Εφαρμογές Τηλεματικής στις Μεταφορές και την Υγεία

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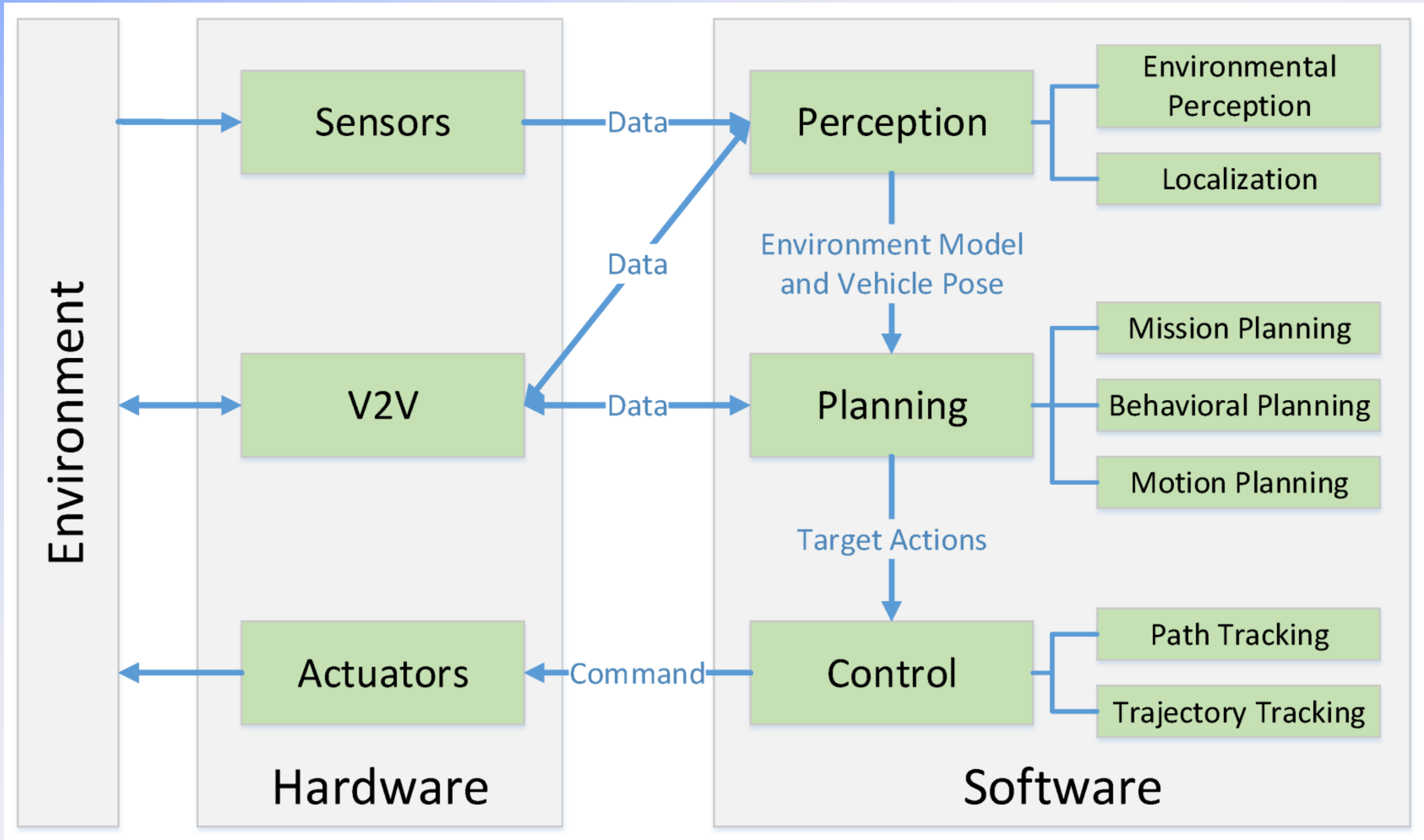
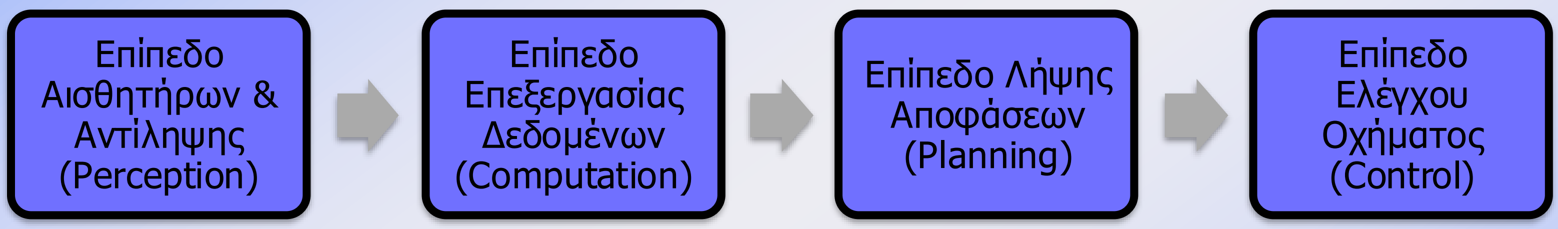
Περιεχόμενα

