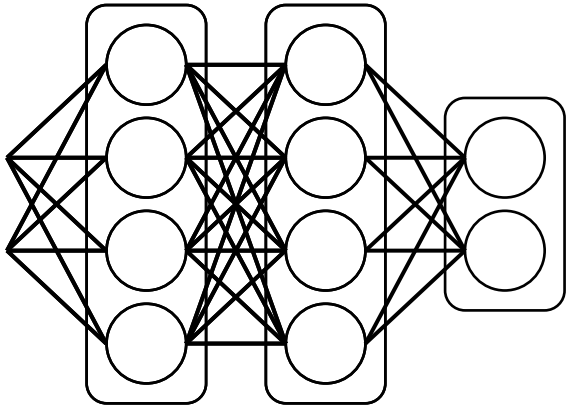
自监督学习

ImageNet 预训练 + 微调

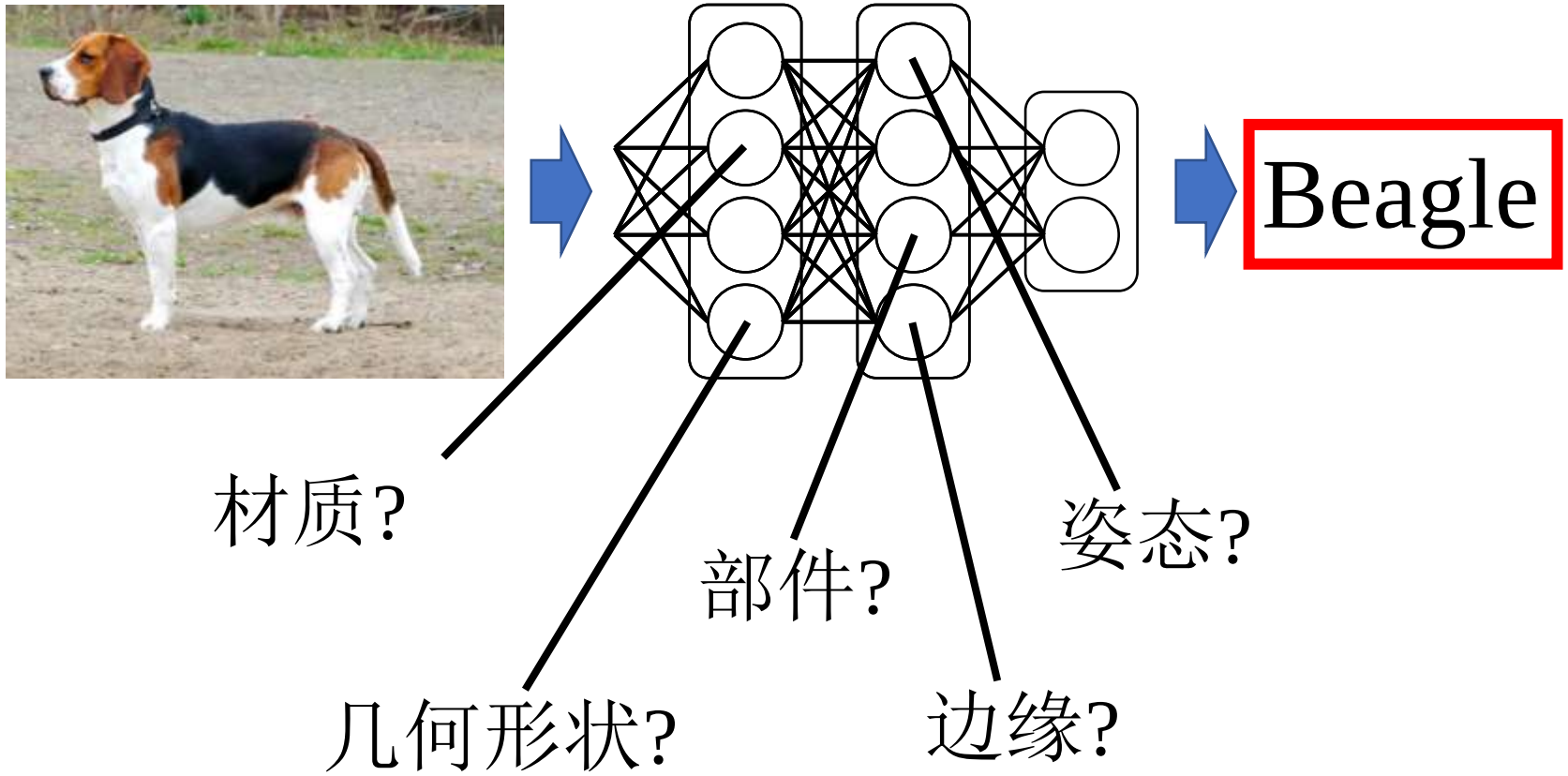


Beagle

- 图像检索
- 物体检测
- 语义分割
- 深度估计
- …

Slide Credit: C. Doersch

我们学到了什么？



这些任务很难标注！我们需要做这些任务吗?

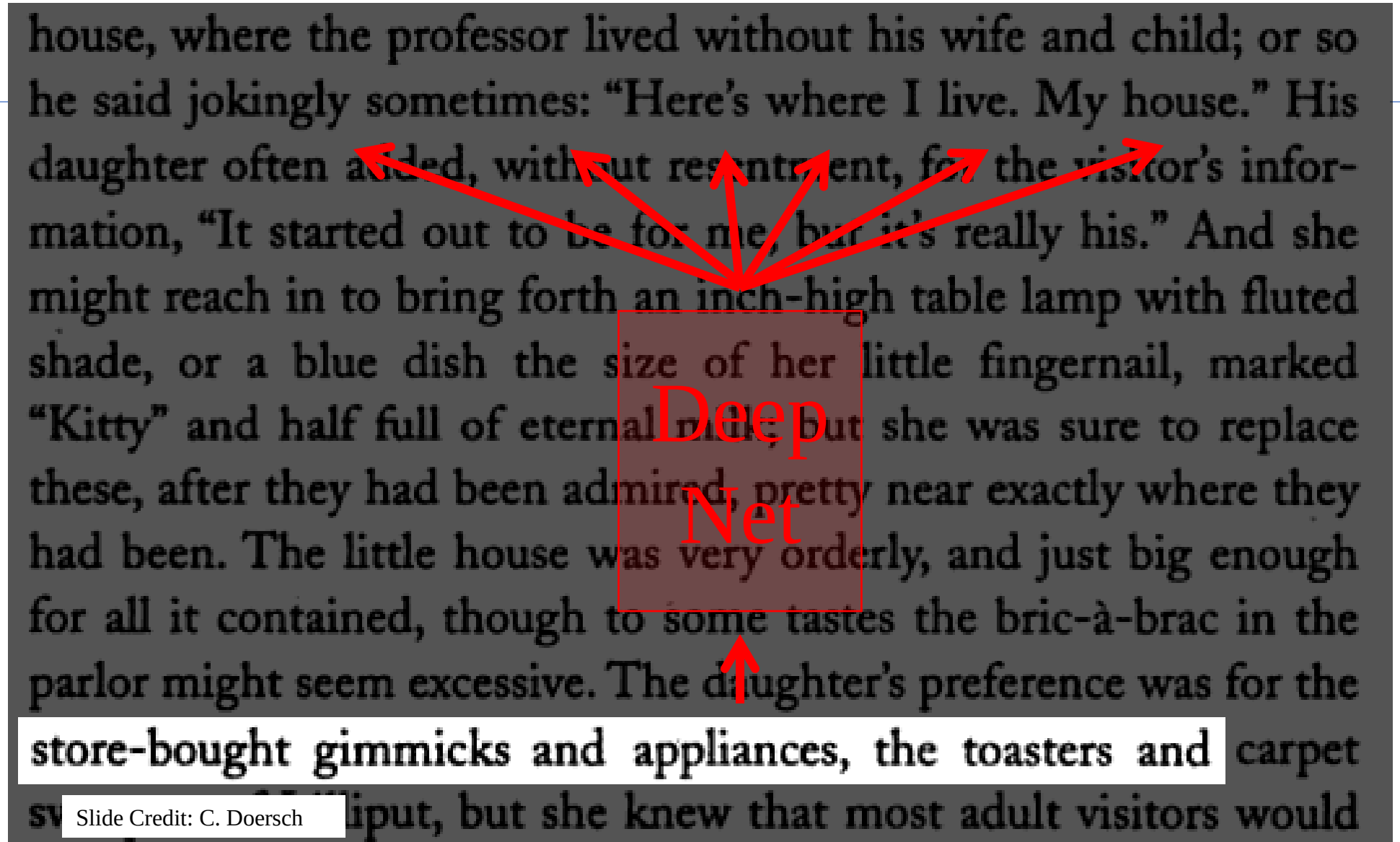
我们需要语义标注吗?

Slide Credit: C. Doersch

Context as Supervision 上下文监督

[Collobert & Weston 2008; Mikolov et al. 2013]

BERT 与 GPT 的核心概念之一

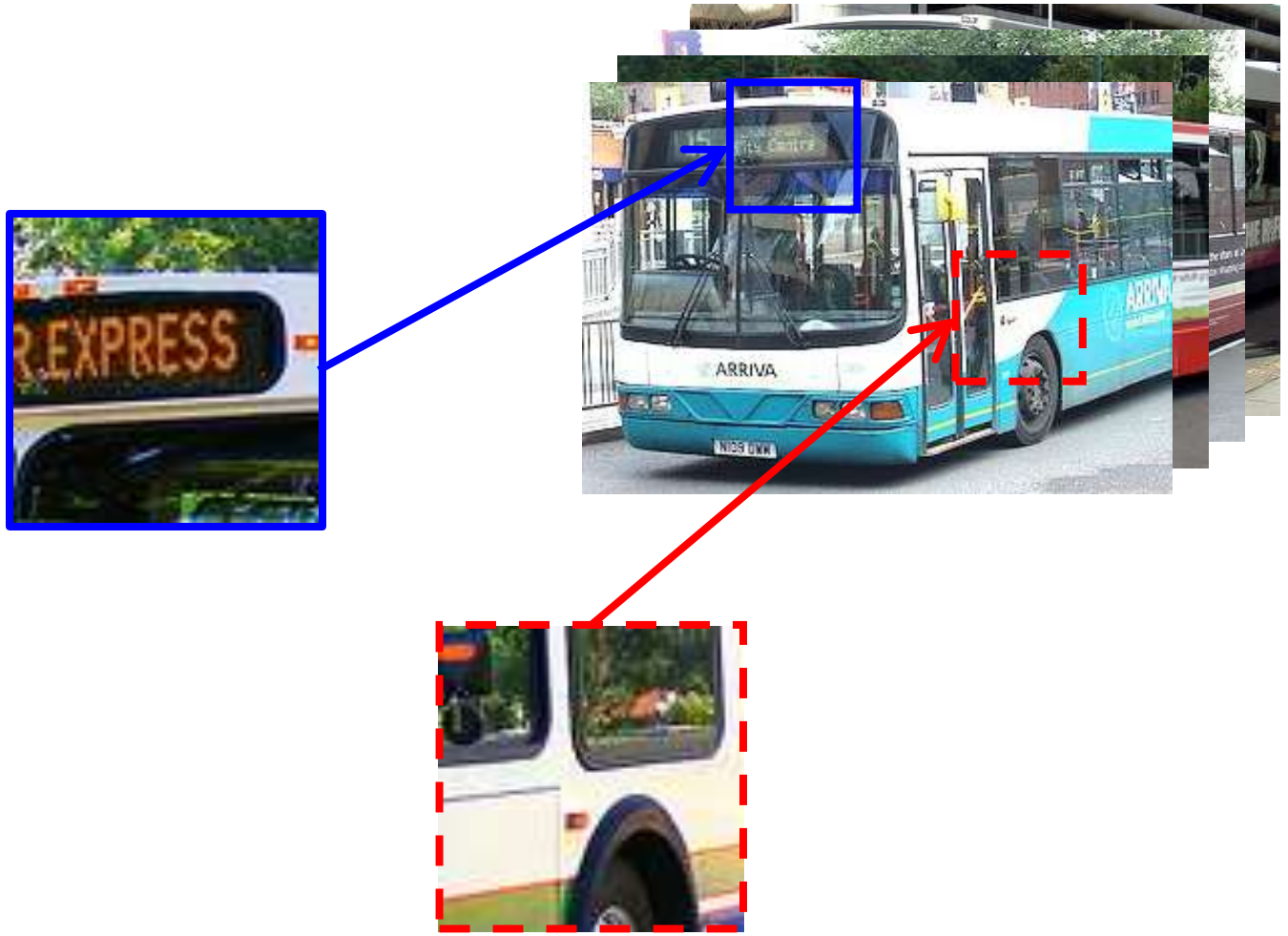


Slide Credit: C. Doersch

图像的上下文预测

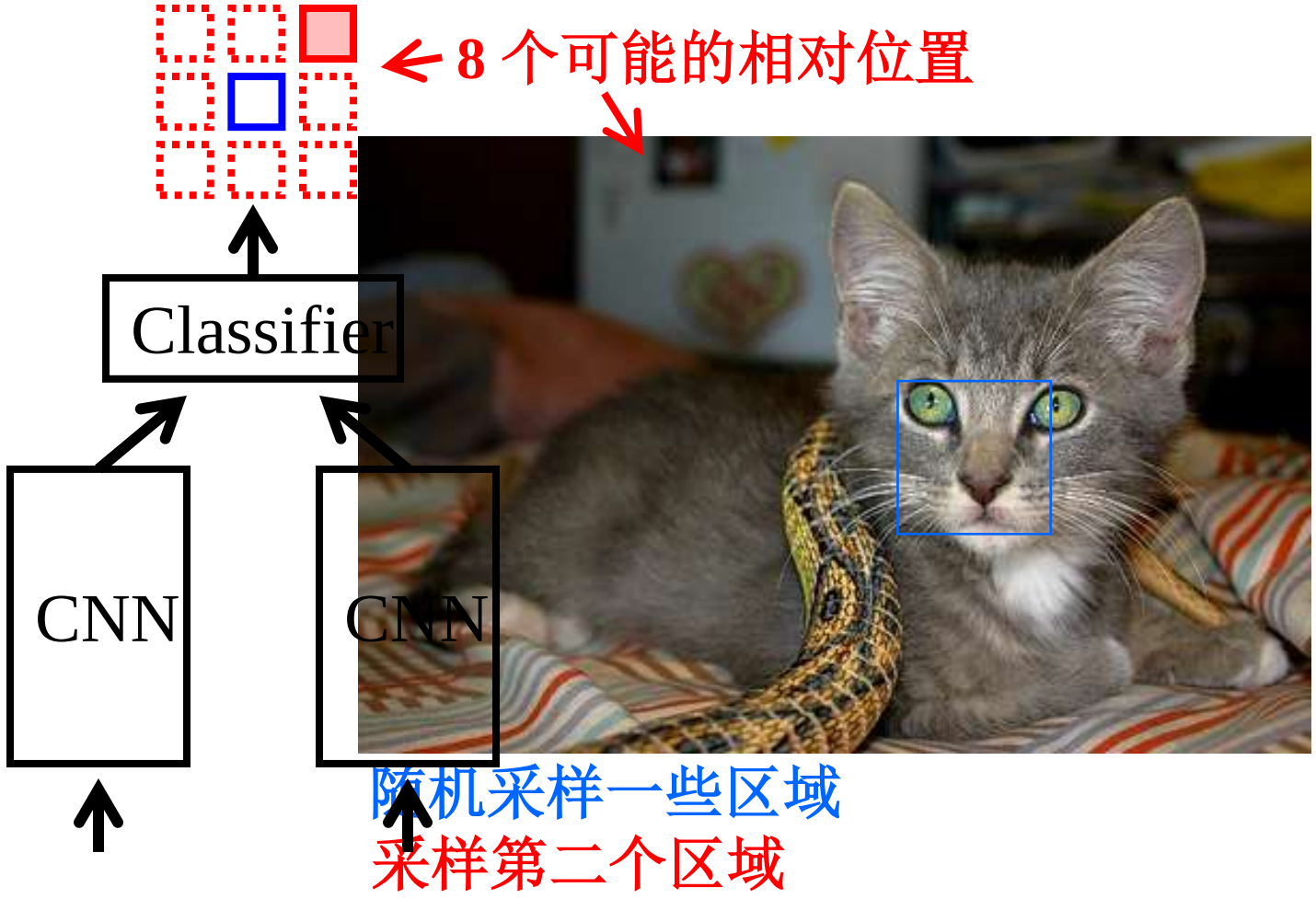
Slide Credit: C. Doersch

这样做能得到什么“语义”信息？

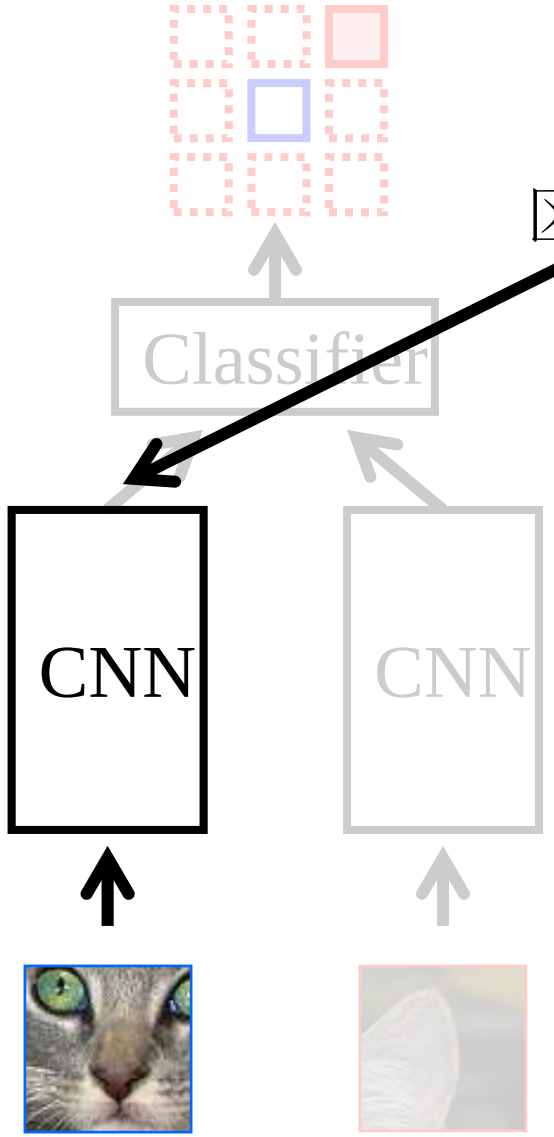


Slide Credit: C. Doersch

相对位置预测



Slide Credit: C. Doersch



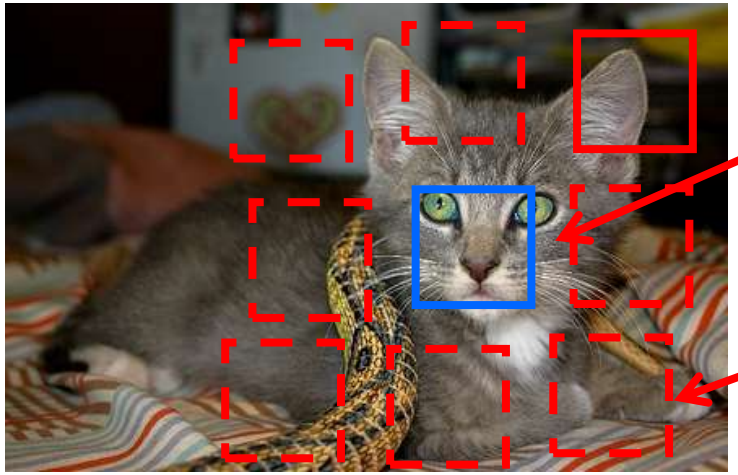
Input

最近邻

在不同的实体之间检索相似的部件

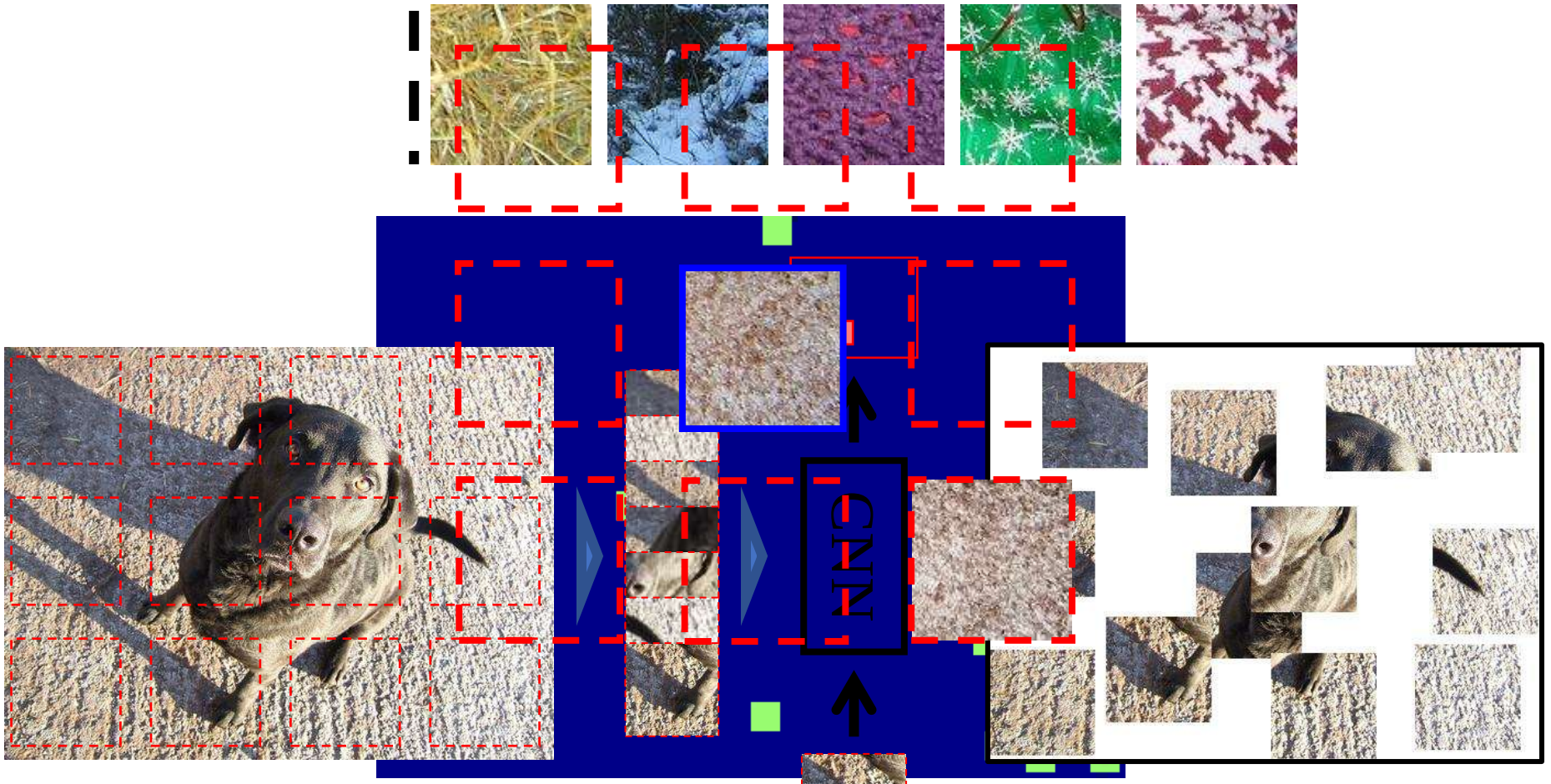
Slide Credit: C. Doersch

避免简单推断



Slide Credit: C. Doersch

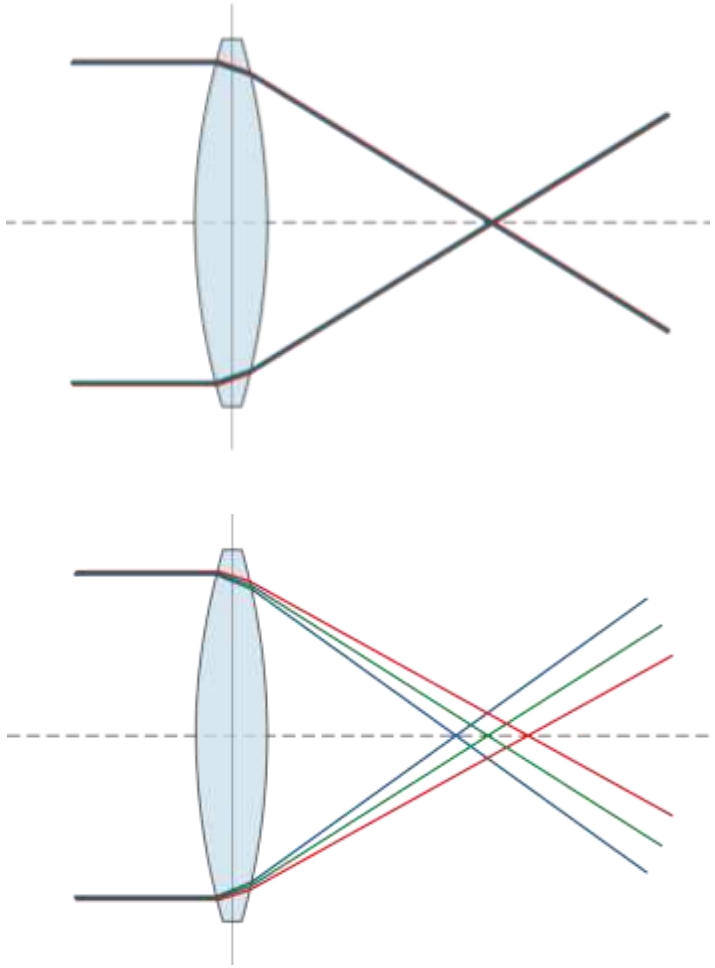
加入位置预测



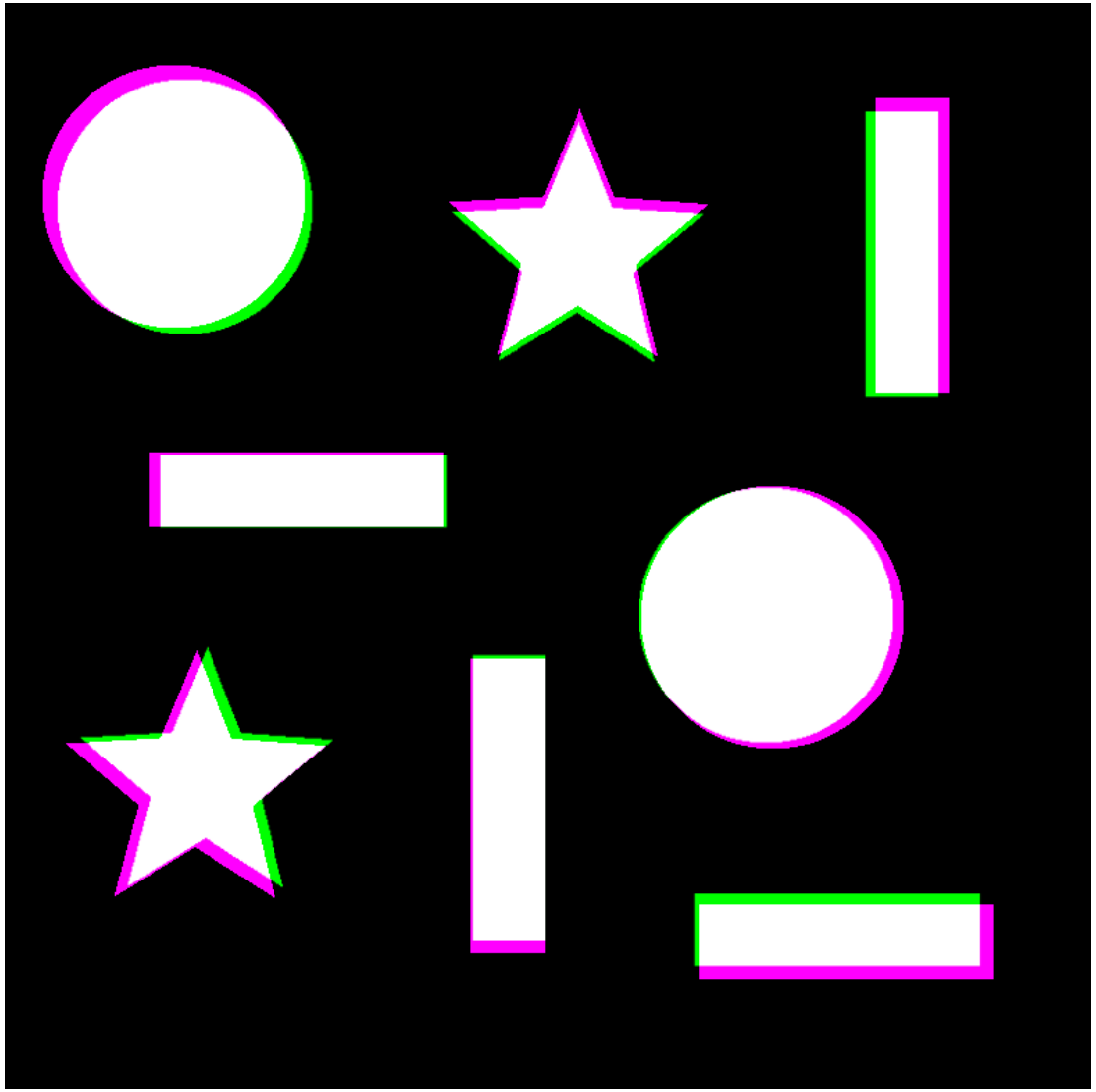
位置预测图

Slide Credit: C. Doersch

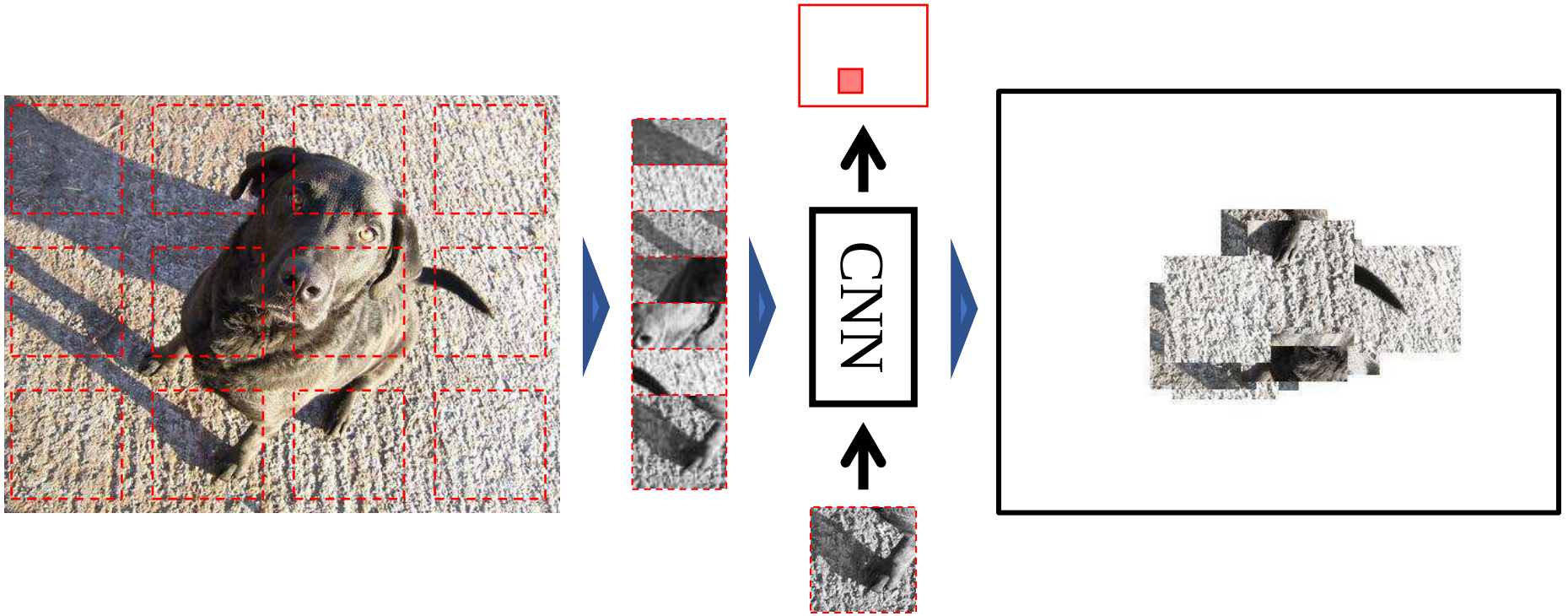
色差估计



Slide Credit: C. Doersch



去掉颜色以后。。。

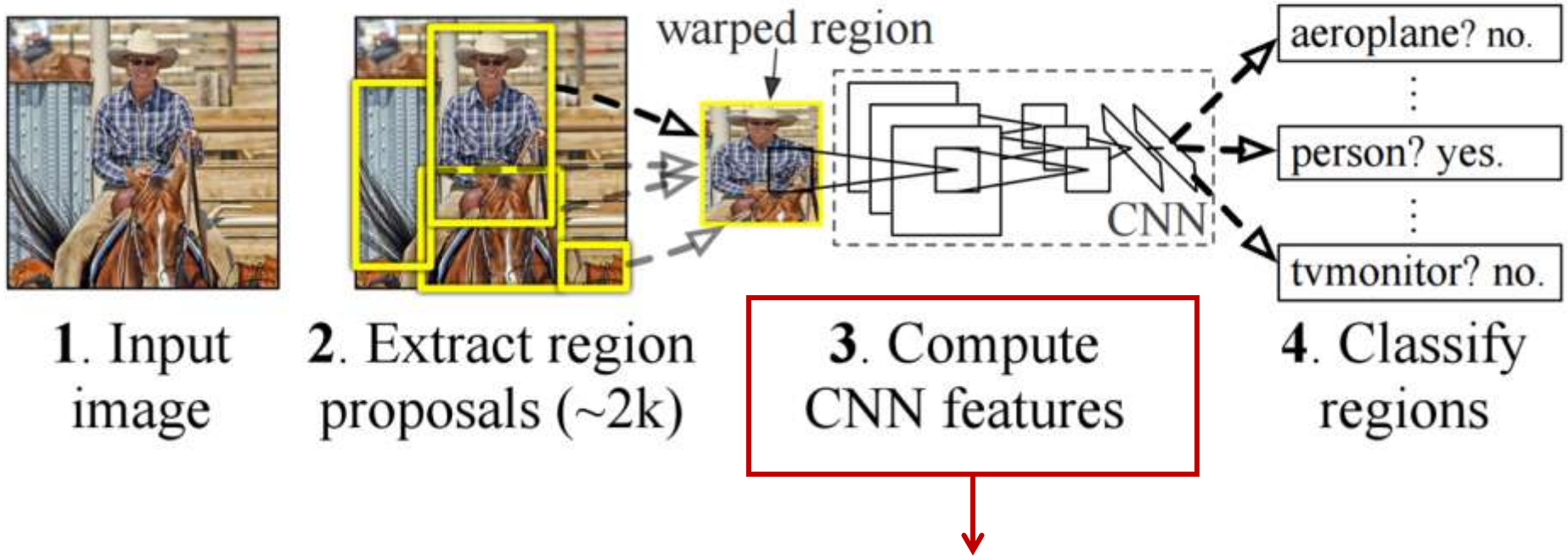


Slide Credit: C. Doersch

这样做学到了什么？

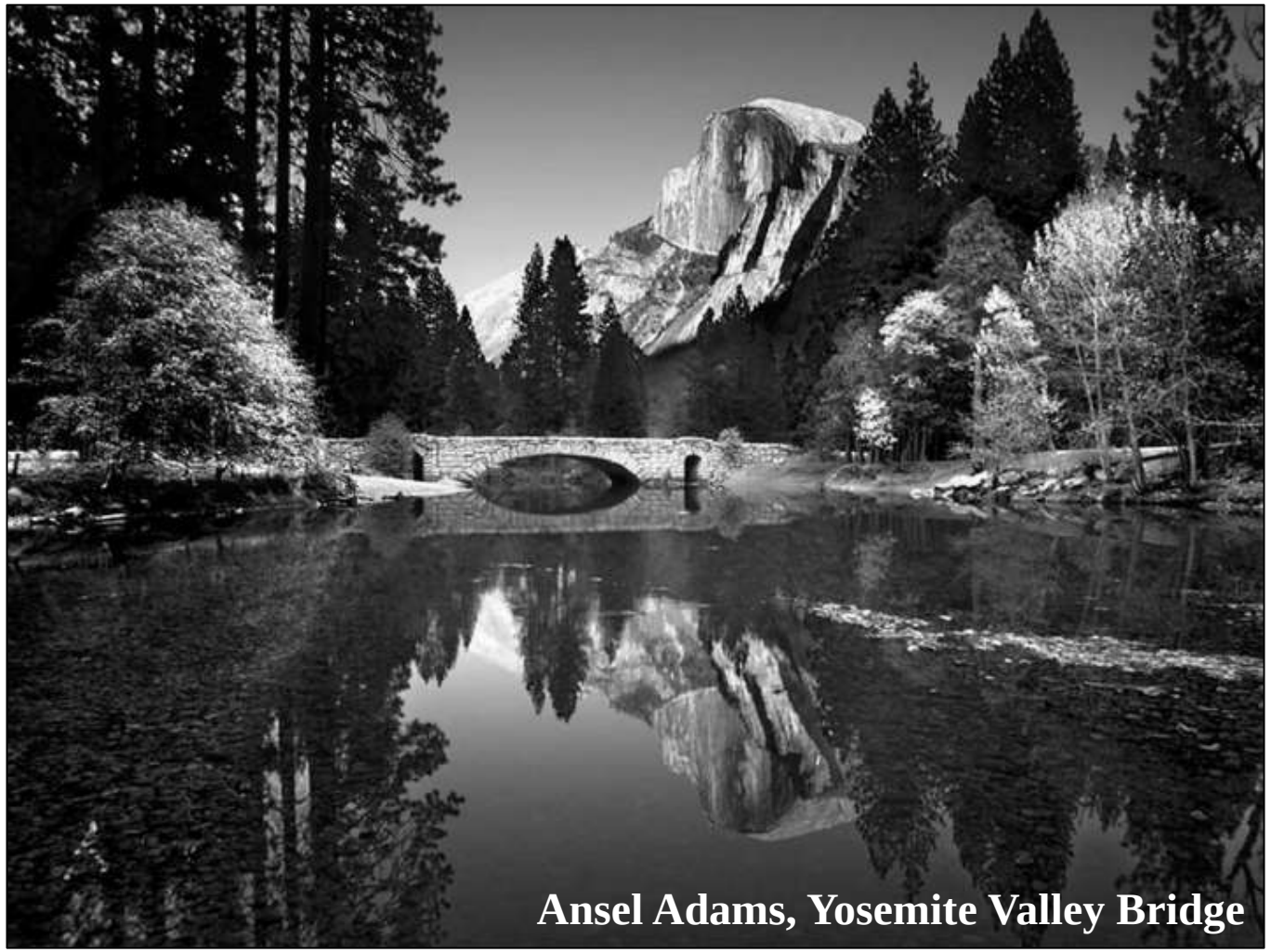
Slide Credit: C. Doersch

R-CNN 的 预训练 CNN

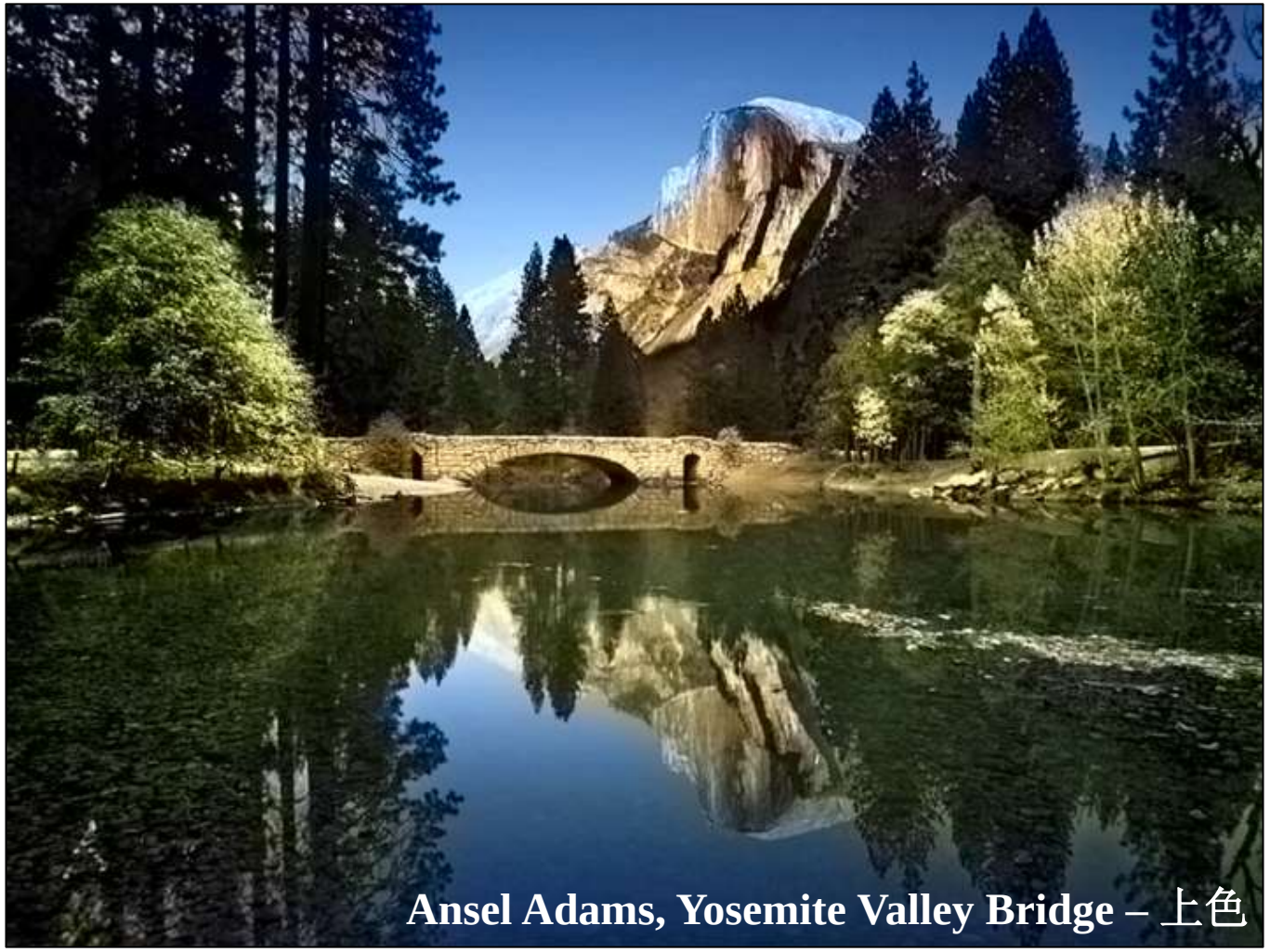


使用相对位置自监督学习的预训练模型

[Girshick et al. 2014]



