CS231A

Computer Vision:

From 3D Reconstruction to Recognition

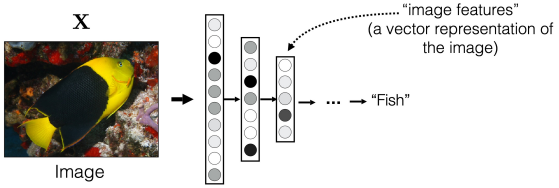
Representation & Representation Learning

How to reach me?

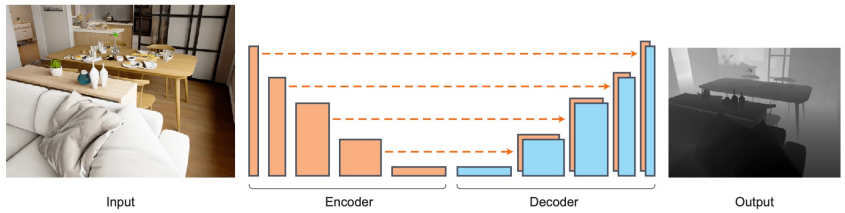
- Jeannette Bohg, CS, Assistant Professor in Robotics
- Office hours, Fridays 9am, zoom
- By appointment

Learning Goals for Upcoming Lectures

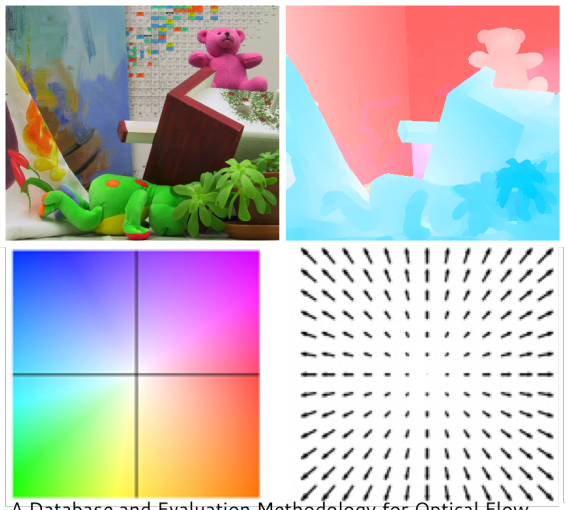
Representations & Representation Learning



Monocular Depth Estimation, Feature Tracking

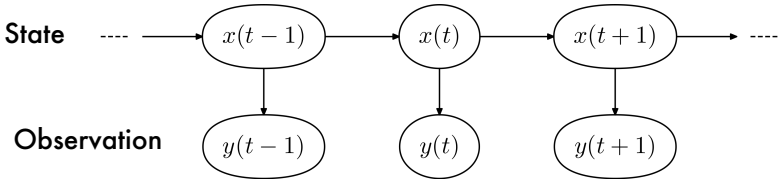


Optical & Scene Flow

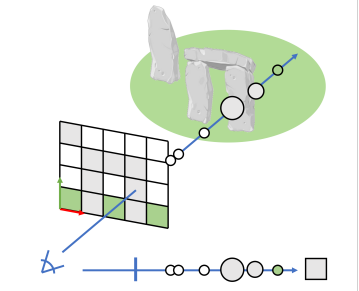


A Database and Evaluation Methodology for Optical Flow.
Baker et al. IJCV. 2011

Optimal Estimation



Neural Radiance Fields



New Course Notes

- For 4 of the five topics
- Ed category for any input/corrections on those

Exercise

- Use the manipulation objects you brought
- What information do you need to solve the task, i.e., to make decision?
- How do you get this information?

Representations for Manipulation Tasks

0 done

0 underway

What information do you need to solve your manipulation task? (one or two words)

Join by Web

1. Go to **PollEv.com**
2. Enter **JEANNETTEBOH707**
3. Respond to activity

Instructions not active. **Log in** to activate

How do you get this information? (Be concise)

Join by Web

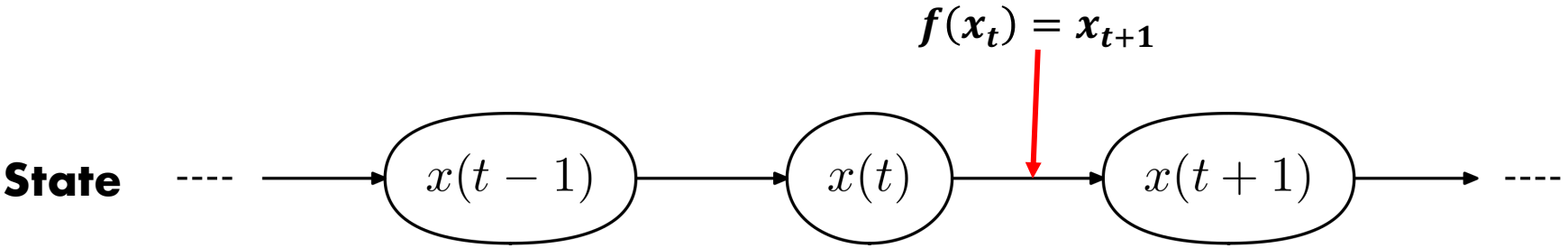
1. Go to **PollEv.com**
2. Enter **JEANNETTEBOH707**
3. Respond to activity

Instructions not active. **Log in** to activate

Outline of this lecture

- What is a state? What is a representation?
- What are the different kinds of representations?
- How can we extract state from raw sensory data?
- What kind of data can we process?

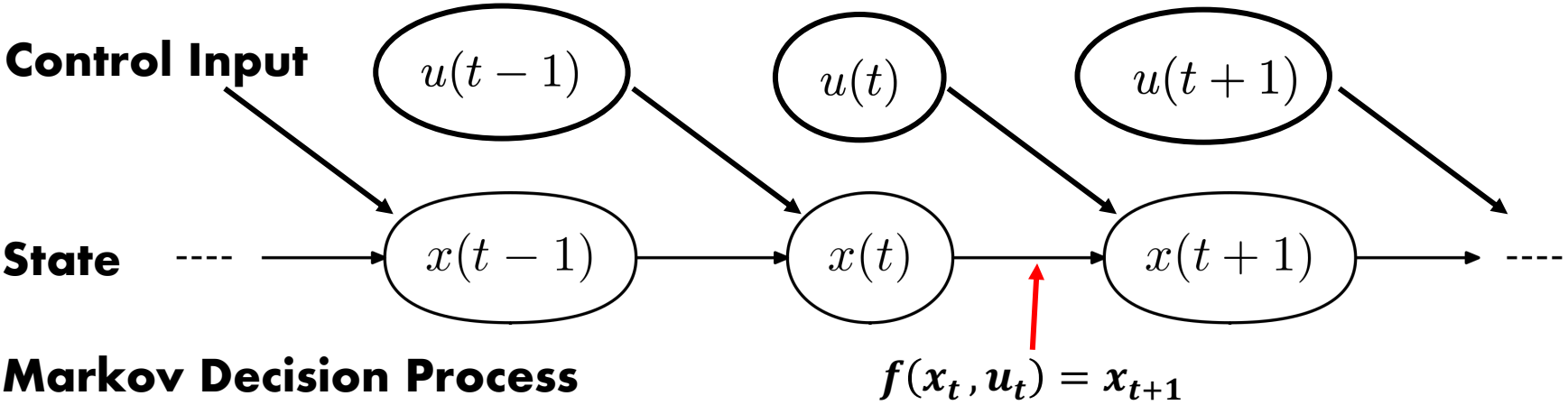
What is a state? What is a representation?



Markov Model

DeepMind Control Suite. Tassa et al. 2018

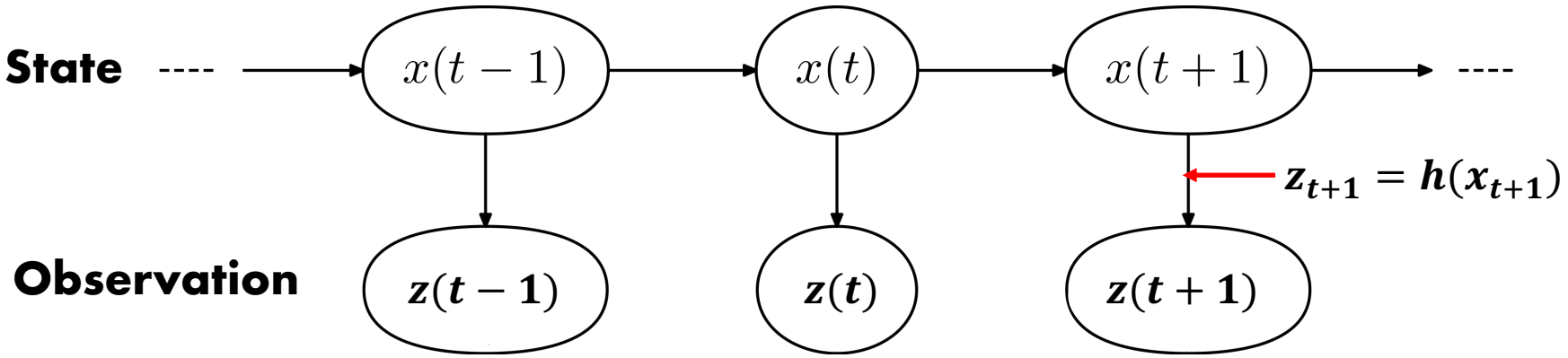
What is a state? What is a representation?



Sparse Cartpole | Acrobot Swingup | Hopper Hop | Walker Run | Quadruped Run

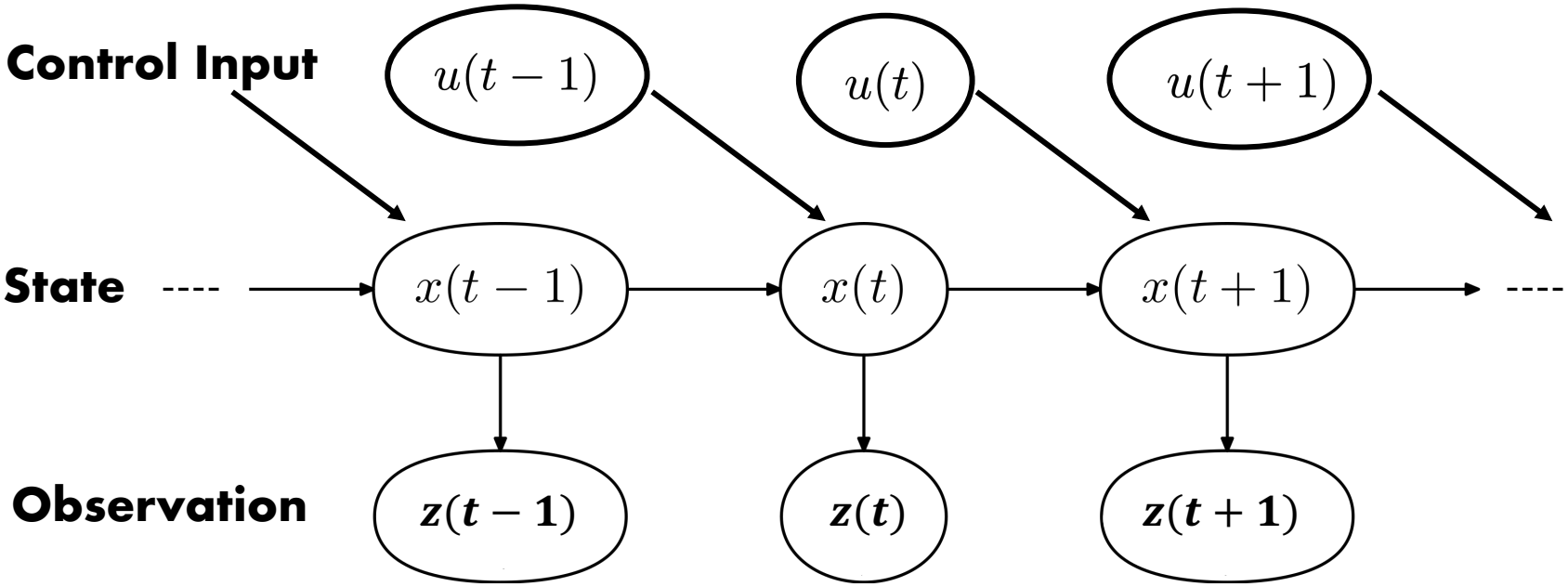
DeepMind Control Suite. Tassa et al. 2018

What is a state? What is a representation?



Hidden Markov Model

What is a state? What is a representation?



