A Deep Neural Network-Based Autonomous System Emulation Toolkits for Self-Driving Vehicle

Dantong Yu

Chief Scientist, Sunrise Technology,

Associate Professor

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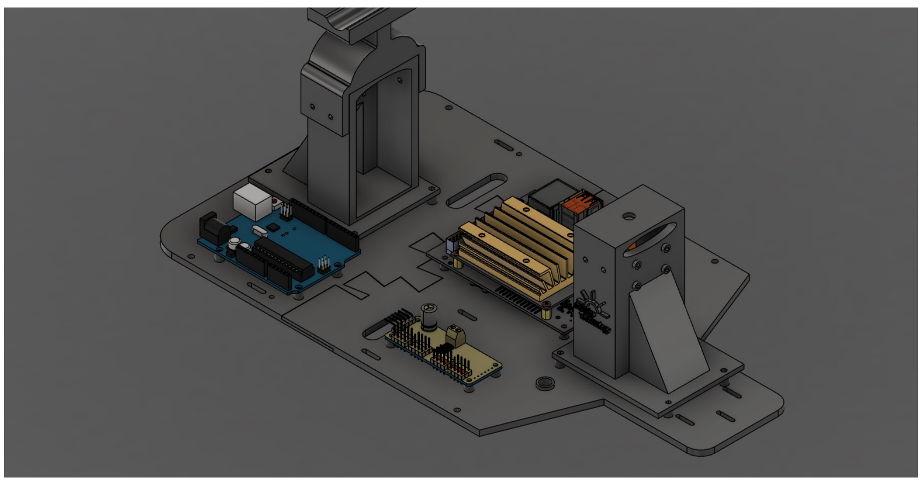
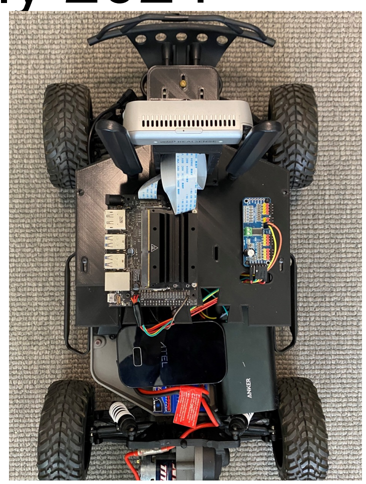
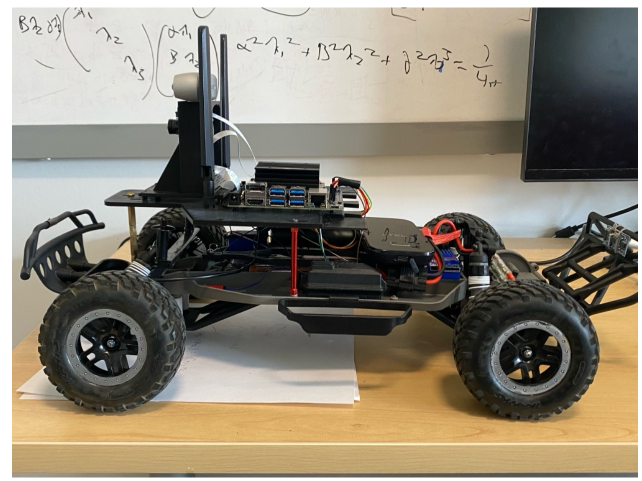
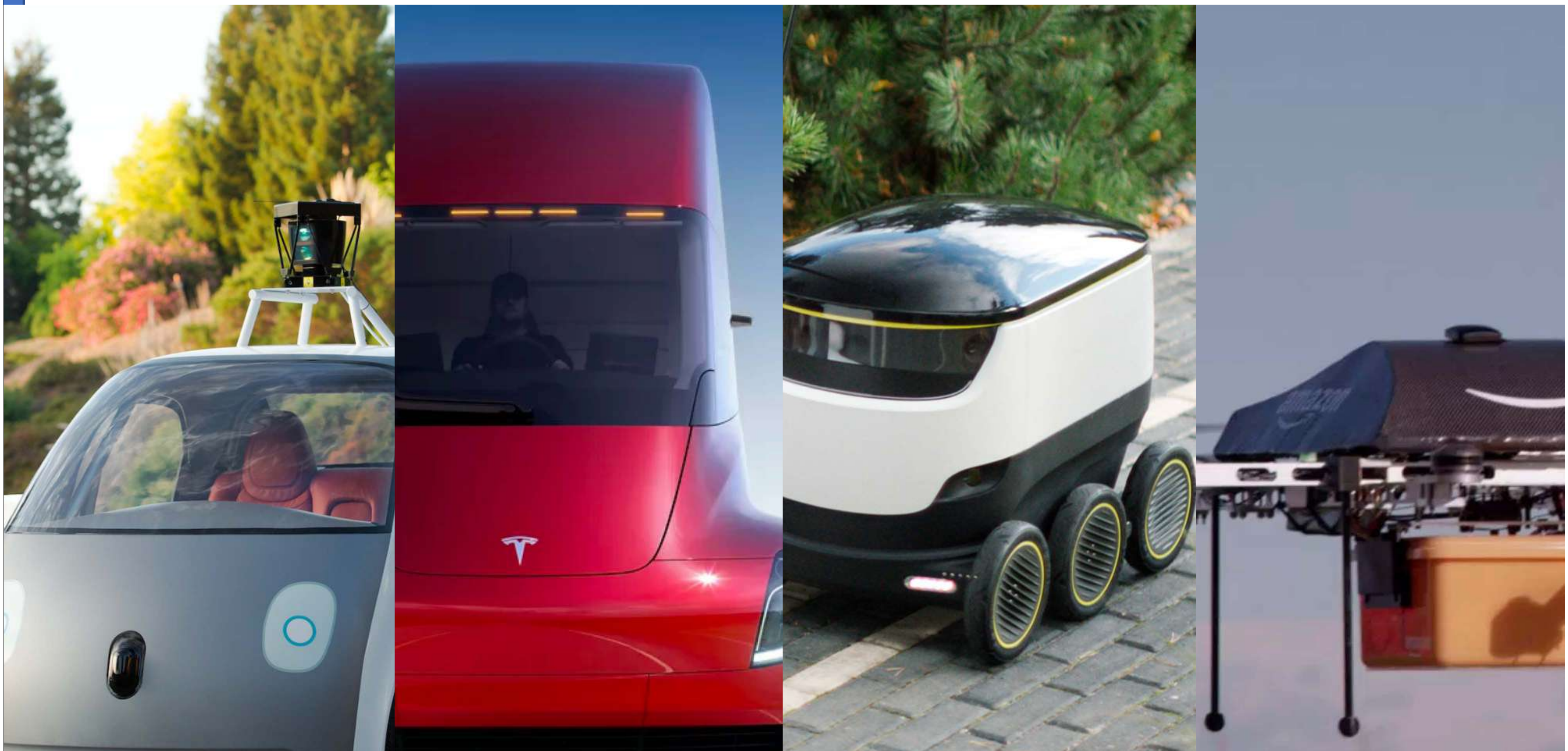








Cars | Trucks | Carts | Drones

Outlines

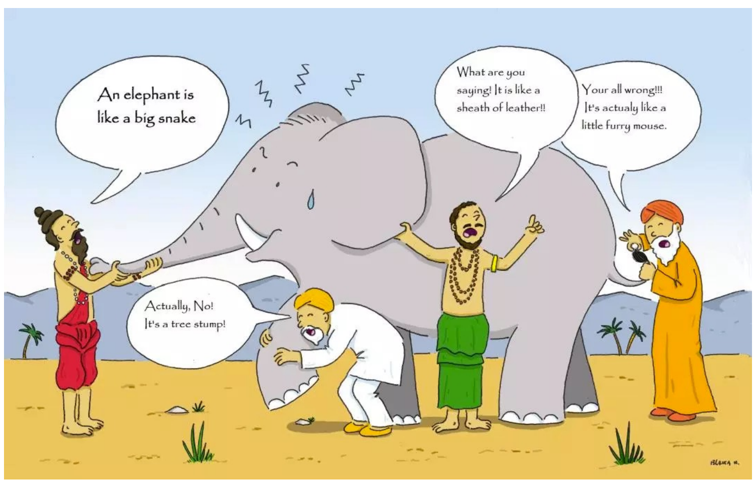
- Self-Driving Introduction and Motivation
- Self-Driving in real vehicles and RC-car
- Self-Driving Perceptron (Brain)
  - Behavior Clone Based Algorithm
- Our Openbot-based Architecture
- Topic 1: Build Reliable Self-driving Systems
- Topic 2: Obstacle Avoidance
- Self-Driving Challenges
- The drawback of Supervised Learning Algorithm
- Look into the Future and Conclusions

What is Self-Driving

❖ What is the Self-Driving?

❖ An autonomous vehicle or driverless vehicle can operate itself and perform necessary functions based on road conditions without any human intervention through ability to sense its surroundings.

erception of What Drivers Do
mi-Autonomous Vehicles



Public Perception of What Drivers Do

➔

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

➔ AI ➔ Deep Learning

SOCIETY OF AUTOMOTIVE ENGINEERS (SAE) AUTOMATION LEVELS

Full Automation

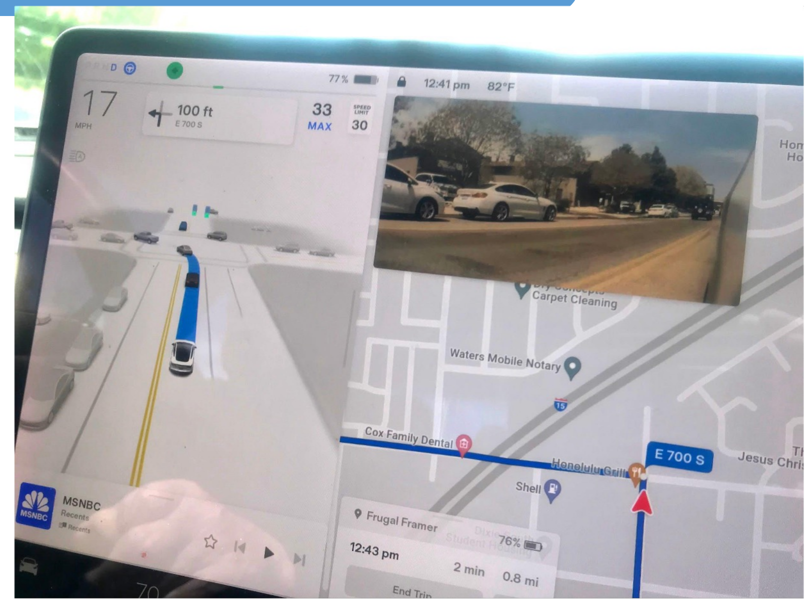
0	1	2	3	4	5
No Automation	**Driver Assistance**	**Partial Automation**	**Conditional Automation**	**High Automation**	**Full Automation**
Zero autonomy; the driver performs all driving tasks.	Vehicle is controlled by the driver, but some driving assist features may be included in the vehicle design.	Vehicle has combined automated functions, like acceleration and steering, but the driver must remain engaged with the driving task and monitor the environment at all times.	Driver is a necessity, but is not required to monitor the environment. The driver must be ready to take control of the vehicle at all times with notice.	The vehicle is capable of performing all driving functions under certain conditions. The driver may have the option to control the vehicle.	The vehicle is capable of performing all driving functions under all conditions. The driver may have the option to control the vehicle.

Some Facts

- 1.35 million deaths worldwide due to vehicle crashes
- 94% of crashes involve human choice or errors.
- Three million Americans age 40 and older are not able to drive due to their vision/blindness
- 79% of seniors age 65 and older living in car-dependent communities
- 42 hours in traffic jams each year per person

Machine Learning-based Self-Driving is a promising future of the workforce

- Autonomous Vehicle will Revolutionize our economy.
- The benefits of autonomous vehicles (AV) extend beyond safety – they could also greatly impact the labor market.
- AVs will create 300K US jobs in development, testing, maintenance, and deployment, as well as a need for technicians and mechanics with expertise in automation.
- https://ts2.space/en/the-impact-of-autonomous-vehicles-on-employment-and-job-market/



Economy Fraction of Autonomous Driving

- ❖ How big the industry will be (Look at the celebrity company Tesla)
- ❖ It is one of the most exciting/critical applications of AI/Machine learning
- ❖ Solving it will bring changes to society, climate change, less dependence on fossil fuel, and bringing the sharing economy to a new level.

