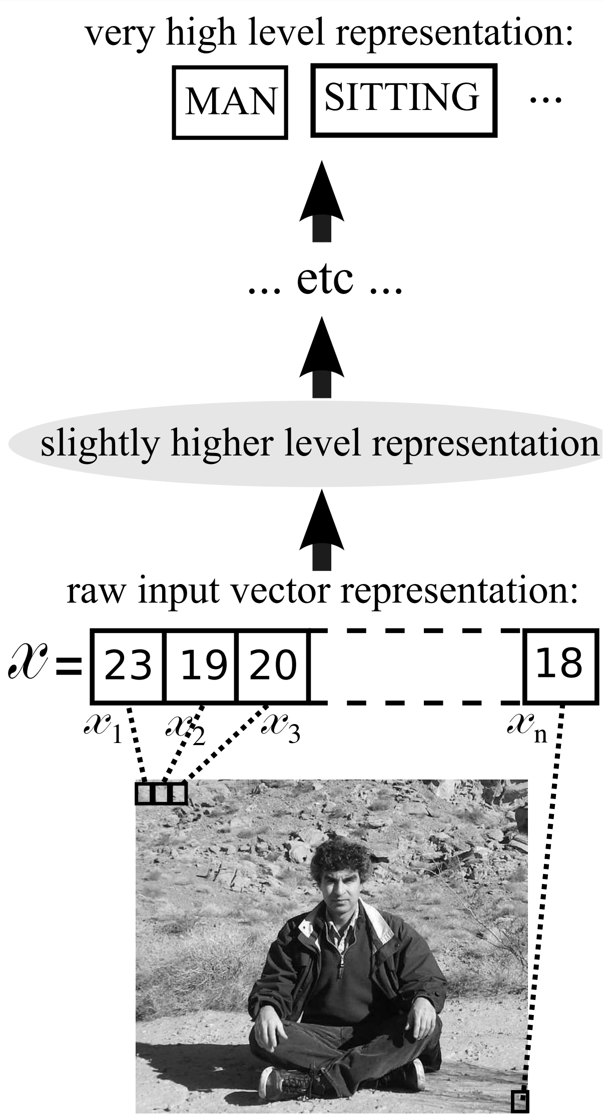
COMP 551 – Applied Machine Learning
Lecture 16: Deep Learning

Instructor: Joelle Pineau (*jpineau@cs.mcgill.ca)*

Class web page: *www.cs.mcgill.ca/~jpineau/comp551*

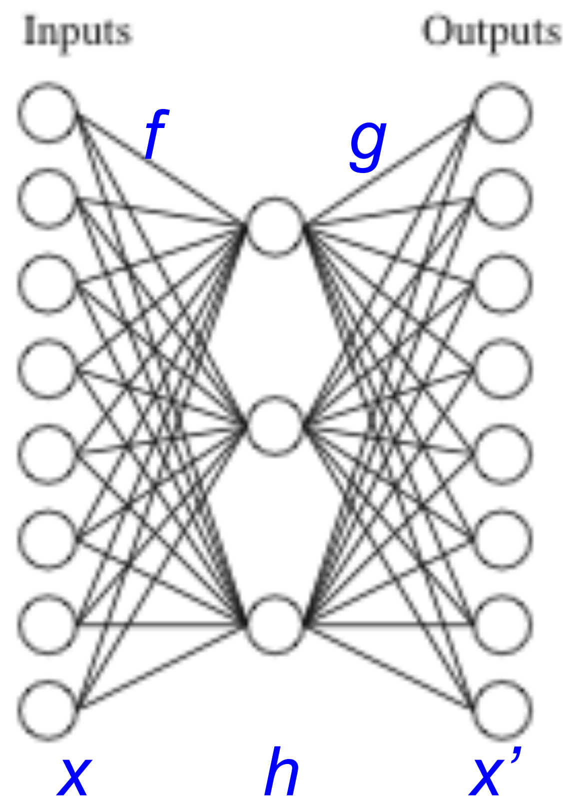
The deep learning objective



Learning an autoencoder function

- **Goal**: Learn a compressed representation of the input data.
- We have two functions:
  - **Encoder**: $h = f_W(x) = s_f(Wx)$
  - **Decoder**: $x' = g_{W'}(h) = s_g(W'h)$

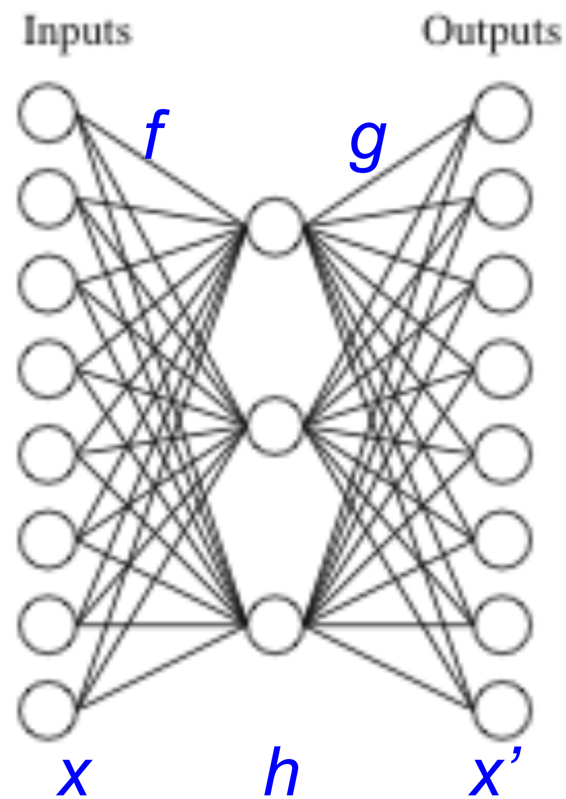
  where $s()$ can be a sigmoid, linear, or other function and W, W' are weight matrices.



Learning an autoencoder function

- **Goal**: Learn a compressed representation of the input data.
- We have two functions:
  - **Encoder**: $h = f_W(x) = s_f(Wx)$
  - **Decoder**: $x' = g_{W'}(h) = s_g(W'h)$

  where $s()$ can be a sigmoid, linear, or other function and W, W' are weight matrices.



- To train, minimize reconstruction error:

  $Err(W,W') = \sum_{i=1:n} L\,[\, x_i\, ,\, g_{W'}(f_W(x_i))\,]$

  using squared-error loss (continuous inputs) or cross-entropy (binary inputs).

PCA vs autoencoders

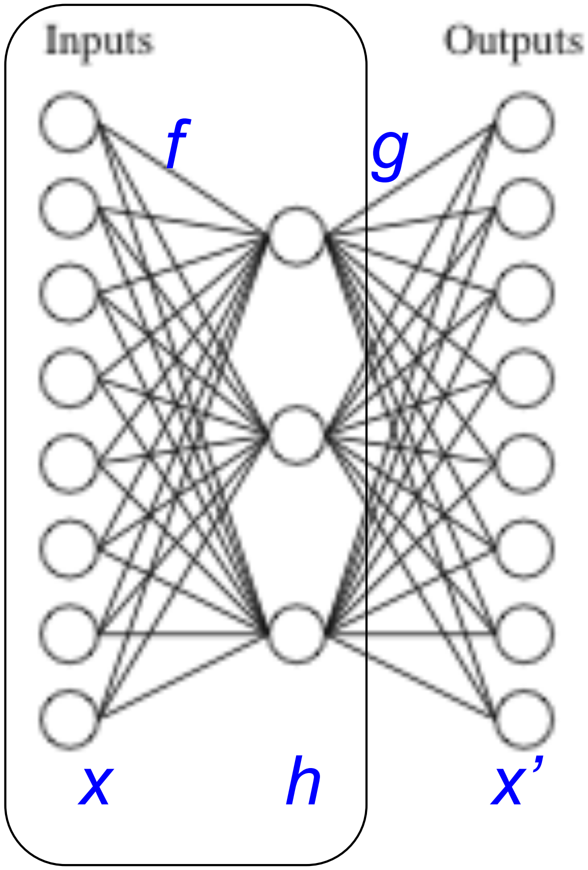
In the case of a linear function:

$f_W(x) = Wx \qquad g_{\hat{W}}(h) = W'h$,

with squared-error loss:

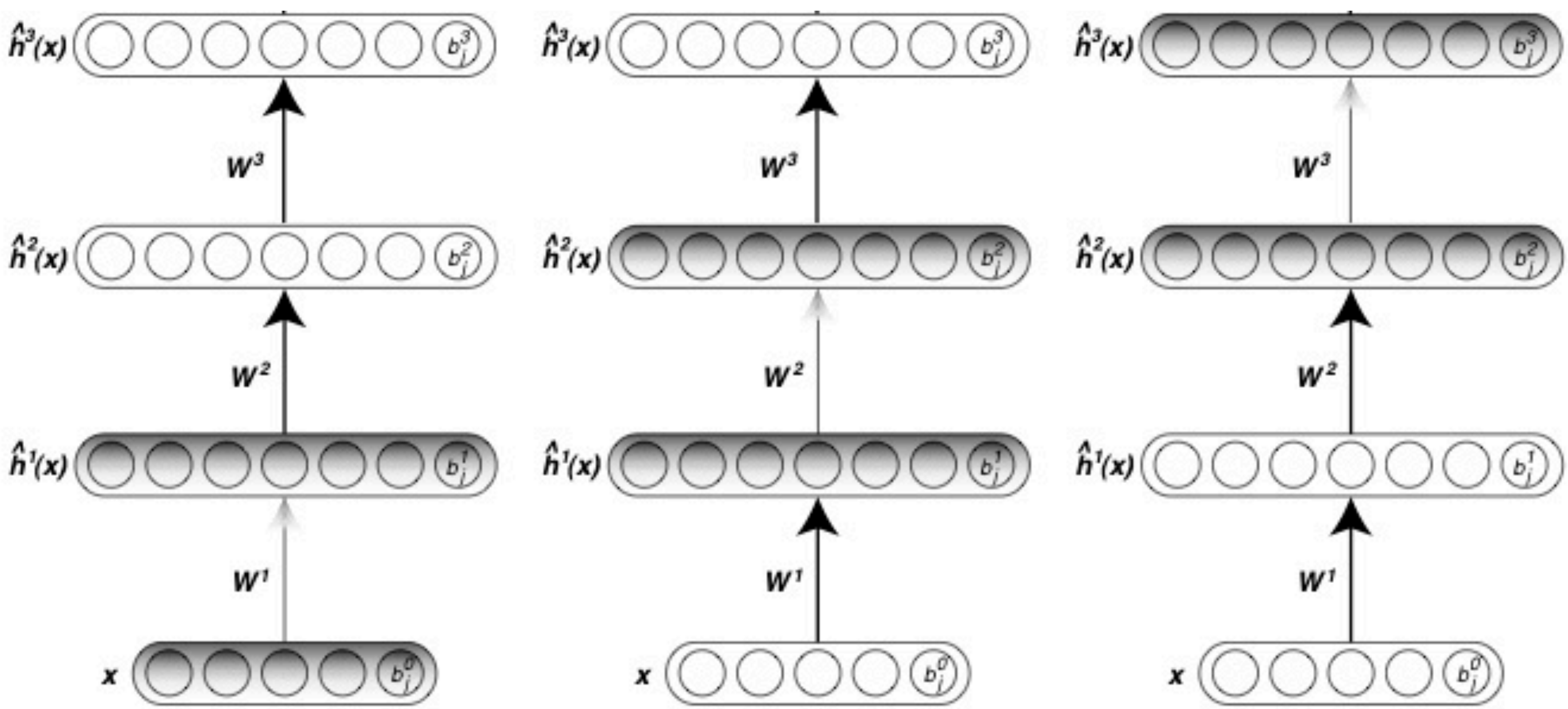
$Err(W,W') = \sum_{i=1:n} || x_i - g_{W'}(f_W(x_i)) ||^2$

we can show that the minimum error solution W yields the same subspace as PCA.



