6.S094: Deep Learning for Self-Driving Cars

Learning to Drive: Convolutional Neural Networks and End-to-End Learning of the Full Driving Tasks

cars.mit.edu

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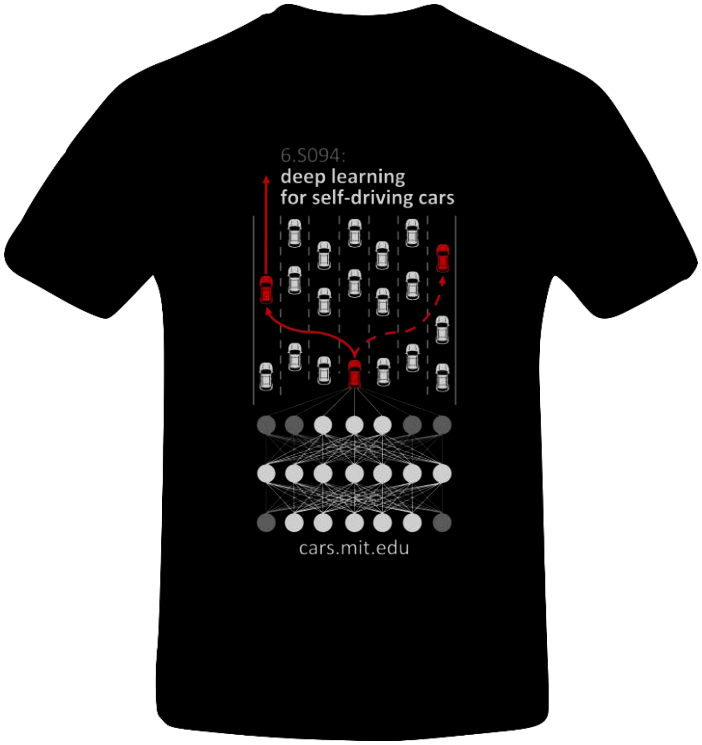

- **Website:** cars.mit.edu
- **Contact Email:** deepcars@mit.edu
- **Required:**
  - Create an account on the website.
  - Follow the tutorial for each of the 2 projects.
- **Recommended:**
  - Ask questions
  - Win competition!
- **Office hours:** Friday, 5-7pm
  (more info coming soon)

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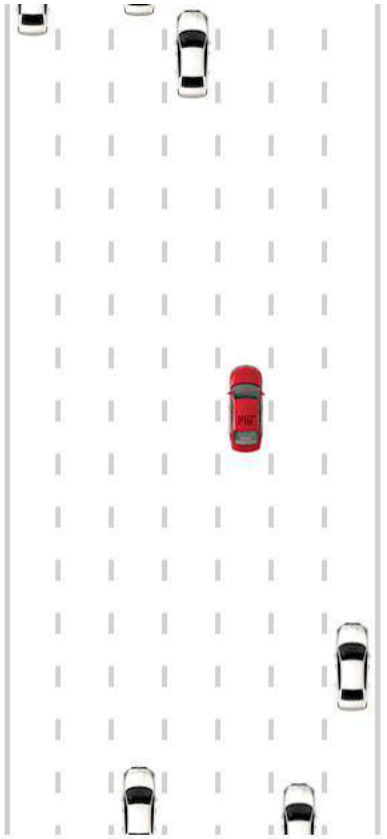
Schedule

Mon, Jan 9	Introduction to Deep Learning and Self Driving Cars
Tue, Jan 10	**Learning to Move:** Reinforcement Learning for Motion Planning
	DeepTraffic: Solving Traffic with Deep Reinforcement Learning
Wed, Jan 11	**Learning to Drive:** End-to-End Learning for the Full Driving Task
	DeepTesla: End-to-End Learning from Human and Autopilot Driving
Thu, Jan 12	**Karl Iagnemma:** From Research to Reality: Testing Self-Driving Cars on Boston Public Roads
Fri, Jan 13	**John Leonard:** Mapping, Localization, and the Challenge of Autonomous Driving
Tue, Jan 17	**Chris Gerdes:** TBD
Wed, Jan 18	**Sertac Karaman:** Past, Present, and Future of Motion Planning in a Complex World
Thu, Jan 19	**Learning to Share:** Driver State Sensing and Shared Autonomy
Fri, Jan 20	**Eric Daimler:** The Future of Artificial Intelligence Research and Development
	Learning to Think: The Road Ahead for Human-Centered Artificial Intelligence

DeepTraffic Leaderboard



Rank	User	MPH
1	cmauck10	72.67
2	Jeffrey Li	72.45
3	Ted Grunberg	72.31
4	Xiaoxue Wang	72.31
5	Ethan Weber	71.73
6	Indra den Bakker	71.35
7	Kavya R.	71.24
8	Rakesh	71.21
9	LCMartin	71.02
10	anyati	70.95

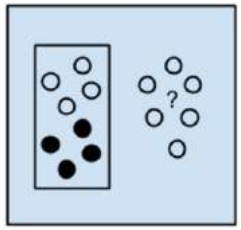
Illustrative Case Study: Traffic Light Detection

DeepTesla: End-to-End Learning from Human and Autopilot Driving

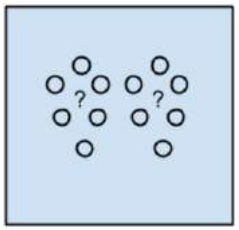
(in ConvnetJS)

DeepTesla: End-to-End Learning from Human and Autopilot Driving
(in TensorFlow)

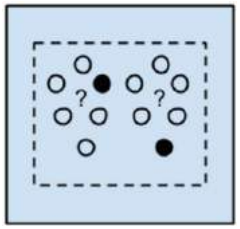
Computer Vision is Machine Learning



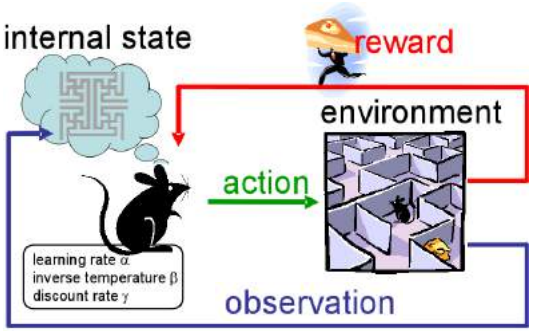
Supervised Learning



Unsupervised Learning



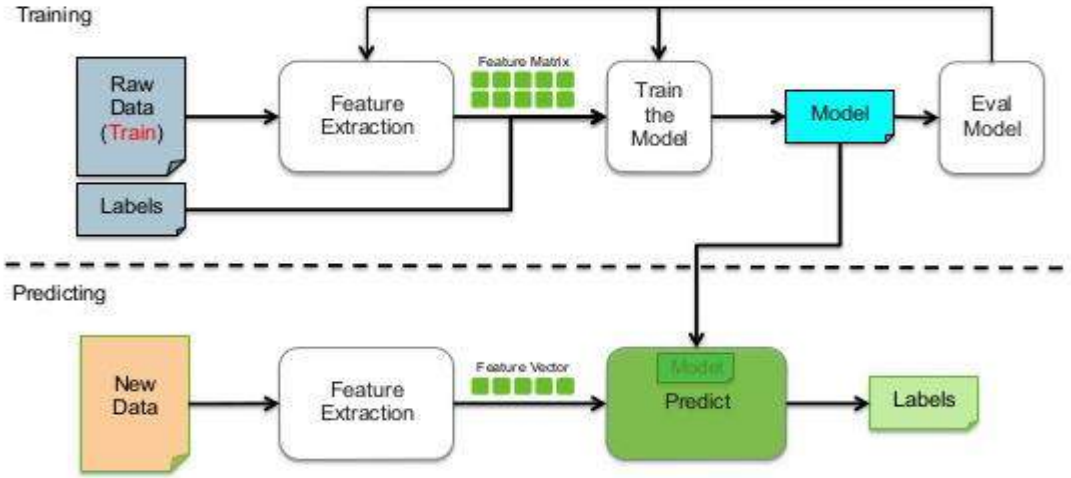
Semi-Supervised Learning



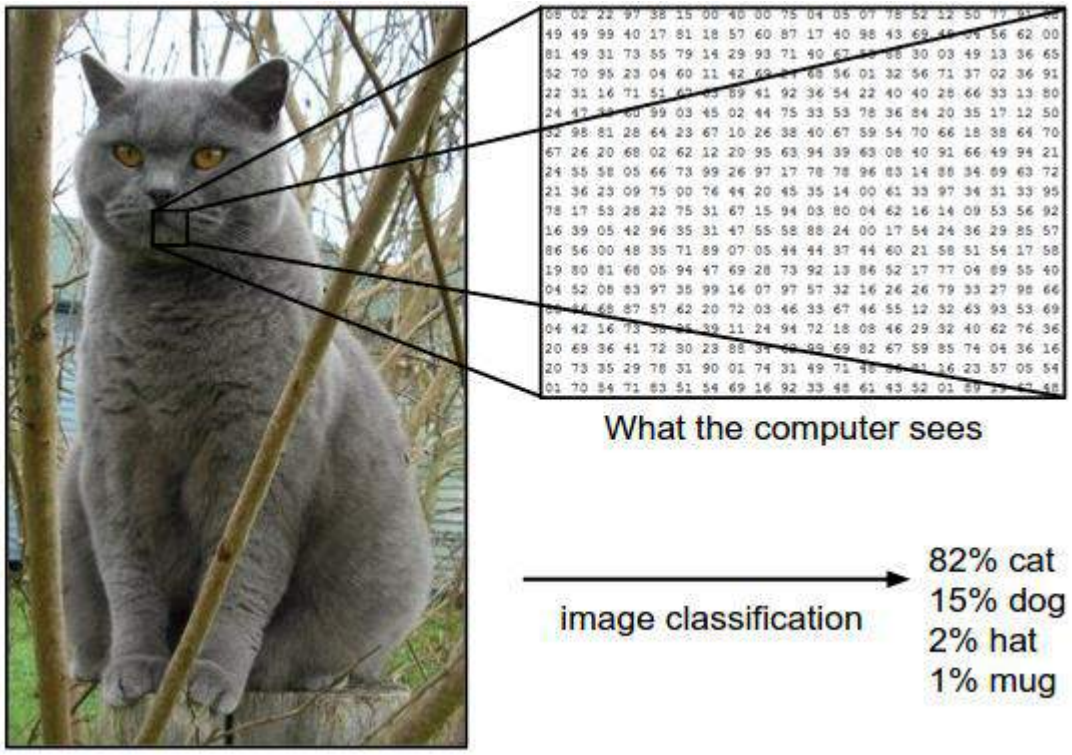
Reinforcement Learning

Computer Vision

Standard supervised learning pipeline:

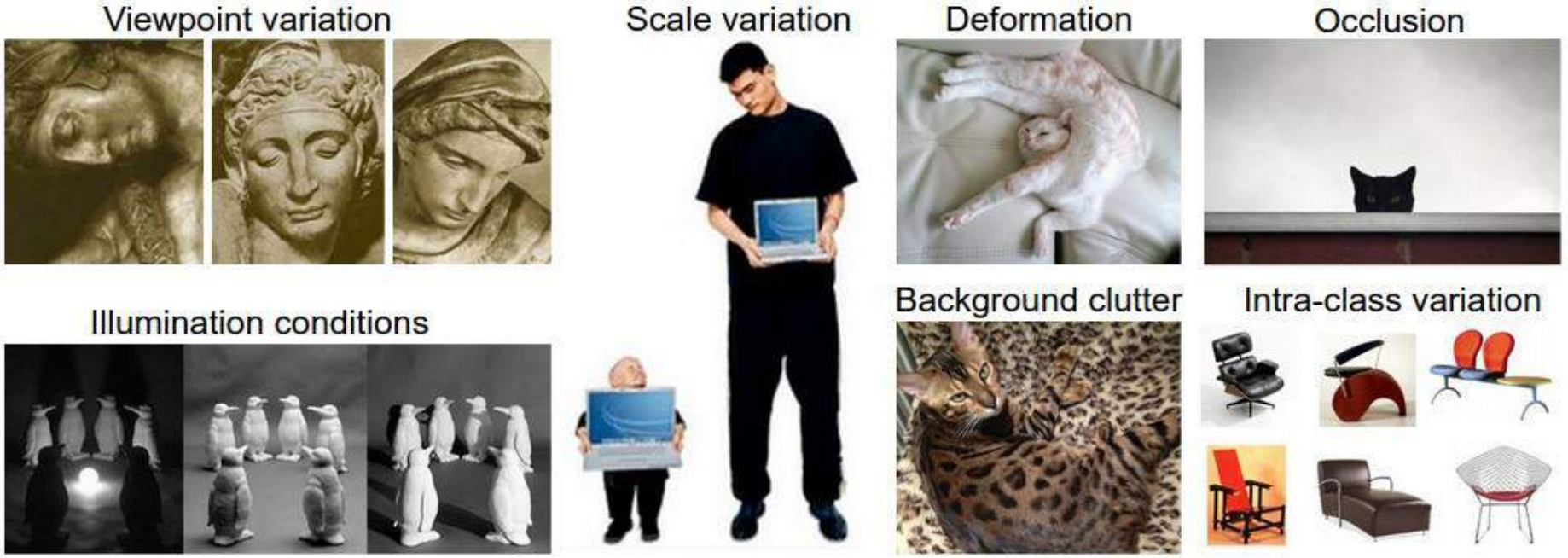


Images are Numbers



- **Regression:** The output variable takes continuous values
- **Classification:** The output variable takes class labels
  - Underneath it may still produce continuous values such as probability of belonging to a particular class.

Computer Vision is Hard



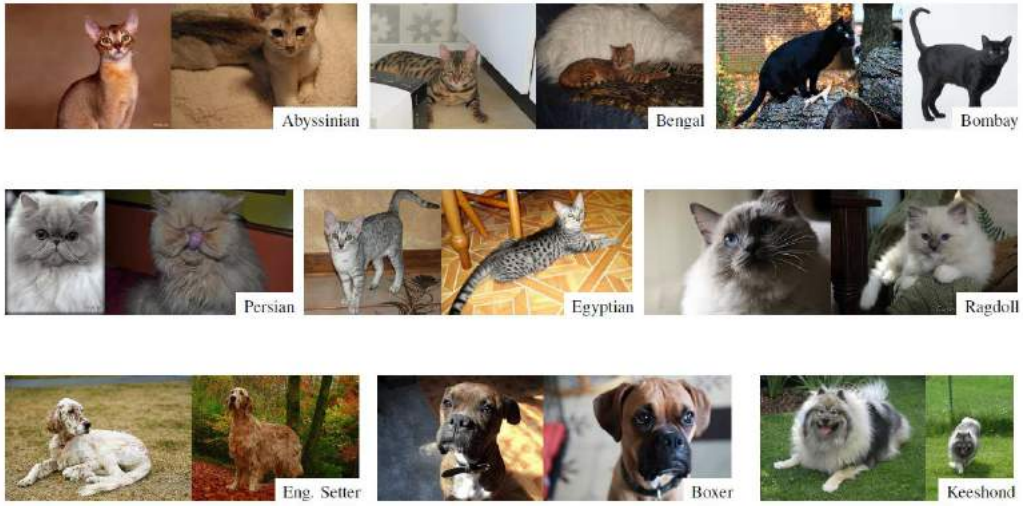
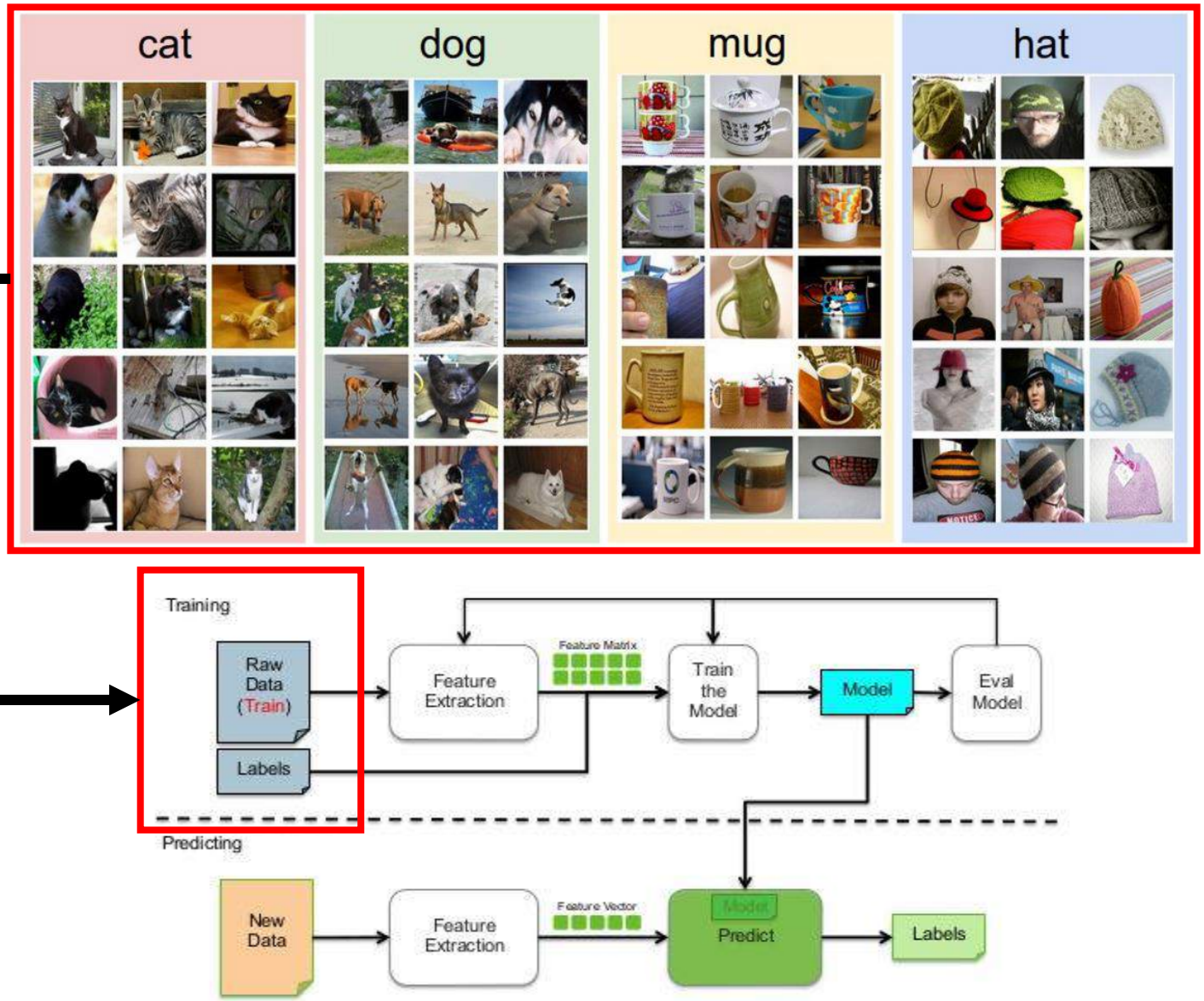


Image Classification Pipeline

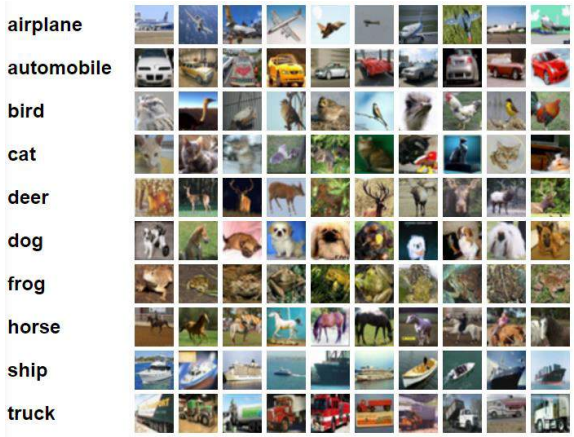


References: [81, 89]

Famous Computer Vision Datasets

MNIST: handwritten digits

ImageNet: WordNet hierarchy

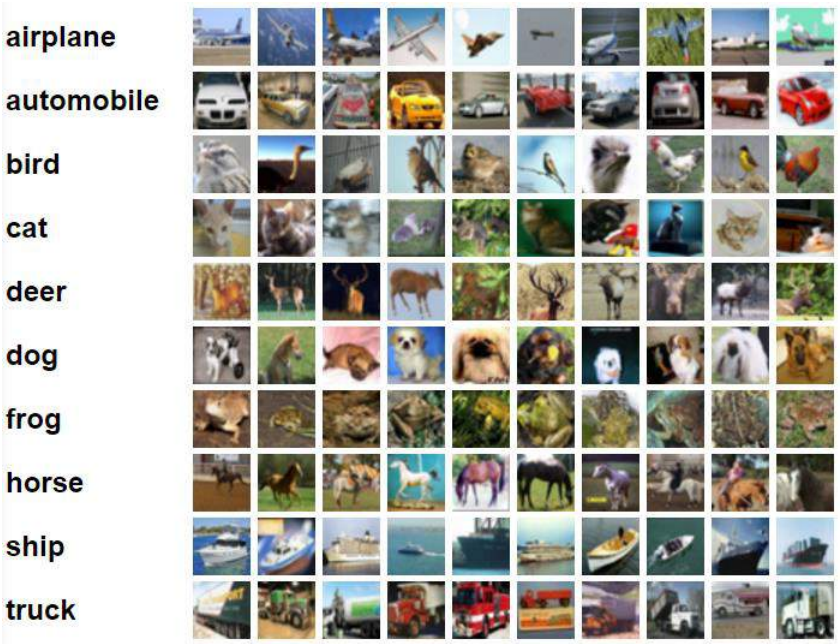


CIFAR-10(0): tiny images

Places: natural scenes

References: [90, 91, 92, 93]

