Autonomous Driving

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What is the problem?

Driving is hard and wasteful.

Transportation is expensive.


17TH ST

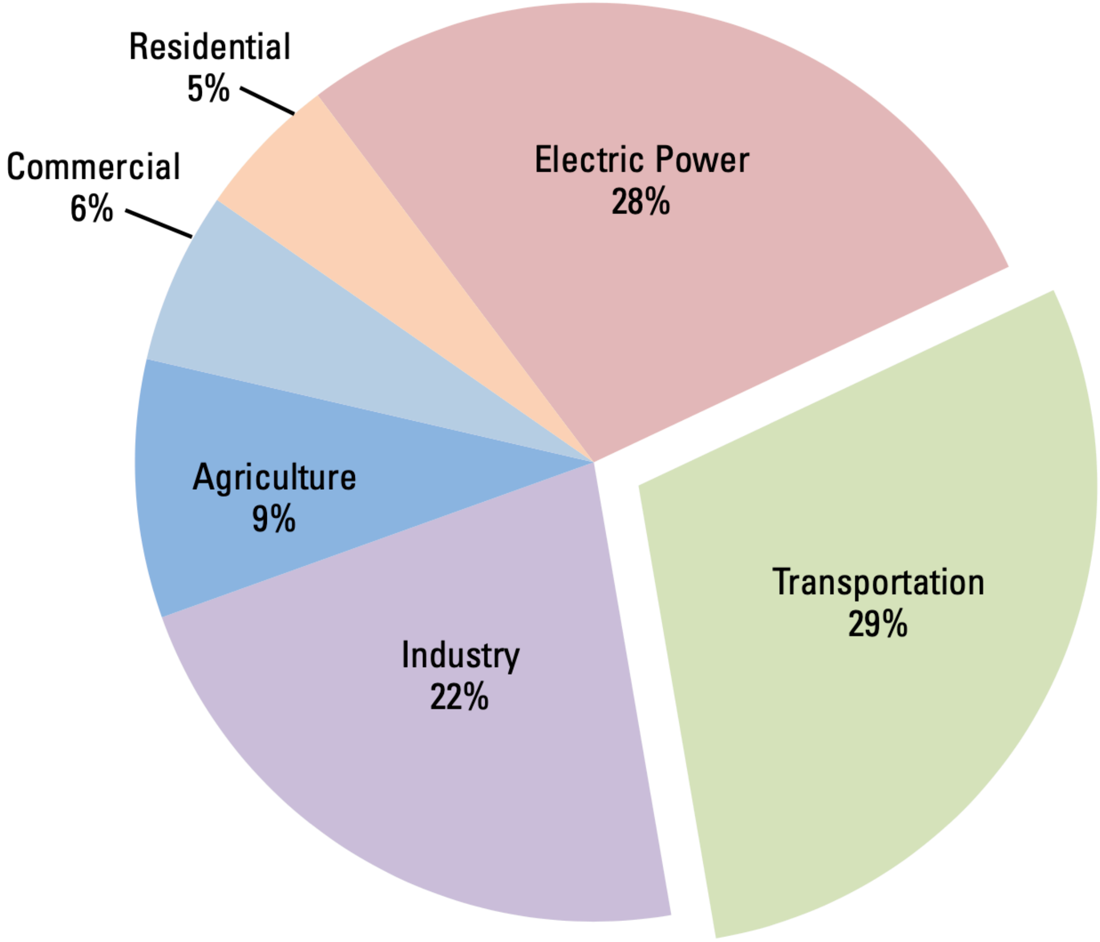
Human Drivers are the ***Problem***

In the United States (2016)

- 7,277,000 reported crashes
- 3,144,000 people were injured
- 37,461 fatalities (1 fatality every 14 minutes)
  - Leading cause of death for ages 16-22
- 94% of all crashes are due to human error

We should be working on this problem!

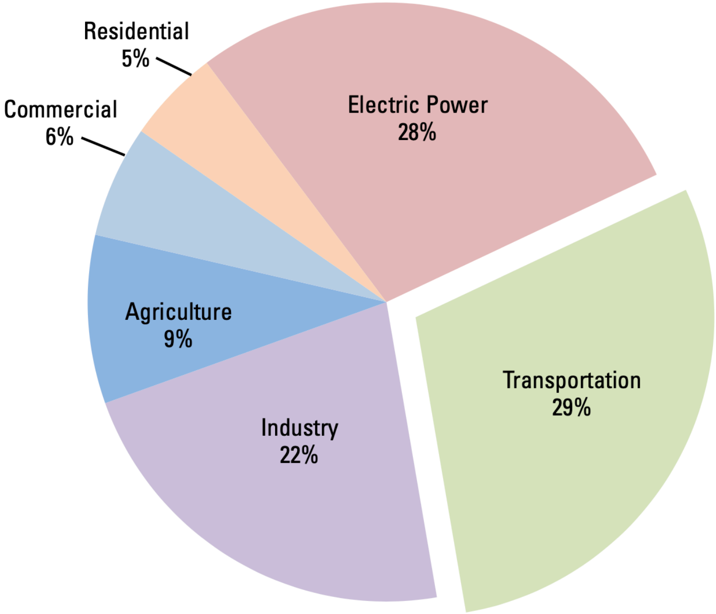
https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/81



Share of U.S. GHG Emissions by Sector, 2017[3,4]

Driving and Climate Change

https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100WUHR.pdf



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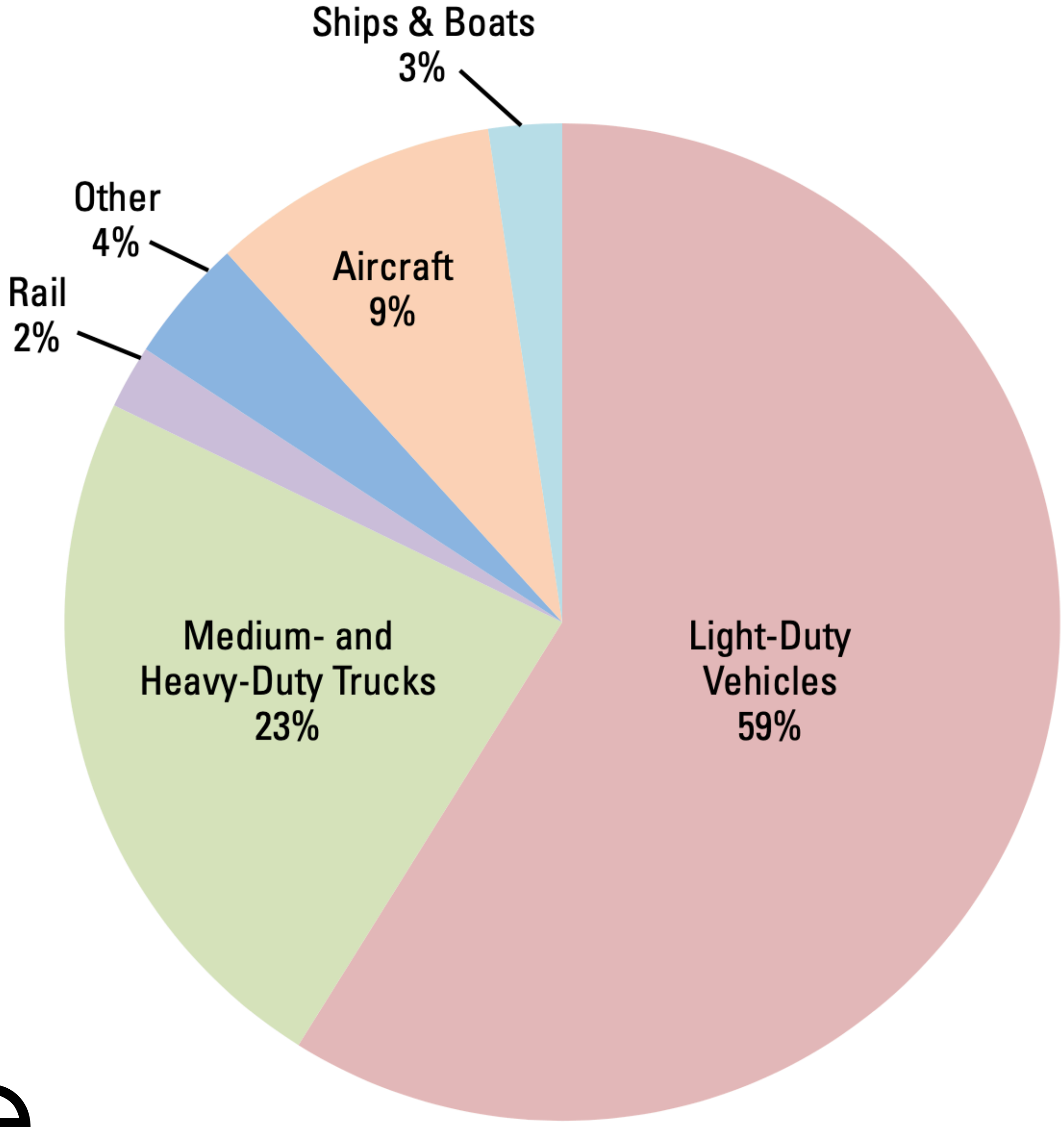

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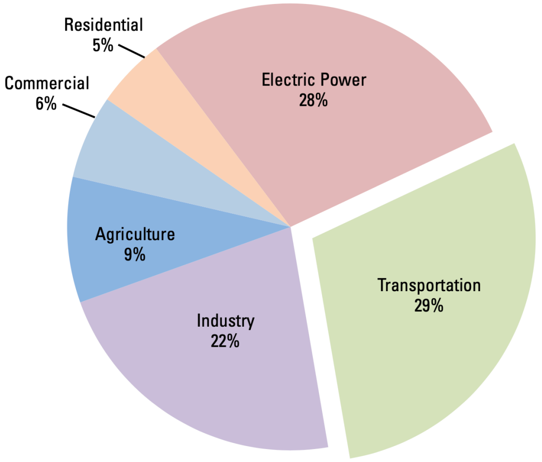

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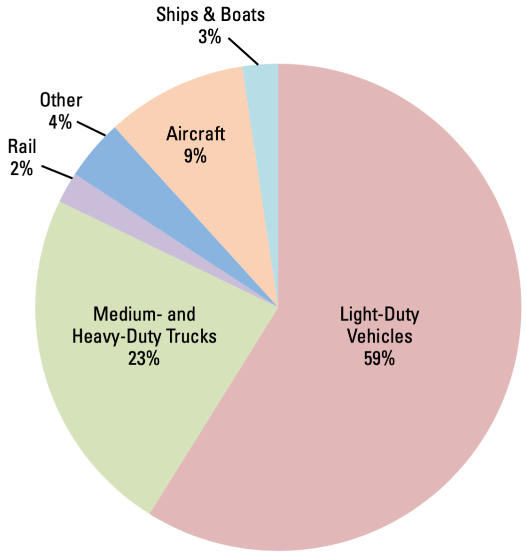

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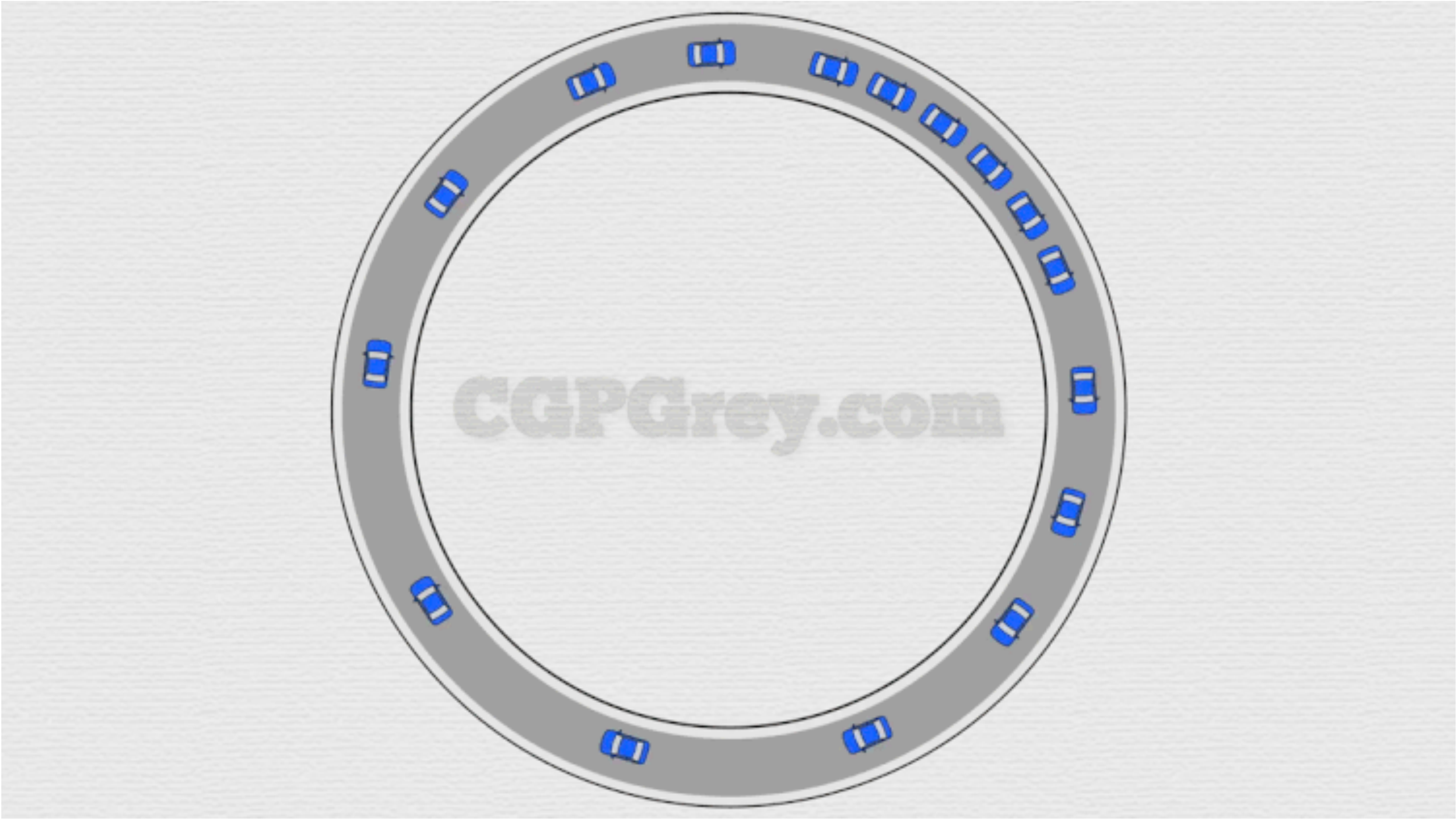

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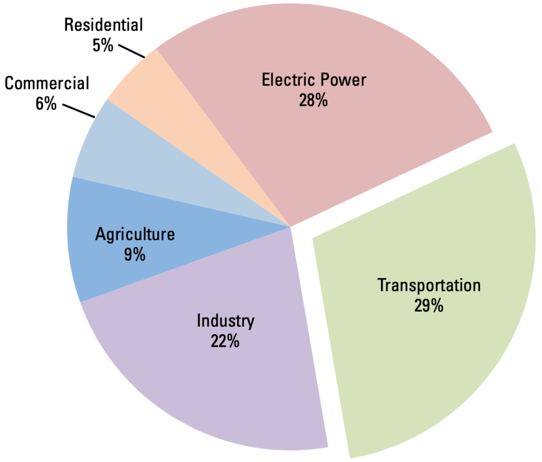

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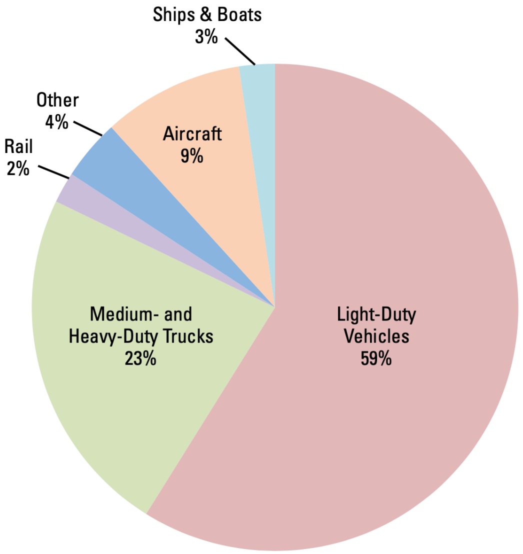

