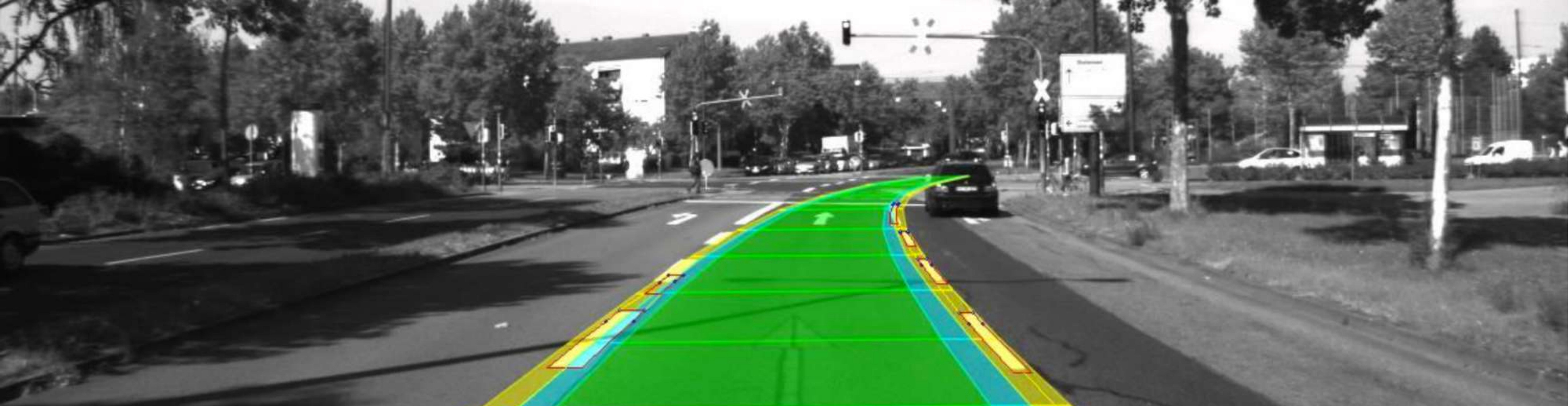


Module 3: Automotive CPS Data driven modeling

Principles of Modeling for Cyber-Physical Systems

Instructor: Madhur Behl

Slides credits:
- Urs Muller

Everything that moves will go autonomous

Cars

Trucks

Carts

Drones

Autonomous Systems

Safe

Secure

Connected

Self Learning

Trusted

Resilient

THE FUTURE OF TRANSPORTATION STACK

COMET LABS

SERVICES

ROUTE PLANNING
SPATIAL, CITIVIZ, waze, CommuteMaster, X, moovit, Citymapper

PARKING
Waypals, Cloud Parc, Aware, VoicePark, SpotHero, PEARL, seevader, Parko, FenSens, LUXE

CAR HAILING + POOLING
TESLOOP, lyft, A, RideCell, 30, 滴滴

OTHER: AFTERMARKET, REPAIR, RENTAL
CARVUE, upshift, WRENCH, PATROL, zipcar, Getaround, URGENT.LY, Tantalum, bitkar

SAFETY & SECURITY

PHYSICAL CAR & DRIVER SAFETY +ACCIDENT DETECTION
drivebetter, splitsecnd, nexar, GUARDIAN Optical Technologies, phrame, LyfeLens, SMART AUTOLABS, tourmalinelabs, iproc, eLSYS, FORESIGHT

EMOTION, FATIGUE & ALCOHOL DETECTION + DISTRACTION AVOIDANCE
CORTEXLABS, eyeris, ALMA care, CARMA, saverone, SMART wheel, Radiomize, EASY, carvi

CYBERSECURITY
CYMOTIVE, cognomotiv, ARGUS, Olympus Sky, Karamba Security, Trillium, Arilou

INTRUSION, TRACKING & RECOVERY
trackntop, nonda, gmt Connect, ROADEYE, caruma

IN-CAR INTELLIGENCE + ASSISTANCE

VEHICLE DIAGNOSTICS & PREDICTIVE MAINTENANCE + SENSOR-BASED VEHICLE SAFETY
TrueMotion, BRAIQ, IQ, metromile, LIGHT METRICS

PASSENGER-FOCUSED SENSORS (INCLUDING USAGE-BASED INSURANCE)
Cartics, Zobie, nauto, SONICLUE, PREDICTSYSTEMS, P, NEBULA, engie

INFOTAINMENT + DISPLAY
link motion, HUDIFY, CARROBOT, swedspot, OverDrive, ROAV, FICONIC, RIGHTWARE, PELAGICORE, CLOUDCAR

PERSONAL / VOICE ASSISTANCE
novideck, AUTOMATIC, dash, GRIN, carIQ

NAVIGATION ASSISTANCE + PEDESTRIAN ANALYSIS & COMMUNICATIONS
PERCEPTIVE AUTOMATA, navdy, hudly

AUTONOMY

AUTOMATION SYSTEM
AutoX, drive.ai, POLYSYNC, OXBOTICA, oryx, ARGO AI, AImotive, PILOT, cruise, nuTonomy, Vector.ai, MOMENTA, cognivue, 中天安驰 AIDRIVING, BWV

MAPPING, SIMULATION, & IMAGE RECOGNITION / ANNOTATION
lvl5, minds.ai, NOMOKO, Mapper.ai, CARMERA, TomTom, IMPROBABLE, UDACITY, DEEPMAP, understand.ai, Civil Maps

AUTONOMOUS VEHICLE MAKER + TOOLS
nuro, WAYMO, ZOOX, FARADAY FUTURE

INFRASTRUCTURE + CONNECTED CAR

SENSOR NETWORKING INFRASTRUCTURE (V2V, V2X) - LPWA, CELLULAR, WIFI
DIGIMONDO, SAVARI, ZIFISense, EVVOS, Actility

CONNECTED CAR - DATA, PLATFORM, SOFTWARE
ACTIVESCALER, INRIX, SMARTCAR, mobiliuz, carvoyant, vinli, otonomo, bright box, mojio

FLEET + TRAFFIC MANAGEMENT
BESTMILE, synovia, Fleetmatics, Motionlogic, Travelr, Automile, Zendrive, GLYDEL, locoNav, Immense Simulations, MOTORWAY BUDDY, mentis, FR, Brisk Synergies

OTA CAR SOFTWARE UPDATION + SMART PHONE ENABLEDTELEMATICS
FIXD, DRIVEBOT, VOYOMOTIVE, ZENE, aryng

INTELLIGENT MANUFACTURING

NEW/ADVANCED MATERIALS
NAWA TECHNOLOGIES, SIRRUS, AQUARIUS, NANOSTEEL

RAPID PROTOTYPING - 3D PRINTING, MODULARIZATION, OPEN SOURCE
DM, Carbon, nanocore, DIVERGENT, LM, OSVehicle, stratasys, VADER

ADVANCED / AUTOMATED ASSEMBLY LINE
Grabit, SYMBIO, CLEARPATH, ROBOMOTIVE, rethink robotics

MATERIAL CHARACTERIZATION & TESTING
SynTouch, SASTRA, VIDI, OPTOFIDELITY

ONBOARD SENSORS

LOCATION - GIS, PRECISION POSITIONING, PATH PLANNING
swift, radiosense

VISION / CAMERA
DEEP VISION, Carnegie Robotics, machines with vision, ROADSENSE, DEEPSCALE, Chronocam, VAYAVISION

LIDAR
Innoviz, PHANTOM INTELLIGENCE, VOYAGE, QUANERGY, AEYE, TRILUMINA, LeddarTech, Velodyne LiDAR, STROBE

RADAR
OCULII, TOPOSENS, RFISEE, 6TH SENSE, SDS

SPECIALTY VEHICLES

2-WHEELERS
smarthalo, superpedestrian, Zagster

PUBLIC TRANSPORT
nauva, LM, Varden Labs, AURO, EASY MILE

TRUCKS / FREIGHT
JAYBRIDGE ROBOTICS, OTTO, PELOTON, TESLA, FLEXPORT, TRUELITE TRACE, STARSKY ROBOTICS

FLIGHT
WRIGHT ELECTRIC, ZUNUM Aero, ZEE, JOBY, Kitty Hawk, LILIUM, AEROMOBIL

OTHER: HYPERLOOP, PERSONAL MOBILITY
hyperloop one, ninebot, 5 WHILL


WAYMO
7XJT313
Google
WAYMO

THE 6 LEVELS OF AUTONOMOUS DRIVING

LØ	L1	L2	L3	L4	L5
No Automation	Driver Assistance	Partial Automation	Conditional Automation	High Automation	Full Automation

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.

1.35 million deaths worldwide due to vehicle crashes

94% of crashes involve human choice or error in the US.

3 million

Americans age 40 and older are blind or have low vision

79%

of seniors age 65 and older living in car-dependent communities

42 hours

wasted in traffic each year per person

Localization and Mapping

Where am I ?

Scene Understanding

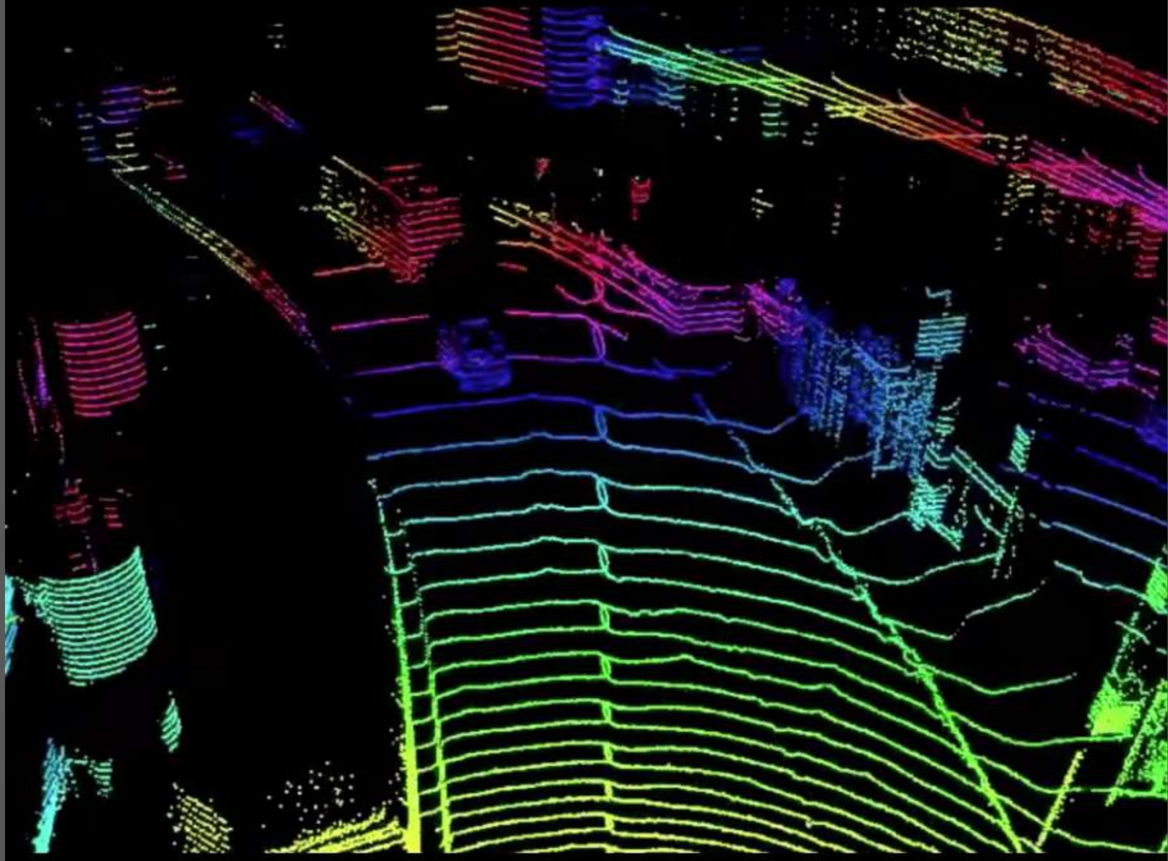
Where/who/what/why of everyone/everything else ?

Trajectory Planning and Control

Where should I go next ?
How do I steer and accelerate ?

Human Interaction

How do I convey my intent to the passenger and everyone else ?



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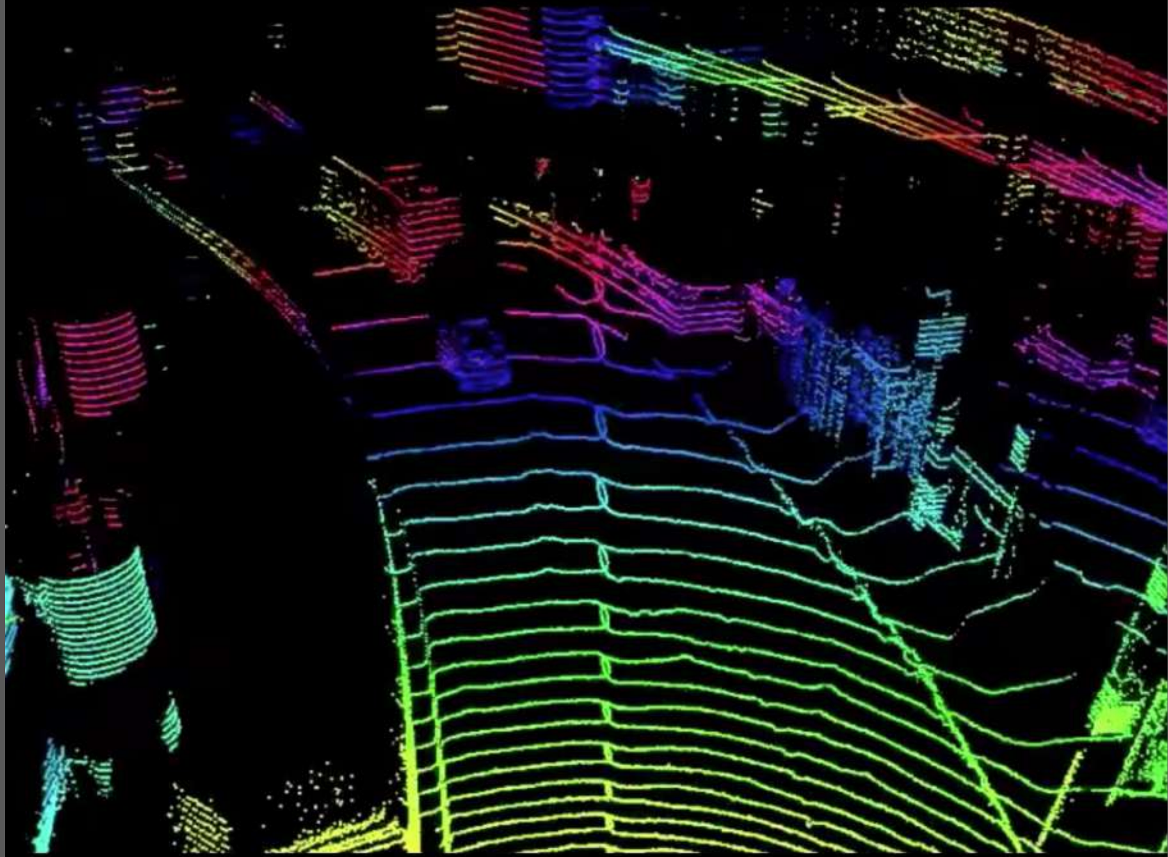
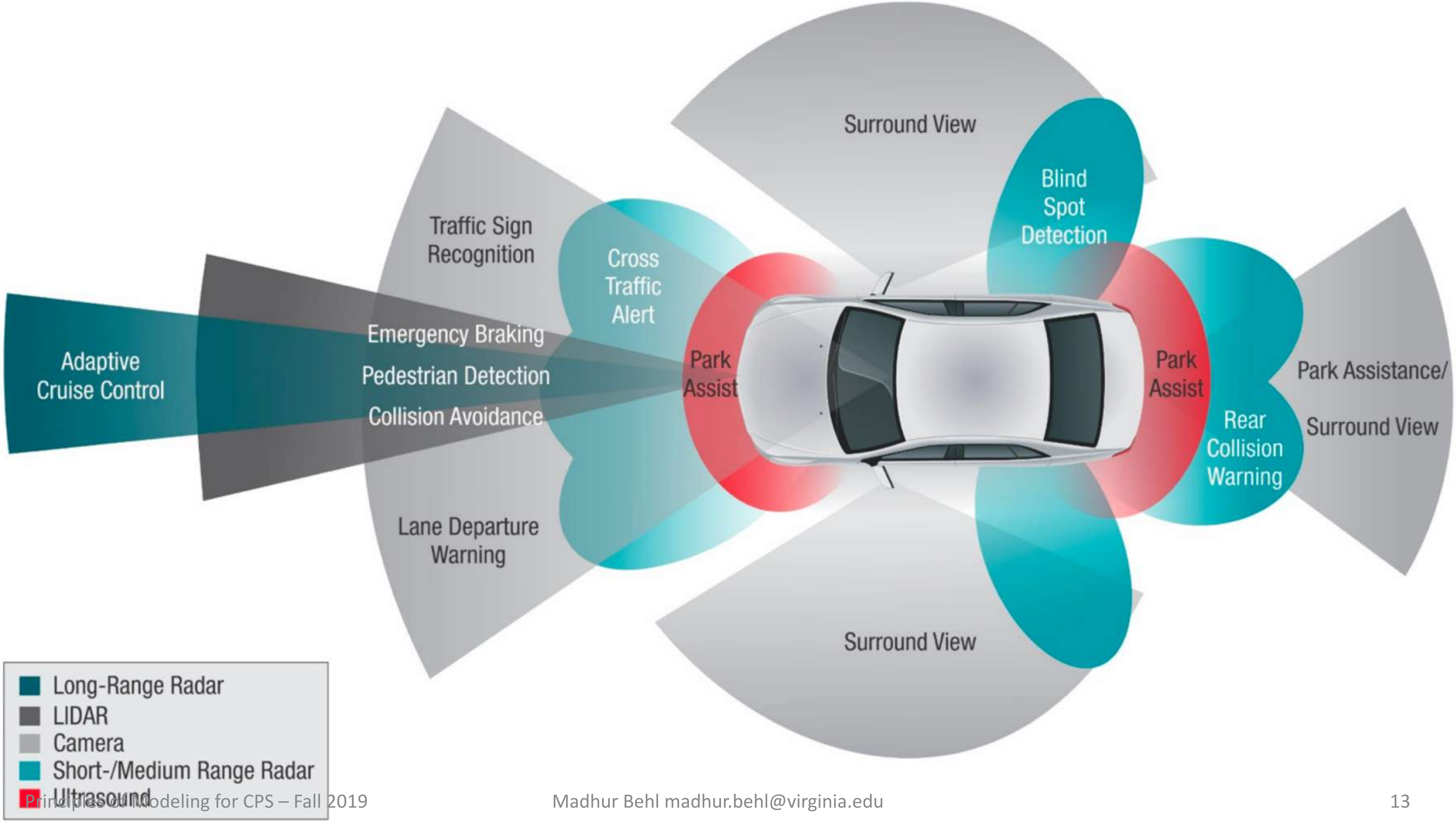
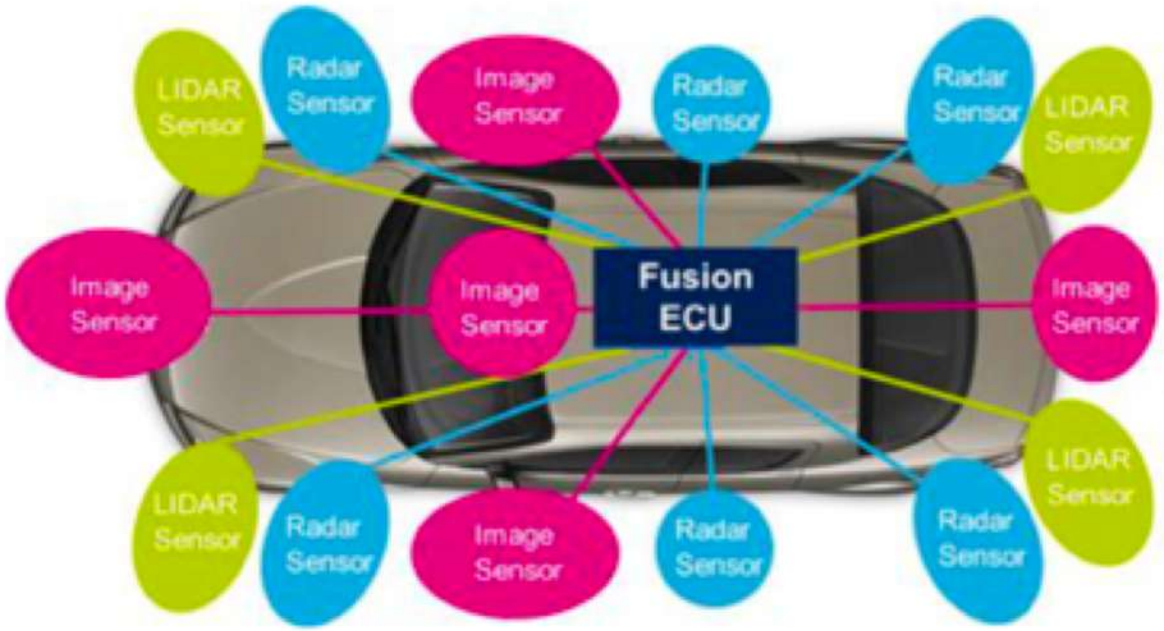




