CS688: Web-Scale Image Search

Deep Neural Nets and Features

Sung-Eui Yoon
(윤성의)

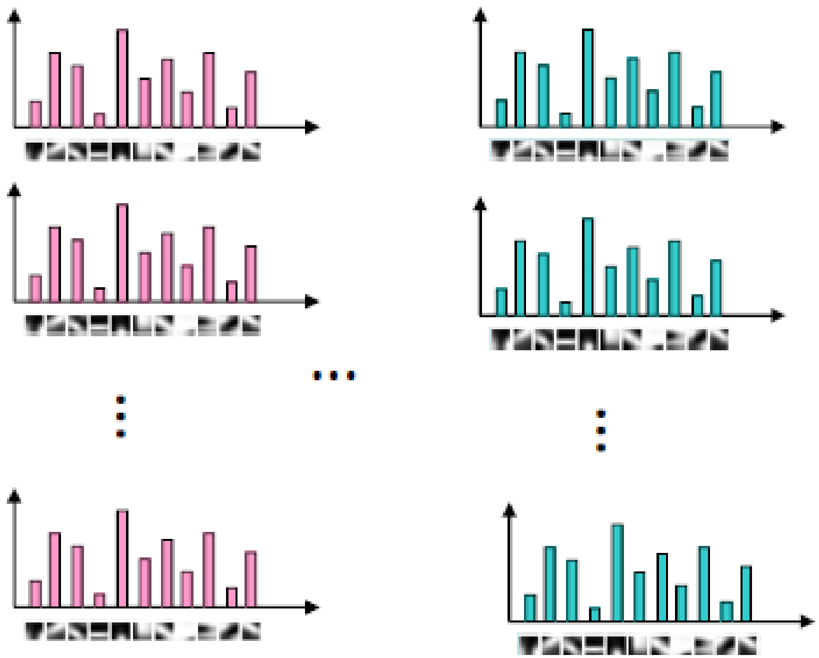
Course URL:
http://sglab.kaist.ac.kr/~sungeui/IR

Class Objectives

- Study neural nets, especially, convolution neural nets (CNNs)
- See its applications to computer vision problems and image search

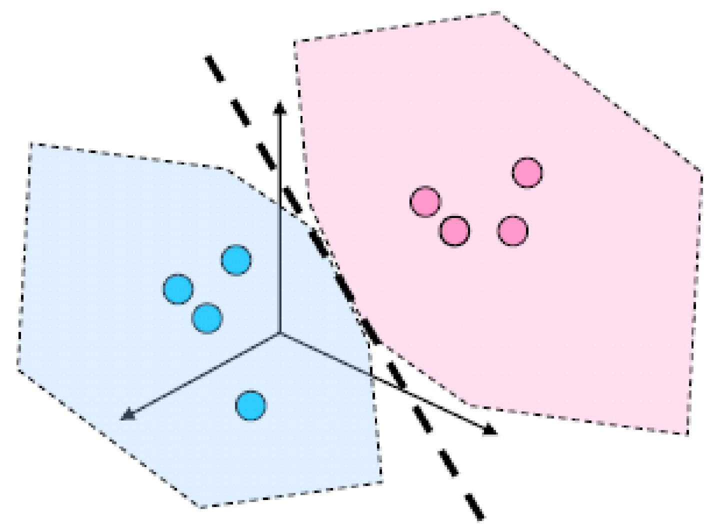
Discriminative classifiers (linear classifier)

category models



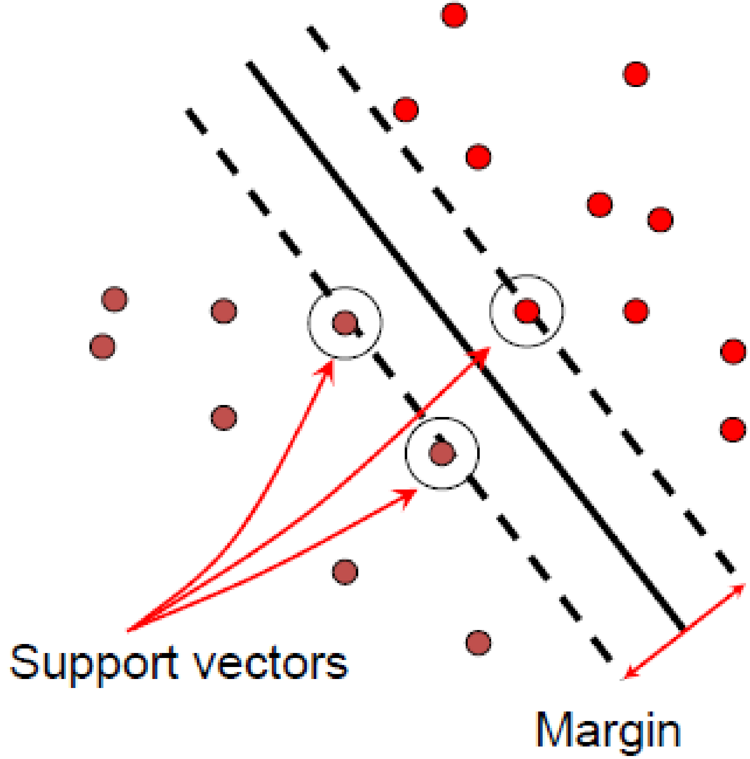
Class 1 Class N

Model space



Support vector machines

- Find hyperplane that maximizes the *margin* between the positive and negative examples



Support vectors: $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Distance between point and hyperplane: $\dfrac{|\mathbf{x}_i \cdot \mathbf{w} + b|}{||\mathbf{w}||}$

Margin = $2 / ||\mathbf{w}||$

Solution: $\boxed{\mathbf{w} = \sum_i \alpha_i y_i \mathbf{x}_i}$

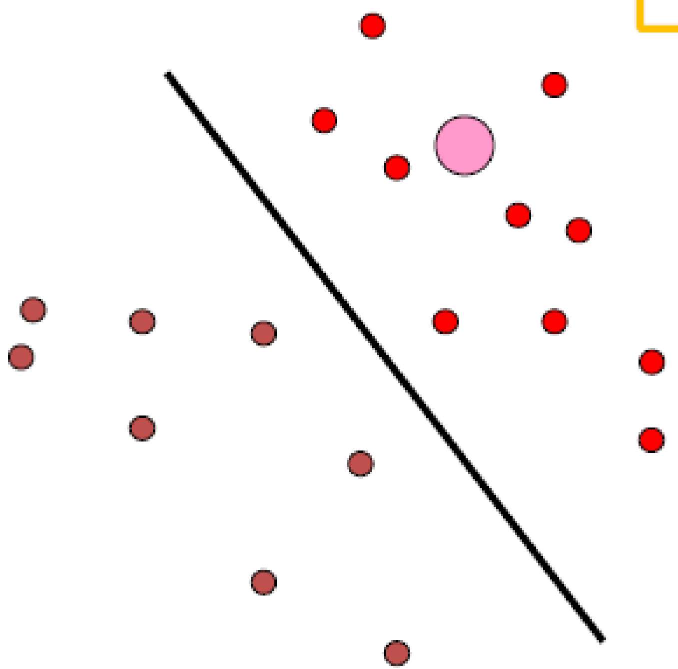
Classification function (decision boundary):

$$\boxed{\mathbf{w} \cdot \mathbf{x} + b = \sum_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b}$$

Credit slide: S. Lazebnik

Support vector machines

- Classification



$$\mathbf{w} \cdot \boxed{\mathbf{x}} + b = \sum_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b$$

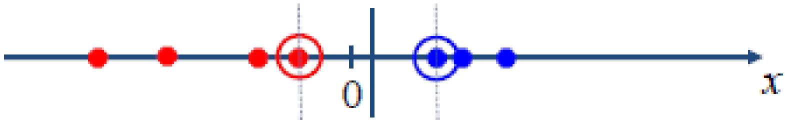
Test point

$$if \quad \mathbf{x} \cdot \mathbf{w} + b \geq 0 \rightarrow \quad class\ 1$$
$$if \quad \mathbf{x} \cdot \mathbf{w} + b < 0 \rightarrow \quad class\ 2$$

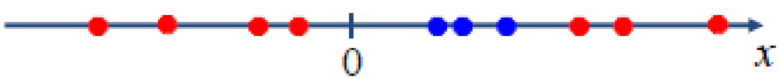
C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

Nonlinear SVMs

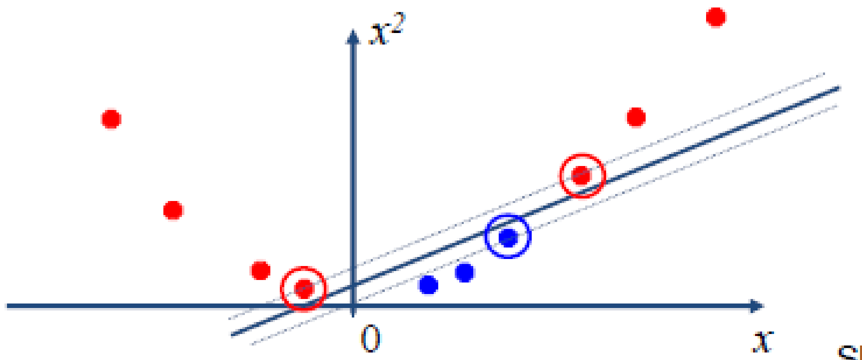
- Datasets that are linearly separable work out great:



- But what if the dataset is just too hard?



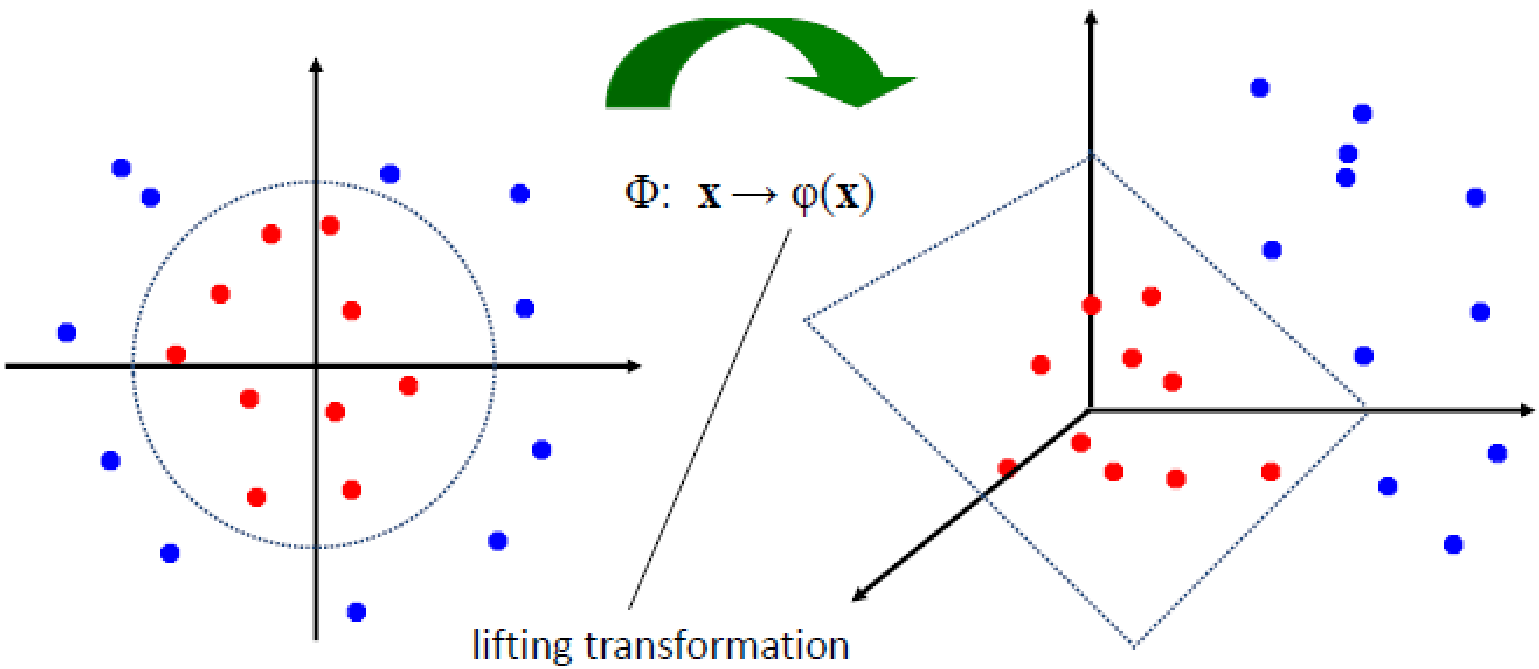
- We can map it to a higher-dimensional space:



Slide credit: Andrew Moore

Nonlinear SVMs

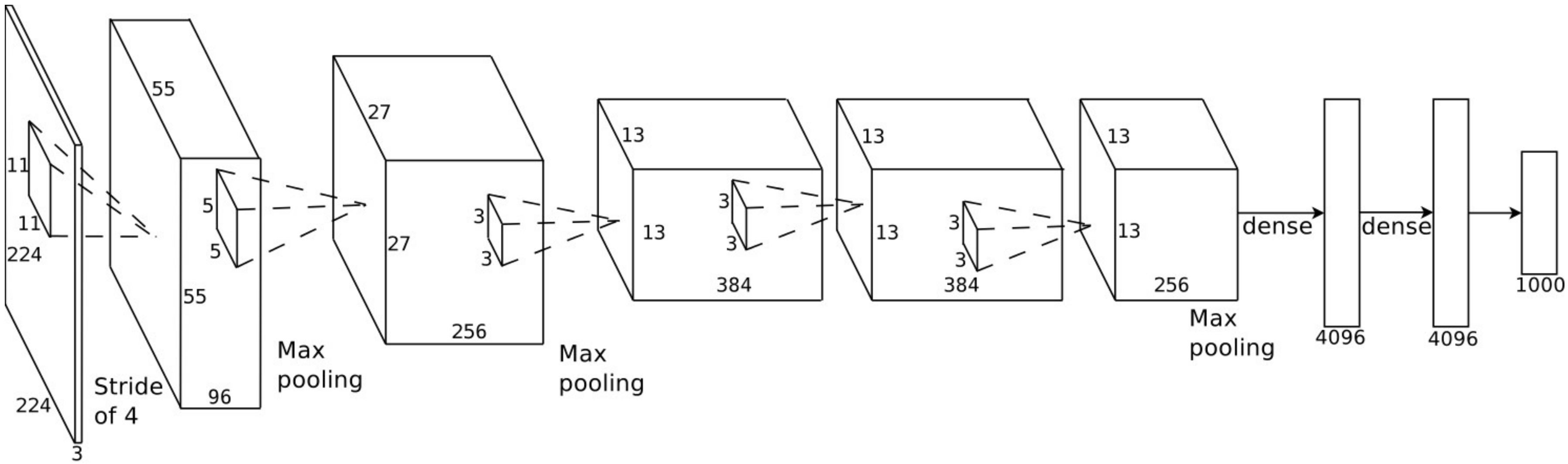
- General idea: the original input space can always be mapped to some higher-dimensional feature space where the training set is separable:



Slide credit: Andrew Moore

High-Level Messages

- **Deep neural nets provide low-level and high-level features**
  - **We can use those features for image search**
- **Achieve the best results in many computer vision related problems**

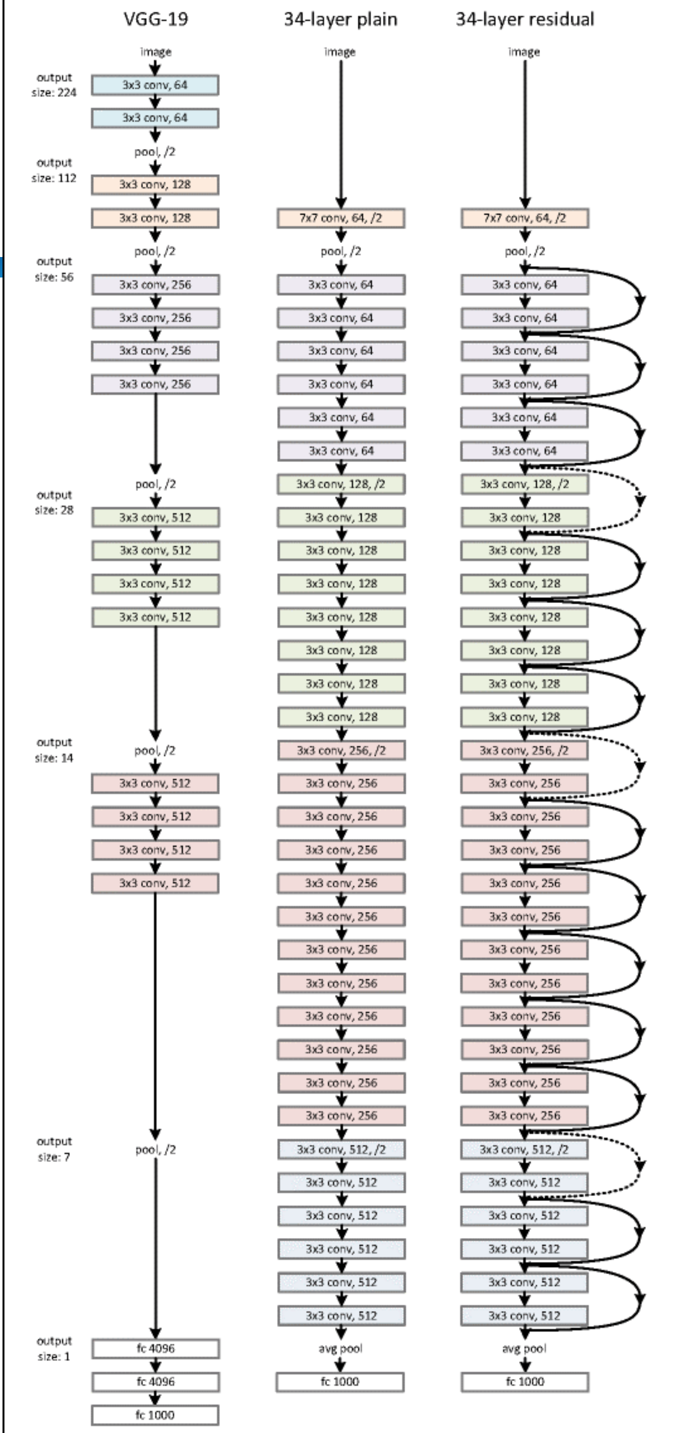


Krizhevsky et al., NIPS 2012

High-Level Messages

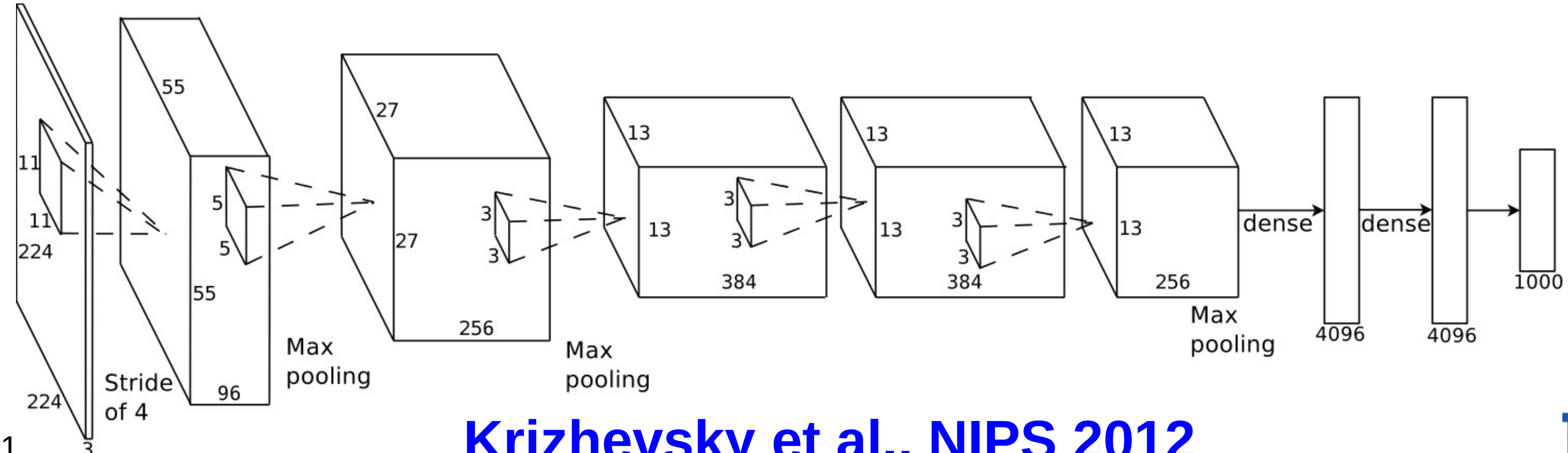
- **Many features and codes are available**
  - **Caffe [Krizhevsky et al., NIPS 2012]**
  - **Very deep convolutional networks [Simonyan et al., ICLR 15]; using up to 19 layers**
  - **Deep Residual Learning [He et al., CVPR 16]; using up to 152 layers**
- **Model Zoo**

github.com/BVLC/caffe/wiki/Model-Zoo



High-Level Messages

- **Perform the end-to-end optimization w/ lots of training data**
  - **Aims not only features, but the accuracy of any end-to-end systems including image search**



Krizhevsky et al., NIPS 2012

Deep Learning for Vision

Adam Coates

Stanford University

(Visiting Scholar: Indiana University, Bloomington)

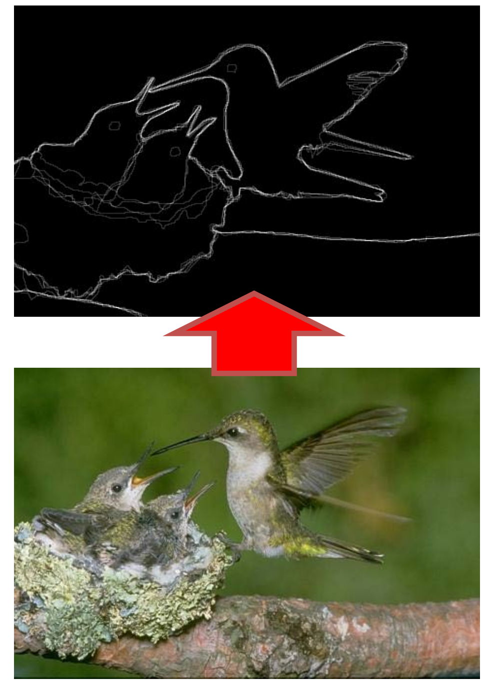
What do we want ML to do?

- Given image, predict complex high-level patterns:

"Cat"

Object recognition

Detection

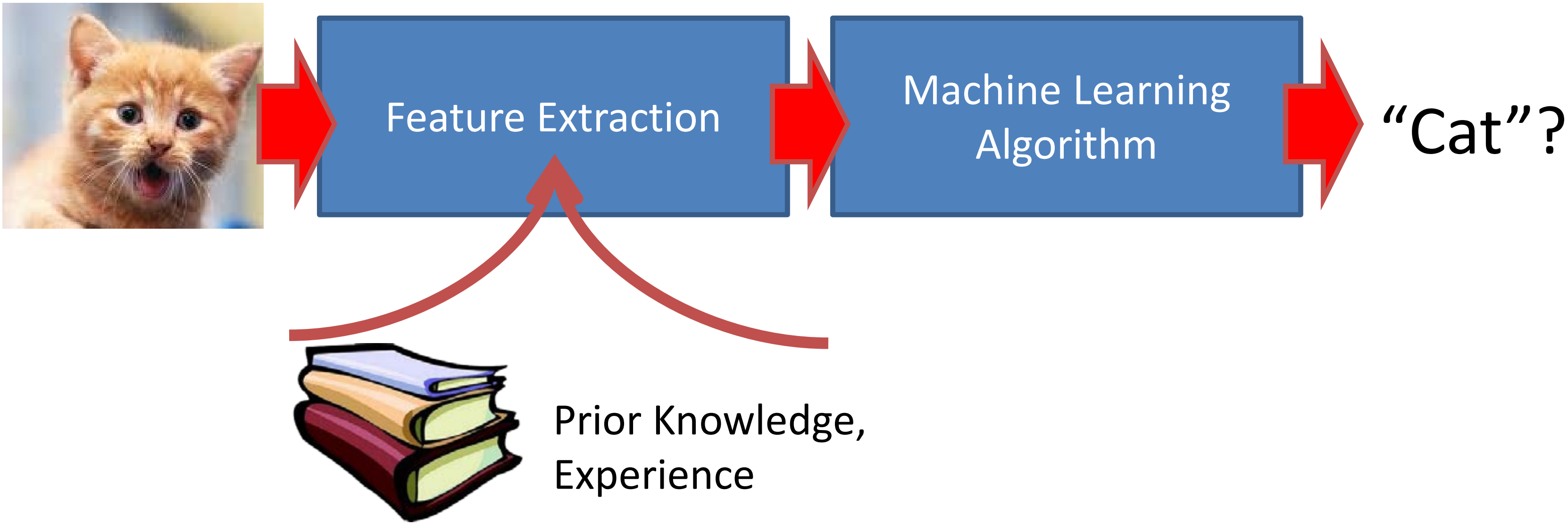


Segmentation

[Martin et al., 2001]