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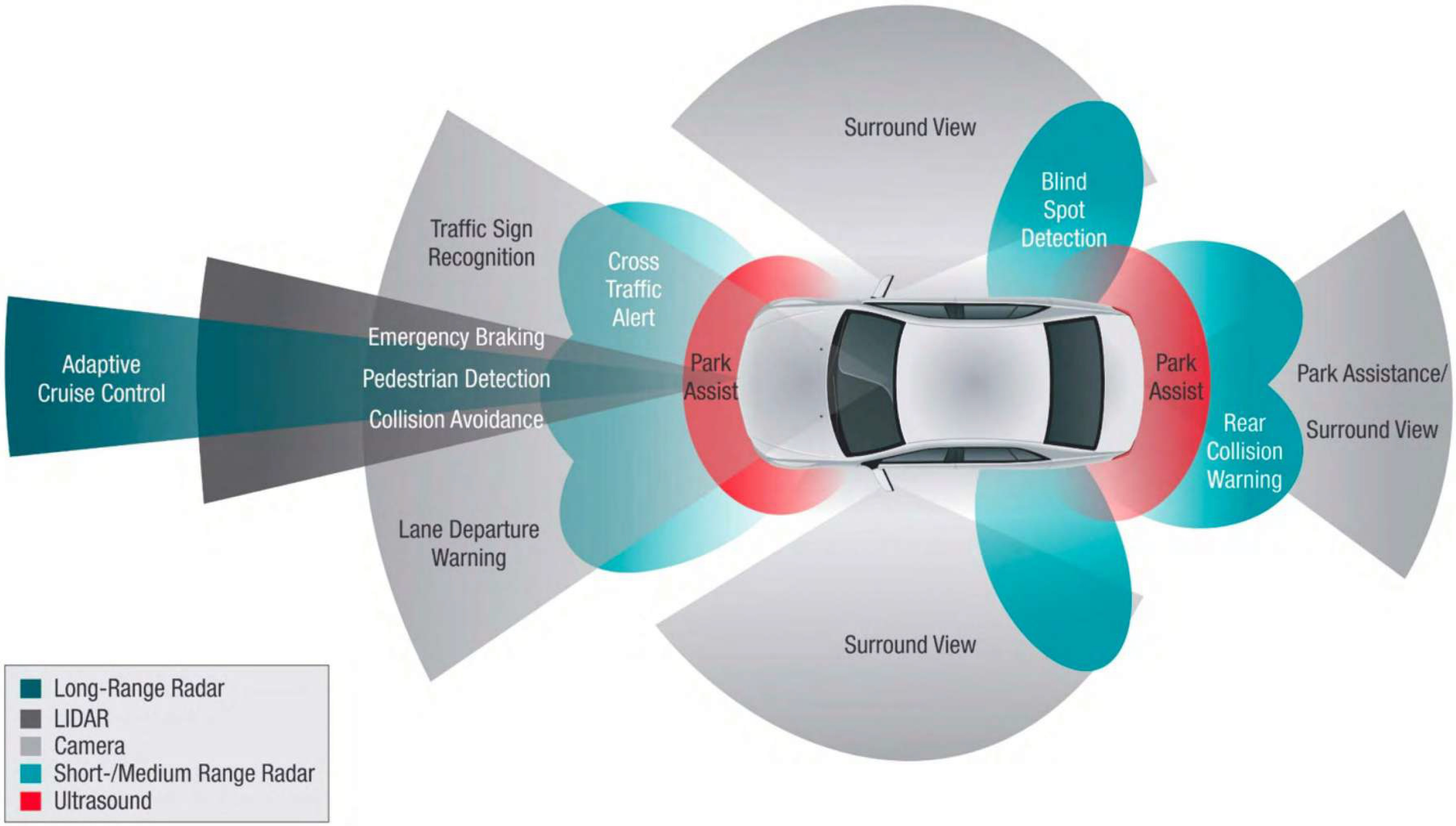
Tesla



Surround View
Blind Spot Detection
Traffic Sign Recognition
Cross Traffic Alert
Adaptive Cruise Control
Emergency Braking
Pedestrian Detection
Collision Avoidance
Park Assist
Park Assist
Park Assistance/
Surround View
Rear Collision Warning
Lane Departure Warning
Surround View
Long-Range Radar
LIDAR
Camera
Short-/Medium Range Radar
Ultrasound

Similar Dynamics, different scales

Traxxas 2WD Chassis

F1/10 Used in College Self-Driving Course ($5000)

We designed Two Systems for the Same Goal.

- We use two different hardware systems to implement autonomous driving.
- Enables flexibility in design and lowers the learning barriers

Jetson

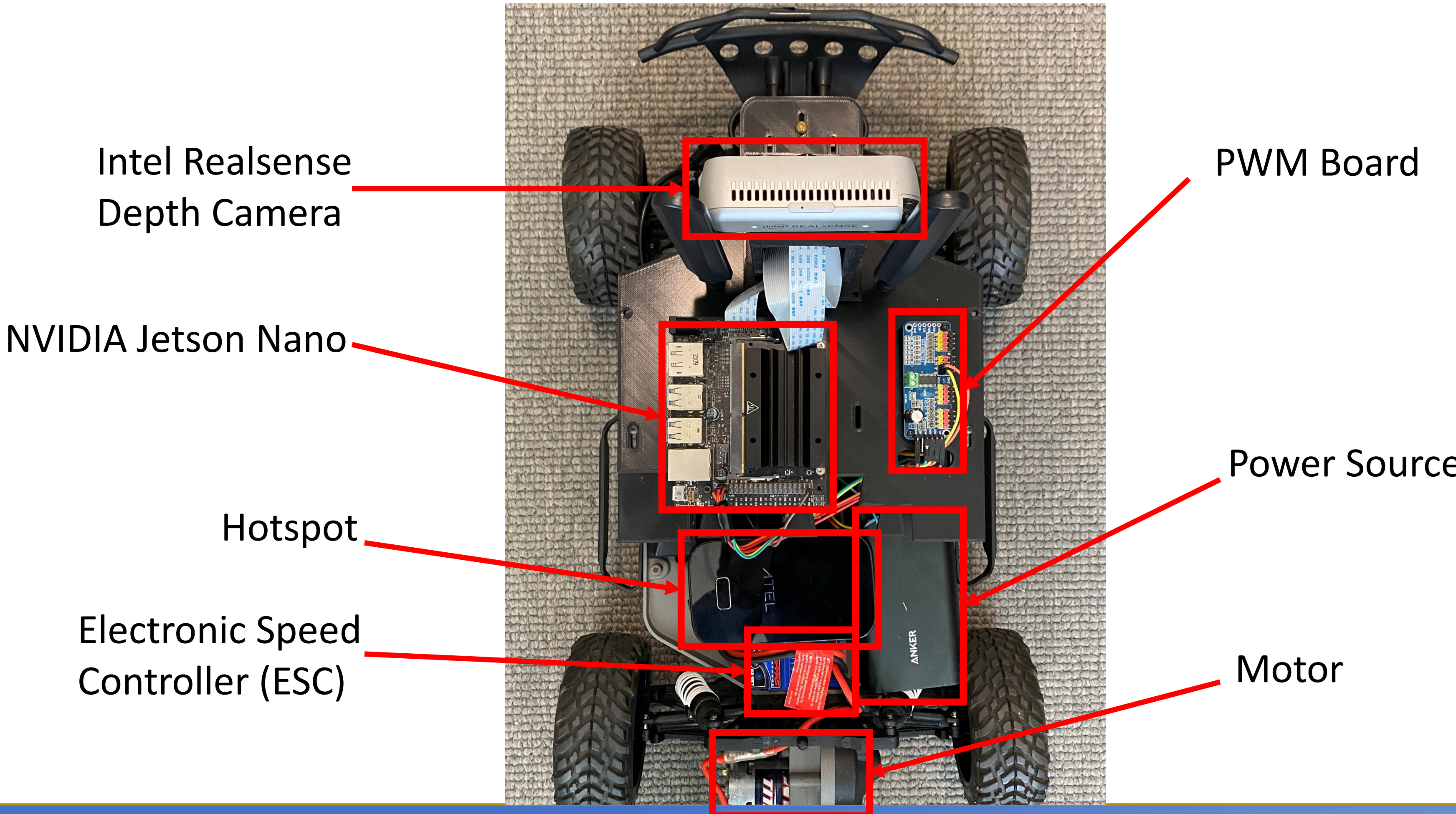
- Powerful embedded GPU
- ROS support for messaging
- Depth Camera

Android

- Application based, very cheap
- Google TPU
- High camera resolution

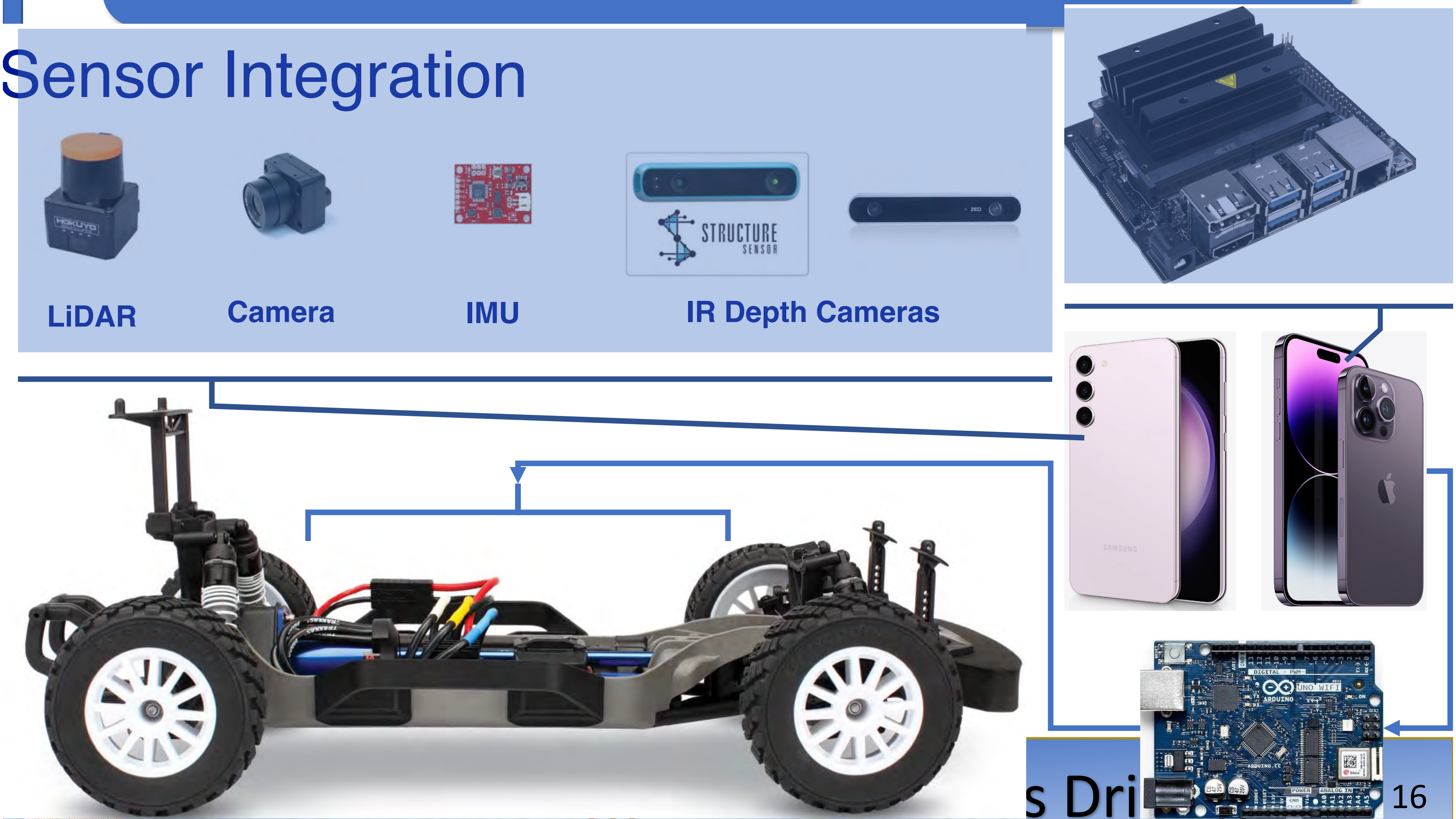
iPhone ➔ Support LiDAR and 3-D scanning (Work-in-progress).