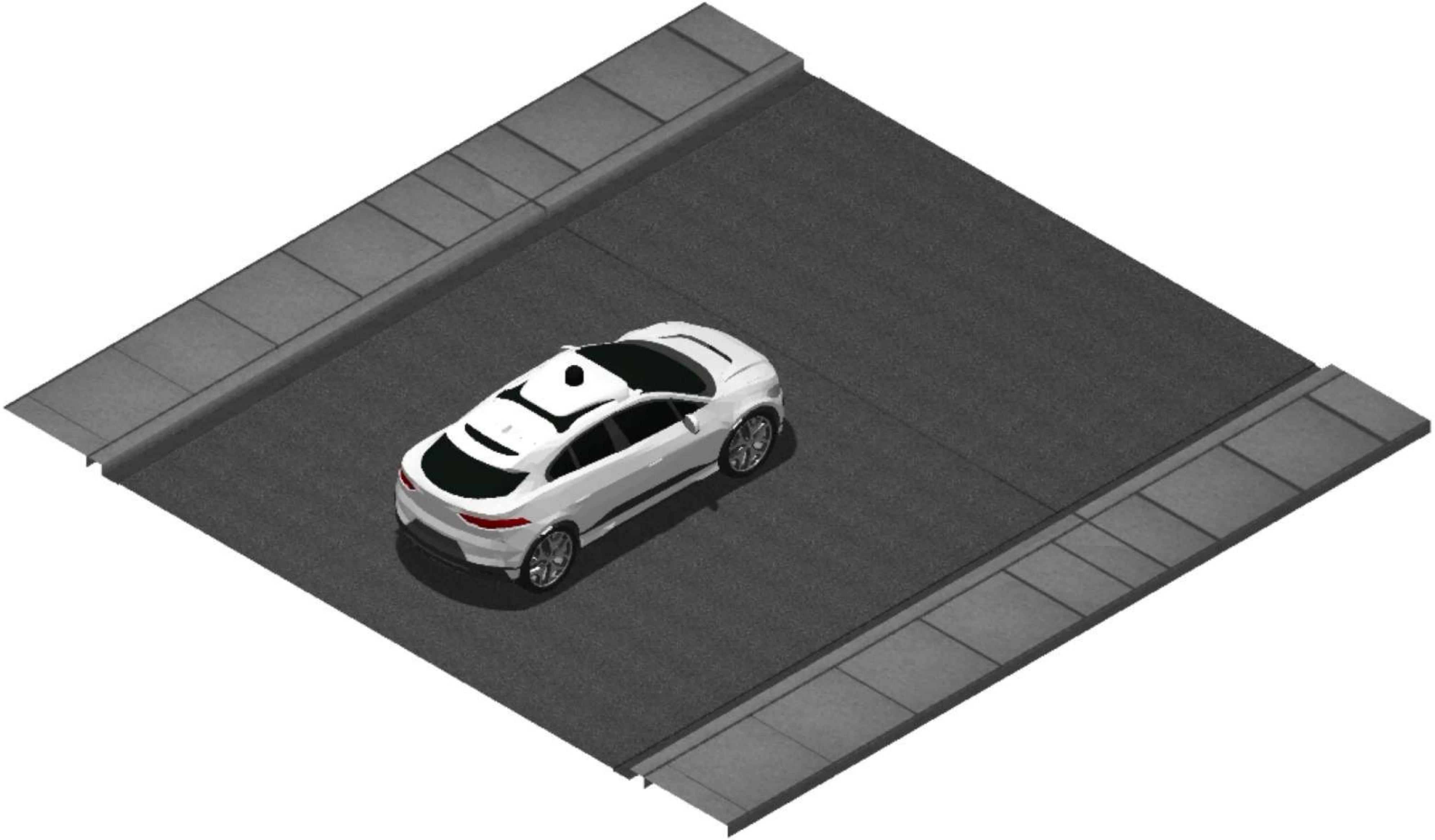
Surround View
Blind Spot Detection
Traffic Sign Recognition
Cross Traffic Alert
Adaptive Cruise Control
Emergency Braking
Pedestrian Detection
Collision Avoidance
Park Assist
Park Assist
Park Assistance/ Surround View
Rear Collision Warning
Lane Departure Warning
Surround View
Long-Range Radar
LIDAR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



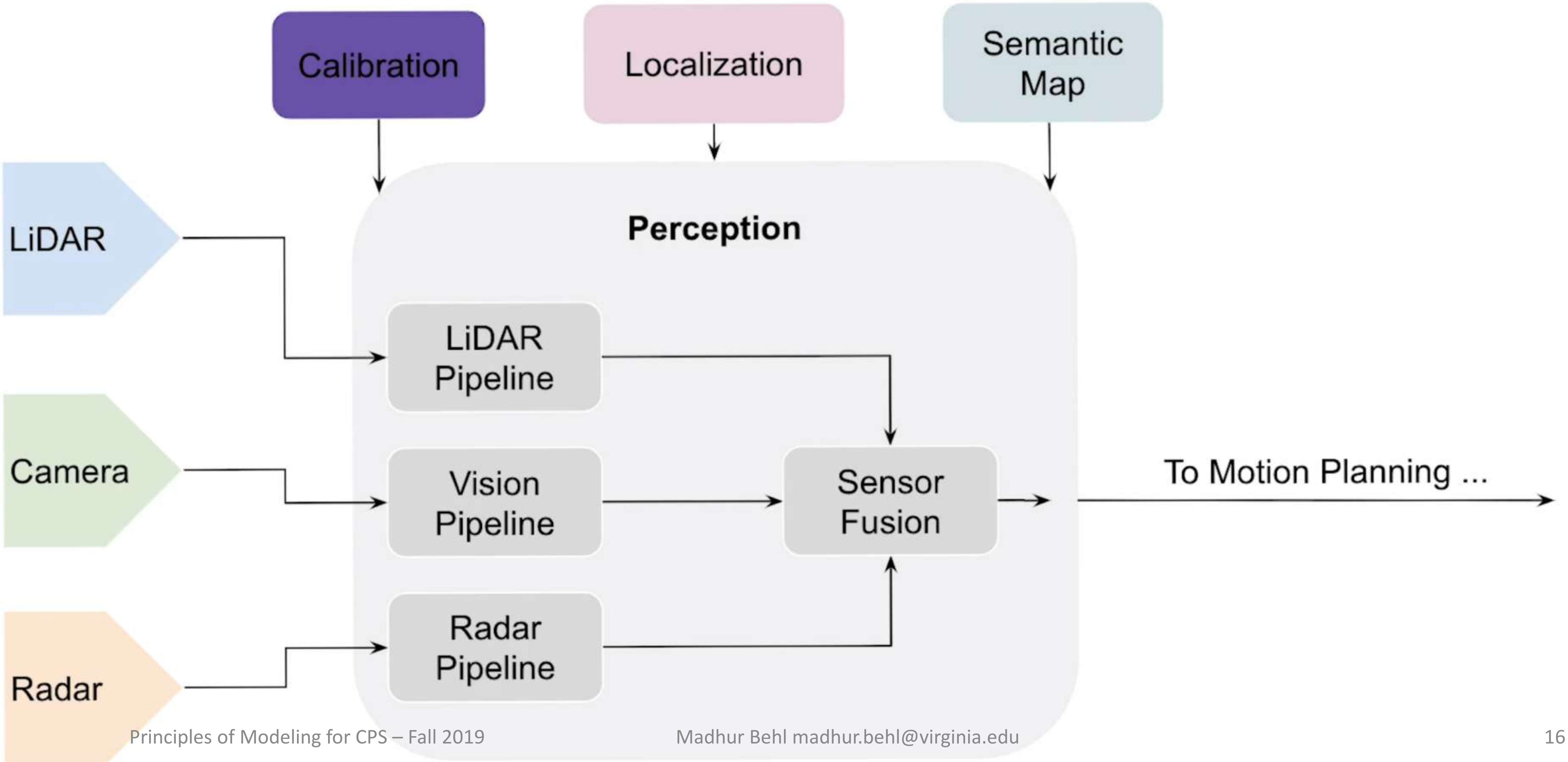
Camera

Radar

LIDAR

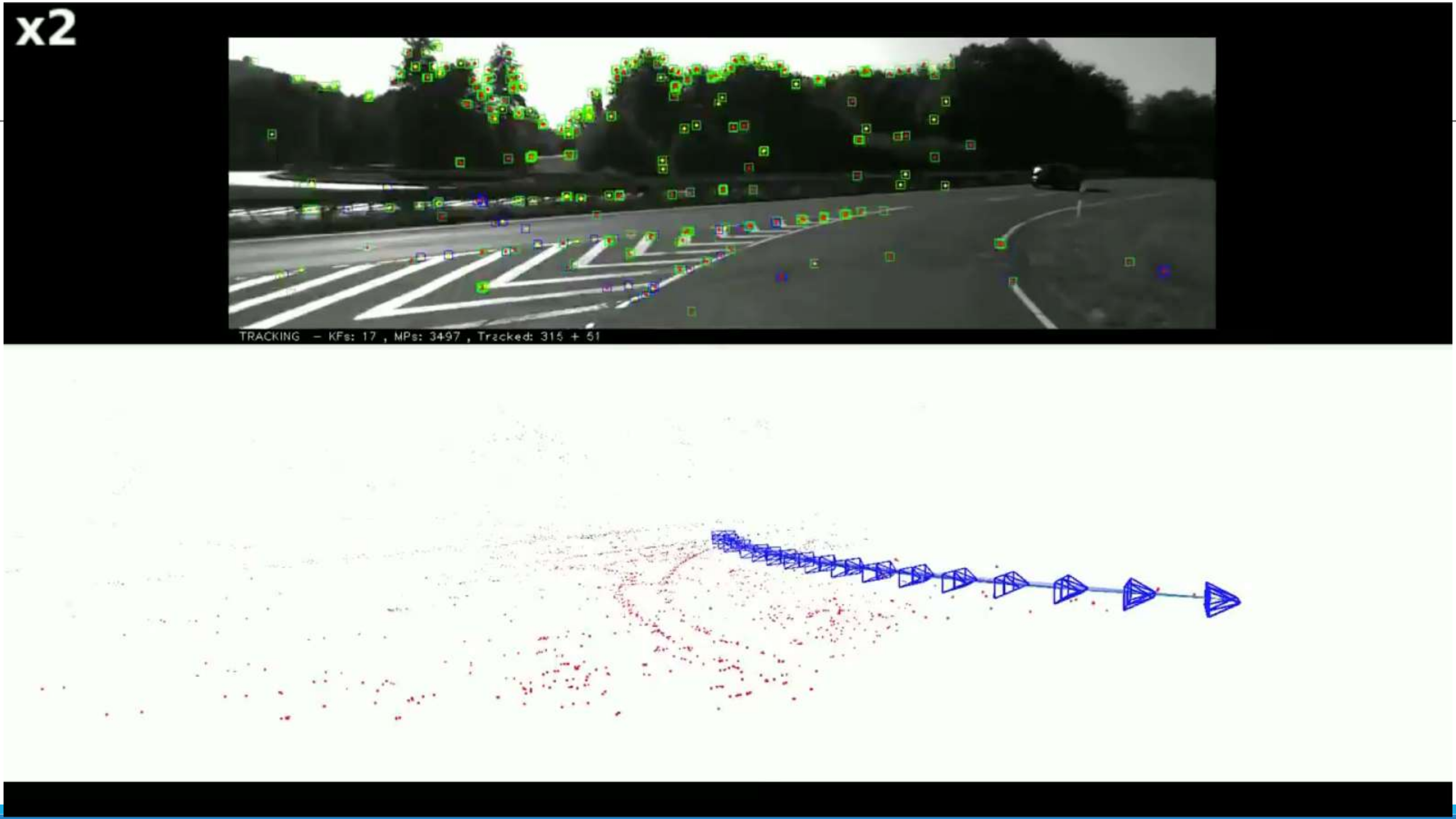


Perception in AV Stack



SLAM: Simultaneous Localization and Mapping

What works: SIFT and optical flow

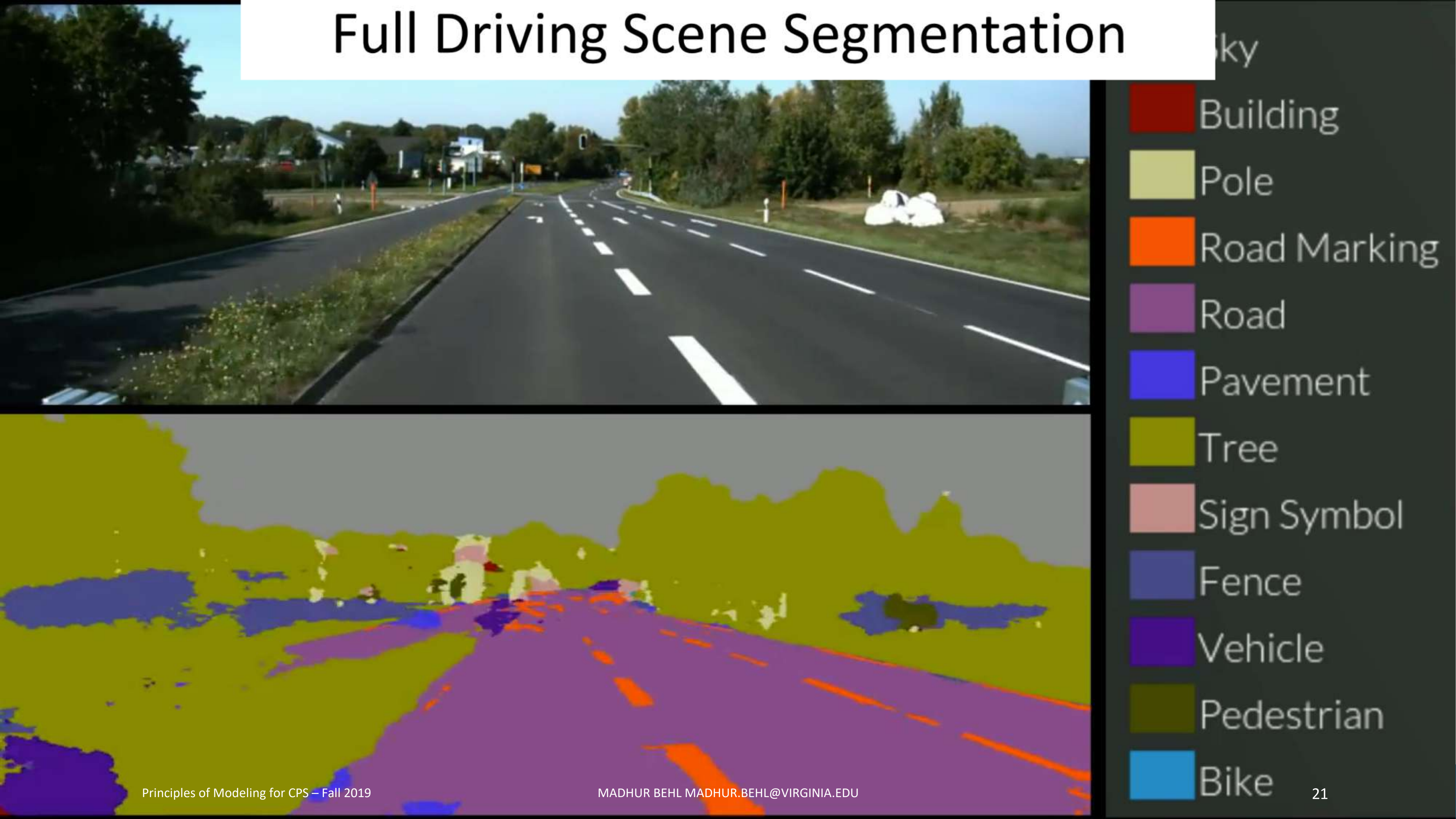


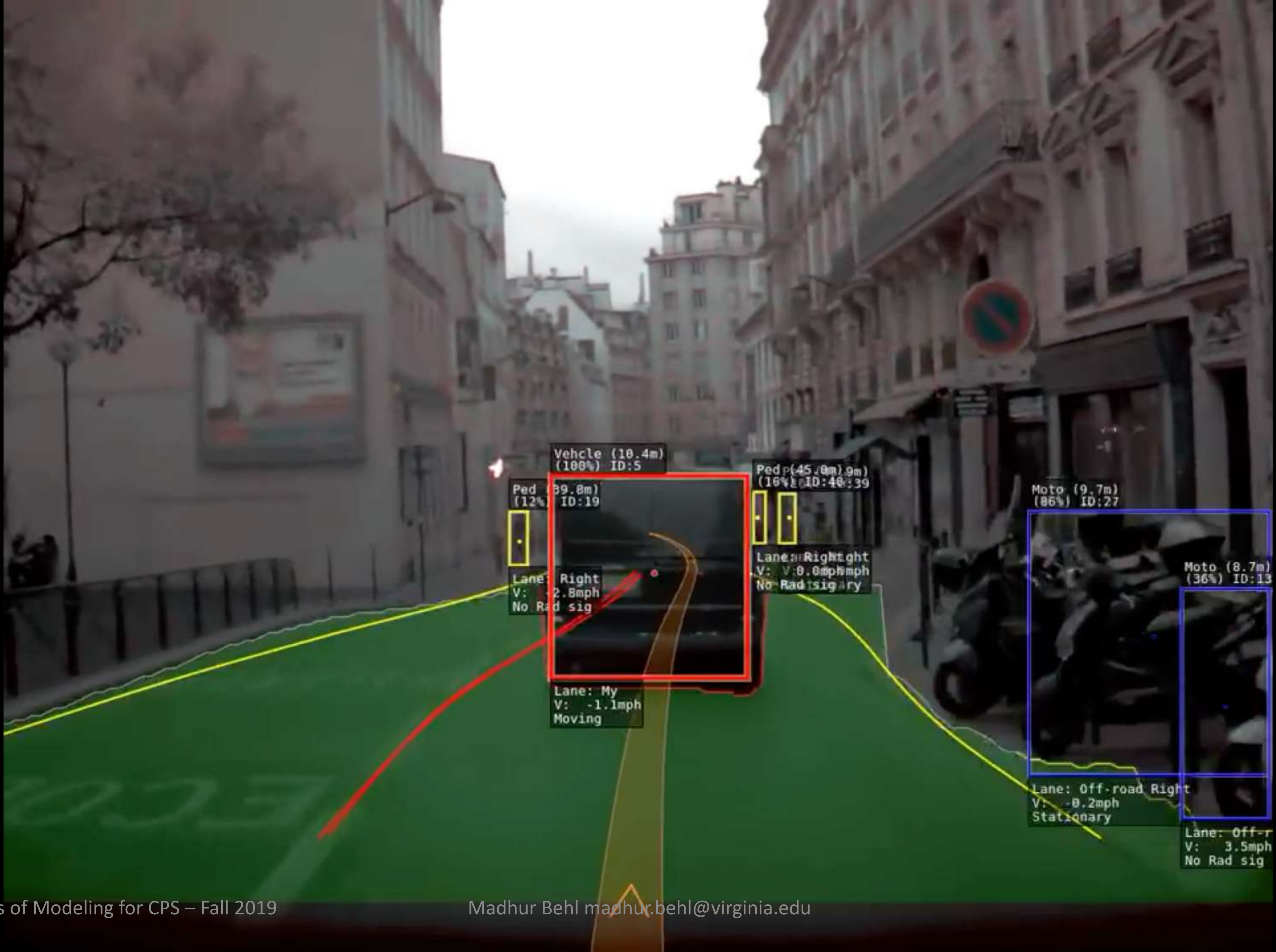
Object Detection

- Past approaches: cascades classifiers (Haar-like features)
- Where deep learning can help:
  recognition, classification, detection


Sensor Fusion
International
CES
TECH EVENTS
ection - NVDriveNet detection
suv-truck car suv-truck suv-truck suv-truck suv-truck
Front:
car car suv-truck suv-truck
Rear :

Full Driving Scene Segmentation





Vehcle (10.4m)
(100%) ID:5
Ped (39.8m)
(12%) ID:19
Lane: Right
No Rad sig
Lane: My
V: -1.1mph
Moving
Moto (9.7m)
(86%) ID:27
Moto (8.7m)
(36%) ID:13
Lane: Off-road Right
V: -0.2mph
Stationary
V: 3.5mph
No Rad sig

Localization and Mapping

Where am I ?

Scene Understanding

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Trajectory Planning and Control

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Human Interaction

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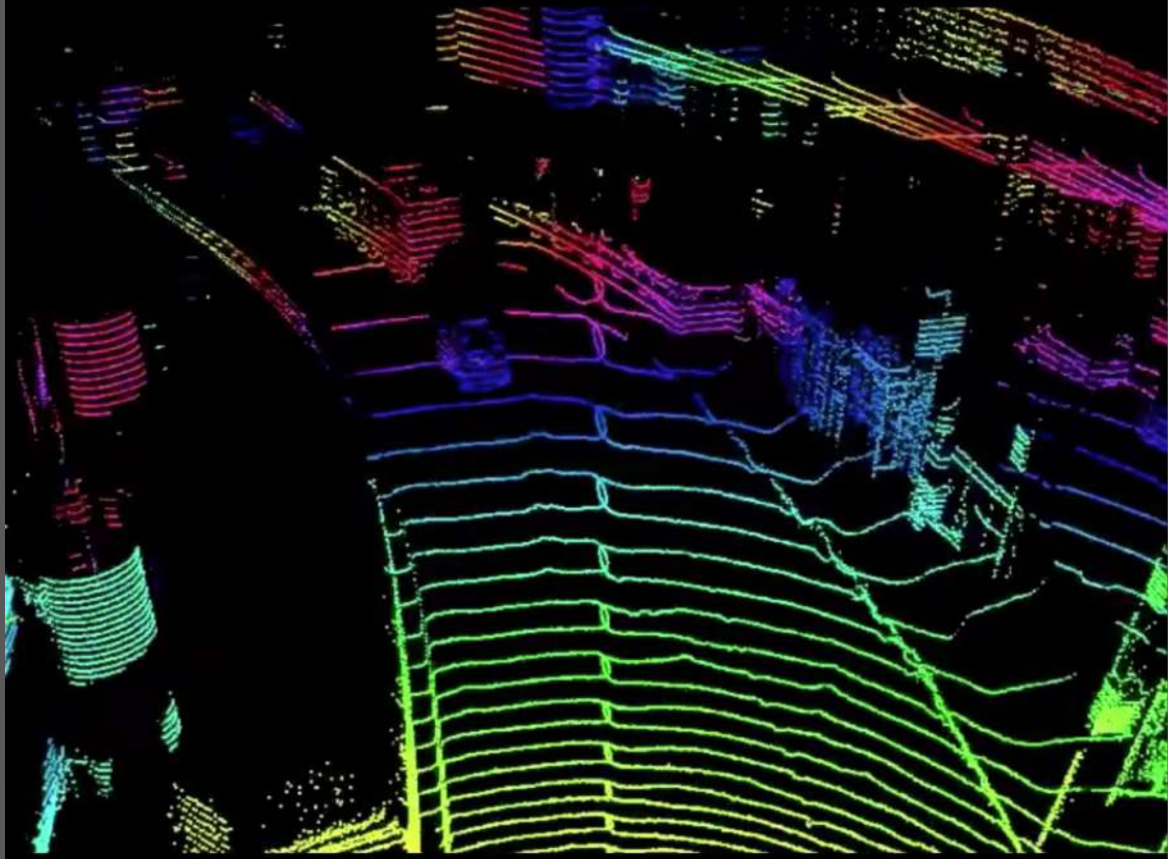



Vehcle (28.9m)
(100%) ID:38
Lane: Overlp-Left
V: -1.2mph
Moving
Vehcle (44.3m)
(100%) ID:20
Lane: Imm-Right
V: 0.7mph
Moving
Moto (9.6m)
(100%) ID:34
Lane: Imm-Right
V: 2.7mph
Moving

Detailed three-dimensional maps that highlight information such as road profiles, curbs and sidewalks, lane markers, crosswalks, traffic lights, stop signs, and other road features.