Partially Observable Markov Decision Process

Representations for Autonomous Driving

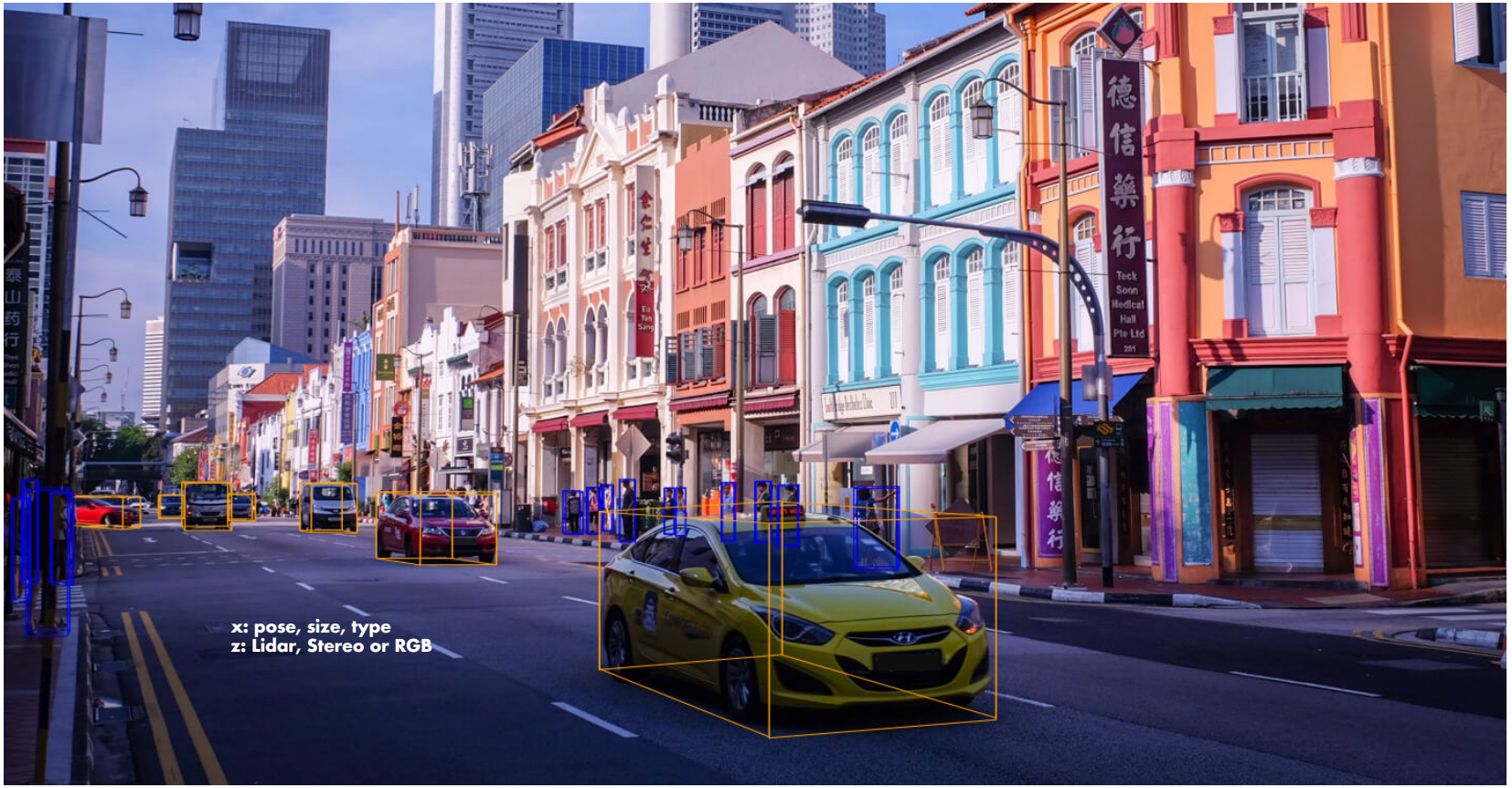
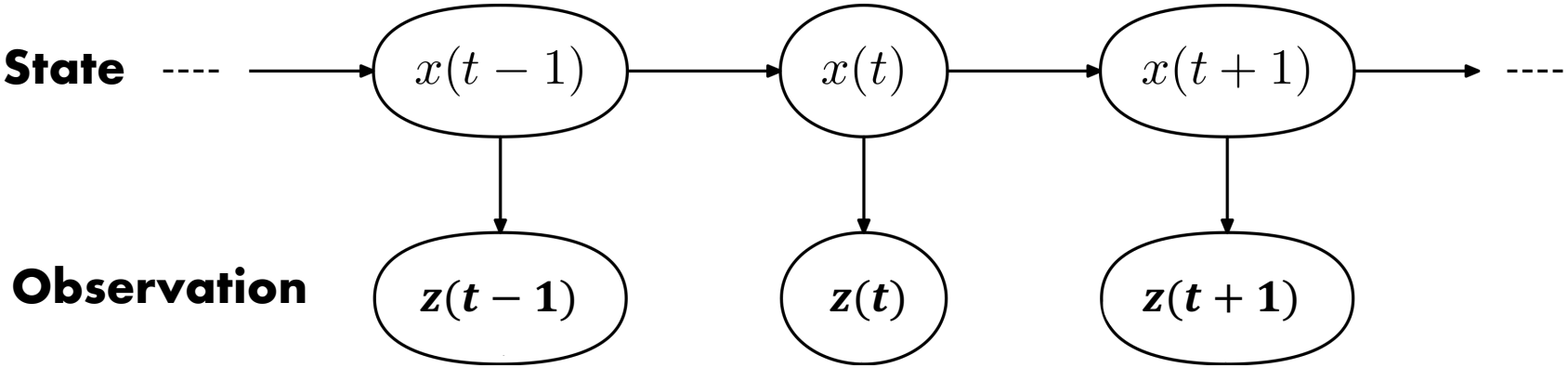


Image adapted from NuScenes by Motional. nuscenes.org

Representations for Manipulation

Manuel Wühtrich et al. "Probabilistic Object Tracking using a Depth Camera", IROS 2013

Examples in Robotics: Generative Observation Model



State x in SE (3)

Point cloud z overplayed with estimated object pose x.

Generative Model

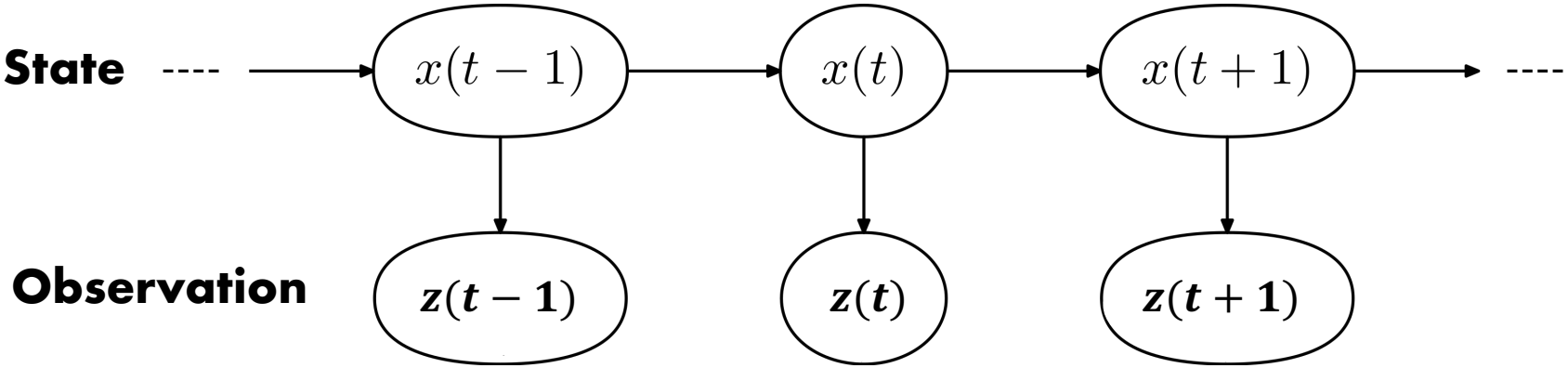
$$z = h(x)$$

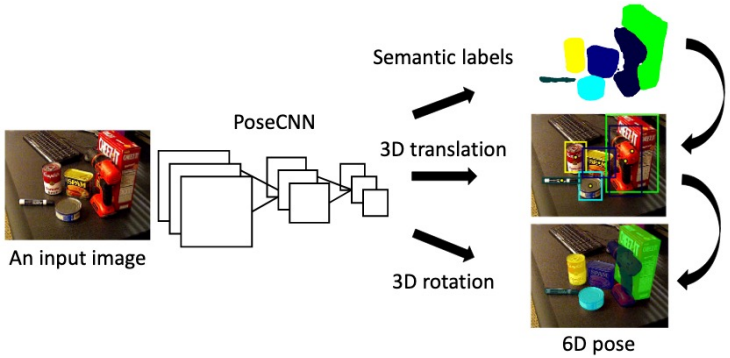
Likelihood

$$P(z|x)$$

Hidden Markov Model

Examples in Robotics: 'Discriminative' Observation Model





Discriminative Model

$$z = g(I)$$

Observation model becomes identity matrix

$$z = x = h(x)$$

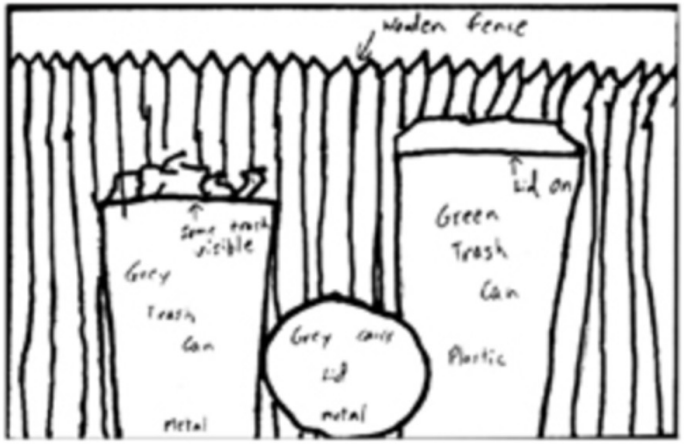
= Tracking by Detection

Yu Xiang et al. PoseCNN: A Convolutional Neural Network for 6D Object Pose Estimation in Cluttered Scenes. RSS 2018.

Representations in Computer Vision

Observed image

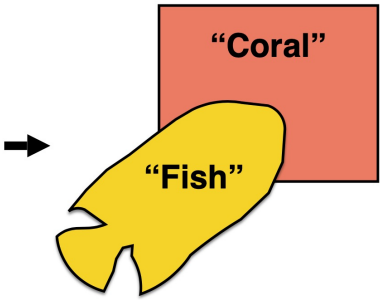
Drawn from memory



[Bartlett, 1932]
[Intraub & Richardson, 1989]