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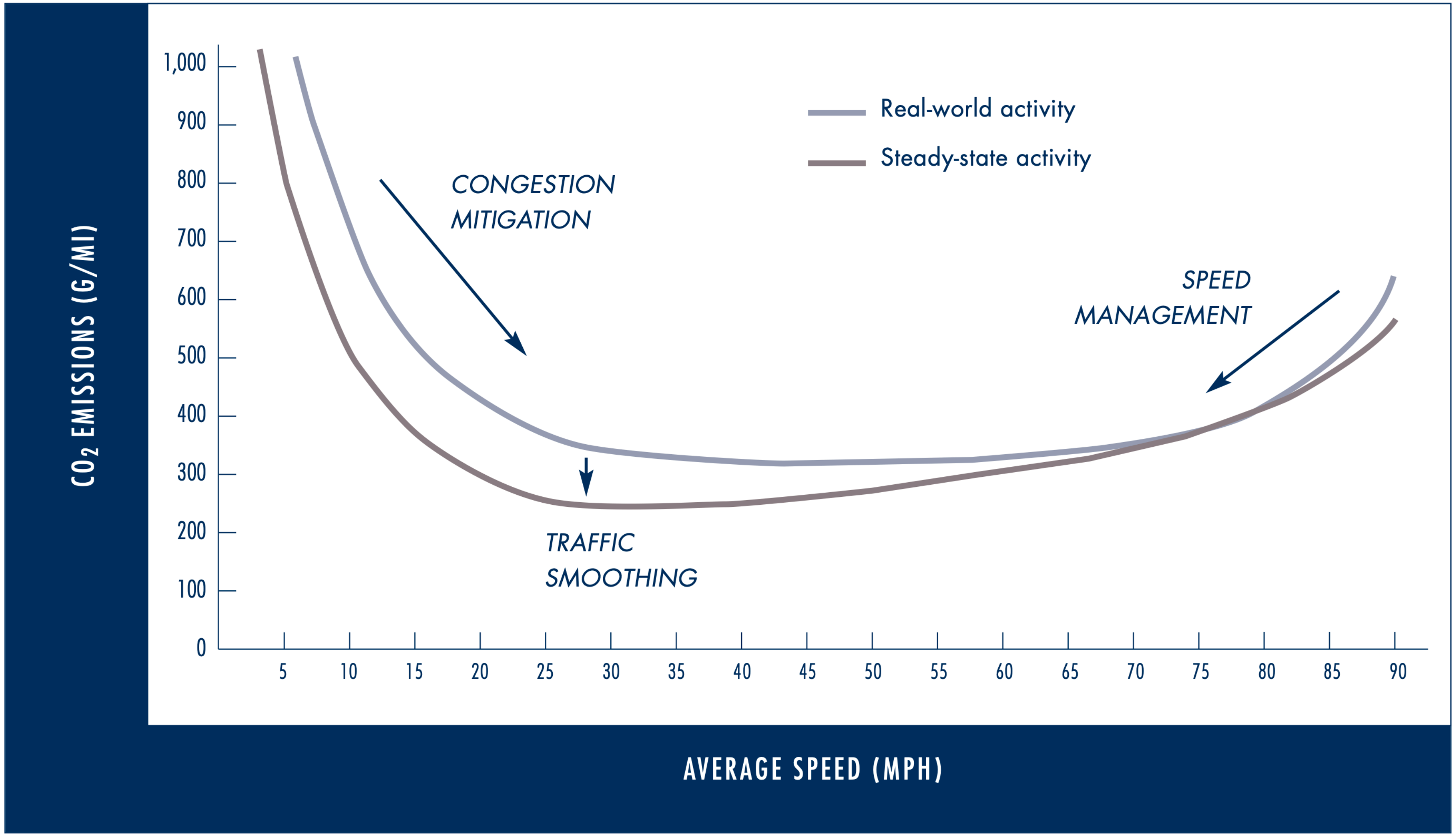
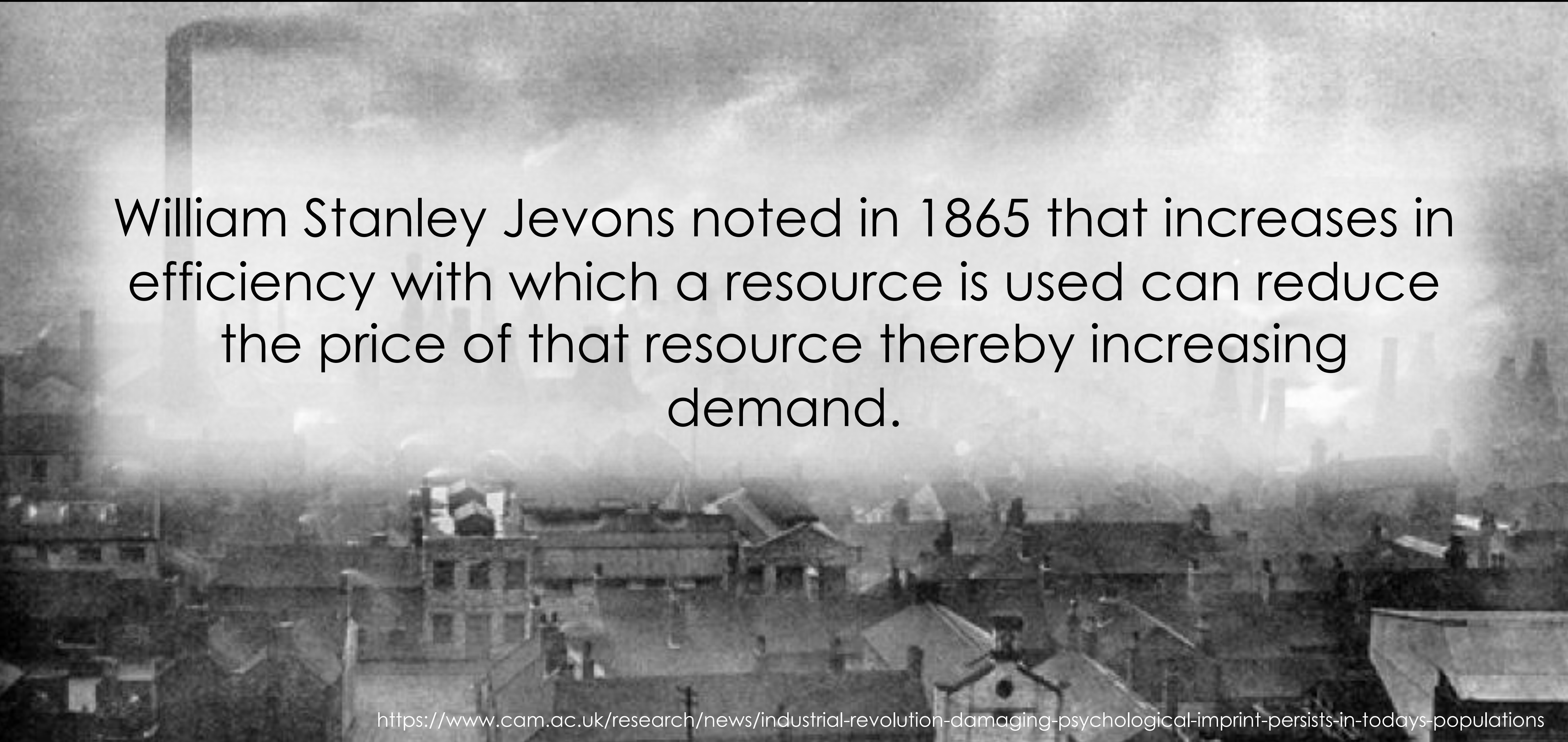


https://www.accessmagazine.org/fall-2009/traffic-congestion-greenhouse-gases/

Jevons Paradox



William Stanley Jevons noted in 1865 that increases in efficiency with which a resource is used can reduce the price of that resource thereby increasing demand.

https://www.cam.ac.uk/research/news/industrial-revolution-damaging-psychological-imprint-persists-in-todays-populations

Jevons Paradox

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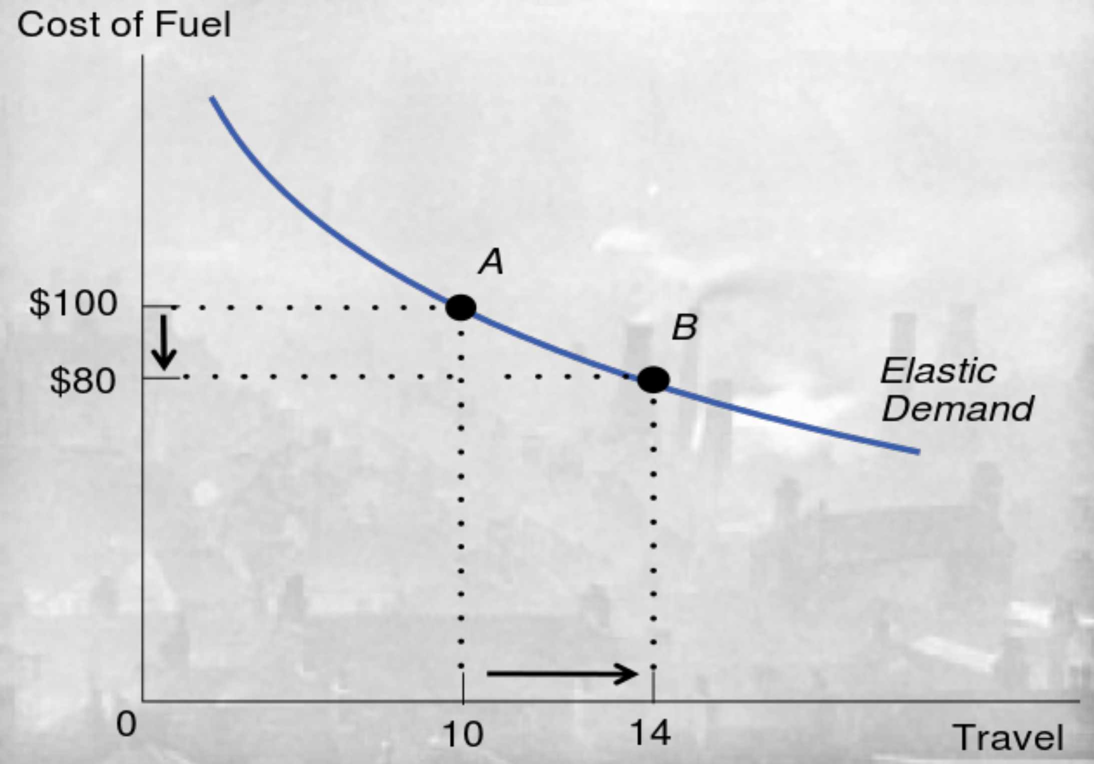

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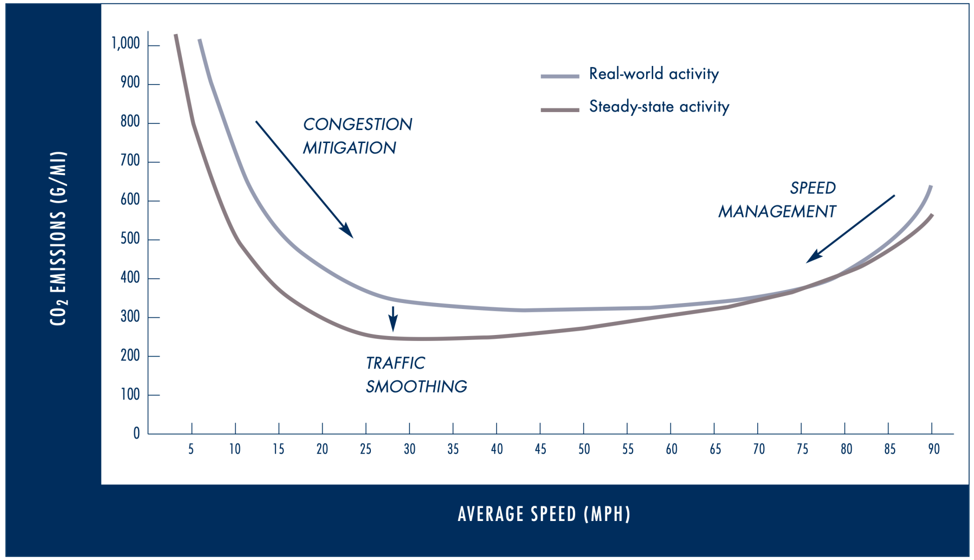
Arguments against Jevons Paradox

- Fuel consumption (commute cost) may decrease
  - Increasing fuel prices/taxes can compensate
- Commute times may not decrease and may increase
  - Slower average speeds
- Convenience → more driving → autonomous vehicles likely electric
  - Need clean energy sources…



Human Driving is a **Real Problem**

- It is stressful and expensive
  - Autonomous vehicles could transform shipping → e-commerce
- Human drivers are killing people
  - 1 motor vehicle fatality every 14 minutes
- Cars are a major cause of green house gas
  - Human related traffic could be addressed

Why now? Why us?

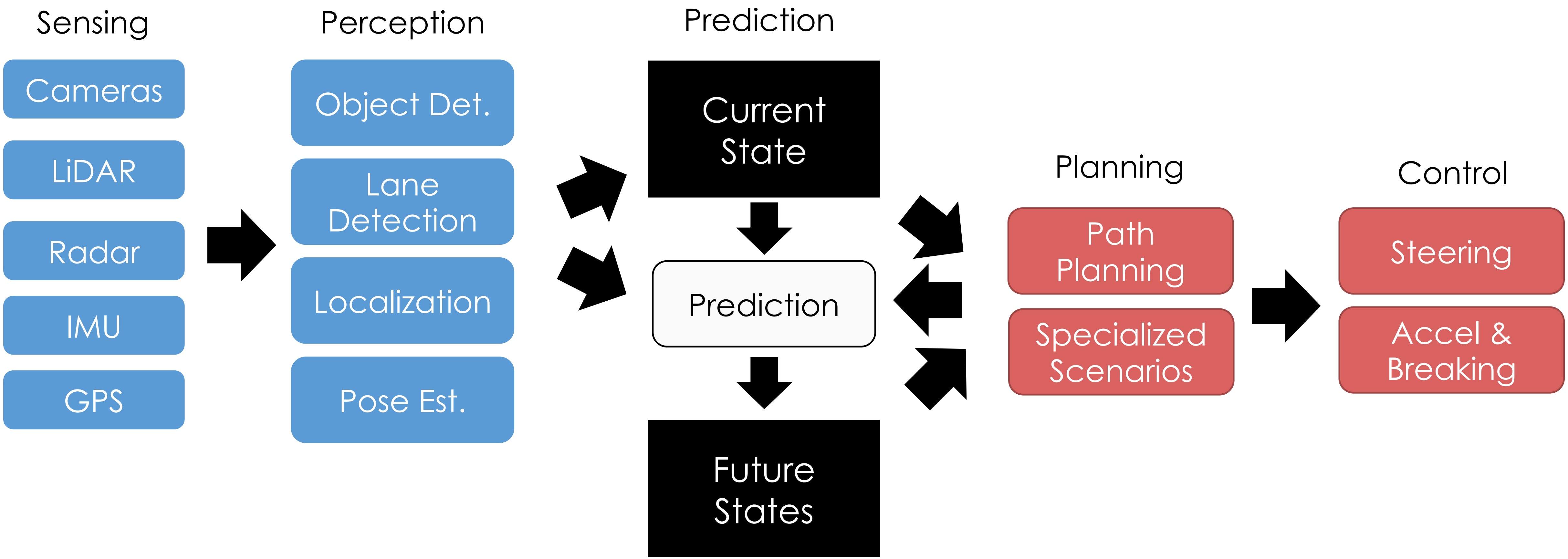
- Sensing and actuation are (mostly) solved problems
  - Unlike many robotics tasks
- Limited by perception (alg.) and compute (arch./sys.)
  - Current research focus is on AI
    - Needed for advanced autonomy
    - AI needed for collision avoidance is partly ready
  - **Gap in research on systems side**
    - Needed: software and hardware platform of an autonomous vehicles
    - Keep device costs down while enabling innovation
- Barrier to Entry
  - Data and test platform → simulation is improving + Berkeley test vehicles

Basics of Autonomous Vehicles

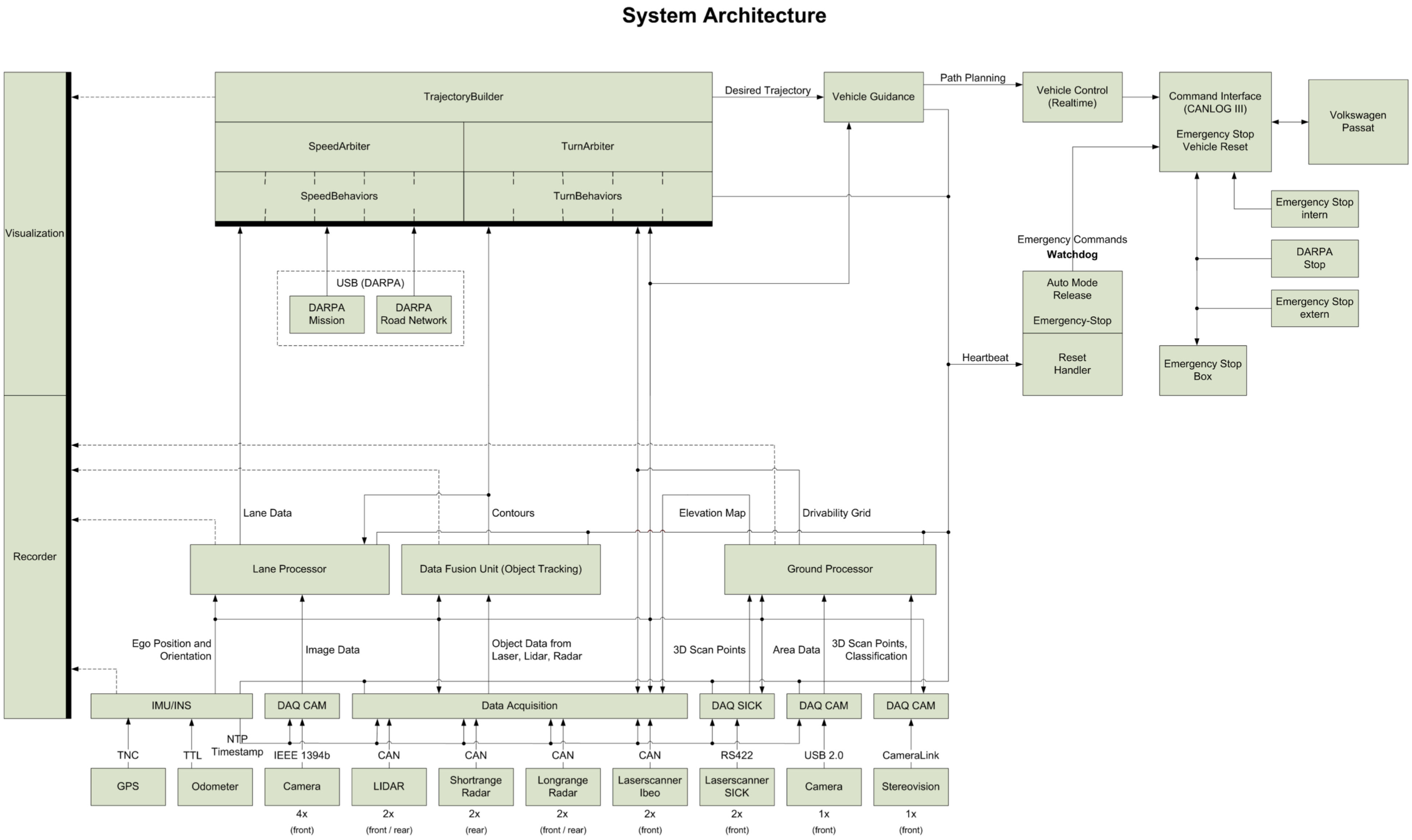
Society of Automotive Engineers (SAE) Levels of Autonomy:

	Name	Description	Steering & Accel.	Env. Monitor	Fallback
1	Driver Assistance ("hands on")	Assistance for **either steering or acceleration** using information about env. with the expectation that human performs all remaining aspects.	Human + System	Human	Human
2	Partial Automation ("hands off*")	**Assistance for both steering and acceleration** using information about env. with the expectation that human performs all remaining aspects.	System	Human	Human
3	Conditional Automation ("eyes off")	Autonomous driving with the **expectation that human will respond to a request to intervene**	System	System	Human
4	High Automation ("mind off")	Autonomous driving with the **ability to take a safe action (e.g., pull over) if a human cannot intervene.**	System	System	System
5	Full Automation	Autonomous driving **under all feasible roadway and environmental conditions.**	System	System	System

Cartoon Autonomous Vehicles Pipeline

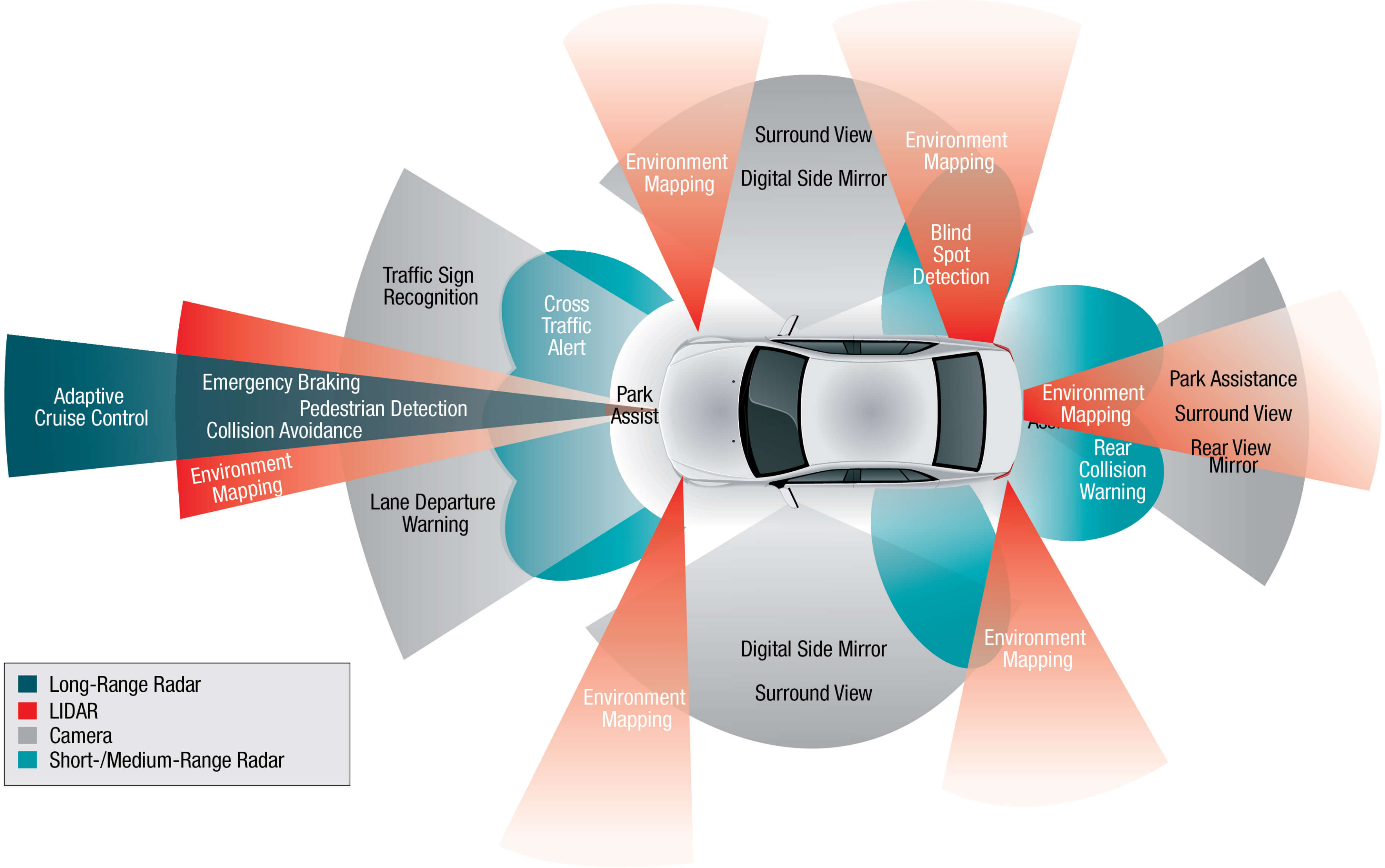


Autonomous Vehicles are Complex Systems



Sensing

Sensors and Their Uses



Sensor Comparison

Sensor	Relative Cost	Resolution	Strengths	Weaknesses
LiDAR	Highest	Mid-range	Depth data 360° view	Susceptible to weather (fog, rain, snow etc.)
Camera	Least expensive	Highest	Traffic lights, pedestrians, signage	Darkness, glare, fog,
RADAR	Cheap	Low	Robust in bad weather	Low Resolution
SONAR	Cheap	Very low	Robust in weather, darkness, brightness	Very Short Range