- Αρχιτεκτονική Συστήματος Αυτόνομου Οχήματος
- Επίπεδο επεξεργασίας δεδομένων
- Σχεδιασμός και λήψη αποφάσεων
- Αυτόνομη πλοήγηση

Αρχιτεκτονική Συστήματος Αυτόνομου Οχήματος I



Αρχιτεκτονική Συστήματος Αυτόνομου Οχήματος II



Επίπεδο επεξεργασίας δεδομένων

- Κατανοεί το περιβάλλον του
- Ανιχνεύει εμπόδια
- Αναγνωρίζει στόχους
- Παρακολουθεί την κατάστασή του.

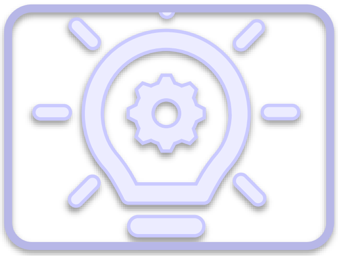
Σχεδιασμός και λήψη αποφάσεων

- Οι αλγόριθμοι αναλύουν τις πληροφορίες, και λαμβάνουν αποφάσεις με βάση προκαθορισμένους κανόνες.
- Οι ενέργειες μπορεί να περιλαμβάνουν
  - Επιβράδυνση
  - Αλλαγή λωρίδας
  - Στάση σε φανάρι με βάση την αντίληψη του περιβάλλοντος

Σχεδιασμός και λήψη αποφάσεων

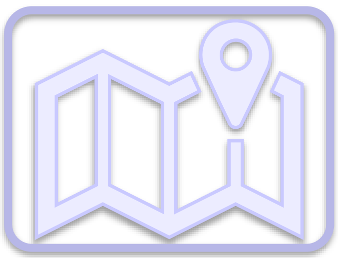
Algorithm Type	**Description**
Rule-based systems	Use predefined rules based on expert knowledge for decision-making
Markov decision processes (MDP)	Model decision-making as a stochastic process, considering state transitions and expected rewards
Reinforcement learning	Train the system through trial and error, learning from rewards or penalties
Deep neural networks	Utilize deep learning techniques, such as CNNs and RNNs, for decision-making tasks
Genetic algorithms	Evolve a population of candidate solutions over generations to find optimal solutions
Potential fields	Guide the system through attractive and repulsive forces in the environment
A* Algorithm	Path-finding algorithm for planning routes in environments with known terrain
Monte Carlo methods	Use statistical sampling for decision-making in complex and uncertain environments

