CMPE 185 Autonomous Mobile Robots

Perception: Learning Based Object Classification and Detection

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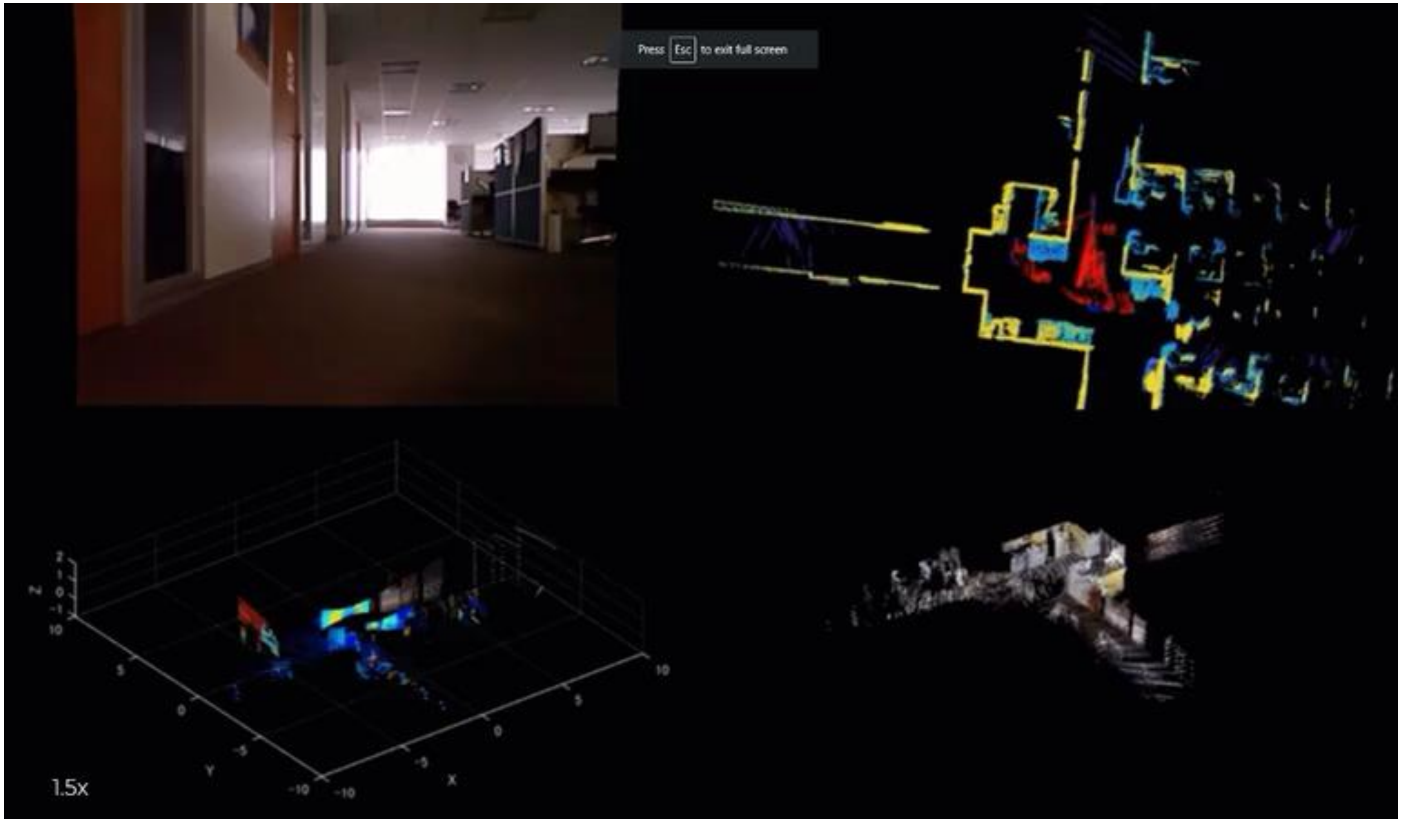
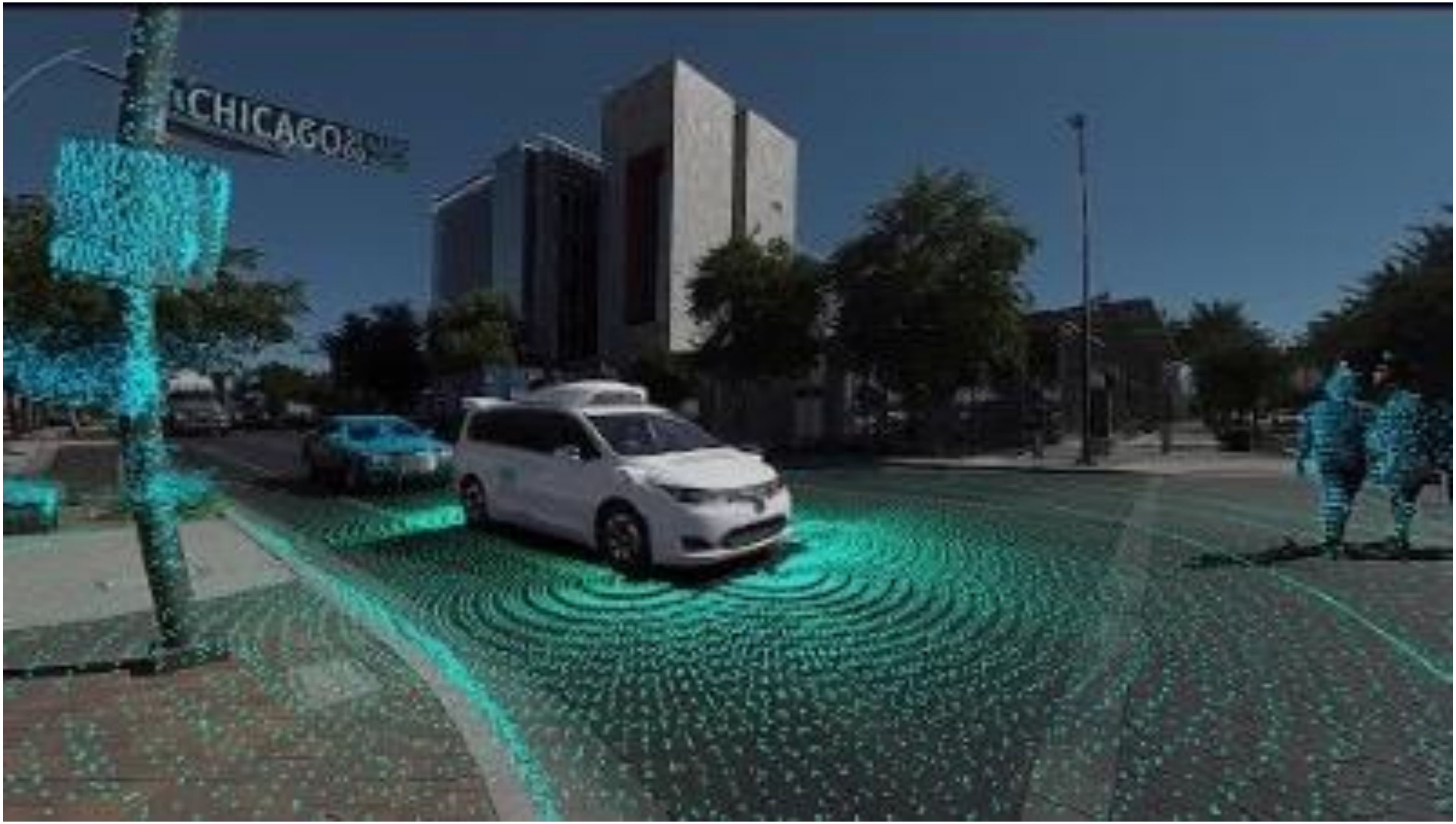
Computer Vision

- Enable robot vision to build environment maps and localize your mobile robot



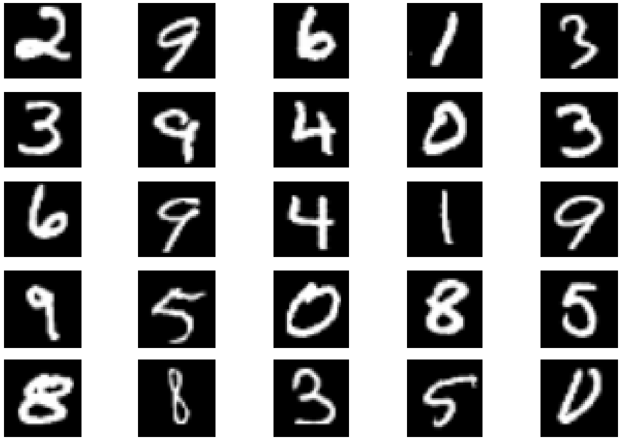
Waymo Experience – Sensor Fusion



Example: Autonomous Parking

Image Classification

- K classes
- Task: assign correct class label to the whole image



Digit classification (MNIST)

Object recognition (Caltech-101)