Stacked autoencoders

Key idea: Apply greedy layerwise unsupervised pre-training.



http://www.dmi.usherb.ca/~larocheh/projects_deep_learning.html

Regularization of autoencoders

- How can we generate **sparse** autoencoders? (And also, why?)

Regularization of autoencoders

- How can we generate **sparse** autoencoders? (And also, why?)
- Weight tying of the encoder and decoder weights ($W=W'$) to explicitly constrain (regularize) the learned function.

Regularization of autoencoders

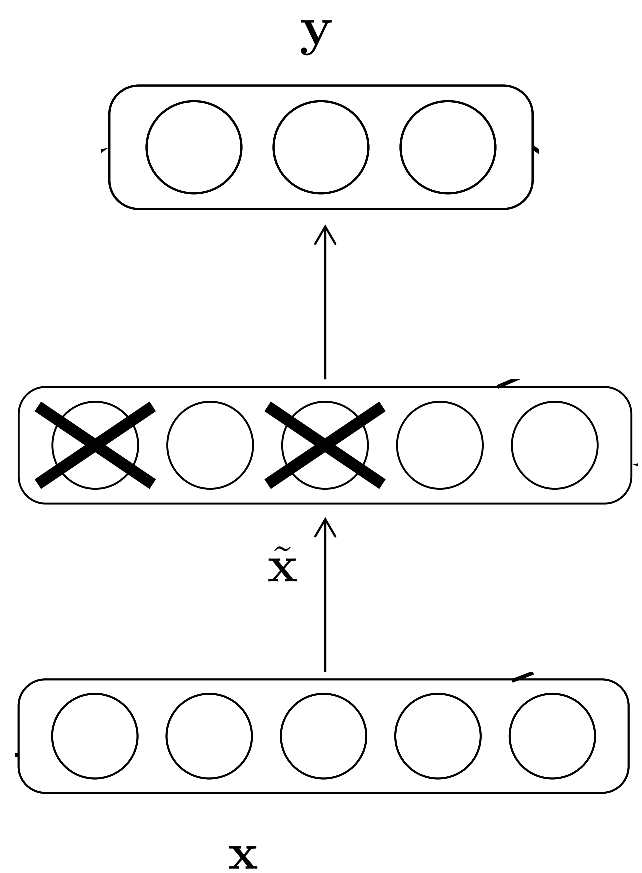
- How can we generate **sparse** autoencoders? (And also, why?)
- Weight tying of the encoder and decoder weights ($W=W'$) to explicitly constrain (regularize) the learned function.
- Directly penalize the output of the hidden units (e.g. with L1 penalty) to introduce sparsity in the weights.

Regularization of autoencoders

- How can we generate **sparse** autoencoders? (And also, why?)
- Weight tying of the encoder and decoder weights ($W=W'$) to explicitly constrain (regularize) the learned function.
- Directly penalize the output of the hidden units (e.g. with L1 penalty) to introduce sparsity in the weights.
- Penalize the average output (over a batch of data) to encourage it to approach a fixed target.

Denoising autoencoders

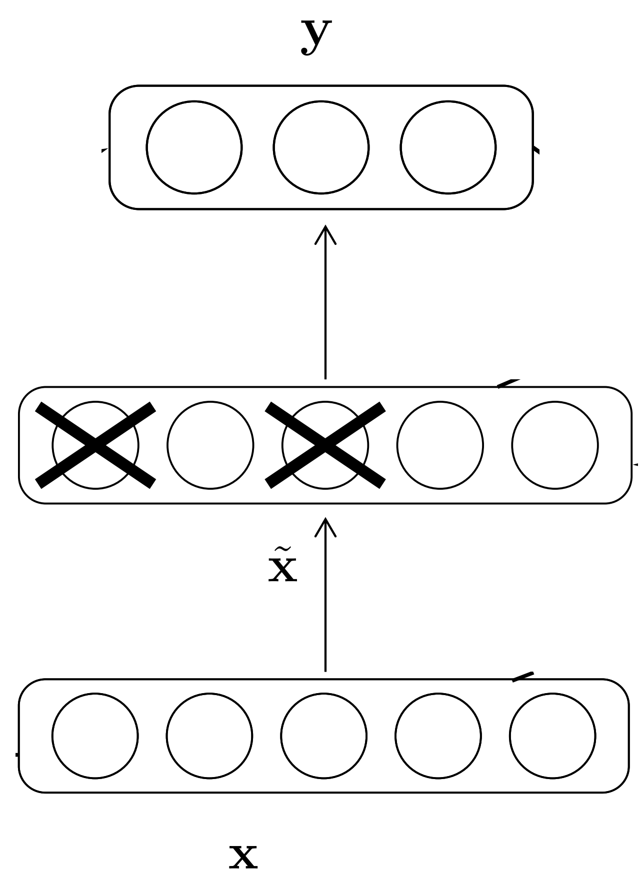
- **Idea**: To force the hidden layer to discover more robust features, train the autoencoder with a corrupted version of the input.



Denoising autoencoders

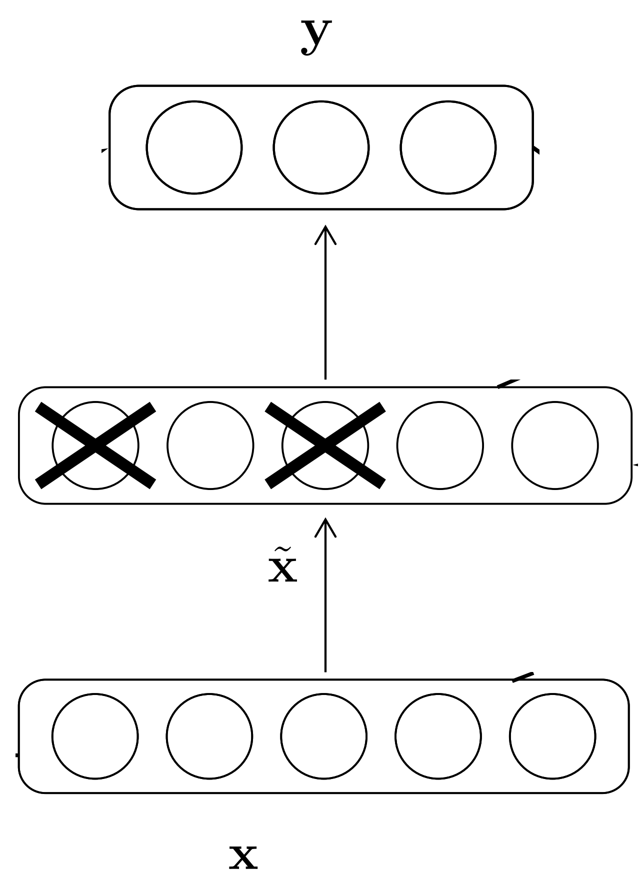
- **Idea**: To force the hidden layer to discover more robust features, train the autoencoder with a corrupted version of the input.

- **Corruption processes**:
  - Additive Gaussian noise
  - Randomly set some input features to zero.
  - *More noise models in the literature*.



Denoising autoencoders

- **Idea**: To force the hidden layer to discover more robust features, train the autoencoder with a corrupted version of the input.



- **Corruption processes**:
  - Additive Gaussian noise
  - Randomly set some input features to zero.
  - *More noise models in the literature*.

- **Training criterion**:

  $Err(W,W') = \sum_{i=1:n} E_{q(x_i'|x_i)} L [x_i , g_{W'} (f_W(x_i'))]$

  where x is the original input, x' is the corrupted input, and $q()$ is the corruption process.

Contractive autoencoders

- **Goal**: Learn a representation that is robust to noise and perturbations of the input data, by regularizing the latent space (represented by L2 norm of the Jacobian of the encoded input.)

- **Contractive autoencoder training criterion**:

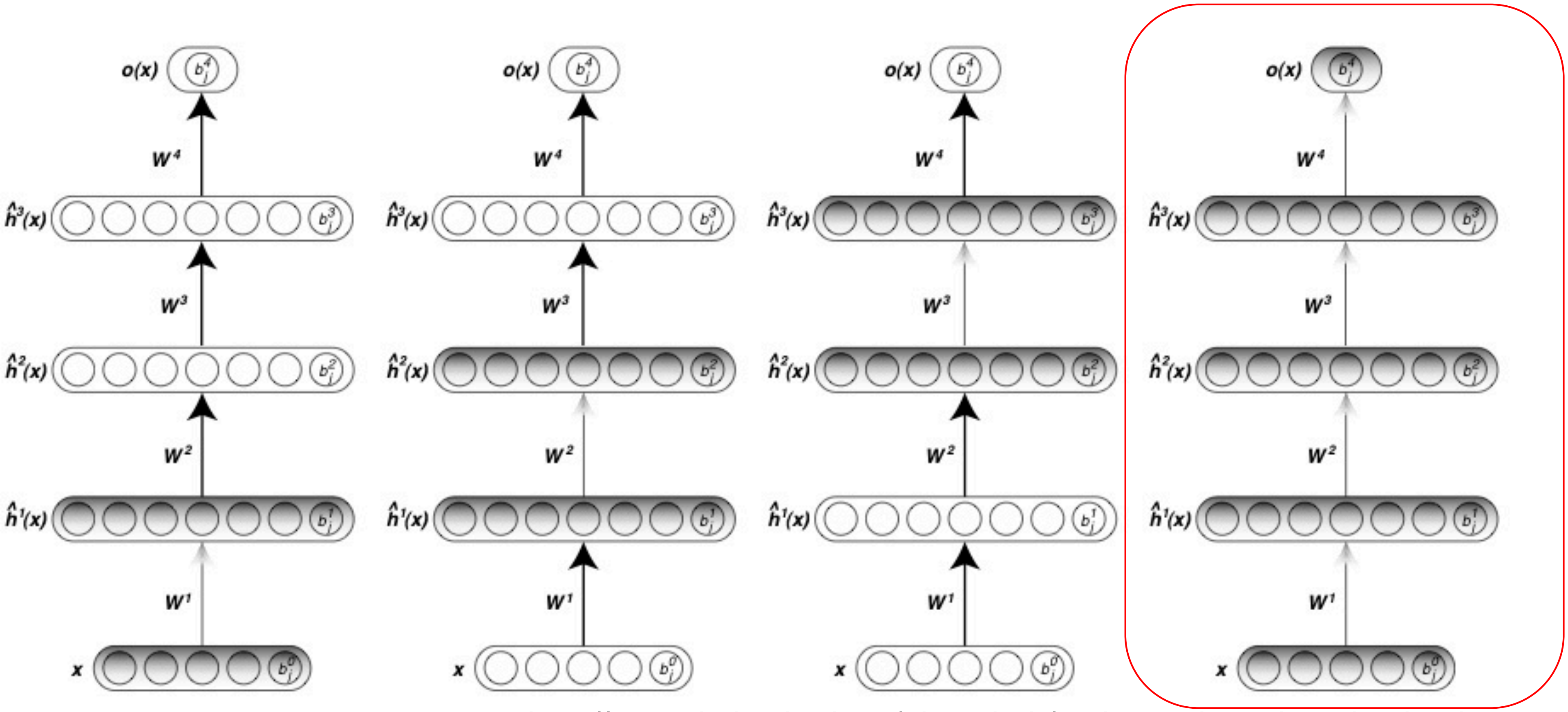
  $Err(W,W') = \sum_{i=1:n} L\ [\ x_i\ ,\ g_{W'}(f_W(x_i'))\ ]\ +\ \lambda||J(x_i)||_F^2$

  where $J(x_i)=\partial f_W(x_i)/\partial x_i$ is a Jacobian matrix of the encoder evaluated at x_i, F is the Frobenius norm, and λ controls the strength of regularization.

Many more similar ideas in the literature…

Supervised learning with deep models

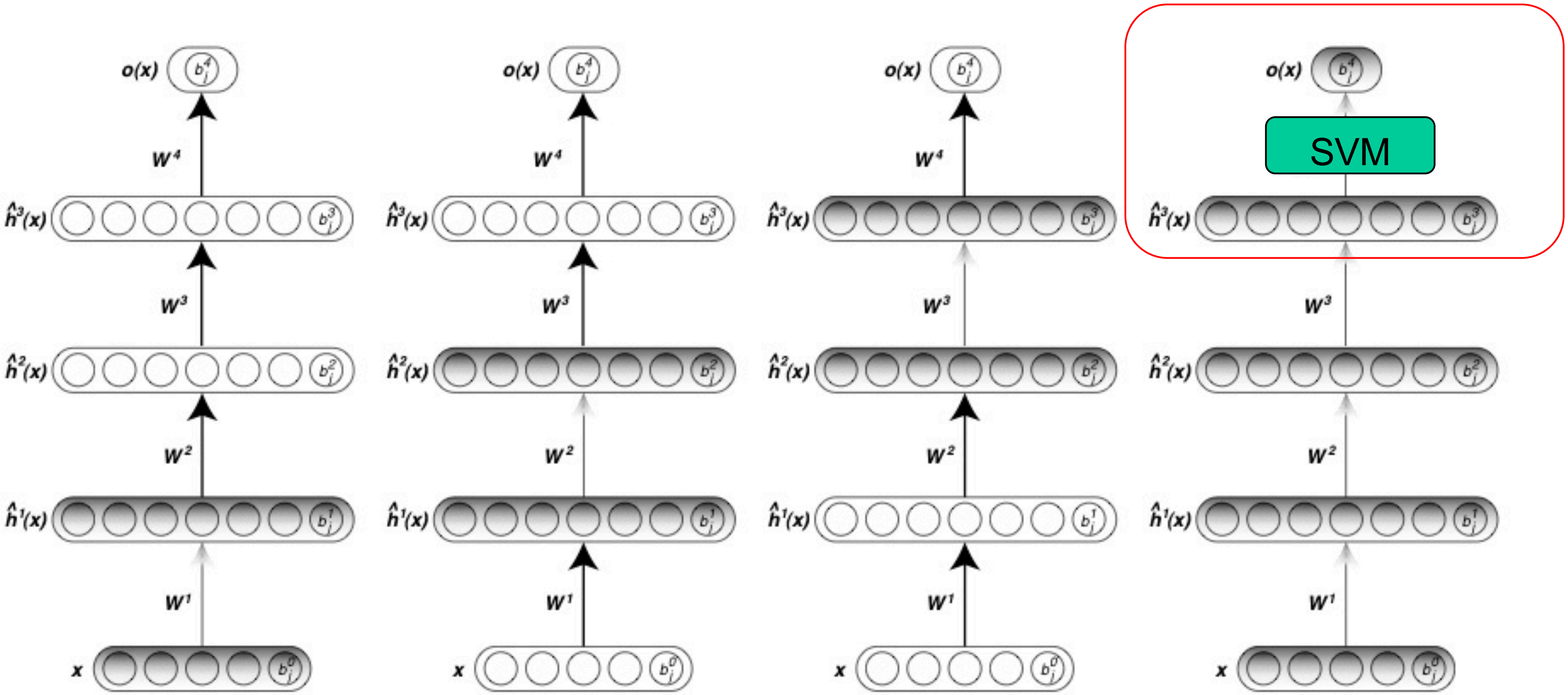
Final step: Train the full network with backpropagation using error on the predicted output, $Err(W) = \sum_{i=1:n} L\,[\,y_i\,,\,o(x_i)\,]$



http://www.dmi.usherb.ca/~larocheh/projects_deep_learning.html

Supervised learning with deep models

Alternatively: Use the last representation layer (or concatenate all layers) as an input to a standard supervised learning predictor (e.g. SVM).



http://www.dmi.usherb.ca/~larocheh/projects_deep_learning.html

Variety of training protocols

- Purely supervised:
  - Initialize parameters randomly.
  - Train in supervised mode (gradient descent w/backprop.)
  - Used in most practical systems for speech and language.

From: *http://www.slideshare.net/philipzh/a-tutorial-on-deep-learning-at-icml-2013*

Variety of training protocols

- Purely supervised:
  - Initialize parameters randomly.
  - Train in supervised mode (gradient descent w/backprop.)
  - Used in most practical systems for speech and language.
- Unsupervised, layerwise + supervised classifier on top:
  - Train each layer unsupervised, one after the other.
  - Train a supervised classifier on top, keeping other layers fixed.
  - Good when very few labeled examples are available.

From: *http://www.slideshare.net/philipzh/a-tutorial-on-deep-learning-at-icml-2013*

Variety of training protocols

- Purely supervised:
  - Initialize parameters randomly.
  - Train in supervised mode (gradient descent w/backprop.)
  - Used in most practical systems for speech and language.
- Unsupervised, layerwise + supervised classifier on top:
  - Train each layer unsupervised, one after the other.
  - Train a supervised classifier on top, keeping other layers fixed.
  - Good when very few labeled examples are available.
- Unsupervised, layerwise + global supervised fine-tuning.
  - Train each layer unsupervised, one after the other.
  - Add a classifier layer, and retrain the whole thing supervised.
  - Good when label set is poor.
- Unsupervised pretraining often uses regularized autoencoders.

From: *http://www.slideshare.net/philipzh/a-tutorial-on-deep-learning-at-icml-2013*

Tip #1: Dropout regularization

- **Goal**: Learn model that generalizes well, robust to variability.

- **Method**: Independently set each hidden unit activity to zero with probability *p* (usually *p*=0.5 works best).

- **Effect**: Can greatly reduces overfitting.

Tip #2: Batch normalization

- Idea: Feature scaling makes gradient descent easier.
  - We already apply this at the input layer; extend to other layers.
  - Use empirical batch statistics to choose re-scaling parameters.

- For each mini-batch of data, at each layer *k* of the network:
  - Compute empirical mean and var independently for each dimension
  - Normalize each input: $\hat{x}^{(k)} = \frac{x^{(k)} - E[x^{(k)}]}{\sqrt{VAR[x^{(k)}]}}$
  - Output has tunable parameters (γ,β) for each layer: $y^k = \gamma^k . \hat{x}^{(k)} + \beta^k$

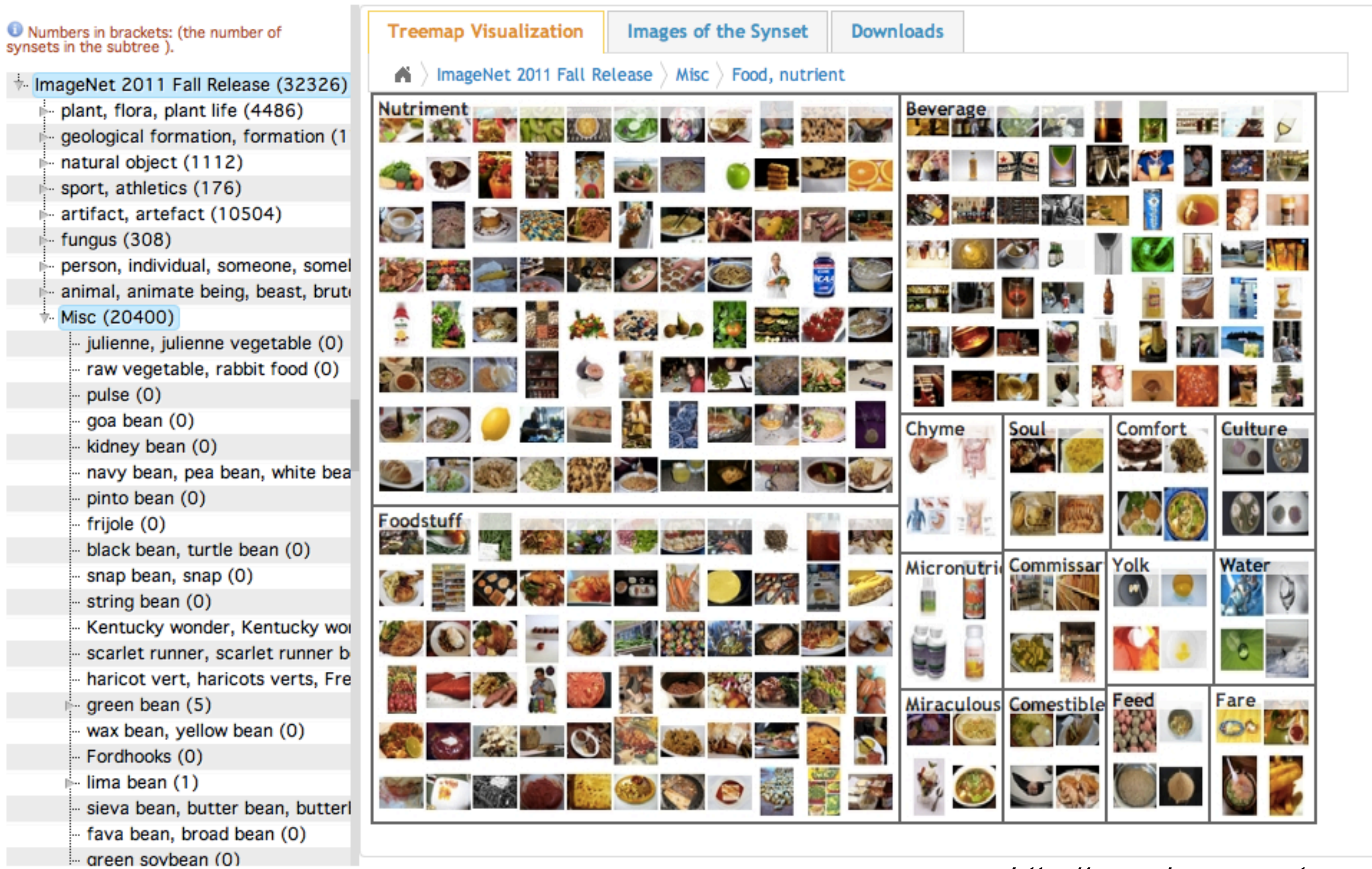
- Effect: More stable gradient estimates, especially for deep networks.