Let's Build an Image Classifier for CIFAR-10



test image

56	32	10	18
90	23	128	133
24	26	178	200
2	0	255	220

-

training image

10	20	24	17
8	10	89	100
12	16	178	170
4	32	233	112

=

pixel-wise absolute value differences

46	12	14	1
82	13	39	33
12	10	0	30
2	32	22	108

→ 456

References: [89, 91]

Let's Build an Image Classifier for CIFAR-10

test image					training image					pixel-wise absolute value differences				
56	32	10	18	-	10	20	24	17	=	46	12	14	1	→ 456
90	23	128	133		8	10	89	100		82	13	39	33	
24	26	178	200		12	16	178	170		12	10	0	30	
2	0	255	220		4	32	233	112		2	32	22	108	

Accuracy

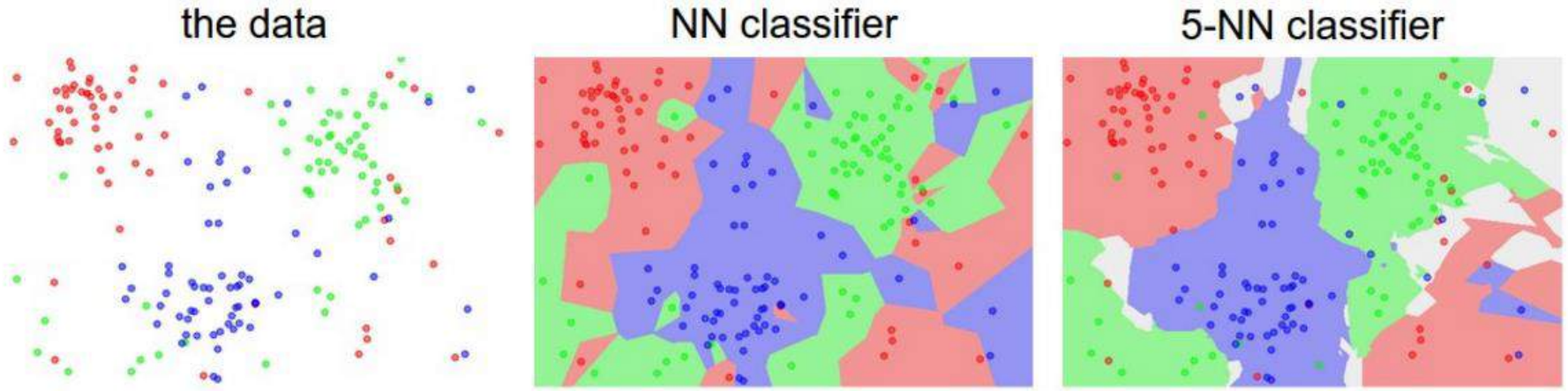
Random: **10%**

Our image-diff (with L1): **38.6%**

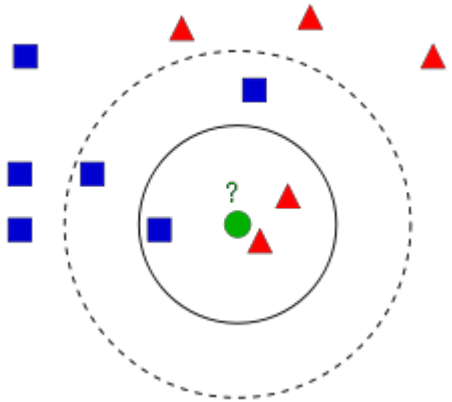
Our image-diff (with L2): **35.4%**

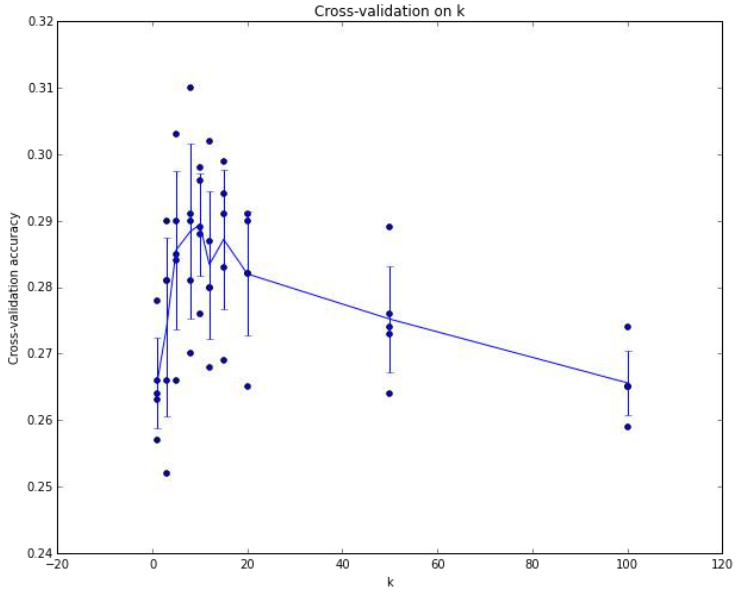
References: [89, 91]

K-Nearest Neighbors: Generalizing the Image-Diff Classifier

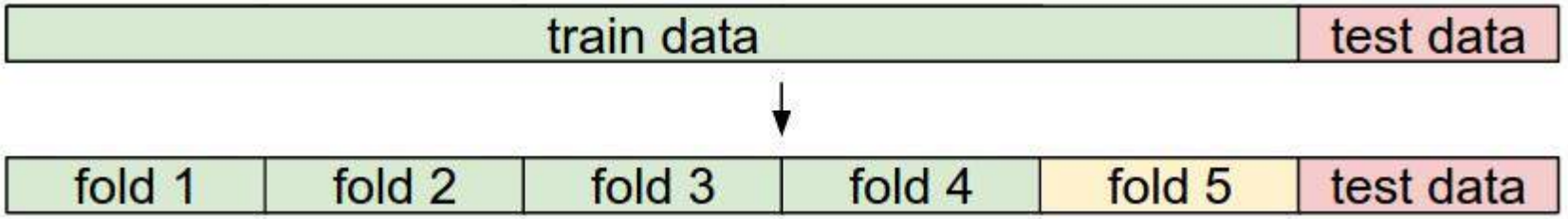


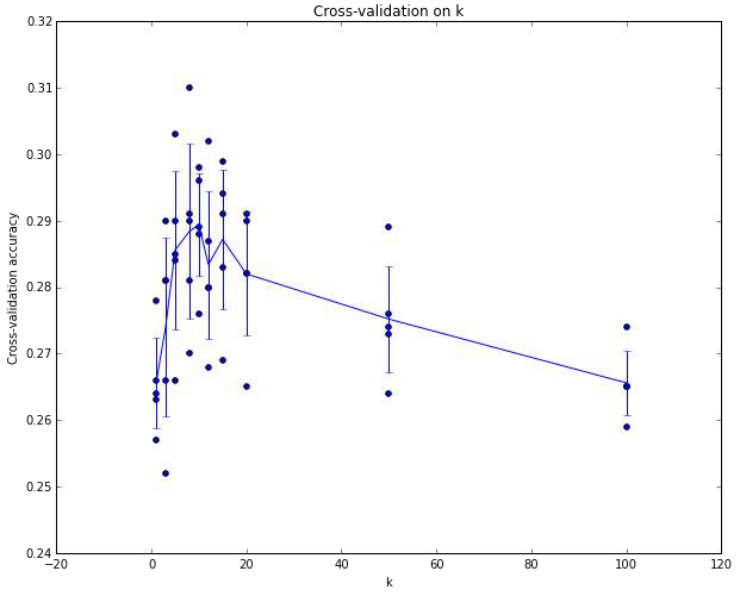
Tuning (hyper)parameters:





K-Nearest Neighbors: Generalizing the Image-Diff Classifier





Accuracy

Random: **10%**

Training and testing on the same data: **35.4%**

7-Nearest Neighbors: **~30%**

Human: **~94%**

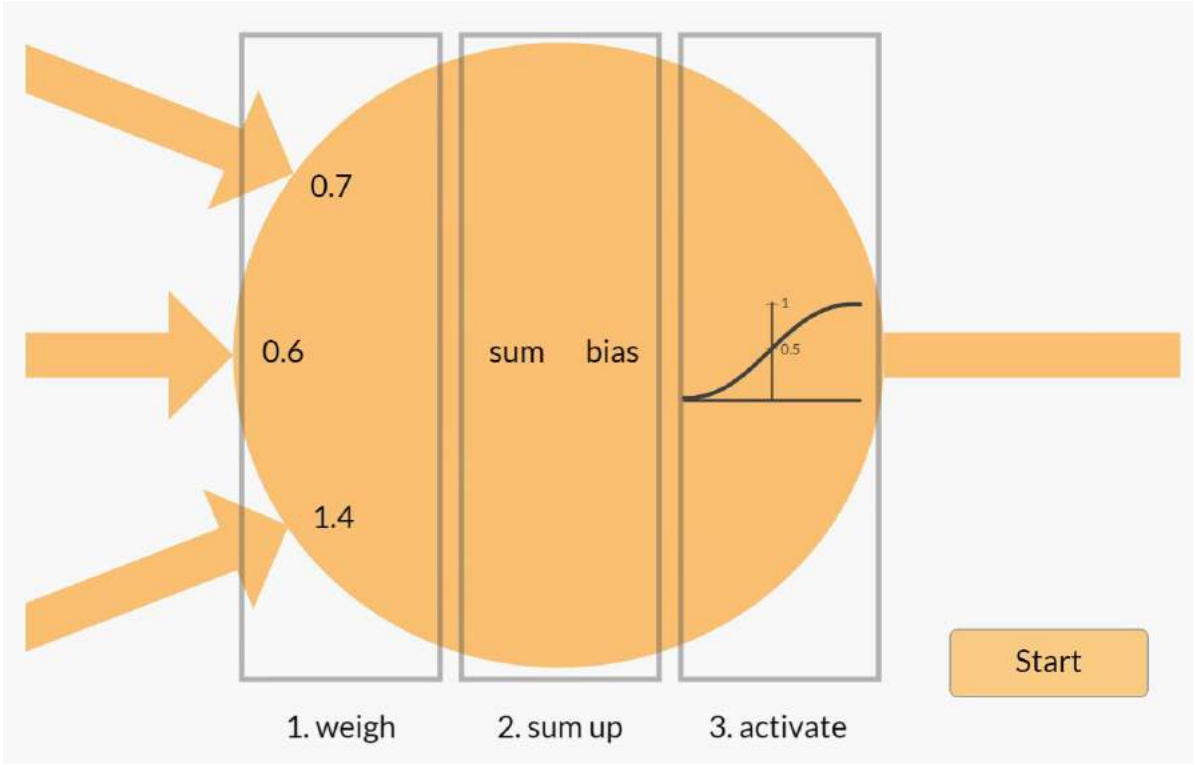
…

Convolutional Neural Networks: **~95%**

References: [89, 94]

Reminder: Weighing the Evidence

Evidence

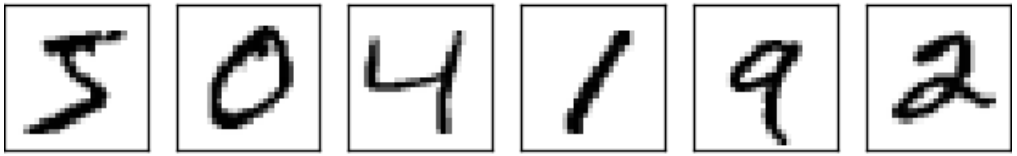


Decisions

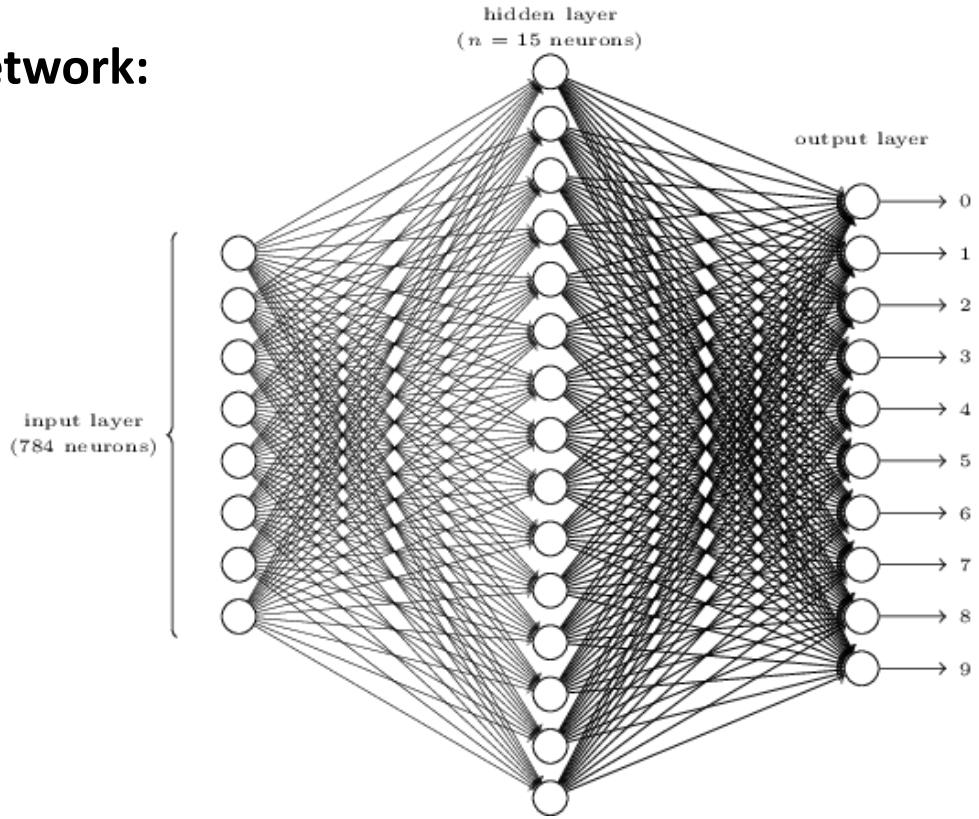
$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

Reminder: Classify and Image of a Number

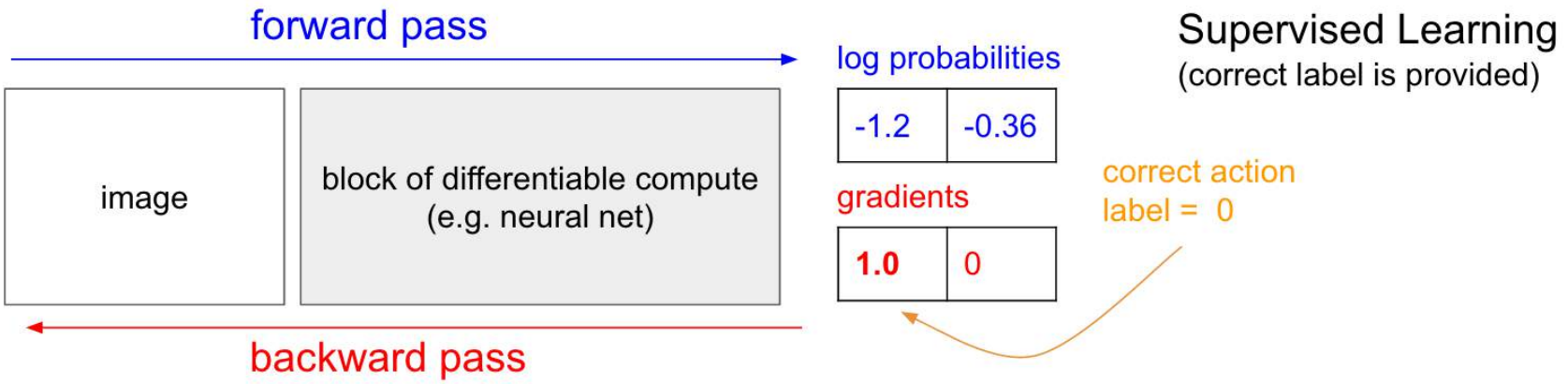
Input:
(28x28)



Network:



Reminder: "Learning" is Optimization of a Function

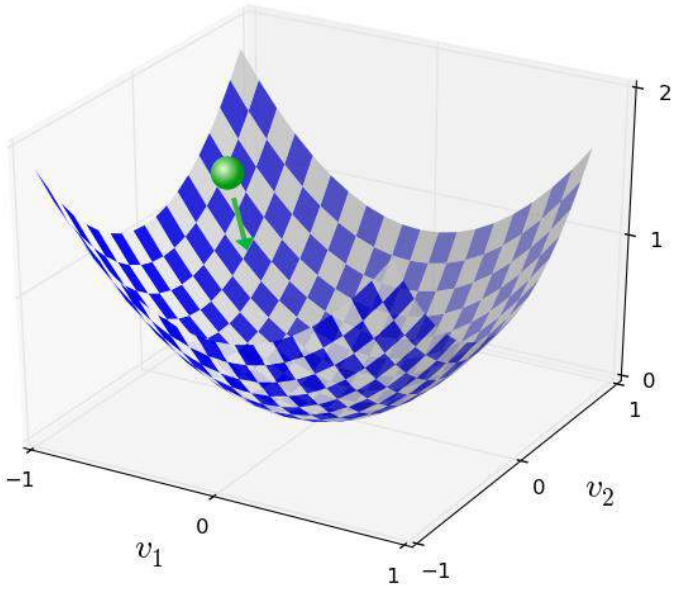


Ground truth for "6":

$$y(x) = (0, 0, 0, 0, 0, 0, 1, 0, 0, 0)^T$$

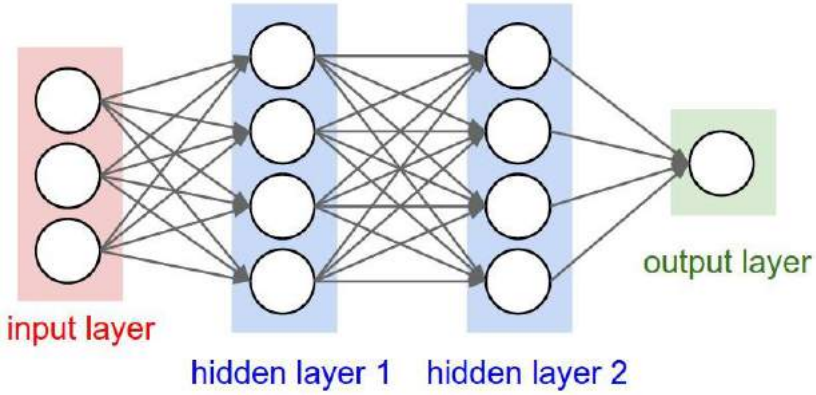
"Loss" function:

$$C(w, b) \equiv \frac{1}{2n} \sum_x \|y(x) - a\|^2$$

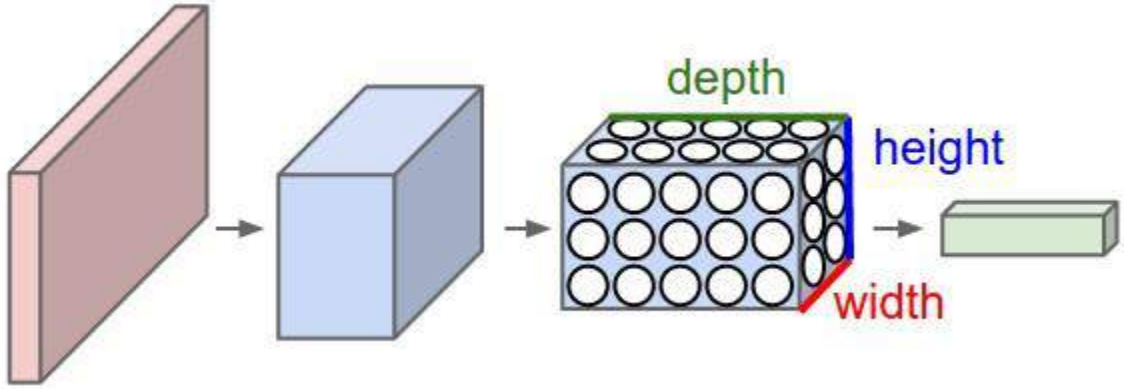


Convolutional Neural Networks

Regular neural network (fully connected):



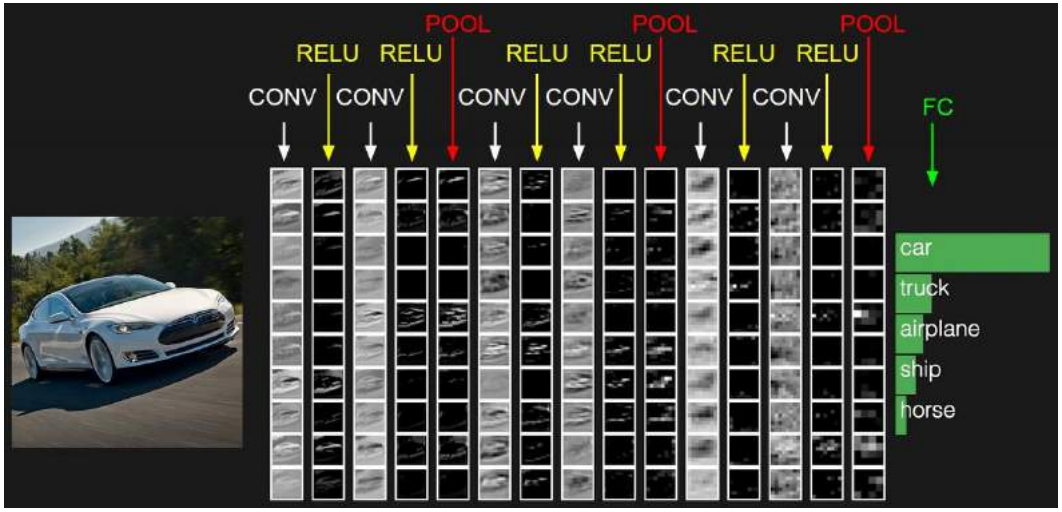
Convolutional neural network:



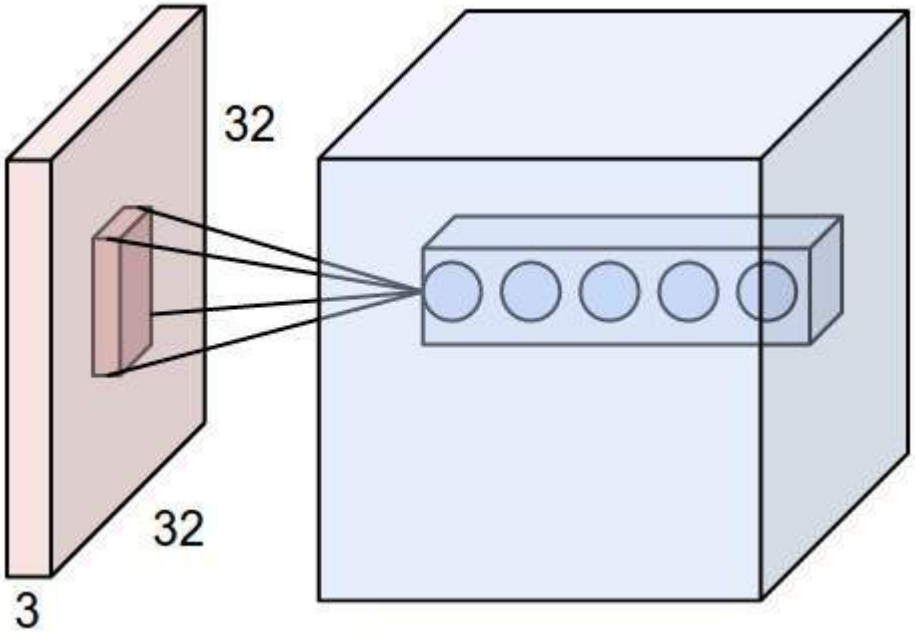
Each layer takes a 3d volume, produces 3d volume with some smooth function that may or may not have parameters.

