Neural Networks for Visual Recognition

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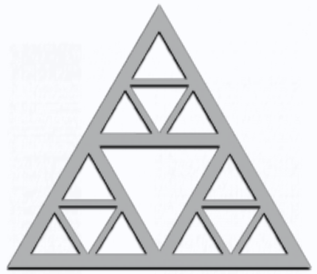
@RecVis, 05.11.2024



With many slides from: J. Sivic, R. Fergus, A. Vedaldi, A. Zisserman, S. Lazebnik, A. Karpathy, L. Fei Fei, M. Aubry, N. Murray, J. Johnson, K. Derpanis, S. Yeung, A. Amini, F. Fleuret

Announcements

Room for next weeks.

Assignment 2 due Tuesday Nov 12.

Assignment 3 Kaggle competition is out. (due Nov 26)

Custom final project topics: email in advance

Neural Networks

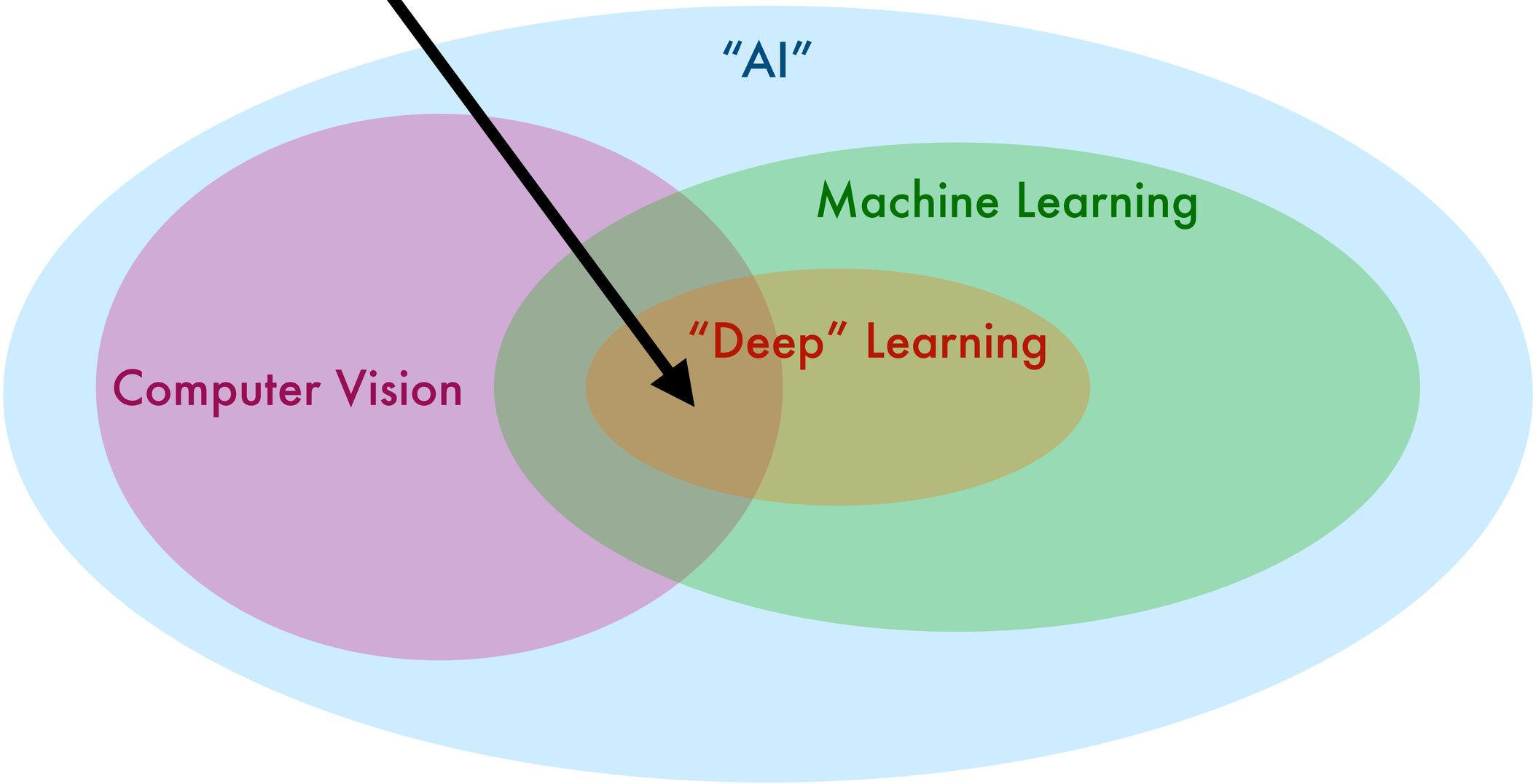
Last week: Introduction to neural networks

This week: Neural networks for **visual recognition:**

Convolutional Neural Networks (CNNs) for image classification

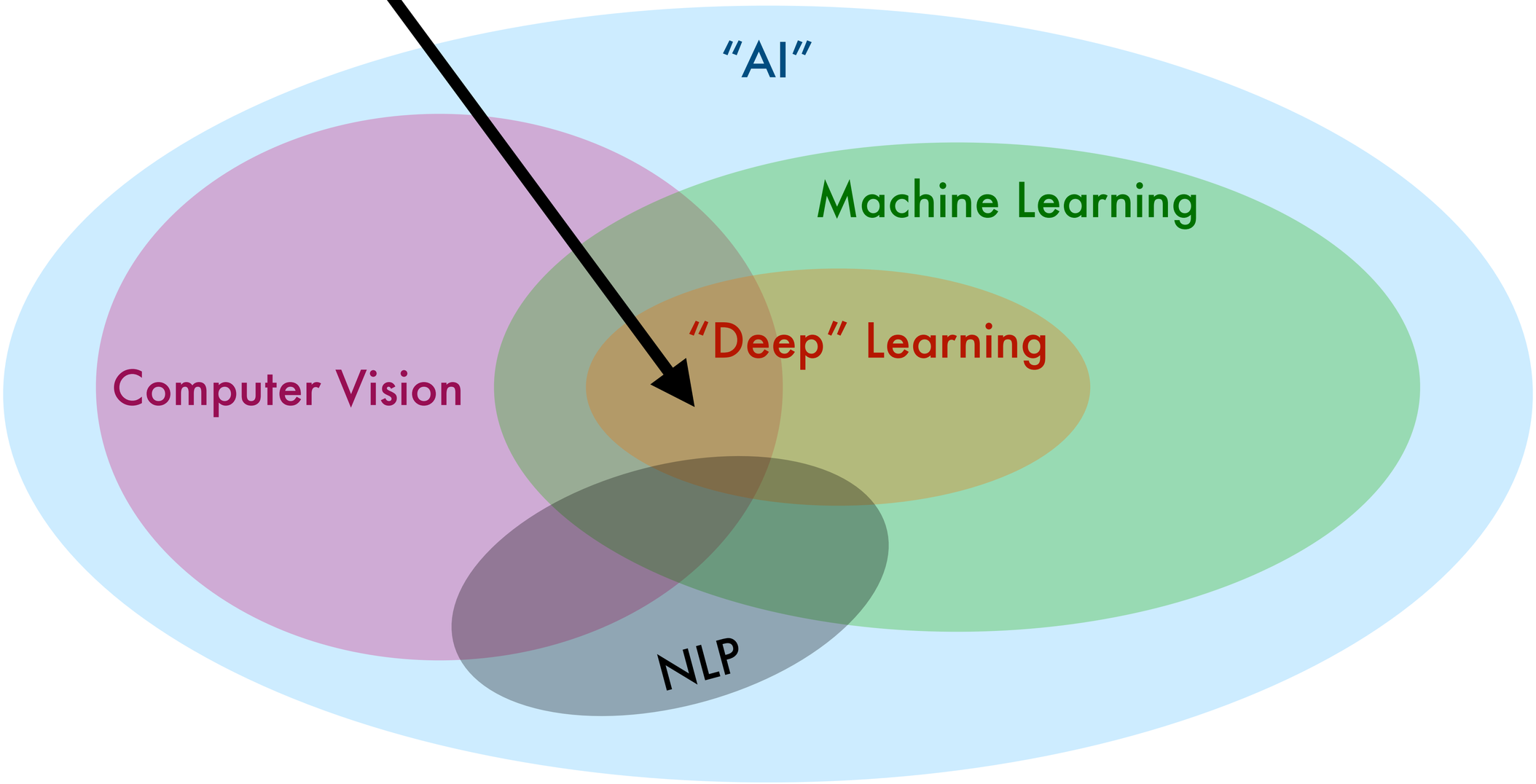
Next week: Beyond classification: Object detection, Segmentation, Human pose;
Beyond CNNs: Transformers

This lecture



Slide credit: Justin Johnson

This lecture



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Agenda

- **1. Recap: Bag of Visual Words, Analogy with NNs**

- **2. Neural networks (NNs) for computer vision:**
  - Applications
  - A brief history: from perceptron to MLPs to CNNs

- **3. Convolutional neural networks (CNNs)**
  - Standard layers
  - Recap: Training NNs
  - Visualizing CNNs
  - Pretraining & finetuning NNs
  - Typical CNN architectures

- **4. Beyond classification - preview**

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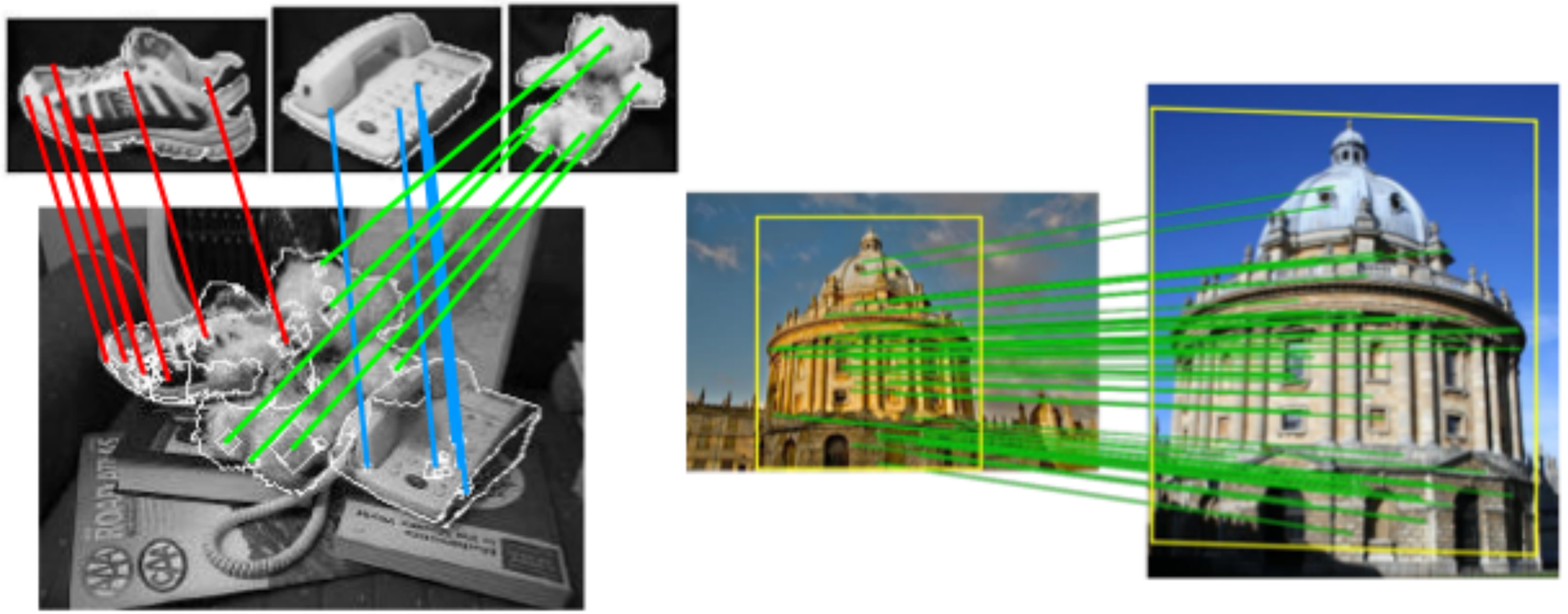
Recap: Image recognition so far

Instance-level recognition



Category Recognition

- Image classification: assigning a class label to the image

Car: present
Cow: present
Bike: not present
Horse: not present
…

Slide: C. Schmid

Category Recognition

- Image classification: assigning a class label to the image

Car: present
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…

- Object localization: define the location and the category

Location

Category

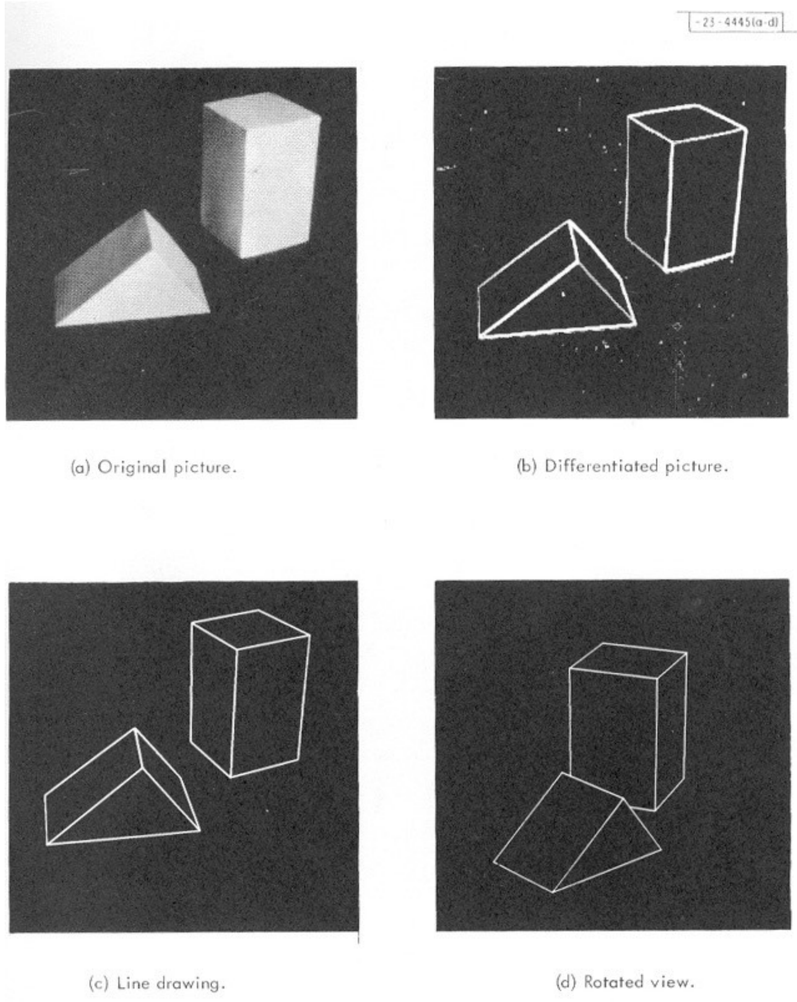
Slide: C. Schmid

Difficulties: within-class variations

Slide: C. Schmid

Why machine learning?

- Early approaches: simple features + handcrafted models
- Can handle only few images, simple tasks



L. G. Roberts, *Machine Perception of Three Dimensional Solids,*
Ph.D. thesis, MIT Department of Electrical Engineering, 1963.

ABSTRACT

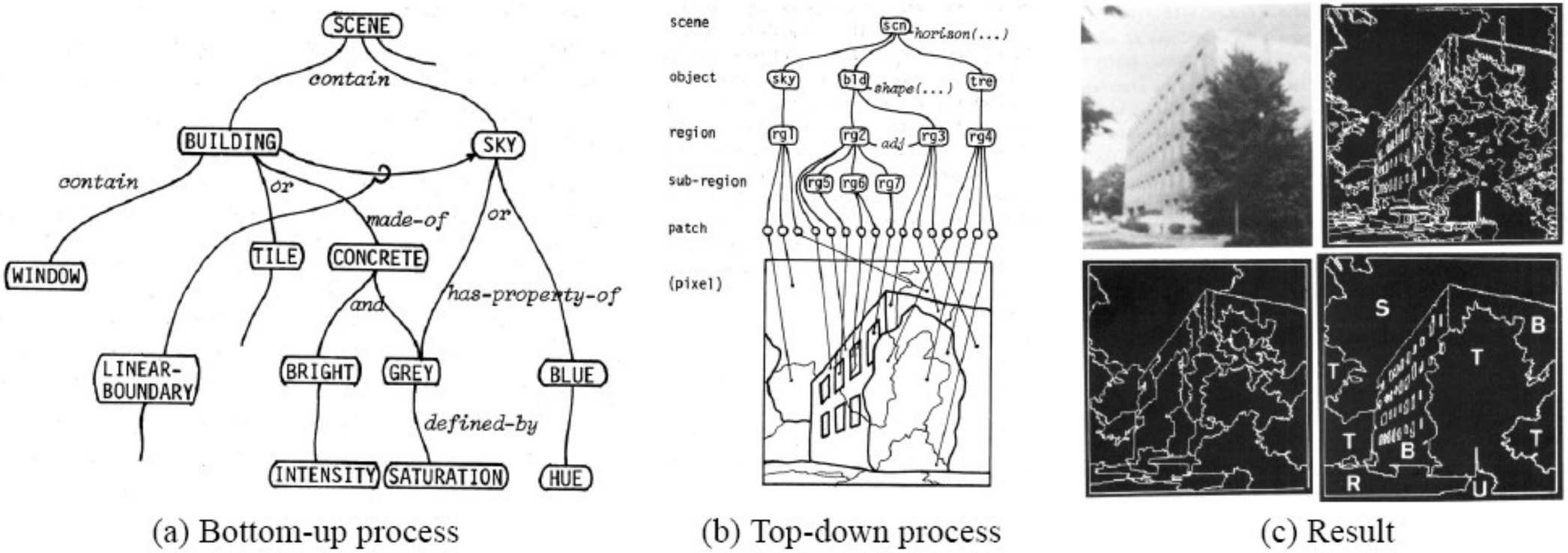
In order to make it possible for a computer to construct and display a three-dimensional array of solid objects from a single two-dimensional photograph, the rules and assumptions of depth perception have been carefully analyzed and mechanized. It is assumed that a photograph is a perspective projection of a set of objects which can be constructed from transformations of known three-dimensional models, and that the objects are supported by other visible objects or by a ground plane. These assumptions enable a computer to obtain a reasonable, three-dimensional description from the edge information in a photograph by means of a topological, mathematical process.

A computer program has been written which can process a photograph into a line drawing, transform the line drawing into a three-dimensional representation, and finally, display the three-dimensional structure with all the hidden lines removed, from any point of view. The 2-D to 3-D construction and 3-D to 2-D display processes are sufficiently general to handle most collections of planar-surfaced objects and provide a valuable starting point for future investigation of computer-aided three-dimensional systems.

Slide: C. Schmid

Why machine learning?

- Early approaches: manual programming of rules
- Tedious. limited. and does not take data into account



(a) Bottom-up process (b) Top-down process (c) Result

Figure 3. A system developed in 1978 by Ohta, Kanade and Sakai [33, 32] for knowledge-based interpretation of outdoor natural scenes. The system is able to label an image (c) into semantic classes: S-sky, T-tree, R-road, B-building, U-unknown.

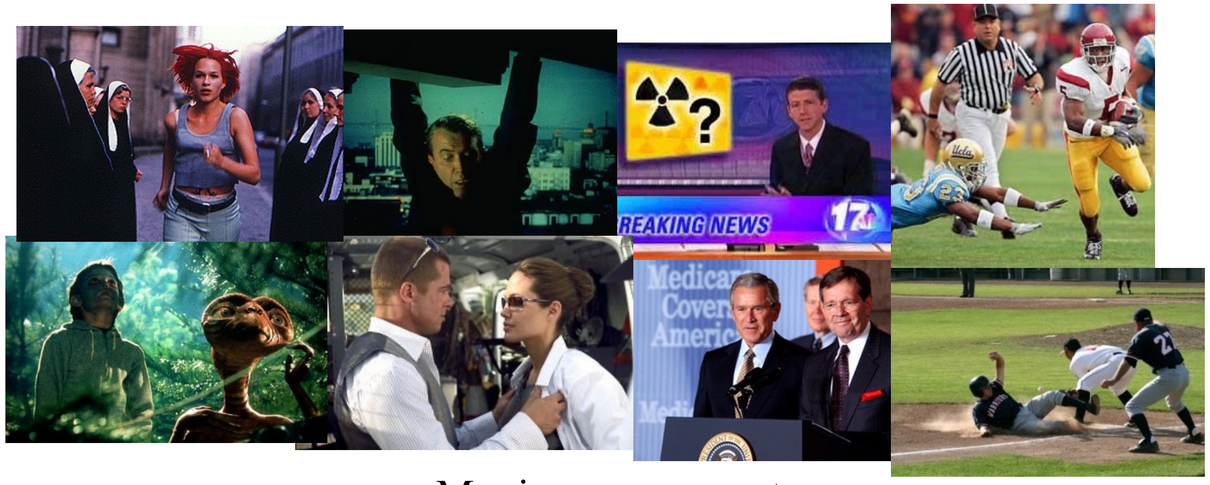
*Y. Ohta, T. Kanade, and T. Sakai, "*An Analysis System for Scenes Containing objects with Substructures,"
International Joint Conference on Pattern Recognition, 1978.

Slide: C. Schmid

Why machine learning?

- Today lots of data, complex tasks

Internet images,
personal photo albums



Movies, news, sports

- Instead of trying to encode rules directly, learn them from examples of inputs and desired outputs

Slide: C. Schmid

Texture Classification

- Profound observation: Grass and sea pictures don't look the same!

- Basic idea: Model the distribution of "texture" over the image (or over a region) and classify in different classes based on the texture models learned from training examples.

Grass

Sea

Image categorization

- Profound observation: Cows and buildings don't look the same!

- Basic idea: Model the distribution of "texture" over the image (or over a region) and classify in different classes based on the texture models learned from training examples.

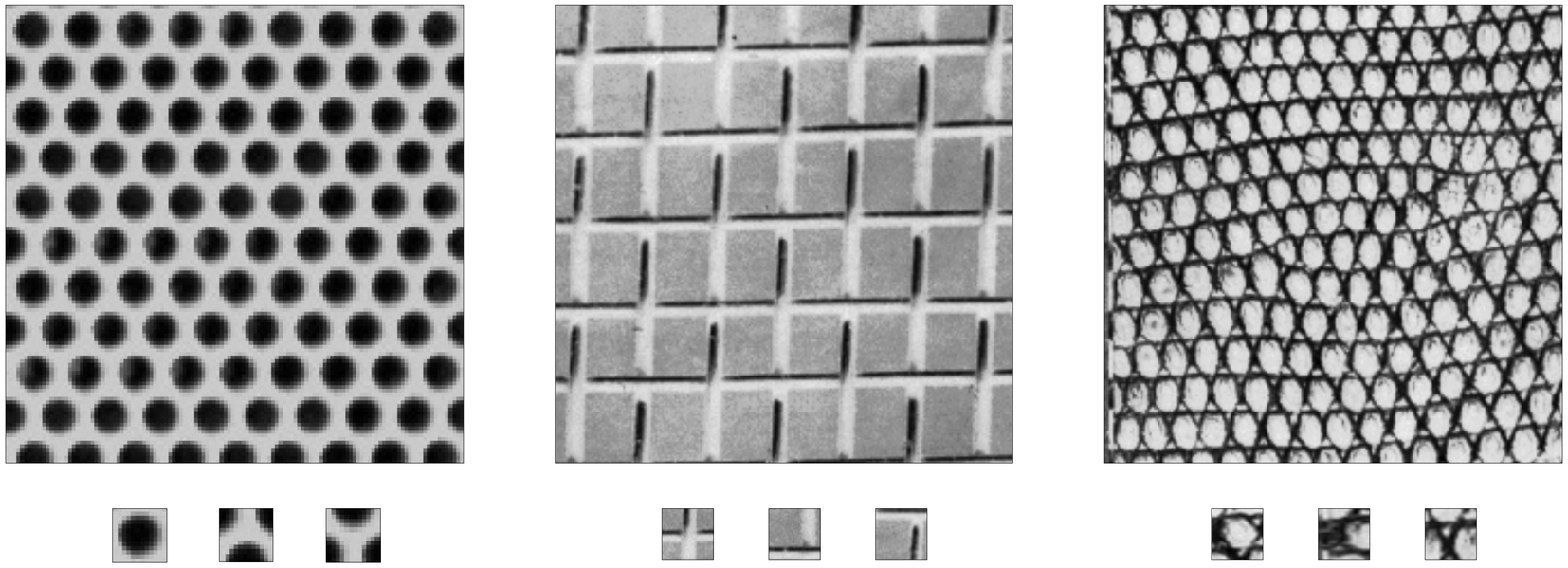
Cow

Building

Bag-of-features for image classification

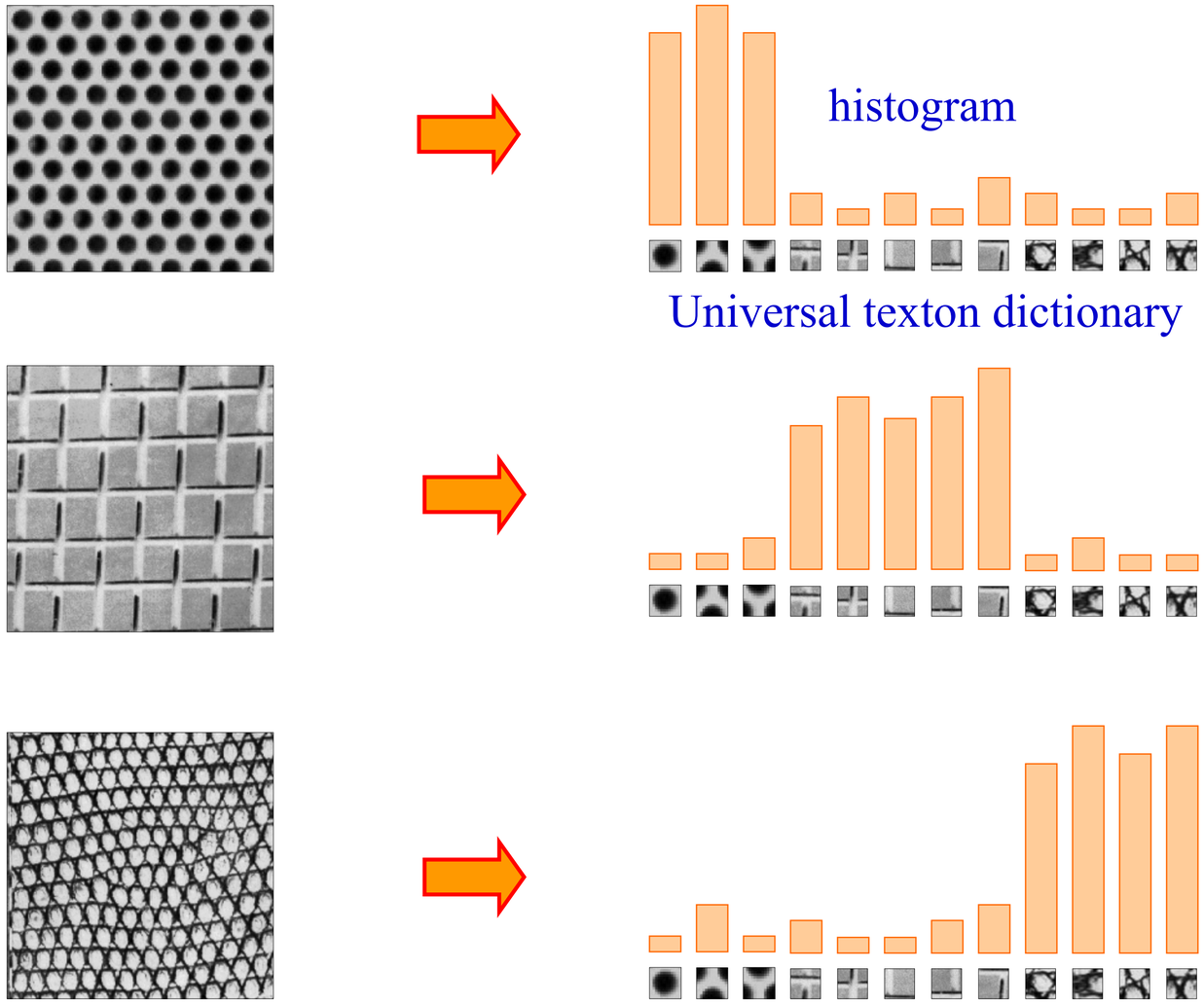
Origin: texture recognition

- Texture is characterized by the repetition of basic elements or *textons*



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

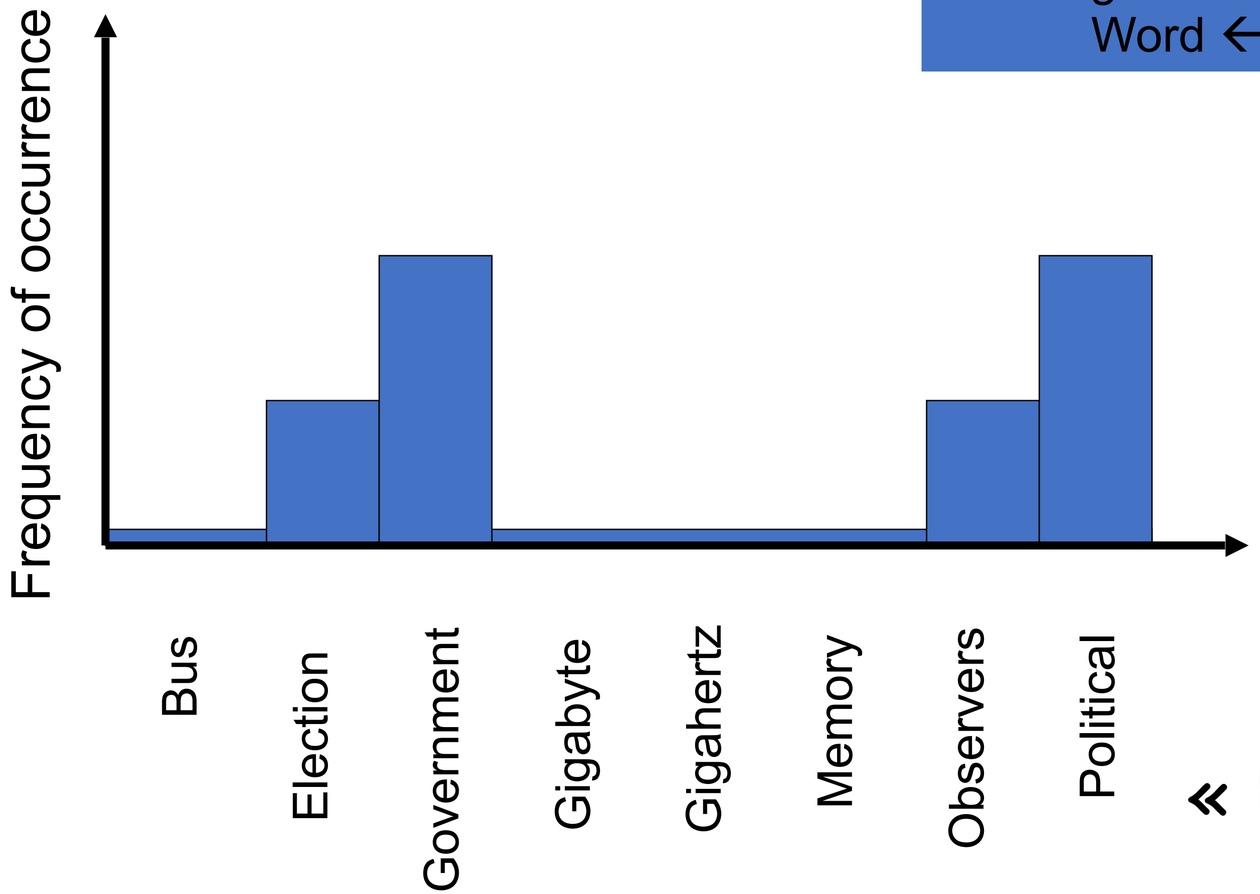
Bag-of-features for image classification



Analogy with Text Analysis

Political observers say that the government of Zorgia does not control the political situation. The government will not hold elections …

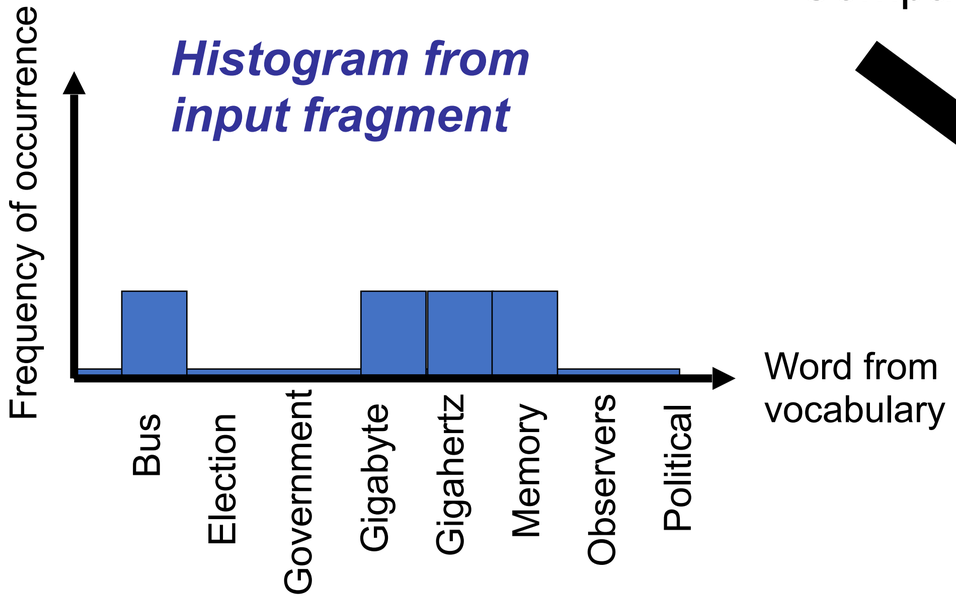
Analogy:
Text fragment ←→ Image region
Word ←→ Texton



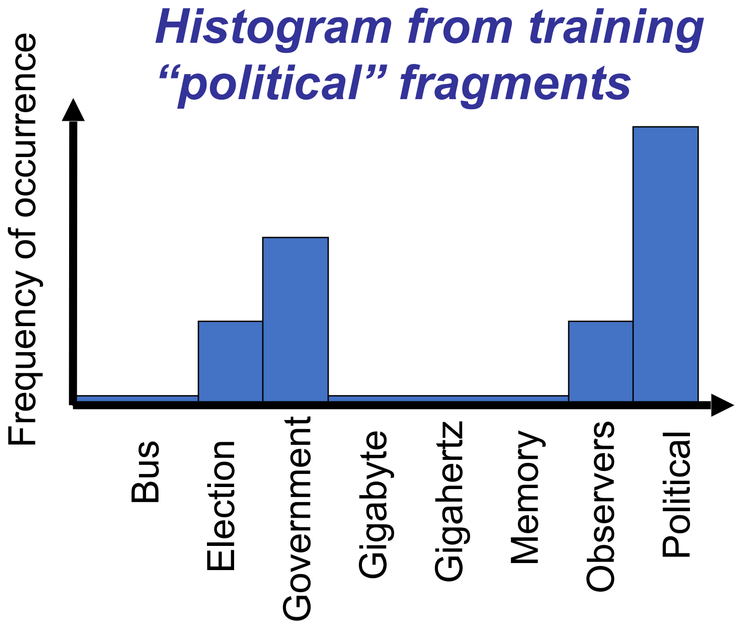
« Bag of words »

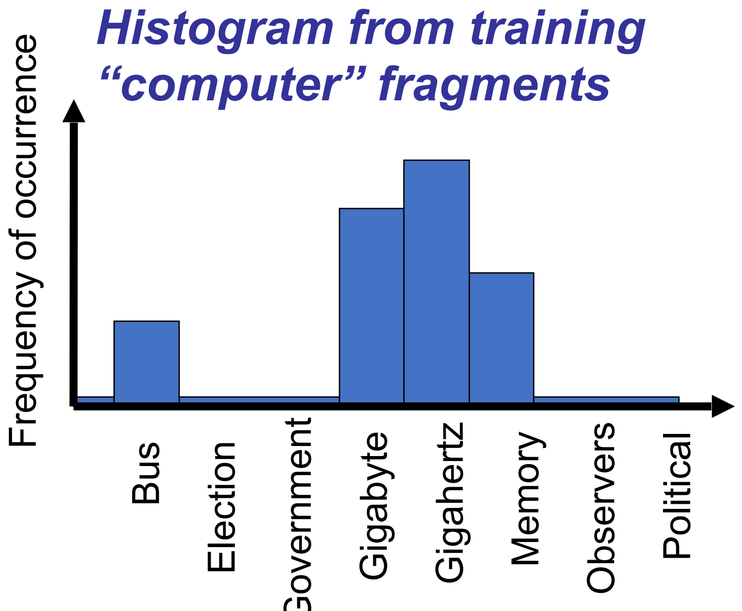
Analogy with Text Analysis

The ZH-20 unit is a 200Gigahertz processor with 2Gigabyte memory. Its strength is its bus and high-speed memory……

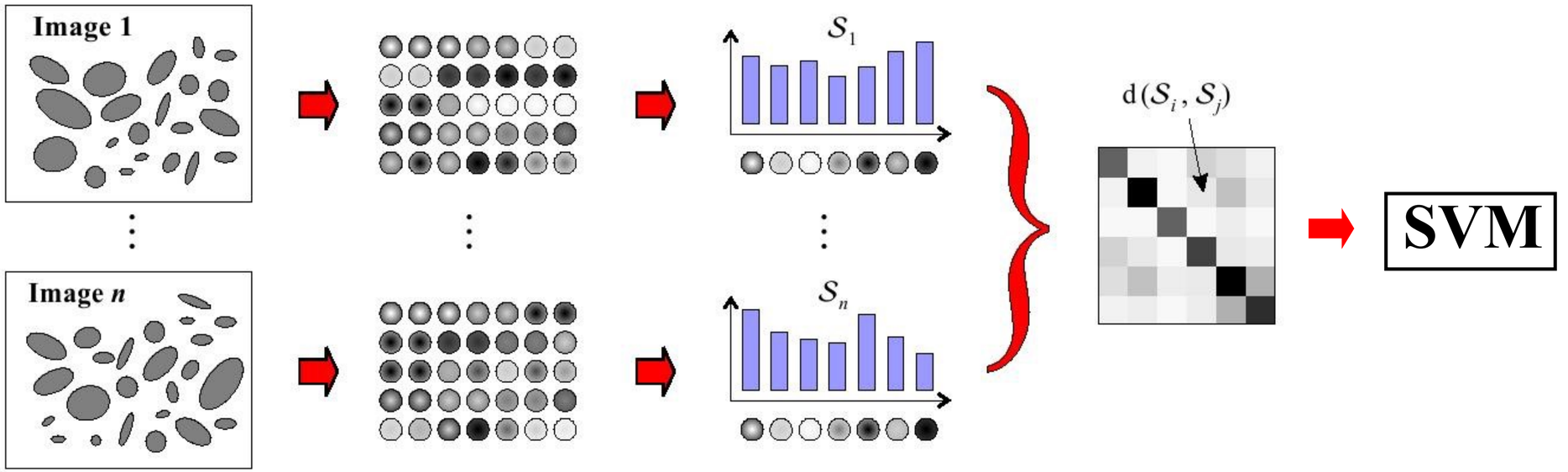


Compare



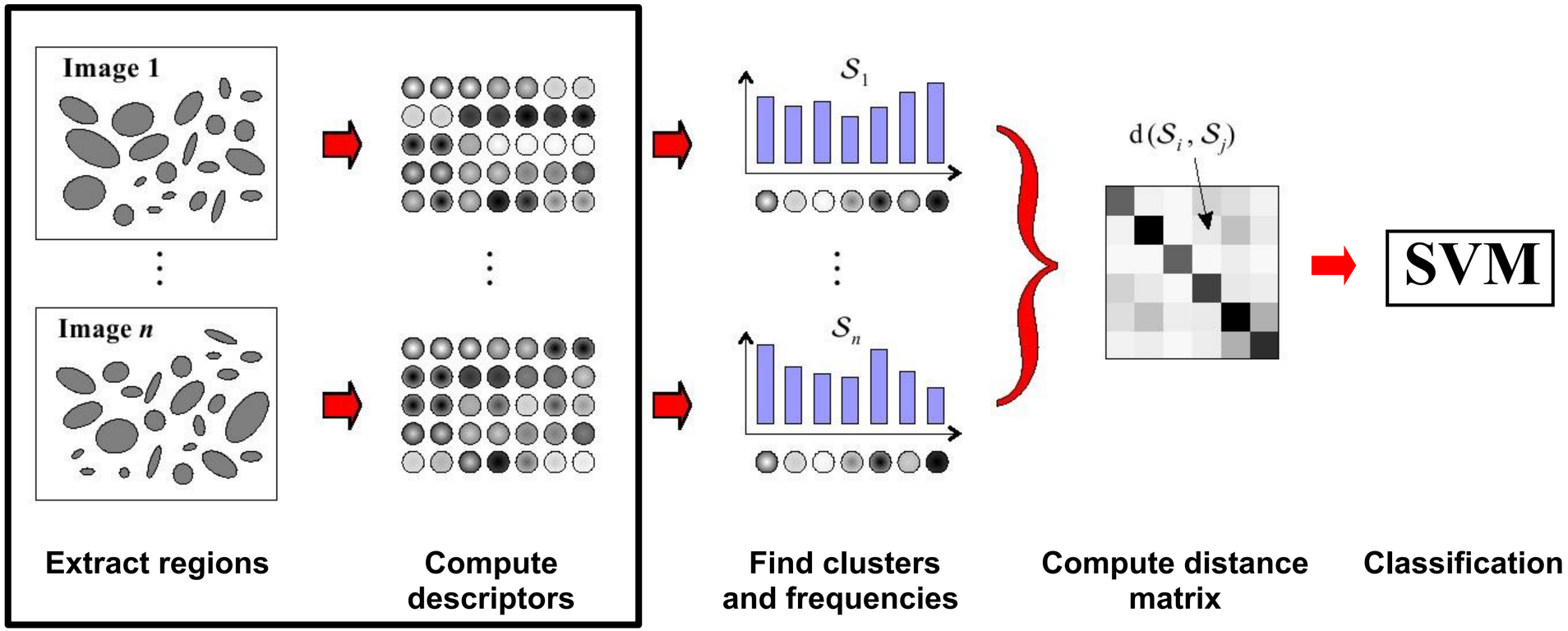


Bag-of-features for image classification



[Csurka et al. WS'2004], [Nowak et al. ECCV'06], [Zhang et al. IJCV'07]

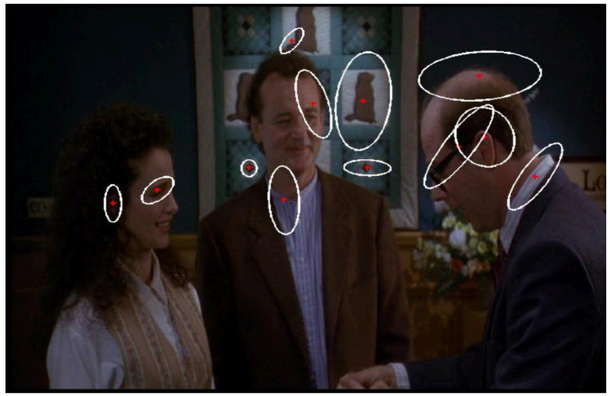
Bag-of-features for image classification



