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Faculty of Mechanical Engineering

Seminar Presentation

Autonomous Parking of an Articulated Vehicle using End-to-End Reinforcement Learning

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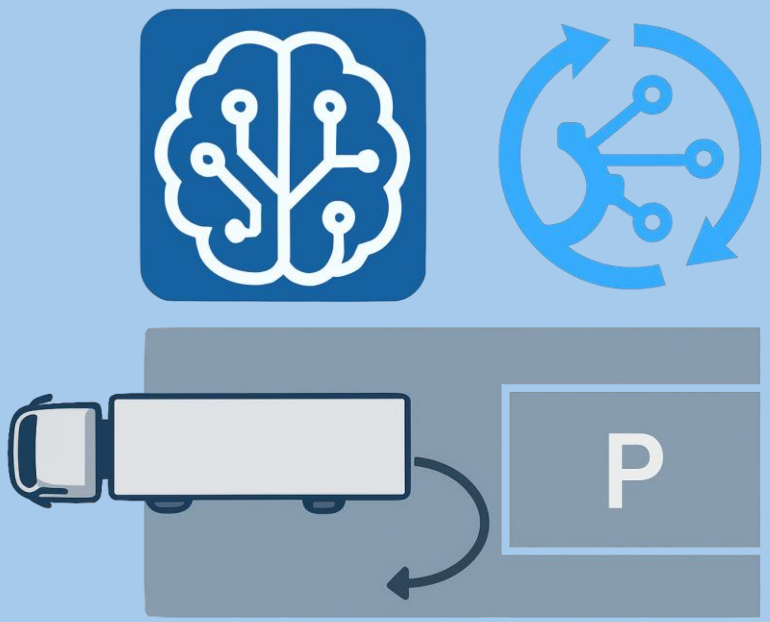
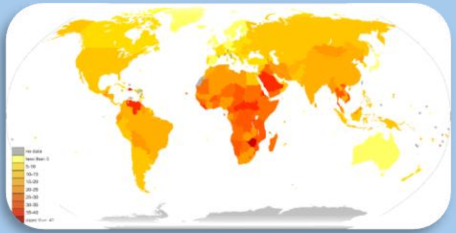


Background and Motivation



Benefits

- Lower risk of accidents
- Providing mobility for elderly and people with disabilities
- Pollution decrease
- New ways of public transportation
- Reducing number of cars (95% of the time a car is parked)

Challenges: Self-Driving is difficult.

- Snow, heavy rain, night
- Unstructured roads, parking lots
- Pedestrians, erratic behavior
- Reflections, dynamics
- Rare and unseen events
- Merging, negotiating, reasoning
- Ethics and legal considerations