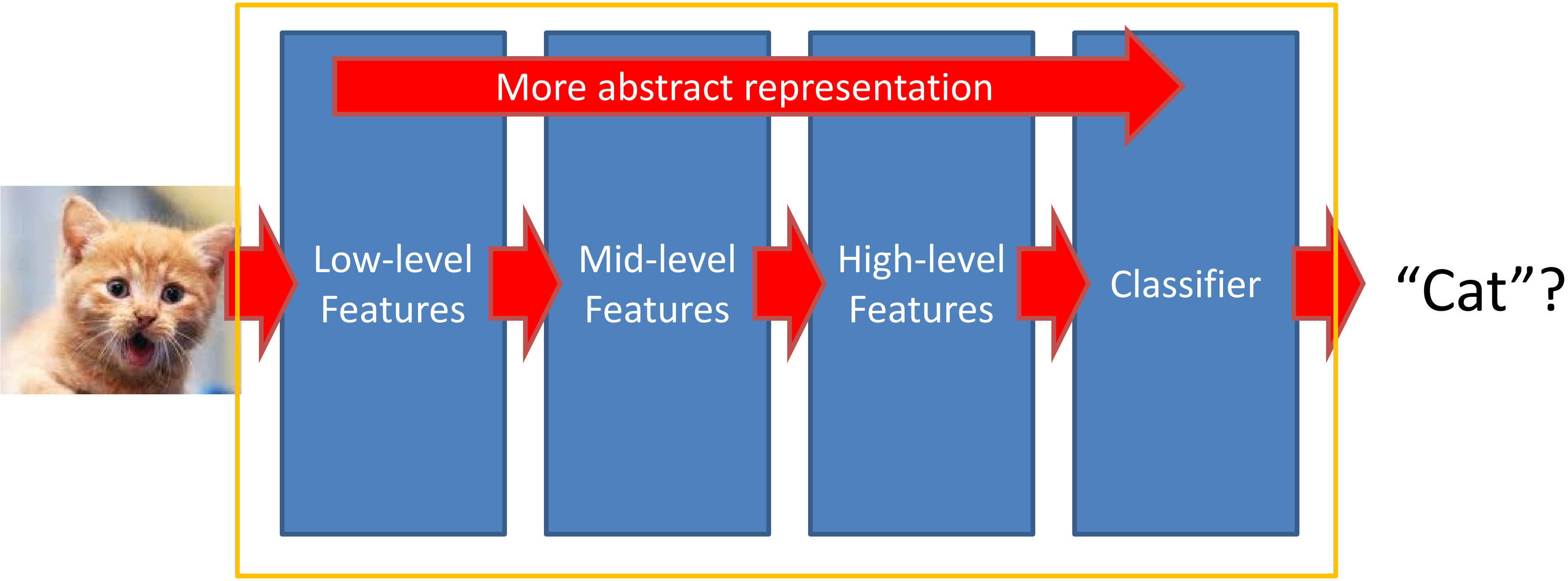
How is ML done?

- Machine learning often uses hand-designed feature extraction.



“Deep Learning”

- Deep Learning
  - Train *multiple layers* of features from data.
  - Try to discover useful *representations*



“Deep Learning”

- Why do we want “deep learning”?
  - Some decisions require many stages of processing.
  - We already hand-engineer “layers” of representation.
  - Algorithms scale well with data and computing power.
    - In practice, one of the most consistently successful ways to get good results in ML.

Have we been here before?

- Yes: Basic ideas common to past ML and neural networks research.

- No.
  - Faster computers; more data.
  - Better optimizers; better initialization schemes.
    - “Unsupervised pre-training” trick [Hinton et al. 2006; Bengio et al. 2006]
  - Lots of empirical evidence about what works.
    - Made useful by ability to “mix and match” components. [See, e.g., Jarrett et al., ICCV 2009]

Real impact

- DL systems are high performers in many tasks over *many domains*.

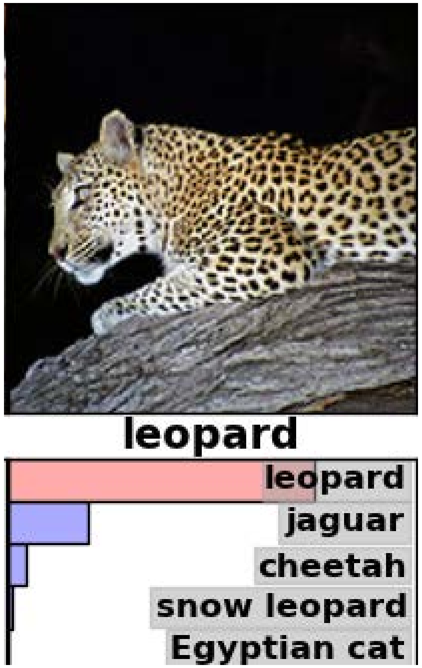
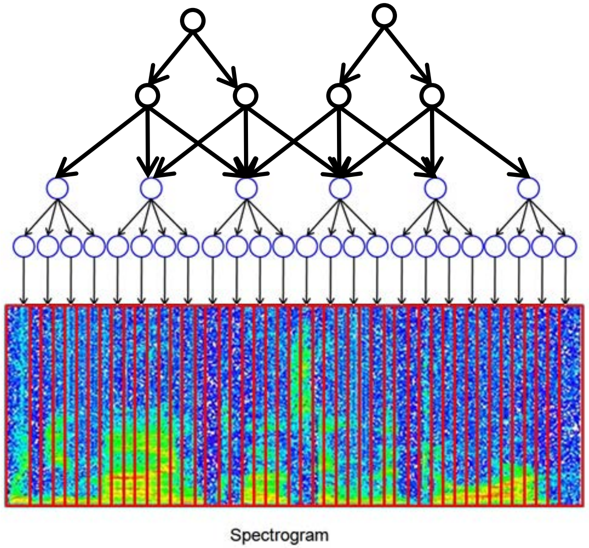
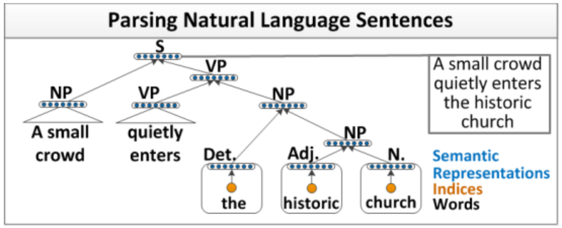


Image recognition
[E.g., Krizhevsky et al., 2012]

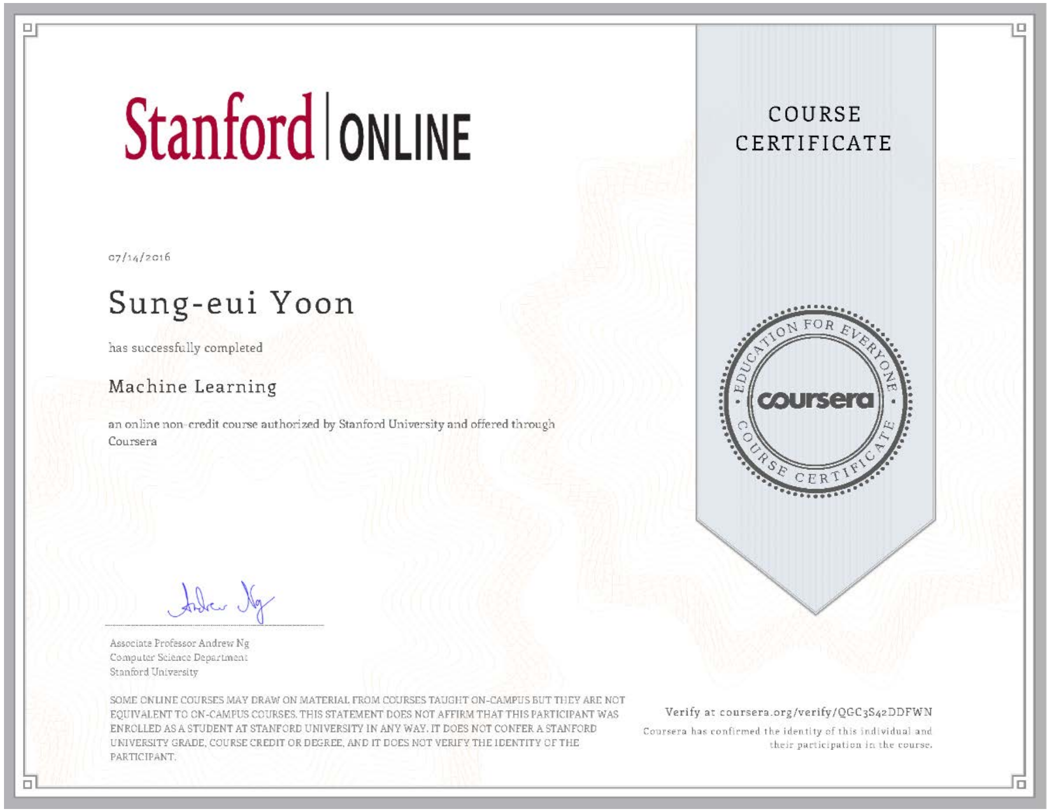


[Honglak Lee]

Speech recognition
[E.g., Heigold et al., 2013]



NLP
[E.g., Socher et al., ICML 2011; Collobert & Weston, ICML 2008]



Crash Course

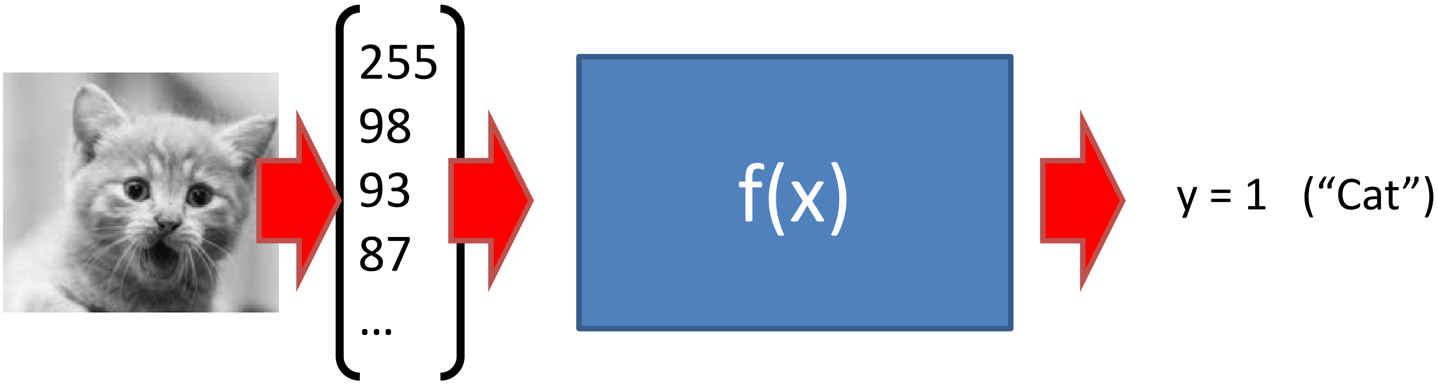
MACHINE LEARNING REFRESHER

Supervised Learning

- Given *labeled* training examples:

$$\mathcal{X} = \{(x^{(i)}, y^{(i)}) : i = 1, \ldots, m\}$$

- For instance: $x^{(i)}$ = vector of pixel intensities.
  $y^{(i)}$ = object class ID.

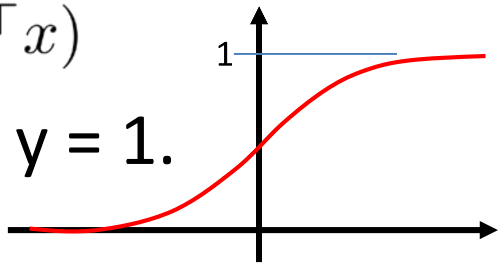


- Goal: find f(x) to predict y from x on training data.
  – Hopefully: learned predictor works on “test” data.