Step 1: feature extraction

Sparse sampling

- SIFT as interest point detector



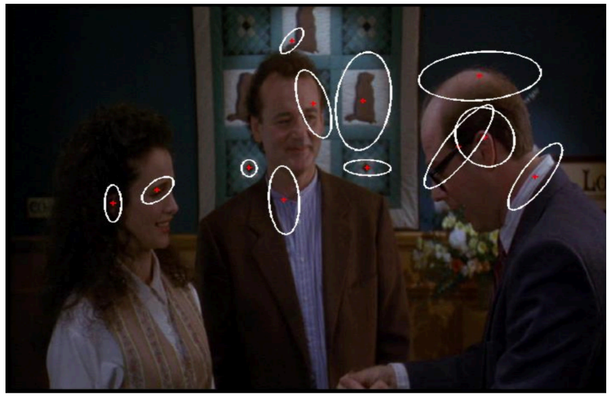
Dense sampling

- Interest points do not necessarily capture “all” features

Step 1: feature extraction

Sparse sampling

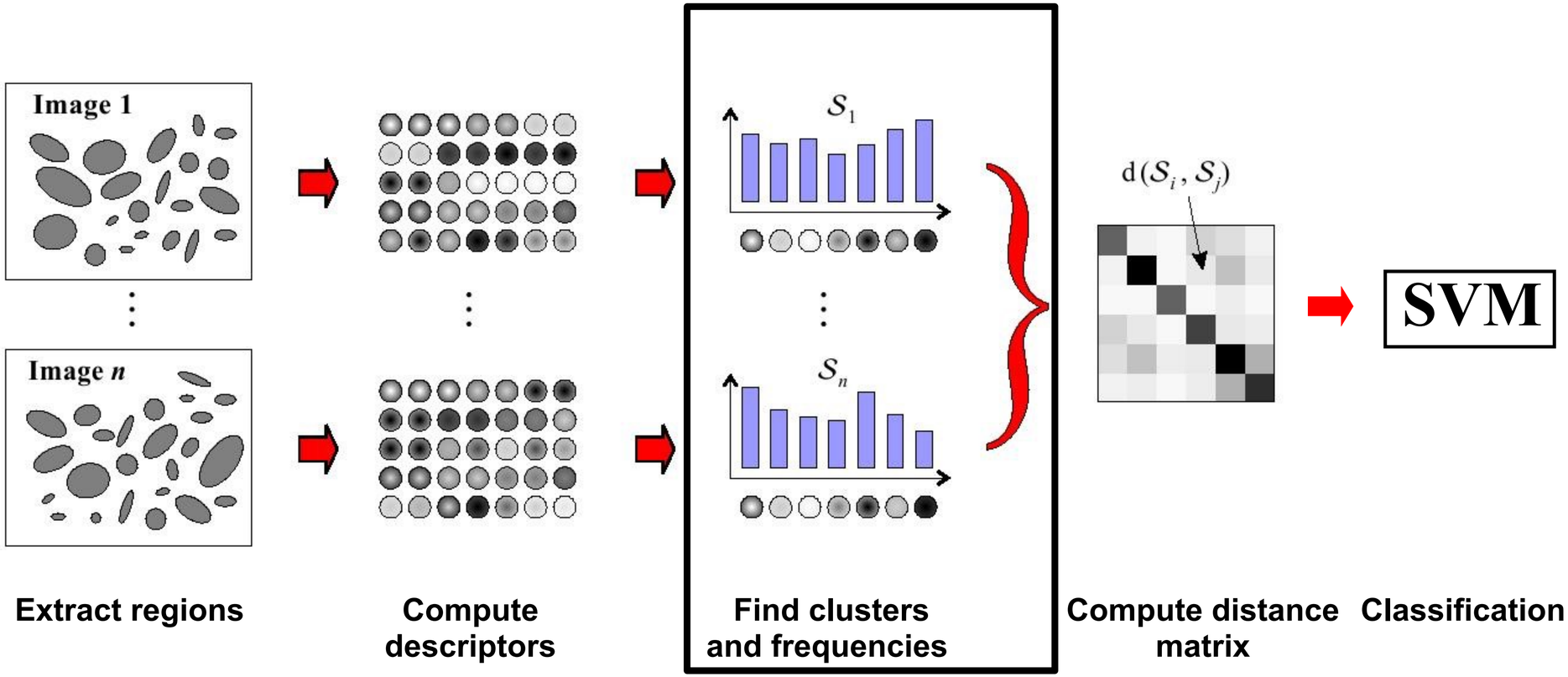
- SIFT as interest point detector



Dense sampling

- Interest points do not necessarily capture “all” features
- Spatial pyramid (Lazebnik, Schmid & Ponce, CVPR 2006)

Bag-of-features for image classification



Step 2: Quantization

Cluster descriptors

- K-means
- Gaussian mixture model

Assign each visual word to a cluster

- Hard or soft assignment

Build frequency histogram

Examples for visual words

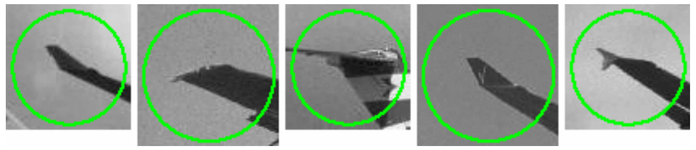
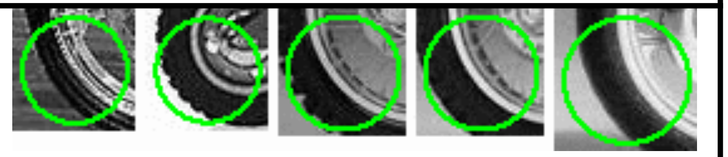
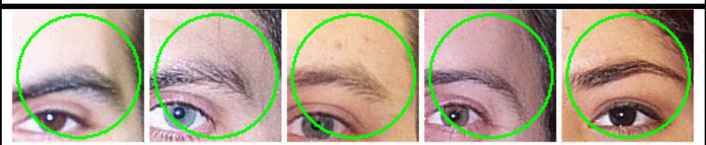
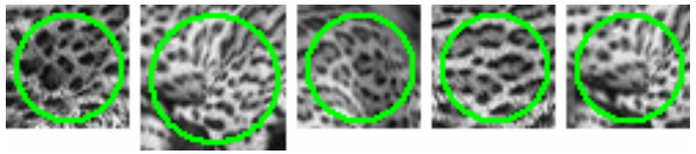
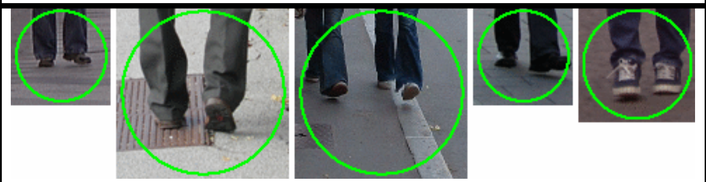
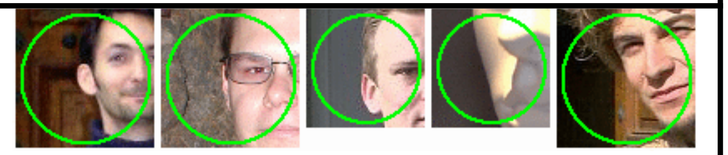
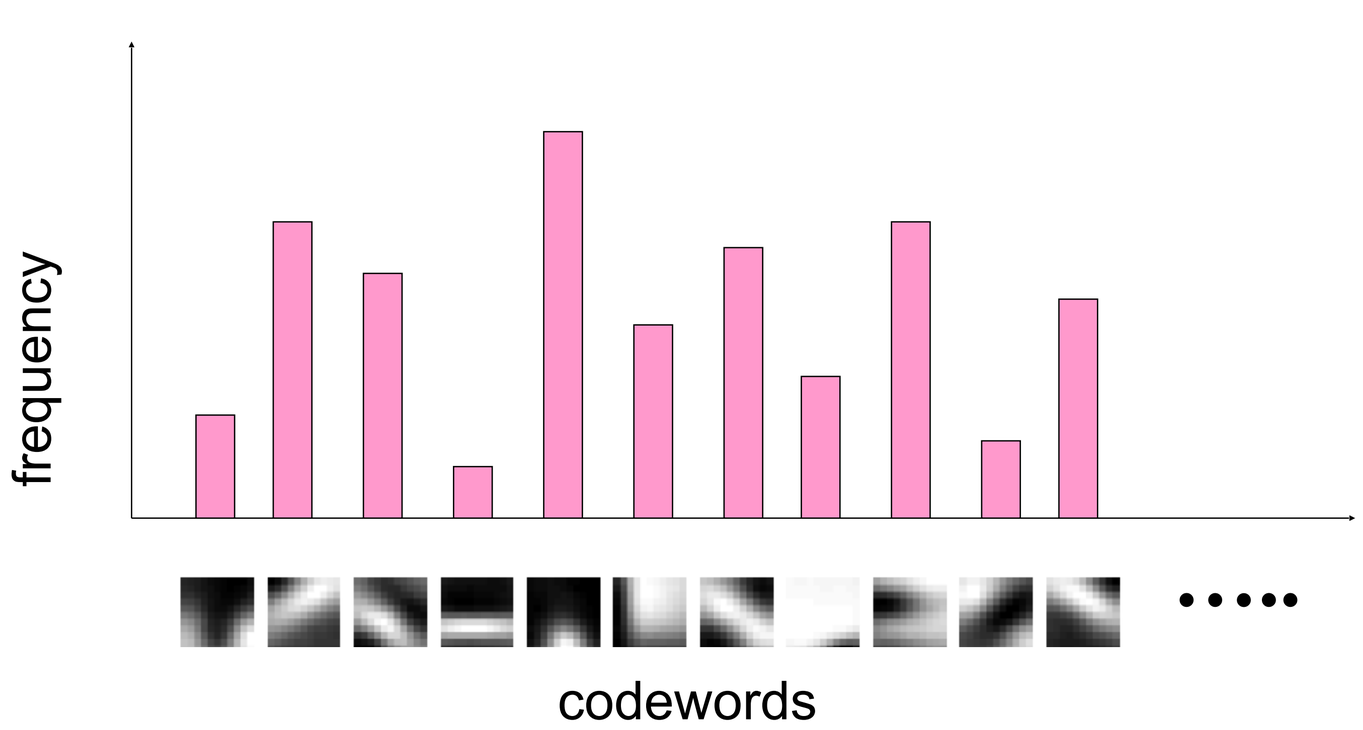
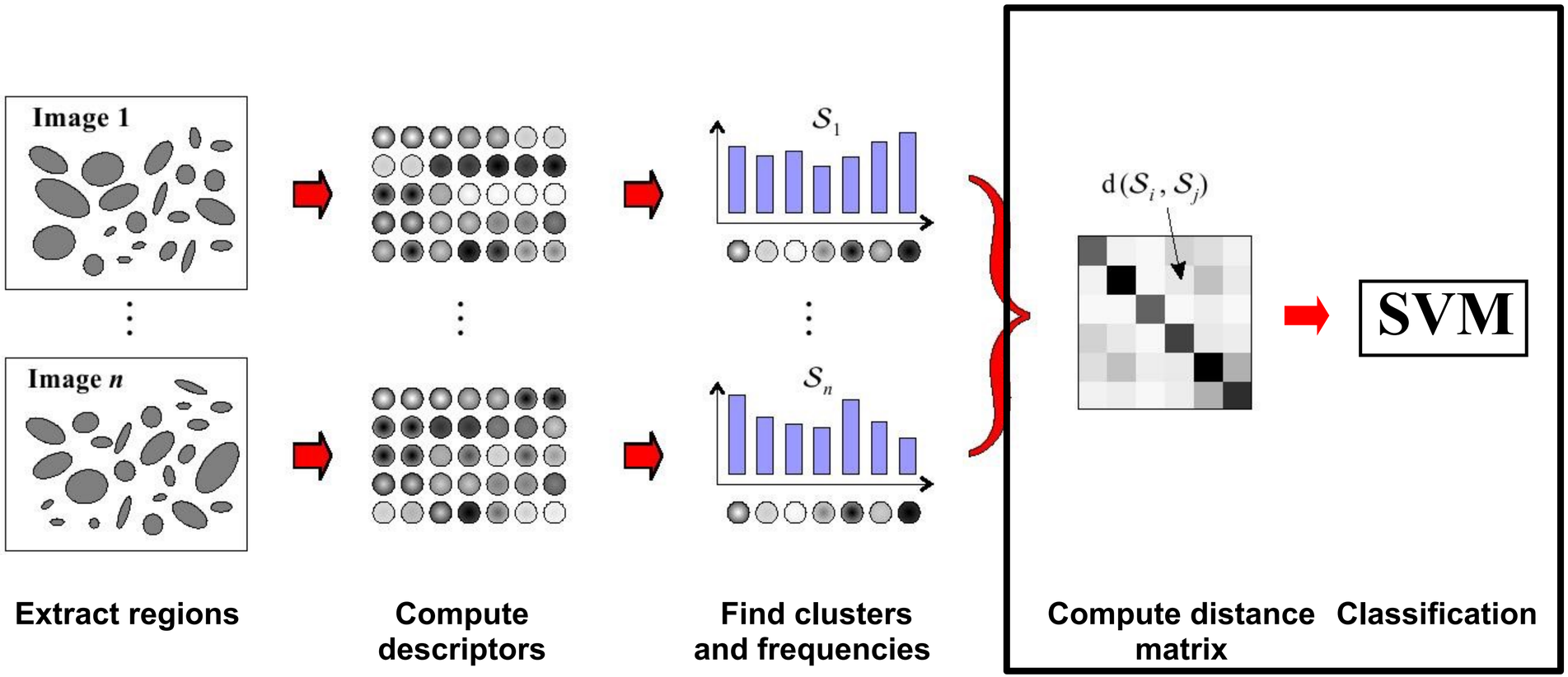
Airplanes		
Motorbikes		
Faces		
Wild Cats		
Leaves		
People		
Bikes		

Image representation



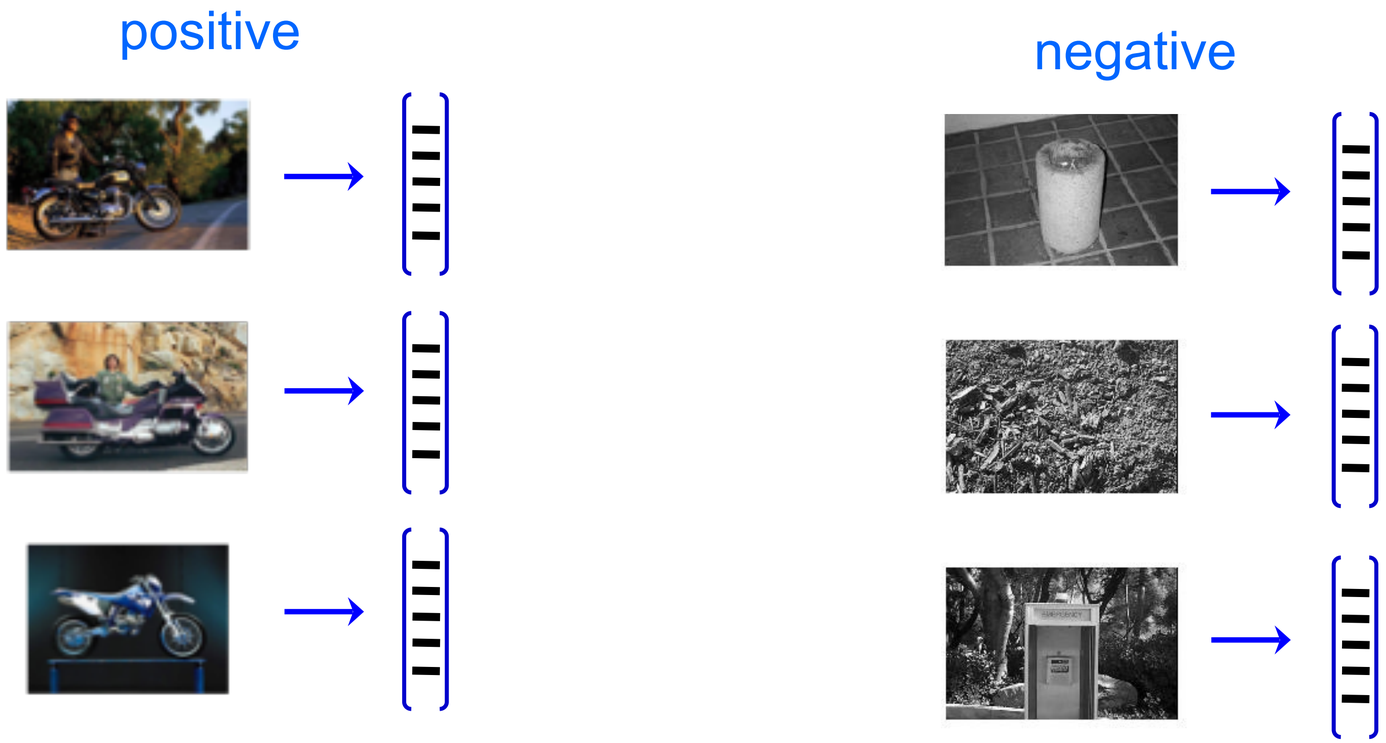
- Each image is represented by an aggregated histogram vector, typically 1000-4000 dimensional
- Normalized with L2 norm
- Fisher Vectors [Perronnin et al. ECCV'10]: improvements over Bag of Features

Bag-of-features for image classification



Step 3: Classification

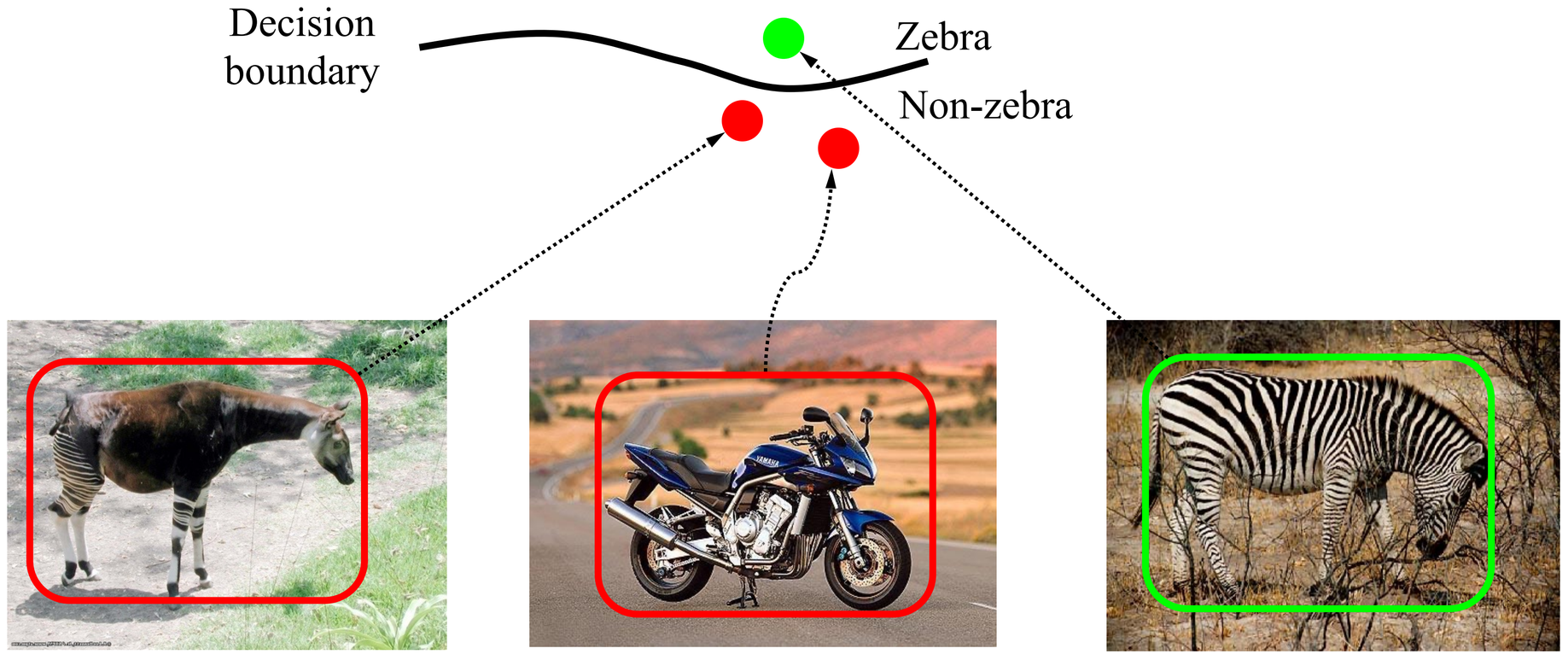
Training data: Vectors are histograms, one from each image



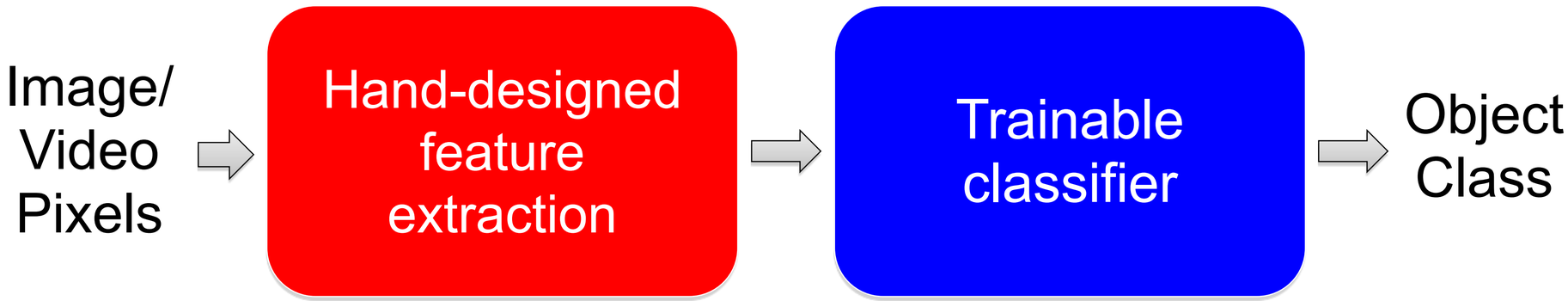
Train classifier,e.g. SVM

Step 3: Classification

Learn a decision rule (classifier) assigning bag-of-features representations of images to different classes

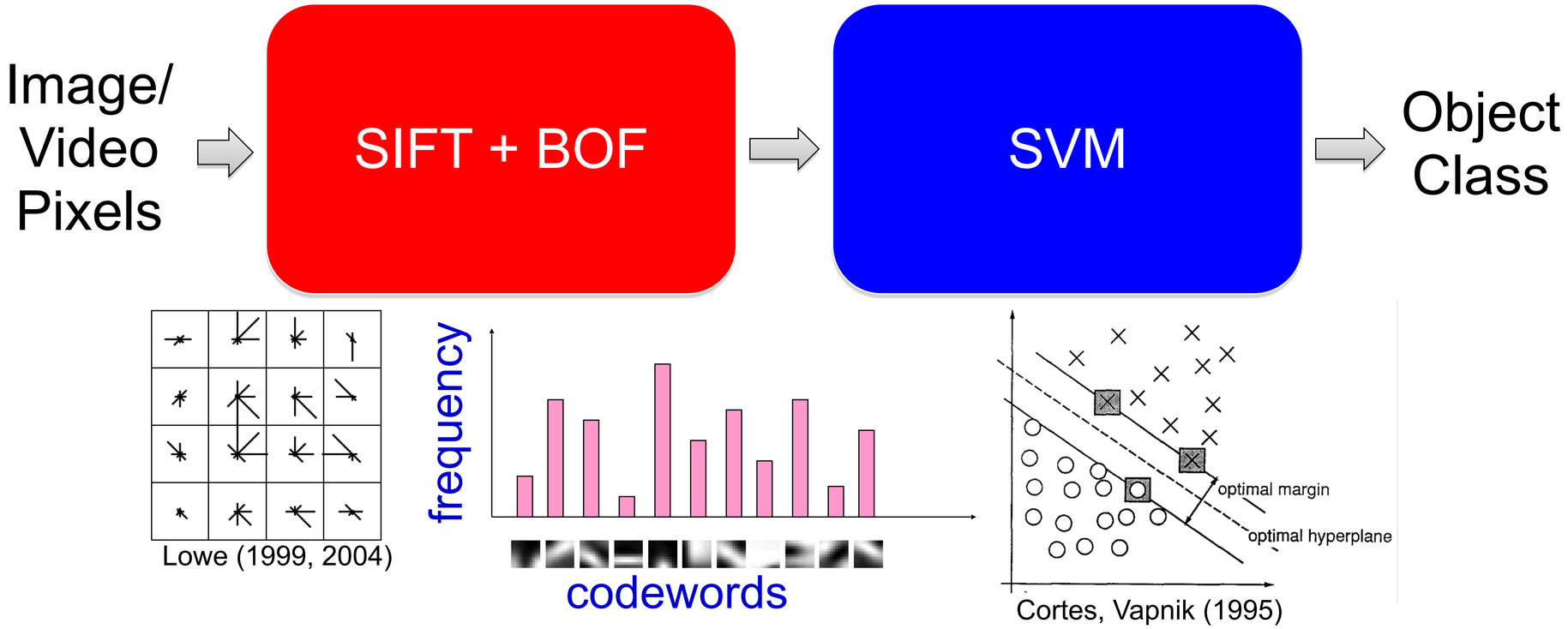


Traditional Recognition Approach



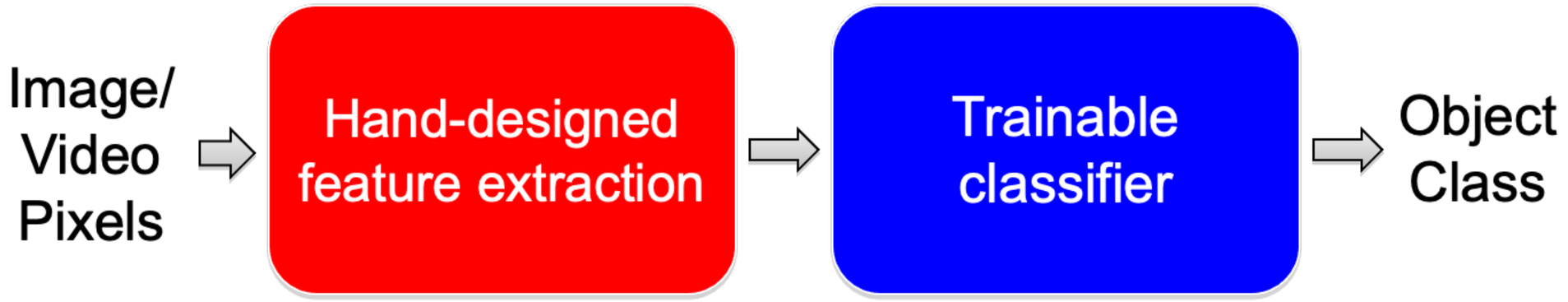
Slide: R. Fergus / S. Lazebnik

Traditional Recognition Example



- SIFT features
- BOF: Bag of Features / Visual Words (inspired by Bag of Words in NLP)
- SVM: Support Vector Machines for classification

Analogy to the traditional visual recognition pipeline



- Features are not learned (e.g., HOG, SIFT, Bag of Features)
- Trainable classifier is often generic (e.g., SVM, Random Forest)

Slide: R. Fergus / S. Lazebnik

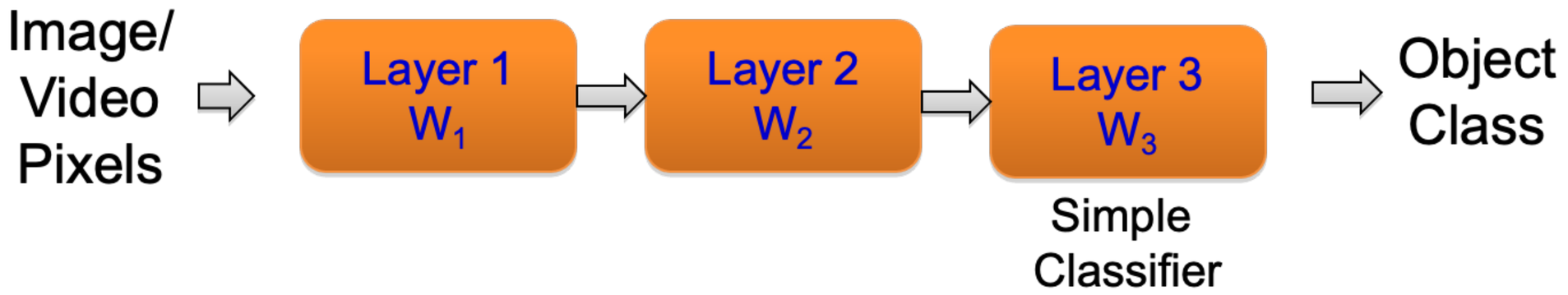
Analogy to the traditional visual recognition pipeline

What about learning the features?

- Features are learned "end-to-end" (i.e., pixels are input)
- "Feature hierarchy" all the way from pixels to classifier
- Each layer extracts features from the output of previous layer
- Train all layers jointly

Slide: R. Fergus / S. Lazebnik

Analogy to the traditional visual recognition pipeline



- Features are learned "end-to-end" (i.e., pixels are input)
- "Feature hierarchy" all the way from pixels to classifier
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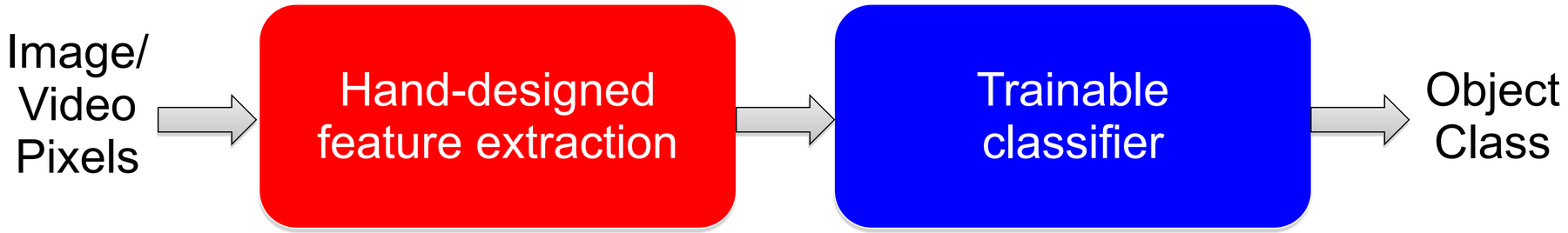
Slide: R. Fergus / S. Lazebnik

“Shallow” vs. “deep” models

Traditional recognition: “Shallow” architecture



Deep learning: “Deep” architecture

Slide: R. Fergus / S. Lazebnik

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Neural Networks in Production

Face detection

Slide credit: Kosta Derpanis

Self-driving cars / Autonomous vehicles

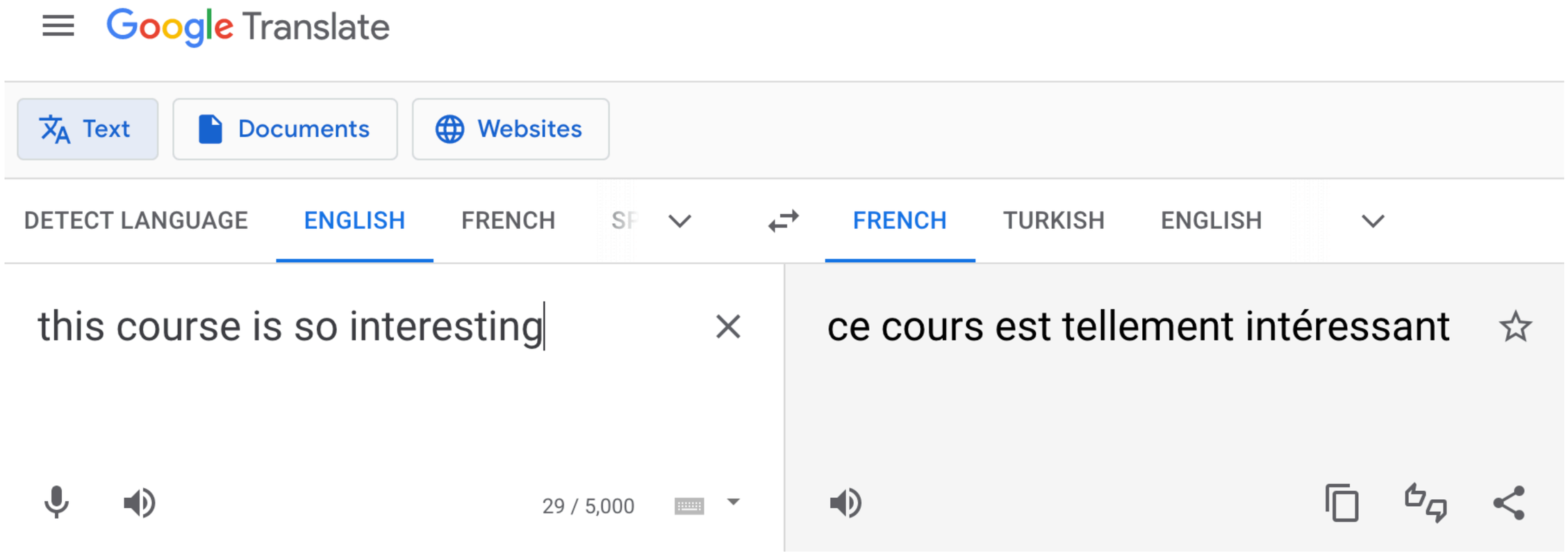
"We've built an AV that is seamlessly integrating into traffic in Munich, **Paris**, Detroit, Jerusalem, New York, Tokyo, and other cities across the globe."

mobileye™

Shopping

Slide credit: Kosta Derpanis

Google Translate



What is “Deep” Learning?

Recap: Basics of supervised learning

- n training data pairs $(x_1, y_1), ..., (x_n, y_n) \in \mathcal{X} \times \mathcal{Y}$
- Learn a predictor/decision function $\hat{f} : \mathcal{X} \to \mathcal{A}$
- By minimizing $\sum_{i=1}^{n} l(f(x_i), y_i)$

Recap: Basics of supervised learning

- n training data pairs
- Learn a predictor/decision function
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$$(x_1, y_1), \ldots, (x_n, y_n) \in \mathcal{X} \times \mathcal{Y}$$

$$\hat{f} : \mathcal{X} \to \mathcal{A}$$

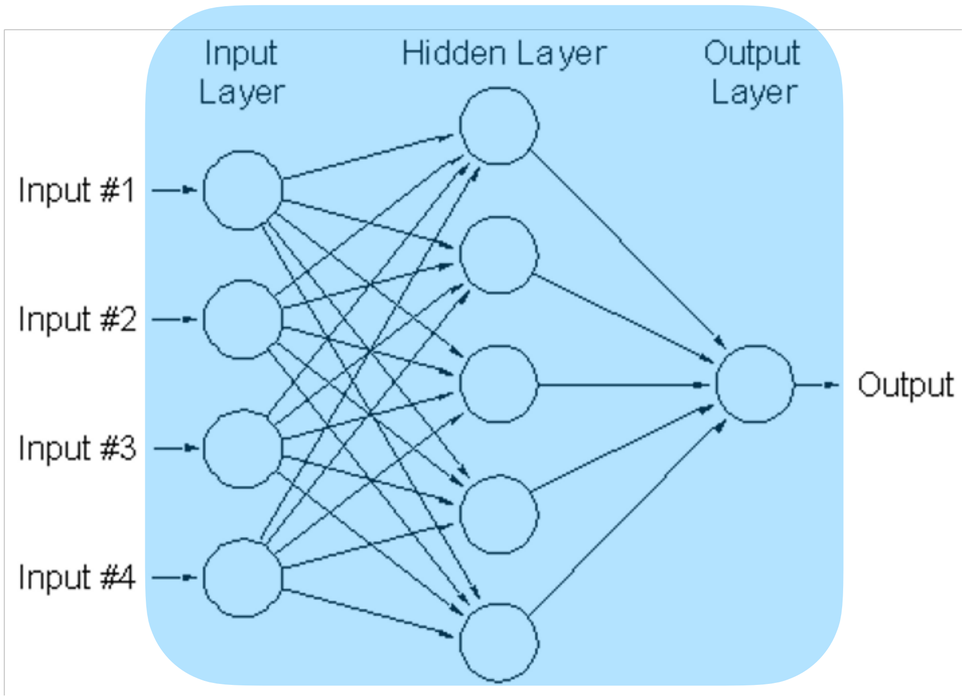
$$\sum_{i=1}^{n} l(f(x_i), y_i)$$

Loss Model Input Label

Deep learning

$$\sum_{i=1}^{n} l(f(x_i), y_i)$$

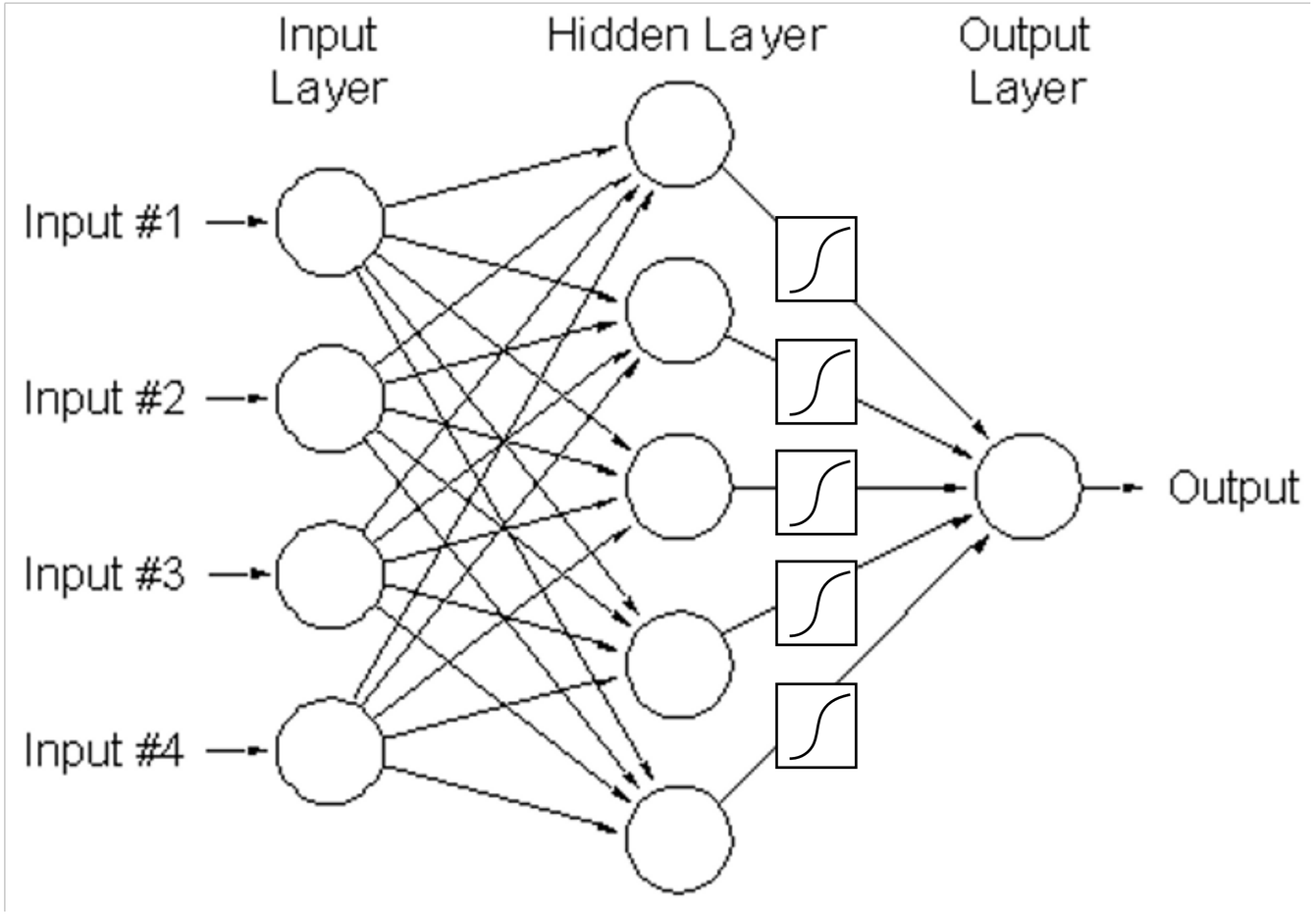
Loss Model Input Label



Deep learning:
Model = neural network

What is a “deep” neural network?

Stacking more than one **layer**



W_1 (Layer 1)

W_2 (Layer 2)

What is a layer?