Jetson Hardware (Research)

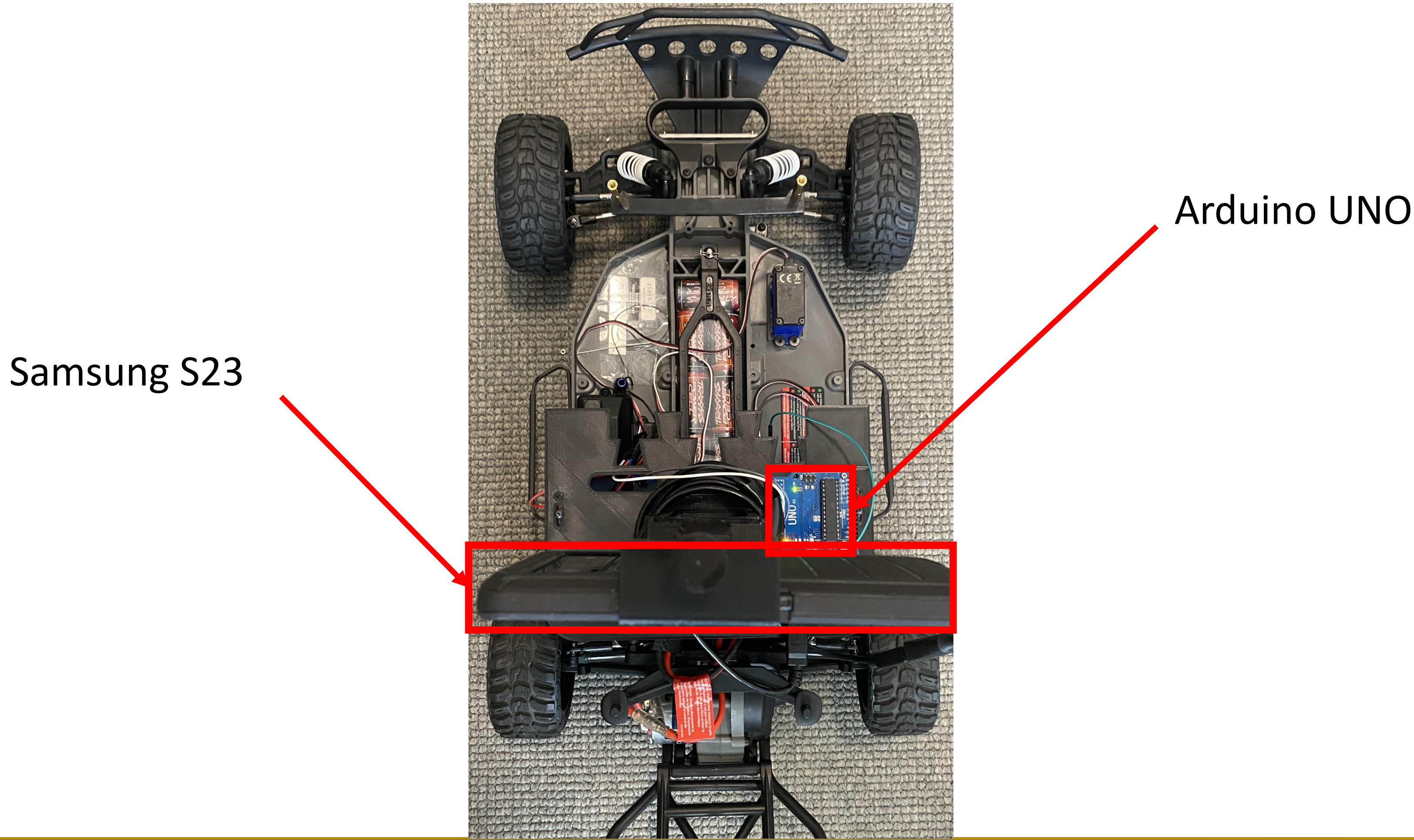


Openbot Based Self-Driving Car

Sensor Integration



Open Bot Hardware $500



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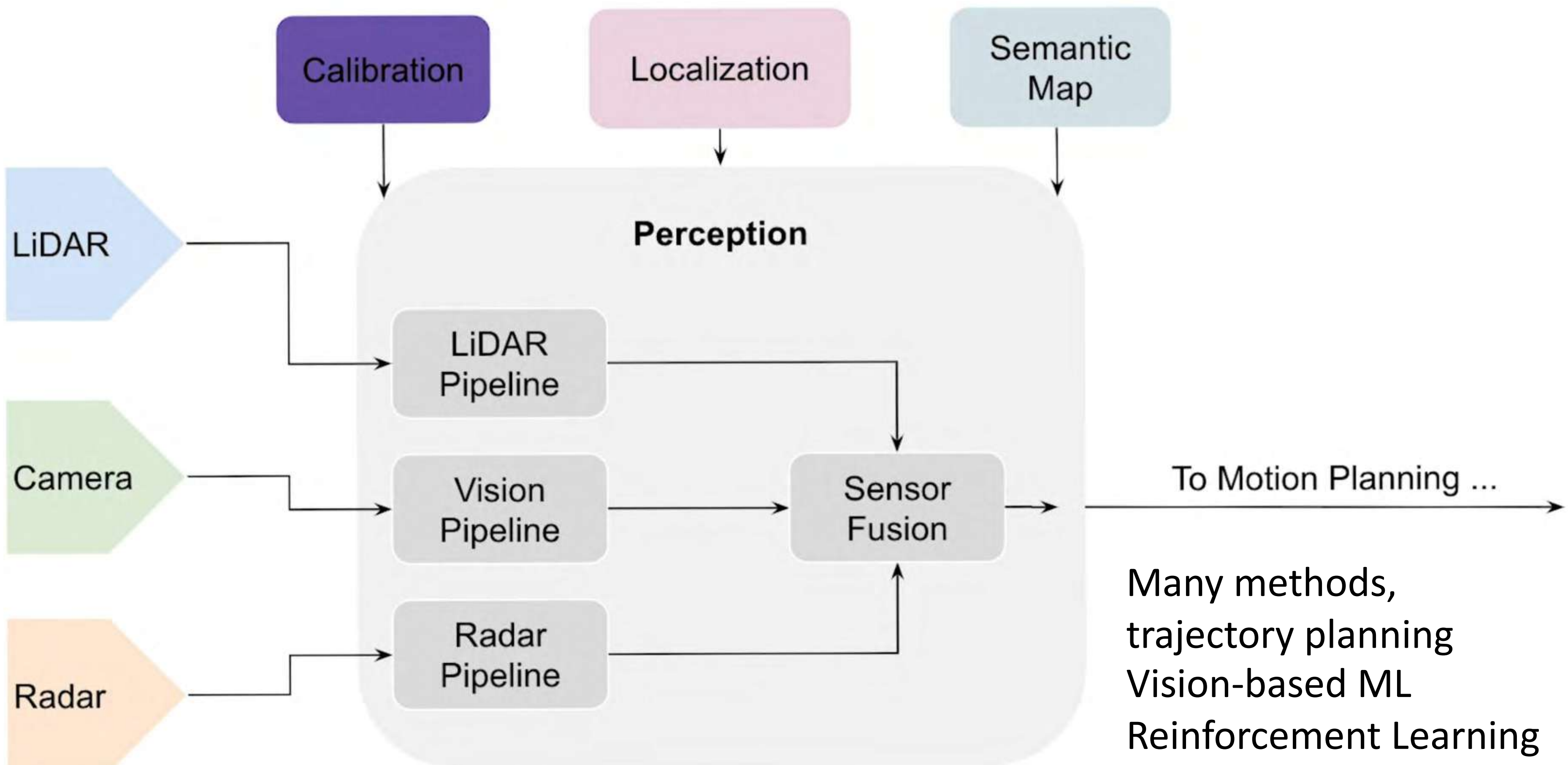
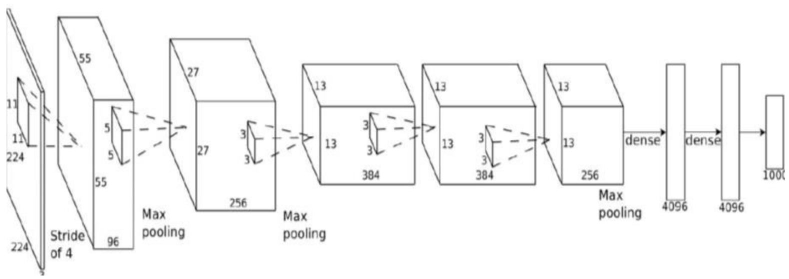
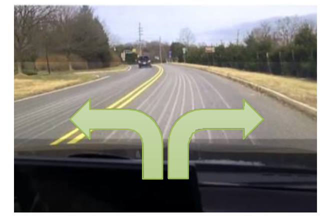
Perceptions in AV Stack



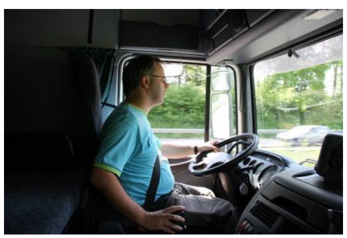
Many methods,
trajectory planning
Vision-based ML
Reinforcement Learning

Imitation Learning





$\mathbf{o}_t$ $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ $\mathbf{a}_t$



Images: Bojarski et al. '16, NVIDIA

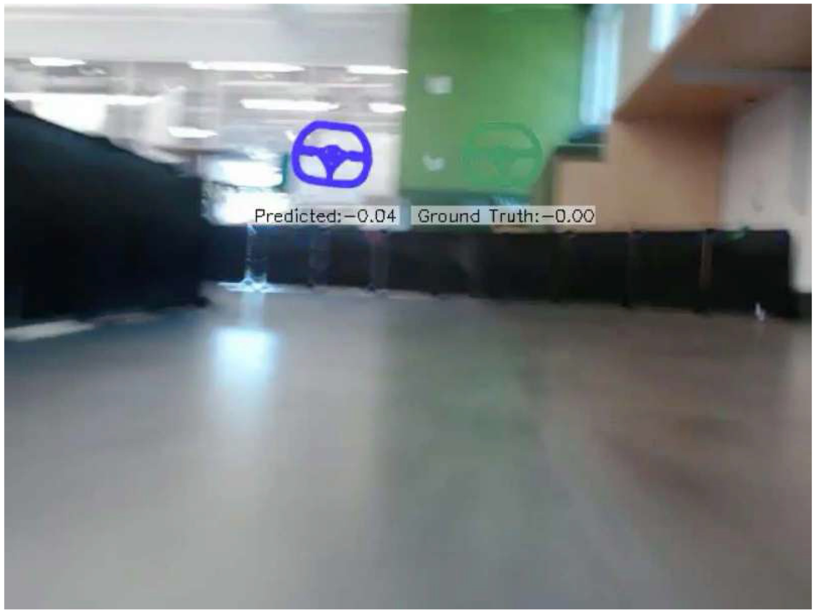
$\mathbf{o}_t$
$\mathbf{a}_t$ → training data → supervised learning → $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$

End-to-End Driving

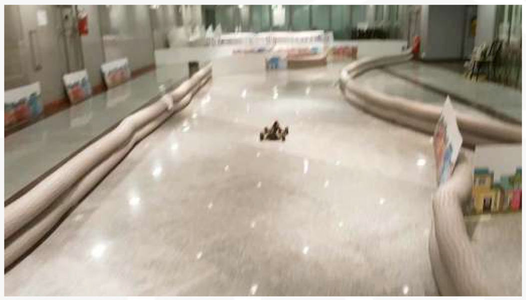
Problem:

End-to-End driving with imitation learning and Behavior Clones.

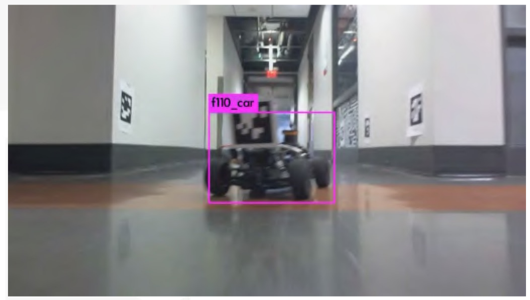
1. Train a network to map pixels to steering angle
2. Pixels to trajectory and throttles