Αυτόνομη πλοήγηση



Scene Perception

- Επεξεργασία πληροφοριών για το περιβάλλον



Localization

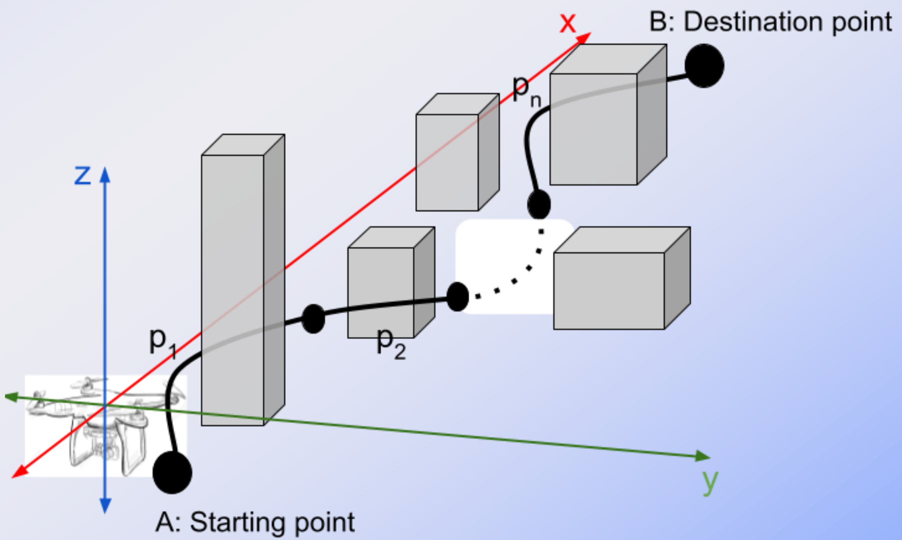
- Εντοπισμός της θέσης του οχήματος

Path Planning

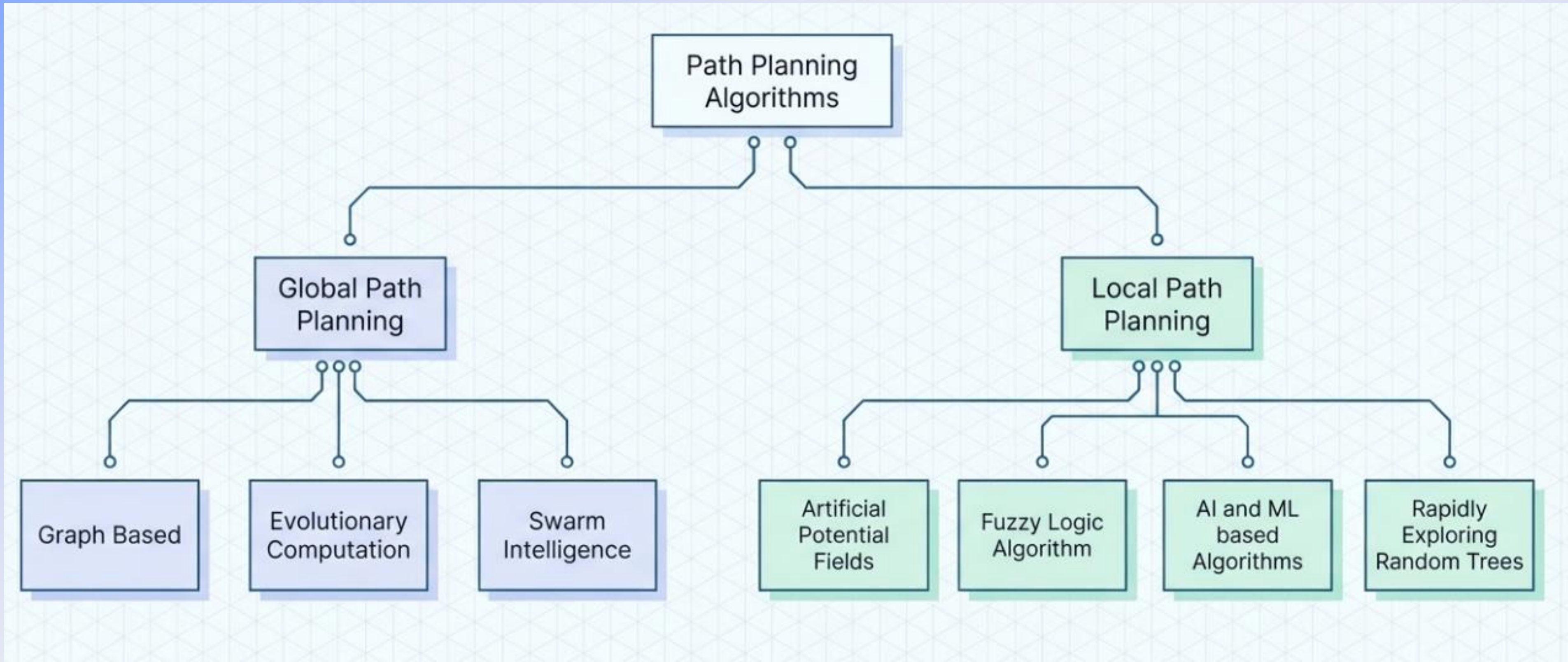
- Δημιουργία βέλτιστης διαδρομής

Path Planning

- **Objective:**
  - To obtain optimal paths from all possible options in the search space, based on execution time, path length, and energy use.



