Convolutional neural networks I

September 27th, 2019

Yong Jae Lee
UC Davis

Many slides from Rob Fergus, Svetlana Lazebnik, Jia-Bin Huang, Derek Hoiem, Adriana Kovashka, Andrej Karpathy

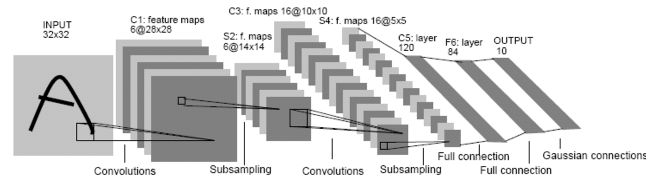
Standard classifiers

Nearest neighbor

10^6 examples

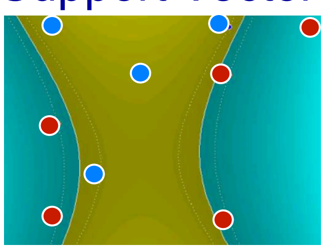
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

Neural networks



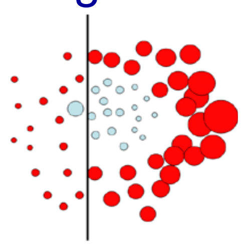
LeCun, Bottou, Bengio, Haffner 1998
Rowley, Baluja, Kanade 1998
…

Support Vector Machines



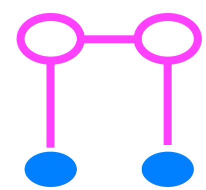
Guyon, Vapnik
Heisele, Serre, Poggio, 2001,…

Boosting



Viola, Jones 2001,
Torralba et al. 2004,
Opelt et al. 2006,…

Conditional Random Fields



McCallum, Freitag, Pereira 2000; Kumar, Hebert 2003
…

Slide adapted from Antonio Torralba

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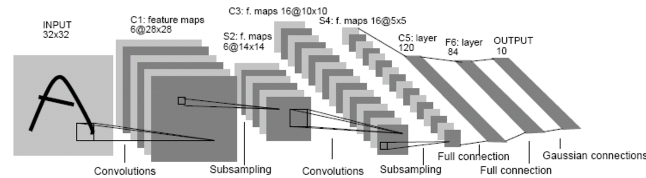

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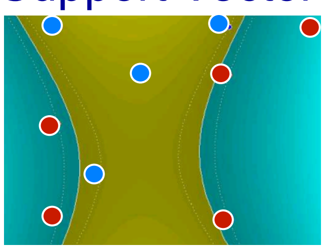

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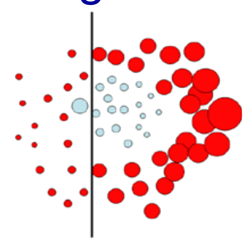

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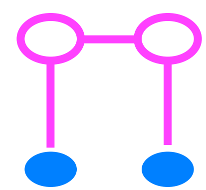

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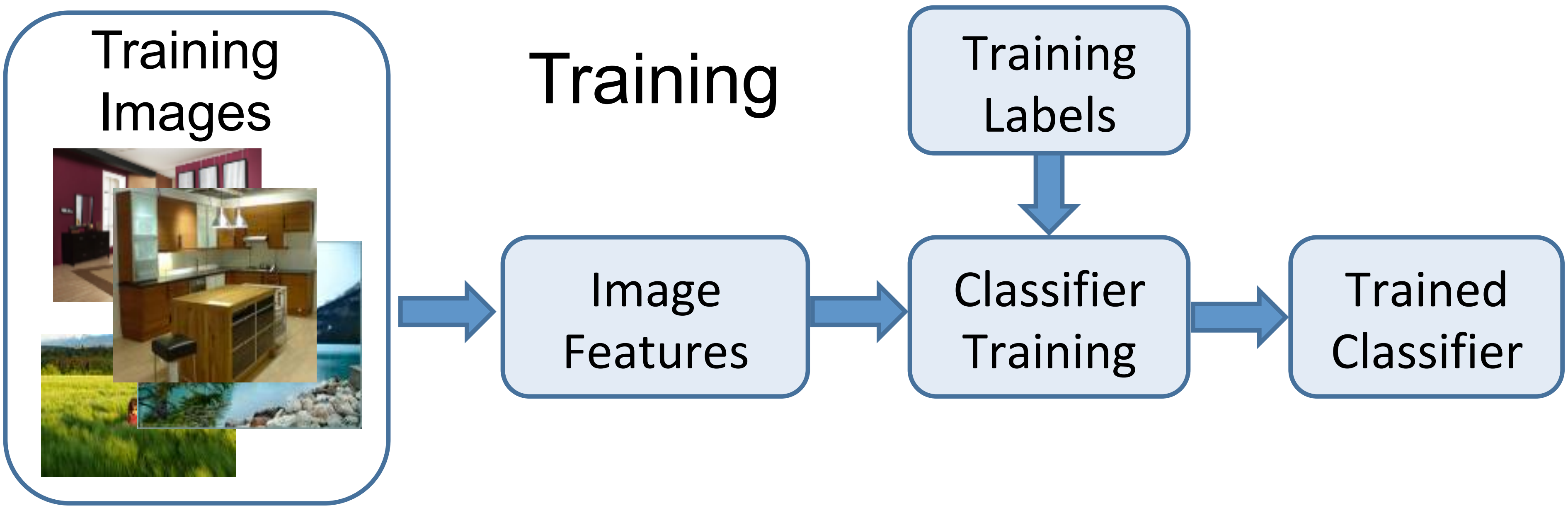
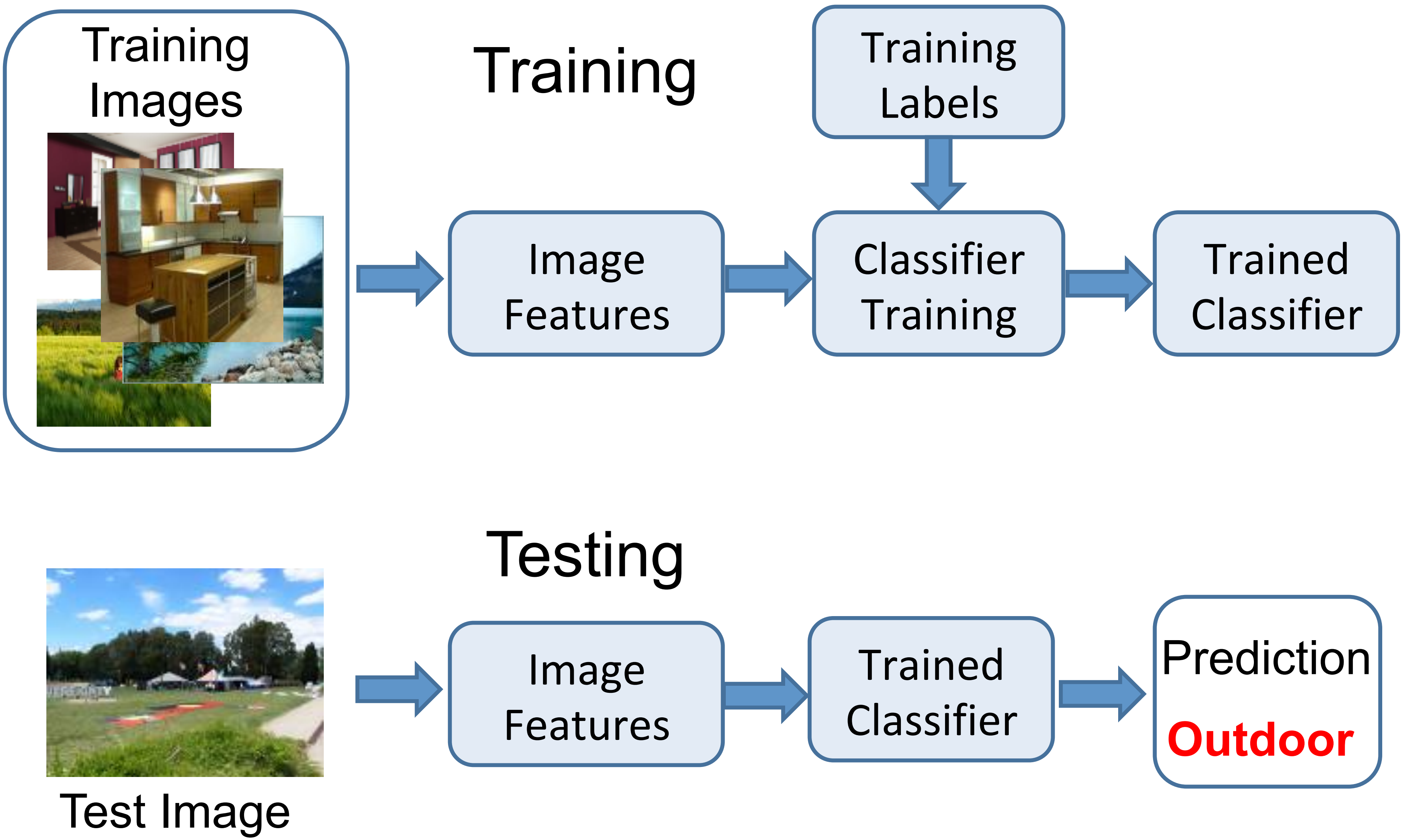
Slide adapted from Antonio Torralba

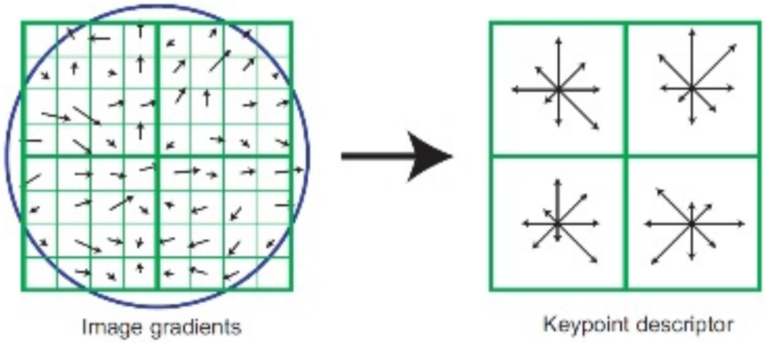
Traditional Image Categorization: Training phase



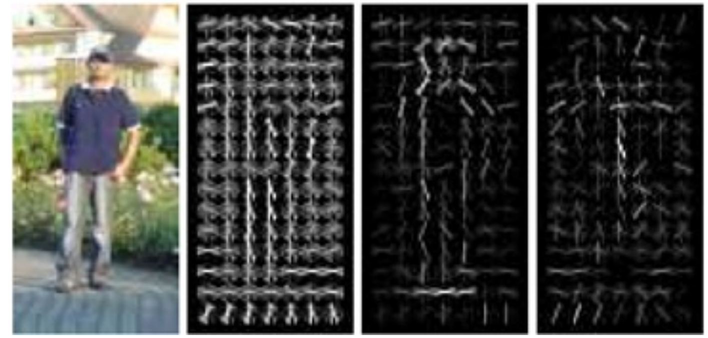
Traditional Image Categorization: Testing phase



Features have been key..