Examples

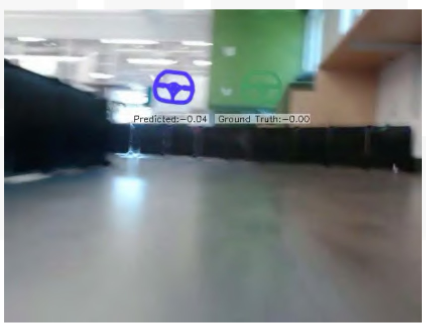


Wall Following

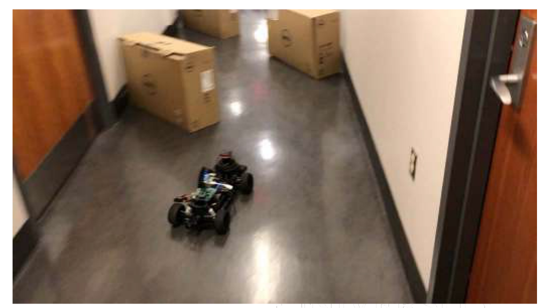


Object Detection and Tracking

Follow the track

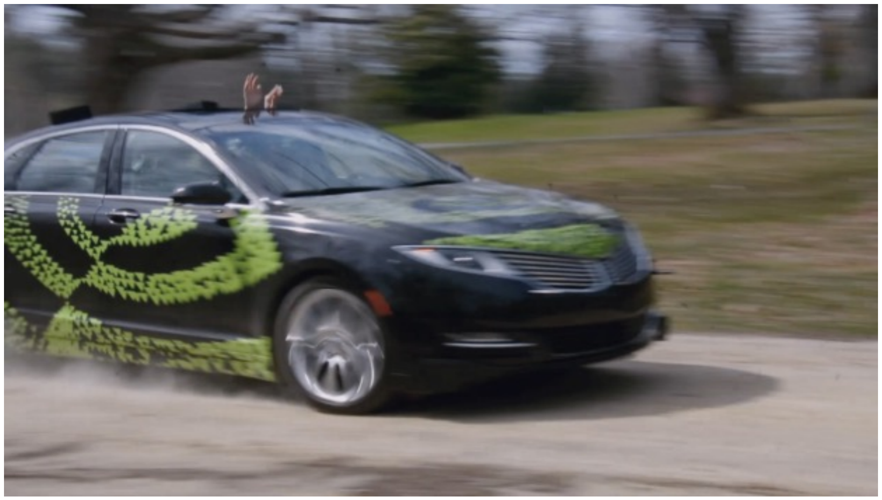


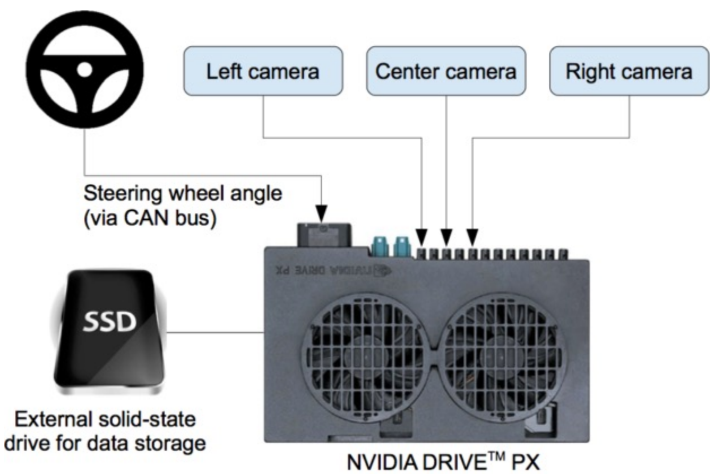
Your Project

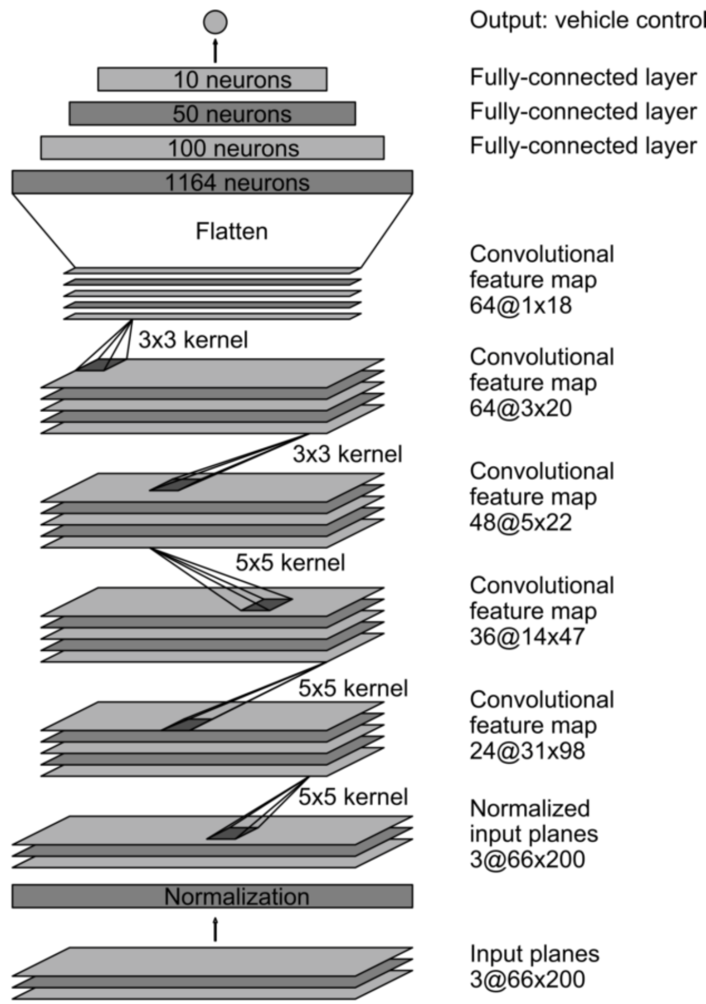


Obstacle Avoidance

Behavior Cloning with Nvidia PilotNet



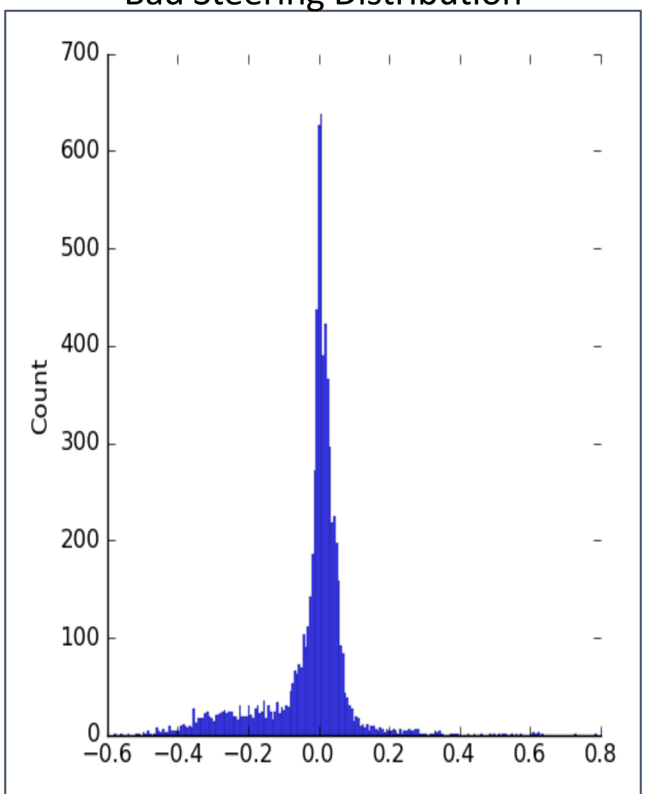




Behavior Cloning : Bias

Understanding how the system collects data is only one part; good data collection involves being aware of bias.

Bad Steering Distribution

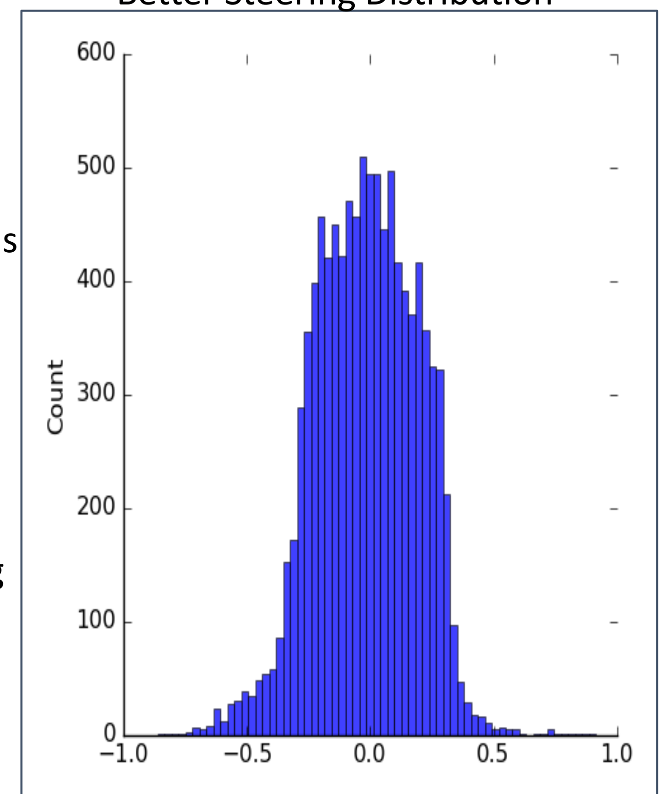


Managing the bias of a dataset is crucial in getting good results.

One way we can do this is by equally representing all events in the dataset, this can mean re-recording data several times.

Considering most driving is done with 0 steering angle, it is good practice to record turns several times

Better Steering Distribution

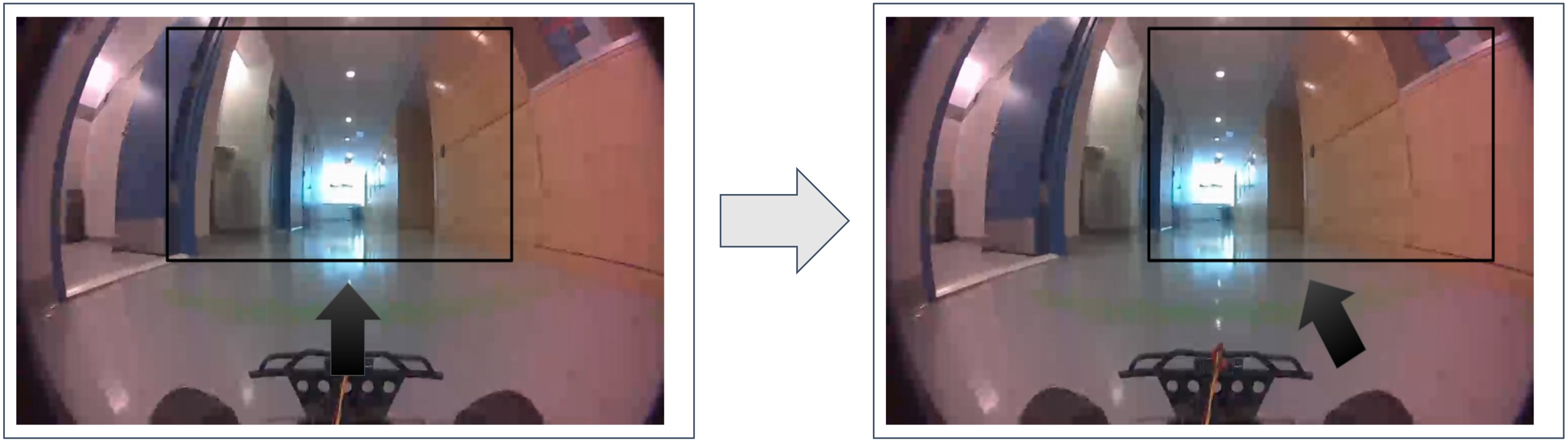


Behavior Cloning : Data Augmentation

- Data augmentation is possibly the most critical part of behavior cloning.
- The bias of the data set can have a drastic effect on the performance of the model. If nothing is done for the bias, the trained model will not perform well, it will reach a situation that it has never seen before and fail.
- This leaves us with two choices, either collect more and more data on every possible situation or augment the current data to widen the distribution.
- Although clipping the image from 1280x720 -> 160x90 does help in terms of speed of computations, it also allows ourselves more room to generate data.

Behavior Cloning : Data Augmentation

An example is shown below, the black box is the clipped image to be input to the model and the arrow is the adjusted steering angle.



Steering angle of 0.0

Steering angle of -0.5

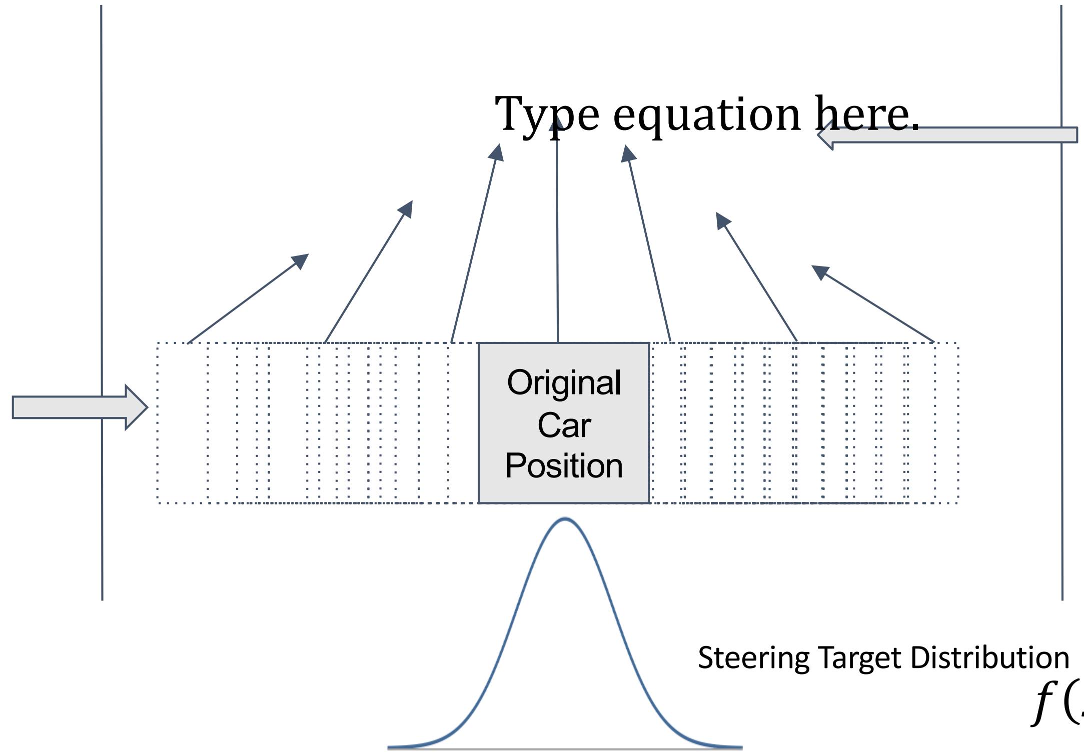
Behavior Cloning : Data Augmentation

The first step in data augmentation that we take is to clip the image from 1280x720 to 160x90. Then by shifting the clipping to the left or right and adjusting the steering accordingly, we can teach the model how to respond without ever collecting that specific data point.