Sensors – Top View

360° LiDAR

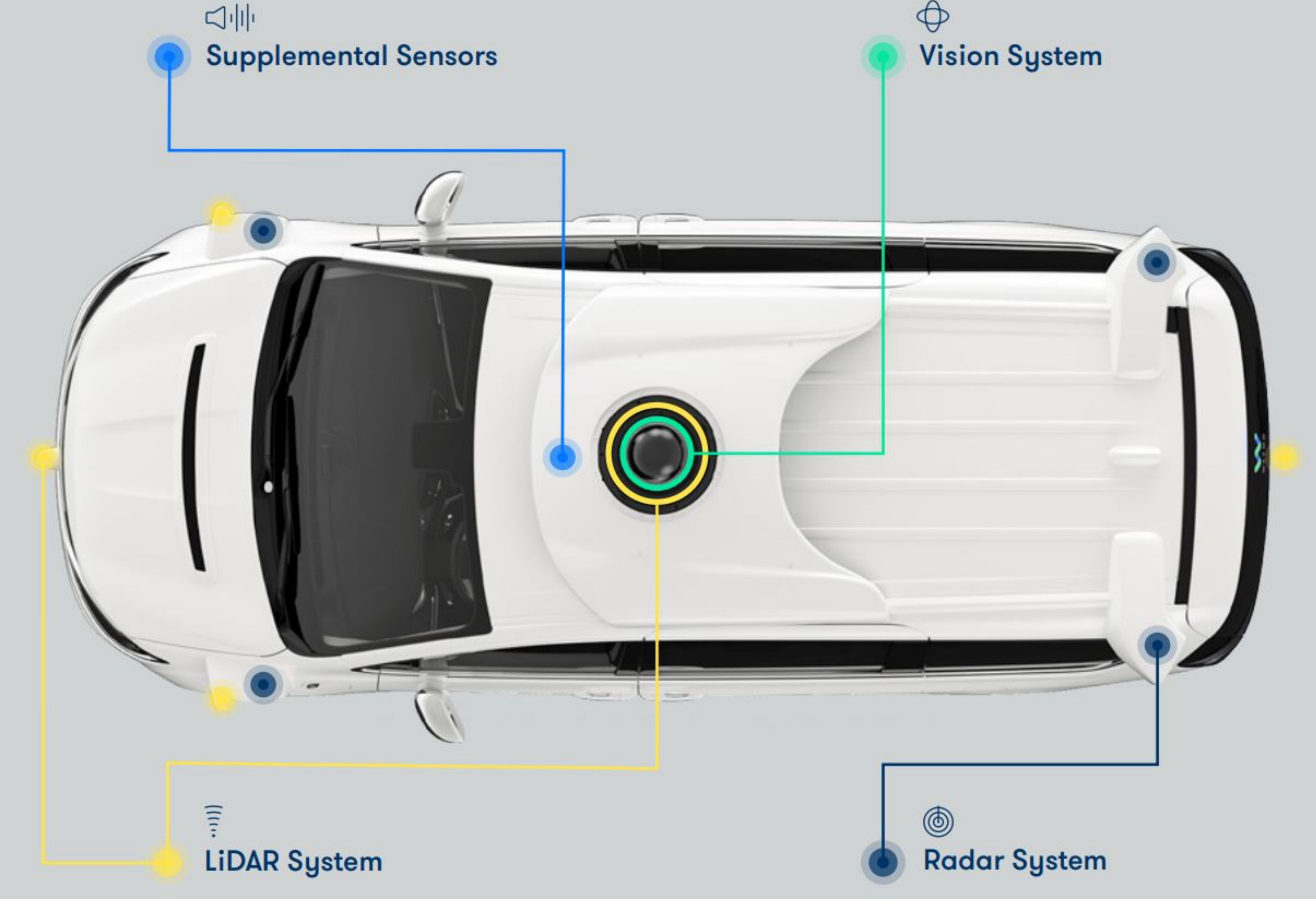
Camera array

Stereo camera pairs

LiDAR

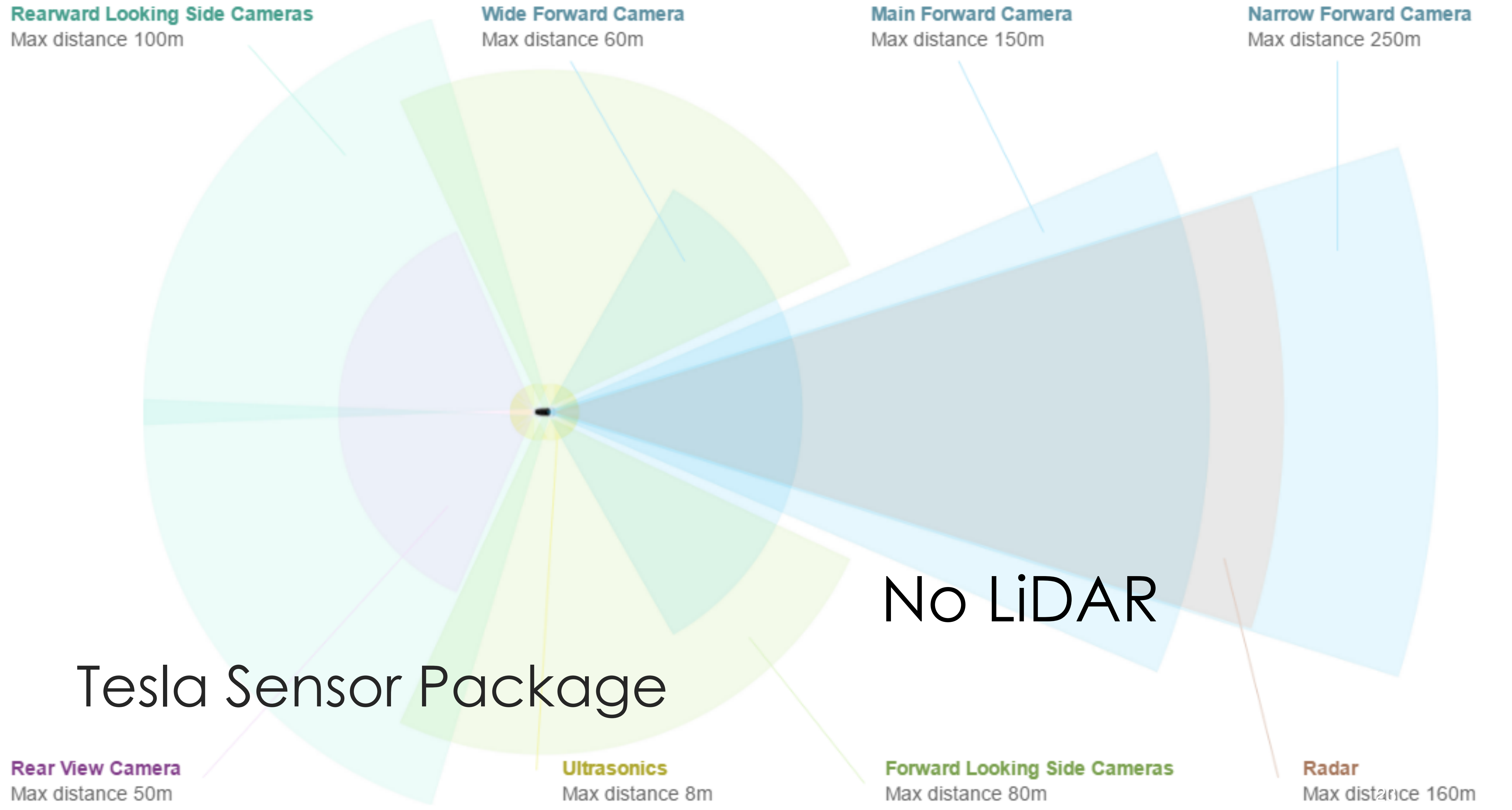
& Radar

Waymo


Supplemental Sensors
Vision System
LiDAR System
Radar System

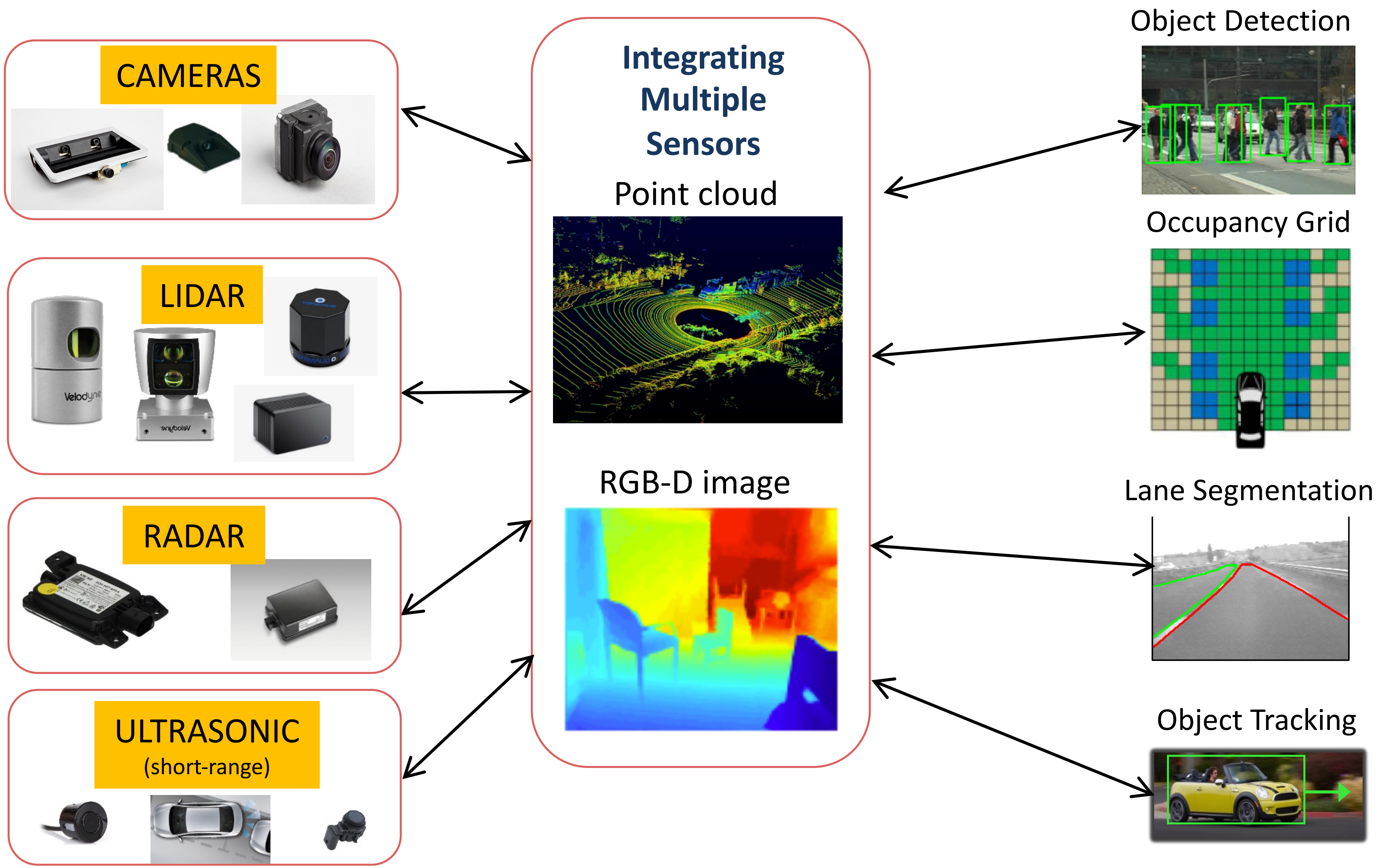
Tesla Sensor Package

No LiDAR

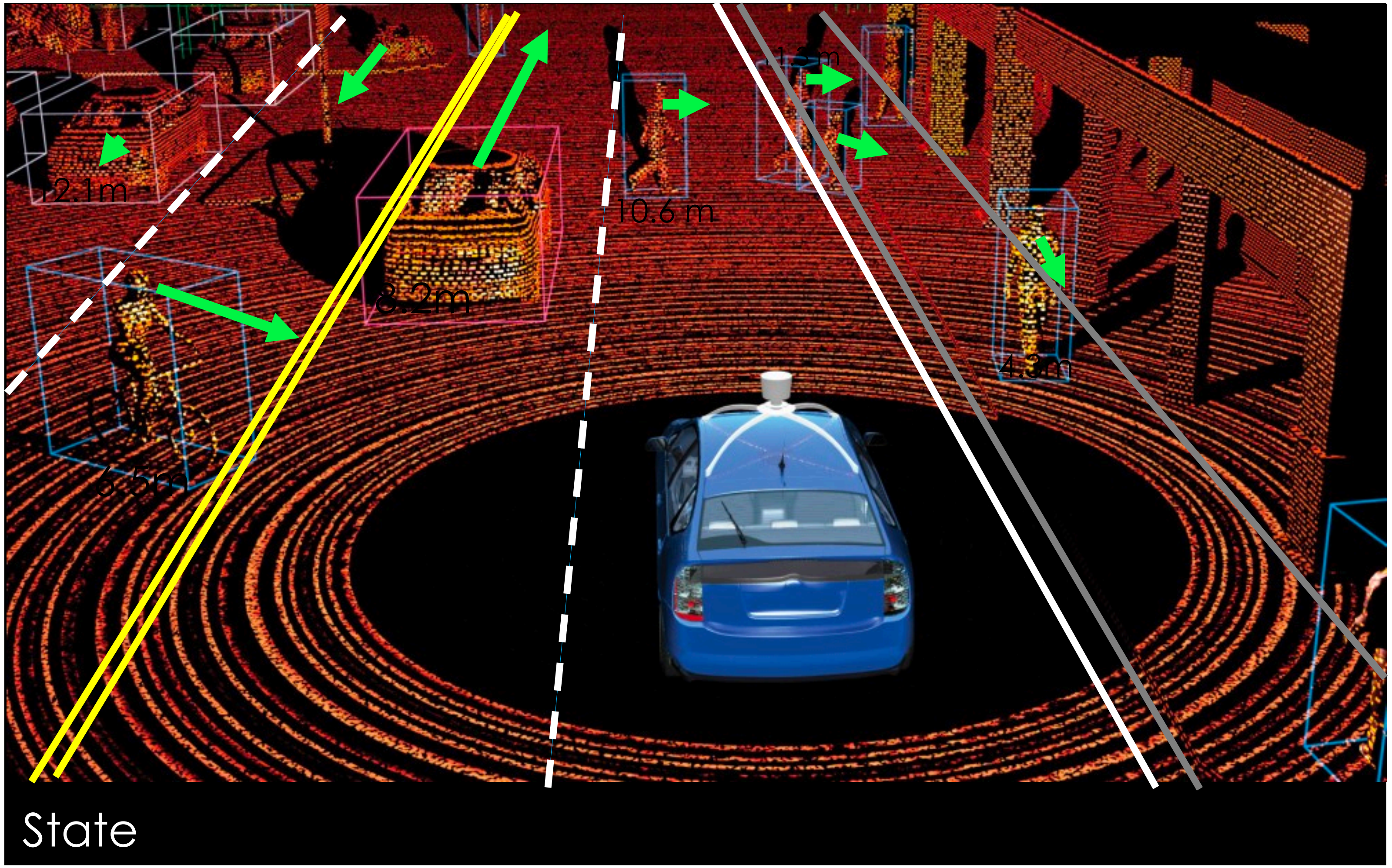


Perception:
From Sensors to State

Applying DNN to Integrated Sensor Data



Typical Approach to State Representation



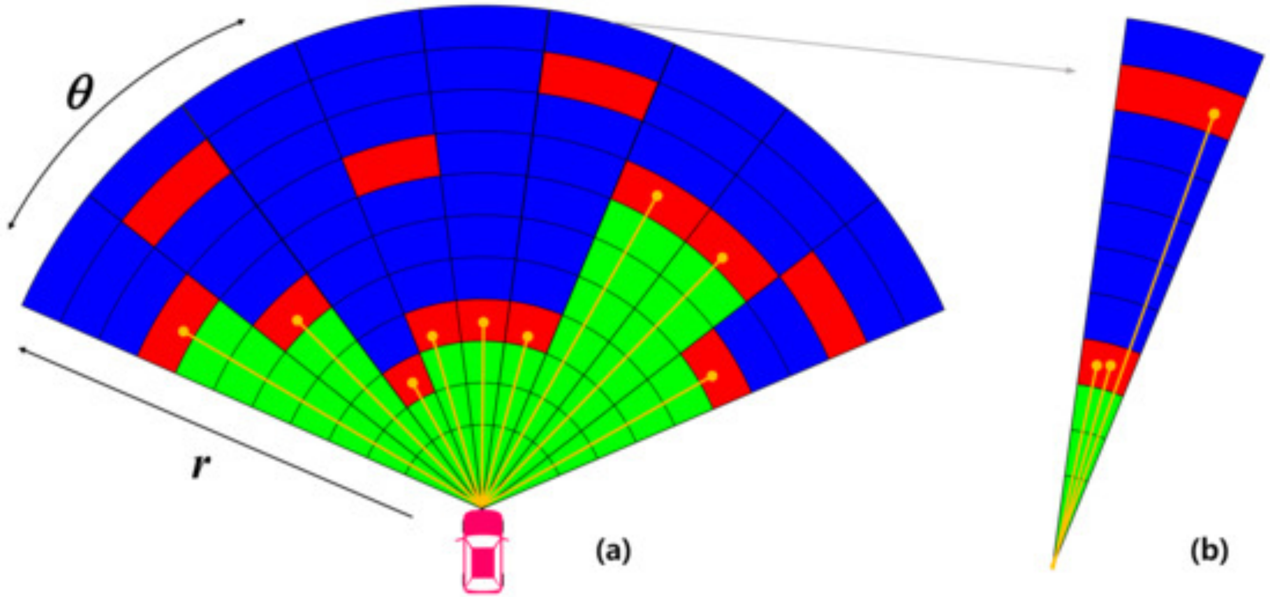
Accurate 3D Models

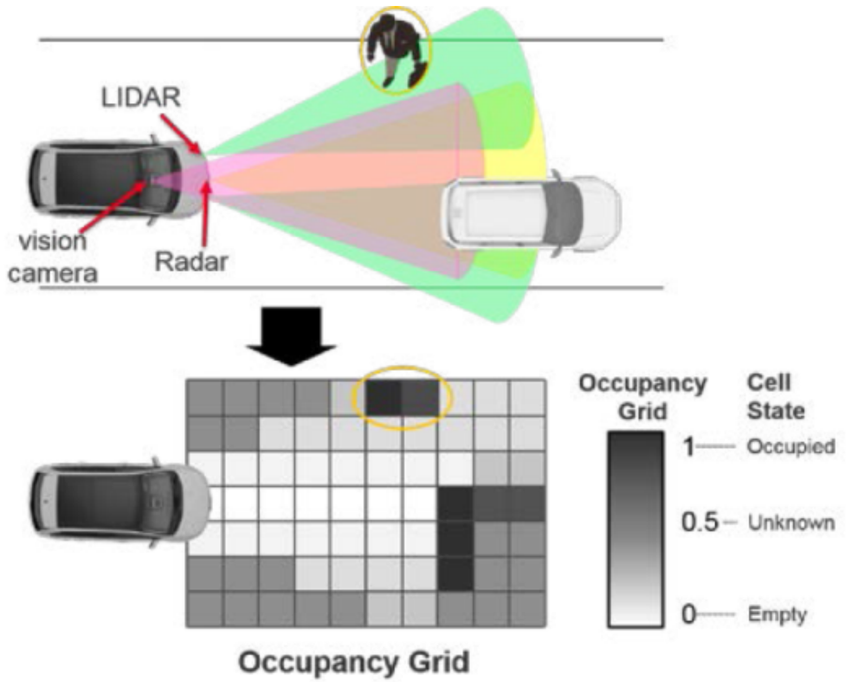
- Individual object detection localization, and pose estimation
- High-resolution maps
- Object trajectories


GO
GO
GO
STOP
STOP
STOP
3 MPH
7 MPH
20 FEET
3 MPH
79 FEET
0 MPH
POLICE CAR
2 MPH
0 MPH
3 FEET
Waymo

Occupancy Grid

- Used in sensor fusion for robotic path planning

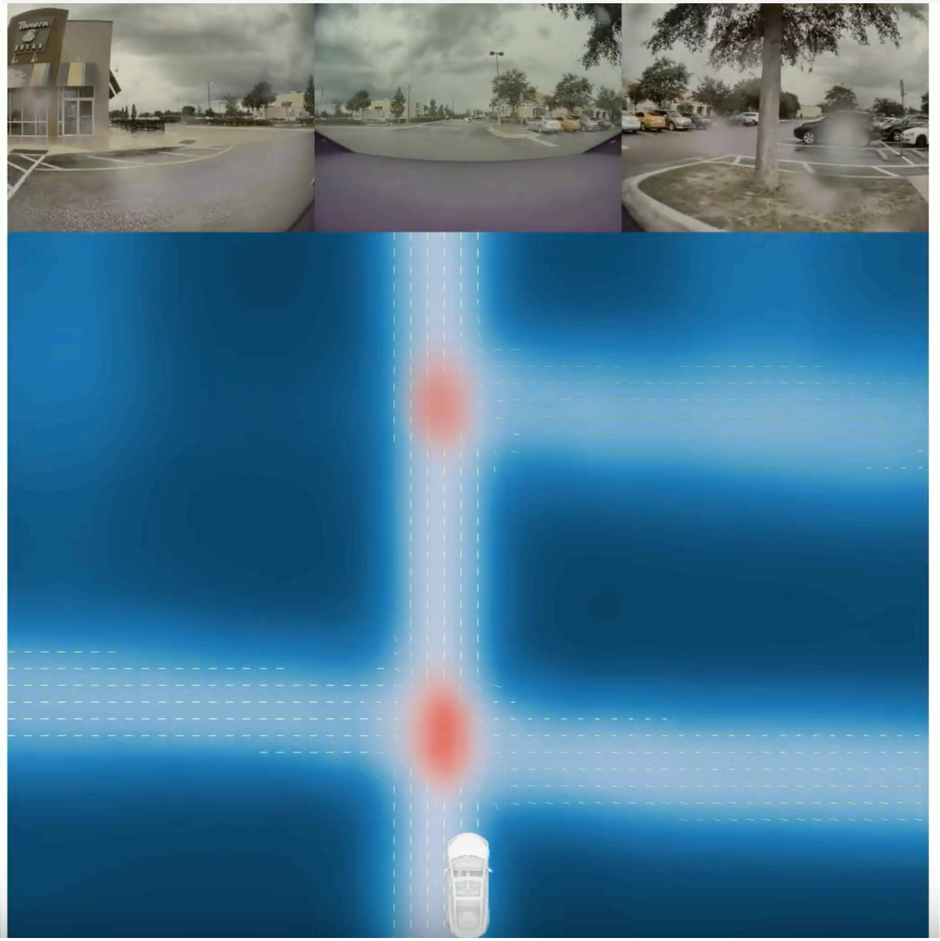




https://www.mdpi.com/1424-8220/18/12/4119

https://www.designnews.com/automation-motion-control/sensor-fusion-software-simplifies-design-robots-autonomous-cars/82637524657038

Tesla's Occupancy Grids
(Smart Summon)



https://youtu.be/oBklltKXtDE

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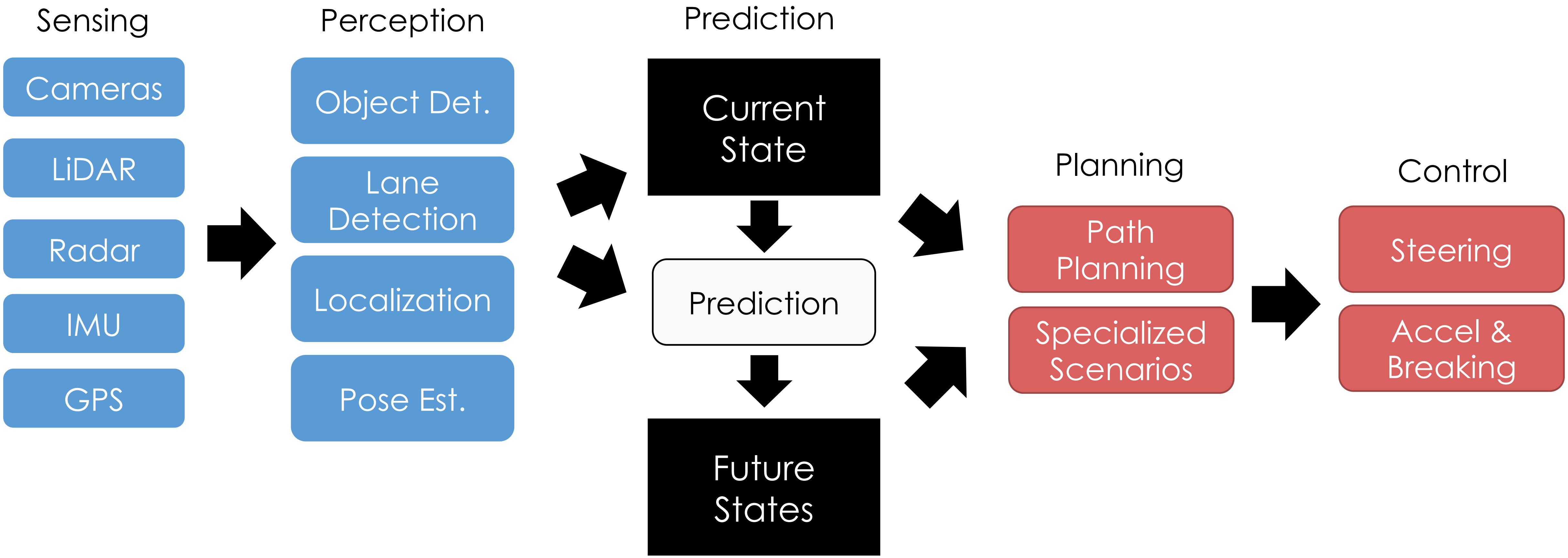
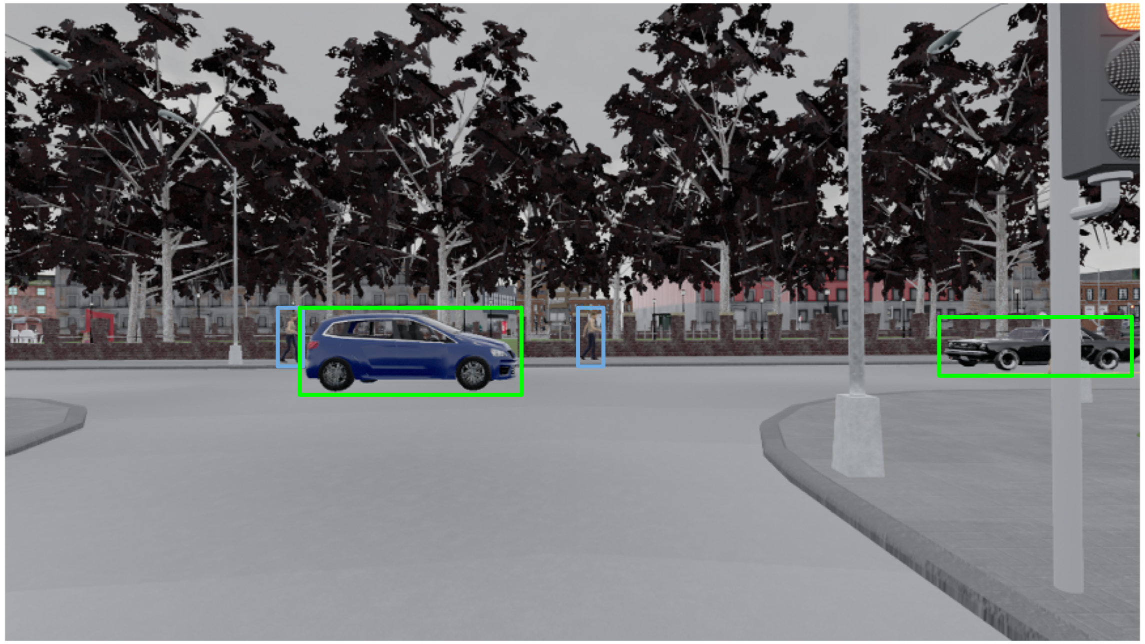
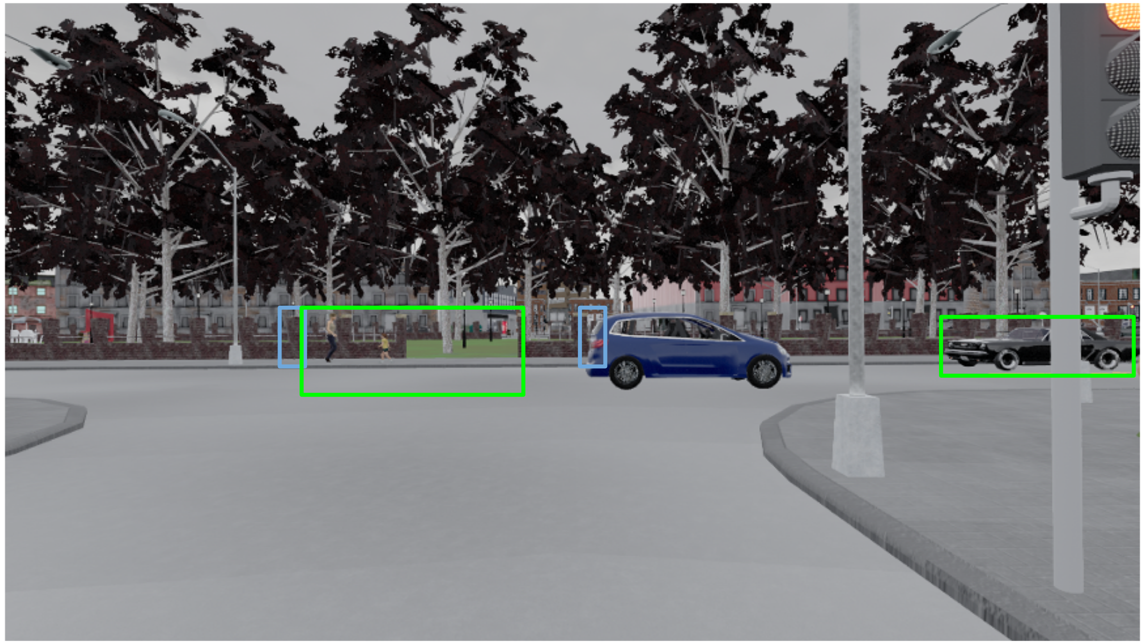