SIFT

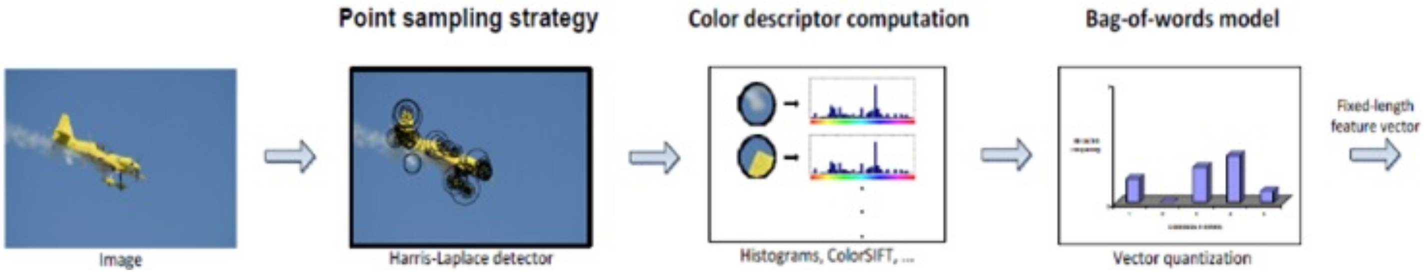


PR 05]

Hand-crafted

SPM [Lazebnik et al. CVPR 06]

DPM [Felzenszwalb et al. PAMI 10]



Color Descriptor [Van De Sande et al. PAMI 10]

What about learning the features?

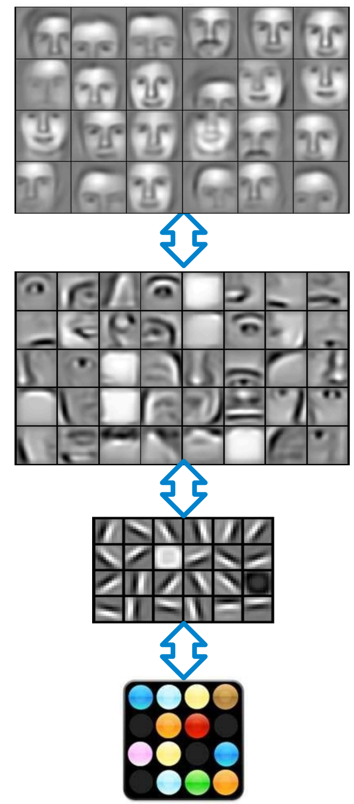
- Learn a *feature hierarchy* all the way from pixels to classifier
- Each layer extracts features from the output of previous layer
- Layers have (nearly) the same structure
- Train all layers jointly (“end-to-end”)

Learning Feature Hierarchy

Goal: Learn **useful higher-level features** from images

Input data

Feature representation



3rd layer
"Objects"

2nd layer
"Object parts"

1st layer
"Edges"

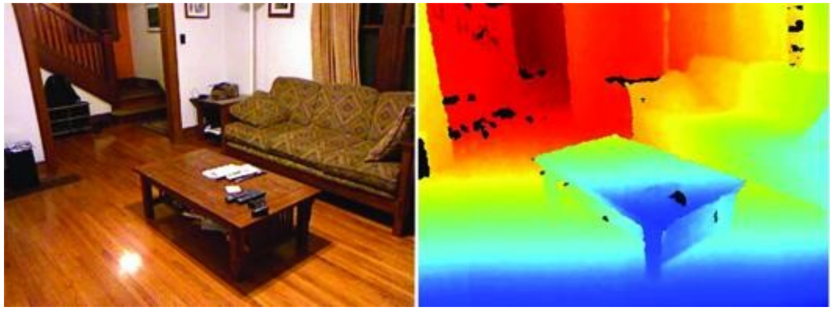
Pixels

Lee et al., ICML 2009;
CACM 2011

Slide: Rob Fergus

Learning Feature Hierarchy

- Better performance
- Other domains (unclear how to hand engineer):
  - Kinect
  - Video
  - Multi spectral

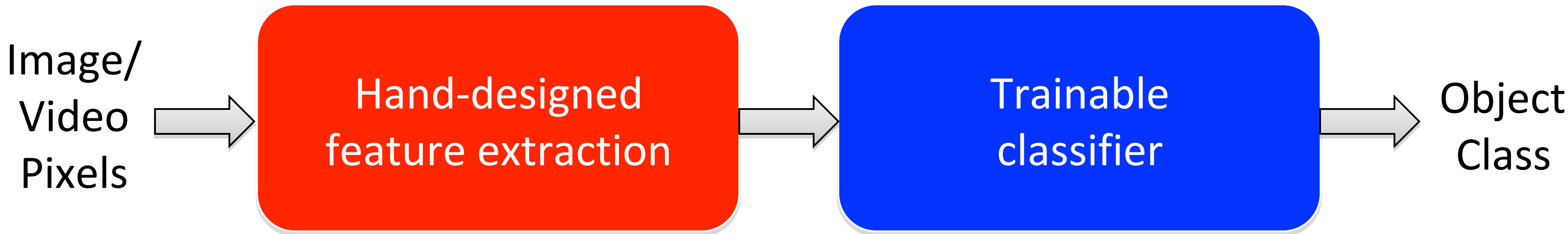


- Feature computation time
  - Dozens of features needed for good performance
  - Prohibitive for large datasets (10's sec /image)

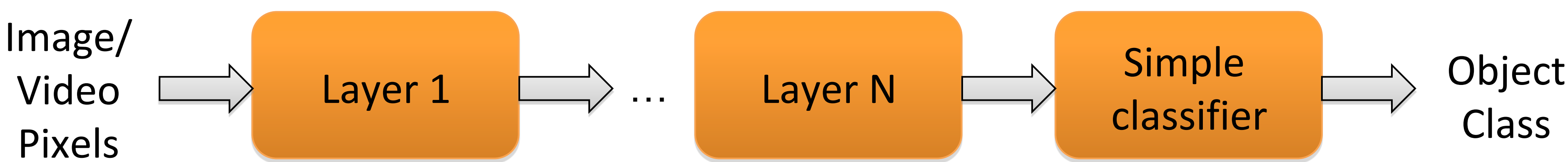
Slide: R. Fergus

“Shallow” vs. “deep” architectures

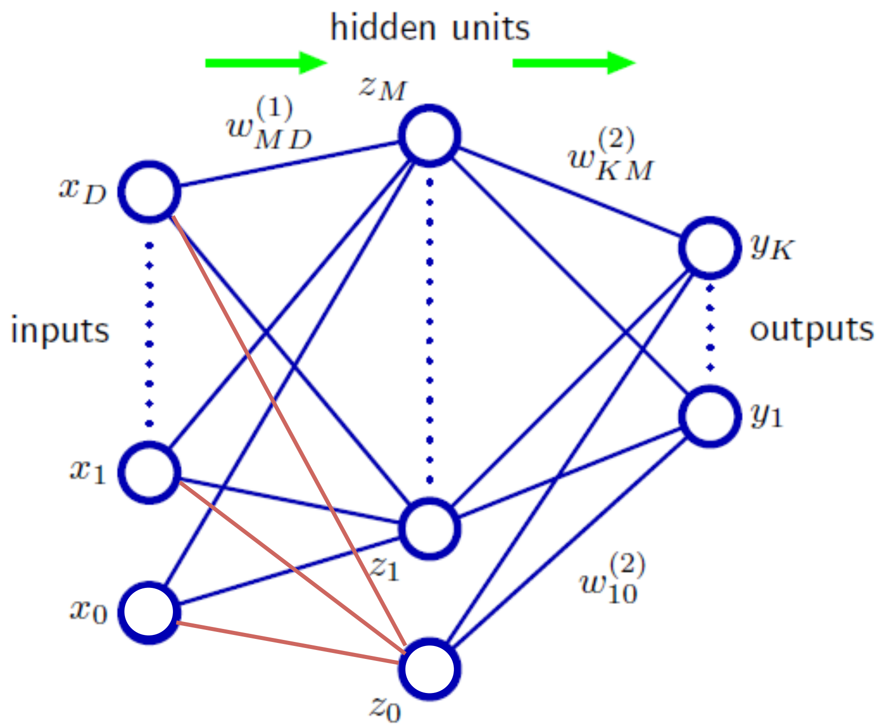
Traditional recognition: “Shallow” architecture



Deep learning: “Deep” architecture



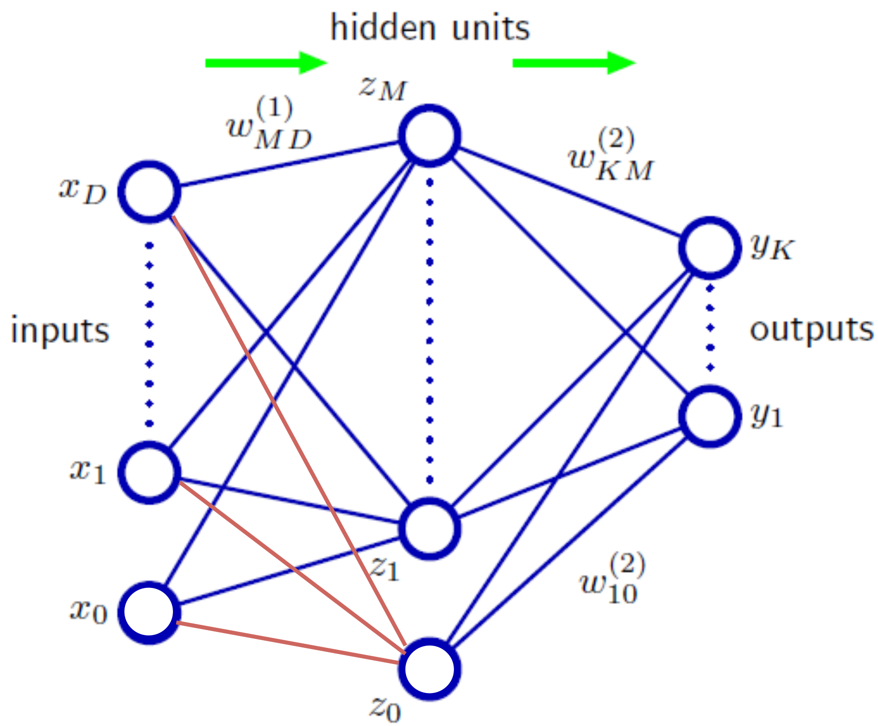
Neural network definition



- *Nonlinear* classifier
- Can approximate any continuous function to arbitrary accuracy given sufficiently many hidden units