Slide Credit: R. Zhang



Slide Credit: R. Zhang

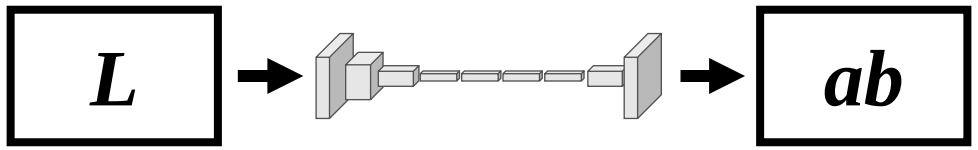
$\mathcal{F}$

灰度图: *L* channel

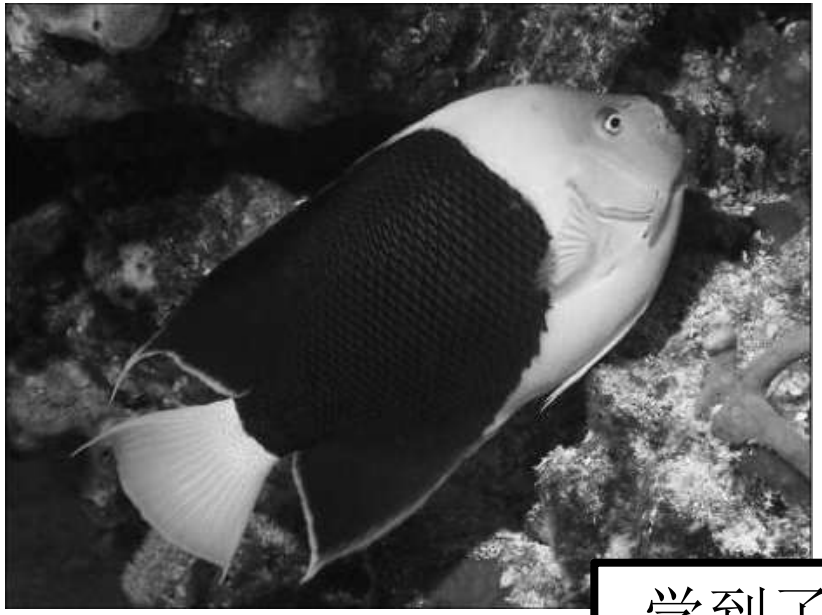
$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$

色彩图: *ab* channels

$\hat{\mathbf{Y}} \in \mathbb{R}^{H \times W \times 2}$



Slide Credit: R. Zhang



$\mathcal{F}$

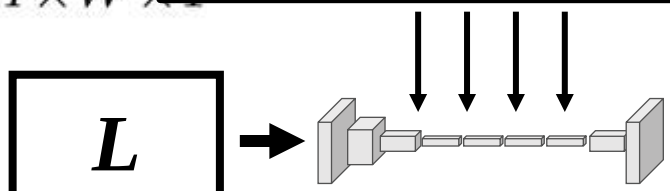
灰度图: *L* chann

彩图: *ab* channels

$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$

$(\mathbf{X}, \hat{\mathbf{Y}})$

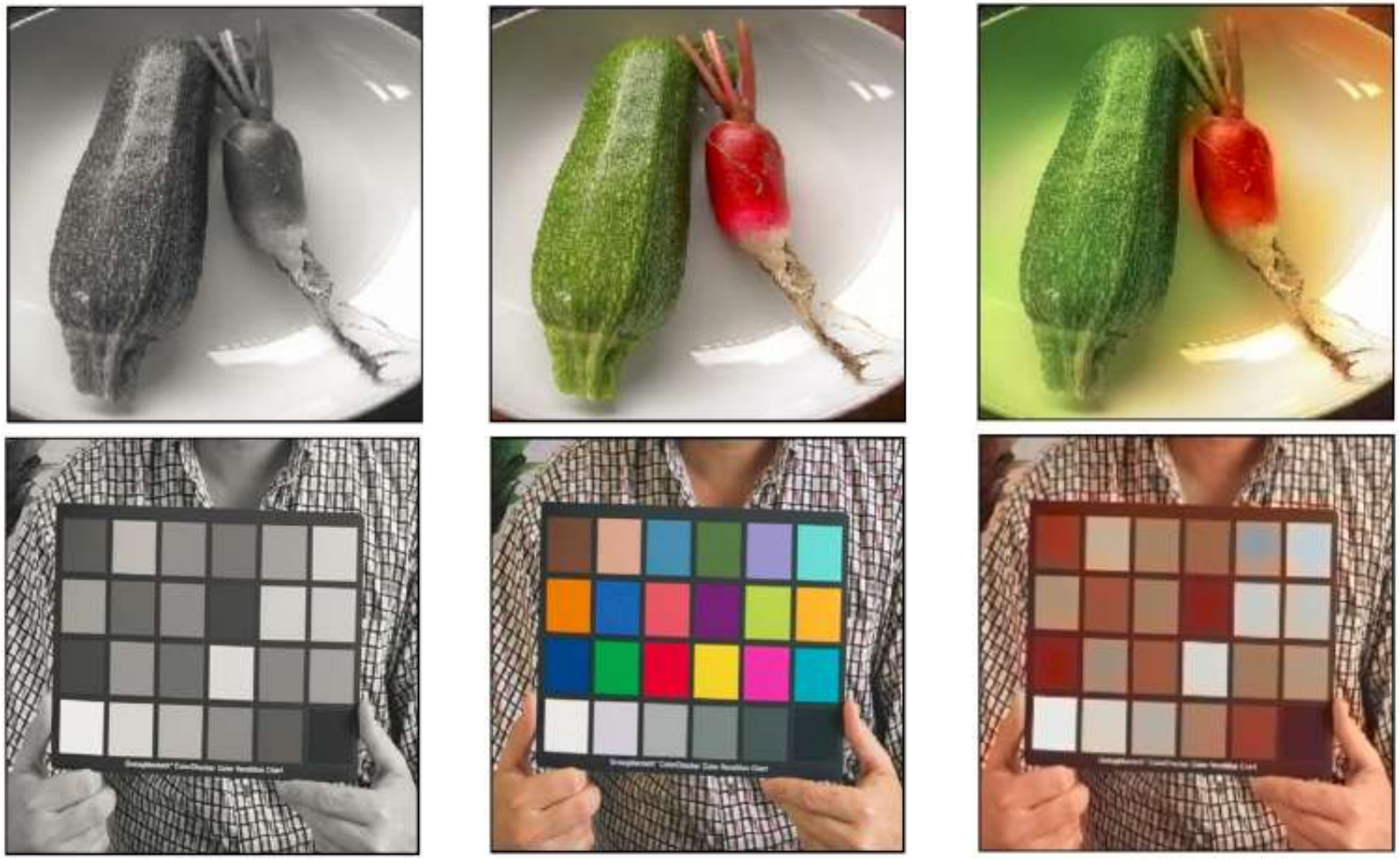
学到了什么？语义？
抽象的信息？



无需标注的自监督训练

Slide Credit: R. Zhang

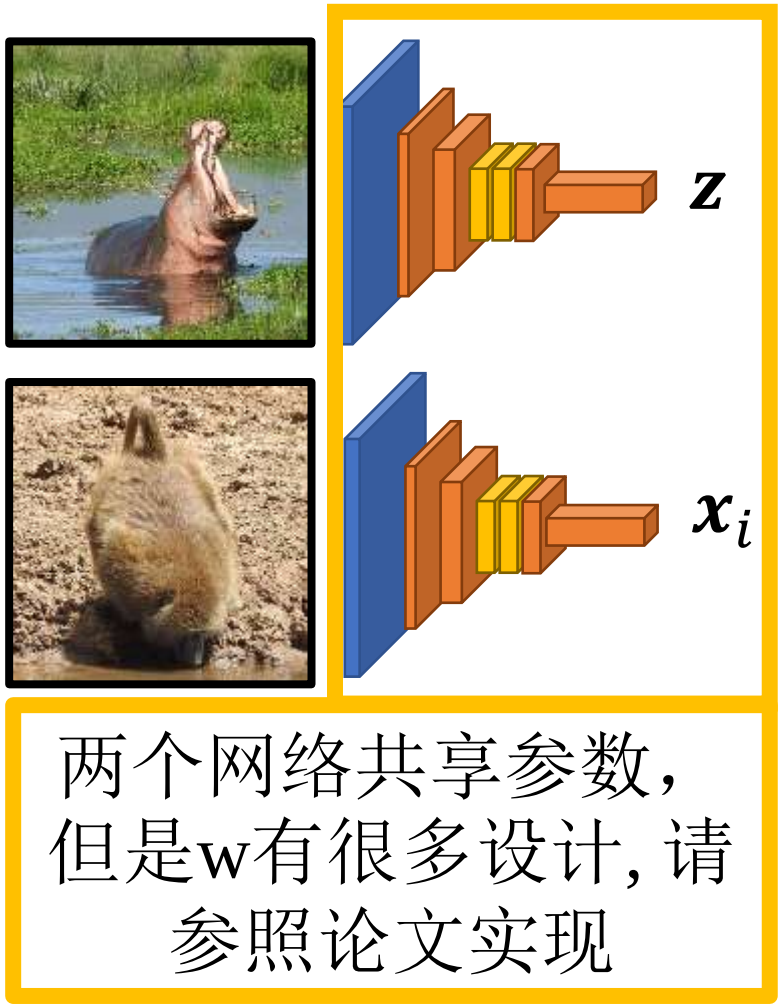
输入 真实图 输出



Slide Credit: R. Zhang

Visually Indicated Sounds
Andrew Owens
Phillip Isola
Josh McDermott
Antonio Torralba
Edward Adelson
William Freeman

Contrastive Learning 对比学习



给定样本，构建特征 z; 对于其他一组样本图像，最小化:

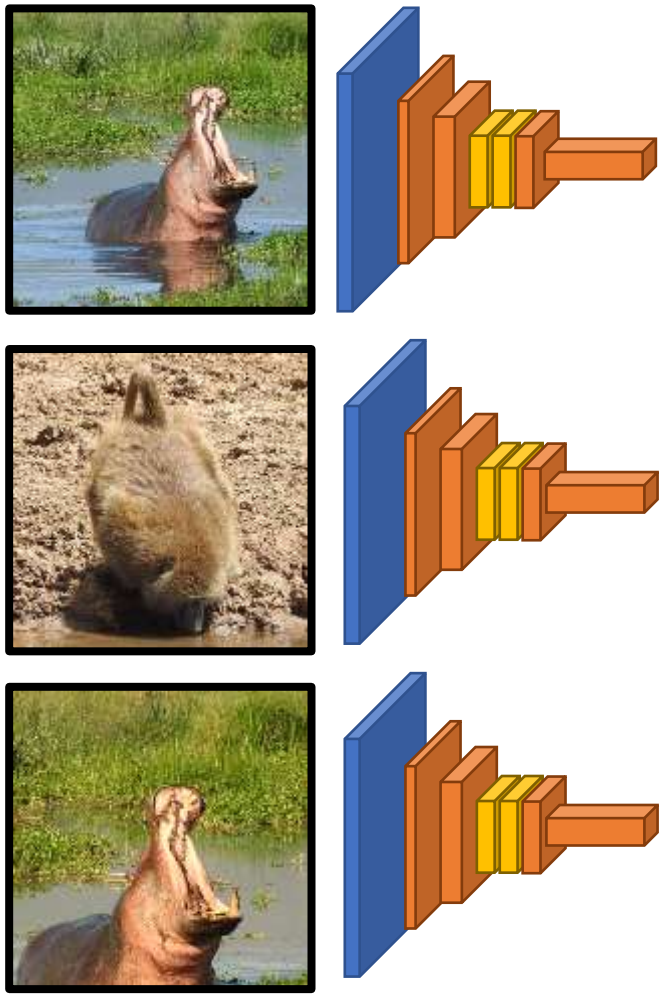
$$\frac{\exp(\boldsymbol{z}^T\boldsymbol{z})}{\exp(\boldsymbol{z}^T\boldsymbol{z}+\sum_i \boldsymbol{z}^T\boldsymbol{x})}$$

会用w替代z来去计算相似度:

$$\frac{\exp(\boldsymbol{w}^T\boldsymbol{z})}{\exp(\boldsymbol{w}^T\boldsymbol{z}+\sum_i \boldsymbol{w}^T\boldsymbol{x})}$$

He et al. Momentum Contrastive Learning, 2019. Wu et al. Instance discrimination 2018

Contrastive Learning 对比学习



z

x_i

z'

最好的方式是找到一个z的增广样本 z':

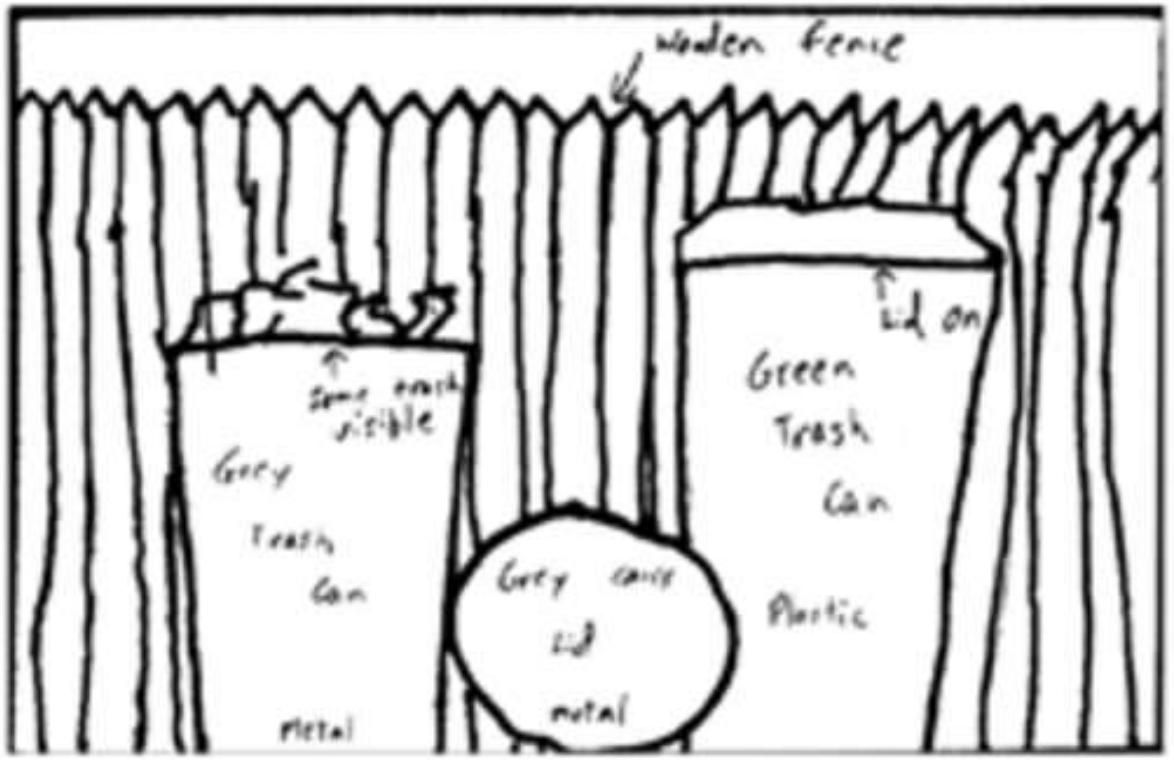
$$\frac{\exp(z^T z')}{\exp(z^T z' + \sum_i z^T x)}$$

目标: 增广样本（与原图有相同语义）的得分高于其他样本.

He et al. Momentum Contrastive Learning, 2019. Wu et al. Instance discrimination 2018

Observed image

Drawn from memory



[Bartlett, 1932]

[Intraub & Richardson, 1989]

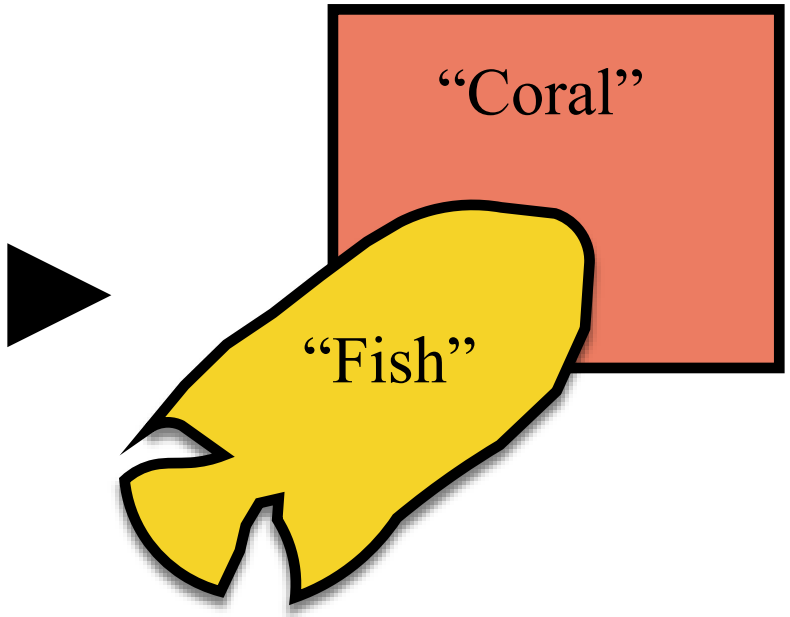
"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees.”

— Max Wertheimer, 1923

Representation learning

$\mathbf{x}$

Image

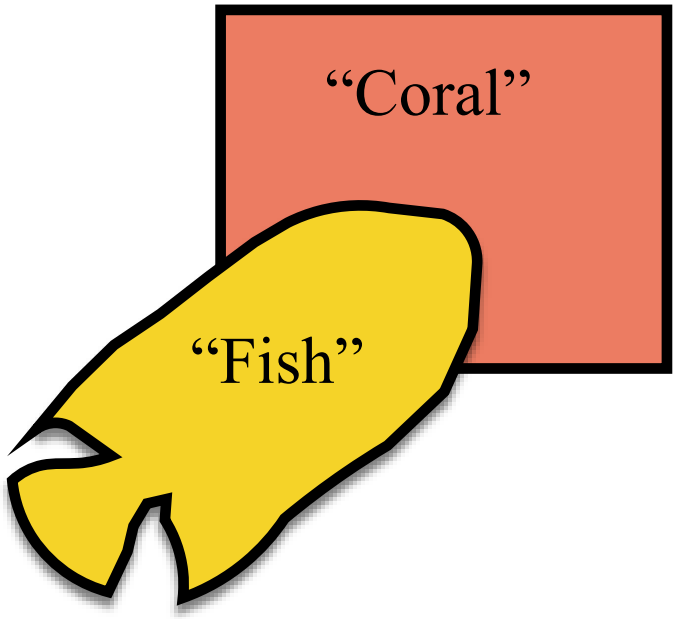


Compact mental representation

Representation learning

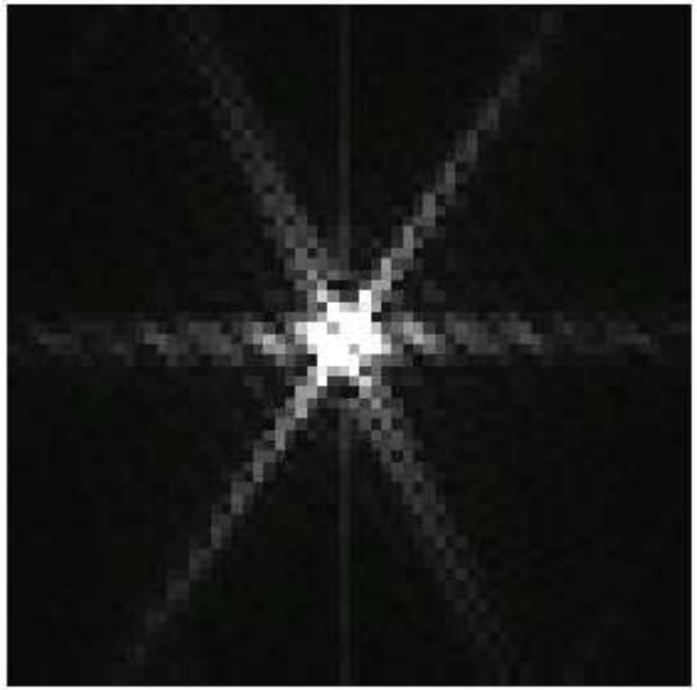
Good representations are:

1. Compact (*minimal*)
2. Explanatory (*sufficient*)
3. Disentangled (*independent factors*)
4. Interpretable
5. *Make subsequent problem solving easy*

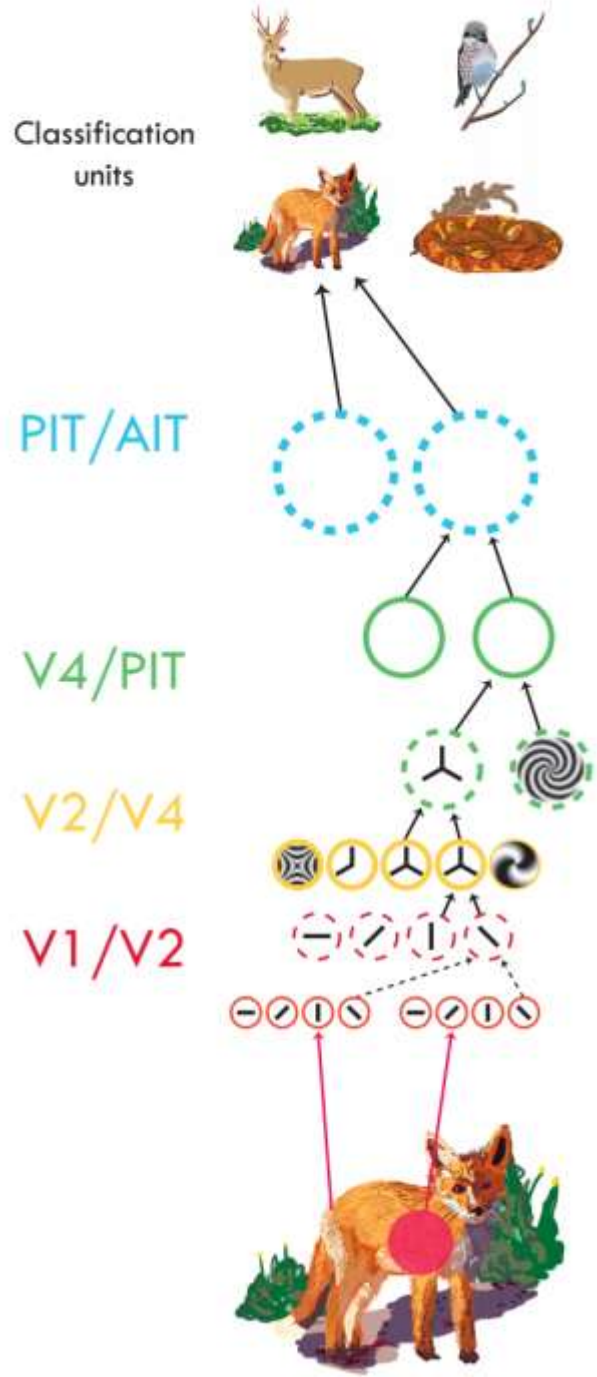


[See “Representation Learning”, Bengio 2013, for more commentary]

Representation learning

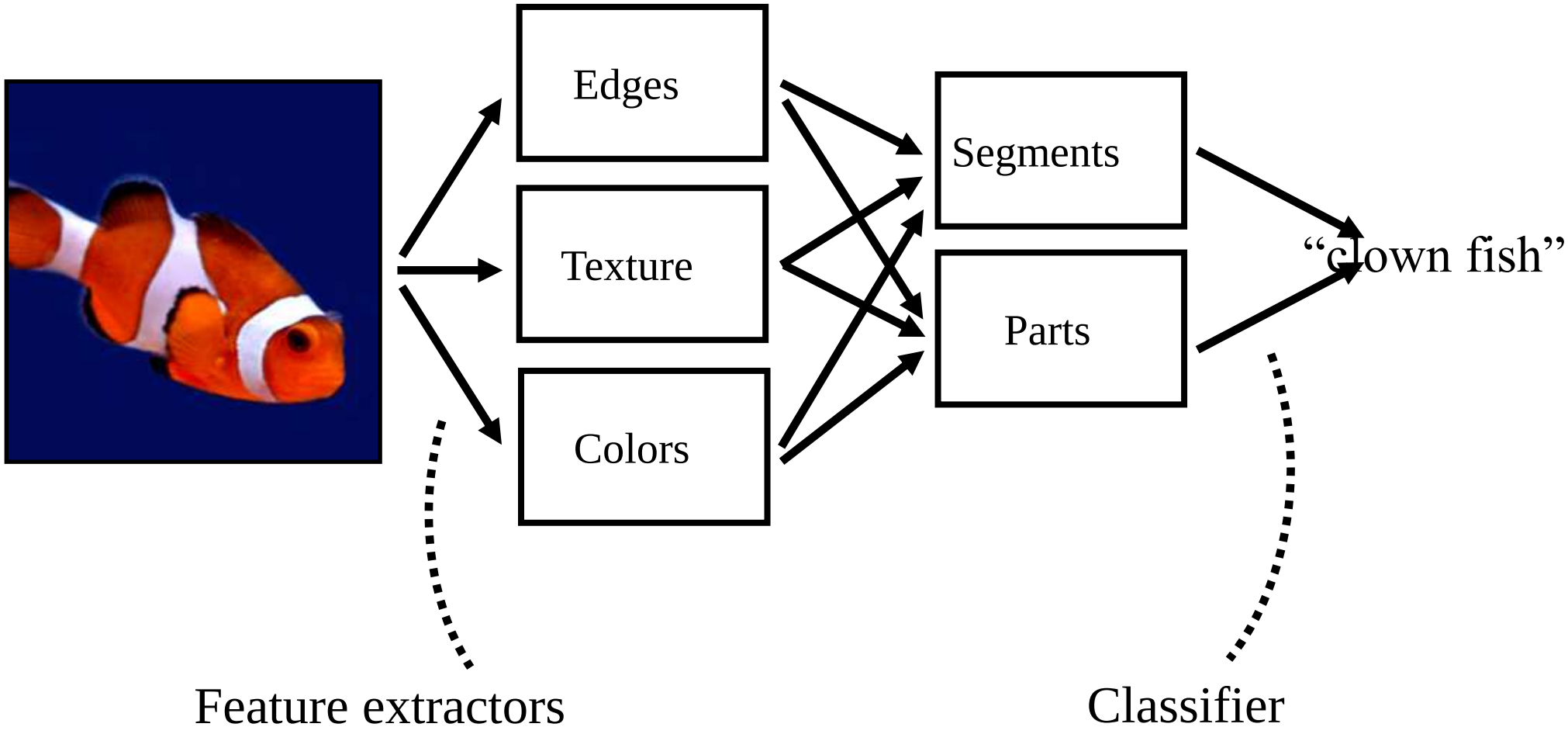


Convolution is pointwise multiplication in the frequency domain.

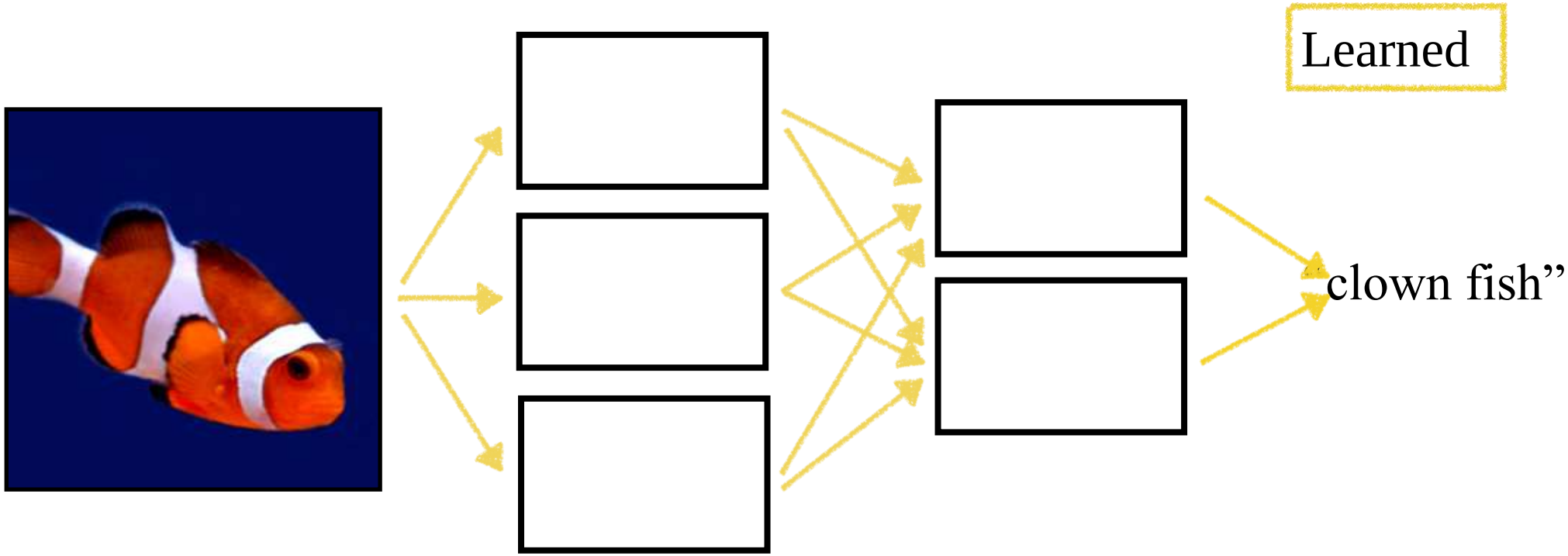


[Serre, 2014]

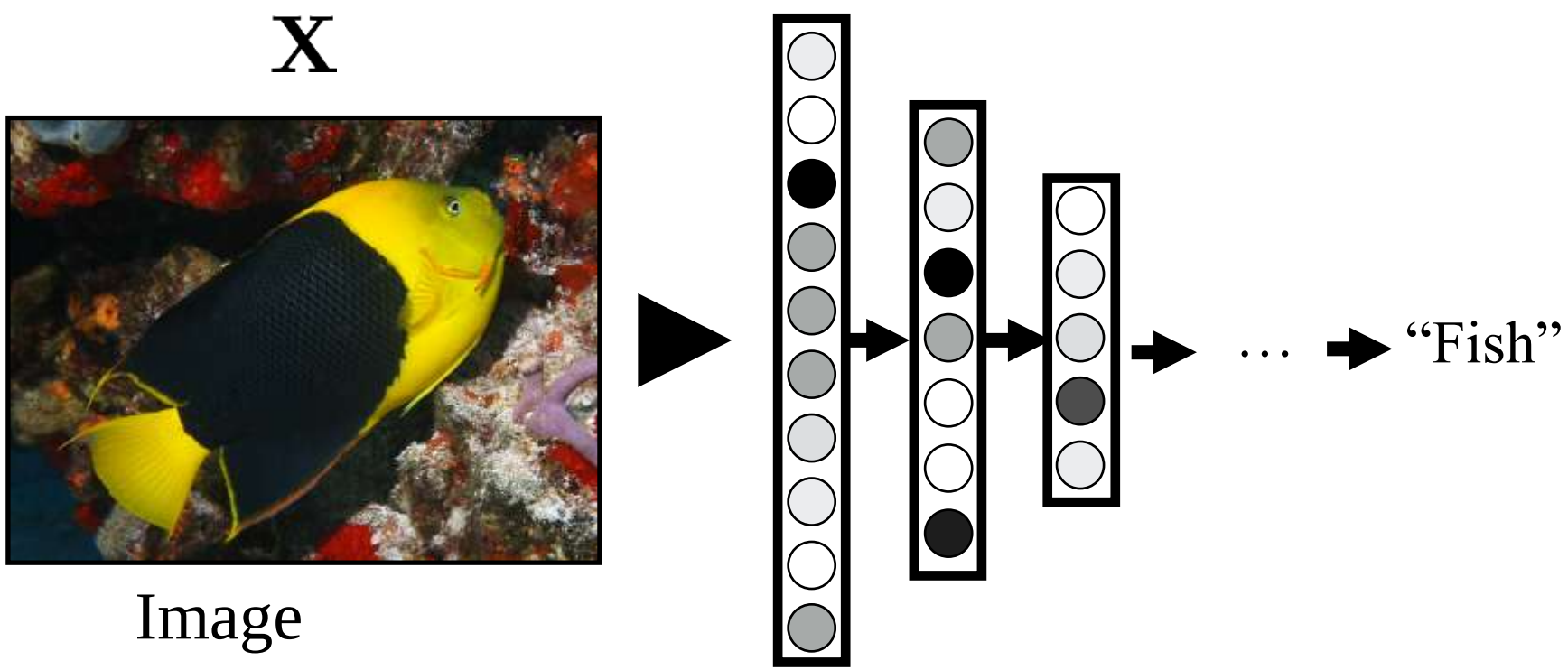
Classical object recognition



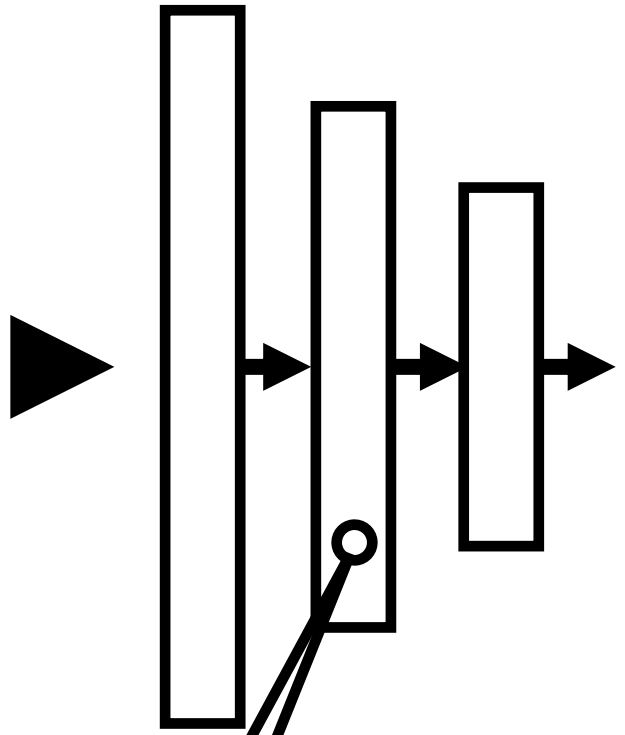
Deep learning

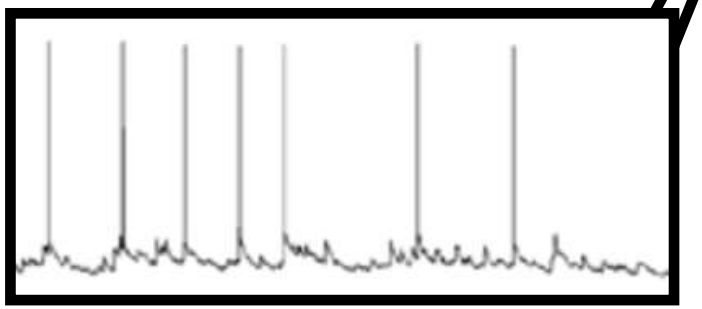


What do deep nets internally learn?