Prediction

Time is Accuracy

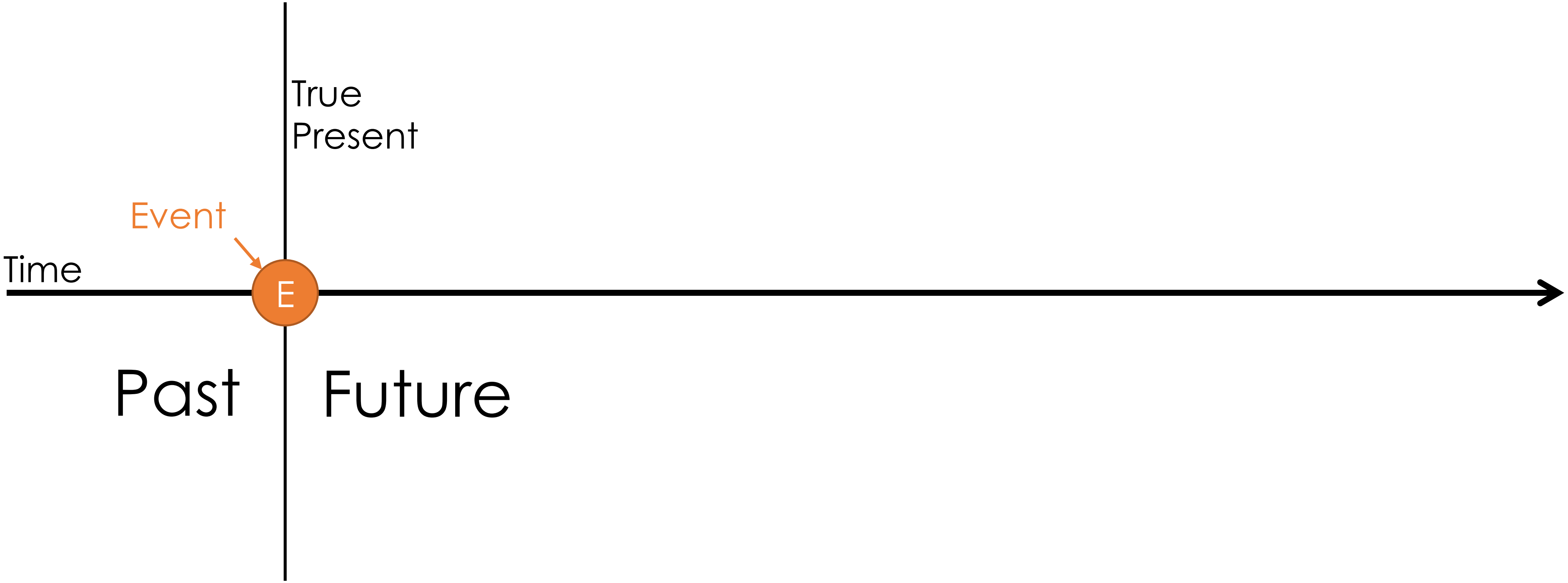


Frame at time t



Frame at time t + 1 seconds

We can only Perceive the Past



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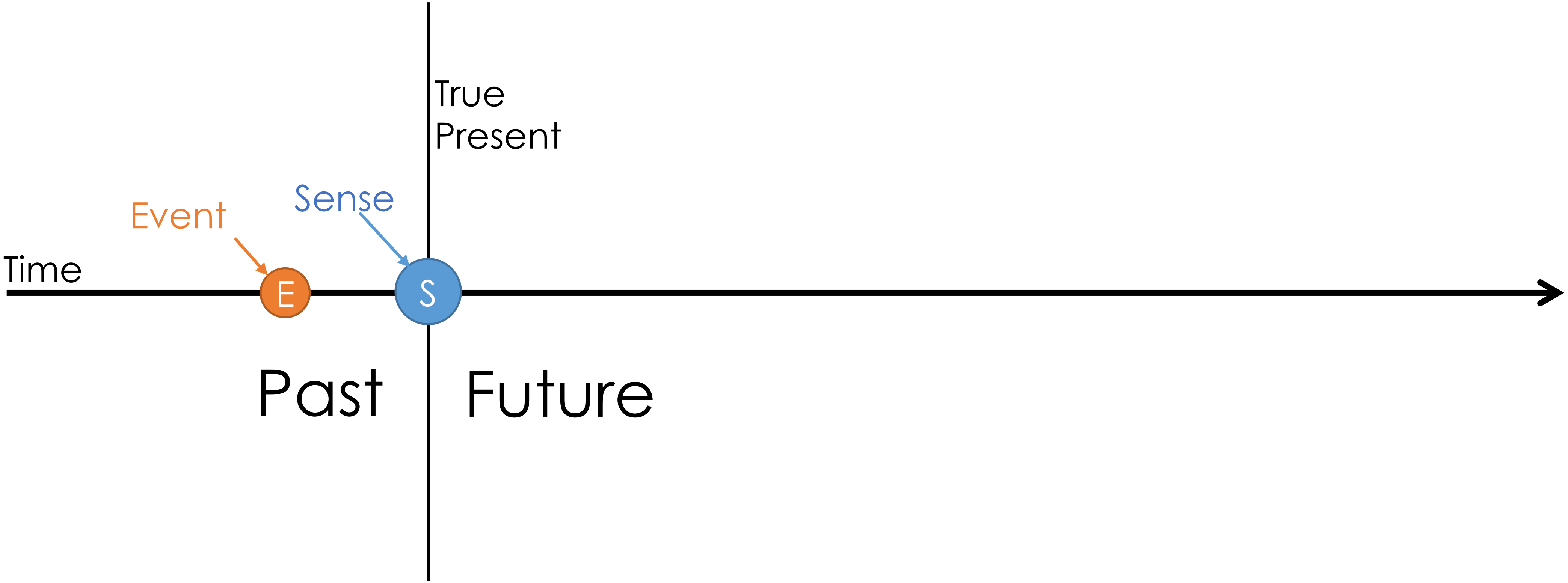

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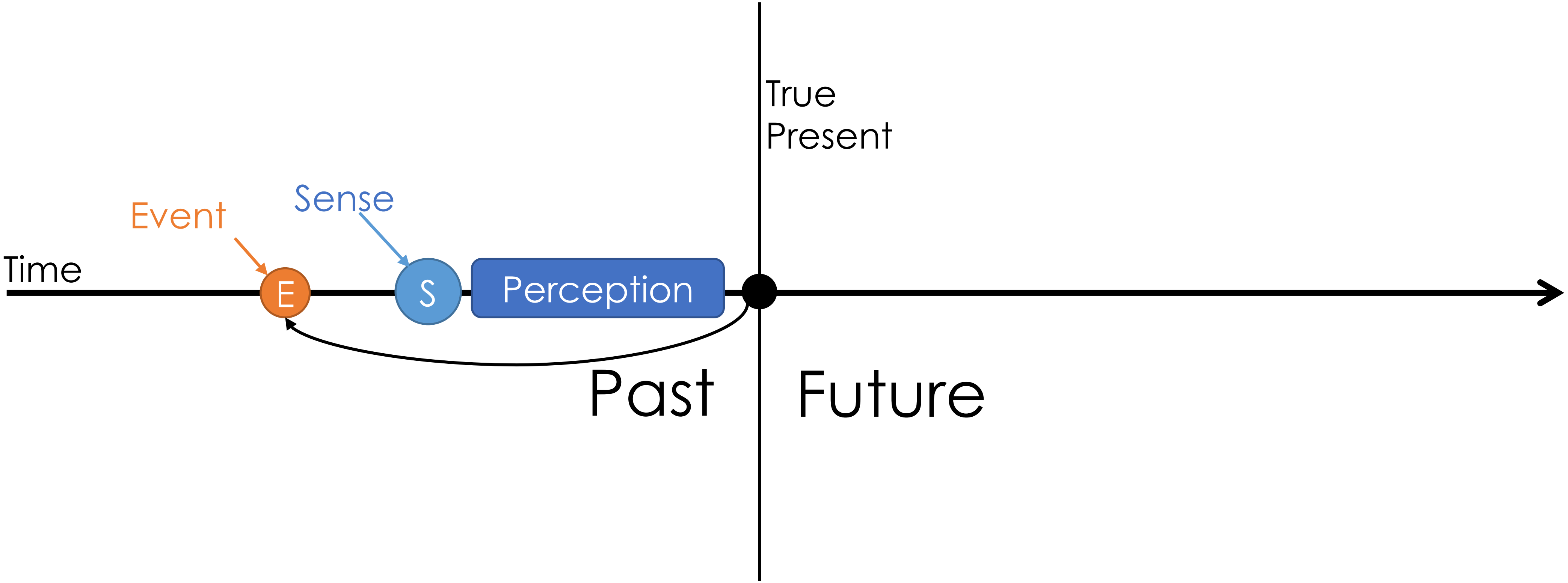

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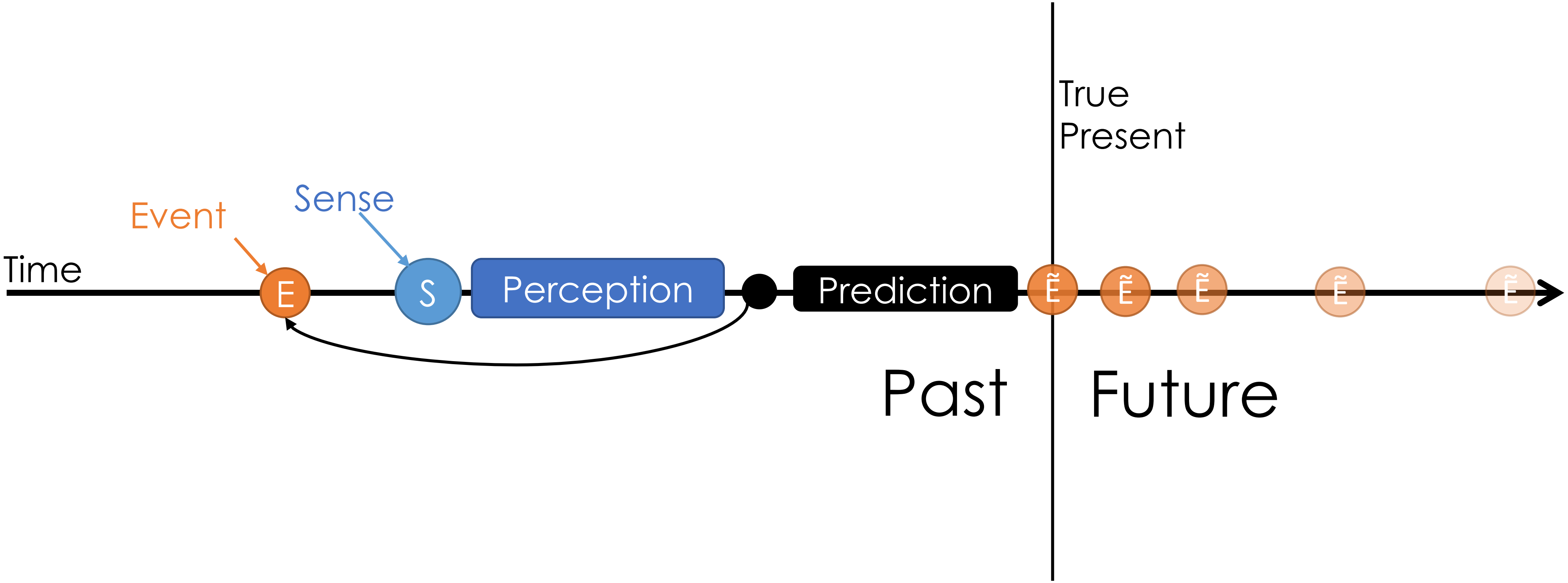
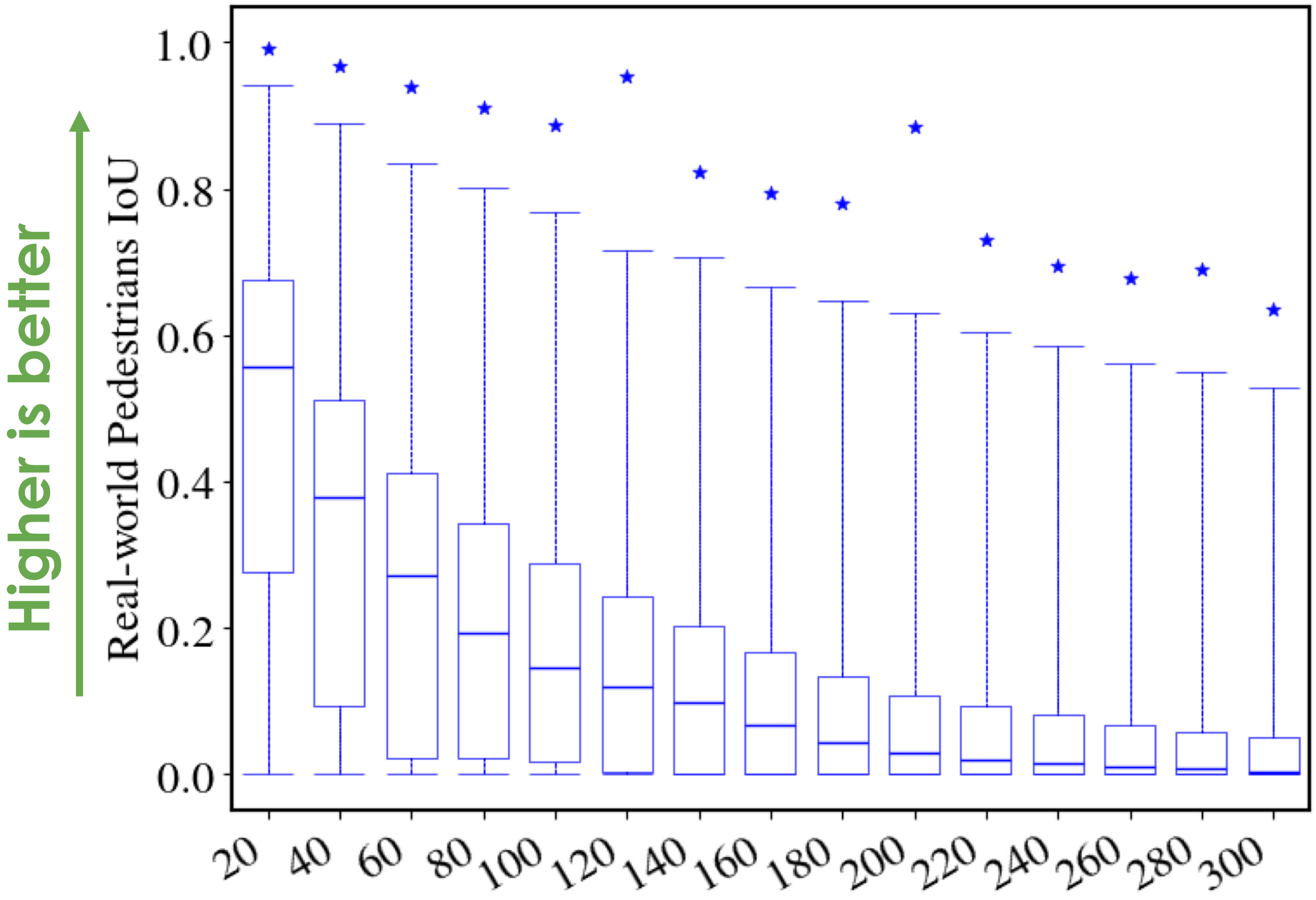
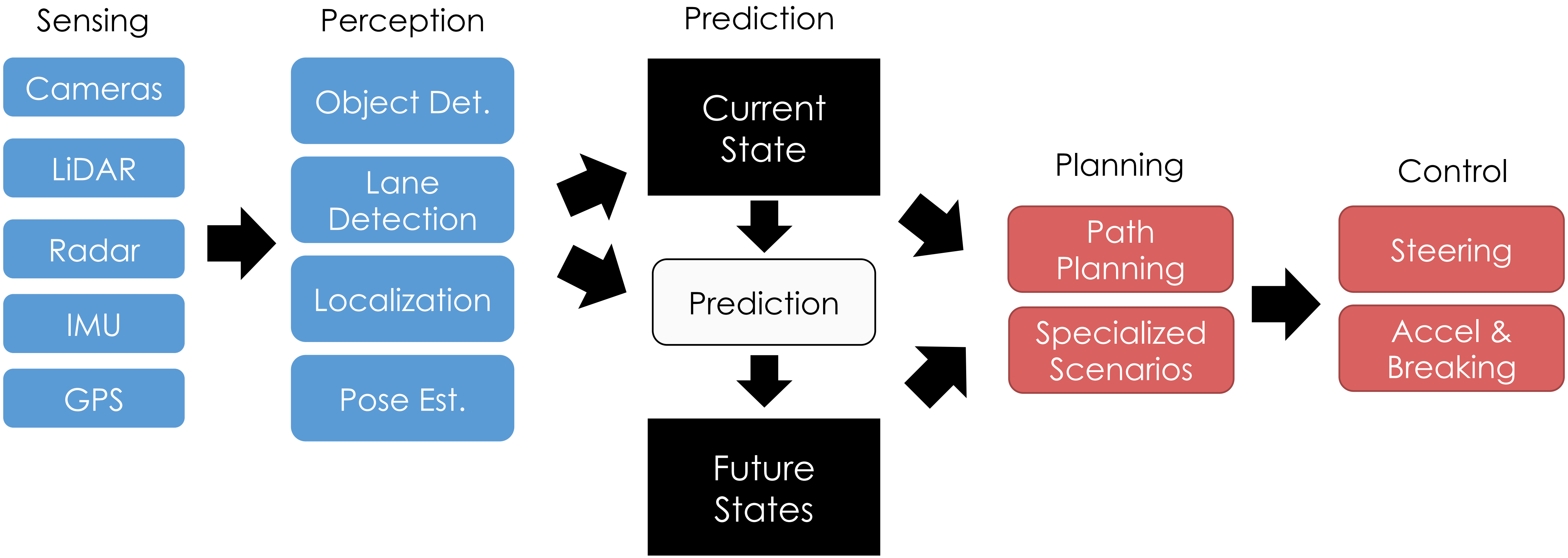