Figure from Christopher Bishop

Neural network definition

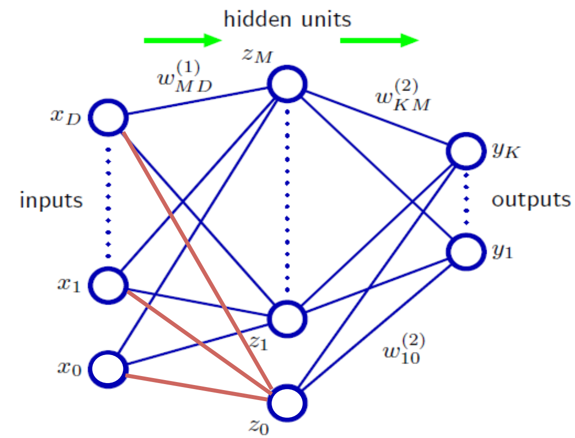


- Activations: $$a_j = \sum_{i=0}^{D} w_{ji}^{(1)} x_i$$
- Nonlinear activation function *h* (e.g. sigmoid, RELU):

$$z_j = h(a_j)$$

Figure from Christopher Bishop

Neural network definition



- Layer 2

$$a_j = \sum_{i=0}^{D} w_{ji}^{(1)} x_i$$

$$z_j = h(a_j)$$

- Layer 3 (final)

$$a_k = \sum_{j=0}^{M} w_{kj}^{(2)} z_j$$

- Outputs (e.g. sigmoid/softmax)

(binary)

$$y_k = \sigma(a_k) = \frac{1}{1 + \exp(-a_k)}$$

(multiclass)

$$y_k = \frac{\exp(a_k)}{\sum_j \exp(a_j)}$$

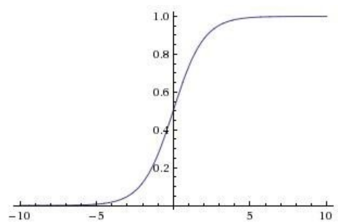
- Putting everything together:

$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=0}^{M} w_{kj}^{(2)} h\left(\sum_{i=0}^{D} w_{ji}^{(1)} x_i \right) \right)$$

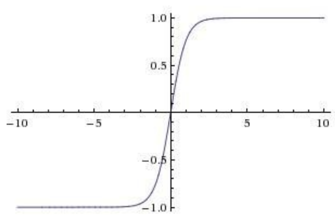
Nonlinear activation functions

Sigmoid

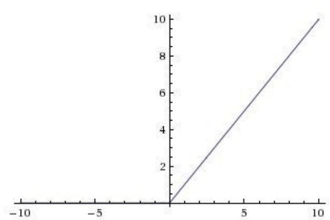
$$\sigma(x) = 1/(1+e^{-x})$$



tanh tanh(x)

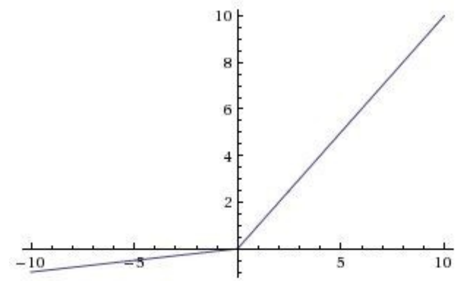


ReLU max(0,x)



Leaky ReLU

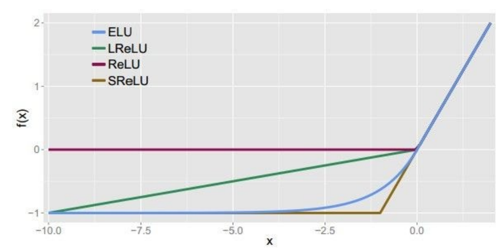
max(0.1x, x)



Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

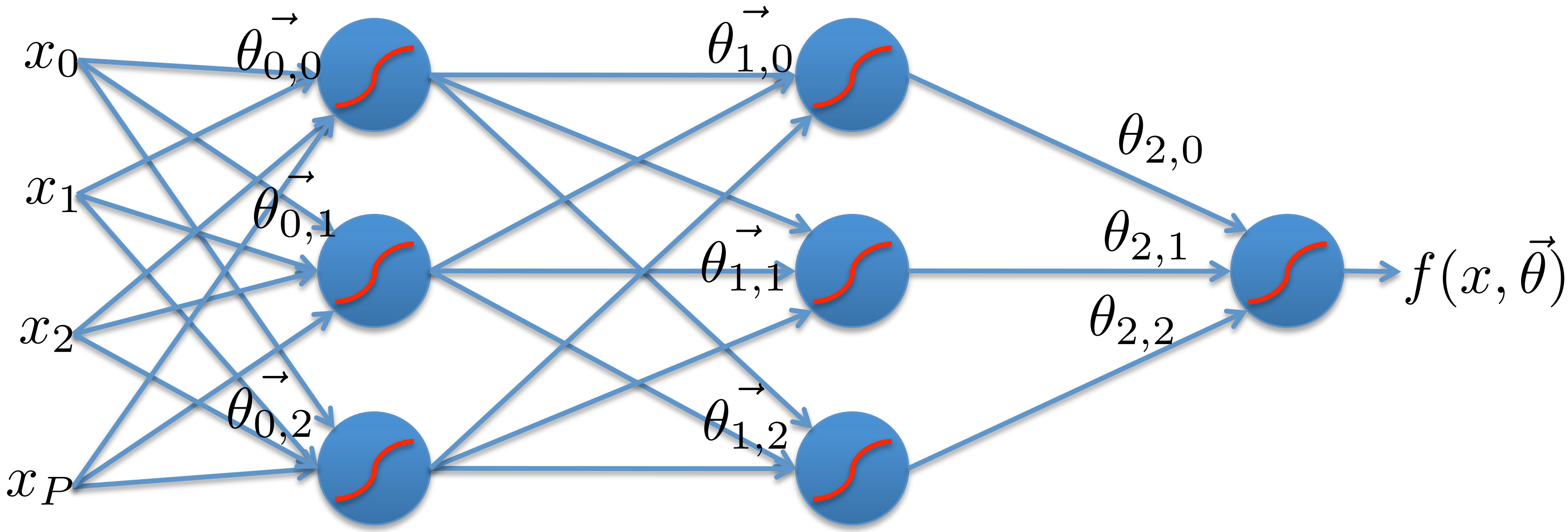
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$



Andrej Karpathy

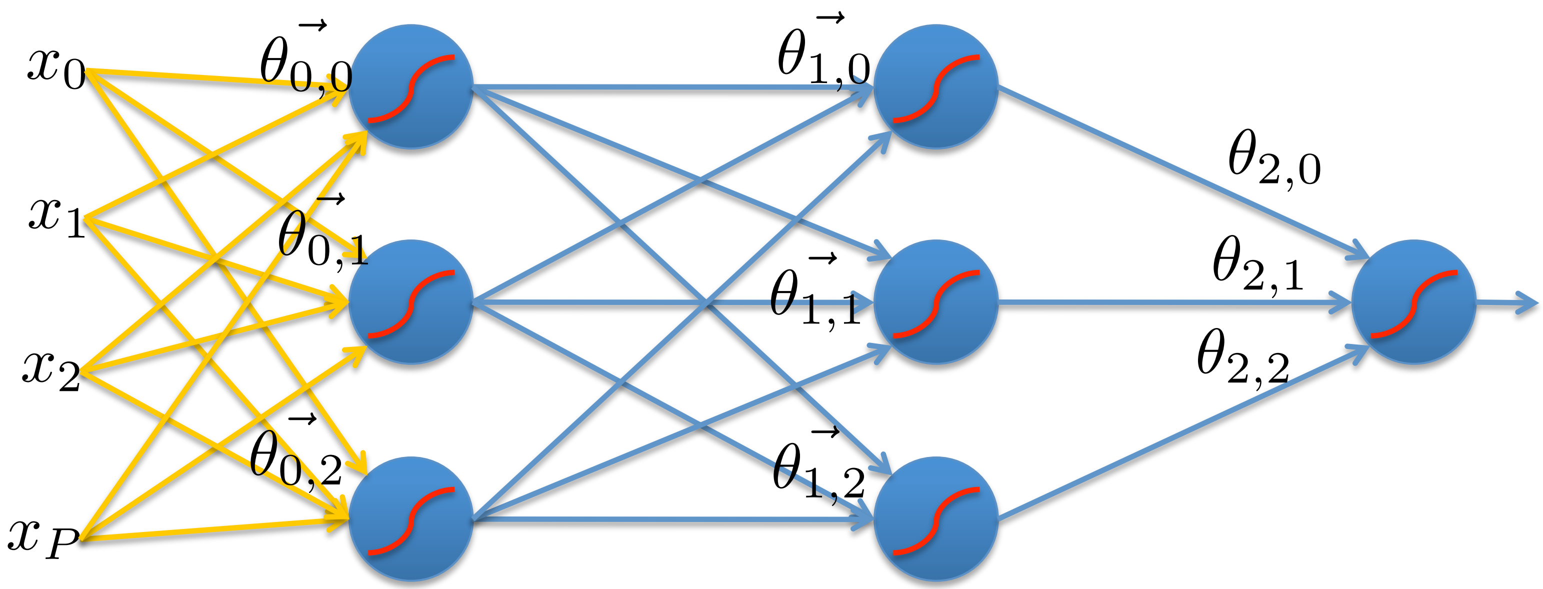
Multilayer networks

- Cascade neurons together
- Output from one layer is the input to the next
- Each layer has its own sets of weights