Path Planning Methods



Path Planning Algorithms

- Global Path Planning
  - Graph Based
  - Evolutionary Computation
  - Swarm Intelligence
- Local Path Planning
  - Rapidly Exploring Rapid Trees
  - Artificial Potential Fields
  - Fuzzy Logic Algorithm
  - AI/ML based

Global Path Planning Algorithms

- The environment is predefined or mapped in advance.

Key features

- Deterministic Behavior
  Produces identical outputs for the same inputs, ensuring predictability and reproducibility
- Strong Mathematical Foundation
  Built on graph theory, geometry, and optimization techniques.
- Efficiency in Low-Dimensional Spaces
  Highly efficient in grid-based or low-dimensional problem spaces.

Challenges of Global Path Planning Algorithms

- Scalability Issues

In high dimensional spaces, the exponential growth of states makes computation costly and often impractical

- Dynamic Environment Limitations

Unable to adapt efficiently to moving obstacles or sudden changes

- Local Minima

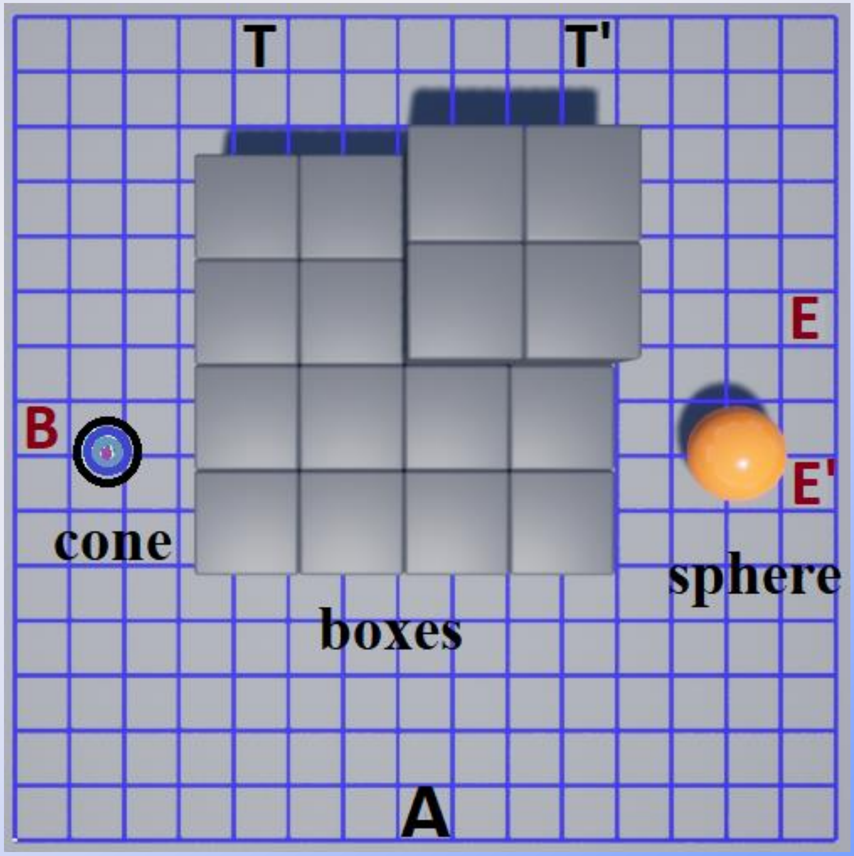
May be susceptible to Local minima that can trap the agent, preventing further progress toward the goal

Limitations of Global Path Planning Algorithms

- Challenges with Large-Scale Maps
  - Performance degrades significantly when operating on vast, large-scale maps
  - Computational cost increases rapidly with map size and complexity
  - Slower convergence and reduced efficiency limit real-time applicability

Global Path Planning Algorithms

- Graph Based Algorithms
  - Utilize a grid-based graph representation
  - The state space (environment) is divided in nodes, which will be connected to form a complete path for the vehicle to follow.
  - Examples: A* or the Dijkstra's algorithm



Global Path Planning Algorithms

- Evolutionary algorithms
  - Inspired by natural selection and evolution.
  - Search based on sharing information between members
  - Combine deterministic and probabilistic approaches
  - Examples: Genetic Algorithm (GA)

