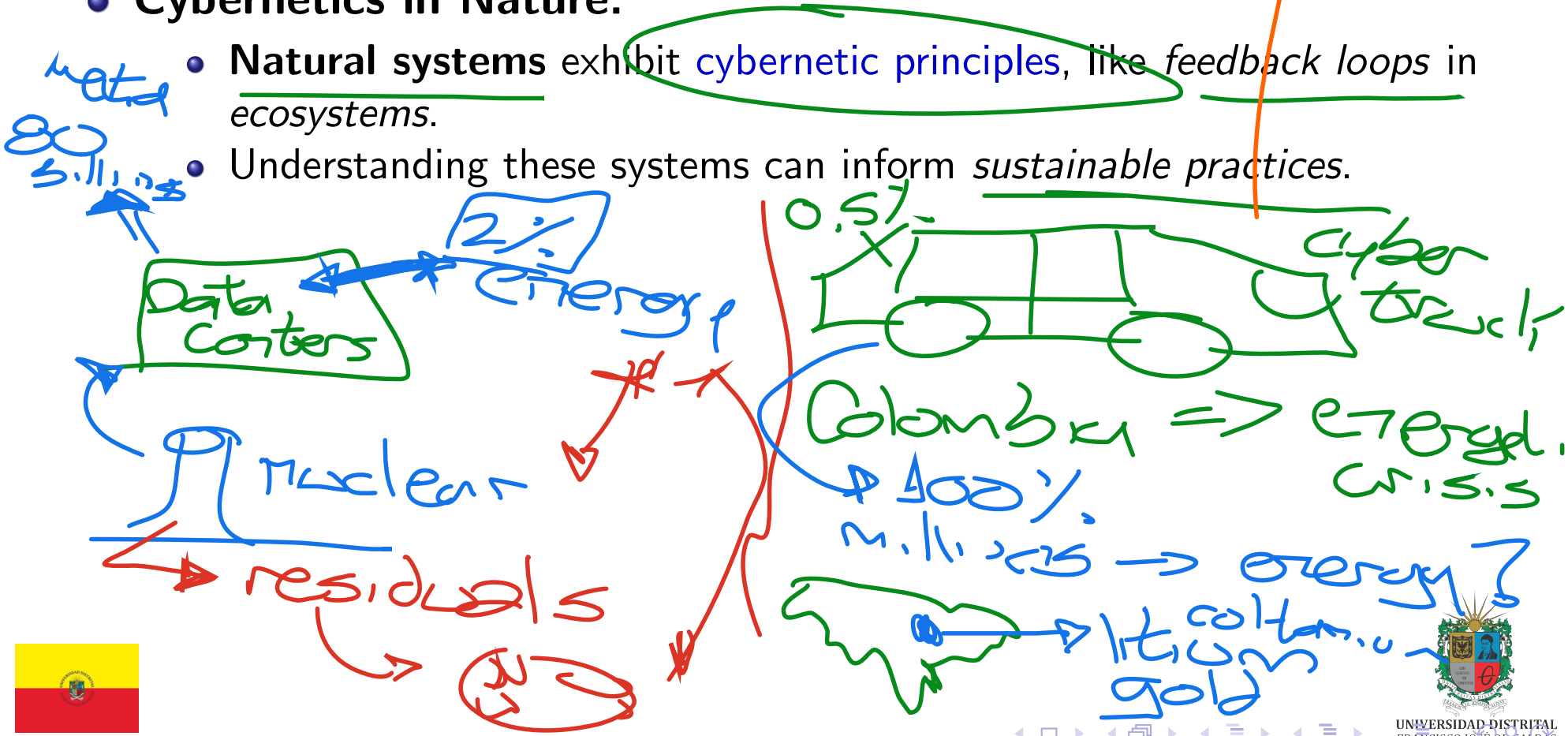

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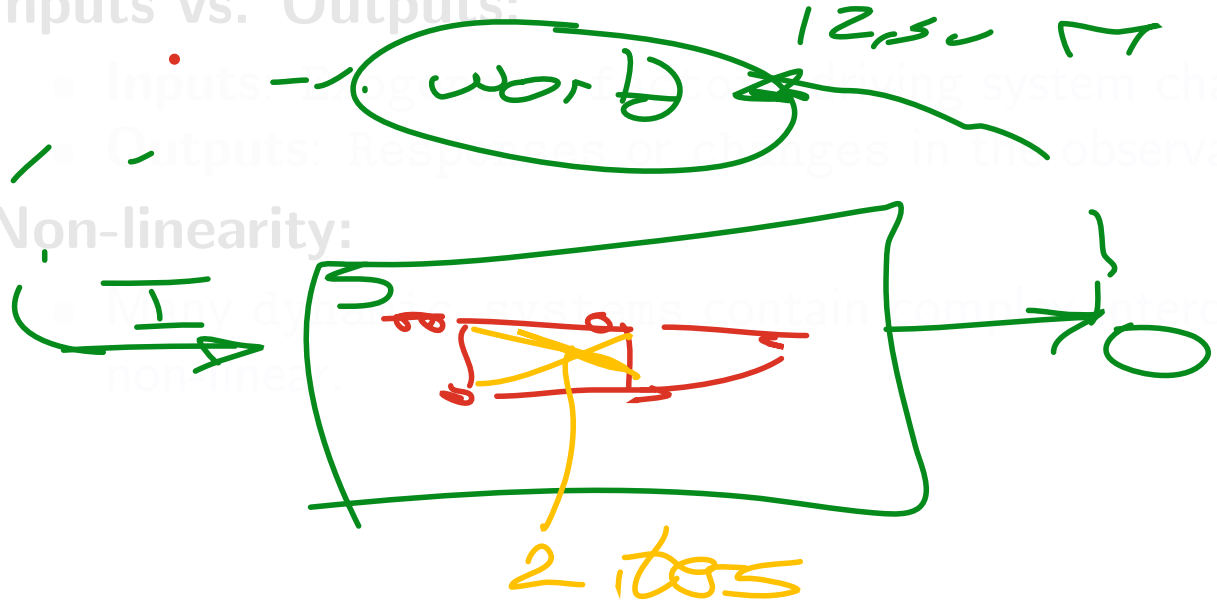
Definitions and System Characteristics

