Imperial College London

Deep Learning within Computer Vision

a whirlwind tour of the key principles

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https://labicvl.github.io/

Slide material acknowledgement: Toby Breckon (Durham University), at BMVA computer vision summer school 2018

The move from **shallow** to **deep** …

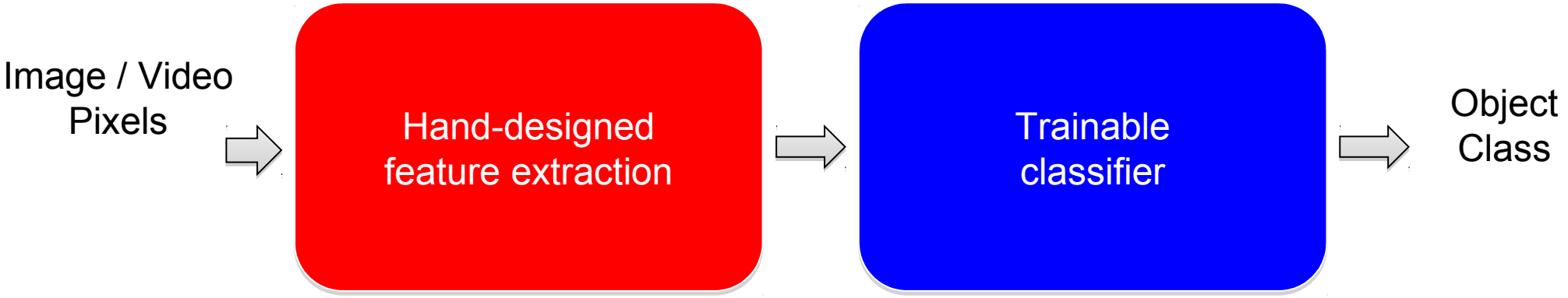
(< ~2013)

pre deep learning / *pre abyssi*

(> ~2013)

post deep learning / *post abyssi*

Traditional (shallow) Approaches



- Features are not learned
  - vectors of shape measures, edge distributions, colours distributions, feature points, HOG, visual words, ... etc.
    - … i.e. calculated **summary** "numerical" **descriptors**

- Trainable classifier is often generic

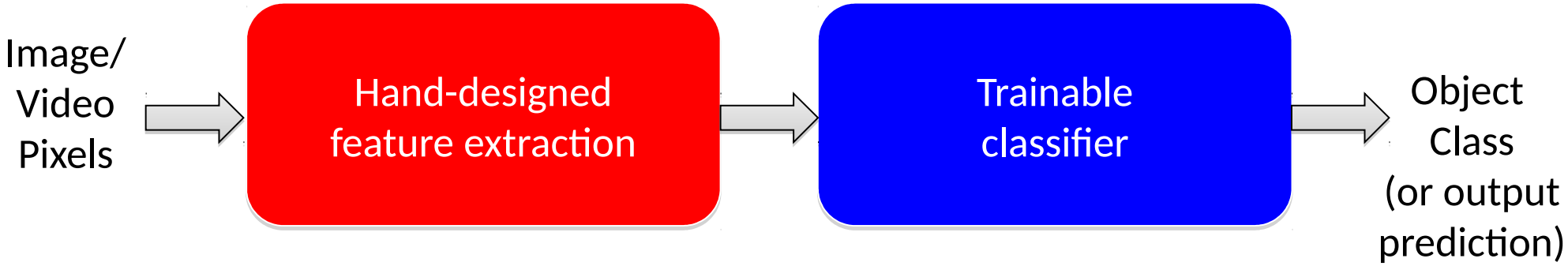
(e.g. SVM kernel, Decision Forest)

Deep Learning – end to end approaches

- Learn a *feature hierarchy* all the way from pixels (or voxels) to classifier
- Each layer extracts *"features"* from the output of previous layer
- Layers have similar structure, performing varying functions
- Train (i.e. optimize) all layers jointly

