Systems Sciences Applications
Systems Sciences Foundations

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2025-I

Outline

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Systems Analysis Process

- **Systems analysis** is the process of studying a system in order to identify its components, interactions, and goals.

- Systems analysis is the process of understanding how a system works and how it can be improved.

- Systems analysis is the first step in the systems development lifecycle.

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Conceptual Design

- Once the initial set of requirements are defined, the next step is to create a **conceptual design** of the system.

- **Conceptual Design** is a high-level design that defines the `structure` and `behavior` of the system. It is achieved by the recogniition of the appropiates components, connections, and responsabilities.

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Process Definition

- A **Process** is a series of steps or actions taken to achieve a particular end.

- Processes are used to **organize** and **manage** work.

Causal Loops

- A **Causal Loop** is a diagram that shows the relationships between different variables in a system.
- Causal loops are used to analyze and understand the dynamics of a system.
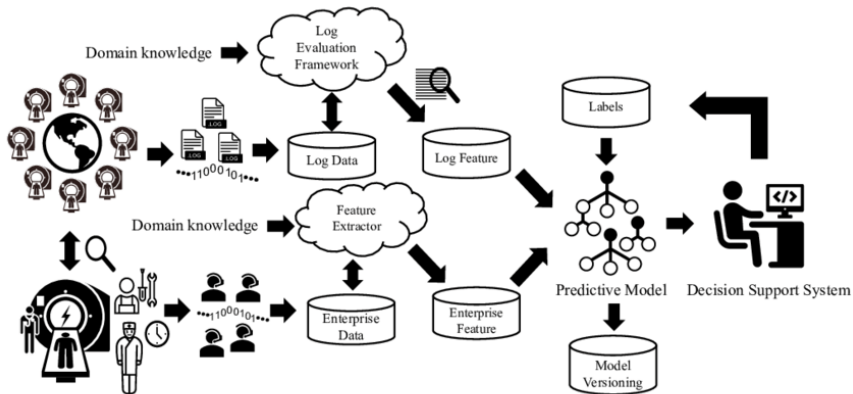- Causal loops can be positive or negative.

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System Schema Example: `Processing Pipeline`

Business Process Model and Notation (BPMN)
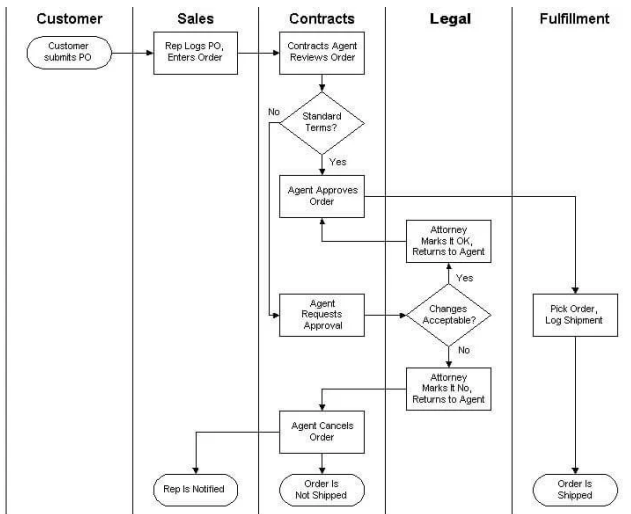
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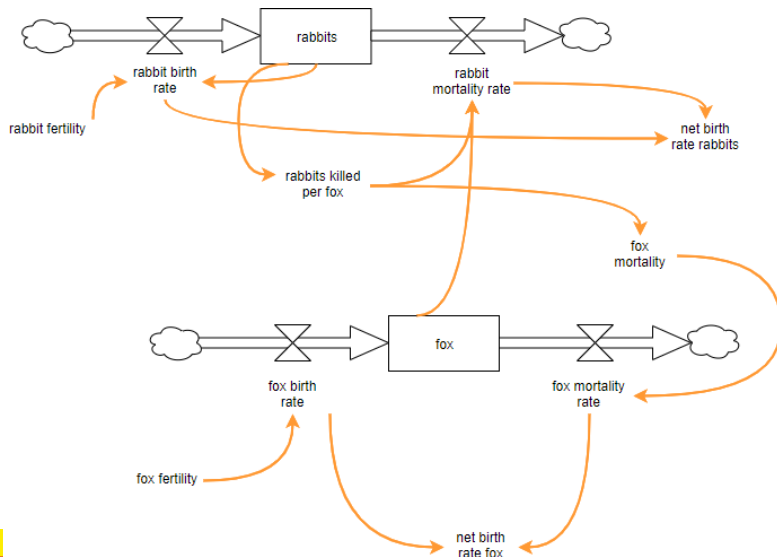
Technical Design

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Systems Design applied to Software Architectures

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Dynamical Systems: Definition

- A **dynamical system** is a system whose state *evolves* with time according to a fixed rule.

- **Dynamical systems** are characterized by state variables that represent the system's condition at a *given time*.

- The evolution of a **dynamical system** is described by differential equations (*continuous time*) or difference equations (*discrete time*).