Classification v.s. Detection

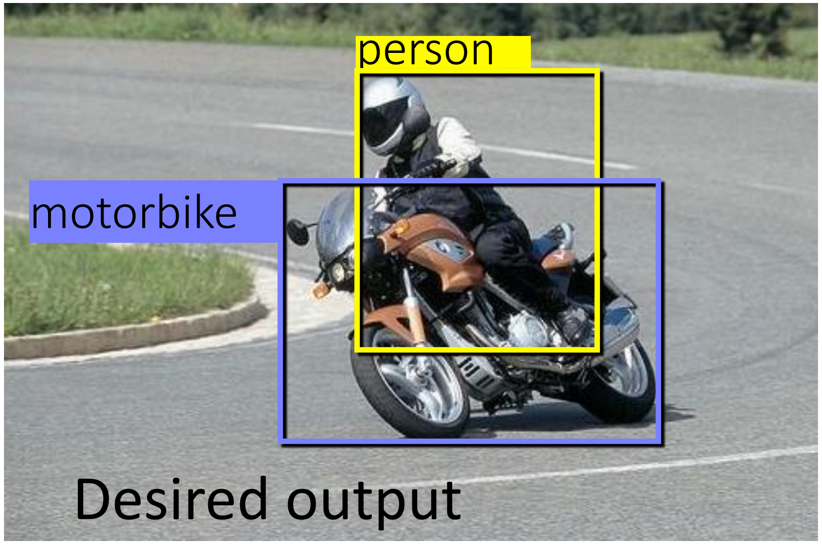
Classification

Detection

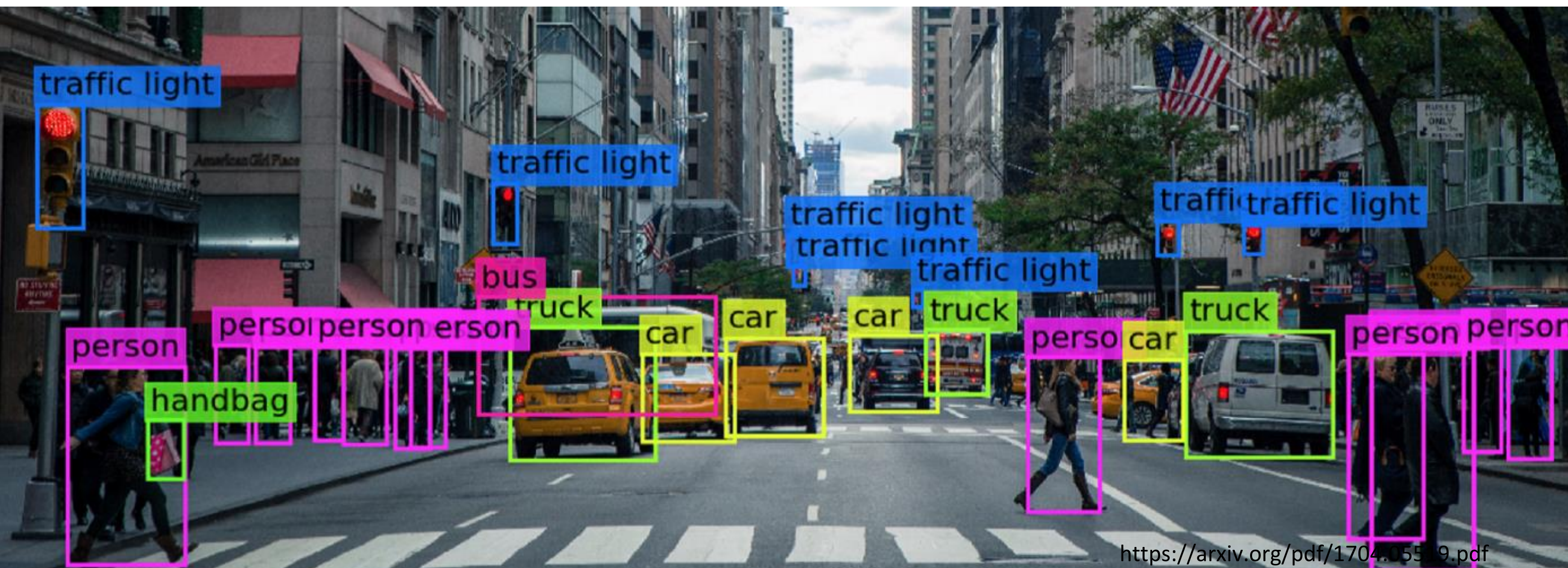
Problem Formulation

- **When performing object detection, we wish to obtain:**
  - A **list of bounding boxes**, or the *(x, y)*-coordinates for each object in an image
  - The **class label** associated with each bounding box
  - The **probability/confidence score** associated with each bounding box and class

{ airplane, bird, motorbike, person, sofa }



Object Detection in Autonomous Driving



https://arxiv.org/pdf/1704.05519.pdf

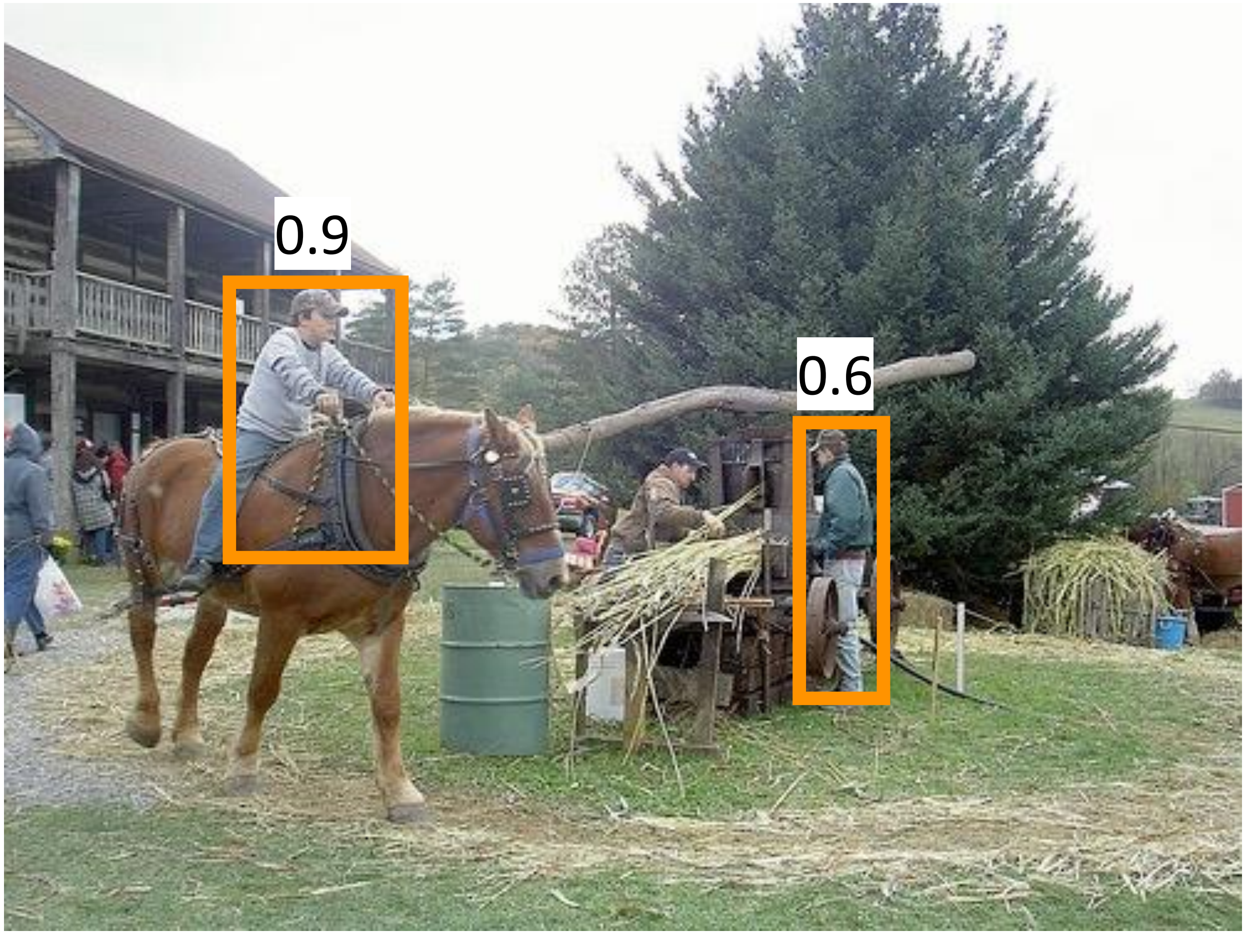
Evaluating a Detector

Test image (previously unseen)