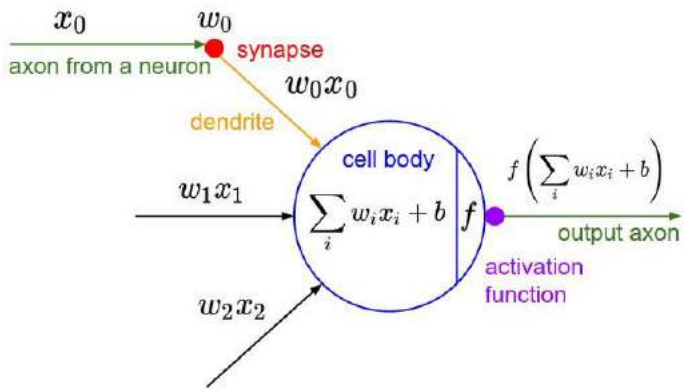
Convolutional Neural Networks: Layers

- **INPUT** [32x32x3] will hold the raw pixel values of the image, in this case an image of width 32, height 32, and with three color channels R,G,B.
- **CONV** layer will compute the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. This may result in volume such as [32x32x12] if we decided to use 12 filters.
- **RELU** layer will apply an elementwise activation function, such as the *max(0,x)* thresholding at zero. This leaves the size of the volume unchanged ([32x32x12]).
- **POOL** layer will perform a downsampling operation along the spatial dimensions (width, height), resulting in volume such as [16x16x12].
- **FC** (i.e. fully-connected) layer will compute the class scores, resulting in volume of size [1x1x10], where each of the 10 numbers correspond to a class score, such as among the 10 categories of CIFAR-10. As with ordinary Neural Networks and as the name implies, each neuron in this layer will be connected to all the numbers in the previous volume.



Dealing with Images: Local Connectivity



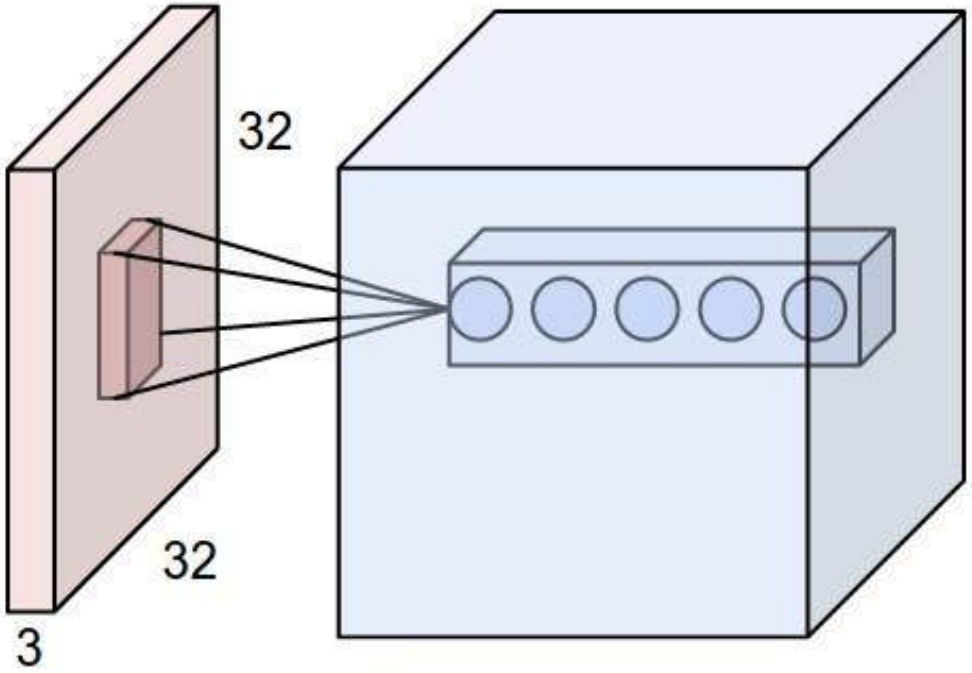


Same neuron. Just more focused (narrow “receptive field”).

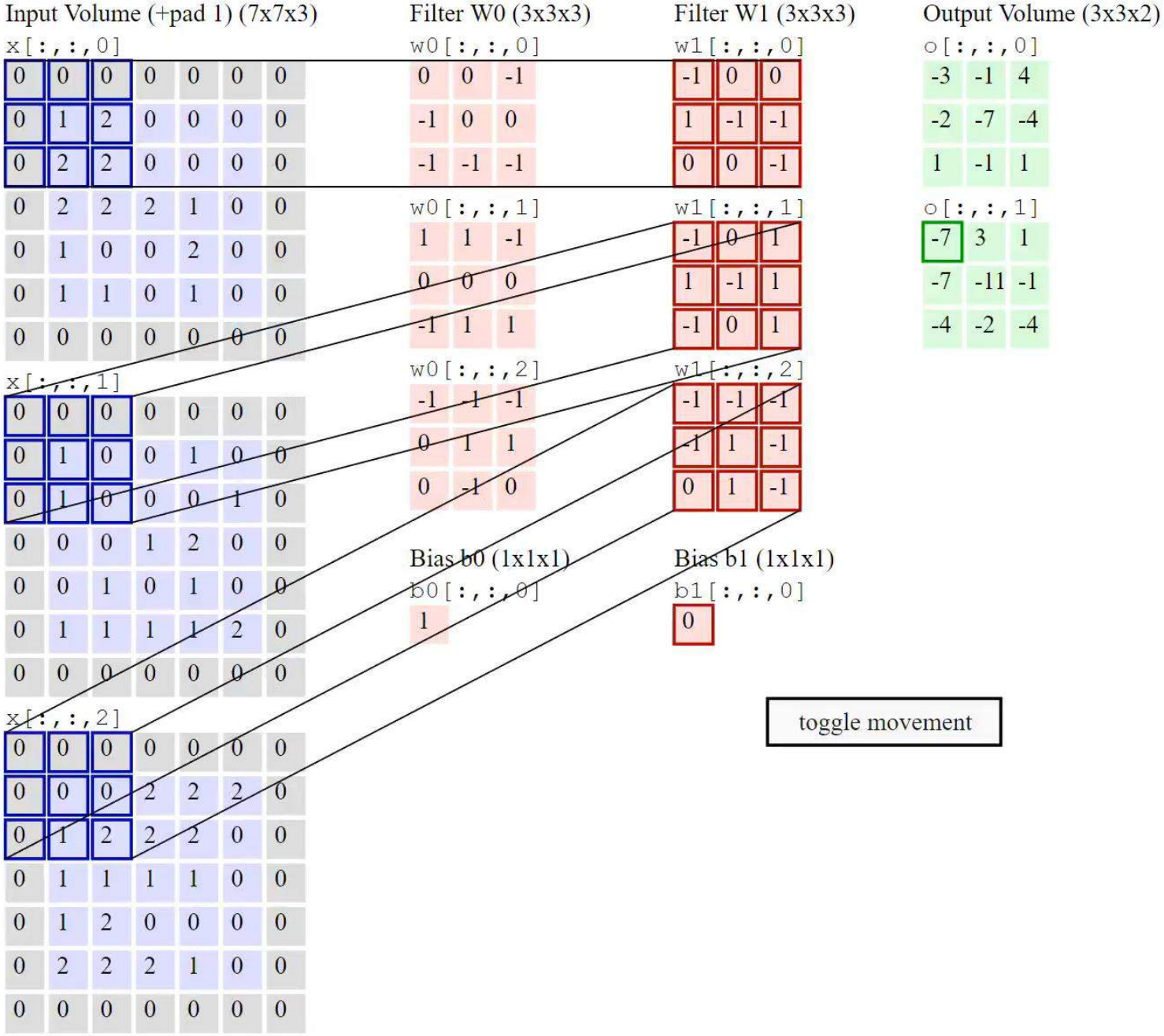
The parameters on a each filter are spatially “shared”

(if a feature is useful in one place, it’s useful elsewhere)

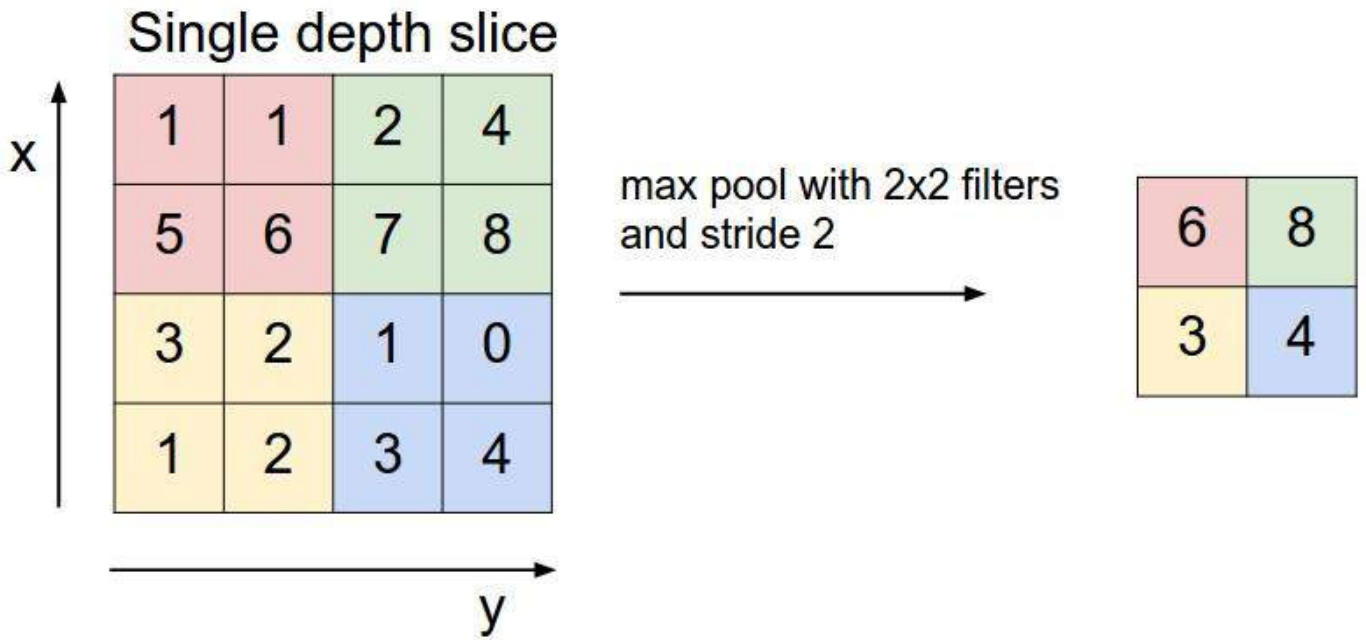
ConvNets: Spatial Arrangement of Output Volume

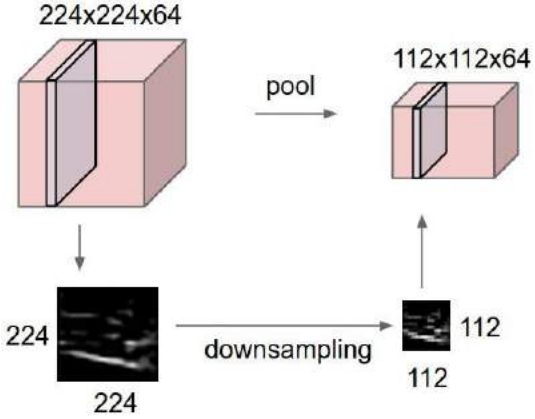


- **Depth:** number of filters
- **Stride:** filter step size (when we “slide” it)
- **Padding:** zero-pad the input

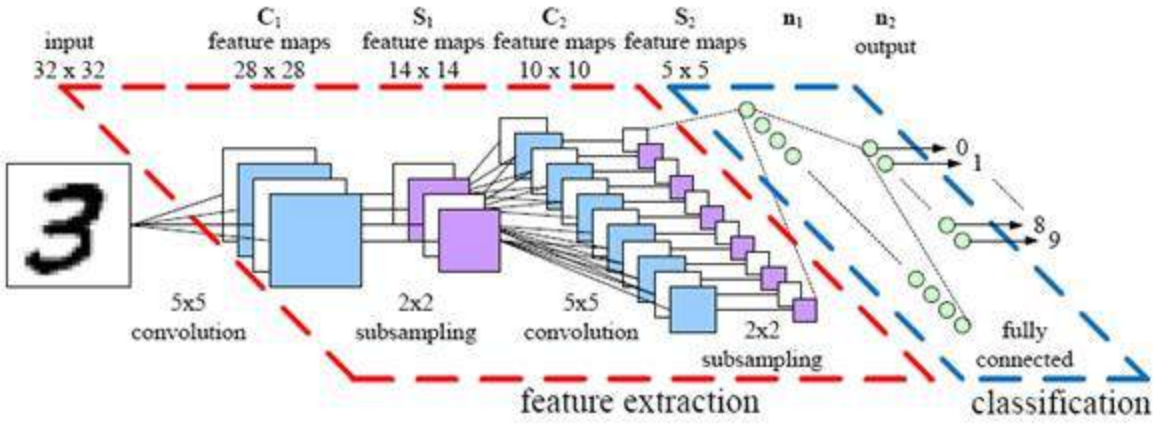

Input Volume (+pad 1) (7x7x3)
x[:,:,0]
0 0 0 0 0 0 0
0 1 2 0 0 0 0
0 2 2 0 0 0 0
0 2 2 2 1 0 0
0 1 0 0 2 0 0
0 1 1 0 1 0 0
0 0 0 0 0 0 0
x[:,:,1]
0 0 0 0 0 0 0
0 1 0 0 1 0 0
0 1 0 0 0 1 0
0 0 0 1 2 0 0
0 0 1 0 1 0 0
0 1 1 1 1 2 0
0 0 0 0 0 0 0
x[:,:,2]
0 0 0 0 0 0 0
0 0 0 2 2 2 0
0 1 2 2 2 0 0
0 1 1 1 1 0 0
0 1 2 0 0 0 0
0 2 2 2 1 0 0
0 0 0 0 0 0 0
Filter W0 (3x3x3)
w0[:,:,0]
0 0 -1
-1 0 0
-1 -1 -1
w0[:,:,1]
1 1 -1
0 0 0
-1 1 1
w0[:,:,2]
-1 -1 -1
0 1 1
0 -1 0
Filter W1 (3x3x3)
w1[:,:,0]
-1 0 0
1 -1 -1
0 0 -1
w1[:,:,1]
-1 0 1
1 -1 1
-1 0 1
w1[:,:,2]
-1 -1 -1
-1 1 -1
0 1 -1
Output Volume (3x3x2)
o[:,:,0]
-3 -1 4
-2 -7 -4
1 -1 1
o[:,:,1]
-7 3 1
-7 -11 -1
-4 -2 -4
Bias b0 (1x1x1)
b0[:,:,0]
1
Bias b1 (1x1x1)
b1[:,:,0]
0
toggle movement

ConvNets: Pooling



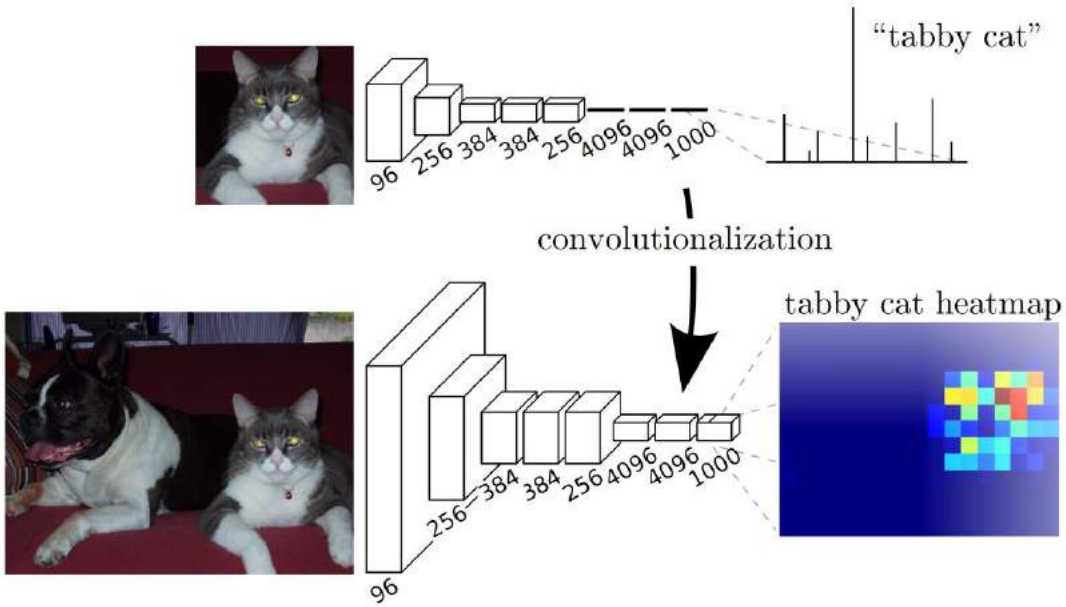


Computer Vision:
Object Recognition / Classification



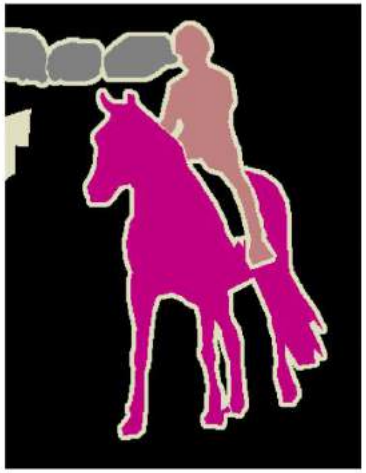
References: [4]

Computer Vision: Segmentation

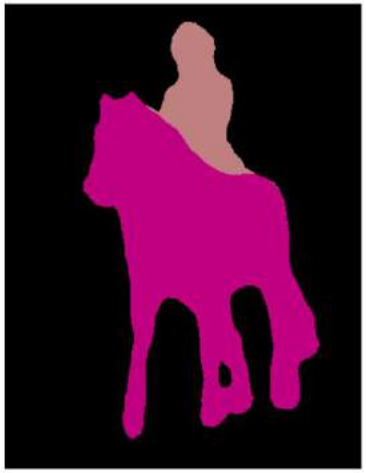


Original

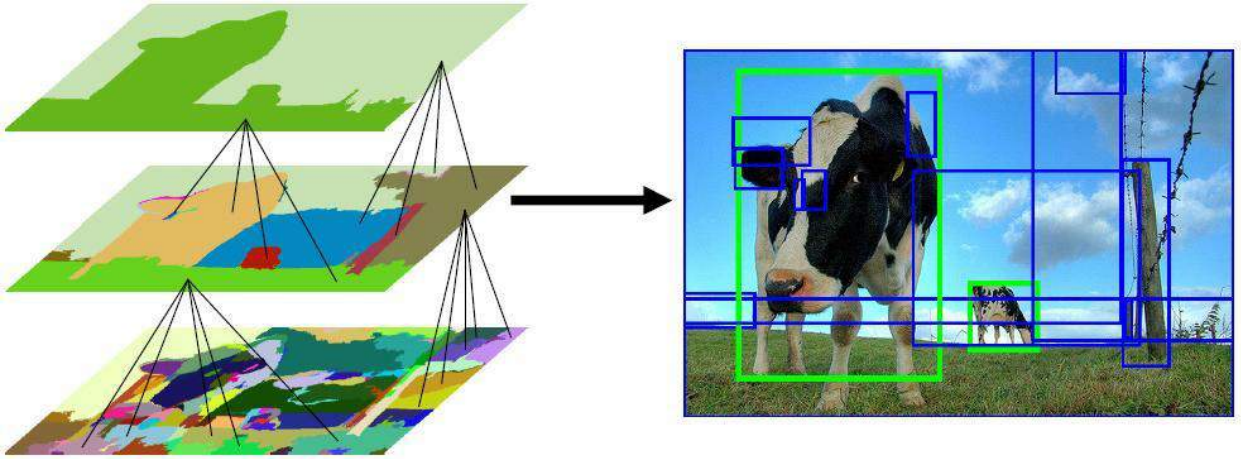
Ground Truth

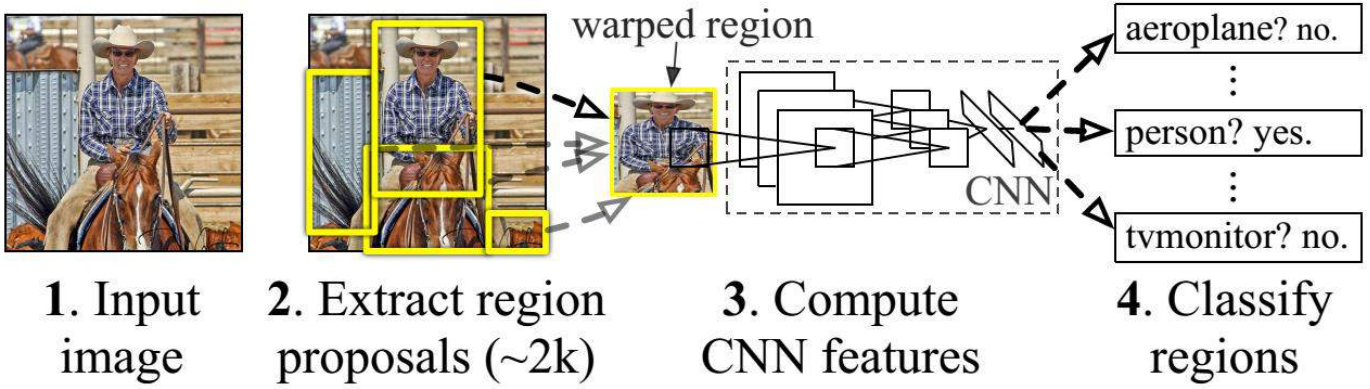


FCN-8



Computer Vision:
Object Detection





How Can Convolutional Neural Networks Help Us Drive?