Deep Net “Electrophysiology”





… “Fish”

[Zeiler & Fergus, ECCV 2014]

[Zhou et al., ICLR 2015]

Visualizing and Understanding CNNs

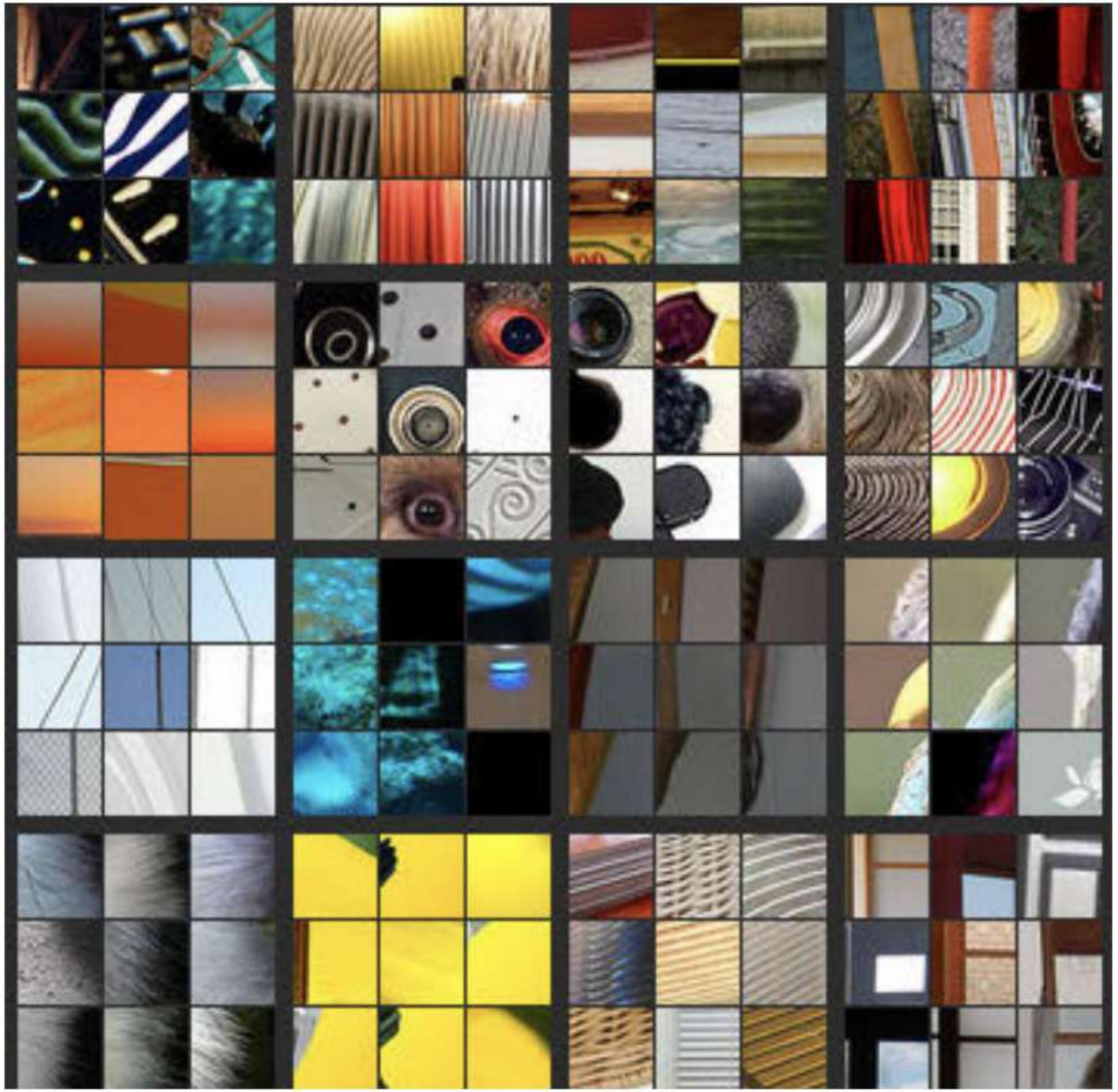
[Zeiler and Fergus, 2014]

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

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

[Zeiler and Fergus, 2014]

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



[Zeiler and Fergus, 2014]

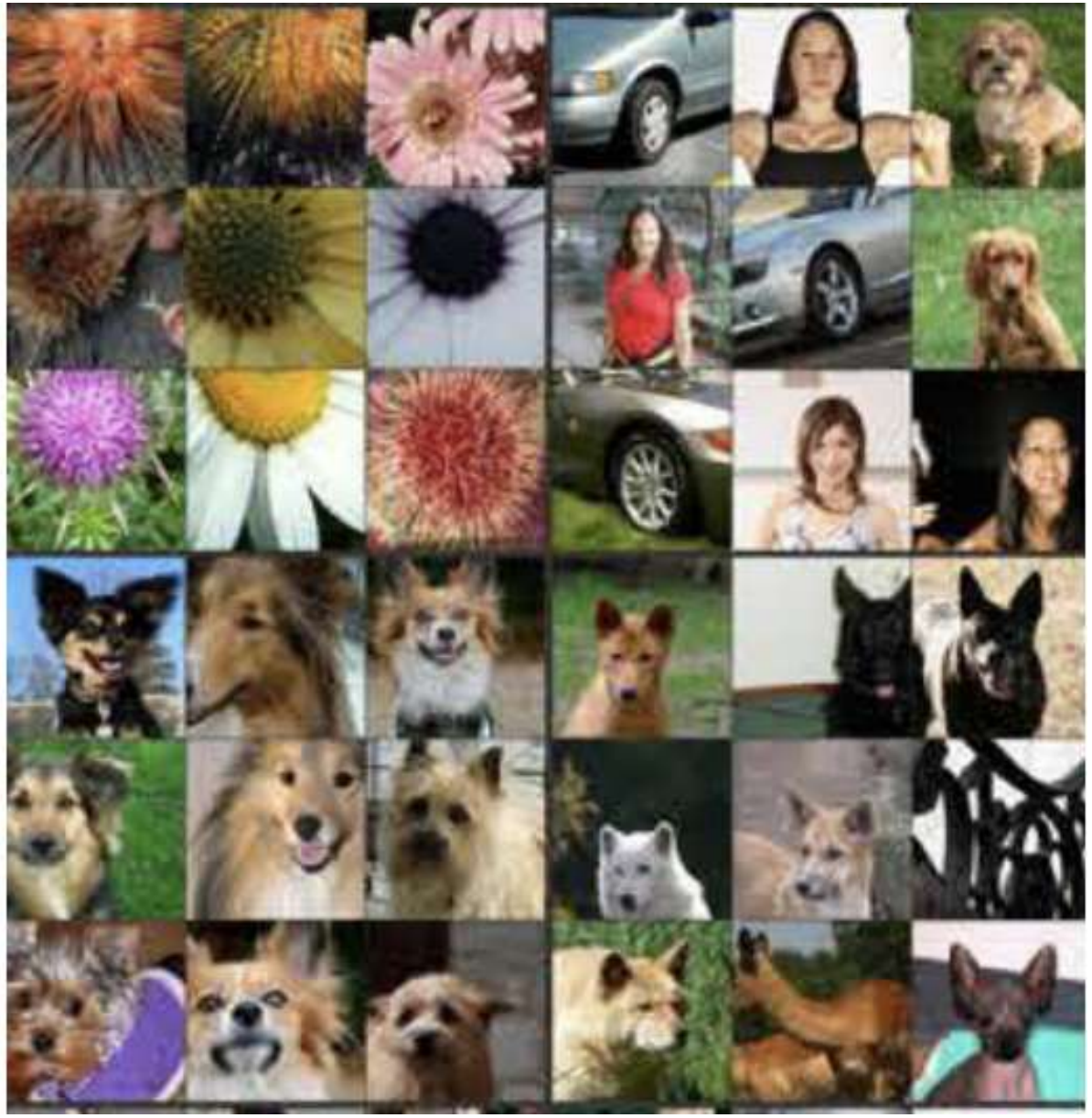
Image patches that activate several of the **layer 3** neurons most strongly

[Zeiler and Fergus, 2014]

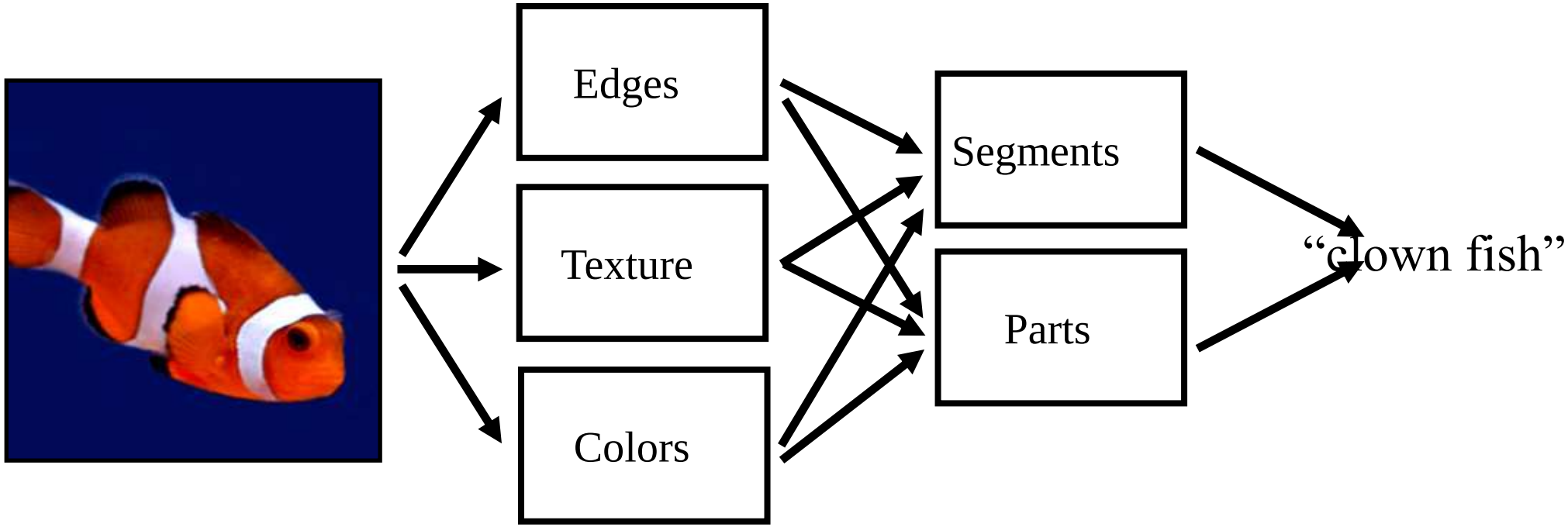
Image patches that activate several of the **layer 4** neurons most strongly

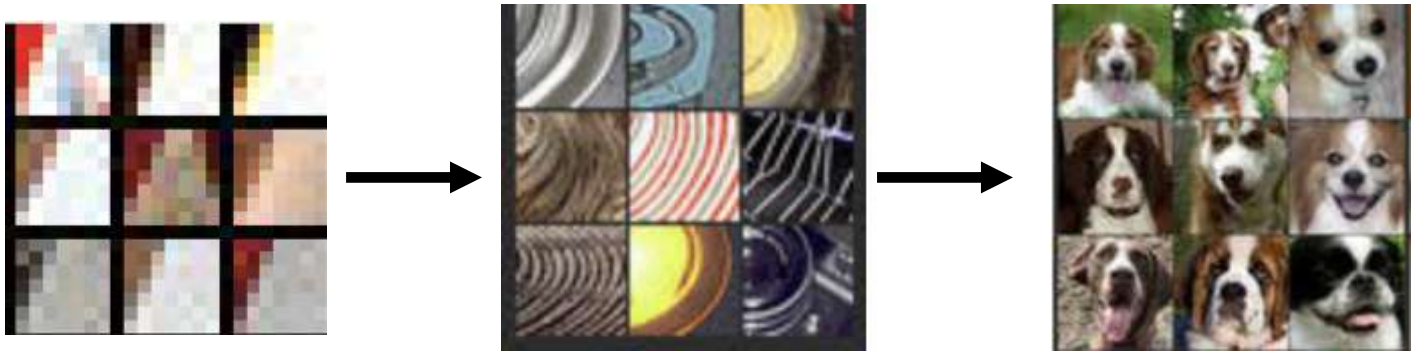
[Zeiler and Fergus, 2014]

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



CNNs *learned* the classical visual recognition pipeline!





Object Detectors Emergence in Deep Scene CNNs

[Zhou et al., ICLR 2015]

AlexNet

- For each unit (neuron) in network, find which images it is most selective for (cause it to have highest activation)
- Find which pixels in these images are responsible by occluding regions and seeing which pixels, when occluded, cause activation to change the most

Object Detectors Emergence in Deep Scene CNNs

[Zhou et al., ICLR 2015]

pool 1

[http://people.csail.mit.edu/torralba/research/drawCNN/drawNet.html]

Object Detectors Emergence in Deep Scene CNNs

[Zhou et al., ICLR 2015]

pool 2

Object Detectors Emergence in Deep Scene CNNs

[Zhou et al., ICLR 2015]

conv 4

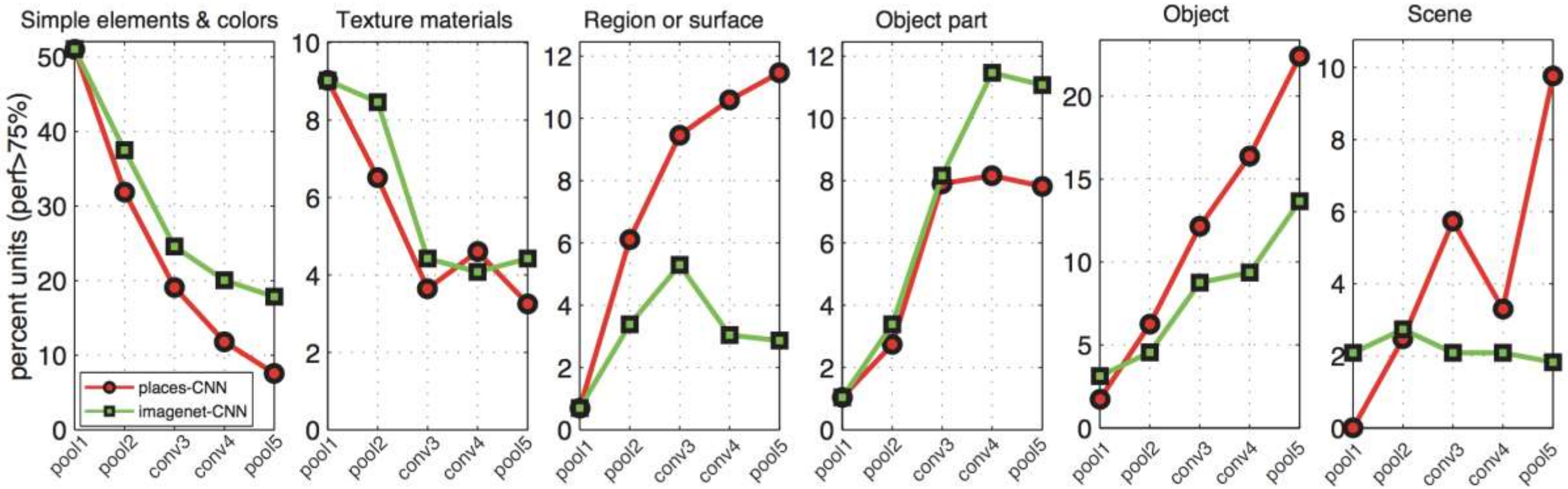
Object Detectors Emergence in Deep Scene CNNs

[Zhou et al., ICLR 2015]

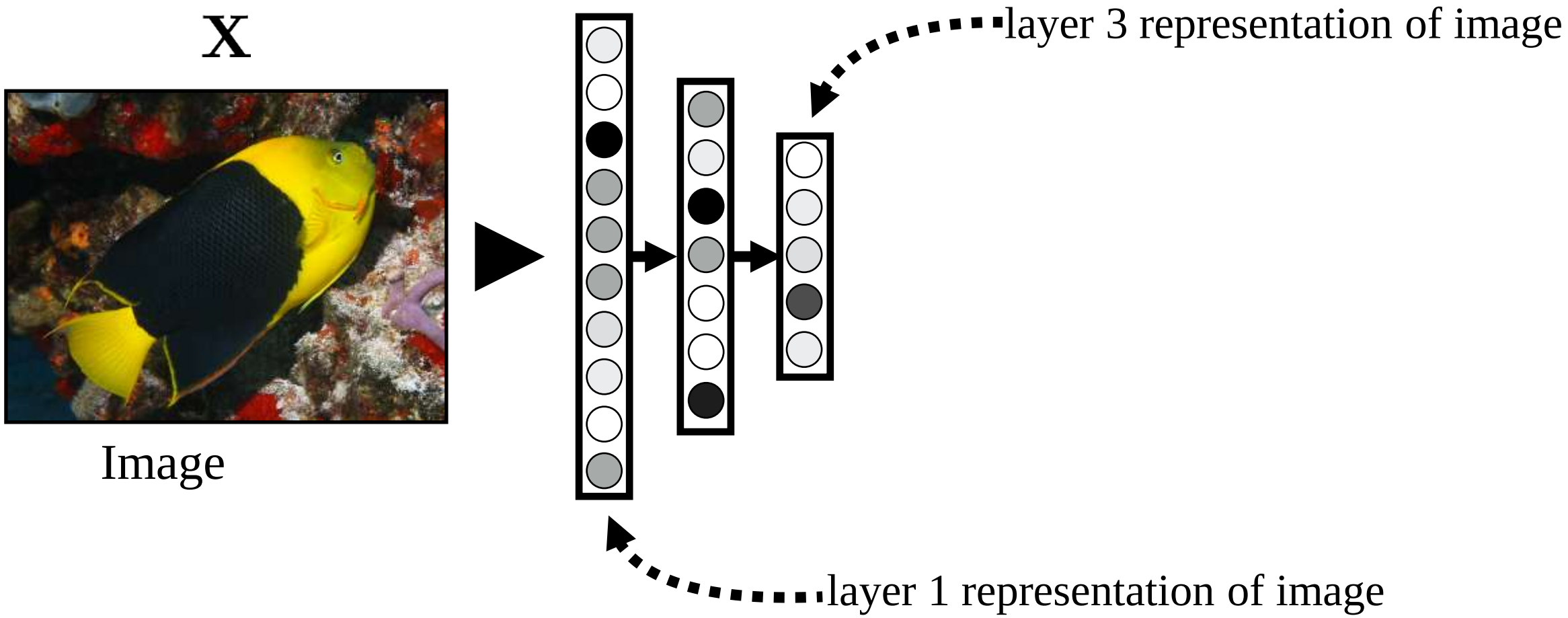
pool 5

Object Detectors Emergence in Deep Scene CNNs

[Zhou, Khosla, Lapedriza, Oliva, Torralba, ICLR 2015]



im2vec



Represent image as a neural **embedding** — a vector/tensor of neural activations
(perhaps representing a vector of detected texture patterns or object parts)

Investigating a representation via similarity analysis

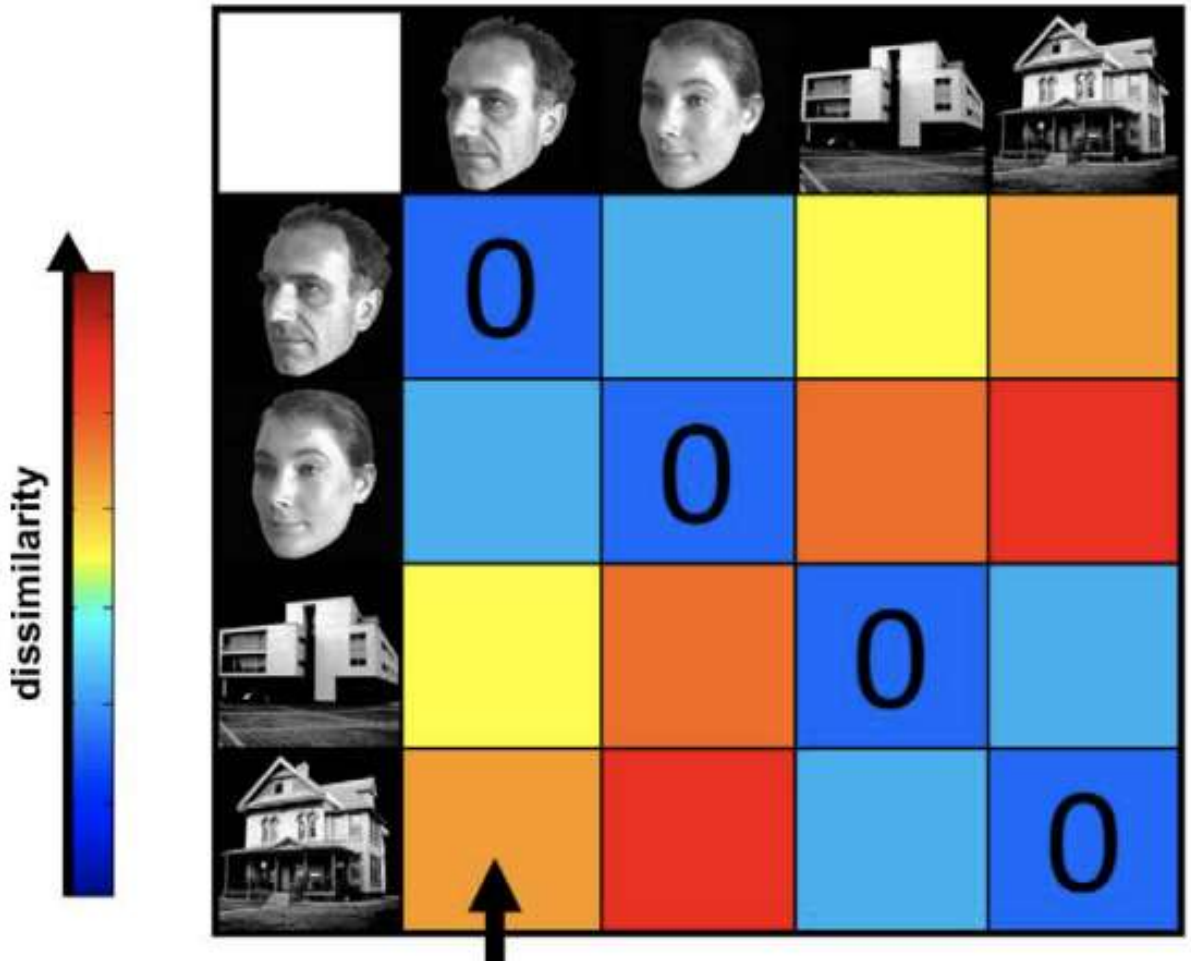
How similar are these two images?

How about these two?

[Kriegeskorte et al. 2008]

Investigating a representation via similarity analysis

Representational Dissimilarity Matrix



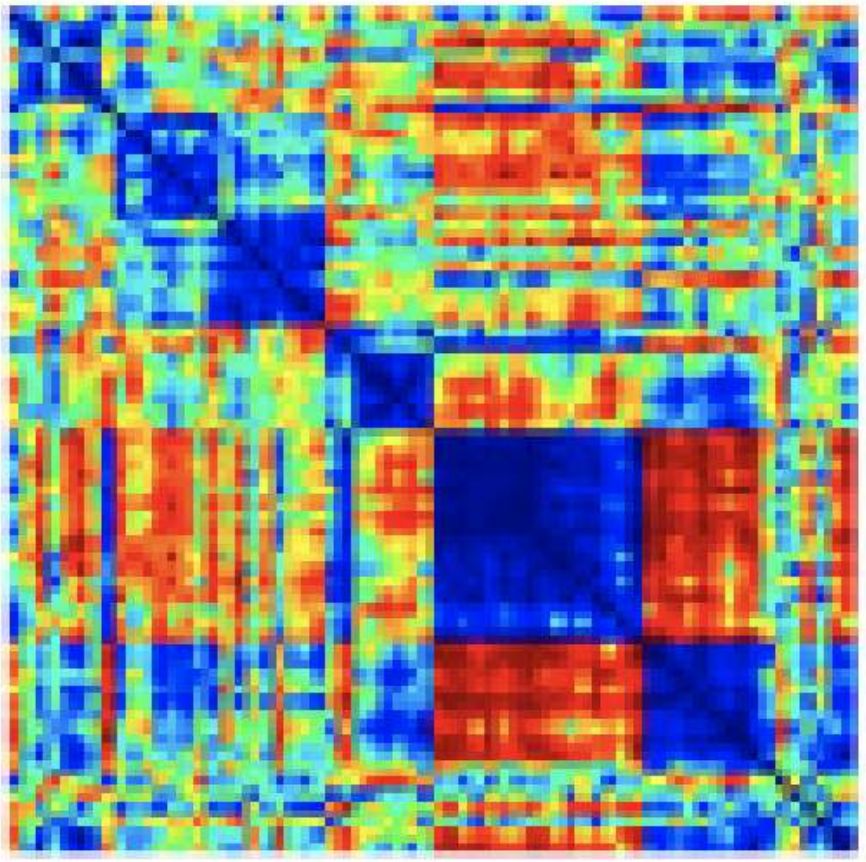
$$\|\mathbf{h}_i - \mathbf{h}_j\|$$

Neural activation vector

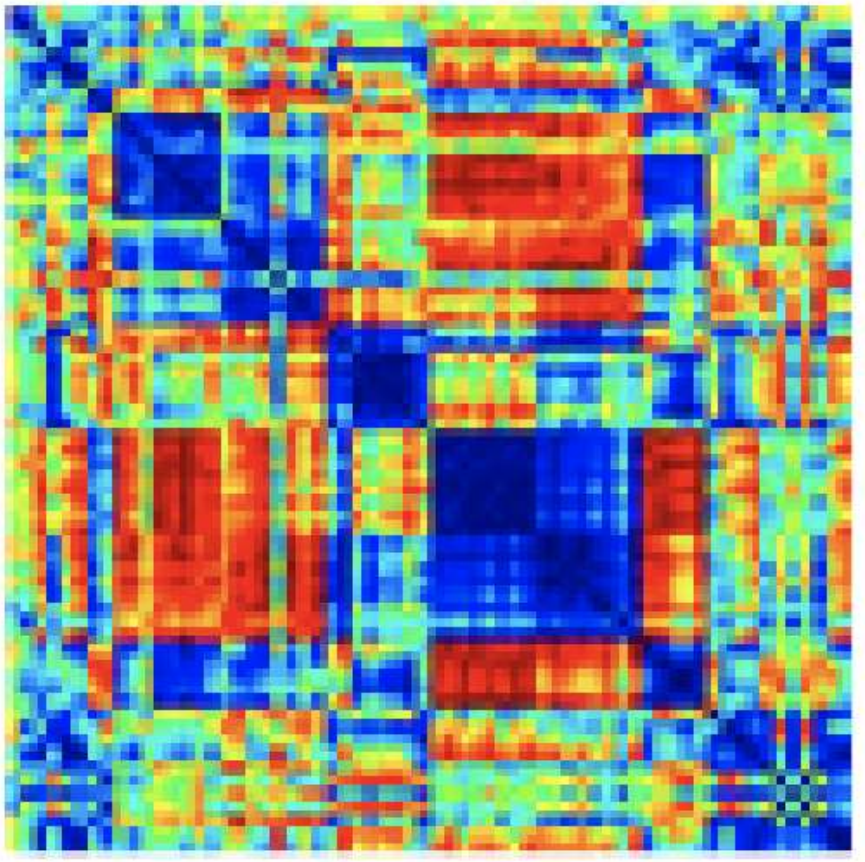
[Kriegeskorte, Mur, Ruff, et al. 2008]

Investigating a representation via similarity analysis

IT Neuronal Units



Deep net (in paricular, HMO)



[Yamins, Hong, Cadieu, Solomon, Seibert, DiCarlo, PNAS 2014]

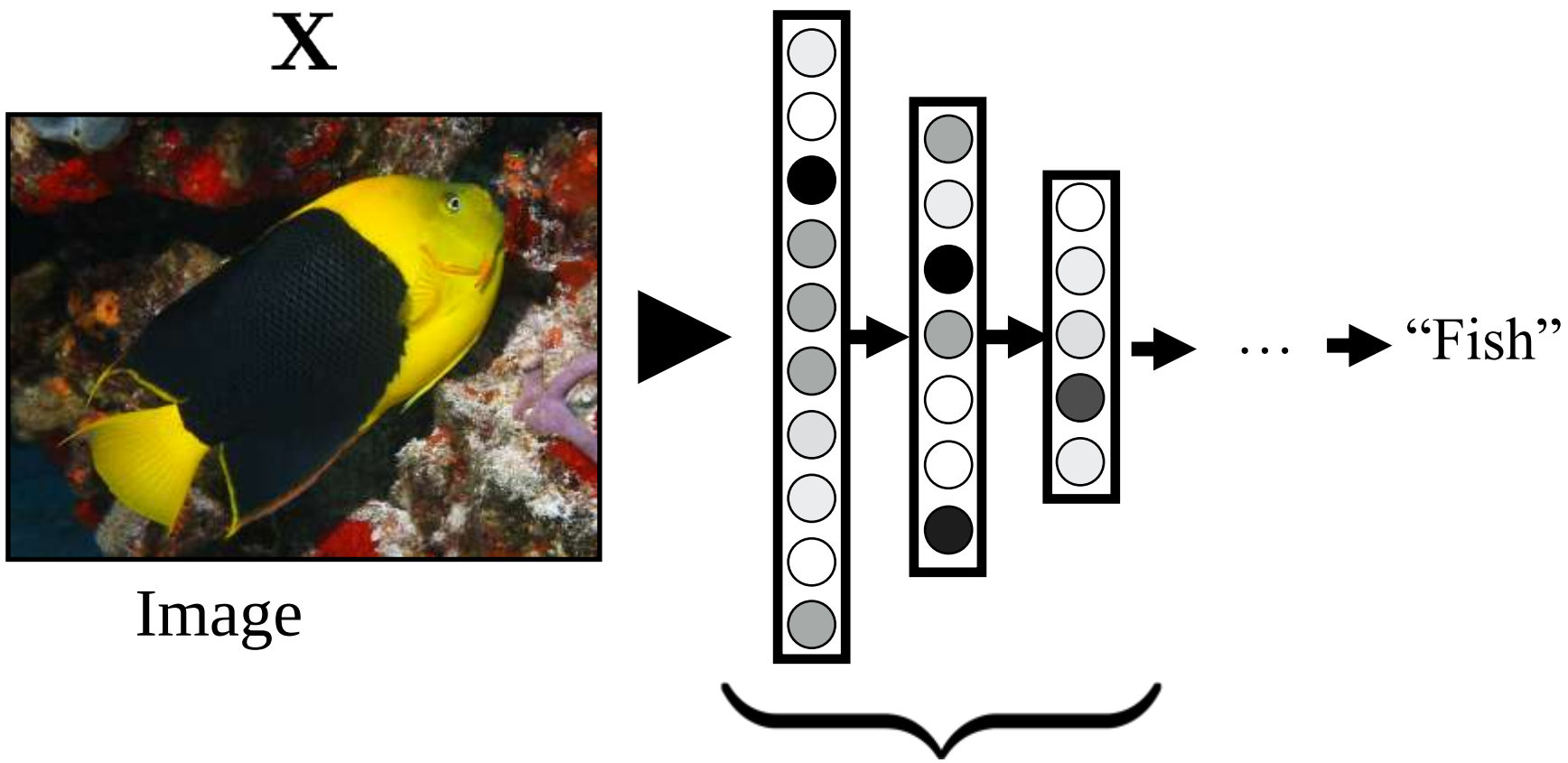
Investigating a representation via similarity analysis

Deep nets and the primate brain both learn similar metric spaces.

Deep nets organize visual information similarly to how our brains do!

[Yamins, Hong, Cadieu, Solomon, Seibert, DiCarlo, PNAS 2014]

What do deep nets internally learn?



A CNN is a multiscale, hierarchical representation of data

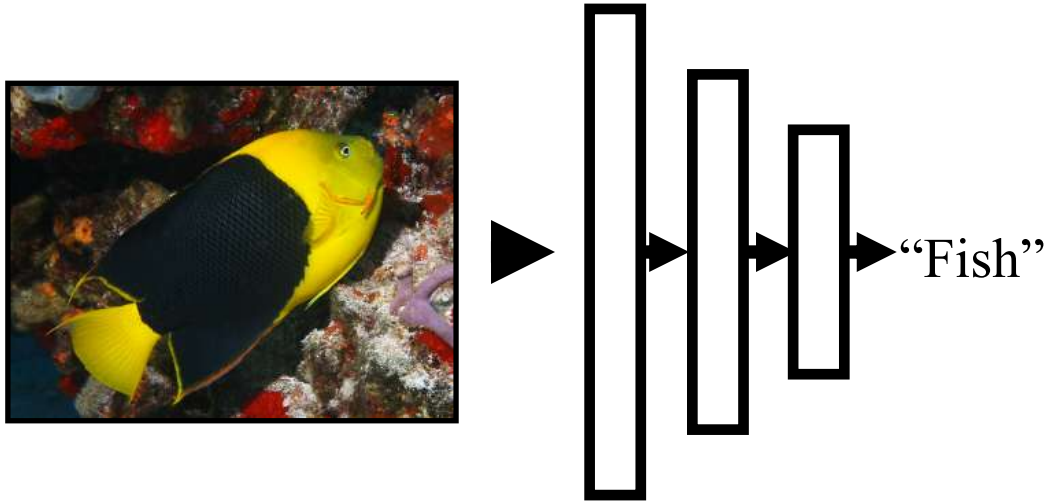
Transfer learning

“Generally speaking, a good representation is one that makes a subsequent learning task easier.” — *Deep Learning*, Goodfellow et al. 2016

?