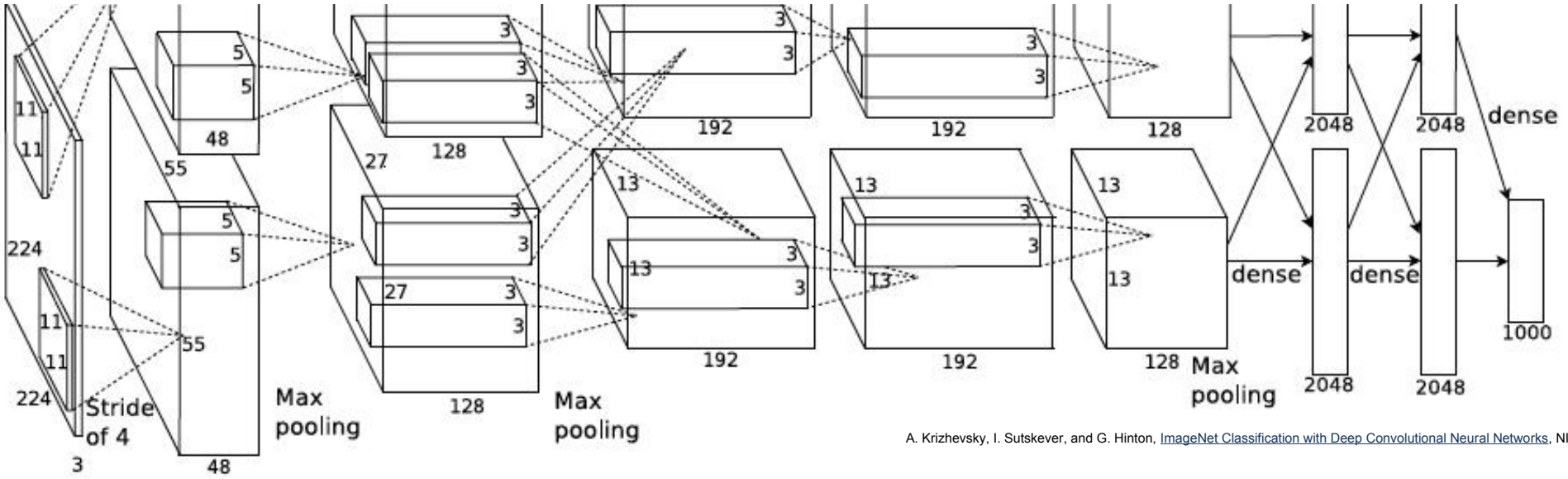
“Shallow” vs. “deep” architectures

Traditional recognition: **“Shallow”** architecture



(modern) Deep learning: **“Deep”** architecture

A *typical* end-to-end deep learning **convolutional neural network** ….

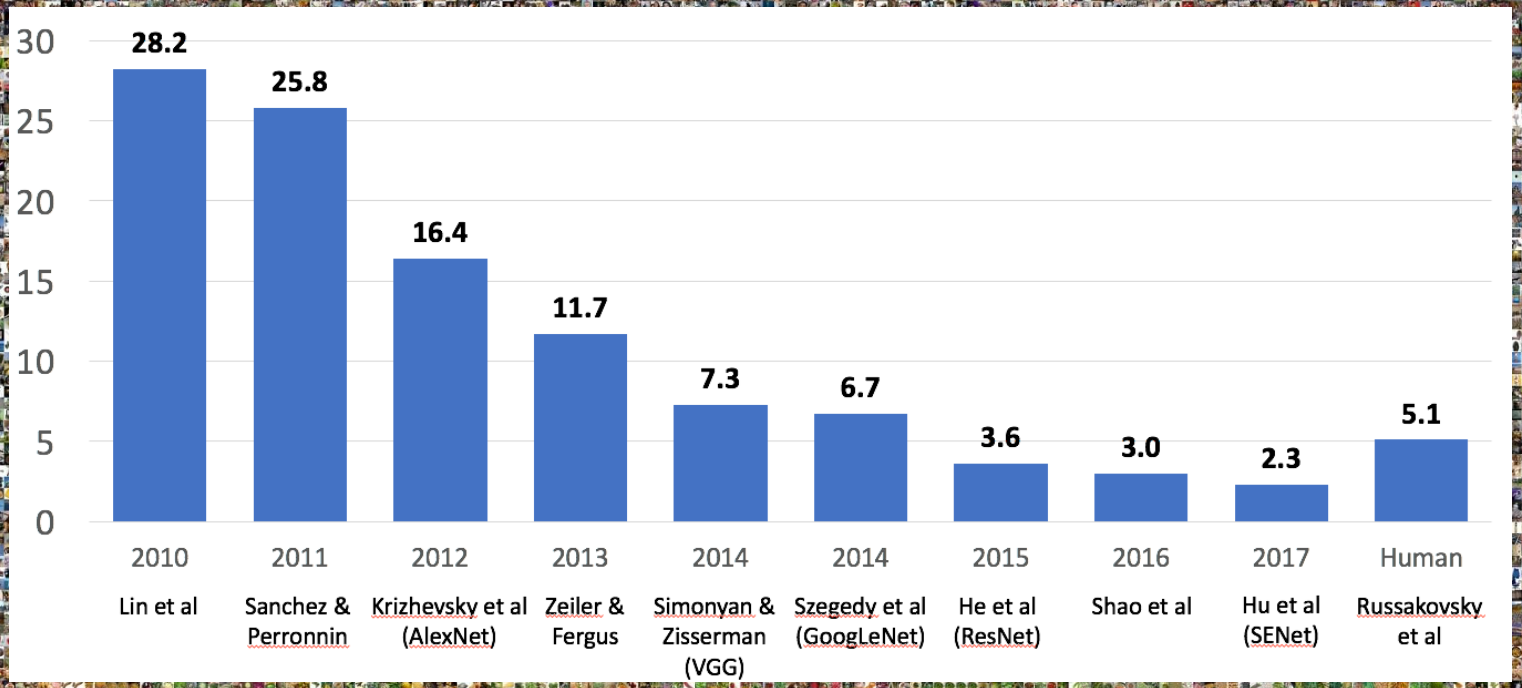


A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

- **"AlexNet":** seminal ImageNet Challenge winner (2012)
  - **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
  - **Algorithms:** better regularization for training (DropOut)

IMAGENET Large Scale Visual Recognition Challenge

The Image Classification Challenge:
1,000 object classes
1,431,167 images



[Human - Russakovsky et al. IJCV 2015]

[This slide – from: Fei-Fei Li & Justin Johnson & Serena Yeung]

AlexNet's performance on this benchmark task was the research event ("discovery") that led to the **shallow** to **deep** transformation in computer vision ...*

* although CNN were not created overnight, and have their origins in [LeCun, 1998] among others