$\mathbf{x}$

Image



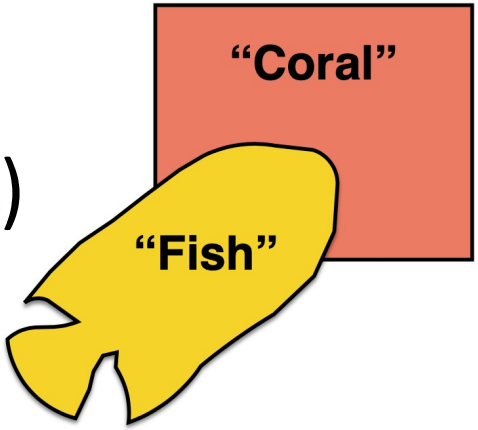
Compact mental representation

Input/Output/Intermediate Representations

Example from Advances in Computer Vision – MIT – 6.869/6.819

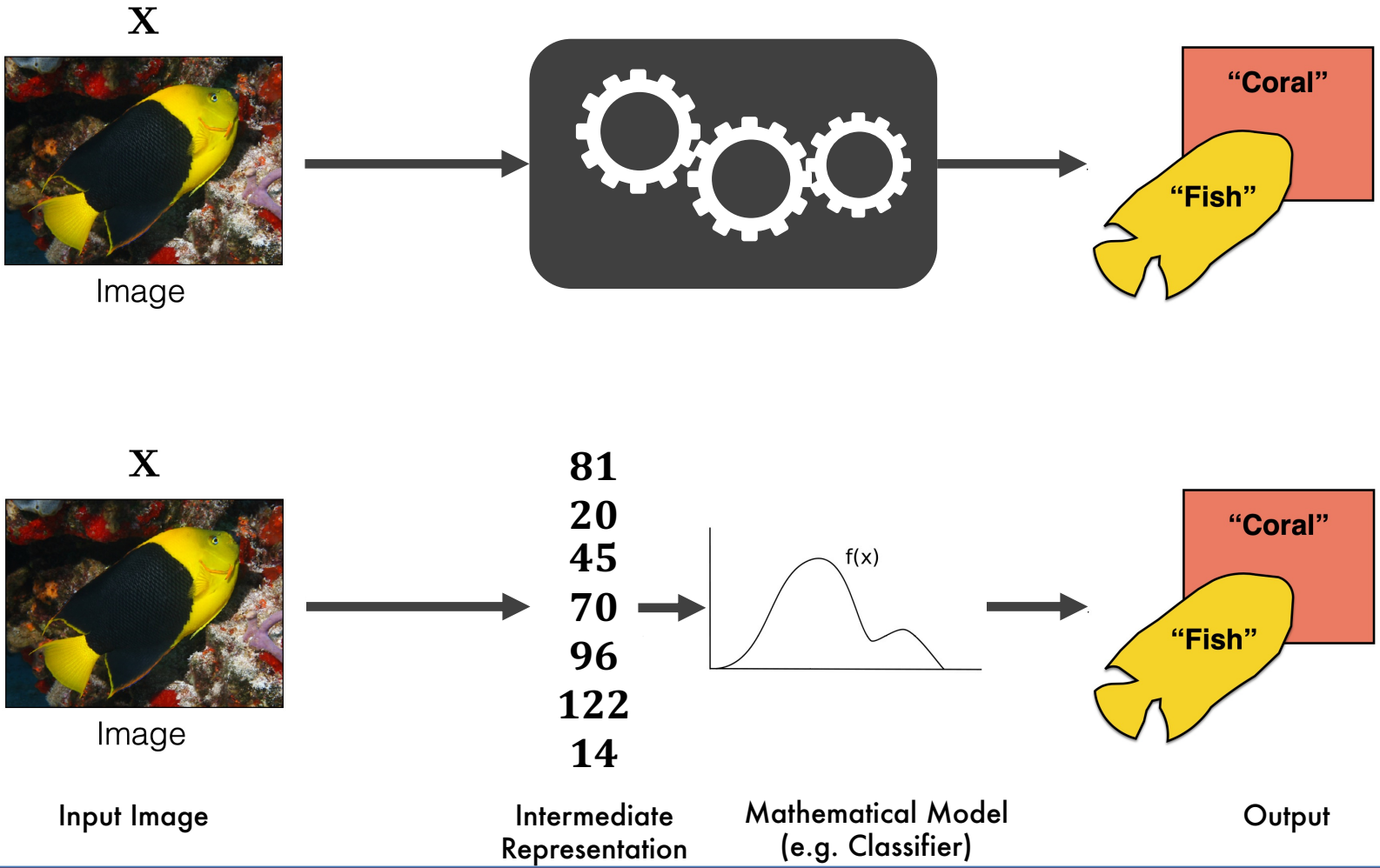
Requirements for Good Representations

- Compact (minimal)
- Explanatory (sufficient)
- Disentangled (independent factors)
- Hierarchical (feature reuse)
- Makes subsequent problem easier

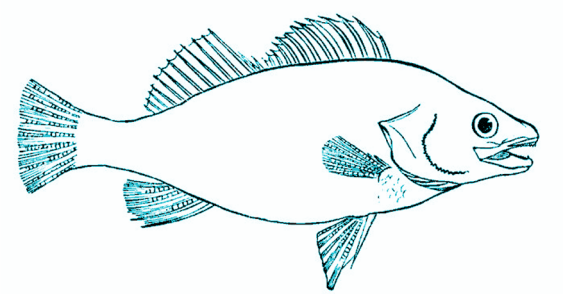


[See "Representation Learning", Bengio 2013, for more commentary]

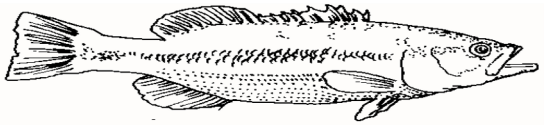
Typical CV Pipeline



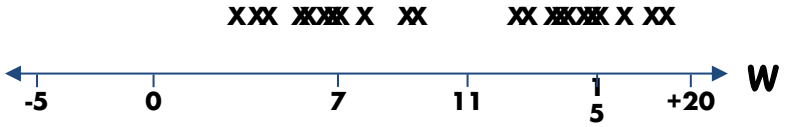
Example



~12 lbs

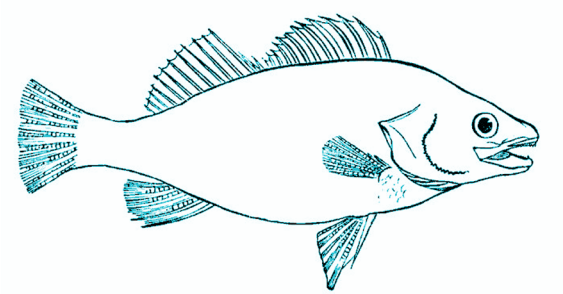


~8 lbs

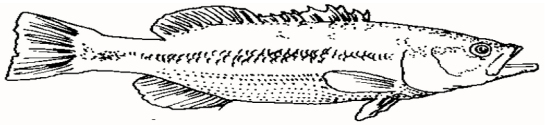


Example from CS331B: Representation Learning in Computer Vision

Example



~12 lbs



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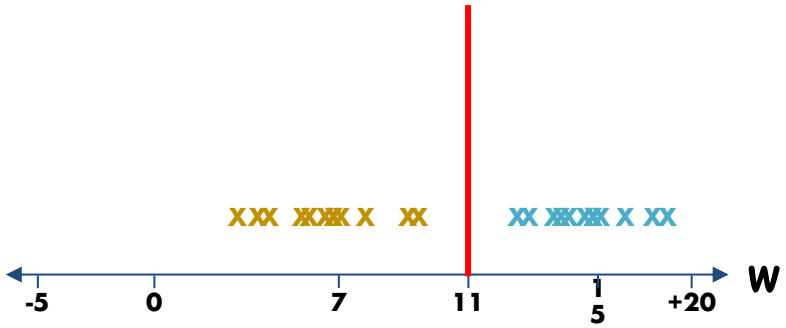
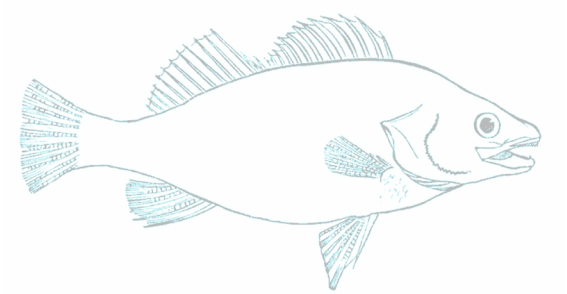


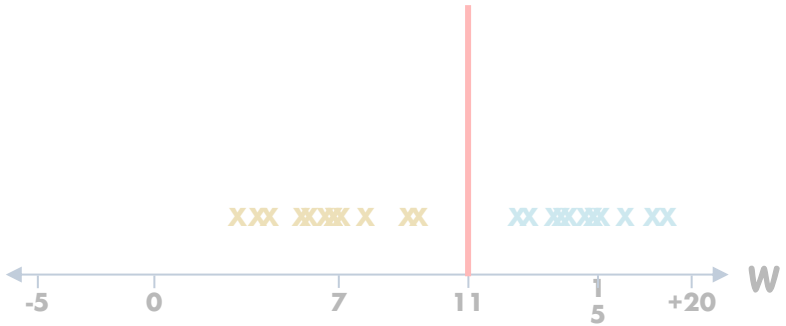
Example from CS331B: Representation Learning in Computer Vision