Major paradigms for deep learning

- **Deep neural networks**: The model should be interpreted as a computation graph.
  - Supervised training: Feedforward neural networks.
  - Unsupervised pre-training: Stacked autoencoders.

- Special architectures for different problem domains.
  - Computer vision => Convolutional neural nets.
  - Text and speech => Recurrent neural nets. *Next class.*

ImageNet dataset



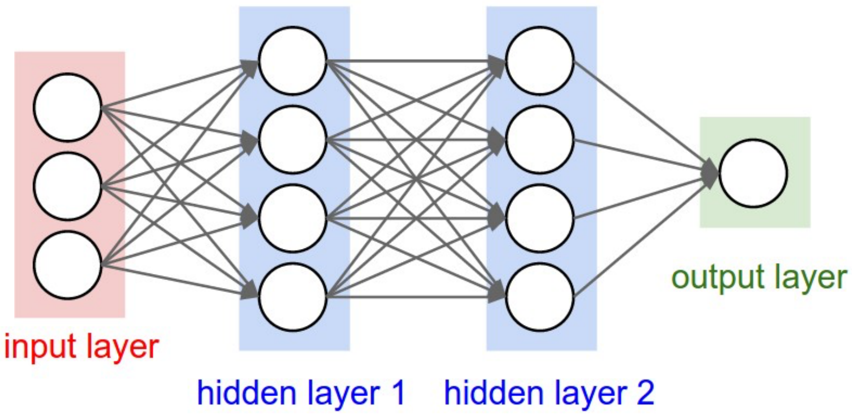
http://www.image-net.org

Neural networks for computer vision

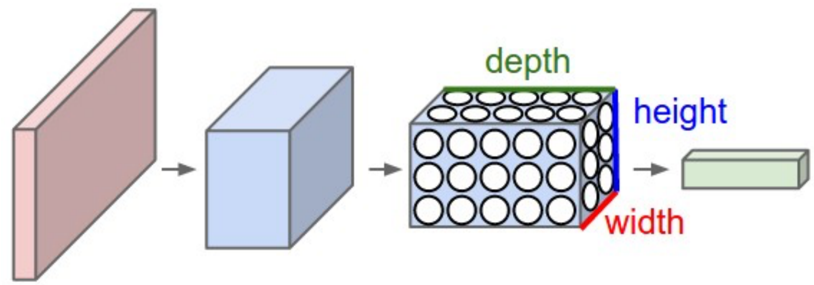
- Design neural networks that are specifically adapted to:
  - Deal with very high-dimensional inputs
    - E.g. 150x150 pixels = 22,500 inputs, or 3x22,500 if RGB
  - Exploit 2D topology of pixels (or 3D for video)
  - Built-in invariance to certain variations we can expect
    - Translations, illumination, etc.

Convolution Neural Networks

<u>Feedforward network</u>



<u>Convolutional neural network (CNN)</u>

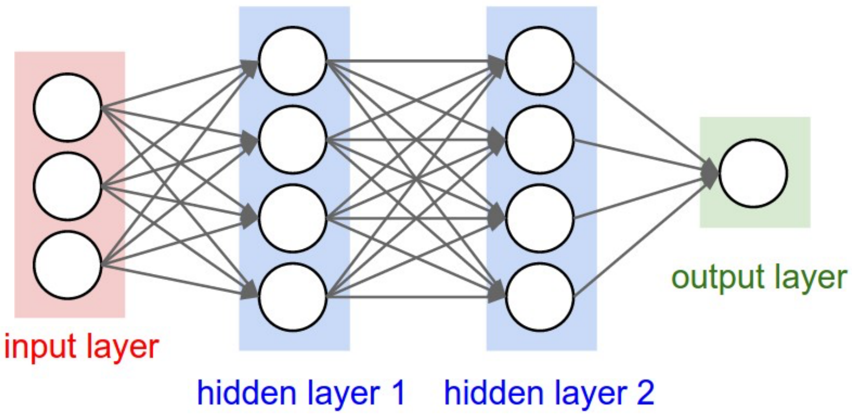


- CNN characteristics:
  - Input is a 3D tensor: 2D image x 3 colours
  - Each layer transforms an input 3D tensor to an output 3D tensor using a differentiable function.

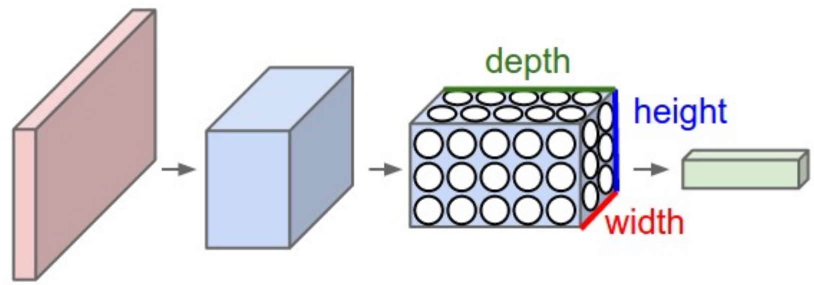
From: *http://cs231n.github.io/convolutional-networks/*

Convolution Neural Networks

<u>Feedforward network</u>



<u>Convolutional neural network (CNN)</u>

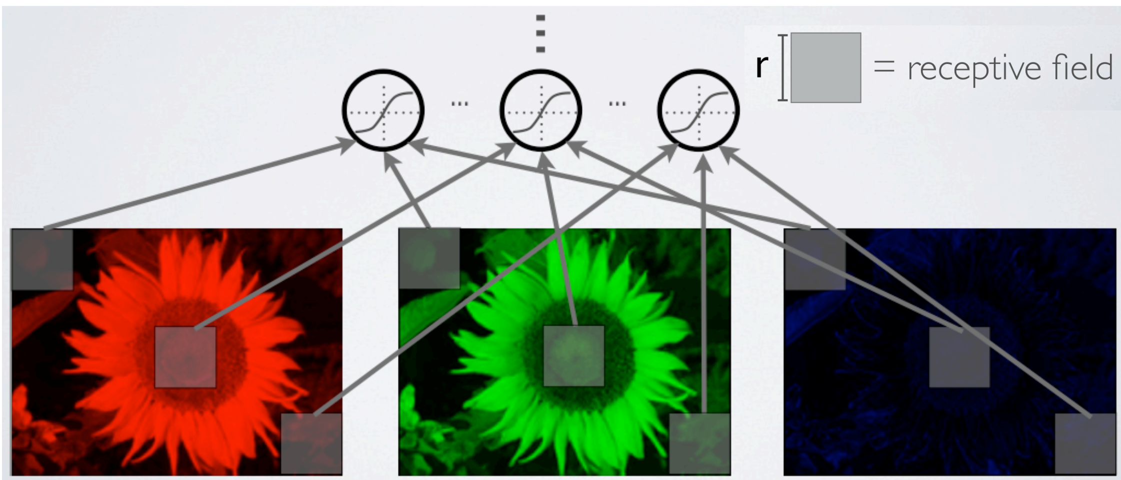


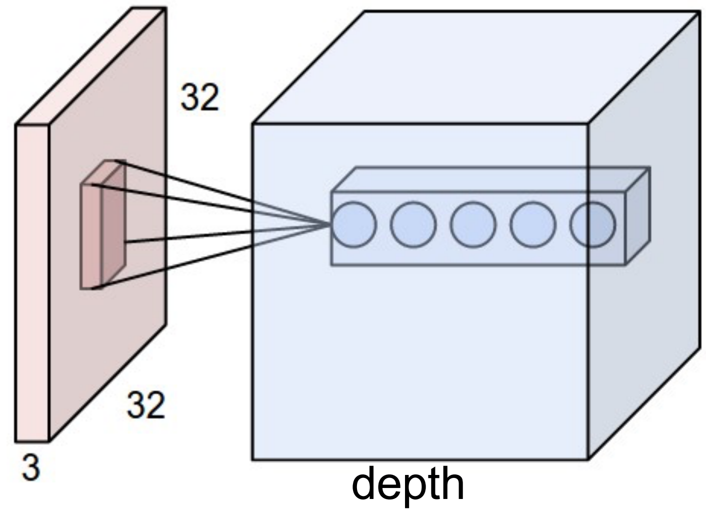
- Convolutional neural networks leverage several ideas.
  1. Local connectivity.
  2. Parameter sharing.
  3. Pooling hidden units.

From: *http://cs231n.github.io/convolutional-networks/*

Convolution Neural Networks

- A few key ideas:
  1. Features have **local receptive fields.**
     - Each hidden unit is connected to a patch of the input image.
     - Units are connected to all 3 colour channels.