→ Generalization and Robust Performance

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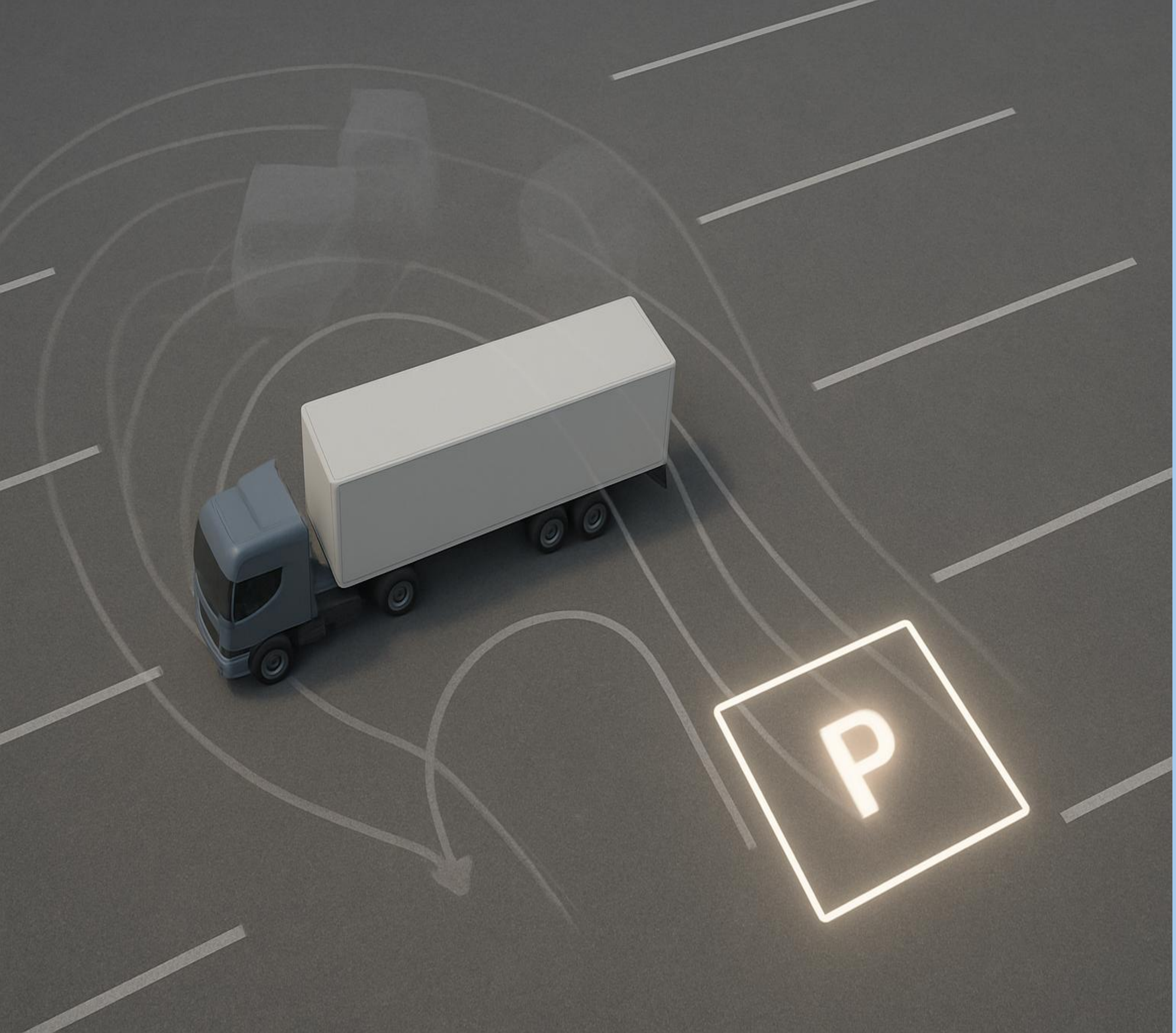

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Background and Motivation

The most difficult task in driving is Parking

- Large Dimensions
- Limited Reverse Maneuvering
- Blind Spots
- Degrees of Freedom
- Non-Holonomic Constraints

Background and Motivation

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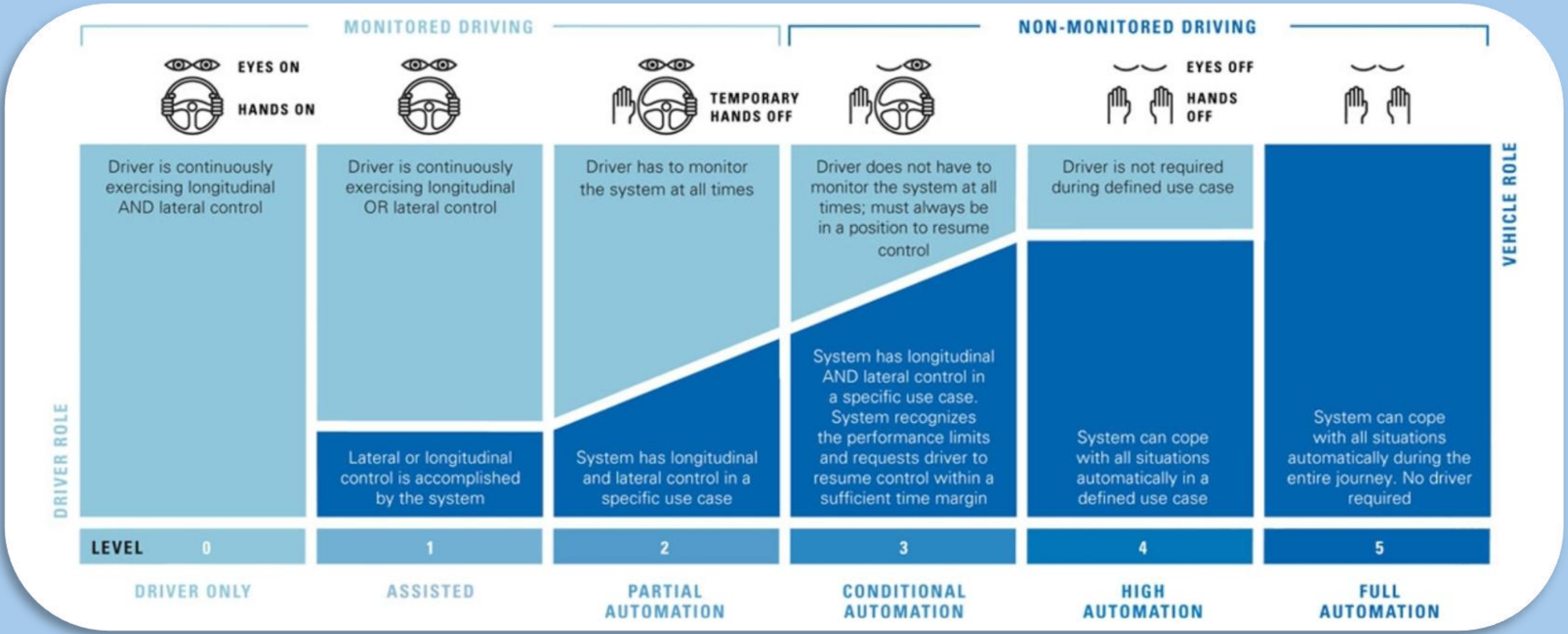