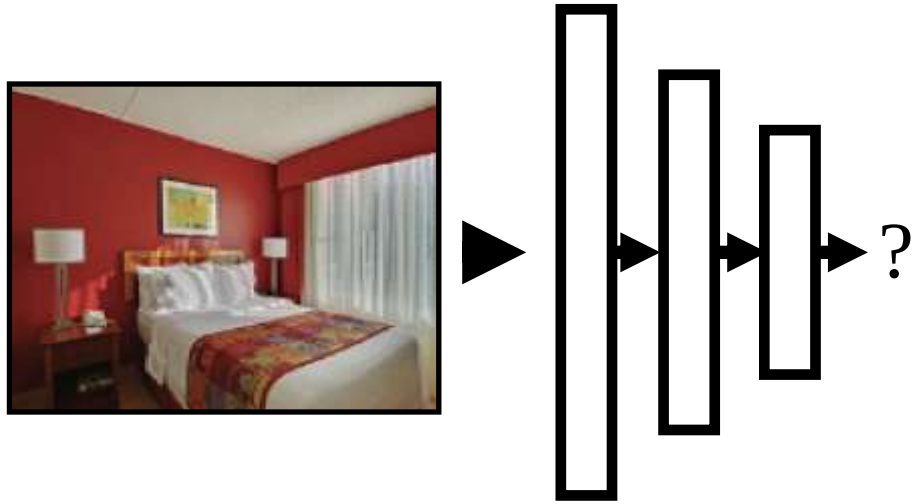
Training

Object recognition

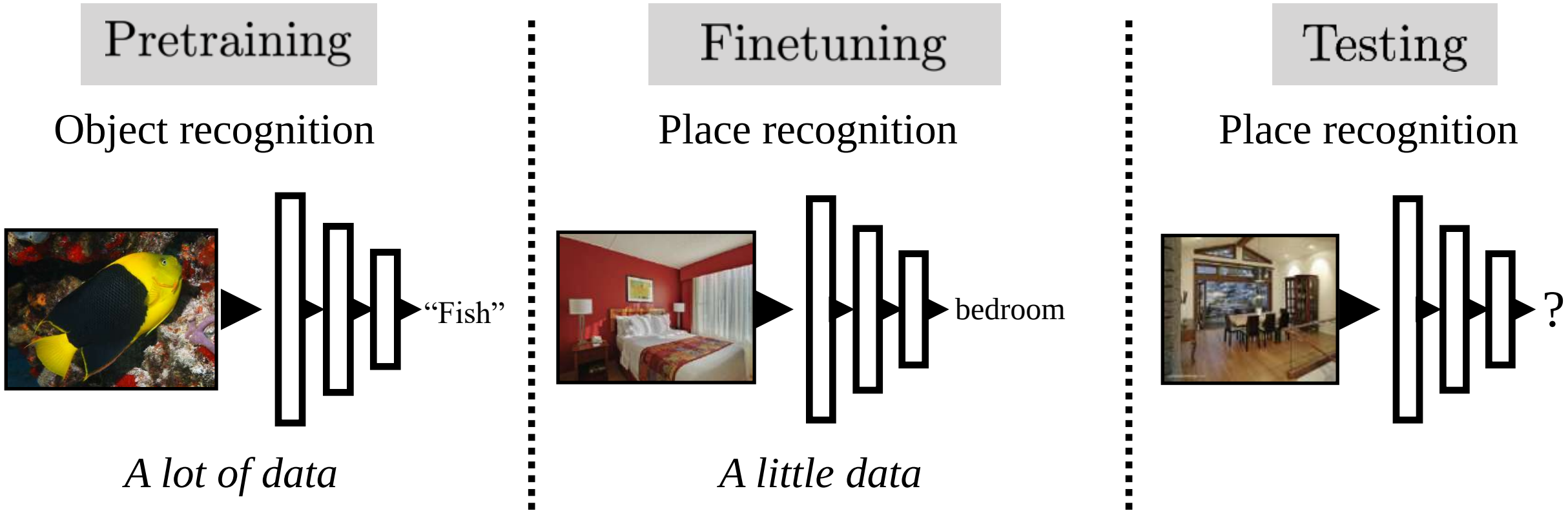


Testing

Place recognition



Often, what we will be "tested" on is to learn to do a new thing.



Finetuning starts with the representation learned on a previous task, and adapts it to perform well on a new task.

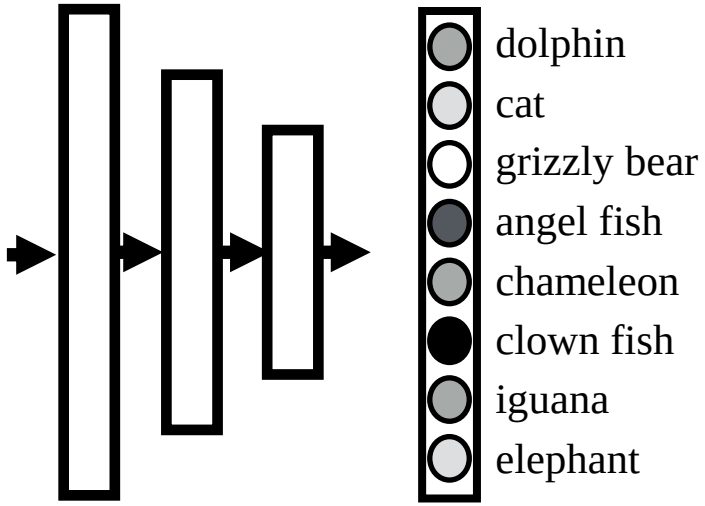
Finetuning in practice

- Pretrain a network on task A (often object recognition), resulting in parameters **W** and **b**
- Initialize a second network with some or all of **W** and **b**
- Train the second network on task B, resulting in parameters **W’** and **b’**

Finetuning in practice

Pretraining

Object recognition



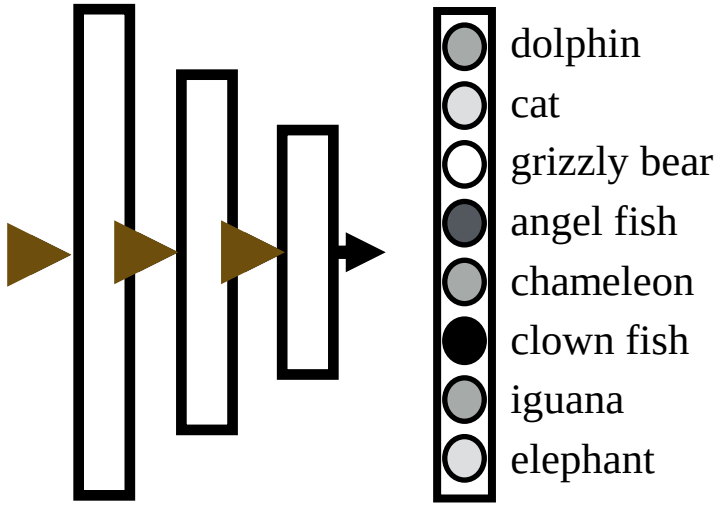
Finetuning

Place recognition

Finetuning in practice

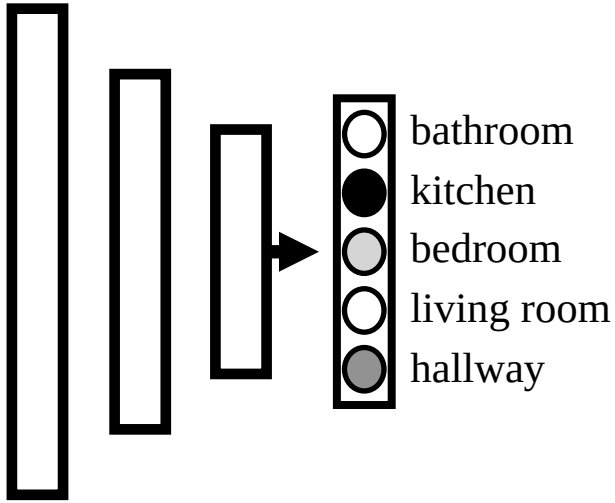
Pretraining

Object recognition



Finetuning

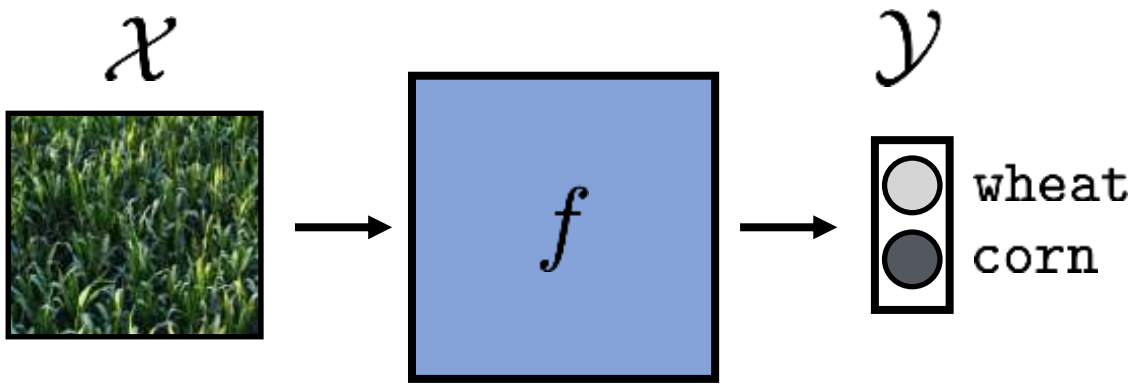
Place recognition



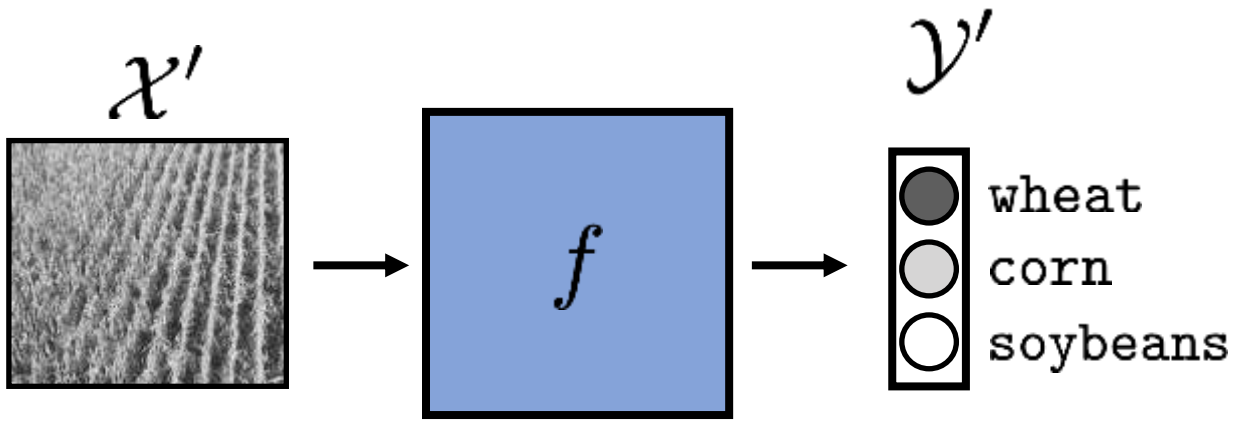
The “learned representation” is just the weights and biases, so that’s what we transfer

What if the input/output dimensions don't match?

Pretraining

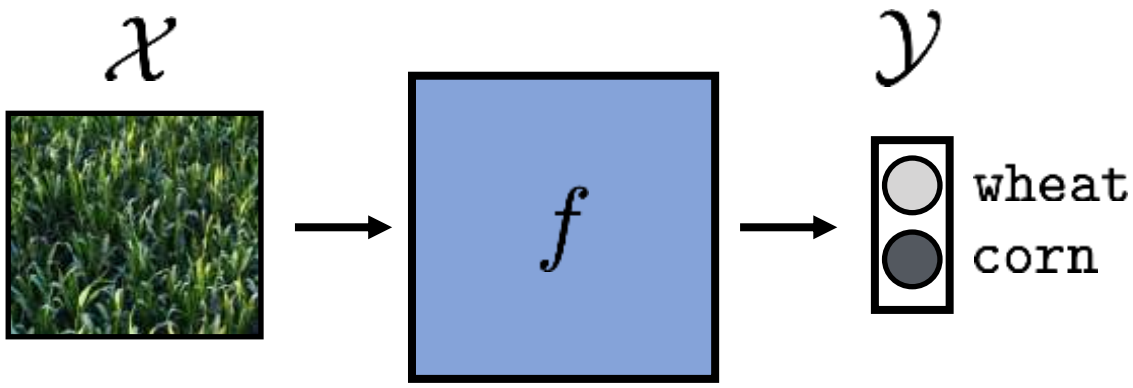


Finetuning

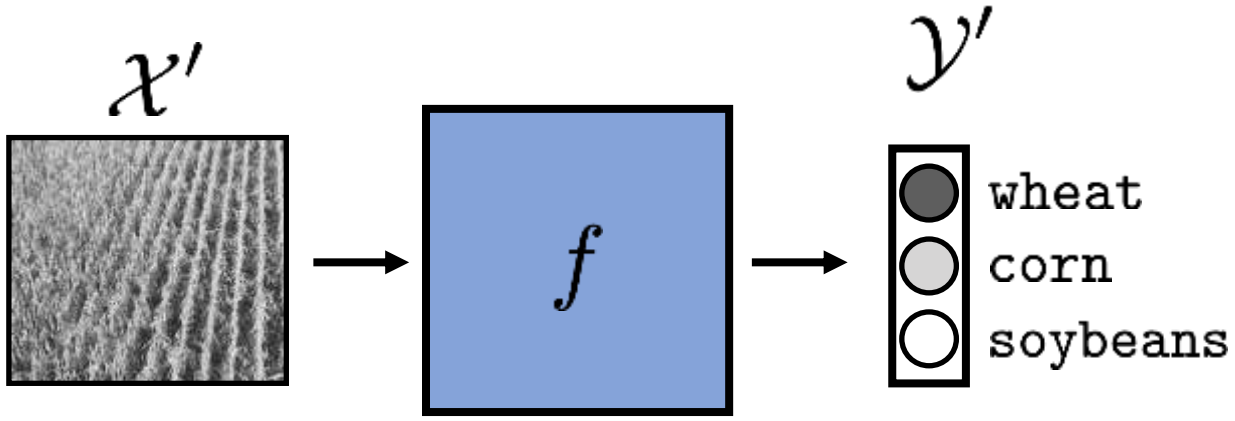


What if the input/output dimensions don't match?

Pretraining



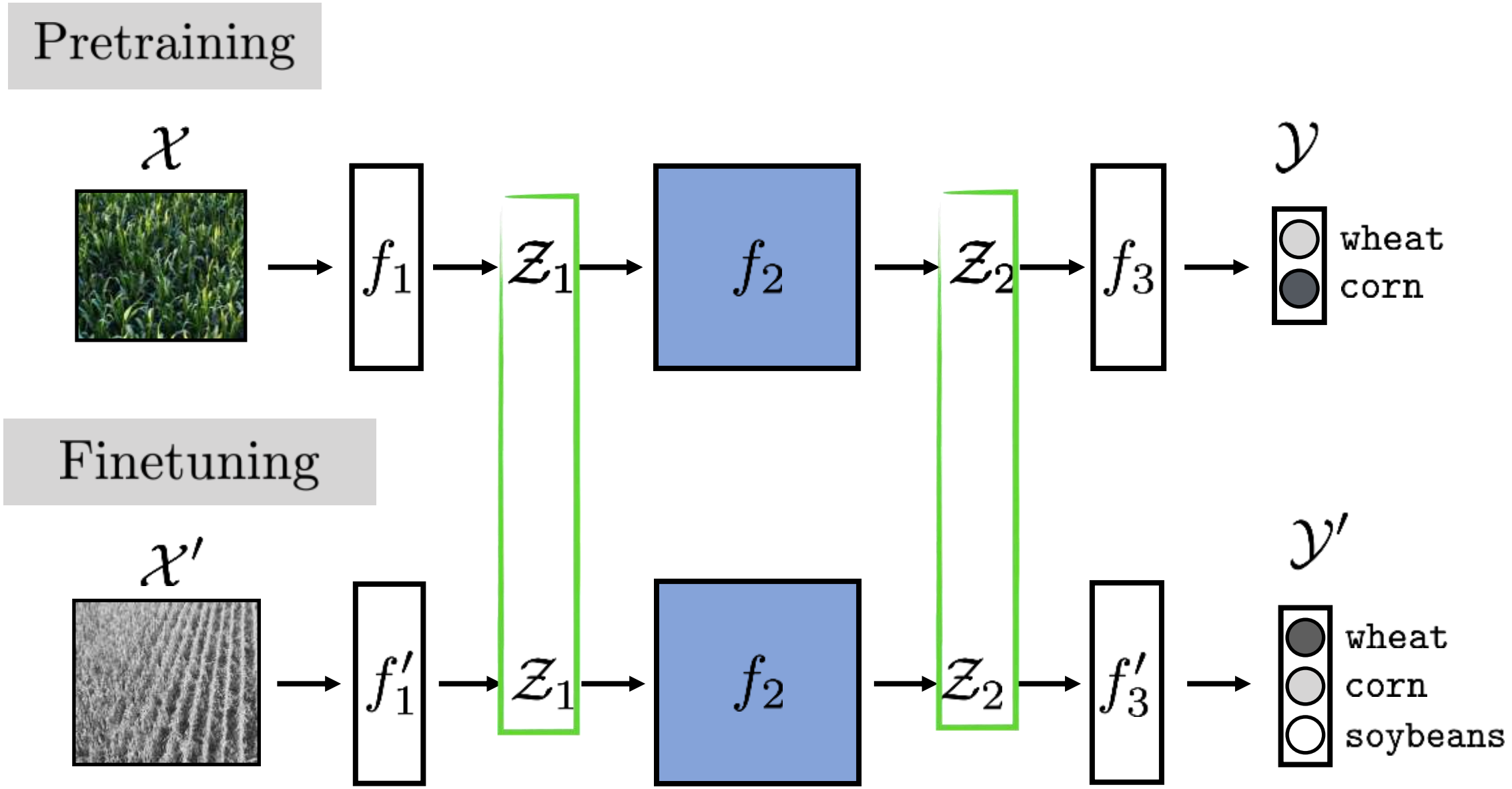
Finetuning



$$\mathcal{X}' \neq \mathcal{X}$$

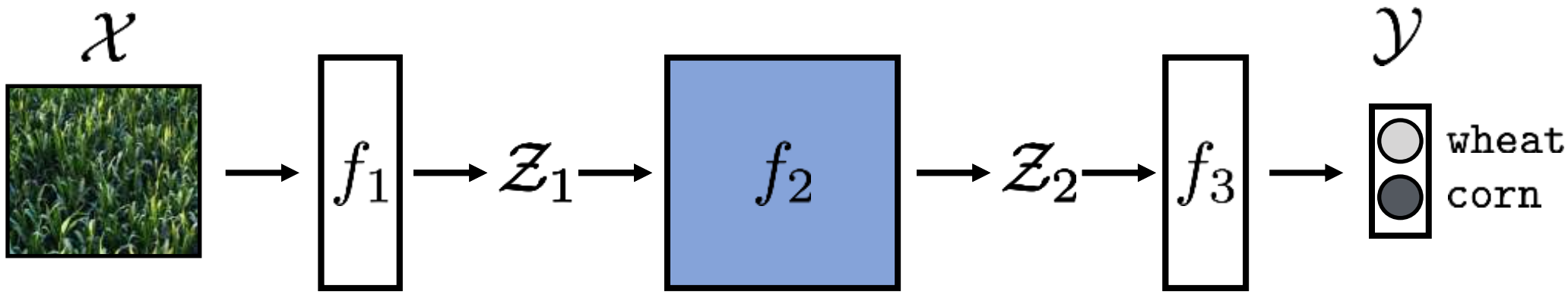
$$\mathcal{Y}' \neq \mathcal{Y}$$

What if the input/output dimensions don't match?

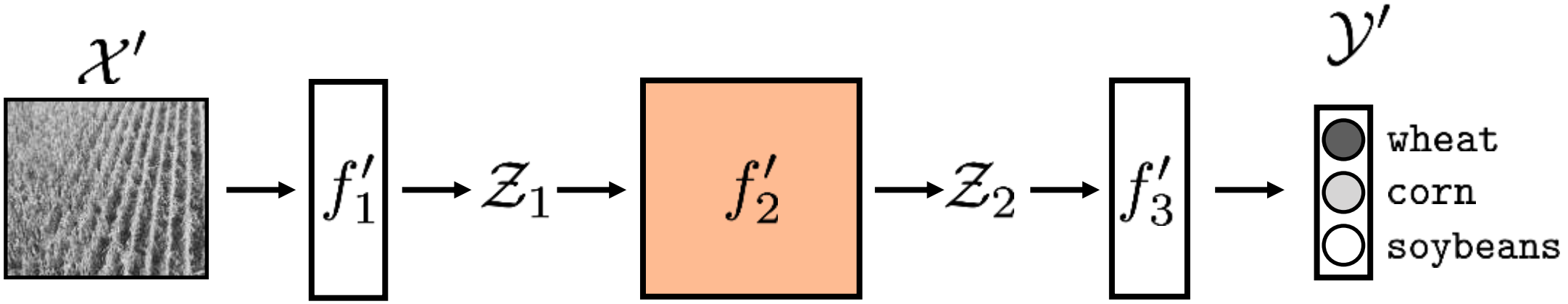


What if the input/output dimensions don't match?

Pretraining

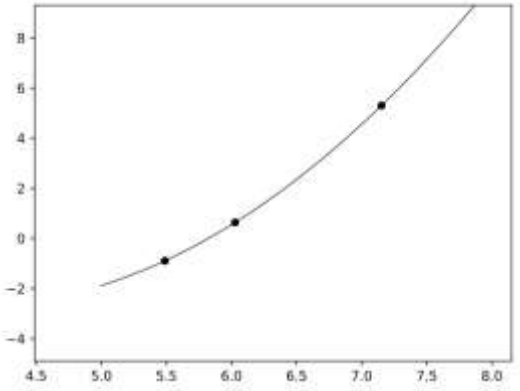


Finetuning

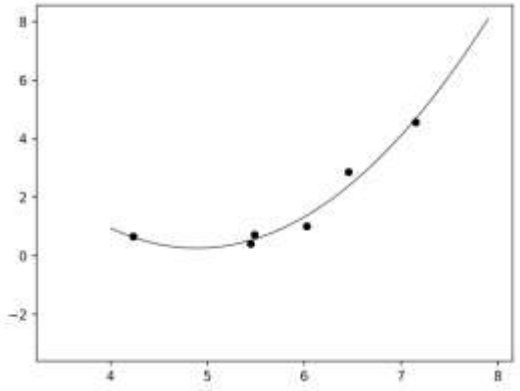


If we keep on finetuning for every new datapoint or task that comes our way, we get **online learning**. Humans seem to do this — we never stop learning.

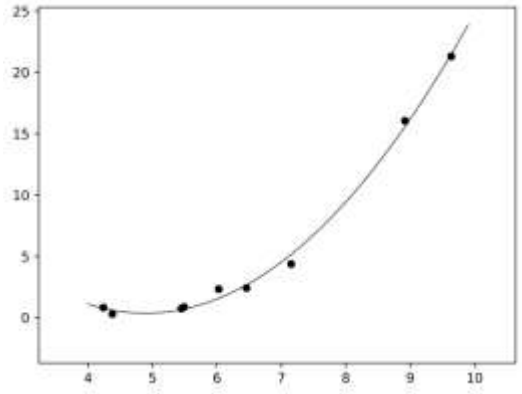
Training



More training



More training



…

Supervised object recognition

image X

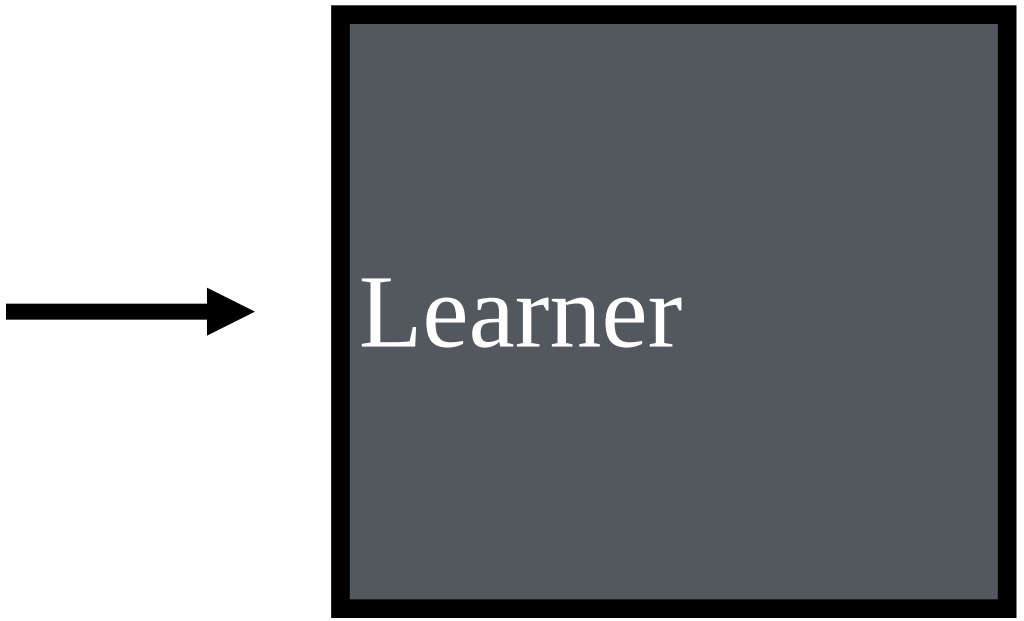
Learner

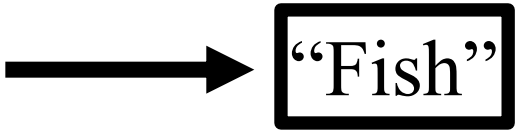
"Fish"

label Y

Supervised object recognition

image X





label Y

Supervised object recognition

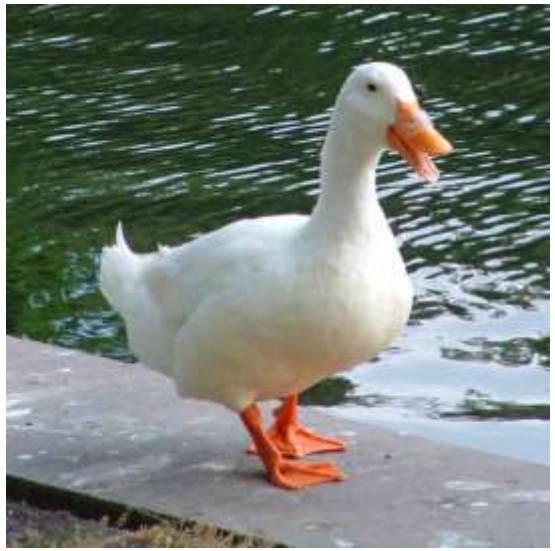
Learner

"Fish"

image X

label Y

Supervised object recognition



Learner

"Duck"

image X

label Y

Supervised computer vision

Hand-curated training data

+ Informative

- Expensive

- Limited to teacher's knowledge

Vision in nature

Raw unlabeled training data

+ Cheap

- Noisy

- Harder to interpret

Learning from examples

(aka **supervised learning**)

Training data

$\{x^{(1)}, y^{(1)}\}$
$\{x^{(2)}, y^{(2)}\}$
$\{x^{(3)}, y^{(3)}\}$
$\ldots$

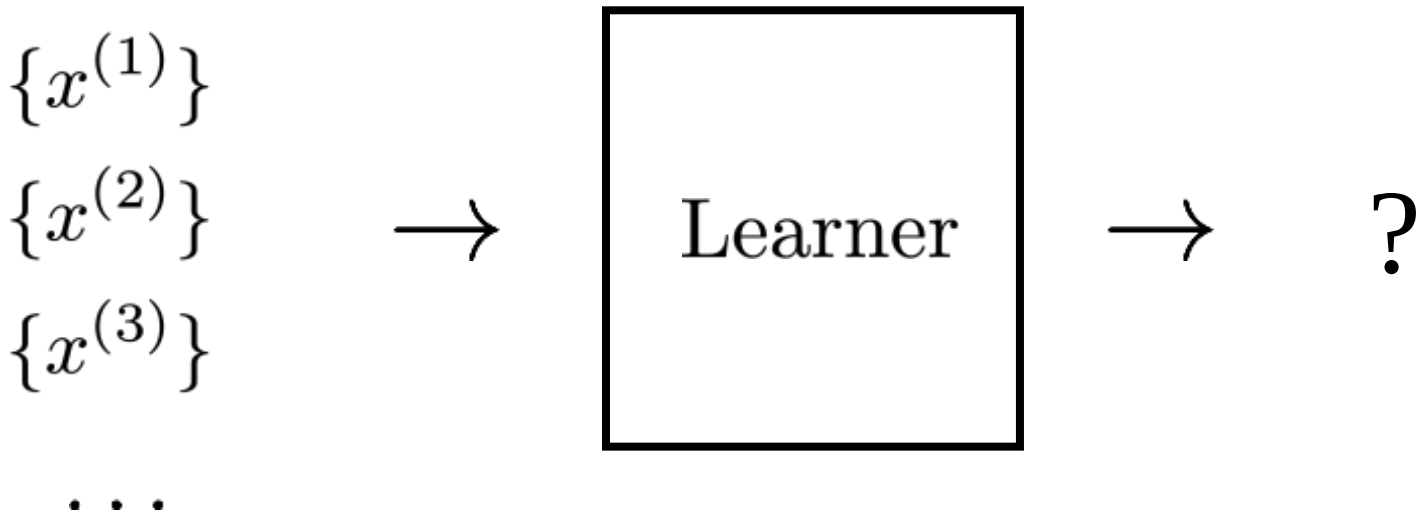
$\rightarrow$ Learner $\rightarrow$ $f : X \rightarrow Y$

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

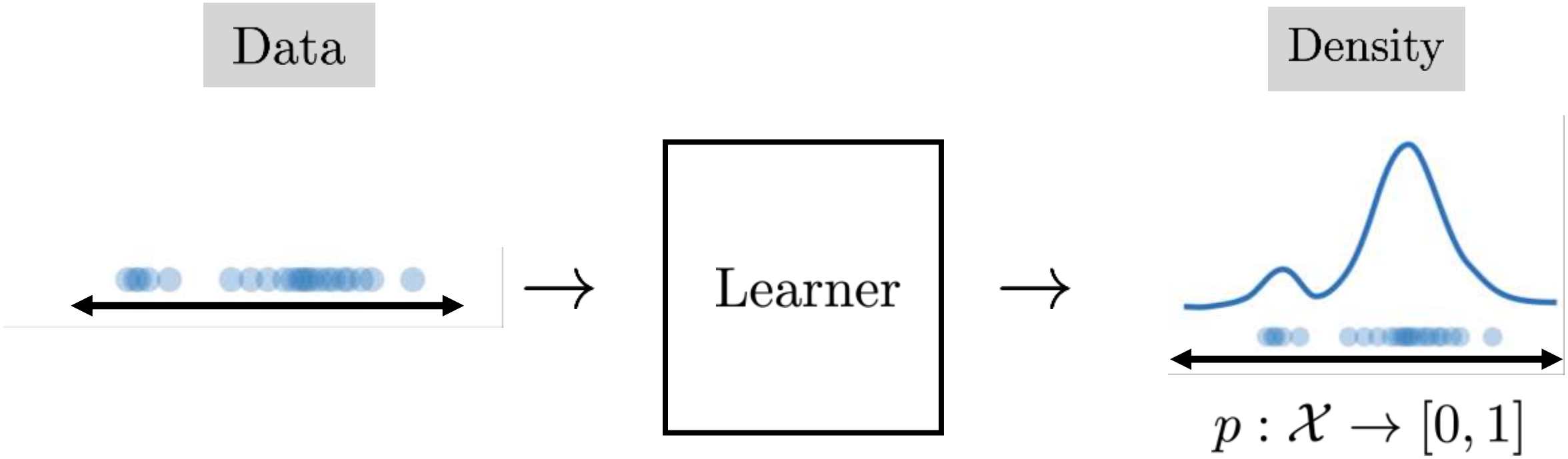
Learning without examples

(includes **unsupervised learning** and **reinforcement learning**)

Data

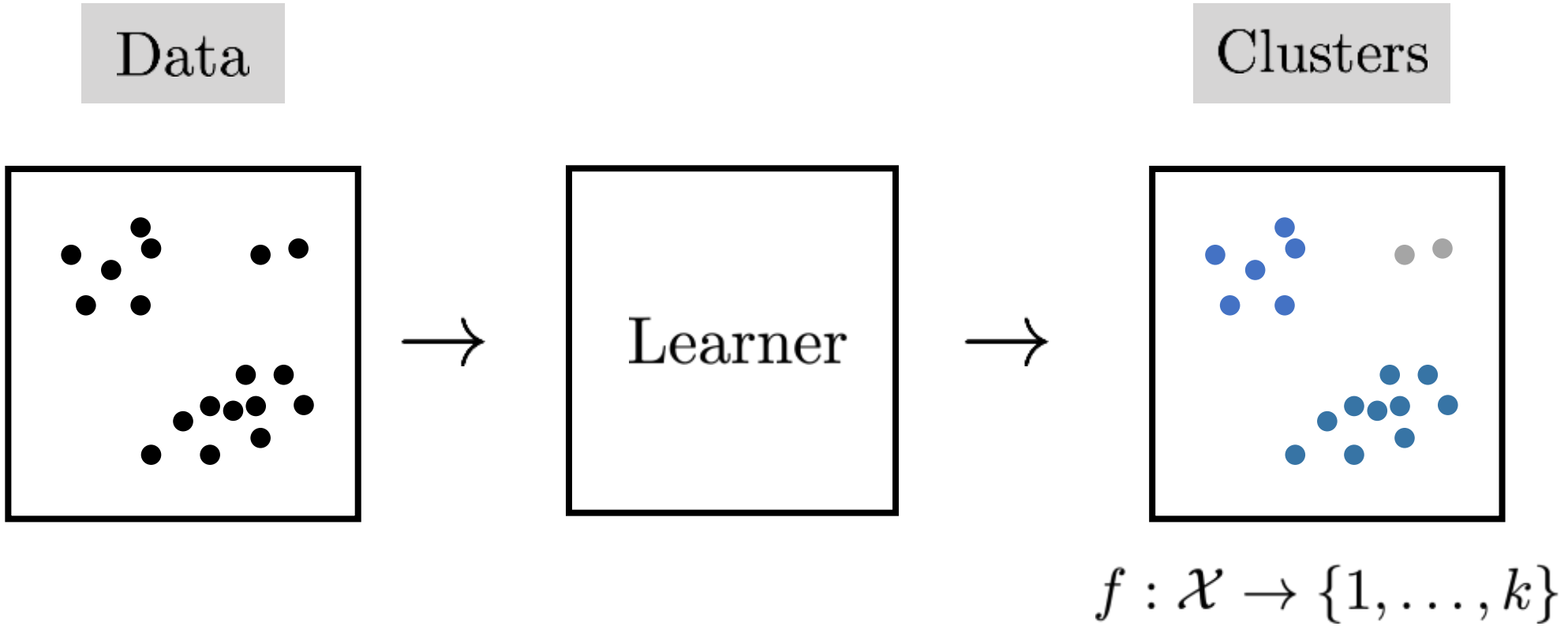


Density modeling



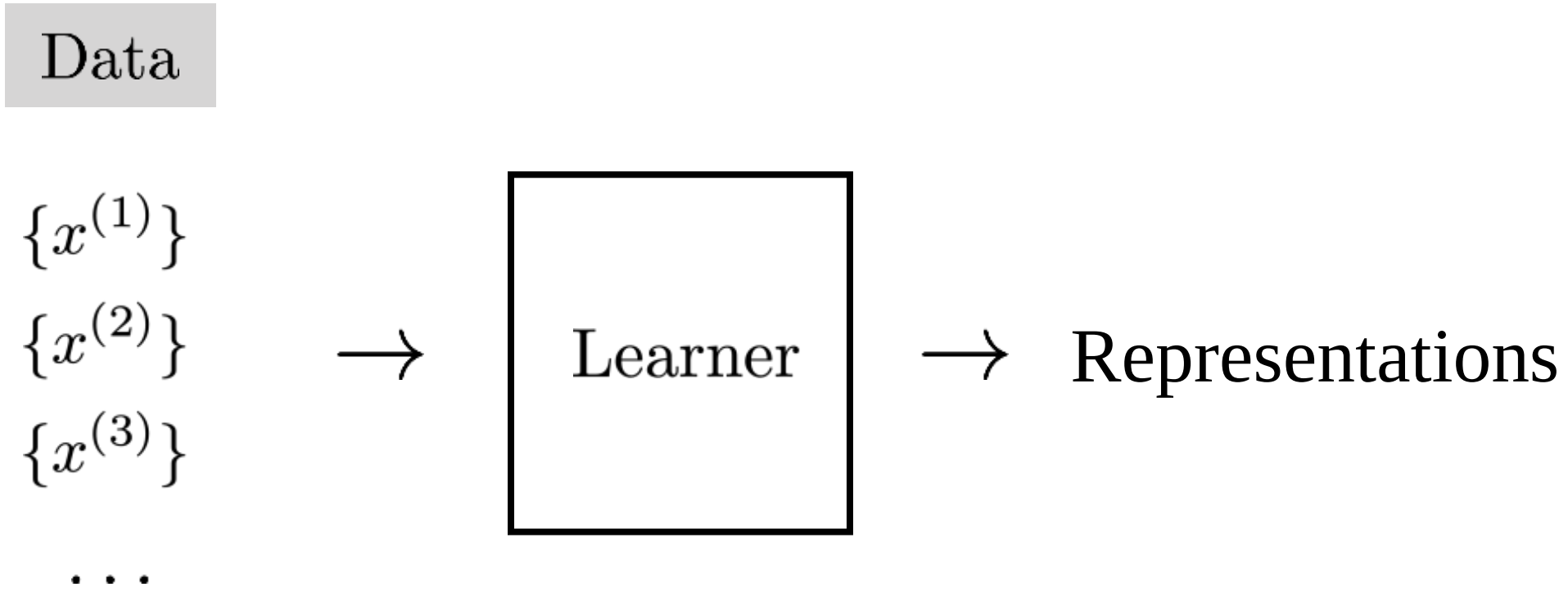
[figs modified from: http://introtodeeplearning.com/materials/2019_6S191_L4.pdf]