Feed-forward networks

- Predictions are fed forward through the network to classify



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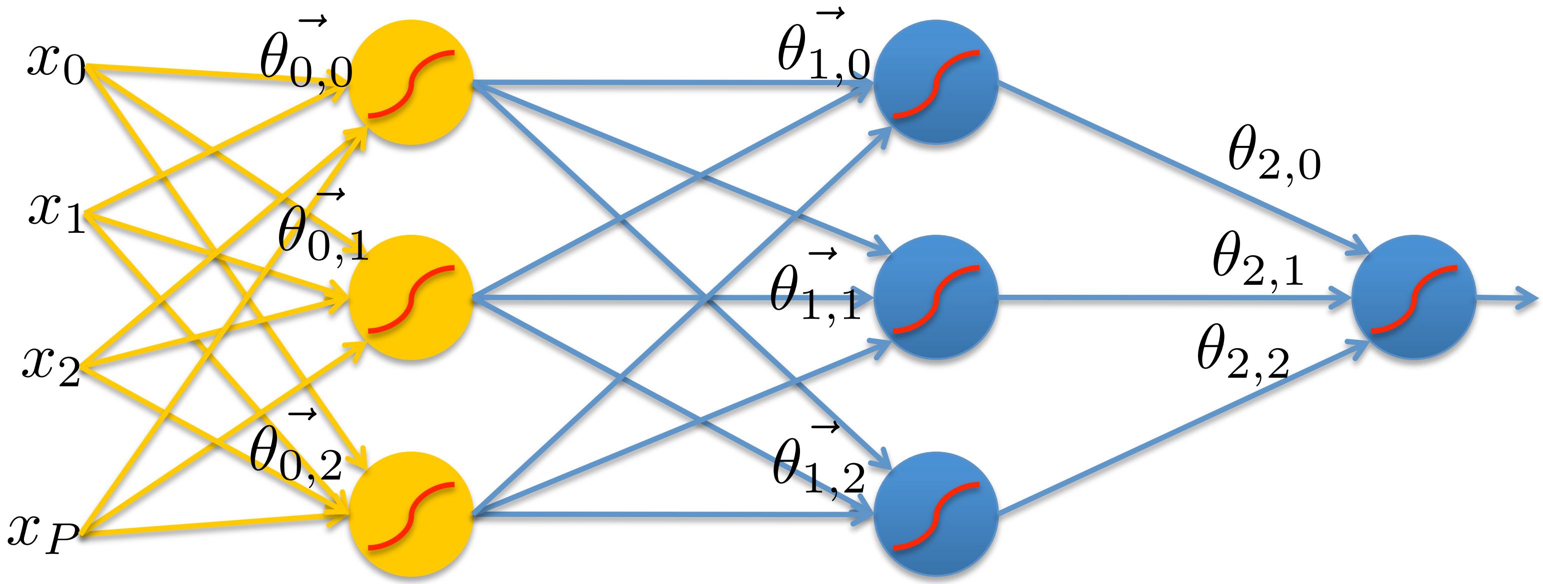

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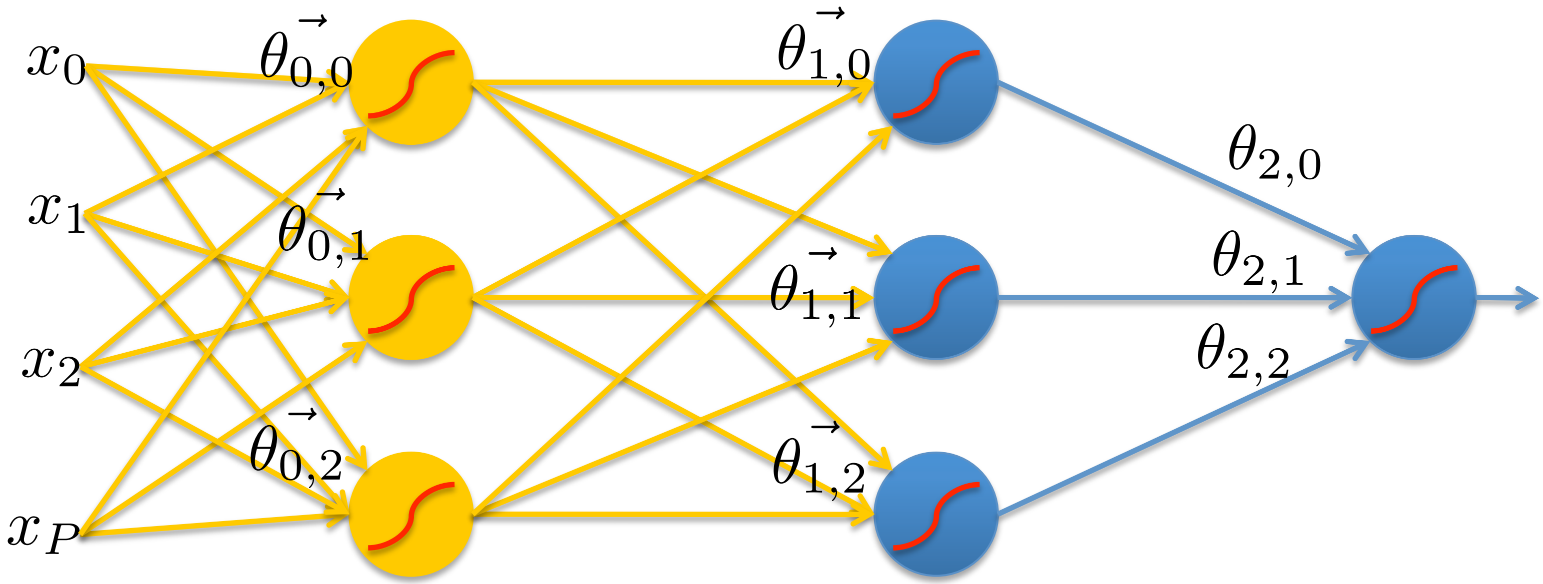

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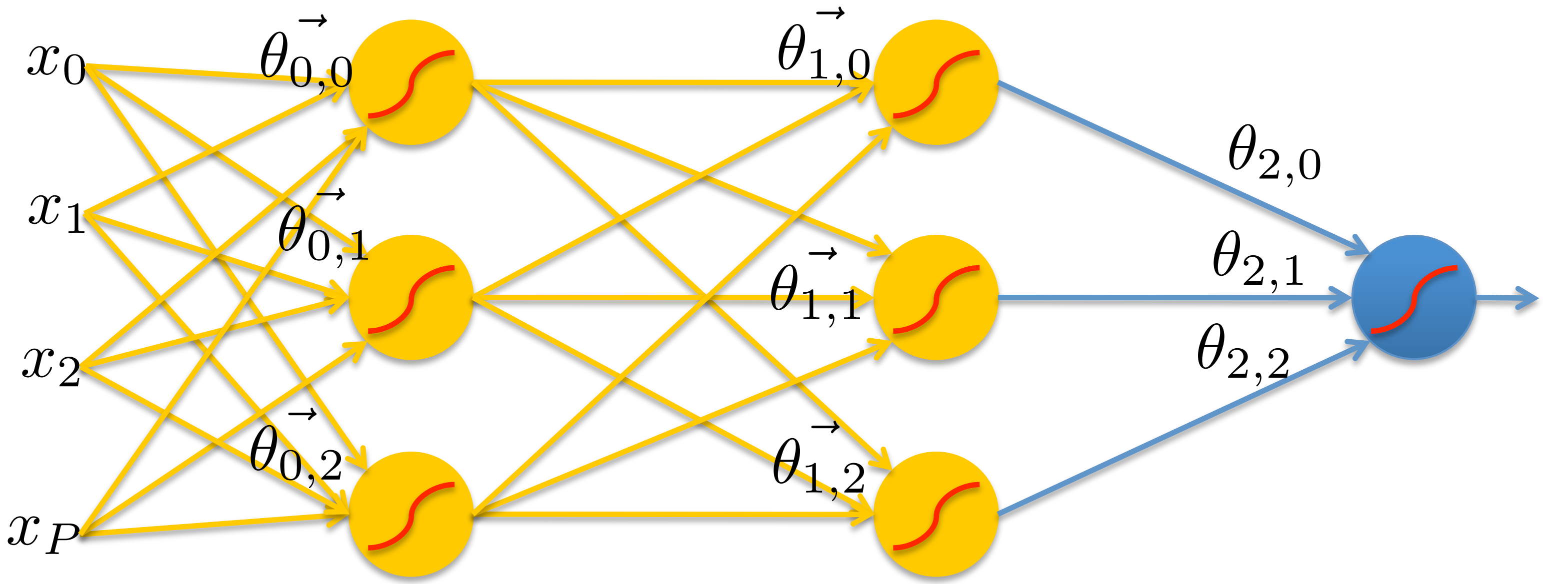

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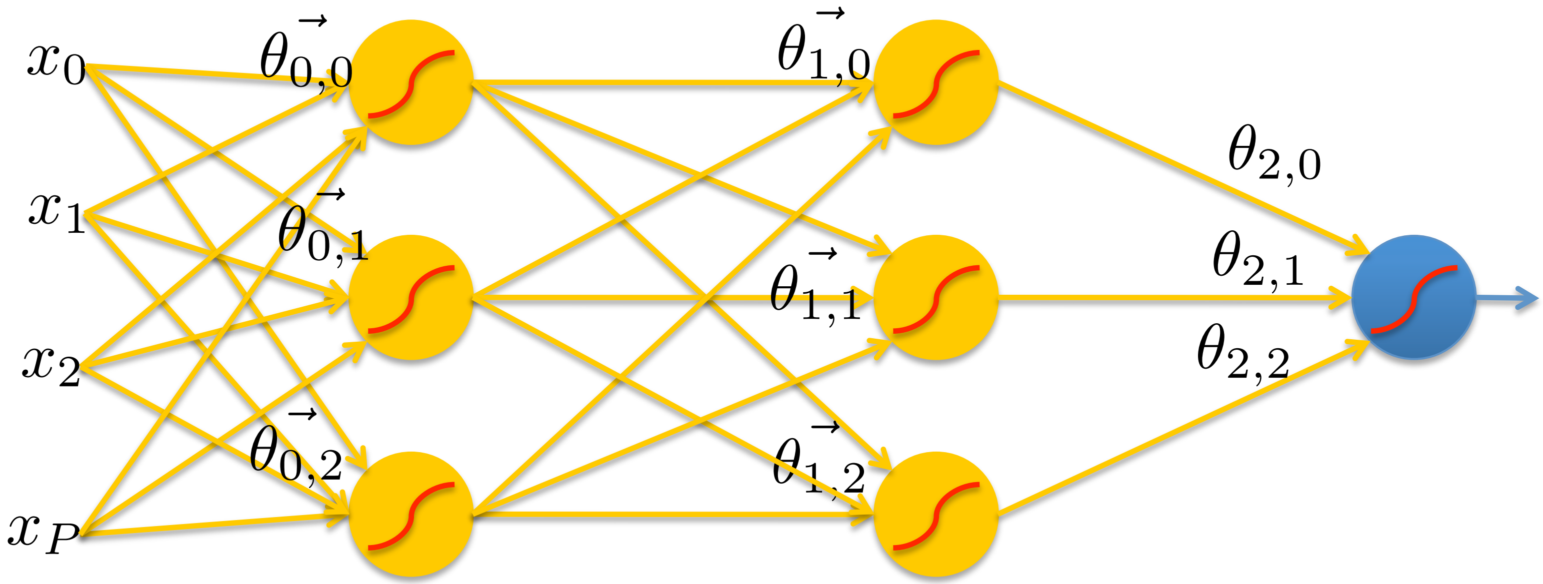