Driving: The Numbers

(in United States, in 2014)

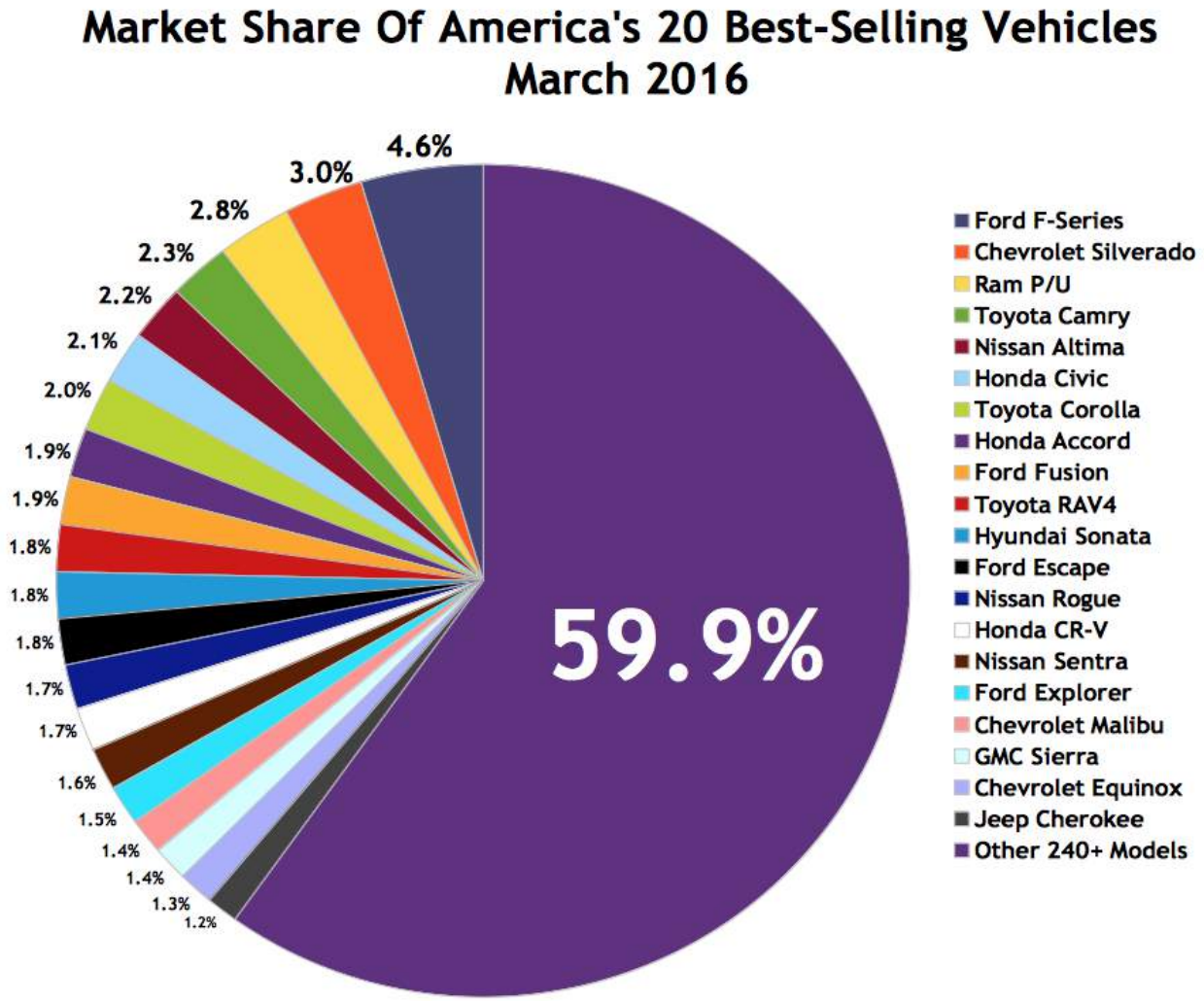
Miles

- **All drivers:** 10,658 miles (29.2 miles per day)
- **Rural drivers:** 12,264 miles
- **Urban drivers:** 9,709 miles

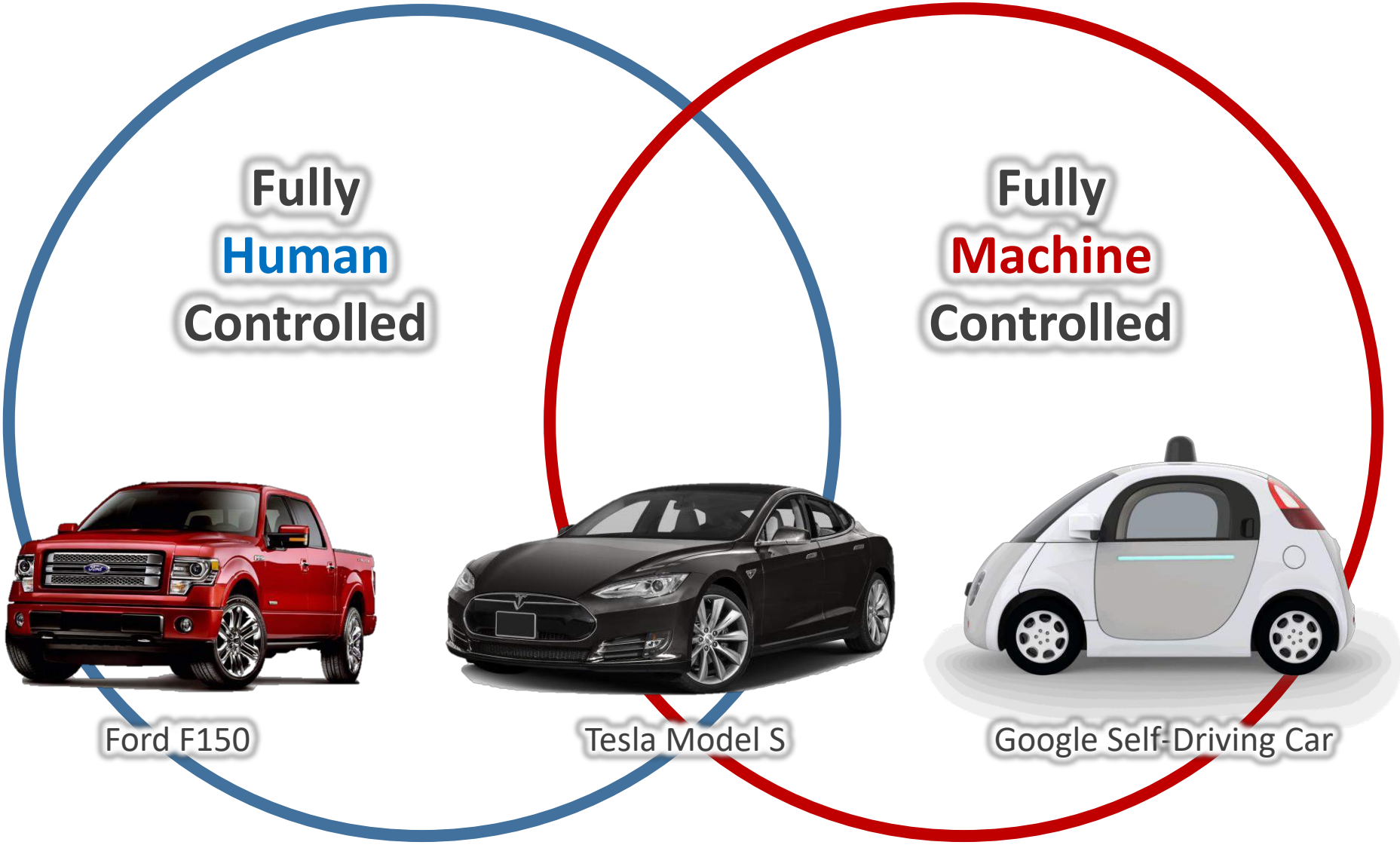
Fatalities

- **Fatal crashes:** 29,989
- **All fatalities:** 32,675
- **Car occupants:** 12,507
- **SUV occupants:** 8,320
- **Pedestrians:** 4,884
- **Motorcycle:** 4,295
- **Bicyclists:** 720
- **Large trucks:** 587

Cars We Drive

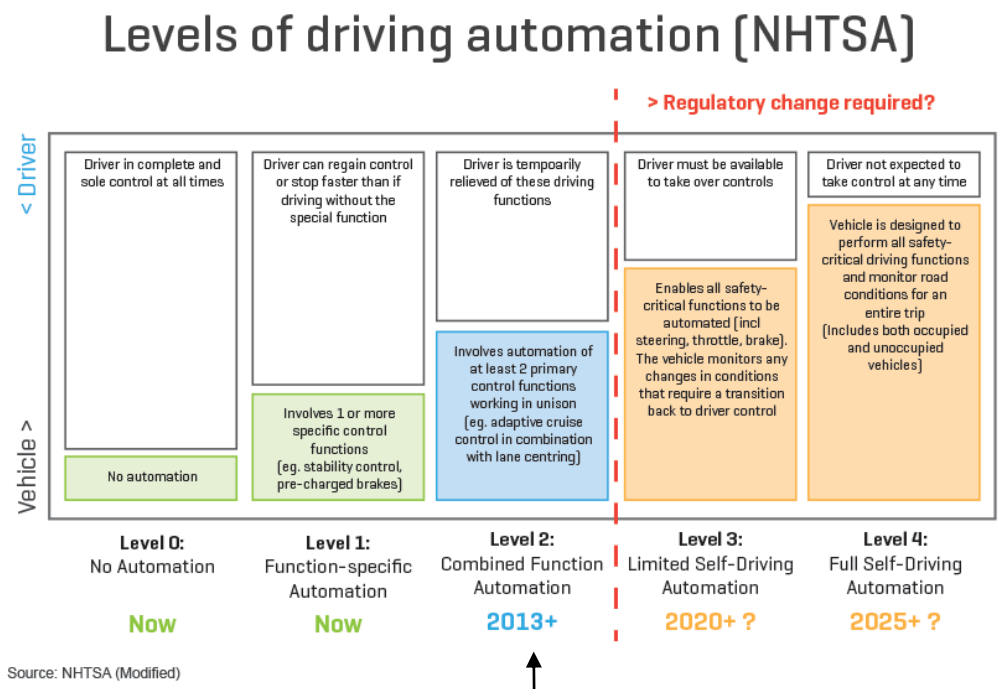


Human at the Center of Automation:
The Way to Full Autonomy Includes the Human



Human at the Center of Automation:
The Way to Full Autonomy Includes the Human

- **Emergency**
  - Automatic emergency breaking (AEB)
- **Warnings**
  - Lane departure warning (LDW)
  - Forward collision warning (FCW)
  - Blind spot detection
- **Longitudinal**
  - Adaptive cruise control (ACC)
- **Lateral**
  - Lane keep assist (LKA)
  - Automatic steering
- **Control and Planning**
  - Automatic lane change
  - Automatic parking



Tesla Autopilot

Distracted Humans

What is distracted driving?

- Texting
- Using a smartphone
- Eating and drinking
- Talking to passengers
- Grooming
- Reading, including maps
- Using a navigation system
- Watching a video
- Adjusting a radio

- **Injuries and fatalities:**
  3,179 people were killed and 431,000 were injured in motor vehicle crashes involving distracted drivers
  (in 2014)
- **Texts:**
  169.3 billion text messages were sent in the US every month.
  (as of December 2014)
- **Eye off road:**
  5 seconds is the average time your eyes are off the road while texting. When traveling at 55mph, that's enough time to cover the length of a football field blindfolded.

4 D's of Being Human:
Drunk, Drugged, Distracted, Drowsy

- **Drunk Driving:** In 2014, 31 percent of traffic fatalities involved a drunk driver.
- **Drugged Driving:** 23% of night-time drivers tested positive for illegal, prescription or over-the-counter medications.
- **Distracted Driving:** In 2014, 3,179 people (10 percent of overall traffic fatalities) were killed in crashes involving distracted drivers.
- **Drowsy Driving:** In 2014, nearly three percent of all traffic fatalities involved a drowsy driver, and at least 846 people were killed in crashes involving a drowsy driver.

In Context: Traffic Fatalities

Total miles driven in U.S. in 2014:

3,000,000,000,000 (3 million million)

Tesla Autopilot miles driven since October 2015:

300,000,000 (300 million)

(as of December 2016)

In Context: Traffic Fatalities

Total miles driven in U.S. in 2014:

3,000,000,000,000 (3 million million)

Fatalities: **32,675**

(1 in 90 million)

Tesla Autopilot miles driven since October 2015:

300,000,000 (300 million)

Fatalities: **1**

In Context: Traffic Fatalities

Total miles driven in U.S. in 2014:

3,000,000,000,000 (3 million million)

We (increasingly) understand this → Fatalities: **32,675**

(1 in 90 million)

Tesla Autopilot miles driven since October 2015:

300,000,000 (300 million)

We do not understand this (yet) → Fatalities: **1**

We need A LOT of real-world semi-autonomous driving data!

Computer Vision + Machine Learning + Big Data = Understanding

The Data

Teslas instrumented: 17

Hours of data: 5,000+ hours

Distance traveled: 70,000+ miles

The Data


Total Time Driving: 0 mins
Autopilot Available: 0 mins
Autopilot Engaged: 0 mins

Camera and Lens Selection

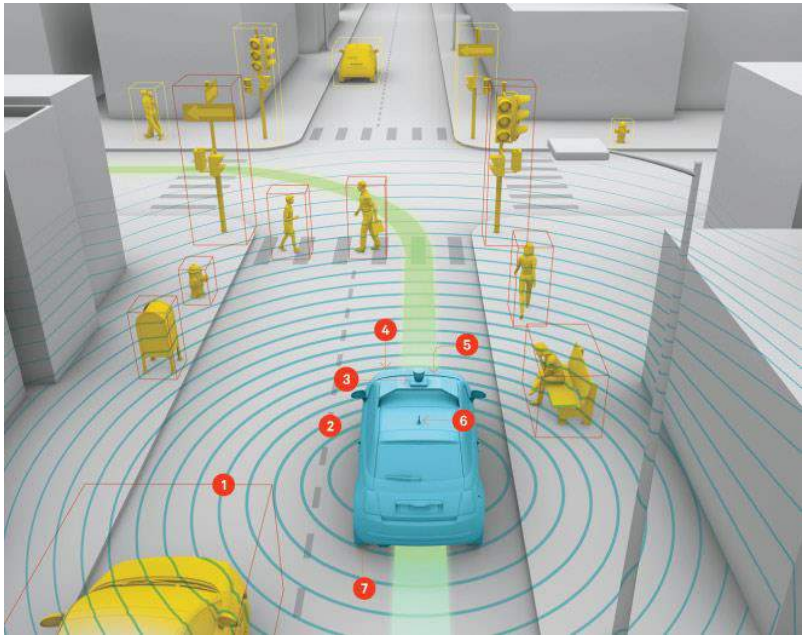
Logitech C920:
On-board H264 Compression

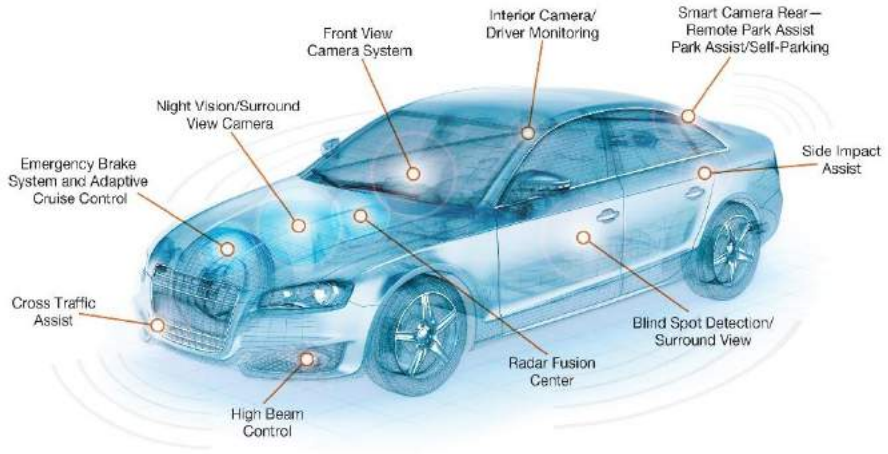
Fisheye: Capture full range of head, body movement inside vehicle.

Case for C-Mount Lens:
Flexibility in lens selection

2.8-12mm Focal Length: "Zoom" on the face without obstructing the driver's view.

Semi-Autonomous Vehicle Components





External

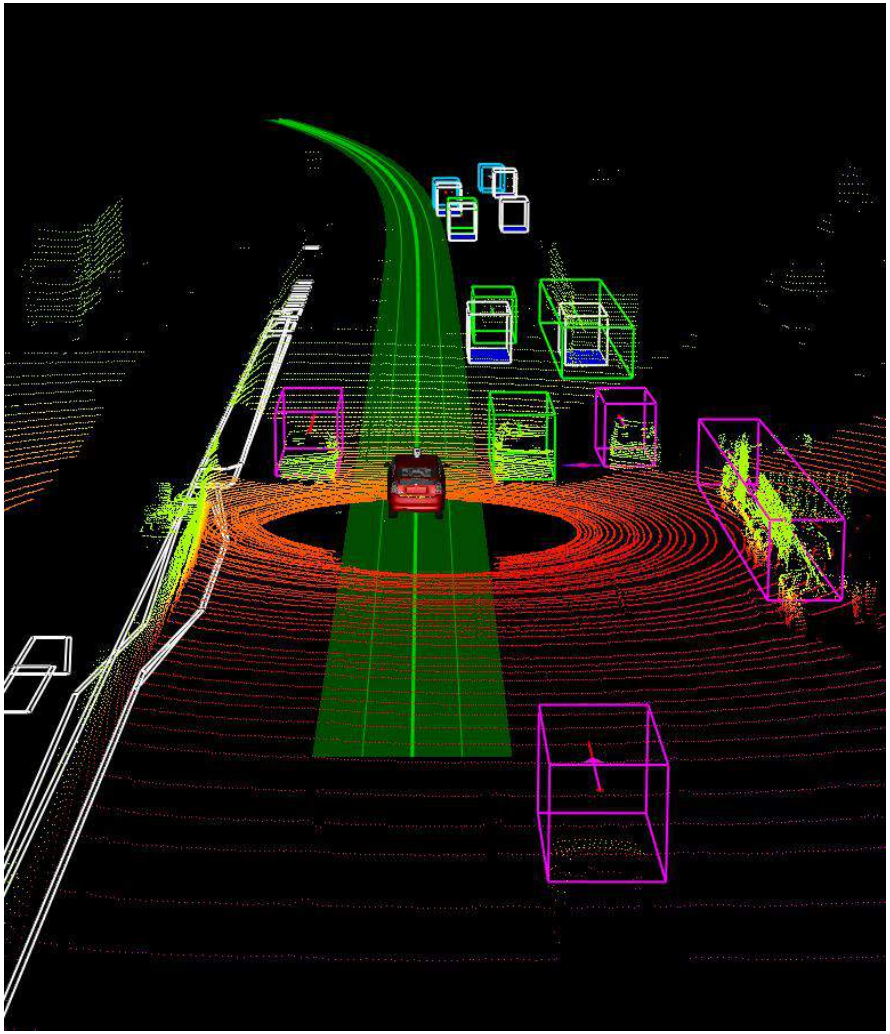
1. Radar
2. Visible-light camera
3. LIDAR
4. Infrared camera
5. Stereo vision
6. GPS/IMU
7. CAN
8. Audio

Internal

1. Visible-light camera
2. Infrared camera
3. Audio

Self-Driving Car Tasks

- **Localization and Mapping:**
  Where am I?
- **Scene Understanding:**
  Where is everyone else?
- **Movement Planning:**
  How do I get from A to B?
- **Driver State:**
  What's the driver up to?