Where am I?

What's around me?

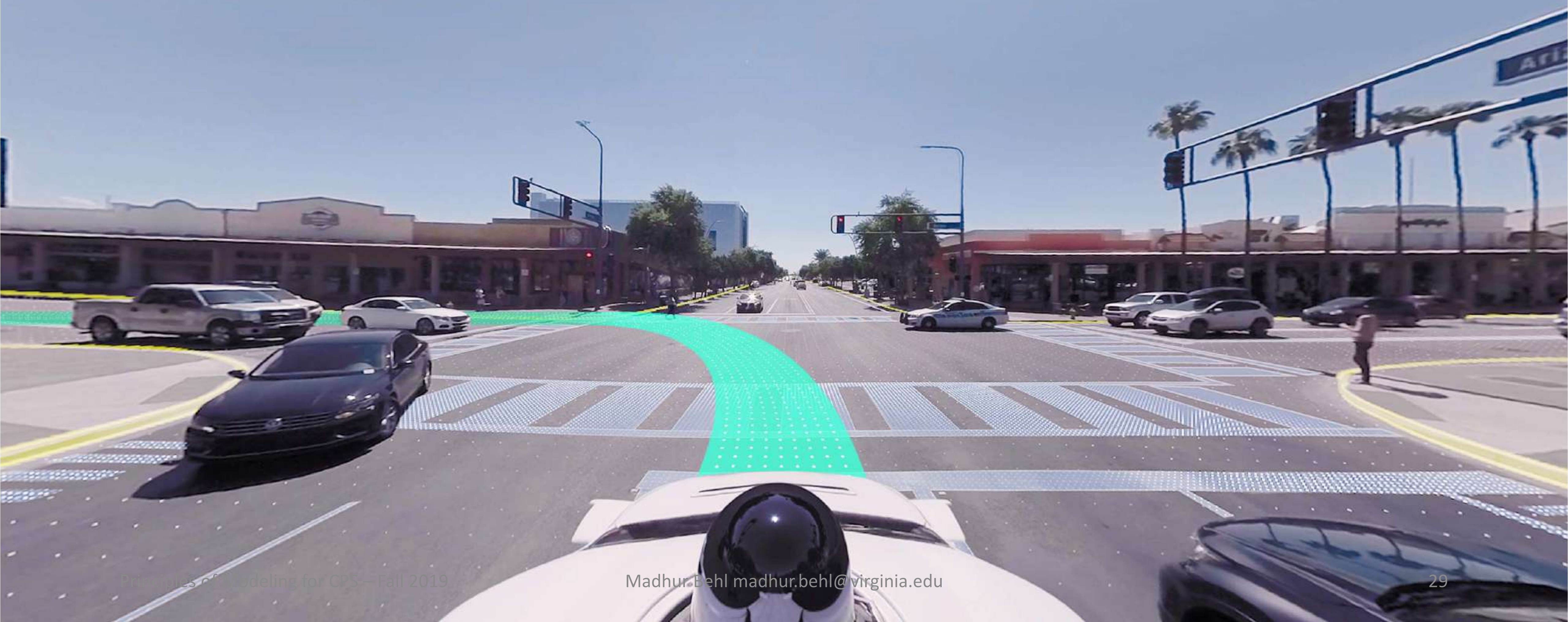
Scan constantly for objects around the vehicle—pedestrians, cyclists, vehicles, road work, obstructions—and continuously read traffic controls, from traffic light color and railroad crossing gates to temporary stop signs.

Predict the movements of everything around you based on their speed and trajectory

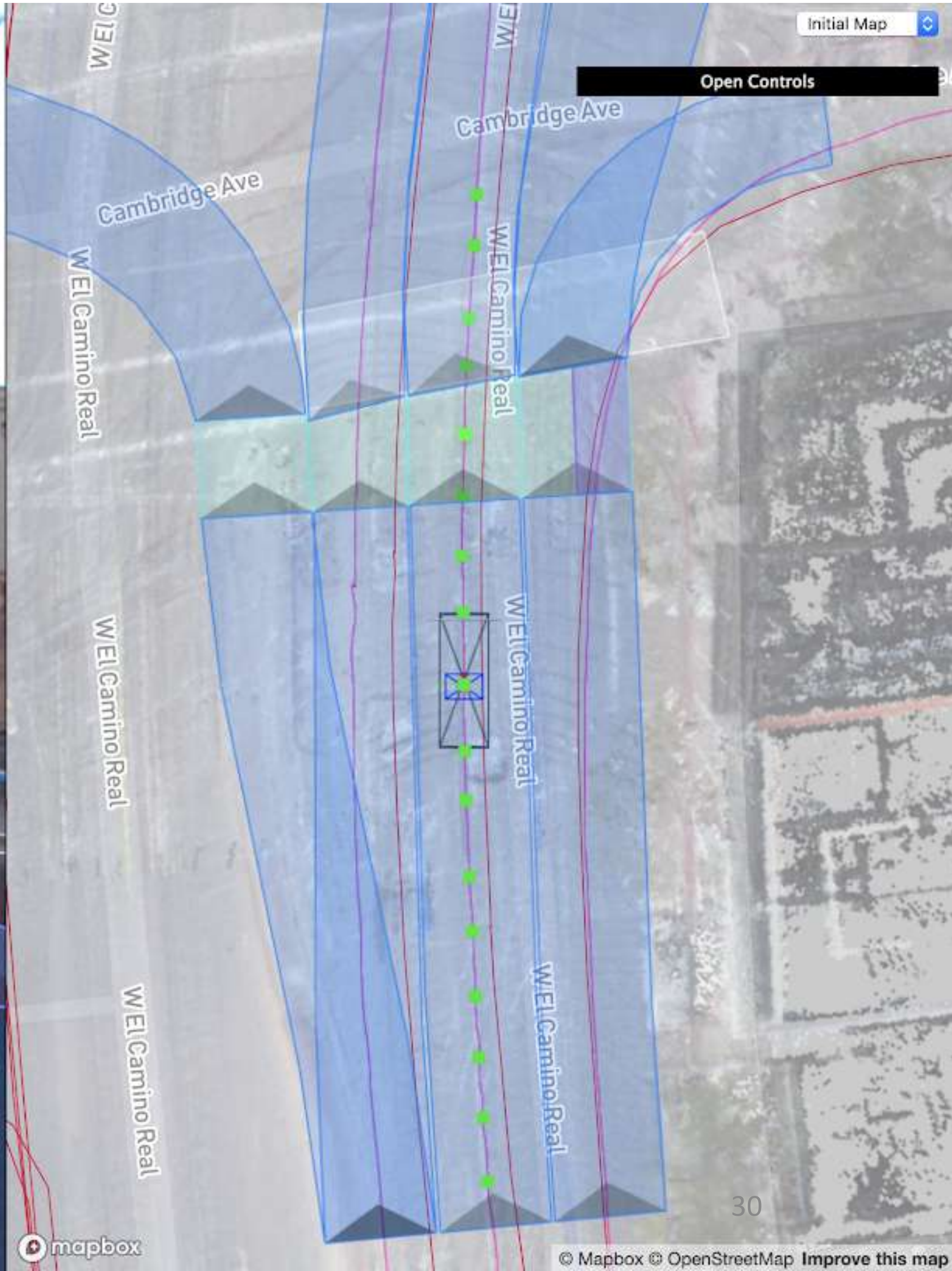
What will happen next?

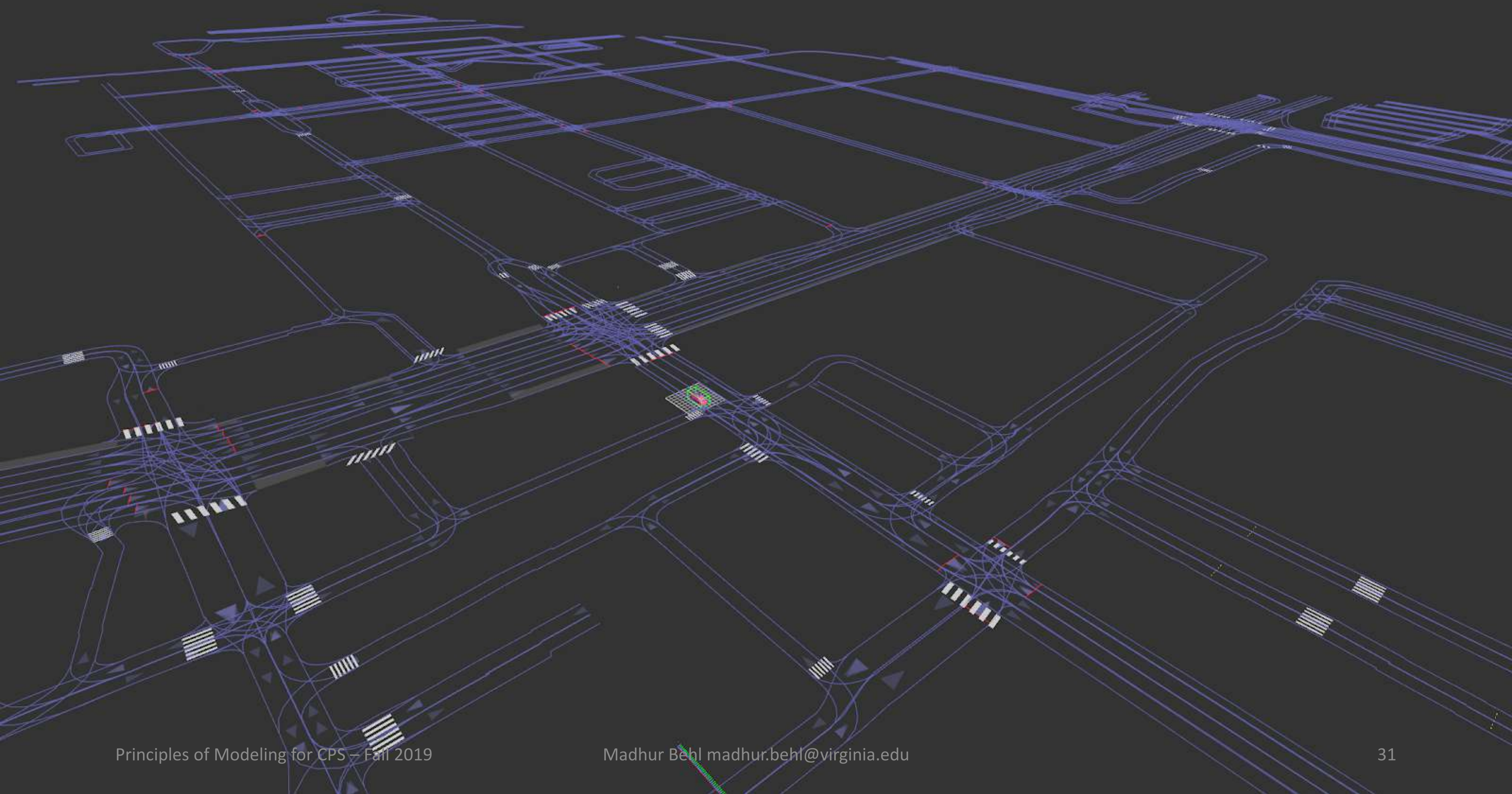
What should I do?

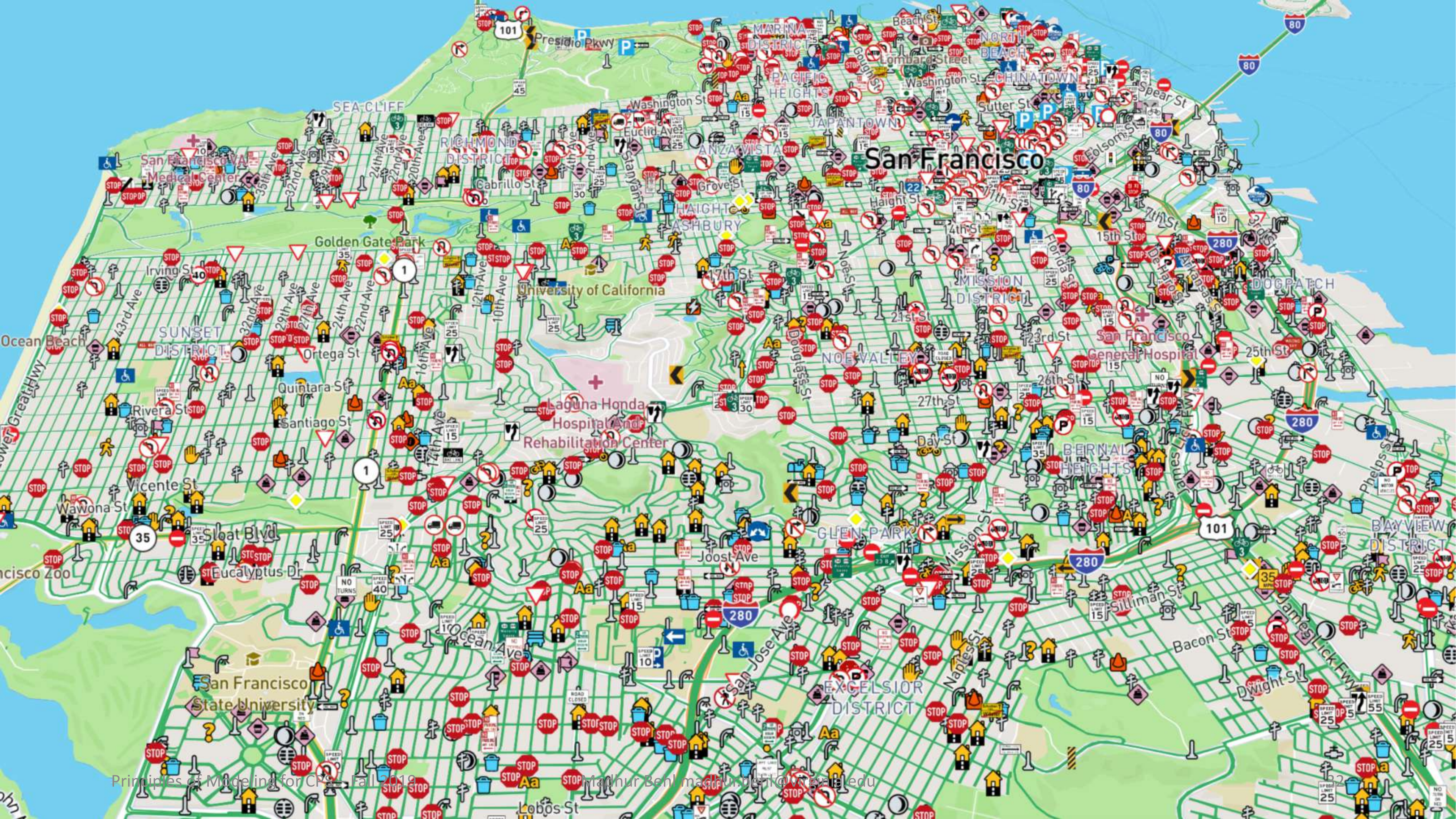
Determine the exact trajectory, speed, lane, and steering maneuvers needed to progress along the route safely



HD Maps: Localization

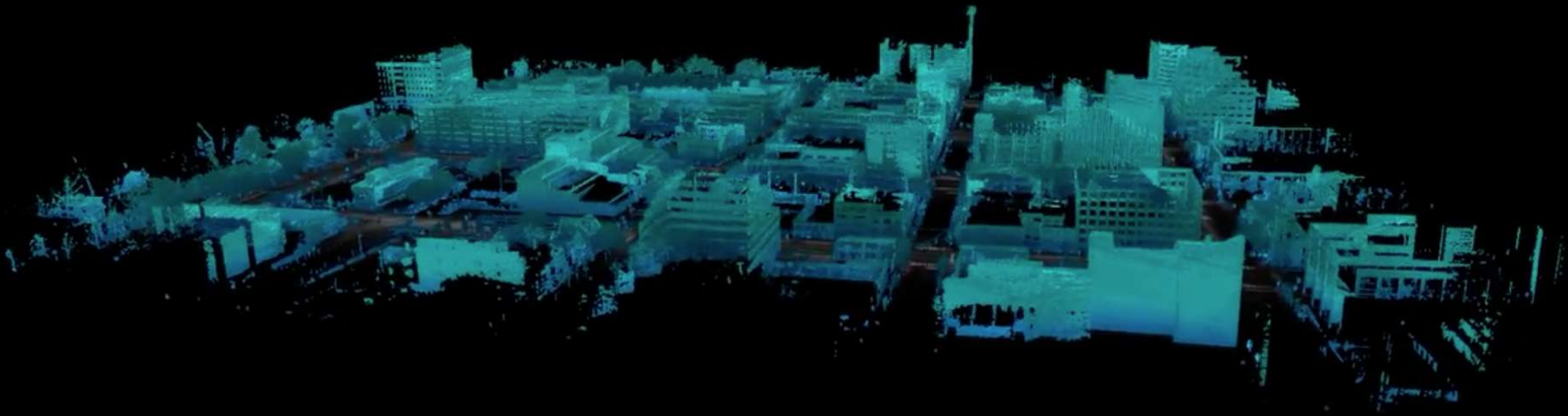


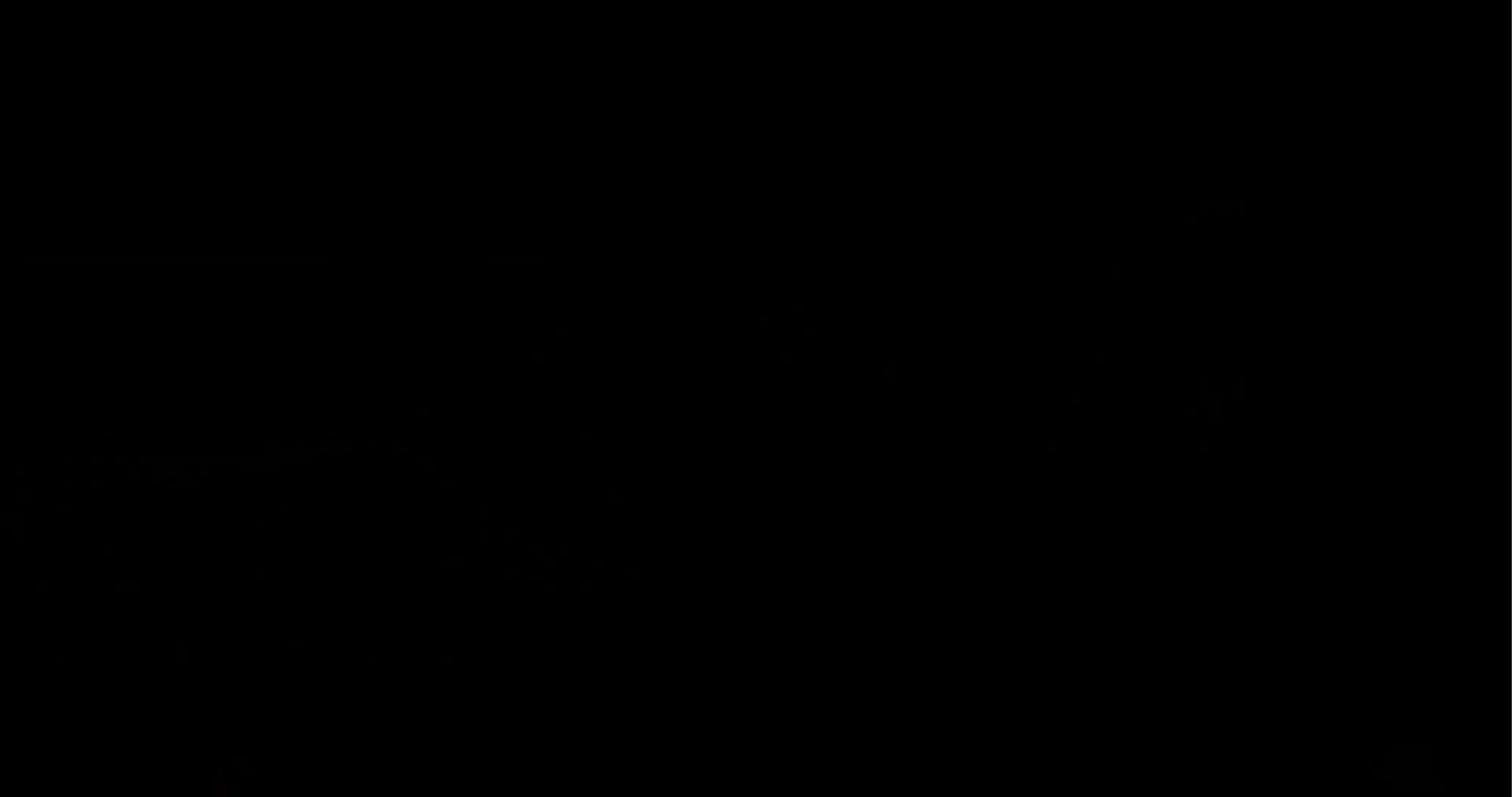




San Francisco
Presidio Pkwy
MARINA DISTRICT
NORTH BEACH
Lombard Street
PACIFIC HEIGHTS
CHINATOWN
Washington St
SEA CLIFF
JAPANTOWN
Sutter St
RICHMOND DISTRICT
Euclid Ave
ANZA VISTA
San Francisco VA Medical Center
Cabrillo St
Grove St
Folsom St
Haight St
HAIGHT-ASHBURY
Golden Gate Park
17th St
15th St
Irving St
University of California
MISSION DISTRICT
DOGPATCH
Ocean Beach
SUNSET DISTRICT
Ortega St
21st St
23rd St
San Francisco General Hospital
25th St
NOE VALLEY
26th St
Quintara St
27th St
Rivera St
Laguna Honda Hospital And Rehabilitation Center
Santiago St
Day St
BERNAL HEIGHTS
Vicente St
Wawona St
Sloat Blvd
GLEN PARK
BAYVIEW DISTRICT
Joost Ave
Eucalyptus Dr
Silliman St
Ocean Ave
Bacon St
San Jose Ave
Dwight St
San Francisco State University
EXCELSIOR DISTRICT
Lobos St