Using a normal distribution, we generate steering angles. By taking the difference between the current steering associated with the image and the sampled steering, we can shift the image by that amount to create a new data point.

Behavior Cloning : Data Augmentation

In this way we can simulate the left/right orientations of the car at every data point.



$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

Behavior Cloning : Training

Training the neural network is fairly straightforward; we randomly sample from the dataset, augment the data, then input it into the model.

Sample from Dataset → Augment → Model Forward Propogation → Compute Loss → Adjust Weights

The model produces steering and throttle predictions that we can test against the actual steering and throttle we recorded (or generated).

Using this, we compute the loss, and through backpropagation, we adjust the weights.

Behavior Cloning : Loss

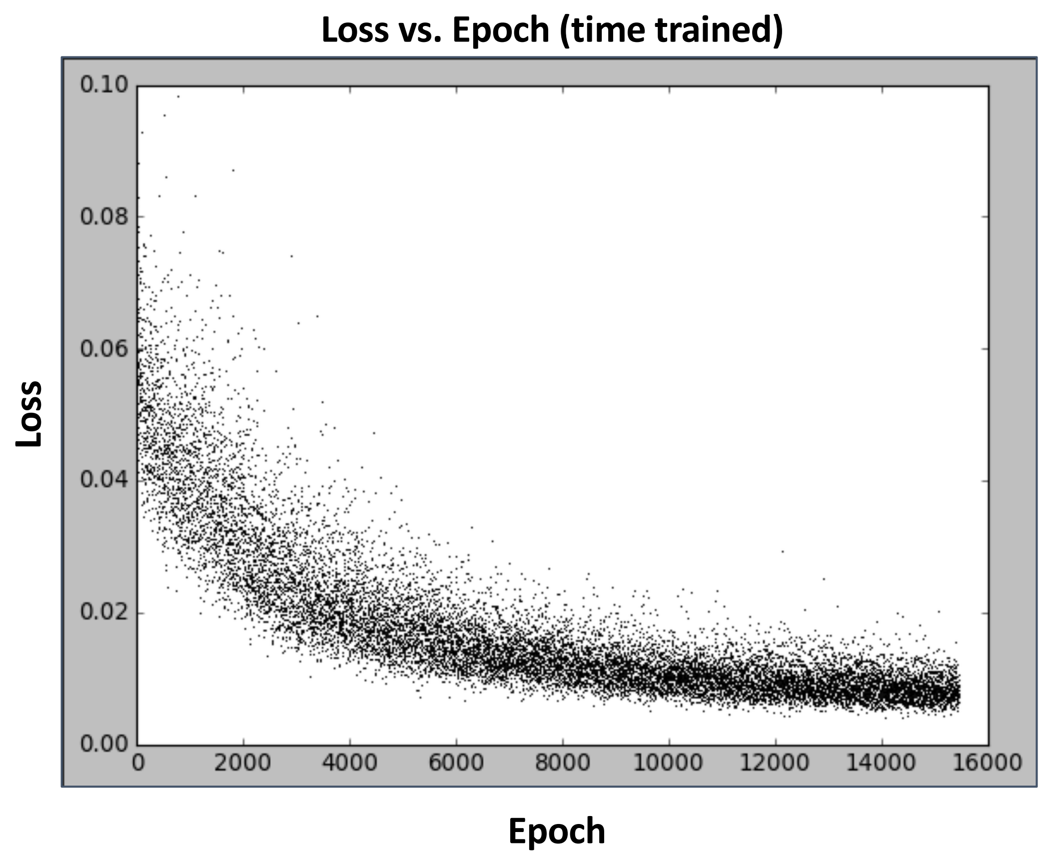
Loss is a metric by which we can test the validity of the model, there are many many functions that can be used. For our purposes we use MSE Loss (Mean Squared Error):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

This function simply takes the error at each point:

y_actual - y_predicted

Then squares and averages over all of them. This penalizes the model more for larger errors than for smaller ones. The graph shown is the loss as the model trains. As the loss tends towards 0 the model gets better and better at the task:



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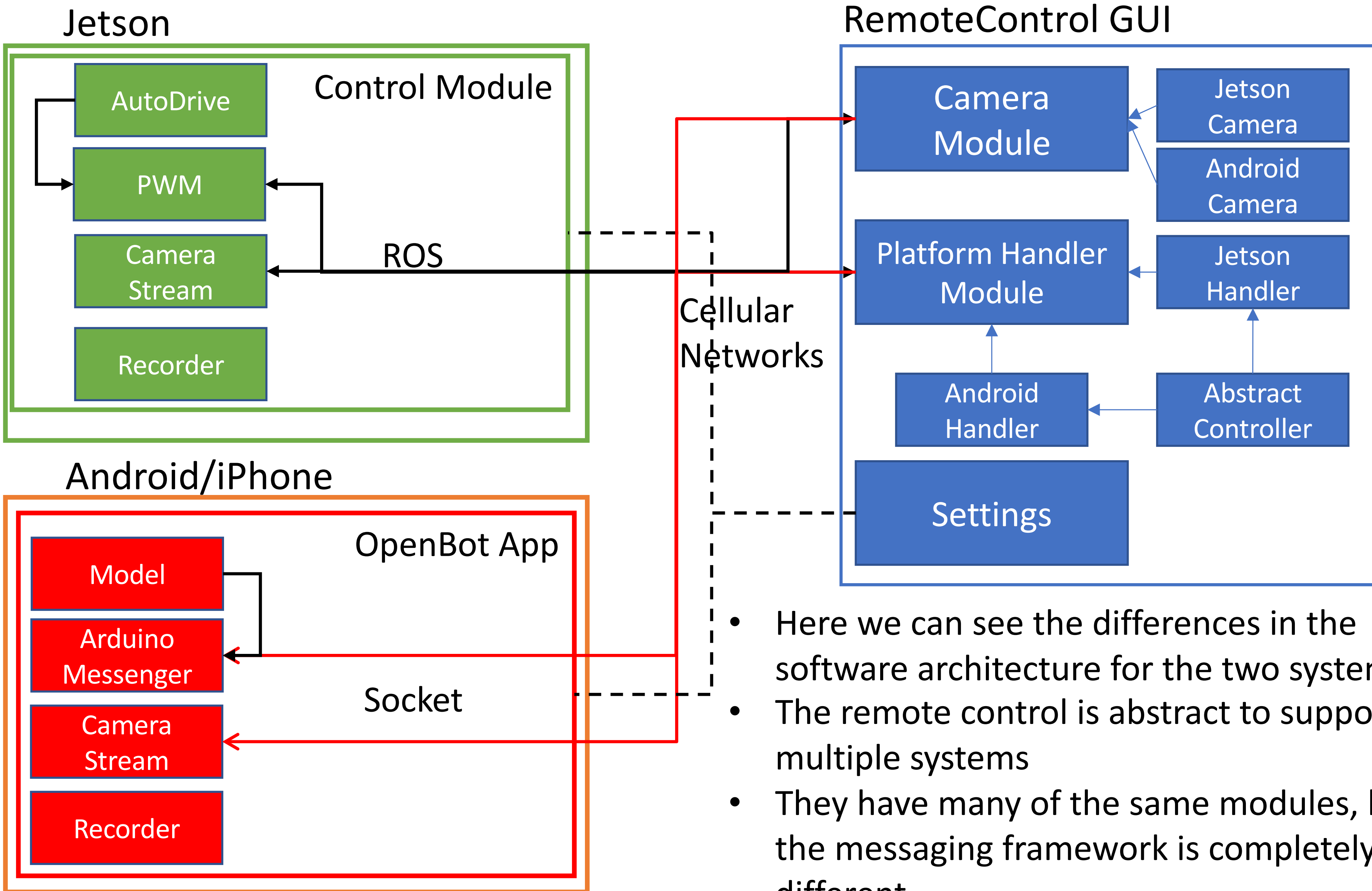
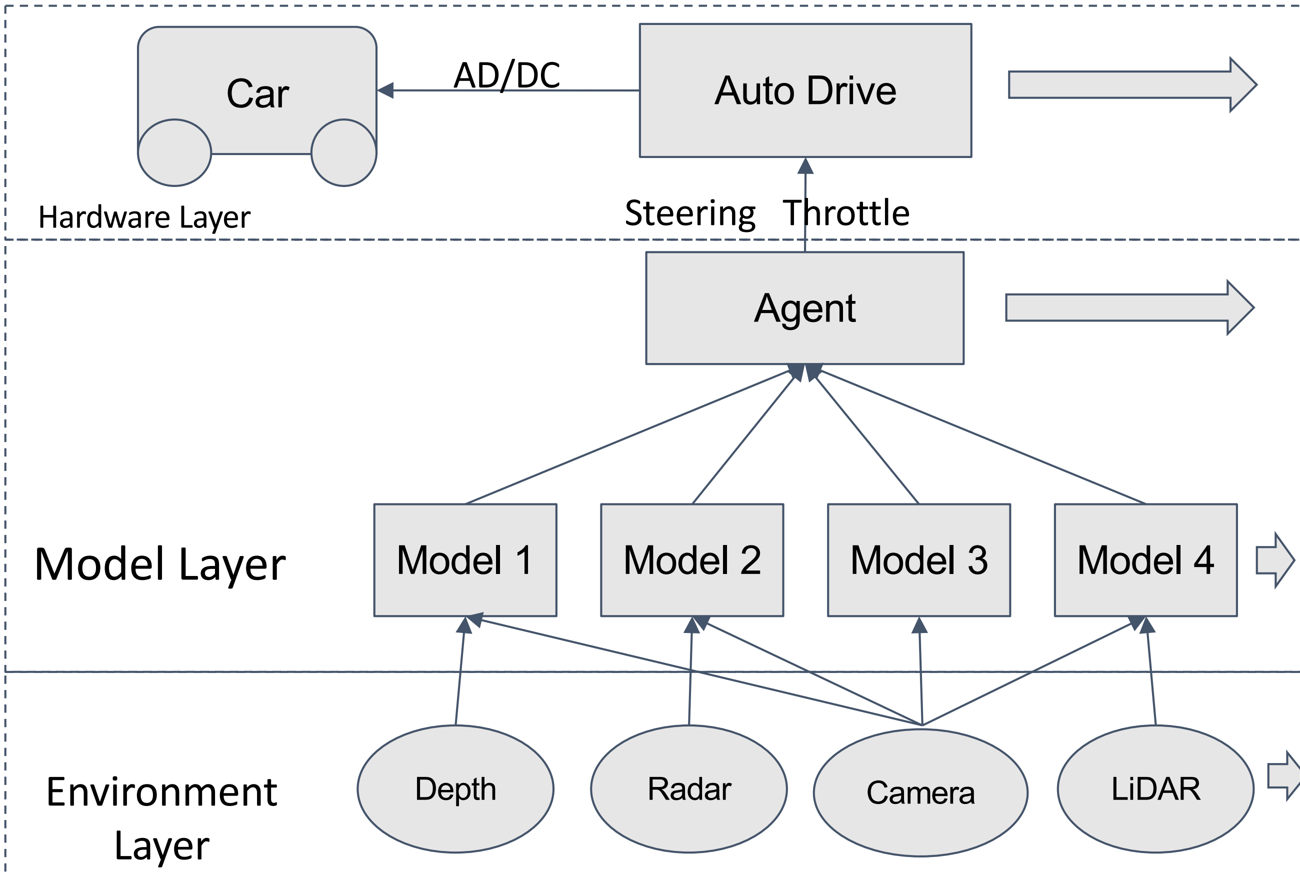
Demo of Openbot self-driving framework



- Here we can see the differences in the software architecture for the two systems.
- The remote control is abstract to support multiple systems
- They have many of the same modules, but the messaging framework is completely different.