Self-Driving Car Tasks

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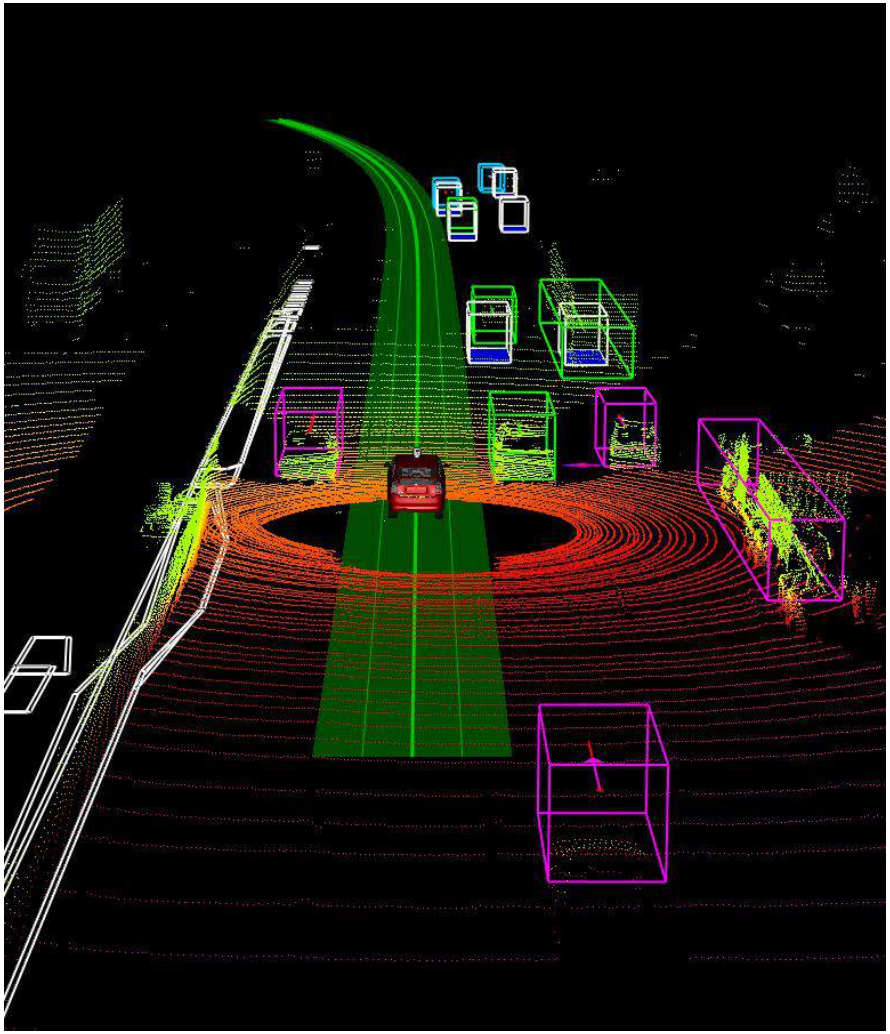
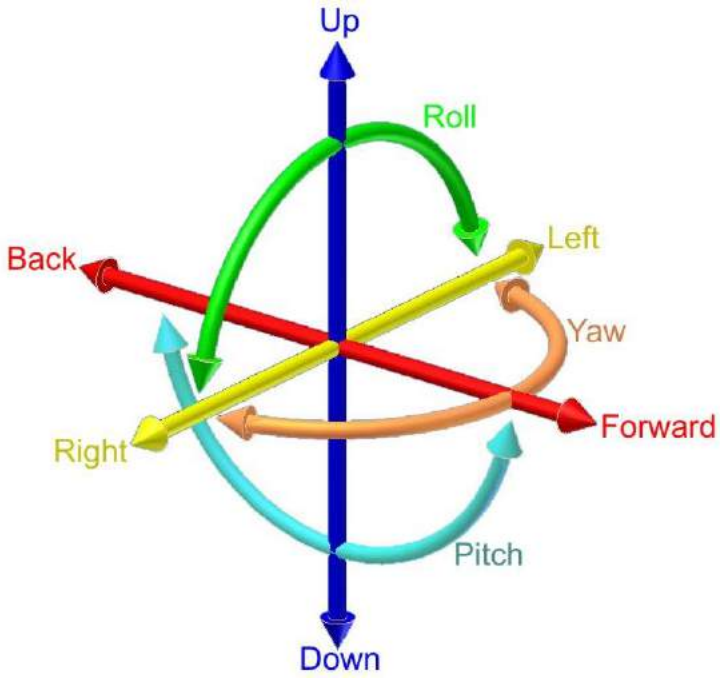


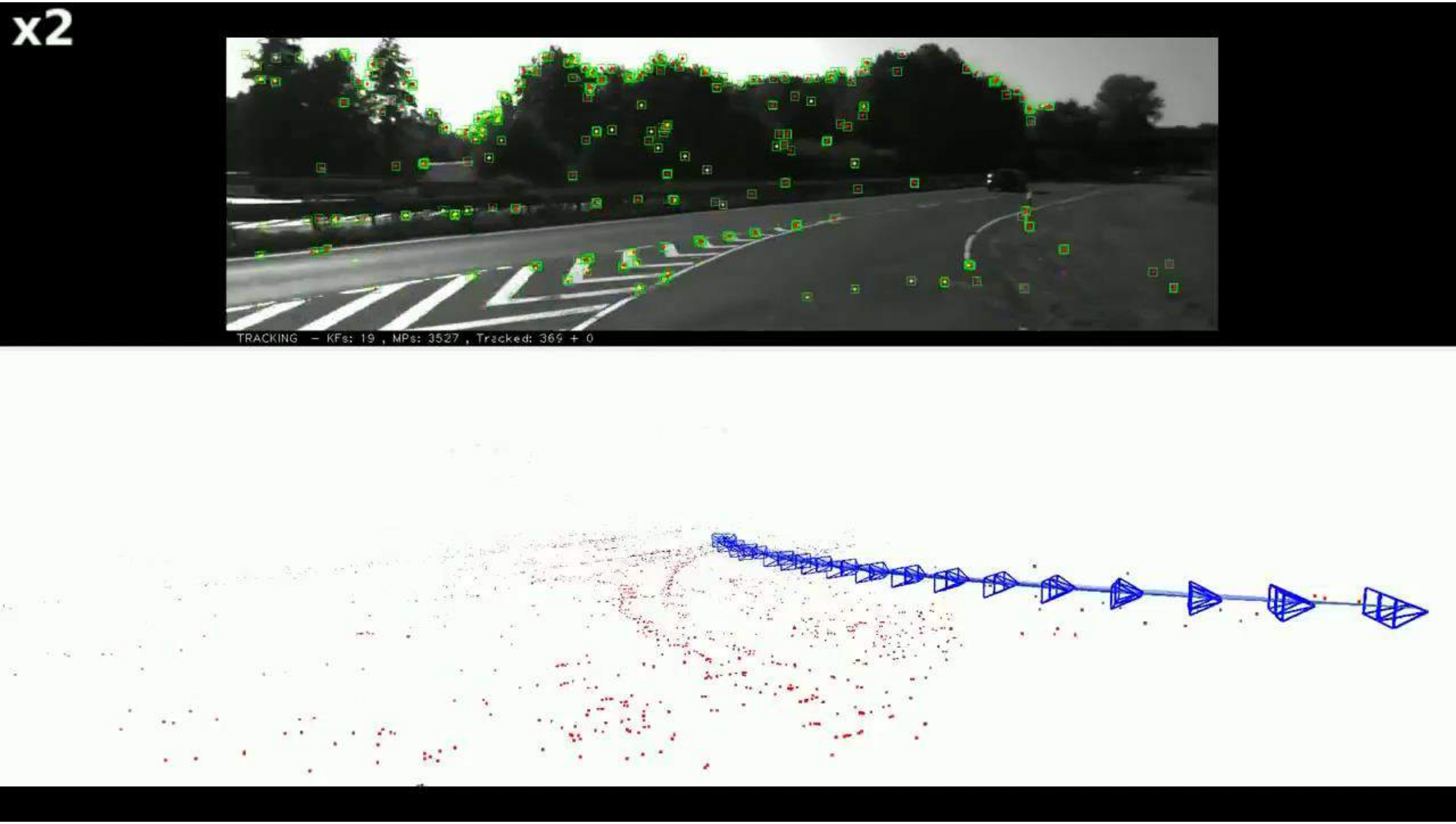
Visual Odometry

- 6-DOF: freed of movement
  - Changes in position:
    - Forward/backward: surge
    - Left/right: sway
    - Up/down: heave
  - Orientation:
    - Pitch, Yaw, Roll
- Source:
  - **Monocular:** I moved 1 unit
  - **Stereo:** I moved 1 meter
  - Mono = Stereo for far away objects
    - PS: For tiny robots everything is “far away” relative to inter-camera distance



SLAM: Simultaneous Localization and Mapping

What works: SIFT and optical flow



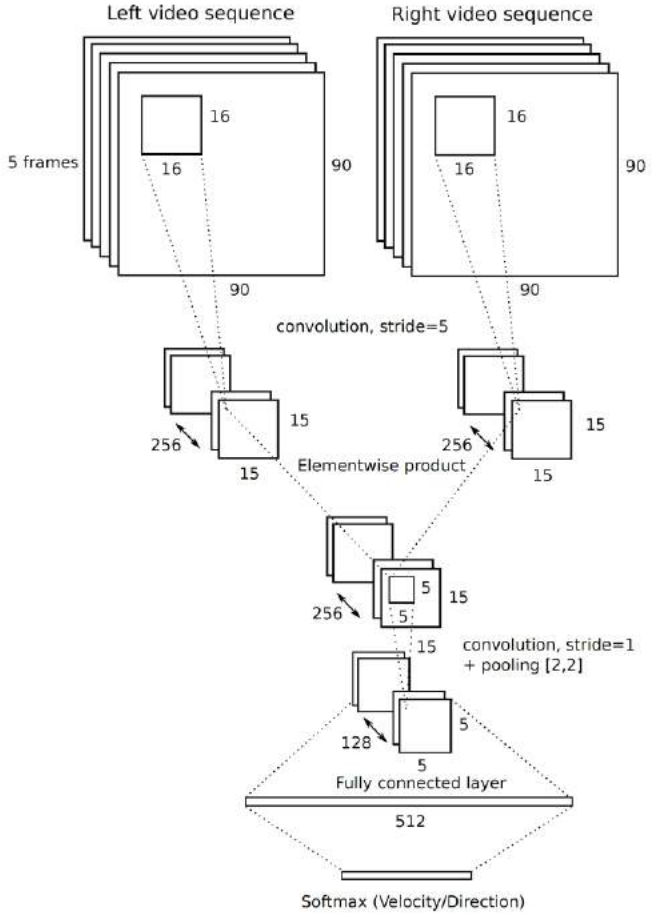
References: [98, 99]

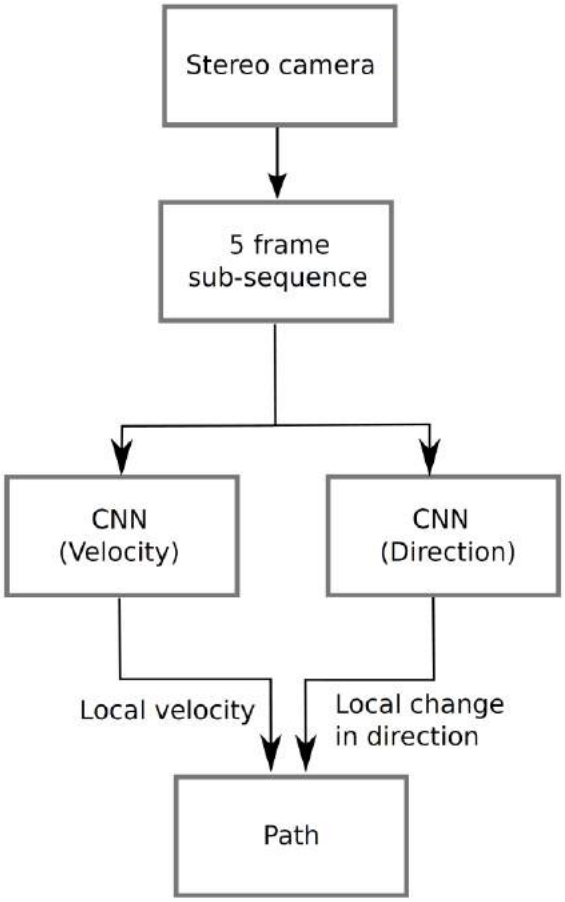
Visual Odometry in Parts

- (Stereo) Undistortion, Rectification
- (Stereo) Disparity Map Computation
- Feature Detection (e.g., SIFT, FAST)
- Feature Tracking (e.g., KLT: Kanade-Lucas-Tomasi)
- Trajectory Estimation
  - Use rigid parts of the scene (requires outlier/inlier detection)
  - For mono, need more info* like camera orientation and height of off the ground

* Kitt, Bernd Manfred, et al. "Monocular visual odometry using a planar road model to solve scale ambiguity." (2011).

End-to-End Visual Odometry

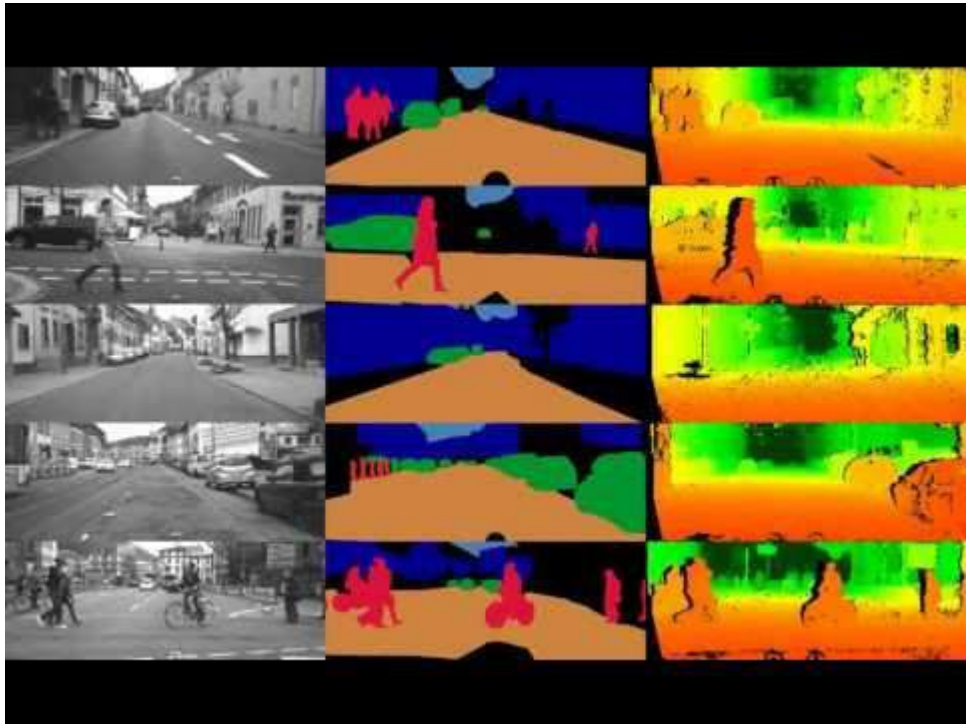




Konda, Kishore, and Roland Memisevic. "Learning visual odometry with a convolutional network." *International Conference on Computer Vision Theory and Applications*. 2015.

Self-Driving Car Tasks

- **Localization and Mapping:**
  Where am I?
- **Scene Understanding:**
  Where is everyone else?
- **Movement Planning:**
  How do I get from A to B?
- **Driver State:**
  What's the driver up to?



Object Detection

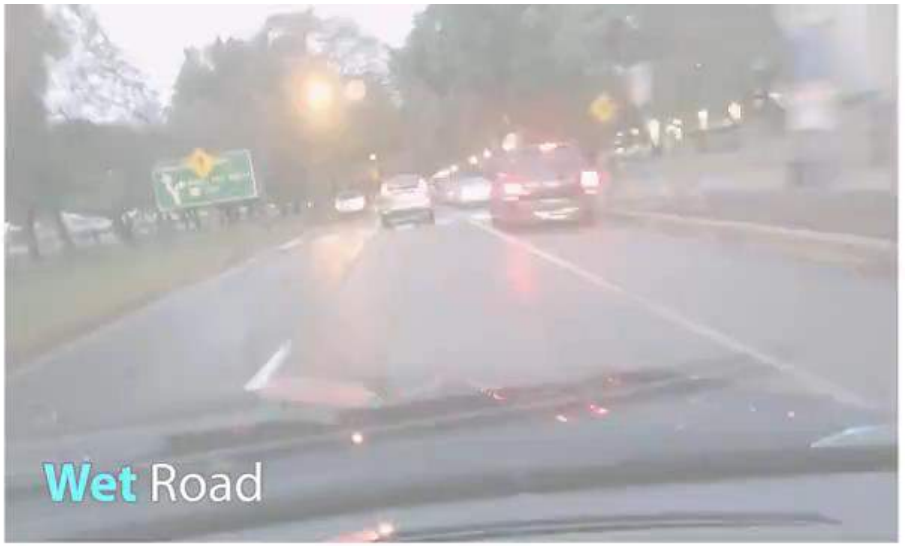
- Past approaches: cascades classifiers (Haar-like features)
- Where deep learning can help:
  recognition, classification, detection

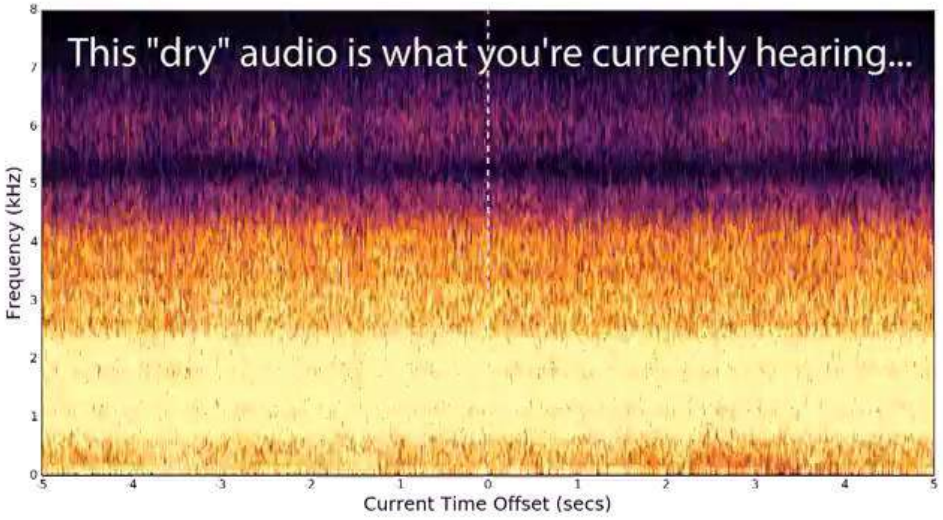
Full Driving Scene Segmentation

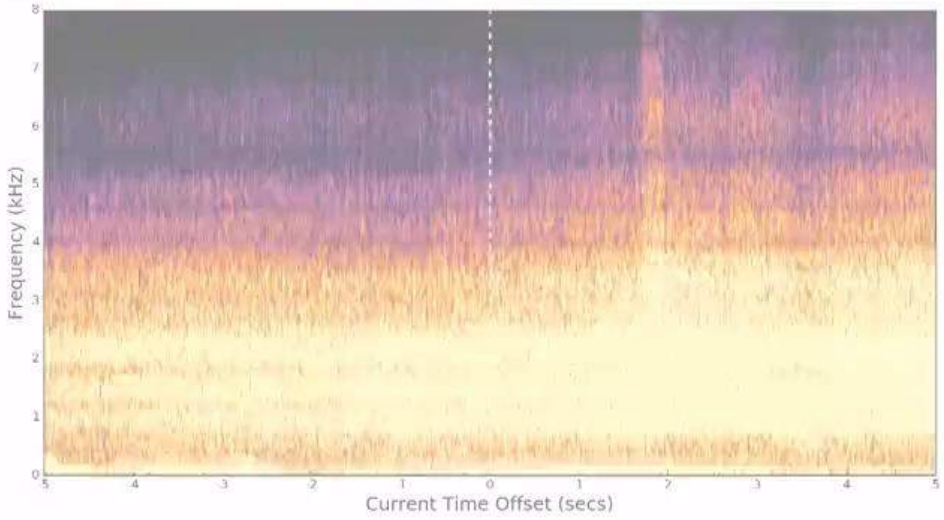
Fully Convolutional Network implementation:
https://github.com/tkuanlun350/Tensorflow-SegNet

Road Texture and Condition from Audio

(with Recurrent Neural Networks)