Typically matrix multiplication! (But the function can take many forms*)

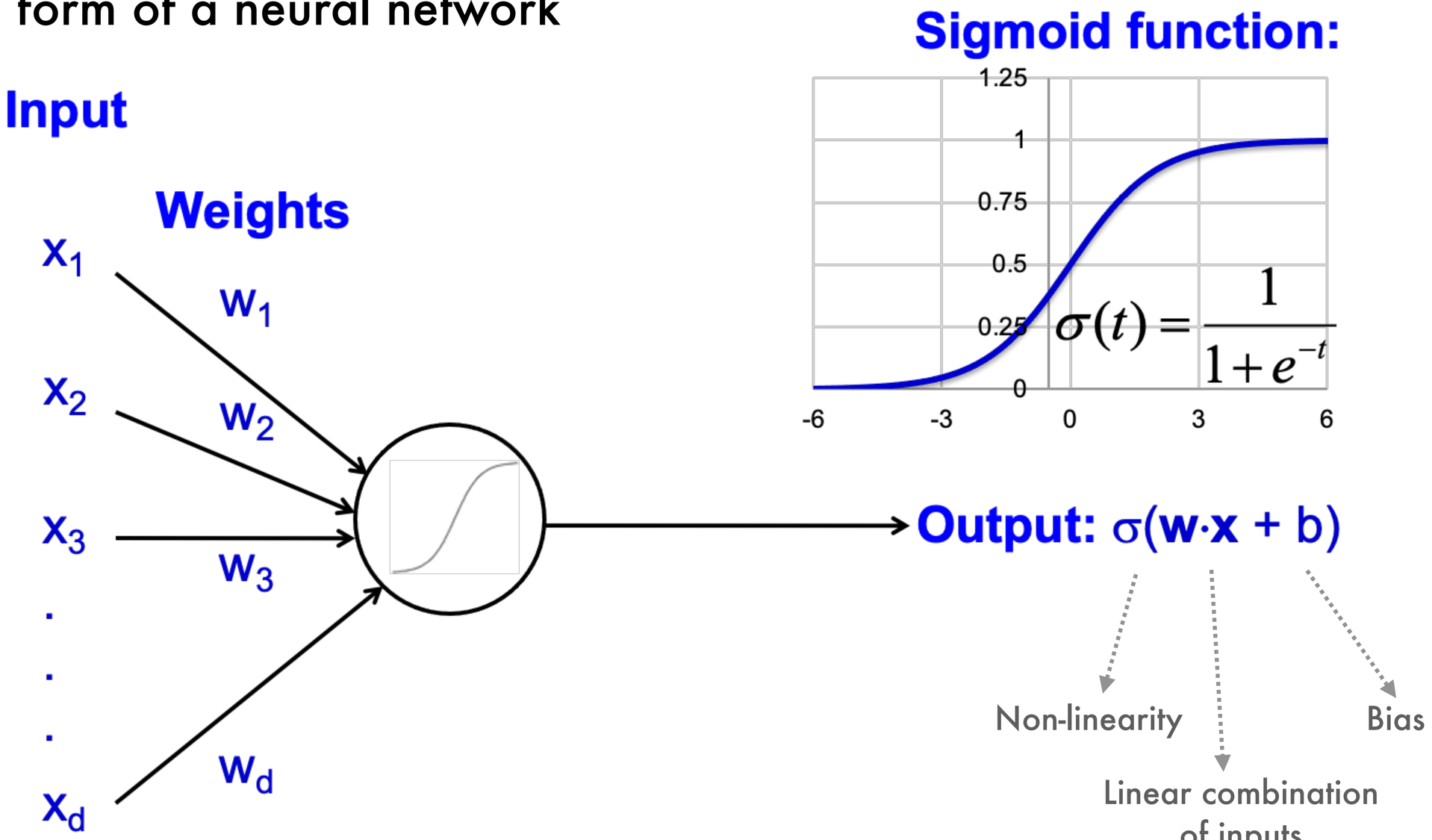
- **Fully-connected** layer
- **Convolution** layer
- **Pooling** layer (e.g., Max-pooling)
- **Non-linearity** layer (e.g., ReLU)
- **Attention** layer
- …

*requirement to be differentiable if optimized with gradient descent algorithm variants

Recap: Perceptrons

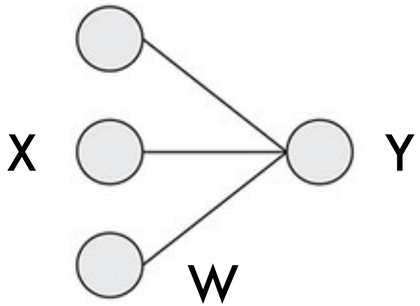
[Rosenblatt, 1957]

Most basic form of a neural network

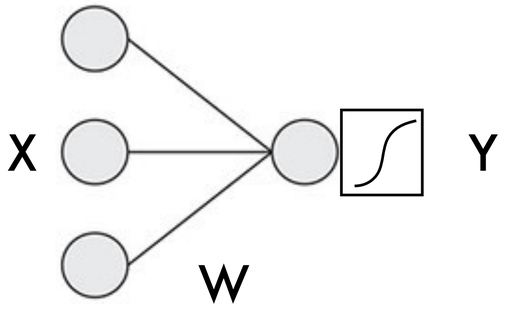


Recap: Multi-Layer Perceptron (MLP)

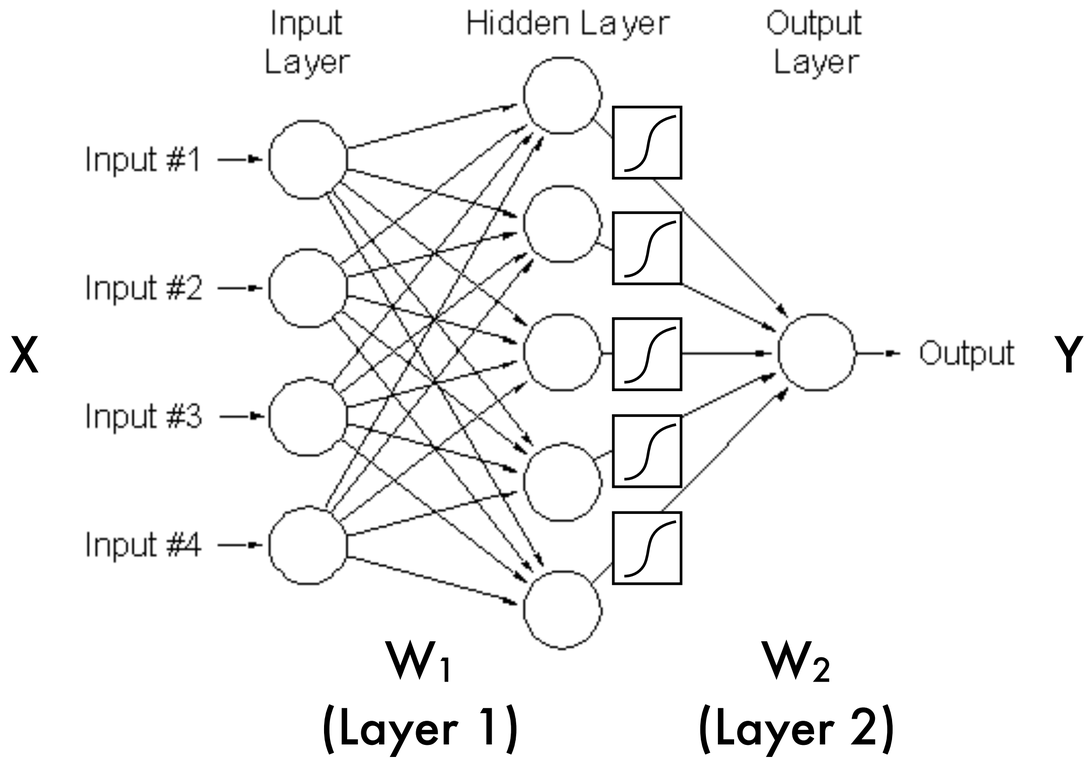
Linear regression:



Perceptron:

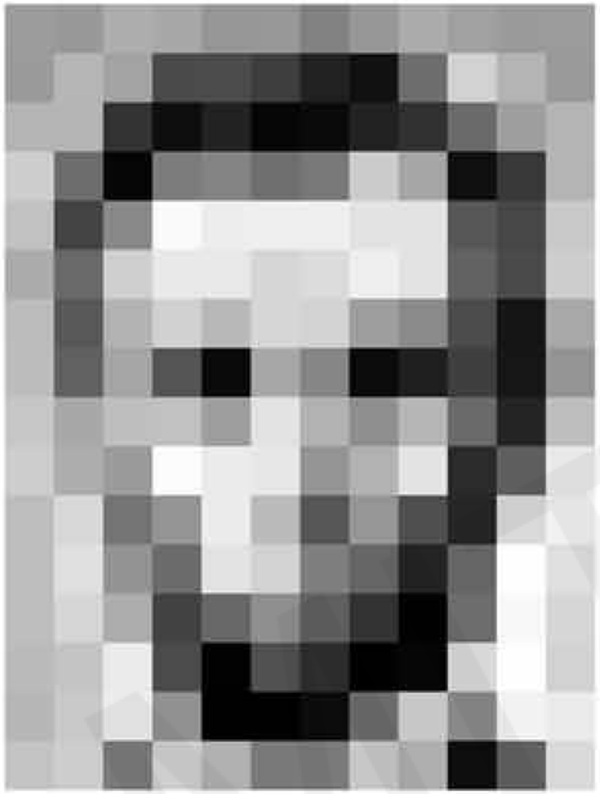


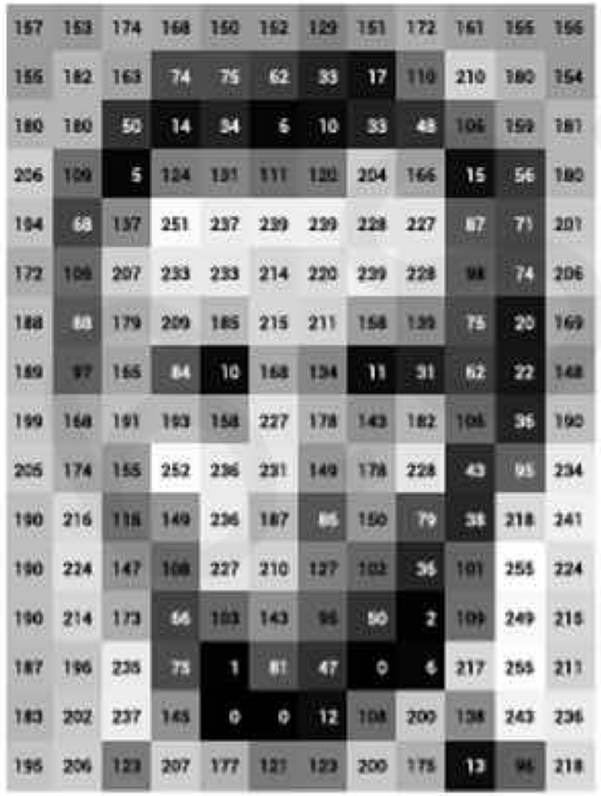
MLP:



Slide: R. Fergus / S. Lazebnik

Images are numbers





What the computer sees

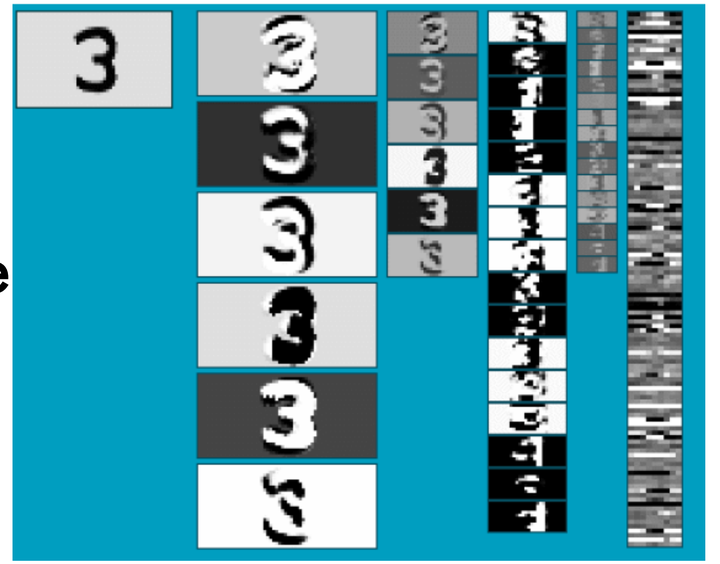
157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
196	206	123	207	177	121	123	200	175	13	96	218

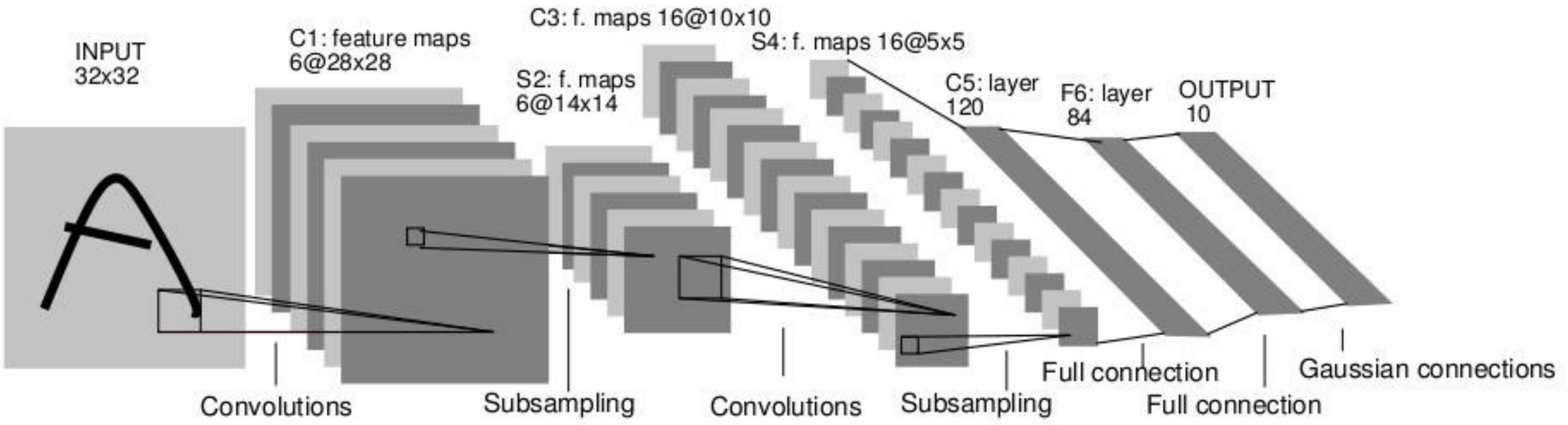
An image is just a matrix of numbers [0,255]!
i.e., 1080x1080x3 for an RGB image

Slide credit: Alexander Amini

Review: Convolutional Neural Networks (CNN)

- Neural network with specialized **connectivity** structure
- Stack multiple stages of feature extractors
- Higher stages compute more global, more invariant feature
- Classification layer at the end

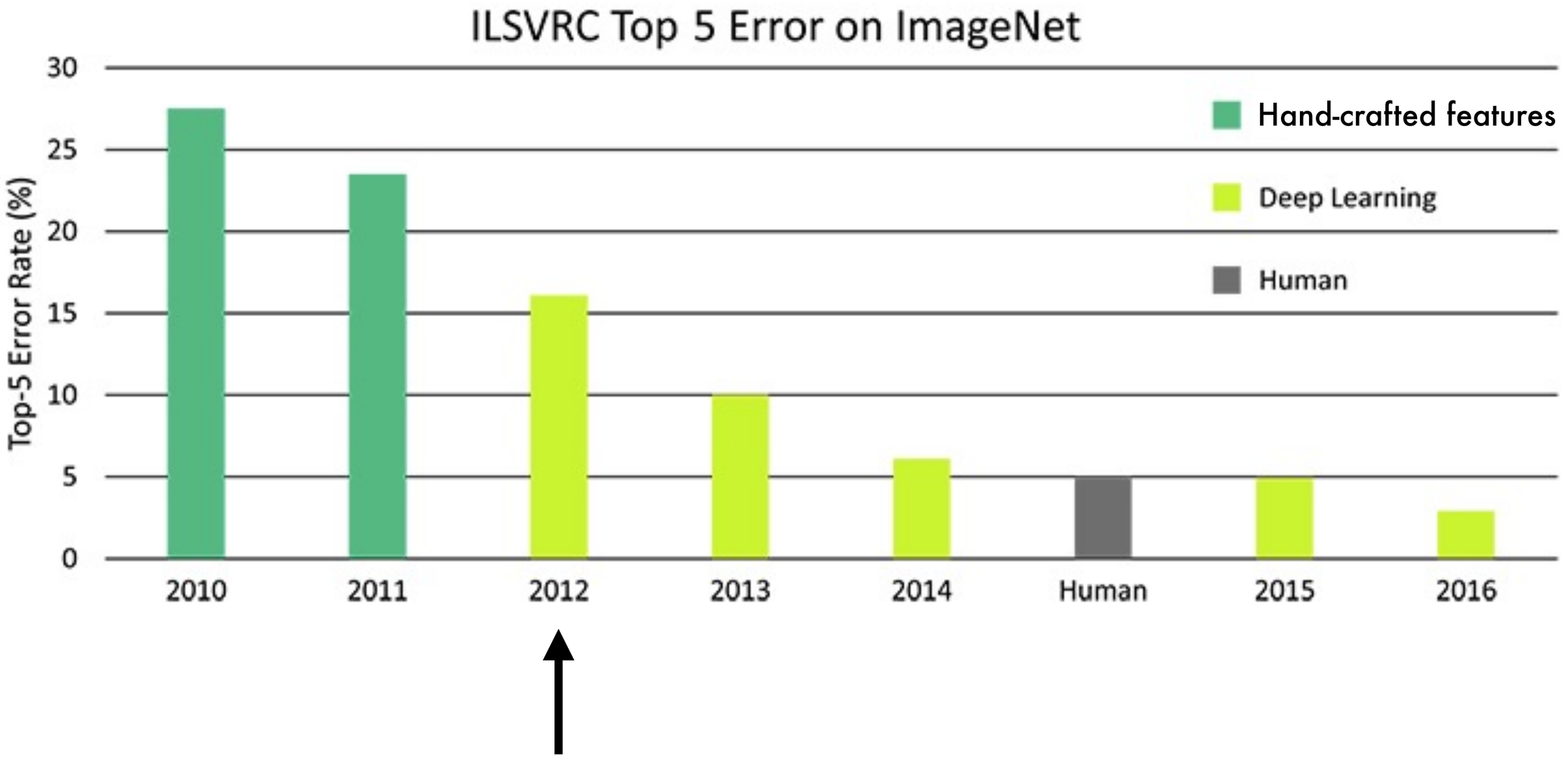




Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Slide: R. Fergus / S. Lazebnik

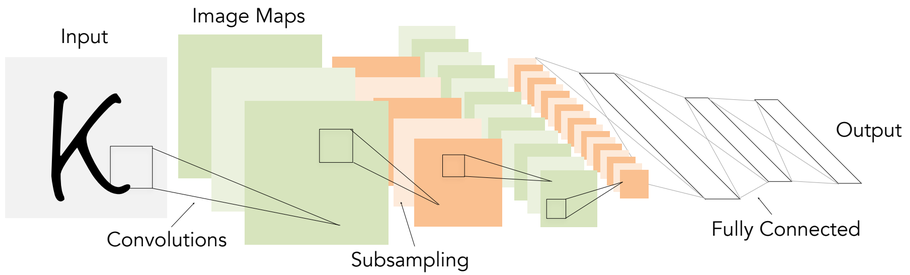
Progress on ImageNet



https://www.dsiac.org

CNNs were not invented overnight

1998
LeCun et al.



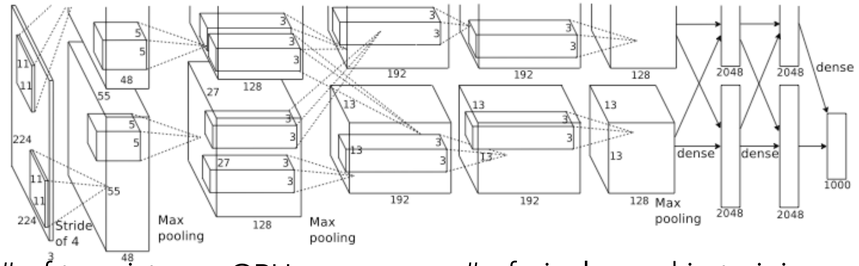
# of transistors

10^6

# of pixels used in training

10^7 NIST

2012
Krizhevsky et al.



# of transistors

10^9

GPUs

# of pixels used in training

10^{14} IMAGENET

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

IMAGENET Large Scale Visual Recognition Challenge

Year 2010

NEC-UIUC

Dense descriptor grid: HOG, LBP

Coding: local coordinate, super-vector

Pooling, SPM

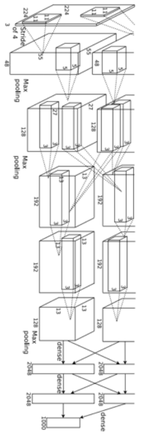
Linear SVM

[Lin CVPR 2011]

Lion image by Swissfrog is licensed under CC BY 3.0

Year 2012

SuperVision

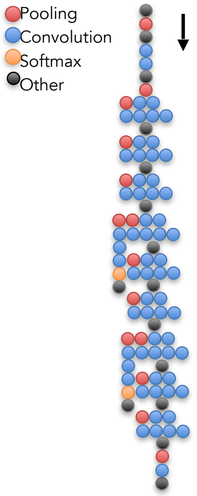


[Krizhevsky NIPS 2012]

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

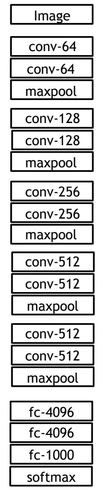
Year 2014

GoogLeNet



[Szegedy arxiv 2014]

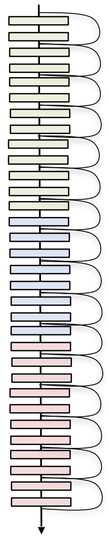
VGG



[Simonyan arxiv 2014]

Year 2015

MSRA

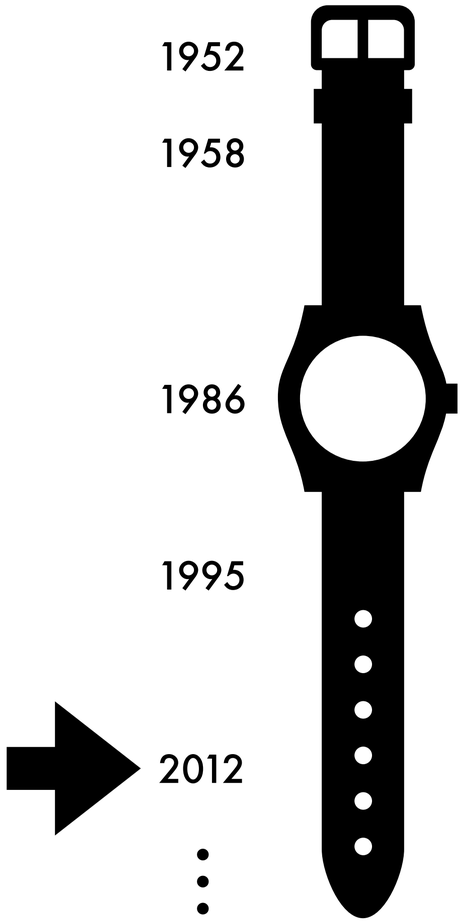


[He ICCV 2015]

Slide credit: Fei-Fei Li & Justin Johnson & Serena Yeung

Why now?

Neural Networks date back decades.



1952 Stochastic Gradient Descent

1958 Perceptron
- Learnable Weights

1986 Backpropagation
- Multi-Layer Perceptron

1995 Deep Convolutional NN
- Digit Recognition

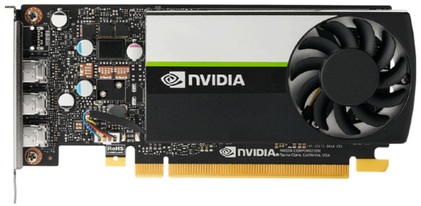
2012 AlexNet

…

1. Big Data
- Larger datasets
- Easier collection & storage

…

2. Hardware
- Graphics Processing Units (GPUs)
- Massively Parallelizable



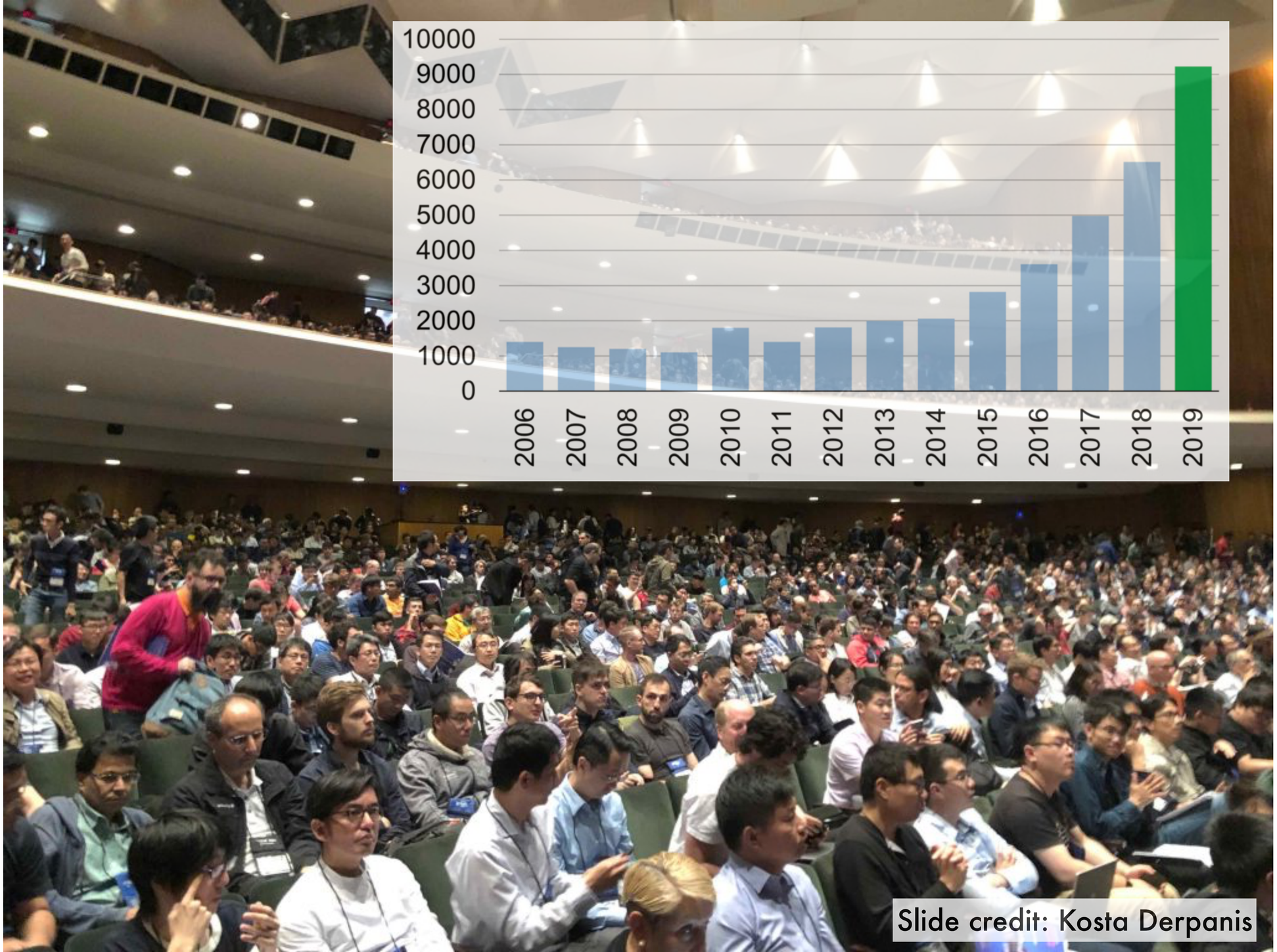
3. Software
- Improved Techniques
- New Models
- Toolboxes

PyTorch

TensorFlow

…

Slide credit: Alexander Amini



Slide credit: Kosta Derpanis

CVPR:
(**C**omputer **V**ision **P**attern **R**ecognition Conference)

Agenda

- **1. Recap: Bag of Visual Words, Analogy with NNs**

- **2. Neural networks (NNs) for computer vision:**
  - Applications
  - A brief history: from perceptron to MLPs to CNNs

- **3. Convolutional neural networks (CNNs)**
  - Standard layers
  - Recap: Training NNs
  - Visualizing CNNs
  - Pretraining & finetuning NNs
  - Typical CNN architectures

- **4. Beyond classification - preview**

Agenda

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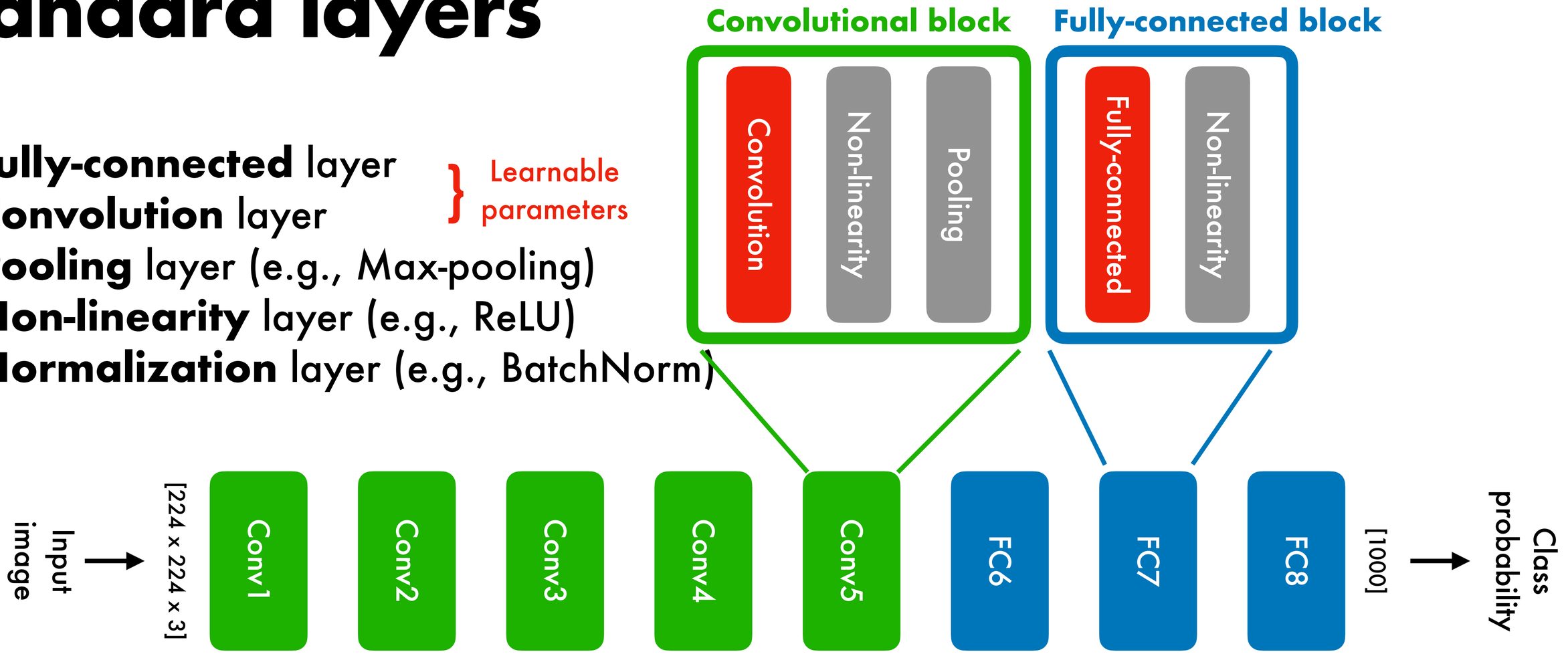
- **4. Beyond classification - preview**

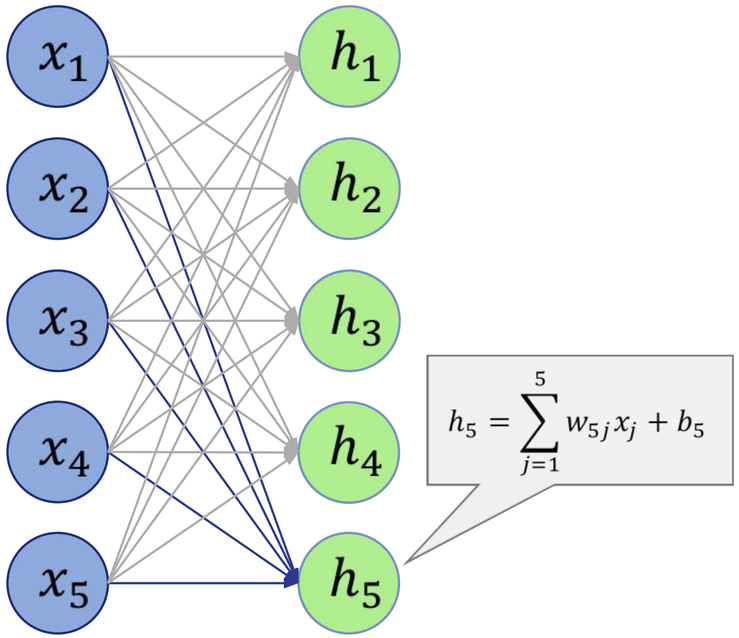
Standard layers

- 1. **Fully-connected** layer
- 2. **Convolution** layer
- 3. **Pooling** layer (e.g., Max-pooling)
- 4. **Non-linearity** layer (e.g., ReLU)
- 5. **Normalization** layer (e.g., BatchNorm)
- …

} Learnable parameters



1. Fully-connected layer

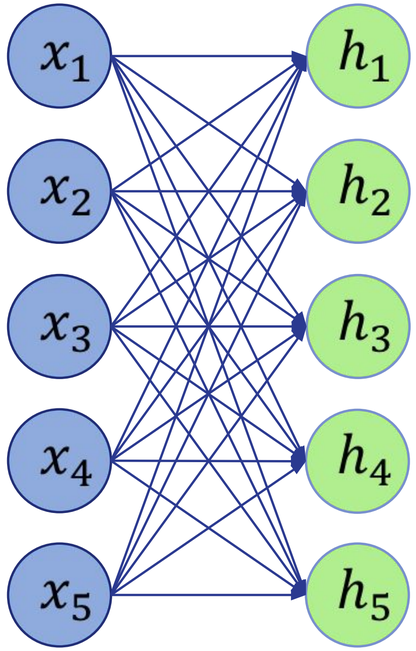


$$\boldsymbol{h} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b};\ h_i = \sum_j w_{ij} x_j + b_i$$

Slide credit: Naila Murray

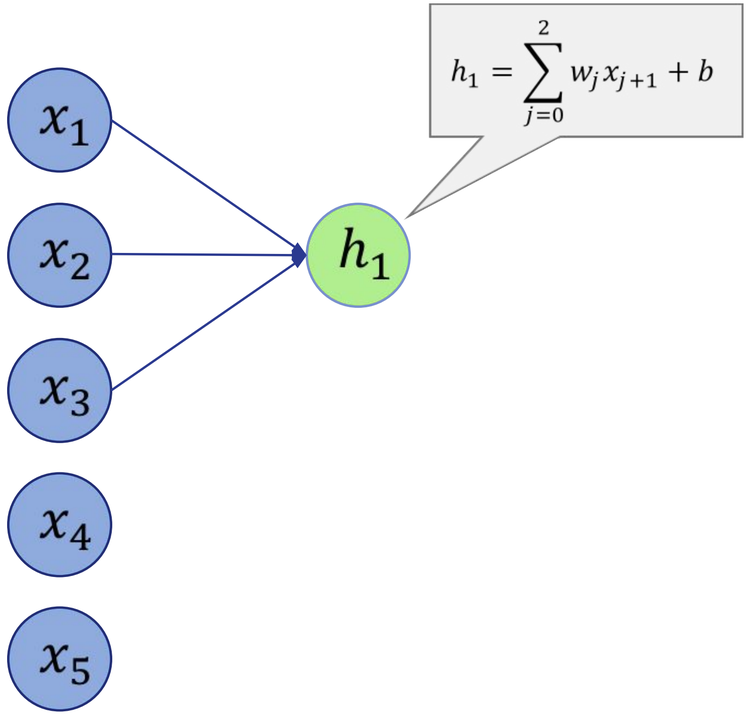
2. Convolution layer

Fully-connected



$$\boldsymbol{h} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b};\ h_i = \sum_j w_{ij} x_j + b_i$$

1D Convolutional



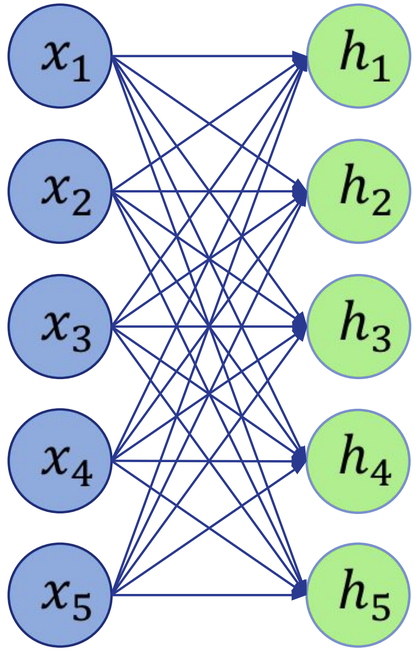
$$h_i = \sum_j w_j x_{j+i} + b$$

- Layer with a special connectivity structure
- Dependencies are local
- Translation invariance

Slide credit: Naila Murray

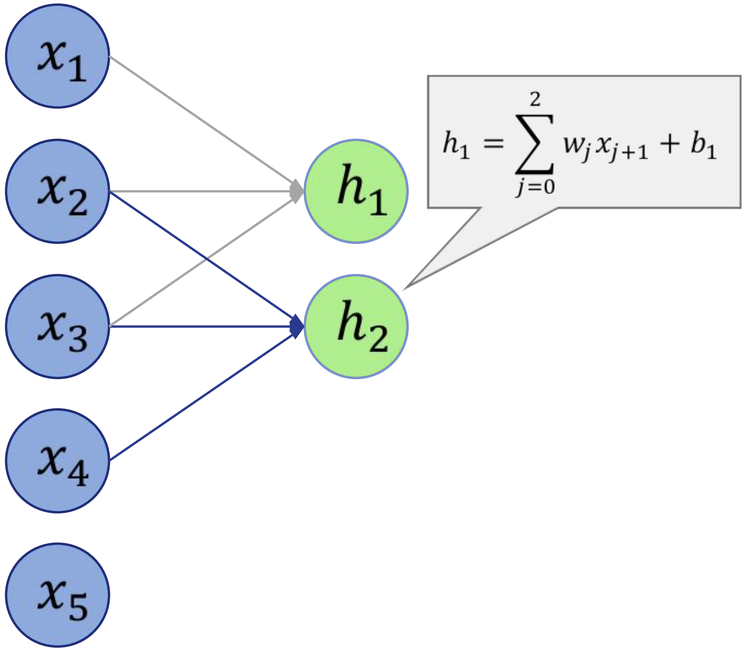
2. Convolution layer

Fully-connected



$$\boldsymbol{h} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b};\ h_i = \sum_j w_{ij} x_j + b_i$$

1D Convolutional

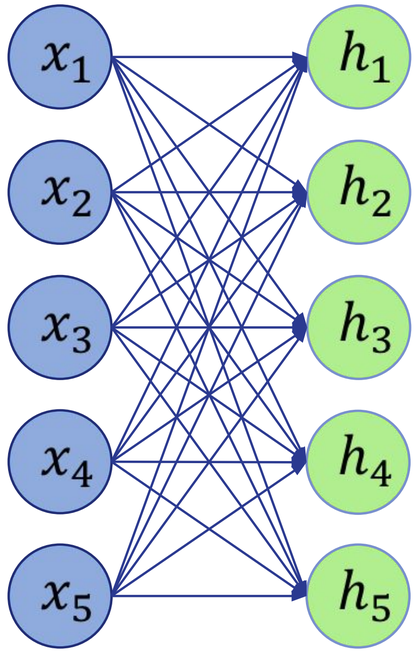


$$h_i = \sum_j w_j x_{j+i} + b$$

Slide credit: Naila Murray

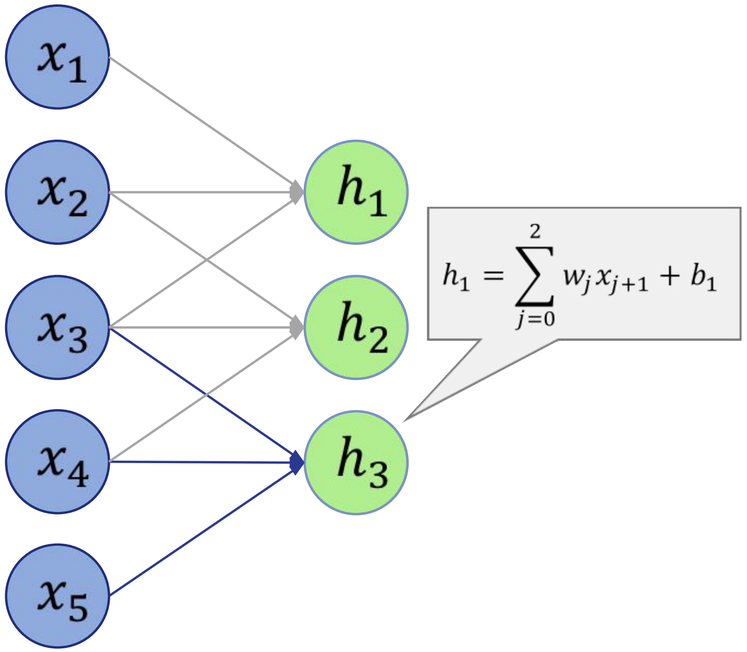
2. Convolution layer

Fully-connected



$$\boldsymbol{h} = \boldsymbol{W}\boldsymbol{x} + \boldsymbol{b};\ h_i = \sum_j w_{ij} x_j + b_i$$

1D Convolutional



$$h_i = \sum_j w_j x_{j+i} + b$$

Slide credit: Naila Murray

2. Convolution layer

2D Convolutions

I

1	0	0	1	2
0	0	0	3	0
0	1	2	1	1
1	1	3	0	0
3	0	0	0	1

$\star$

K

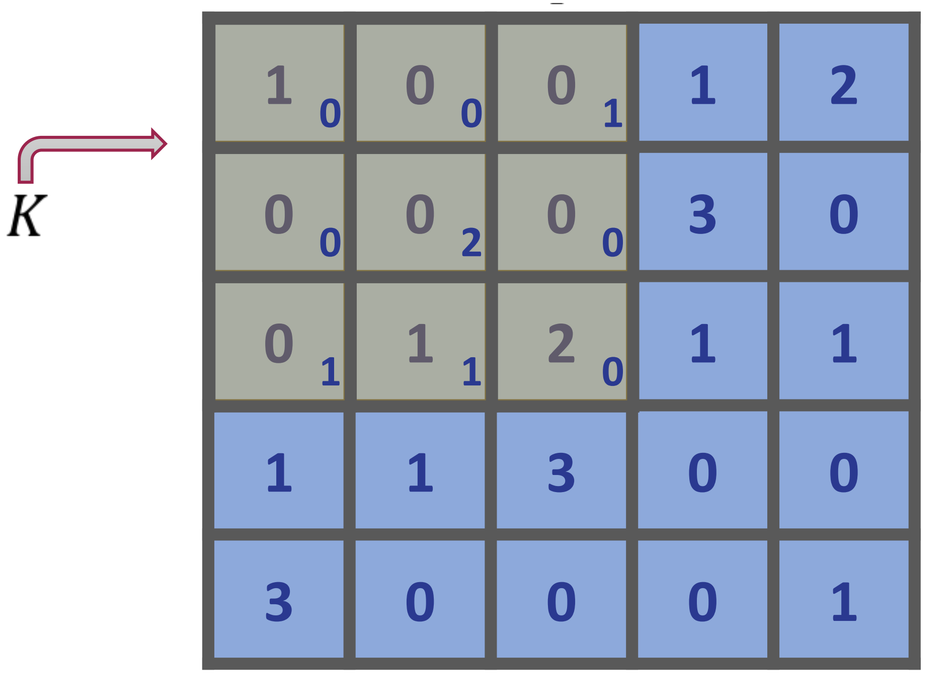
0	0	1
0	2	0
1	1	0

$$(I \star K)(i,j) == \sum_m \sum_n I(m,n)K(i+m, j+n)$$

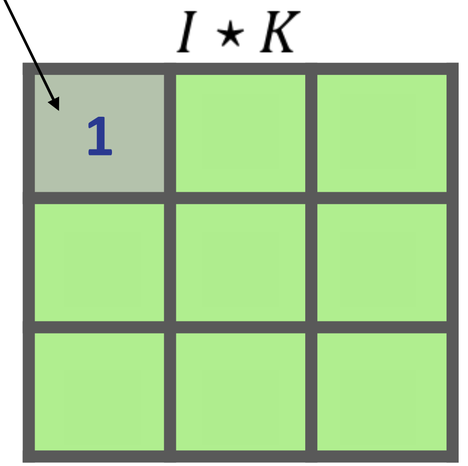
Slide credit: Naila Murray

2. Convolution layer

2D Convolutions



(1x0) + (0x0) + (0x1) +
(0x0) + (0x2) + (0x0) +
(0x1) + (1x1) + (2x0)

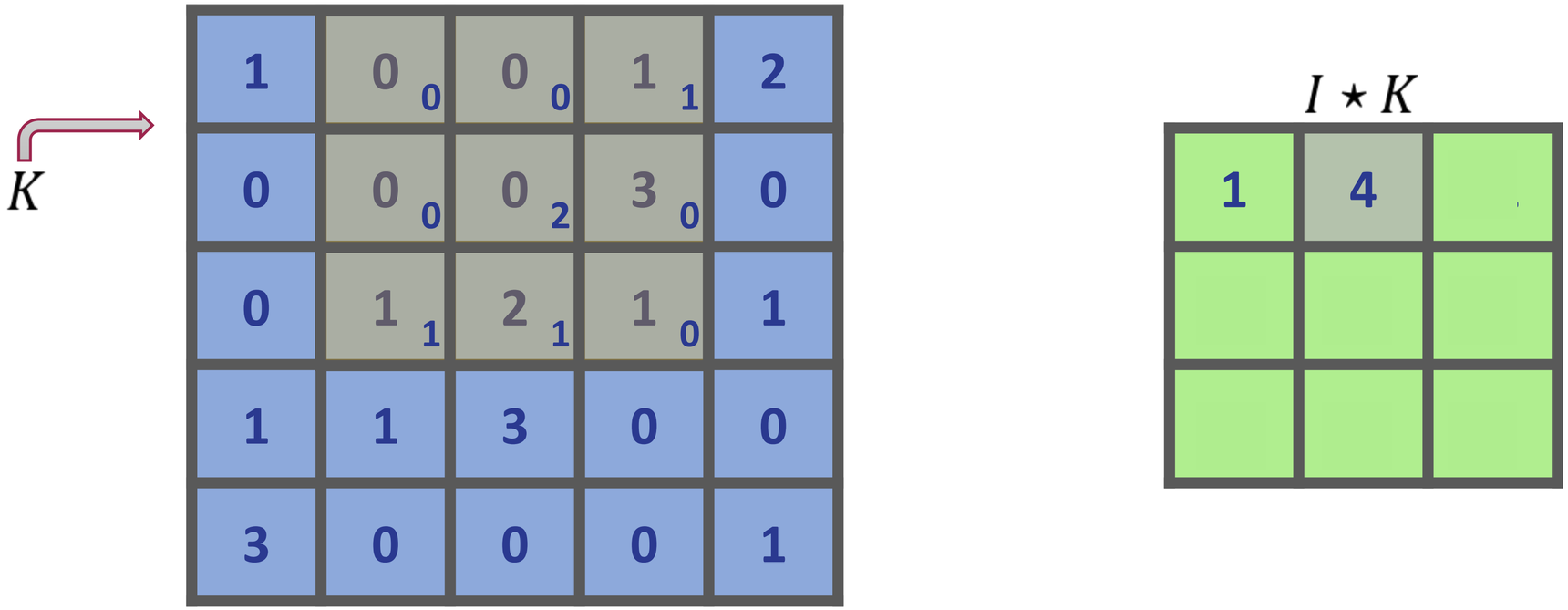


$$(I \star K)(i,j) == \sum_m \sum_n I(m,n)K(i+m, j+n)$$

Slide credit: Naila Murray

2. Convolution layer

2D Convolutions



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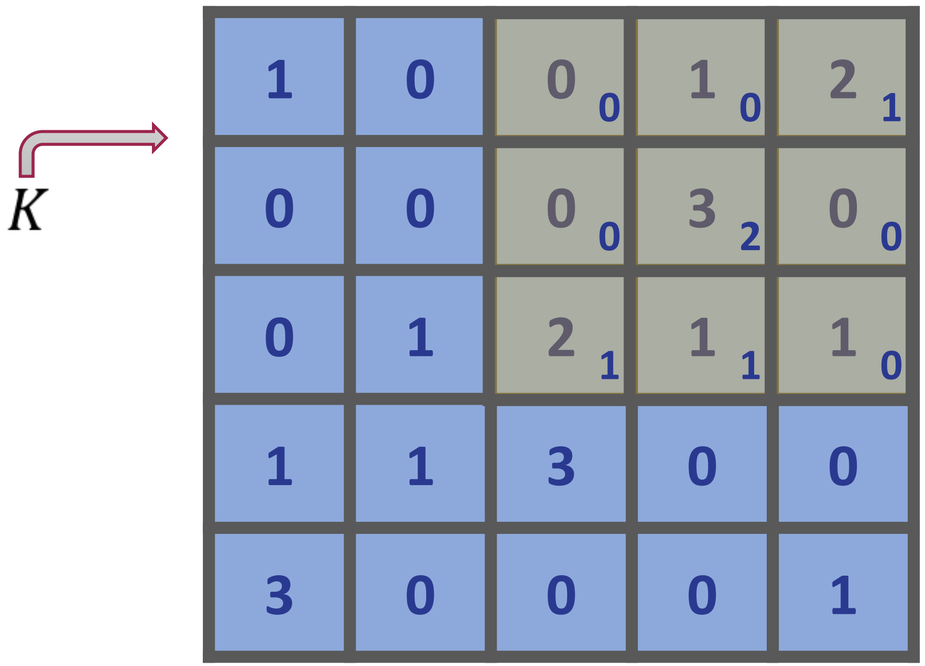
Slide credit: Naila Murray

2. Convolution layer

2D Convolutions



$I \star K$

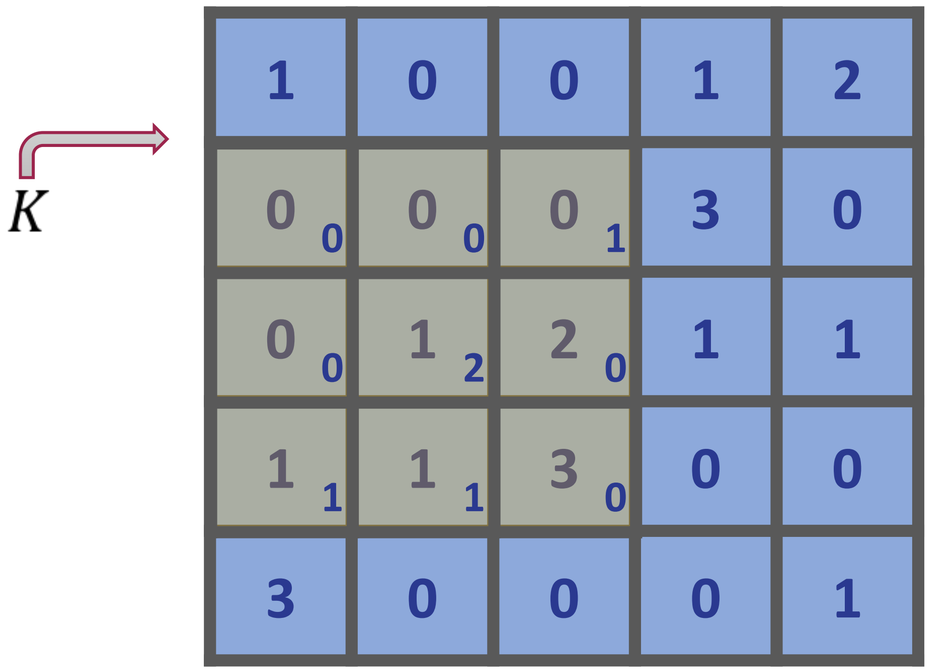
1	4	11

$$(I \star K)(i,j) == \sum_m \sum_n I(m,n)K(i+m, j+n)$$

Slide credit: Naila Murray

2. Convolution layer

2D Convolutions



$I \star K$

1	4	11
?		