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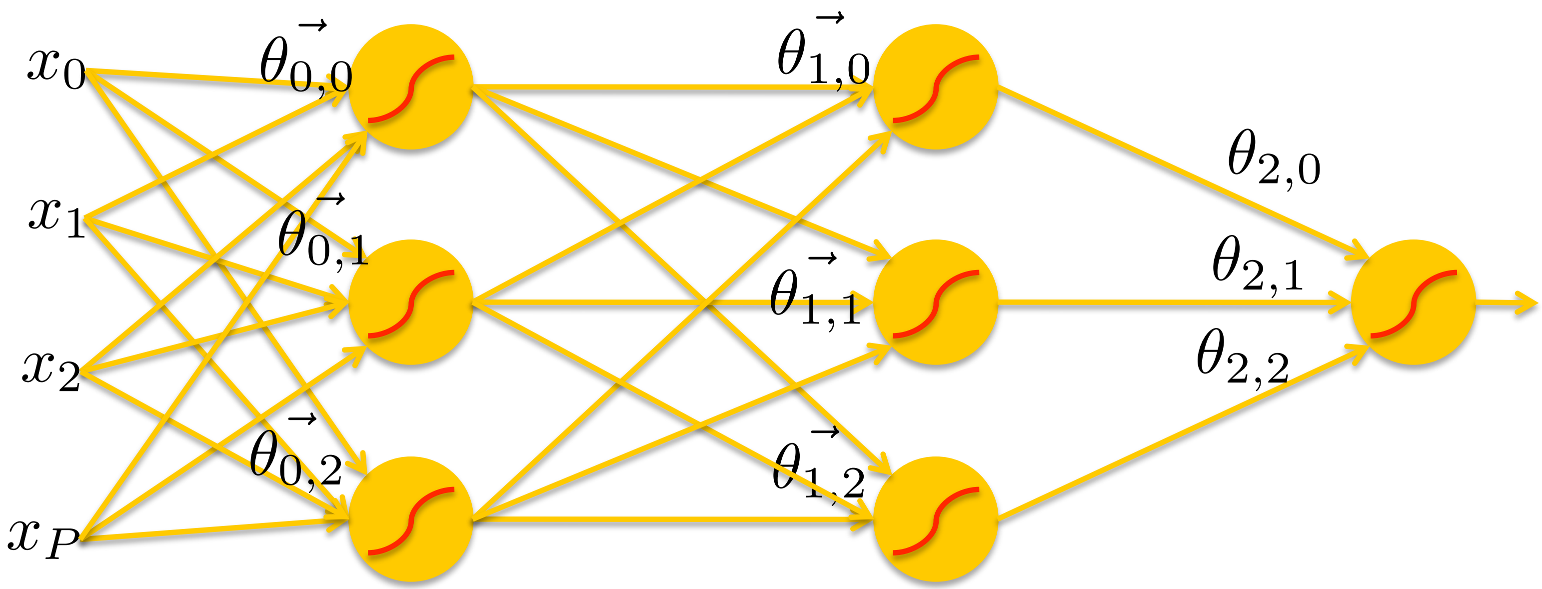


Deep neural networks

- Lots of hidden layers
- Depth = power (usually)

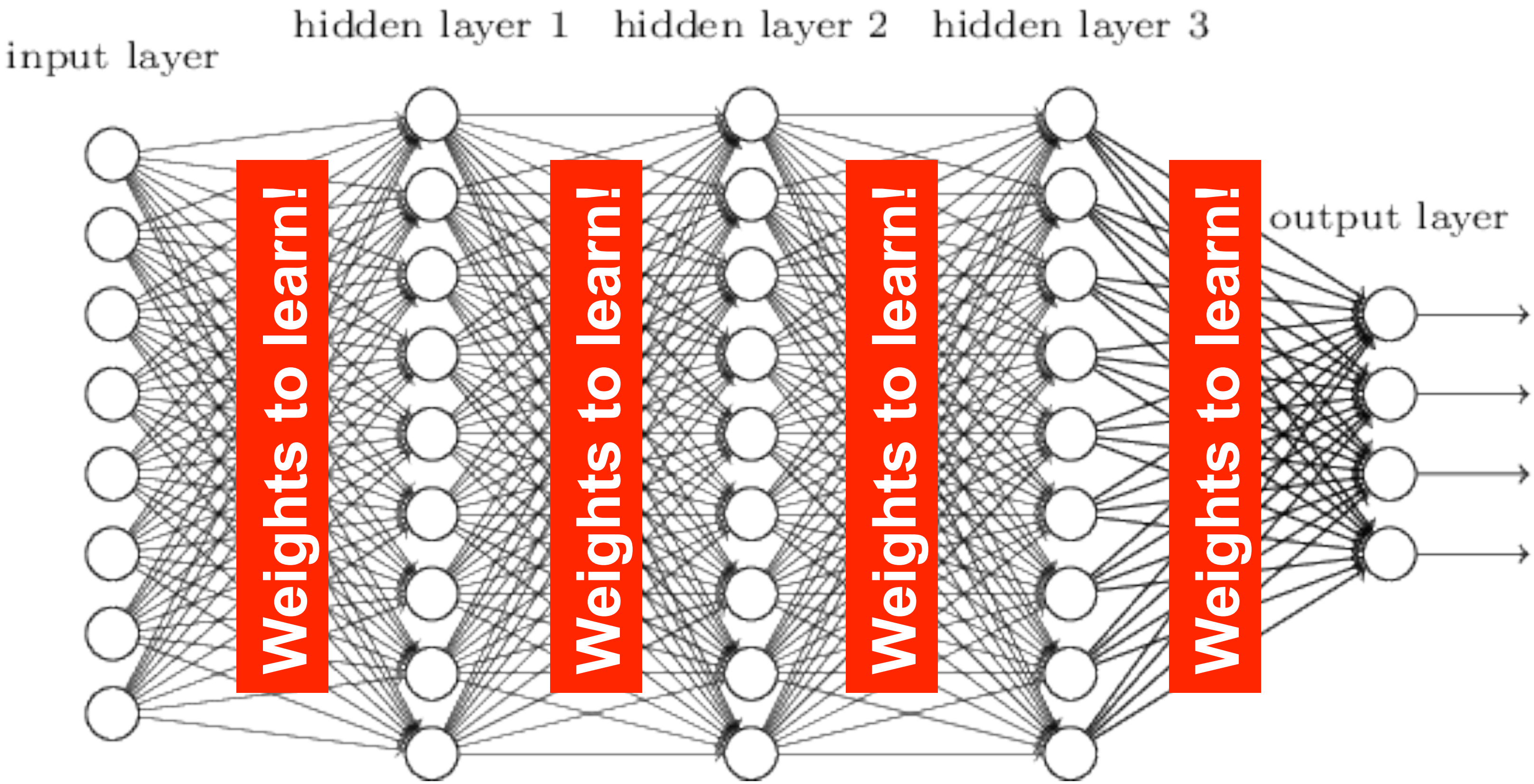


Figure from http://neuralnetworksanddeeplearning.com/chap5.html

Convolutional Neural Networks (CNN, ConvNet, DCN)

- CNN = a multi-layer neural network with
  - **Local** connectivity:
    - Neurons in a layer are only connected to a small region of the layer before it
  - **Share** weight parameters across spatial positions:
    - Learning shift-invariant filter kernels

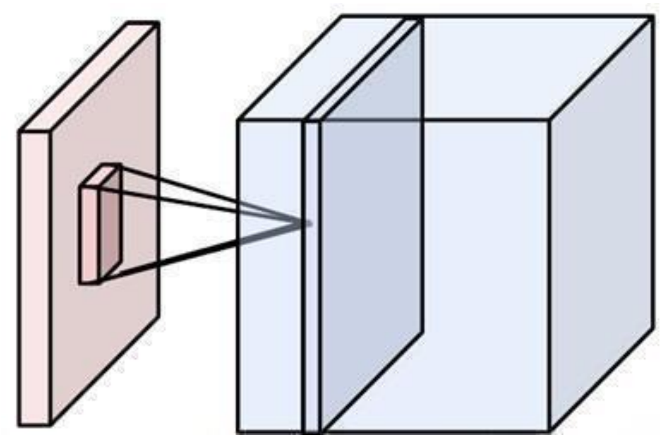
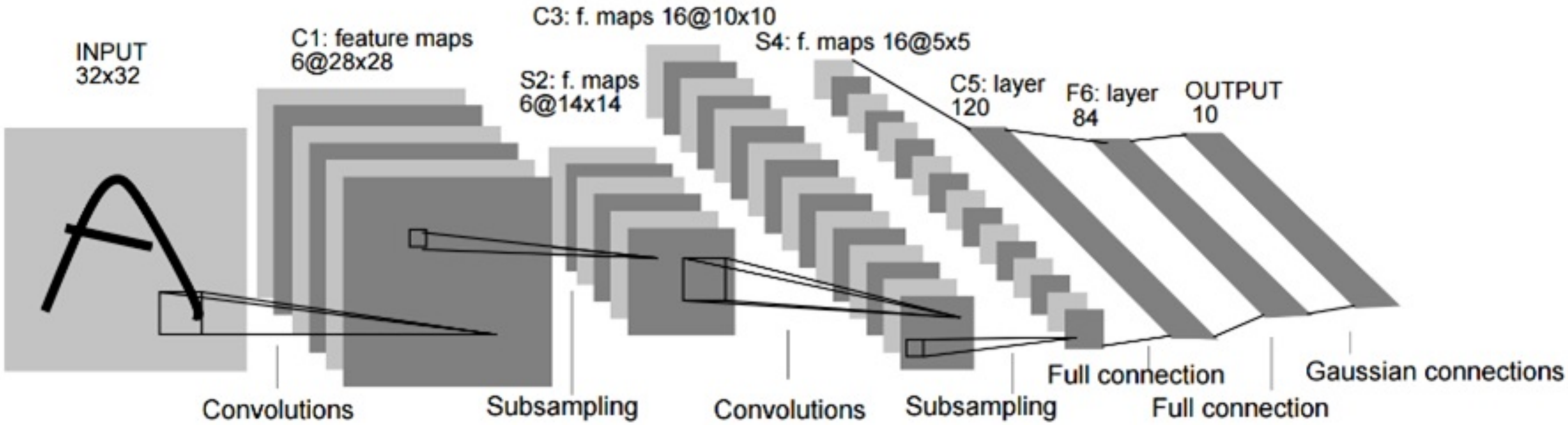


Image credit: A. Karpathy

LeNet [LeCun et al. 1998]