Logistic Regression

- Simple binary classification algorithm
  - Start with a function of the form:

$$f(x;\theta) \equiv \sigma(\theta^\top x) = \frac{1}{1+\exp(-\theta^\top x)}$$



  - Interpretation: f(x) is probability that y = 1.
  - Find choice of θ that minimizes objective:

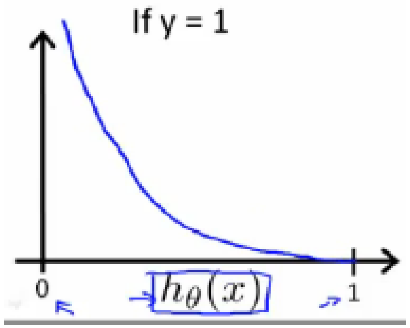
$\mathbb{P}(y^{(i)} = 1 | x^{(i)})$

$$\mathcal{L}(\theta) = -\sum_i^m 1\{y^{(i)} = 1\}\log(f(x^{(i)};\theta)) +$$

$\mathbb{P}(y^{(i)} = 0 | x^{(i)})$

$$1\{y^{(i)} = 0\}\log(1 - f(x^{(i)};\theta))$$

cost



From Ng's slide

Optimization

- How do we tune θ to minimize $\mathcal{L}(\theta)$?
- One algorithm: gradient descent
  - Compute gradient:

$$\nabla_\theta \mathcal{L}(\theta) = \sum_i^m x^{(i)} \cdot (y^{(i)} - f(x^{(i)}; \theta))$$

  - Follow gradient "downhill":

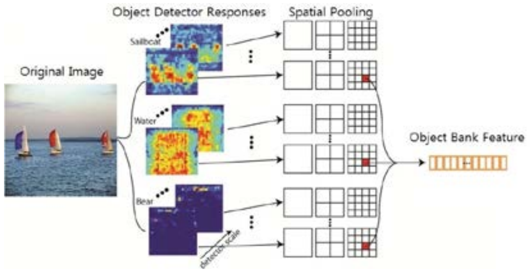
$$\theta := \theta - \eta \nabla_\theta \mathcal{L}(\theta)$$

- Stochastic Gradient Descent (SGD): take step using gradient from only small batch of examples.
  - Scales to larger datasets. [Bottou & LeCun, 2005]

Features

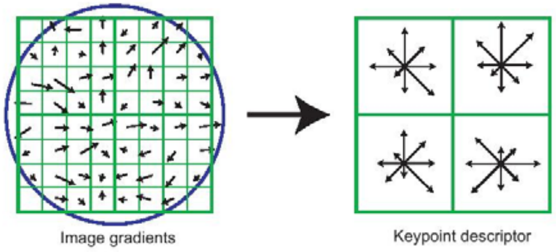
- Huge investment devoted to building application-specific feature representations.

Object Bank [Li et al., 2010]

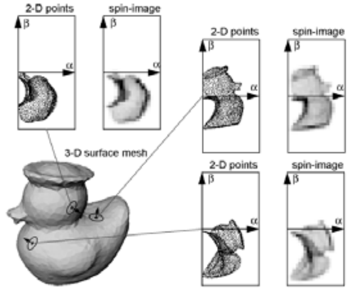


Super-pixels
[Gould et al., 2008; Ren & Malik, 2003]

SIFT [Lowe, 1999]



Spin Images [Johnson & Hebert, 1999]



Extension to neural networks

SUPERVISED DEEP LEARNING

Basic idea

- We saw how to do supervised learning when the "features" ϕ(x) are fixed.
  - Let's extend to case where features are given by tunable functions with their own parameters.

$$\mathbb{P}(y = 1|x) = f(x; \theta, W) = \sigma(\theta^\top \underline{\sigma(Wx)})$$

Outer part of function is same as logistic regression.

Inputs are "features"---one feature for each row of W:

$$\begin{bmatrix} \sigma(w_1 x) \\ \sigma(w_2 x) \\ \cdots \\ \sigma(w_K x) \end{bmatrix}$$

Basic idea

- To do supervised learning for two-class classification, minimize:

$$\mathcal{L}(\theta, W) = -\sum_{i}^{m} 1\{y^{(i)} = 1\} \log(f(x^{(i)}; \theta, W)) + 1\{y^{(i)} = 0\} \log(1 - f(x^{(i)}; \theta, W))$$

- Same as logistic regression, but now f(x) has multiple stages (“layers”, “modules”):

$$f(x; \theta, W) = \sigma(\theta^\top \sigma(Wx))$$

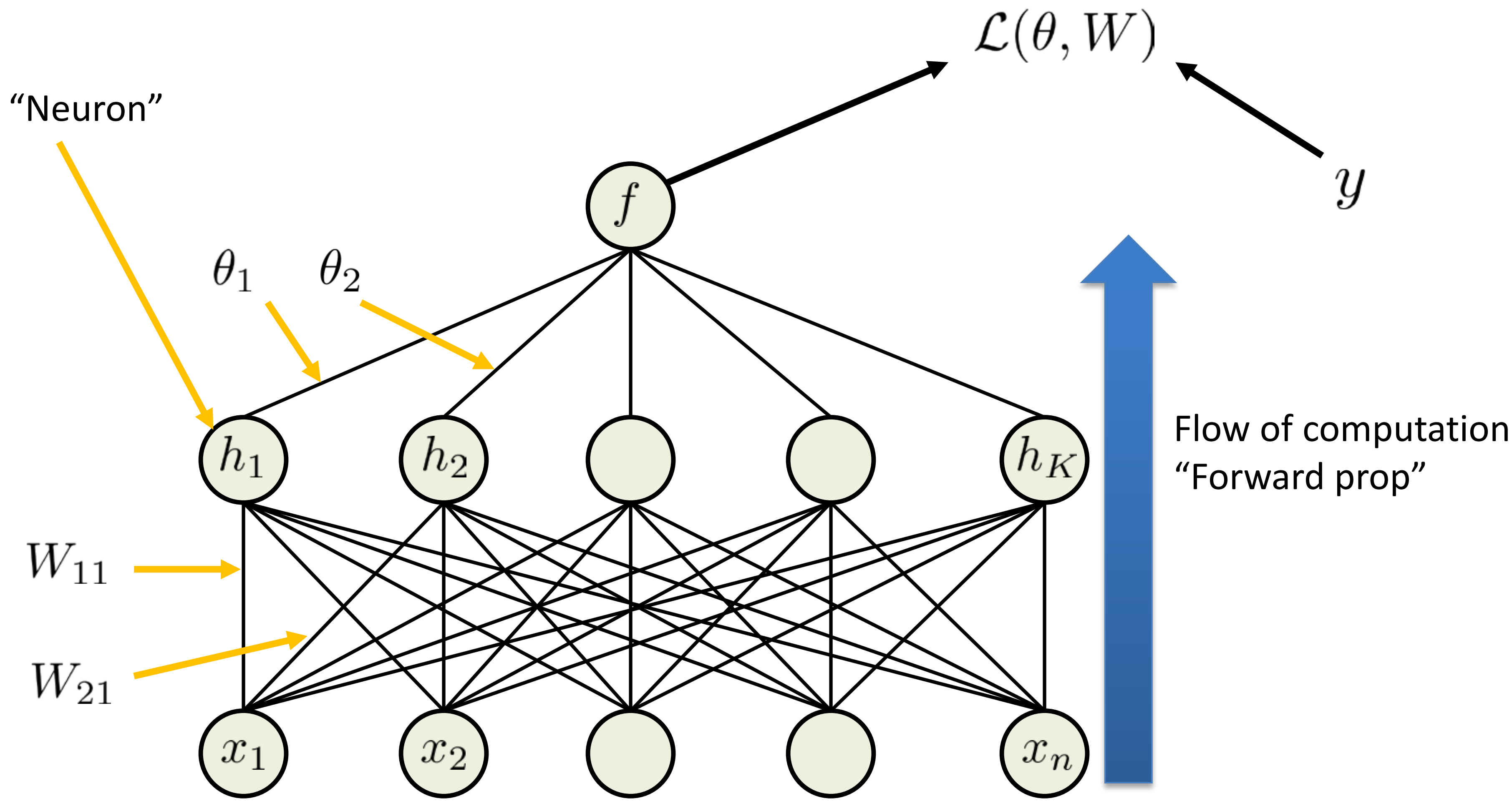
$$x \longrightarrow \boxed{\sigma(Wx)} \longrightarrow h \longrightarrow \boxed{\sigma(\theta^\top h)} \longrightarrow f$$

Intermediate representation (“features”)

Prediction for $\mathbb{P}(y = 1 | x)$

Neural network

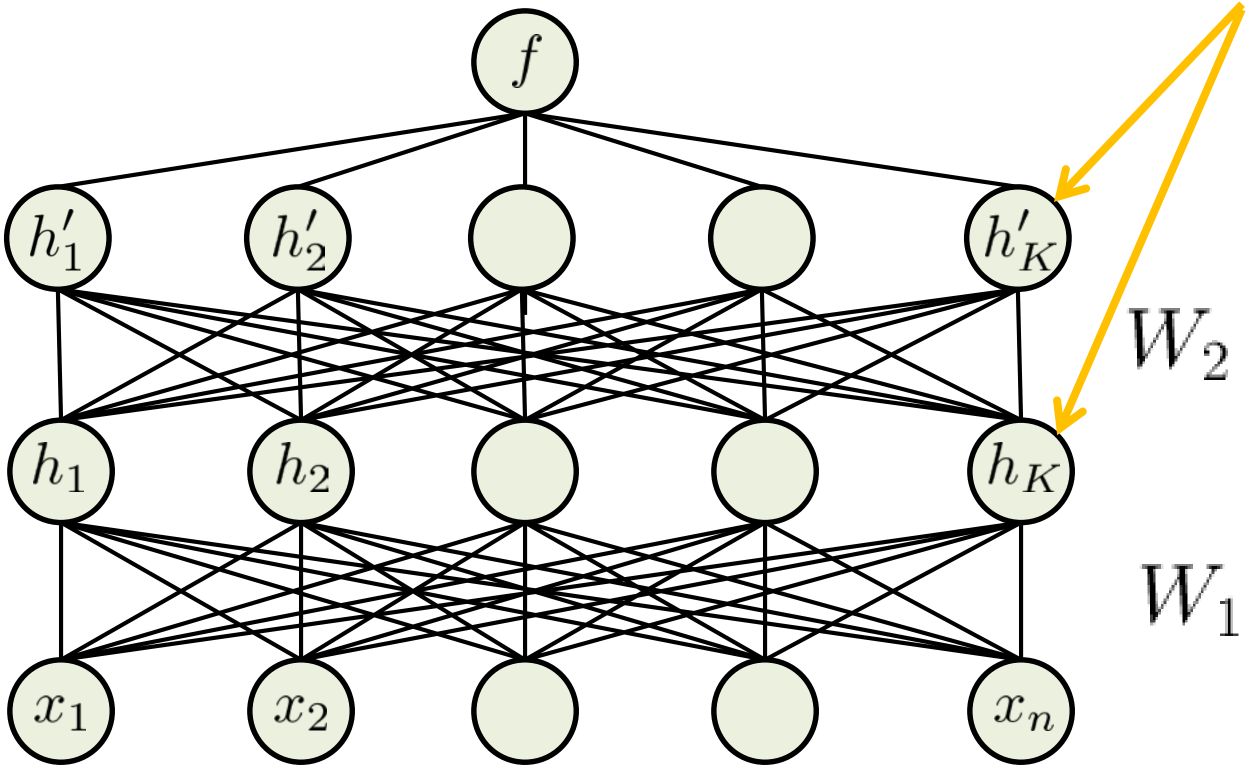
- This model is a sigmoid "neural network":



Neural network

- Can stack up several layers:

Must learn multiple stages of internal “representation”.



$$x \longrightarrow \boxed{\sigma(W_1 x)} \longrightarrow h \longrightarrow \boxed{\sigma(W_2 h)} \longrightarrow h' \longrightarrow \boxed{\sigma(\theta^\top h')} \longrightarrow f$$

Back-propagation

- Minimize:

$$\mathcal{L}(\theta, W) = -\sum_{i}^{m} 1\{y^{(i)} = 1\} \log(f(x^{(i)}; \theta, W)) +$$
$$1\{y^{(i)} = 0\} \log(1 - f(x^{(i)}; \theta, W))$$

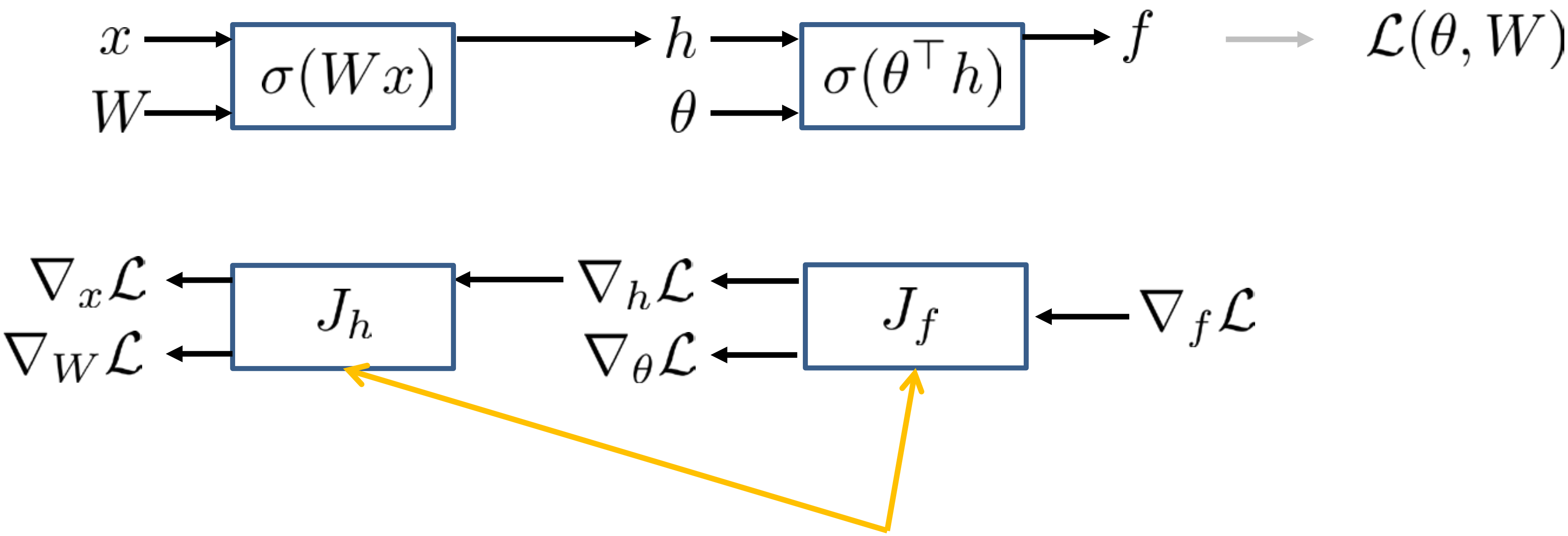
- To minimize $\mathcal{L}(\theta, W)$ we need gradients:

$$\nabla_\theta \mathcal{L}(\theta, W) \text{ and } \nabla_W \mathcal{L}(\theta, W)$$

  – Then use gradient descent algorithm as before.
- Formula for $\nabla_\theta \mathcal{L}(\theta, W)$ can be found by hand (same as before); but what about W?
  – Beyond the scope of this course

Back-propagation

- Can re-apply chain rule to get gradients for all intermediate values and parameters.