Clustering



$$f : \mathcal{X} \to \{1, \ldots, k\}$$

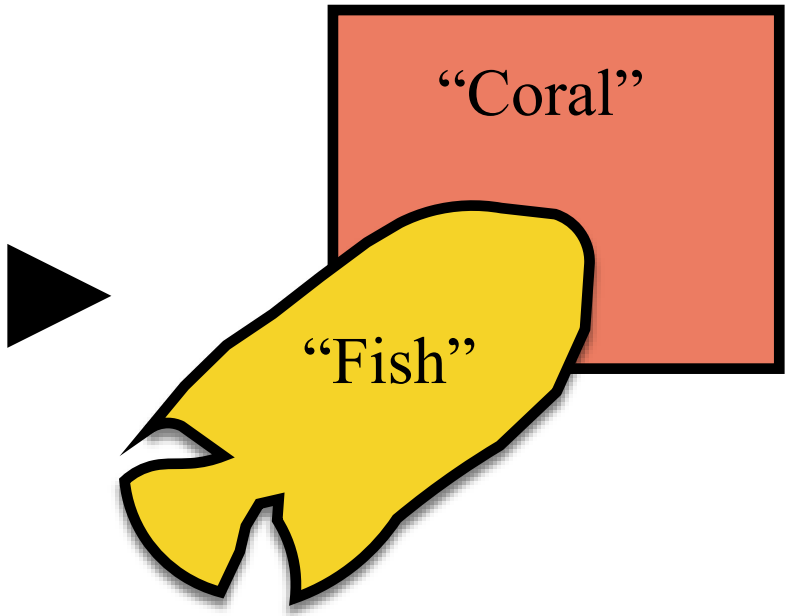
Representation Learning



Unsupervised Representation Learning

x

Image



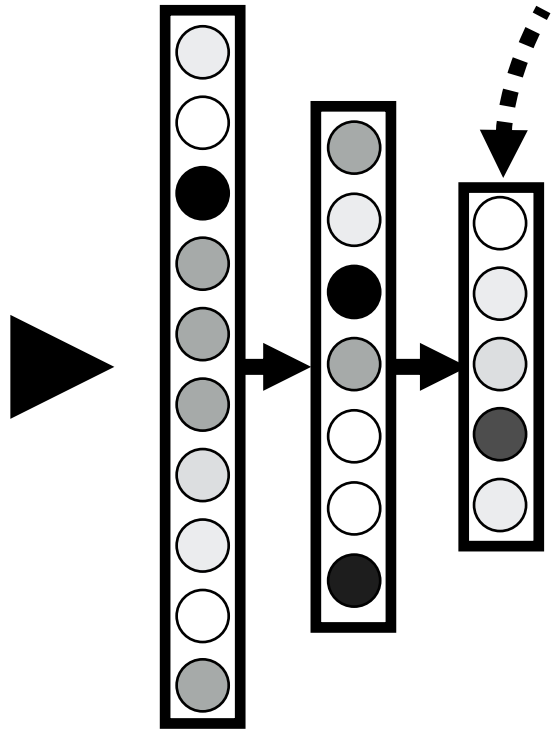
Compact mental representation

Unsupervised Representation Learning

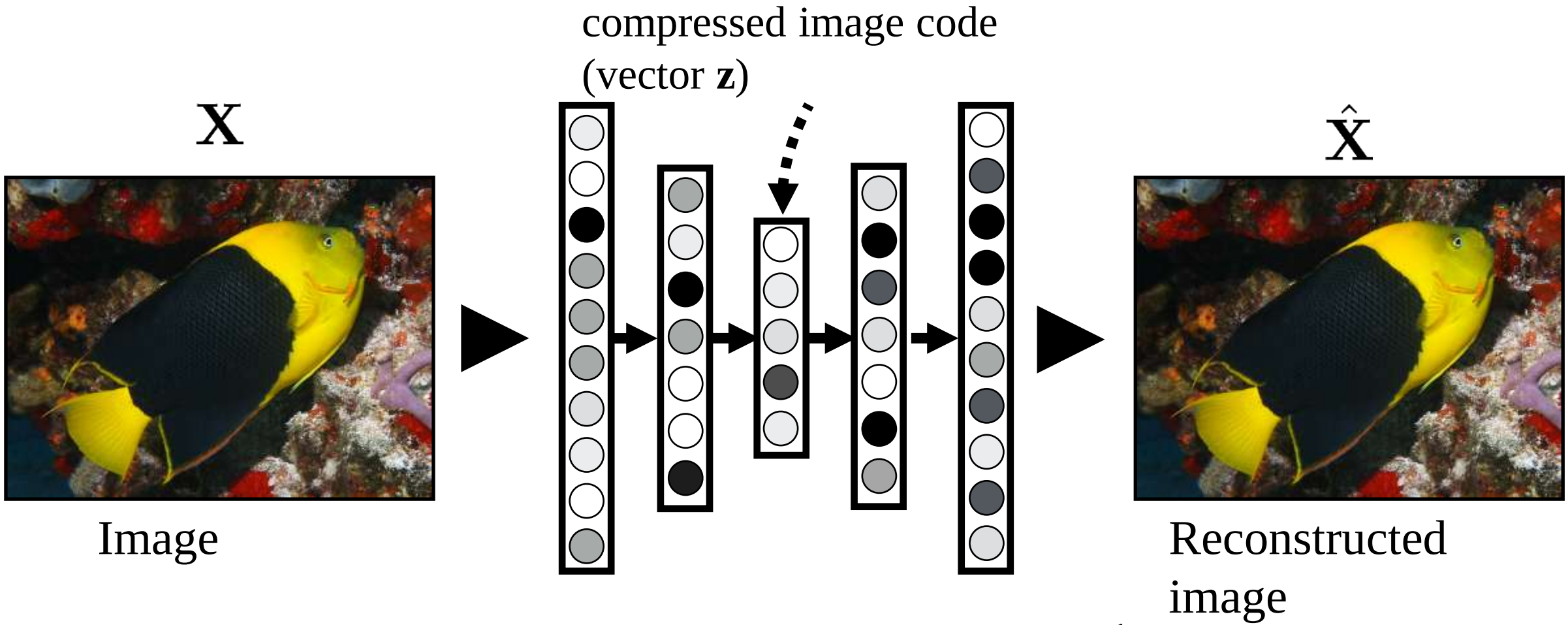
compressed image code
(vector **z**)

x

Image



Unsupervised Representation Learning



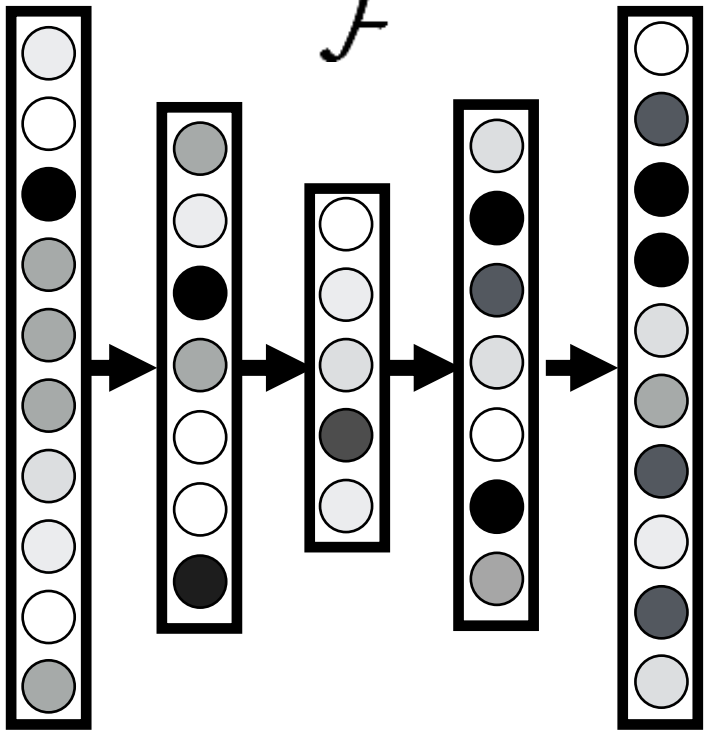
[e.g., Hinton & Salakhutdi

Autoencoder

$\mathbf{X}$

Image

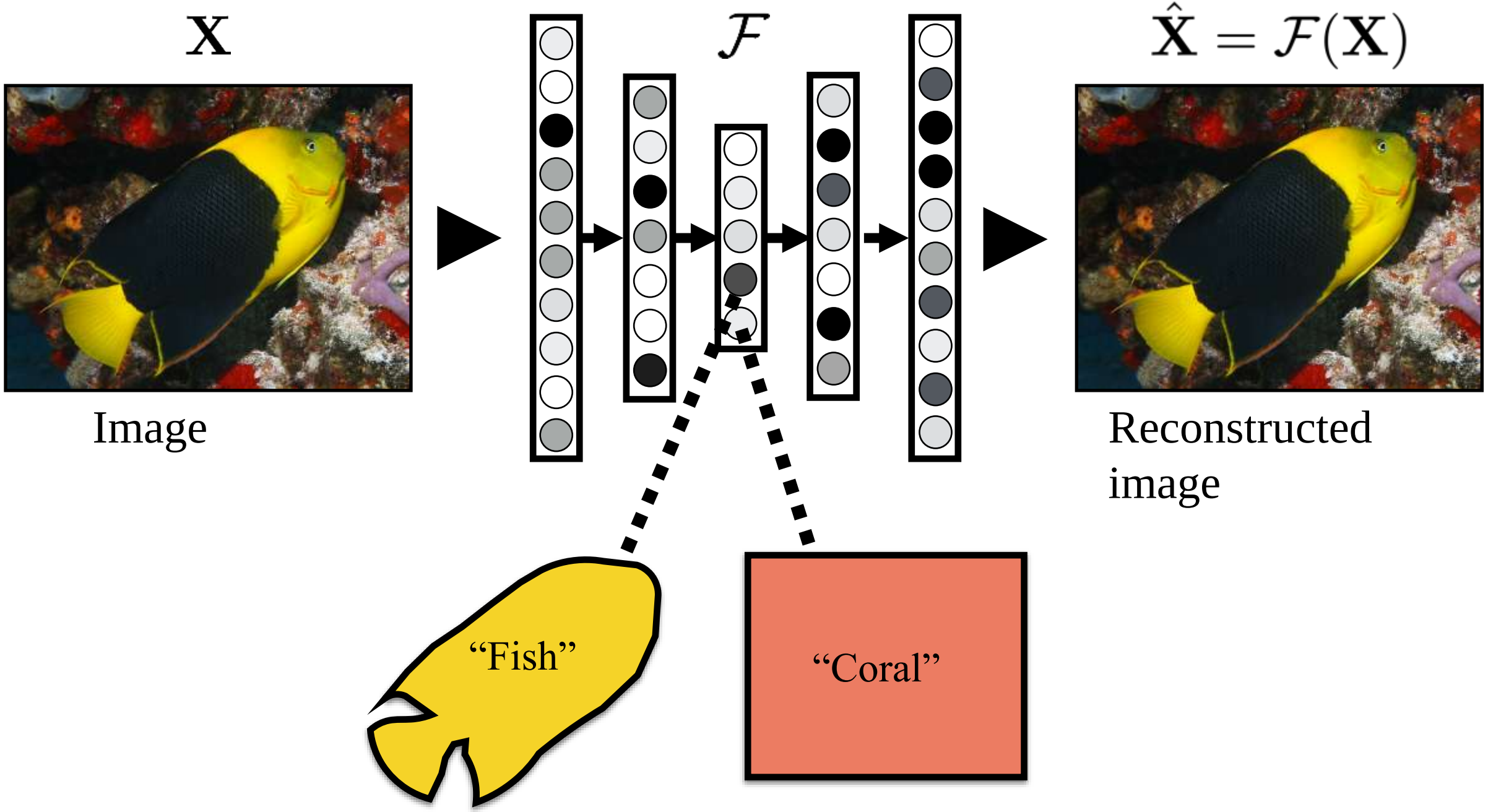
$\mathcal{F}$



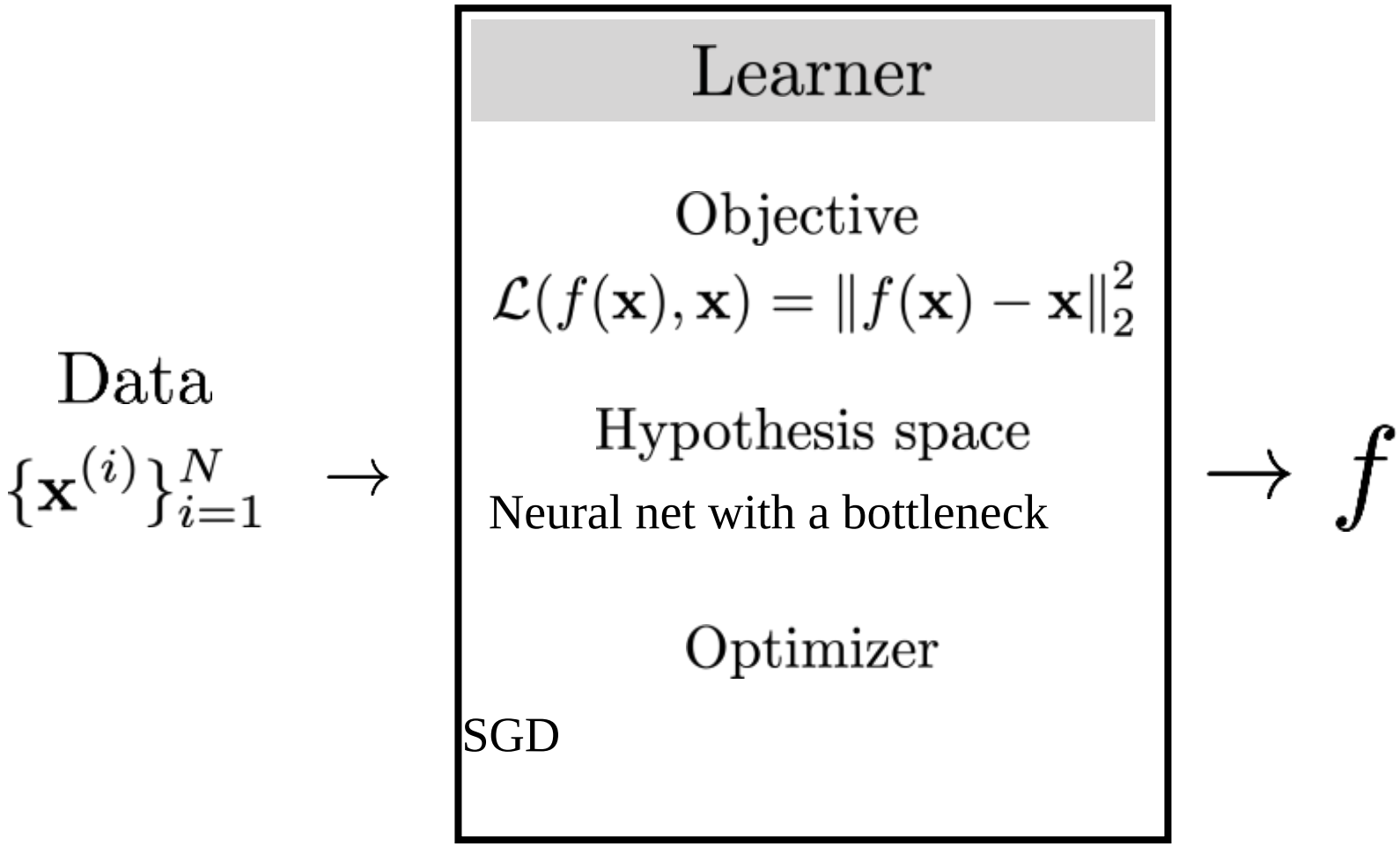
$\hat{\mathbf{X}} = \mathcal{F}(\mathbf{X})$

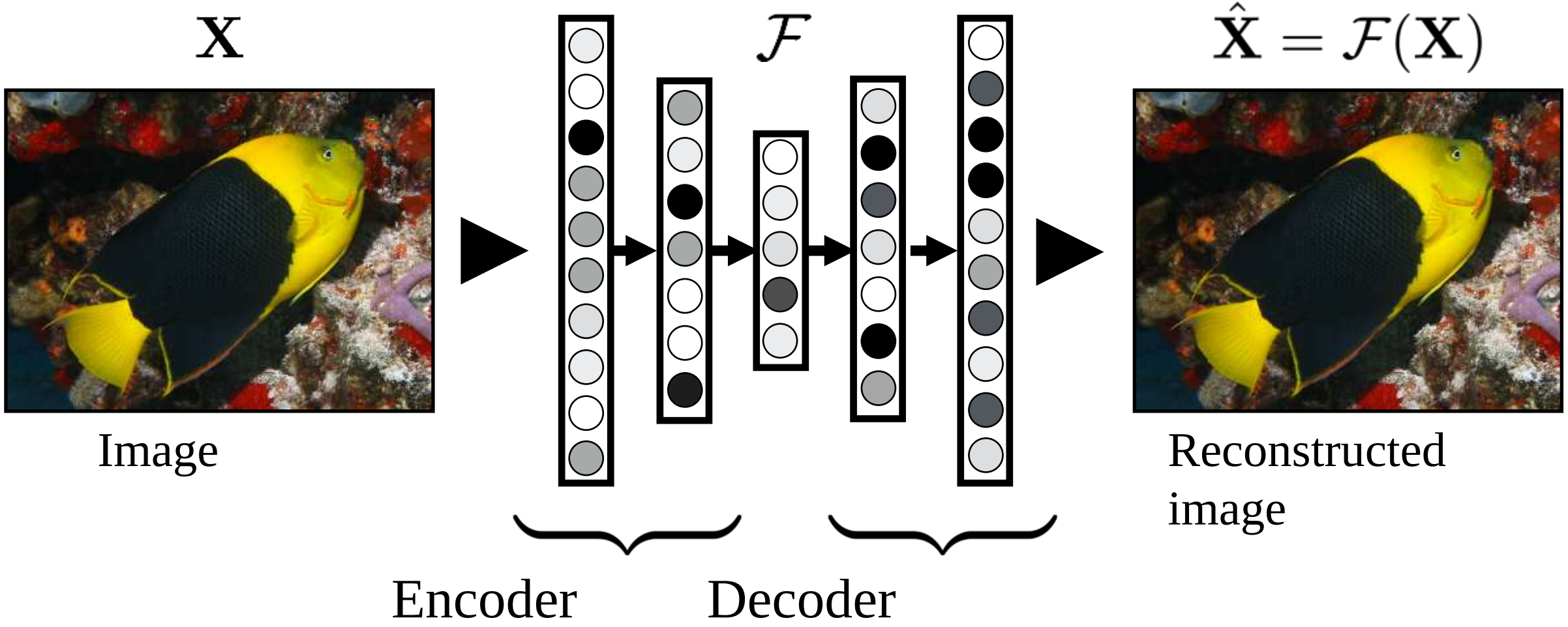
Reconstructed image

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


$\mathbf{X}$
$\mathcal{F}$
$\hat{\mathbf{X}} = \mathcal{F}(\mathbf{X})$
Image
Reconstructed image
"Fish"
"Coral"

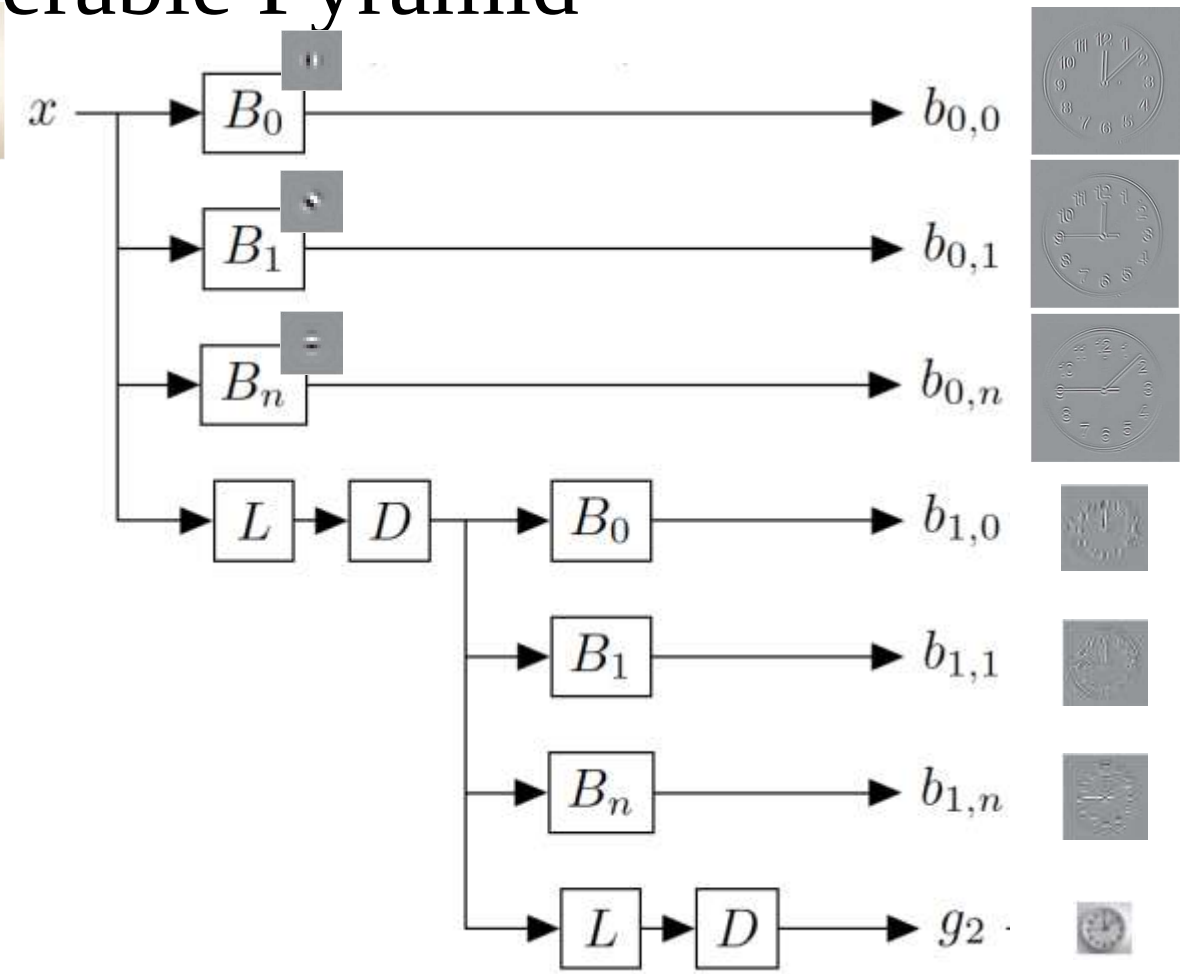
Autoencoder

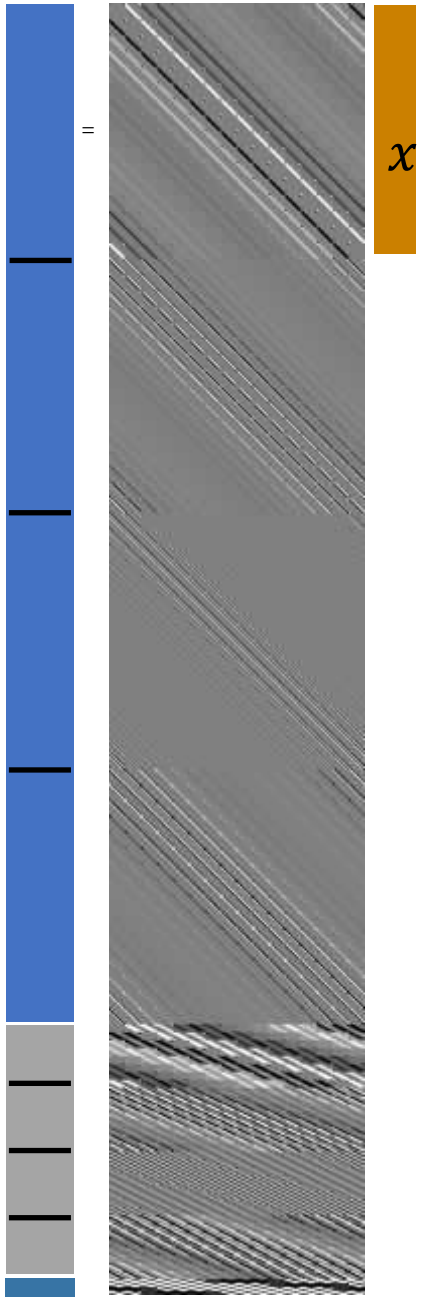



$\mathbf{X}$
$\mathcal{F}$
$\hat{\mathbf{X}} = \mathcal{F}(\mathbf{X})$
Image
Reconstructed image
Encoder
Decoder

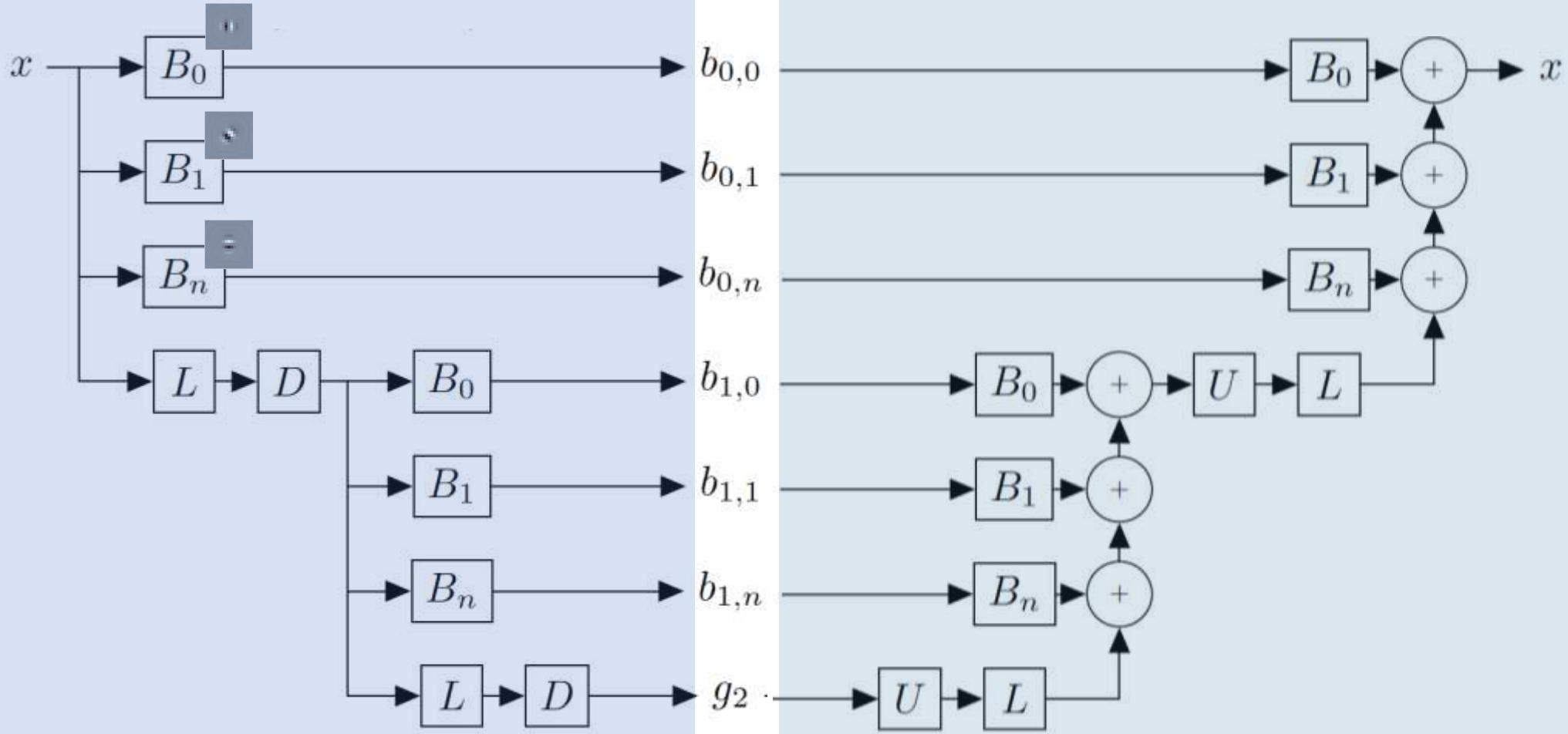
Steerable Pyramid

Steerable Pyramid





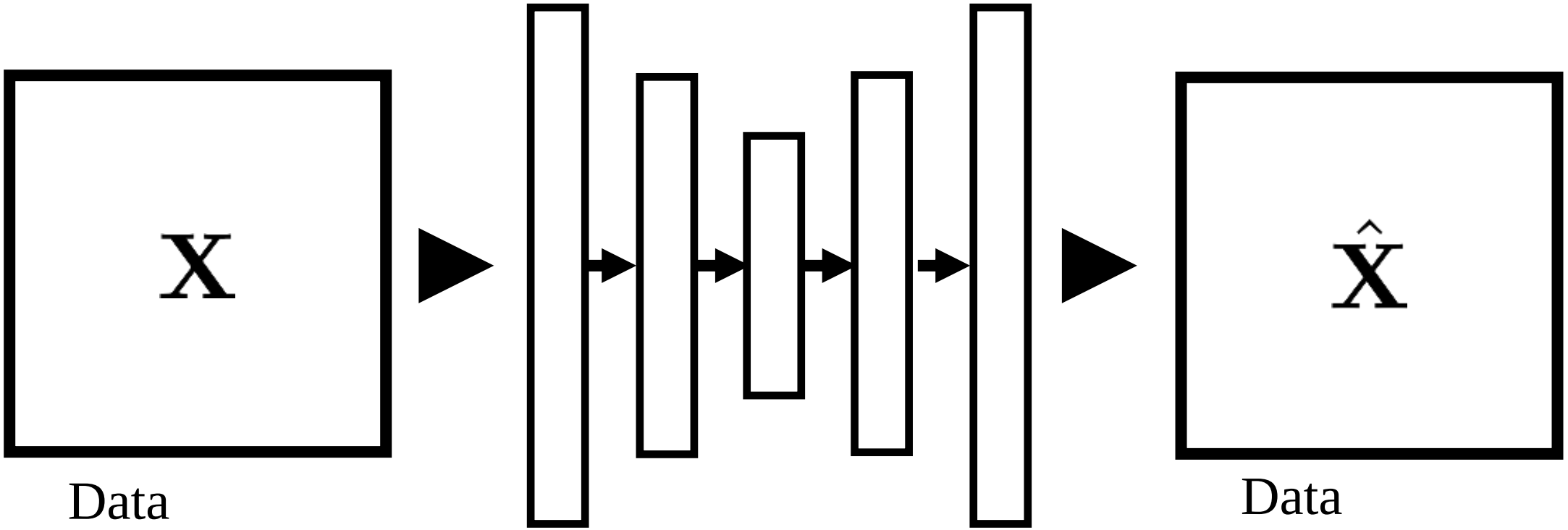
Steerable Pyramid — *A hard-coded autoencoder*



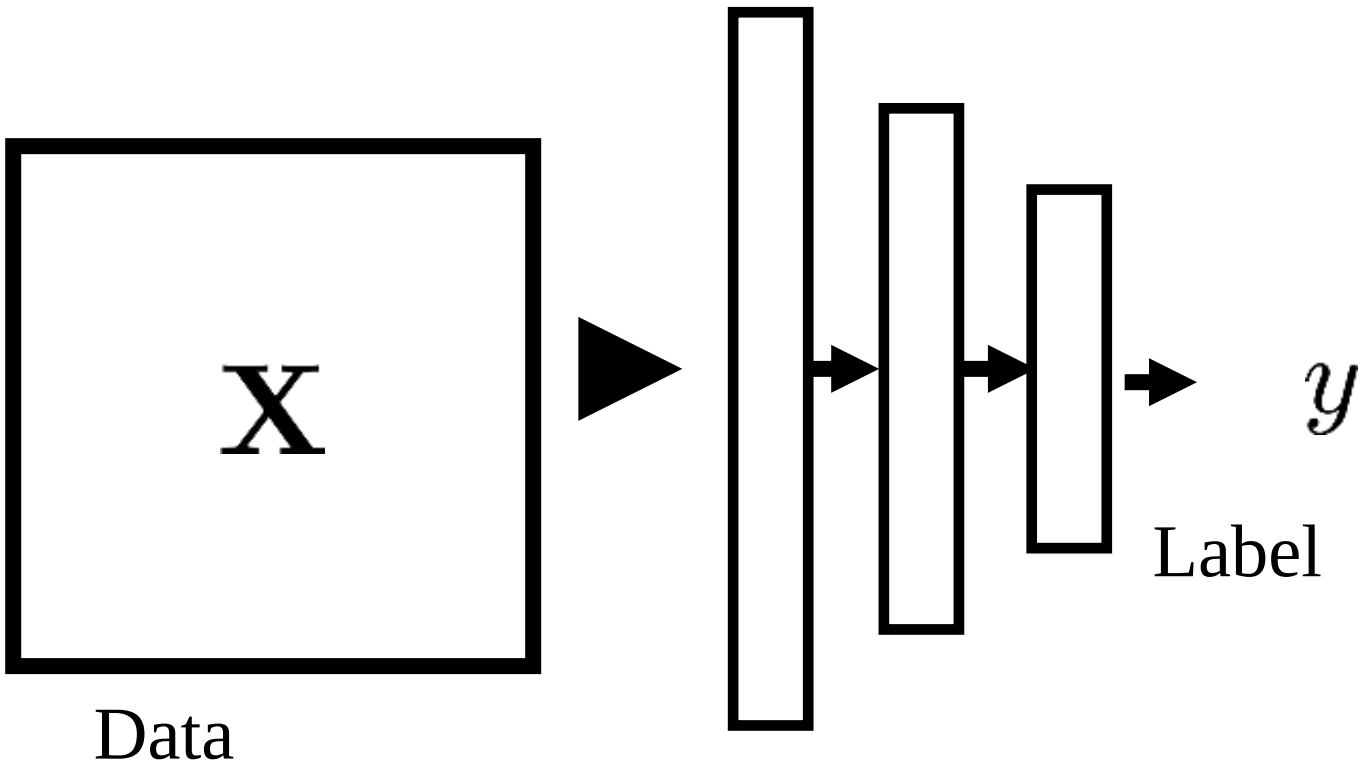
Analysis/Encoder

Synthesis/Decoder

Data compression



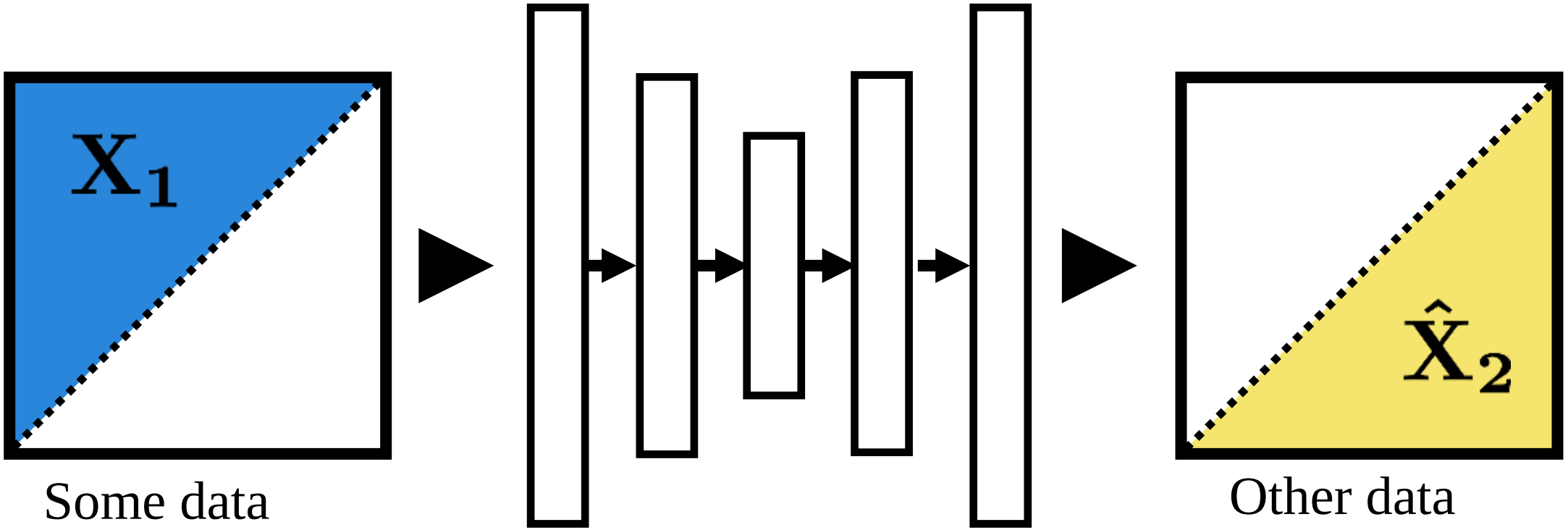
Label prediction



e.g., image classification

Data prediction

aka “self-supervised learning”