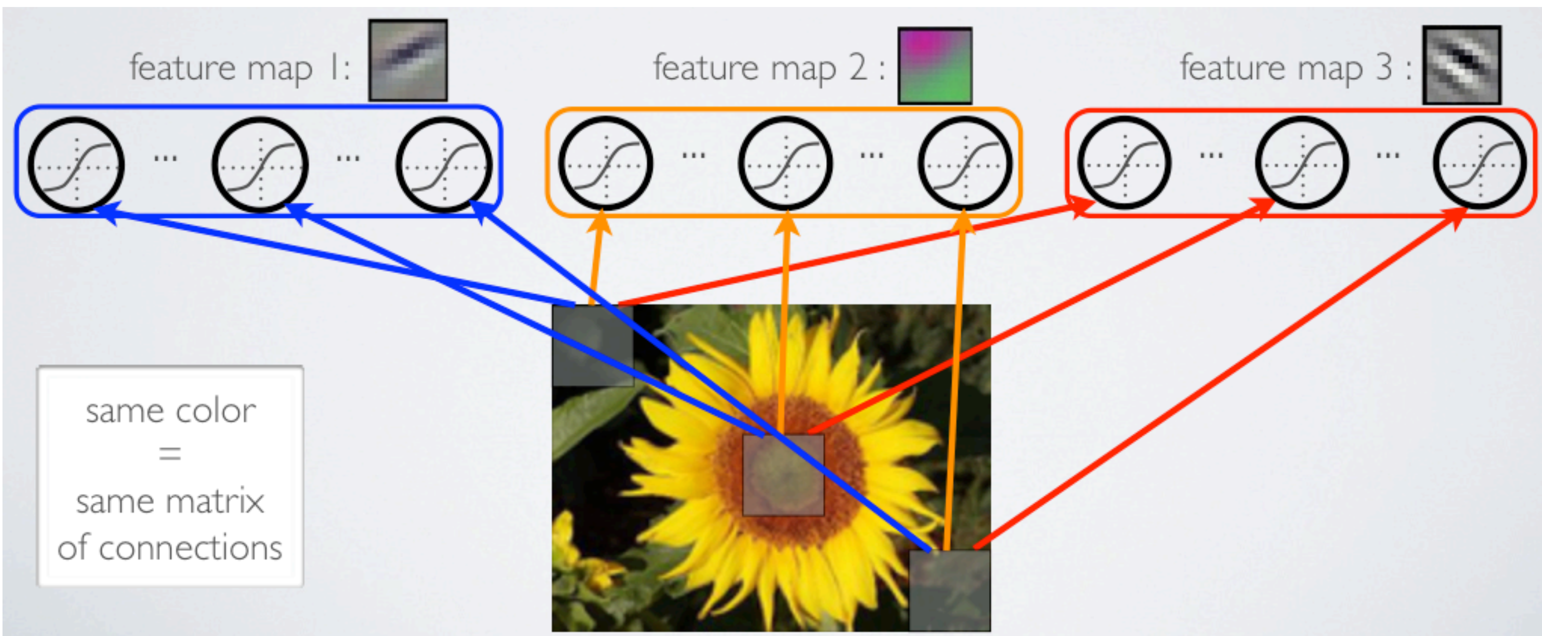




depth = # filters
(a hyperparameter)

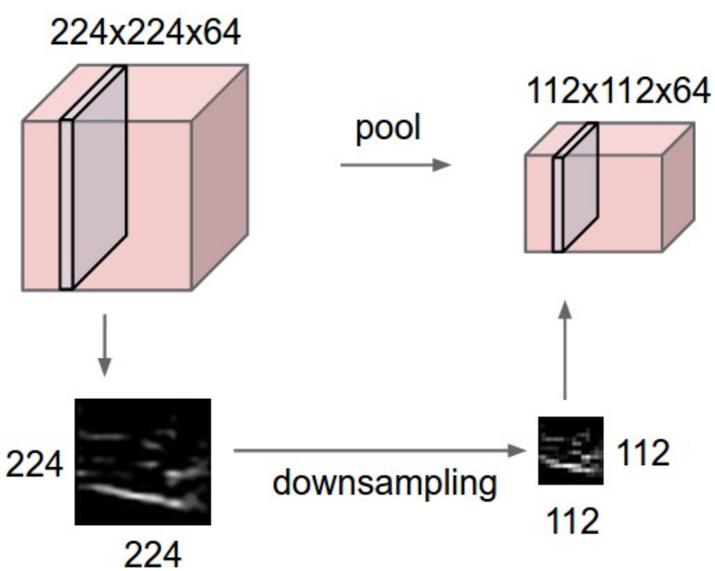
Convolution Neural Networks

- A few key ideas:
  1. Features have **local receptive fields.**
  2. **Share matrix of parameters** across units.
     - Constrain units within a depth slice (at all positions) to have **same** weights.
     - Feature map can be computed via discrete convolution with a kernel matrix.

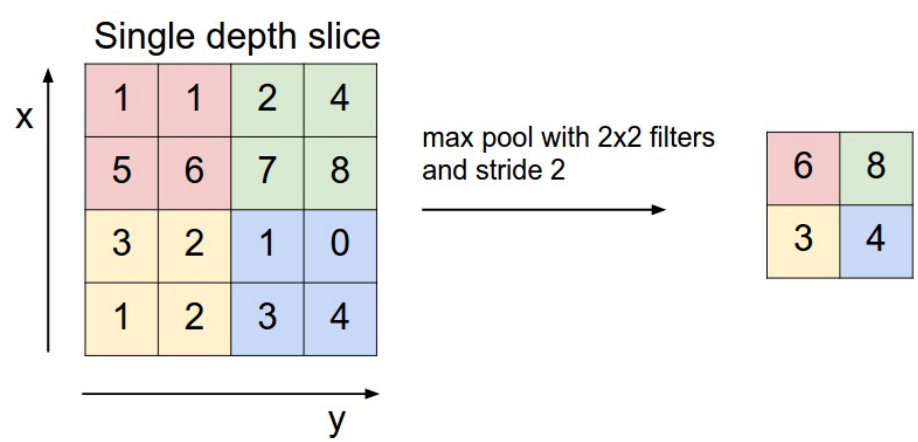


Convolution Neural Networks

- A few key ideas:
  1. Features have **local receptive fields.**
  2. **Share matrix of parameters** across units.
  3. **Pooling/subsampling** of hidden units in same neighbourhood.



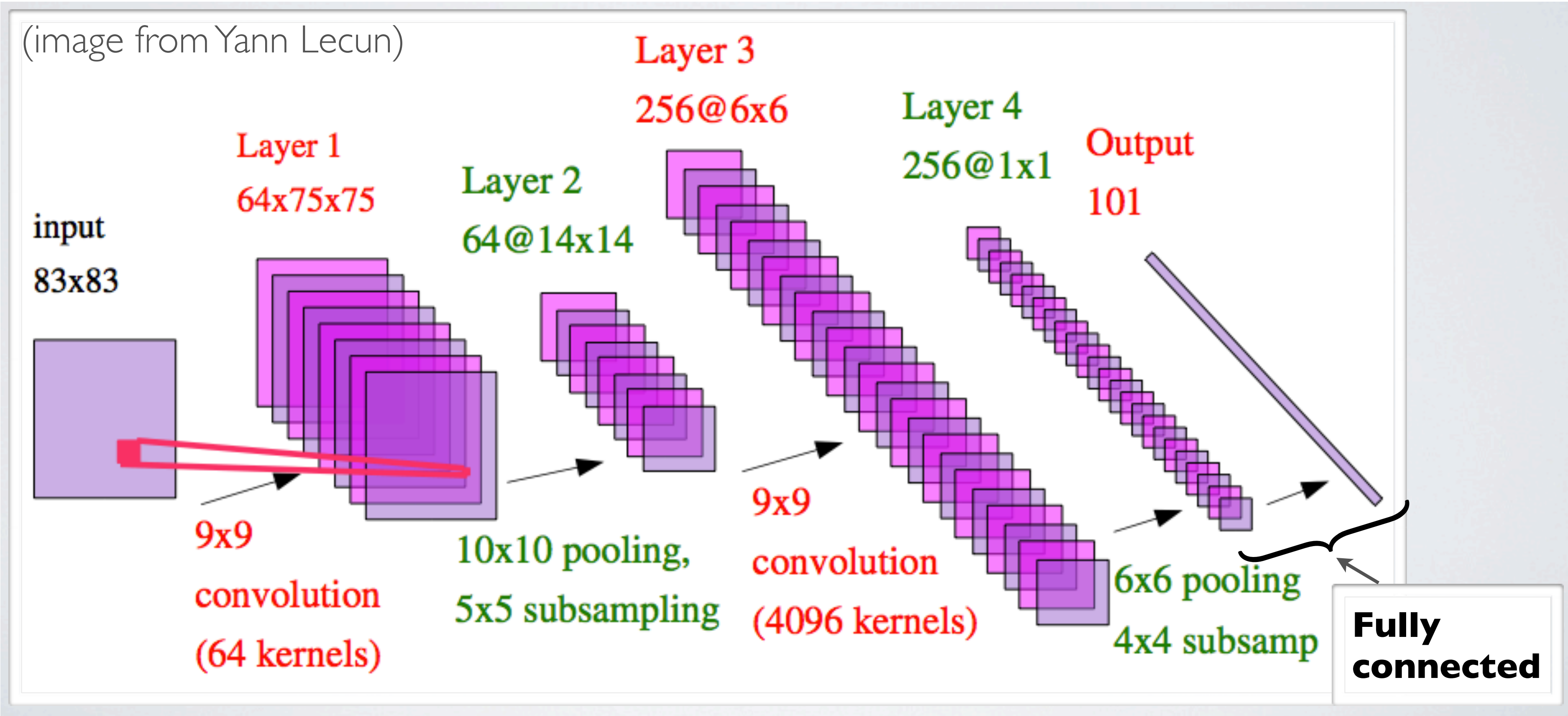
Example:



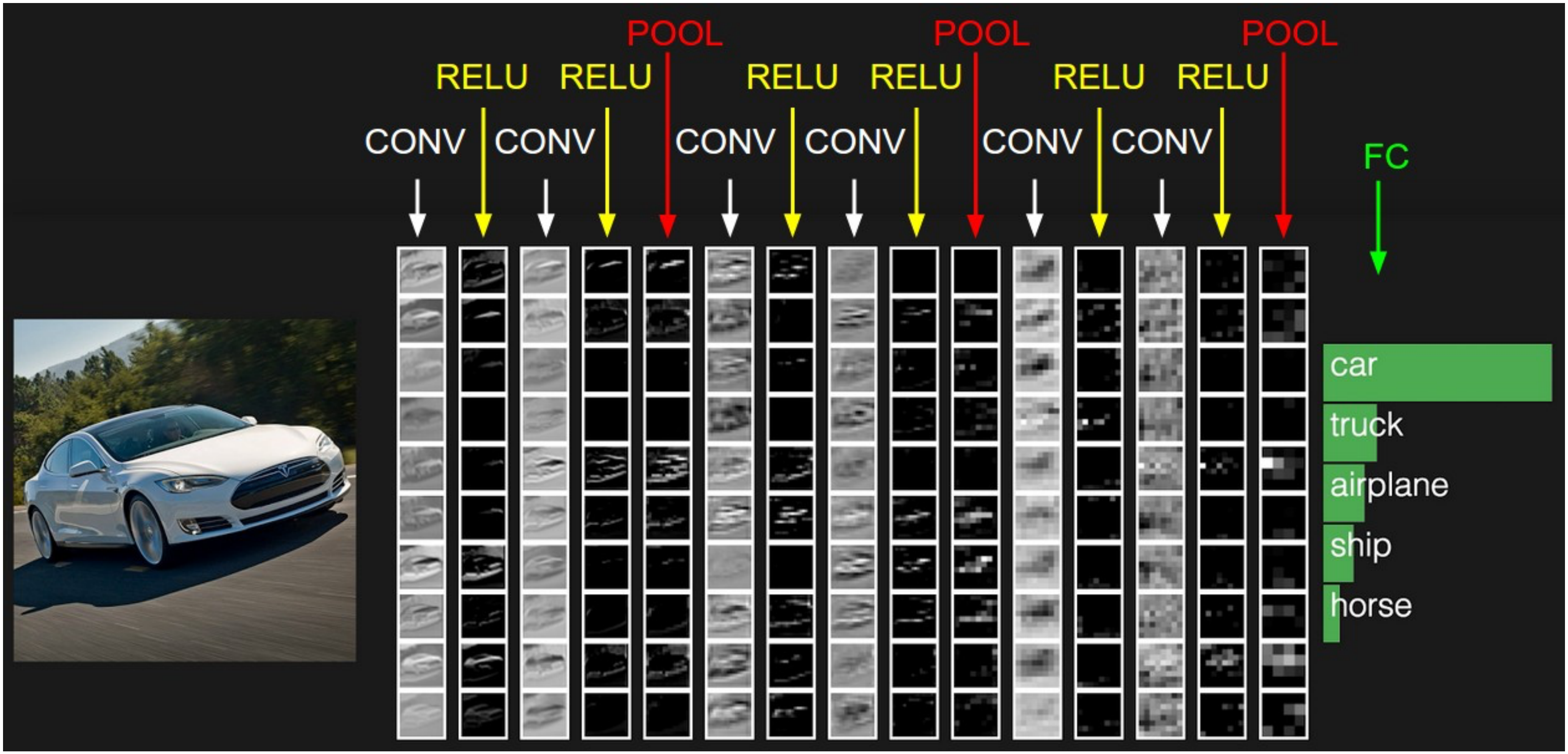
From: *http://cs231n.github.io/convolutional-networks/*

Convolutional neural nets (CNNs)

- Alternate between **convolutional**, **pooling**, and **fully connected** layers.
  - Fully connected layer typically only at the end.
- Train full network using **backpropagation**.



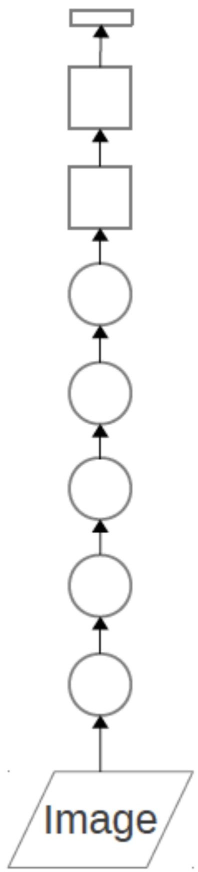
Convolutional neural nets (CNNs)



From: *http://cs231n.github.io/convolutional-networks/*

Example: ImageNet

- SuperVision (a.k.a. AlexNet, 2012):



- **Deep**: 7 hidden "weight" layers
- **Learned**: all feature extractors initialized at white Gaussian noise and learned from the data
- Entirely supervised
- **More data = good**

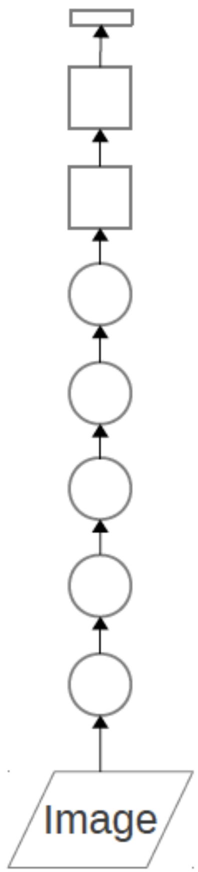
Convolutional layer: convolves its input with a bank of 3D filters, then applies point-wise non-linearity

Fully-connected layer: applies linear filters to its input, then applies point-wise non-linearity

From: *http://www.image-net.org/challenges/LSVRC/2012/supervision.pdf*

Example: ImageNet

- SuperVision (a.k.a. AlexNet, 2012):



- Trained with stochastic gradient descent on two NVIDIA GPUs for about a week
- 650,000 neurons
- 60,000,000 parameters
- 630,000,000 connections
- **Final feature layer:** 4096-dimensional

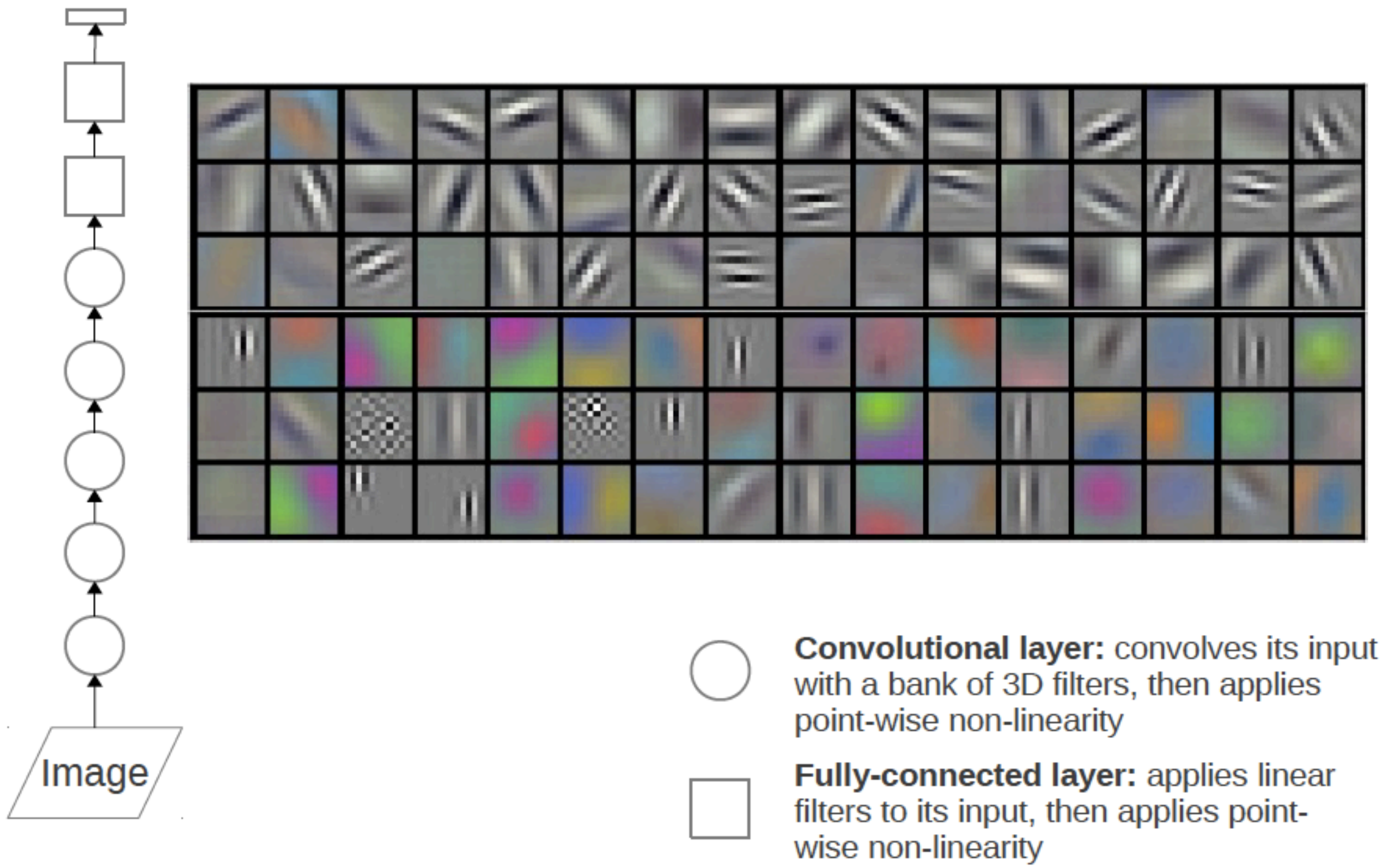
○ **Convolutional layer:** convolves its input with a bank of 3D filters, then applies point-wise non-linearity

□ **Fully-connected layer:** applies linear filters to its input, then applies point-wise non-linearity