Self-Driving Software Framework



Auto drive converts the steering and throttle controls from the agent into ROS topics to control the car

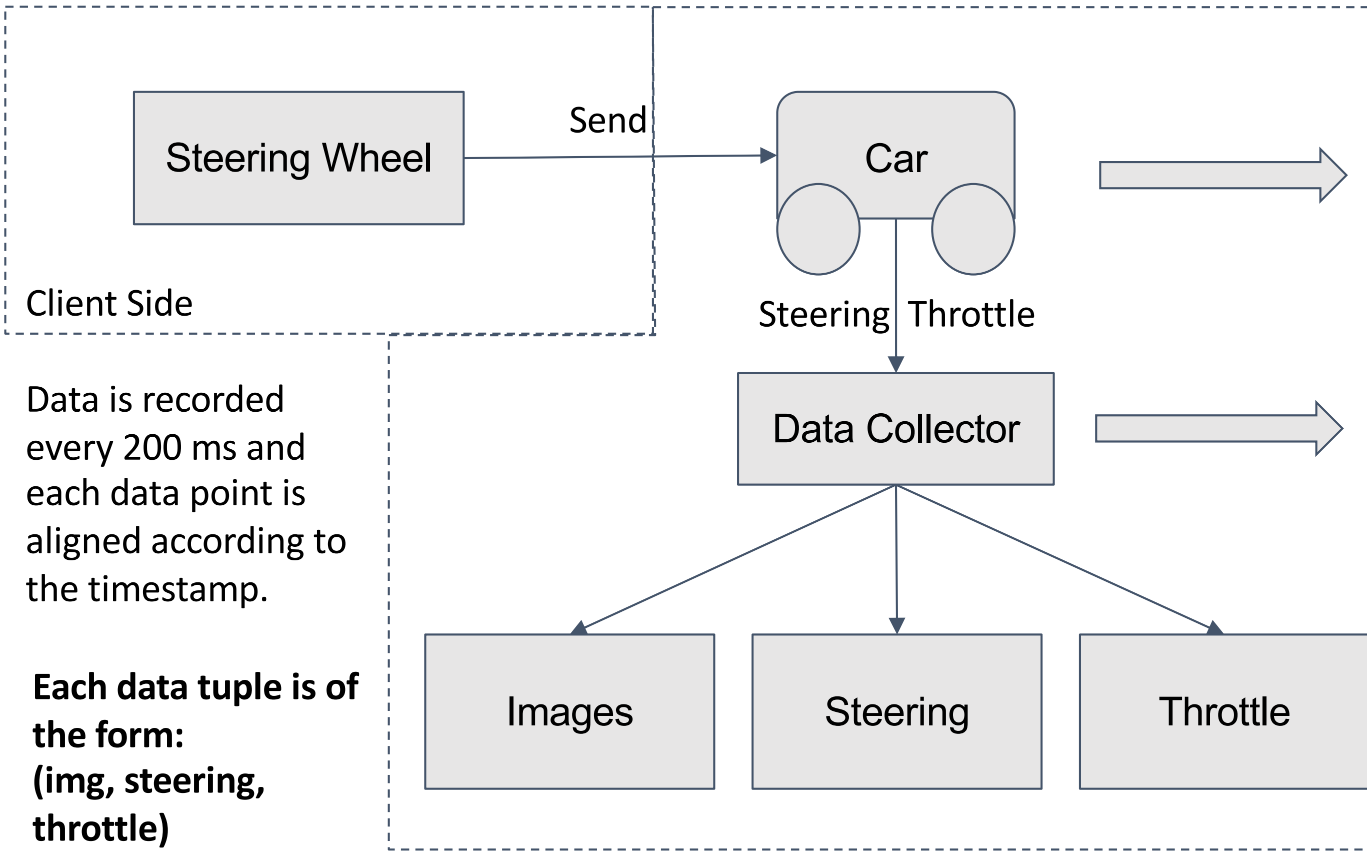
The agent class decides which model's output to use

Each model may be trained to produce a steering and throttle value with different sensor inputs

Sensors are agnostic of how they are used, they just produce data

****Note: For the android system this is roughly the same pipeline, the only difference being the messaging framework (Socket vs. ROS). Also note that the android system does not have access to other sensors beside the camera**

Data Collections in Software Framework



The steering wheel directly controls the car's movements from the client-side

On the car side the data collector stores all relevant information:

- Images
- Steering
- Throttle
- etc.

Data is recorded every 200 ms and each data point is aligned according to the timestamp.

Each data tuple is of the form: (img, steering, throttle)

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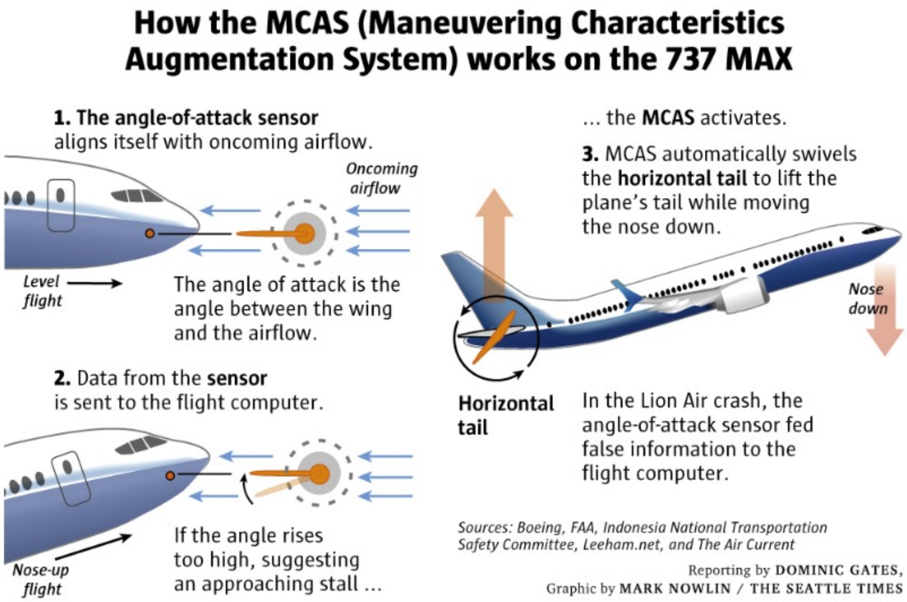
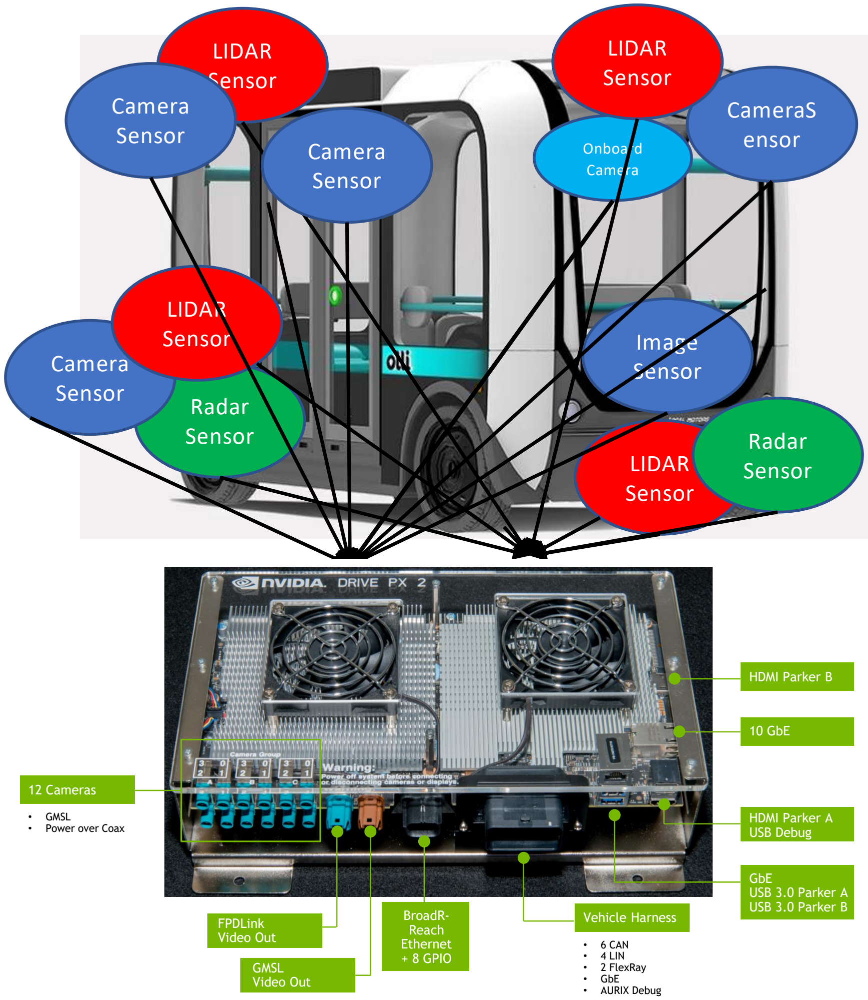
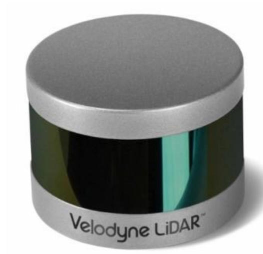
Build Reliable Autonomous Vehicles