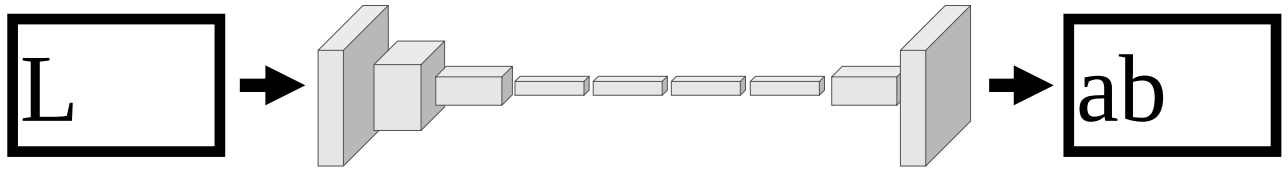
$\mathcal{F}$

Grayscale image: L channel

$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$

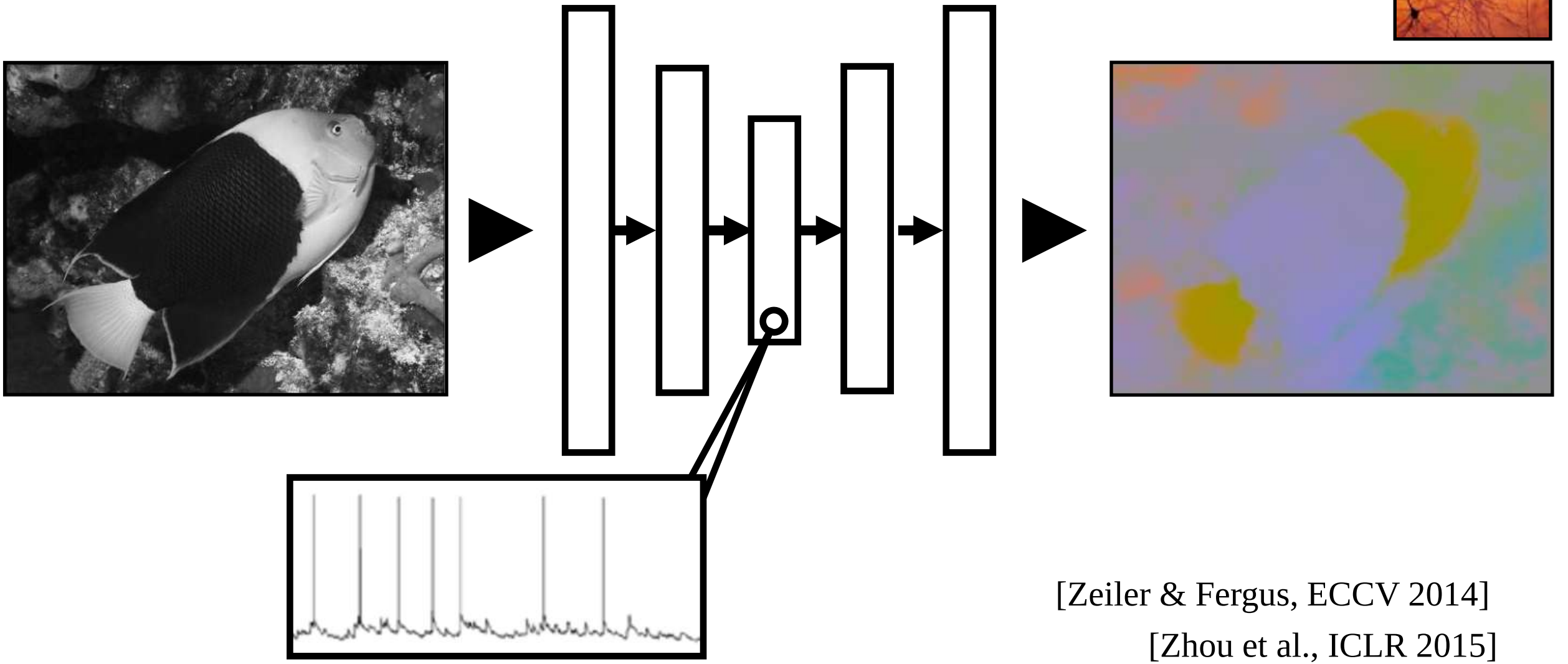
Color information: ab channels

$\hat{\mathbf{Y}} \in \mathbb{R}^{H \times W \times 2}$



[Zhang, Isola, Efros, ECCV 2016]

Deep Net “Electrophysiology”



[Zeiler & Fergus, ECCV 2014]

[Zhou et al., ICLR 2015]

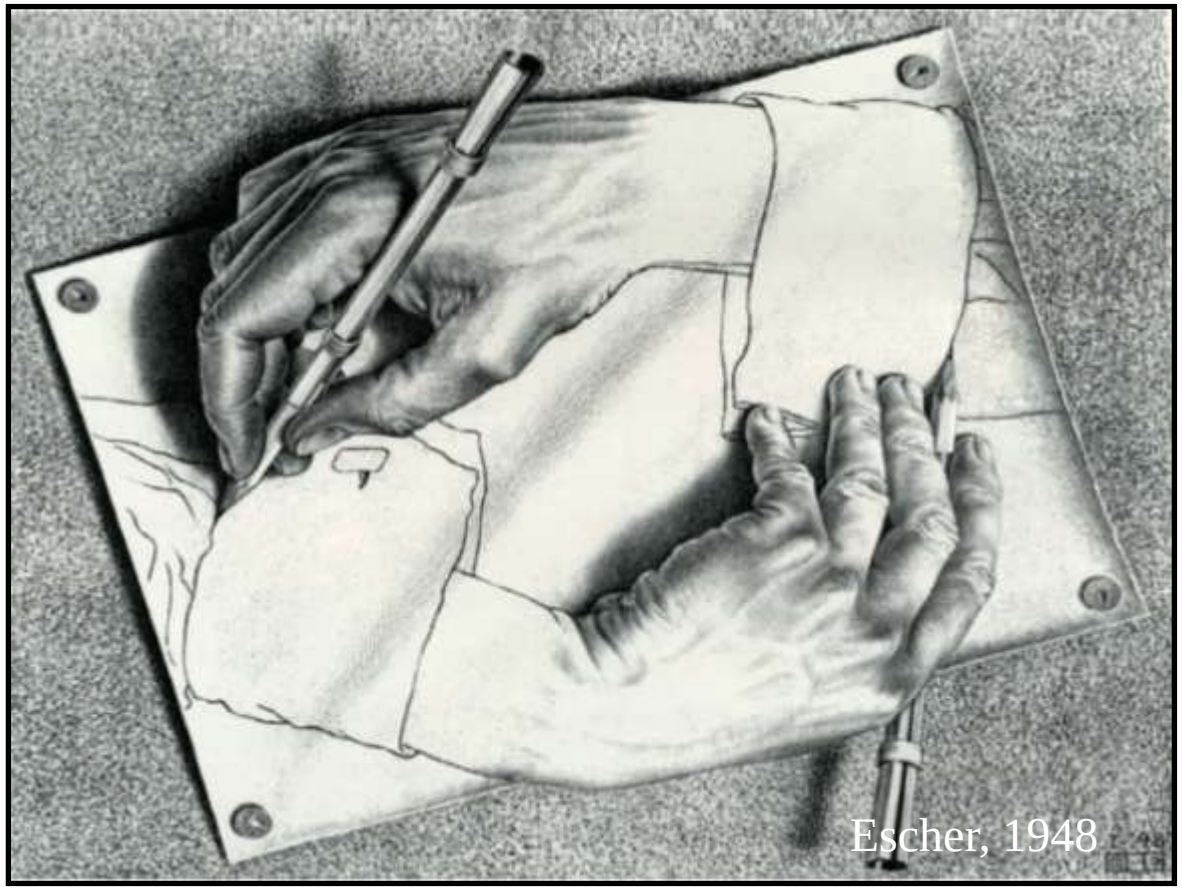
Stimuli that drive selected neurons (conv5 layer)

faces

dog faces

flowers

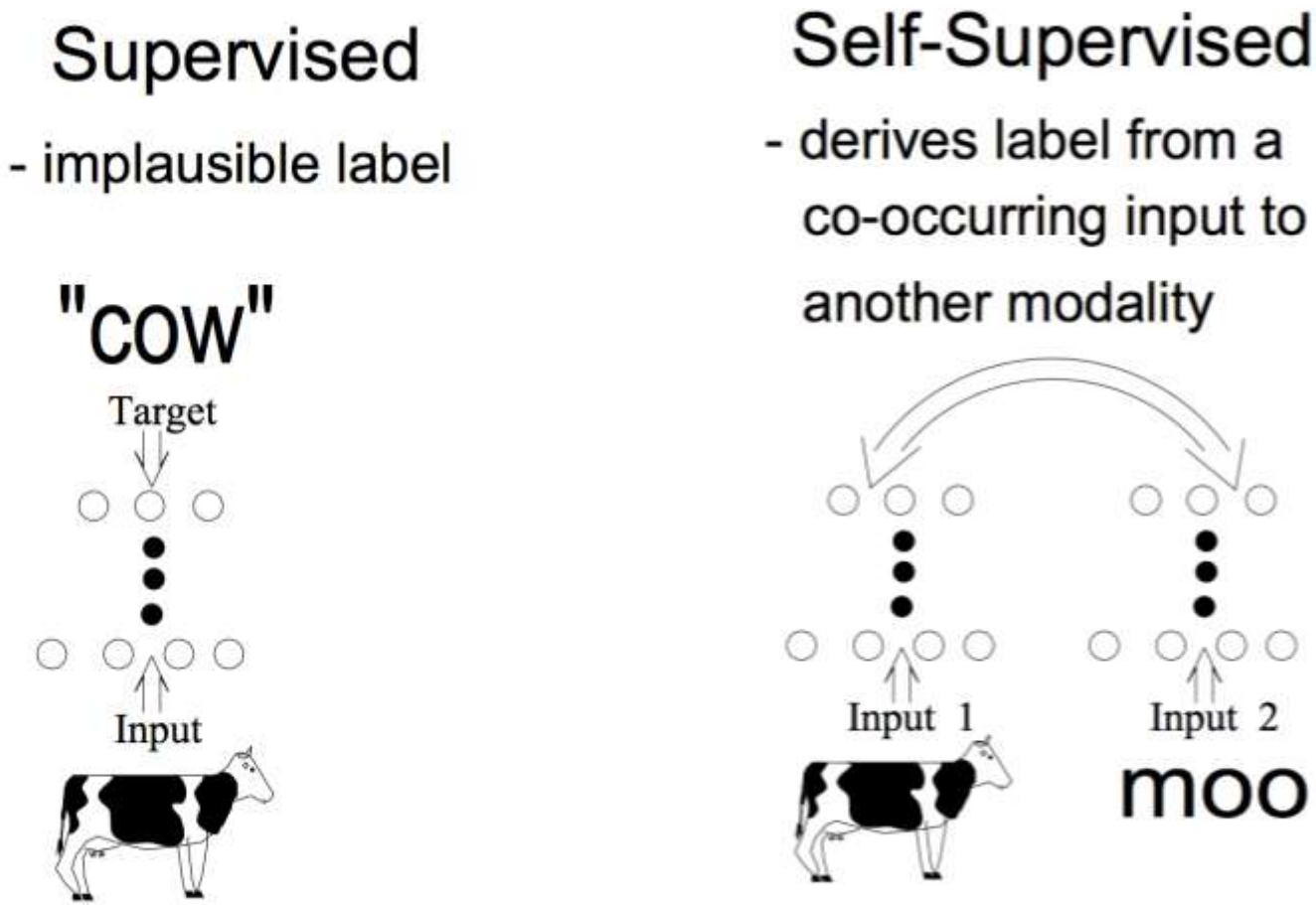
Self-supervised learning



Common trick:

- Convert “unsupervised” problem into “supervised” empirical risk minimization
- Do so by cooking up “labels” (prediction targets) from the raw data itself

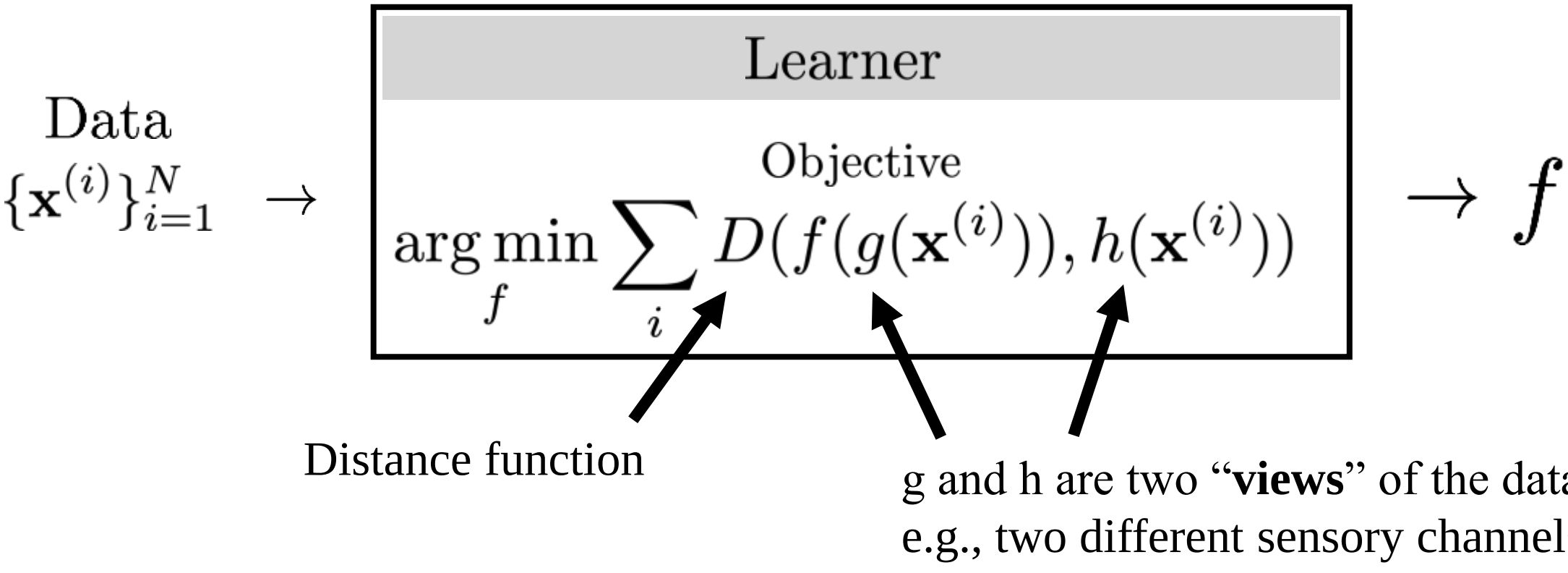
Multisensory self-supervision



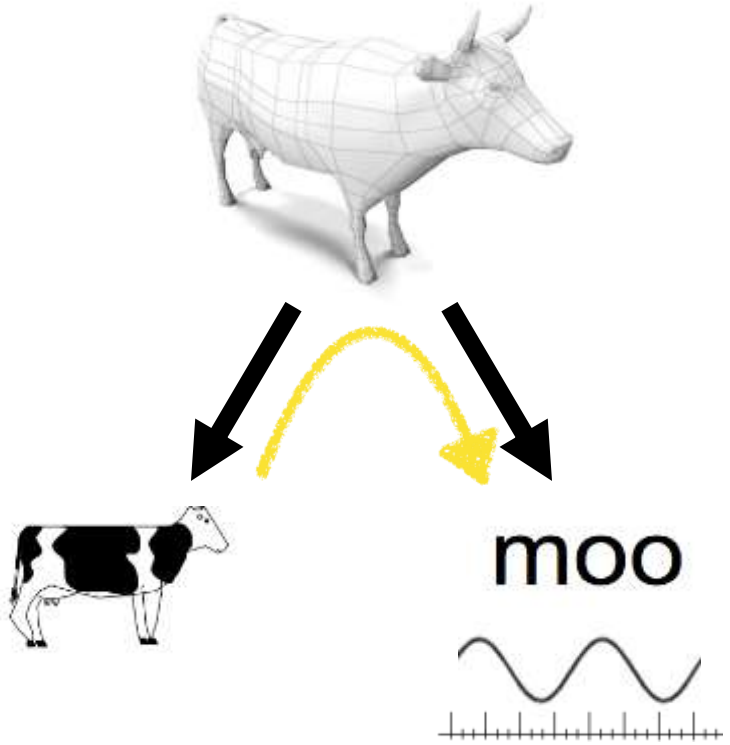
Virginia de Sa. *Learning Classification with Unlabeled Data*. NIPS 1994.

[see also “Six lessons from babies”, Smith and Gasser 2005]

“Multiview” self-supervised predictive learning

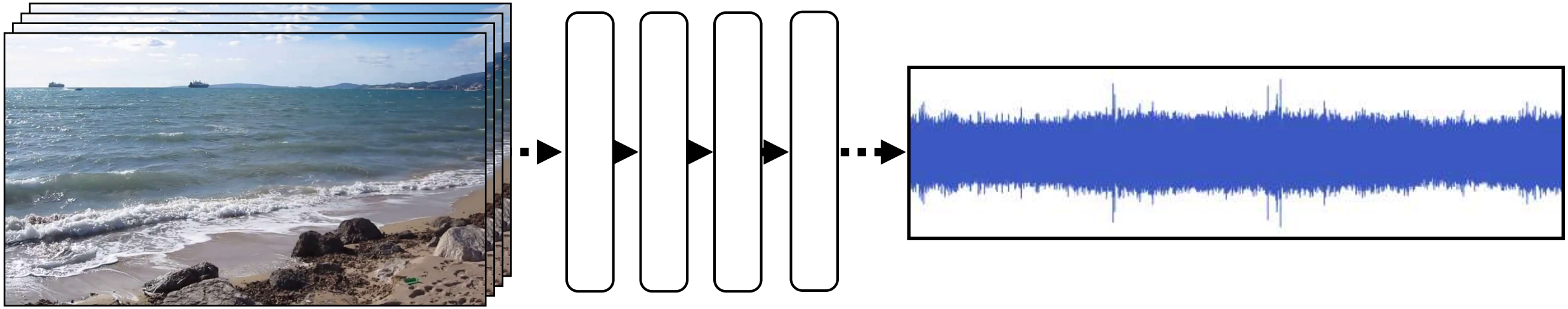


“Multiview” self-supervised predictive learning



[Slide credit: Andrew Owens]

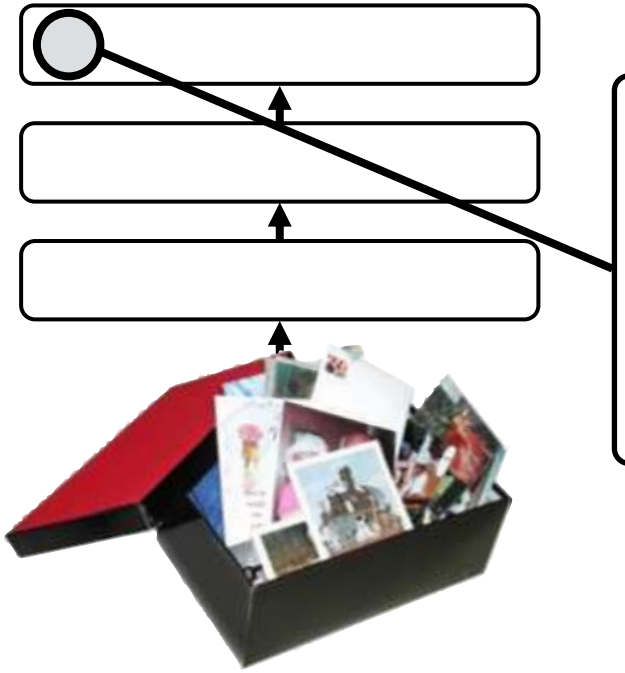
Predicting ambient sound



[Slide credit: Andrew Owens]

What did the model learn?

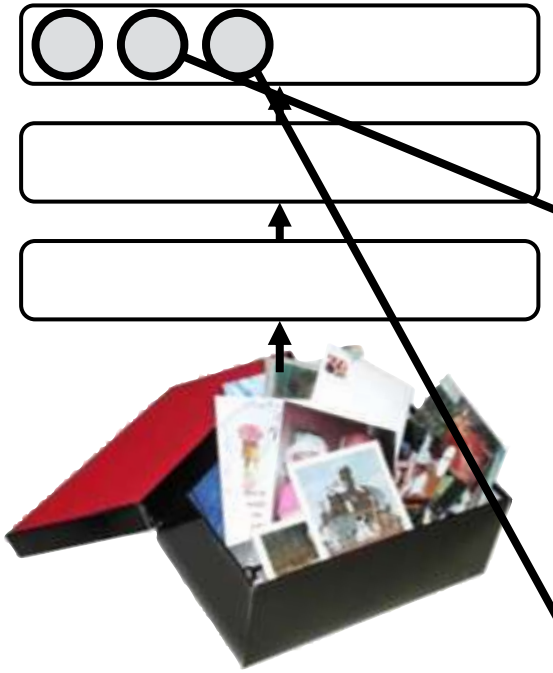
Unit #90 of 256



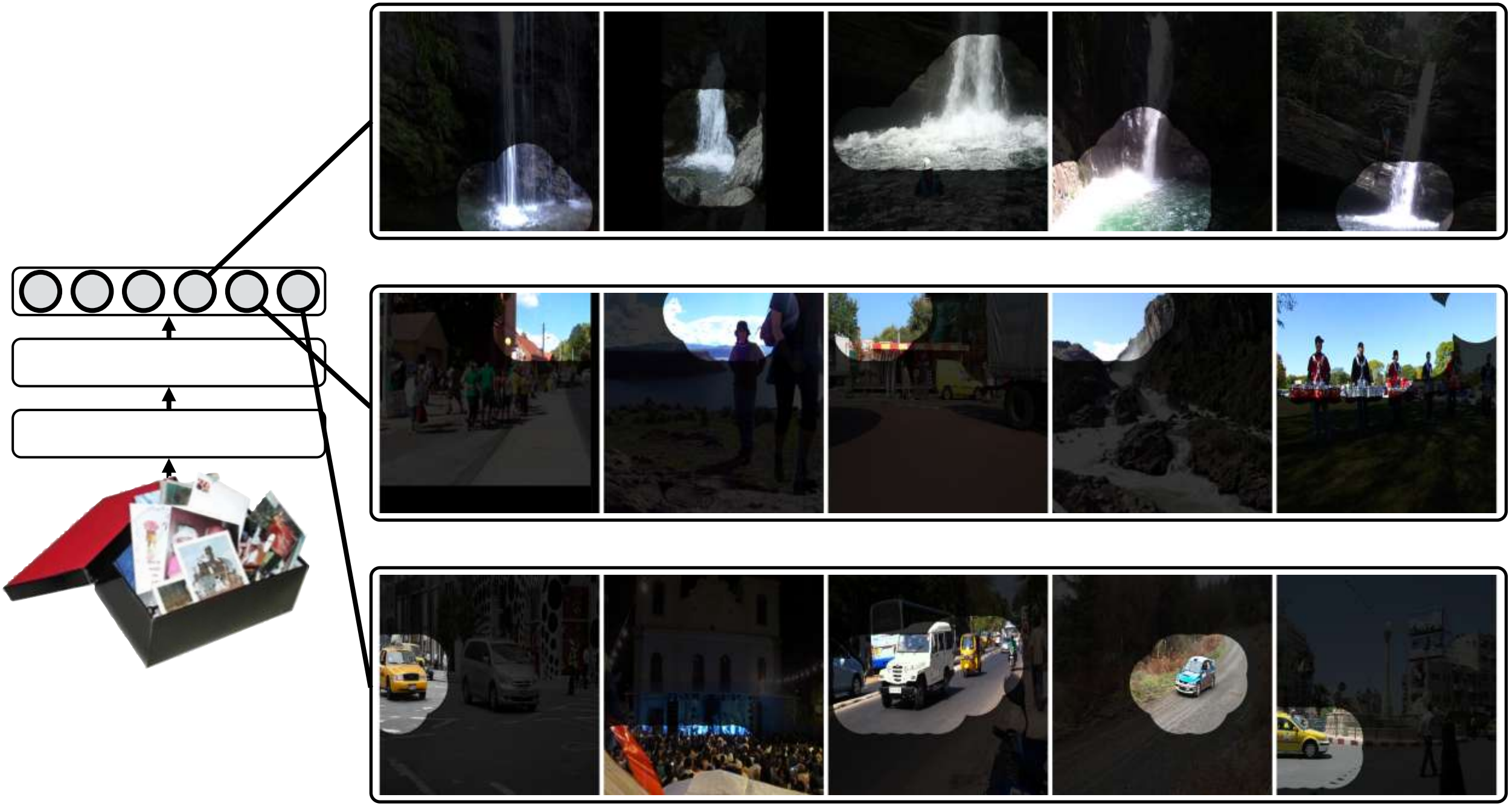
Strongest responses in dataset

Visualization method from (Zhou 2015)

[Slide credit: Andrew Owens]



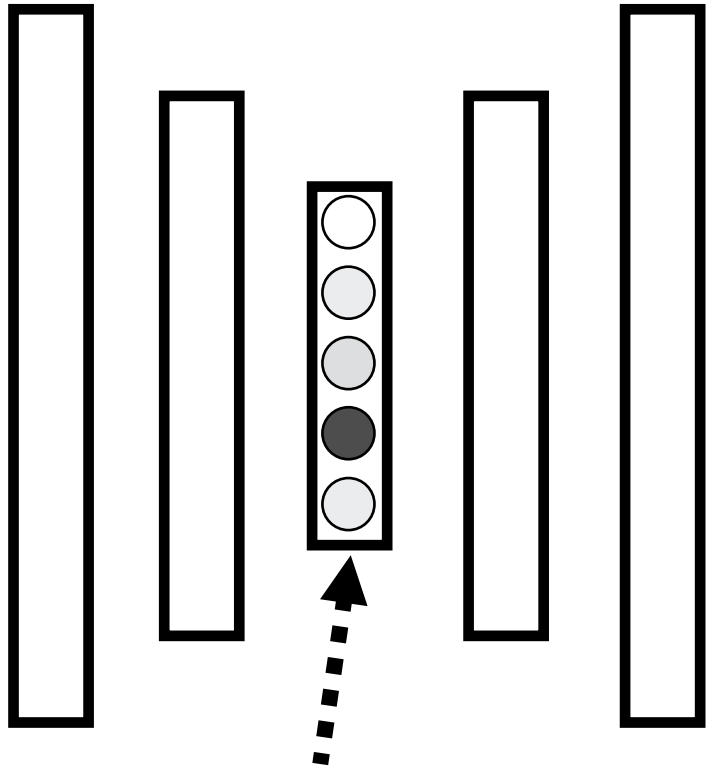
[Slide credit: Andrew Owens]



[Slide credit: Andrew Owens]

$\mathbf{x}$

Image



compressed image code
(vector $\mathbf{z}$)

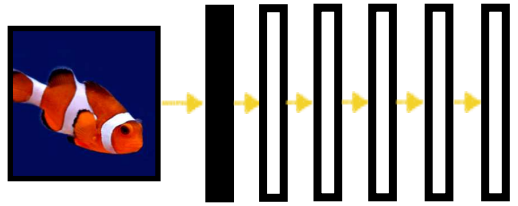
$\hat{\mathbf{x}}$

Reconstructed image

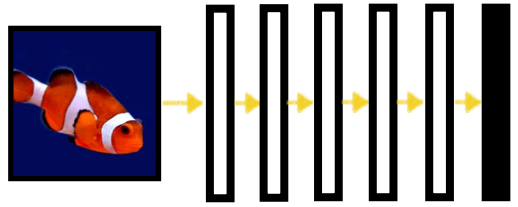
Is the code informative about object class ? y

Logistic regression:

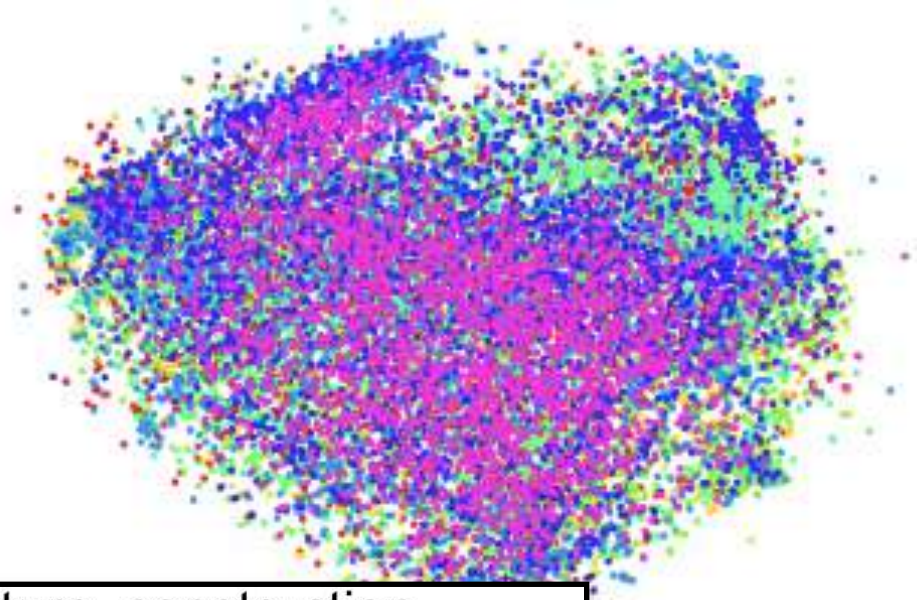
$$y = \sigma(\mathbf{W}\mathbf{z} + \mathbf{b})$$

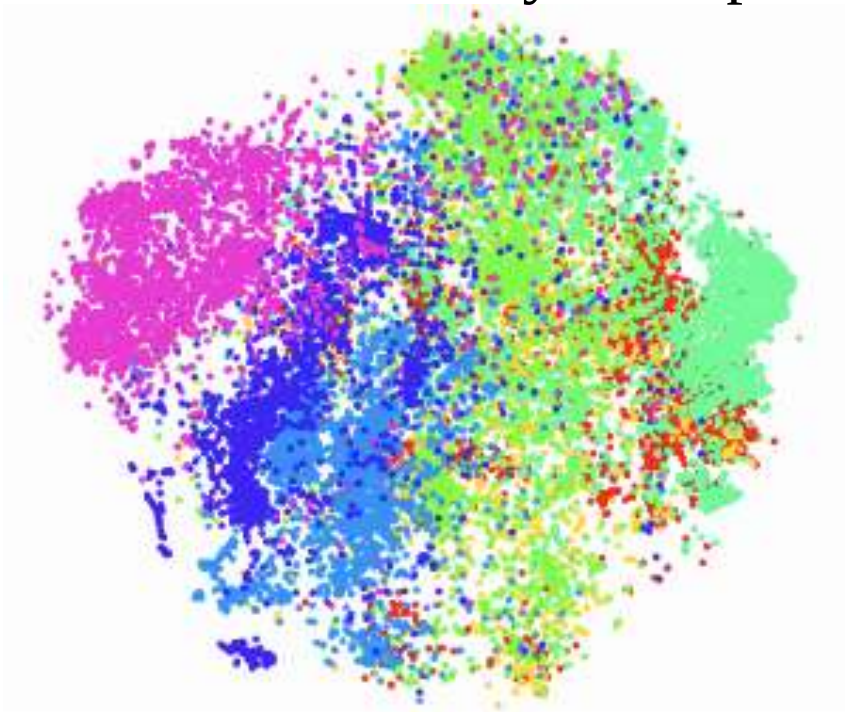


Layer 1 representation



Layer 6 representation

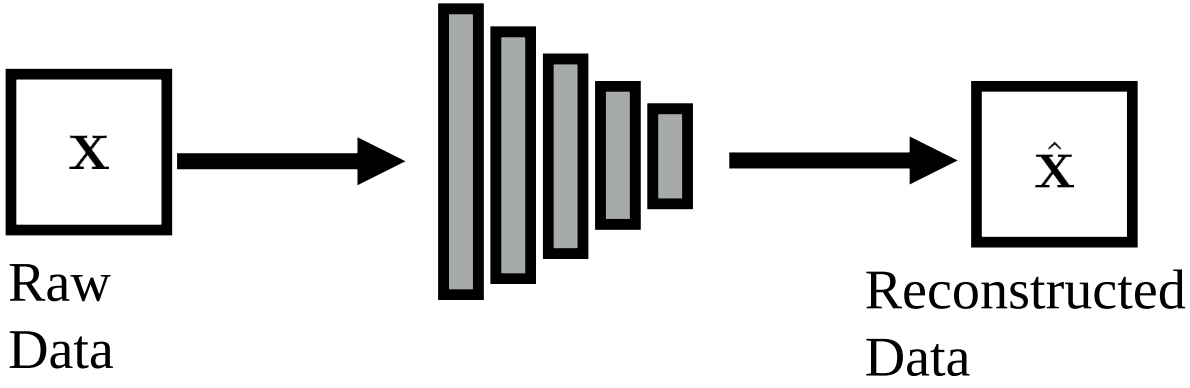


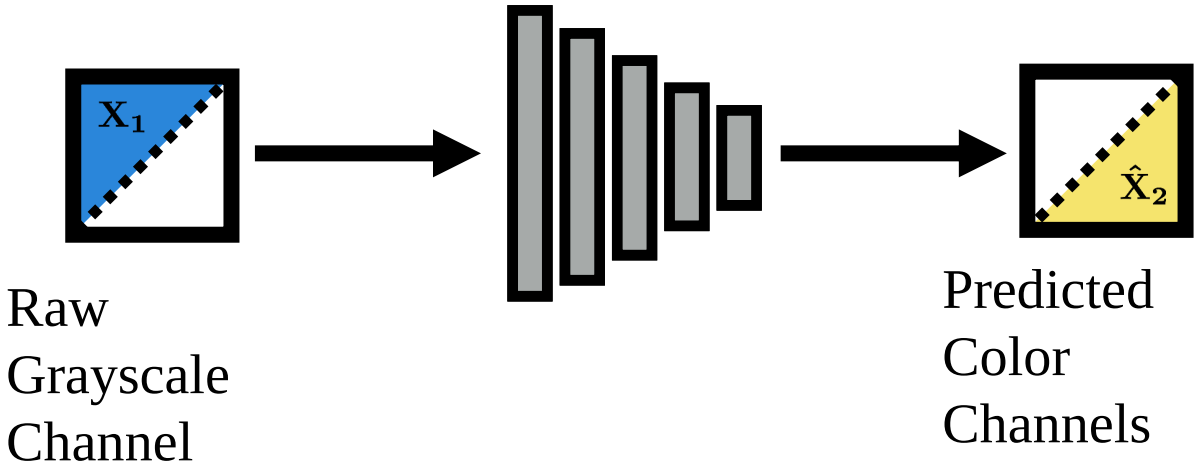


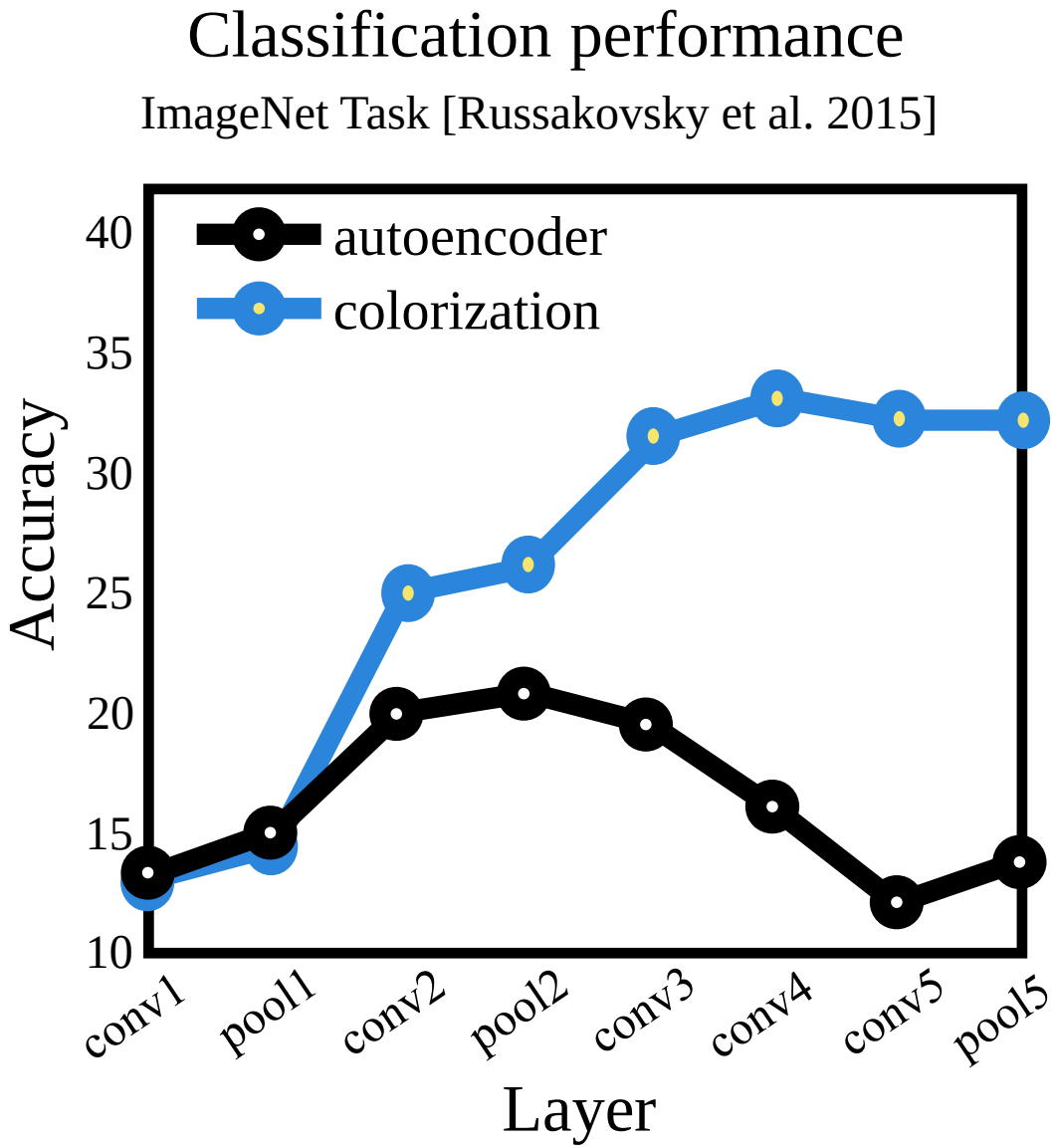
- structure, construction
- covering
- commodity, trade good, good
- conveyance, transport
- invertebrate
- bird
- hunting dog

[DeCAF, Donahue, Jia, et al. 2013]

[Visualization technique : t-sne, van der Maaten & Hinton, 2008]