Localization: Scan Matching





Localization and Mapping

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Trajectory Planning and Control

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Human Interaction

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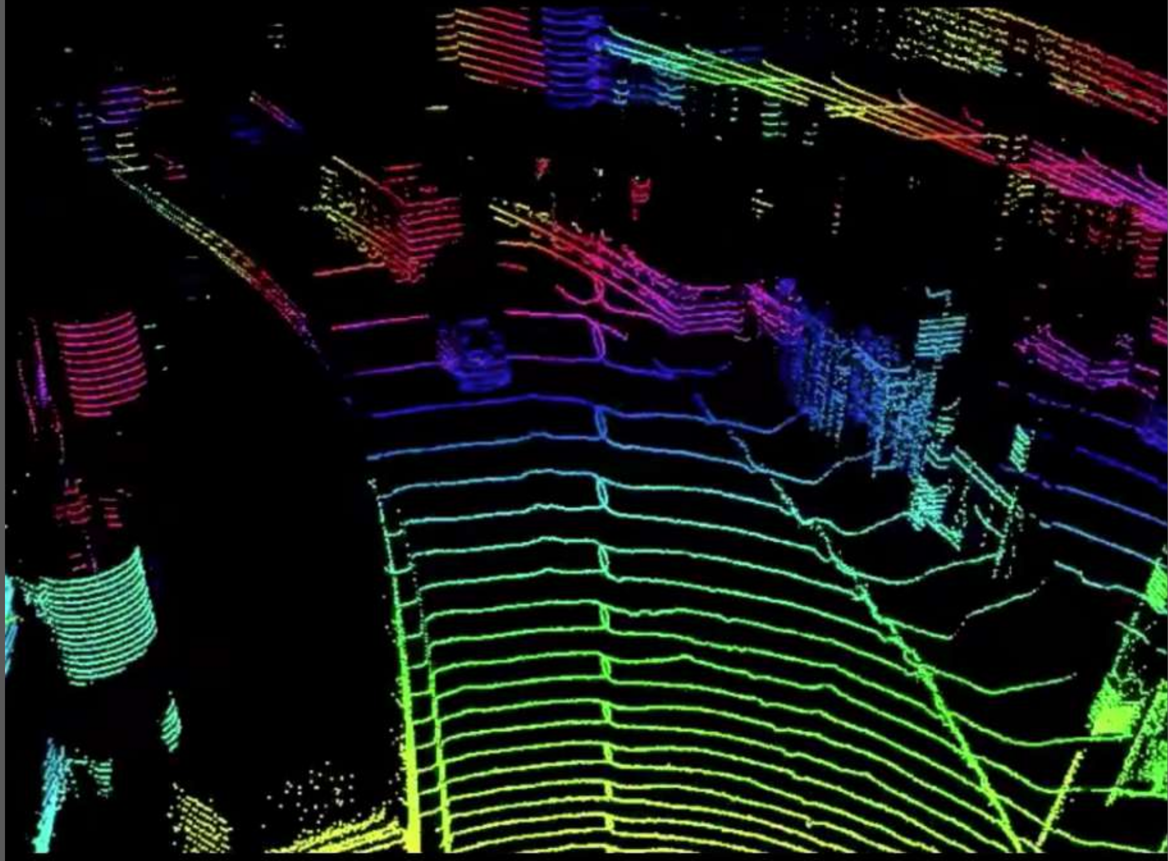
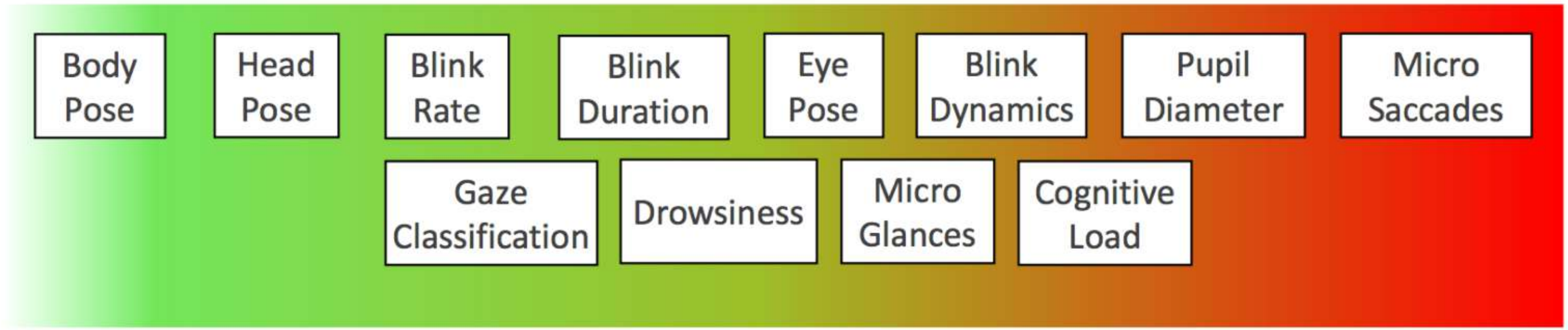
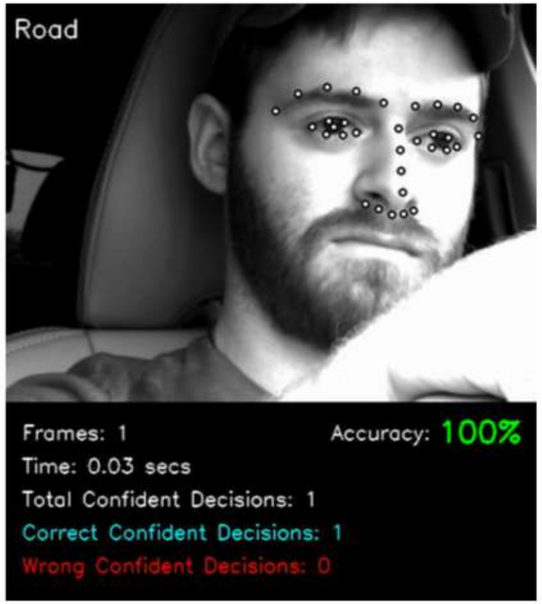
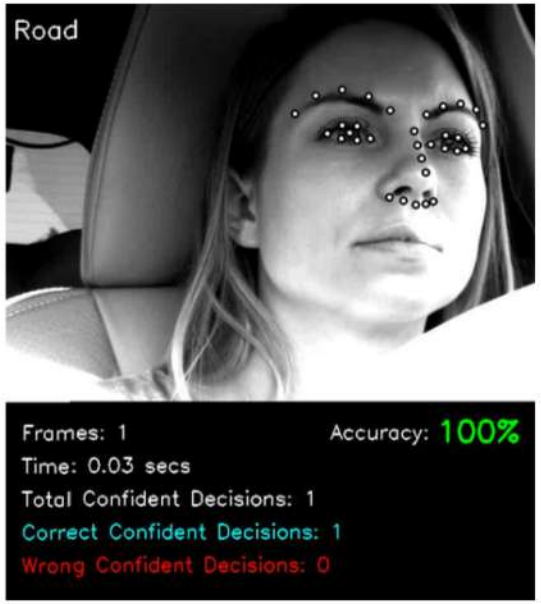


Drive State Detection:
A Multi-Resolutional View

Increasing level of detection resolution and difficulty







Localization and Mapping

Where am I ?

Scene Understanding

Where/who/what/why of
everyone/everything else ?

Trajectory Planning and Control

Where should I go next ?
How do I steer and accelerate ?

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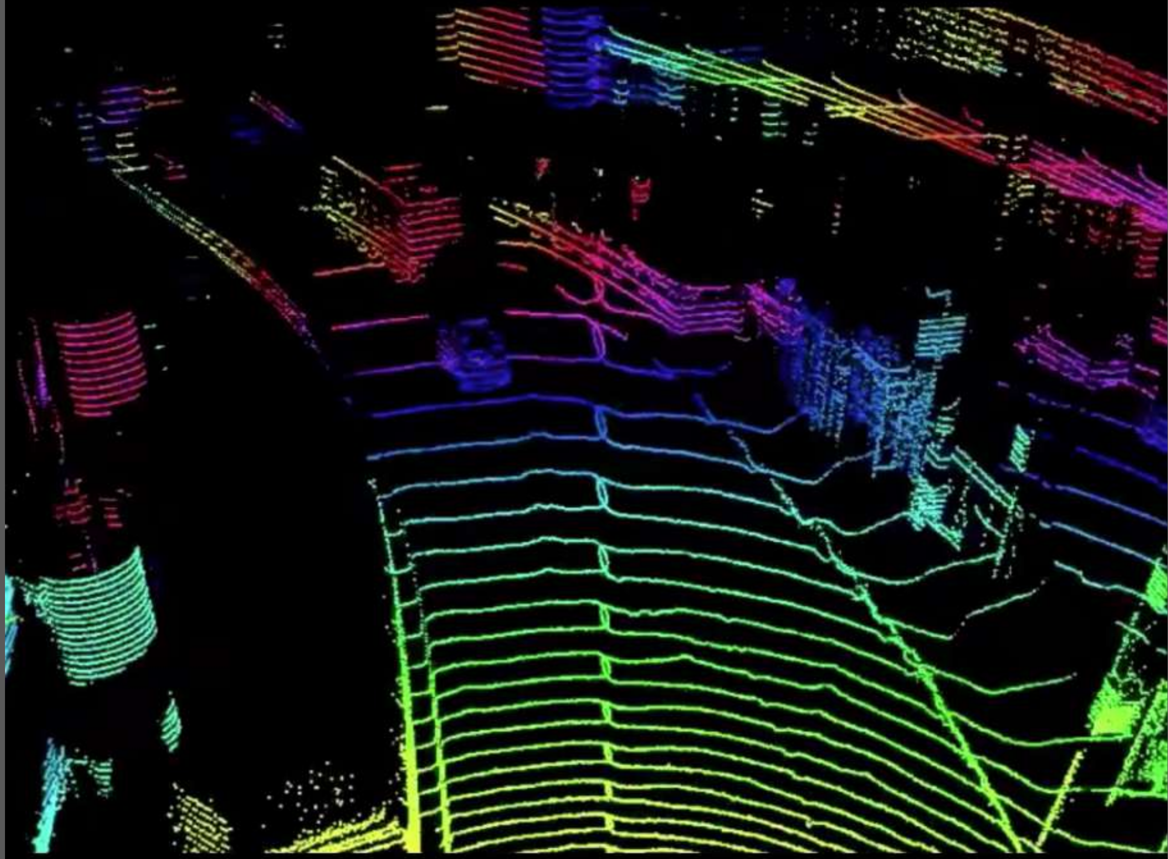


Localization and Mapping

Where am I ?

Scene Understanding

Where/who/what/why of everyone/everything else ?

Deep Neural Networks

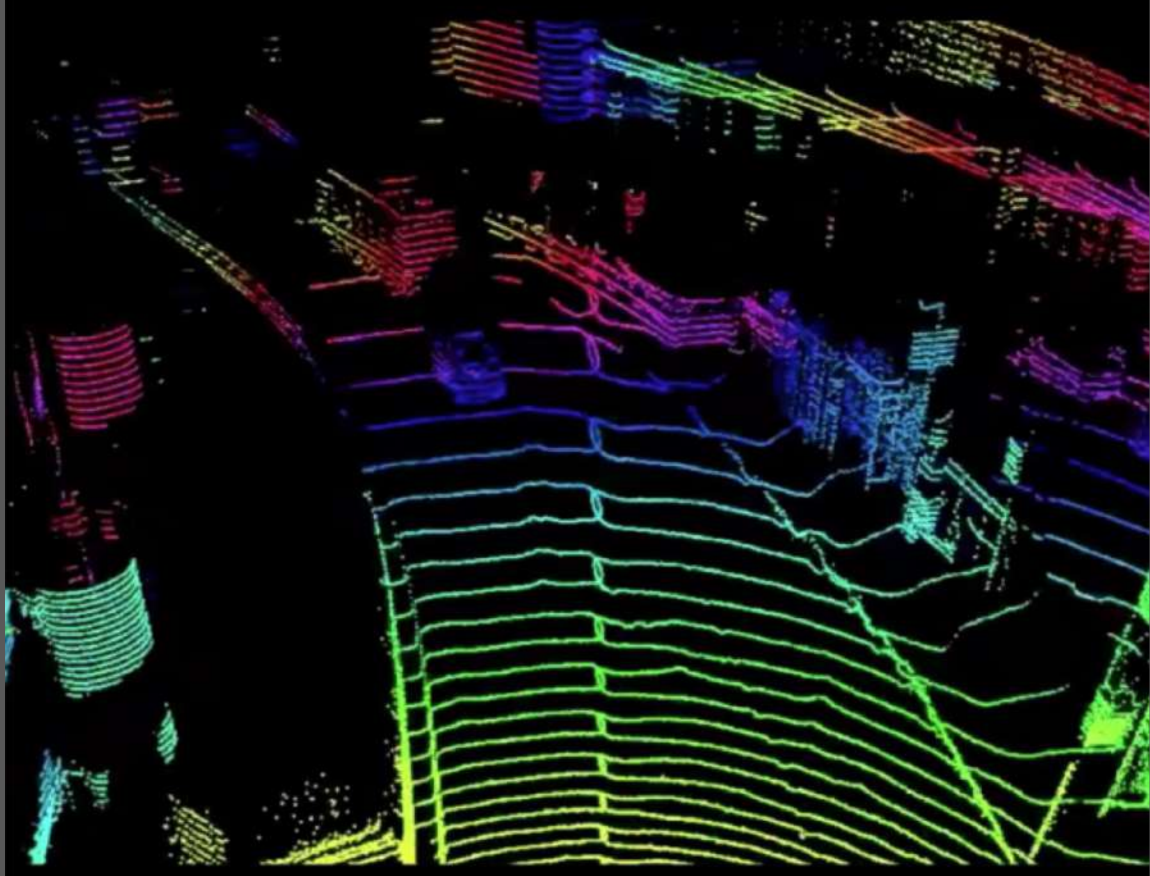
Trajectory Planning and Control

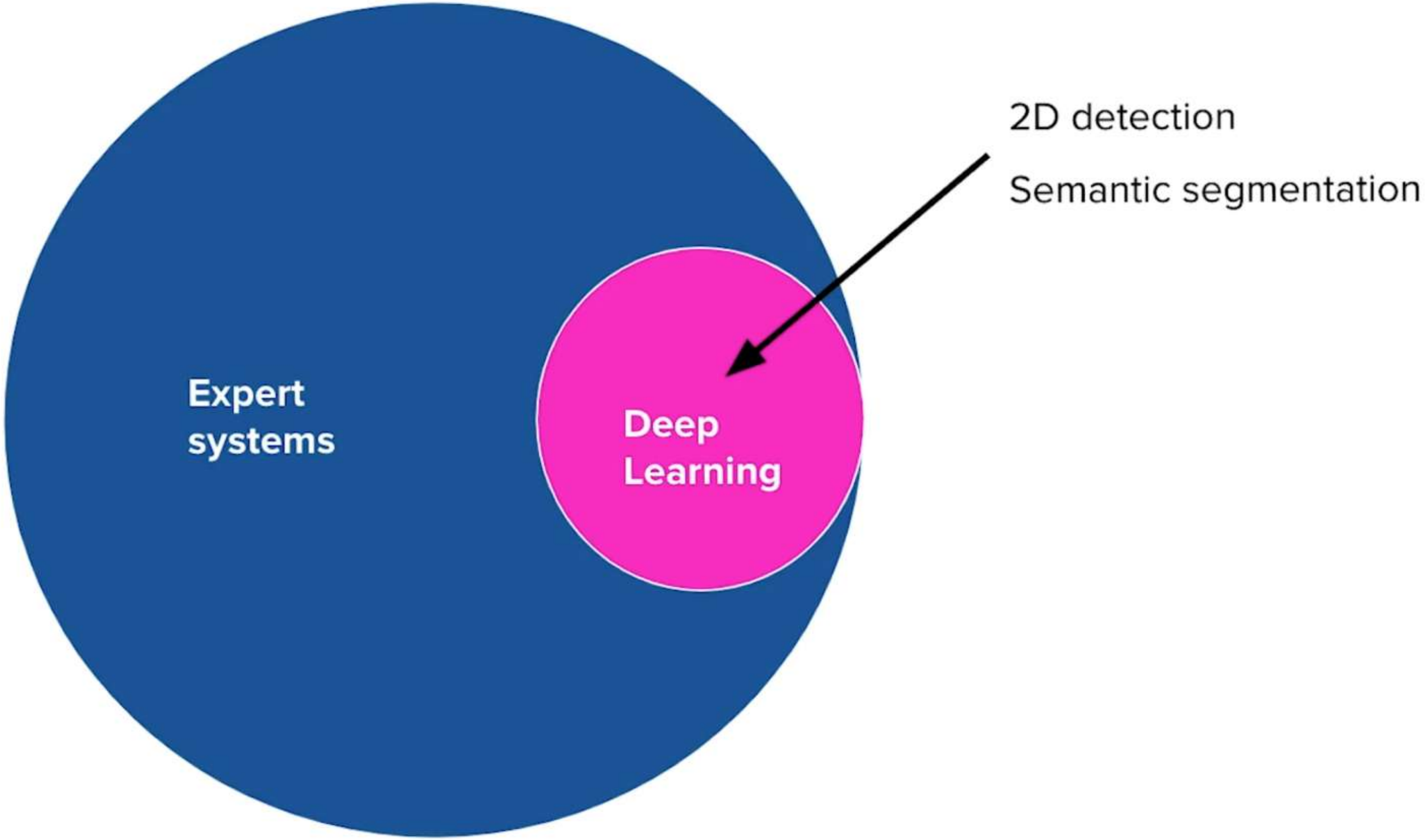
Where should I go next ?
How do I steer and accelerate ?

End-to-end learnable

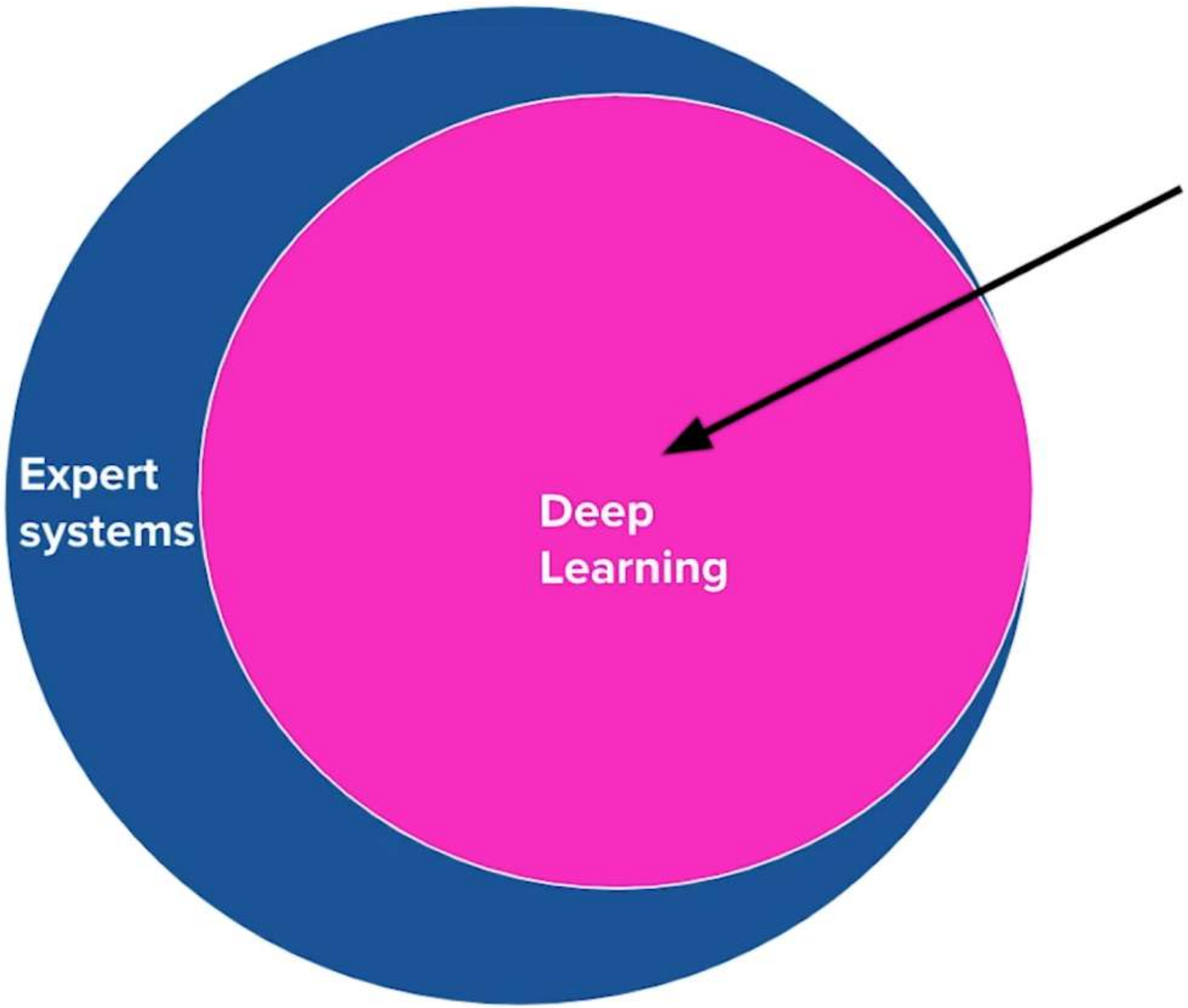
Human Interaction

How do I convey my intent to the passenger and everyone else ?