Time is accuracy: semantic segmentation



Both accuracy and runtime matter

Cartoon Autonomous Vehicles Pipeline

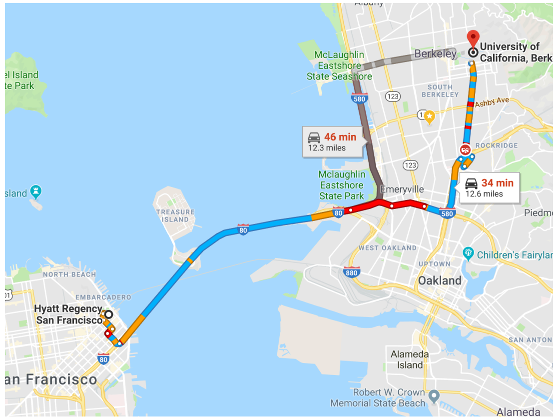


Planning and Control

Classic Hierarchical Approach

Decompose motion planning and control into stages

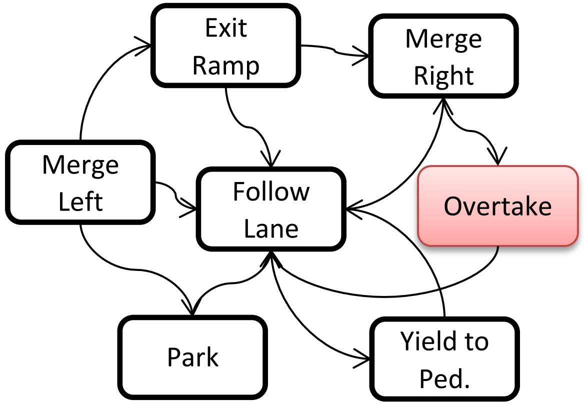
Route Planning



Road Networks
Traffic Information
Obstacles …

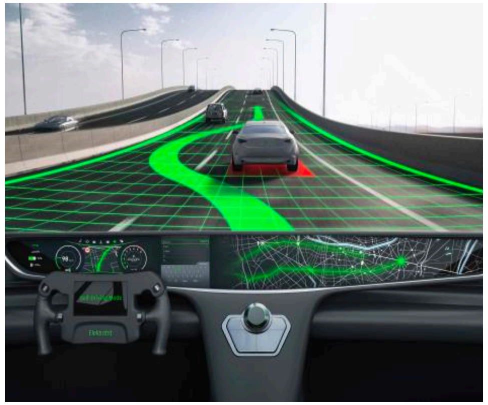
Sequence of roads and intersections

Behavior Planning



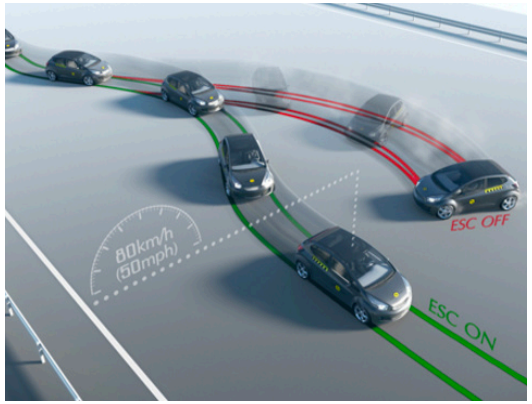
Target State Configurations

Path Planning



Detailed Path to Follow

Local Control



1. Model of the world around the car including predicted future states.
2. Model of the vehicle's dynamics.

Berkeley DeepDrive

Route Planning

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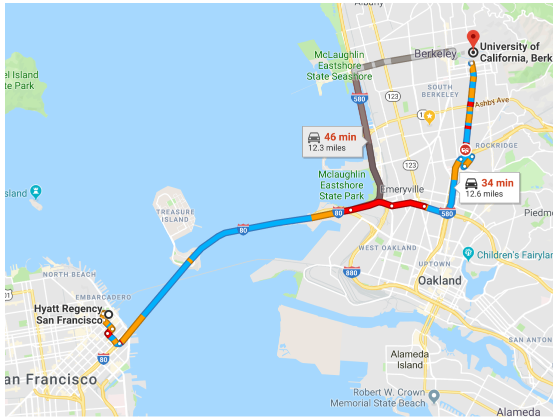
Route Planning



Sequence of roads and intersections

Road Networks
Traffic Information
Obstacles …

- Determine best route between origin and destination
  - survey [“Route Planning in Transportation Networks”]

Google Maps

Apple Maps

Big Maps

- **Input:** source and destination as well as the road network, traffic information, obstacles
- **Output:** Sequence of roads (paths) including GPS coordinates.
- Relies on **optimizations** of classic graph algorithms to plan in seconds across entire contents.

Classic Hierarchical Approach

Decompose motion planning and control into stages

Route Planning

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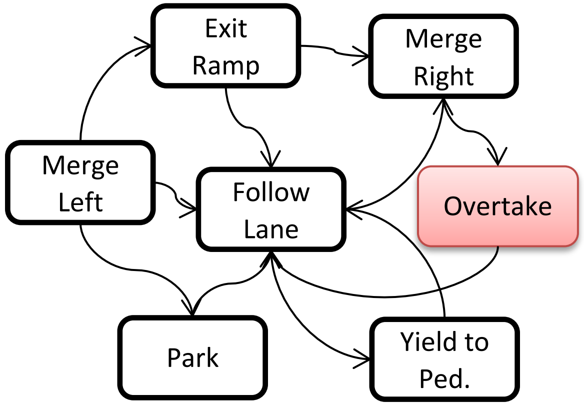
Traffic Information
Obstacles …

Sequence of roads and intersections

Behavior Planning



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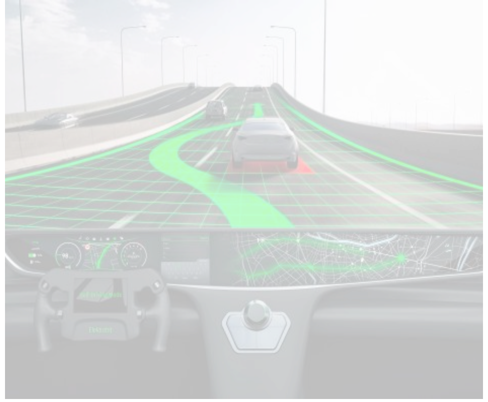

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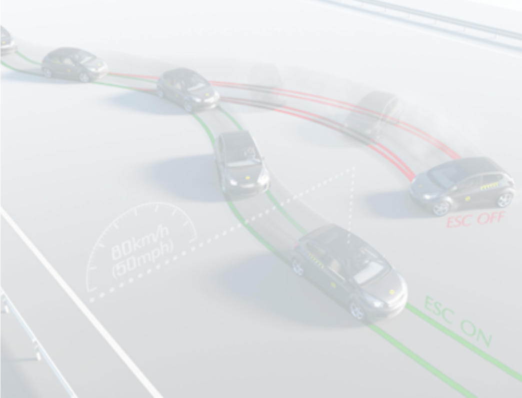

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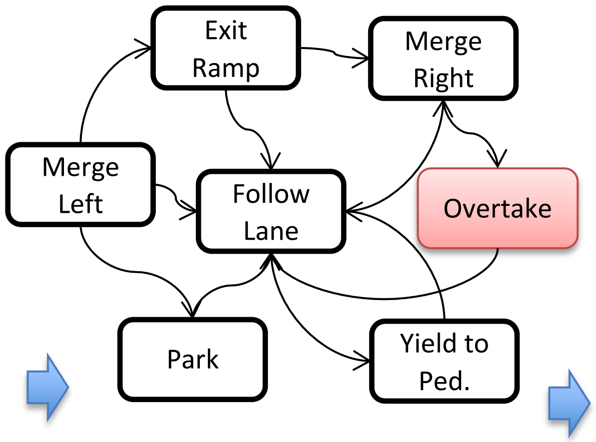
Behavior Planning

Behavior Planning



Sequence of roads and intersections

Target State Configurations

- Determines the **high-level actions** need to move through the input road network in response to observations and future state predictions.
  - Example:
    - *Exit right from parking lot.*
    - *Merge into left lane*
    - *Turn left at intersection*
    - *Avoid [observed] construction worker ...*
- **Inputs:** Road sequence as well as observations and predictions from perception systems.
- **Outputs:** Actions which can be mapped to state configurations (e.g., GPS waypoints, orientation, speed…)
- **Solutions:** Finite state machines as well as probabilistic generalizations (MDPs).
  - **Area of potential future innovation** → Learned behaviors

Berkeley DeepDrive

Classic Hierarchical Approach

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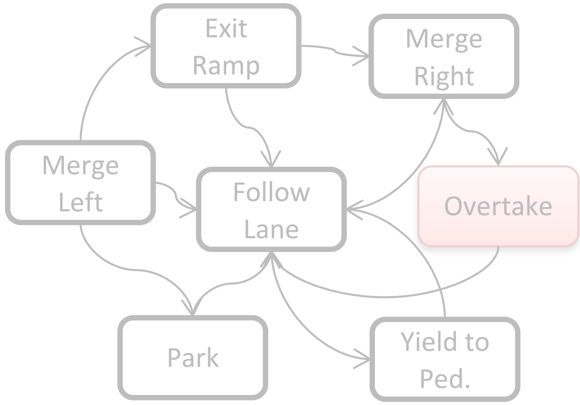
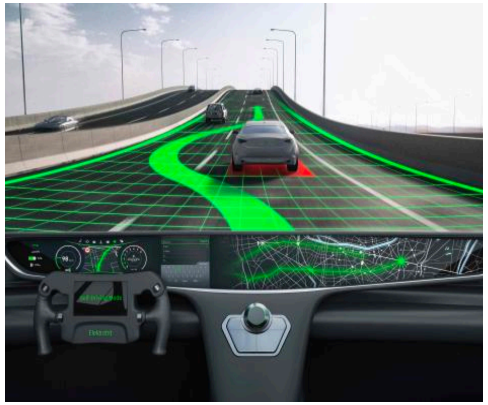


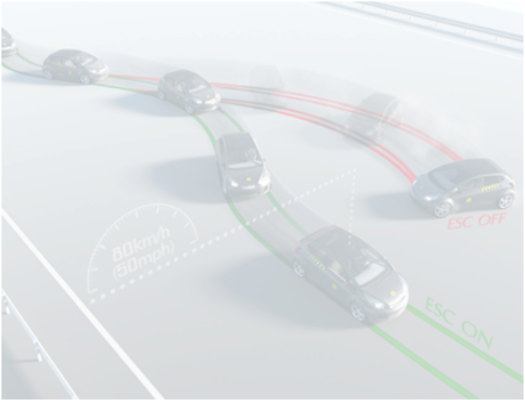
Target State Configurations

Path Planning



Detailed Path to Follow

Local Control



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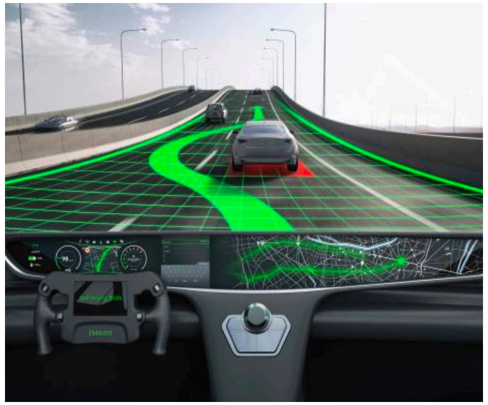
Path Planning

Path Planning



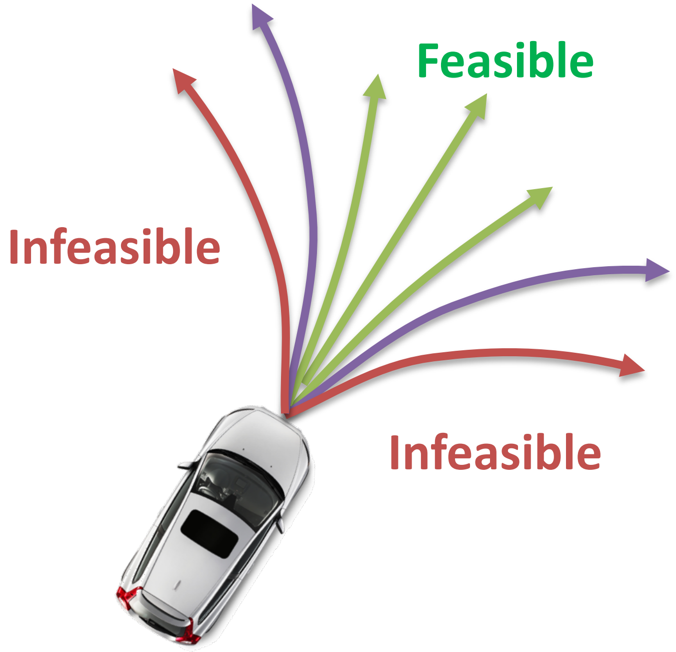
Target State Configurations

Detailed Path to Follow

- Compute an "optimal" sequence of state configurations (e.g., locations and velocities) that terminates in the desired end state.
- **Path**: sequence of state configurations including
  - Position, orientation, velocity
- **Optimal**
  - Feasible with respect to vehicle dynamics
  - Avoid collisions or violating road laws
  - Comfortable (limited acceleration, jerk, …)
  - Efficient (reduce wasted energy and time)
- **Dependencies**
  - Road network
  - Behavior of other vehicles and pedestrians
  - Vehicle dynamics model
- **Hard problem but well studied!**

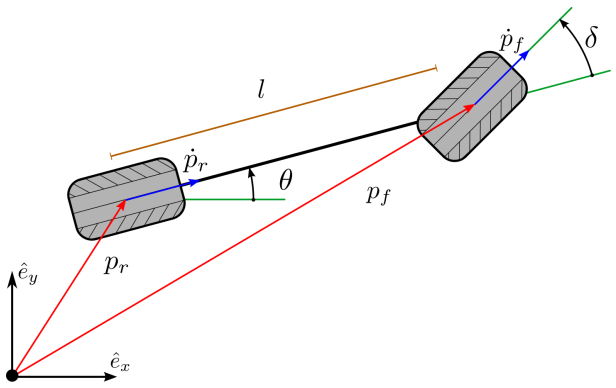
Vehicle Dynamics Models

- Typically adopt simplified physical model of vehicle dynamics that capture constraints on the **velocity** and **acceleration** of the vehicle to determine feasible paths.