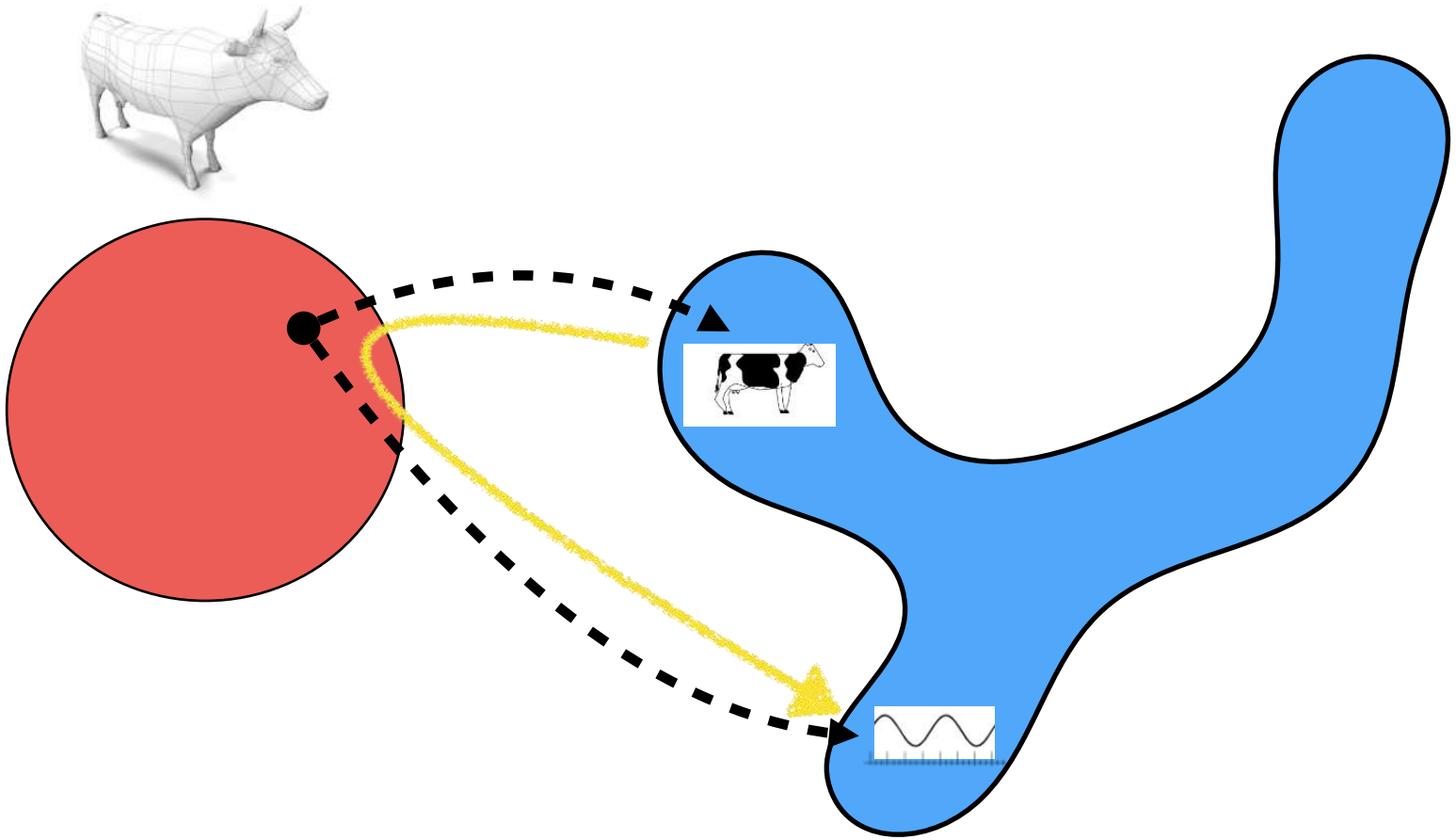

x
x̂
Raw
Data
Reconstructed
Data

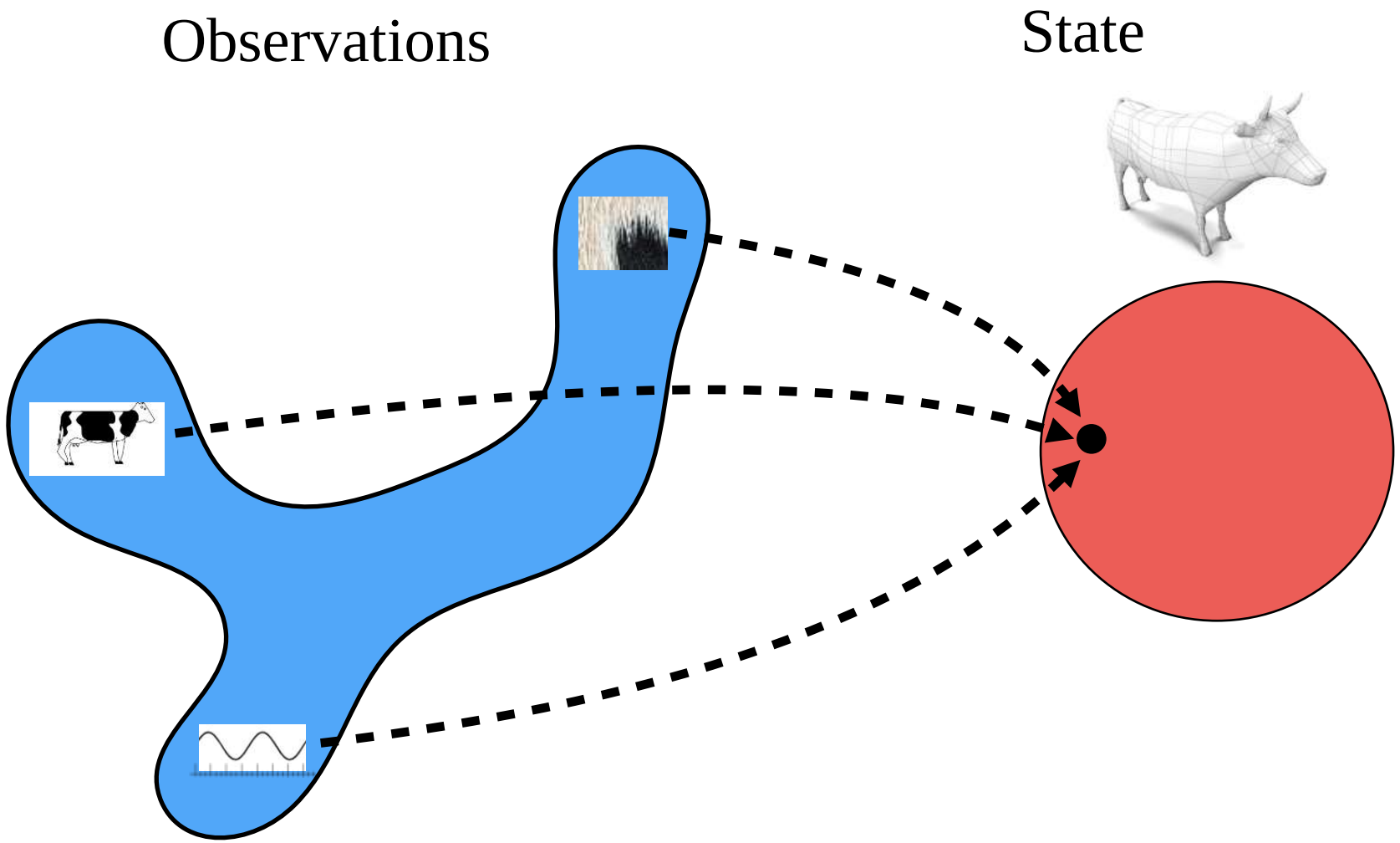

x1
x̂2
Raw
Grayscale
Channel
Predicted
Color
Channels


Classification performance
ImageNet Task [Russakovsky et al. 2015]
autoencoder
colorization
Accuracy
40
35
30
25
20
15
10
conv1
pool1
conv2
pool2
conv3
conv4
conv5
pool5
Layer

State

Observations

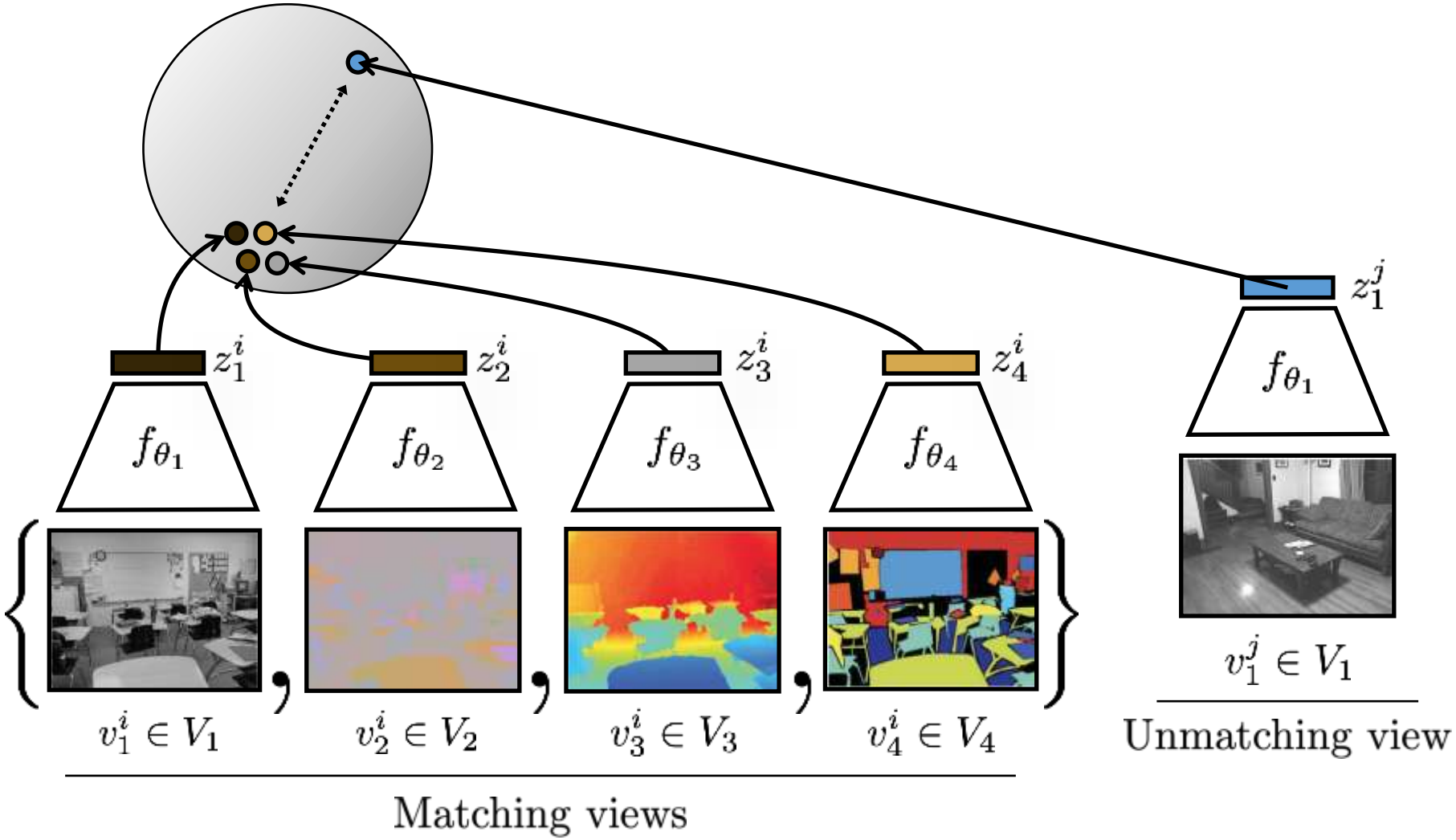




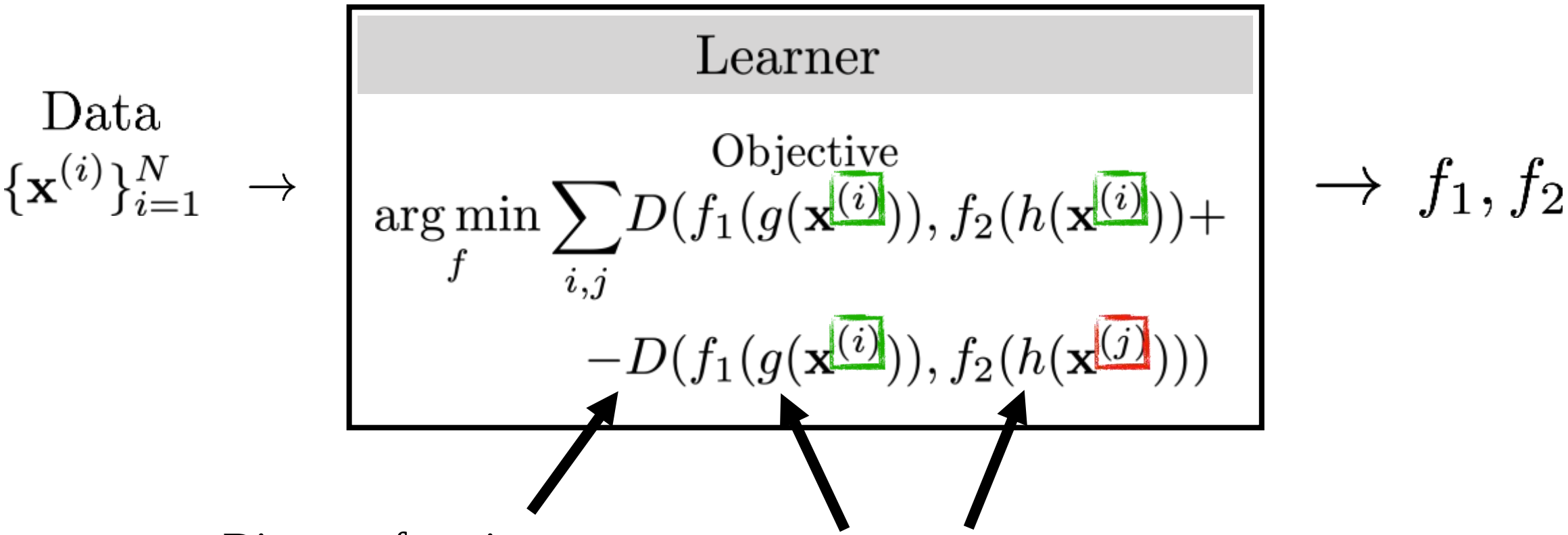
The way you measure the world does not change the underlying state

Contrastive Multiview Coding

[Tian, Krishnan, Isola, ECCV 2020]

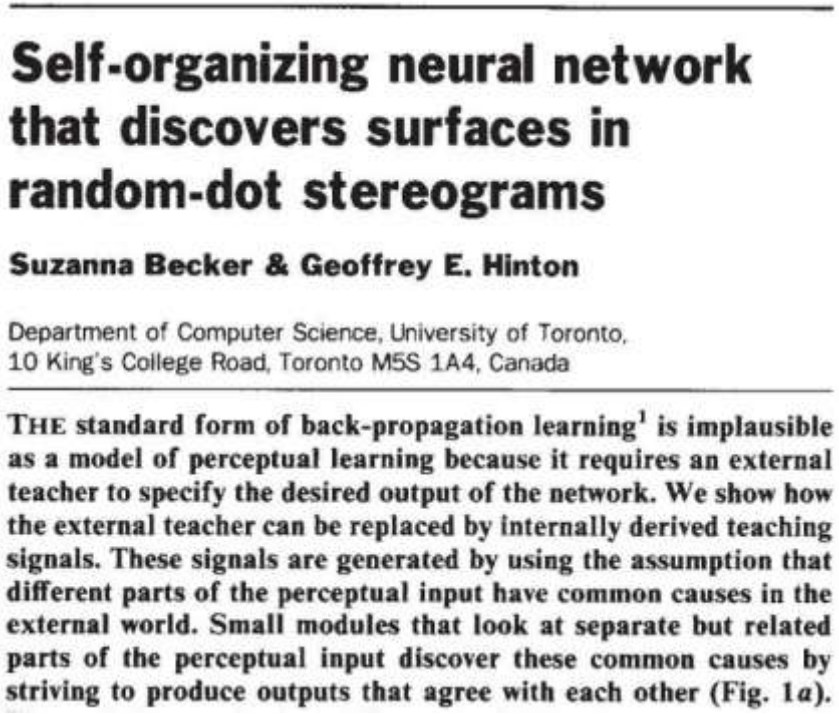


"Multiview" self-supervised **contrastive** learning



SimCLR

[Chen, Kornblith, Norouzi, Hinton, ICML 2020]



Self-organizing neural network that discovers surfaces in random-dot stereograms

Suzanna Becker & Geoffrey E. Hinton

Department of Computer Science, University of Toronto,
10 King's College Road, Toronto M5S 1A4, Canada

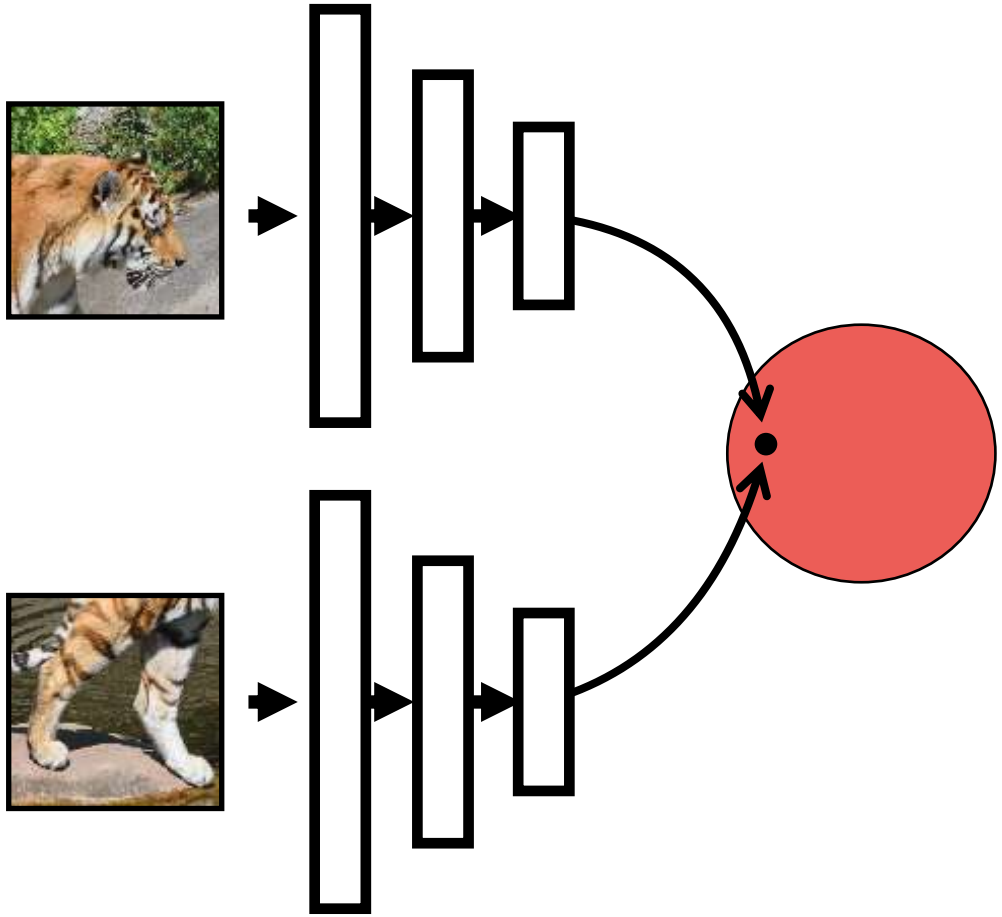
THE standard form of back-propagation learning[1] is implausible as a model of perceptual learning because it requires an external teacher to specify the desired output of the network. We show how the external teacher can be replaced by internally derived teaching signals. These signals are generated by using the assumption that different parts of the perceptual input have common causes in the external world. Small modules that look at separate but related parts of the perceptual input discover these common causes by striving to produce outputs that agree with each other (Fig. 1*a*).

[c.f. Becker & Hinton, Nature 1992]

Contrastive pre-training

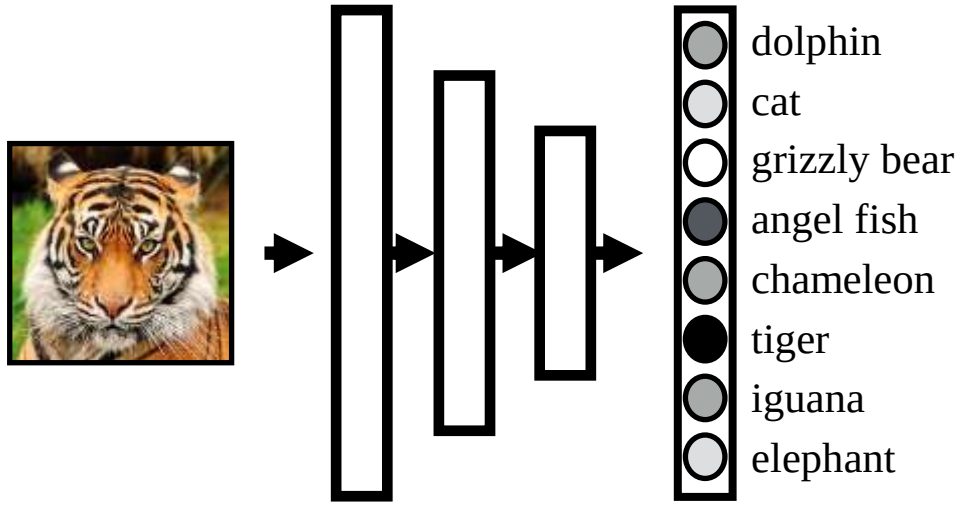
Pretraining

Self-supervised contrastive learning



Testing

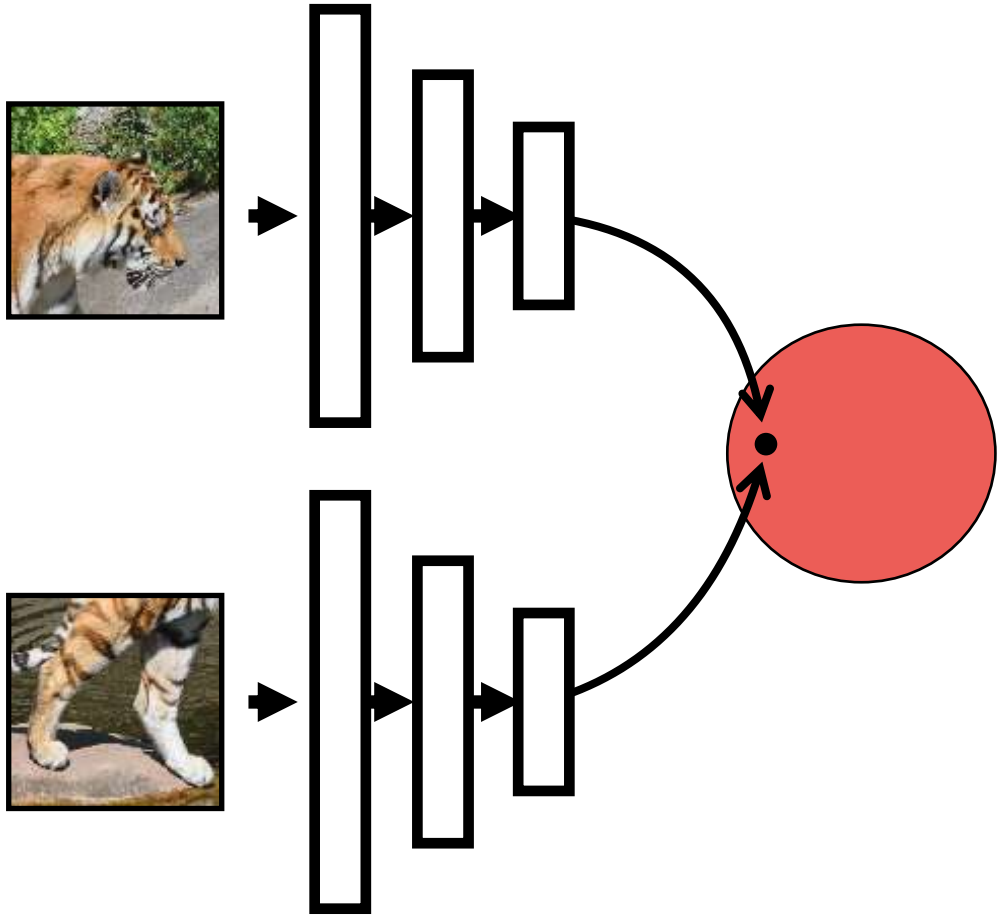
New recognition task



Contrastive pre-training

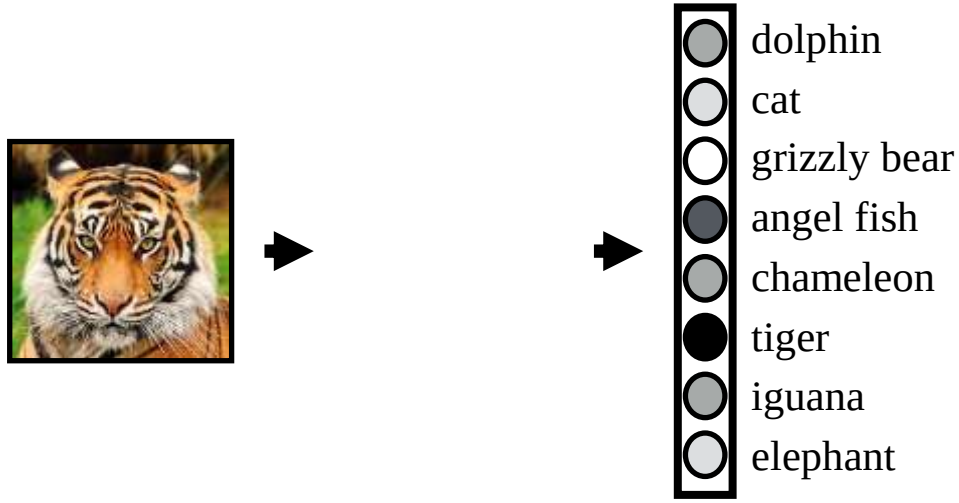
Pretraining

Self-supervised contrastive learning



Finetuning

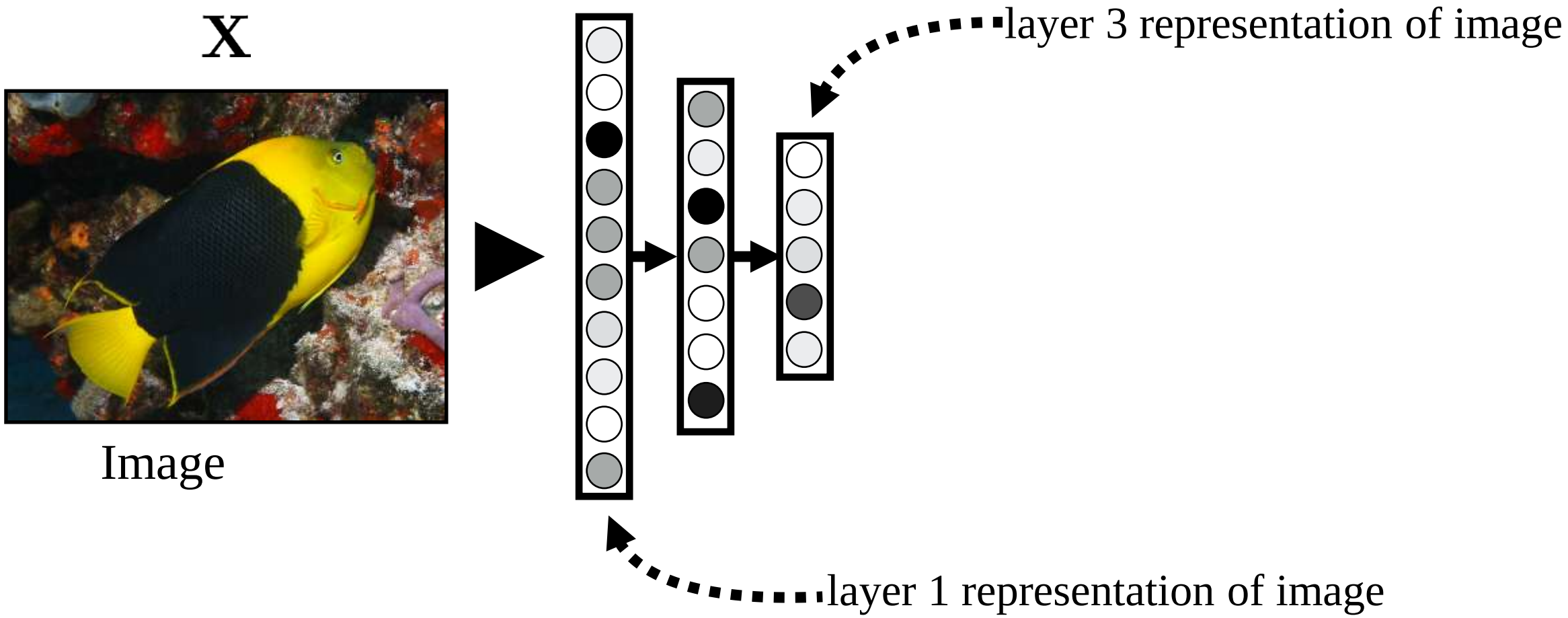
New recognition task



How to represent words as numbers

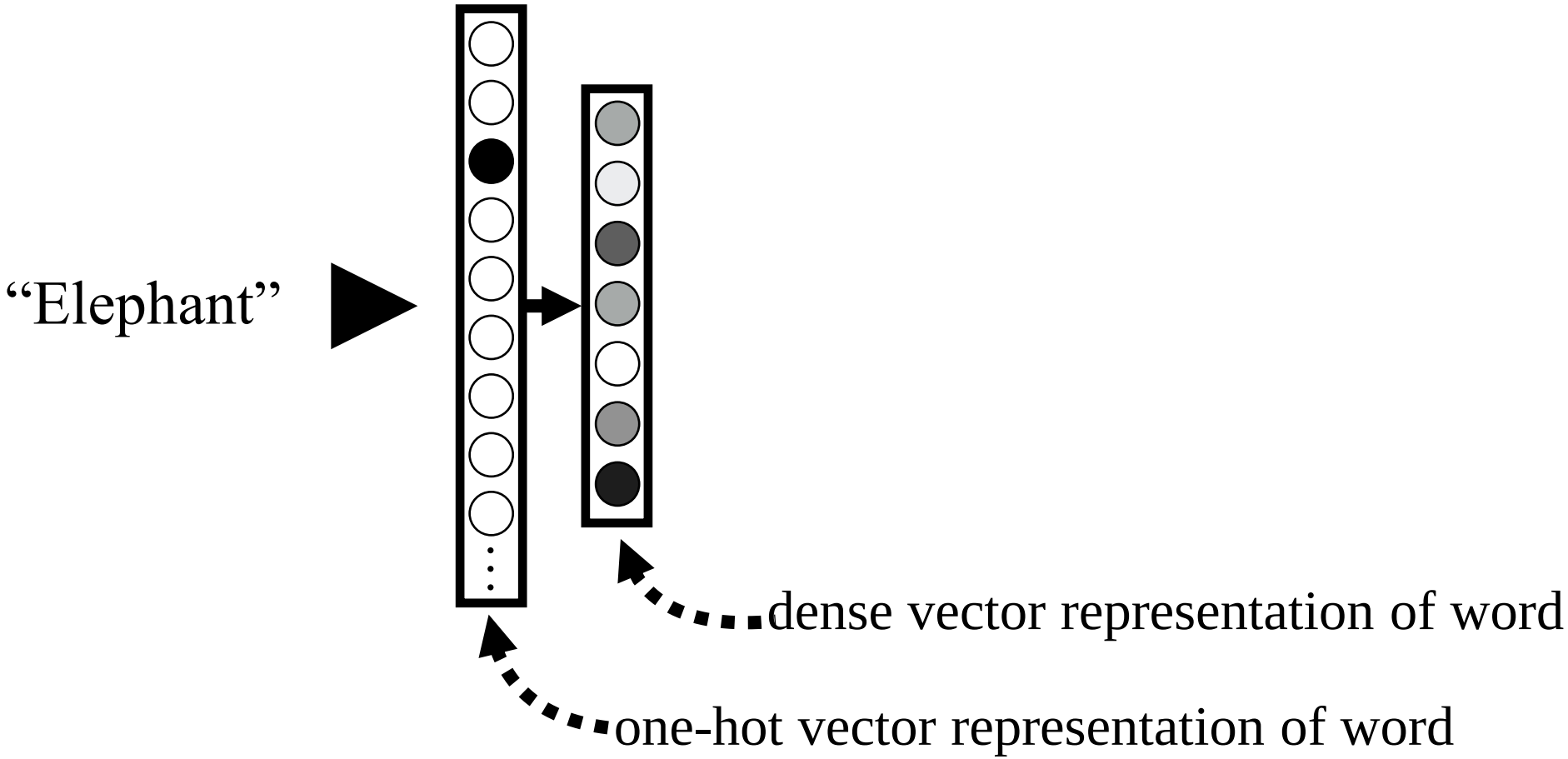
“Fish”	→	[**1**,0,0,0,0,0,0,…]
“Shark”	→	[0,**1**,0,0,0,0,0,…]
“Whale”	→	[0,0,**1**,0,0,0,0,…]
“Water”	→	[0,0,0,**1**,0,0,0,…]
“Cat”	→	[0,0,0,0,**1**,0,0,…]
“Couch”	→	[0,0,0,0,0,**1**,0,…]
“Sun”	→	[0,0,0,0,0,0,**1**,…]

im2vec

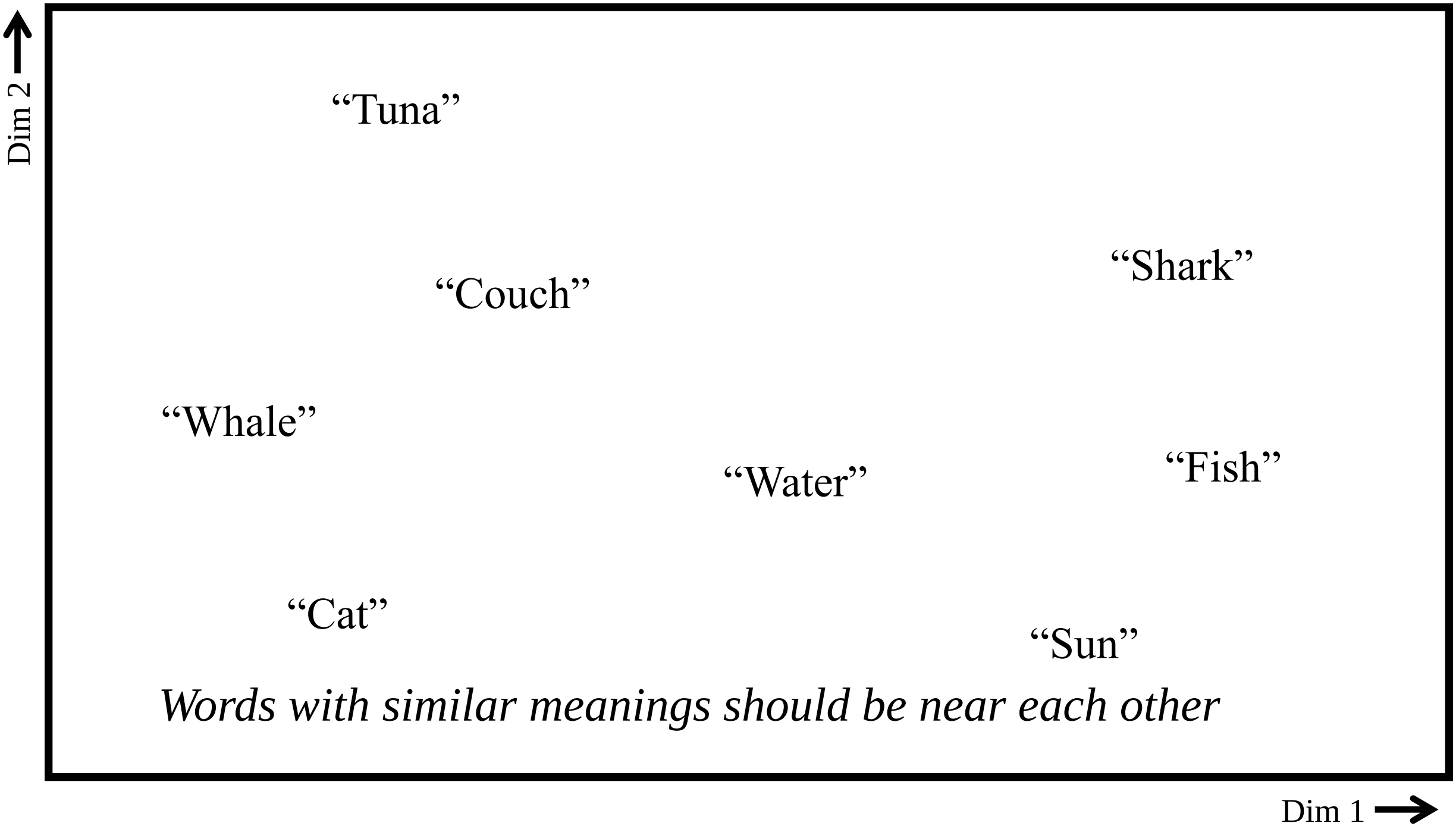


Represent image as a neural **embedding** — a vector/tensor of neural activations
(perhaps representing a vector of detected texture patterns or object parts)

word2vec



X2vec methods are also called embeddings of X, e.g., a **word embedding**


Dim 2
“Tuna”
“Couch”
“Shark”
“Whale”
“Water”
“Fish”
“Cat”
“Sun”
Words with similar meanings should be near each other
Dim 1