“Backward” modules for each forward stage.

Training Procedure

- Collect labeled training data
  - For SGD: Randomly shuffle after each epoch!

$$\mathcal{X} = \{(x^{(i)}, y^{(i)}) : i = 1, \ldots, m\}$$

- For a batch of examples:
  - Compute gradient w.r.t. all parameters in network.

$$\Delta_\theta := \nabla_\theta \mathcal{L}(\theta, W)$$

$$\Delta_W := \nabla_W \mathcal{L}(\theta, W)$$

  - Make a small update to parameters.

$$\theta := \theta - \eta_\theta \Delta_\theta$$

$$W := W - \eta_W \Delta_W$$

  - Repeat until convergence.

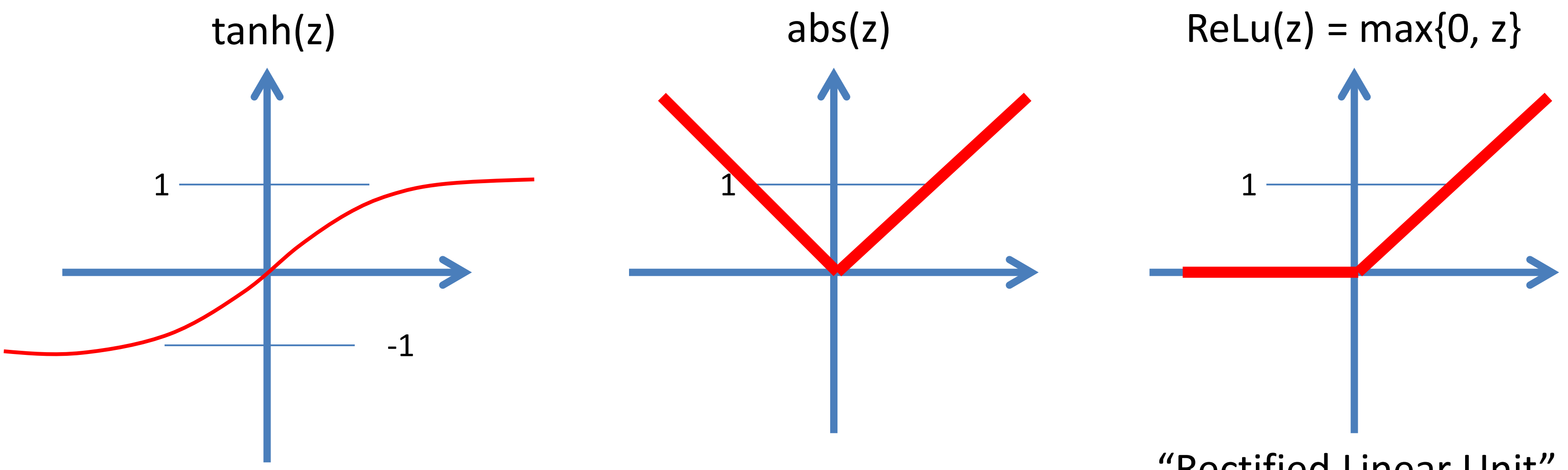
Training Procedure

- Historically, this has not worked so easily.
  - Non-convex: Local minima; convergence criteria.
  - Optimization becomes difficult with many stages.
    - "Vanishing gradient problem"
  - Hard to diagnose and debug malfunctions.

- Many things turn out to matter:
  - Choice of nonlinearities.
  - Initialization of parameters.
  - Optimizer parameters: step size, schedule.

Nonlinearities

- Choice of functions inside network matters.
  - Sigmoid function turns out to be difficult.
  - Some other choices often used:

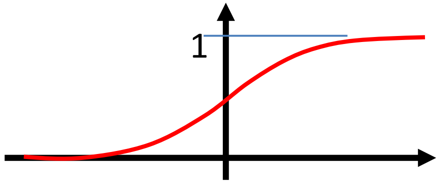


"Rectified Linear Unit"
→ Increasingly popular.

[Nair & Hinton, 2010]

Initialization

- Usually small random values.
  - Try to choose so that typical input to a neuron avoids saturating / non-differentiable areas.



- Initialization schemes for particular units:
  - tanh units: Unif[-r, r]; sigmoid: Unif[-4r, 4r].

$$r = \sqrt{6/(\text{fan-in} \ + \ \text{fan-out})}$$

See [Glorot et al., AISTATS 2010]

- Use features from unsupervised learning

Application

SUPERVISED DL FOR VISION

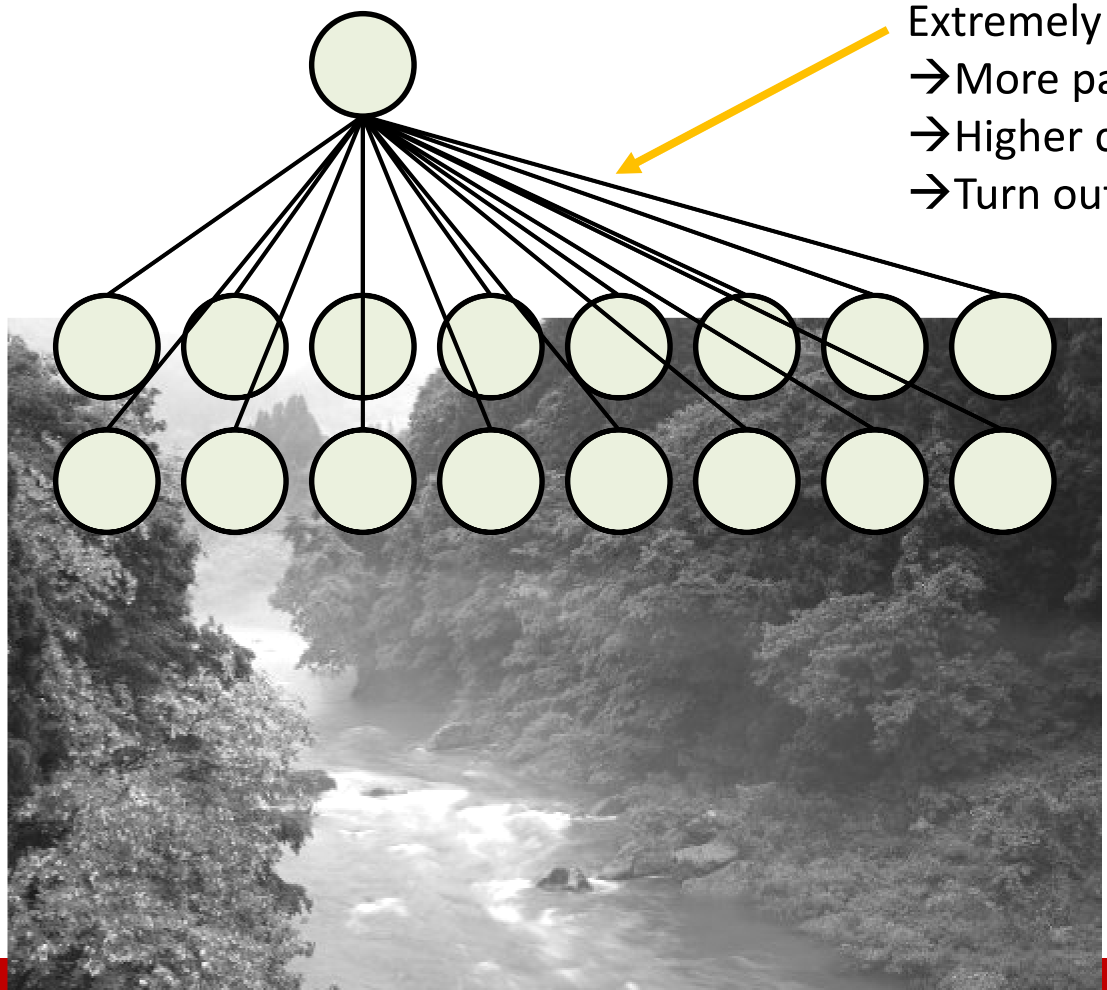
Working with images

- Major factors:
  - Want to have "selective" features and "invariant" features.
  - Try to exploit knowledge of images to accelerate training or improve performance.

- Generally try to avoid wiring detailed visual knowledge into system --- prefer to learn.

Local connectivity

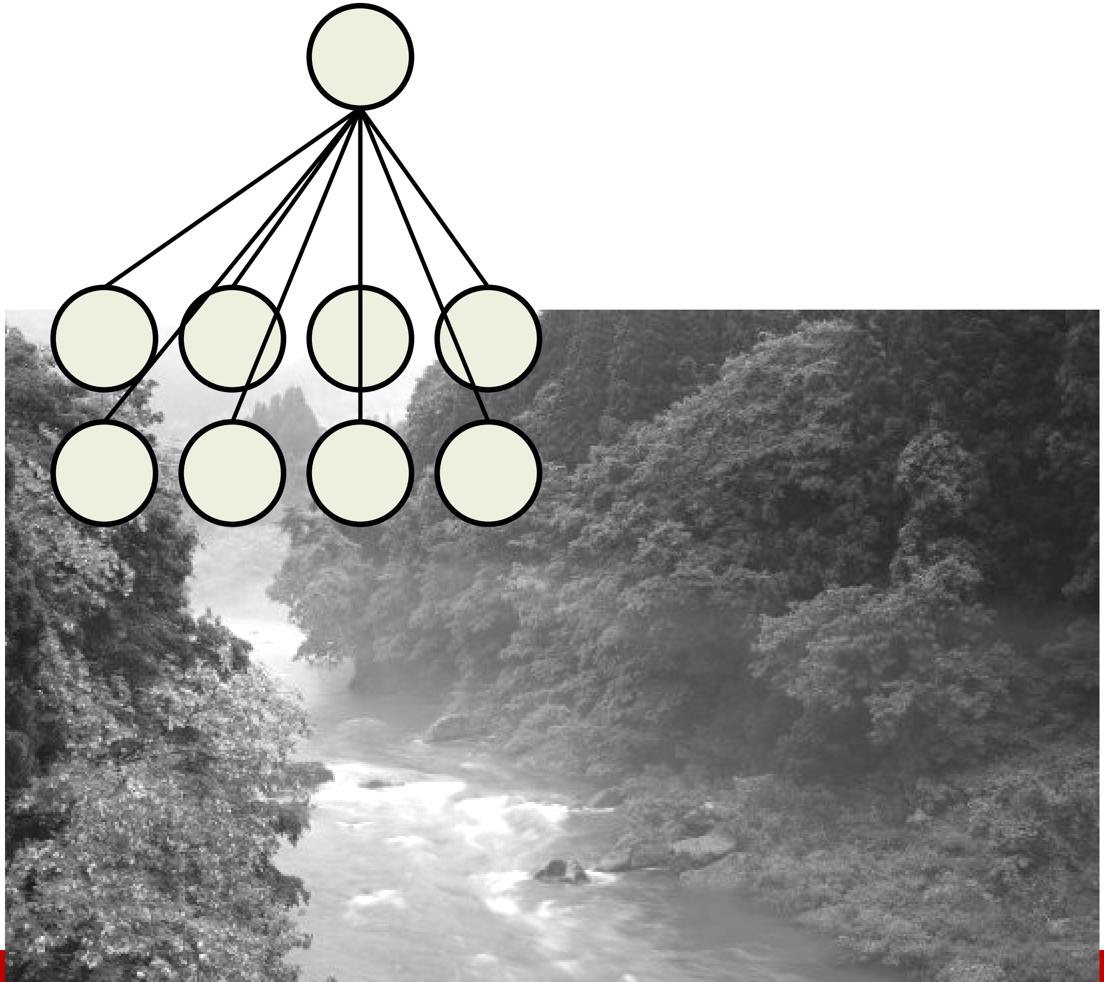
- Neural network view of single neuron:



Extremely large number of connections.
→More parameters to train.
→Higher computational expense.
→Turn out not to be helpful in practice.