Key question – **why does this stuff work so well ?**

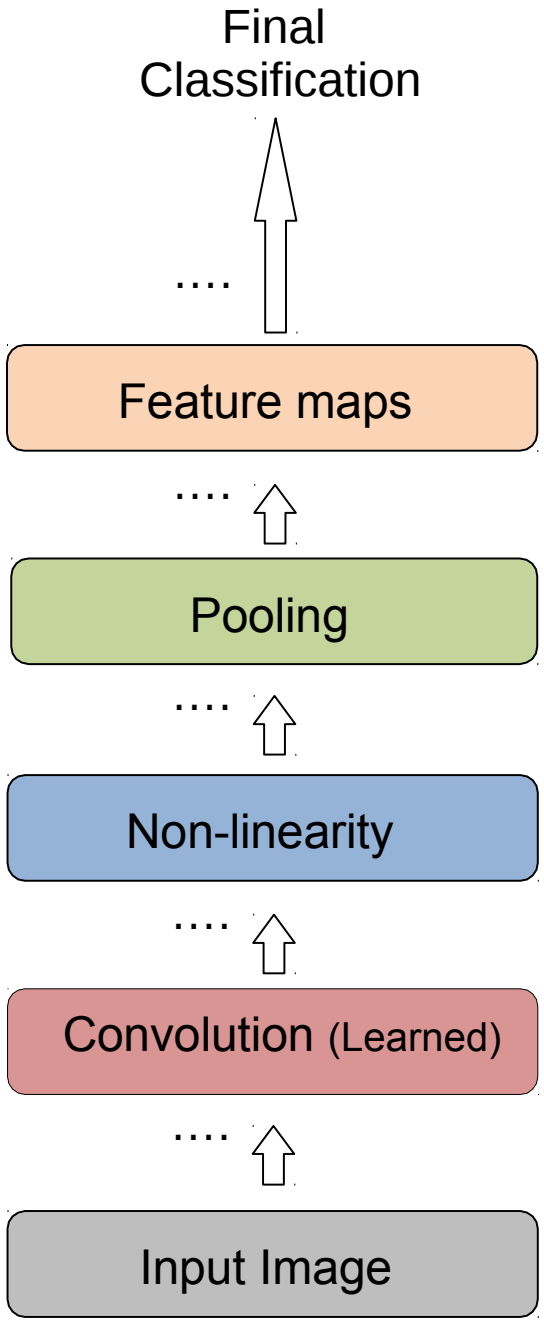
(let's examine some of the fundamentals)

Key **Principle**

Each layer in a **deep network performs a different transformation (function)** to map from input to output – these vary from {convolution, pooling, sub-sampling, non-linear mapping (fully connected), ….}.

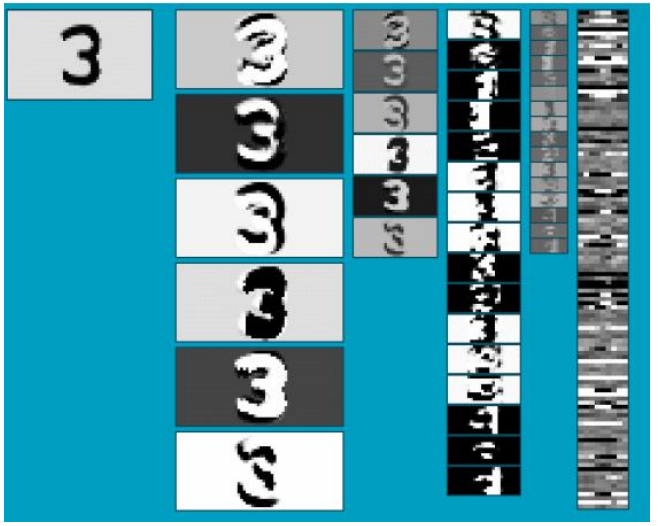
Within a **traditional (shallow) Neural Network**, the perceptron **activation functions are all the same** (but we vary the weights).

This provides the network with a **larger parameterization space to represent (complex) input to output relationships.**

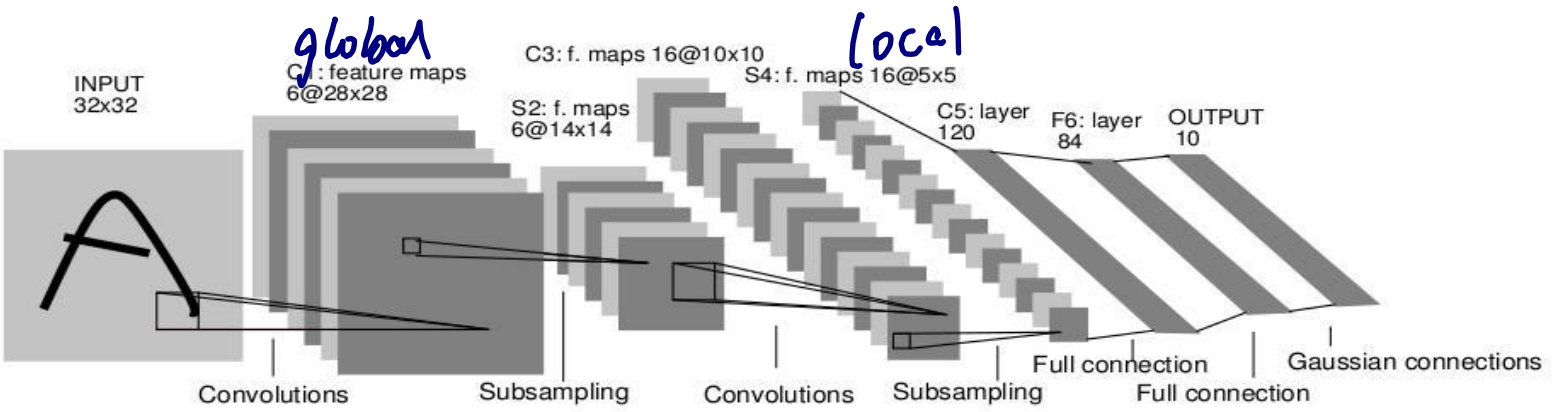


Convolutional Neural Networks (CNN)

- Multi-layer Neural network with:
  - **Local** connectivity
  - **Shared** weight parameters across spatial positions
- Stack **multiple stages of feature extractors** operating **directly on the image**
- Higher **stages compute more global, more invariant feature representation**
- **Final classification** layer at the end



Task: digit recognition



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.