First Detection

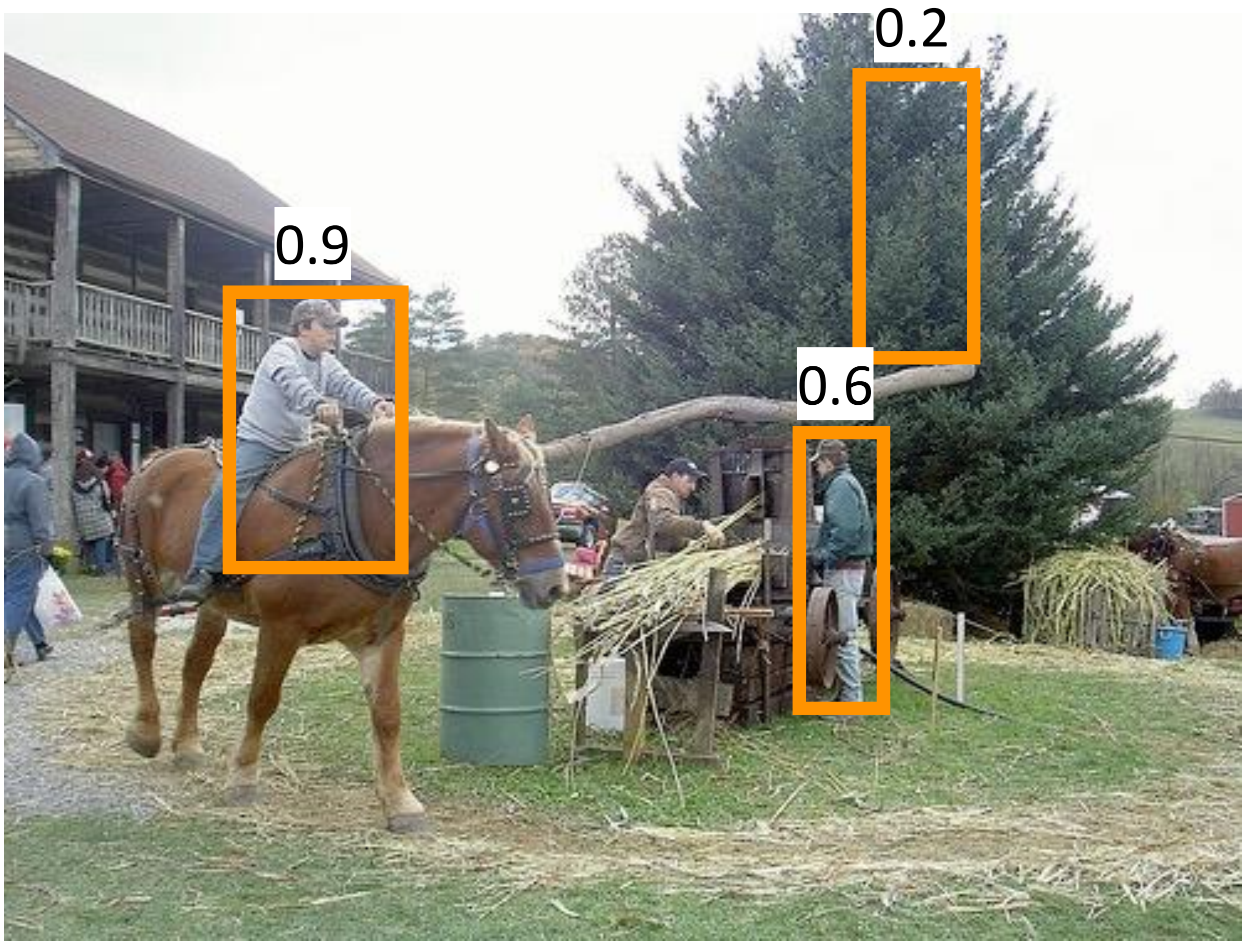
'person' detector predictions

Second Detection



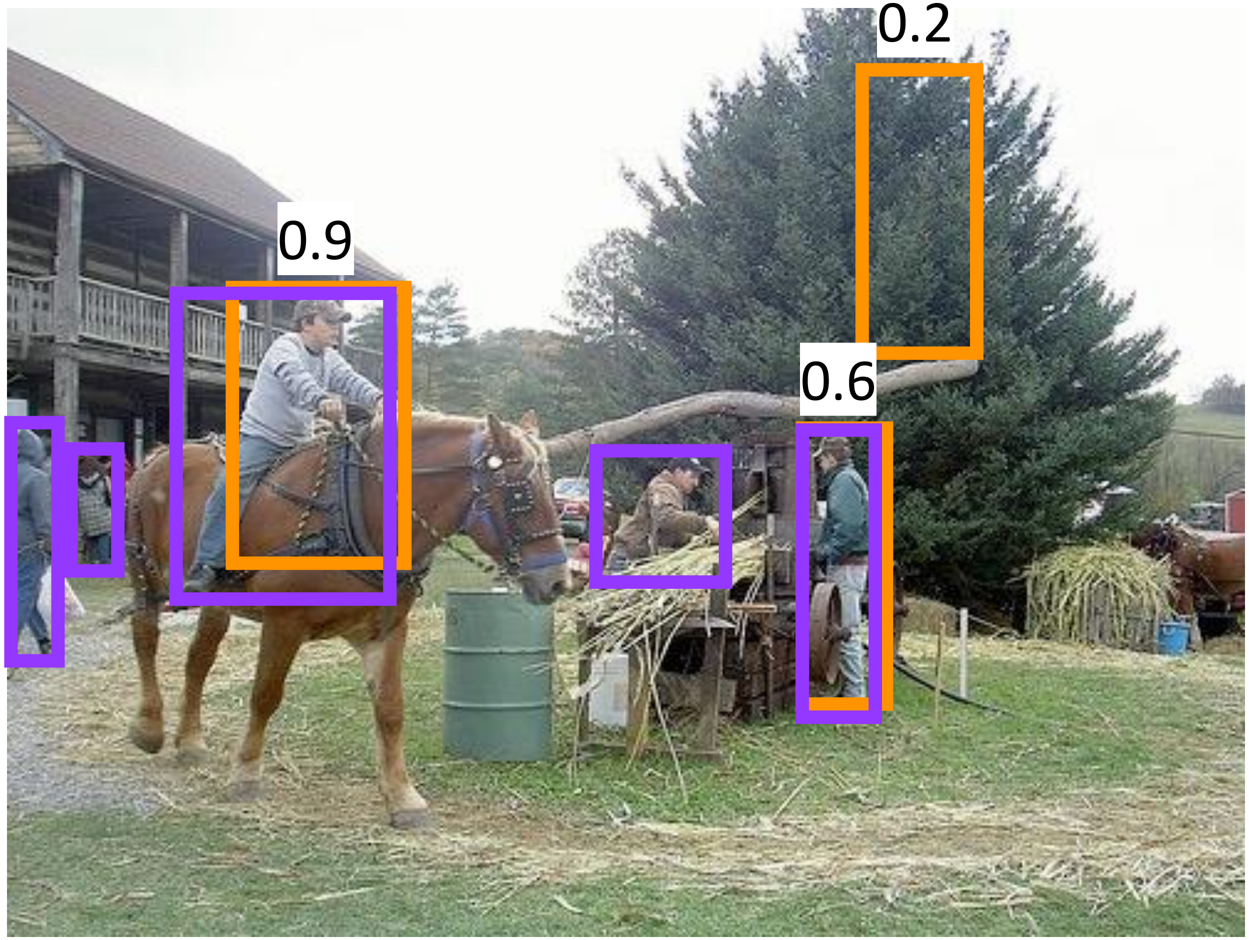
'person' detector predictions

Third Detection



'person' detector predictions

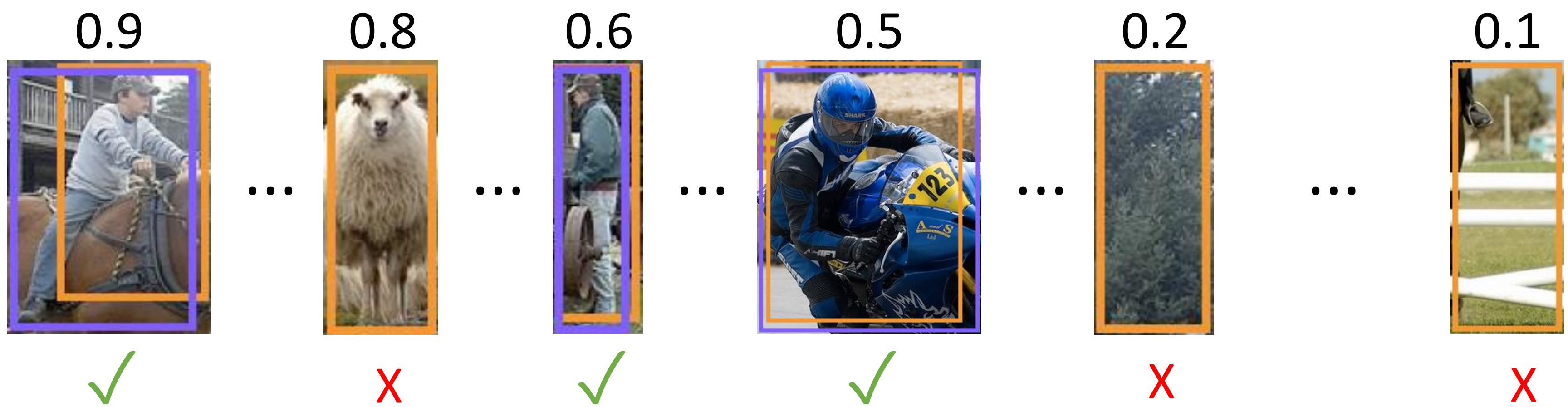
Compare to Ground Truth



‘person’ detector predictions

ground truth ‘person’ boxes

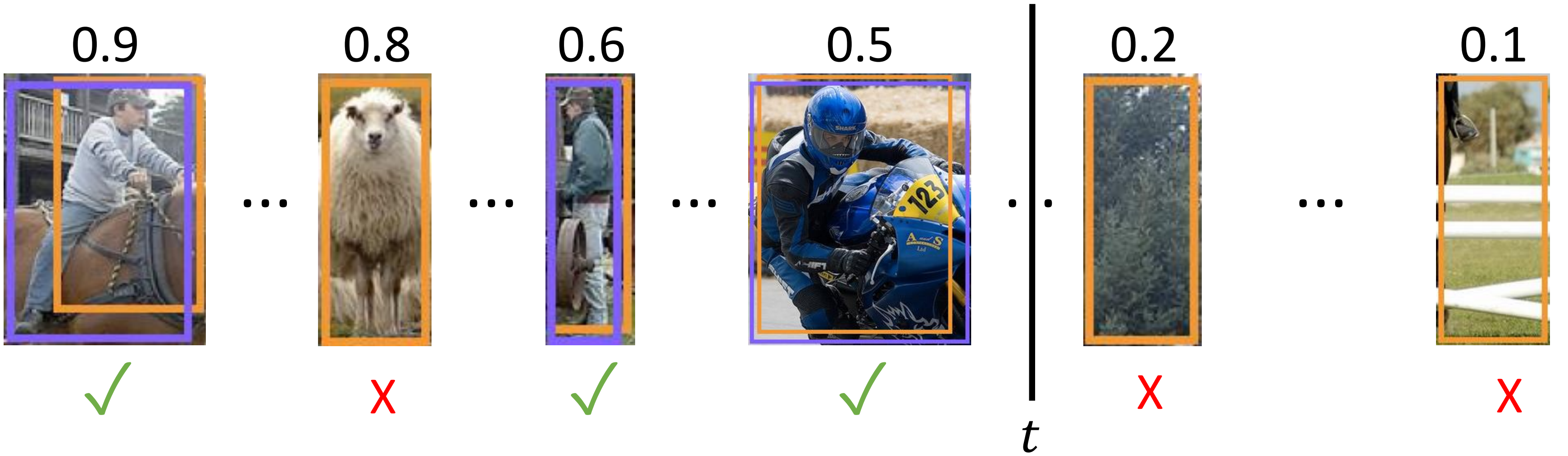
Sort by Confidence



true positive
(high overlap)

false positive
(no overlap, low overlap, or duplicate)

Evaluation Metric



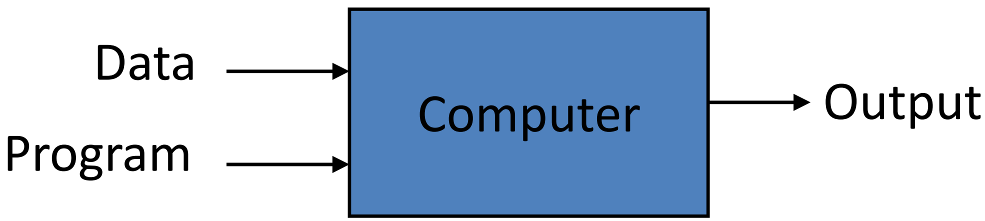
$$precision@t = \frac{\#true\ positives@t}{\#true\ positives@t + \#false\ positives@t} \qquad \frac{\checkmark}{\checkmark + \text{X}}$$

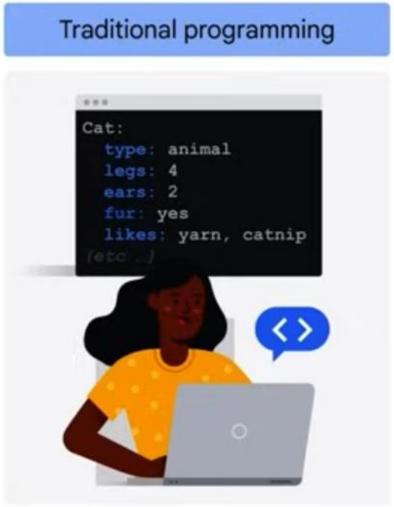
$$recall@t = \frac{\#true\ positives@t}{\#ground\ truth\ objects}$$

Machine Learning Based Object Detection

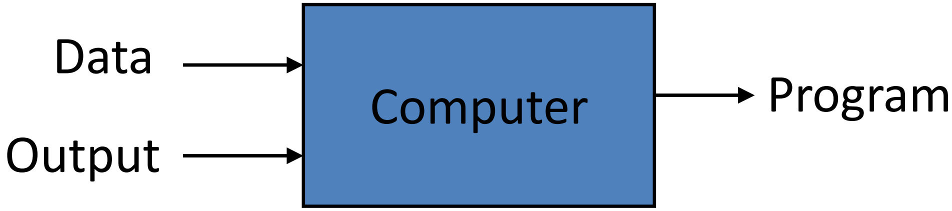
Traditional Programming v.s. Machine Learning

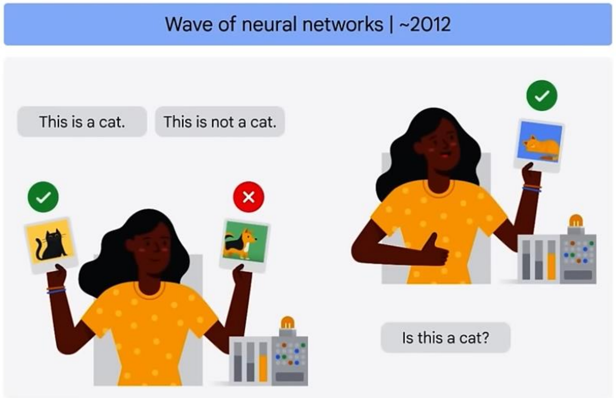
- ML gives computers the ability to learn without explicit programming
- Traditional Programming





- Machine Learning





Why Machine Learning is Hard?

Is this a tree?

A brown trunk moving upwards
and branching with leaves…?

Defining is Hard: Recognizing is Easy

- **Hard** to give a complete mathematical definition of a tree