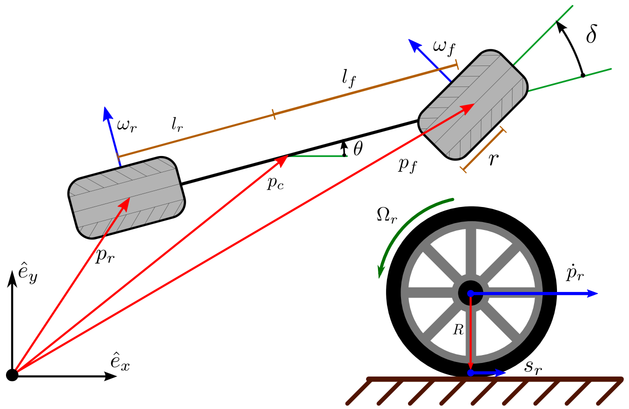
Common Dynamics Models

Single Track No Slip



Used in **low speed** settings (e.g., Parking)

Single Track with Frictional Forces



Needed for driving at **higher speeds**. (e.g., highway driving)

Illustrations of dynamics models from "A Survey of Motion Planning and Control Techniques for Self-driving Urban Vehicles"

Optimal Path Planning Problem

Optimization Problem:

Path Objective Function
Comfort + Safety

path

$$\underset{\sigma \in \Sigma(\mathcal{X})}{\arg\min} \quad J(\sigma)$$

Set of all continuous paths

Path terminates in a goal state (e.g., car is parked)

Constraints:

$$\begin{aligned} \text{subj. to} \quad & \sigma(0) = \mathbf{x}_{\text{init}} \text{ and } \sigma(1) \in X_{\text{goal}} \\ & \sigma(\alpha) \in \mathcal{X}_{\text{free}} & \forall \alpha \in [0,1] \\ & D(\sigma(\alpha), \sigma'(\alpha), \sigma''(\alpha), \ldots) & \forall \alpha \in [0,1] \end{aligned}$$

The path remains in the drivable space (obeys laws and doesn't hit obstacles)

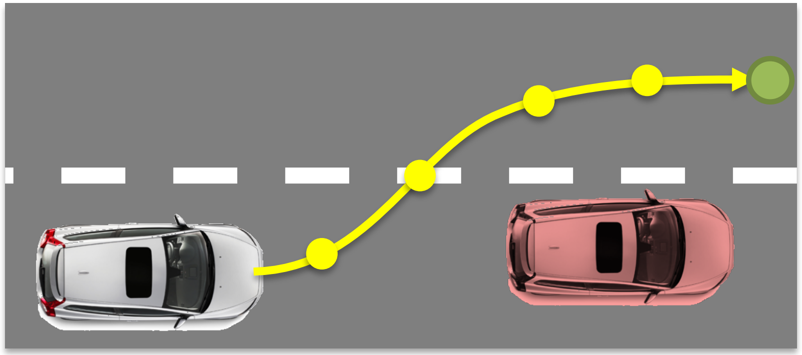
Differential Constraints on path curvature (given by vehicle dynamics)

Solving the general problem is PSPACE-hard

☹

Approximate Solutions to Optimal Path Planning

Variational Methods



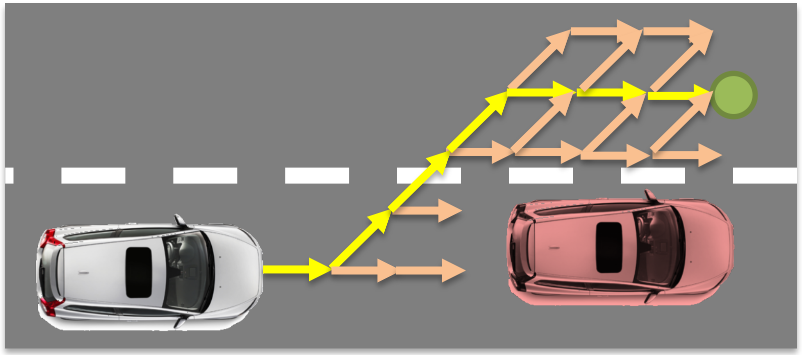
Approximate smooth paths with parametric functions (e.g., splines) and optimize control points.

- Get stuck in local minima

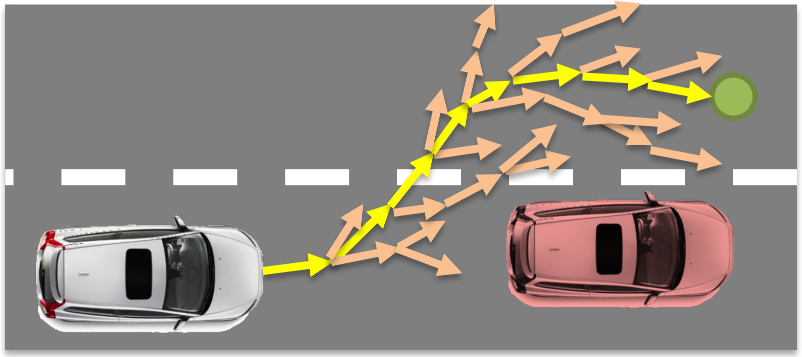
Graph Search Methods (commonly used)

Discretize space of possible paths and optimize

Regular Lane or Geometric Graphs



Random or Incremental Graphs



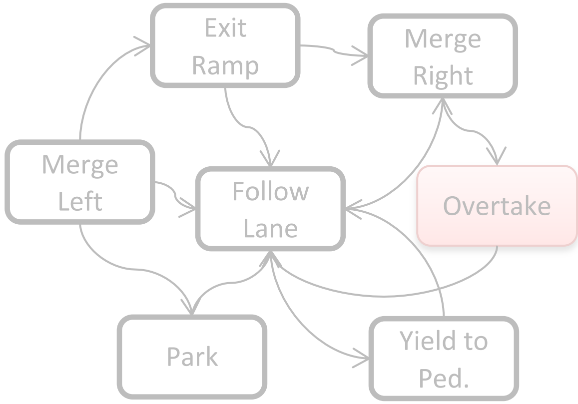
Classic Hierarchical Approach

Decompose motion planning and control into stages

g

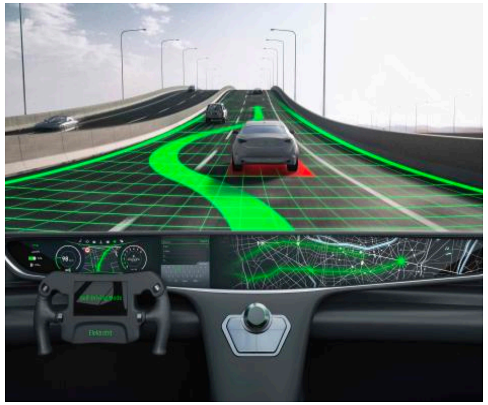
Sequence of roads and intersections

Behavior Planning



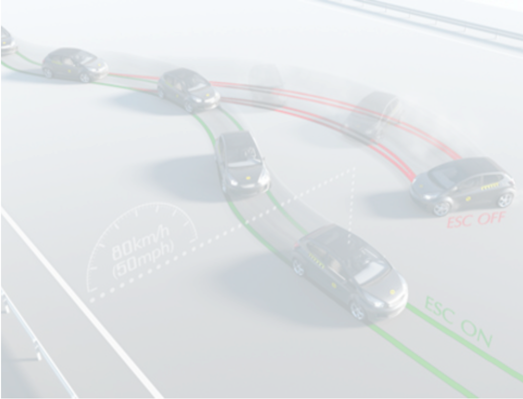
Target State Configurations

Path Planning



Detailed Path to Follow

Local Control



Steering Angle
Acceleration

1. Model of the world around the car including predicted future states.
2. Model of the vehicle's dynamics.

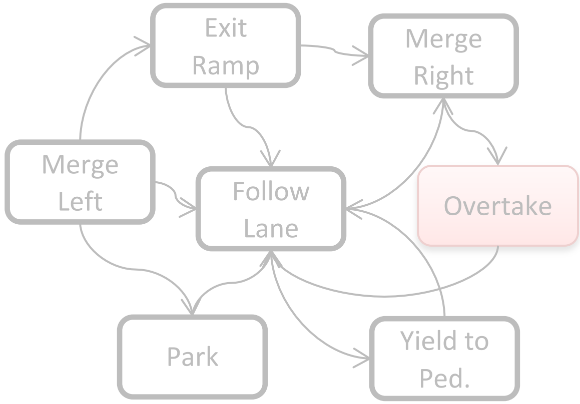
Classic Hierarchical Approach

Decompose motion planning and control into stages

g

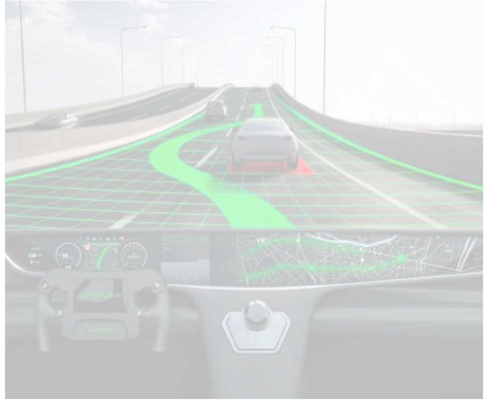
Sequence of roads and intersections

Behavior Planning



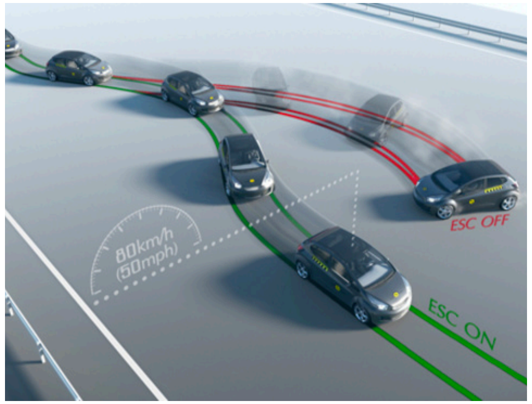
Target State Configurations

Path Planning



Detailed Path to Follow

Local Control



Steering Angle
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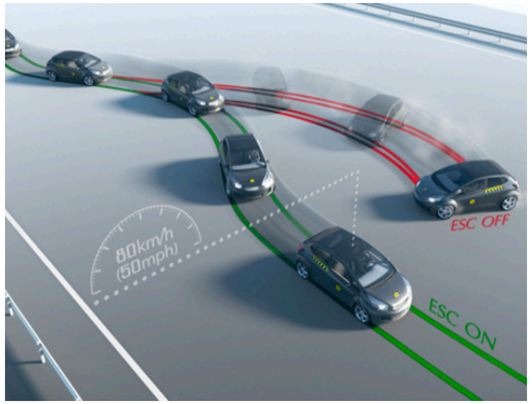


Steering Angle
Acceleration

Basis for established technologies like electronic stability control

- Use classic **closed-loop** controllers to actuate **steering** and **acceleration** along the planned path
- Requires frequent control responses (real-time system) to correct for errors.

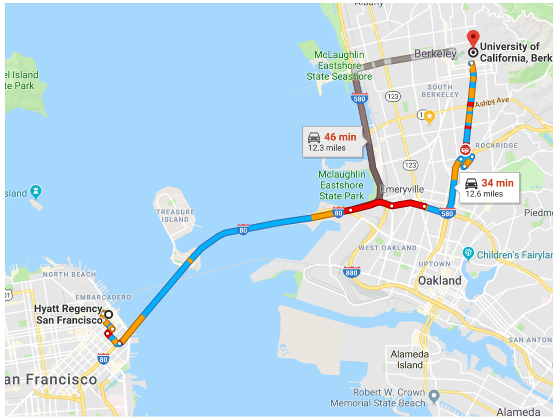
Common techniques often adopt locally linear approximations to the system

- **PID Controllers:** Proportional-–integral—derivative controller corrects the steering and acceleration proportional to their deviation with damping
- **Linear Quadratic Regulators:** Optimally controls a linear approximation of the system.

Classic Hierarchical Approach

Decompose motion planning and control into stages

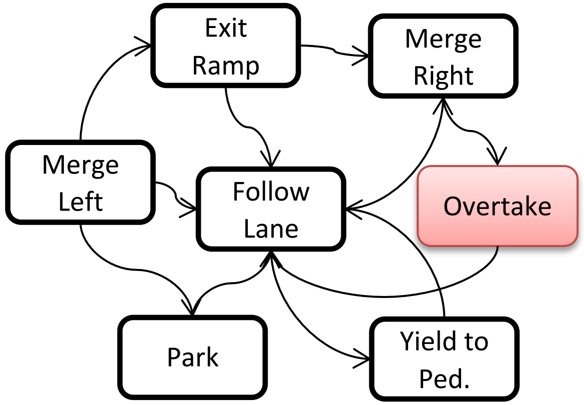
Route Planning



Road Networks
Traffic Information
Obstacles …

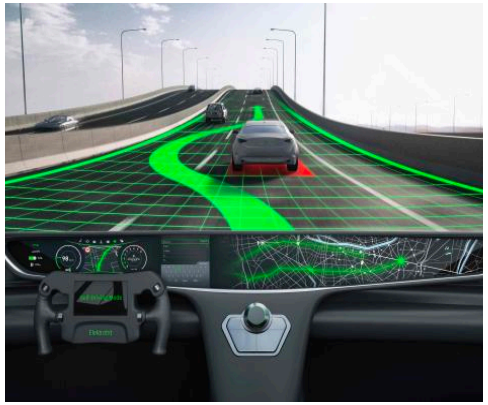
Sequence of roads and intersections

Behavior Planning



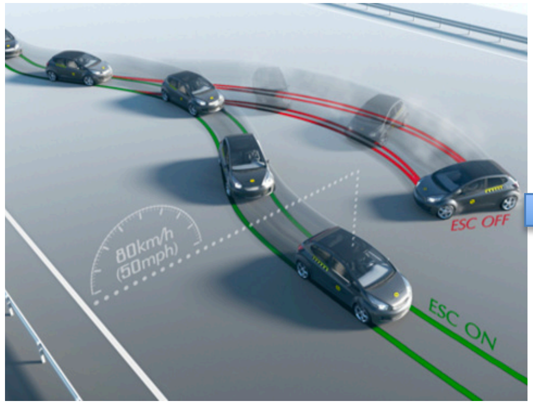
Target State Configurations

Path Planning



Detailed Path to Follow

Local Control



1. Model of the world around the car including predicted future states.
2. Model of the vehicle's dynamics.

More details can be found here in ["A Survey of Motion Planning and Control Techniques for Self-driving Urban Vehicles"]

Berkeley DeepDrive

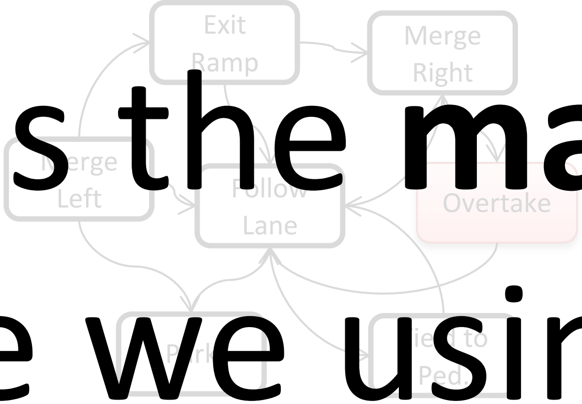
Classic Hierarchical Approach

BAIR

Decompose motion planning and control into stages

Route Planning

Behavior Planning



Path Planning

Local Control

Where is the **machine learning**?

How are we using **data**?

Sequence of roads and intersections

Target State Configurations

Detailed Path to Follow

Road Networks
Traffic Information
Obstacles …

1. Model of the world around the car including predicted future states.
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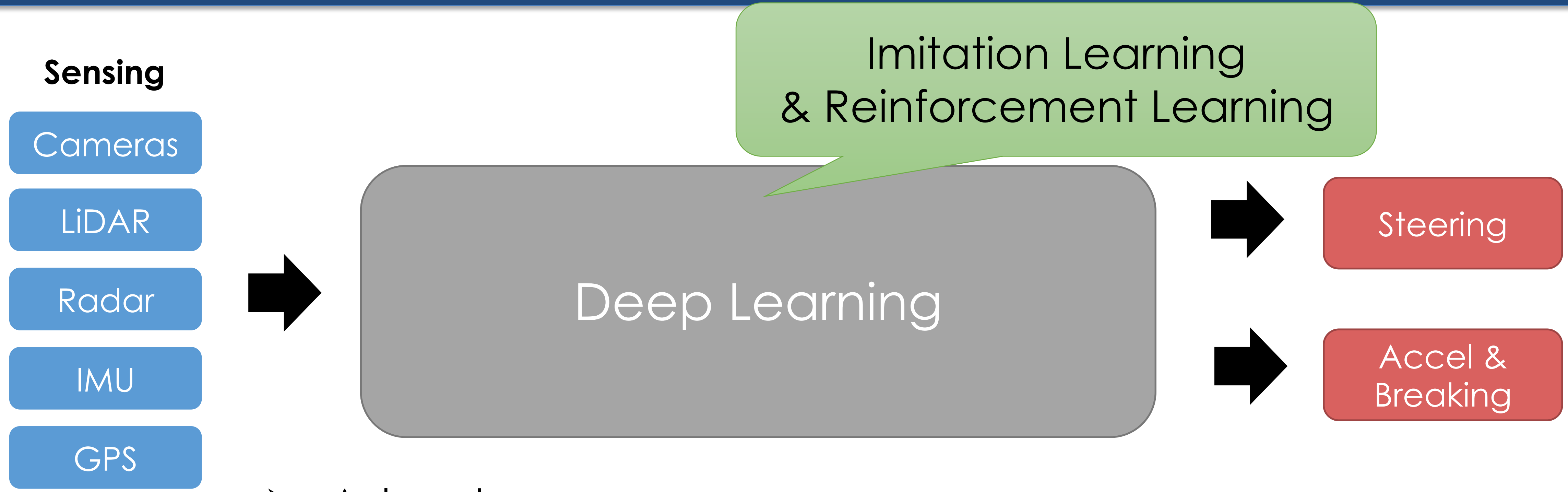
More details can be found here in ["A Survey of Motion Planning and Control Techniques for Self-driving Urban Vehicles"]

End-to-End Control (Behavior Cloning)



- Advantages:
  - Leverage large quantities of driving data without annotation
  - Address complex scenarios without hand coded heuristics
- Disadvantages:
  - Requires substantial data in good and bad scenarios
  - Doesn’t leverage domain knowledge

ALVINN 1989

Autonomous Land Vehicle in a Neural Network

Trained in simulation could follow some roads.