Self-Driving Car Tasks

- **Localization and Mapping:**
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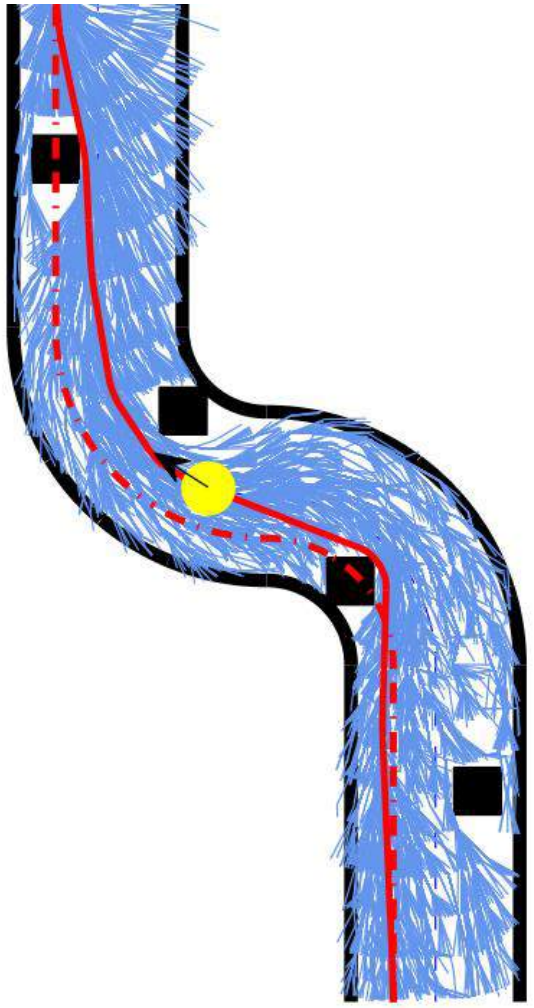
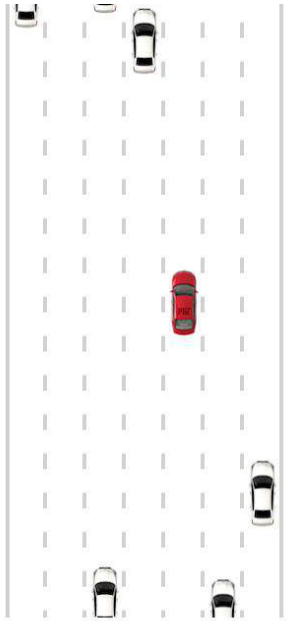
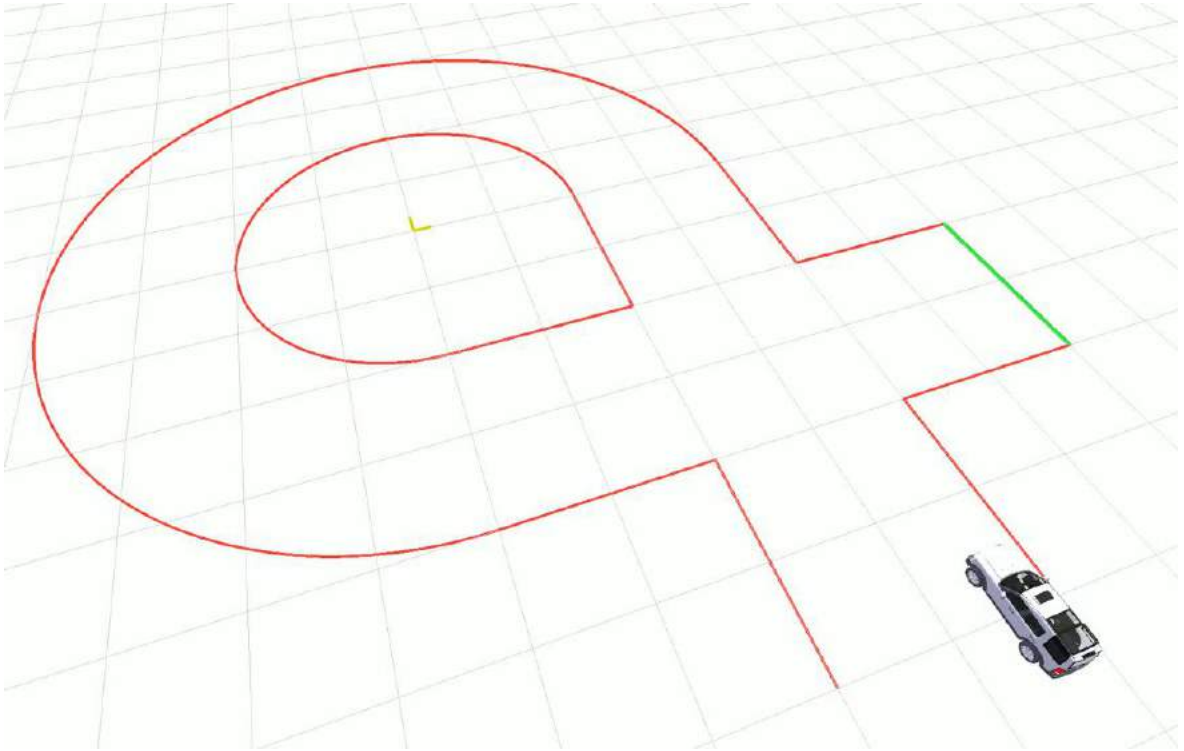


- Previous approaches: optimization-based control
- Where deep learning can help: reinforcement learning





Deep Reinforcement Learning implementation:
https://github.com/nivwusquorum/tensorflow-deepq

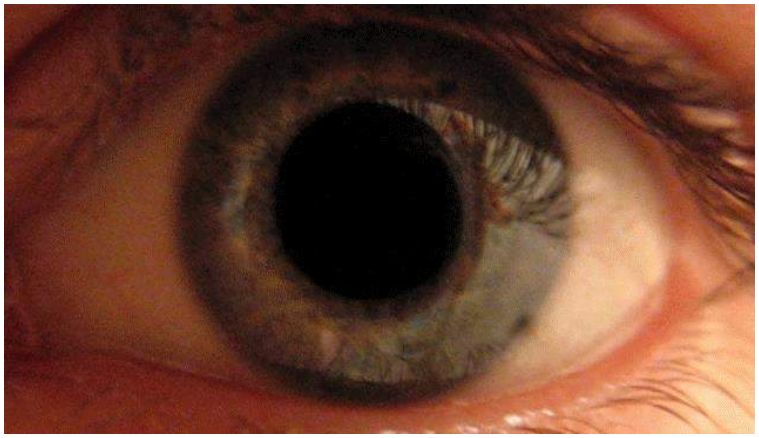
Self-Driving Car Tasks

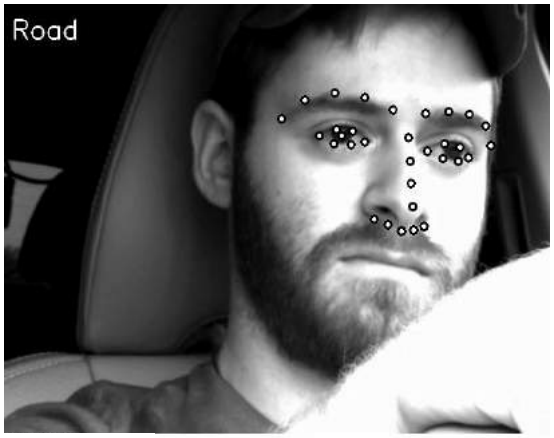
- **Localization:**
  Where am I?

- **Object detection:**
  Where is everyone else?

- **Movement planning:**
  How do I get from A to B?

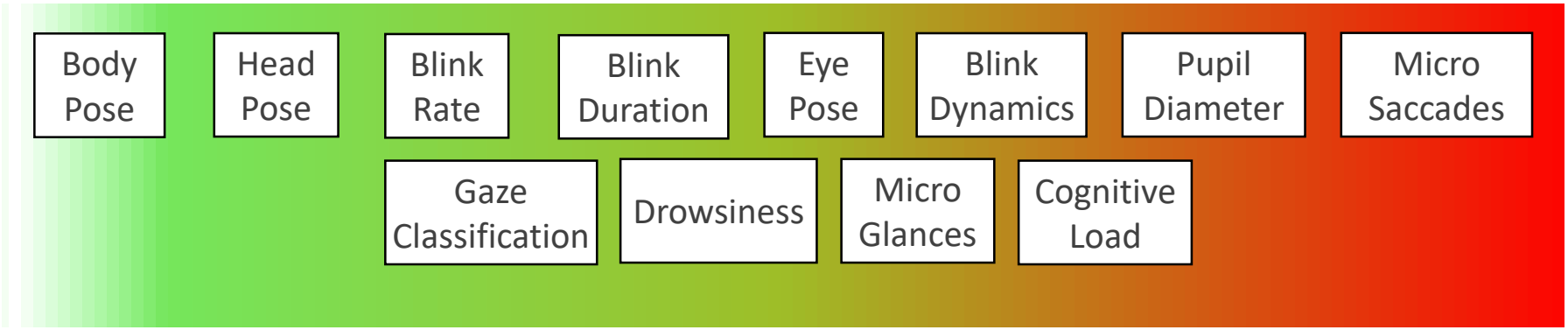
- **Driver state:**
  What's the driver up to?

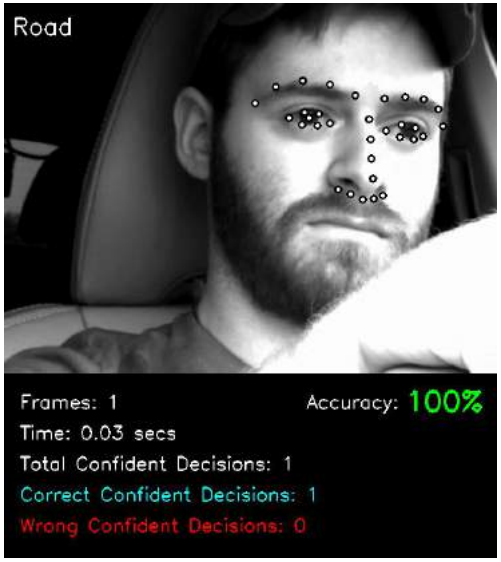


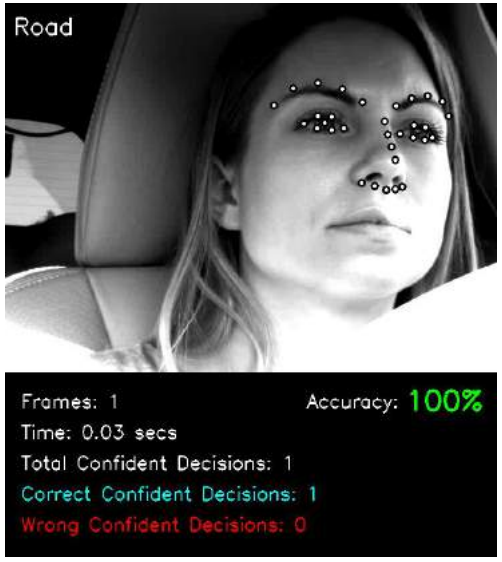


Drive State Detection:
A Multi-Resolutional View

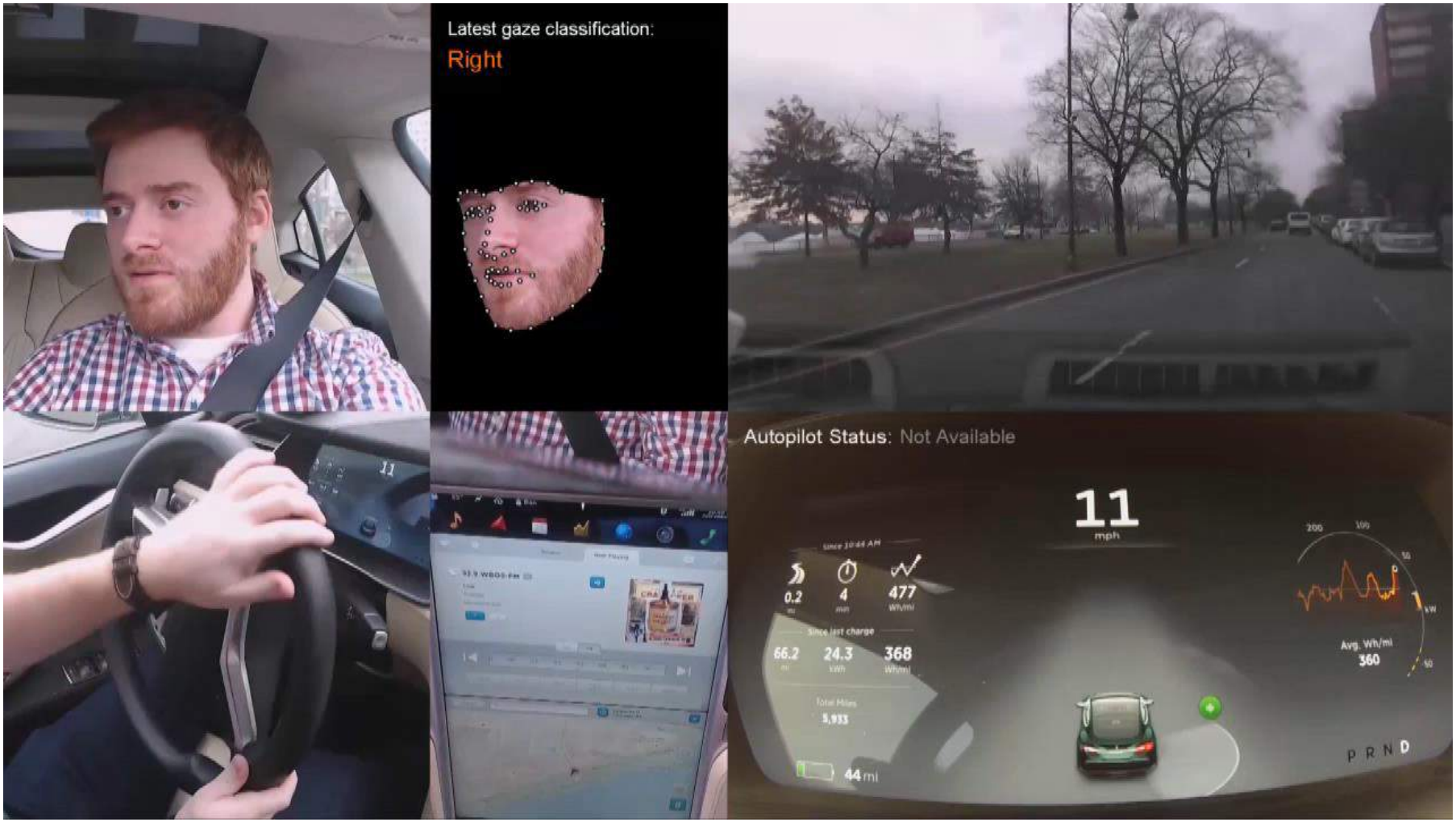
Increasing level of detection resolution and difficulty







Gaze Region and Autopilot State



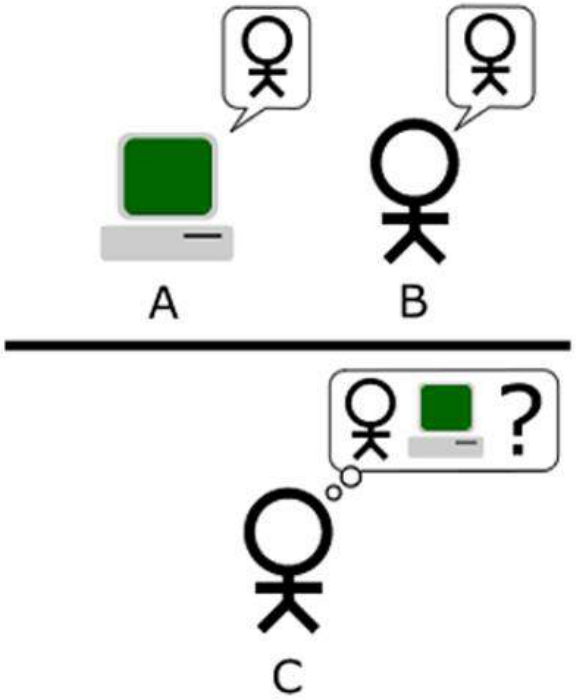
Driver Emotion

Class 1: Satisfied with Voice-Based Interaction

Class 2: Frustrated with Voice-Based Interaction

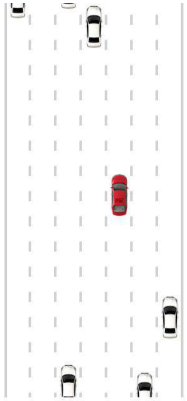
If Driving is a Conversation, this is an

End-to-End Natural Language Generation



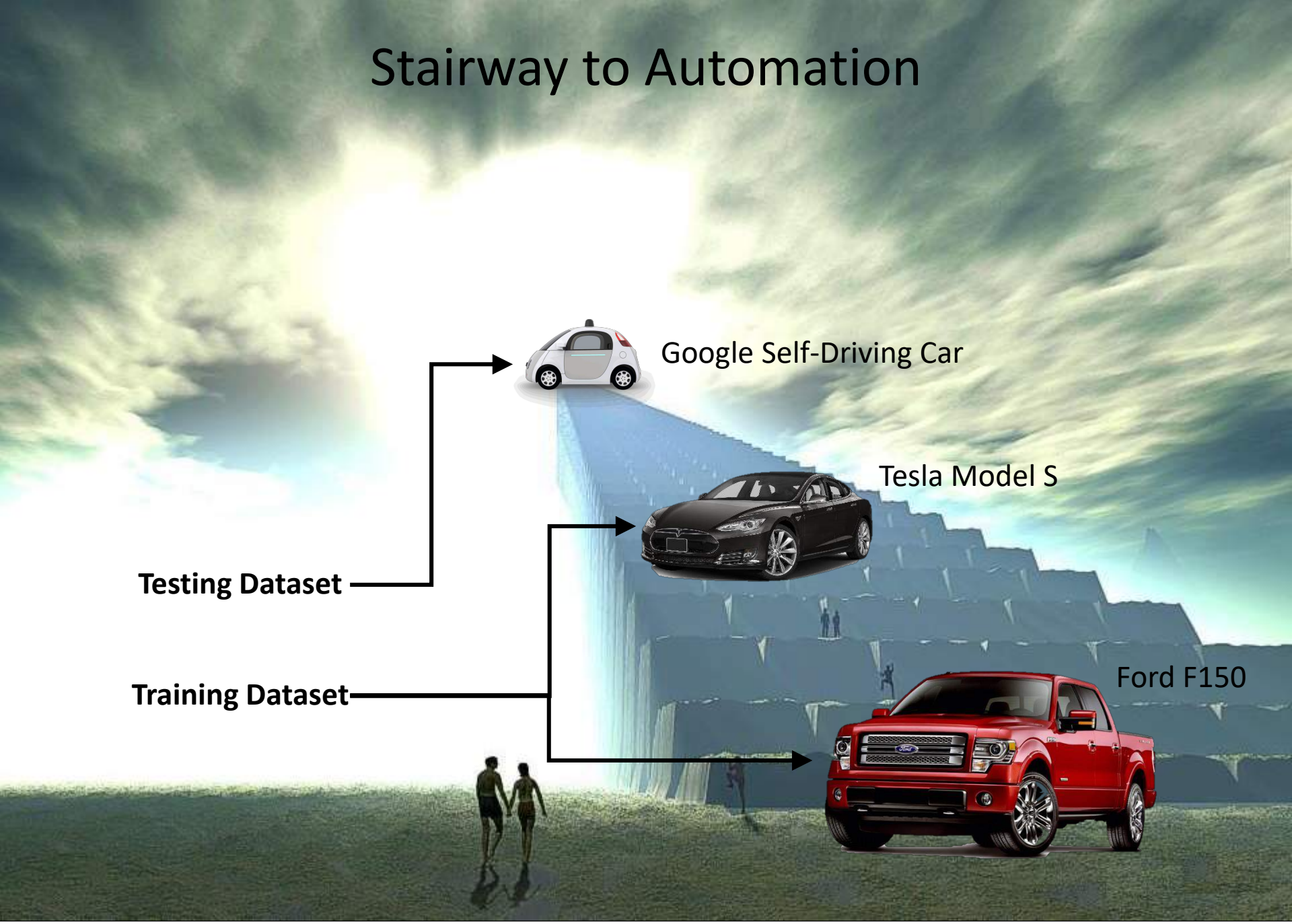
1. **Natural language processing** to enable it to communicate successfully
2. **Knowledge representation** to store information provided before or during the interrogation
3. **Automated reasoning** to use the stored information to answer questions and to draw new conclusions

Turing Test:
Can a computer be mistaken for a human more than 30% of the time?