AV Perception in 2015



2D detection

Instance segmentation

Point cloud segmentation

Tracking

Intent prediction

Monocular depth estimation

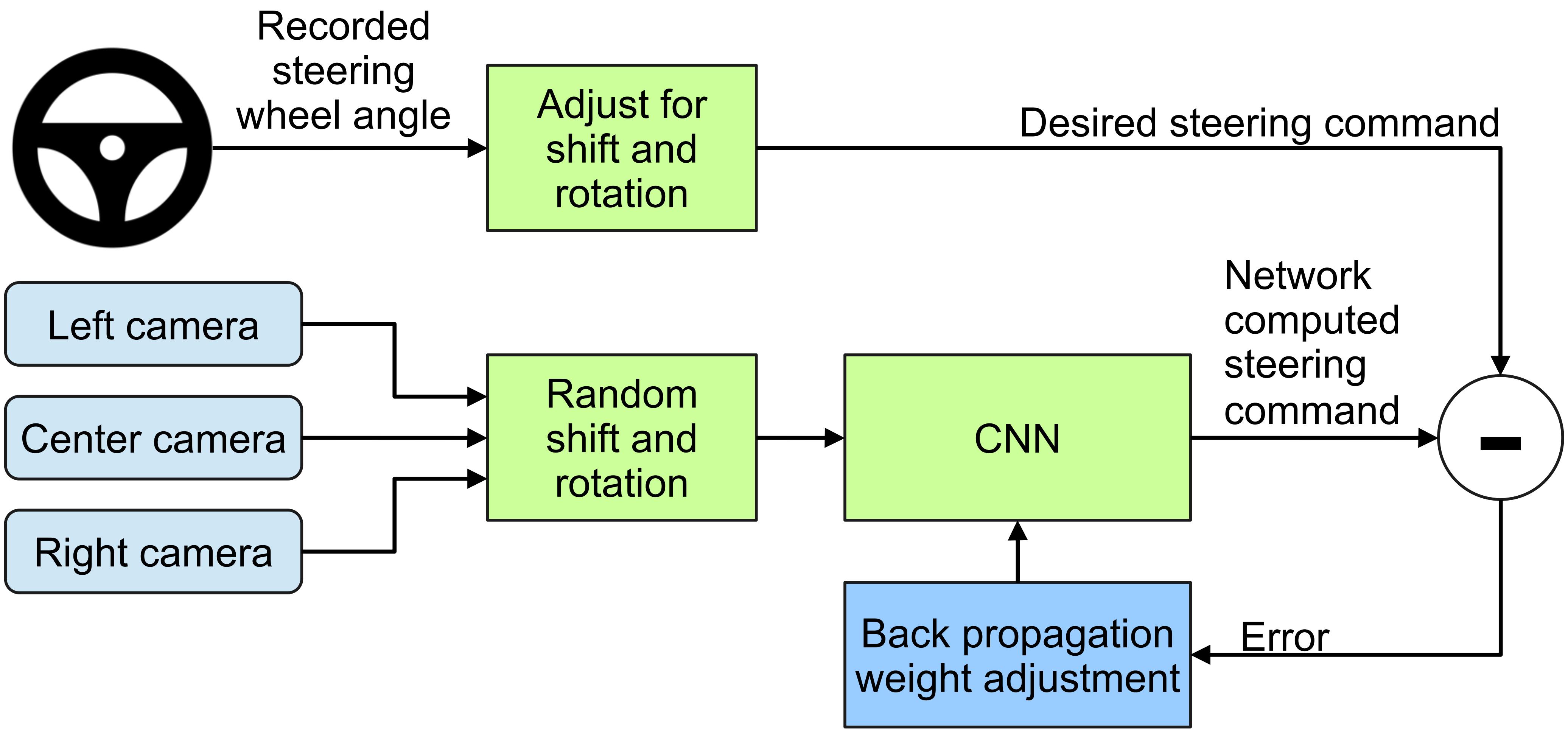
Scene flow

Anomaly detection

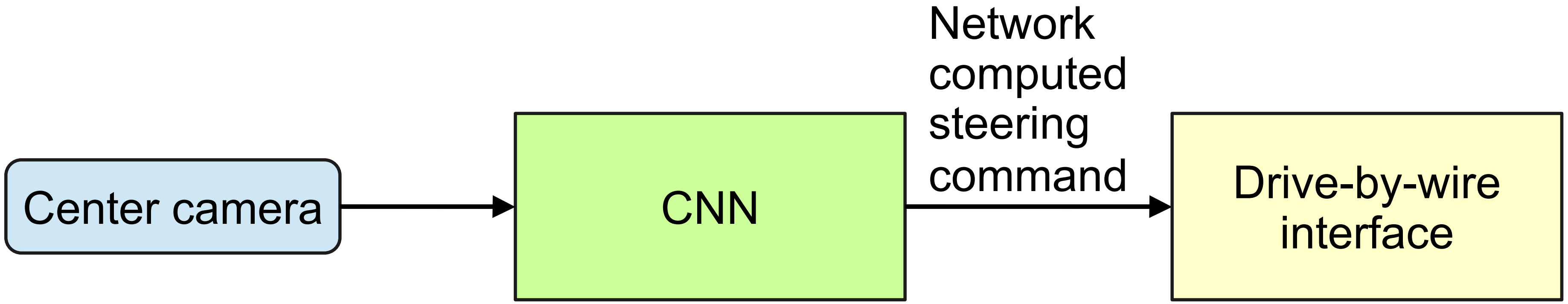
……

AV Perception today

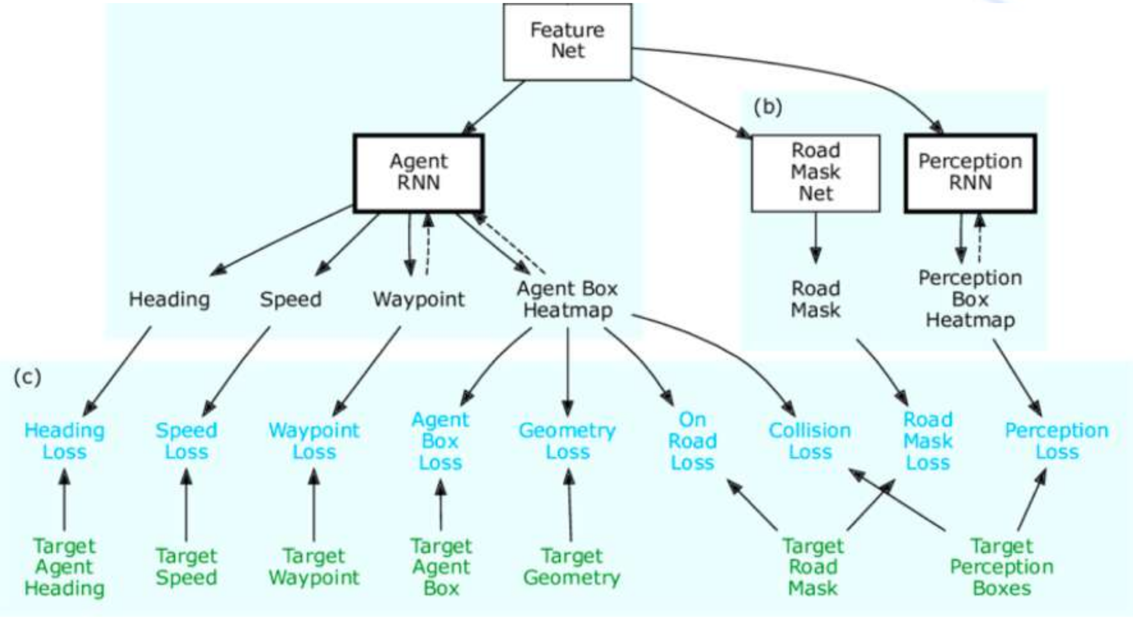
End-to-End Driving: PilotNET

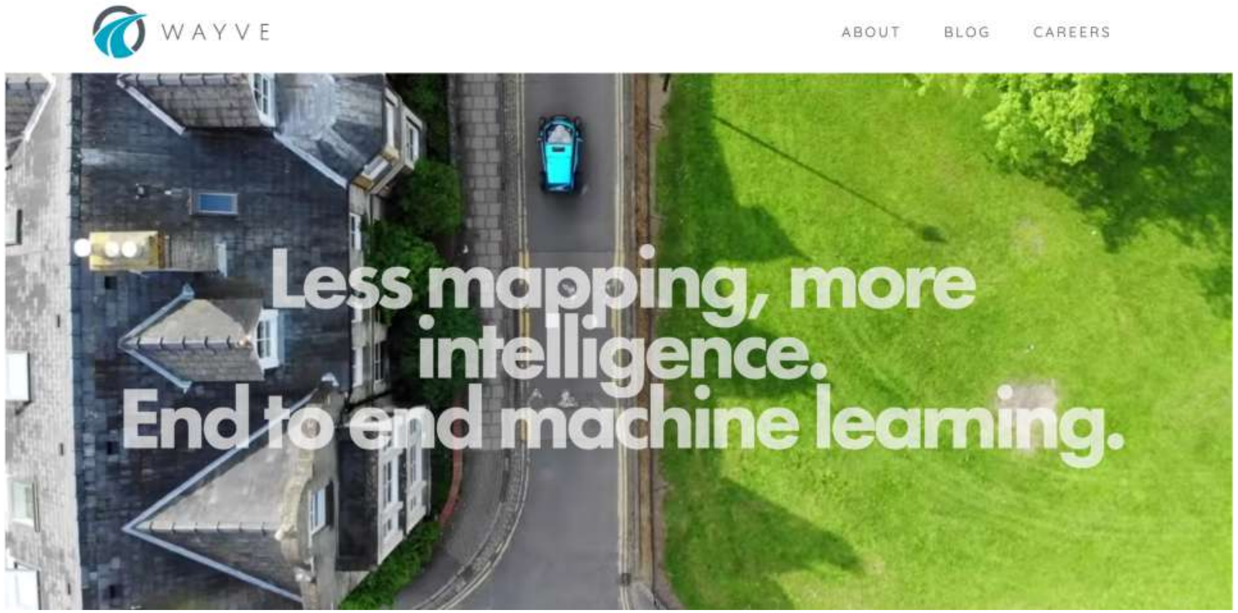


With a single front-facing camera




ChauffeurNet
A Deep Learned Driving Network


Feature Net
(b)
Agent RNN
Road Mask Net
Perception RNN
Heading
Speed
Waypoint
Agent Box Heatmap
Road Mask
Perception Box Heatmap
(c)
Heading Loss
Speed Loss
Waypoint Loss
Agent Box Loss
Geometry Loss
On Road Loss
Collision Loss
Road Mask Loss
Perception Loss
Target Agent Heading
Target Speed
Target Waypoint
Target Agent Box
Target Geometry
Target Road Mask
Target Perception Boxes


WAYVE
ABOUT
BLOG
CAREERS
Less mapping, more intelligence.
End to end machine learning.


openpilot
SPEED LIMIT 50
MAX 65
40
mph
openpilot on the comma EON

Machine intelligence is largely about training data.

When's a pedestrian not a pedestrian? When it's a decal.

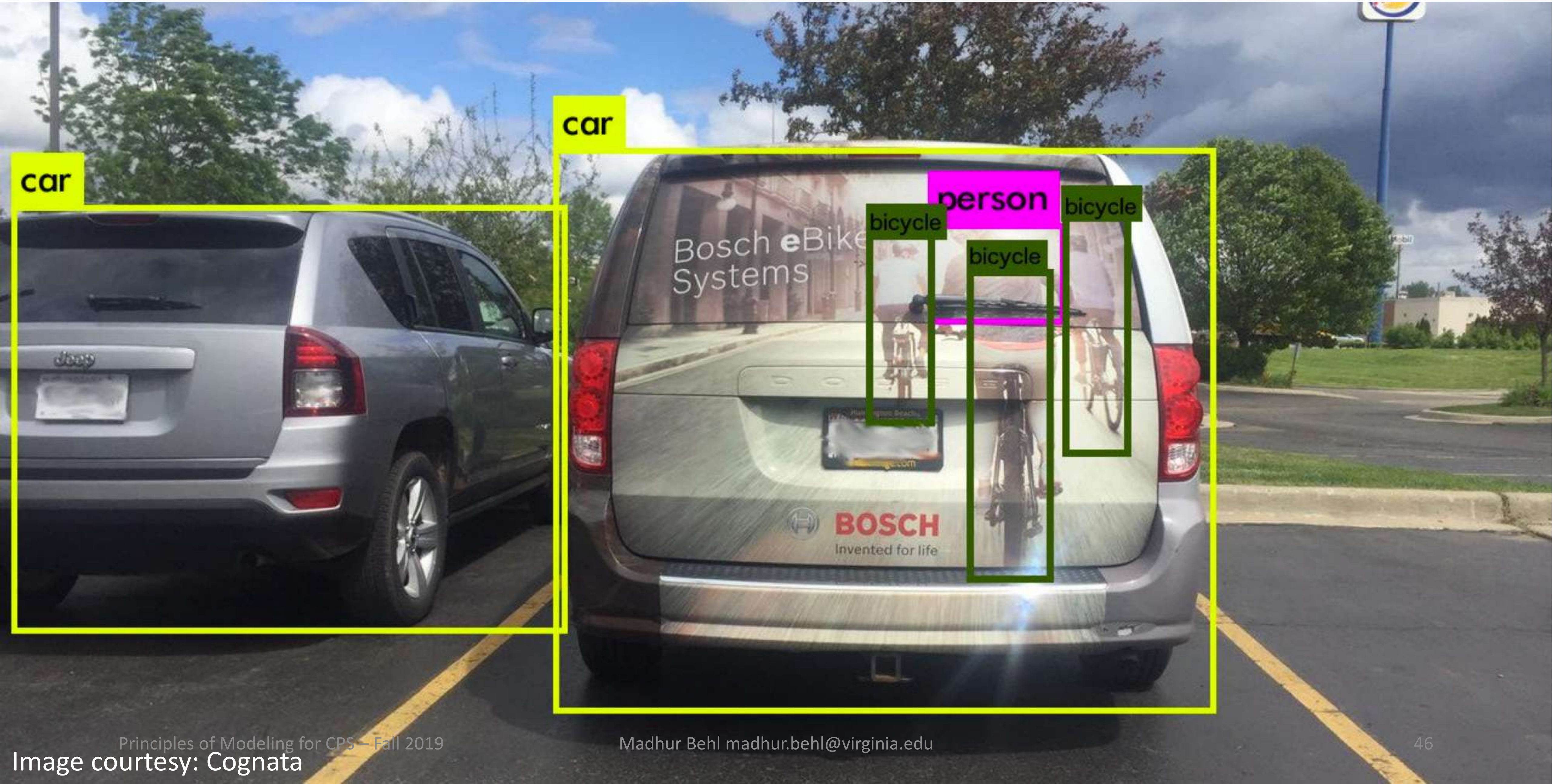


Image courtesy: Cognata

One car ? or Multiple cars ?

Ramen Noodle place or Do Not Enter Sign ?

下鳥羽城ノ越町
20m
MENU
現在地
AUDIO
今日
明日
16:10
12/5
9/3
60
40
12°C
A 77.5km
000160km
x1000
r/min
km/h


今日
明日
16:10
12/5
9/3
60
40
12℃
77.5km
000160 km
50

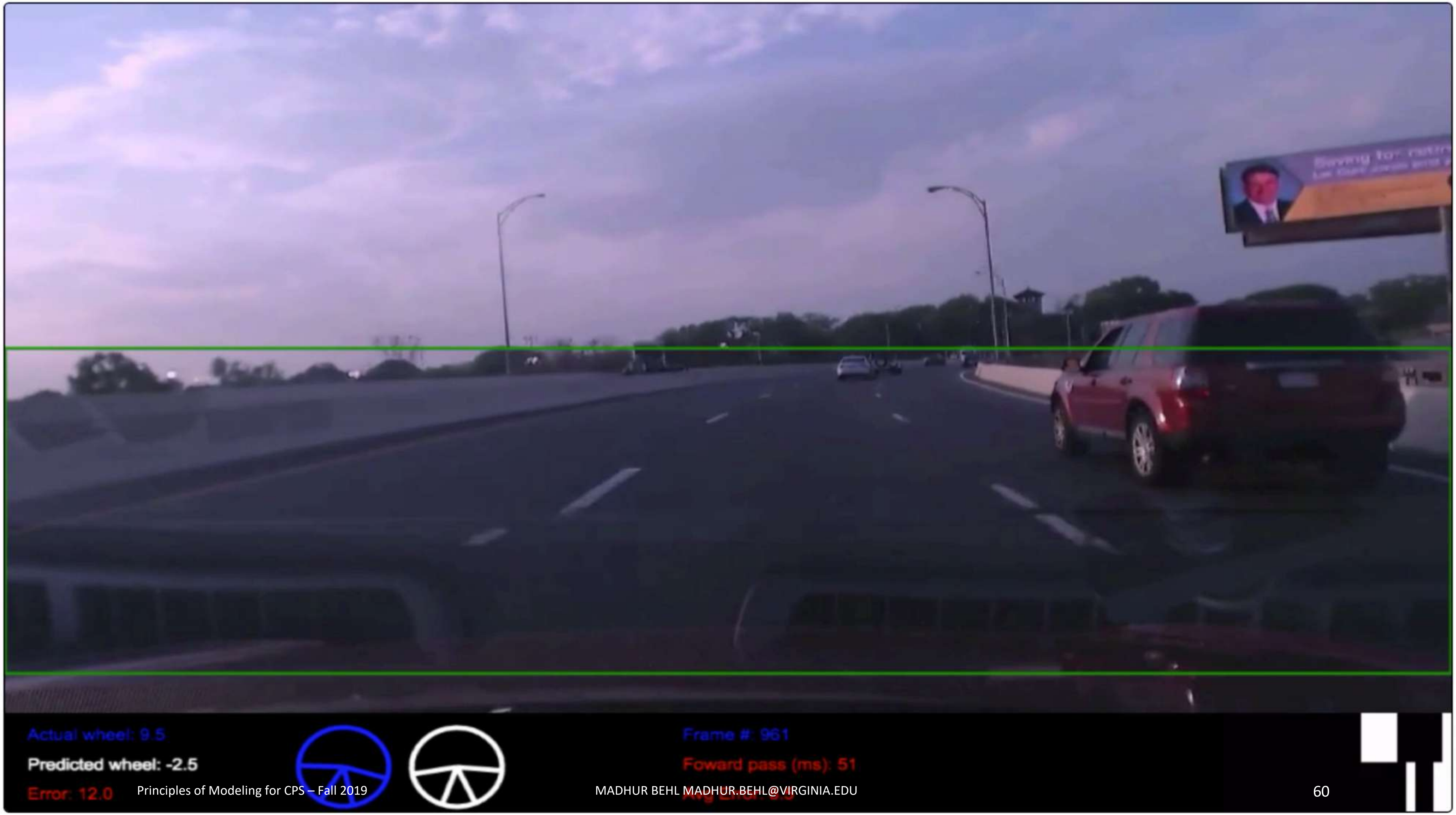
There is a bus right next to you!!


EXIT 23 B
30 BY-PASS WEST
Killingsworth St
EXIT ONLY
0MPH
20/01/2018 16:03:15


ENTERING
CITY OF
Richmond
NEXT 4 EXITS

How can we ensure that an autonomous vehicle drives safety upon encountering an unusual traffic situation ?

How can CNNs help us drive ?