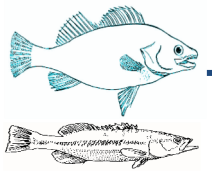
Example

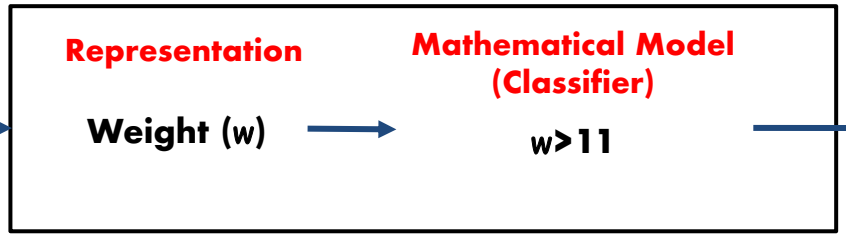


~12 lbs

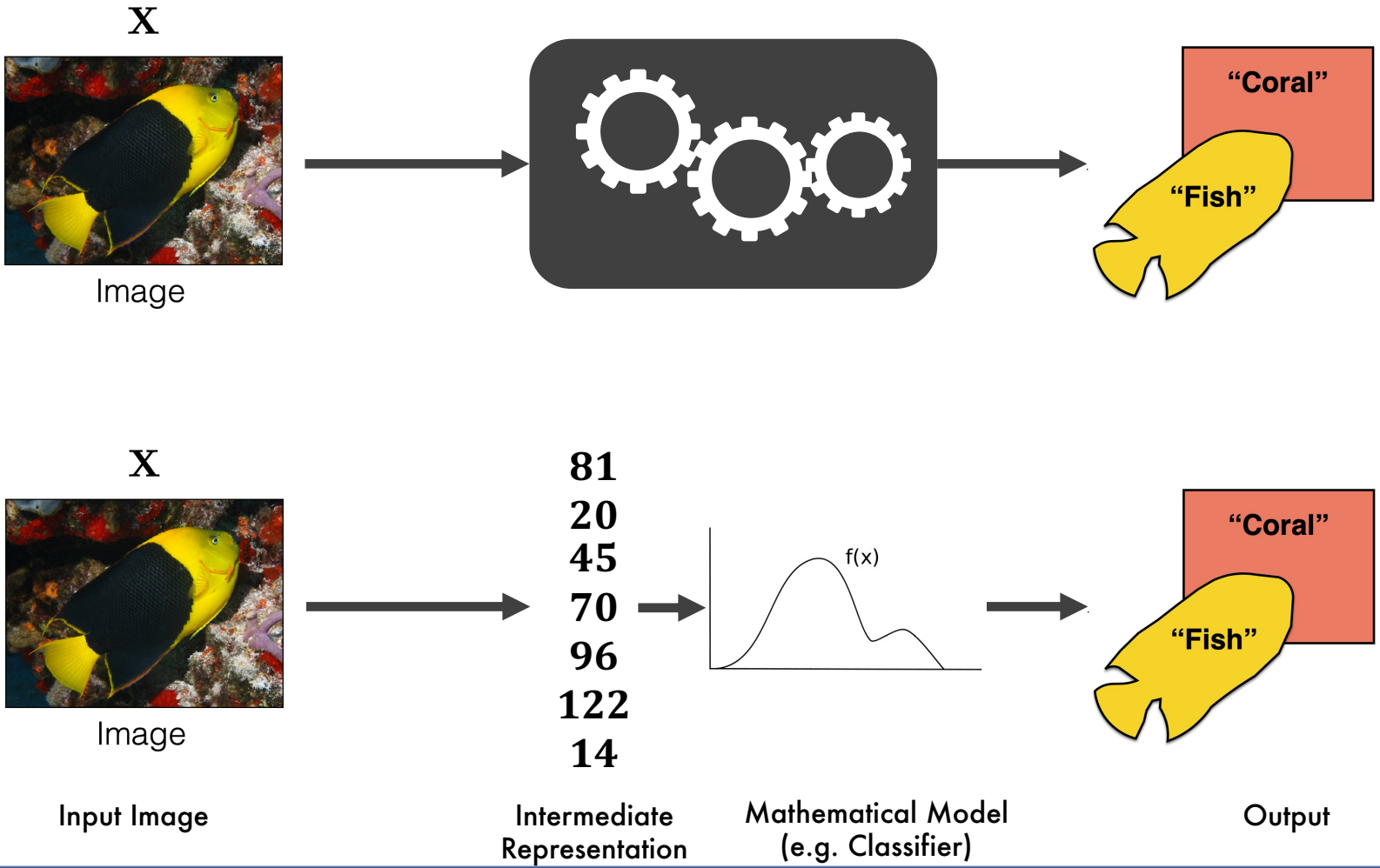
~8 lbs



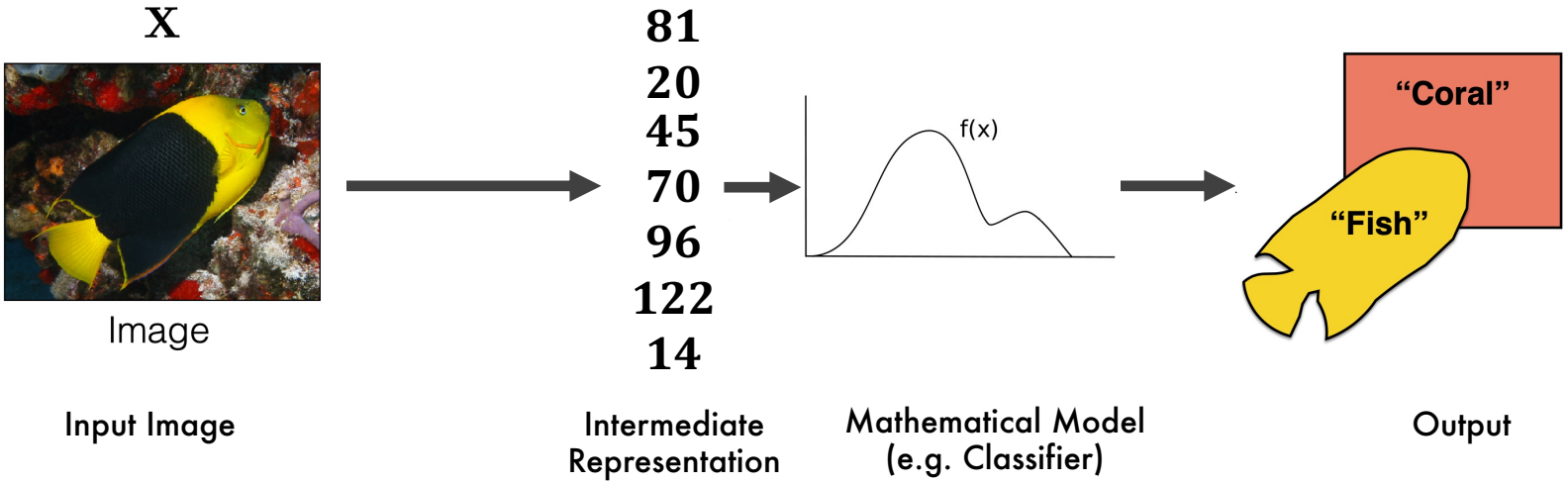


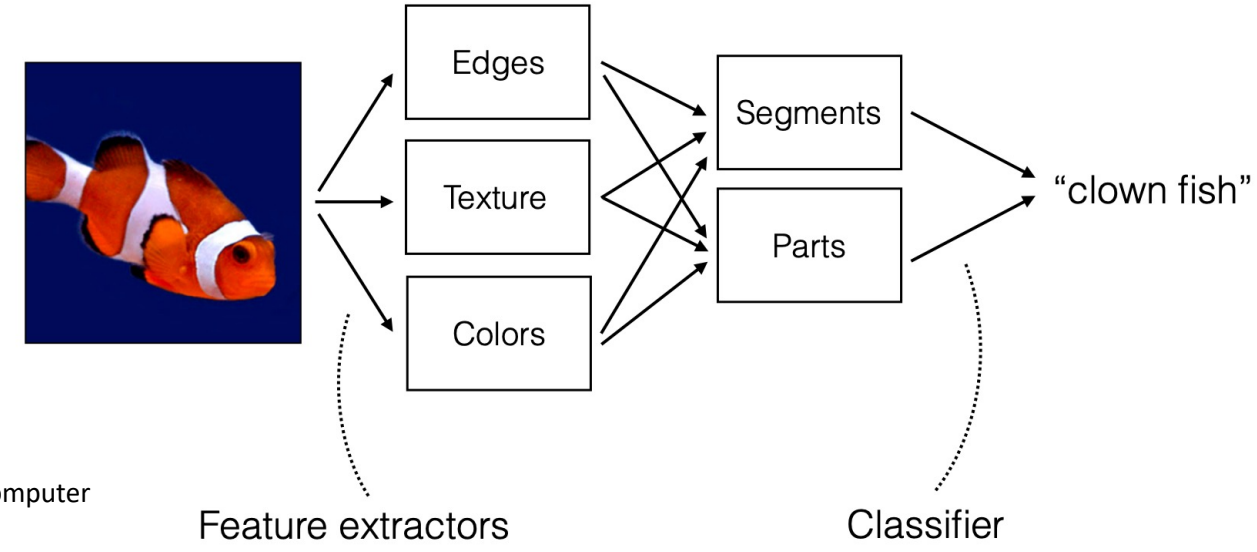


Typical CV Pipeline



Traditional CV Pipeline



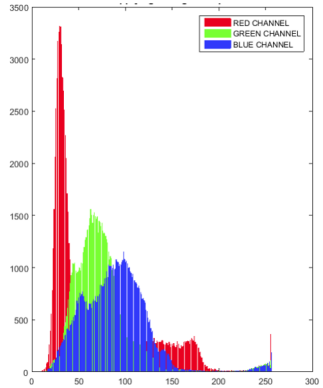


Example from Advances in Computer Vision – MIT – 6.869/6.819

Represent these cats with a cat detector!

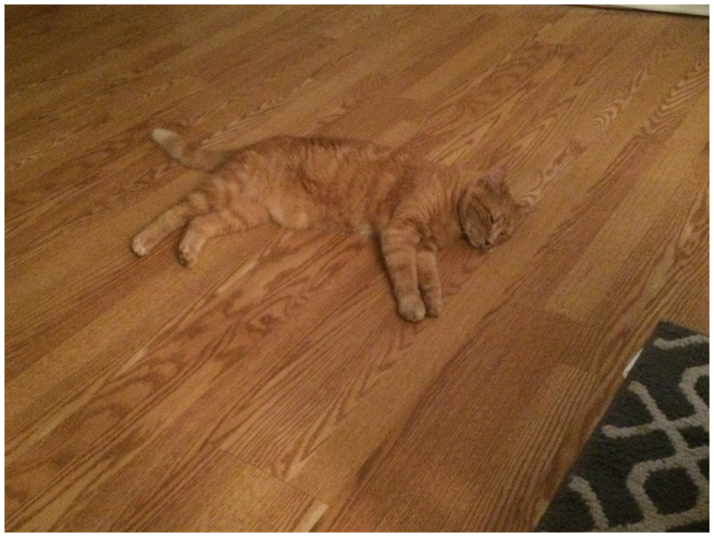


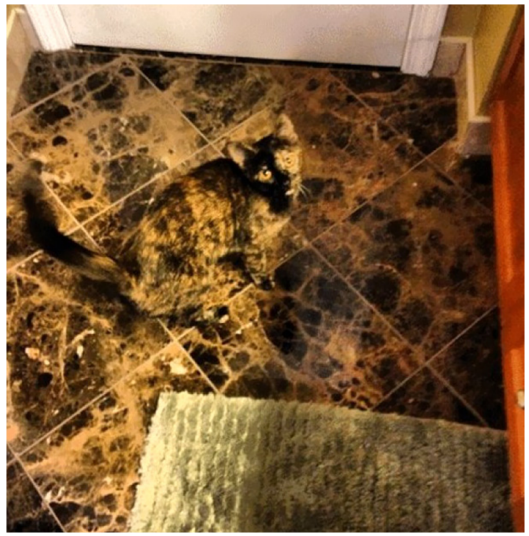


Example from CS331B: Representation Learning in Computer Vision

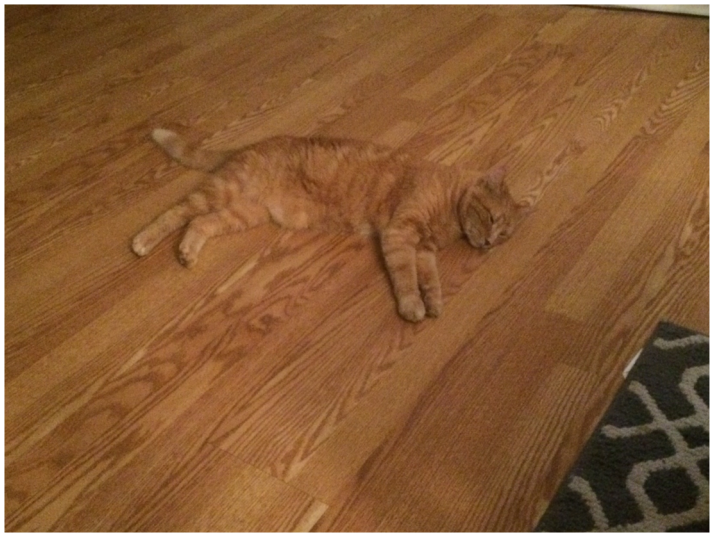
Represent these cats with a cat detector! (II)

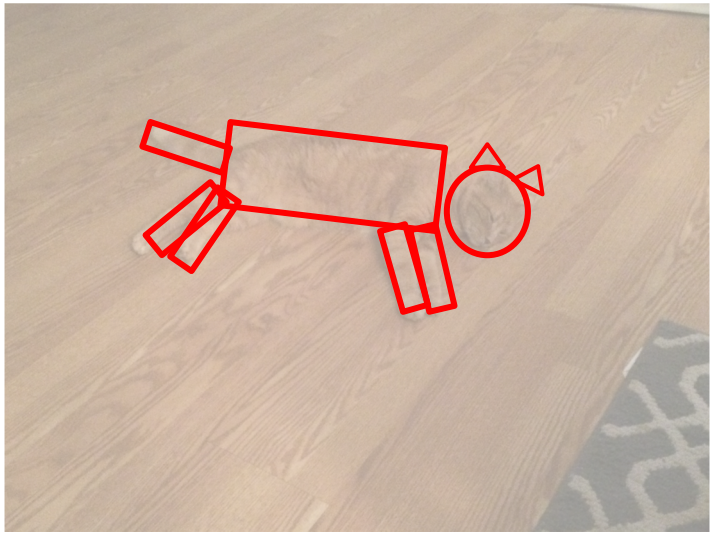




Example from CS331B: Representation Learning in Computer Vision

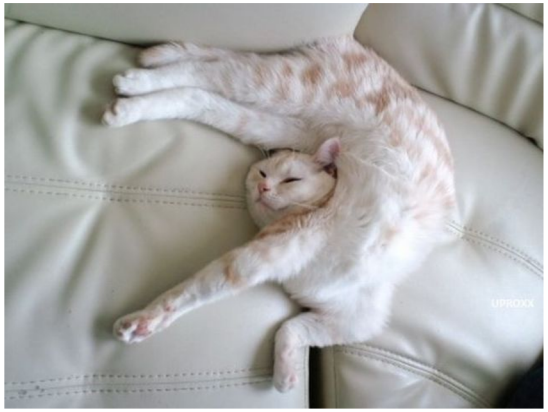
Represent these cats with a cat detector! (II)

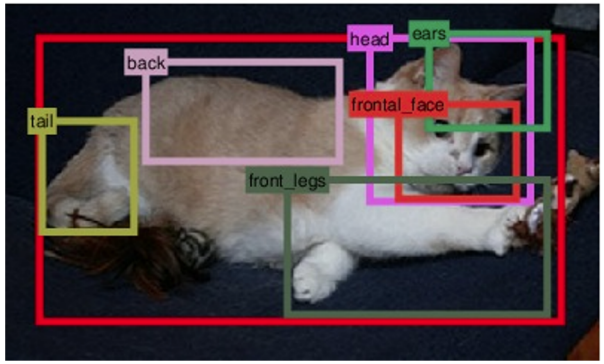




Example from CS331B: Representation Learning in Computer Vision

Represent these cats with a cat detector! (III)

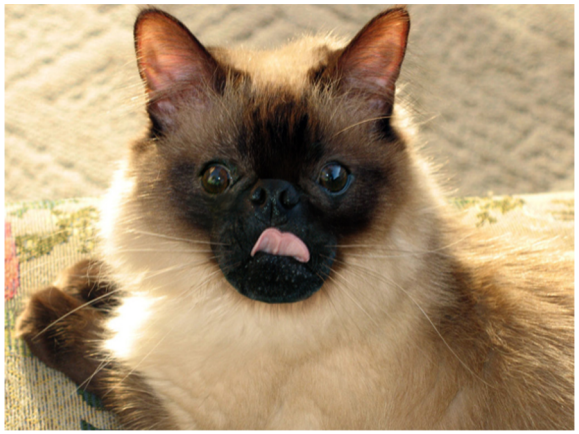
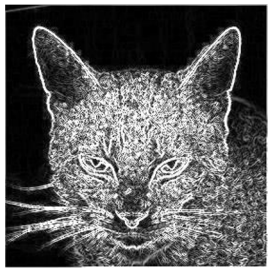
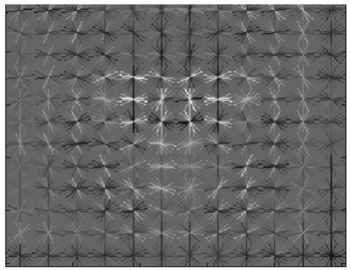




Example from CS331B: Representation Learning in Computer Vision

Represent these cats with a cat detector! (IV)