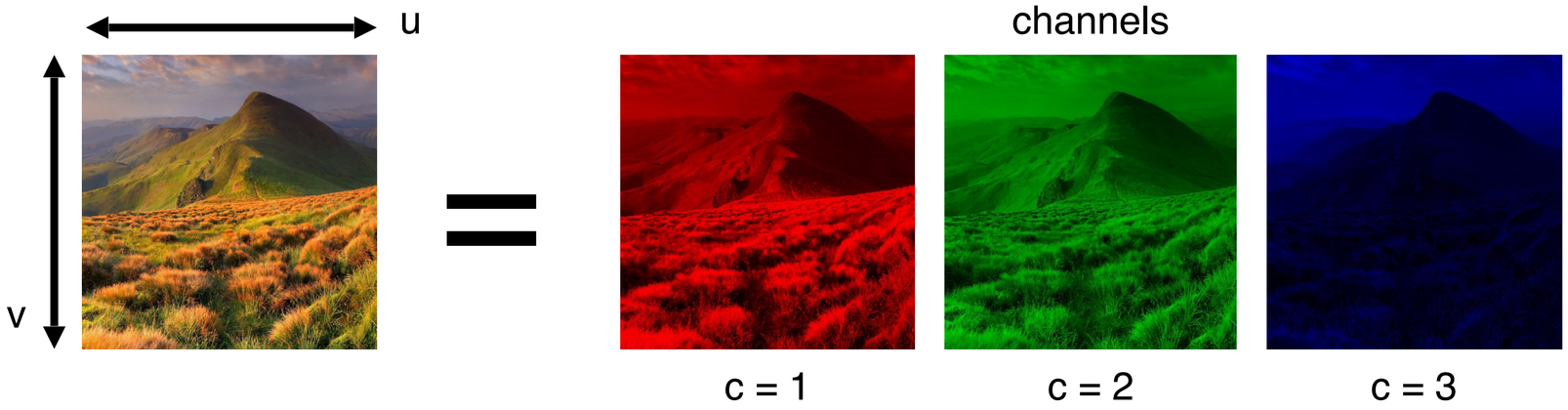
$$(I \star K)(i,j) == \sum_m \sum_n I(m,n)K(i+m, j+n)$$

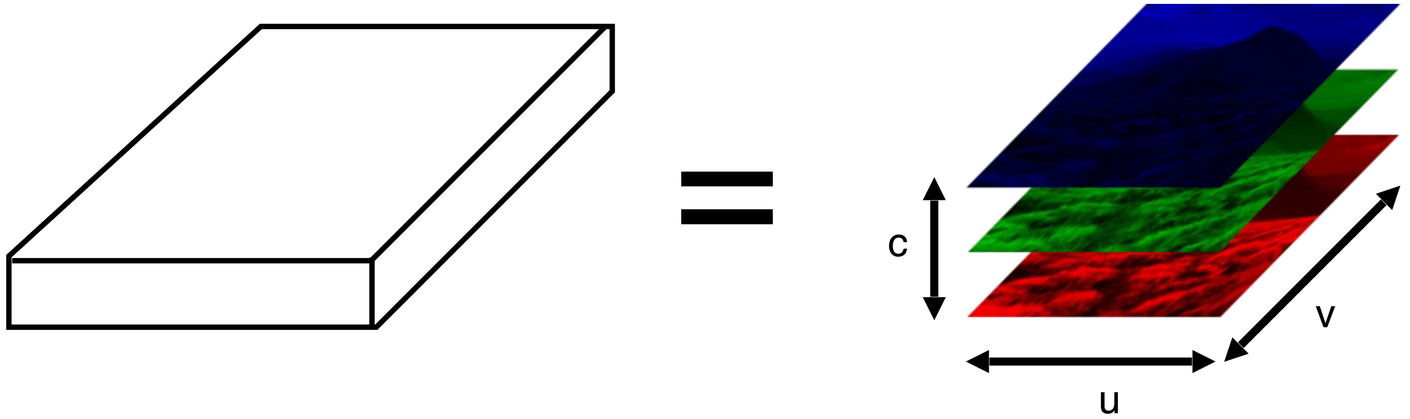
Slide credit: Naila Murray

2. Convolution layer

The data manipulated by a CNN has the form of 3D tensors. These are interpreted as **discrete vector fields** **x**, assigning a feature vector (x_{uv1}, …, x_{uvC}) at each spatial location (v,u).

A colour image is a simple example of a vector field with 3D features (RGB):

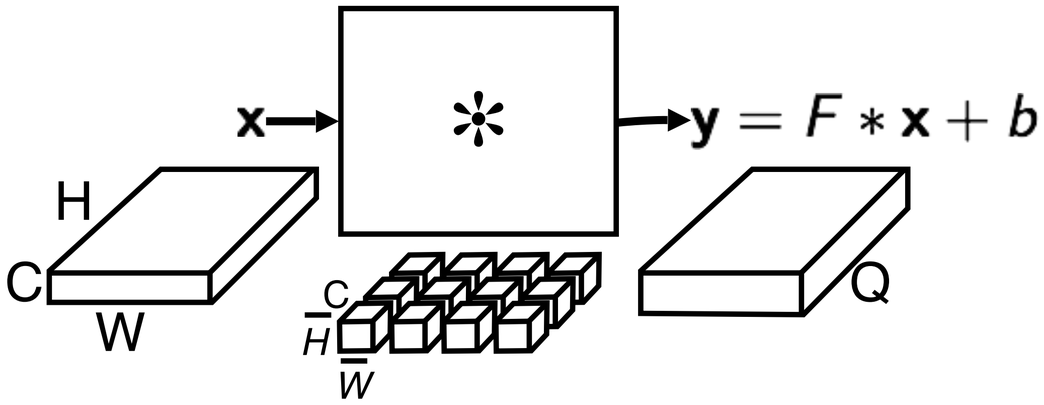




Slide: A. Vedaldi

2. Convolution layer

With a bank of 3D filters



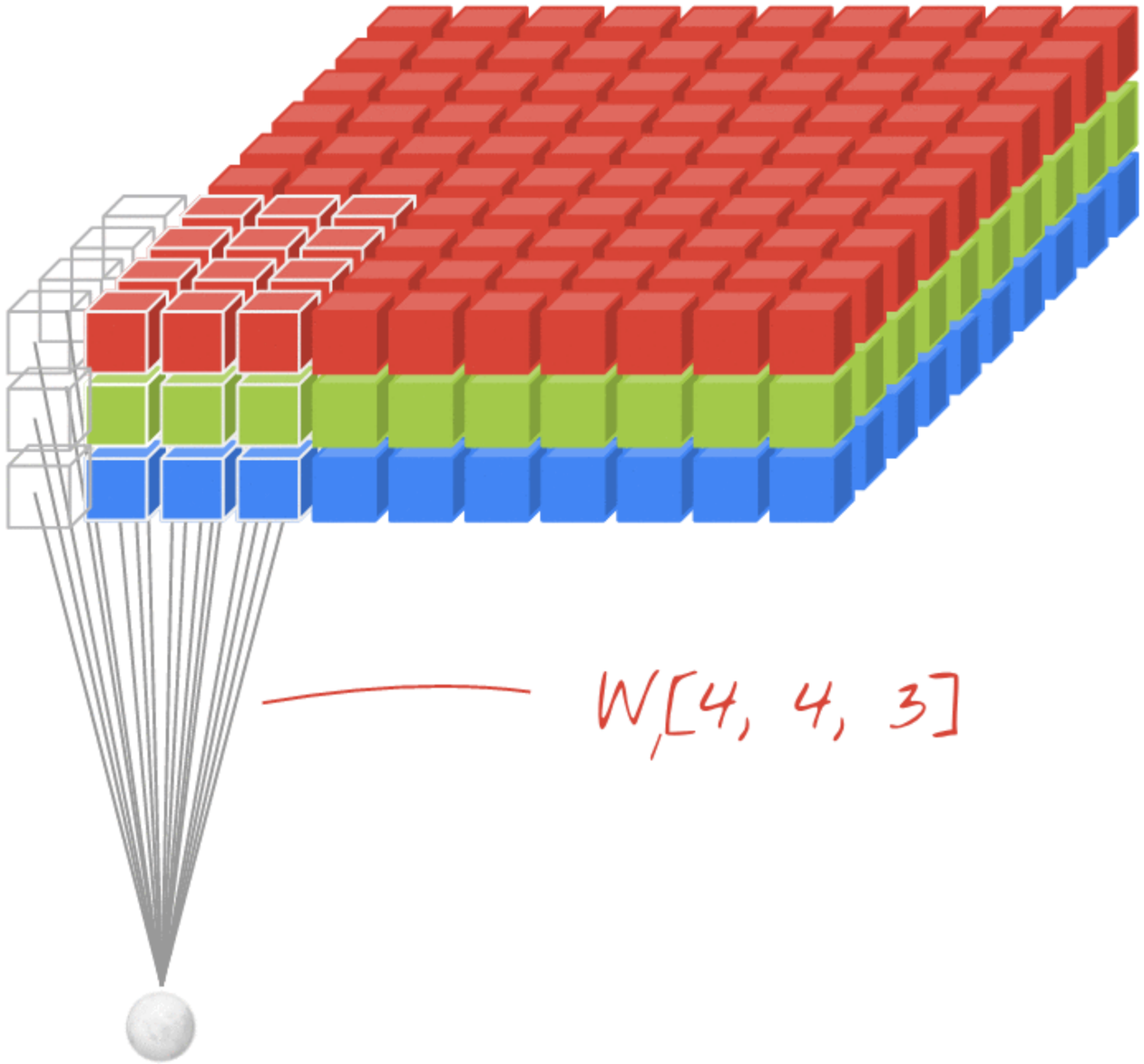
$$y_{v'u'q'} = b_{q'} + \sum_{\bar{v}=1}^{\bar{H}} \sum_{\bar{u}=1}^{\bar{W}} \sum_{c=1}^{C} x_{v'+\bar{v}-1,u'+\bar{u}-1,c} f_{\bar{v}\bar{u}cq'}$$

Linear convolution applies a bank of linear filters F to the input tensor **x**.

- Input tensor **x** = H × W × C array
- Filter bank F = $\bar{H}$ × $\bar{W}$ × C × Q array
- Output tensor **y** = (H - $\bar{H}$ + 1) × (W - $\bar{W}$ + 1) × Q array

Slide: A. Vedaldi

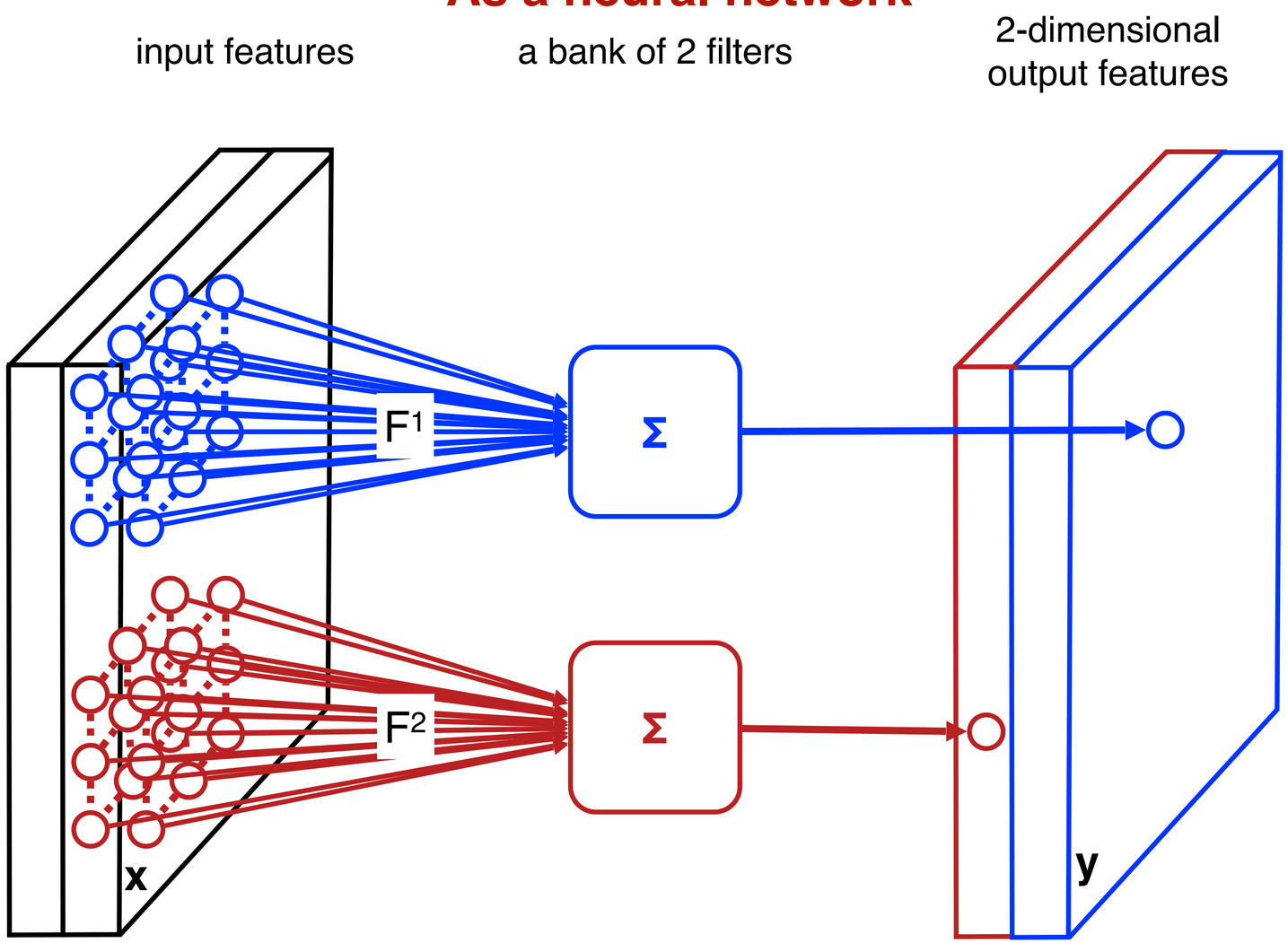
2. Convolution layer



Credit: Martin Görner

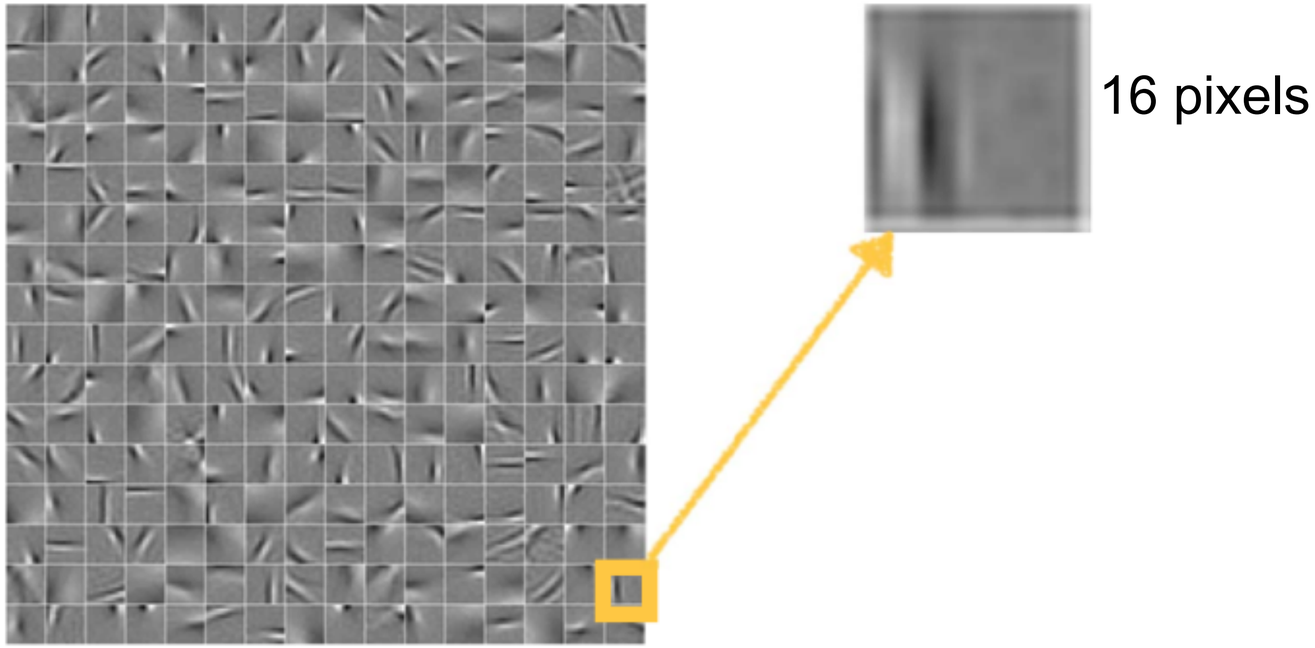
2. Convolution layer

As a neural network



Filter bank example

- A bank of 256 filters (learned from data)
- Each filter has 1 channel (it applies to a grayscale image)
- Each filter is 16x16 pixels

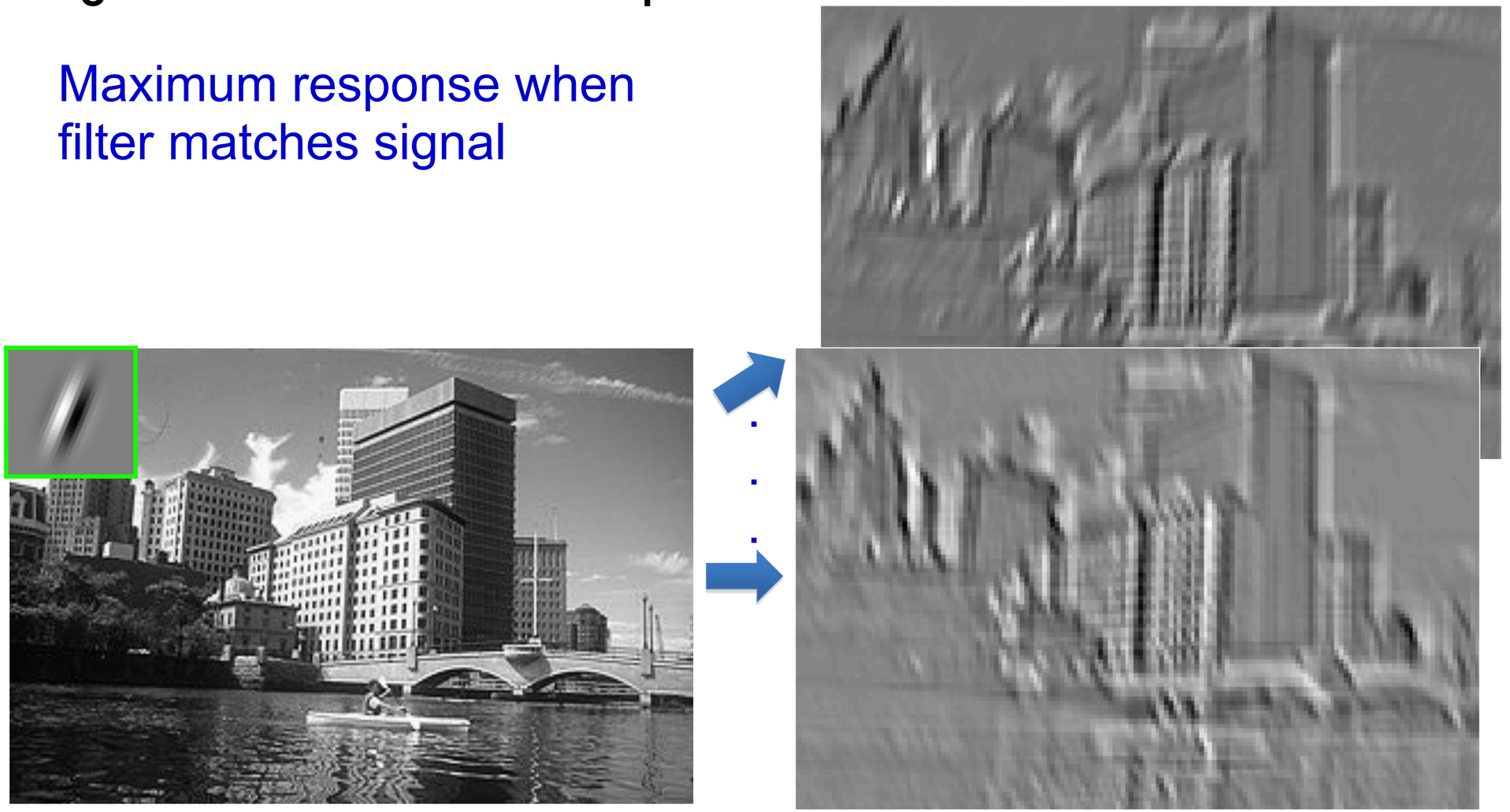


Slide: A. Zisserman

Filtering

Each filter generates a "feature map"

Maximum response when filter matches signal



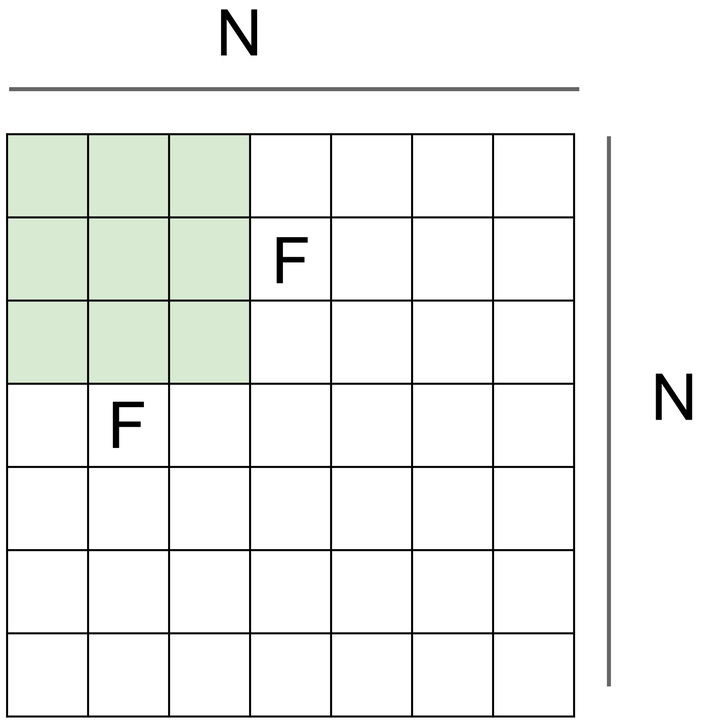
Input

Feature Map

Slide: R. Fergus / S. Lazebnik

Convolution details

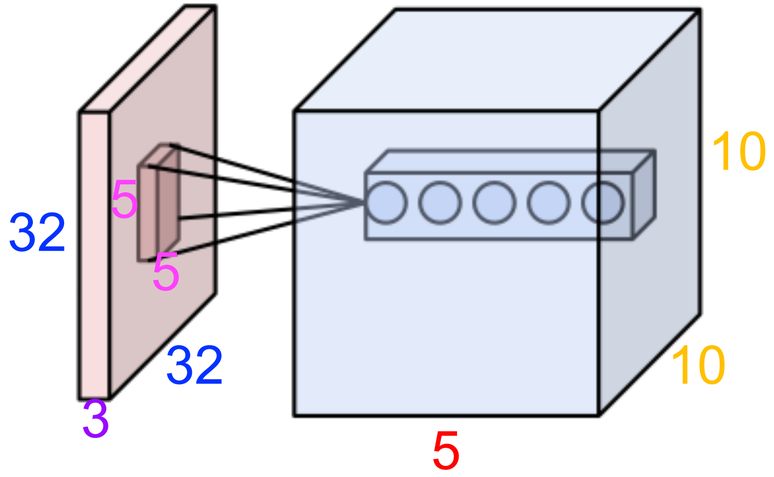
What is the output size?



Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = … :\

Example: What is the output volume?

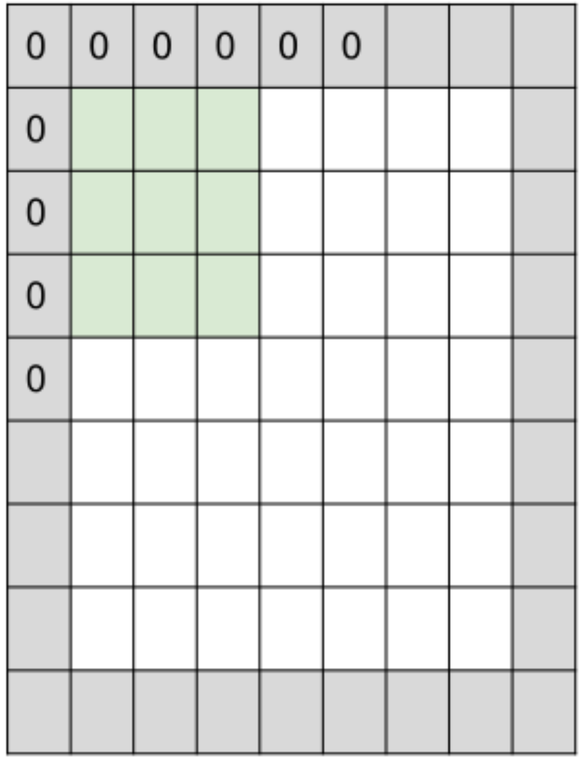


Input volume: 32x32x3
Receptive fields: 5x5, stride 3
Number of neurons: 5

Output volume: (32 - 5) / 3 + 1 = 10, so: 10x10x5

Slide: A. Karpathy / L. Fei Fei

Zero padding (in each channel)



e.g. input 7x7
neuron with receptive field 3x3, stride 1
pad with 1 pixel border => what is the output?

7x7 => preserved size!

in general, common to see stride 1, size F, and zero-padding with (F-1)/2.
(Will preserve input size spatially)

Slide: A. Karpathy / L. Fei Fei

What is the number of parameters?

- Consider an input gray-scale image of 1000x1000 pixels.
- What is the number of parameters of a filter bank of 100 7x7 filters?
- How does it compare to a fully connected layer that considers the entire input image?

Convolution:
100x 7x7
= 4900 parameters

vs.

Fully connected layer:
1000x1000
x
1000x1000
= 1B parameters.

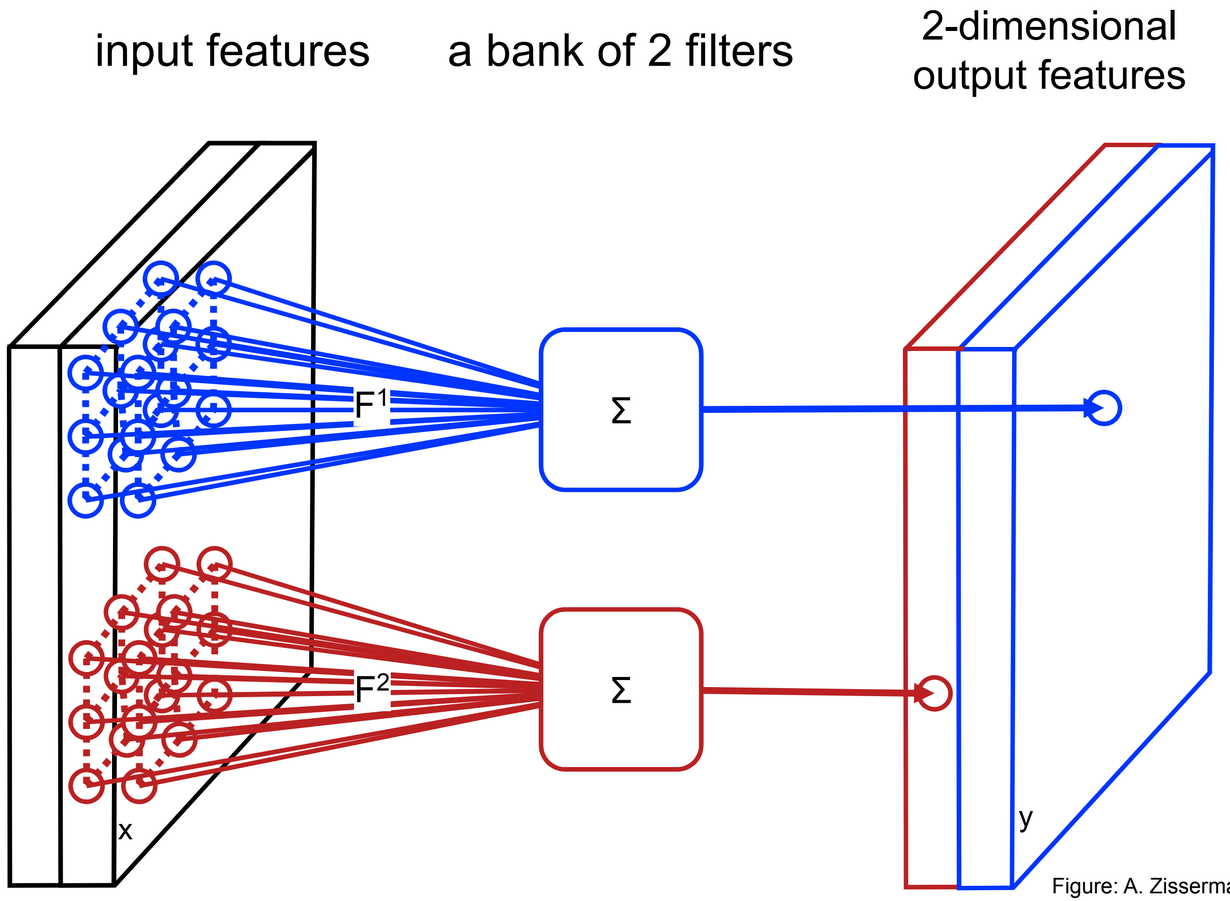
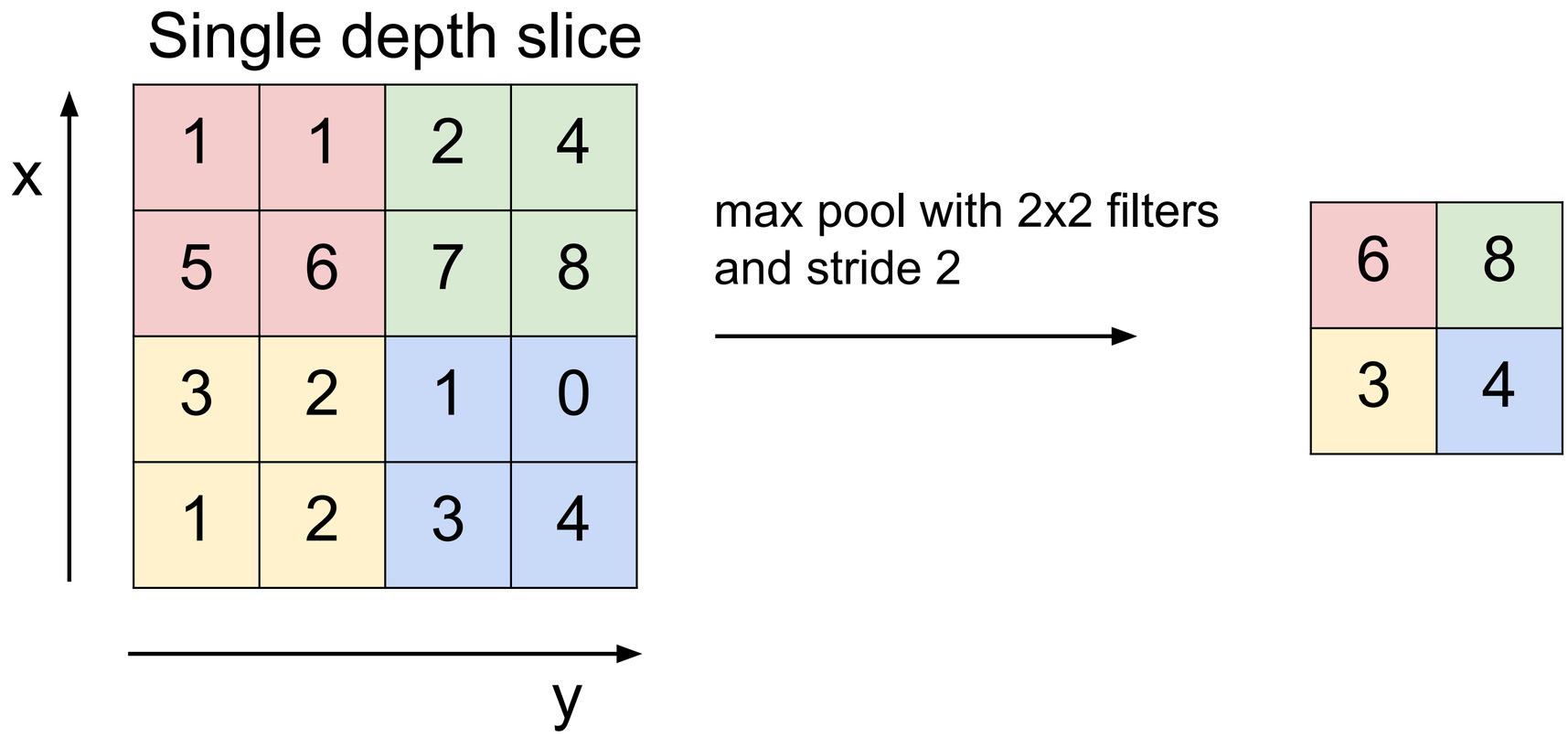


Figure: A. Zisserman

3. Spatial Max Pooling



Slide credit: Andrej Karpathy & Fei-Fei Li

3. Spatial Max Pooling

Dimensions of pooling outputs

Input volume of size [W1 x H1 x D1]
Pooling unit receptive fields F x F and applying them at strides of S gives

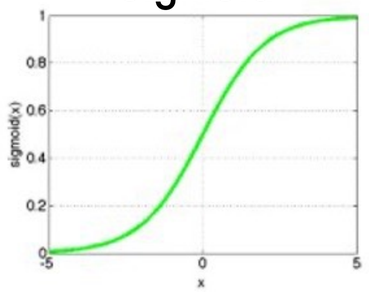
Output volume: [W2, H2, D1]
W2 = (W1-F)/S+1, H2 = (H1-F)/S+1

Note: pooling happens independently in each channel/slice

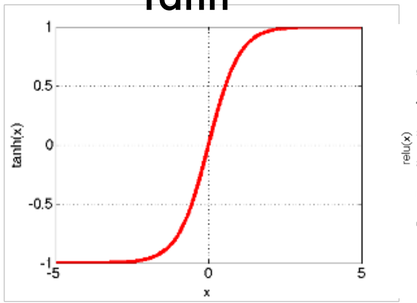
Slide: A. Karpathy / L. Fei Fei

4. Non-linearity

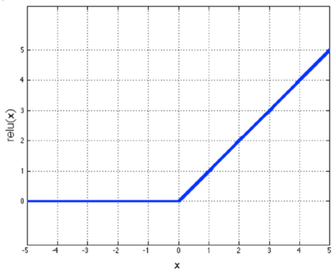
Sigmoid



Tanh



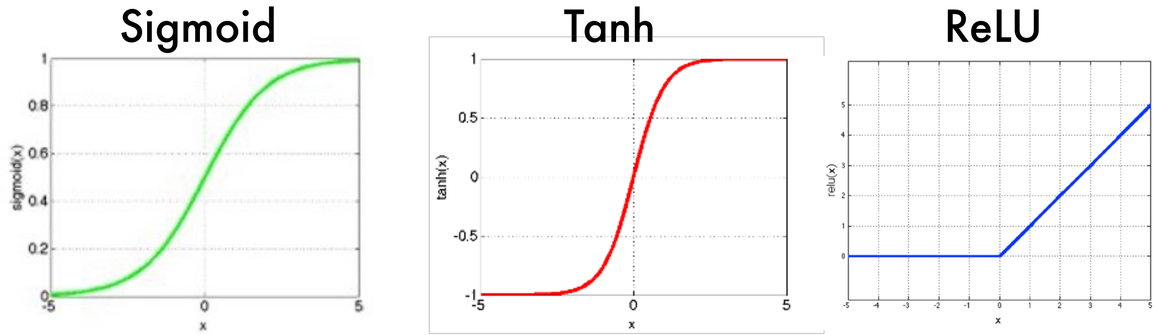
ReLU



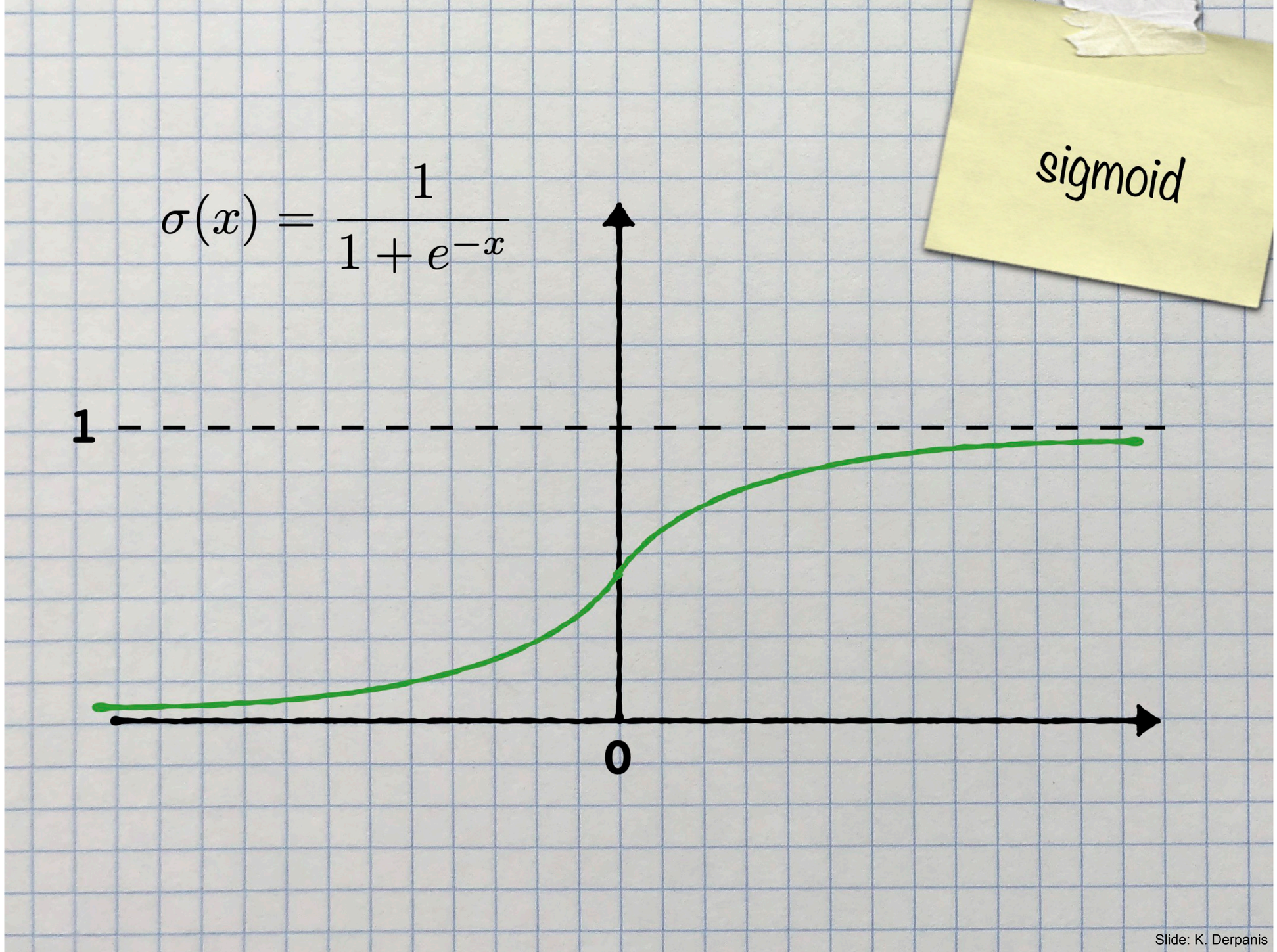
- The non-linear activation functions are essential. Why?