Autonomous Driving: End-to-End

Stairway to Automation



Autonomous Driving: End-to-End

End to End Learning for Self-Driving Cars

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Jiakai Zhang
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Xin Zhang
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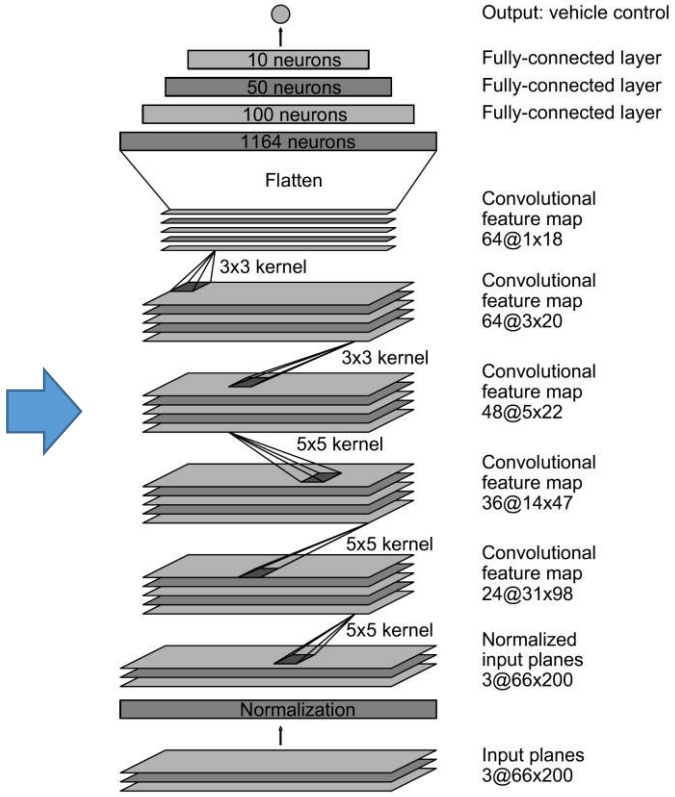
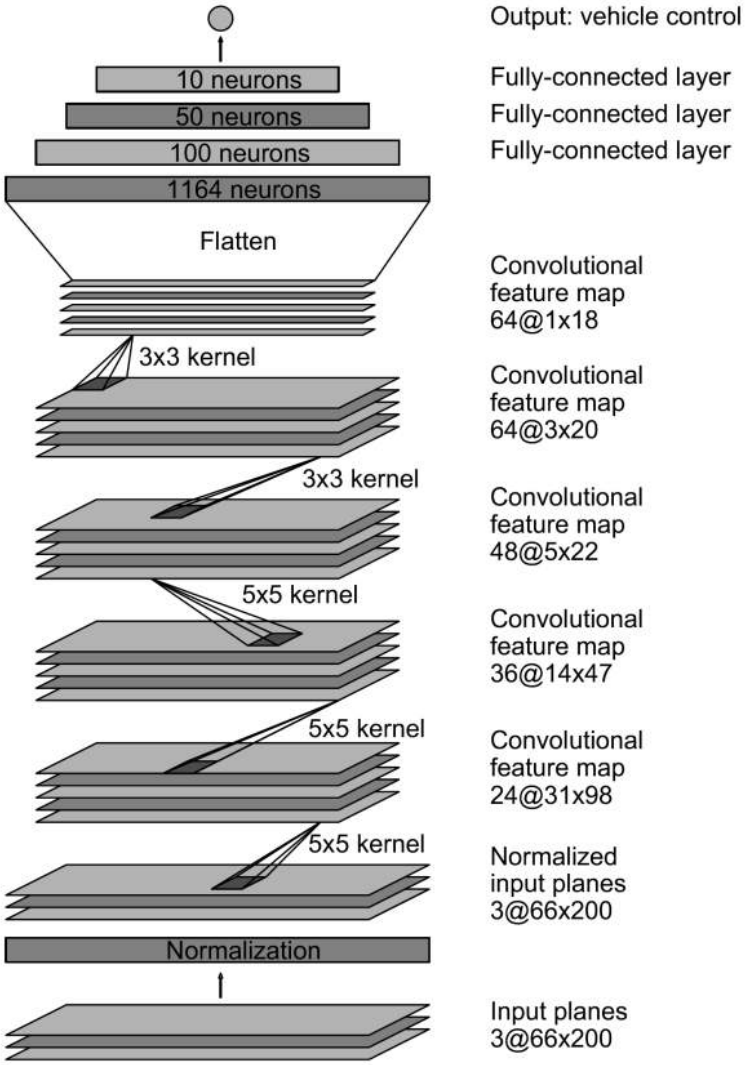
Jake Zhao
NVIDIA Corporation
Holmdel, NJ 07735

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

End-to-End Driving with ConvnetJS

Tutorial on http://cars.mit.edu/deeptesla

End-to-end Steering

- By the end of this lecture, you'll be able to train a model that can steer a vehicle
- Our input to our network will be a single image of the forward roadway from a Tesla
- Our output will be a steering wheel value between -20 and 20

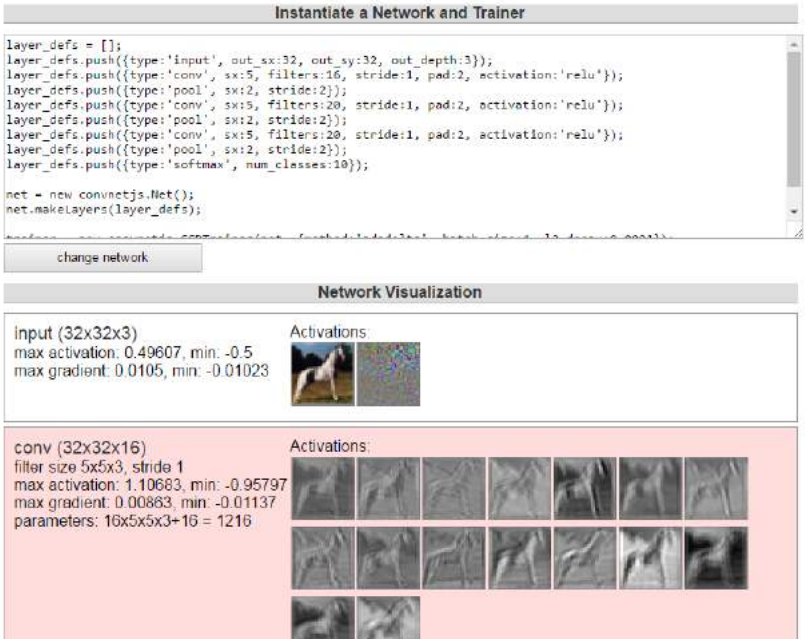
Creating the Dataset

- We recorded and extracted 10 video clips of highway driving from a Tesla
- The wheel value was extracted from the in-vehicle CAN
- We cropped/extracted a window from each video frame and provide a CSV linking the window to a wheel value

Lighting and Road Conditions

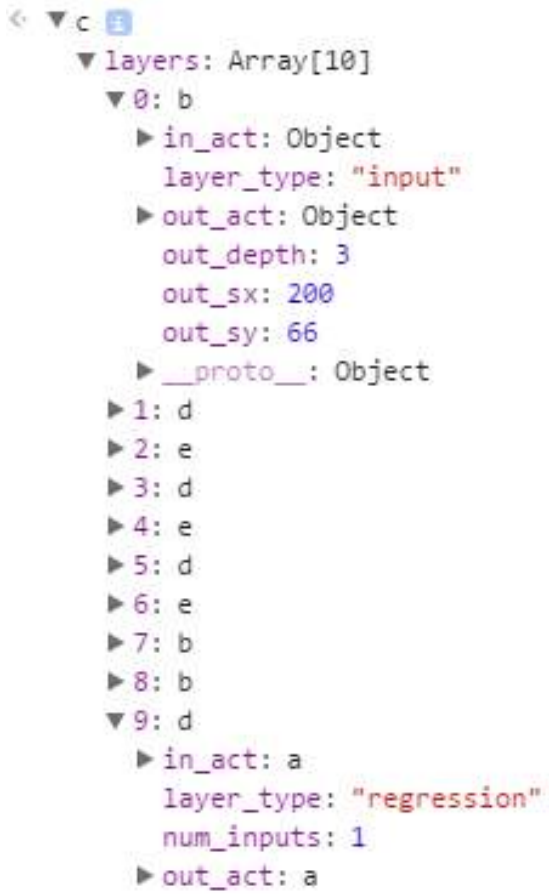
ConvNetJS Overview

- ConvNetJS is a Javascript implementation for using and training neural networks within the browser
- It supports simple networks with several different layer types and training algorithms
- Constructing and training a network can be performed in very few lines of code, great for demonstrations



ConvNetJS – Neural Network Representation

- The network is represented by a single Javascript object which contains a list of layers
- Each layer contains a plain array of weights (w), the activation/activation gradients of the last forward pass, as well as the shape and layer type



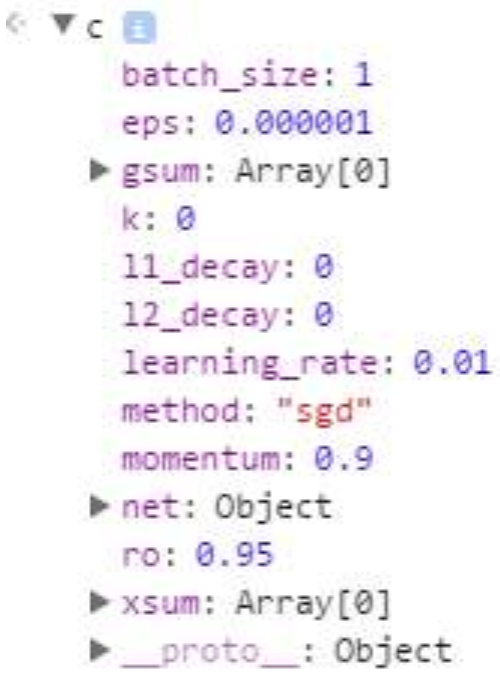
Layer Types

- ConvNetJS implements several different layer types: convolutional, pooling, fully-connected, local contrast normalization, and loss layers
- There are three available output types: regression, softmax, and SVM

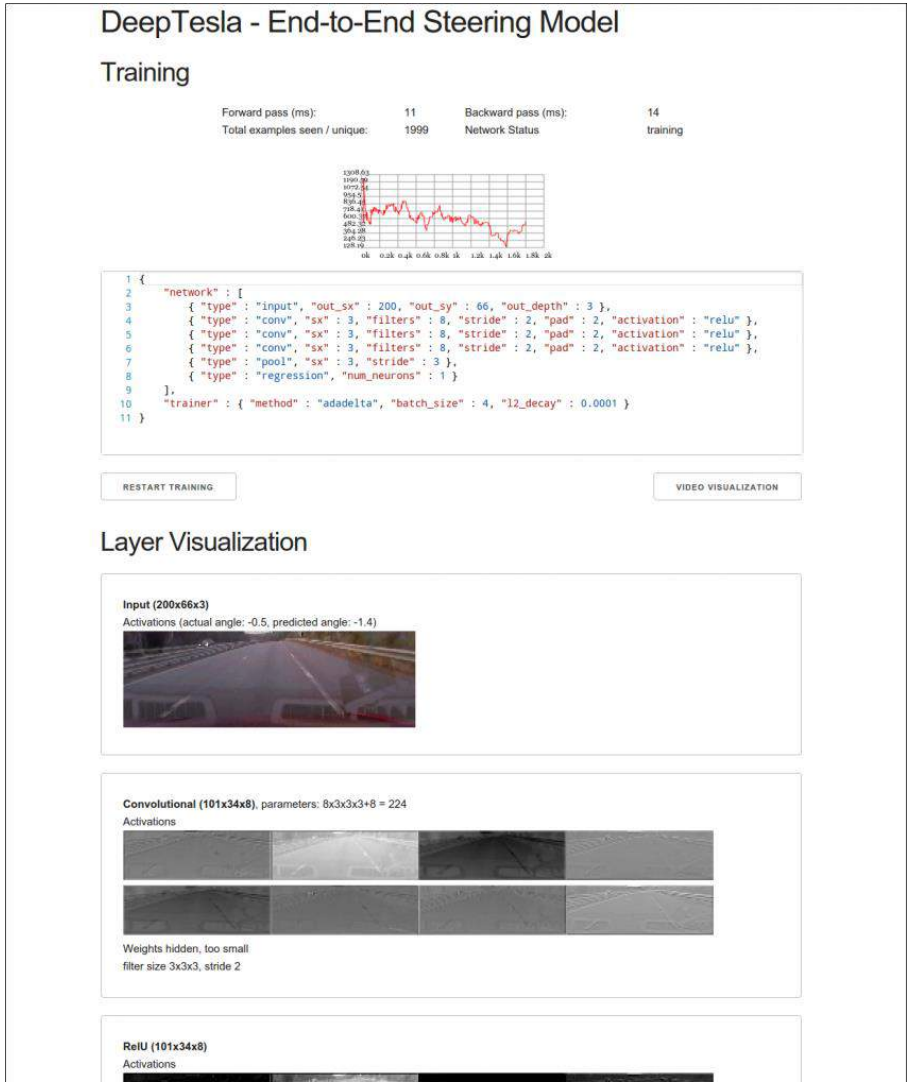
```
{
    "network" : [
        { "type" : "input", "out_sx" : 200, "out_sy" : 66, "out_depth" : 3 },
        { "type" : "conv", "sx" : 3, "filters" : 8, "stride" : 1, "pad" : 2, "activation" : "relu" },
        { "type" : "pool", "sx" : 2, "stride" : 2 },
        { "type" : "conv", "sx" : 3, "filters" : 8, "stride" : 1, "pad" : 2, "activation" : "relu" },
        { "type" : "pool", "sx" : 2, "stride" : 2 },
        { "type" : "conv", "sx" : 3, "filters" : 8, "stride" : 1, "pad" : 2, "activation" : "relu" },
        { "type" : "pool", "sx" : 3, "stride" : 3 },
        { "type" : "regression", "num_neurons" : 1 }
    ],
    "trainer" : { "method" : "adadelta", "batch_size" : 4, "l2_decay" : 0.0001 }
}
```

ConvNetJS – Training Overview

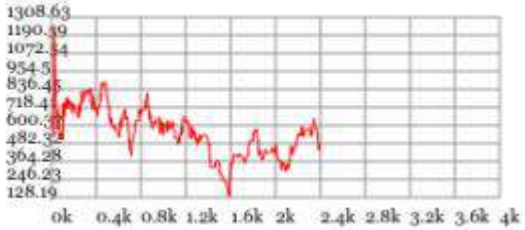
- To train a network, you first must initialize a “Trainer” object
  - var trainer = new convnetjs.SGDTrainer(net, { method: ‘adadelta’, batch_size: 1, l2_decay: 0.0001});
- There are three training algorithms available: SGD, Adadelta, and Adagrad.
- Training is performed by manually calling trainer.train(input_volume, expected_output)
- Returns an object containing timing and loss function information



DeepTesla Overview



Model Metrics



Forward pass (ms):	7	Backward pass (ms):	9
Total examples seen / unique:	2827	Network Status	training

Network Designer

```
{
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        { "type" : "input", "out_sx" : 200, "out_sy" : 66, "out_depth" : 3 },
        { "type" : "conv", "sx" : 3, "filters" : 8, "stride" : 2, "pad" : 2, "activation" : "relu" },
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    ],
    "trainer" : { "method" : "adadelta", "batch_size" : 4, "l2_decay" : 0.0001 }
}
```
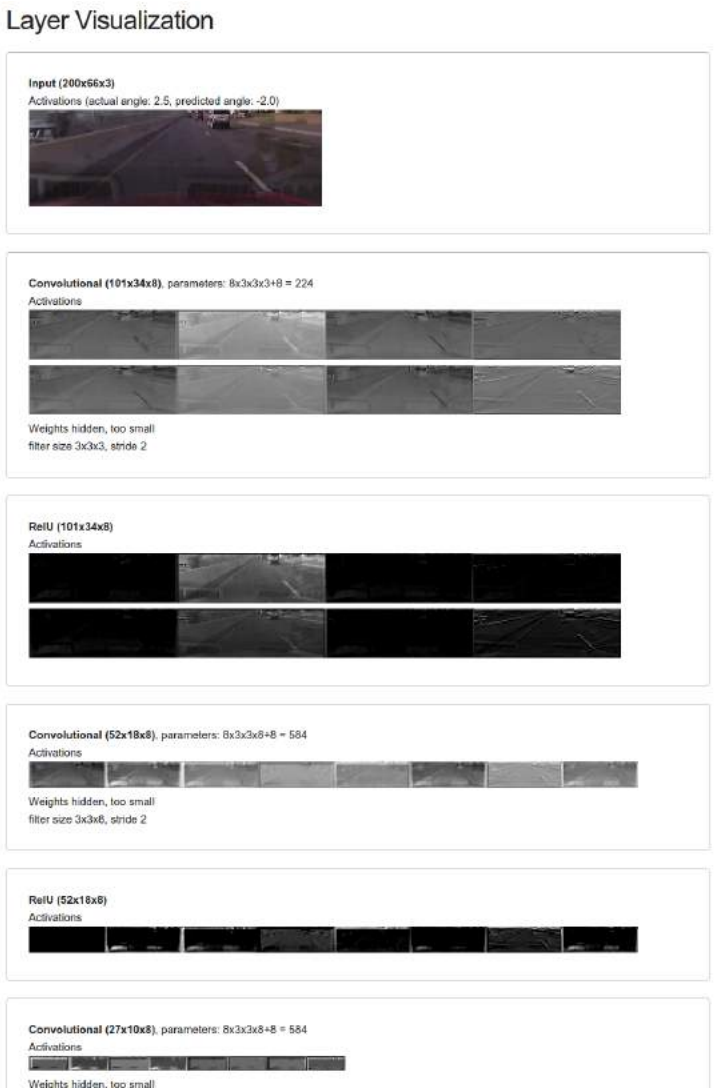

RESTART TRAINING

VIDEO VISUALIZATION

Training Interaction

Layer Visualization



Input Layer

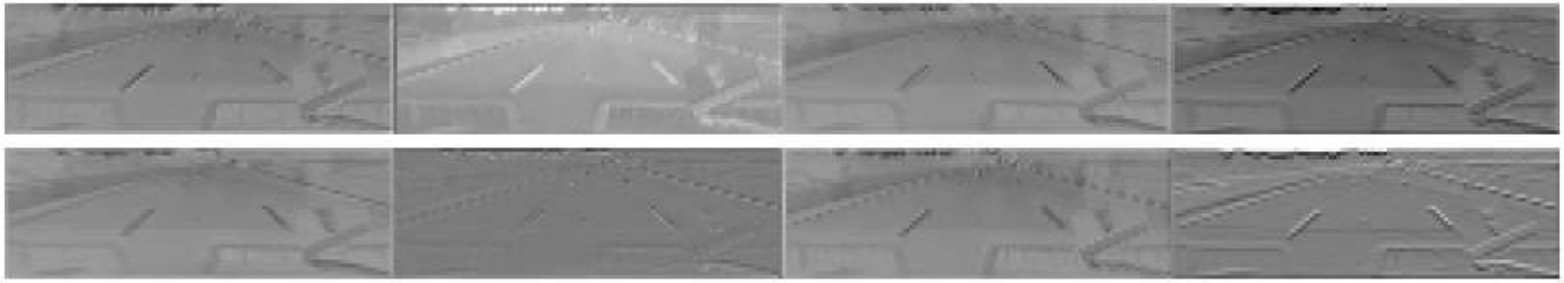
Input (200x66x3)

Activations (actual angle: 1.0, predicted angle: 1.5)

Convolutional Layer Visualization

Convolutional (101x34x8), parameters: 8x3x3x3+8 = 224

Activations



Weights hidden, too small

filter size 3x3x3, stride 2

Video Visualization

Information Bar

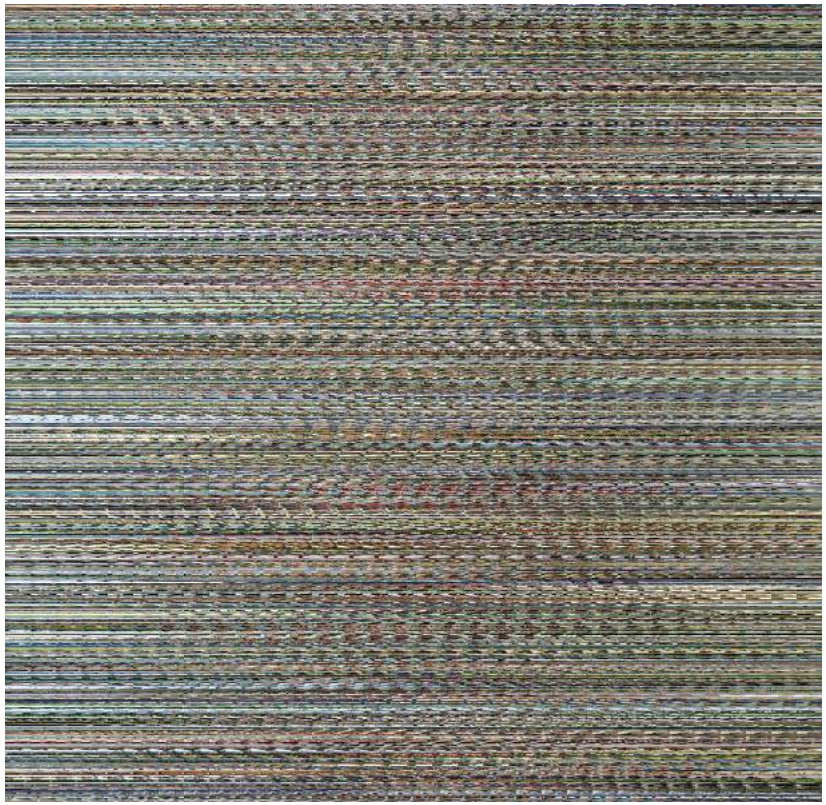
Input Box

Barcodes

- 17 bit, sign-magnitude
- Encoded into actual video
- 0 = black, 1 = white
- Frame on top, wheel on bottom (divided by two)

Image Batches

- Each image loaded of the network contains an entire batch
- There is one image per row, and 250 rows in total
- These images are reassembled into volumes upon download

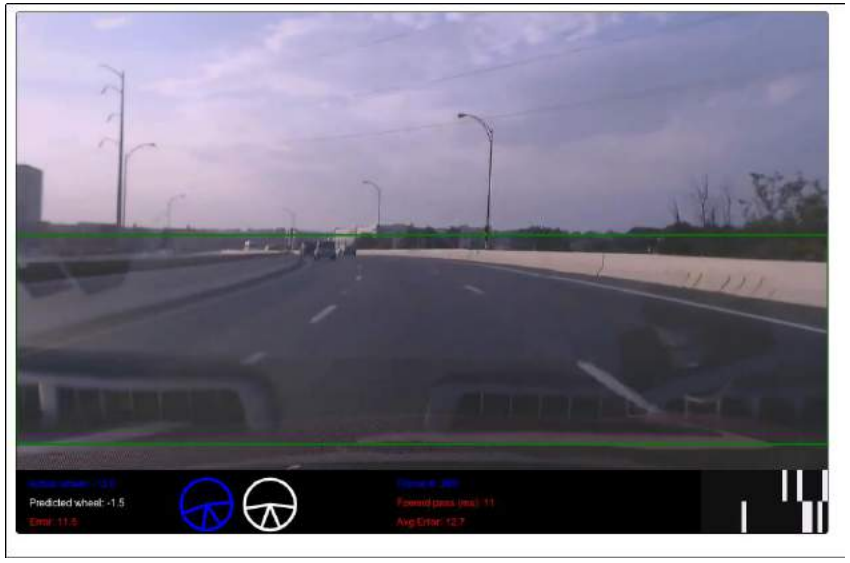


Training Explanation

- One web worker used for loading examples
  - Each batch of training images is one large image with each row as a single training example
  - After an image finishes loading asynchronously, sends the training examples to another worker
- One web worker used for training network
  - Train on each image and push the network/outputs to visualization worker
- One web worker used for visualization
  - For a specified training example interval, blit the activation/gradient output of each training example onto a canvas
- Each web worker behaves as a single thread, and we use message passing to communicate state between the workers

ConvNetJS Evaluation - Video Explanation

- The videos are encoded as 1280x820 in H264/MKV with 17 bit sign-magnitude barcodes
- The video main video frame is stored in the box (0, 1280, 0, 720)
- The frame barcode is in box (1144, 720, 1280, 770)
- The wheel value barcode is in box (1144, 770, 1280, 820)



ConvNetJS Evaluation - Creating the Video

- Each epoch is synchronized to 30 fps
- We extract the wheel value from the CAN data and synchronize each message to a frame (both the frame and the CAN message are timestamped)
- Using OpenCV, we process the data
  - Generate a bar code for the frame containing the wheel data
  - Crop the image portion used for training
  - Create single images containing batches of training data
- The epochs and associated data are copied to our web server which serves