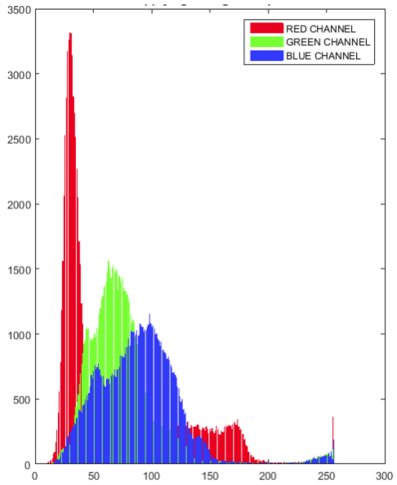


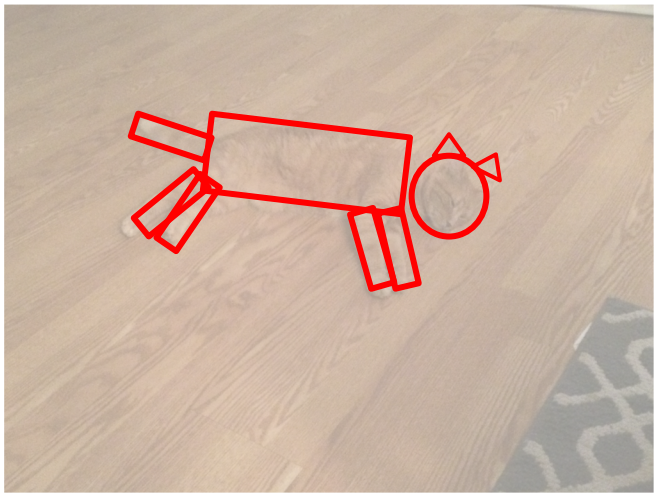




Example from CS331B: Representation Learning in Computer Vision

Summary of Traditional Components

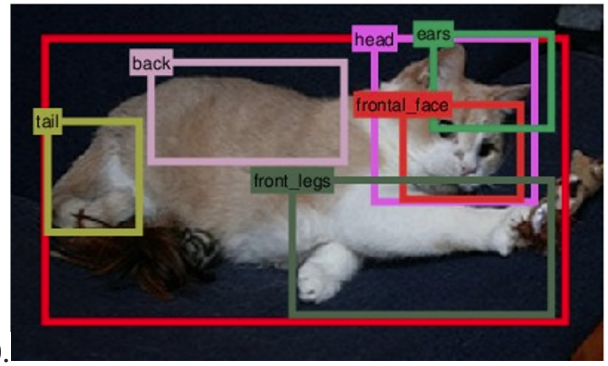
Color Histograms

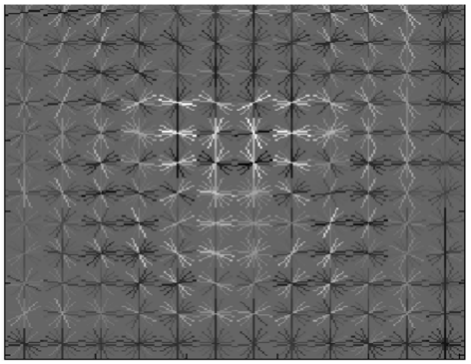




Model based Shapes

Deformable Part based Models (DPM)



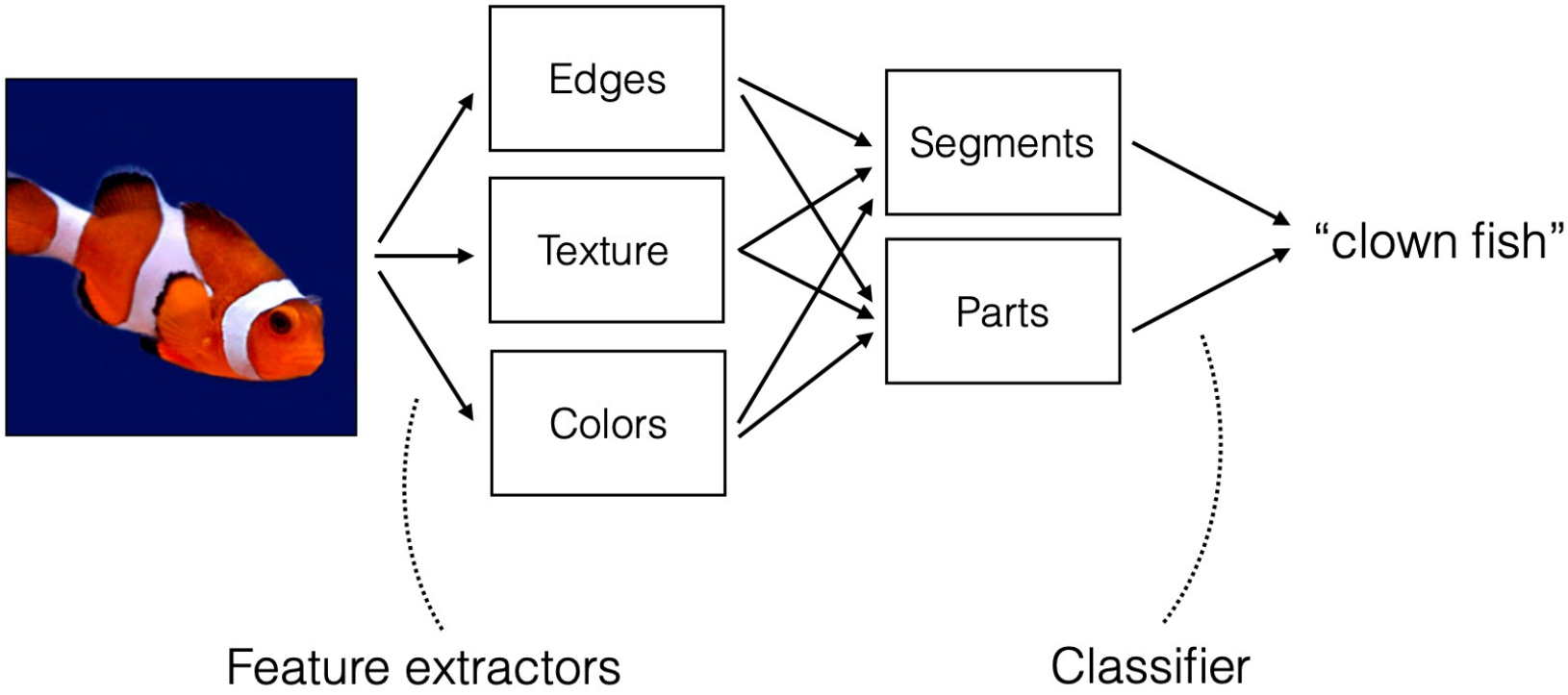


Histogram of Gradients (HOG)

Felzenszwalb et al. 2010.
Dalal and Triggs, 2005.
Beis and Lowe, 1997.

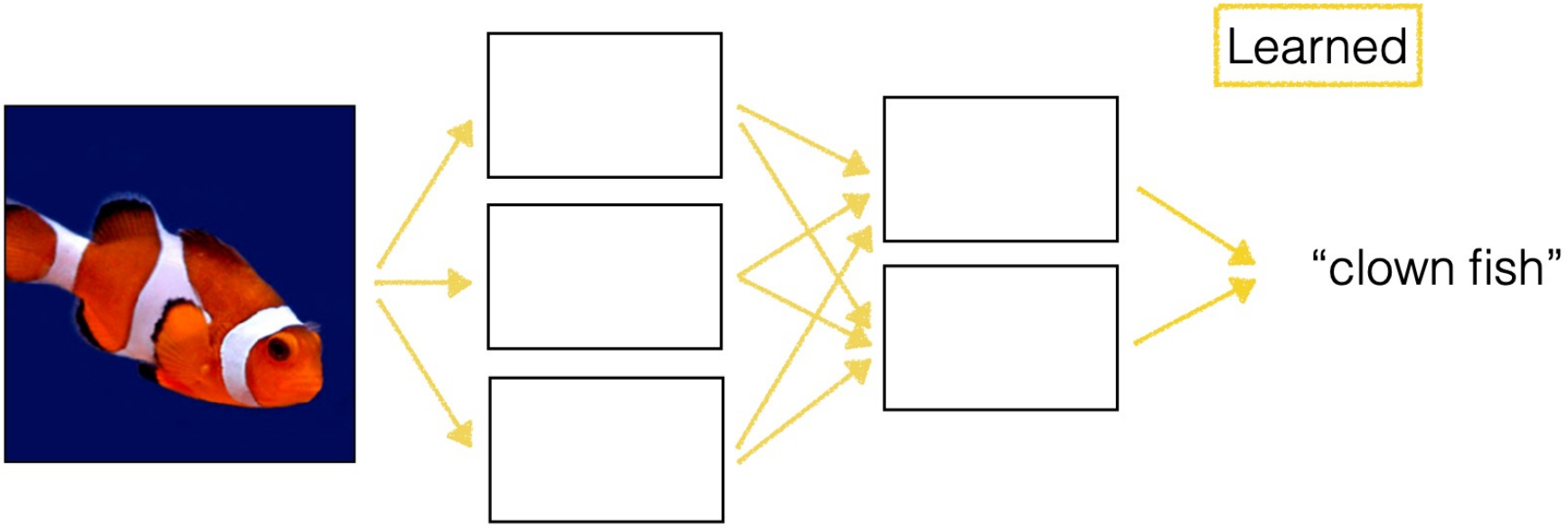
Example from CS331B: Representation Learning in Computer Vision

Traditional CV Pipeline



Example from Advances in Computer Vision – MIT – 6.869/6.819

Learned CV Pipeline



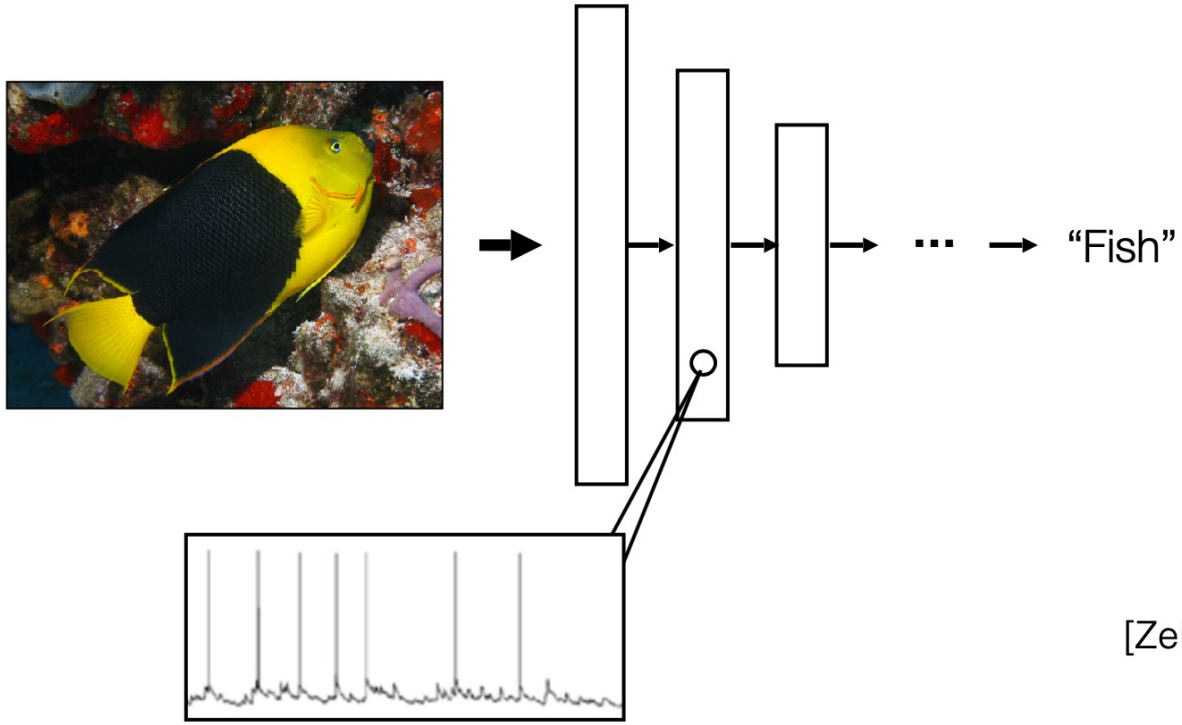
Example from Advances in Computer Vision – MIT – 6.869/6.819

Introduction to Neural Networks and CNNs

- Check Last Friday's CA Session

How do you interpret what the network has learned?