SAE Levels of Autonomy for Automated Driving Systems (ADS)

Literature Review

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Title	Author	Year
ALVINN: An Autonomous Land Vehicle in a Neural Network	Pomerleau, Dean A.	1988
Autonomous Docking and Parking of Articulated Mobile Robots	Delrobaei, M.	2010
Automatic Parking of an Articulated Vehicle Using ANFIS	Azadi, Sh., et al.	2013
Autonomous Parking for Articulated Vehicles	Kusumakar, R.	2017
Reinforcement Learning-Based Motion Planning for Automatic Parking System	Zhang, J., et al.	2020
Survey of Deep Reinforcement Learning for Motion Planning of Autonomous Vehicles	Aradi, S.	2022
End-to-end Autonomous Driving: Challenges and Frontiers	Chen, Li., et al.	2023

Literature Review: Open-Source Projects

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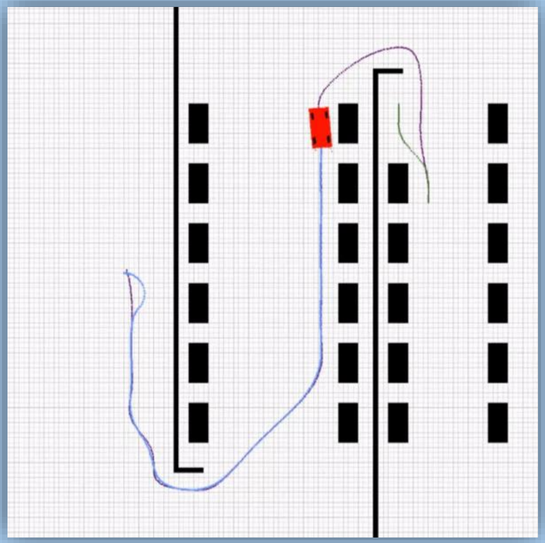