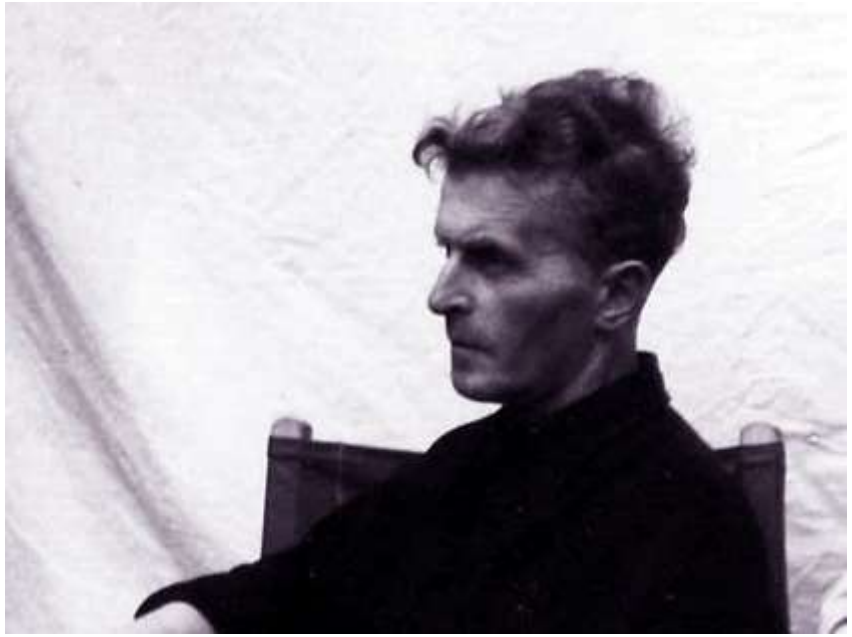
word2vec

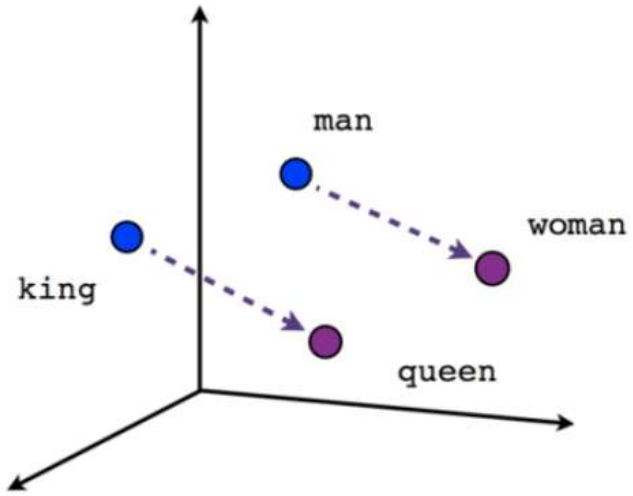
Words with similar meanings should be near each other

Proxy: words that are used in the same context tend to have similar meanings

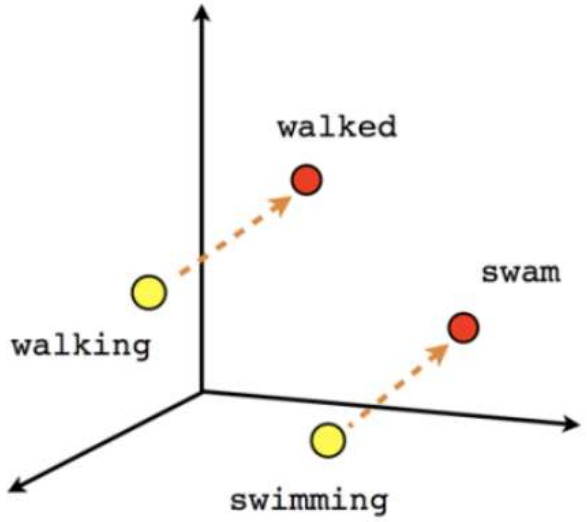
words with similar contexts should be near each other

“Meaning is use” — Wittgenstein

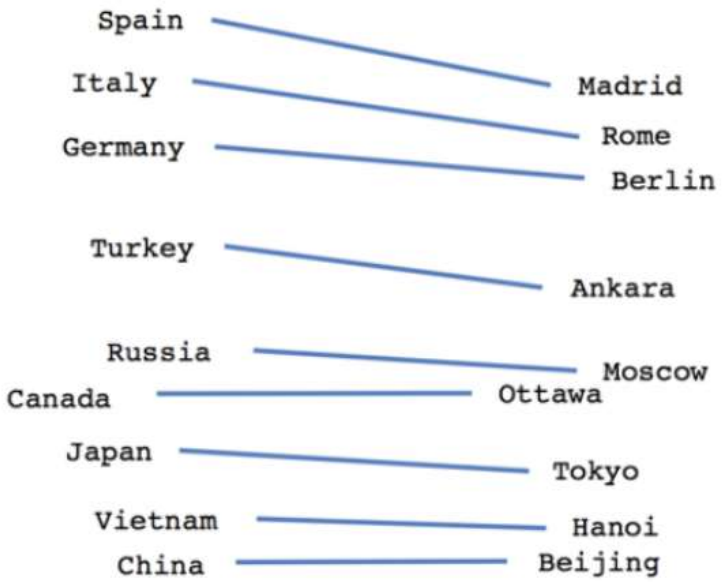




Male-Female



Verb tense



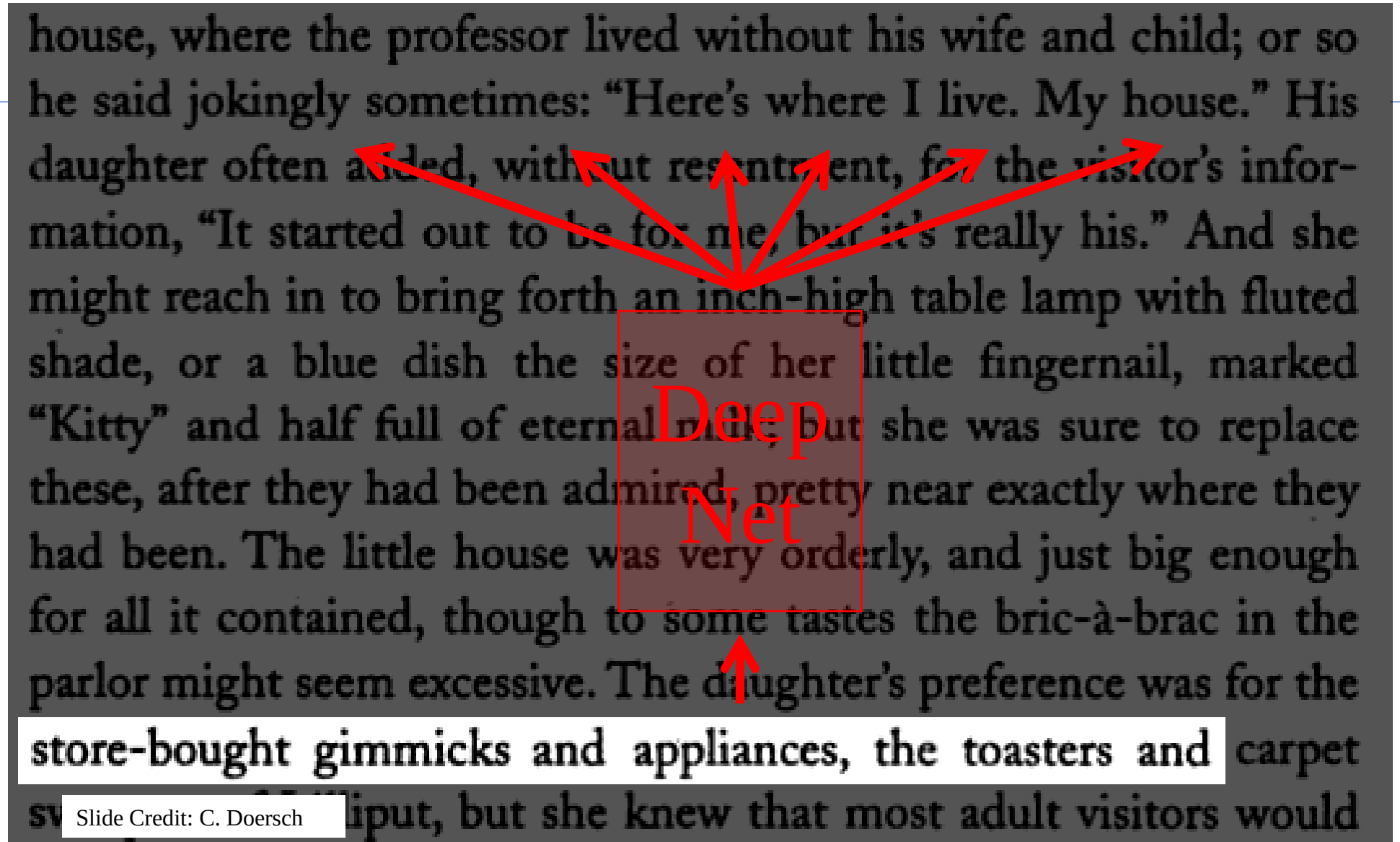
Country-Capital

Examples from https://www.tensorflow.org/tutorials/representation/word2vec

Context as Supervision 上下文监督

[Collobert & Weston 2008; Mikolov et al. 2013]

BERT 与 GPT 的核心概念之一

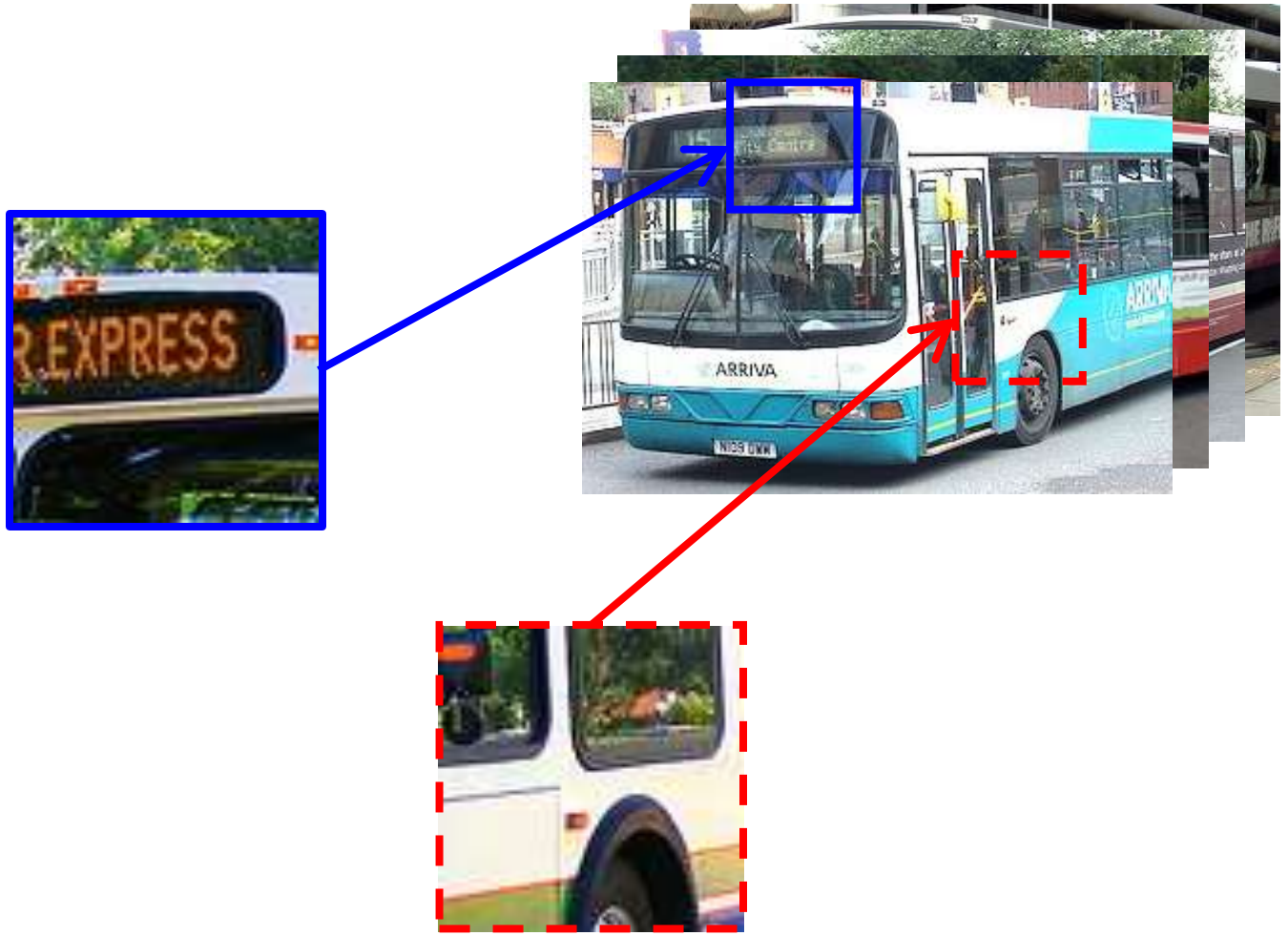


Slide Credit: C. Doersch

图像的上下文预测

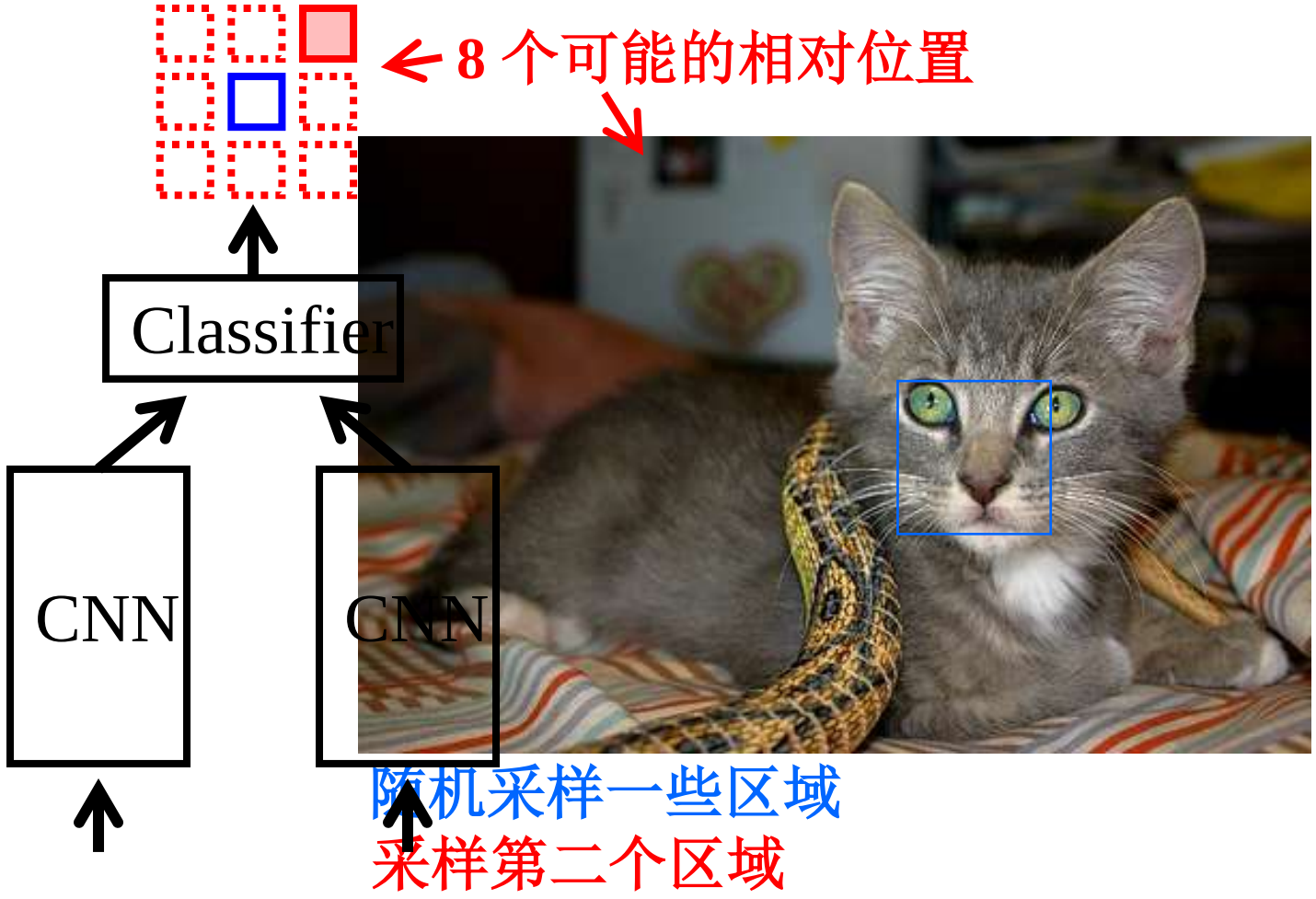
Slide Credit: C. Doersch

这样做能得到什么“语义”信息？

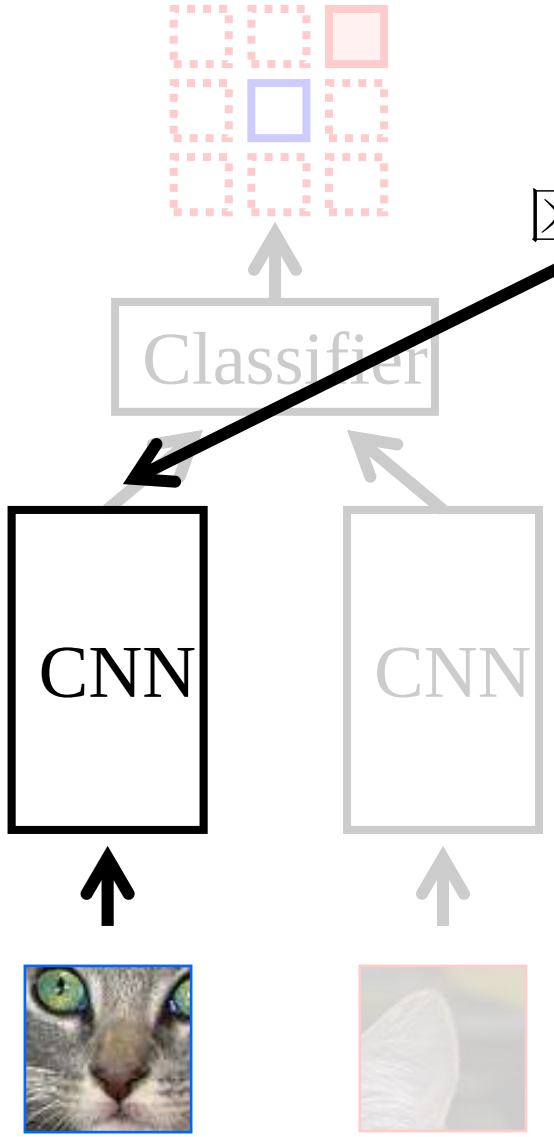


Slide Credit: C. Doersch

相对位置预测



Slide Credit: C. Doersch



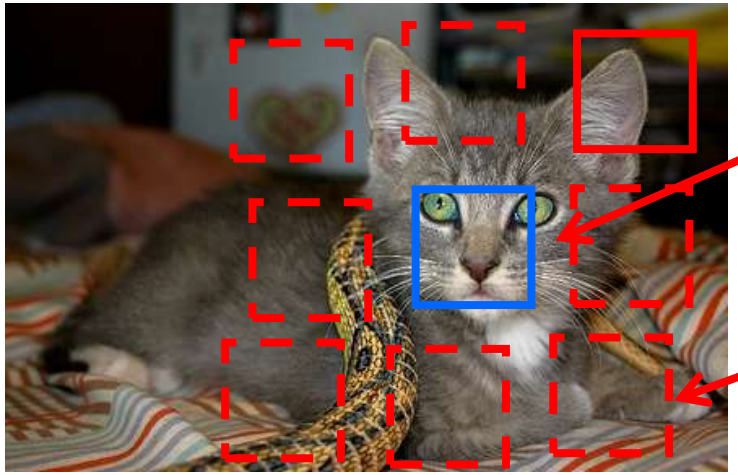
Input

最近邻

在不同的实体之间检索相似的部件

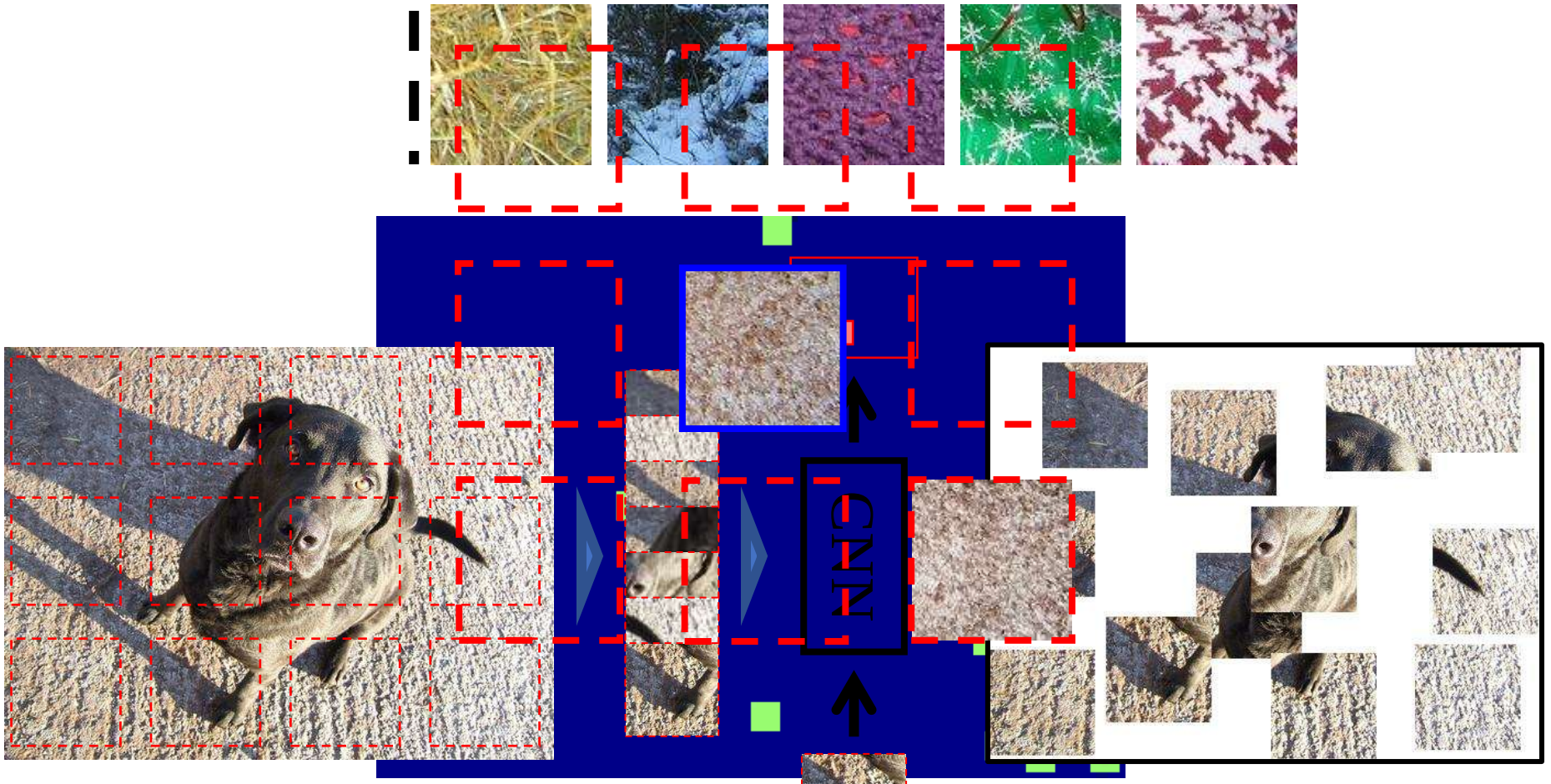
Slide Credit: C. Doersch

避免简单推断



Slide Credit: C. Doersch

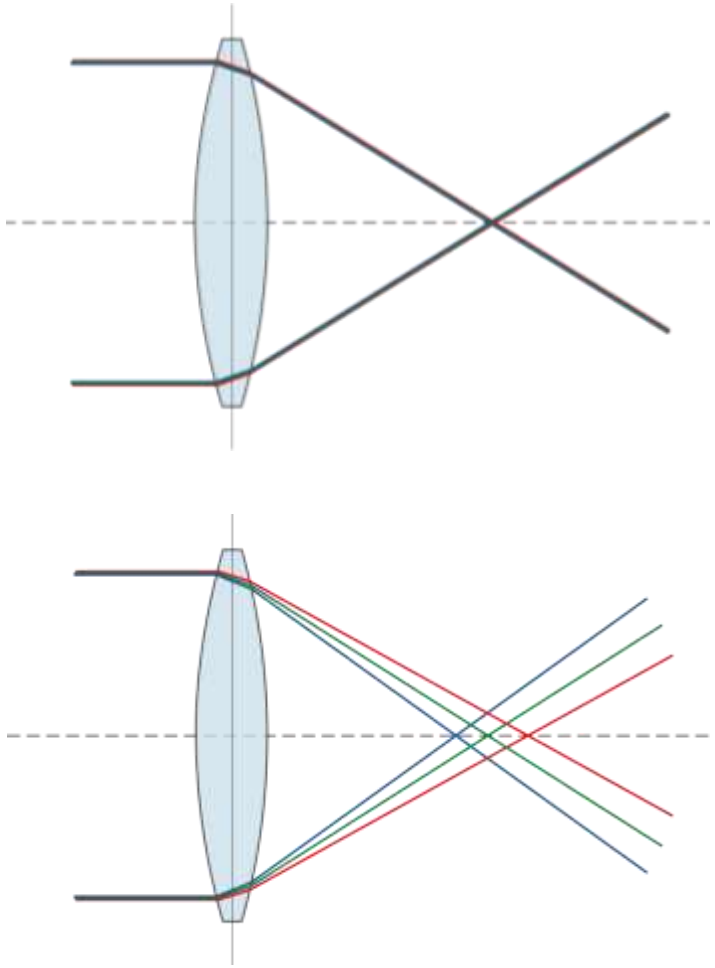
加入位置预测



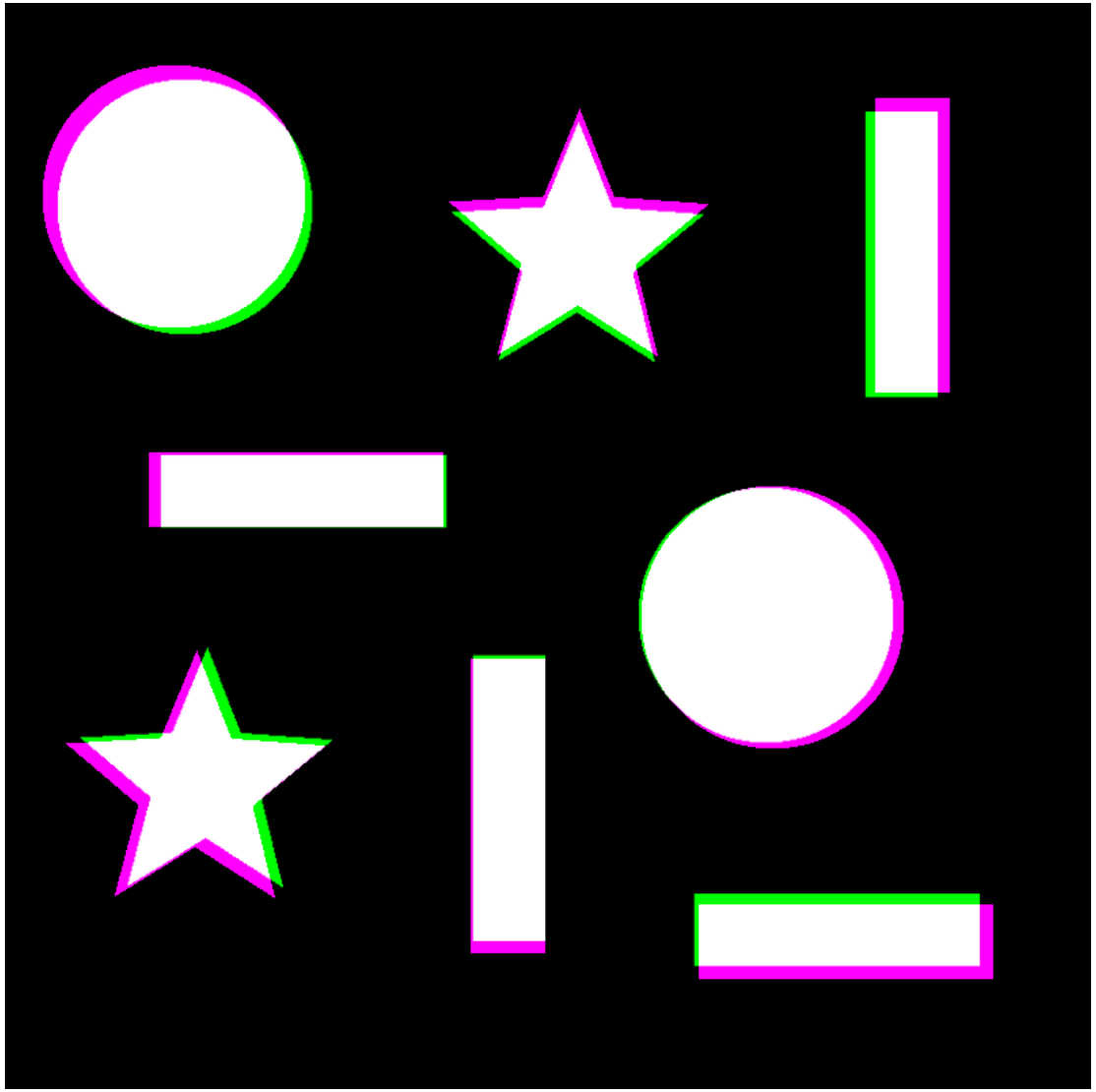
位置预测图

Slide Credit: C. Doersch

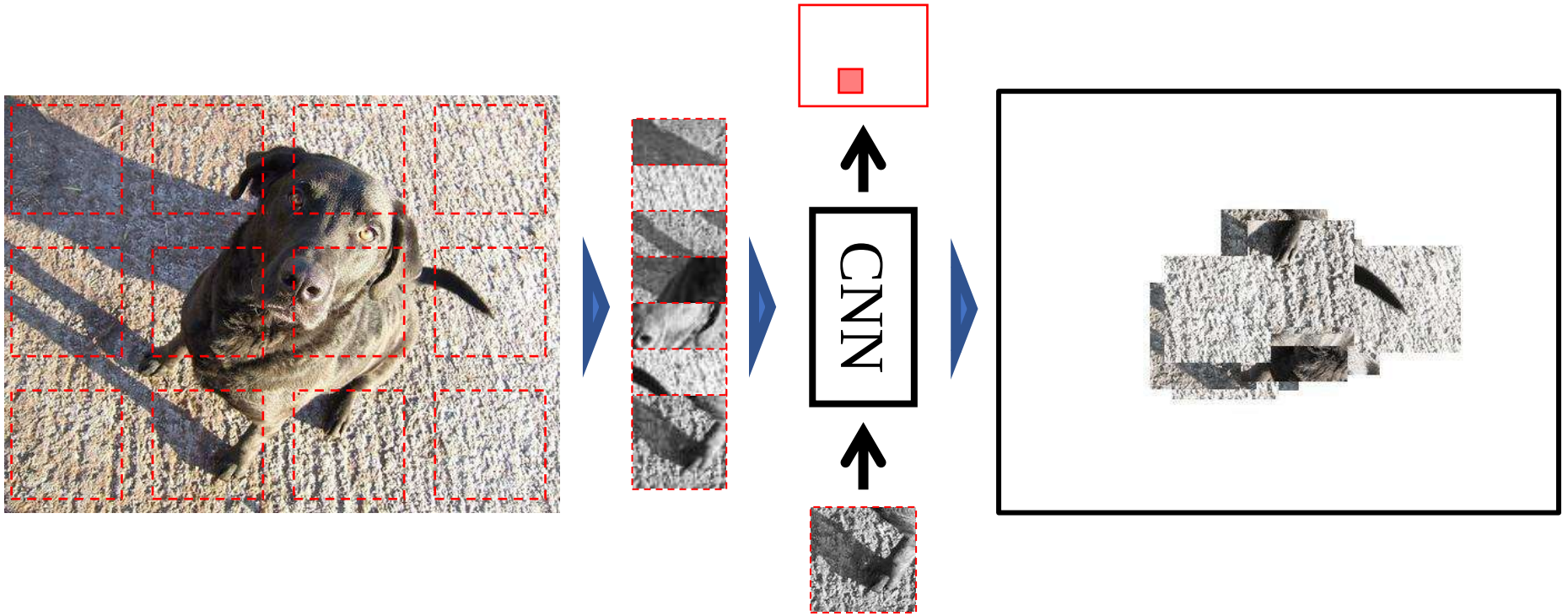
色差估计



Slide Credit: C. Doersch



去掉颜色以后。。。



Slide Credit: C. Doersch

这样做学到了什么？

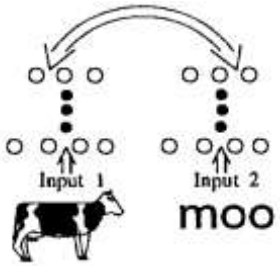
Slide Credit: C. Doersch

Variations: DINO

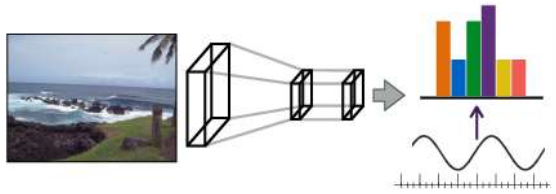
[cs.CV

Figure 1: **Self-attention from a Vision Transformer with 8×8 patches trained with no supervision.** We look at the self-attention of the `[CLS]` token on the heads of the last layer. This token is not attached to any label nor supervision. These maps show that the model automatically learns class-specific features leading to unsupervised object segmentations.

Audio

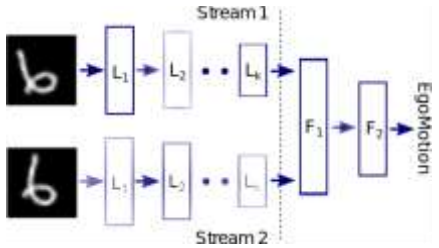


de Sa. NIPS 1994.



Owens et al. ECCV 2016.

Egomotion



Agrawal et al. ICCV 2015.

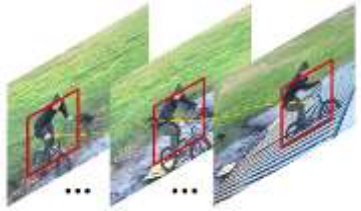
Jayaraman et al. ICCV 2015.

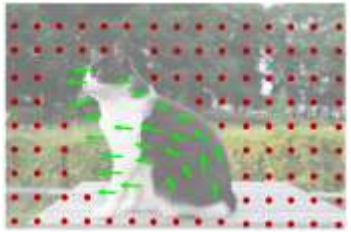
Context

Pathak et al. CVPR 2016.

Noroozi and Favaro. ECCV 2016.
Doersch et al. ICCV 2015.

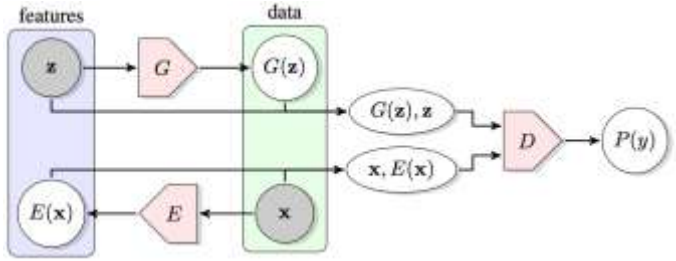
Video





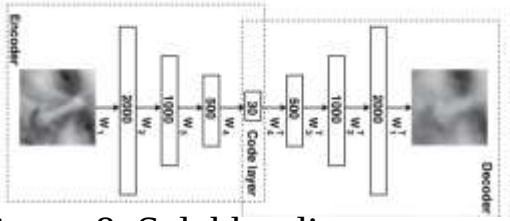
Wang et al. ICCV 2015. Pathak et al. CVPR 2017.
Misra et al. ECCV 2016.

Generative Modeling



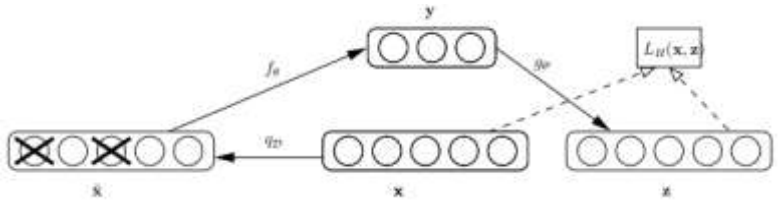
Donahue et al. Dumoulin et al. ICLR 2017.

Autoencoders



Hinton & Salakhutdinov.
Science 2006.

Denoising Autoencoders



Vincent et al. ICML 2008.

Goal: Set up a pre-training scheme to induce a “useful” representation

[Slide credit: Richard Zhang]

How Much Information is the Machine Given during Learning?

- **"Pure" Reinforcement Learning (cherry)**
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning (icing)**
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- **Self-Supervised Learning (cake génoise)**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

[Slide Credit: Yann LeCun]

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Summary

1. Deep nets learn *representations*, just like our brains do

2. This is useful because representations transfer — they act as prior knowledge that enables quick learning on new tasks

3. Representations can also be learned without labels, which is great since labels are expensive and limiting

4. Without labels there are many ways to learn representations. We saw:

    1. representations as compressed codes

    2. representations that are shared across sensory modalities

    3. representations that are predictive of their context