Deep Net "Electrophysiology"



[Zeiler & Fergus, ECCV 2014]
[Zhou et al., ICLR 2015]

Example from Advances in Computer Vision – MIT – 6.869/6.819

Visualizing and Understanding CNNs

[Zeiler and Fergus, 2014]

Gabor-like filters learned by **layer 1**

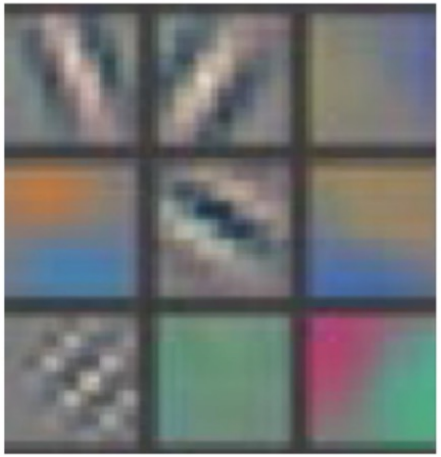
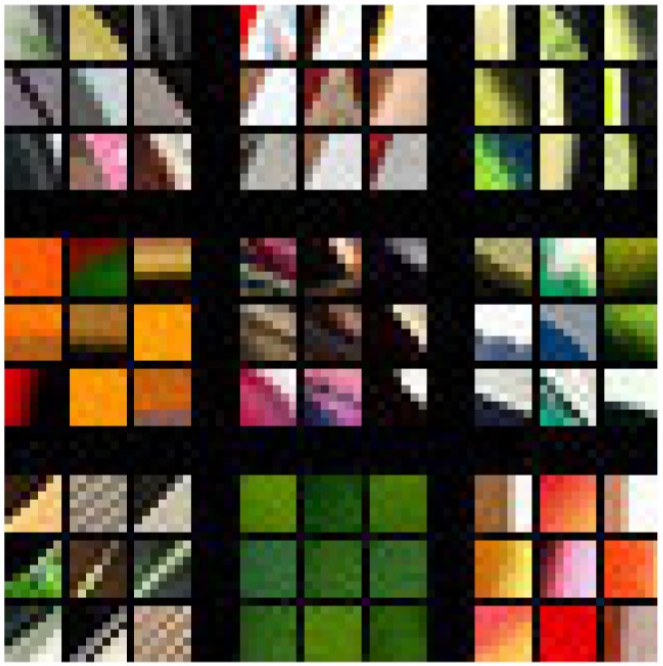


Image patches that activate each of the **layer 1** filters most strongly

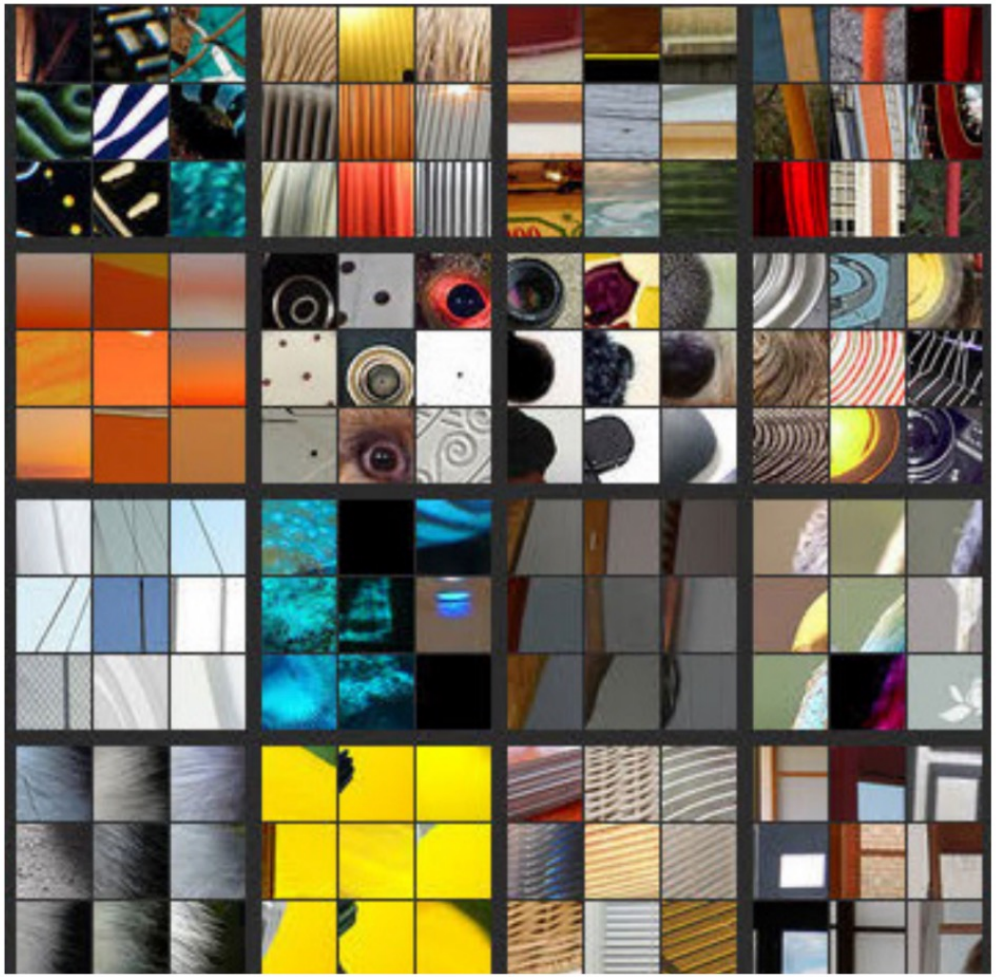


Example from Advances in Computer Vision – MIT – 6.869/6.819

Visualizing and Understanding CNNs

[Zeiler and Fergus, 2014]

Image patches that activate each of the **layer 2** neurons most strongly



Example from Advances in Computer Vision – MIT – 6.869/6.819

Visualizing and Understanding CNNs

[Zeiler and Fergus, 2014]

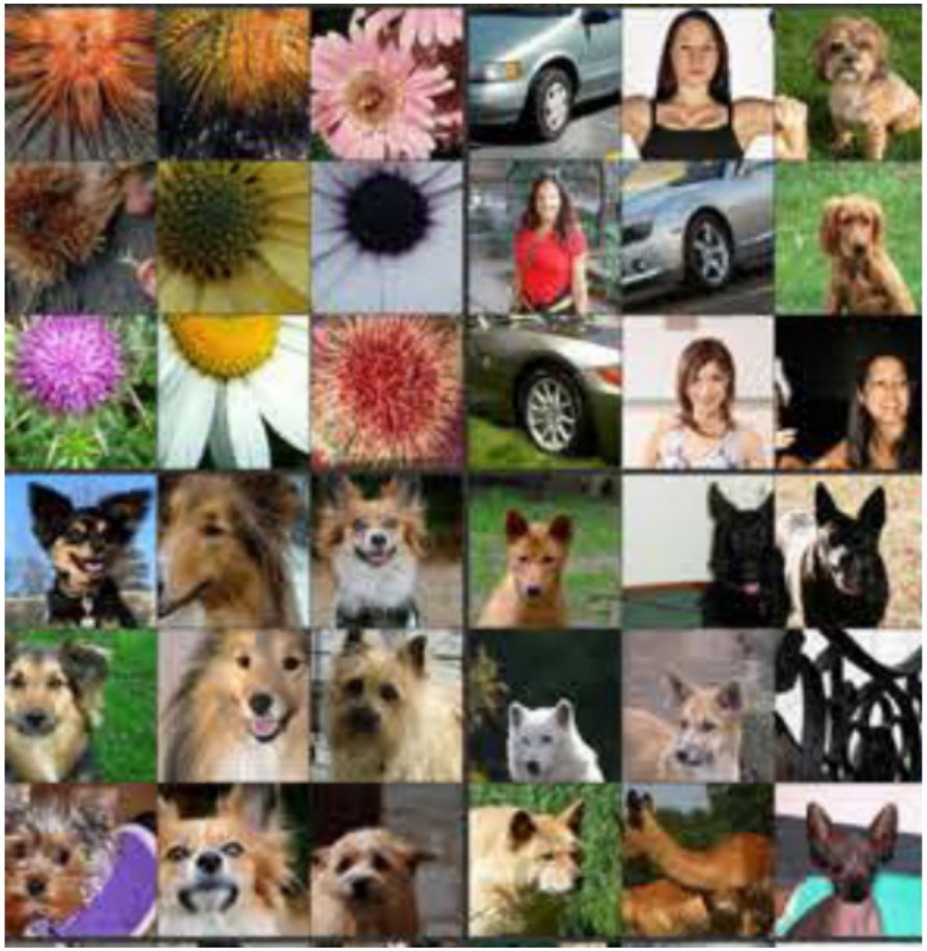
Image patches that activate each of the **layer 4** neurons most strongly

Example from Advances in Computer Vision – MIT – 6.869/6.819

Visualizing and Understanding CNNs

[Zeiler and Fergus, 2014]

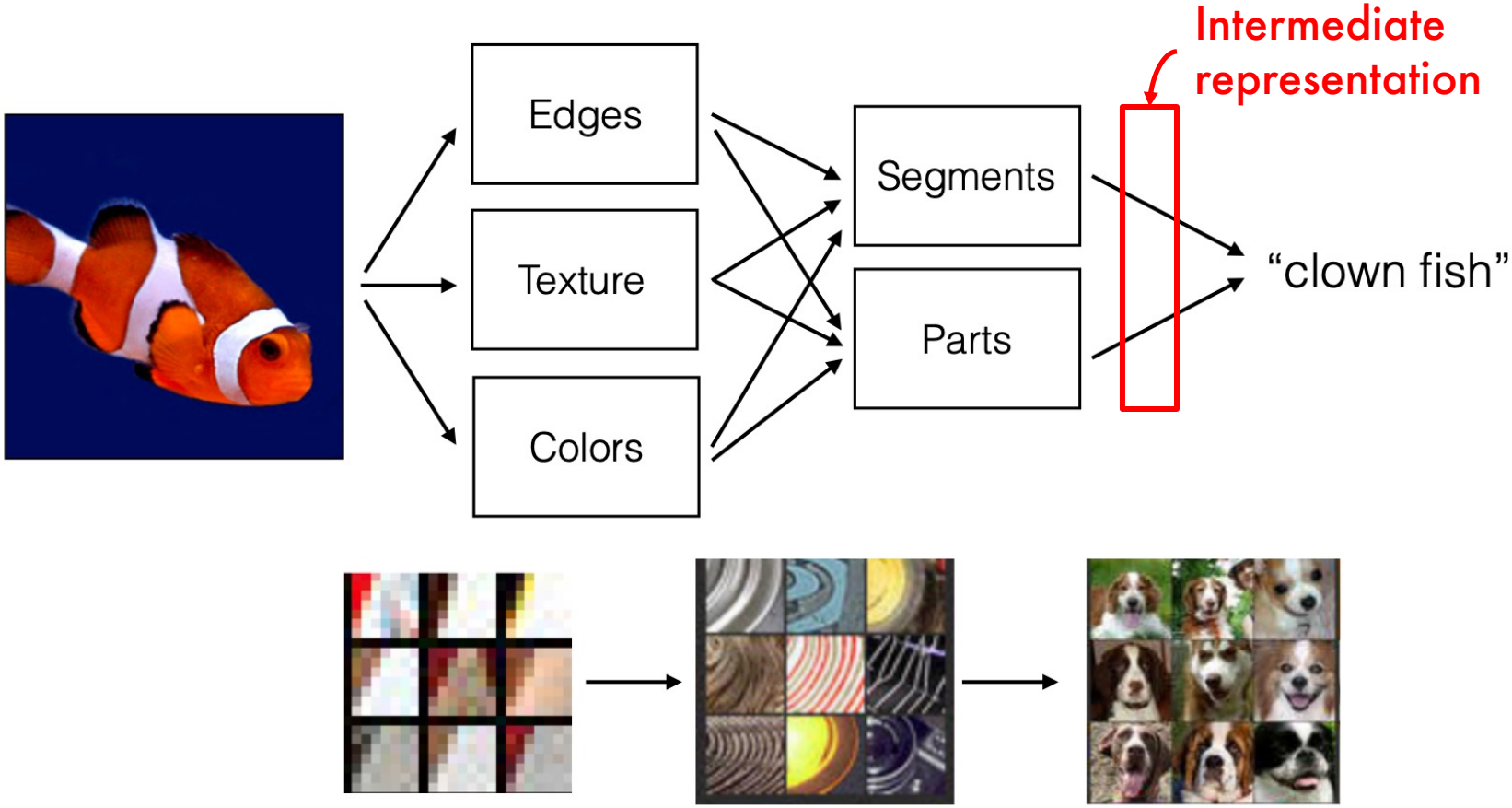
Image patches that activate each of the **layer 5** neurons most strongly