Global Path Planning Algorithms

- Swarm Intelligence algorithms
  - Simulates the social behavior of birds flocking or fish schooling.
  - Model the movement of particles through the solution space and adjusts their positions based on personal and collective best experiences
  - Examples: Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO)

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Local Path Planning Algorithms

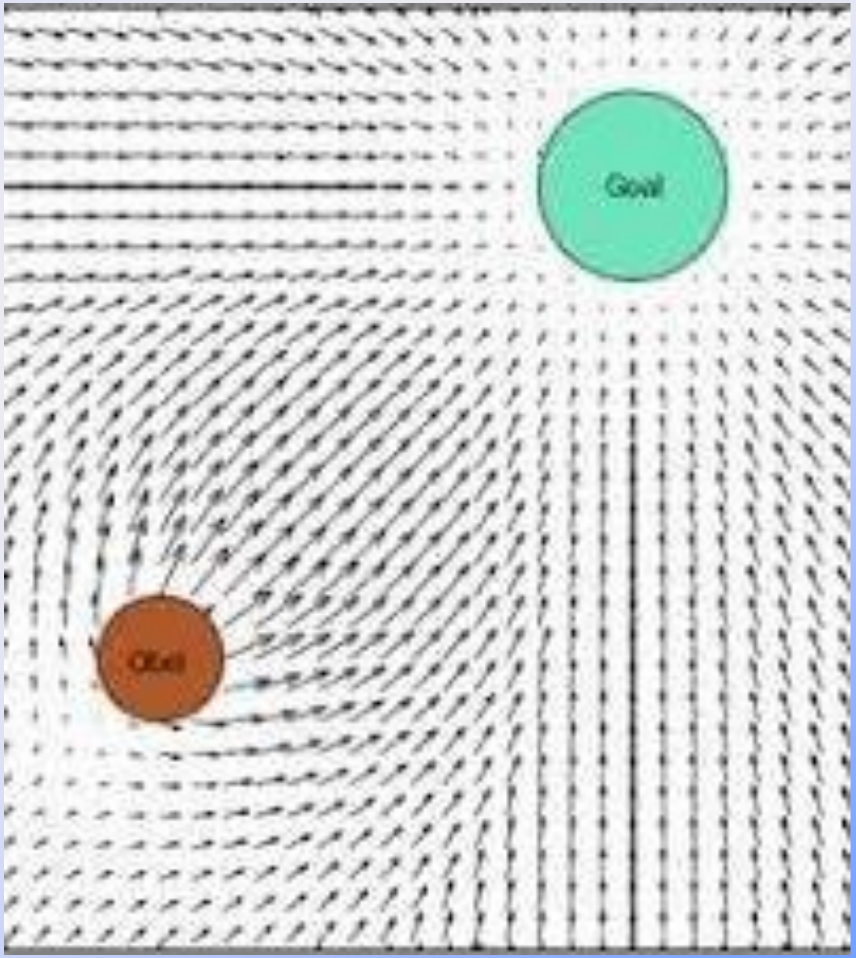
- Local path planners focus on real-time decision-making on navigation and are suited for unknown environments
- Encompass one or more agents engaging in real-time interactions with an environment
- The agents learn to select optimal strategies by reinforcing an action that improves performance

Rapidly Exploring Random Trees (RRT)

- Sampling-based path planning algorithm
- Efficiently explores high-dimensional spaces
- Well suited for complex and cluttered environments
- Generates feasible paths quickly but not always optimal

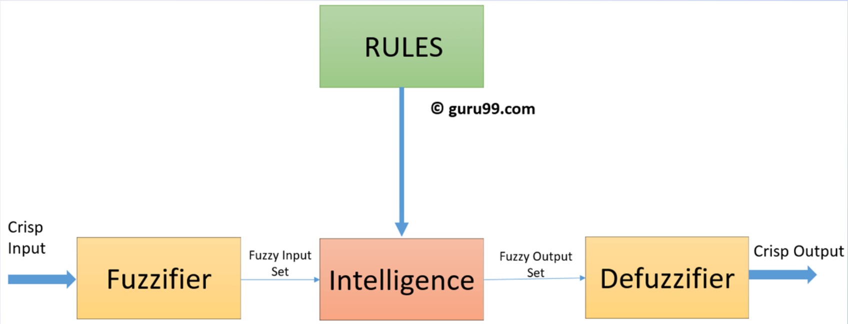
Artificial Potential Fields (APF)

- Navigation based on virtual attractive and repulsive forces
- Goal exerts attraction; obstacles generate repulsion
- Simple and computationally efficient
- Effective for real-time applications
- Susceptible to local minima, which may trap the agent



Fuzzy Logic Algorithm

- Uses fuzzy rules to model human-like decision making
- Handles uncertainty and imprecise sensor data effectively
- Suitable for dynamic and uncertain environments
- Does not require an exact mathematical model
- Performance depends on rule design and tuning



Supervised Learning

- Rely on labeled datasets to learn mappings from environmental states to optimal actions
- A model is trained using data where the correct output (optimal path) is provided for each input (environmental state).