4. Non-linearity

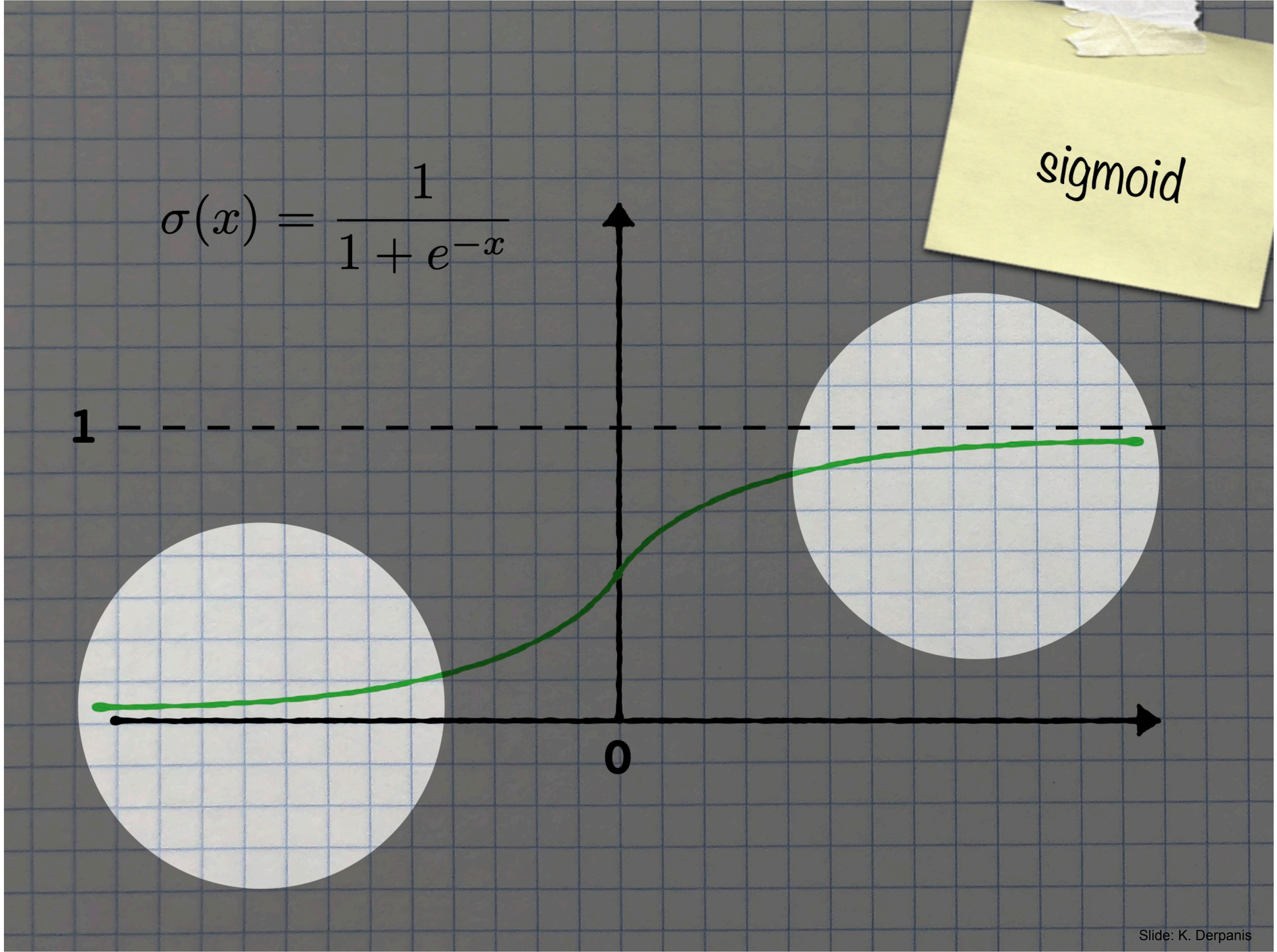
Why?



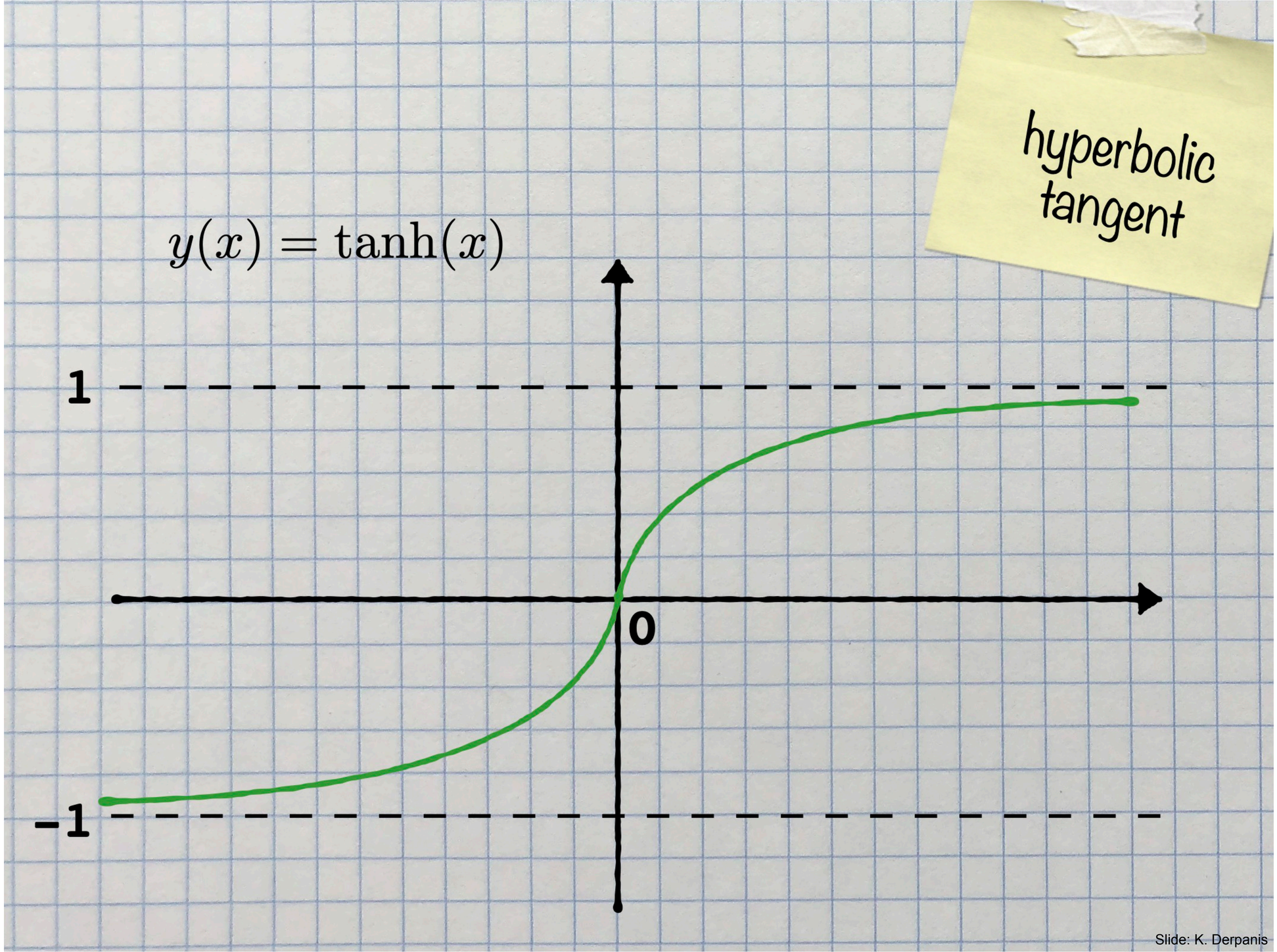
- Non-linearities allow us to approximate arbitrarily **complex functions**.
- **Universal approximation theorem**: A two-layer multilayer perceptron (MLP) with increasing continuous and bounded non-linearity can approximate any continuous function on a compact given enough hidden neurons. [Cybenko 1989]
- Linear activation functions produce **linear decisions no matter what the model size**, i.e., stacking multiple linear functions can be expressed with a single linear function.



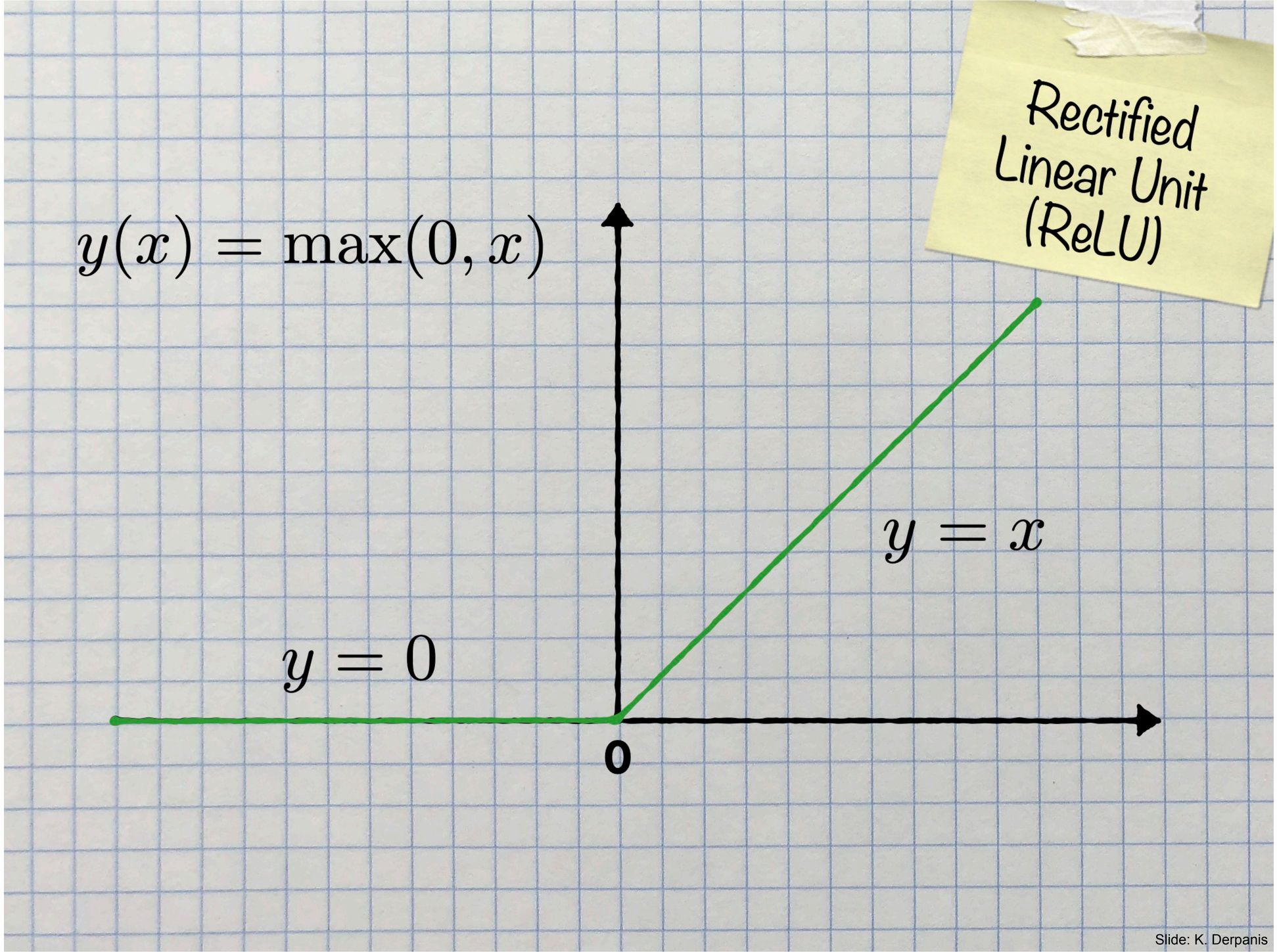
Slide: K. Derpanis



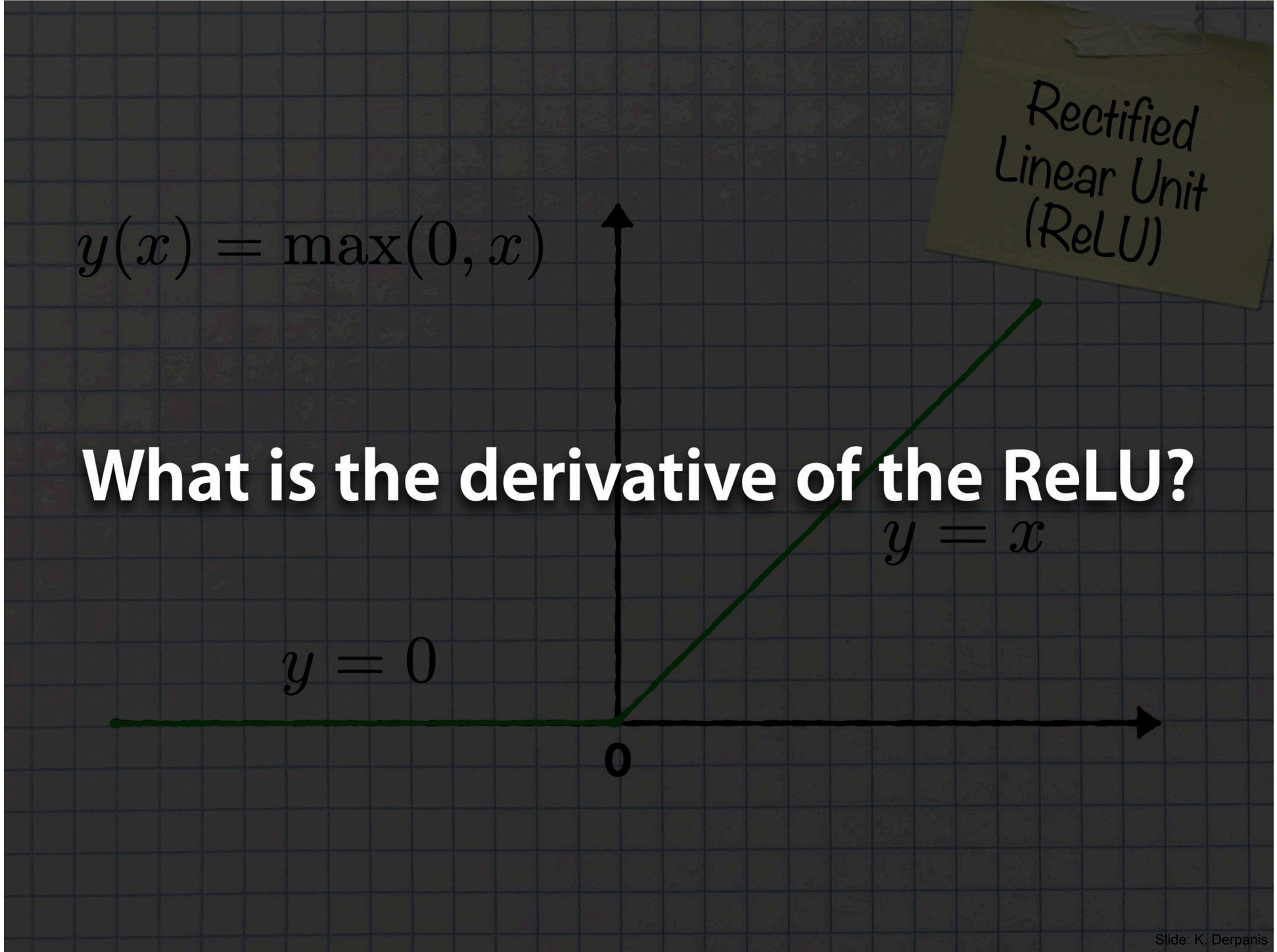
Slide: K. Derpanis



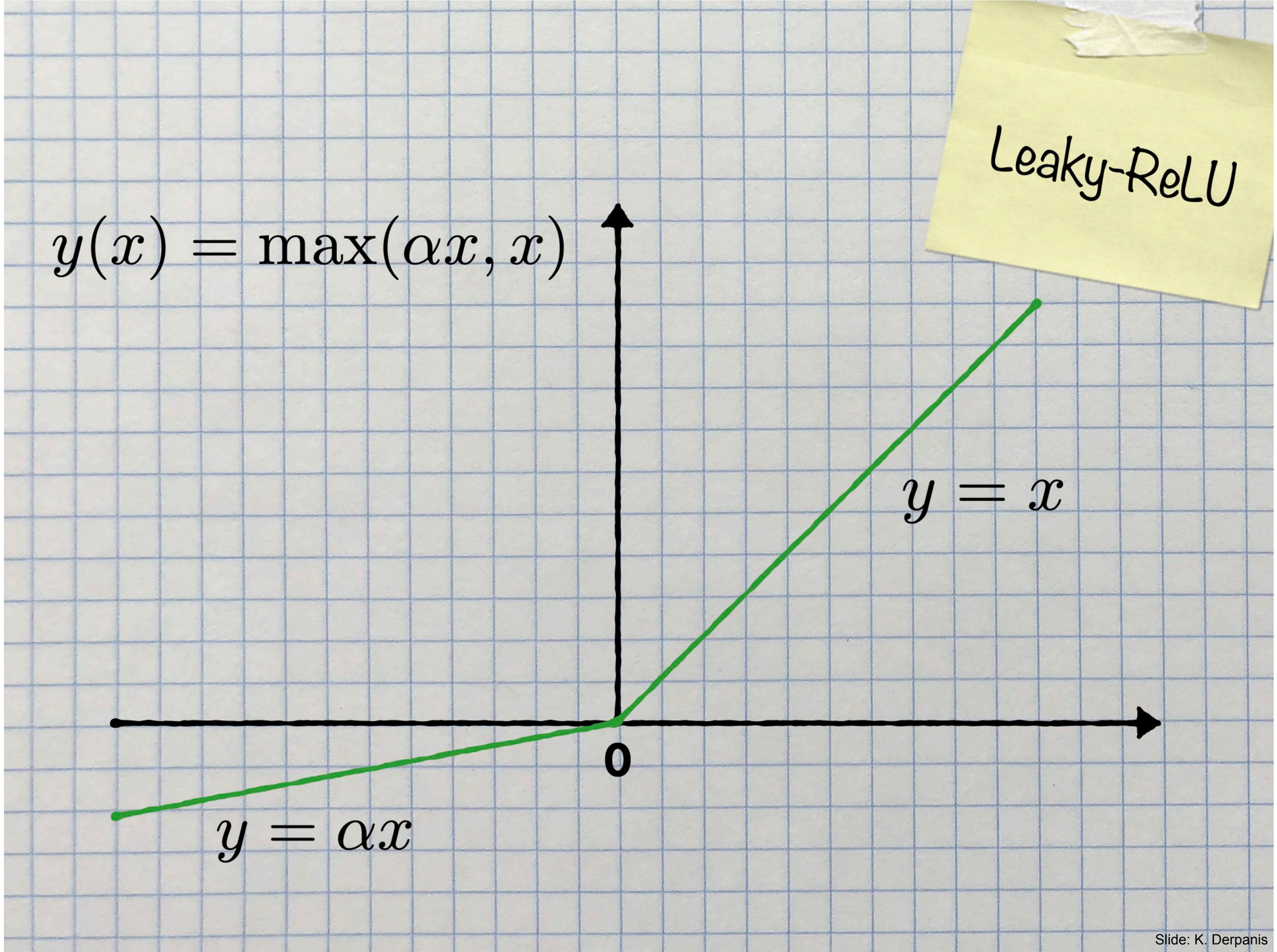
Slide: K. Derpanis



Slide: K. Derpanis



Slide: K. Derpanis



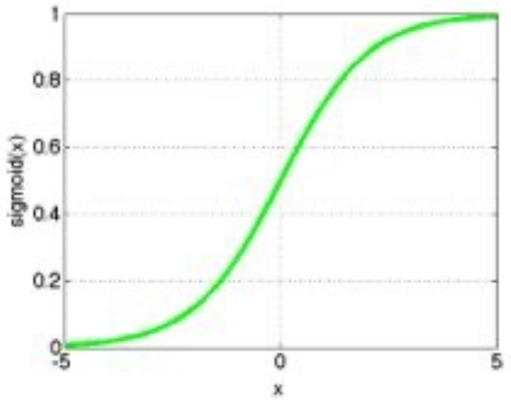
Slide: K. Derpanis

4. Non-Linearity

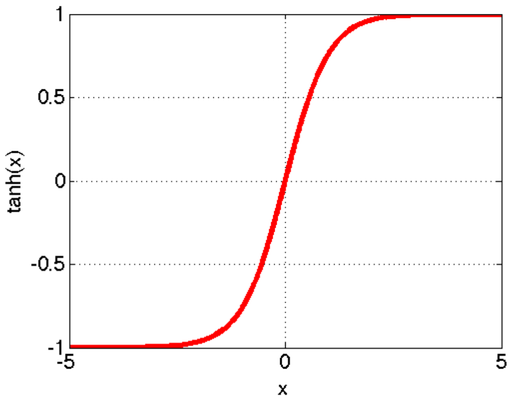
- Per-element (independent)

- Options:
  - Sigmoid: 1/(1+exp(-x))
  - Tanh
  - Rectified linear unit (ReLU)
    - Simplifies backpropagation
    - Makes learning faster
    - Avoids saturation issues
  - Variants of ReLU, e.g. Leaky ReLU

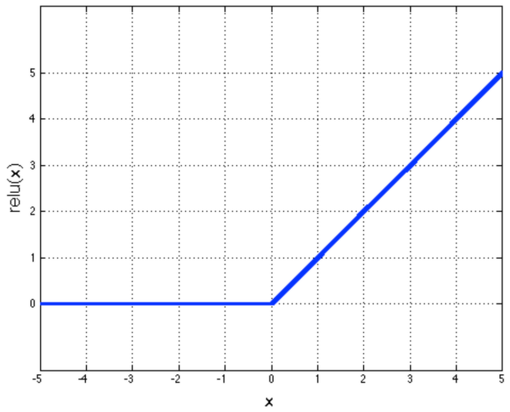
Sigmoid



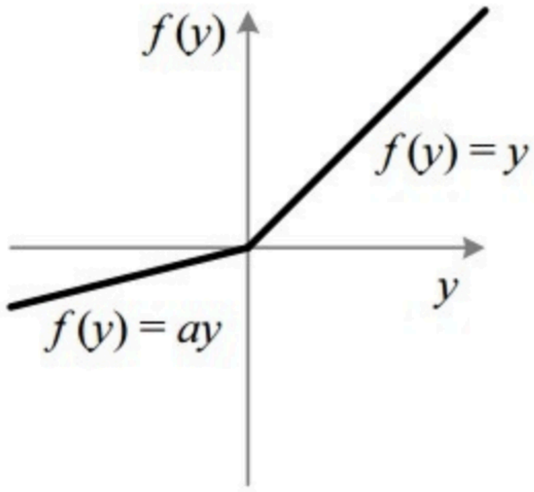
Tanh



ReLU



Leaky ReLU



Slide: R. Fergus / S. Lazebnik

5. Normalization

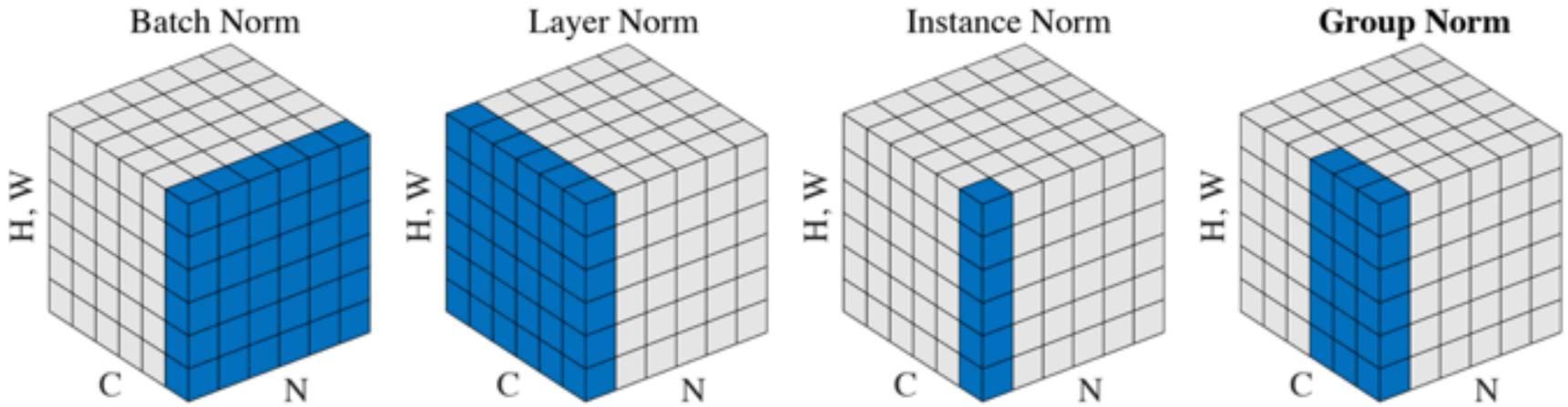


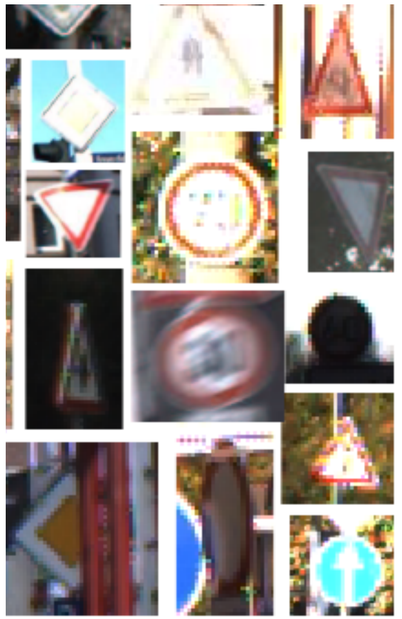
Figure 2. **Normalization methods**. Each subplot shows a feature map tensor, with N as the batch axis, C as the channel axis, and (H, W) as the spatial axes. The pixels in blue are normalized by the same mean and variance, computed by aggregating the values of these pixels.

[Wu & He, “Group normalization”, ECCV 2018]

CNN Successes

- Handwritten text/digits
  - MNIST (0.17% error [Ciresan et al. 2011])
  - Arabic & Chinese [Ciresan et al. 2012]

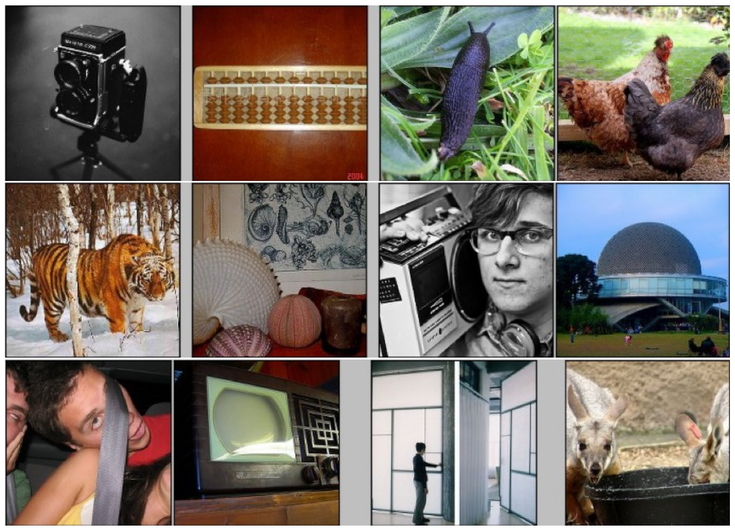
- Simpler recognition benchmarks
  - CIFAR-10 (9.3% error [Wan et al. 2013])
  - Traffic sign recognition (0.56% error vs 1.16% for humans [Ciresan et al. 2011])



- But until recently, less good at more complex datasets
  - Caltech-101/256 (few training examples)

Slide: R. Fergus / S. Lazebnik

ImageNet Dataset



[Deng et al. CVPR 2009]

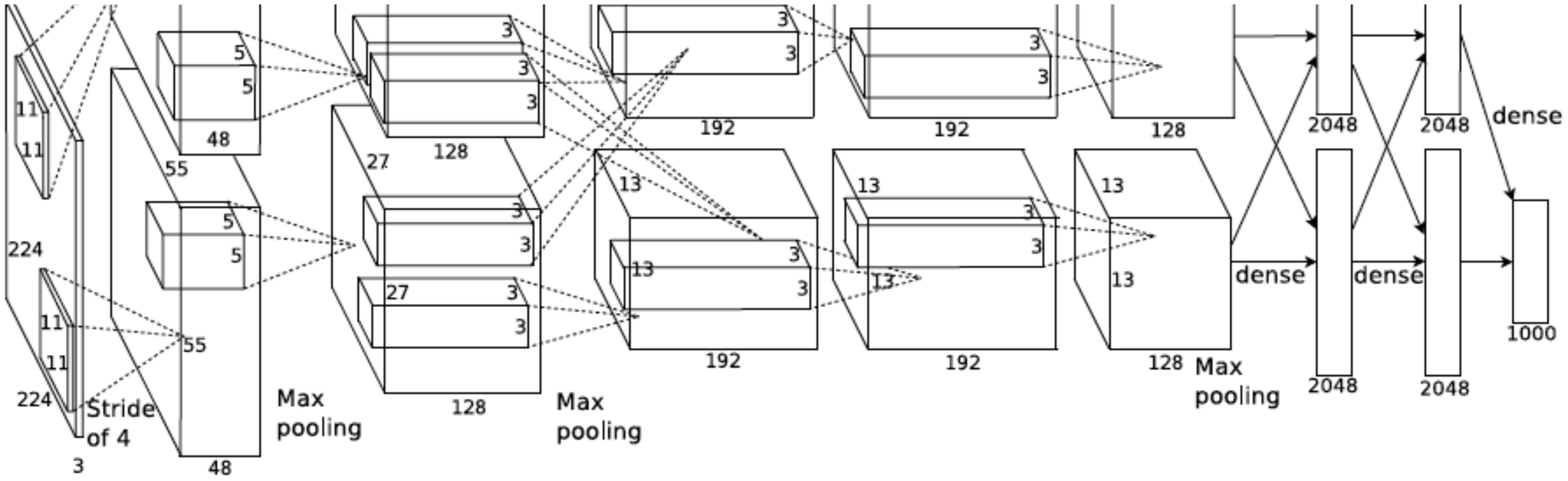
- ~14 million labeled images, 20k classes
- Challenge: 1.2 million training images, 1000 classes
- Images gathered from Internet
- Human labels via Amazon Mechanical Turk

Slide: R. Fergus / S. Lazebnik

ImageNet Challenge 2012 (ILSVRC)

- Similar framework to LeCun'98 but:
  - **Bigger model** (7 hidden layers, 60,000,000 params)
  - **More data** (10^6 vs. 10^3 images)
  - **GPU** implementation (50x speedup over CPU)
    - Trained on two GPUs for a week
  - Better regularization for training (DropOut)

AlexNet



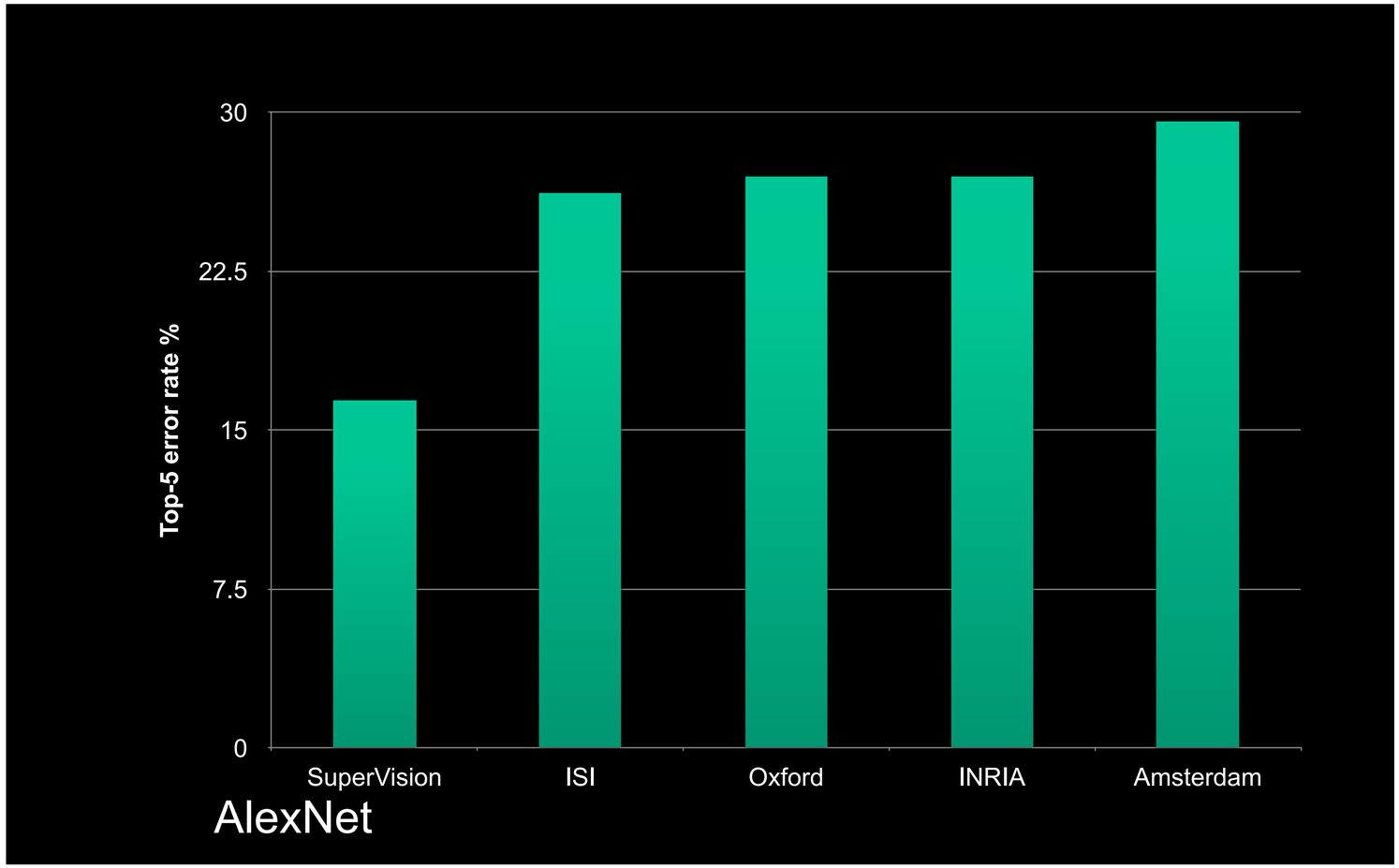
Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton,
ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

Slide: R. Fergus / S. Lazebnik

ImageNet Challenge 2012 (ILSVRC)

AlexNet – **16.4% error** (top-5)

Next best (non-convnet) – **26.2% error**



Slide: R. Fergus / S. Lazebnik

Agenda

- **1. Recap: Bag of Visual Words, Analogy with NNs**

- **2. Neural networks (NNs) for computer vision:**
  - Applications
  - A brief history: from perceptron to MLPs to CNNs

- **3. Convolutional neural networks (CNNs)**
  - Standard layers
  - Recap: Training NNs
  - Visualizing CNNs
  - Pretraining & finetuning NNs
  - Typical CNN architectures

- **4. Beyond classification - preview**

Recap: Stochastic Gradient Descent (SGD)

The objective function is an average over all N training data points:

$$\theta_{t+1} \rightarrow \theta_t - \frac{\alpha_t}{N} \sum_i \frac{\partial \ell(\theta, X_i, Y_i)}{\partial \theta}$$

(gradient descent)

Key idea: approximate the gradient with 1 random datapoint:

$$\theta_{t+1} \rightarrow \theta_t - \alpha_t \frac{\partial \ell(\theta, X^{(i_t)}, Y^{(i_t)})}{\partial \theta}$$

(stochastic gradient descent)

Pick K random points instead of picking 1 (with $K << N$):

$$\theta_{t+1} \rightarrow \theta_t - \frac{\alpha_t}{K} \sum_{i=1}^{K} \frac{\partial \ell(\theta, X_i, Y_i)}{\partial \theta}$$

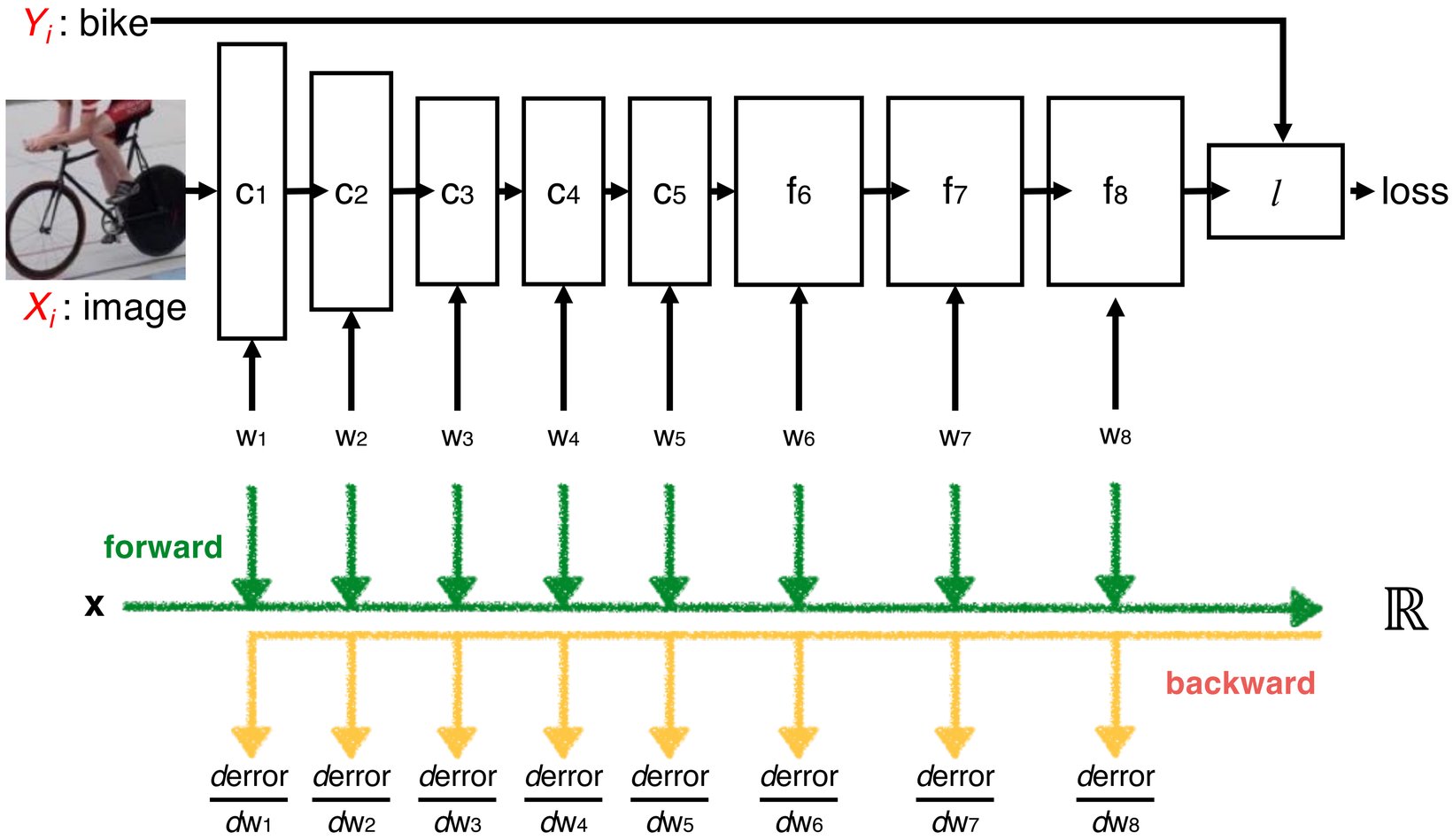
(stochastic gradient descent with mini-batches)

=> commonly used

Slide credit: Andrea Vedaldi

Recap: Backpropagation

Computing the gradients: While in theory, we just have the gradients of composite functions and for that apply **chain rule**, there is an **efficient** way to do it, called **backpropagation**.



Slide credit: Andrea Vedaldi [Derivatives, Backpropagation, and Vectorization] http://cs231n.stanford.edu/handouts/derivatives.pdf

Recap: Training a neural network

Given a (X, Y) pair:

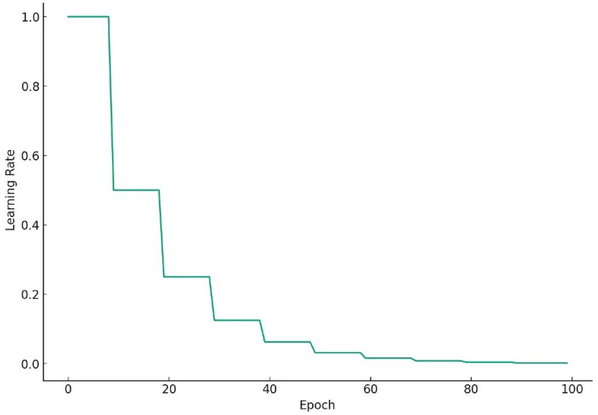
- **Forward pass**: apply network to X to produce an output $\hat{Y}$
- **Evaluation**: Compute loss function, i.e., $\ell(\hat{Y}, Y)$
- **Backward pass**: compute the gradient with backprogation
- **Update:** Take a step in the direction of the gradient

Slide: A. Joulin

Recap: Learning rate policy

- There is no standard policy with NNs.
- The best is usually to pick a LR as high as possible without having divergence, keep it constant until convergence, then decrease it.
- Other more complex approaches are also widely used such as sinusoidal LR schedules, linear warmup etc.
- LR schedules even help with adaptive optimizers (e.g., AdaGrad)
- There are no guarantees with NNs, looking at training curves is crucial!