Local connectivity

- Reduce parameters with local connections.
  - Weight vector is a spatially localized “filter”.

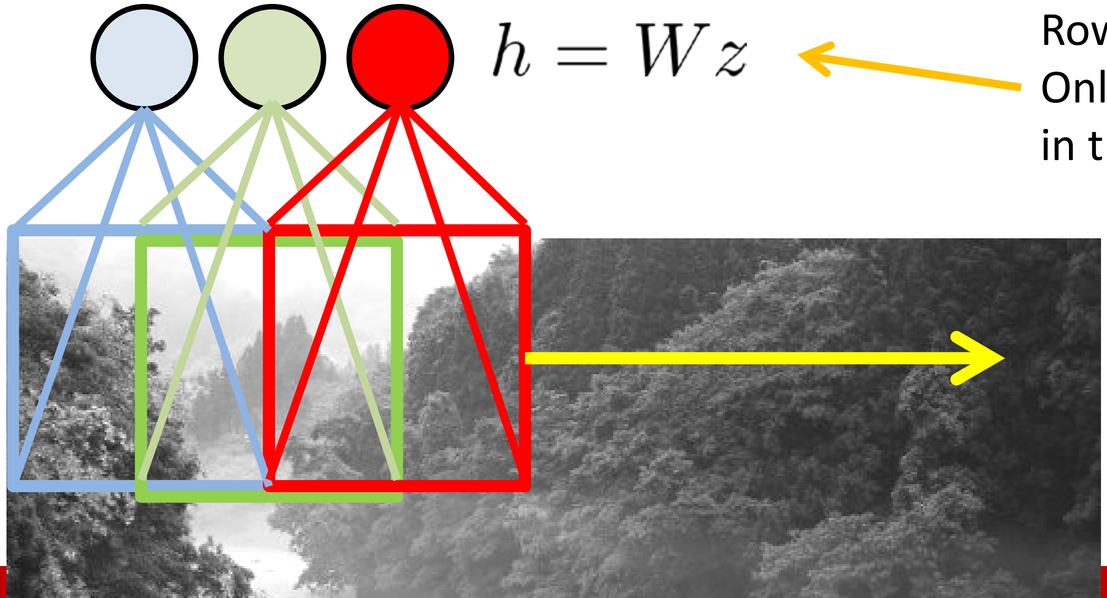


Local connectivity

- Sometimes think of neurons as viewing small adjacent windows.
  - Specify connectivity by the size (“receptive field” size) and spacing (“step” or “stride”) of windows.
    - Typical RF size = 5 to 20
    - Typical step size = 1 pixel up to RF size.

$$h = Wz$$

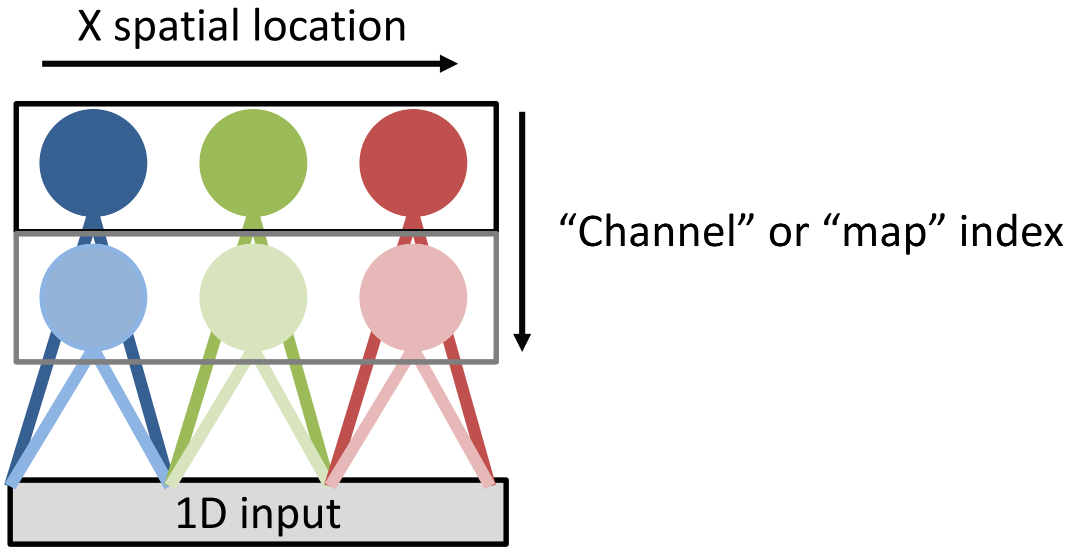
Rows of W are sparse.
Only weights connecting to inputs in the window are non-zero.



Local connectivity

- Spatial organization of filters means output features can also be organized like an image.
  - X,Y dimensions correspond to X,Y position of neuron window.
  - "Channels" are different features extracted from same spatial location. (Also called "feature maps", or "maps".)

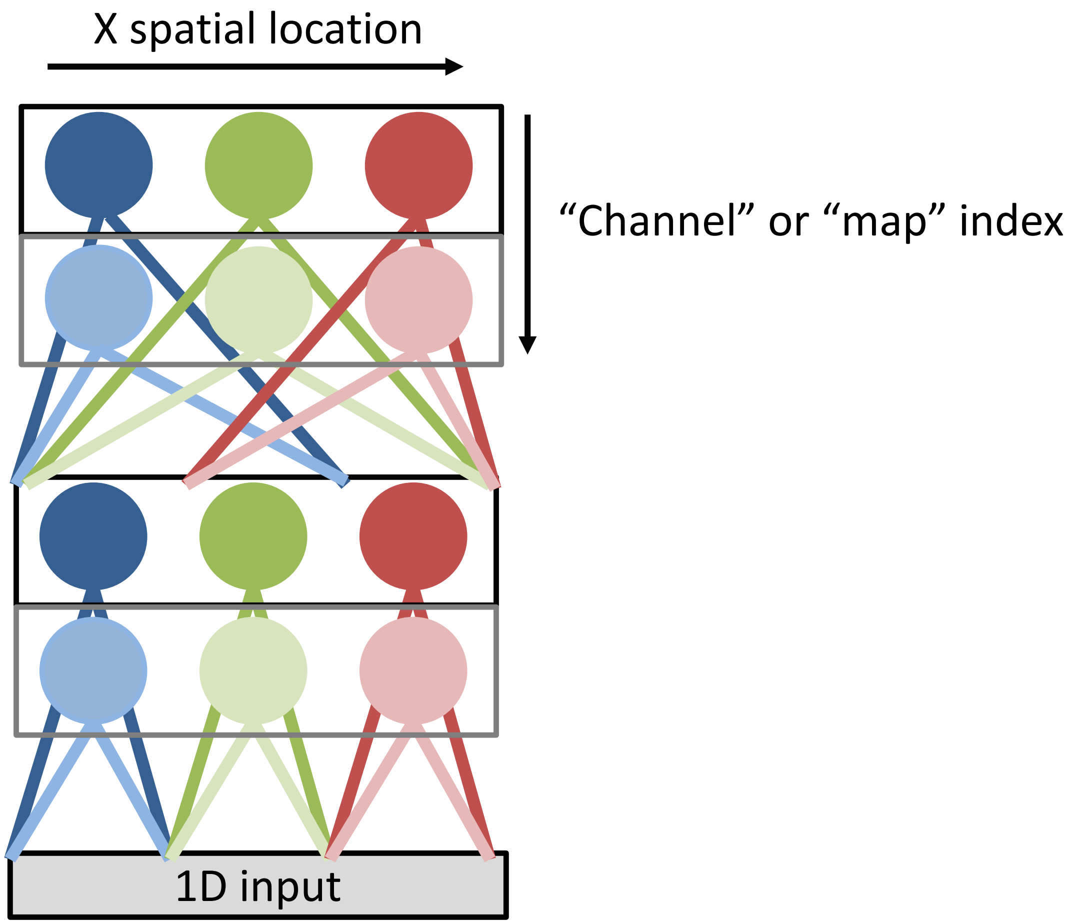
1-dimensional example:



Local connectivity

- We can treat output of a layer like an image and re-use the same tricks.

1-dimensional example:

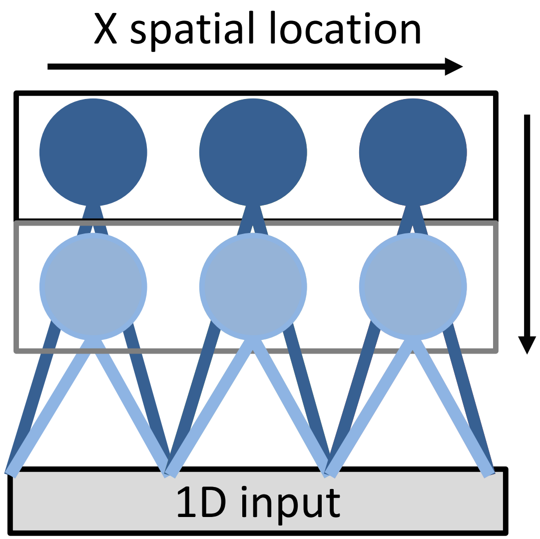


Weight-Tying

- Even with local connections, may still have too many weights.
  - Trick: constrain some weights to be equal if we know that some parts of input should learn same kinds of features.
  - Images tend to be “stationary”: different patches tend to have similar low-level structure.

Weight-Tying or Convolutional Network

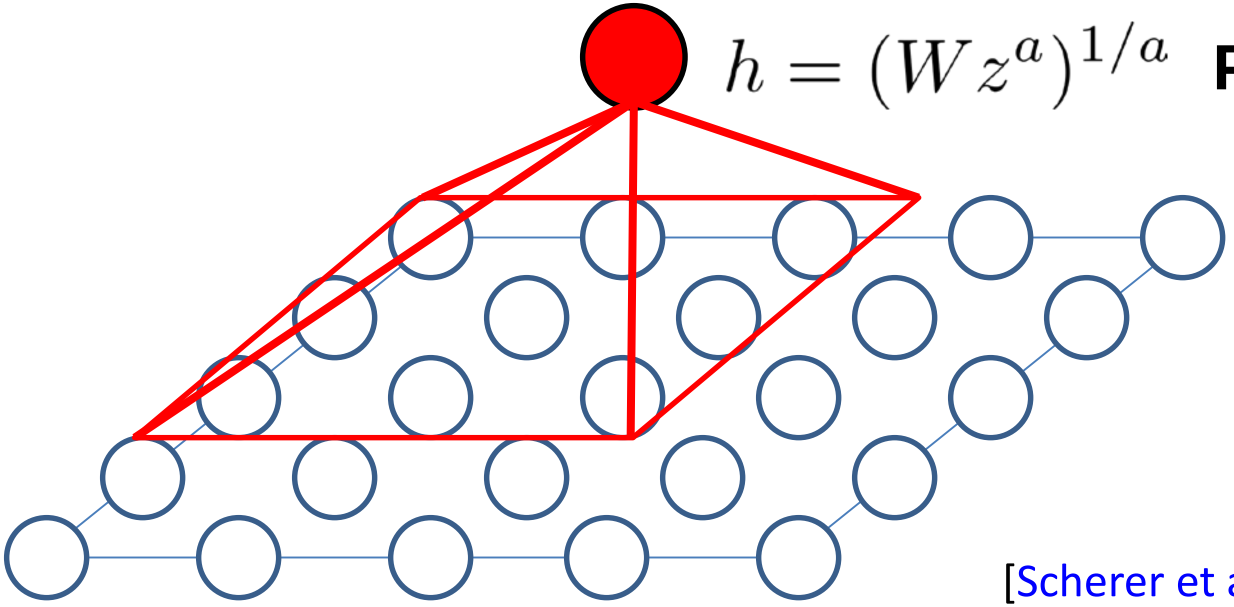
- Reduce parameters by making them equal.



- Each unique filter is spatially convolved with the input to produce responses for each map. [LeCun et al., 1989; LeCun et al., 2004]

Pooling

- Functional layers designed to represent invariant features.
- Usually locally connected with specific nonlinearities.
  - Combined with convolution, corresponds to hard-wired translation invariance.
- Usually fix weights to local box or gaussian filter.
  - Easy to represent max-, average-, or 2-norm pooling.