Example from Advances in Computer Vision – MIT – 6.869/6.819

Visualizing and Understanding CNNs

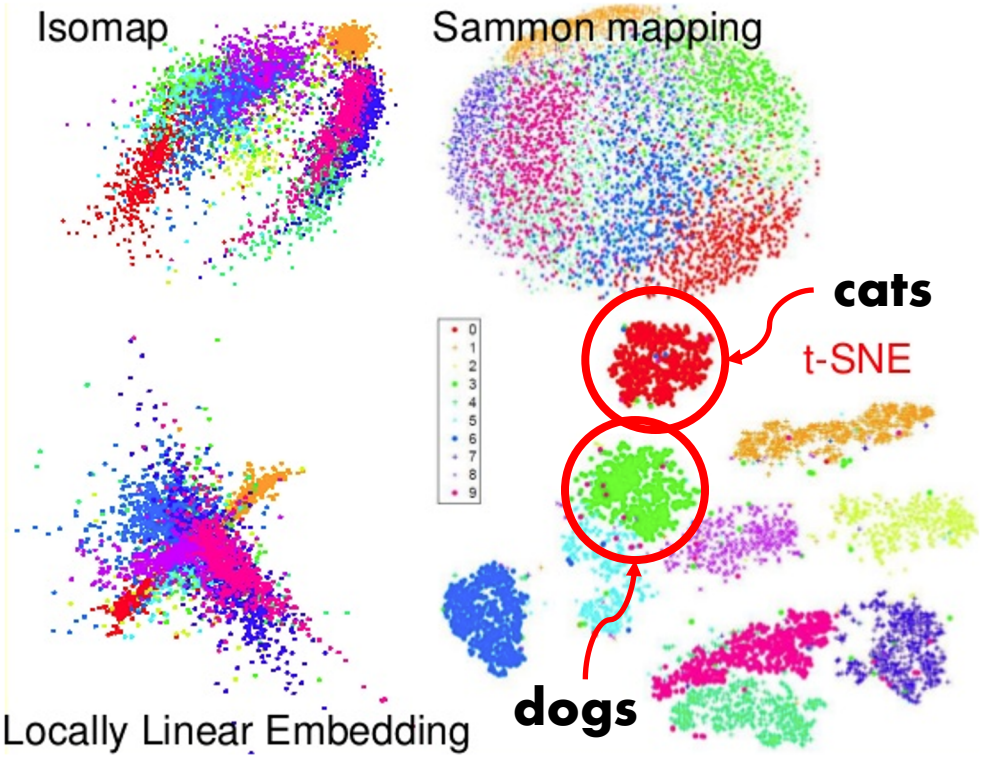
CNNs *learned* the classical visual recognition pipeline!



Example from Advances in Computer Vision – MIT – 6.869/6.819

Understanding representations through low-dimensional embeddings

- 6000 MNIST Digit
  - tSNE
  - Isomap
  - Sammon M
  - LLE

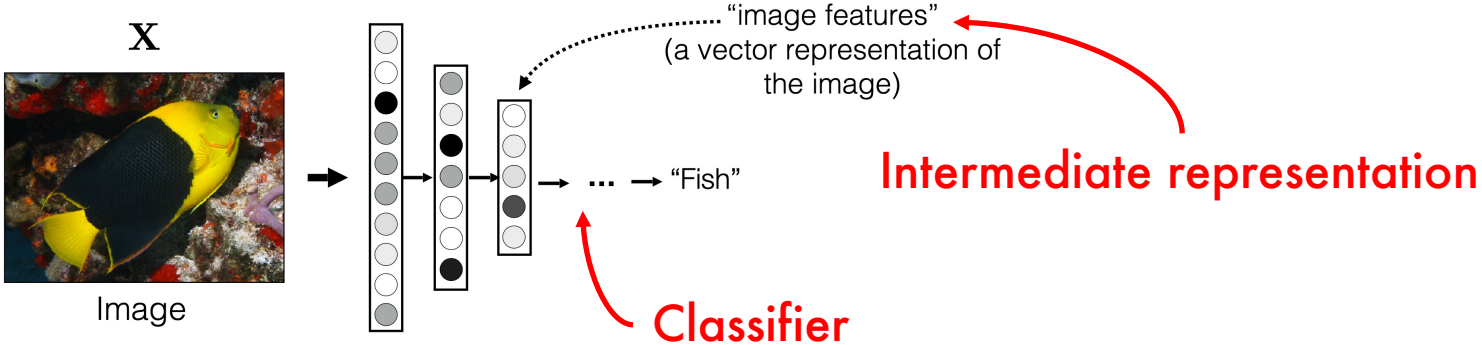


Understanding representations through low-dimensional embeddings

- tSNE

Van der Maaten & Hinton. 2008

How do you learn a representation?



Training data

Input images

Labels

$$\{x_1, y_1\}$$
$$\{x_2, y_2\}$$
$$\{x_3, y_3\}$$
$$\dots$$

$$\rightarrow \quad \text{Learner} \quad \rightarrow \quad f : X \rightarrow Y$$

$$f^* = \arg\min_{f \in \mathcal{F}} \sum_{i=1}^{N} \mathcal{L}(f(x_i), y_i)$$

Loss function/Cost

Supervised Object Recognition

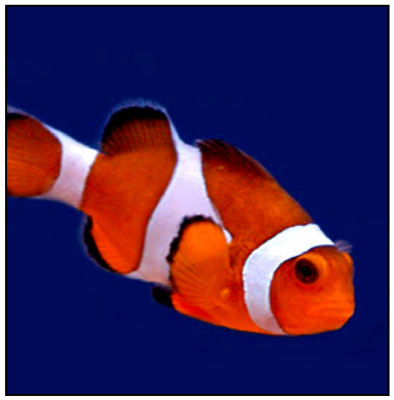


image X

"Fish"

label Y

Supervised Object Recognition

image X

"Fish"

label Y

Supervised Object Recognition

Learner

"Fish"

image X

label Y

Supervised Object Recognition

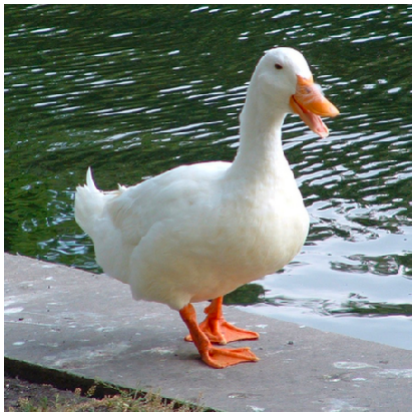


image X

Learner

"Duck"

label Y

Learning in the wild

Time lapse of a baby playing with toys. Francis Vachon. YouTube

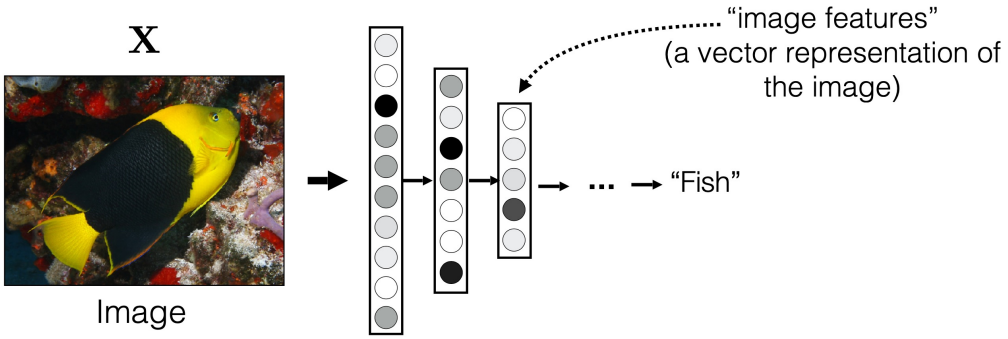
Supervised Computer Vision

- Informative
- Expensive
- Limited to teacher knowledge

Vision in Nature

- Cheap
- Noisy
- Harder to interpret

Learning without Labels



Training data

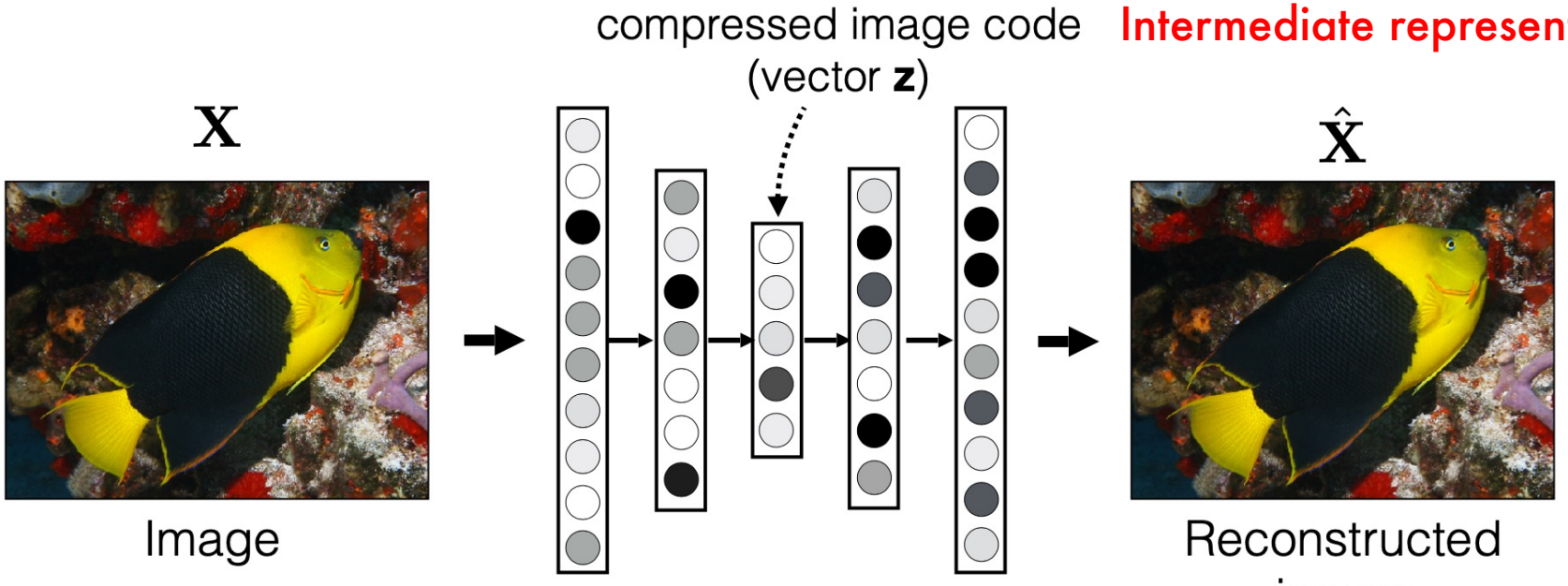
$$\{x_1, y_1\}$$
$$\{x_2, y_2\}$$
$$\{x_3, y_3\}$$
$$\dots$$

$$\rightarrow \quad \rightarrow \quad f : X \rightarrow Y$$

$$f^* = \arg\min_{f \in \mathcal{F}} \sum_{i=1} \mathcal{L}(f(\quad, y_i)$$

Unsupervised Representation Learning

No category or symbolic label. Instead: learn to reconstruct.