Actual wheel: 9.5
Predicted wheel: -2.5
Error: 12.0
Frame #: 961
Foward pass (ms): 51

Autonomous Driving: End-to-End

End to End Learning for Self-Driving Cars

Mariusz Bojarski
NVIDIA Corporation
Holmdel, NJ 07735

Davide Del Testa
NVIDIA Corporation
Holmdel, NJ 07735

Daniel Dworakowski
NVIDIA Corporation
Holmdel, NJ 07735

Bernhard Firner
NVIDIA Corporation
Holmdel, NJ 07735

Beat Flepp
NVIDIA Corporation
Holmdel, NJ 07735

Prasoon Goyal
NVIDIA Corporation
Holmdel, NJ 07735

Lawrence D. Jackel
NVIDIA Corporation
Holmdel, NJ 07735

Mathew Monfort
NVIDIA Corporation
Holmdel, NJ 07735

Urs Muller
NVIDIA Corporation
Holmdel, NJ 07735

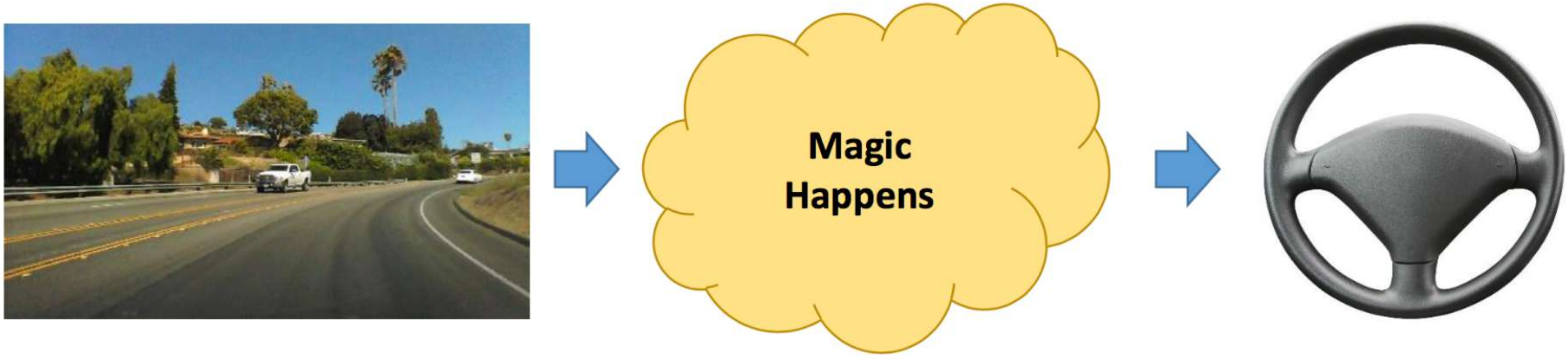
Jiakai Zhang
NVIDIA Corporation
Holmdel, NJ 07735

Xin Zhang
NVIDIA Corporation
Holmdel, NJ 07735

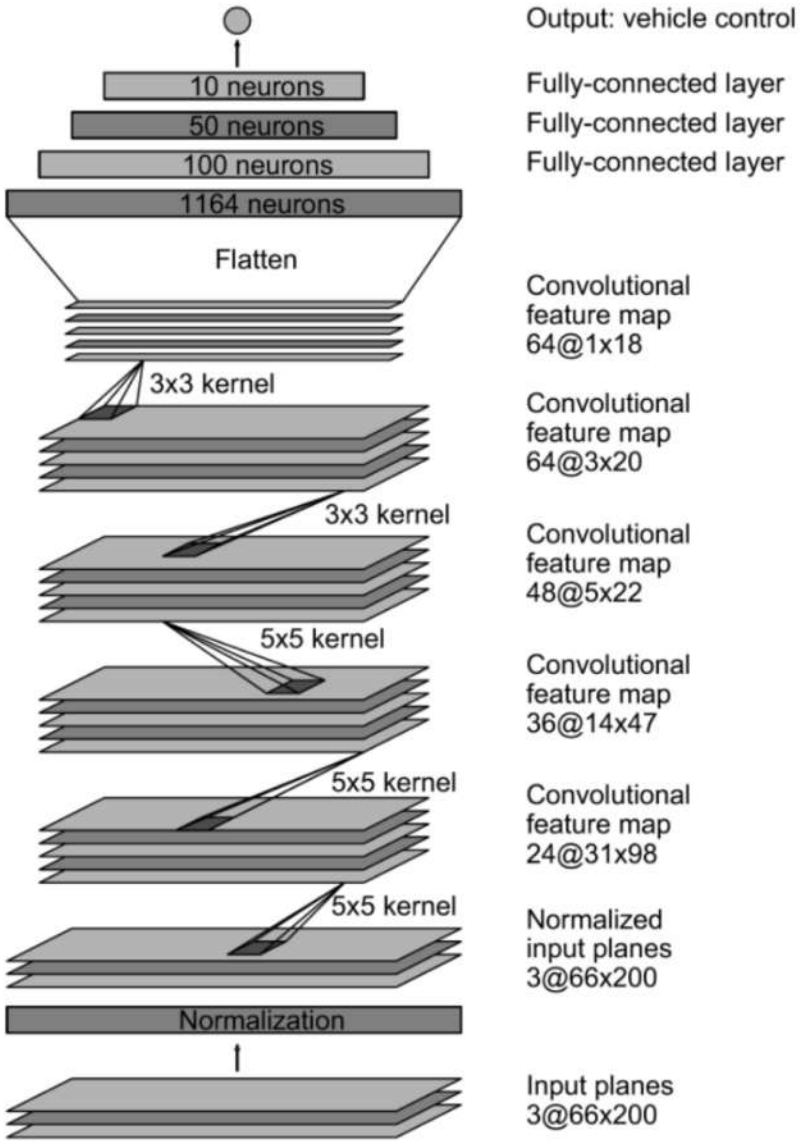
Jake Zhao
NVIDIA Corporation
Holmdel, NJ 07735

Karol Zieba
NVIDIA Corporation
Holmdel, NJ 07735

Autonomous Driving: End-to-End

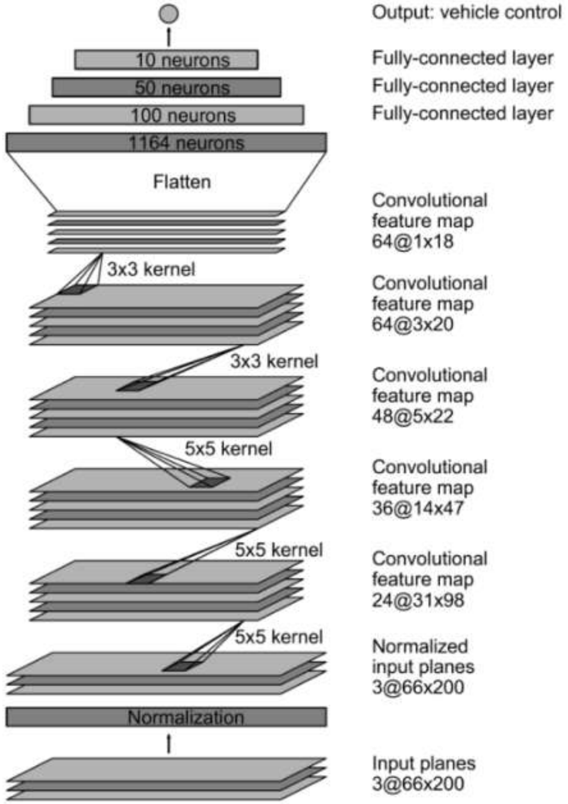


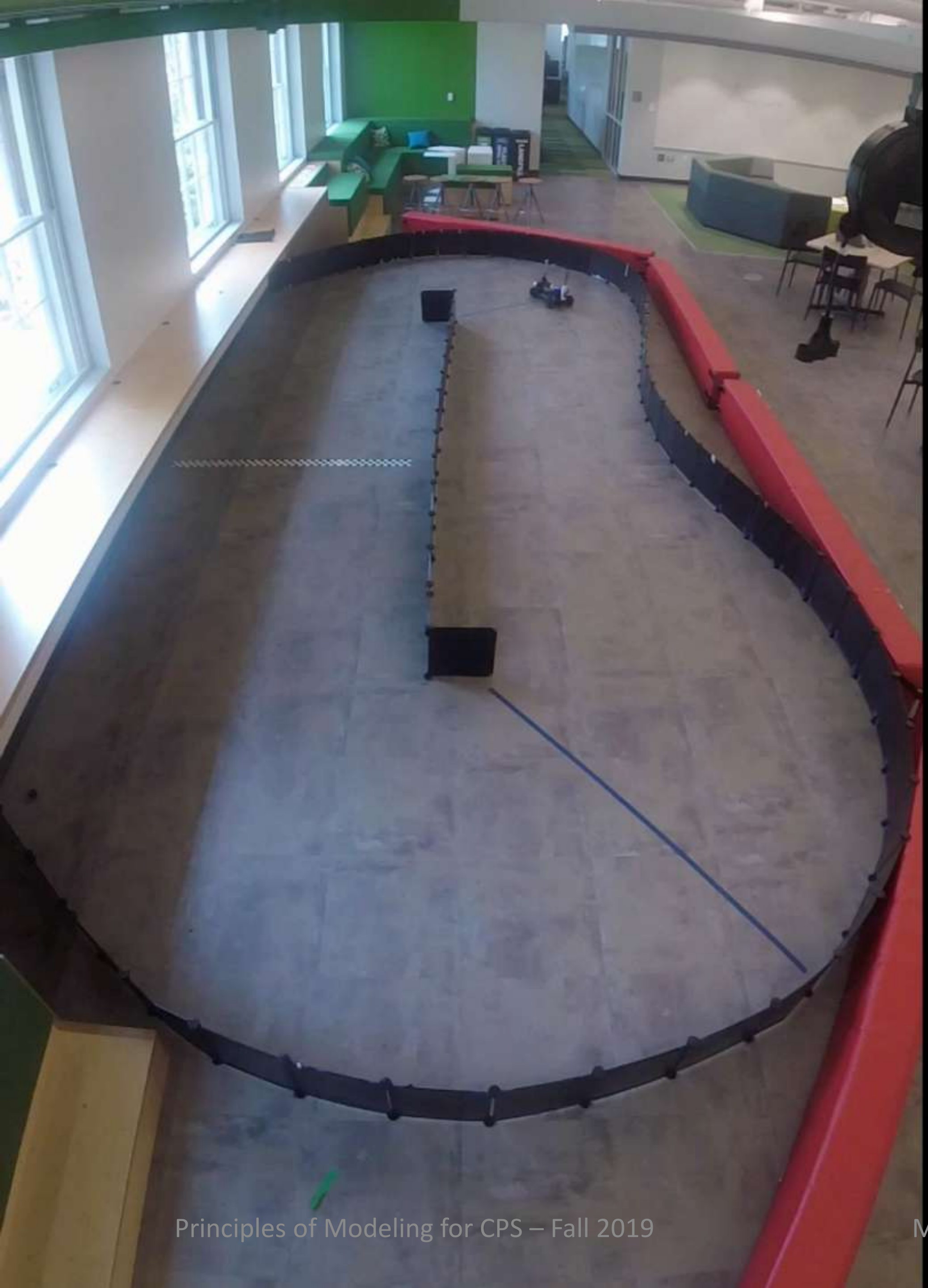
Autonomous Driving: End-to-End



- 9 layers
  - 1 normalization layer
  - 5 convolutional layers
  - 3 fully connected layers
- 27 million connections
- 250 thousand parameters

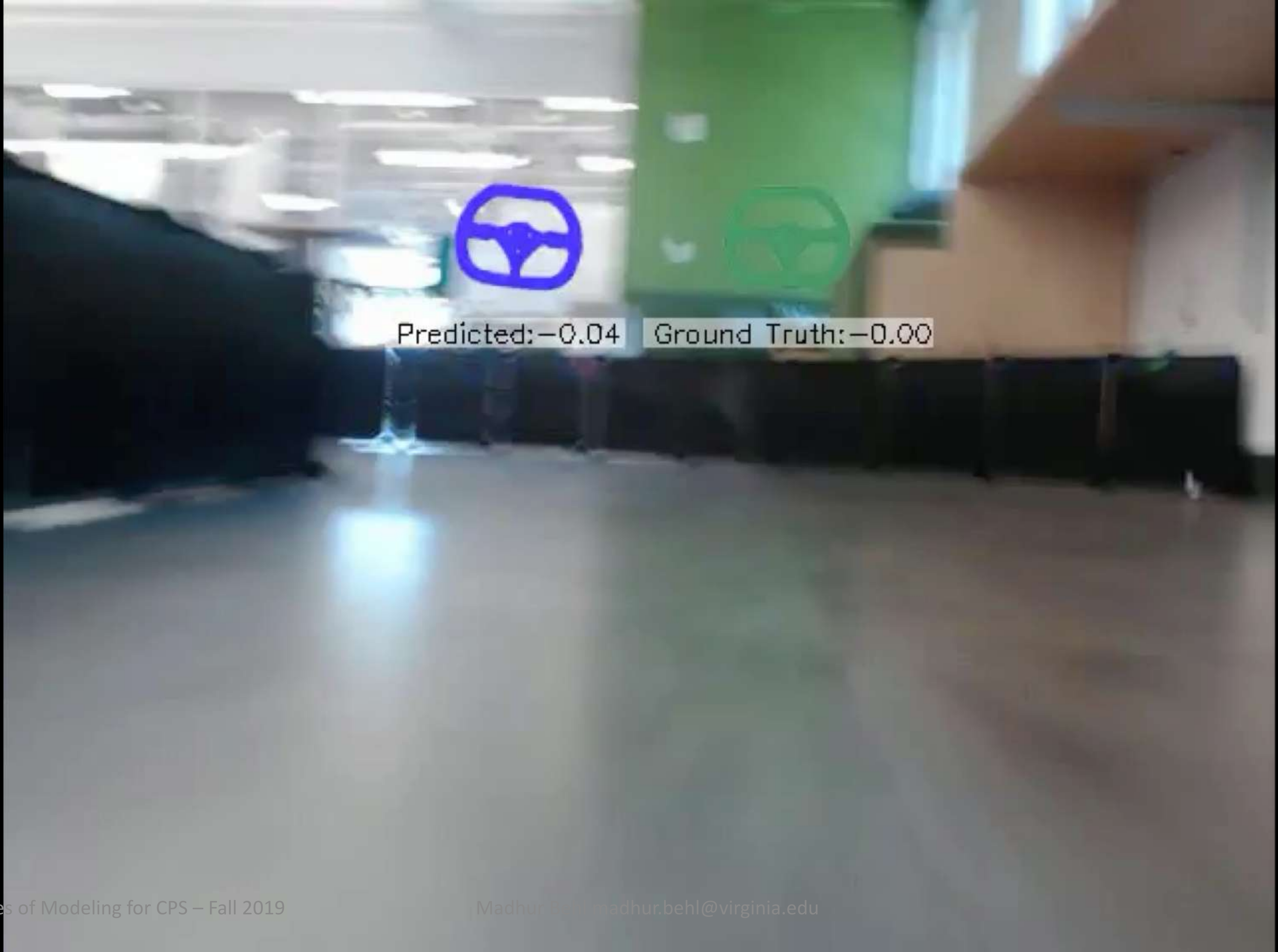
Autonomous Driving: End-to-End





F1/10 FPV Driving


CAUTION

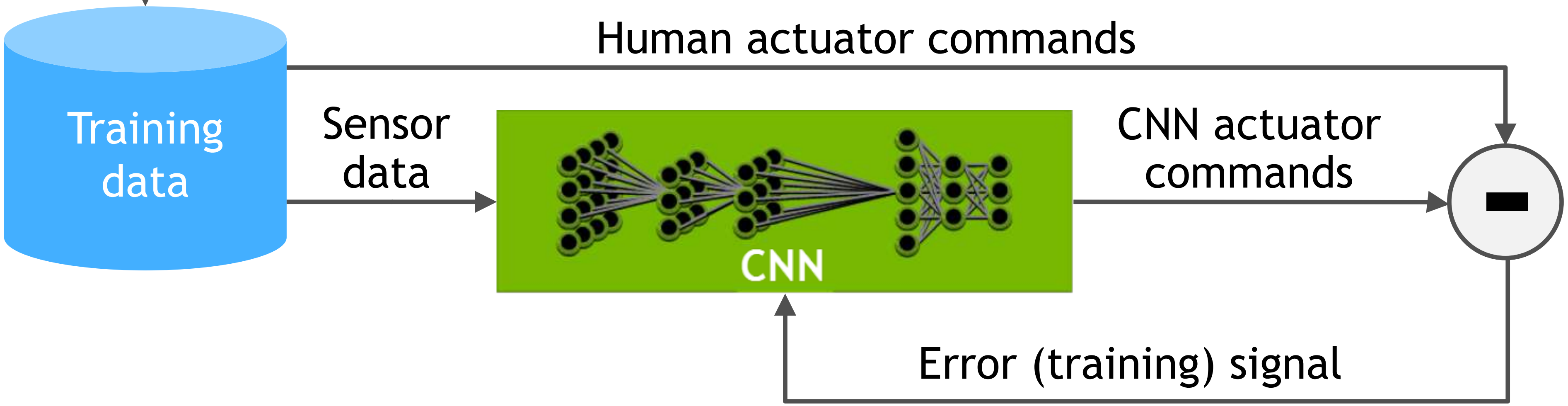

Predicted:-0.04
Ground Truth:-0.00

THE BASIC IDEA

Learn from human drivers

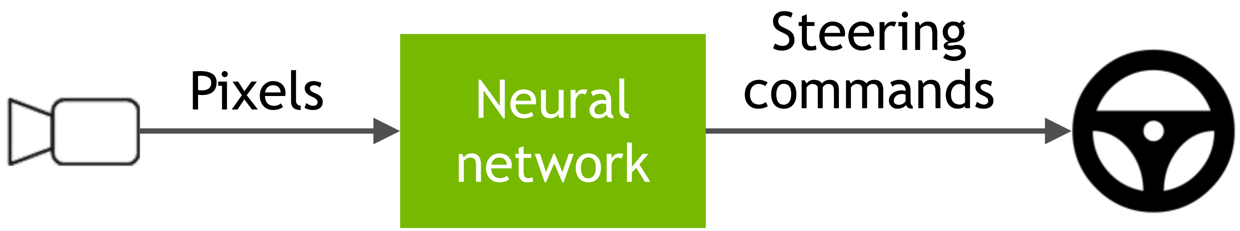
Record data from lots of humans driving their cars:

- ➤ Sensor data
- ➤ Actuator data



EARLY EXAMPLES

Of end-to-end learning



ALVINN, CMU, late 80es
(Pomerleau et Al.)

Lane following with a small 2-layer fully connected network and low-resolution video input

30x32 pixel

DAVE, Net-Scale/NYU, 2004
(LeCun et Al.)

Off-road obstacle avoidance using a convolutional network (ConvNet)

149x48 pixel

TRAINING EXAMPLES

Label: turn right

Label: go straight

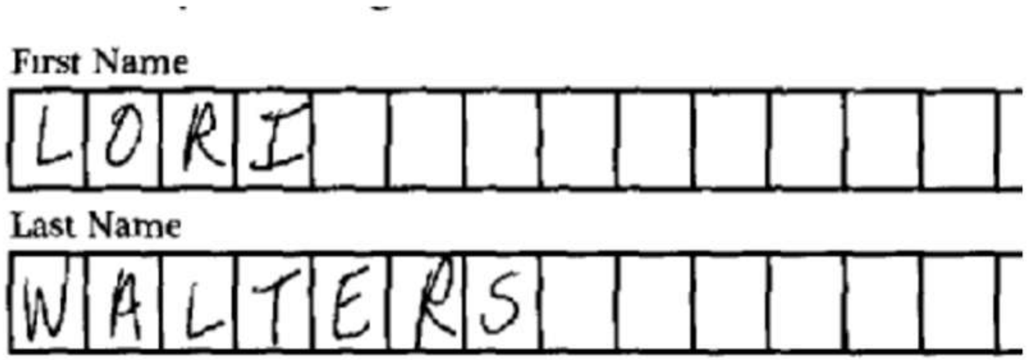
Label: turn right

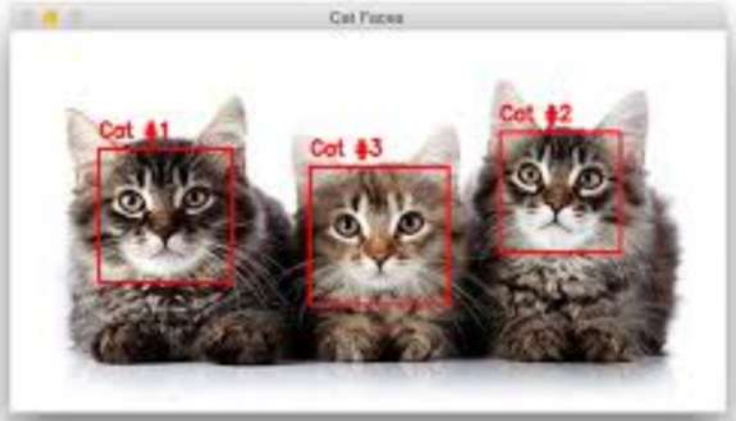
Label: turn left

225K images

Machine Learning

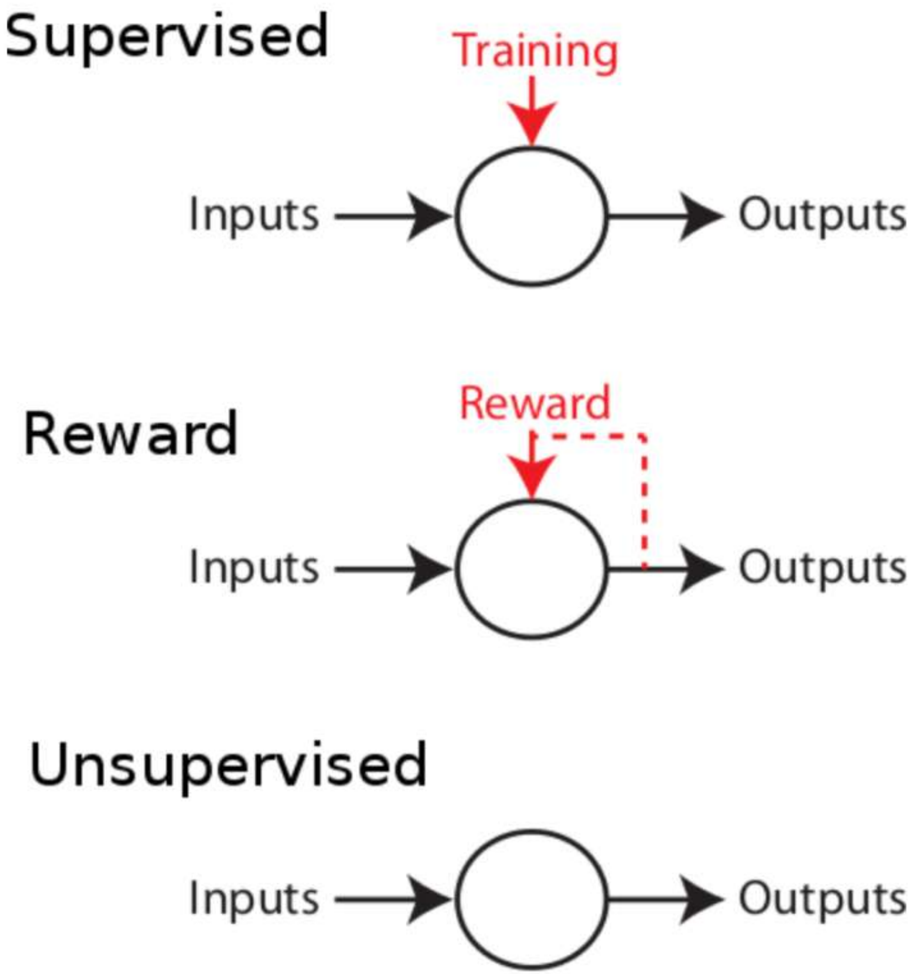
- Machine Learning is the ability to teach a computer without explicitly programming it
- Examples are used to train computers to perform tasks that would be difficult to program