From: *http://www.image-net.org/challenges/LSVRC/2012/supervision.pdf*

Training results: ImageNet

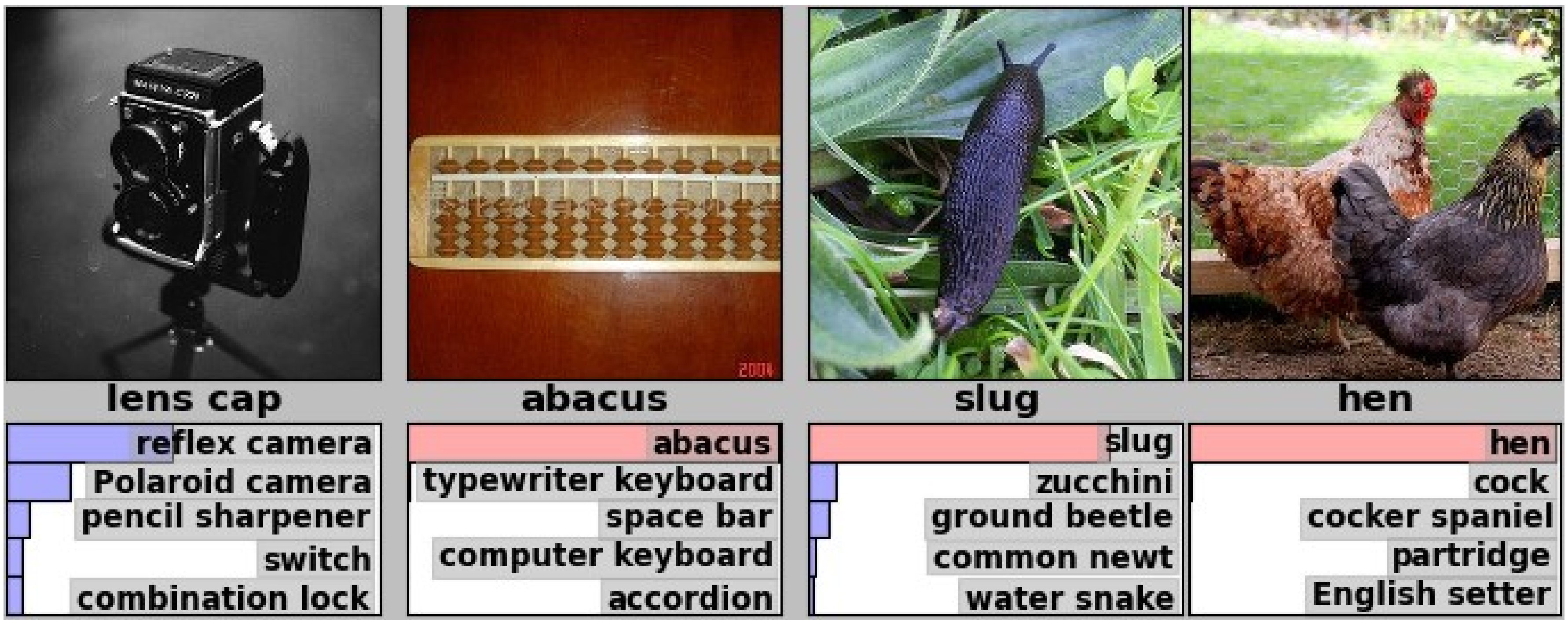
- 96 learned low-level filters



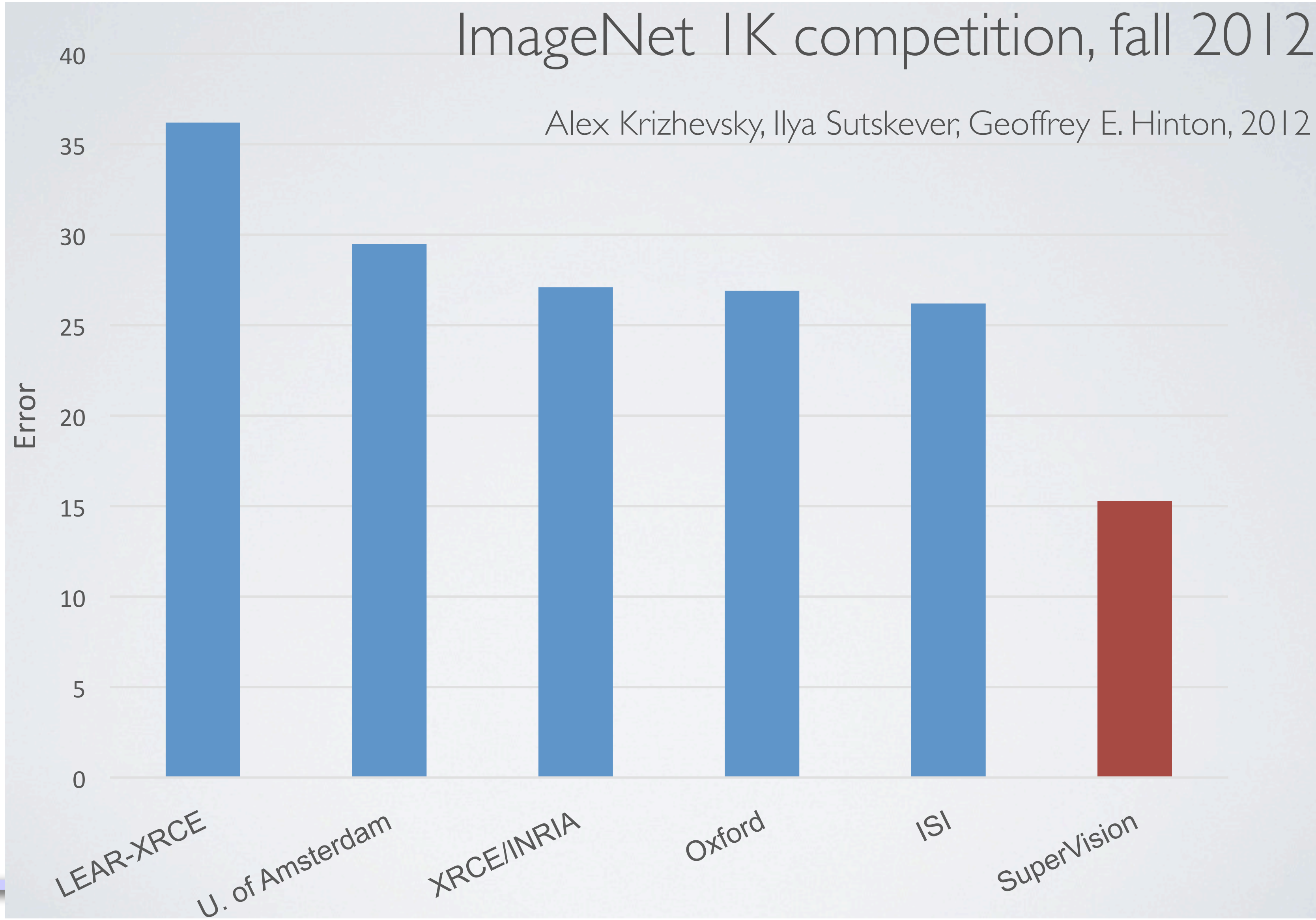
From: *http://www.image-net.org/challenges/LSVRC/2012/supervision.pdf*

Image classification

- 95% accuracy (on top 5 predictions) among 1,000 categories. Better than average human.

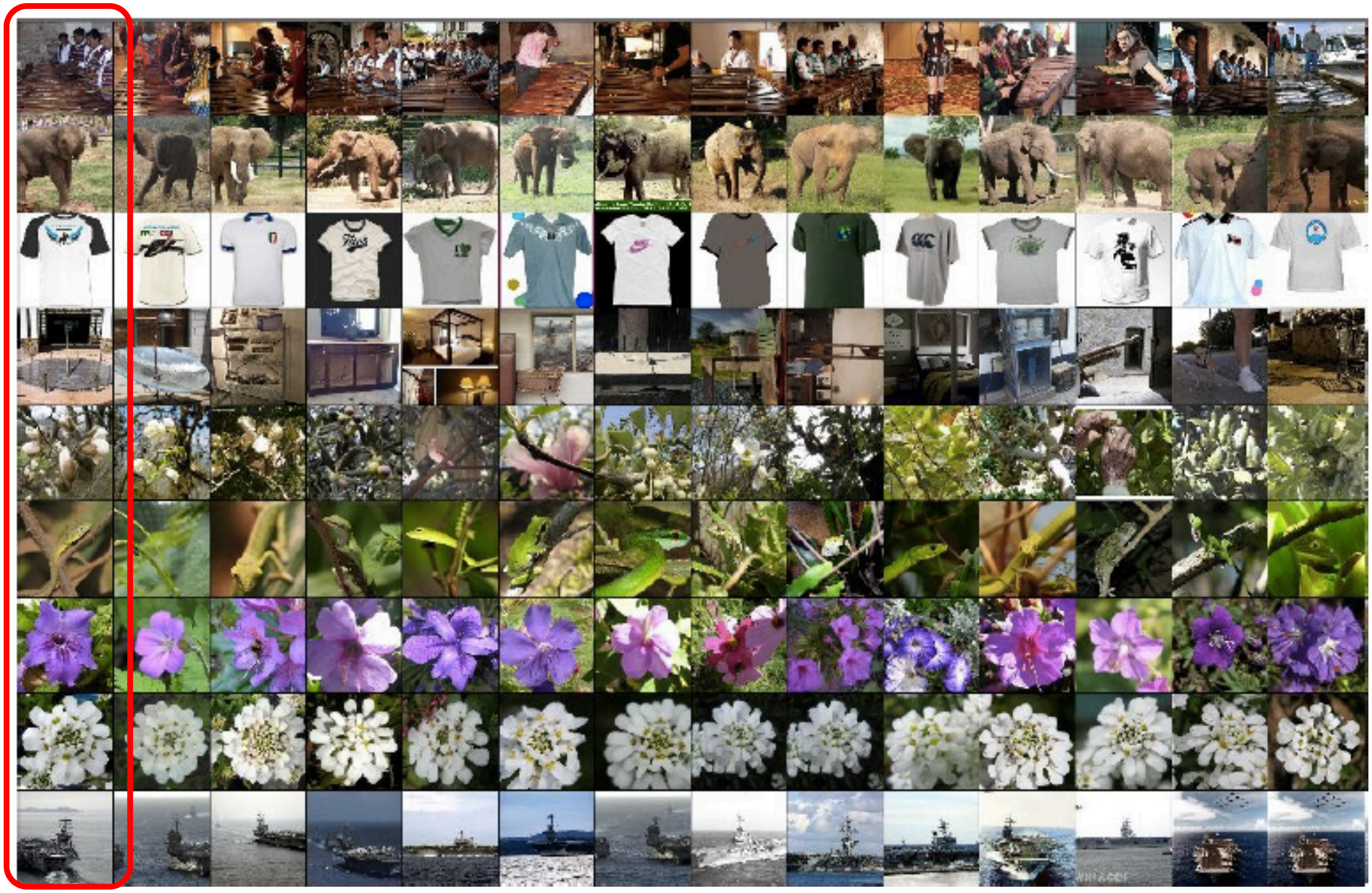


Empirical results (2012)