Step decay



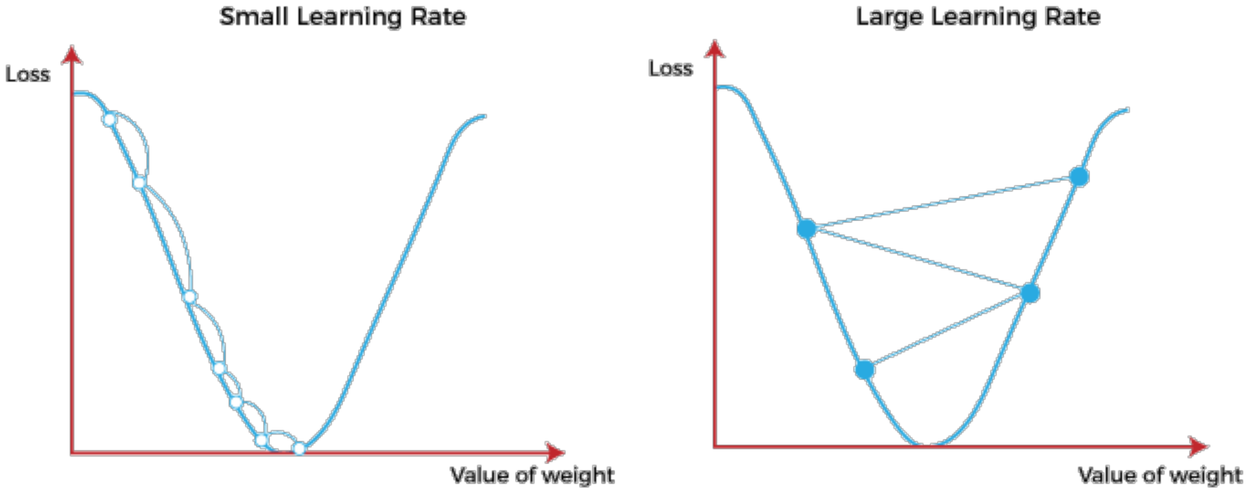
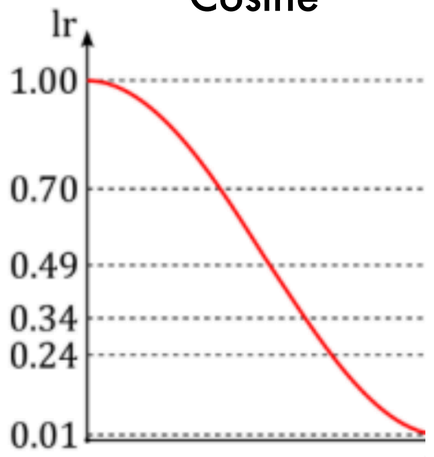
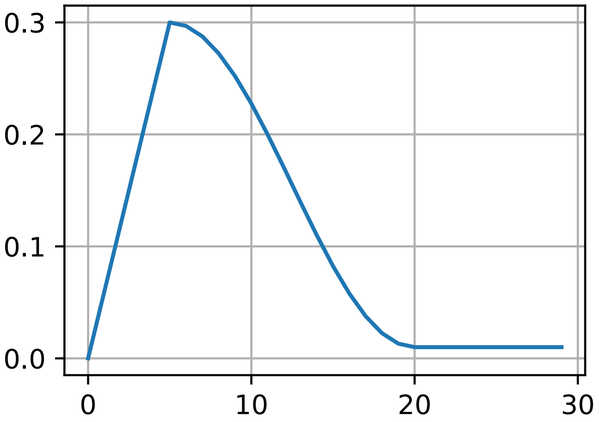


Image source

Cosine



Linear warmup

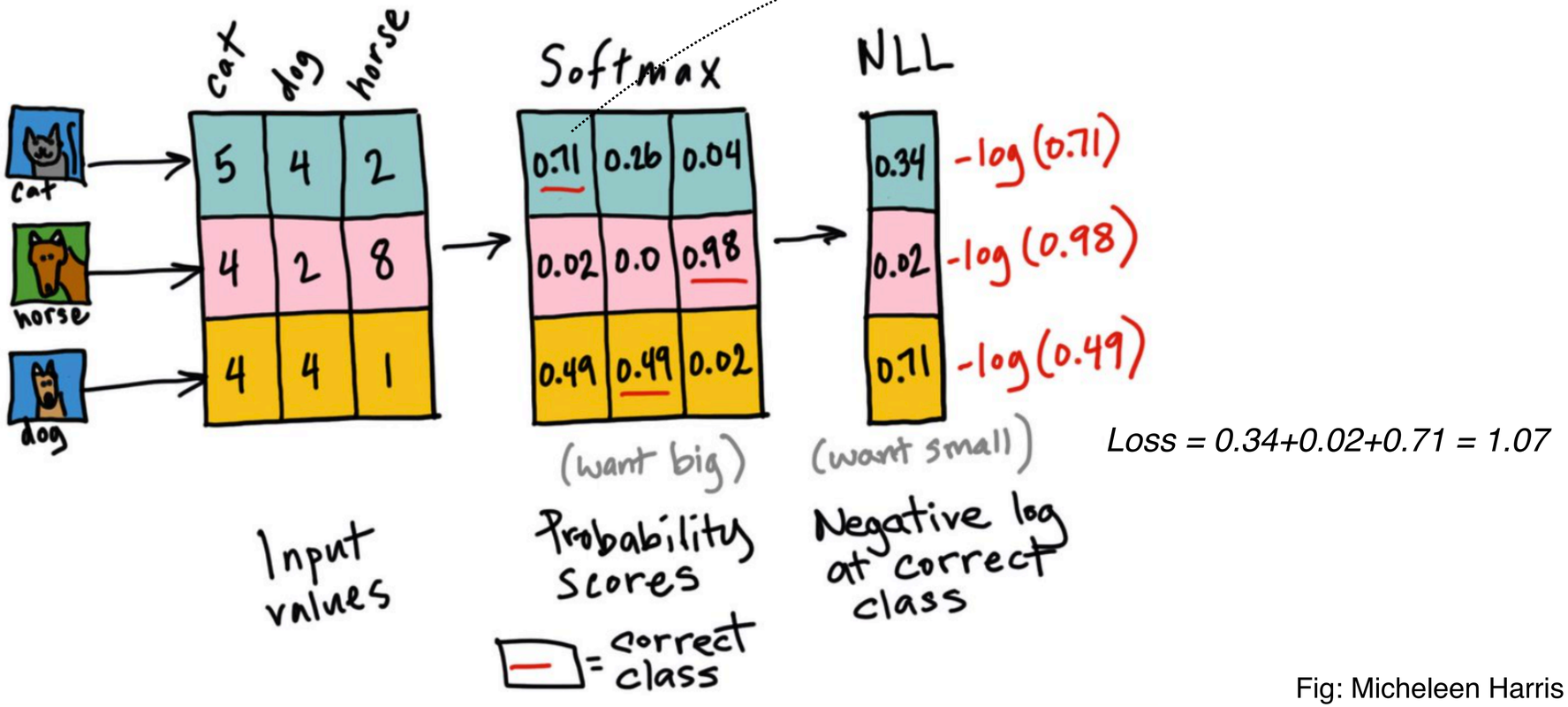


Recap: Classification loss

- Cross-entropy loss = softmax + negative log-likelihood

$$\text{loss}(x, \text{class}) = -\log\left(\frac{\exp(x[\text{class}])}{\sum_j \exp(x[j])}\right)$$

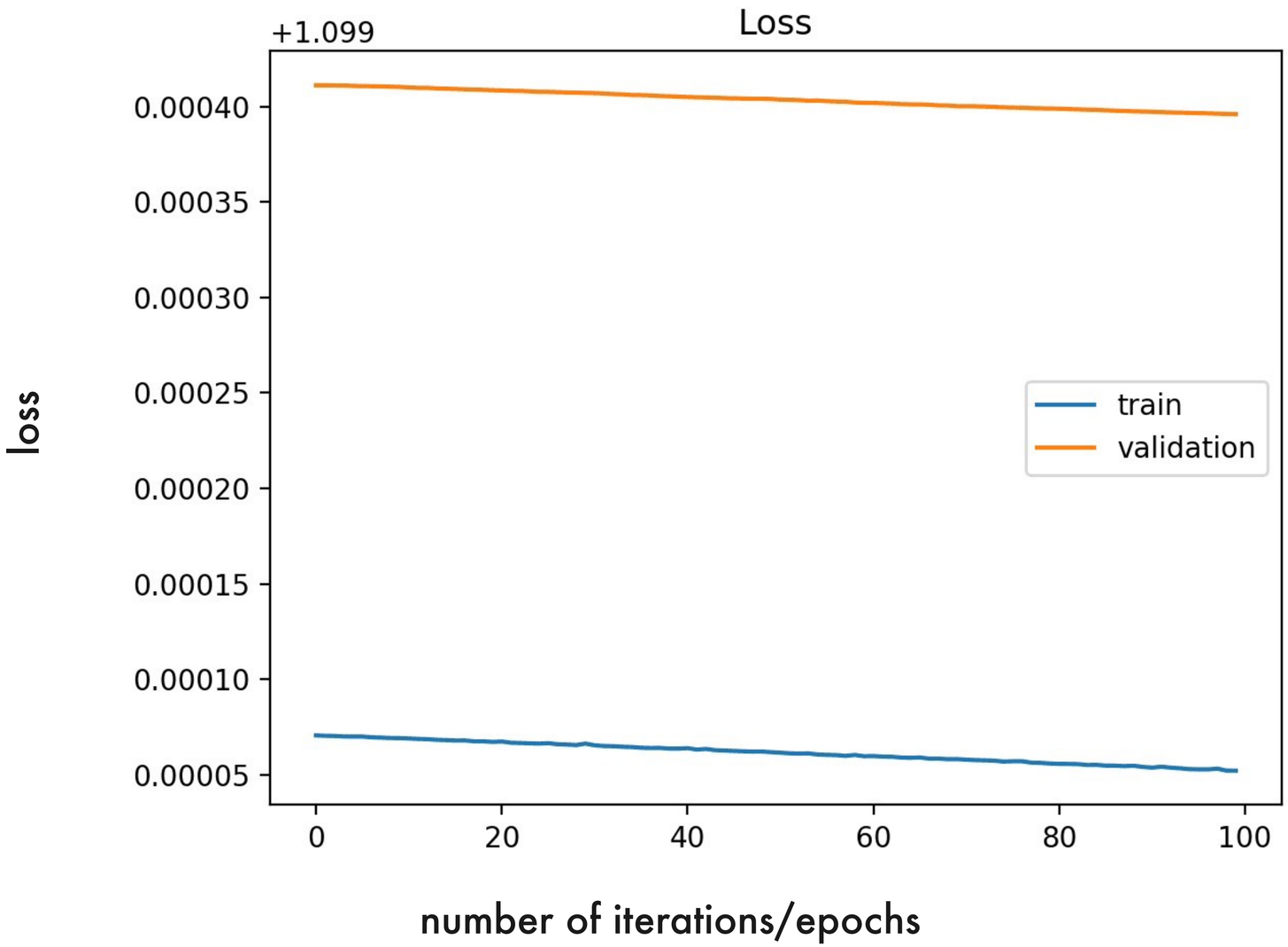
$$\frac{e^5}{e^5 + e^4 + e^2}$$



Loss = 0.34+0.02+0.71 = 1.07

Fig: Micheleen Harris

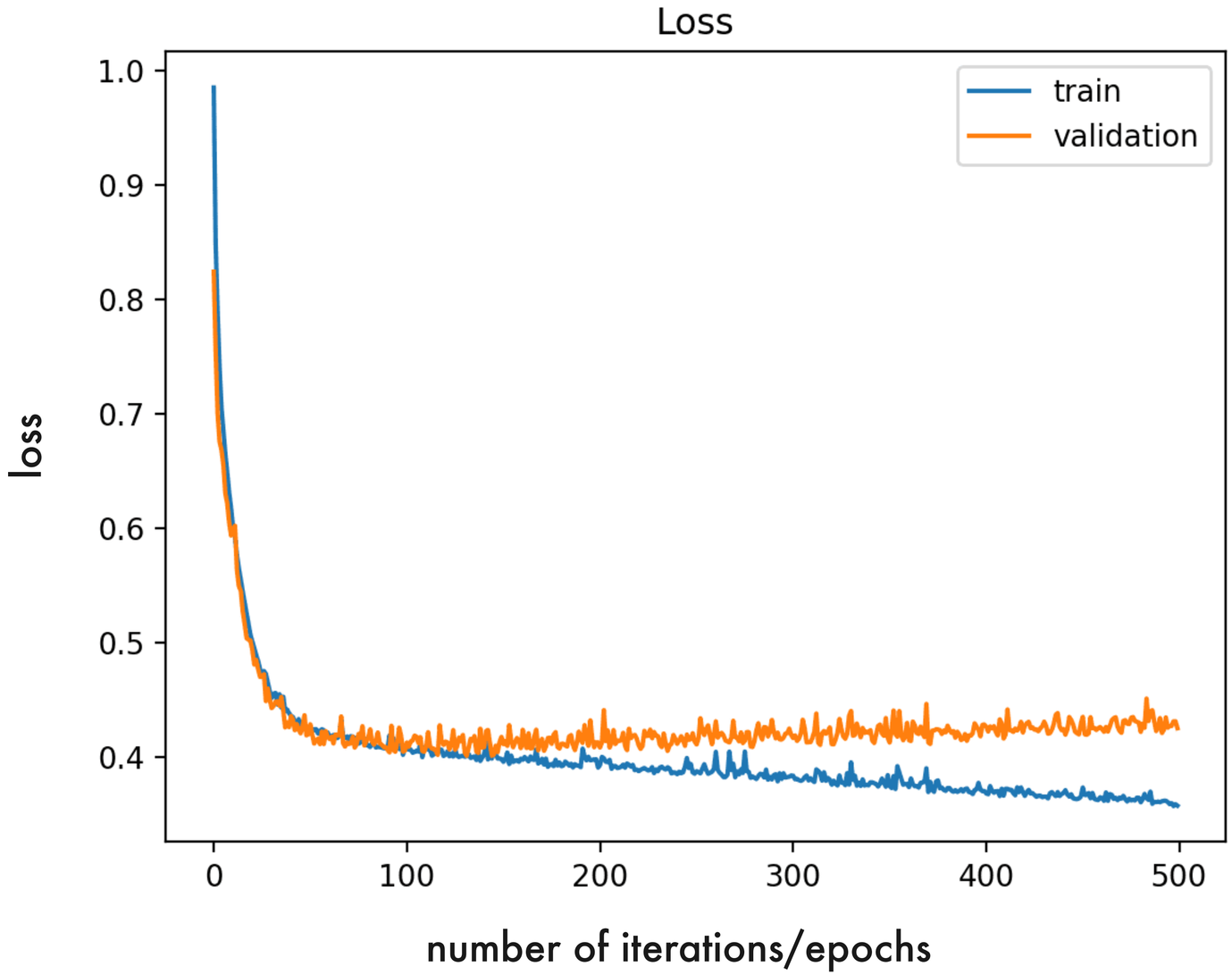
How can I resolve the problem with training?



Credit: **Jason Brownlee**

Image sources

How can I resolve the problem with training?



Credit: **Jason Brownlee**

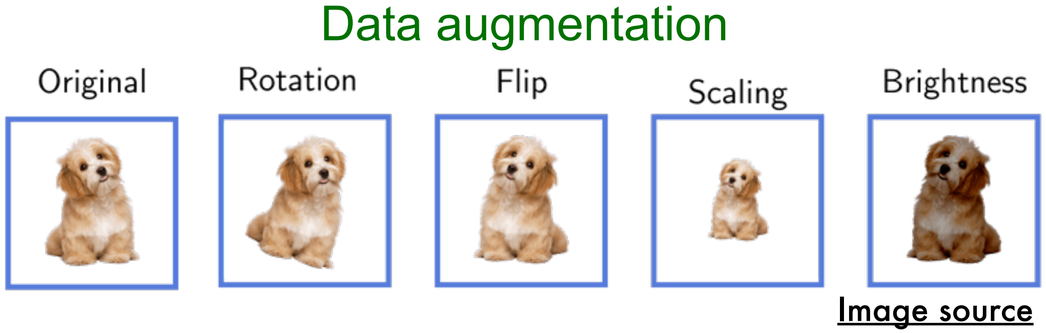
Image sources

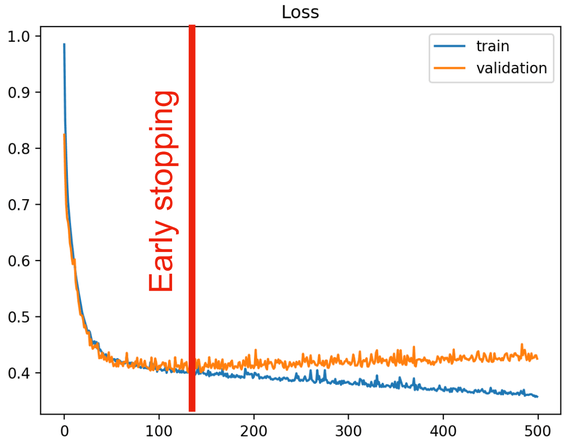
How to avoid overfitting?

Deep networks have many parameters.

Some regularization techniques:

- Smaller network, i.e., less parameters
- Data augmentation
- Suboptimize, i.e., "early stopping"
- Force redundancy in hidden units, i.e., "dropout"
- Penalize parameter norms, i.e., "weight decay"





L2 penalty:
encourages the norm of
the parameters to be low

$$L(\theta) + \frac{\lambda}{2} \left| |\theta| \right|_2^2$$

$$\theta_{t+1} \rightarrow \theta_t - \alpha \frac{\partial L}{\partial \theta_t} - \alpha \lambda \theta_t$$

gradient

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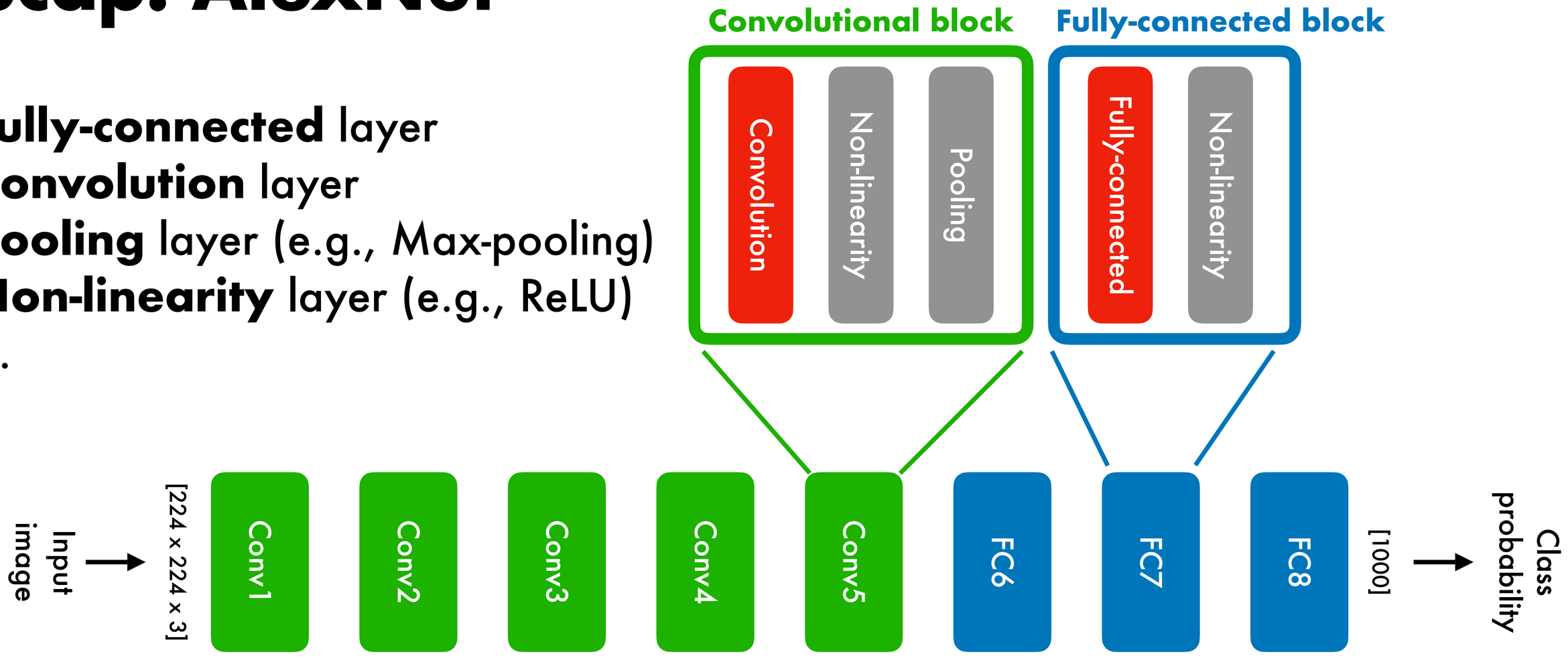
Visualizing CNNs

What does CNN learn once it is trained?

Recap: AlexNet

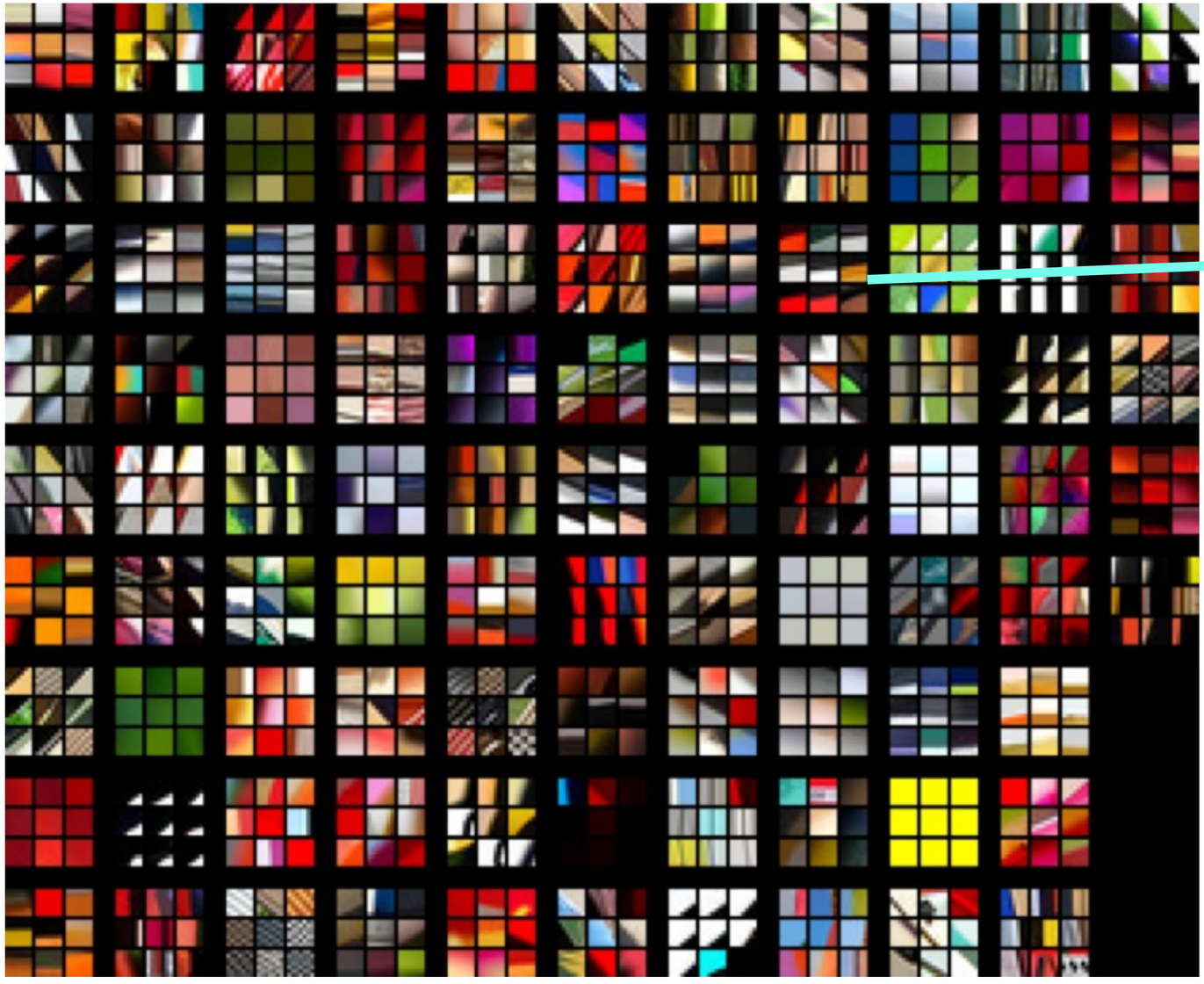
- **Fully-connected** layer
- **Convolution** layer
- **Pooling** layer (e.g., Max-pooling)
- **Non-linearity** layer (e.g., ReLU)
- …



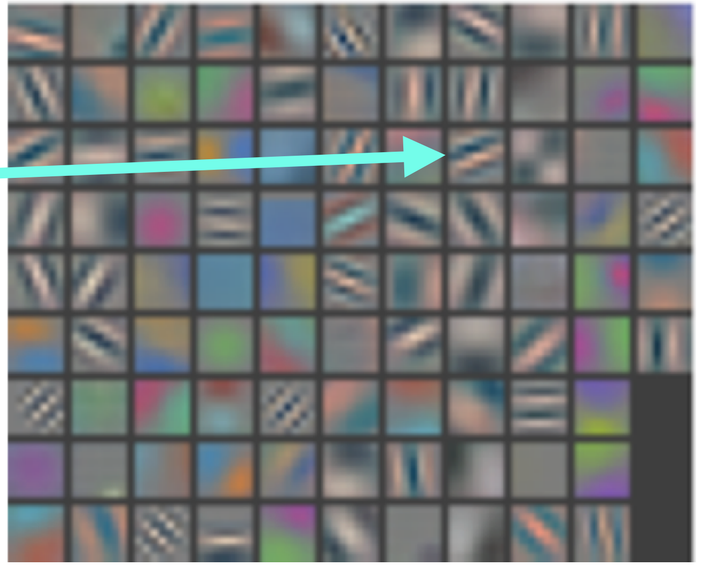
AlexNet: [Krizhevsky 2012]

Layer 1: Top-9 patches

Patches from validation images that give maximal activation of a given feature map

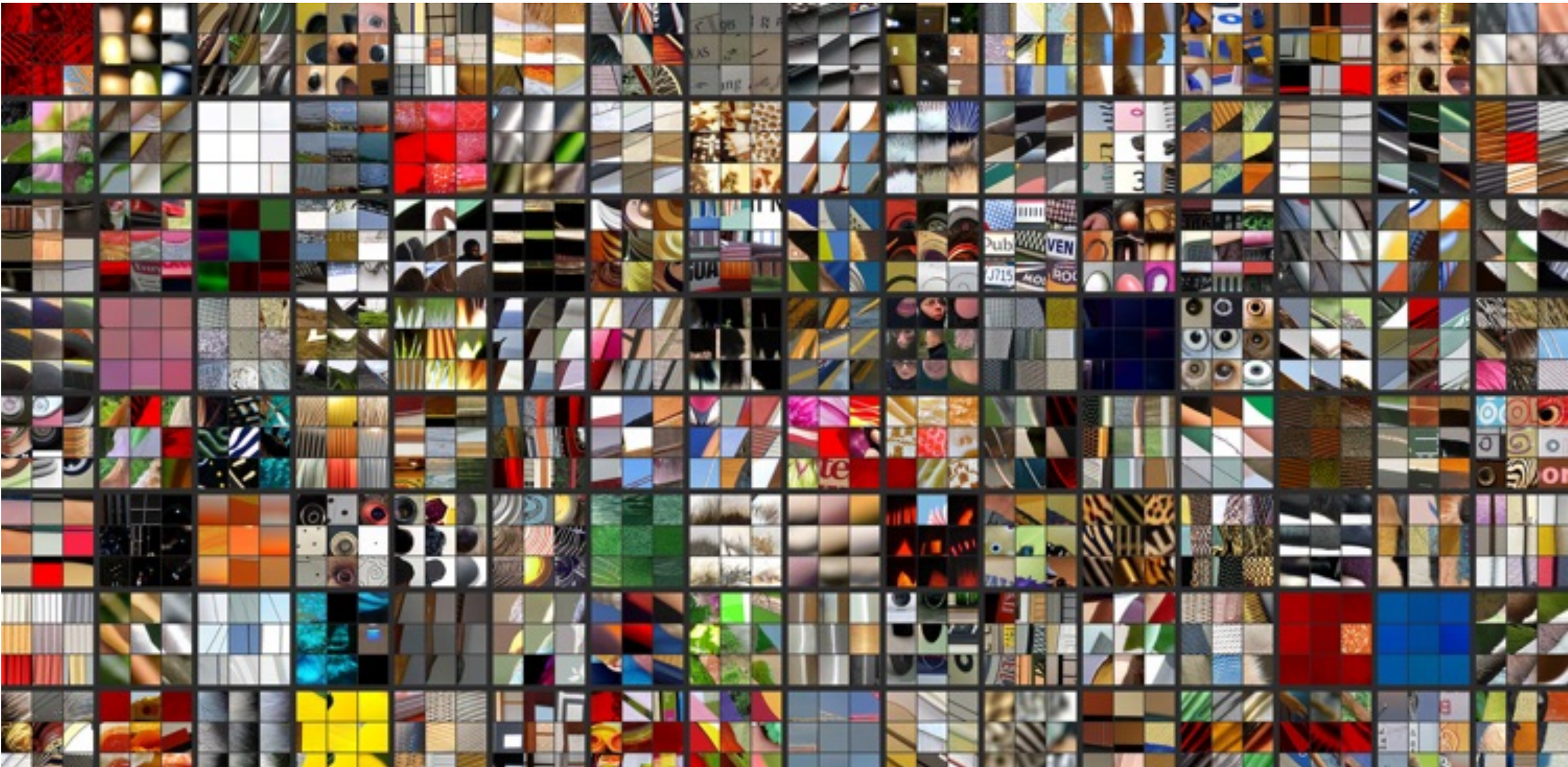


Learned filters



[Zeiler and Fergus, Visualizing and Understanding Convolutional Networks, ECCV 2014]

Layer 2: Top-9 patches



Layer 3: Top-9 patches

Layer 4: Top-9 patches

Layer 5: Top-9 patches

References: Visualizing and understanding NNs

Analysis tools

Visualizing higher-layer features of a deep network
Ethan et al. 2009
[intermediate features]

Deep inside convolutional networks
Simonyan et al. 2014
[deepest features, aka “deep dreams”]

DeConvNets
Zeiler et al. In ECCV, 2014
[intermediate features]

Understanding neural networks through deep visualisation
Yosinksi et al. 2015
[intermediate features]

Artistic tools

Google’s “inceptionism”
Mordvintsev et al. 2015

Style synthesis and transfer

Gatys et al. 2015

Slide: A. Vedaldi

Agenda

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  - A brief history: from perceptron to MLPs to CNNs

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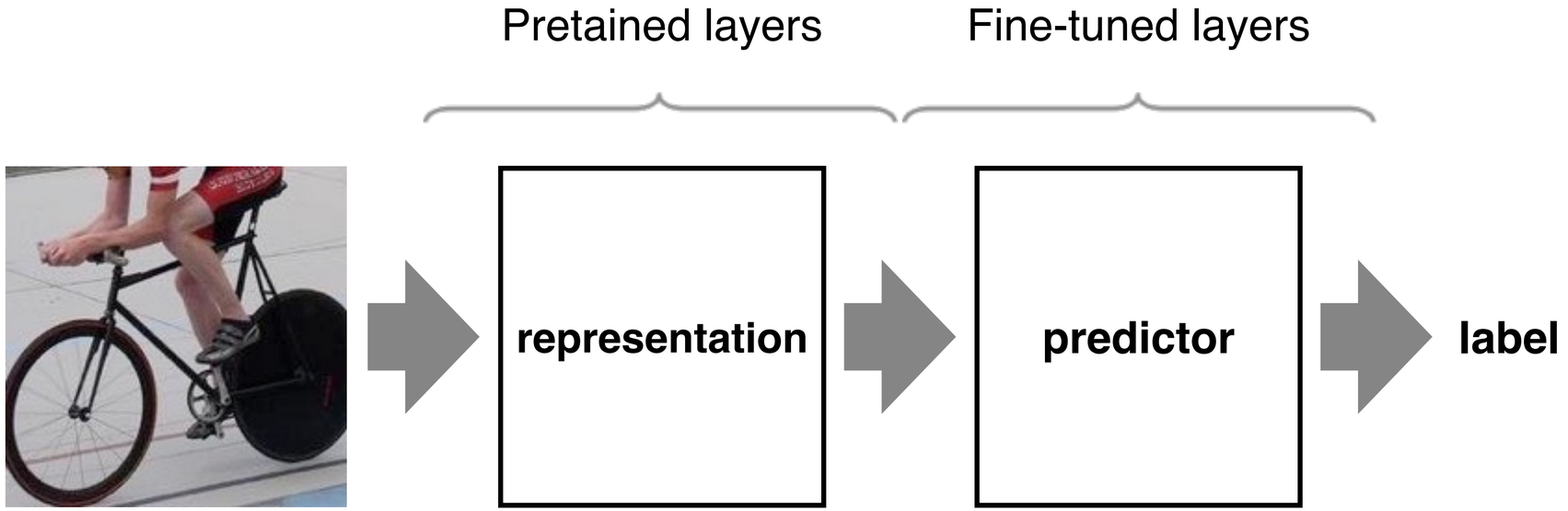
  - Visualizing CNNs
  - Pretraining & finetuning NNs
  - Typical CNN architectures

- **4. Beyond classification - preview**

Transferring learnt representations

"pretraining"

“Pre-training” and transfer learning



CNN as universal representations

- First several layers in most CNNs are generic
- They can be reused when training data is comparatively scarce

Application

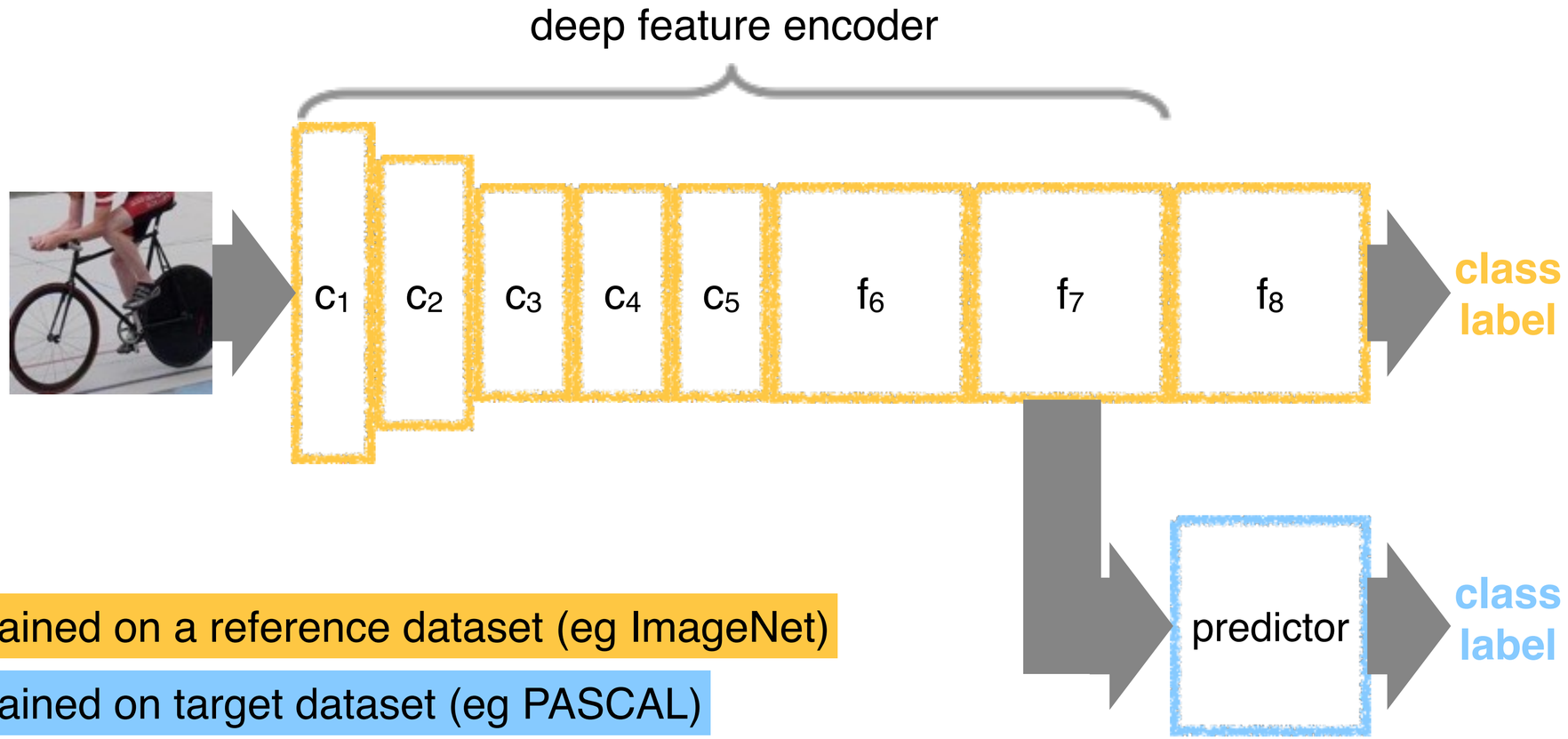
- Pre-train on ImageNet classification 1M images
- Cut at some deep conv or FC layer to get features

[Evaluations in A. S. Razavian, 2014, Chatfield et al., 2014]

Slide: A. Vedaldi

“Pre-training” and transfer learning

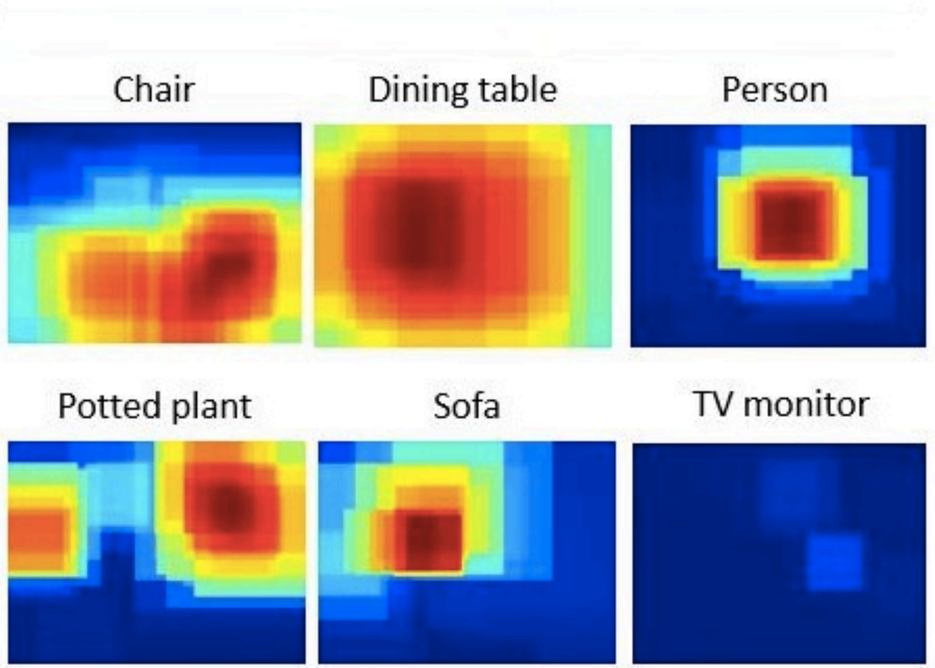
Deep representations are generic



A general purpose deep encoder is obtained by chopping off the last layers of a CNN trained on a large dataset.

Slide: A. Vedaldi

Example



Learning and Transferring Mid-Level Image Representations using Convolutional Neural Networks

M. Oquab, L. Bottou, I. Laptev, J. Sivic

In CVPR 2014

http://www.di.ens.fr/willow/research/cnn/

Slide: A. Vedaldi

ImageNet classification challenge

ImageNet classification challenge

Object centric

1000 classes

1.2M images

What about other recognition tasks and datasets?

ImageNet classification challenge

Object centric

1000 classes

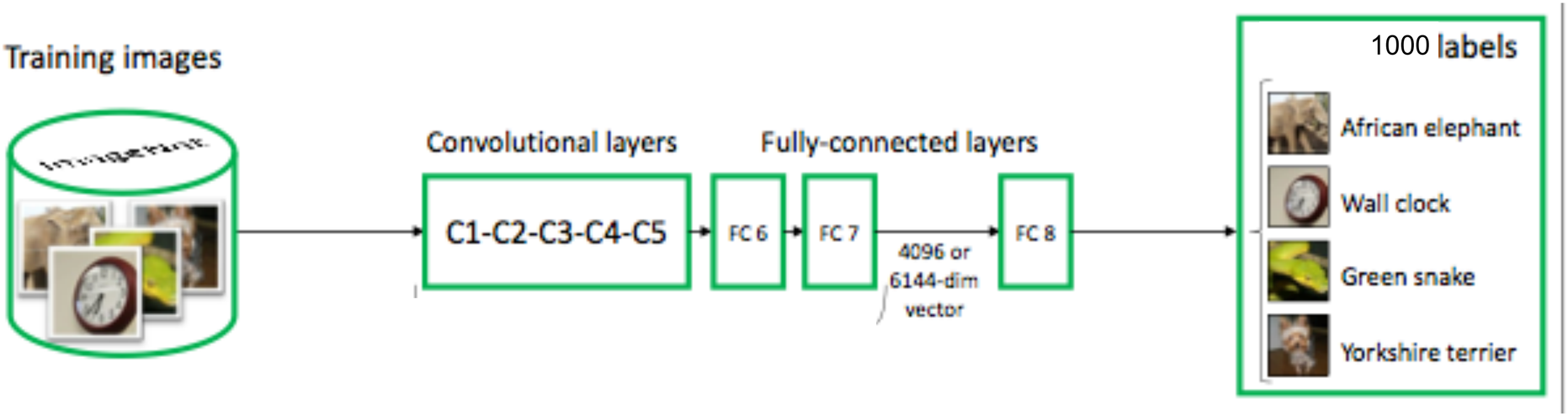
1.2M images

Complex scenes

20 classes

10k images

Background – Convolutional neural network of [Krizhevsky et al. 2012]



Input: ~1M **labelled** images (1000 images / 1000 classes)

Number of parameters: ~60 million --- image representation

Training time: ~1 week on one GPU

Learn parameters using stochastic gradient descent on cross-entropy error function.

Can we transfer learnt parameters to other tasks with limited training data?

Challenge

The dataset statistics between the source task (ImageNet) and the target task (Pascal VOC) can be very different.