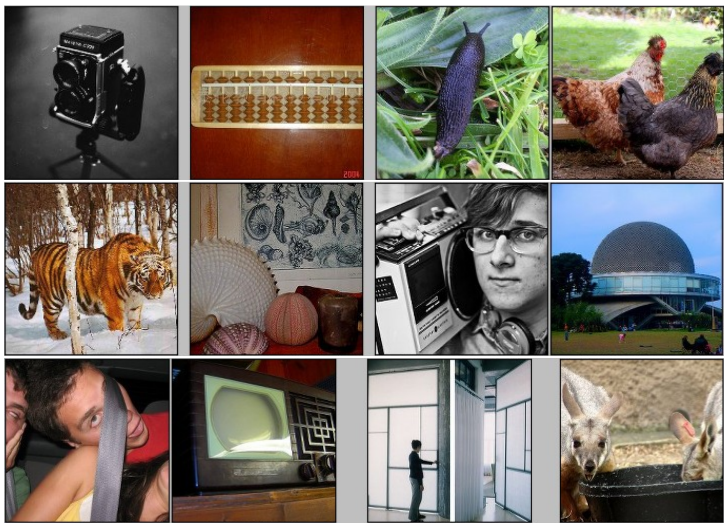


- Stack multiple stages of feature extractors
- Higher stages compute more global, more invariant features
- Classification layer at the end

LeNet-1 from 1993

Gradient-based learning applied to document recognition [LeCun, Bottou, Bengio, Haffner 1998]

ImageNet Challenge 2012



[Deng et al. CVPR 2009]

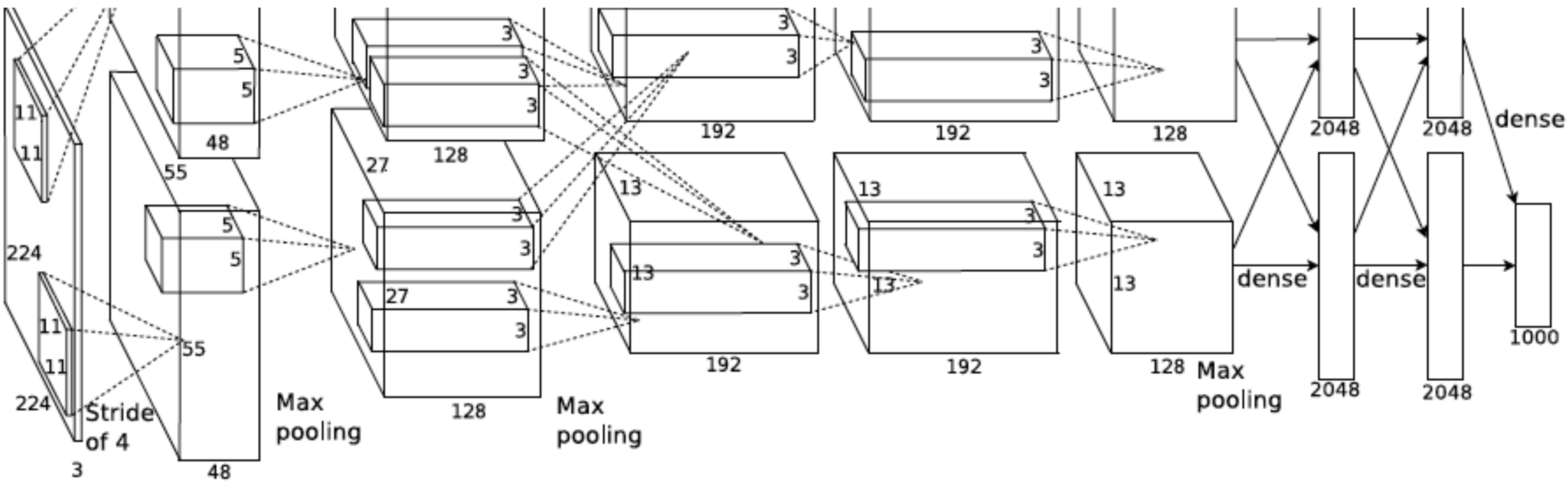
- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon Turk
- **ImageNet Challenge**: *1.2 million training images, 1000 classes*

A. Krizhevsky, I. Sutskever, and G. Hinton,
ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

AlexNet

Similar framework to LeCun'98 but:

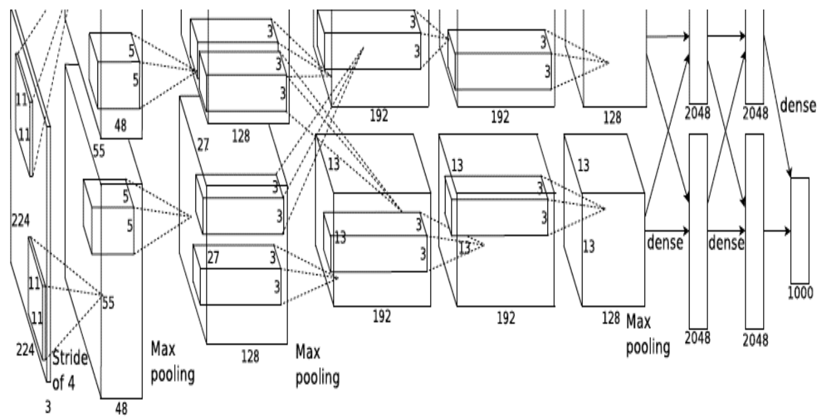
- Bigger model (7 hidden layers, 650,000 units, 60,000,000 params)
- More data (10^6 vs. 10^3 images)
- GPU implementation (50x speedup over CPU)
  - Trained on two GPUs for a week



A. Krizhevsky, I. Sutskever, and G. Hinton,
[ImageNet Classification with Deep Convolutional Neural Networks](), NIPS 2012

AlexNet for image classification

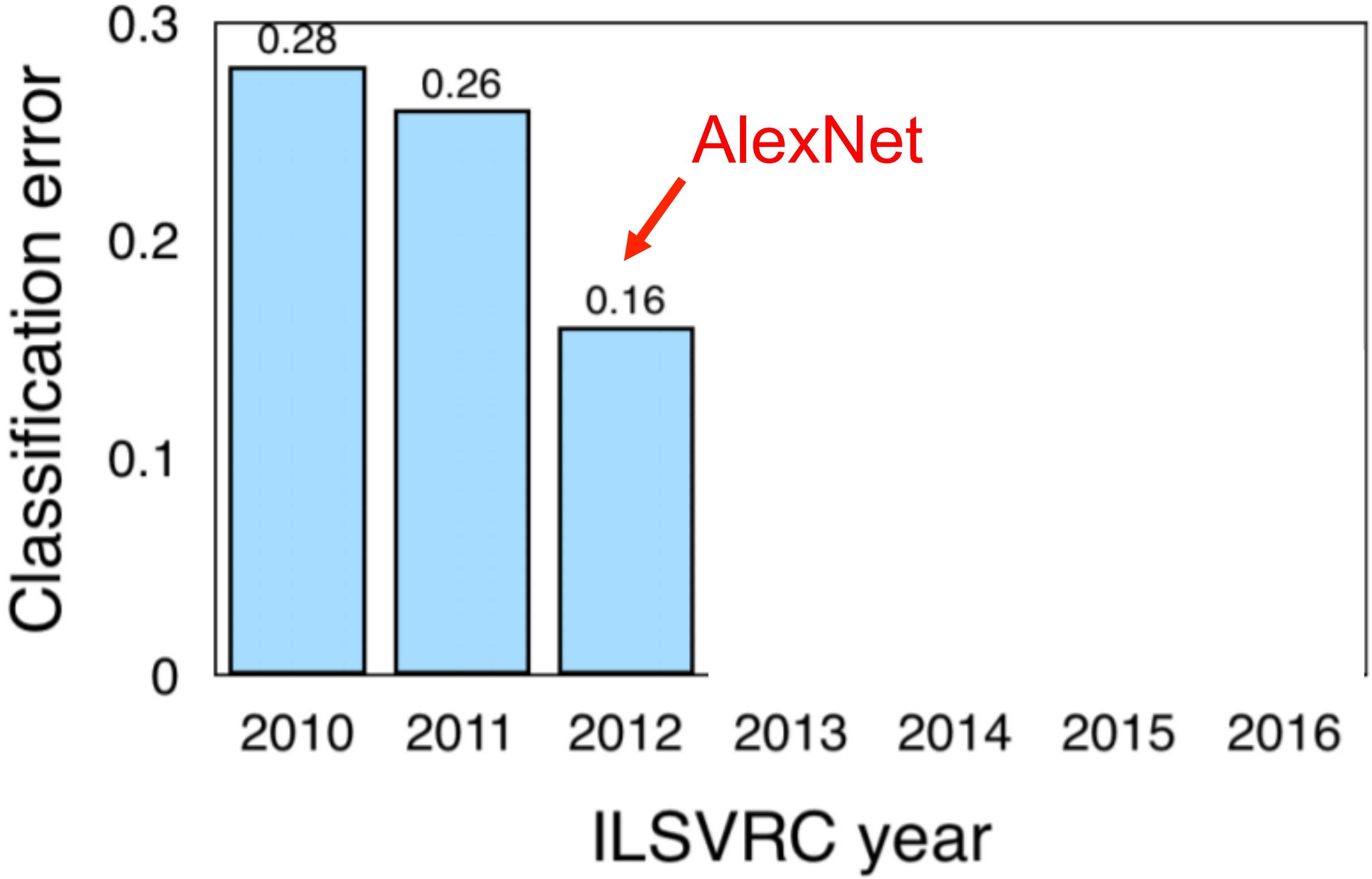
AlexNet



“car”

Fixed input size: 224x224x3

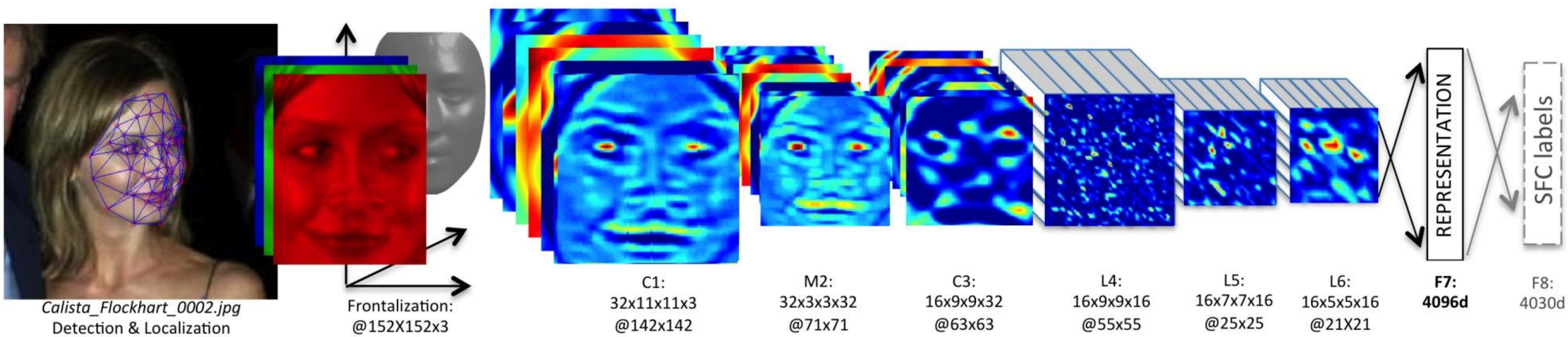
ImageNet Classification Challenge



http://image-net.org/challenges/talks/2016/ILSVRC2016_10_09_clsloc.pdf

Industry Deployment

- Used in Facebook, Google, Microsoft
- Startups
- Image Recognition, Speech Recognition, ...
- Fast at test time