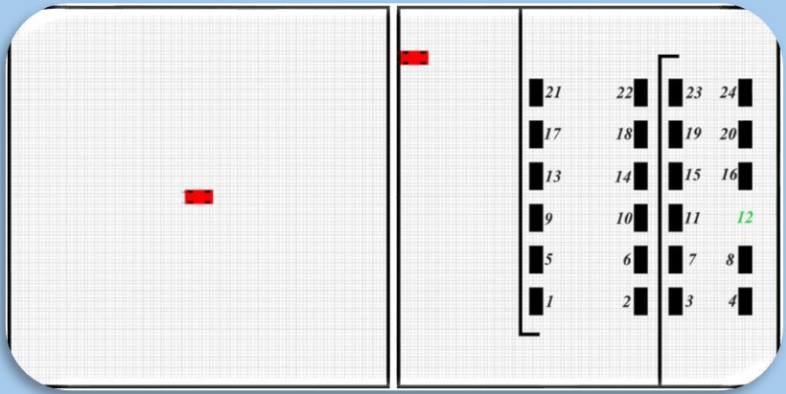
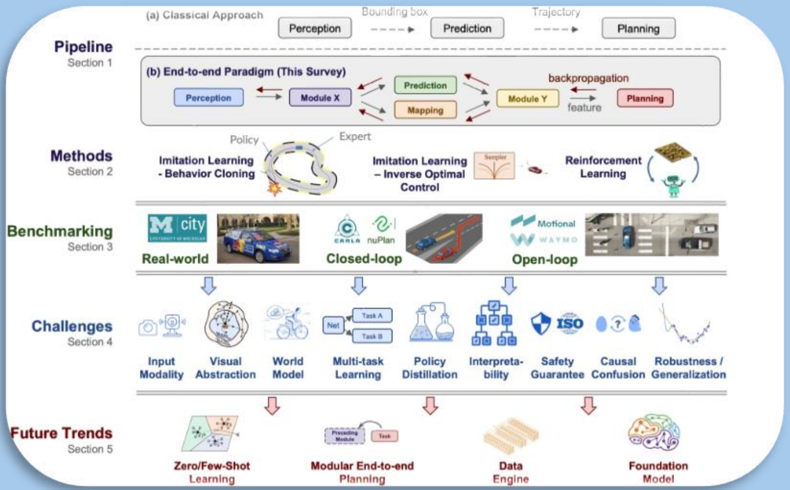
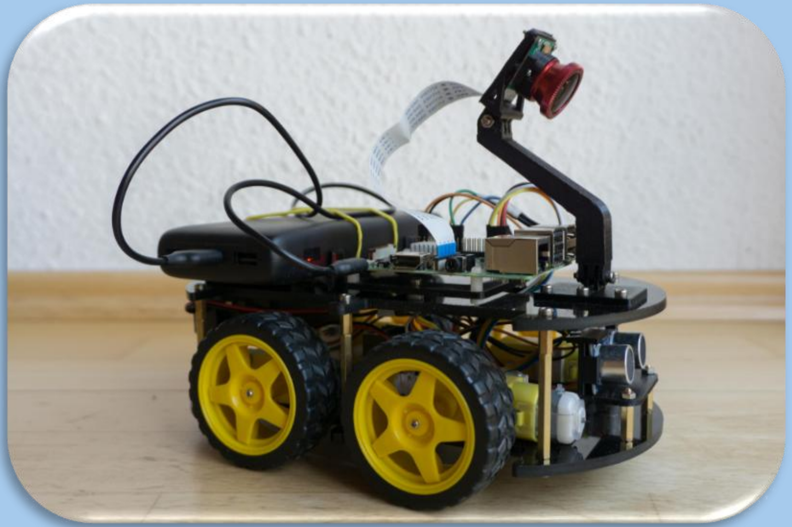


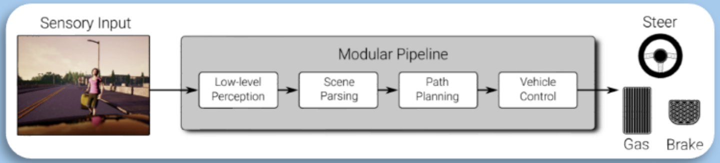






Approaches to Self-Driving

Modular Pipeline



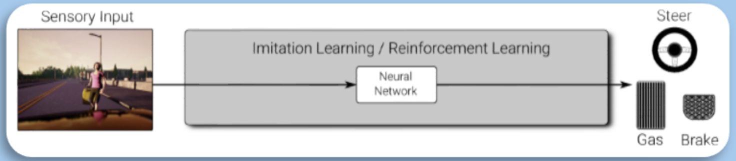
Pros

- Small components, easy to develop in parallel
- Interpretability
- Theoretical Stability

Cons

- Piece-wise training (not jointly) Localization and planning
- Heavily relies on HD maps

End-to-End Learning



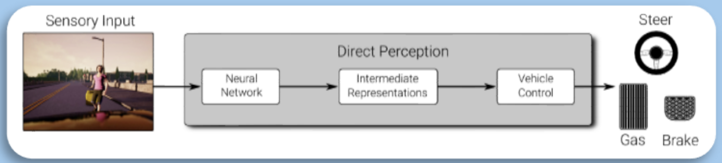
Pros

- End-to-End training (Main Objective)
- Cheap annotations
- Easy for Implementation

Cons

- Training / Generalization
- Interpretability

Direct Perception



Pros

- Compact Representation
- Interpretability

Cons

- Control typically not learned jointly
- How to choose representations?