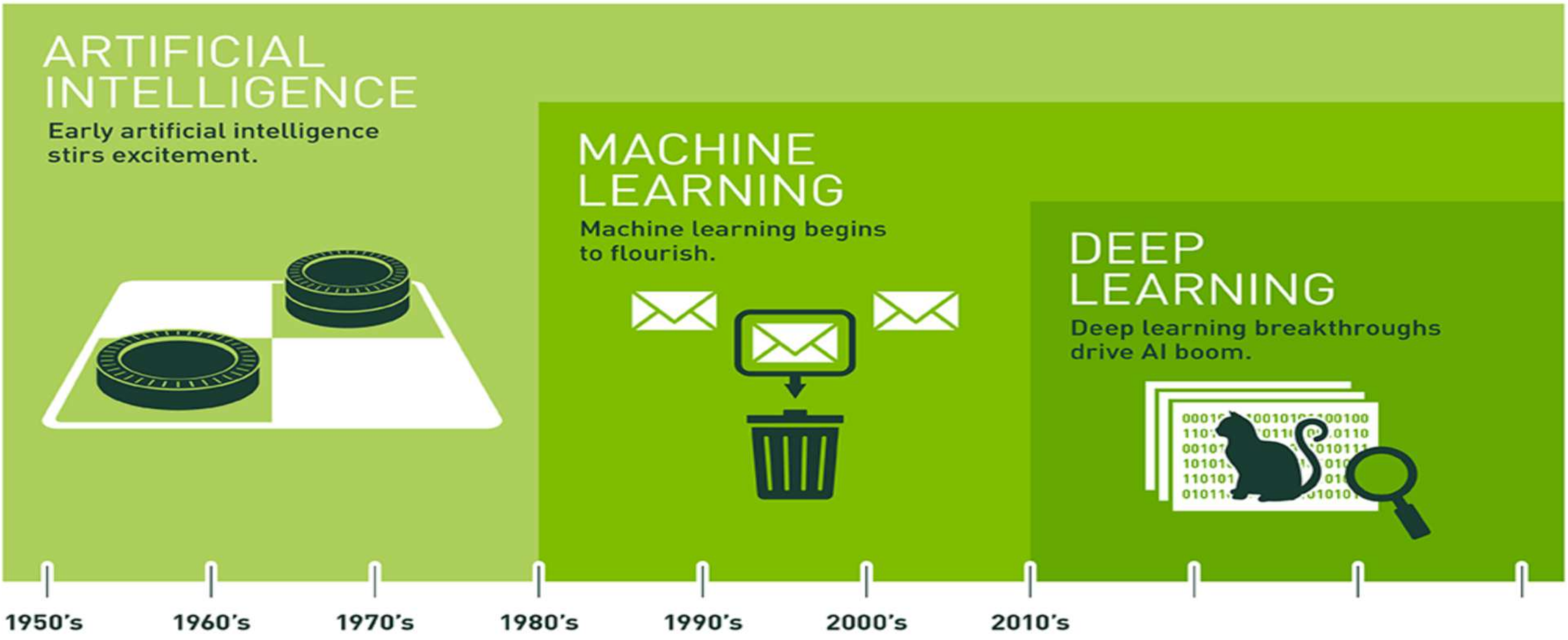


Types of machine Learning

- Supervised Learning
  - Training data is labeled
  - Goal is correctly label new data
- Reinforcement Learning
  - Training data is unlabeled
  - System receives feedback for its actions
  - Goal is to perform better actions
- Unsupervised Learning
  - Training data is unlabeled
  - Goal is to categorize the observations



Capability of Machine to imitate intelligent behavior



Supervised learning setup

Inputs (AKA features) - real-valued vectors of data

e.g. Image pixels, audio spectrograms, character sequences

Outputs (AKA labels) - real-valued or categorical “truth” vectors

e.g. class labels for images, audio transcription, sentiment

Training data - many samples of input-output pairs

Score function (AKA model)

A function that predicts the output given an input

Example: linear regression

Data

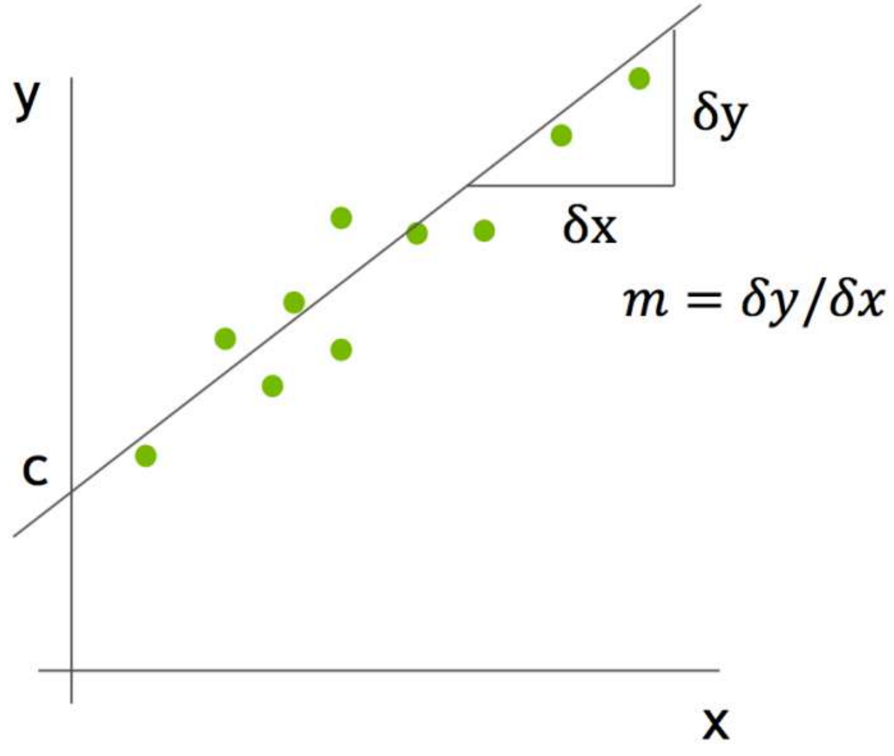
$$y_i = mx_i + c$$

Predicted output

Slope

Intercept

Together, m and c are called the **model parameters**



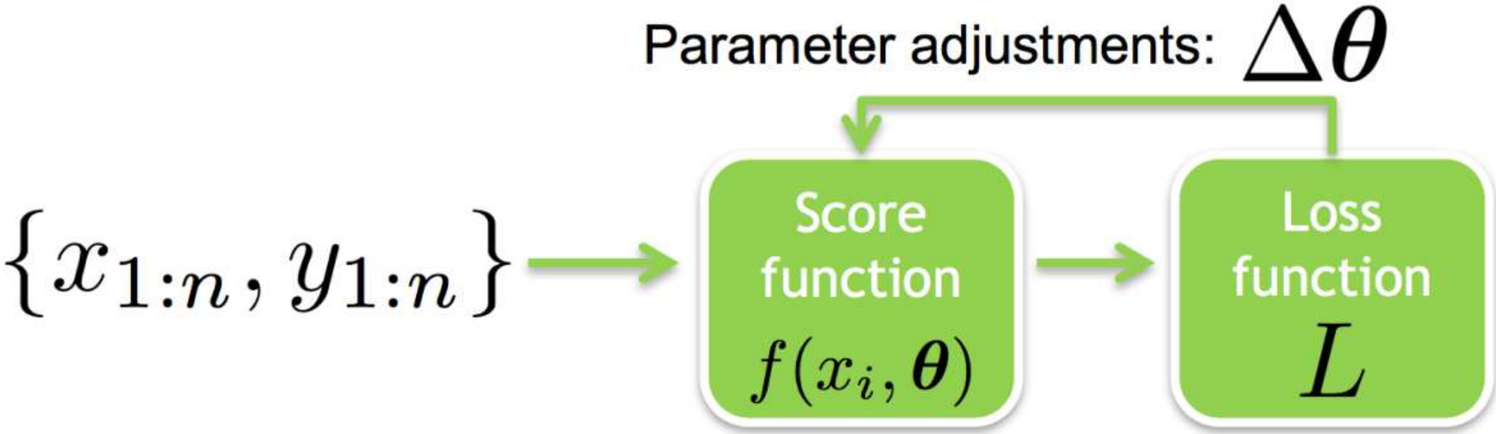
Supervised learning

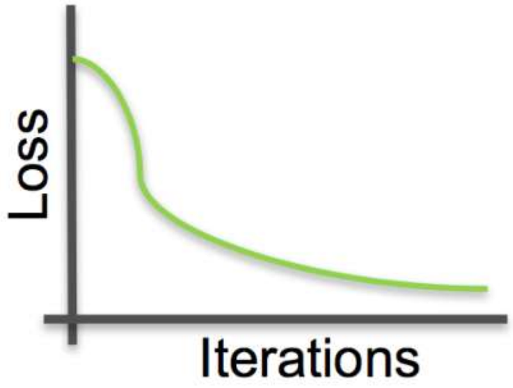
How do we do this?

Repeatedly feed training data into a learning algorithm

Iteratively modify the model parameters to optimize (e.g. minimize) the loss function

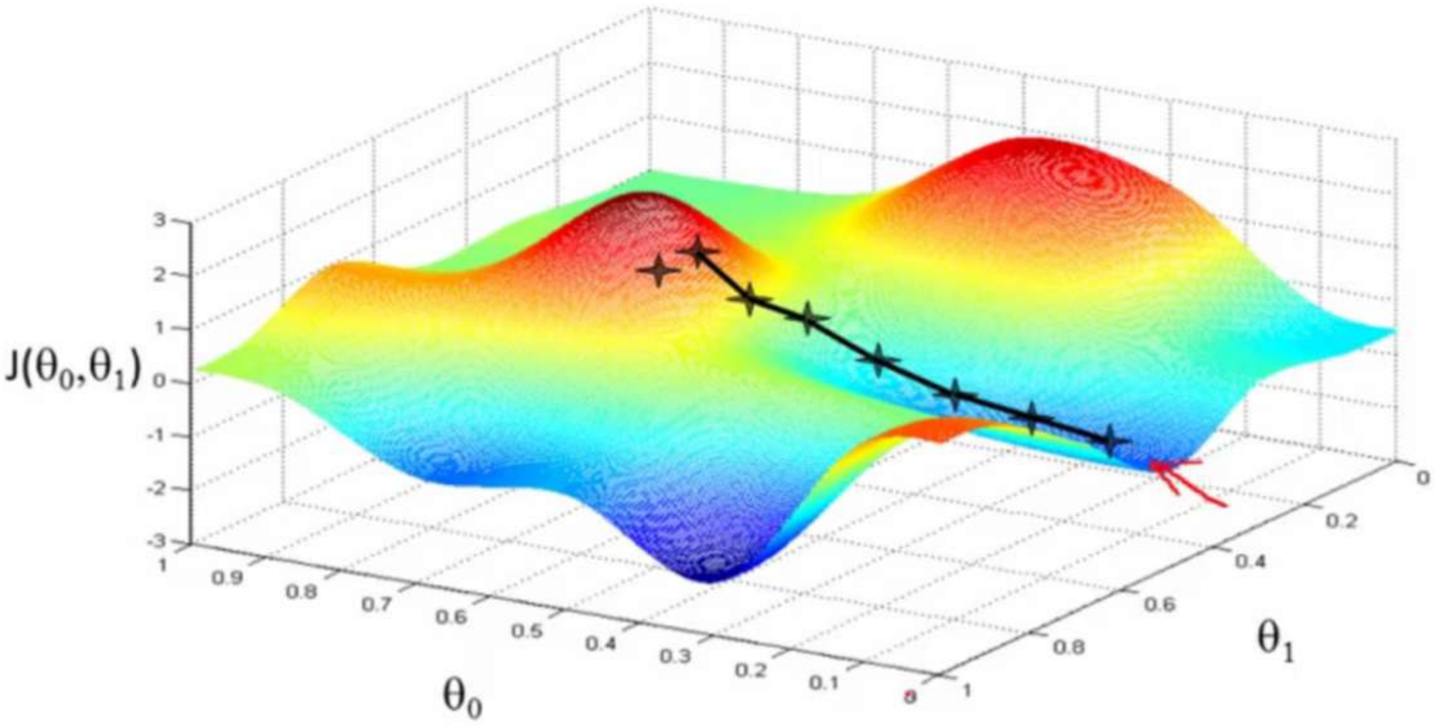
Repeat until the model is “good enough”

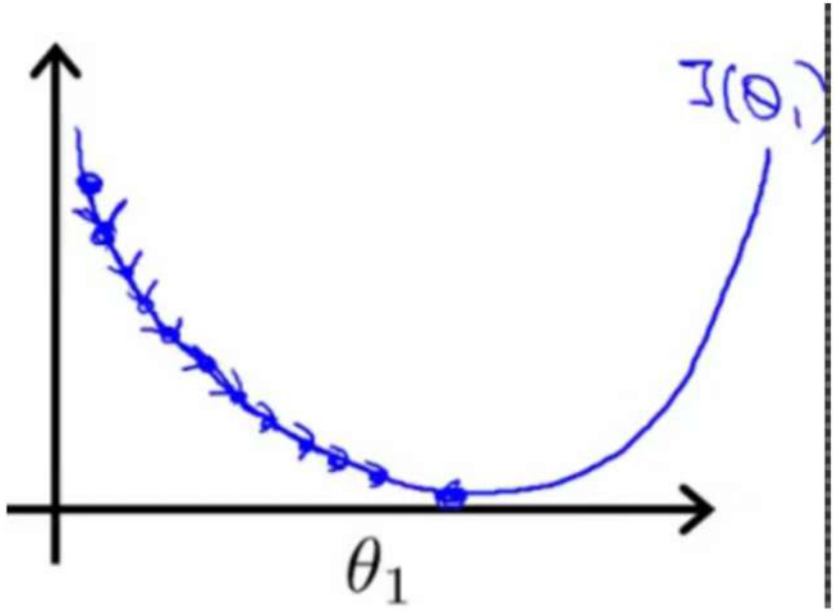




Gradient descent

Finding the Optimal Parameters for our Hypothesis

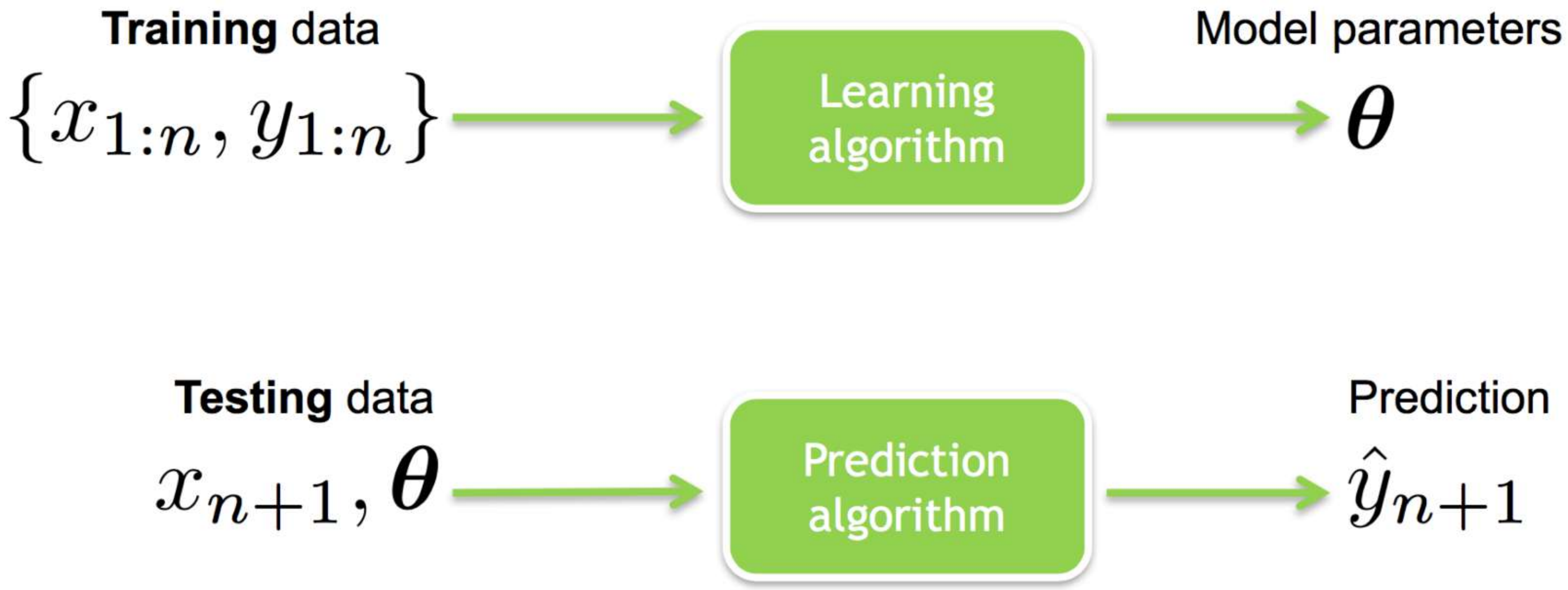




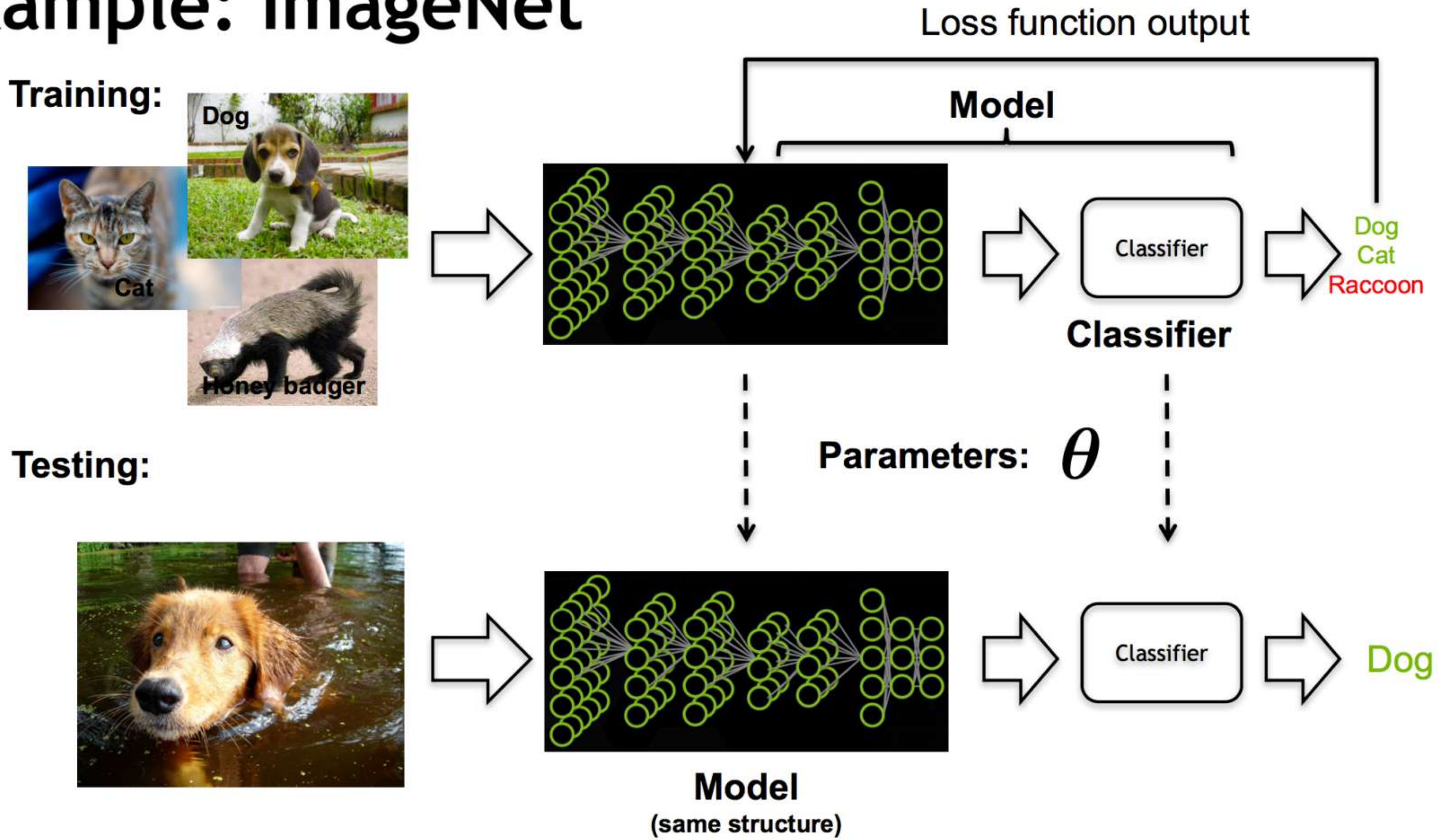
Supervised learning

Why do we do this?