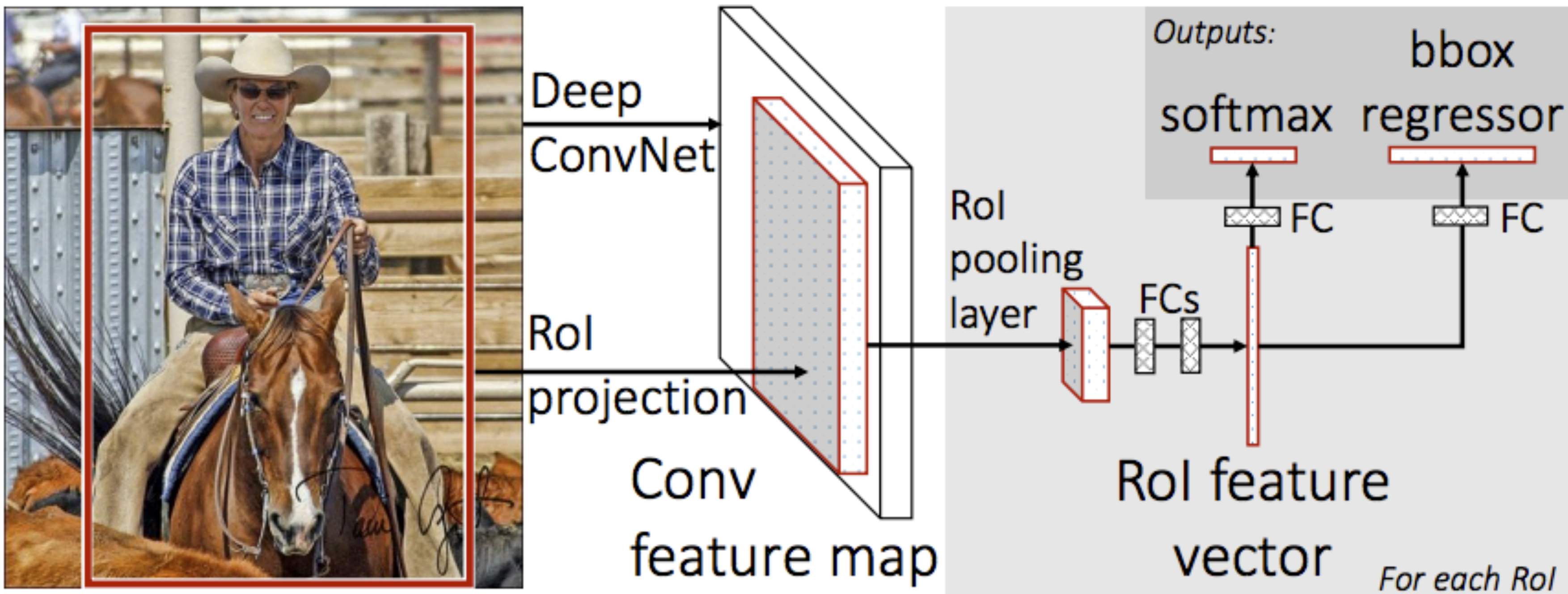
Taigman et al. DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR'14

Beyond classification

- Detection
- Segmentation
- Regression
- Pose estimation
- Matching patches
- Synthesis

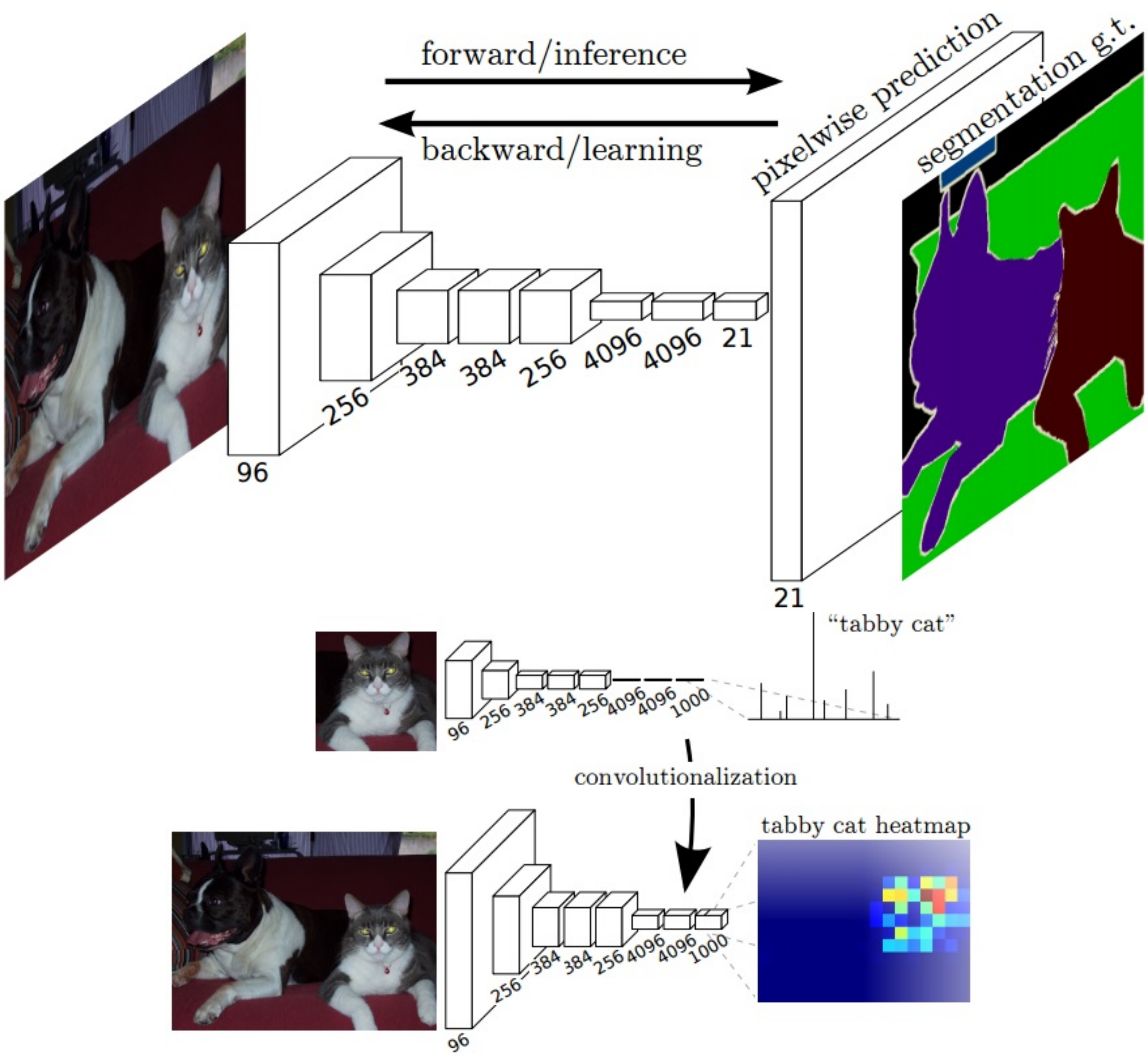
and many more…

CNNs for Object detection



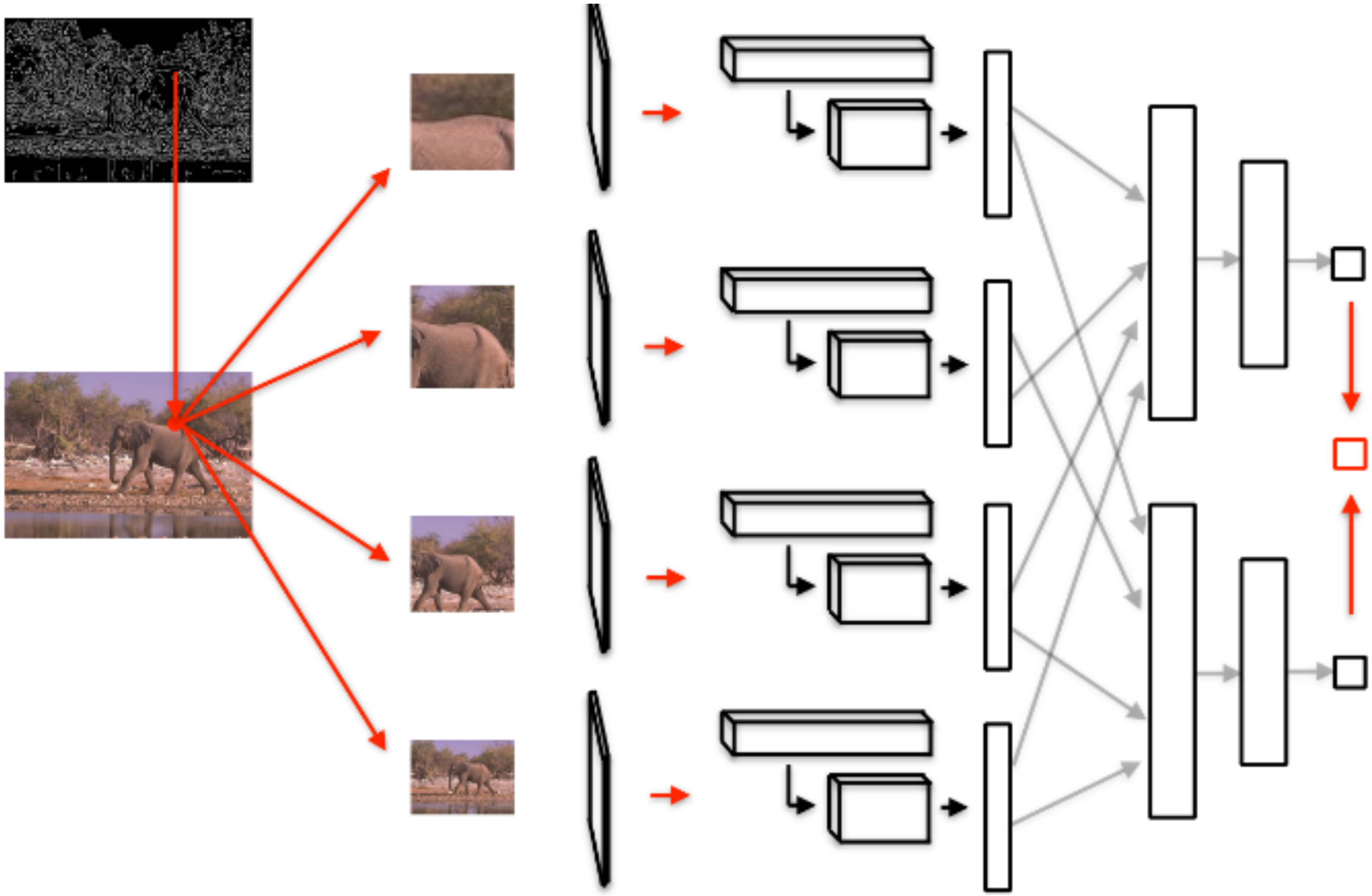
Fast-RCNN [Girshick et al. ICCV 2015]