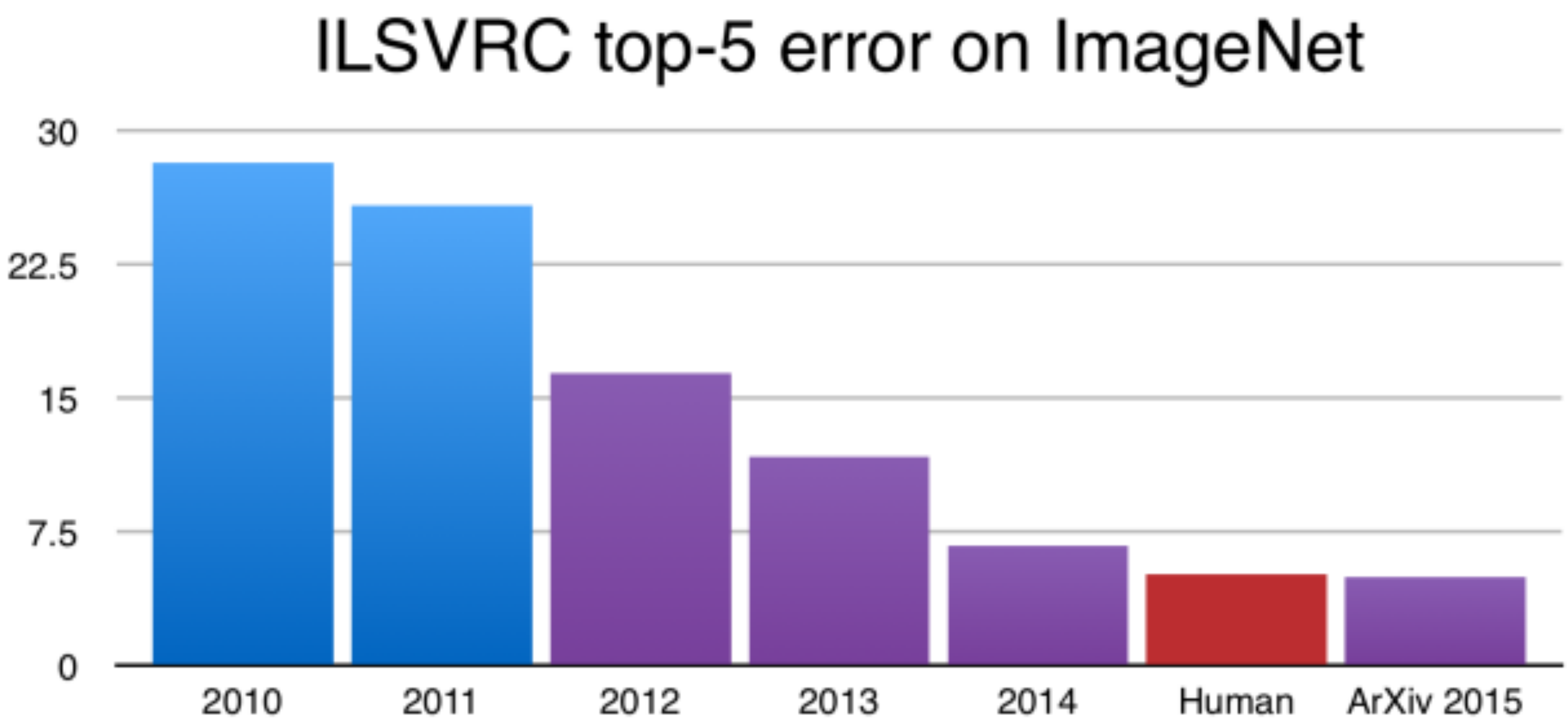
Empirical results for image retrieval

- Query items in leftmost column:



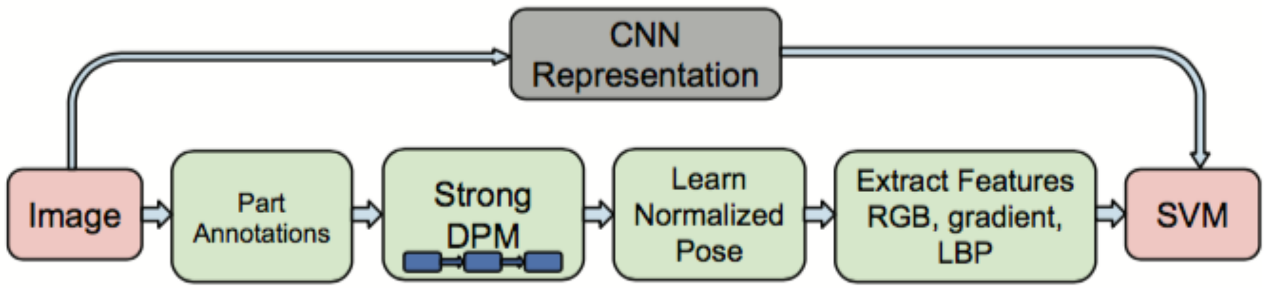
From: *http://www.image-net.org/challenges/LSVRC/2012/supervision.pdf*

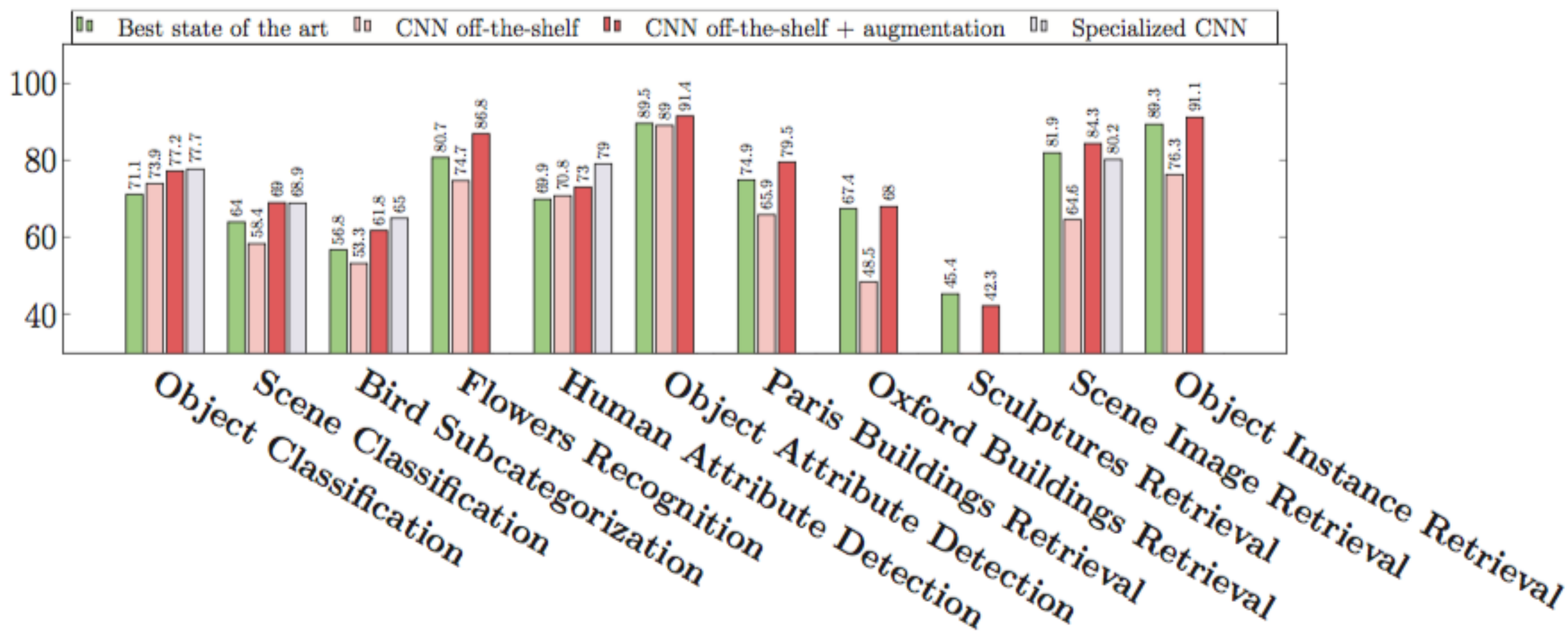
Empirical results (2015)



http://devblogs.nvidia.com/parallelforall/mocha-jl-deep-learning-julia/

CNNs vs traditional computer vision





From: *Razavian et al. CVPR workshop paper. 2014.*

Picture tagging (From *clarifai.com*)

Predicted Tags:

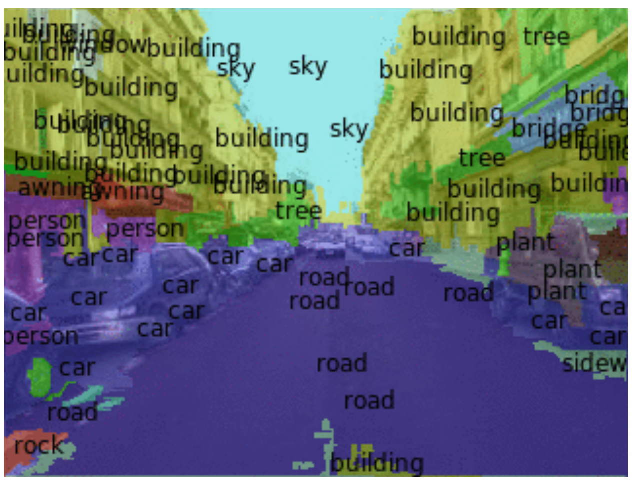
food	(16.00%)
dinner	(3.10%)
bbq	(2.90%)
market	(2.50%)
meal	(1.40%)
turkey	(1.40%)
grill	(1.30%)
pizza	(1.30%)
eat	(1.10%)
holiday	(1.00%)

Stats:

Size: 247.24 KB

Time: 110 ms

Scene parsing



(Farabet et al., 2013)

Achieving super-human performance?

- Estimated 3% error in the labels.
- Differences between labeling process and human assessment:
  - Labels acquired as binary task. *Is there a dog in this picture?*
  - Human performance measured on 1K classes (>120 species of dogs in the dataset).
  - Labels acquired from experts (dog experts label the dogs, etc.).
- Machines and humans make different kinds of mistakes.
  - Both have trouble with multiple objects in an image.
  - Machines struggle with small/thin objects, image filters.
  - Humans struggle with fine-grained recognition.

http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/

Practical tips for CNNs

- Many hyper-parameters to choose!
- Architecture: filters (start small, e.g. 3x3, 5x5), pooling, number of layers (start small, add more).
- Training: learning rate, regularization, dropout rate (=0.5), initial weight size, batch size, batch norm.
- Read papers, copy their method, then do local search.

Do we really need deep architectures?

- We can approximate any function to arbitrary levels of precision with shallow (2-level) architectures.
- Deep learning is more efficient for representing certain classes of functions, where there is certain types of structure.
  - Natural signals (images, speech) typically have such structure.
- Deep learning architectures can represent more complex functions with fewer parameters.
  - Trade-off (less) space for (more) time.
- So far, very little theoretical analysis of deep learning.

Quick recap + more resources

- A good survey paper:
  - Bengio, Courville, Vincent. Representation learning: A Review and New Perspectives. IEEE T-PAMI. 2013. *http://arxiv.org/pdf/1206.5538v2.pdf*

- Notes and images in today's slides taken from:
  - *http://cs231n.github.io/convolutional-networks/*
  - *http://www.cs.toronto.edu/~hinton/csc2535*
  - *http://deeplearning.net/tutorial/*
  - *http://www.slideshare.net/philipzh/a-tutorial-on-deep-learning-at-icml-2013*
  - *http://www.iro.umontreal.ca/~bengioy/papers/ftml.pdf*
  - *http://www.cs.toronto.edu/~larocheh/publications/icml-2008-denoising-autoencoders.pdf*

What you should know

- Types of deep learning architectures:
  - Stacked autoencoders
  - Convolutional neural networks
- Typical training approaches (unsupervised / supervised).
- Examples of successful applications.