Clarification:

Convolutional Neural Networks (CNN)
(i.e. networks using convolution layers)

are **a subset of** the **generalized**
Deep Learning extension to
Neural Networks

(i.e. **Deep Neural Networks**)

CNN are a specific to images (or similar densely sampled signals)**

A deep multi-layer architecture ...

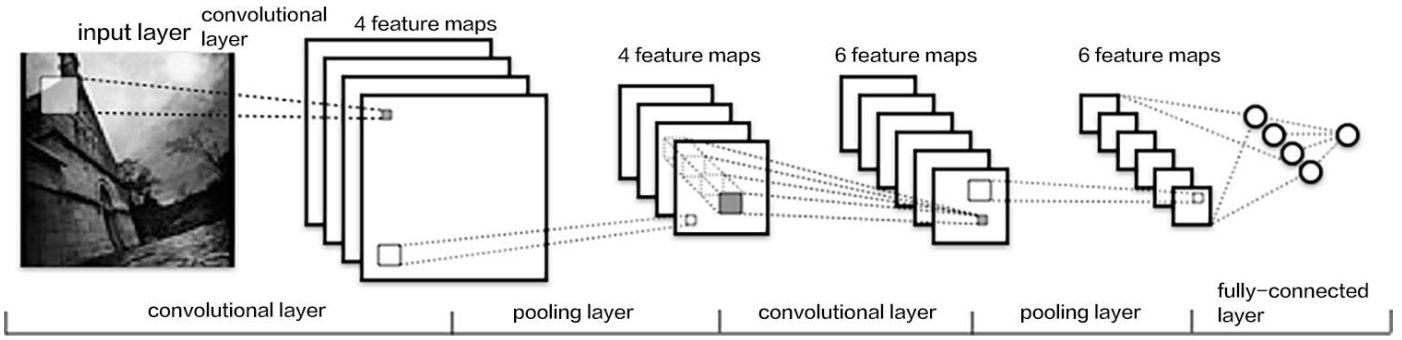
Convolutional Neural Networks (CNN)

- Feed-forward network:
  - Convolve input (feature extraction)
  - Non-linearity (rectified linear)
  - Pooling (local max)

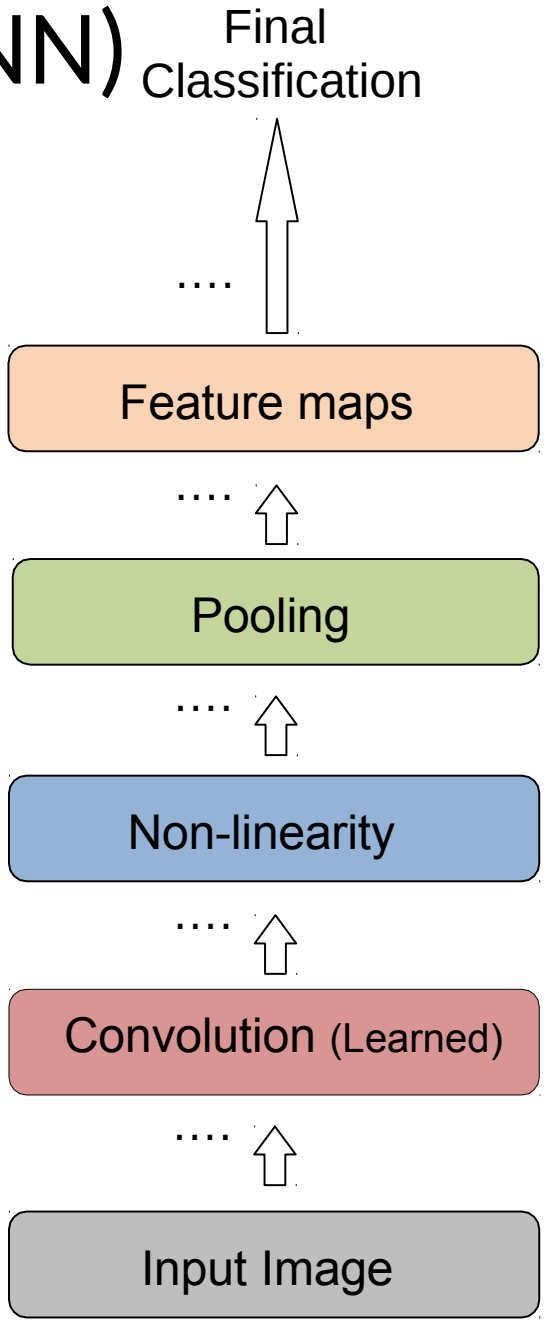
Pooling: down-sampling

Supervised learning (with labels)