Supervised Learning

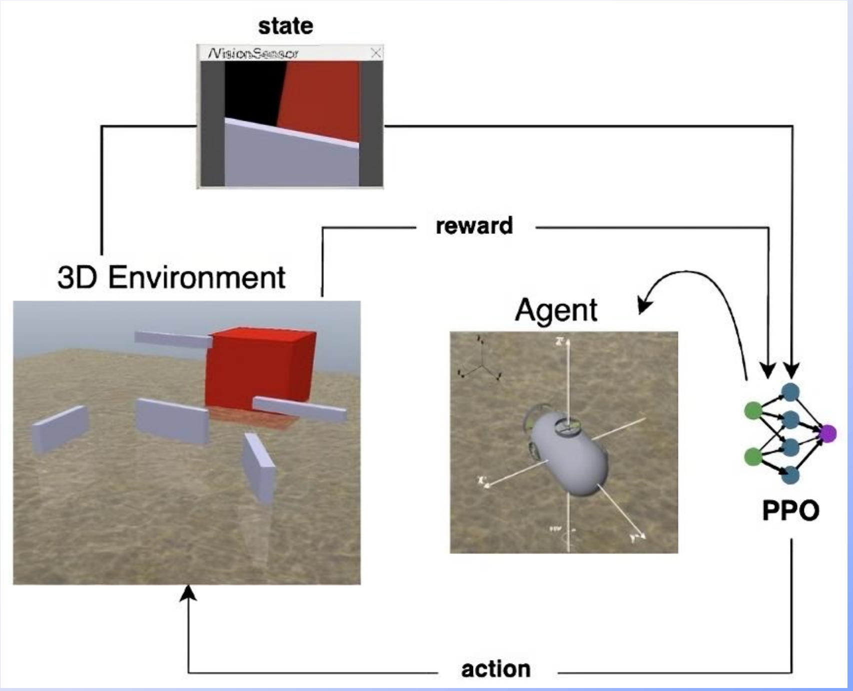
- Key benefits
  - Suitable for relatively stable and predictable environments, such as traffic navigation systems.
  - Advantageous when dealing with structured and well-defined scenarios

Unsupervised Learning

- Relies on unlabeled data, enabling the model to identify hidden patterns and structures without predefined labels.
- This approach reduces the need for extensive pre-processing

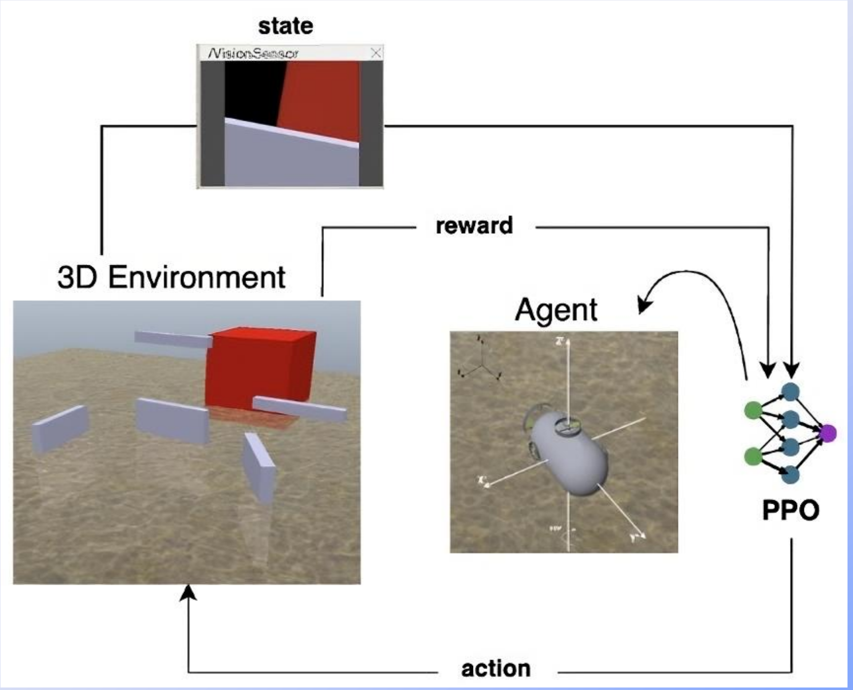
Reinforcement Learning (RL)