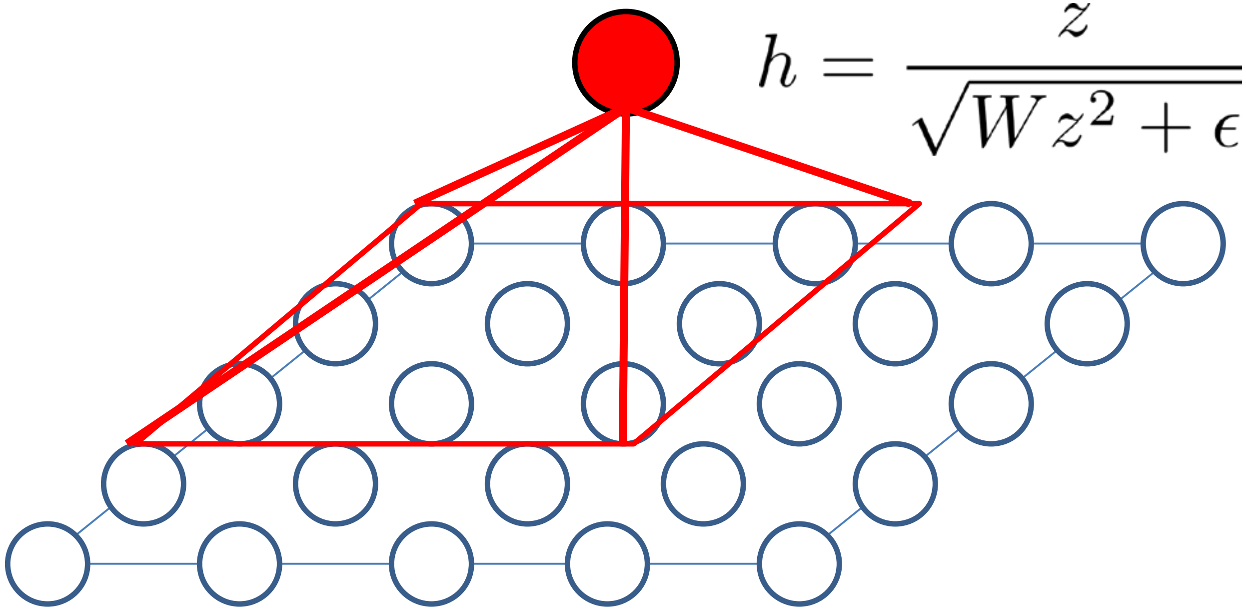


$h = (Wz^a)^{1/a}$ **Power mean**

[Scherer et al., ICANN 2010]
[Boureau et al., ICML 2010]

Contrast Normalization

- Empirically useful to soft-normalize magnitude of groups of neurons.
  - Sometimes we subtract out the local mean first.

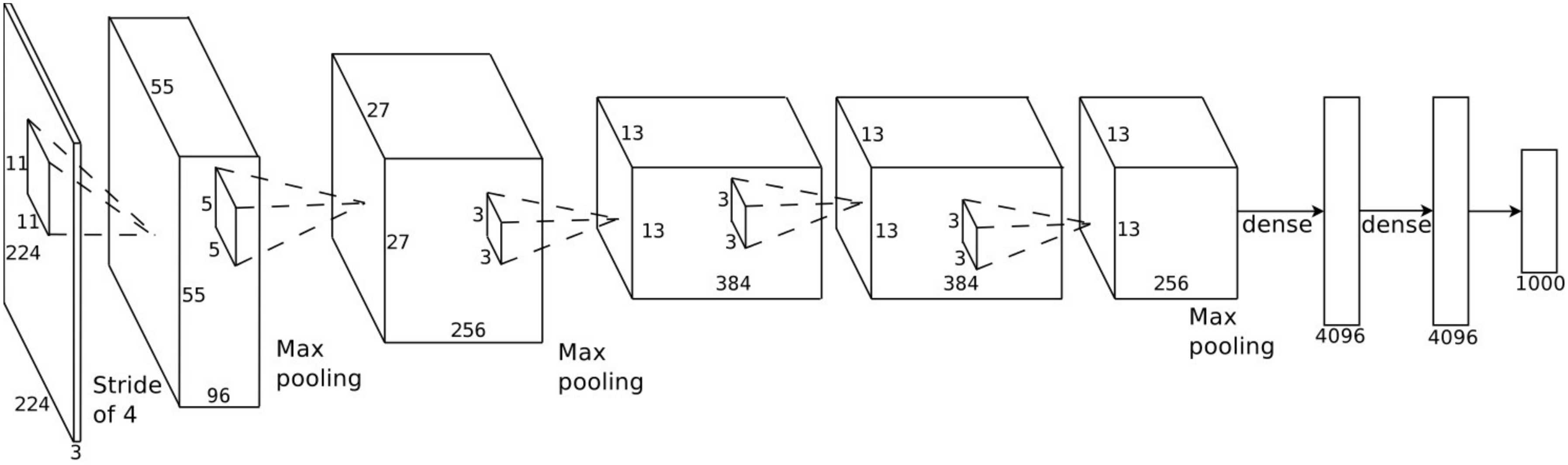


$$h = \frac{z}{\sqrt{W z^2 + \epsilon}}$$

[Jarrett et al., ICCV 2009]

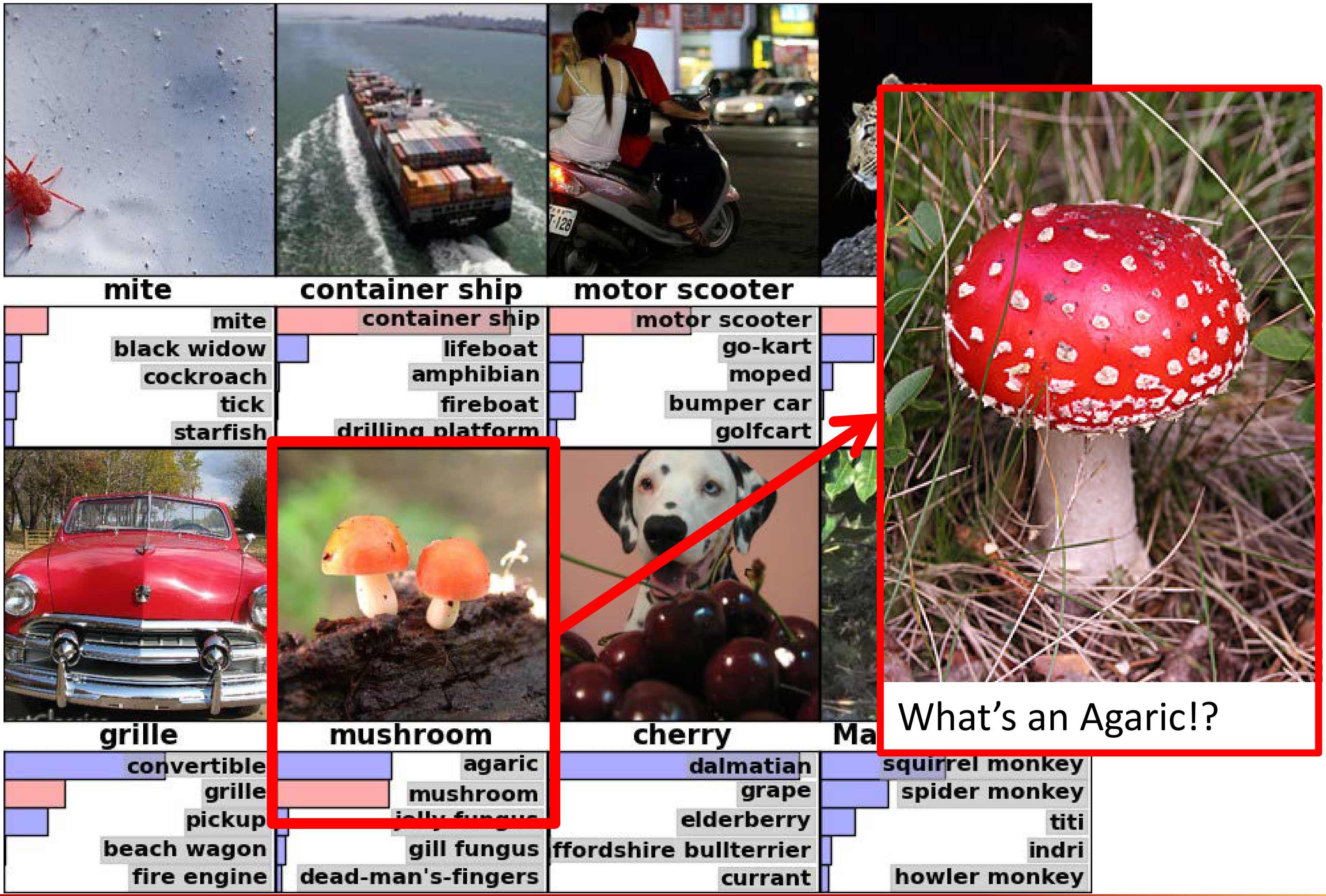
Application: Image-Net

- System from Krizhevsky et al., NIPS 2012:
  - Convolutional neural network.
  - Max-pooling.
  - Rectified linear units (ReLu).
  - Contrast normalization.
  - Local connectivity.



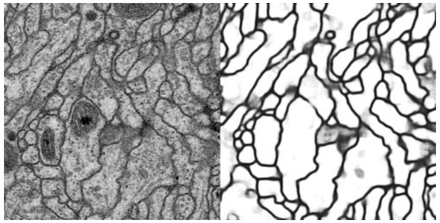
Application: Image-Net

- Top result in LSVRC 2012: ~85%, Top-5 accuracy.



More applications

- Segmentation: predict classes of pixels / super-pixels.



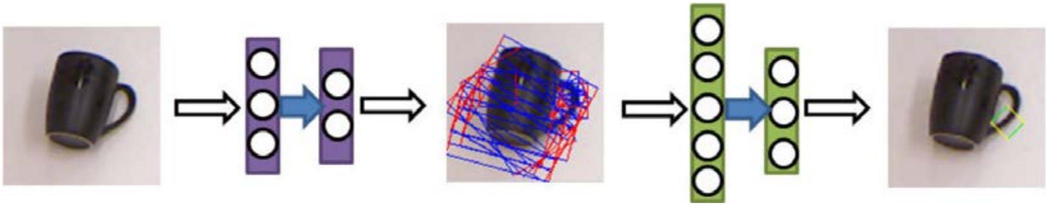
Farabet et al., ICML 2012 →

← Ciresan et al., NIPS 2012

- Detection: combine classifiers with sliding-window architecture.
  - Economical when used with convolutional nets.

Pierre Sermanet (2010) →

- Robotic grasping. [Lenz et al., RSS 2013]



http://www.youtube.com/watch?v=f9CuzqI1SkE

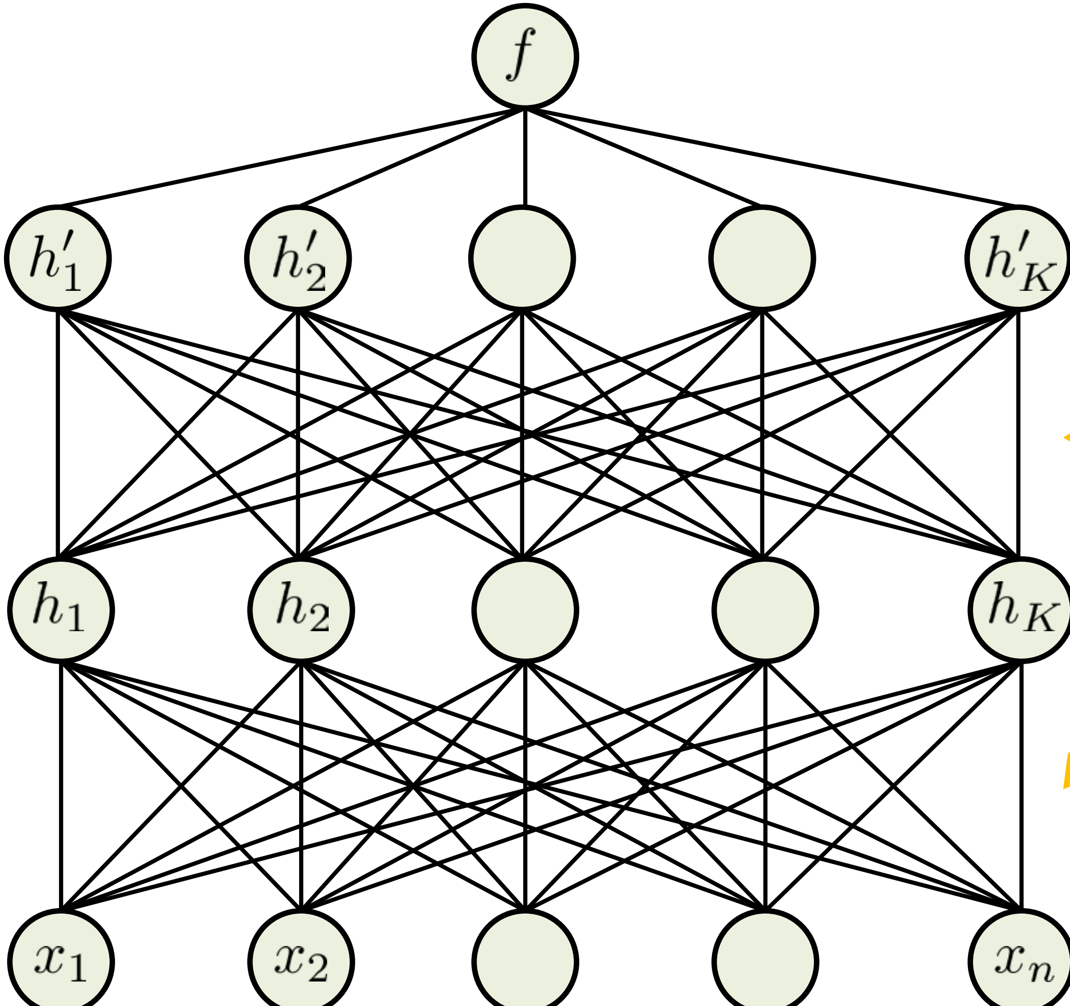
PA3

- Apply binary code embedding and inverted index to PA2
  - k-means or product quantization (PQ) for inverted index
  - Spherical hashing or PQ for binary code embedding