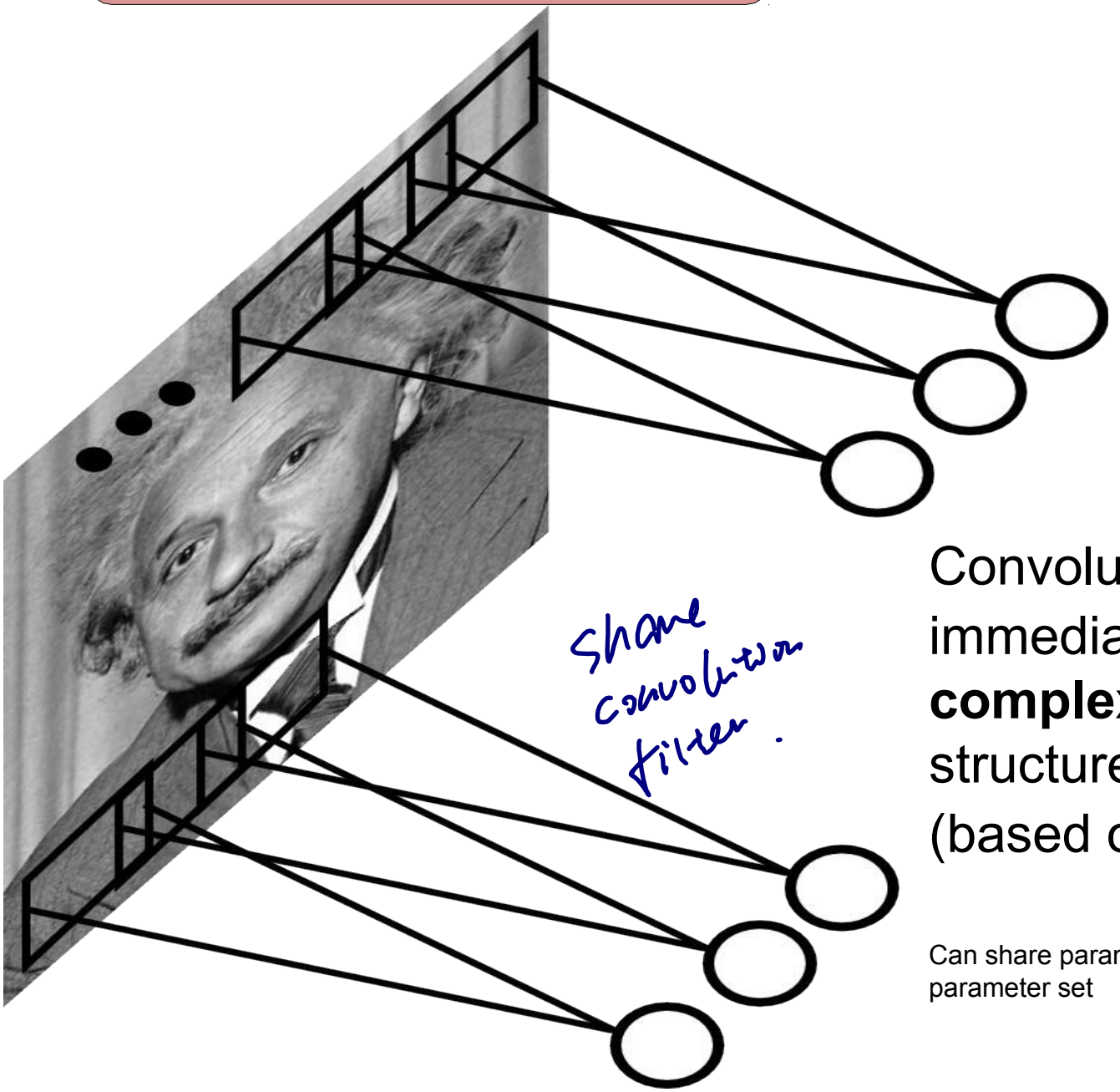
Train convolution filters by backpropogation



Example: LeNet—5 (http://book.paddlepaddle.org/03.image_classification/)



Convolution Layer(s)



Convolution in the first layer immediately **reduces the complexity of the input** in a structured and meaningful way (based on learnt weights)

Can share parameters across filters to reduce to size of parameter set

Convolution Layer(s)

- Convolutional
  - dependencies are local
  - translation invariance
  - few parameters (filter weights)
  - filter stride can be > 1 (faster, less memory)

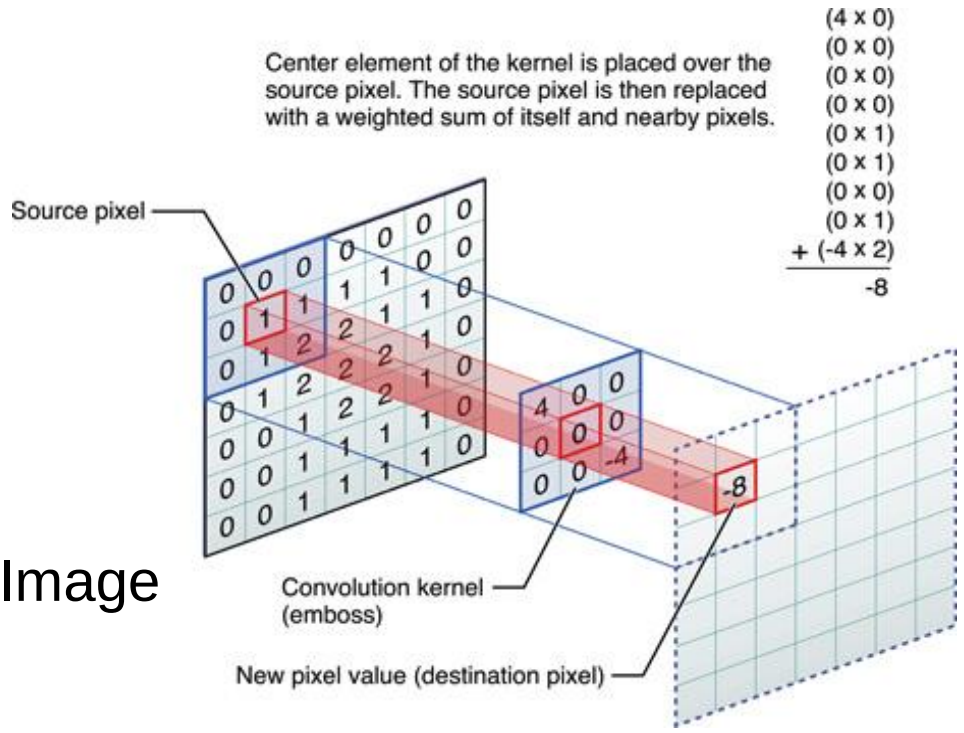
Input (image)