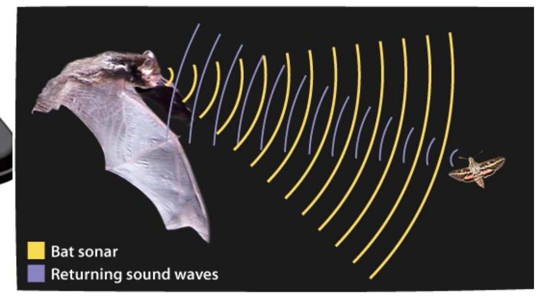


Multi-Data Source Fusion to Improve Reliability

Olli Bus

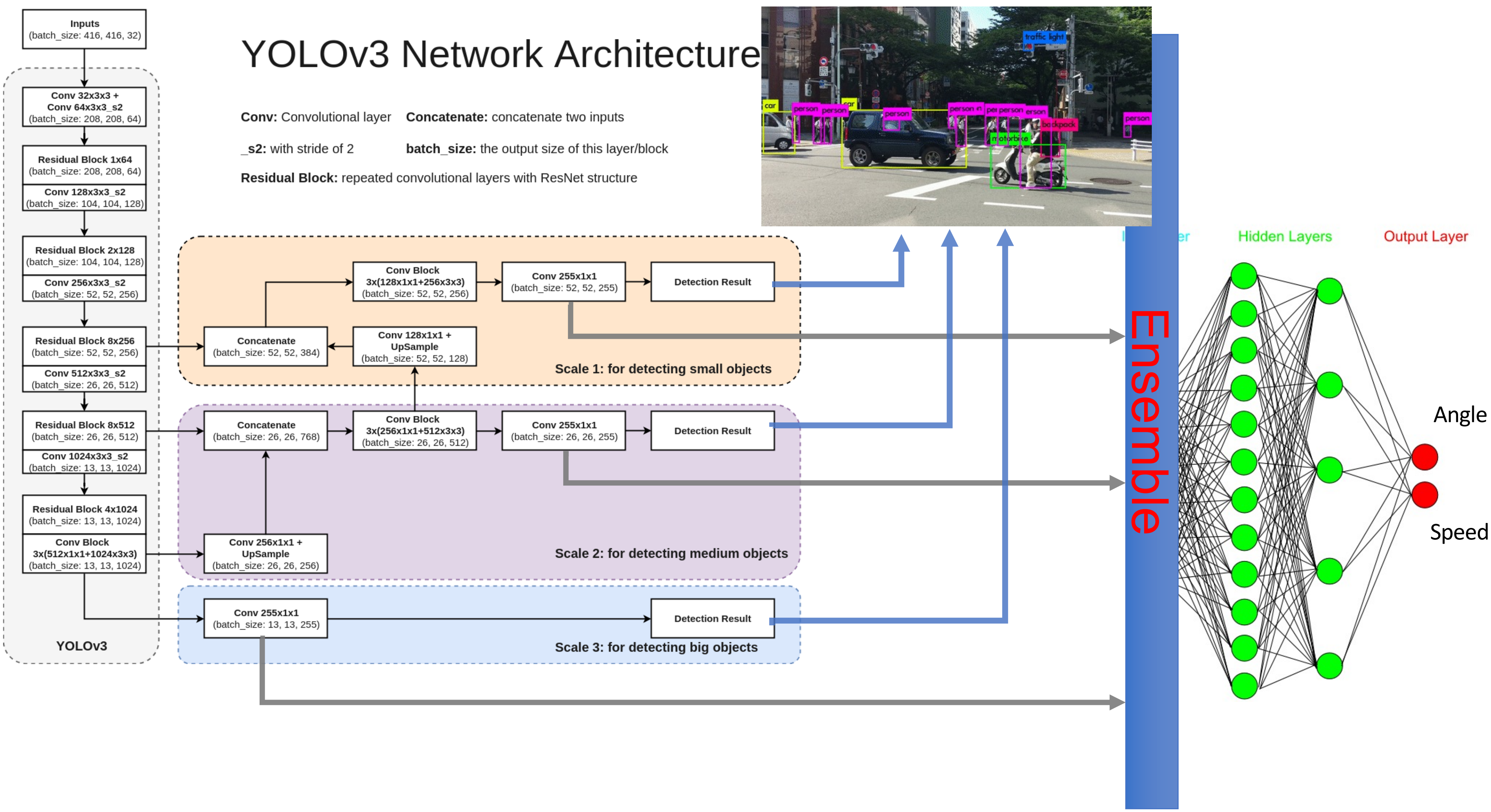




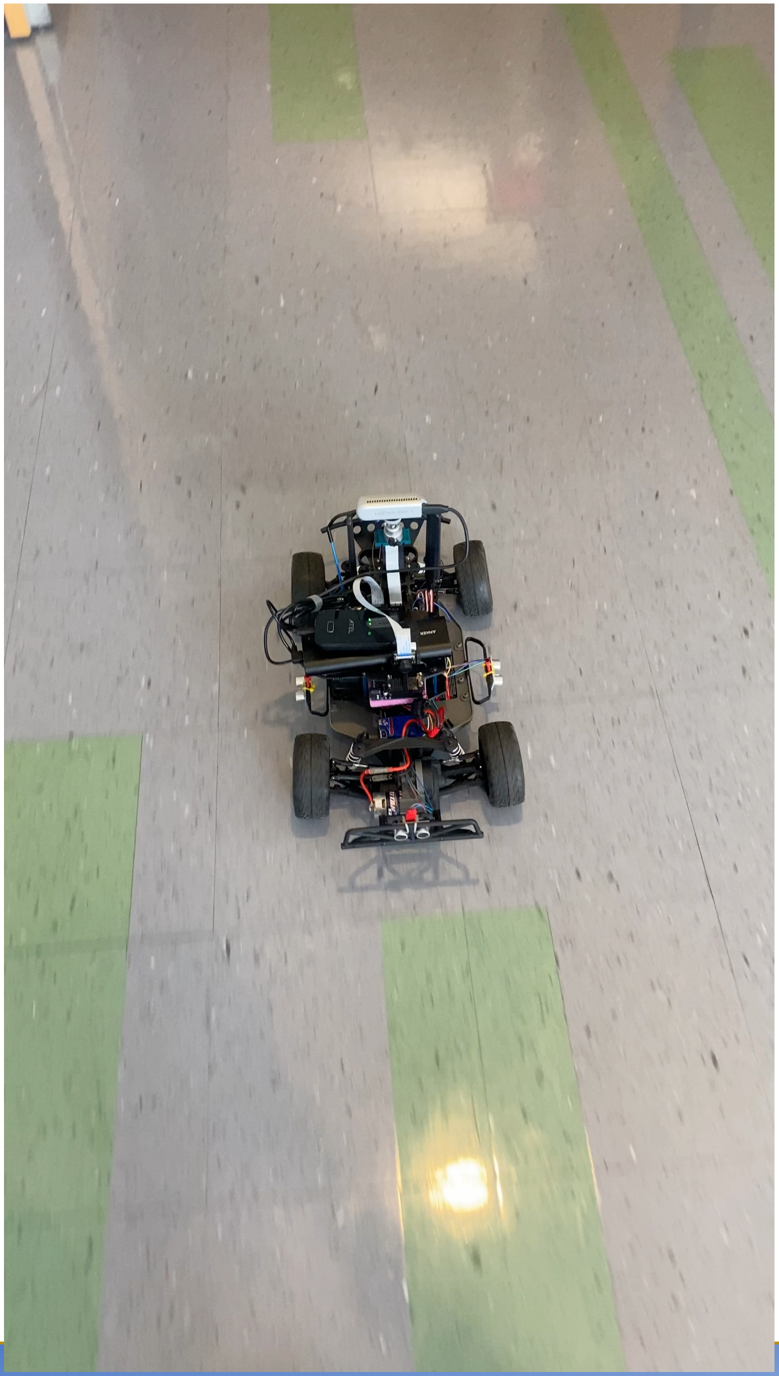


Ineffective during heavy rain or low hanging clouds: LiDAR pulses may be affected by heavy rains or low hanging clouds because of the effects of refraction. No way to differentiate color

Transfer Learning for Object Recognitions and Representations in Latent Space

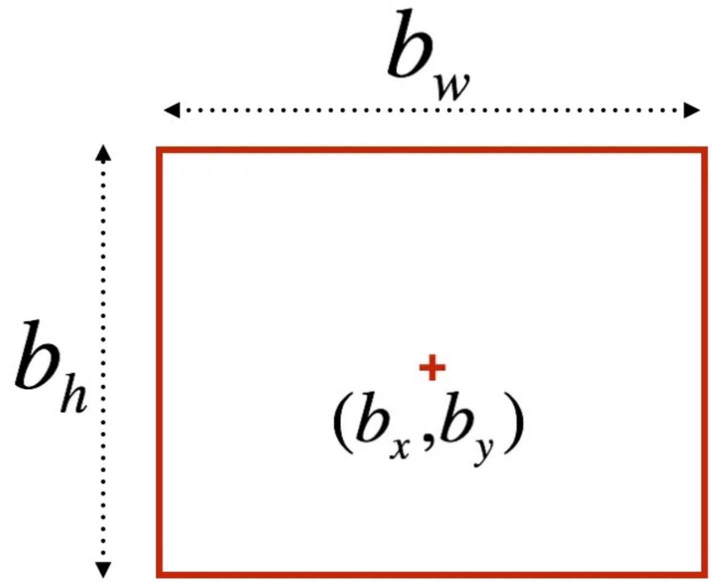


Obstacle Avoidance



Yolo (You only Look Once)

$$y = (p_c, b_x, b_y, b_h, b_w, c)$$



$p_c = 1$: confidence of an object being present in the bounding box

$c = 3$: class of the object being detected (here 3 for "car")

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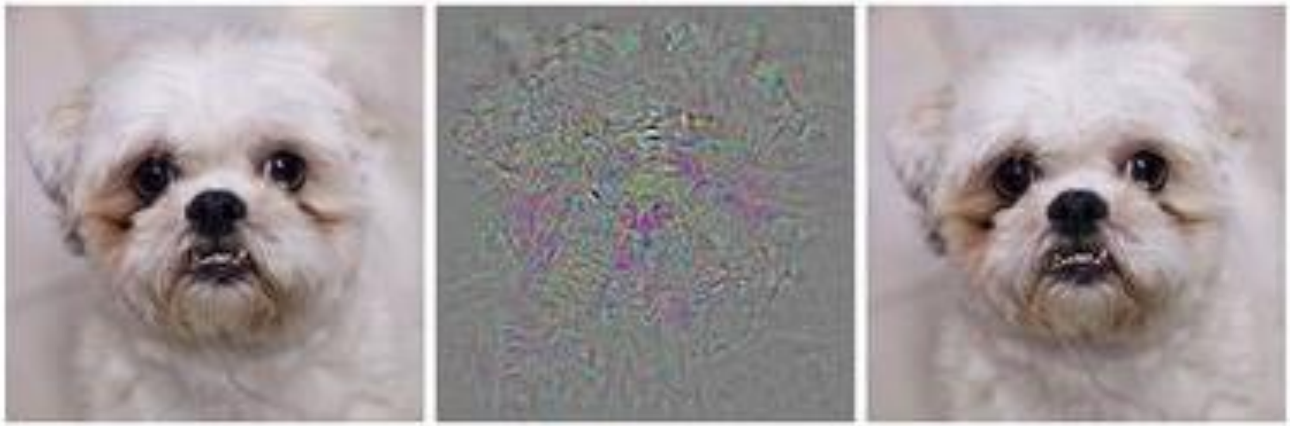
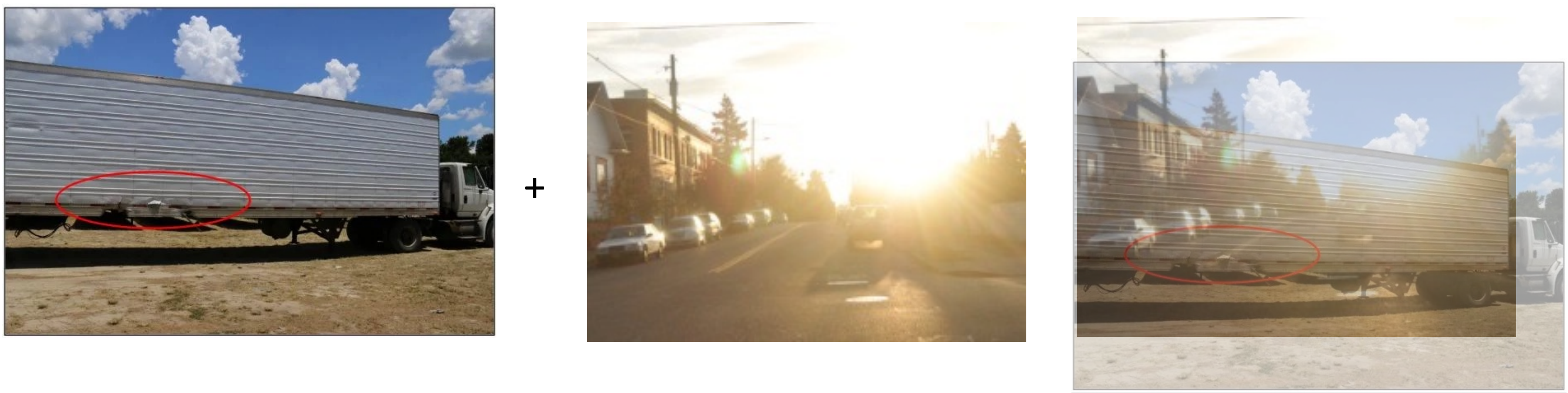
Challenge: Self-Driving Security



Prediction: **Dog** + Distortion Prediction: **Ostrich**



Prediction: **Semi-Truck** + Attacks Prediction: **Clouds**

Challenge: Will Behavior Clone Work?

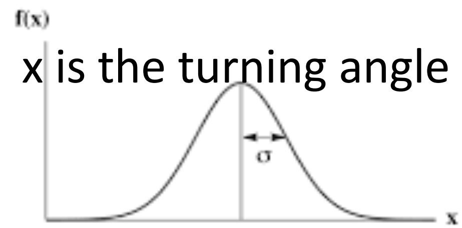
Small Mismatch will accumulate

Corrective actions

Discrete Action is OK, Soft-max on Left or Right

What about Continuous Actions?