UNSUPERVISED DL

Representation Learning

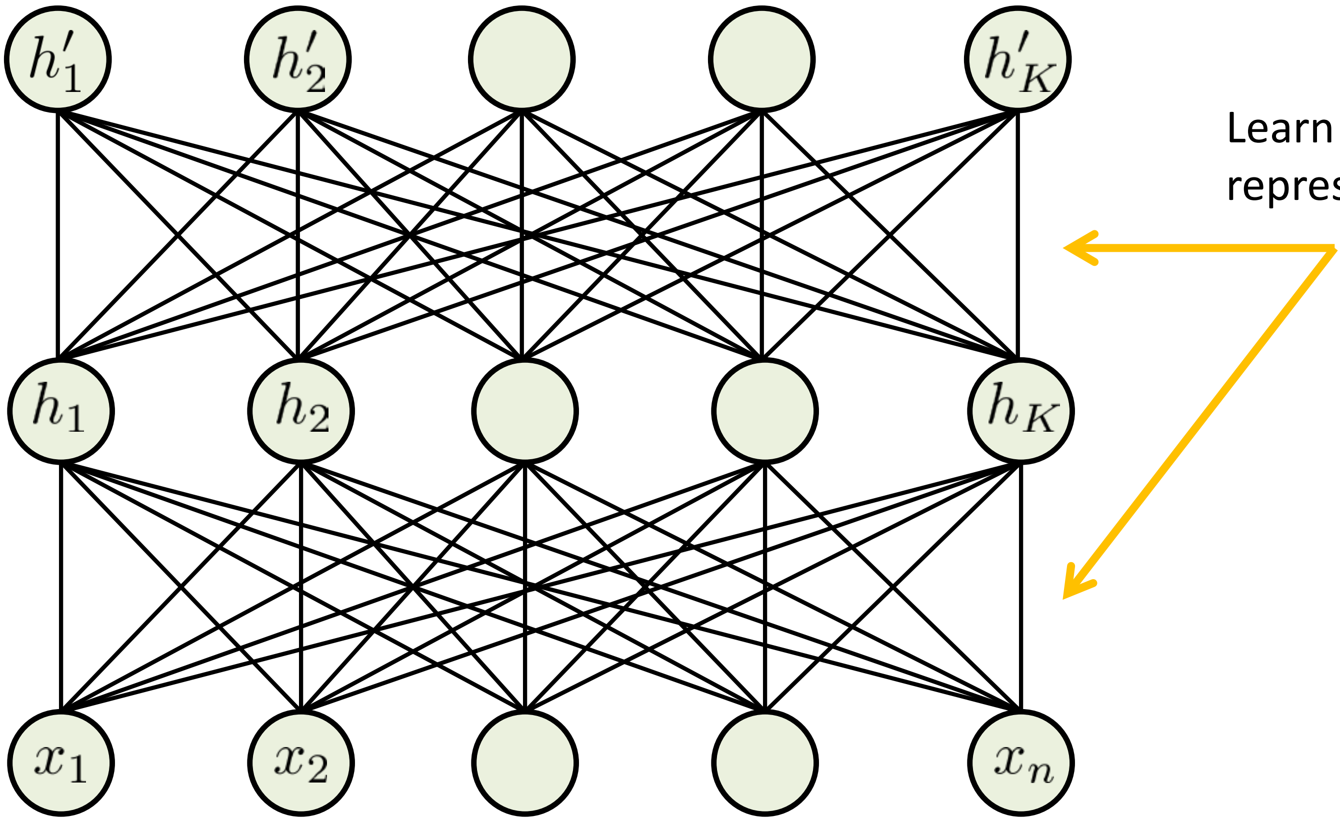
- In supervised learning, train "features" to accomplish top-level objective.



But what if we have too few labels to train all these parameters?

Representation Learning

- Can we train the “representation” without using top-down supervision?



Learn a “good” representation directly?

Representation Learning

- What makes a good representation?
  - Distributed: roughly, K features represents more than K types of patterns.
    - E.g., K binary features that can vary independently to represent 2^K patterns.
  - Invariant: robust to local changes of input; more abstract.
    - E.g., pooled edge features: detect edge at several locations.
  - Disentangling factors: put separate concepts (e.g., color, edge orientation) in separate features.

Bengio, Courville, and Vincent (2012)

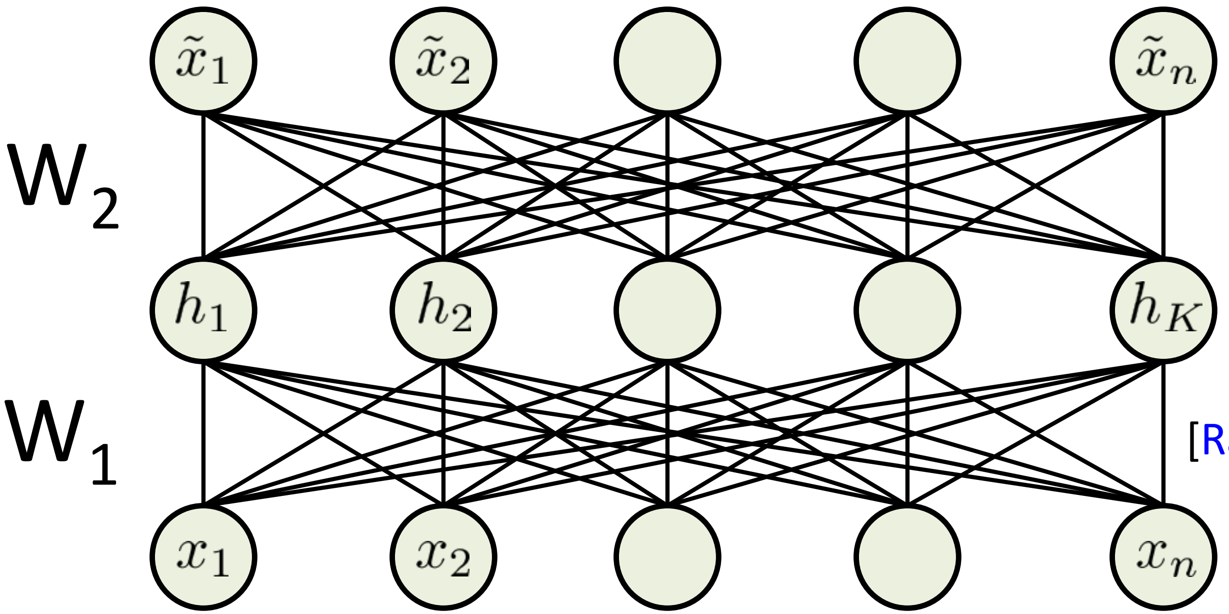
Sparse auto-encoder

- Train two-layer neural network by minimizing:

$$\underset{W_1, W_2}{\text{minimize}} \sum_i ||W_2 h(W_1 x^{(i)}) - x^{(i)}||_2^2 + \lambda ||h(W_1 x^{(i)})||_1$$

$$h(z) = \text{ReLu}(z)$$

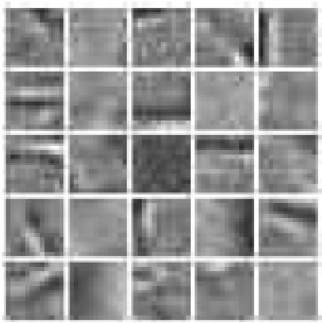
- Remove "decoder" and use learned features (h).



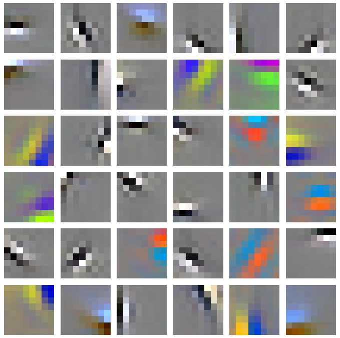
[Ranzato et al., NIPS 2006]

What features are learned?

- Applied to image patches, well-known result:



Sparse auto-encoder
[Ranzato et al., 2007]



Sparse auto-encoder

Summary

- Supervised deep-learning
  - Practical and highly successful in practice. A general-purpose extension to existing ML.
  - Optimization, initialization, architecture matter!

- Unsupervised deep-learning
  - Pre-training often useful in practice.
  - Difficult to train many layers of features without labels.

Resources

Tutorials

Stanford Deep Learning tutorial:
  http://ufldl.stanford.edu/wiki

Deep Learning tutorials list:
  http://deeplearning.net/tutorials

IPAM DL/UFL Summer School:
  http://www.ipam.ucla.edu/programs/gss2012/

ICML 2012 Representation Learning Tutorial
  http://www.iro.umontreal.ca/~bengioy/talks/deep-learning-tutorial-2012.html

References

http://www.stanford.edu/~acoates/bmvc2013refs.pdf

Overviews:

Yoshua Bengio,
“Practical Recommendations for Gradient-Based Training of Deep Architectures”

Yoshua Bengio & Yann LeCun,
“Scaling Learning Algorithms towards AI”

Yoshua Bengio, Aaron Courville & Pascal Vincent,
“Representation Learning: A Review and New Perspectives”

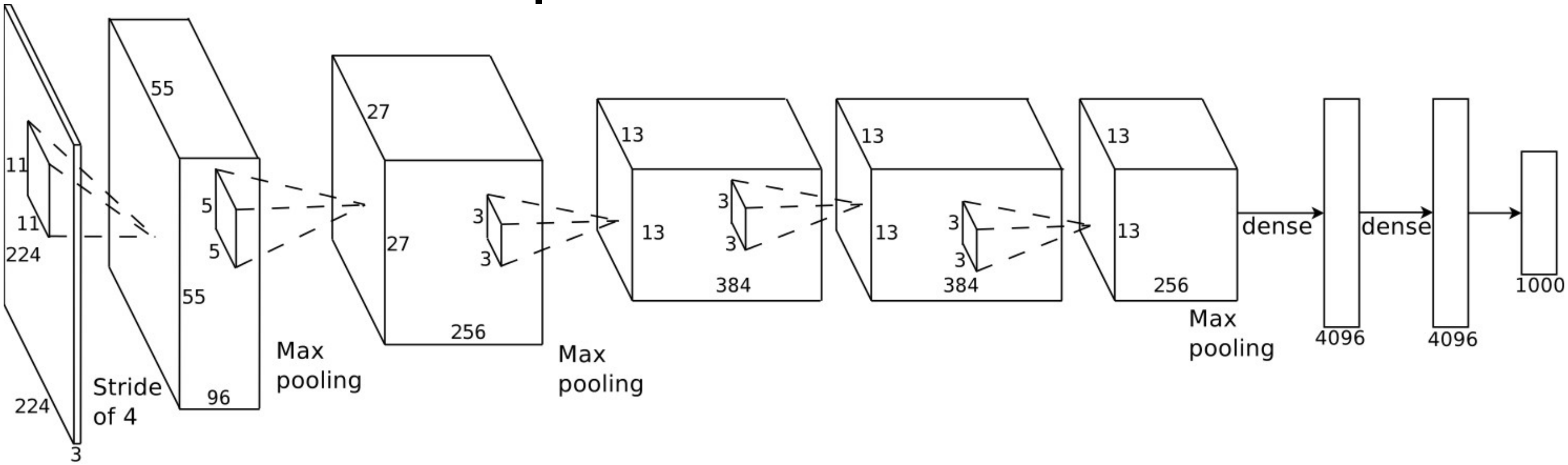
Software:

Theano GPU library: http://deeplearning.net/software/theano

SPAMS toolkit: http://spams-devel.gforge.inria.fr/

High-Level Messages

- Deep neural nets provide low-level and high-level features
  - We can use those features for image search
- Achieve the best results in many computer vision related problems



Krizhevsky et al., NIPS 2012