Sensors

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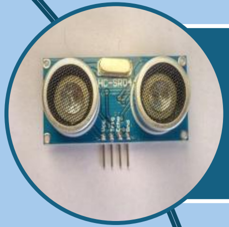
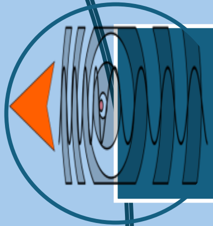
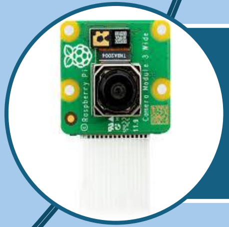


Sonar



Radar

Lidar



Camera

Modeling: Kinematics

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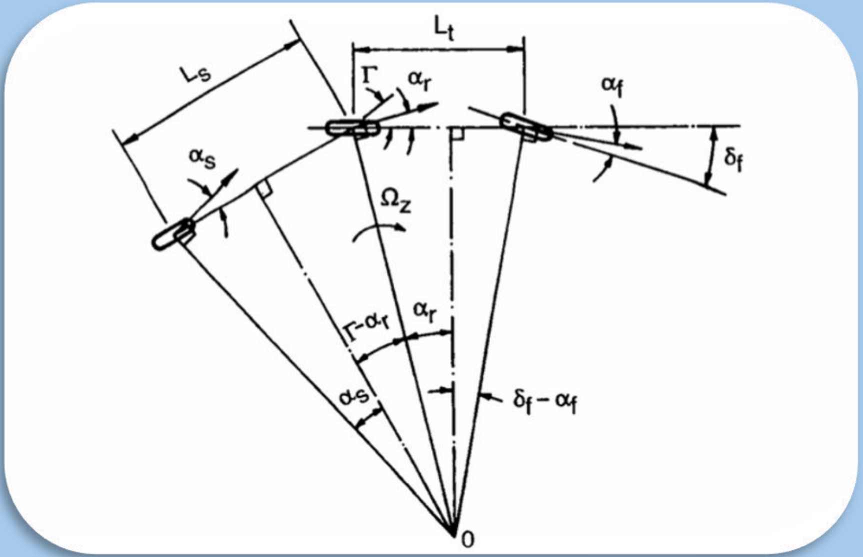

Assumptions:

- Low Speed: Rigid Tires and No Slip
- Steady State Cornering
- Single Instantaneous Center of Rotation
- Large Yaw Radius
- Fifth wheel is on top of the rear tractor axis

Steering Geometry

$$\tan(\delta_f - \alpha_f) + \tan(\alpha_r) = \frac{L_t}{R}$$

$$\tan(\Gamma - \alpha_r) + \tan(\alpha_s) = \frac{L_s}{R}$$

$$\tan(\delta_f) = \frac{L_t}{R} = L_t \frac{\Omega_z}{V}$$

$$\tan(\Gamma) = \frac{L_s}{R} = L_s \frac{\Omega_z}{V}$$

Modeling: Inverse Kinematics

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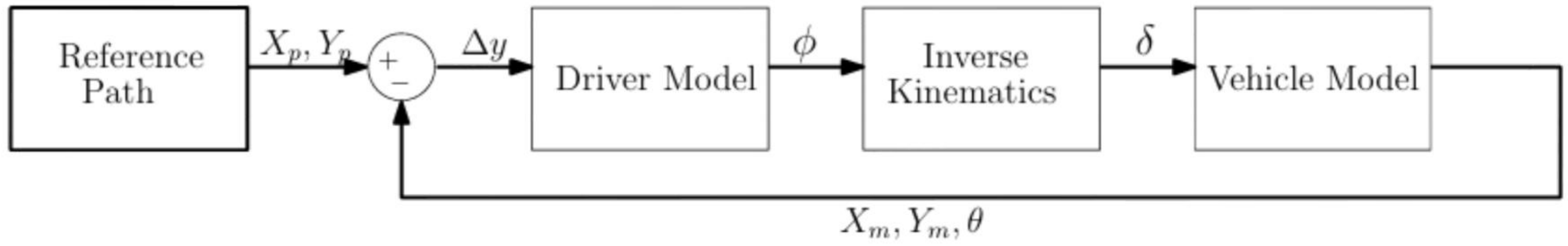