- Even a 3 year old can tell a tree from a non-tree
- The 3 year old has **learned from data**

Key Essence of Machine Learning

- Exists some 'underlying pattern' to be learned
  - So 'performance measure' can be improved
- But no programmable (easy) definition
  - So 'ML' is needed
- Somehow there is data about the pattern
  - So ML has some 'inputs' to learn from

Key essence: help decide whether to use ML

Fun Time

Which of the following is best suited for machine learning?

A. Predicting whether the next cry of the baby girl happens at an even-numbered minute or not
B. Determining whether a given graph contains a cycle
C. Deciding whether to approve credit card to some customers
D. Guessing whether the earth will be destroyed by the misuse of nuclear power in the next ten years

Types of Learning

- **Supervised learning**
  - Given: training data + desired outputs (labels)
- **Unsupervised learning**
  - Given: training data (without desired outputs)
- **Reinforcement learning**
  - Rewards from sequence of actions
- **Generative AI**

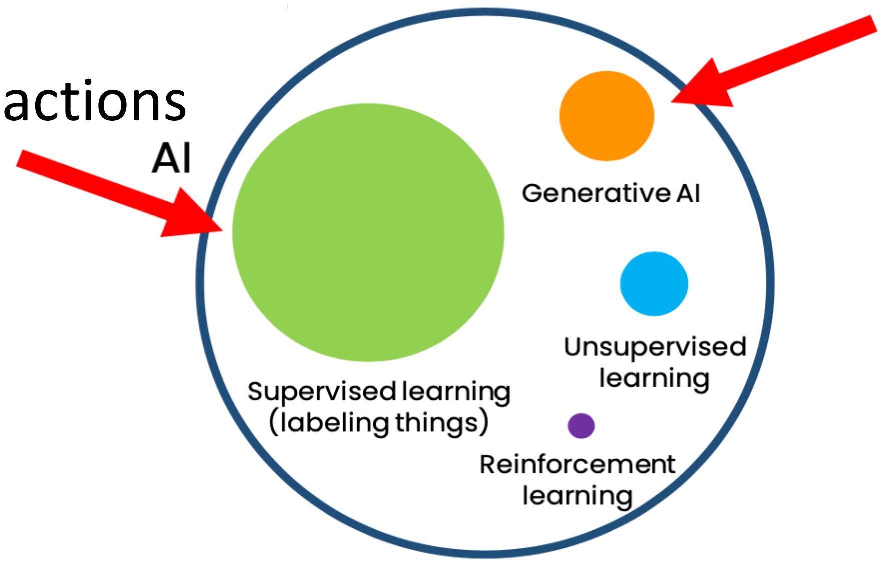


Figure from DeepLearning.AI

Supervised Learning: Classification

- Given $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$
- Learn a function *f(x)* to predict *y* given *x*
  - *y* is categorical == classification