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- **Classical control theory** focuses on designing controllers for single-input, single-output systems.
- Key techniques include:
  - PID Control *Proportional Integral-Derivative controllers*
  - Root Locus *Analysis of closed-loop poles*
  - Frequency Response *Bode and Nyquist plots*
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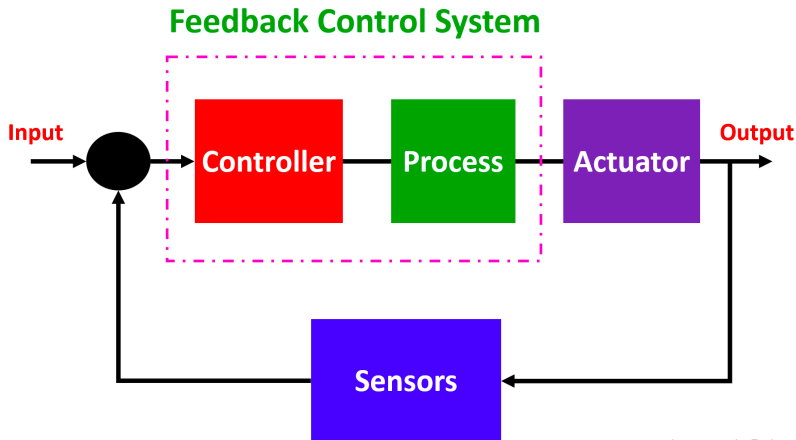# Feedback Control Loop

Figure: Typical feedback control system architecture

Adaptive Control

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- Main approaches:
  - Model Reference Adaptive Control (MRAC): System tries to follow a reference model.
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- Key methods include:
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    - Backstepping: Recursive Lyapunov-based design for cascaded systems.
    - Sliding Mode Control: Ensures robustness under disturbances.
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- Key advantages:
  - Learning from Data: *No need for explicit mathematical models*
  - Adaptation: *Continuous improvement through experience*
  - Handling Complexity: *Manage high dimensional complex systems*
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- Key components:
    - States: System conditions.
    - Actions: Control inputs.
    - Rewards: Feedback on performance.
    - Policy: Mapping from states to actions.

- Popular algorithms:
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Model Predictive Control with AI

- **Model Predictive Control (MPC)** optimizes control actions over a future horizon.
- AI enhances MPC by:
    - Providing accurate prediction models trained on data.
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Case Study: Autonomous Vehicles
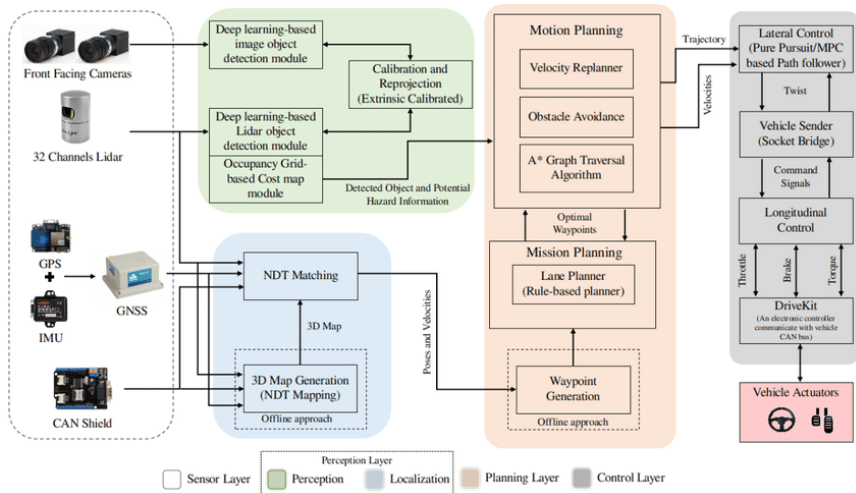
Figure: AI-driven control architecture for autonomous vehicles

Outline

Complex Adaptive Systems

- **Complex Adaptive Systems (CAS)** are systems that can learn and adapt to changing environments.
- Key research areas:
  - Emergence: How complex behaviors arise from simple rules.
  - Self-organization: Spontaneous order without central control.
  - Adaptation: System's ability to adjust to environmental changes.
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- **Digital twins** are virtual representations of physical systems that use real-time data to mirror behavior.
- Research directions:
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  - Real-time synchronization between physical and digital systems
  - Scaling and safeguarding the computing infrastructure
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Smart Manufacturing

- **Smart manufacturing** integrates AI and cybernetic principles to create `self-regulating production` systems.

- Key technologies:
    - Predictive maintenance using sensor data and machine learning
    - Quality control with computer vision and deep learning
    - Production scheduling through adaptive control systems
    - Supply chain management with dynamic feedback networks

- Benefits include increased efficiency, reduced downtime, and improved resource utilization.

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Smart Grids

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- Applications:

  - Demand forecasting using *time-series analysis* and *neural networks.*
  - Dynamic pricing through *reinforcement learning.*
  - Fault localization via *machine learning* classification.
  - Renewable integration to handle *intermittent sources* of energy.
  - Predictive maintenance through *anomaly detection* methods.

- These systems enable energy efficiency, reliability, and sustainability.

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- **Healthcare systems** benefit from AI and cybernetic approaches for `patient care` and management.
- Applications:
  - Personalized medicine through *predictive models*
  - Disease monitoring with *wearable sensors and feedback*
  - Integration of electronic health records, imaging, genomics
  - Drug discovery with ML-assisted engineering loops
  - Predictive triage models with automated alerting systems
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    - Public safety through predictive policing and emergency response
    - Waste management with AI-coordinated collection
    - Environmental monitoring for pollution and climate impacts
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Outline

Thanks!

Questions?

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