Labeling Pixels: Semantic Labels



Fully Convolutional Networks for Semantic Segmentation [Long et al. CVPR 2015]

Labeling Pixels: Edge Detection

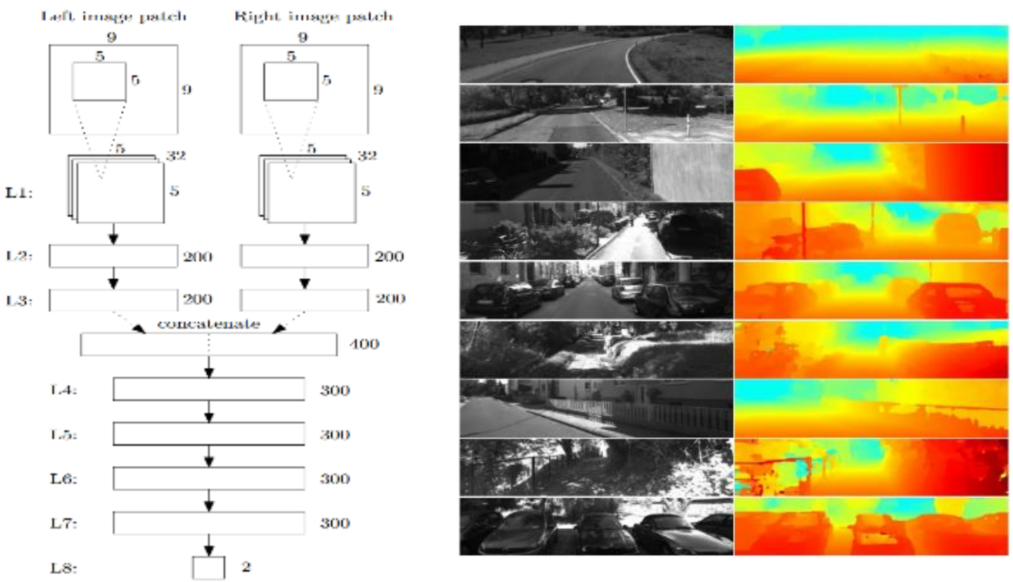


DeepEdge: A Multi-Scale Bifurcated Deep Network for Top-Down Contour Detection
[Bertasius et al. CVPR 2015]

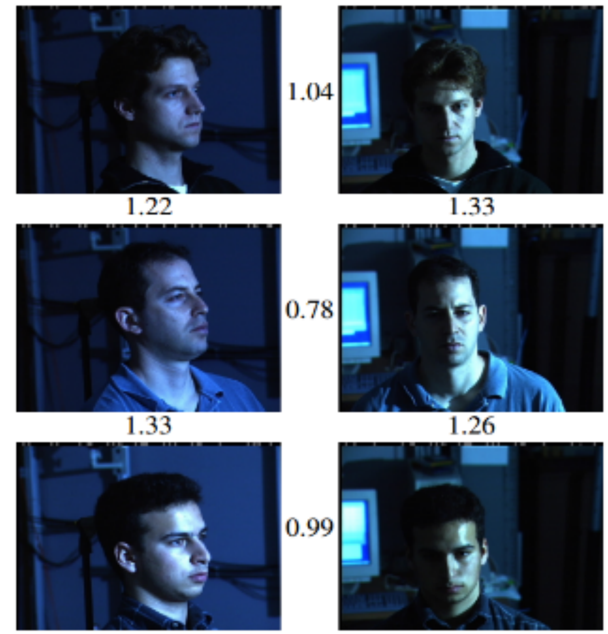
CNN for Regression

DeepPose [Toshev and Szegedy CVPR 2014]

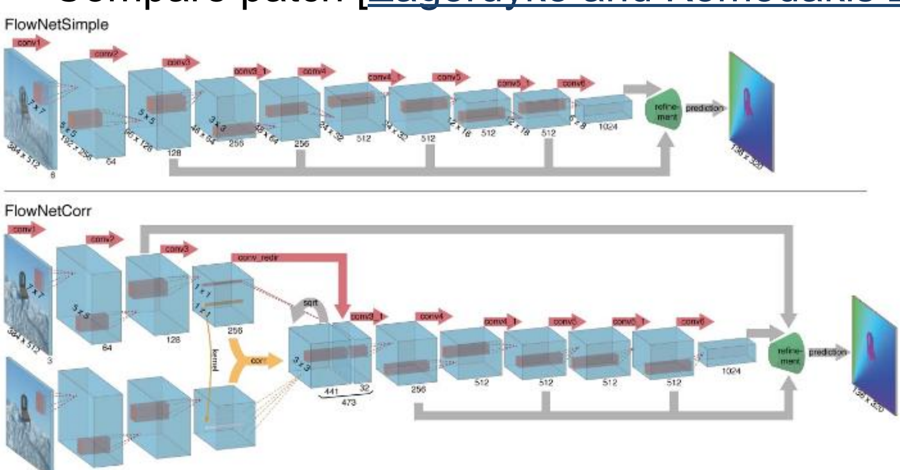
CNN as a Similarity Measure for Matching



Stereo matching [Zbontar and LeCun CVPR 2015]
Compare patch [Zagoruyko and Komodakis 2015]



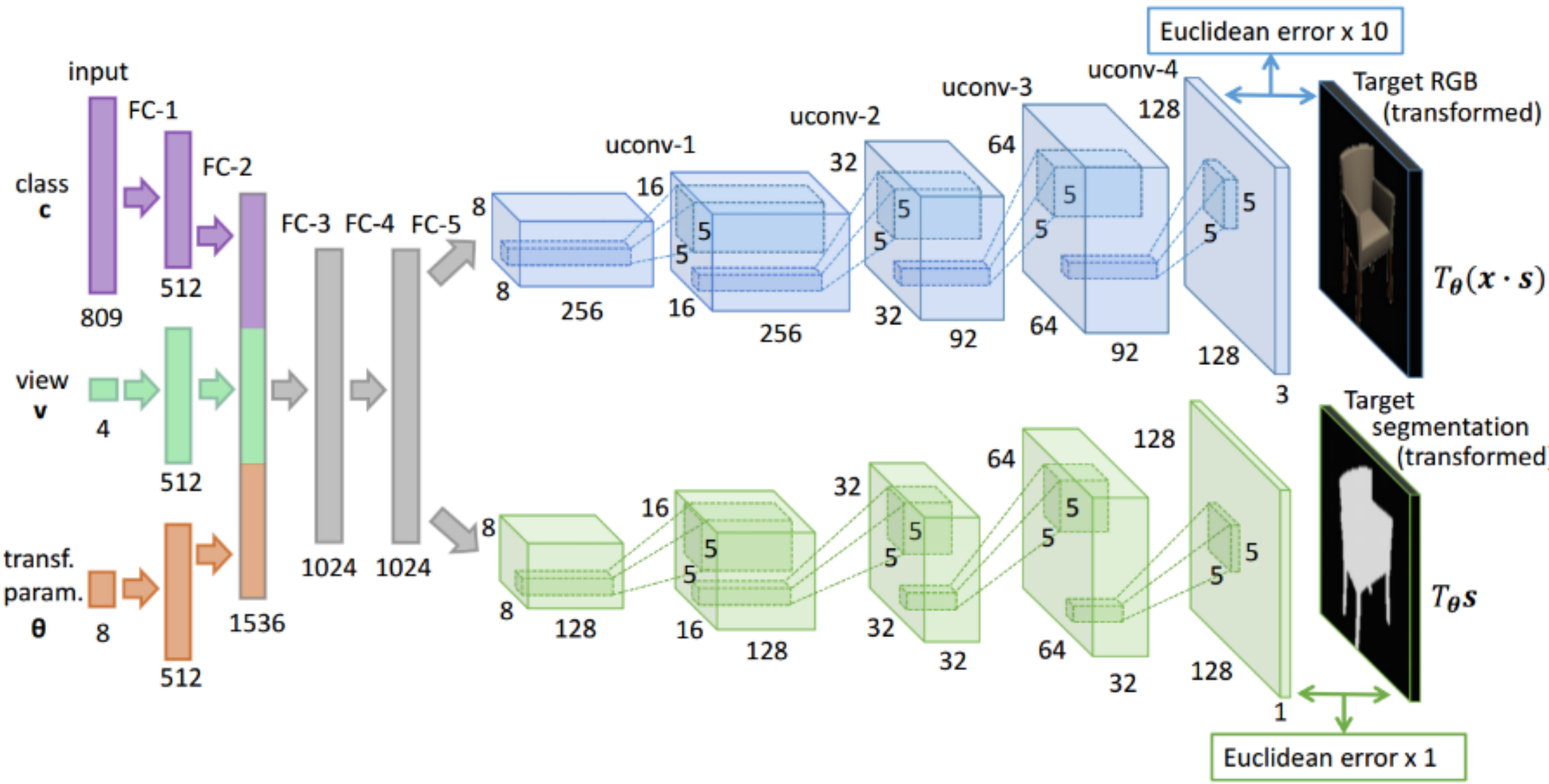
FaceNet [Schroff et al. 2015]



FlowNet [Fischer et al 2015]

Match ground and aerial images
[Lin et al. CVPR 2015]

CNN for Image Generation



Learning to Generate Chairs with Convolutional Neural Networks [Dosovitskiy et al. CVPR 2015]

Chair Morphing

Learning to Generate Chairs with Convolutional Neural Networks [Dosovitskiy et al. CVPR 2015]

Questions?

See you Monday!