Ocular Tumor (Malignant / Benign)

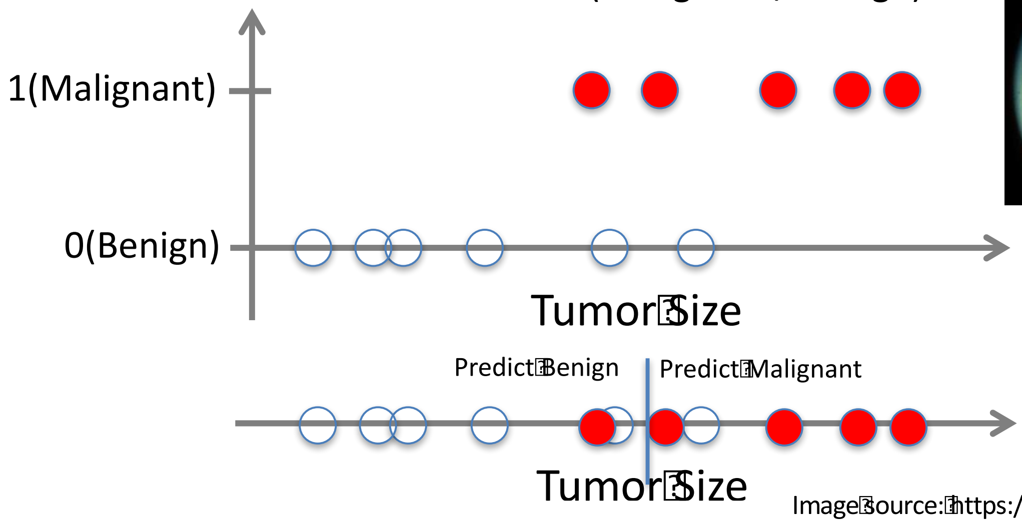
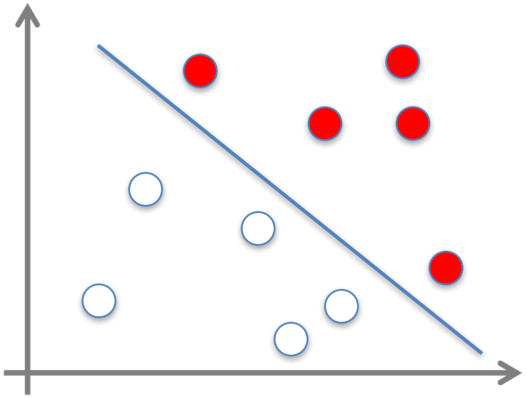


Image source: https://eyecancer.com/uncategorized/choroidal-metastasis-test/

Supervised Learning: Classification

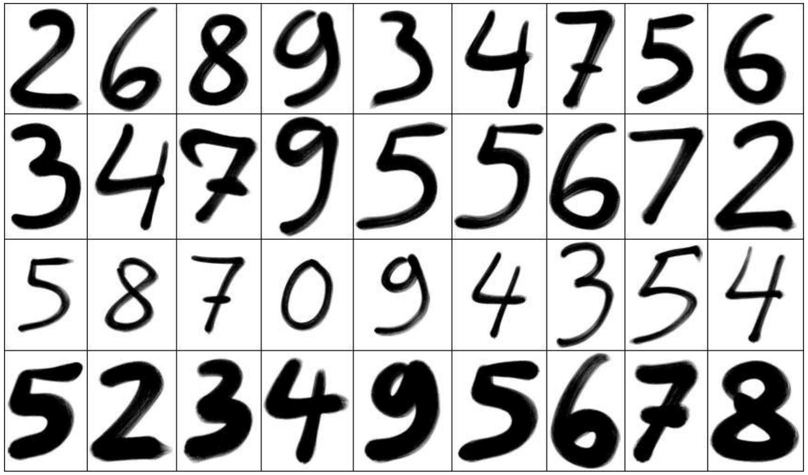
- *x* can be multi-dimensional
  - each dimension corresponds to an attribute:
    - clump thickness
    - color
    - distance from optic nerve
    - …

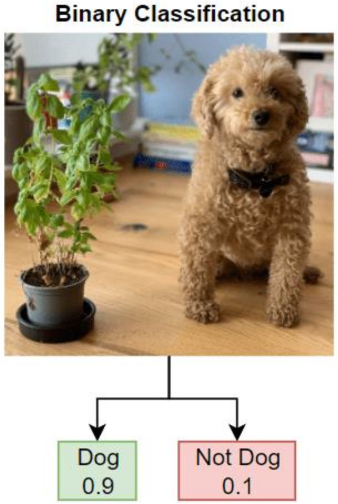


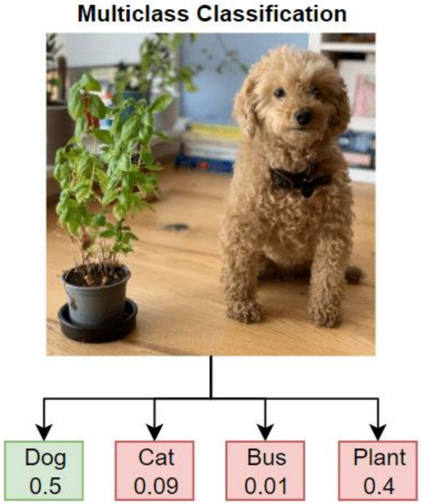
- Cell type is the most telling feature, but it's risky to do a biopsy of the eye
  - ML can help determine *when* a feature is needed

Supervised Learning: Multiclass Classification

- Multiclass classification problems
  - Written digits → 0, 1, …, 9
  - Pictures → apple, orange, strawberry
  - Emails → spam, primary, social, promotion





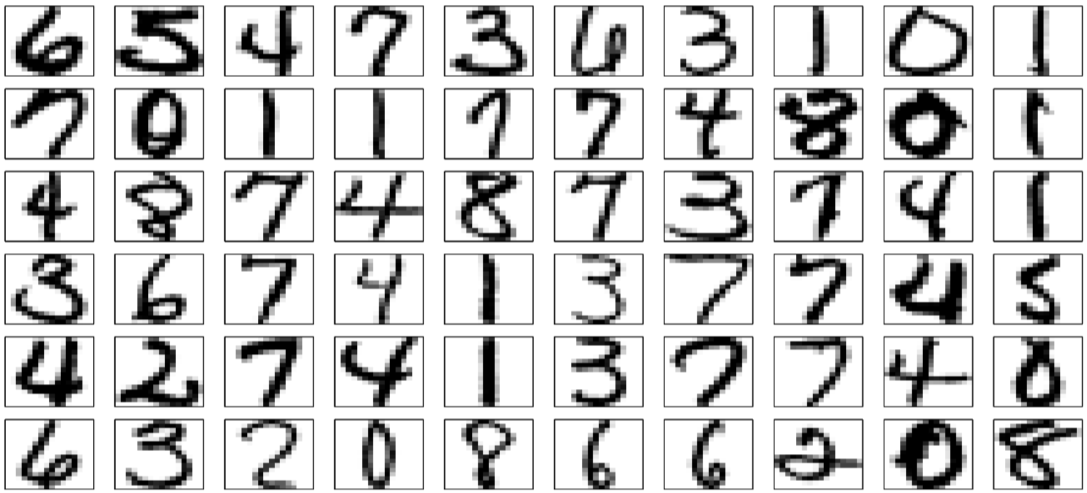


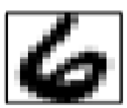
Example Data from ImageNet

Machine Learning Example

- Digit recognition

Each digit is a 16 × 16 image.