Given the **model** we can take previously unseen inputs and predict the corresponding output. We call this **testing** or **deployment.**



Example: ImageNet



Deep Learning success

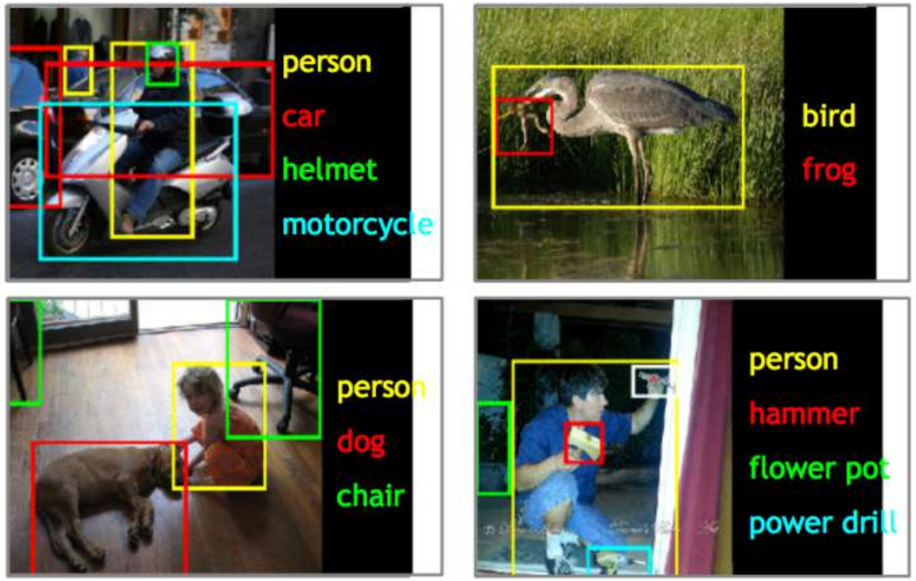
Object classification and localization in images

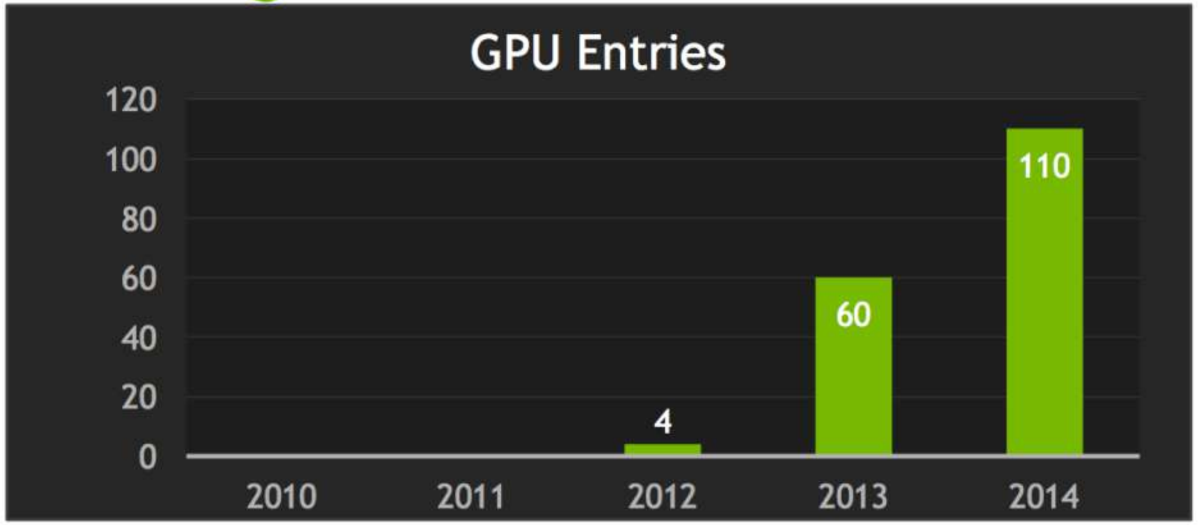
Image Recognition Challenge

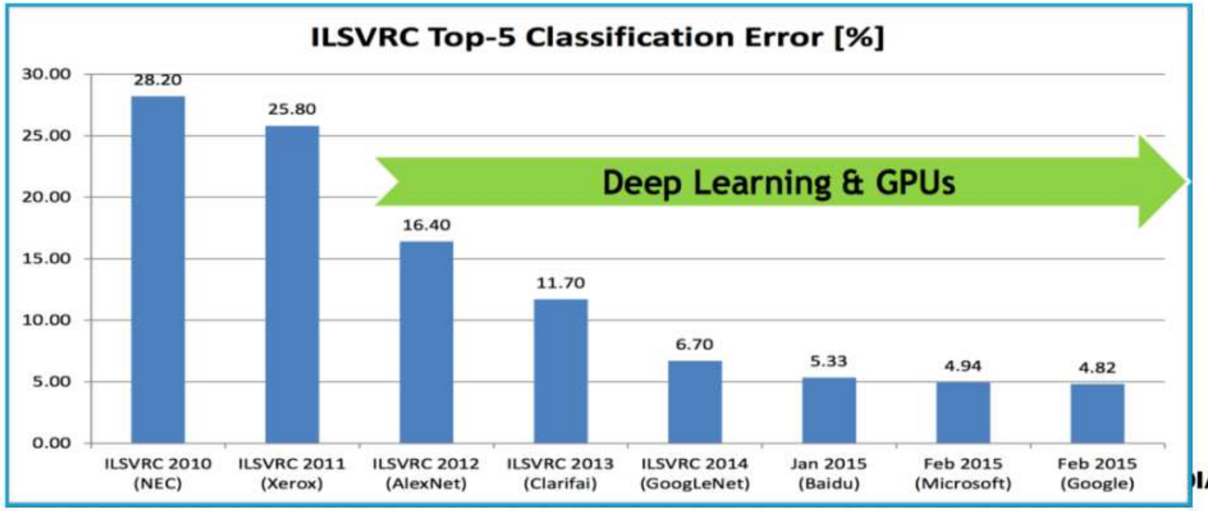
1.2M training images • 1000 object categories

Hosted by

IMAGENET







Training problems

Two major problems

Underfitting: model is bad at it's objective for all data

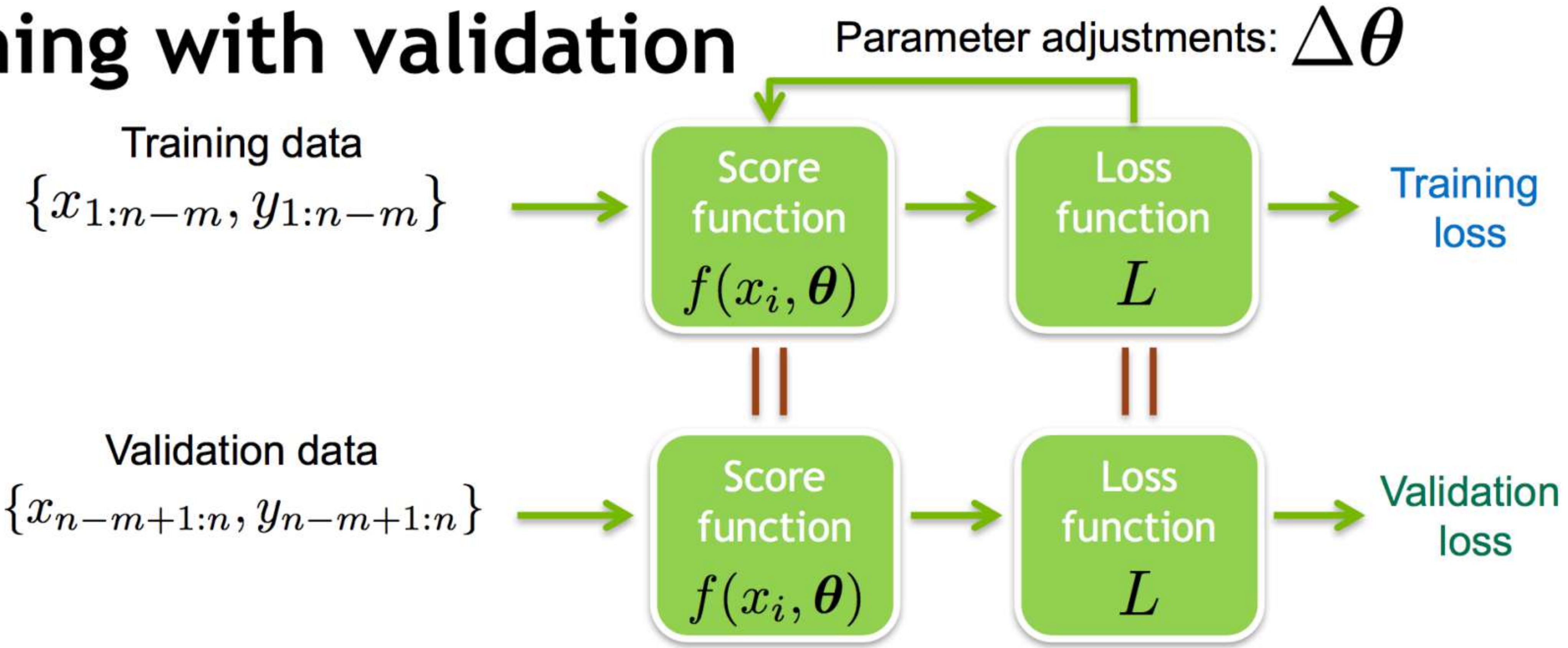
Overfitting: model is really good at the objective for the training data but bad on the testing data

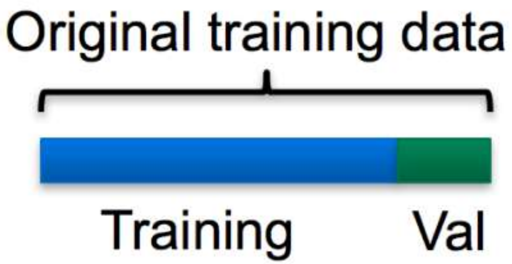
First line of defense:

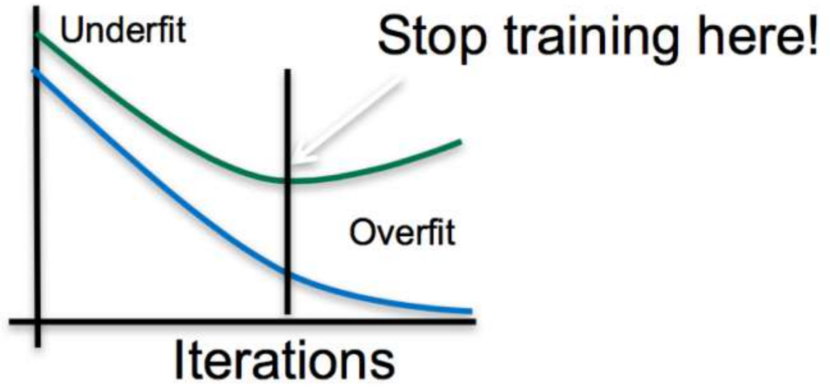
Break off a **validation** dataset from the training data, e.g. 25%

Use it during training to check model performance on unseen data

Training with validation







Deep Learning

Learning Representation/Features

The traditional model of pattern recognition (since the late 50's)

Fixed/engineered features (or fixed kernel) + trainable classifier

→ Hand-crafted Feature Extractor → "Simple" Trainable Classifier →

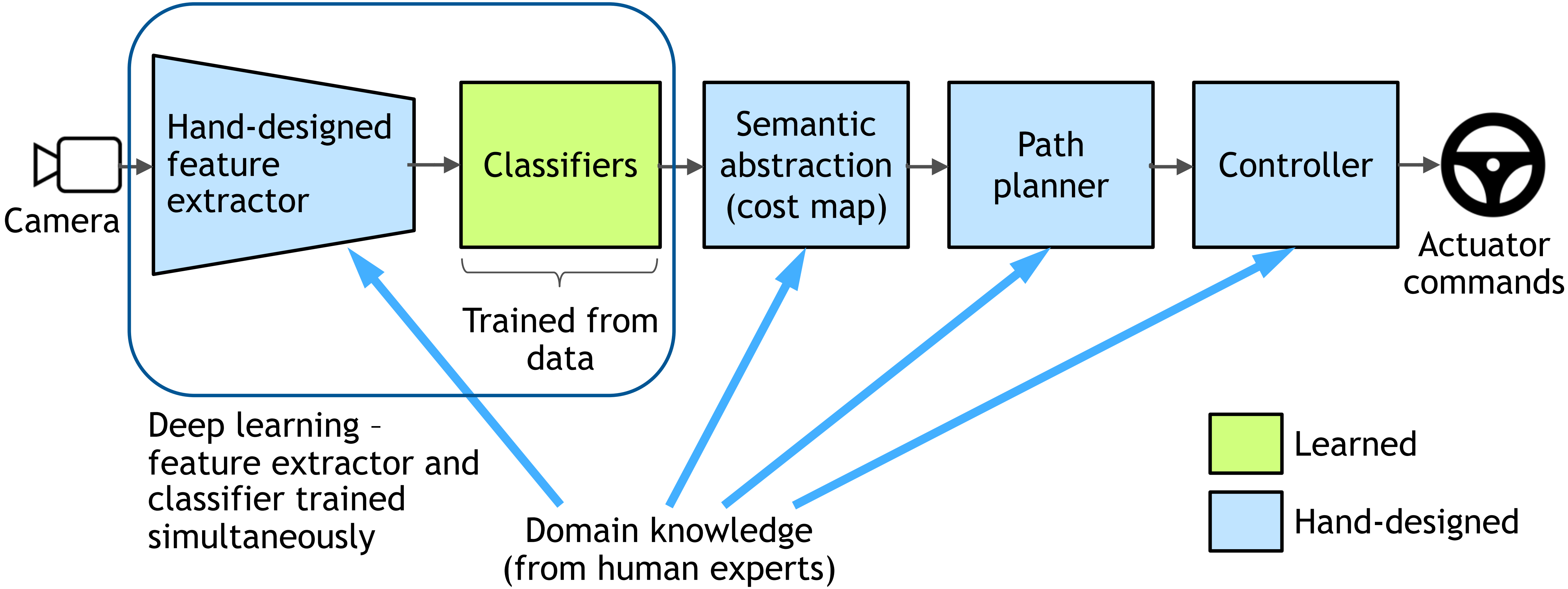
End-to-end learning / Feature learning / Deep learning

Trainable features (or kernel) + trainable classifier

→ Trainable Feature Extractor → Trainable Classifier →

TRADITIONAL DECOMPOSITION

Necessary approach when data and compute power are limited



EXAMPLE: ROAD FOLLOWING

Good quality lane markers, good driving conditions

Traditional lane detection-based systems expected to work well

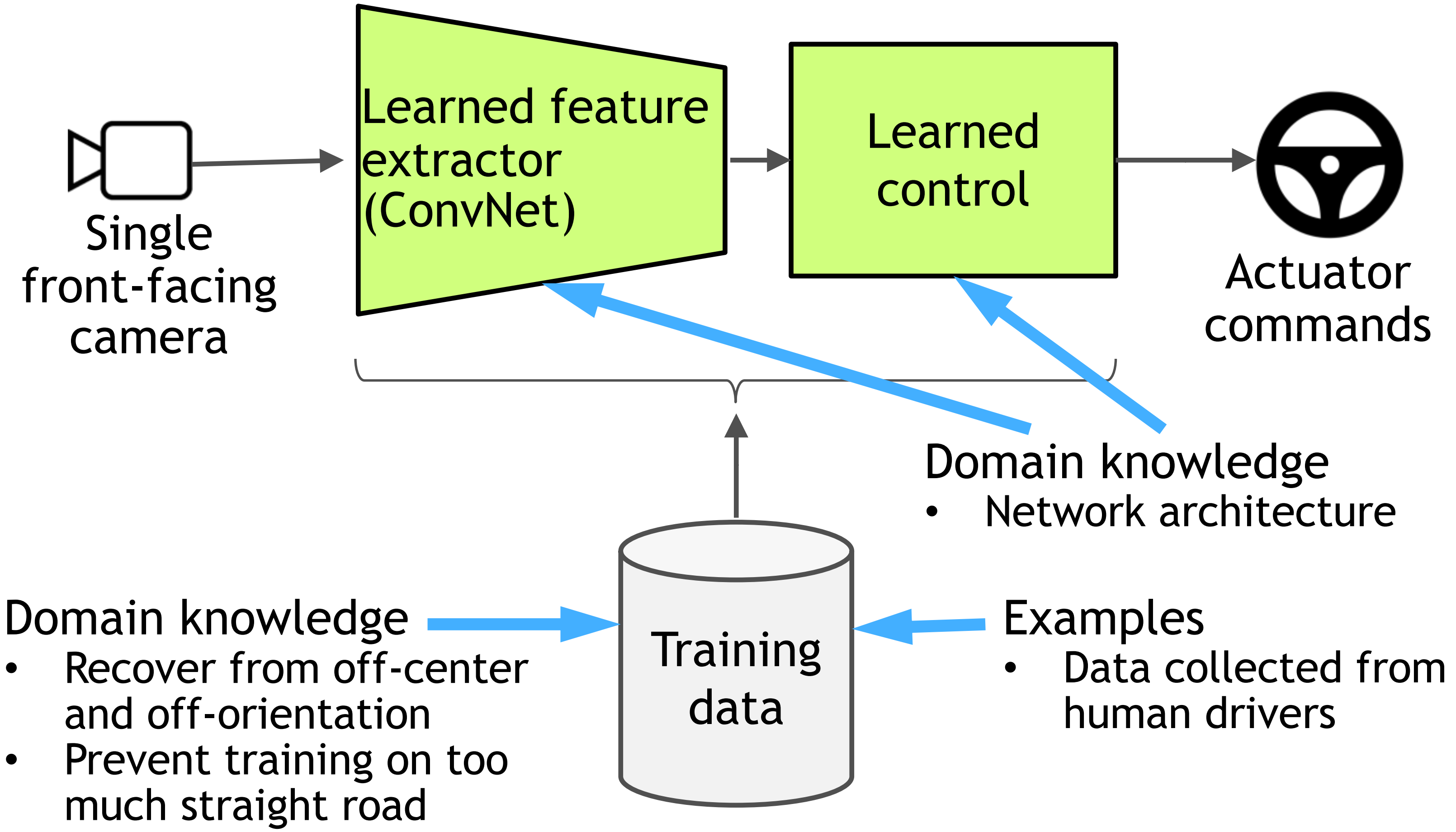
Poor quality lane markers

Lane detection-based systems struggle

End-to-end learning empowers the network to use additional cues

LEARNED ROAD FOLLOWING (PILOTNET)

Highway, local, residential – with or without lane markings



Both blocks trained simultaneously

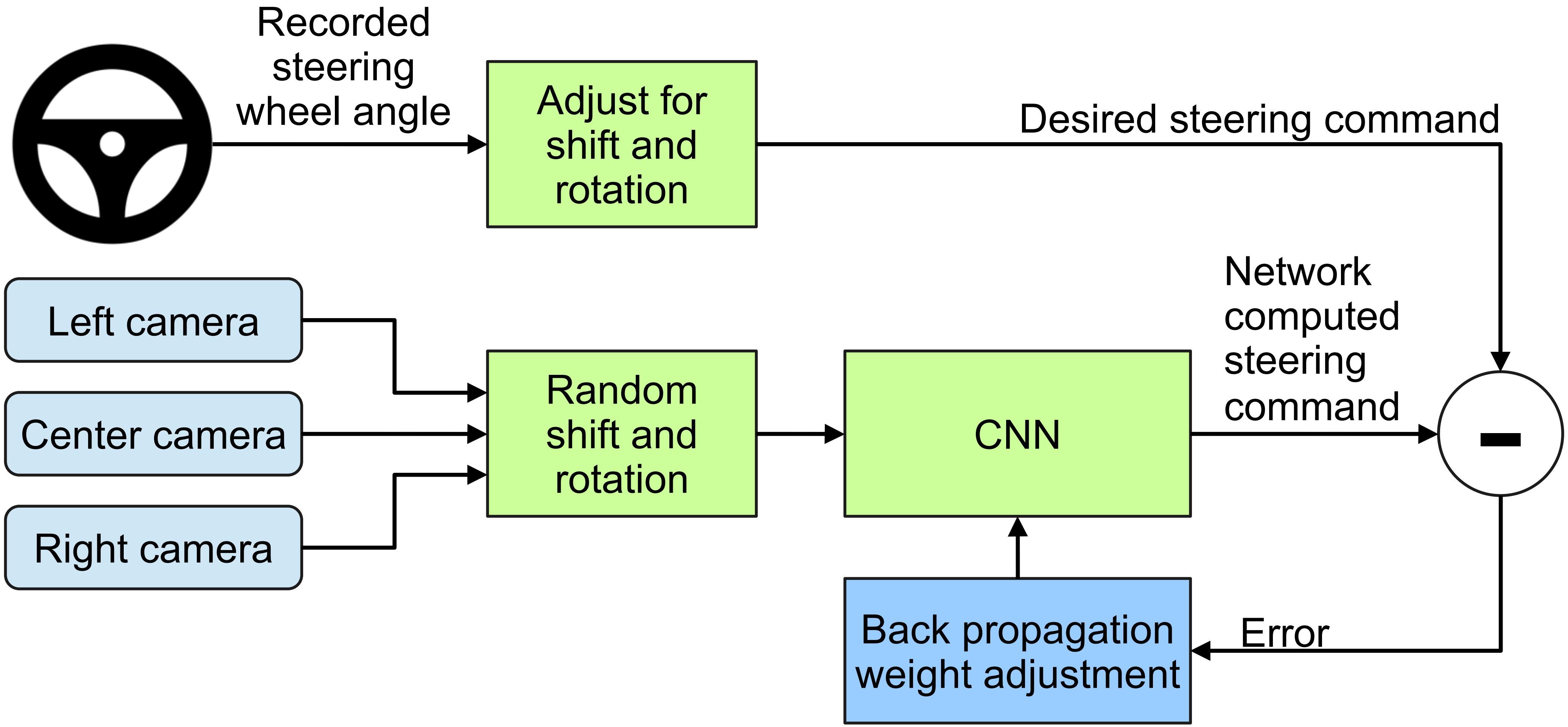
No explicit object detection nor path planning

→ Maps pixels directly to steering

Learned

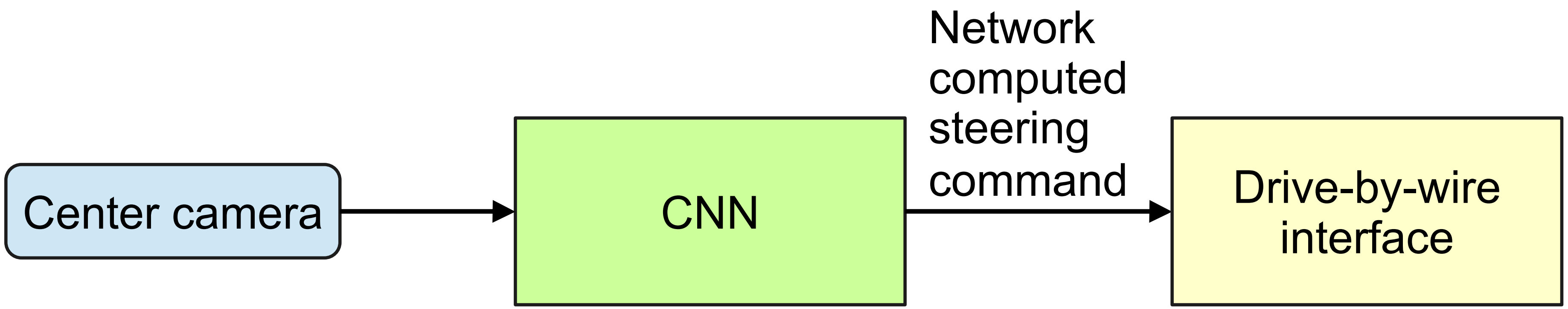
Hand-designed

TRAINING THE NEURAL NETWORK



DRIVING

With a single front-facing camera





VISUALIZATION

What the network pays attention to