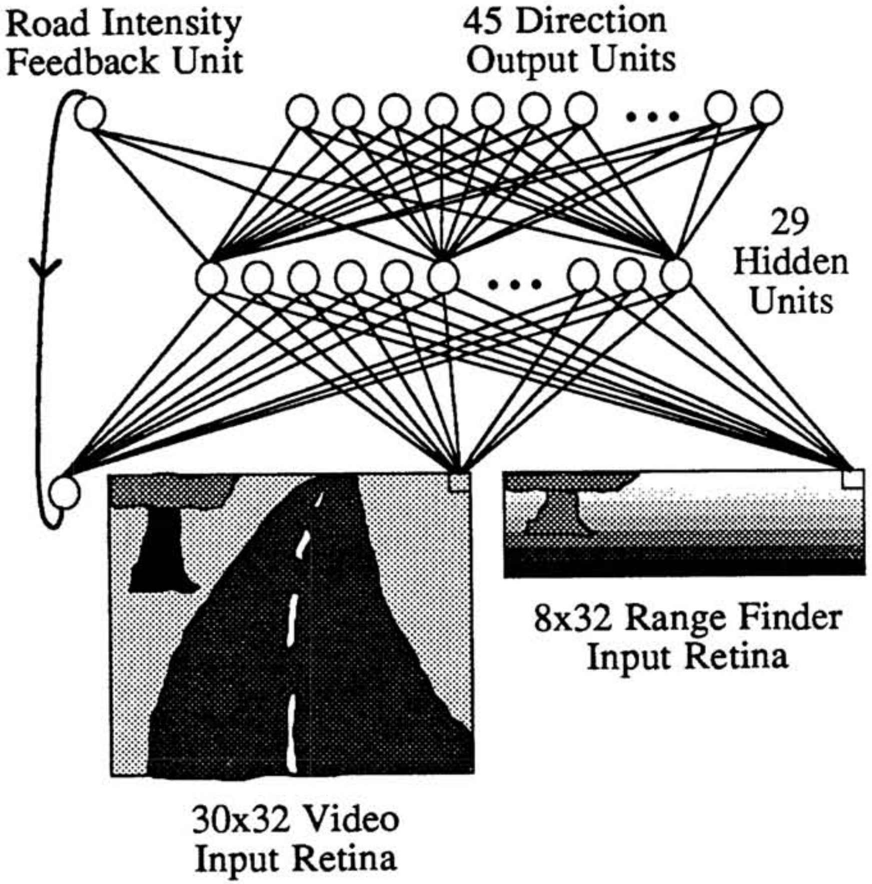
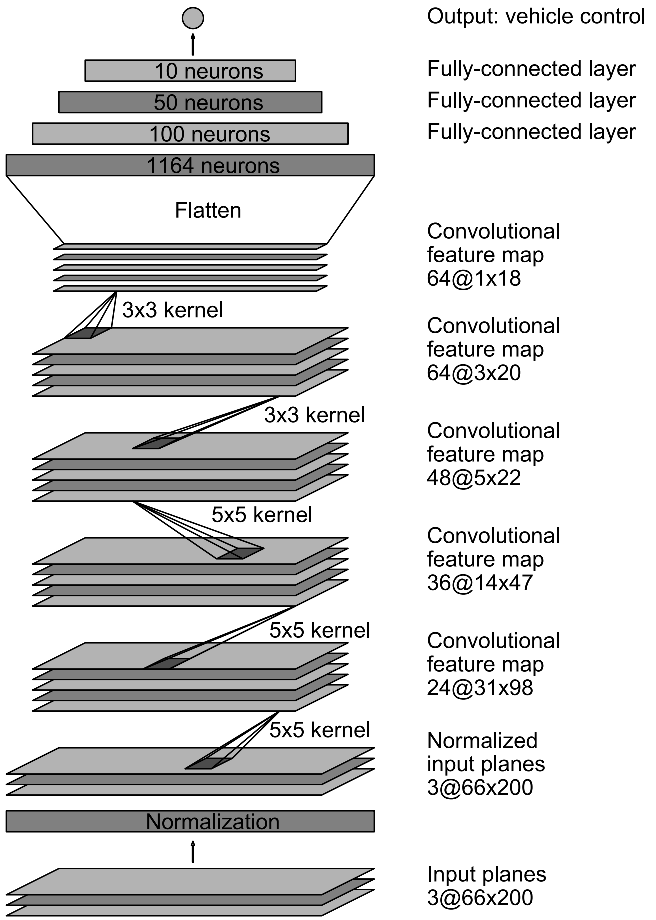


Figure 1: ALVINN Architecture

Nvidia DAVE-2 System (2016)

- Trained a deep neural network to control steering by behavior cloning (supervised loss).



Limitations of End-to-End Approach

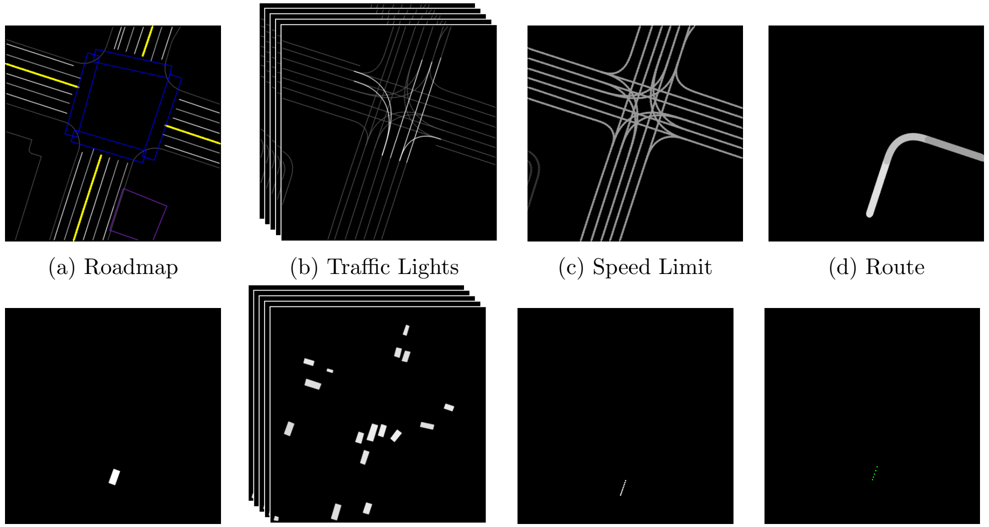
- Doesn't leverage physical models of vehicle control
- Forced to learn and reason about scenes from driving supervision
  - Model must learn the concepts of people, vehicles, obstacles directly from driving behavior demonstrations
- Often doesn't perform well in new situations
  - Earlier examples were focused on the simple task of staying in the lane

Hybrid Approach

- Leverage output of perception as well as the classic planning and control hierarchy and instead learn to output paths as a function of the output of perception.
  - Example: **Waymo ChauffeurNet**

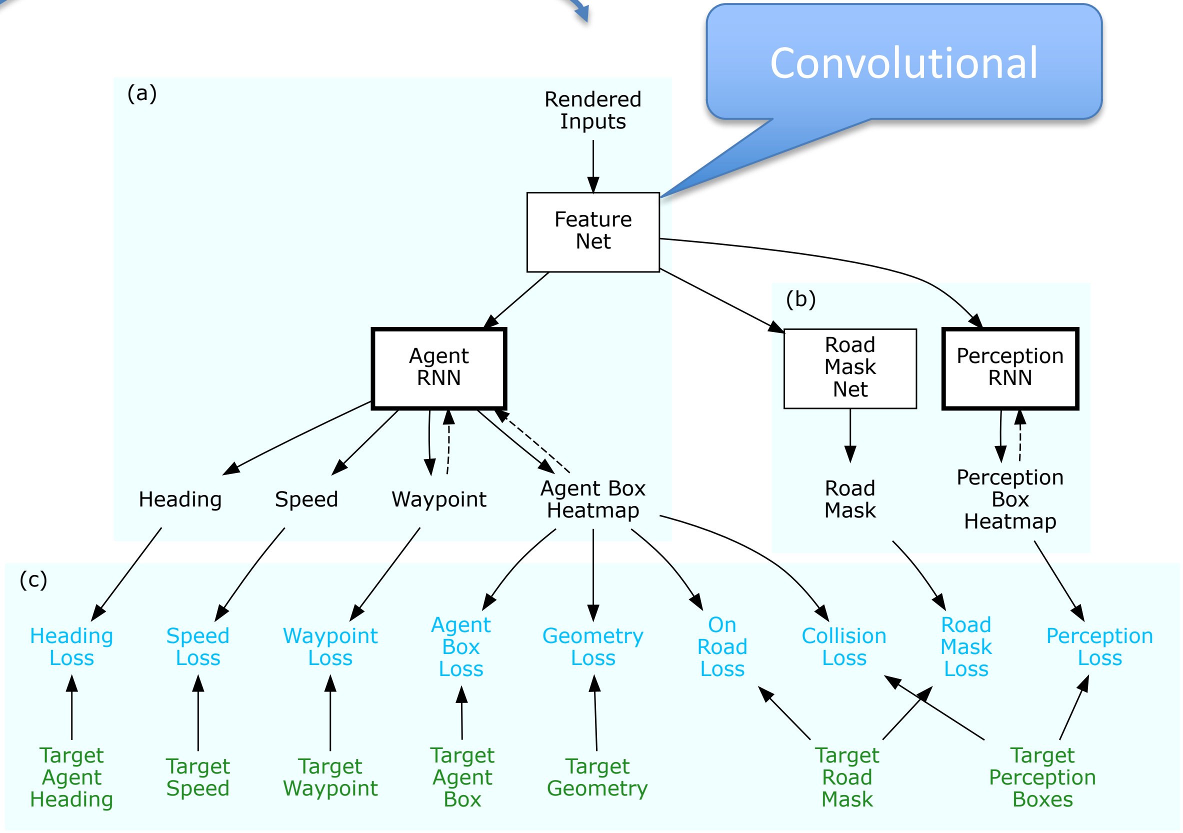
ChauffeurNet

Rasterized Encoding of Current and Predicted States Produced by Perception Pipelines



(a) Roadmap (b) Traffic Lights (c) Speed Limit (d) Route

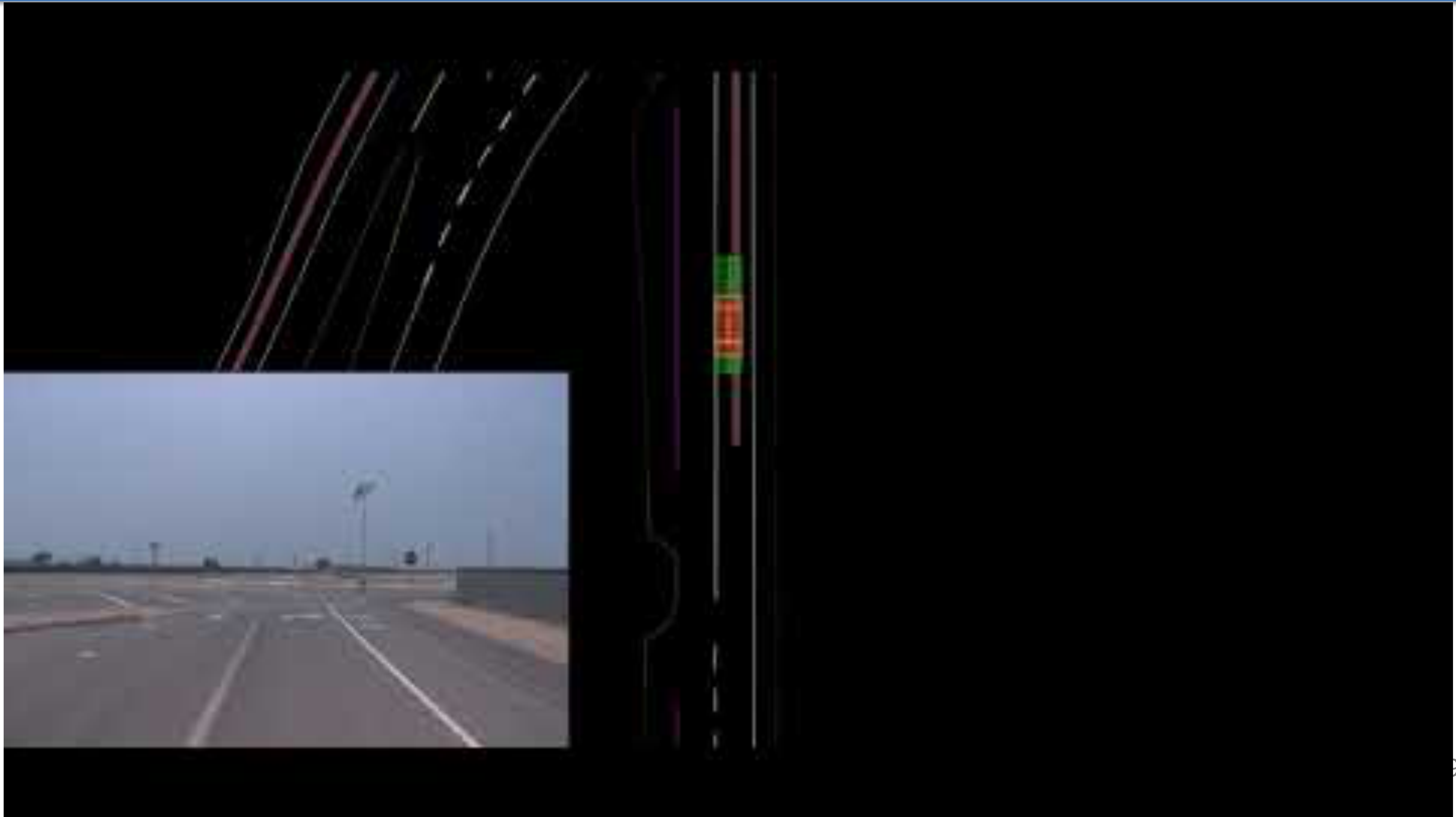
(e) Current Agent Box (f) Dynamic Boxes (g) Past Agent Poses (h) Future Agent Poses



Predict future states of the world

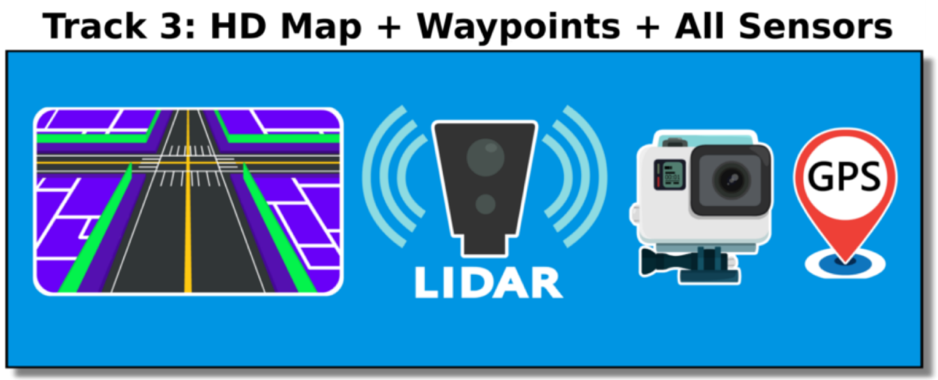
[ChauffeurNet: Learning to Drive by Imitating the Best and Synthesizing the Worst]()

ChauffeurNet Examples



Simulation

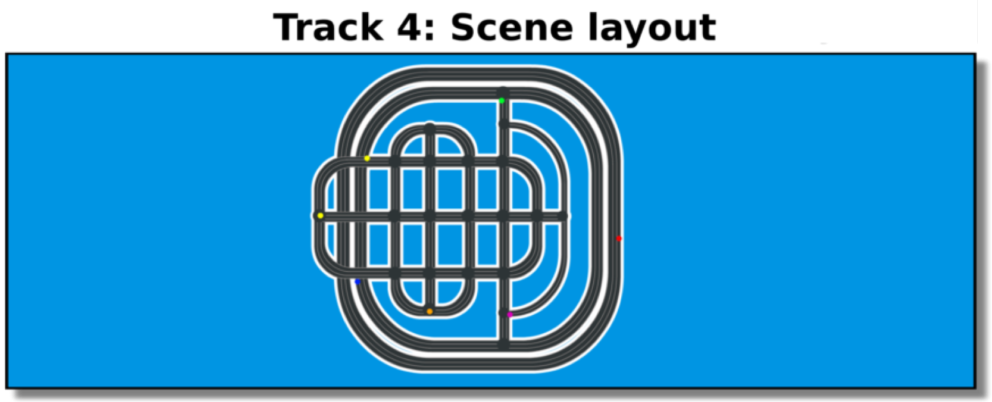
Carla challenge: carlachallenge.org/

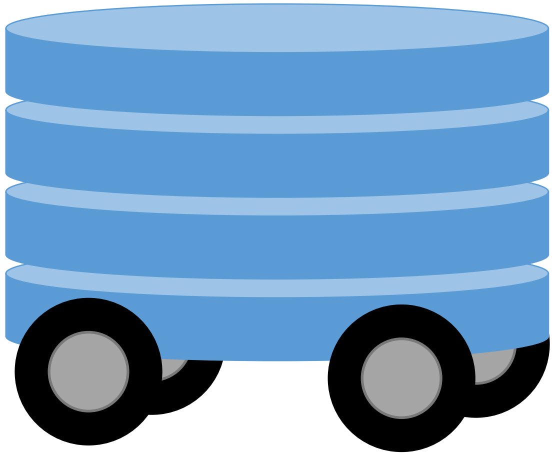


Sensors: Lidar, camera, and fine-grained waypoints (every 3 meters)

Sensors: Lidar, camera, and fine-grained waypoints (every 30 meters)

Sensors: camera, and coarse waypoints (every 30 meters)





An Autonomous Vehicles is a **Streaming Dataflow System** on Wheels

Requirements:

Extensible	Low/Predictable Latency	High Throughput	Fault Tolerant	Secure

To address these needs we have been developing:

ERDOS: Elastic Robot Dataflow Operating System

Reading This Week

Reading for the Week

- Self-Driving Cars: A Survey (arXiv'19)
  - Provides an overview of autonomous driving systems
- The Architectural Implications of Autonomous Driving: Constraints and Acceleration (ASPLOS'18)
  - Discusses the systems requirements for autonomous driving
- ChauffeurNet: Learning to Drive by Imitating the Best and Synthesizing the Worst (arXiv'18)
  - Presents a recent neural network architecture for planning in autonomous driving.

Done!