- Type of objects and labels
- Object size, object location, scene clutter
- Object viewpoints, imaging conditions

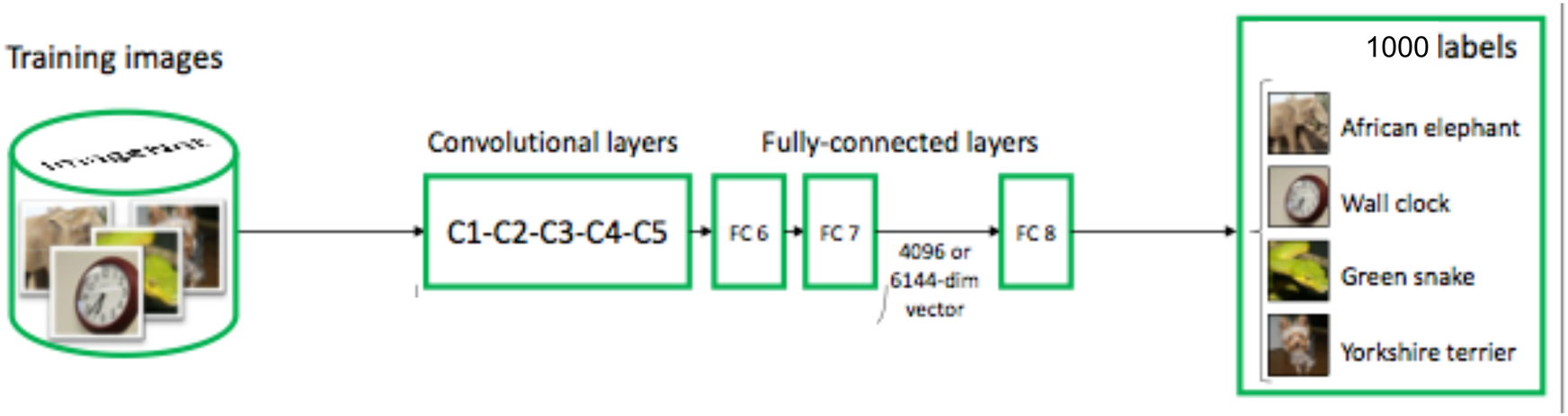
ImageNet

Maltese terrier

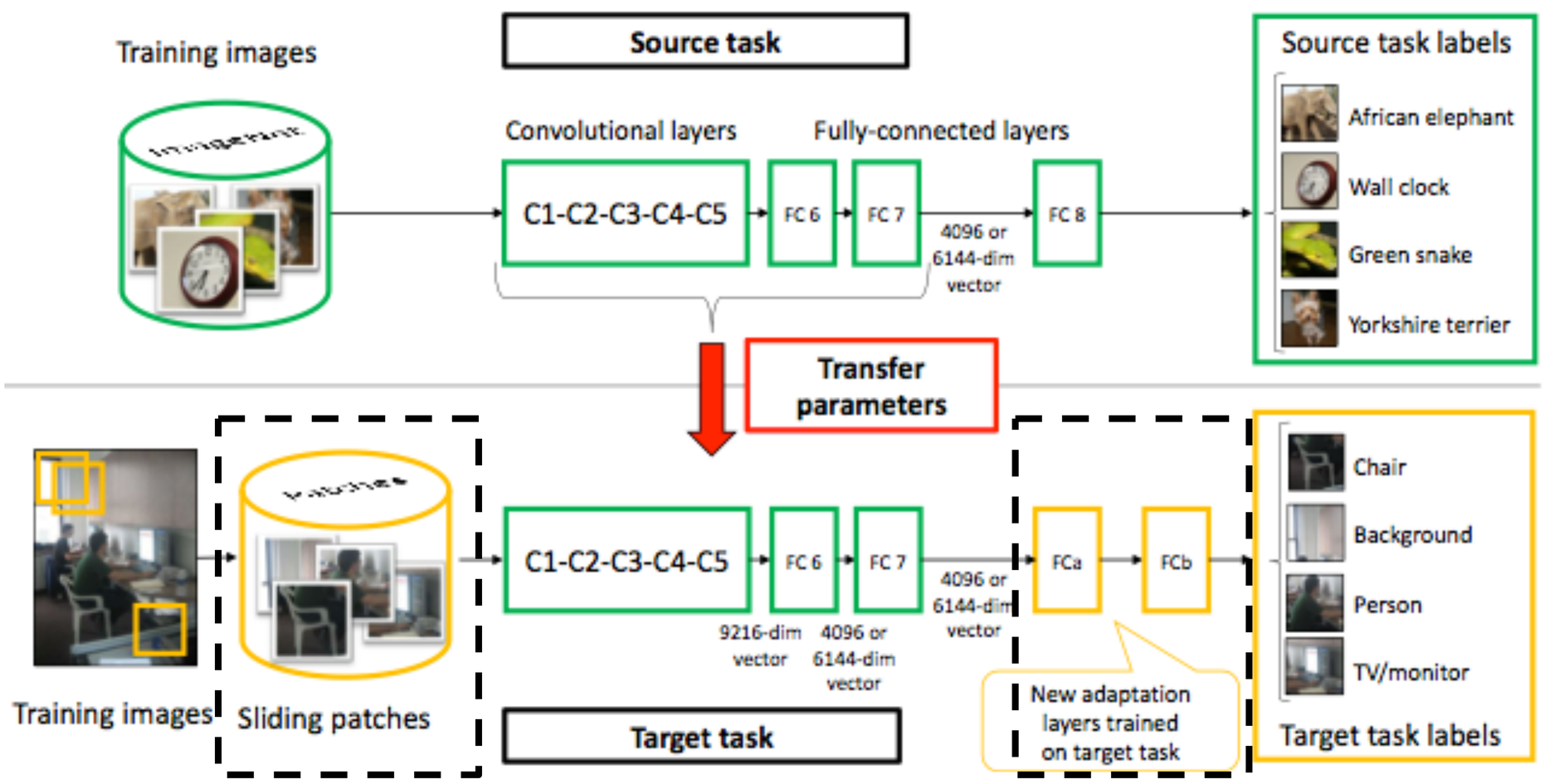
Pascal VOC

Dog

Approach


Training images
Convolutional layers
Fully-connected layers
C1-C2-C3-C4-C5
FC 6
FC 7
4096 or
6144-dim
vector
FC 8
1000 labels
African elephant
Wall clock
Green snake
Yorkshire terrier

Approach [Oquab, Bottou, Laptev, Sivic, CVPR'14]



1. Design training/test procedure using sliding windows
2. Train adaptation layers to map labels

See also [Girshick et al.'13], [Donahue et al.'13], [Sermanet et al. '14], [Zeiler and Fergus '13]
Transfer learning workshop at ICCV'13, ImageNet workshop at ICCV'13

Pre-training helps

	plane	bike	bird	boat	btl	bus	car	cat	chair	cow	table	dog	horse	moto	pers	plant	sheep	sofa	train	tv	**mAP**
NO PRETRAIN	85.2	75.0	69.4	66.2	48.8	82.1	79.5	79.8	62.4	61.9	49.8	75.9	71.4	82.7	93.1	59.1	69.7	49.3	80.0	76.7	70.9
PRE-1000C	93.5	78.4	*87.7*	80.9	57.3	85.0	81.6	*89.4*	66.9	73.8	62.0	*89.5*	83.2	87.6	*95.8*	*61.4*	79.0	54.3	88.0	78.3	78.7
PRE-1000R	93.2	77.9	83.8	80.0	55.8	82.7	79.0	84.3	66.2	71.7	59.5	83.4	81.4	84.8	95.2	59.8	74.9	52.9	83.8	75.7	76.3
PRE-1512	94.6	82.9	**88.2**	84.1	60.3	89.0	84.4	**90.7**	72.1	**86.8**	69.0	**92.1**	**93.4**	88.6	**96.1**	**64.3**	**86.6**	62.3	91.1	79.8	**82.8**

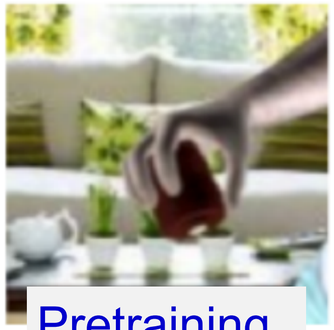
- Pascal VOC 2012 object classification

Action	jump	phon	instr	read	bike	horse	run	phot	comp	walk	**mAP**
NO PRETRAIN	43.2	30.6	50.2	25.0	76.8	80.7	75.2	22.2	37.9	55.6	49.7
PRE-1512	73.4	44.8	**74.8**	43.2	92.1	94.3	83.4	**45.7**	65.5	66.8	68.4
PRE-1512U	74.8	46.0	**75.6**	**45.3**	93.5	95.0	86.5	**49.3**	66.7	69.5	**70.2**

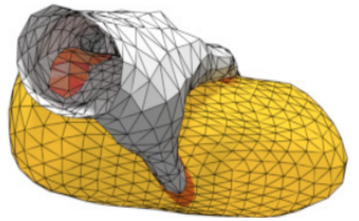
- Pascal VOC 2012 action classification

Other "pre-training" examples

3D hand-object reconstruction



Pretraining



Finetuning

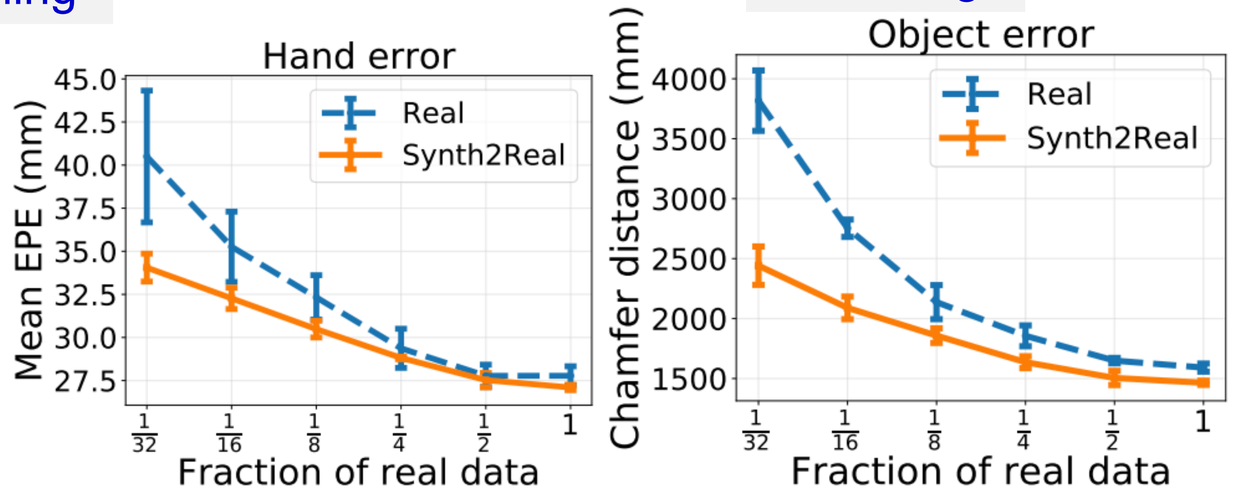


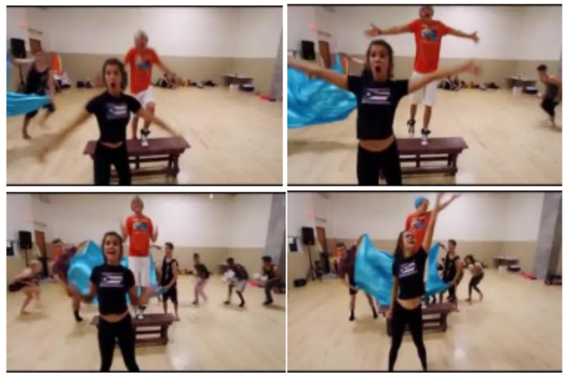
Figure 8: We compare training on FHB only (Real) and pre-training on synthetic, followed by fine-tuning on FHB (Synth2Real). As the amount of real data decreases, the benefit of pre-training increases. For both the object and the hand reconstruction, synthetic pre-training is critical in low-data regimes.

Hasson et al. "**Learning joint reconstruction of hands and manipulated objects**", CVPR 2019.

Text-to-Video Retrieval

Pretraining on millions of images & videos

Finetuning on MSRVTT with 9K training videos



1. A man and a woman performing a musical.
2. A teenage couple perform in an amateur musical
3. Dancers are playing a routine.
4. People are dancing in a musical.
5. Some people are acting and singing for performance.

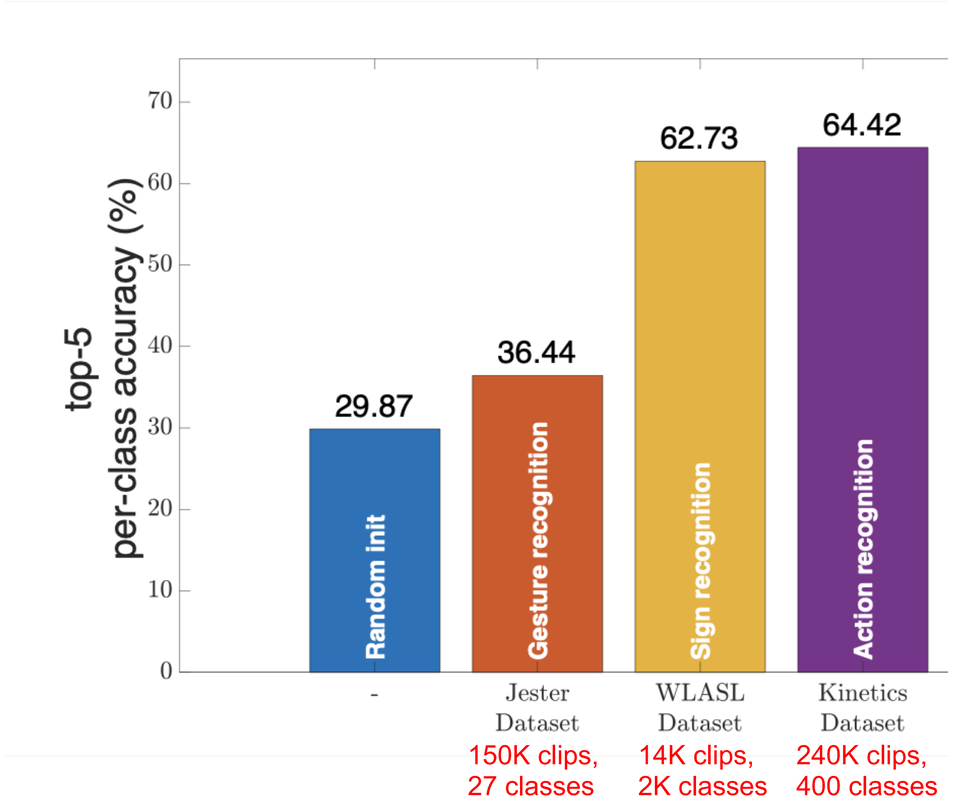
	Pre-training (for 1 epoch)	#pairs	↑R@1	↑R@10	↓MedR
	-	-	5.6	22.3	55
📷	ImageNet		15.2	54.4	9.0
Noisy 🎞	HowTo-17M subset	17.1M	24.1	63.9	5.0
📷	CC3M	3.0M	24.5	62.7	5.0
🎞	WebVid2M	2.5M	26.0	64.9	5.0
📷+🎞	**CC3M + WebVid2M**	5.5M	**27.3**	**68.1**	**4.0**

Bain et al. "**Frozen in Time: A Joint Video and Image Encoder for End-to-End Retrieval**", ICCV 2021.

Sign Language Recognition

Pretraining on various tasks on different datasets

Finetuning on 50K videos from BSL-1K sign language dataset



Albanie et al. "**BSL-1K: Scaling up co-articulated sign language recognition using mouthing cues",** ECCV 2020.

Pretraining Summary

- Common practice: Pretrain on large data, finetune on small data.
  - Remove the last class-specific layer (e.g. 1000 categories)
  - Add new layer(s) for the new task randomly initialized
  - Either “freeze” the pretrained parameters and train a simple classifier on top,
  - Or train “end-to-end” all parameters.
- Avoids overfitting
- Shortens training time
- Lots of pretrained models available online
- Task and domain-relevant pretraining is usually better

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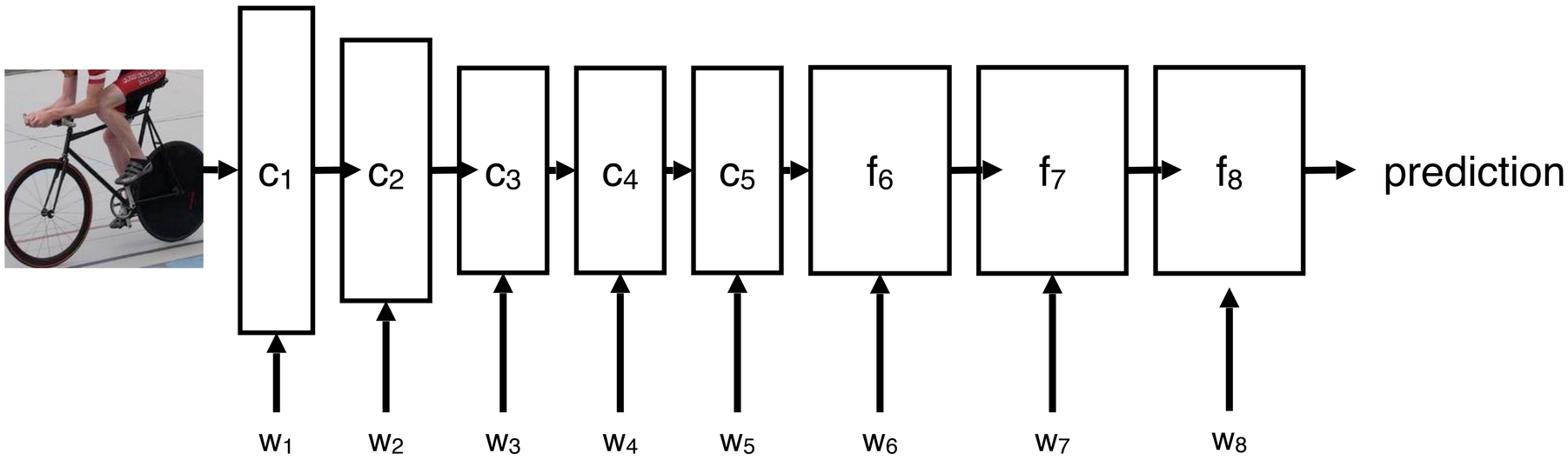
  - Visualizing CNNs
  - Pretraining & finetuning NNs
  - Typical CNN architectures

- **4. Beyond classification - preview**

A CNN for image classification

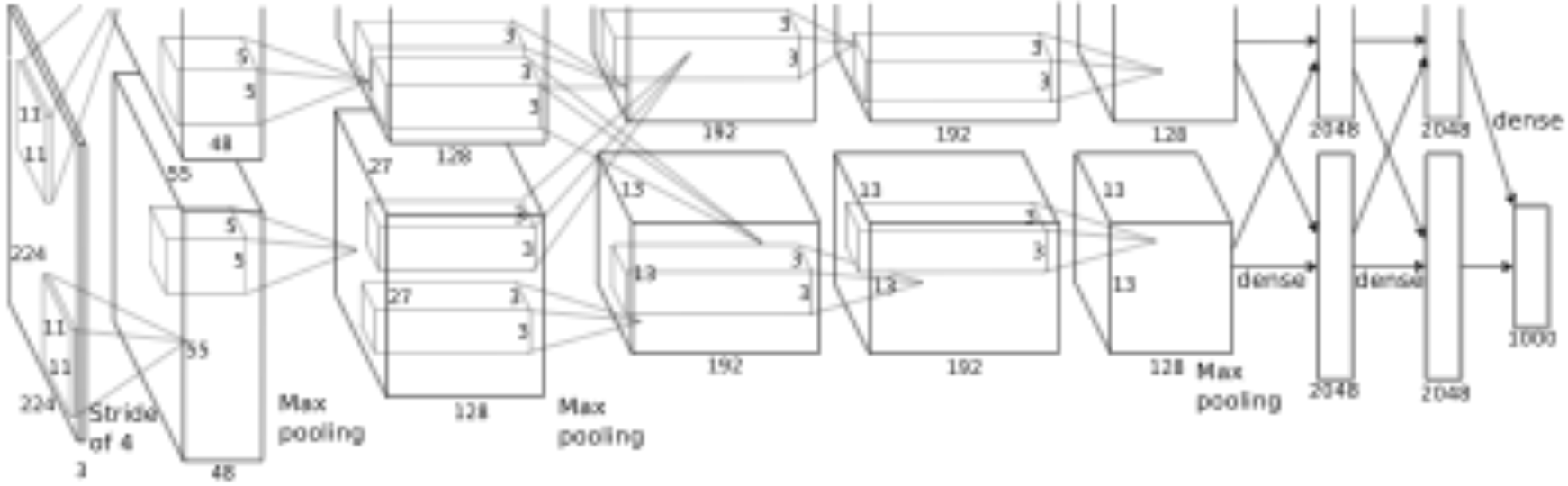


Recall: the goal of this model is to map an input image to a class prediction.

Slide: A. Vedaldi

Recall: The AlexNet model

A breakthrough in image understanding



[AlexNet by Krizhevsky et al. 2012]

Each large block represents a data tensor

Each smaller block represents a filter

The filter size and stride are shown

The number of filters can be deduced from the number of feature channels

There are two parallel streams in this network (for efficiency reasons)

Slide: A. Vedaldi

How deep is deep enough?

AlexNet (2012)

5 convolutional layers

3 fully-connected layers

Slide: A. Vedaldi

How deep is deep enough?

AlexNet (2012)

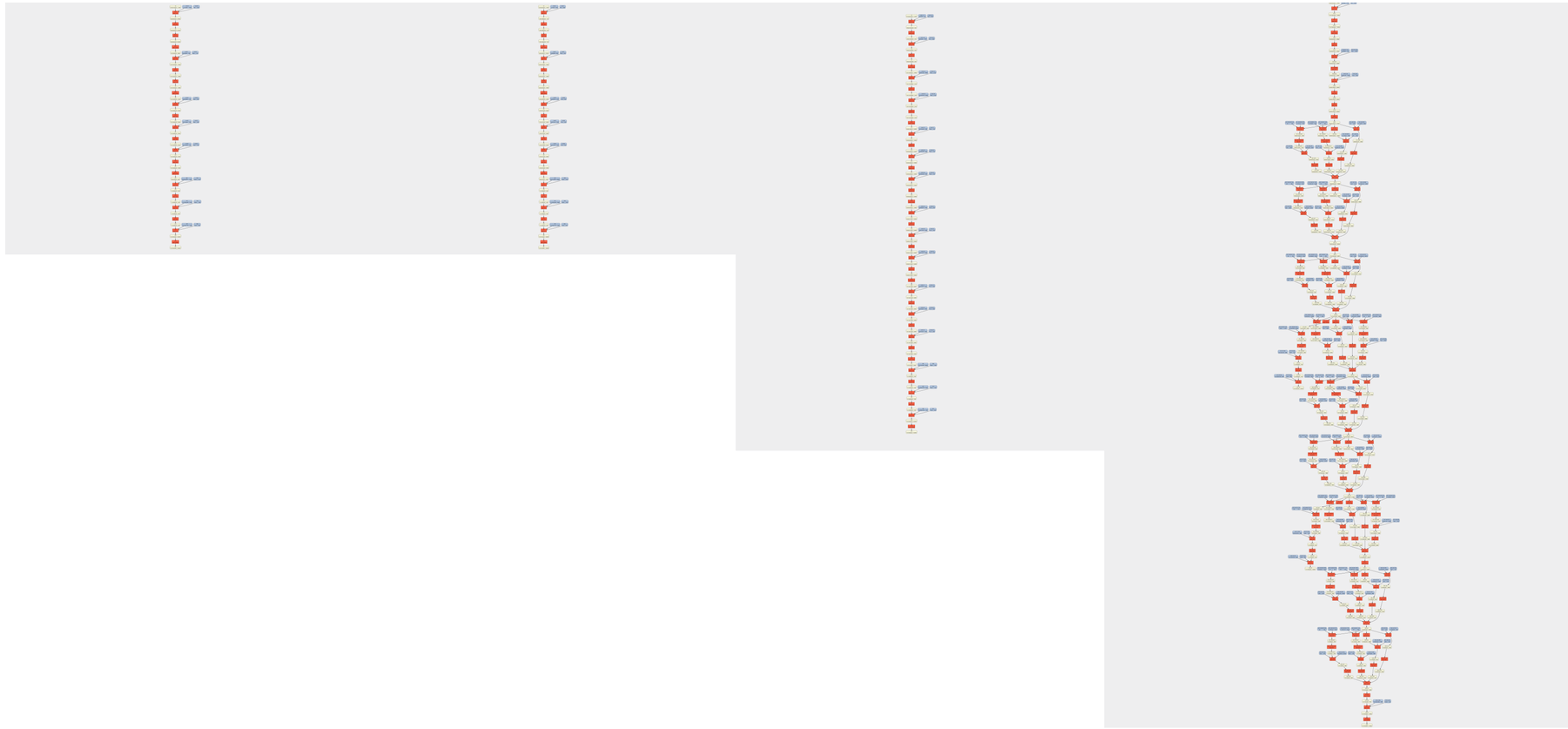
VGG-M (2013)

VGG-VD-16 (2014)

Slide: A. Vedaldi

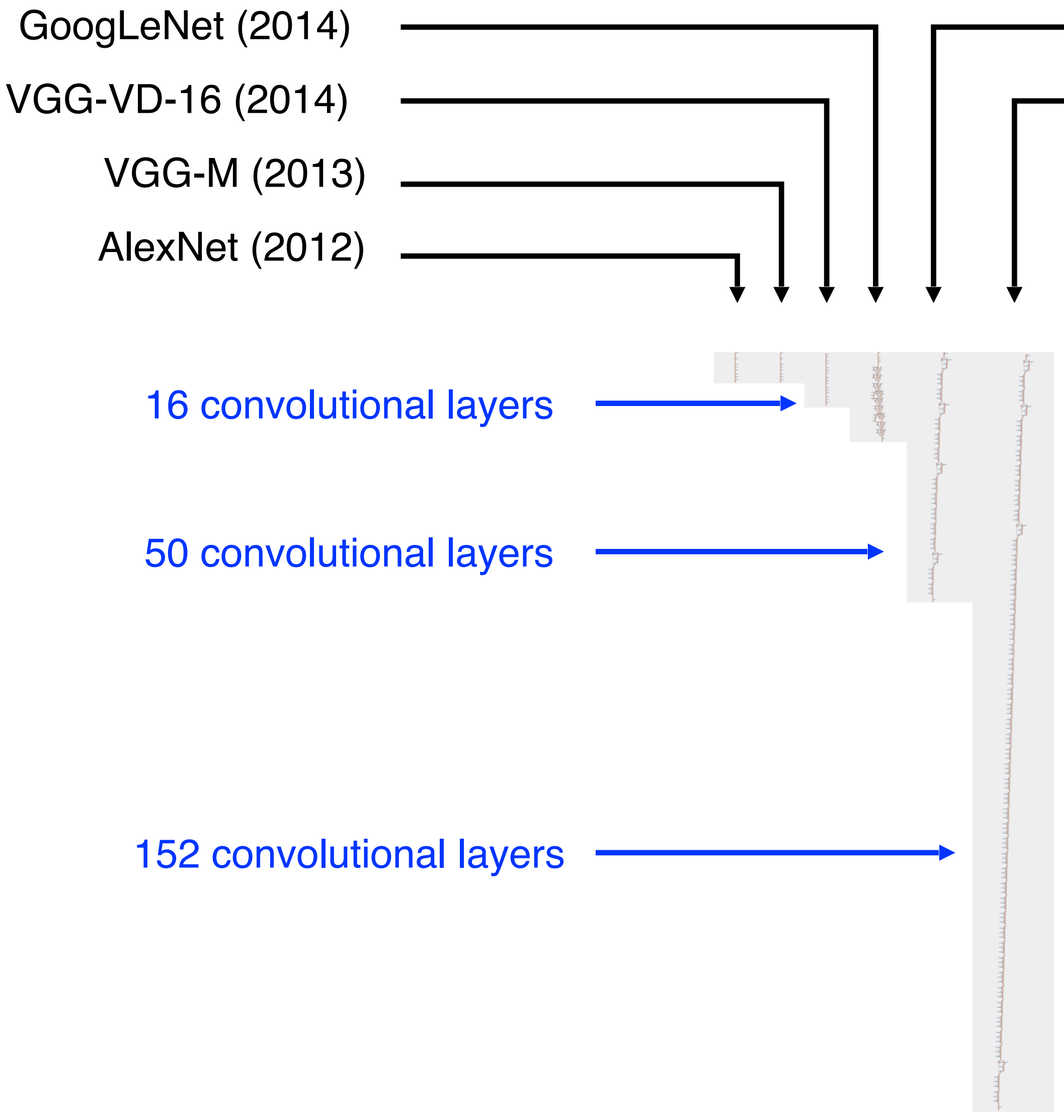
How deep is deep enough?

AlexNet (2012) VGG-M (2013) VGG-VD-16 (2014) GoogLeNet (2014)



Slide: A. Vedaldi

How deep is deep enough?



Krizhevsky, I. Sutskever, and G. E. Hinton. *ImageNet classification with deep convolutional neural networks*. In Proc. NIPS, 2012.

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. *Going deeper with convolutions*. In Proc. CVPR, 2015.

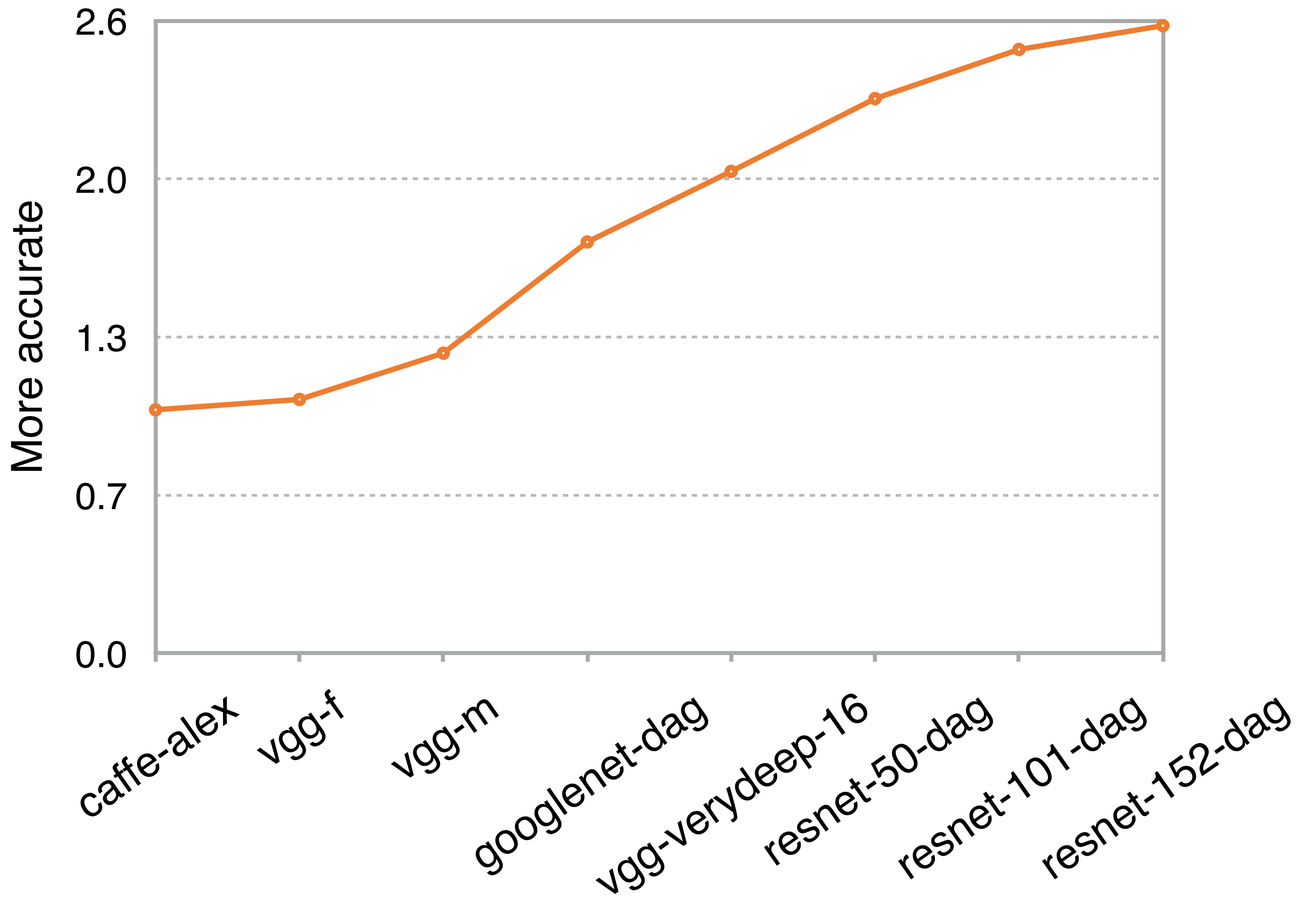
K. Simonyan and A. Zisserman. *Very deep convolutional networks for large-scale image recognition*. In Proc. ICLR, 2015.

K. He, X. Zhang, S. Ren, and J. Sun. *Deep residual learning for image recognition*. In Proc. CVPR, 2016.

Slide: A. Vedaldi

Accuracy

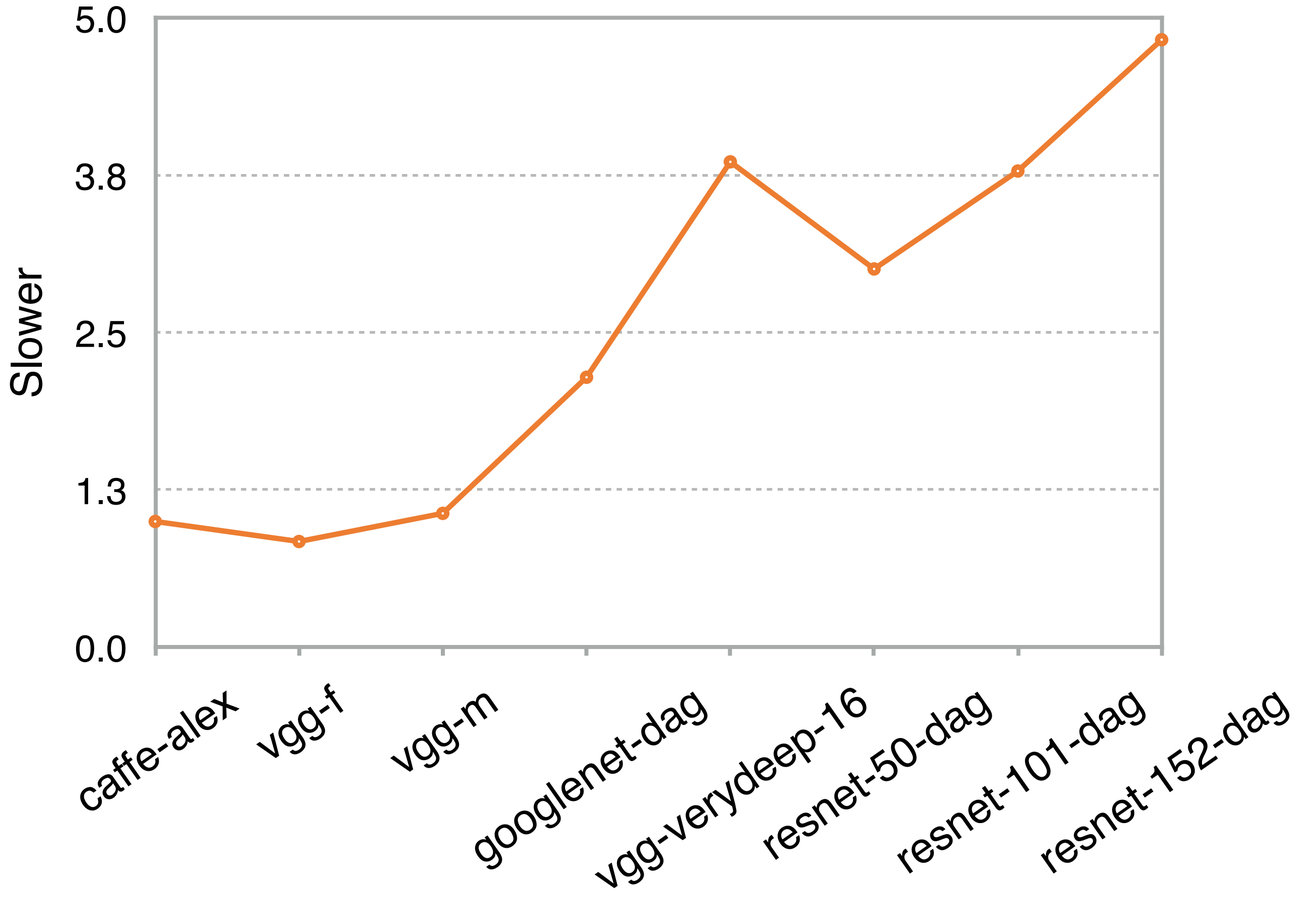
3 × more accurate in 3 years



Slide: A. Vedaldi

Speed

5 × slower



Remark: *101 ResNet* layers same size/speed as *16 VGG-VD* layers

Reason: far fewer feature channels (quadratic speed/space gain)

Moral: optimize your architecture

Slide: A. Vedaldi

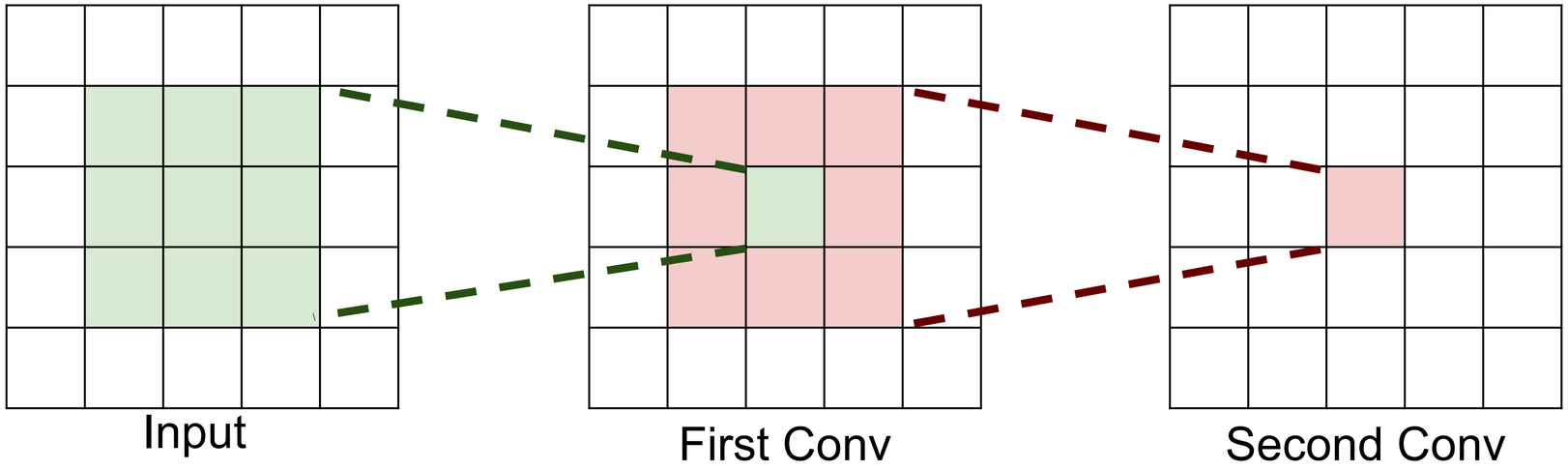
CNN architectures – notes and details

- Increased depth of recent architectures
- Number of parameters matter (How to count parameters?)
- Power of small filters, e.g. 3x3 convolutions
- ResNet architecture

The power of small filters

Suppose we stack two CONV layers with **receptive field** size 3x3

Q: What region of input does each neuron in 2nd CONV see?

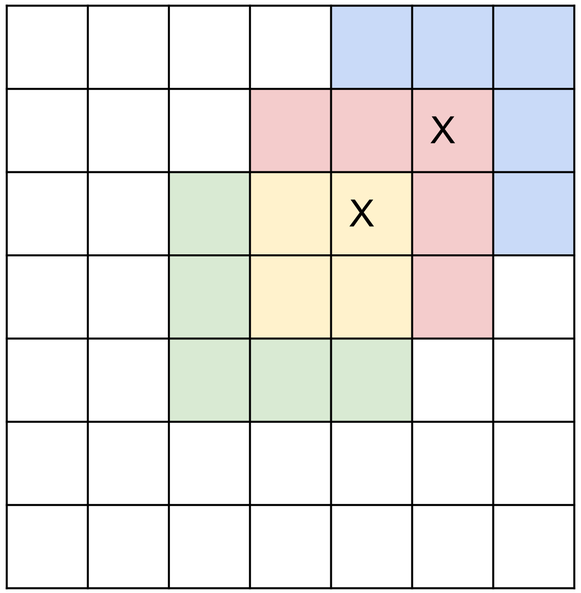


Answer: [5x5]

The power of small filters

Suppose we stack three CONV layers with receptive filed size 3x3

Q: What region of input does each neuron in 3rd CONV see?



Answer: [7x7]

The power of small filters

Suppose input has depth C & we want output depth C as well.