[-1 -1 -1 -1 -1 -1 -1 -0.63 0.86 -0.17 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -0.99 0.3 1 0.31 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -0.41 1 0.99 -0.57 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -0.68 0.83 1 0.56 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -0.94 0.54 1 0.78 -0.72 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 0.1 1 0.92 -0.44 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -0.26 0.95 1 -0.16 -1 -1 -1 -0.99 -0.71 -0.83 -1 -1 -1 -1 -1 -0.8 0.91 1 0.3 -0.96 -1 -1 -0.55 0.49 1 0.88 0.09 -1 -1 -1 -1 0.28 1 0.88 -0.8 -1 -0.9 0.14 0.97 1 1 1 0.99 -0.74 -1 -1 -0.95 0.84 1 0.32 -1 -1 0.35 1 0.65 -0.10 -0.18 1 0.98 -0.72 -1 -1 -0.63 1 1 0.07 -0.92 0.11 0.96 0.30 -0.88 -1 -0.07 1 0.64 -0.99 -1 -1 -0.67 1 1 0.75 0.34 1 0.70 -0.94 -1 -1 0.54 1 0.02 -1 -1 -1 -0.90 0.79 1 1 1 1 0.53 0.18 0.81 0.83 0.97 0.86 -0.63 -1 -1 -1 -1 -0.45 0.82 1 1 1 1 1 1 1 1 0.13 -1 -1 -1 -1 -1 -1 -0.48 0.81 1 1 1 1 1 1 0.21 -0.94 -1 -1 -1 -1 -1 -1 -1 -0.97 -0.42 0.30 0.82 1 0.48 -0.47 -0.99 -1 -1 -1 -1]

$$\mathbf{x} = (1, x_1, \cdots, x_{256}) \longleftarrow \text{ input}$$

The Key Players

- Pictures
  - input $\mathbf{x} \in Rd$ = $\boldsymbol{X}$
- Classes: cat, dog, desk, etc….
  - output y ∈ {1, 2,…} = $\boldsymbol{Y}$
- True relationship between x and y
  - target function f: $\boldsymbol{X} \rightarrow \boldsymbol{Y}$
- Data
  - data set $\boldsymbol{D} = (\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)$
  - $y_n = f(\mathbf{x}_n)$

We learn the function f from the data $\boldsymbol{D}$

- $\boldsymbol{X}$, $\boldsymbol{Y}$, and $\boldsymbol{D}$ are given by the learning problem; the target f is fixed but unknown

Learning

- Start with a set of candidate hypotheses $\boldsymbol{H}$ which you think are likely to represent f

$$\boldsymbol{H} = \{h_1, h_2, \ldots,\}$$

$\boldsymbol{H}$ is called the hypothesis set or model

- Select a hypothesis h from $\boldsymbol{H}$. The way we do this is called a *learning algorithm*
- Use h for new input. We hope $h \approx f$
- Again, $\boldsymbol{X}$, $\boldsymbol{Y}$, and $\boldsymbol{D}$ are given by the learning problem; the target f is fixed but unknown

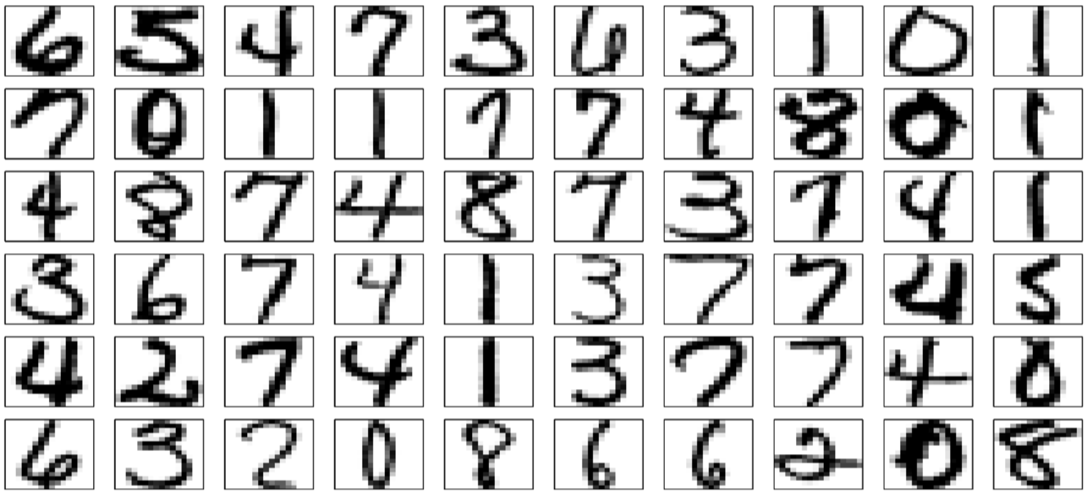
We choose $\boldsymbol{H}$ and the learning algorithm

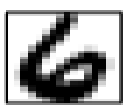
This is a very general setup (e.g. choose $\boldsymbol{H}$ to be all possible hypotheses)

Revisit: Digit Recognition Problem

- Digit recognition

Each digit is a 16 × 16 image.





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0.56 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -0.94 0.54 1 0.78 -0.72 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 0.1 1 0.92 -0.44 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -0.26 0.95 1 -0.16 -1 -1 -1 -0.99 -0.71 -0.83 -1
-1 -1 -1 -1 -0.8 0.91 1 0.3 -0.96 -1 -1 -0.55 0.49 1 0.88 0.09 -1 -1 -1 -1 0.28 1 0.88 -0.8 -1 -0.9 0.14 0.97 1 1 1 0.99 -0.74 -1 -1 -0.95 0.84 1 0.32 -1 -1 0.35 1 0.65 -0.10 -0.18 1 0.98
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0.86 -0.63 -1 -1 -1 -1 -0.45 0.82 1 1 1 1 1 1 1 1 0.13 -1 -1 -1 -1 -1 -1 -0.48 0.81 1 1 1 1 1 1 0.21 -0.94 -1 -1 -1 -1 -1 -1 -1 -0.97 -0.42 0.30 0.82 1 0.48 -0.47 -0.99 -1 -1 -1 -1]

$\mathbf{x} = (1, x_1, \cdots, x_{256}) \longleftarrow$ input

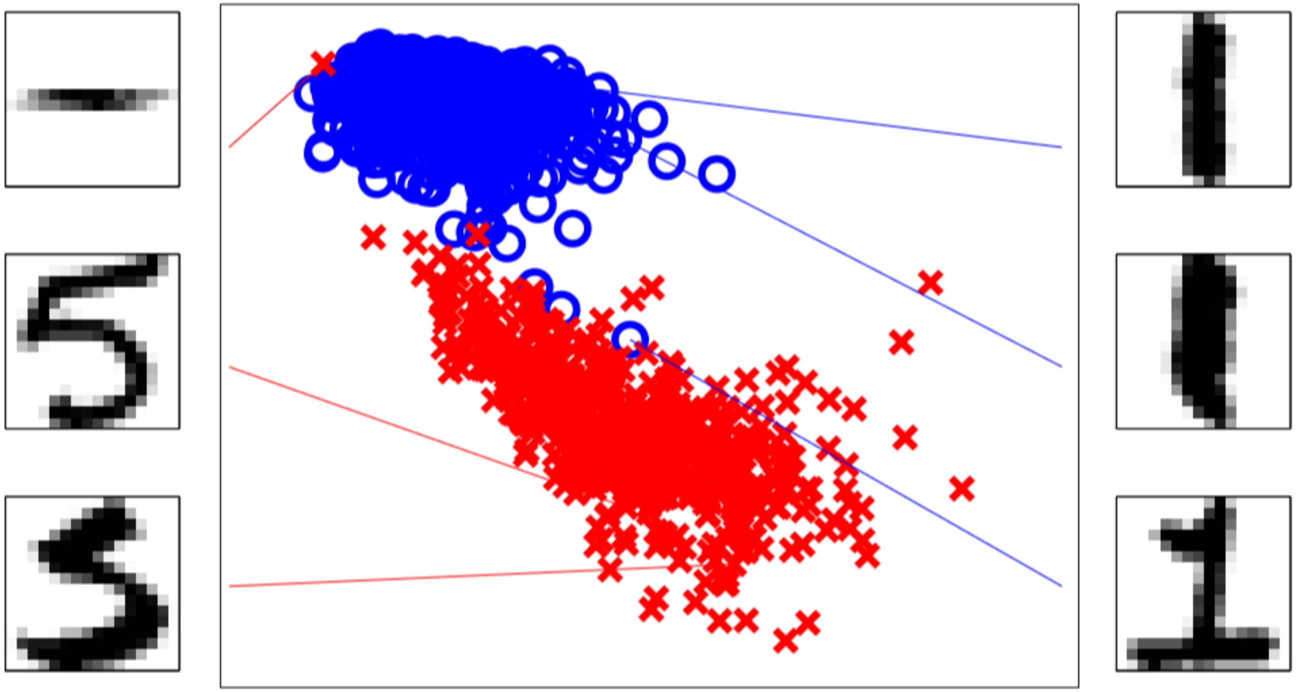
$\mathbf{w} = (w_0, w_1, \cdots, w_{256}) \longleftarrow$ linear model