Intermediate Feature Map

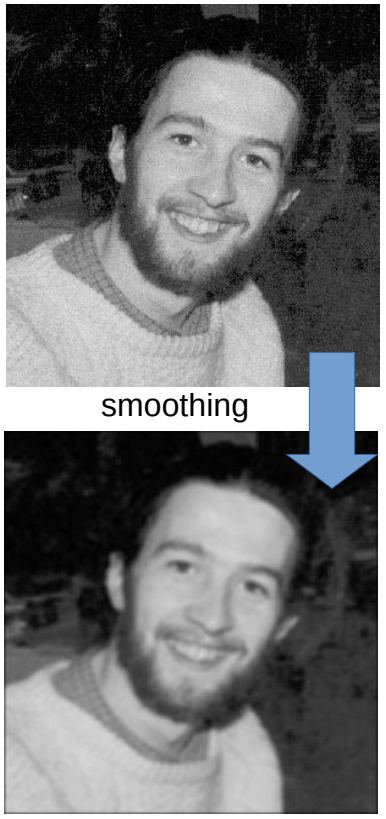
Aside : image convolution

(in general image processing)

- … is essentially the **localised weighted sum of the image and a convolution kernel (mask weights)** over a N x M pixel neighbourhood, at a given location within the image (x,y).



Input Image



Output Image

[used in image filtering operations (e.g. smoothing)]

Image source: developer.apple.com

Convolution is *very powerful* ...

original

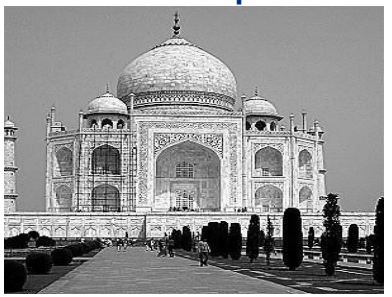
filter (3 x 3)

1	1	1
1	1	1
1	1	1

blur

0	-1	0
1	5	1
0	-1	0

sharpen

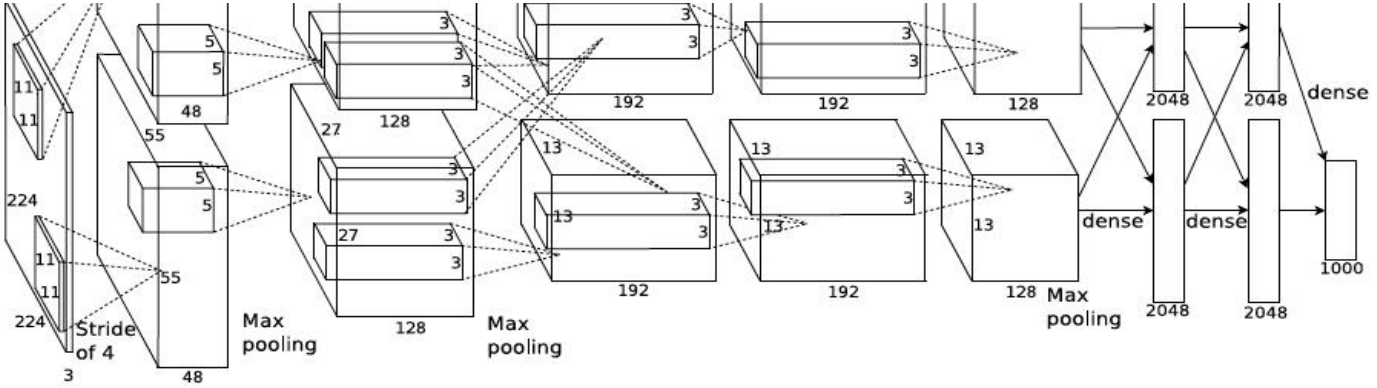


1	2	1
0	0	0
-1	-2	-1

edges

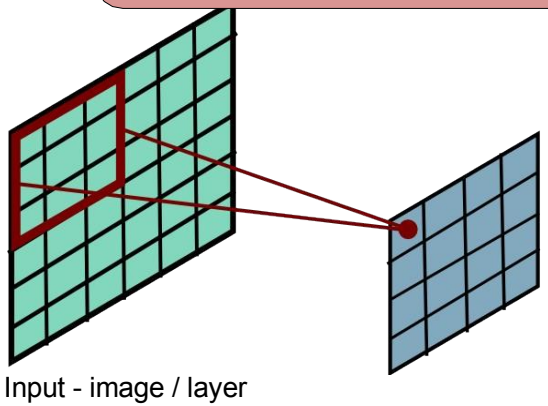
Different weights have do a wide range of effects on input data ….

hence → multiple layers of convolution ("convolutions upon convolutions")



can approximate and provide most **feature extraction** and **image pre-filtering** *(de-noising)* approaches ...