1x CONV with 7x7 filters

Number of weights:

C*(7*7*C)
= **49 C^2**

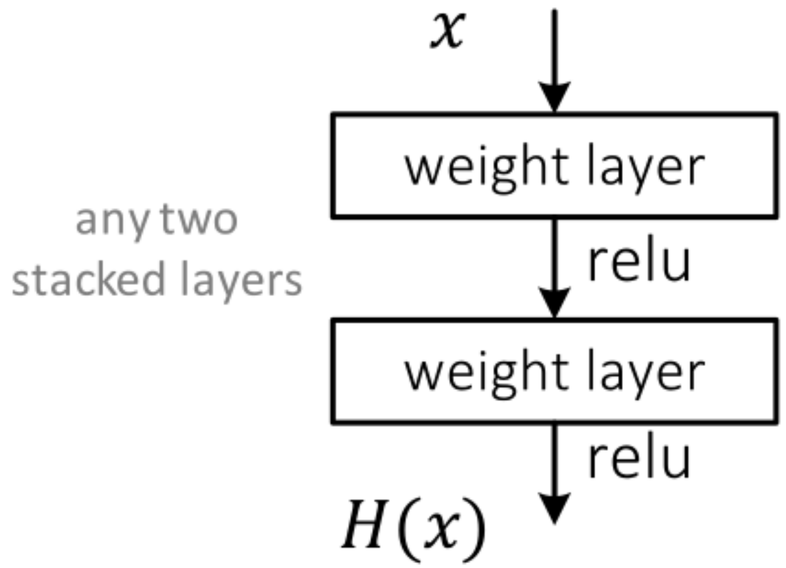
3x CONV with 3x3 filters

Number of weights:

C*(3*3*C) + C*(3*3*C) + C*(3*3*C)
= 3 * 9 * C^2
= **27 C^2**

Residual networks [ResNets]

Plain net



$H(x)$ is any desired mapping,

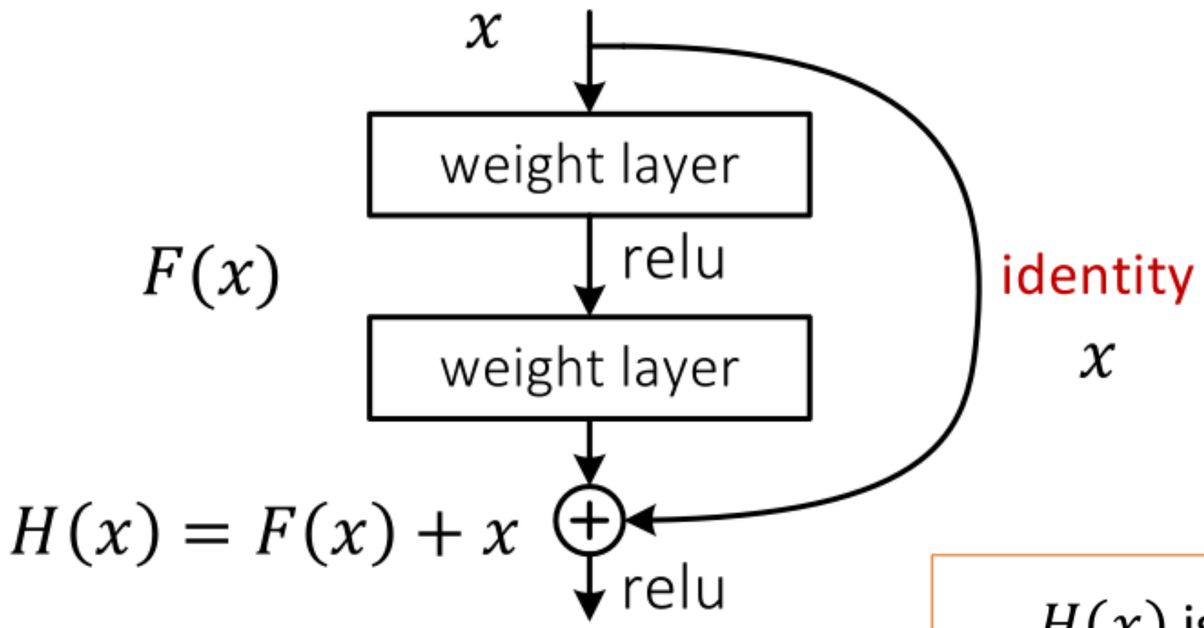
hope the 2 weight layers fit $H(x)$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Slide: K. He

Residual networks [ResNets]

Residual net



$H(x)$ is any desired mapping,

~~hope the 2 weight layers fit $H(x)$~~

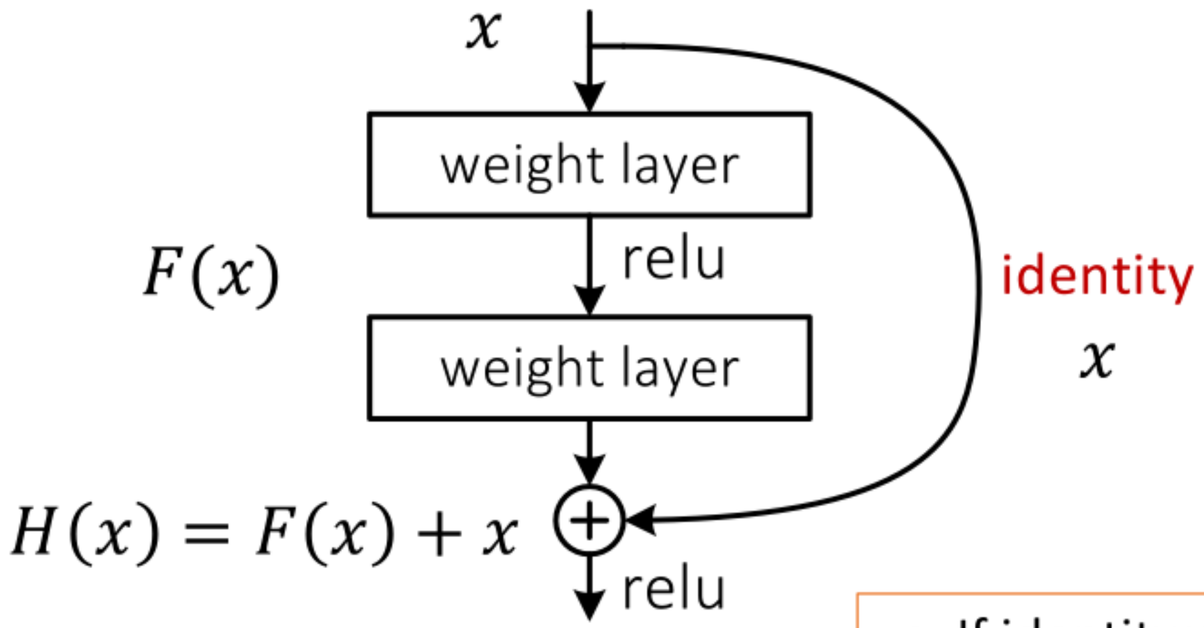
hope the 2 weight layers fit $F(x)$

let $H(x) = F(x) + x$

Slide: K. He

Residual networks [ResNets]

$F(x)$ is a residual mapping w.r.t. identity



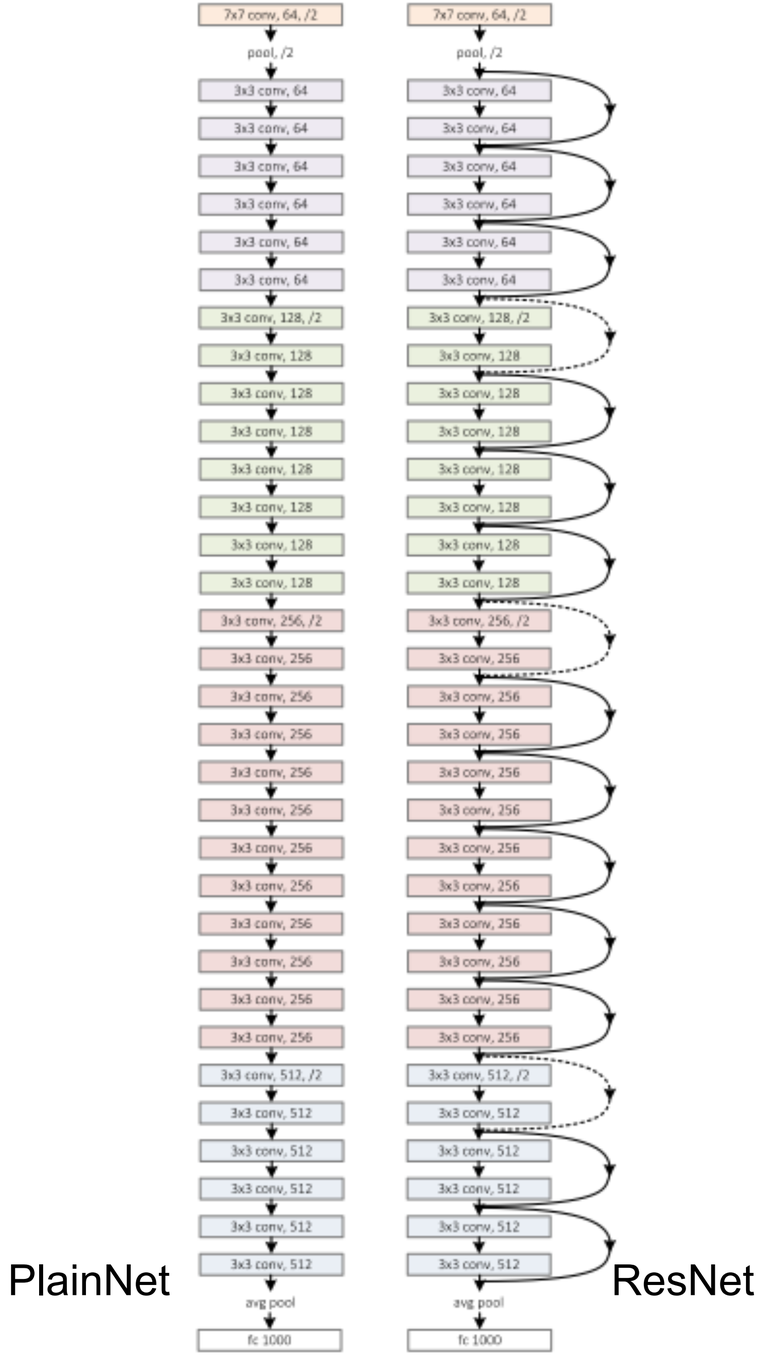
- If identity were optimal, easy to set weights as 0
- If optimal mapping is closer to identity, easier to find small fluctuations

Slide: K. He

Network design

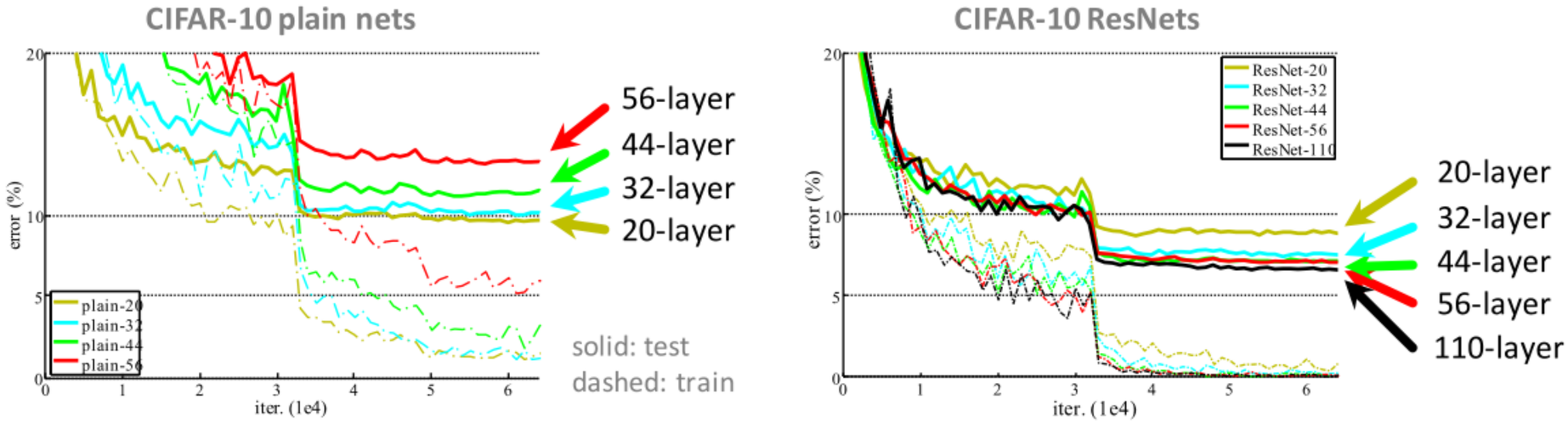
Basic design (vgg-style)

- almost all 3x3 conv
- Spatial size /2 => # filters x2
- Simple design, just deep
- No fully connected layers
- No dropout



Slide: K. He

CIFAR-10 experiments

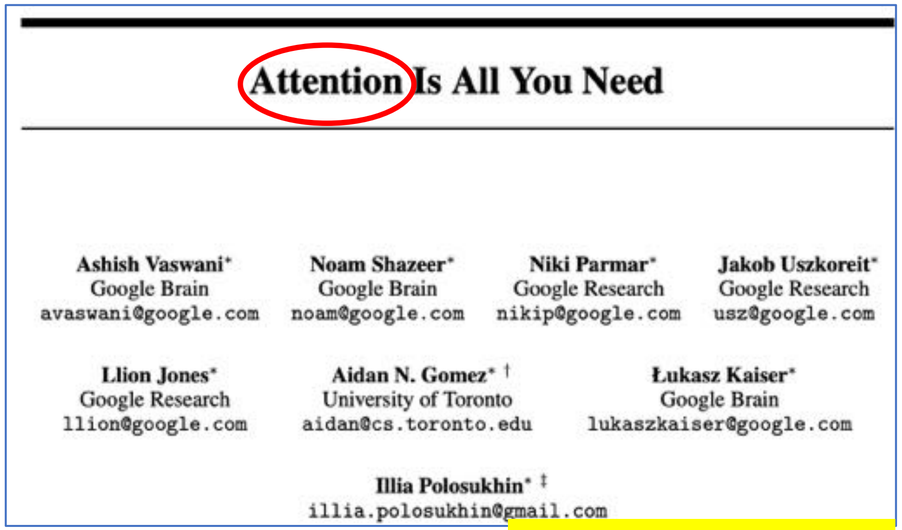


- Deep ResNets can be trained without difficulties
- Deeper ResNets have lower training error and lower test error

Slide: K. He

Do we need convolutions?

[next week] Beyond CNNs



Attention Is All You Need

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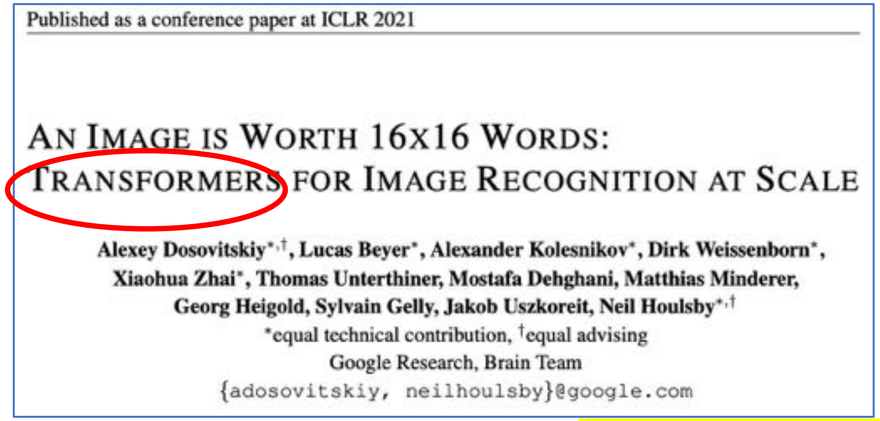
NeurIPS 2017



Published as a conference paper at ICLR 2021

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

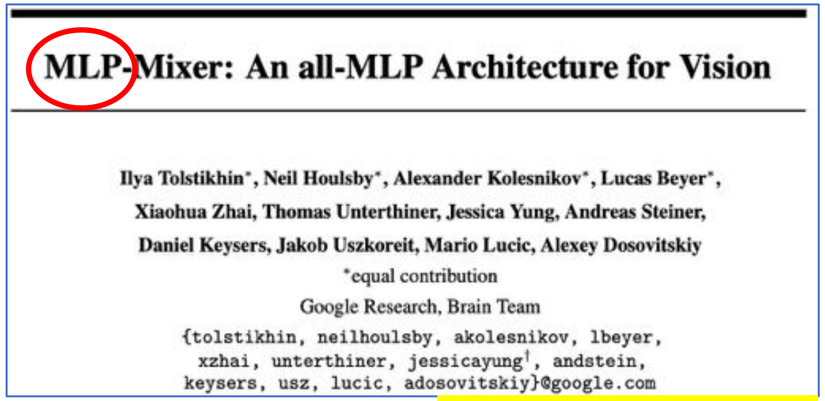
Alexey Dosovitskiy*,†, Lucas Beyer*, Alexander Kolesnikov*, Dirk Weissenborn*, Xiaohua Zhai*, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby*,†

*equal technical contribution, †equal advising

Google Research, Brain Team

{adosovitskiy, neilhoulsby}@google.com

ICLR 2021



MLP-Mixer: An all-MLP Architecture for Vision

Ilya Tolstikhin*, Neil Houlsby*, Alexander Kolesnikov*, Lucas Beyer*, Xiaohua Zhai, Thomas Unterthiner, Jessica Yung, Andreas Steiner, Daniel Keysers, Jakob Uszkoreit, Mario Lucic, Alexey Dosovitskiy

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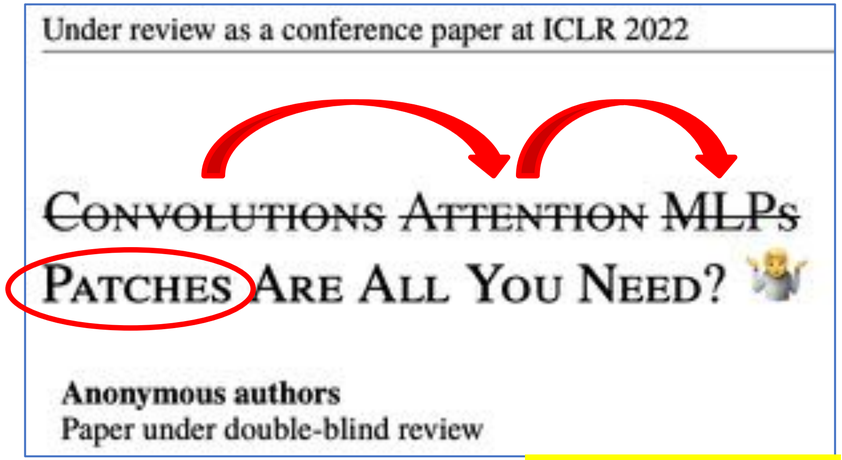
{tolstikhin, neilhoulsby, akolesnikov, lbeyer, xzhai, unterthiner, jessicayung†, andstein, keysers, usz, lucic, adosovitskiy}@google.com

NeurIPS 2021



Under review as a conference paper at ICLR 2022

~~CONVOLUTIONS~~ ~~ATTENTION~~ ~~MLPS~~

PATCHES ARE ALL YOU NEED?

Anonymous authors

Paper under double-blind review

arXiv 2022

https://github.com/KentoNishi/awesome-all-you-need-papers

Agenda

- **1. Recap: Bag of Visual Words, Analogy with NNs**

- **2. Neural networks (NNs) for computer vision:**
  - Applications
  - A brief history: from perceptron to MLPs to CNNs

- **3. Convolutional neural networks (CNNs)**
  - Standard layers
  - Recap: Training NNs
  - Visualizing CNNs
  - Pretraining & finetuning NNs
  - Typical CNN architectures

- **4. Beyond classification - preview**

The field makes progress

Beyond Classification

Computer vision tasks

Extracting meaning from visual signals *

Object recognition,
Object detection,
Pixel-level segmentation,
3D localization,
etc.

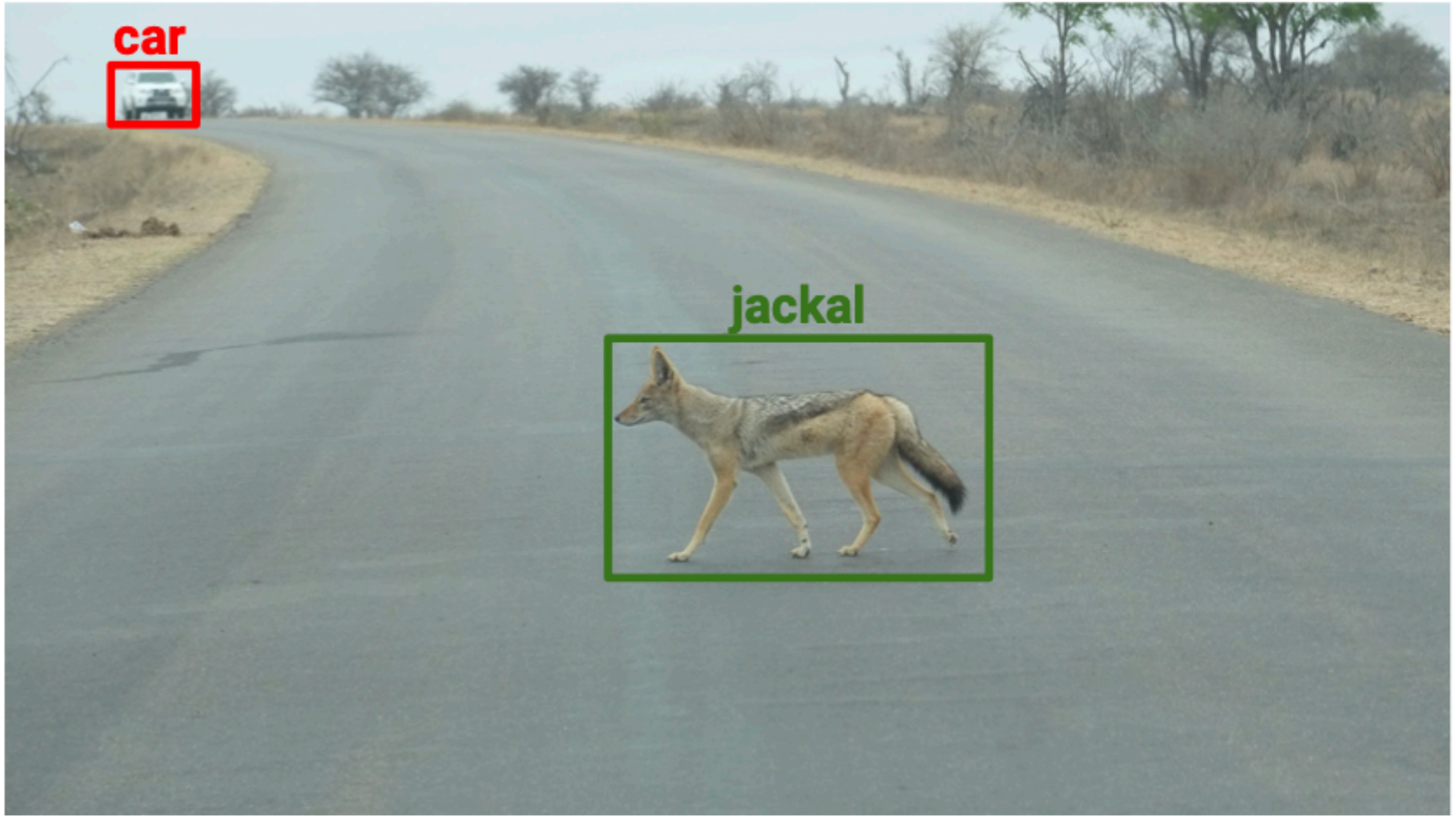
*Visual signal: Image, video, depth, 3D point cloud, MRI, scans, …

Slide credit: Naila Murray

Example tasks

Slide credit: Naila Murray

Object recognition and localization (detection)



Slide credit: Naila Murray

Visual question answering

Q: Is this an outdoor scene?
A: Yes

Q: What is the weather like?
A: Cloudy but dry

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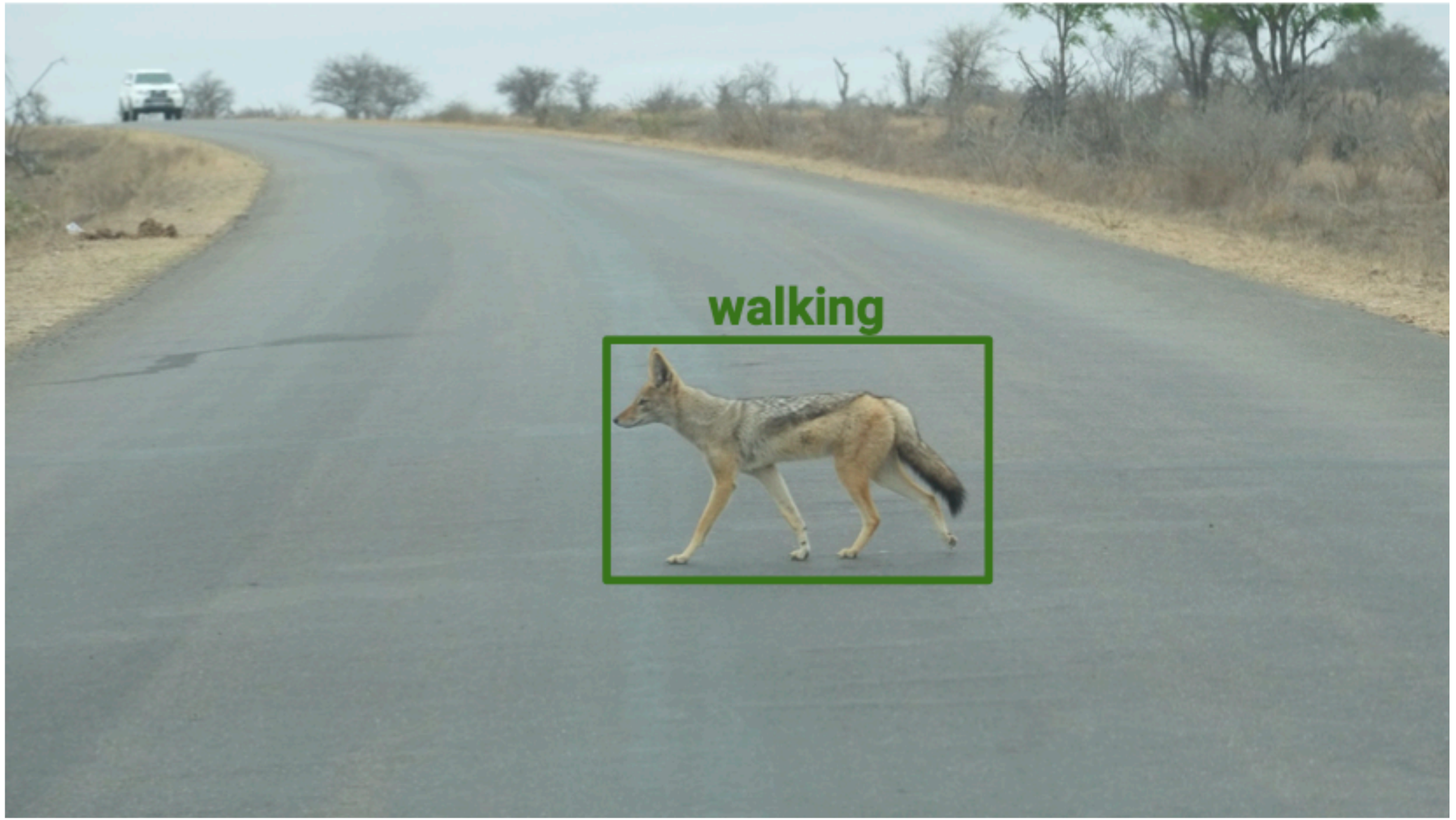
Activity recognition



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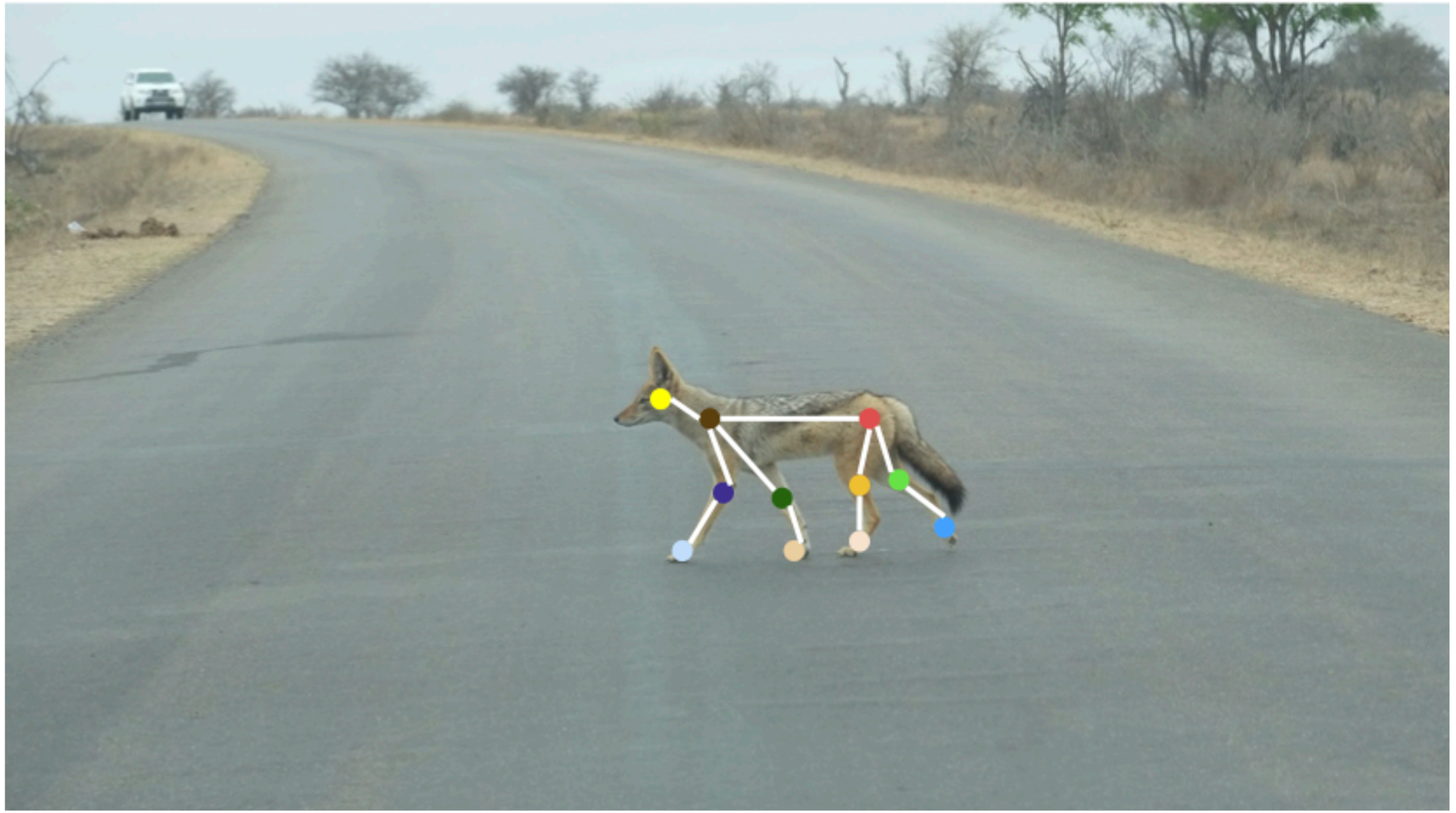
Pose estimation



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Captioning

A jackal walking across a rural asphalt road

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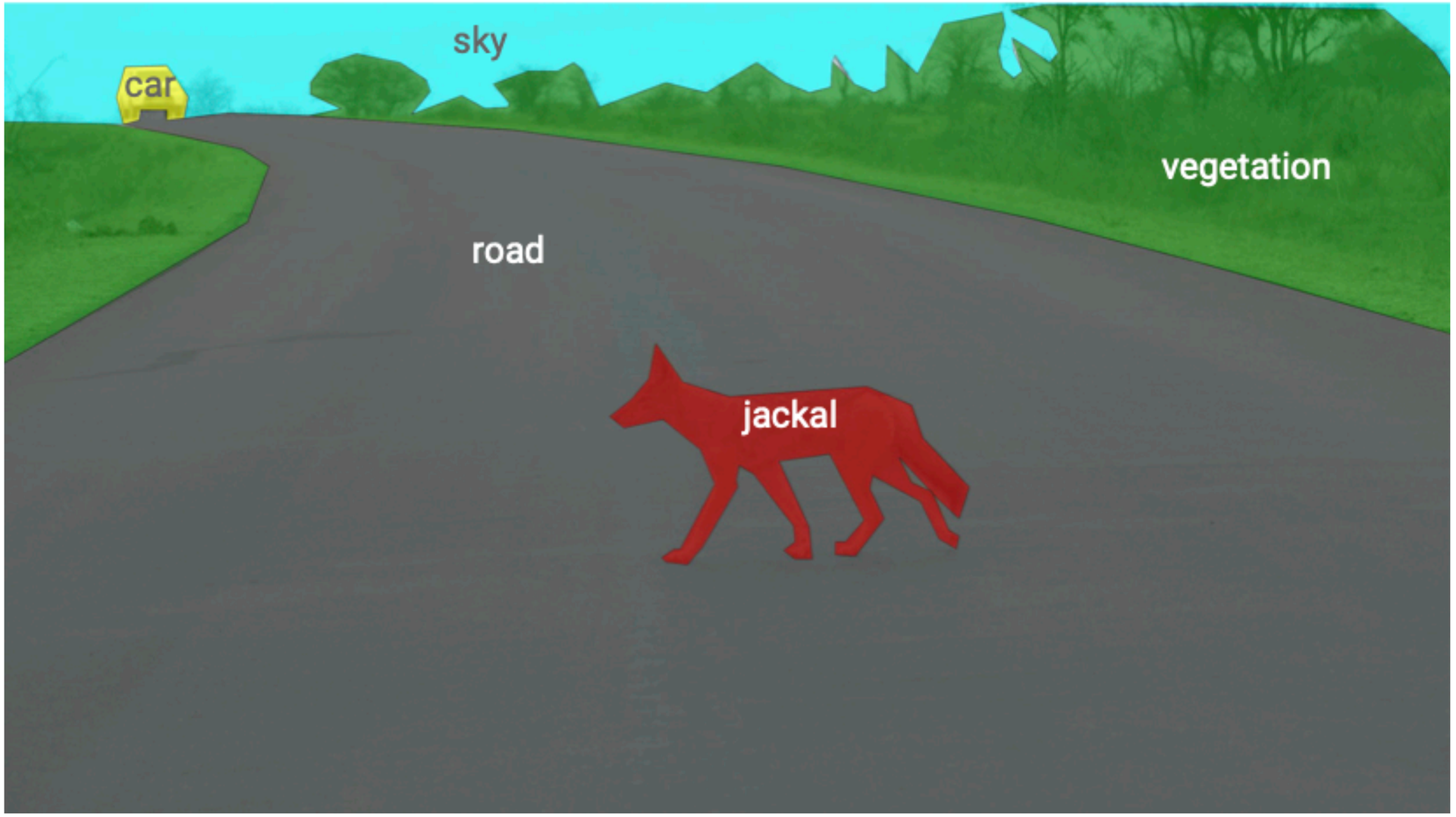
Semantic segmentation



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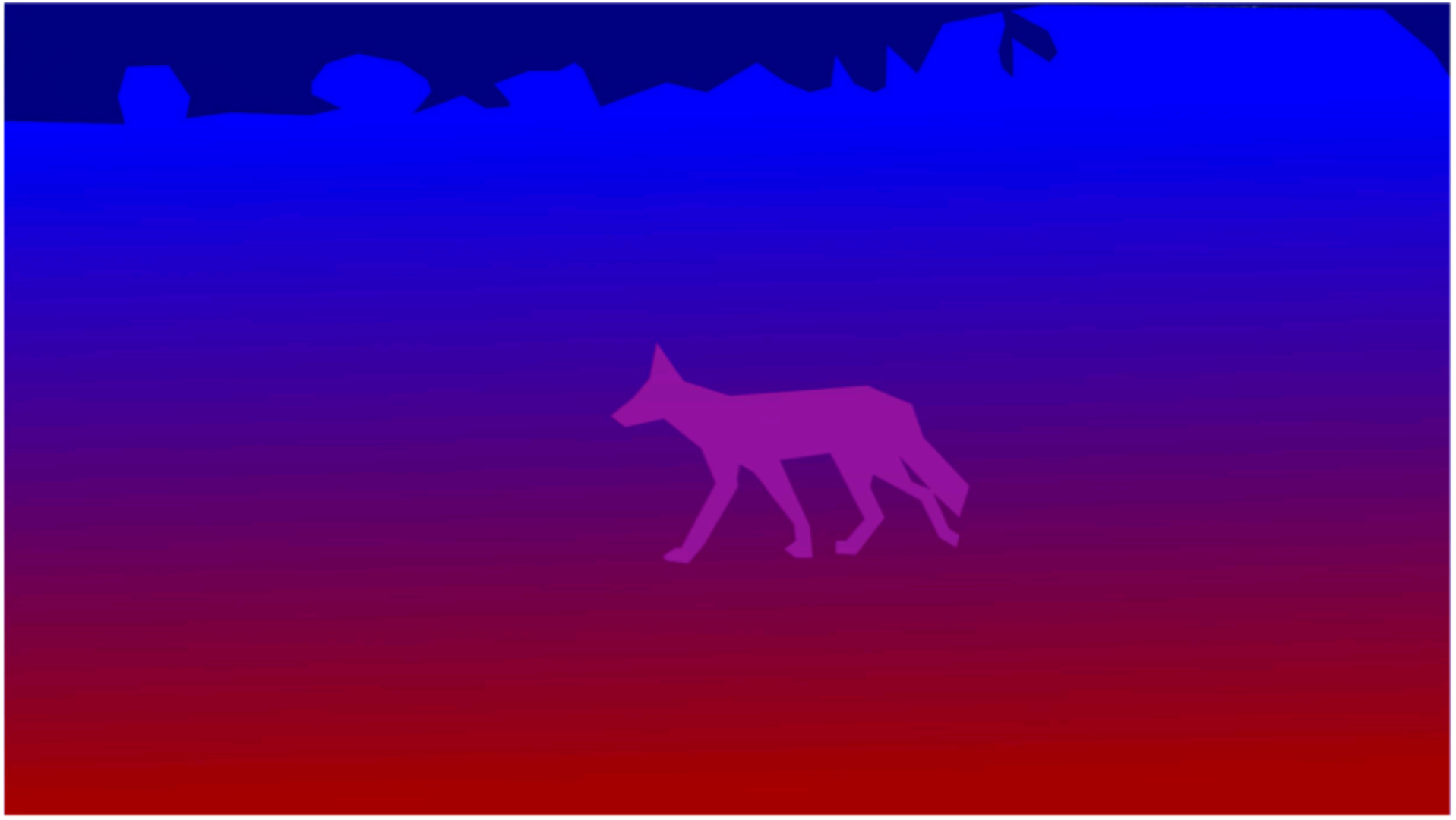
Depth estimation



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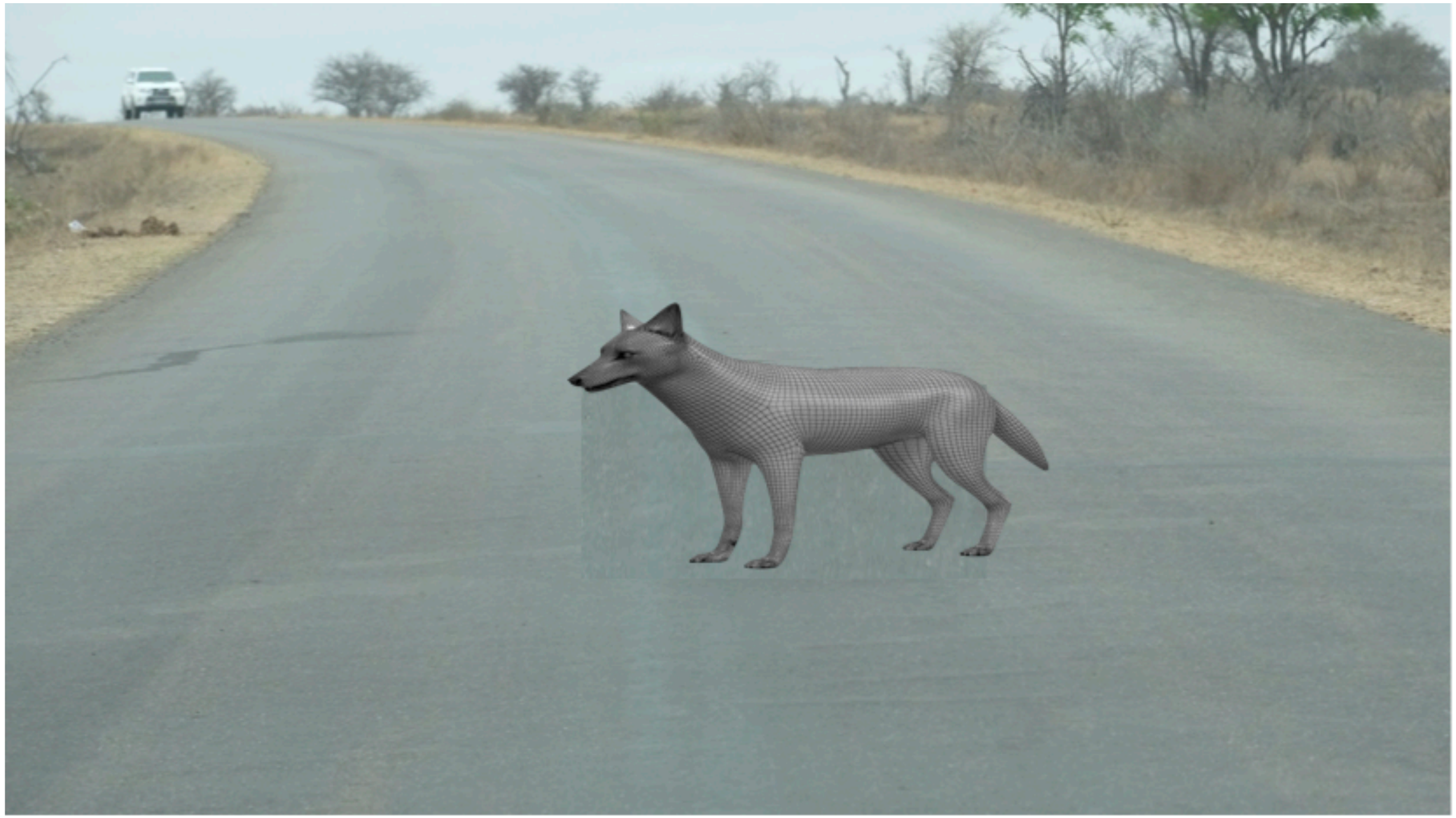
3D shape estimation



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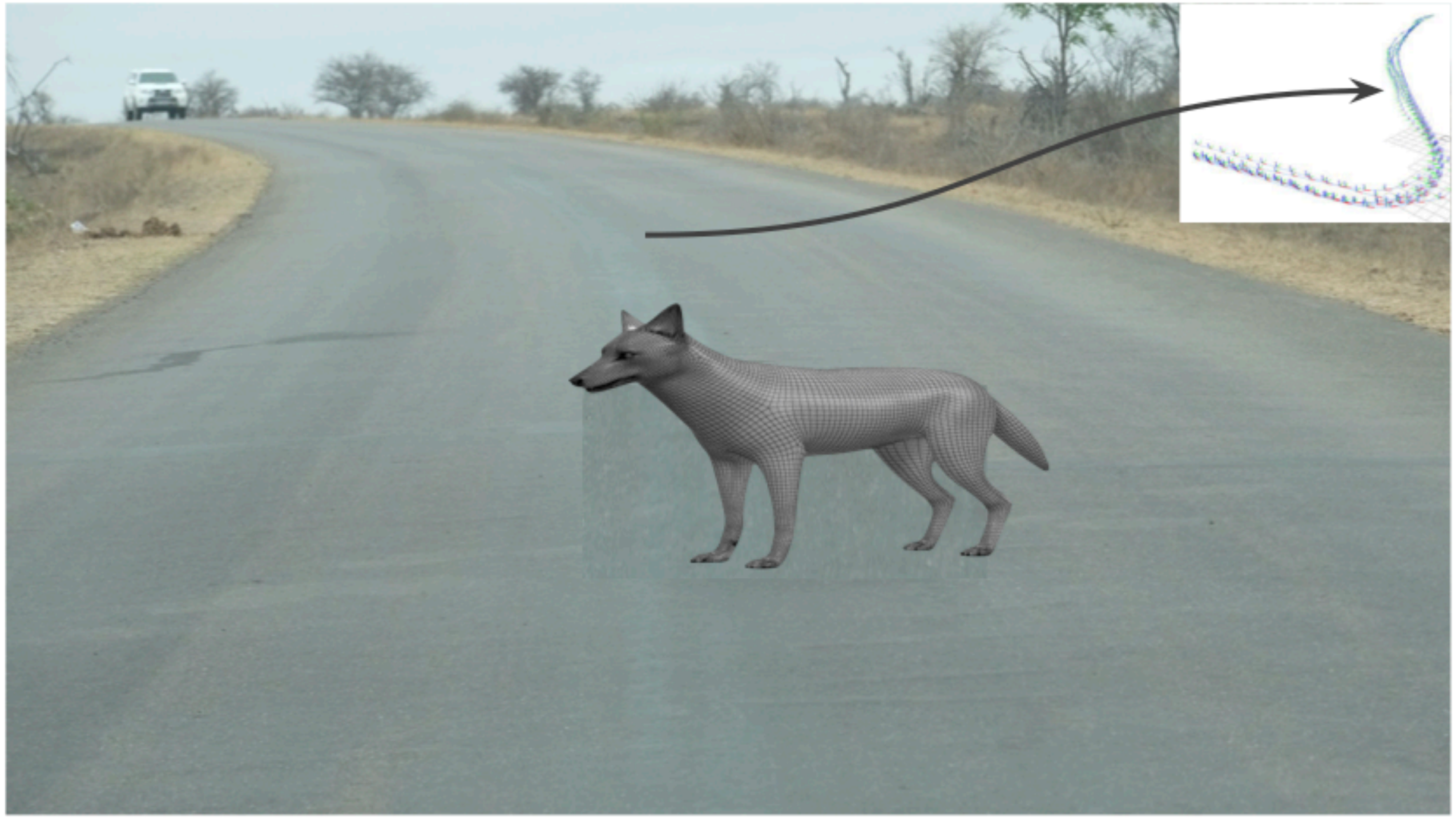
Visual localization



Slide credit: Naila Murray

Summary of today

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