- A type of machine learning where an agent learns by interacting with its environment.
- Agent takes actions in an environment.
- Receives feedback through rewards or penalties.
- Adjusts actions to maximize cumulative rewards



Reinforcement Learning (RL)

- Key benefits:
  - Adaptability: Learns from experience and adjusts to changing conditions
  - No prior knowledge of the environment needed
  - Handles complex, dynamic environments more effectively
  - Real time trajectory generation



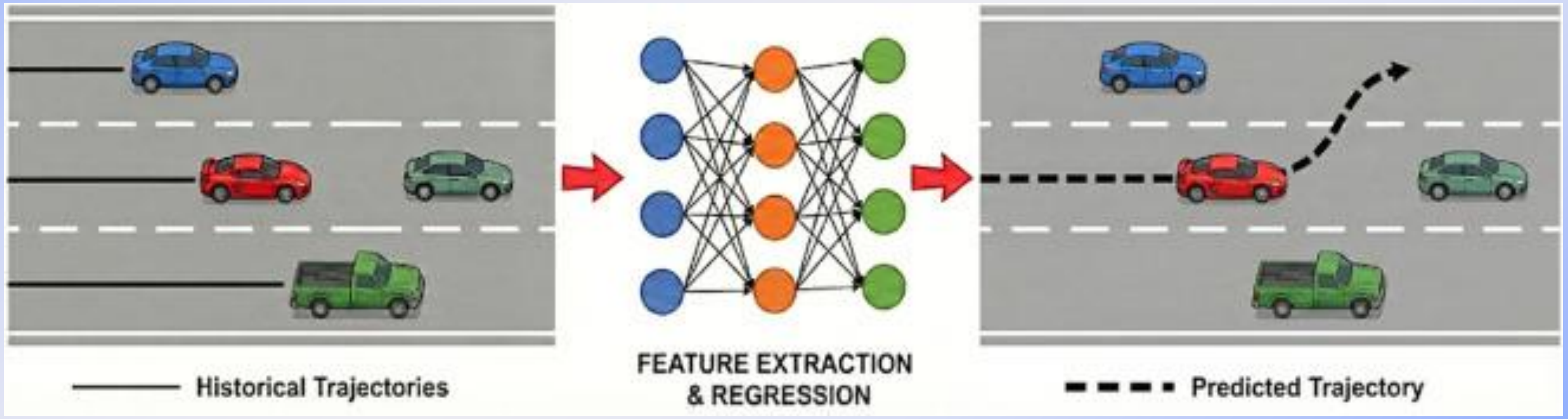
Deep Learning

- Deep learning is a subcategory of machine learning.
- Utilises neural networks with multiple layers (deep neural networks).
- Learns and models complex patterns from data

Deep Learning

- Key Benefits
  - Neural networks act as model approximators for large, complex problems.
  - Neural networks process vast sensor data (e.g., cameras, LiDAR) to interpret the environment.
  - Unlike traditional rule-based systems, deep learning models learn from data, enabling greater adaptability.

Deep Learning



Building Blocks of Autonomy

Recommended literature

- *Autonomous vehicles: technologies, regulations, and societal impacts*. George Dimitrakopoulos, Aggelos Tsakanikas, and Elias Panagiotopoulos, Elsevier, 2021.
- Anurag Verma, Chapter 2 - Introduction to autonomous systems, Editor(s): Muhammad H. Rashid, Handbook of Power Electronics in Autonomous and Electric Vehicles, Academic Press, 2024.
- Armingol, J. M., Alfonso, J., Aliane, N., Clavijo, M., Campos-Cordobés, S., de la Escalera, A., ... & Villalonga, G. (2018, January). Environmental perception for intelligent vehicles. In *Intelligent vehicles* (pp. 23-101). Butterworth-Heinemann.

Many Thanks

Any Questions?