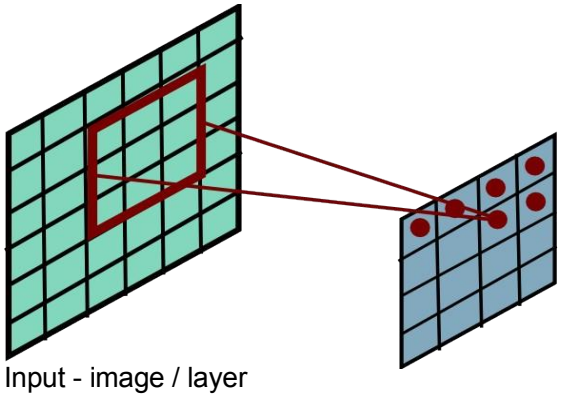
Convolution Layer(s)



Input - image / layer

Output - Feature Map

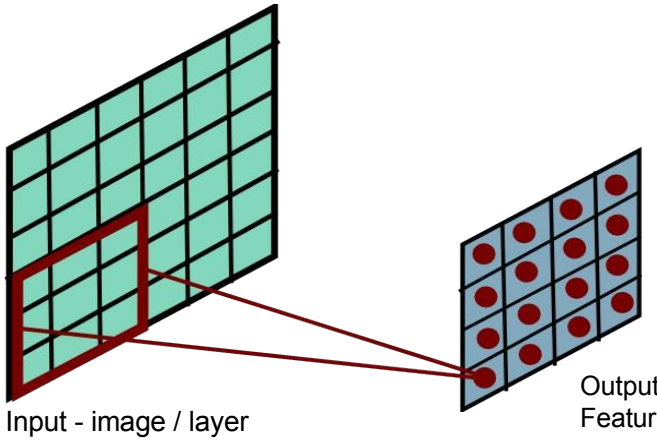
....



Input - image / layer

Output - Feature Map

....



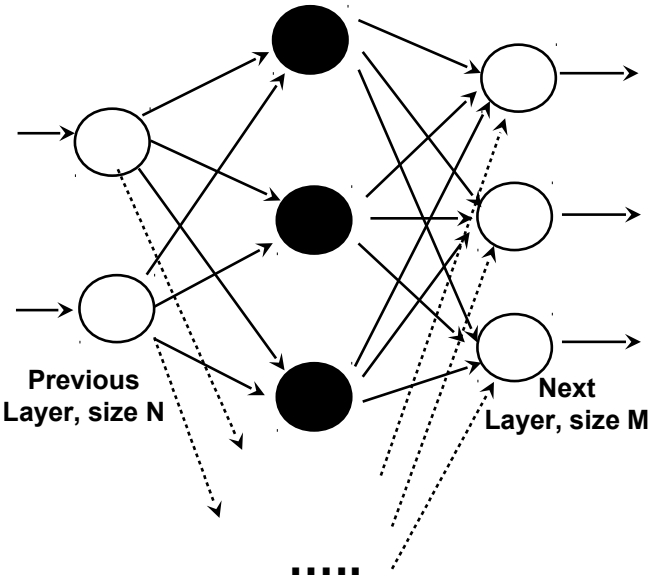
Input - image / layer

Output - Feature Map

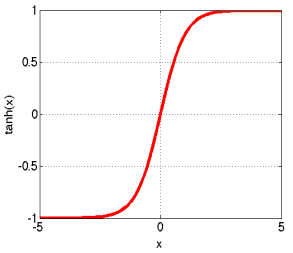
Produces a structured intermediate feature map from the input image (or previous layer in the network)

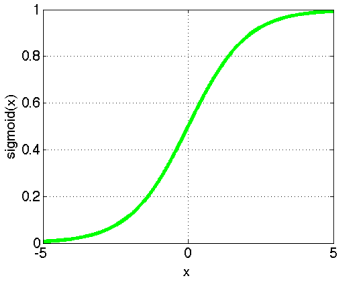
Non-linearity Layer(s)

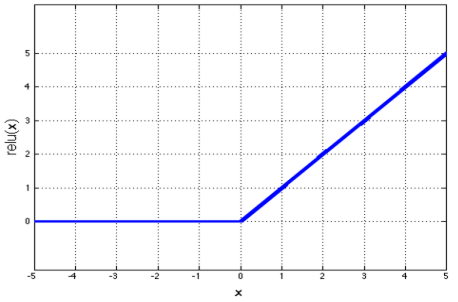
(a.k.a. fully connected)