Hypothesis: $h = g(\boldsymbol{w}^T \boldsymbol{x})$

e.g.,: $h = \mathrm{sign}(\boldsymbol{w}^T \boldsymbol{x})$

Supervised Learning Example

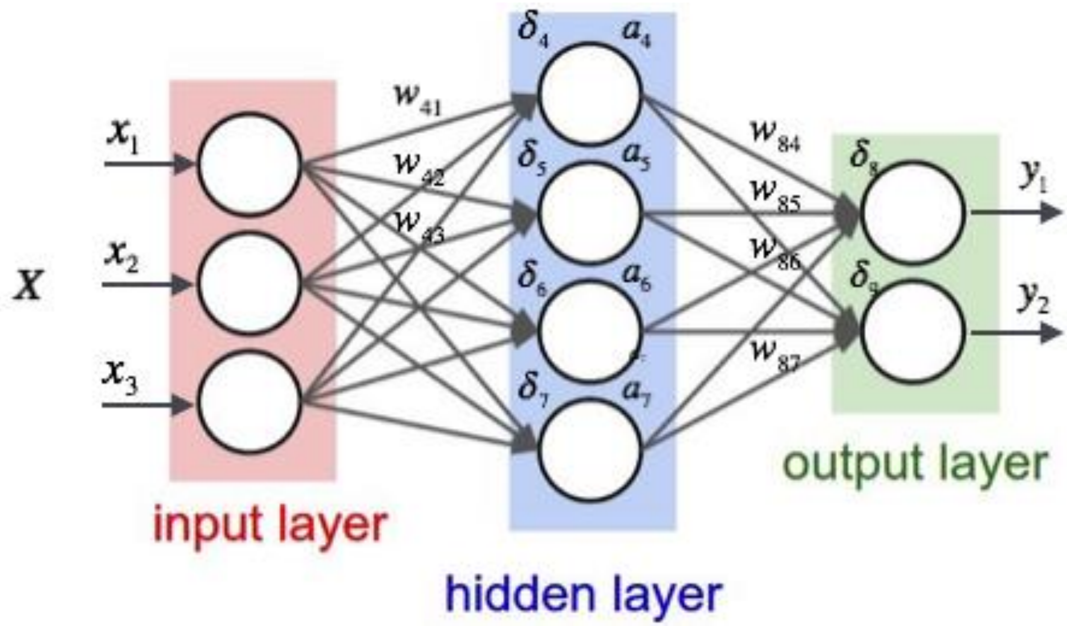
- Feature: an important property of the input that you think is useful for classification, e.g.,

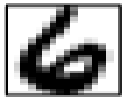


$\mathbf{x} = (x_0, x_1, x_2)$ x_1: intensity x_2: symmetry

Neural Network

- How does a neural network work?





Input

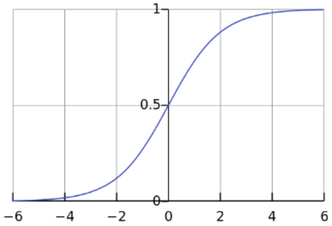
$\boldsymbol{x} = (x_1, x_2 \dots,)^T$

Activation function

$a_j = g(\boldsymbol{w}_j^T \boldsymbol{x})$

Example:

$$g(t) = \frac{1}{1 + e^{-t}}$$



Goal: learn $\boldsymbol{w}$!

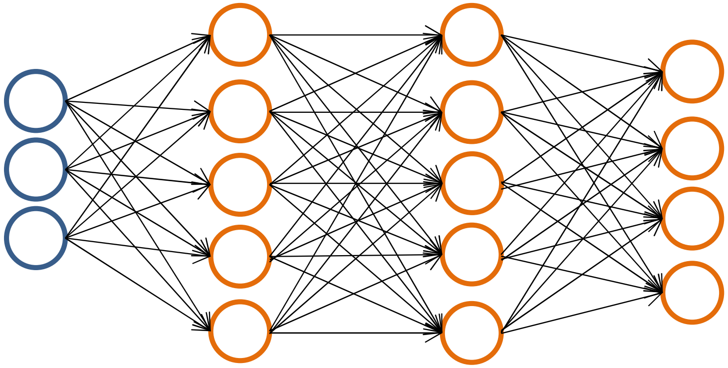
Neural Network for Object Classification

Pedestrian

Car

Motorcycle

Truck



$$h_\Theta(\mathbf{x}) \in \mathbb{R}^K$$

- We want

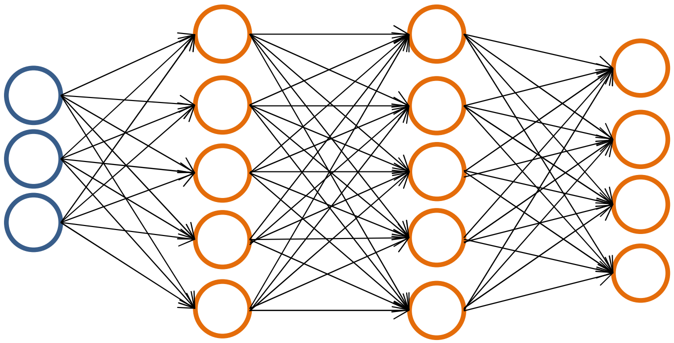
$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$
when pedestrian

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$
when car

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$
when motorcycle

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$
when truck

Neural Network for Object Classification



$$h_\Theta(\mathbf{x}) \in \mathbb{R}^K$$

- We want

$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$ when pedestrian

$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$ when car

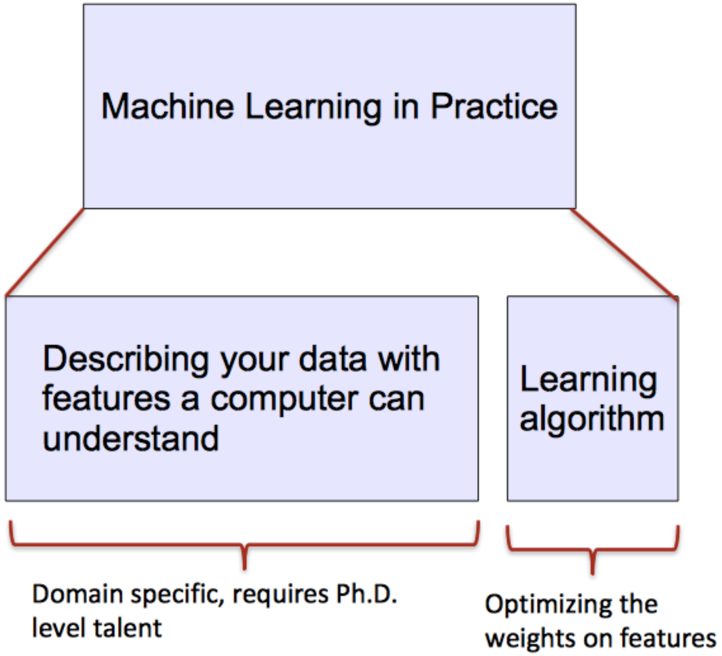
$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$ when motorcycle

$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$ when truck

- Given $\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_n, y_n)\}$
- Must convert labels to 1-of-K representation
  - e.g., $y_i = [0 \quad 0 \quad 1 \quad 0]^T$ when motorcycle, $y_i = [0 \quad 1 \quad 0 \quad 0]^T$ when car

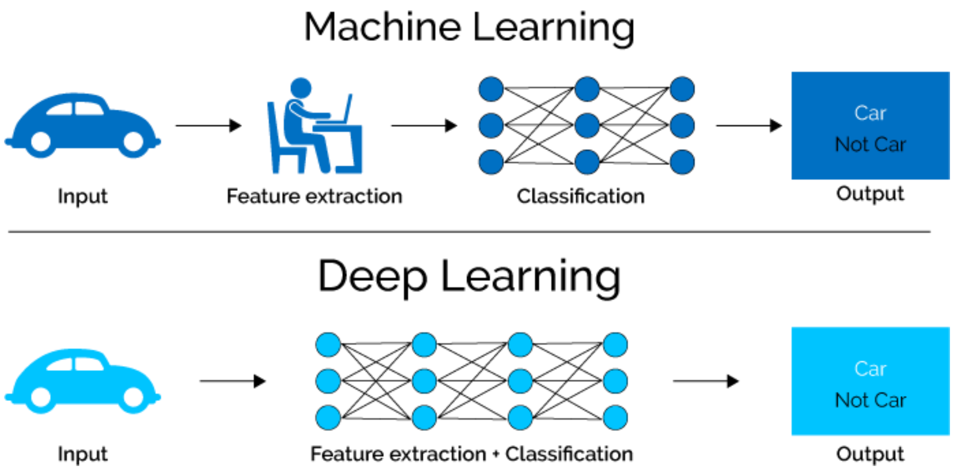
ML vs. Deep Learning

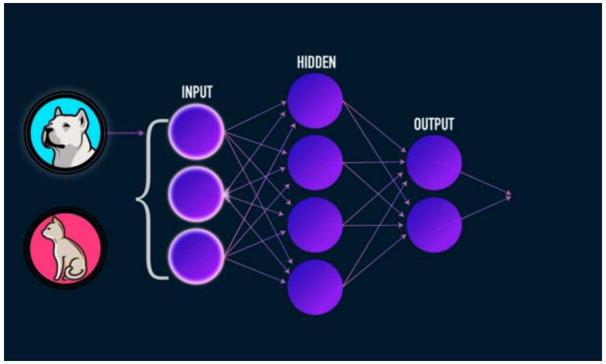
- Most machine learning methods work well because of **human-designed representations** and **input features**
- ML becomes just **optimizing weights** to best make a final prediction



What is Deep Learning (DL) ?