x is the turning angle



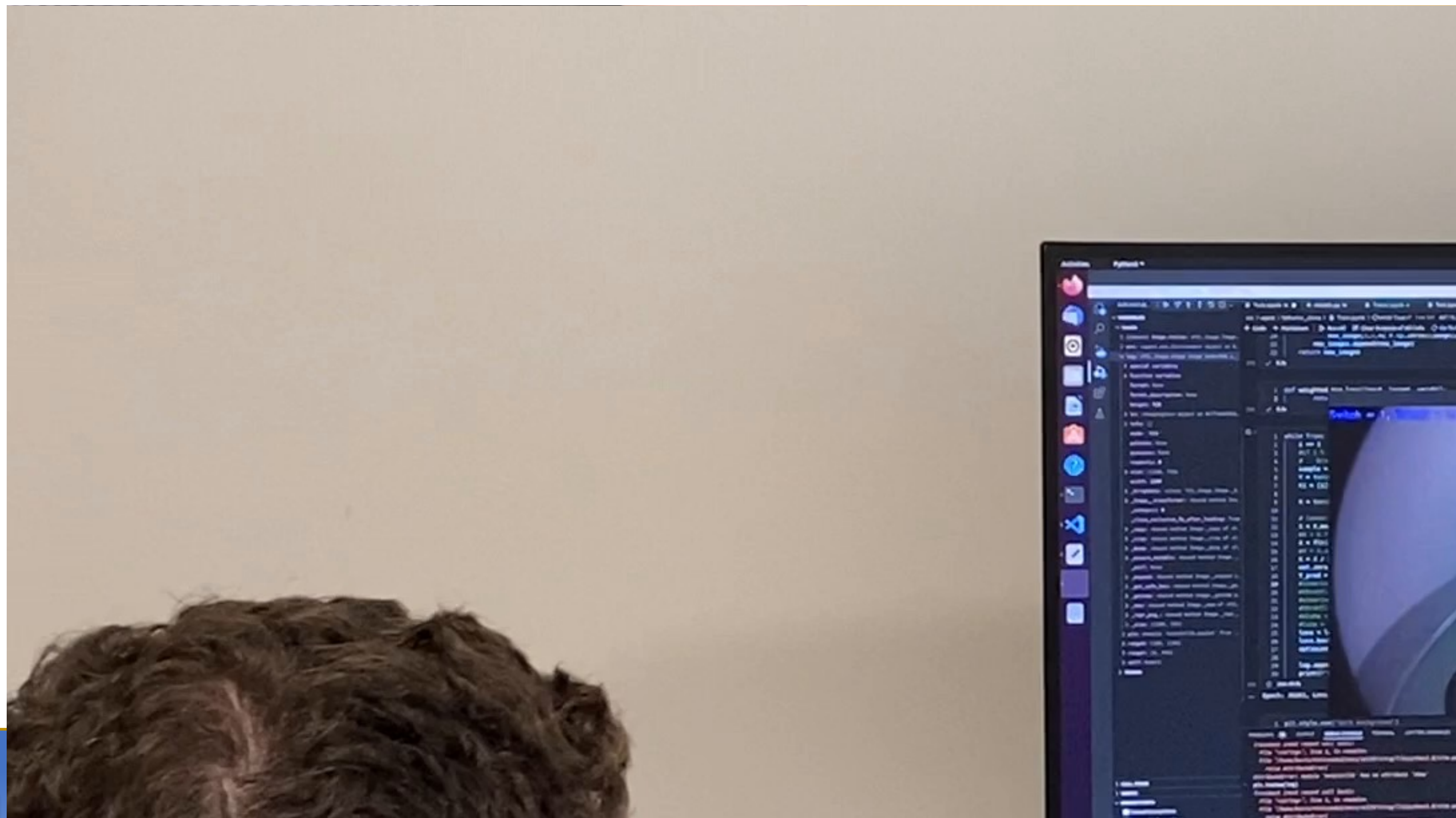
left right

$$f(x) = \frac{1}{\boxed{\sigma}\sqrt{2\pi}} e^{-(x-\boxed{\mu})^2/2\sigma^2}$$

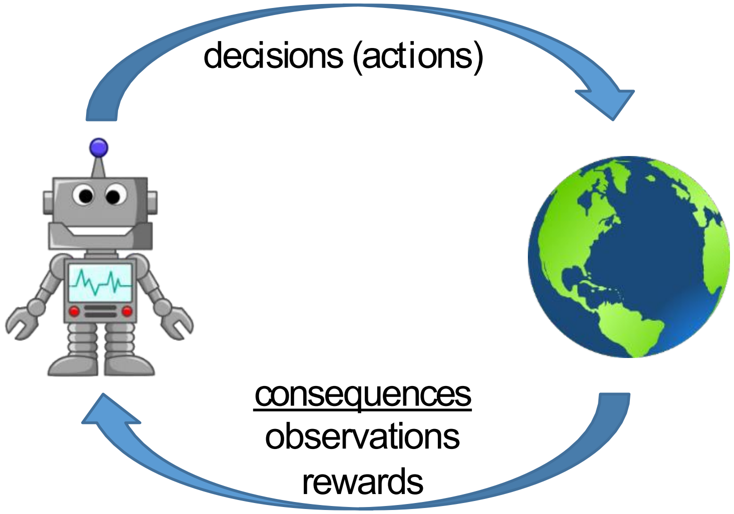
$e = 2.71828$

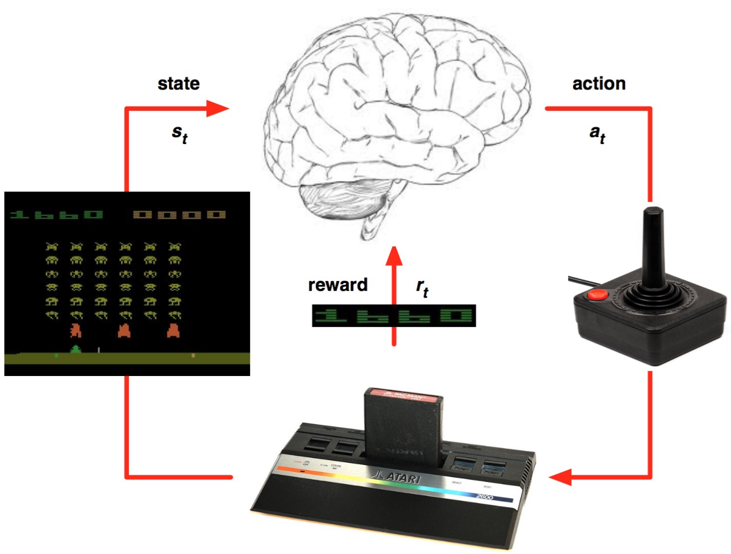
Look into Future

- The question: When will full autonomous driving happen?
- What are the potential intermediate steps:
  - A) Algorithm Development for an Explainable AI system (phantom brake in Tesla)
  - B) Education and Outreach for public acceptance, Crowd-source, and Crowd development)
  - C) Infrastructure support: Star-Link and 5G/6G (99.999% wireless networks) to allow remote monitoring and control
  - D) Basic IT infrastructure development (fast, low-latency communications).



Reinforcement learning provides a formalism for *behavior*





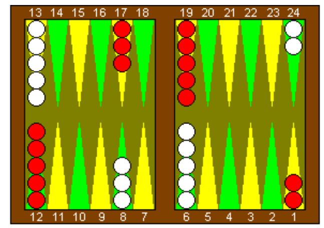
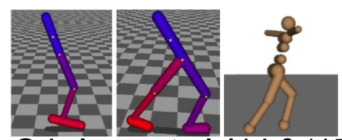
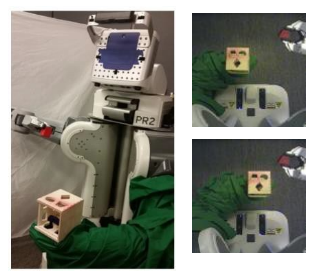


Figure 2. An illustration of the normal opening position in backgammon. TD-Gammon has sparked a near-universal conversion in the way experts play certain opening rolls. For example, with an opening roll of 4-1, most players have now switched from the traditional move of 13-9, 6-5, to TD-Gammon's preference, 13-9, 24-23. TD-Gammon's analysis is given in Table 2.



Schulman et al. '14 & '15



Levine*, Finn*, et al. '16

Mnih et al. '13

Conclusions

- Self-Driving depends on an accurate learning model. Small errors accumulate and lead to substantial deviations from the track.
- No sensor works 100%; multiple sensors add reliability.
- Representation (embedding) is the key to uncovering the state information of observations and enhancing learning capability.
- Large training data is needed to mitigate the limitation of a supervised learning model.
- Performance and QoS are critical in self-driving: low power consumption, real-time decision making, and the flexibility to support transfer learning: incremental training, and independence from cloud and data center.
- Planning/controlling autonomous vehicles involves decision makings continuously in an episode to maximize future values rather than clone experts' behavior.

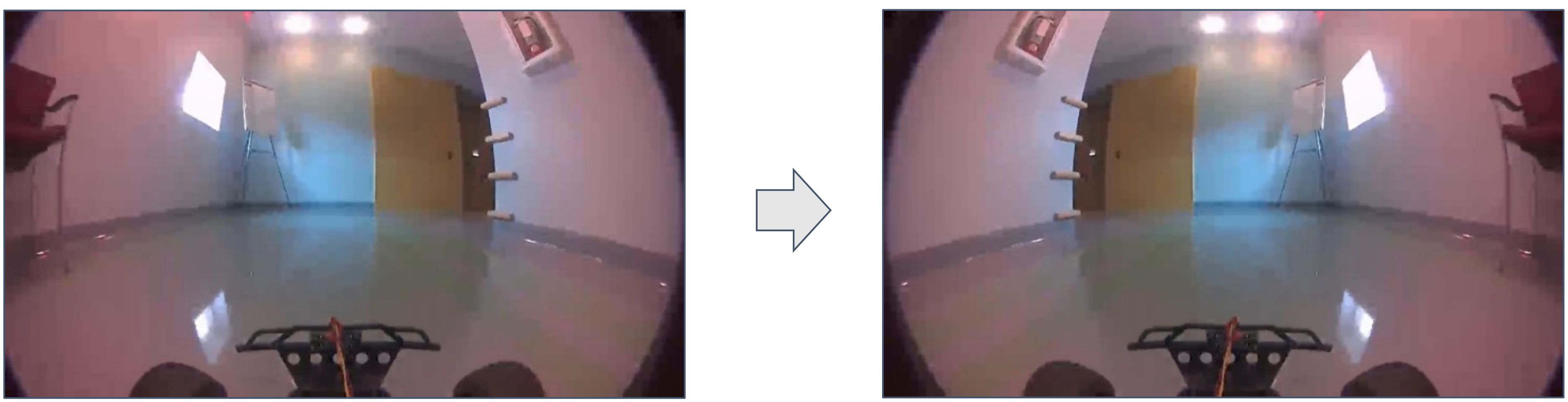
Thank You!

https://docs.google.com/forms/d/e/1FAIpQLSciz6nKh-niYosMPEePIesnC4K-lxOddMg1j7krGLpUn9q37A/viewform?usp=sharing https://colab.research.google.com/drive/1KxivPKlVEO6aLZMf56LEOsrIAHRlnqRO

Behavior Cloning : Data Augmentation

Flipping: Flip the image horizontally and flip the steering angle to match

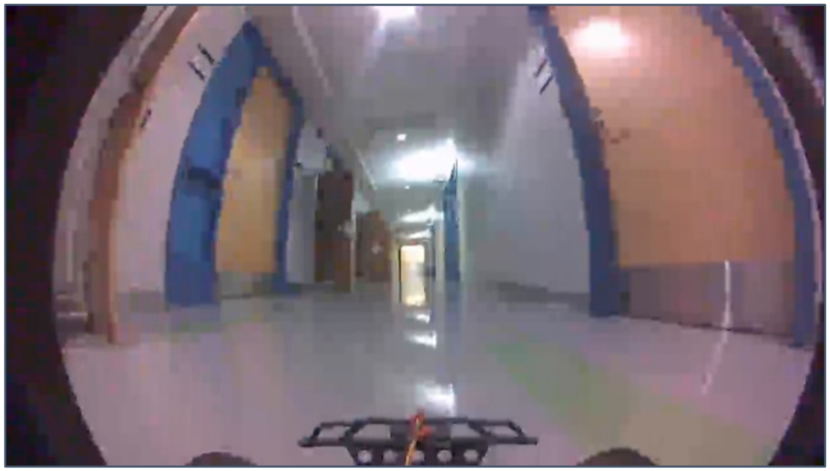
Equally trains left and right, further reduces bias

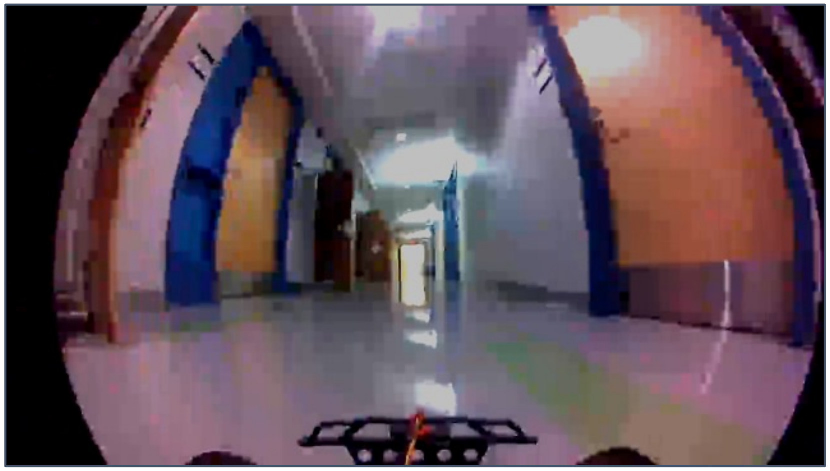


Behavior Cloning : Data Augmentation

Lighting - Randomly adjust the contrast and brightness

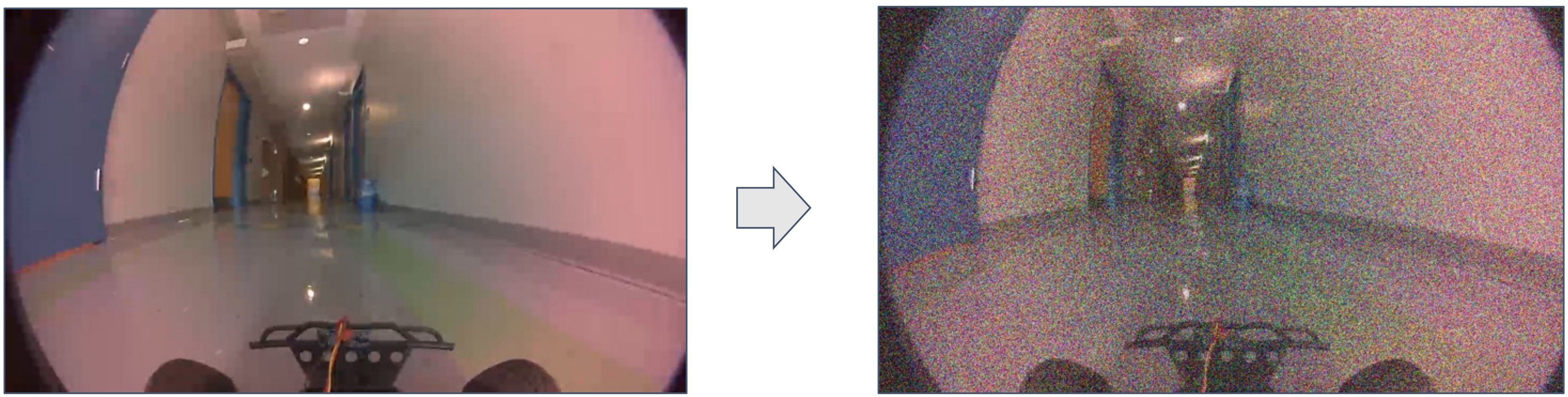
Used to increase robustness of the model to lighting effects





Behavior Cloning : Data Augmentation

Noise - add gaussian noise to the image



Behavior Cloning : Data Augmentation

Grayscale - although not used, the option to convert the rgb image to grayscale remains in our training notebook. Furthermore, you can also equalize the histograms

This can be useful for reducing the computation cost associated with the channels of the image or for reducing the model's dependency on recognizing certain colors.