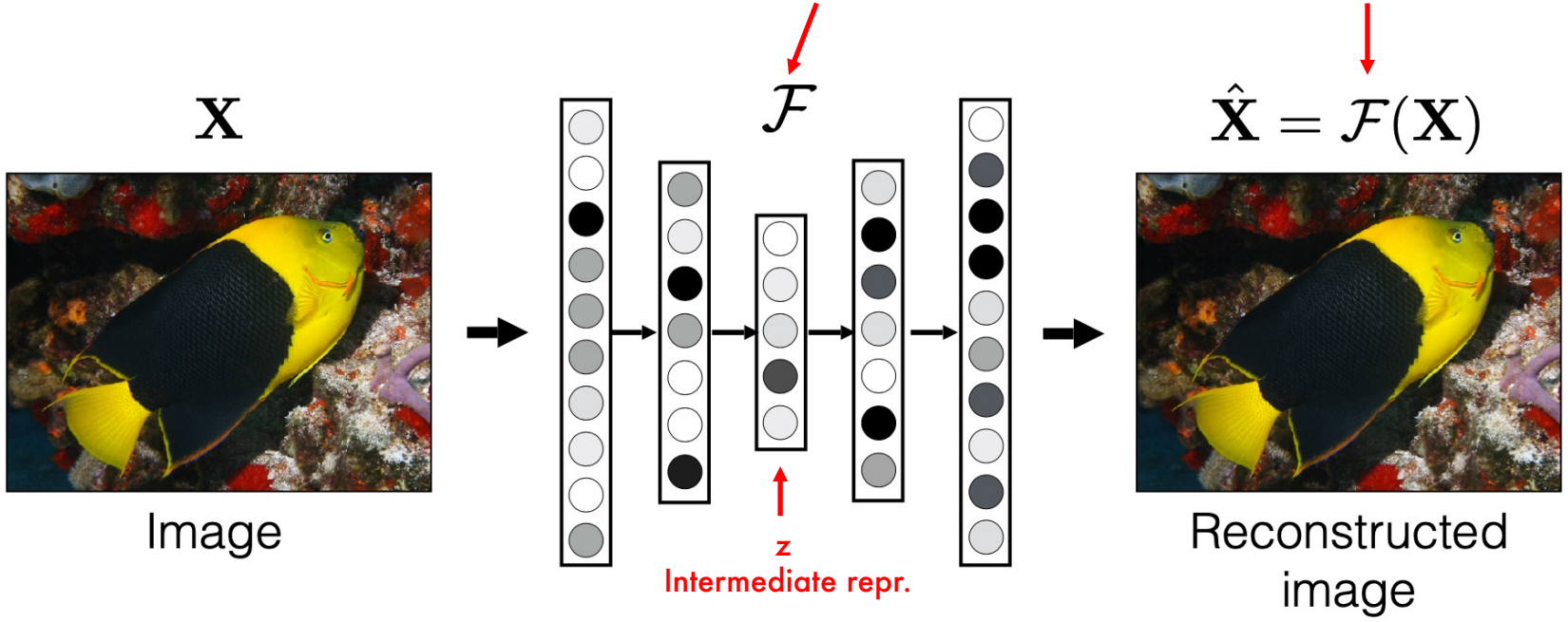


One kind of unsupervised model: "Autoencoder"

[e.g., Hinton & Salakhutdinov, Science 2006]

Autoencoder

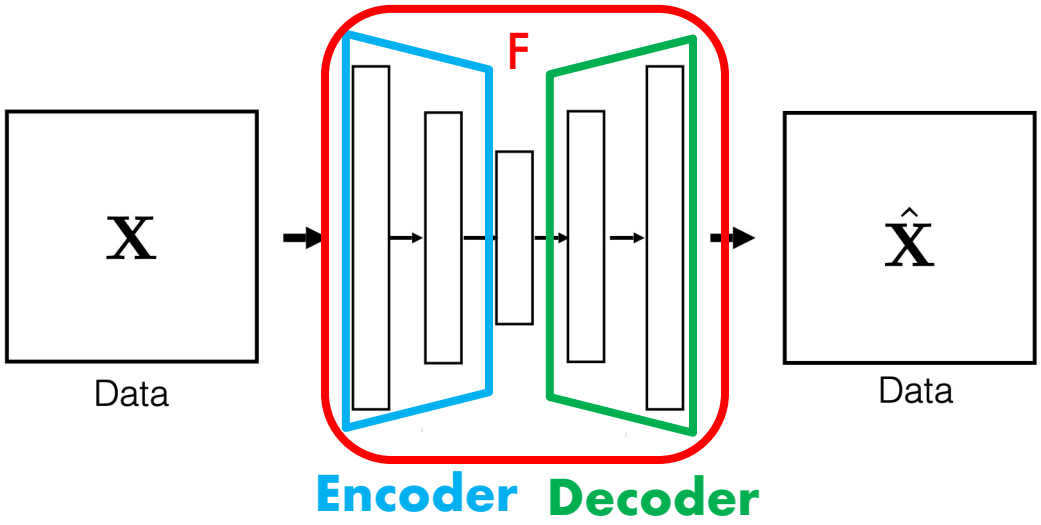
Not the Fundamental Matrix, but a function representing the autoencoder

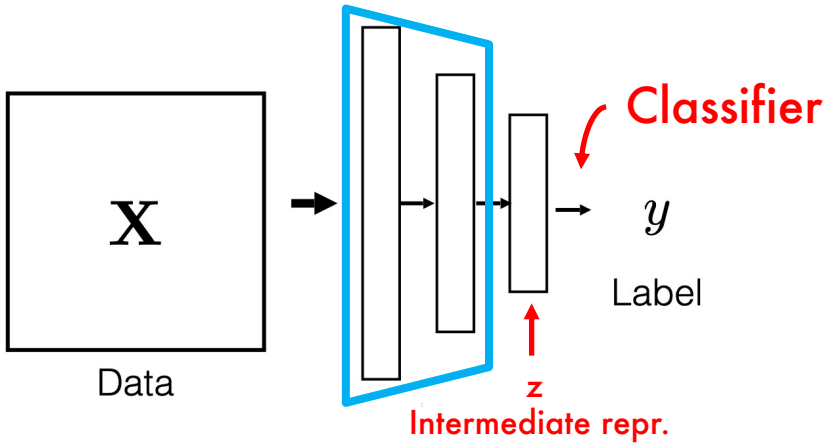


$$\arg\min_{\mathcal{F}} \mathbb{E}_{\mathbf{X}}[||\mathcal{F}(\mathbf{X}) - \mathbf{X}||]$$

Reconstruction loss to minimize by finding optimal F

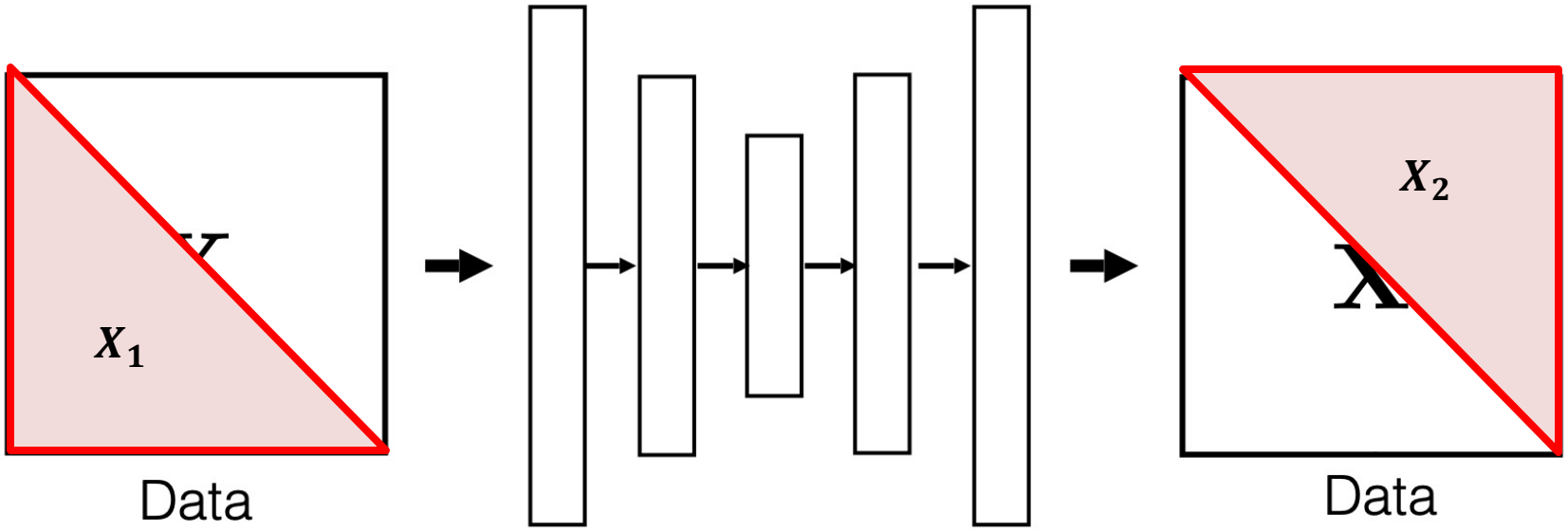
Data Compression & Task Transfer





e.g., image classification

Self-Supervision



$$F(X) = \hat{X}$$
$$F(X_1) = \hat{X}_2$$

Representation Learning

Reinforcement Learning (Cherry)

Predicting a scalar reward given once in a while

A few bits for some samples

Supervised Learning (Chocolate Coat)

Predicting category or vector of scalars per input as provided by human labels.

10-10k bits per sample

Unsupervised / Self-Supervised Learning (Cake)

Predicting parts of observed input or predicting future observations or events

Millions of bits per sample

Visualisation Idea by Yann LeCun
Photo by Kristina Paukshtite from Pexels

Summary of what you learned today

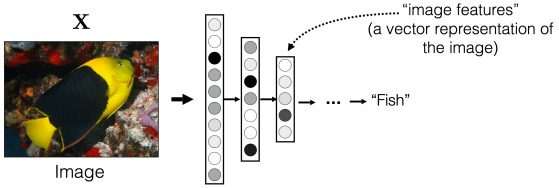
- **State:** Quantity that describes the most important aspect of a dynamical system at time t
- **Representation:** data format of input or output including a low-dimensional representation of sensor data

Summary of what you learned today

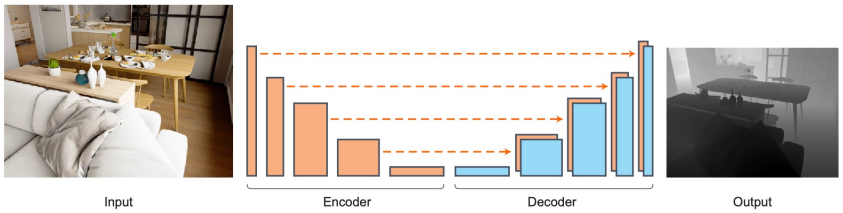
- Learned versus interpretable representations
- Visualize learned representations
- How to learn representations?
  - Supervised
  - Unsupervised
  - Self-supervised

Next Lectures

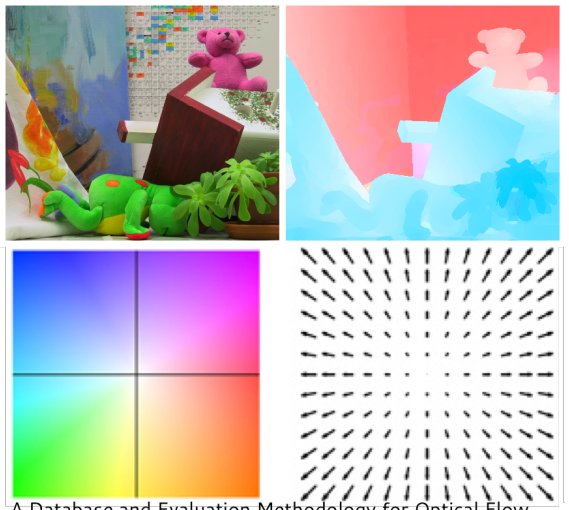
Representations & Representation Learning



Monocular Depth Estimation, Feature Tracking

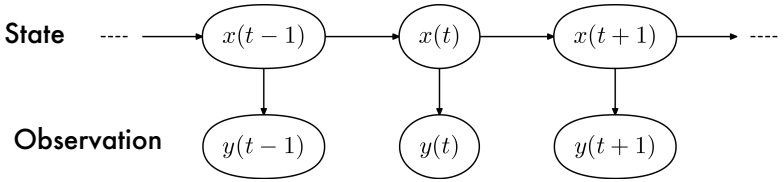


Optical & Scene Flow

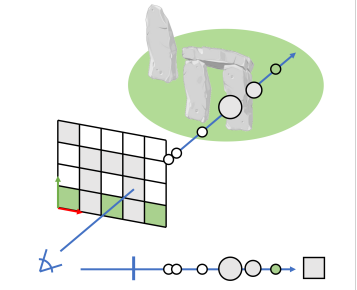


A Database and Evaluation Methodology for Optical Flow.
Baker et al. IJCV. 2011

Optimal Estimation

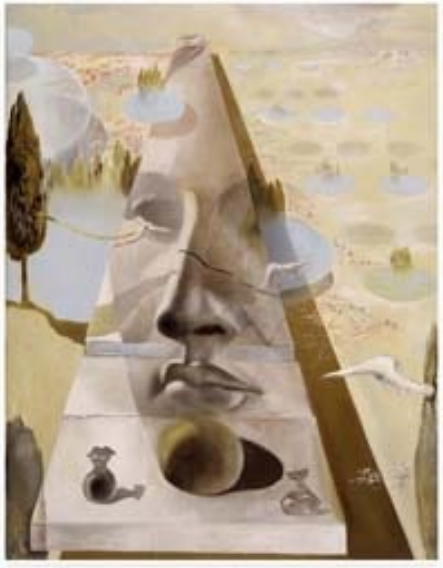


Neural Radiance Fields



CS231

Introduction to Computer Vision



Next lecture:

Monocular Depth Estimation

Low Level Tracking