ConvNetJS Evaluation - Playing the Video

- To be able to use the video in the neural network, we need to do some preprocessing
- First, we have a hidden video element and rely on modern HTML5 video implementations
- When the user requests the video to play, we begin tracking each redraw of the page
- With each redraw, we grab the currently rendered video frame, extract the RGBA values and blit them to two different canvases: one canvas, which the user sees, and another canvas which is hidden and only contains a cropped portion of the frame (the part we will use for the neural network)

ConvNetJS Evaluation - Playing the Video

- Next, we read the image data from the hidden canvas and shape it into a ConvNetJS volume
- For each image we first create a volume:
  - var image_vol = new convnetjs.Vol(x_size, y_size, depth, default_value)
- Next, we extract each pixel from the canvas and set the equivalent voxel (volume pixel) to the value (skipping the alpha value)
- We can also extract the expected steer value by parsing the barcode (a 17 bit, signed-magnitude barcode, where white = 1, black = 0)

ConvNetJS Evaluation - Forward Pass

- Now we can use our extracted volume in the forward pass by calling net.forward(our_volume)
- The predicted value is stored in the output neuron:
  - var prediction = net.forward(vol);
  - var raw_regression_value = prediction.w[0];

- Because we min-max normalized our inputs while training the network, we need to transform our outputs – this is just the reverse transformation we performed on input:
  - Wheel value = (raw_regression_value * total_wheel_range) – wheel_min

- We visualize the predicted and actual steering wheel values and calculate the error

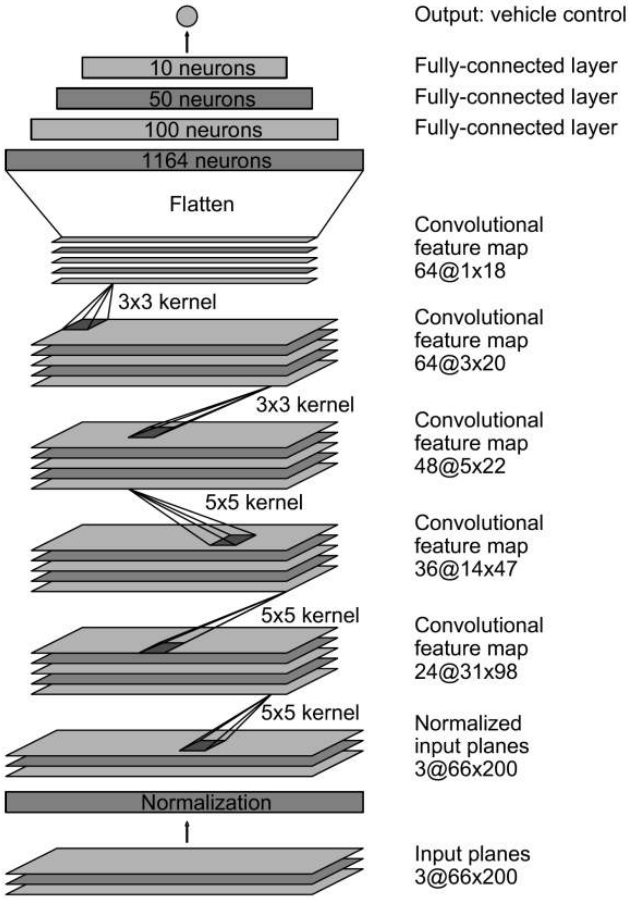
End-to-End Driving with ConvnetJS

Tutorial on http://cars.mit.edu/deeptesla

End-to-End Driving with TensorFlow

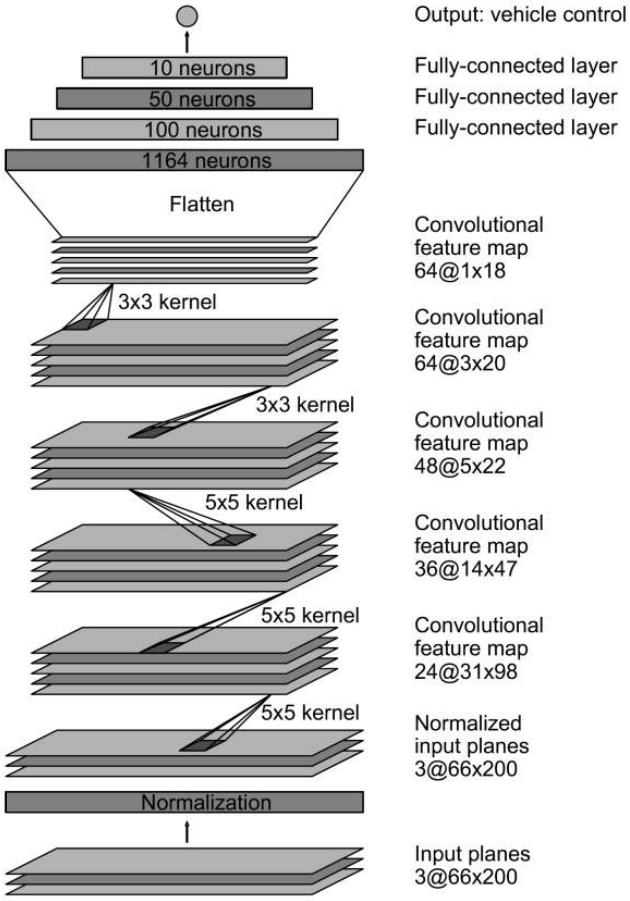
Available on http://github.com/lexfridman/deeptesla

Build the Model: Input and Output



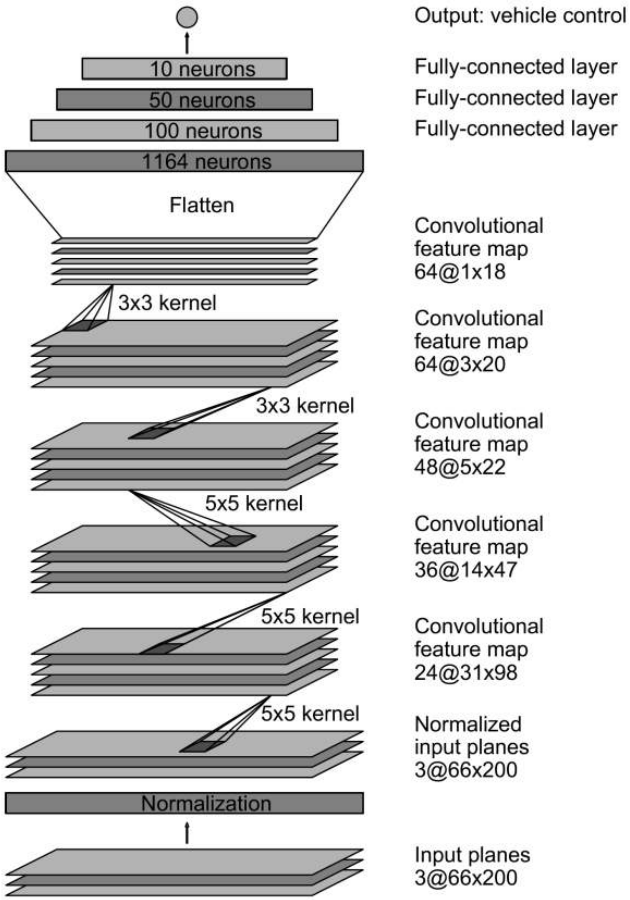

```
def weight_variable(shape):
  initial = tf.truncated_normal(shape, stddev=0.1)
  return tf.Variable(initial)

def bias_variable(shape):
  initial = tf.constant(0.1, shape=shape)
  return tf.Variable(initial)

def conv2d(x, W, stride):
  return tf.nn.conv2d(x, W, strides=[1, stride, stride, 1],
padding='VALID')

x = tf.placeholder(tf.float32, shape=[None, 66, 200, 3])
y_ = tf.placeholder(tf.float32, shape=[None, 1])

x_image = x
```

Build the Model: Convolutional Layers




```
#first convolutional layer
W_conv1 = weight_variable([5, 5, 3, 24])
b_conv1 = bias_variable([24])

h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1, 2) + b_conv1)

#second convolutional layer
W_conv2 = weight_variable([5, 5, 24, 36])
b_conv2 = bias_variable([36])

h_conv2 = tf.nn.relu(conv2d(h_conv1, W_conv2, 2) + b_conv2)

#third convolutional layer
W_conv3 = weight_variable([5, 5, 36, 48])
b_conv3 = bias_variable([48])

h_conv3 = tf.nn.relu(conv2d(h_conv2, W_conv3, 2) + b_conv3)

#fourth convolutional layer
W_conv4 = weight_variable([3, 3, 48, 64])
b_conv4 = bias_variable([64])

h_conv4 = tf.nn.relu(conv2d(h_conv3, W_conv4, 1) + b_conv4)

#fifth convolutional layer
W_conv5 = weight_variable([3, 3, 64, 64])
b_conv5 = bias_variable([64])

h_conv5 = tf.nn.relu(conv2d(h_conv4, W_conv5, 1) + b_conv5)
```

Build the Model: Fully Connected Layers




```
# fully connected layer 1
W_fc1 = weight_variable([1152, 1164])
b_fc1 = bias_variable([1164])

h_conv5_flat = tf.reshape(h_conv5, [-1, 1152])
h_fc1 = tf.nn.relu(tf.matmul(h_conv5_flat, W_fc1) + b_fc1)

keep_prob = tf.placeholder(tf.float32)
h_fc1_drop = tf.nn.dropout(h_fc1, keep_prob)

# fully connected layer 2
W_fc2 = weight_variable([1164, 100])
b_fc2 = bias_variable([100])

h_fc2 = tf.nn.relu(tf.matmul(h_fc1_drop, W_fc2) + b_fc2)

h_fc2_drop = tf.nn.dropout(h_fc2, keep_prob)

# fully connected layer 3
W_fc3 = weight_variable([100, 50])
b_fc3 = bias_variable([50])

h_fc3 = tf.nn.relu(tf.matmul(h_fc2_drop, W_fc3) + b_fc3)

h_fc3_drop = tf.nn.dropout(h_fc3, keep_prob)

# fully connected layer 4
W_fc4 = weight_variable([50, 10])
b_fc4 = bias_variable([10])

h_fc4 = tf.nn.relu(tf.matmul(h_fc3_drop, W_fc4) + b_fc4)

h_fc4_drop = tf.nn.dropout(h_fc4, keep_prob)

#Output
W_fc5 = weight_variable([10, 1])
b_fc5 = bias_variable([1])

y = tf.mul(tf.atan(tf.matmul(h_fc4_drop, W_fc5) + b_fc5), 2)
```

Train the Model

```
sess = tf.InteractiveSession()

loss = tf.reduce_mean(tf.square(tf.sub(model.y_, model.y)))
train_step = tf.train.AdamOptimizer(1e-4).minimize(loss)
sess.run(tf.initialize_all_variables())

saver = tf.train.Saver()

for i in range(int(driving_data.num_images * 0.3)):
    xs, ys = driving_data.LoadTrainBatch(100)
    train_step.run(feed_dict={model.x: xs, model.y_: ys, model.keep_prob: 0.8})
    if i % 10 == 0:
        xs, ys = driving_data.LoadValBatch(100)
        print("step %d, val loss %g"%(i, loss.eval(feed_dict={
            model.x:xs, model.y_: ys, model.keep_prob: 1.0})))
    if i % 100 == 0:
        if not os.path.exists(LOGDIR):
            os.makedirs(LOGDIR)
        checkpoint_path = os.path.join(LOGDIR, "model.ckpt")
        filename = saver.save(sess, checkpoint_path)
        print("Model saved in file: %s" % filename)
```

Run the Model

```
import tensorflow as tf
import scipy.misc
import model
import cv2

sess = tf.InteractiveSession()
saver = tf.train.Saver()
saver.restore(sess, "save/model.ckpt")

img = cv2.imread('steering_wheel_image.jpg',0)
rows,cols = img.shape

smoothed_angle = 0

cap = cv2.VideoCapture(0)
while(cv2.waitKey(10) != ord('q')):
    ret, frame = cap.read()
    image = scipy.misc.imresize(frame, [66, 200]) / 255.0
    degrees = model.y.eval(feed_dict={model.x: [image], model.keep_prob:
1.0})[0][0] \
              * 180 / scipy.pi
    cv2.imshow('frame', frame)
    smoothed_angle += 0.2 * pow(abs((degrees - smoothed_angle)), 2.0 / 3.0) * \
                      (degrees - smoothed_angle) / abs(degrees - smoothed_angle)
    M = cv2.getRotationMatrix2D((cols/2,rows/2),-smoothed_angle,1)
    dst = cv2.warpAffine(img,M,(cols,rows))
    cv2.imshow("steering wheel", dst)

cap.release()
cv2.destroyAllWindows()
```

End-to-End Driving with TensorFlow

Available on http://github.com/lexfridman/deeptesla

TrafficLight Classification with TensorFlow



We will be implementing a simple traffic light classifier, with 3 classes (red, green, yellow)

Parameters

```
# Basic parameters

max_epochs = 25
base_image_path = "images/"
image_types = ["red", "green", "yellow"]
input_img_x = 32
input_img_y = 32
train_test_split_ratio = 0.9
batch_size = 32
checkpoint_name = "model.ckpt"
```

- Max epochs: the number of times the neural network will see all training examples
- Input_img_x/y: the size we will use for inputs into the the network
- Batch size: # of examples the neural network will see before making a gradient step

Helper Functions

```
# Helper layer functions
def weight_variable(shape):
    initial = tf.truncated_normal(shape, stddev=0.1)
    return tf.Variable(initial)

def bias_variable(shape):
    initial = tf.constant(0.1, shape=shape)
    return tf.Variable(initial)

def conv2d(x, W, stride):
    return tf.nn.conv2d(x, W, strides=[1, stride, stride, 1], padding='SAME')

def max_pool_2x2(x):
    return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],
                          strides=[1, 2, 2, 1], padding='SAME')
```

We use some helper functions to make adding layers easier/more consistent

Model Input/Output

```
x = tf.placeholder(tf.float32, shape=[None, input_img_x, input_img_y, 3])
y_ = tf.placeholder(tf.float32, shape=[None, len(image_types)])
```

- We specify our input and output types in the same lines to make sure they agree with our idea of the network
- Our input is an image of sized 32x32x3 (RGB channels)
- Our output consists of 3 neurons, representing the probability of each class

Convolutional Layer

```
# Our first three convolutional layers, of 16 3x3 filters
W_conv1 = weight_variable([3, 3, 3, 16])
b_conv1 = bias_variable([16])
h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1, 1) + b_conv1)
```

- Here we specify our first convolutional layer using our helper function
- W_conv1 – a 4D tensor representing the weights [filter_x, filter_y, previous layer neurons, # of filters]
- b_conv1 – our simple addition variable
- h_conv1 – our actual layer/activation

Pooling Layer

```
h_pool4 = max_pool_2x2(h_conv3)
```

Flattening Pool Layer

```
n1, n2, n3, n4 = h_pool4.get_shape().as_list()

W_fc1 = weight_variable([n2*n3*n4, 3])
b_fc1 = bias_variable([3])

# We flatten our pool layer into a fully connected layer

h_pool4_flat = tf.reshape(h_pool4, [-1, n2*n3*n4])
```

We calculate the total number of neurons needed in our first fully-connected layer by multiplying all the dimensions of the pool layer shape

Output Layer

```
y = tf.matmul(h_pool4_flat, W_fc1) + b_fc1
```

Loss and Optimizer

```
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(y, y_))
train_step = tf.train.AdamOptimizer(1e-4).minimize(loss)
sess.run(tf.initialize_all_variables())
```

- Our loss function performs softmax and then computes cross-entropy
- We use the AdamOptimizer and specify a learning rate

Saver Object

```
saver = tf.train.Saver()
time_start = time.time()
```

Loading Images

```
full_set = []

for im_type in image_types:
    for ex in glob.glob(os.path.join(base_image_path, im_type, "*")):
        im = cv2.imread(ex)
        if not im is None:
            im = cv2.resize(im, (32, 32))

            # Create an array representing our classes and set it
            one_hot_array = [0] * len(image_types)
            one_hot_array[image_types.index(im_type)] = 1
            assert(im.shape == (32, 32, 3))

            full_set.append((im, one_hot_array))

random.shuffle(full_set)
```

- Iterate over each image, resize to 32x32
- Create a one hot encoding of our class
- Shuffle the entire dataset

Splitting the Dataset

```
# We split our data into a training and test set here

split_index = int(math.floor(len(full_set) * train_test_split_ratio))
train_set = full_set[:split_index]
test_set = full_set[split_index:]
```

```
train_x, train_y = zip(*train_set)
test_x, test_y = zip(*test_set)
```

- Split our data set into train and test
- We truncate our sets to a multiple of batch size (all batches have to be the same size)

Training Loop

```
for tt in range(0, (len(train_x) / batch_size)):
    start_batch = batch_size * tt
    end_batch = batch_size * (tt + 1)
    train_step.run(feed_dict={x: train_x[start_batch:end_batch], y_: train_y[start_batch:end_batch]})
    ex_seen = "Current epoch, examples seen: {:20} / {} \r".format(tt * batch_size, len(train_x))
    sys.stdout.write(ex_seen.format(tt * batch_size))
    sys.stdout.flush()
```

- Iterate over each batch and train on it
- (we assume training examples are a multiple of the batch size)

Best Model

```
t_loss = loss.eval(feed_dict={x: train_x, y_: train_y})
v_loss = loss.eval(feed_dict={x: test_x, y_: test_y})

sys.stdout.write("Epoch {:5}: loss: {:15.10f}, val. loss: {:15.10f}".format(i + 1, t_loss, v_loss))

if v_loss < least_loss:
    sys.stdout.write(", saving new best model to {}".format(checkpoint_name))
    least_loss = v_loss
    filename = saver.save(sess, checkpoint_name)
```

- We evaluate the loss on all of our training examples and test examples
- If the validation loss is lower than the lowest loss, we save our model

Expected Output

```
I tensorflow/stream_executor/dso_loader.cc:108] successfully opened CUDA library libcublas.so locally
I tensorflow/stream_executor/dso_loader.cc:108] successfully opened CUDA library libcudnn.so locally
I tensorflow/stream_executor/dso_loader.cc:108] successfully opened CUDA library libcufft.so locally
I tensorflow/stream_executor/dso_loader.cc:108] successfully opened CUDA library libcuda.so.1 locally
I tensorflow/stream_executor/dso_loader.cc:108] successfully opened CUDA library libcurand.so locally
I tensorflow/core/common_runtime/gpu/gpu_init.cc:102] Found device 0 with properties:
name: GeForce GTX 980 Ti
major: 5 minor: 2 memoryClockRate (GHz) 1.076
pciBusID 0000:02:00.0
Total memory: 6.00GiB
Free memory: 5.52GiB
I tensorflow/core/common_runtime/gpu/gpu_init.cc:126] DMA: 0
I tensorflow/core/common_runtime/gpu/gpu_init.cc:136] 0:   Y
I tensorflow/core/common_runtime/gpu/gpu_device.cc:838] Creating TensorFlow device (/gpu:0) -> (device: 0, n
orce GTX 980 Ti, pci bus id: 0000:02:00.0)
Starting training... [1312 training examples]
Epoch     1: loss:    3.4614486694, val. loss:    4.1707162857, saving new best model to model.ckpt
Epoch     2: loss:    1.8578453064, val. loss:    1.8420848846, saving new best model to model.ckpt
Epoch     3: loss:    1.2075960636, val. loss:    1.1884875298, saving new best model to model.ckpt
Epoch     4: loss:    0.7959808707, val. loss:    0.8523907661, saving new best model to model.ckpt
Epoch     5: loss:    0.5186702609, val. loss:    0.8251042366, saving new best model to model.ckpt
Epoch     6: loss:    0.3895130754, val. loss:    0.7883402705, saving new best model to model.ckpt
Epoch     7: loss:    0.2840102911, val. loss:    0.8282299042
Epoch     8: loss:    0.2281106114, val. loss:    0.7970542312
Epoch     9: loss:    0.1889465898, val. loss:    0.8308163881
Epoch    10: loss:    0.1507862508, val. loss:    0.8214046359
Epoch    11: loss:    0.1126181334, val. loss:    0.7745668888, saving new best model to model.ckpt
Epoch    12: loss:    0.0972050354, val. loss:    0.7550495267, saving new best model to model.ckpt
Epoch    13: loss:    0.0831822604, val. loss:    0.7207581401, saving new best model to model.ckpt
Epoch    14: loss:    0.0760012567, val. loss:    0.7217628956
Epoch    15: loss:    0.0637019351, val. loss:    0.7158752084, saving new best model to model.ckpt
Epoch    16: loss:    0.0536490902, val. loss:    0.7022477984, saving new best model to model.ckpt
Epoch    17: loss:    0.0512478650, val. loss:    0.6906370521, saving new best model to model.ckpt
Epoch    18: loss:    0.0333782099, val. loss:    0.6657178402, saving new best model to model.ckpt
Epoch    19: loss:    0.0367136374, val. loss:    0.6645810008, saving new best model to model.ckpt
Epoch    20: loss:    0.0175283104, val. loss:    0.6335256100, saving new best model to model.ckpt
Epoch    21: loss:    0.0203501396, val. loss:    0.6400516629
Epoch    22: loss:    0.0372636504, val. loss:    0.6770884395
Epoch    23: loss:    0.0096475044, val. loss:    0.5926443338, saving new best model to model.ckpt
Epoch    24: loss:    0.0095629999, val. loss:    0.5750324726, saving new best model to model.ckpt
Epoch    25: loss:    0.0072135003, val. loss:    0.5805844069
```

TrafficLight Classification with TensorFlow



We will be implementing a simple traffic light classifier, with 3 classes (red, green, yellow)

References

All references cited in this presentation are listed in the following Google Sheets file:

https://goo.gl/9Xhp2t