Direct Kinematics →

Inverse Kinematics ←

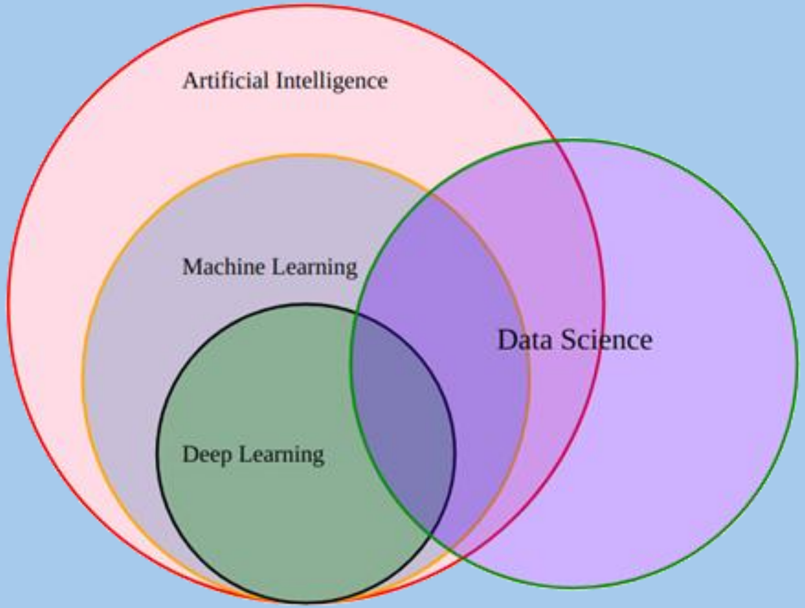
Inputs

- Steering Angle
- Velocity

Desired Outputs

- Yaw Rate
- Articulation Angle

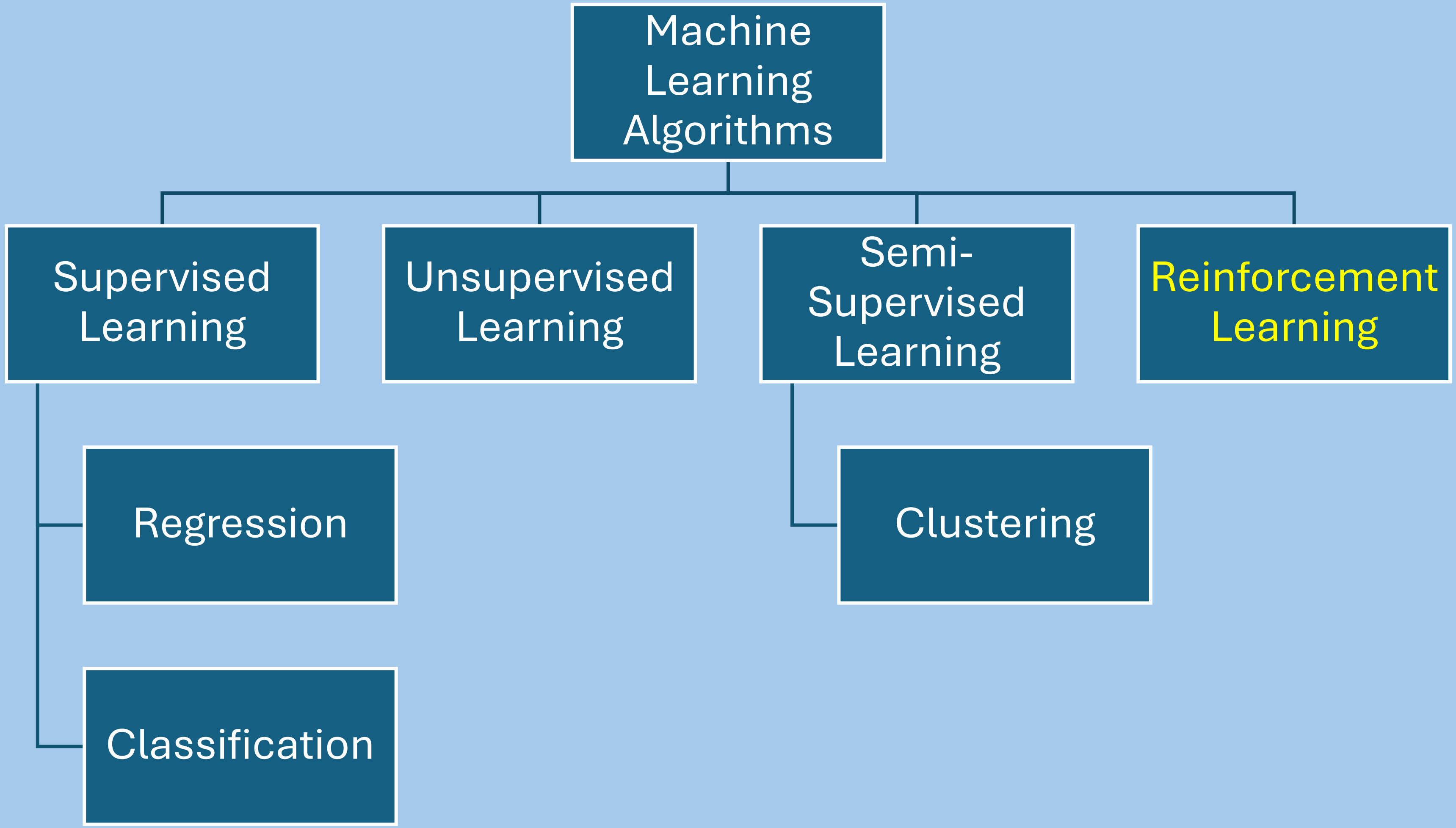
Methodology: Machine Learning



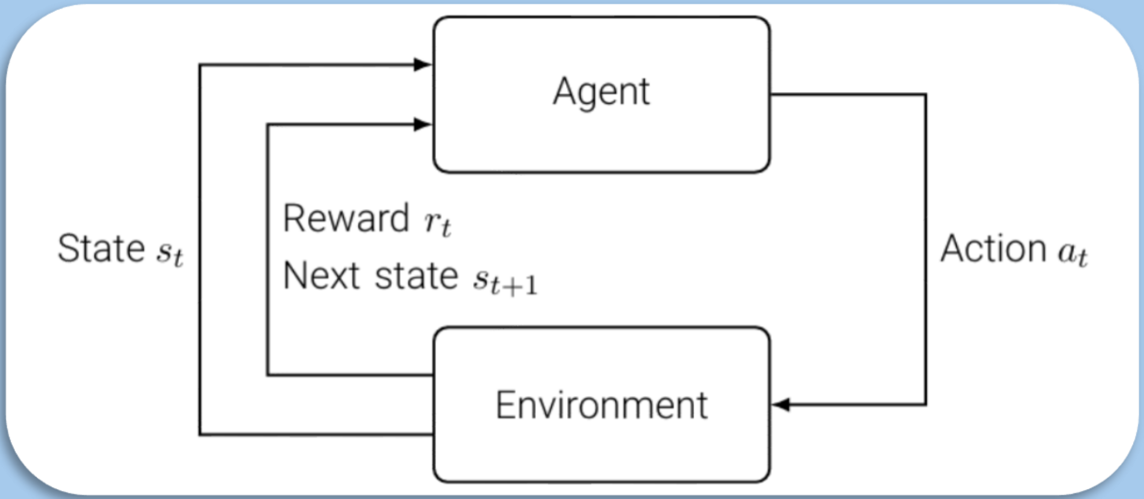
Machine Learning is great for:

- Problems with a lot of hand-tuning or long lists of rules
- Complex problems for which there is no good solution at all using a traditional approach
- Fluctuating environments: a Machine Learning system can adapt to new data.
- Getting insights about complex problems and large amounts of data.

Methodology: Machine Learning



Methodology: Reinforcement Learning



Process

1. Agent observes environment state at time t.
2. Agent sends action at time t to the environment.
3. Environment returns the reward/penalty and its new state to the agent.

Objective

Learning the best policy to maximize total future rewards

Methodology: Reinforcement Learning

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Pros

- End-to-End Control Algorithm
- No dataset is required.
- Future Based Decision Making
- Real-world Loss Functions

Cons

- Heavy simulations
- Complex Theory

Markov Decision Process → Bellman Optimality → Deep Q Learning

Conclusion

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- ✓ Foundation Established
- ✓ Problem Contextualized: Statement, Challenges and innovations
- ✓ Theoretical Core Defined: Simplified Kinematics and Inverse Kinematics
- ✓ Methodology Selected: End-to-End Machine learning and Reinforcement Learning

Future Work

- ➢ Coding the foundations using Python and OpenAI Gymnasium
- ➢ Advanced Programming in Python, Pytorch and Real-World Simulations using Carla
- ➢ Completion of the Thesis
- ➢ Implementation and Experimenting on an Articulated Mobile Robot

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Thank you