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



Definitions and System Characteristics

- **Dynamic System:**
  - **System** whose state evolves over time based on inputs, initial conditions, and internal feedback.
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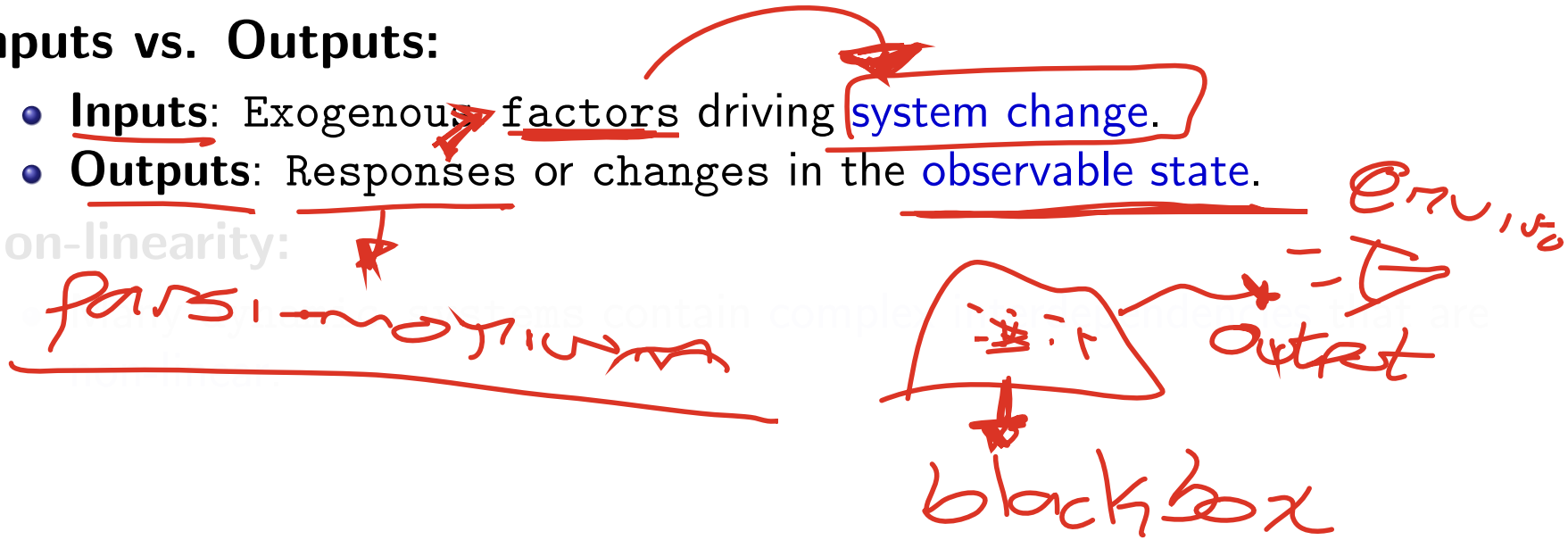

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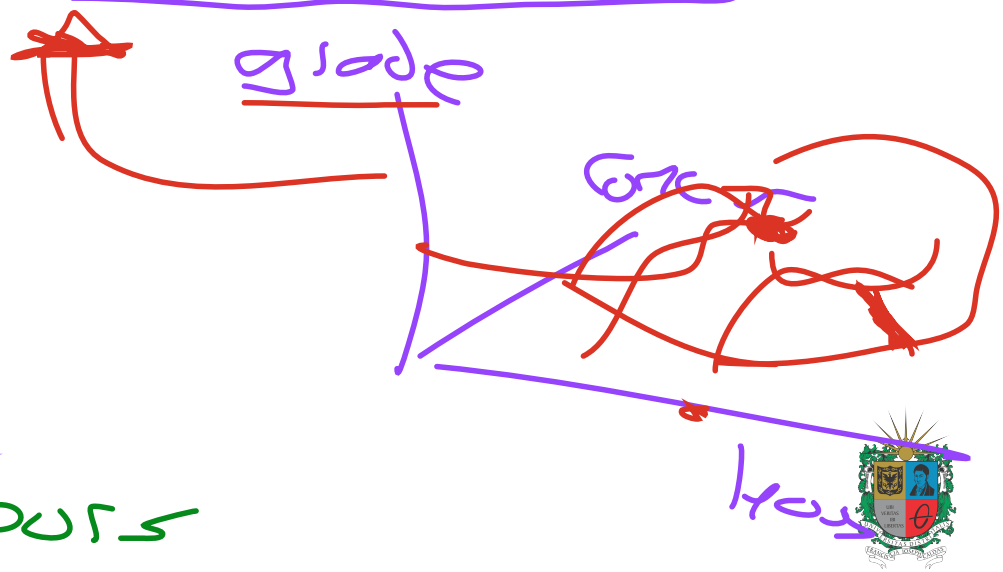

Chaos Theory and Sensitivity

- **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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- **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).
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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.
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- **Dynamic Systems in Technology:**
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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`.

Outline

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Thanks!

Questions?

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

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