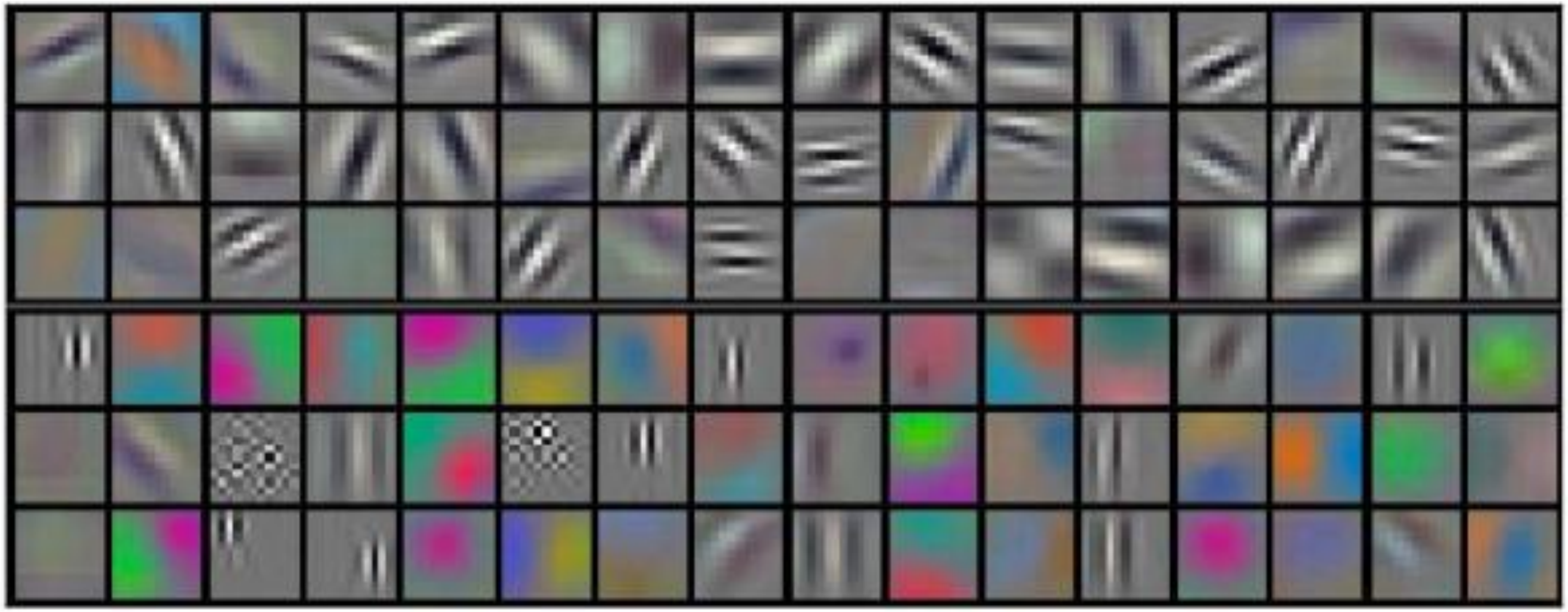
- A machine learning subfield of learning **representations** of data. Exceptional effective at **learning patterns**.
- Deep learning algorithms attempt to learn (multiple levels of) representation by using a **hierarchy of multiple layers**
- If you provide the system **tons of information**, it begins to understand it and respond in useful ways.





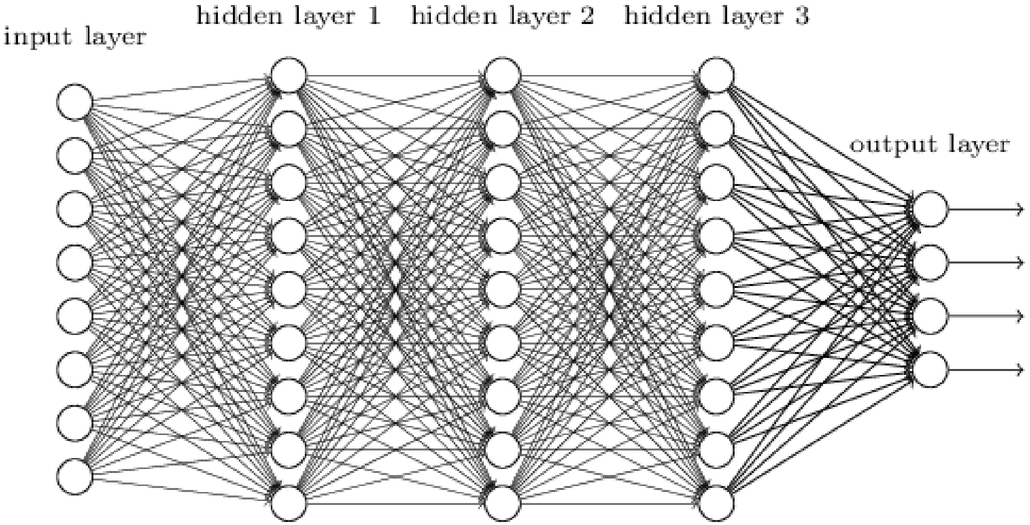
https://www.xenonstack.com/blog/static/public/uploads/media/machine-learning-vs-deep-learning.png

Example: Learned low-level filters



A Fully-Connected Neural Network

- Do we really need all the edges in a fully connected NN?
- Can some of these be shared?

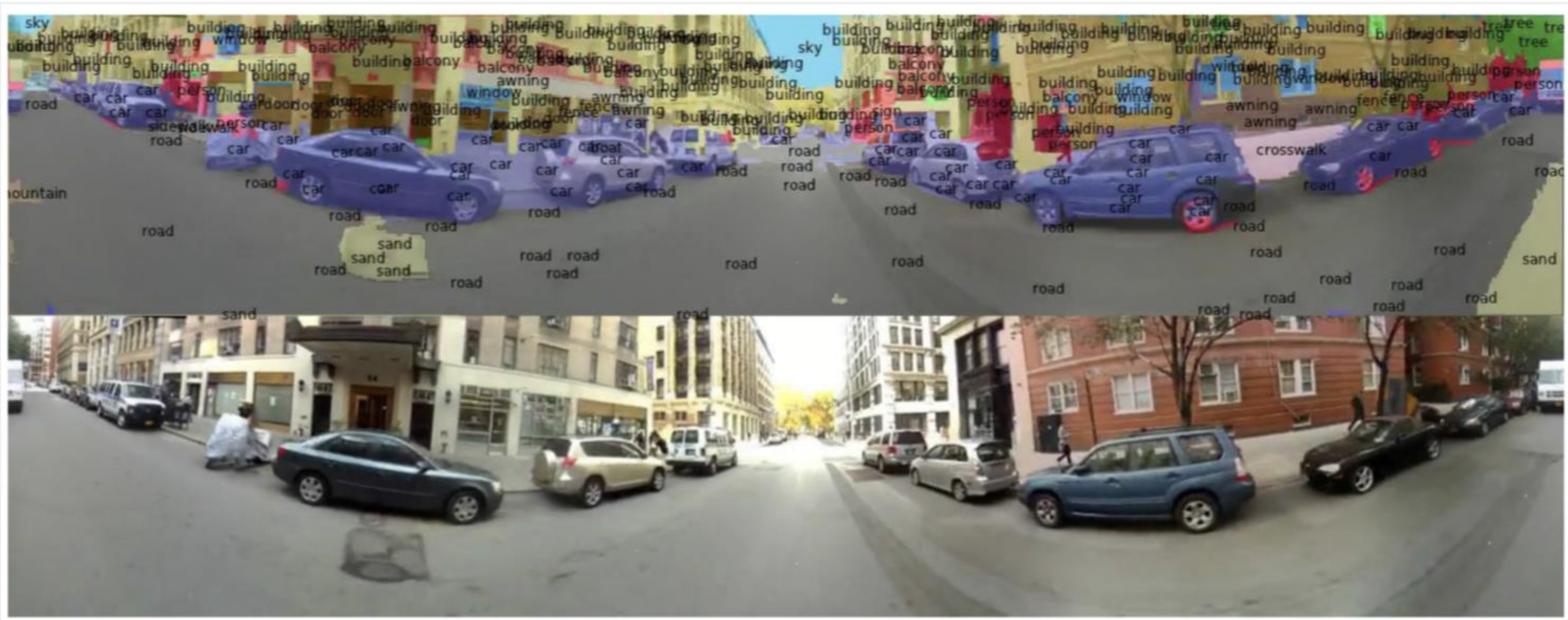


- From NN to CNN
  - Local connectivity
  - Shared ("tied") weights
  - Multiple feature maps
  - Pooling

Various Architectures of Deep Learning

- **Convolutional Neural Networks (CNNs)**
  - Primarily used for image and video recognition tasks.
  - Convolution layers extract spatial features from the input.
- **Recurrent Neural Networks (RNNs)**
  - Designed for sequential data such as time series or natural language.
  - Capable of handling temporal dependencies by maintaining a memory of previous inputs.
  - LSTMs, GRUs
- **Transformers**
  - Architecture designed for handling sequential data, replacing traditional RNNs and LSTMs.
  - Used in NLP tasks like machine translation and text generation (e.g., GPT, BERT).
- **Others**

Scene Labeling via Deep Learning



[Farabet et al. ICML 2012, PAMI 2013]

- Thank You!