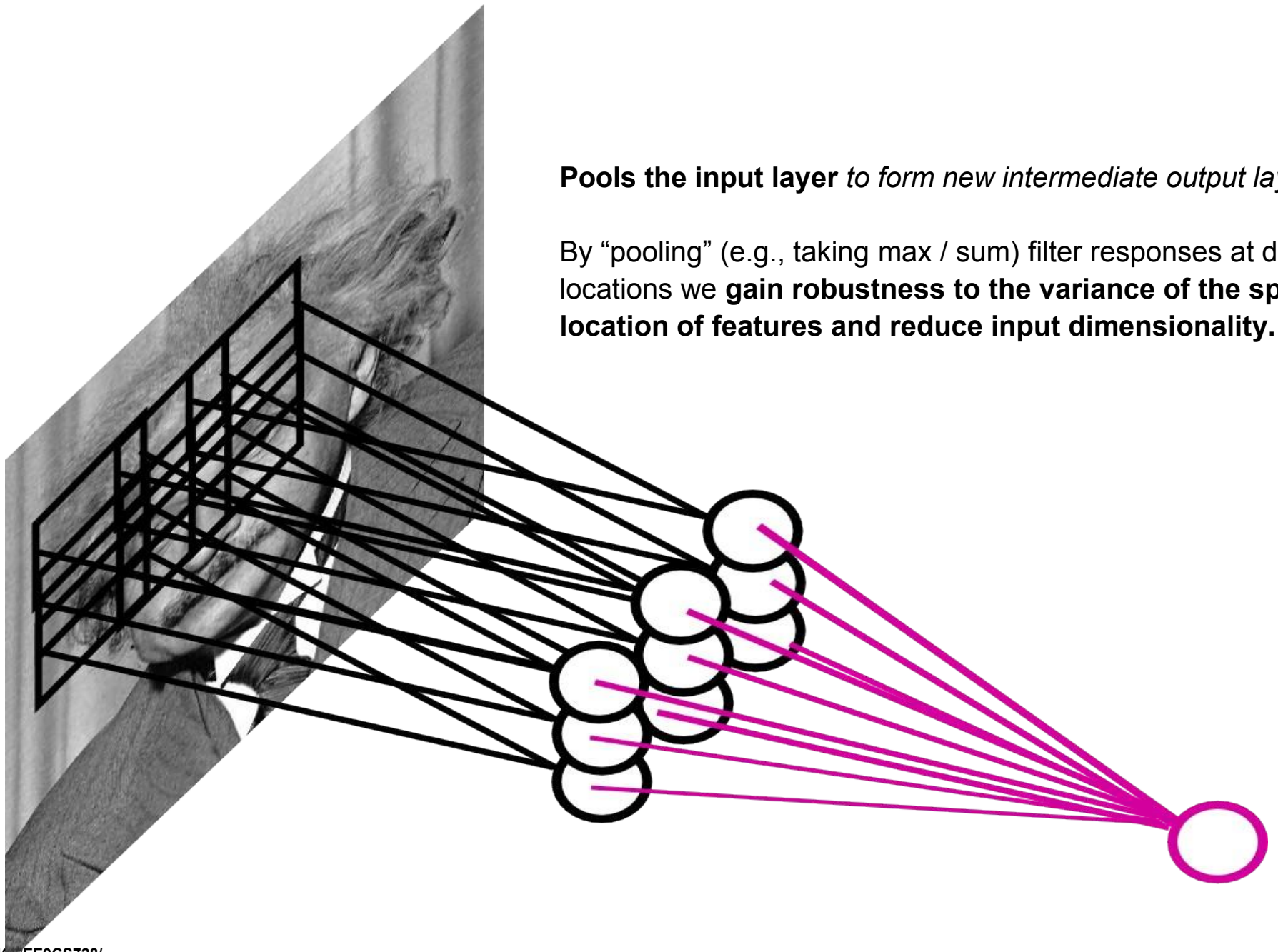
- Provides a non-linear input to output mapping **via a (traditional) activation function approach** layer of neurons
  - maybe either **sub-sampling (N→ M) or fully connected (N → M, N=M)** via per element activation function, e.g.
    - Tanh
    - Sigmoid: 1/(1+exp(-x))
    - Rectified linear (most common)
      - » Simplifies backprop
      - » Makes learning faster
      - » Avoids output saturation issues







Pooling layer(s)

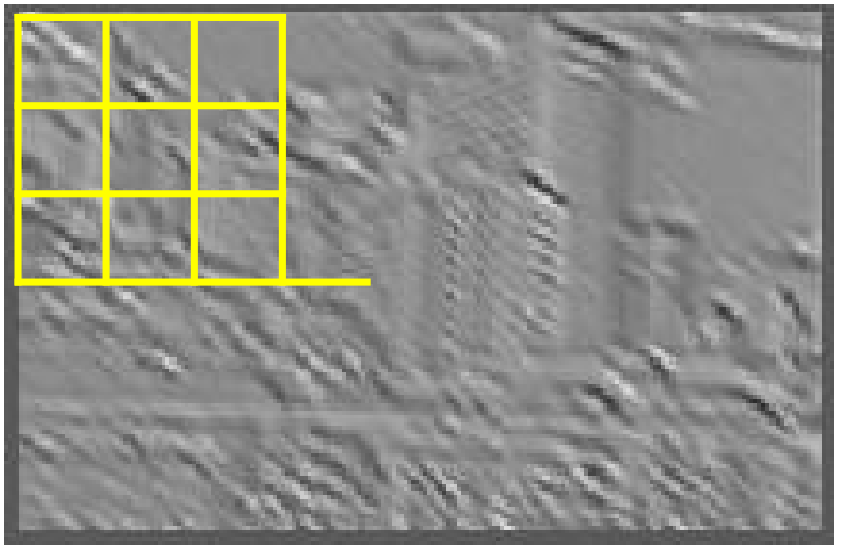


Pools the input layer *to form new intermediate output layer.*

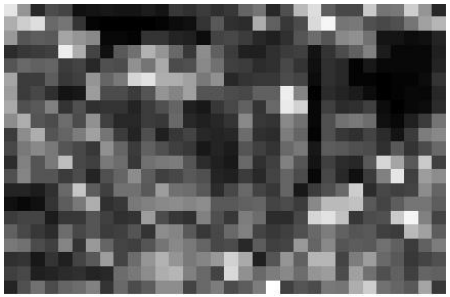
By “pooling” (e.g., taking max / sum) filter responses at different locations we **gain robustness to the variance of the spatial location of features and reduce input dimensionality.**

Pooling layer(s)

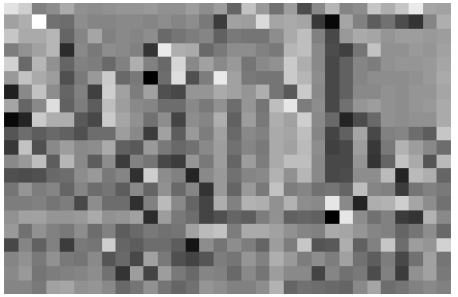
- Performs **localized sum() or max()** over sub windows/regions
  - non-overlapping Vs. overlapping regions
  - Role of pooling:
    - **Invariance** to small transformations
    - **Larger receptive fields** (see more of input)



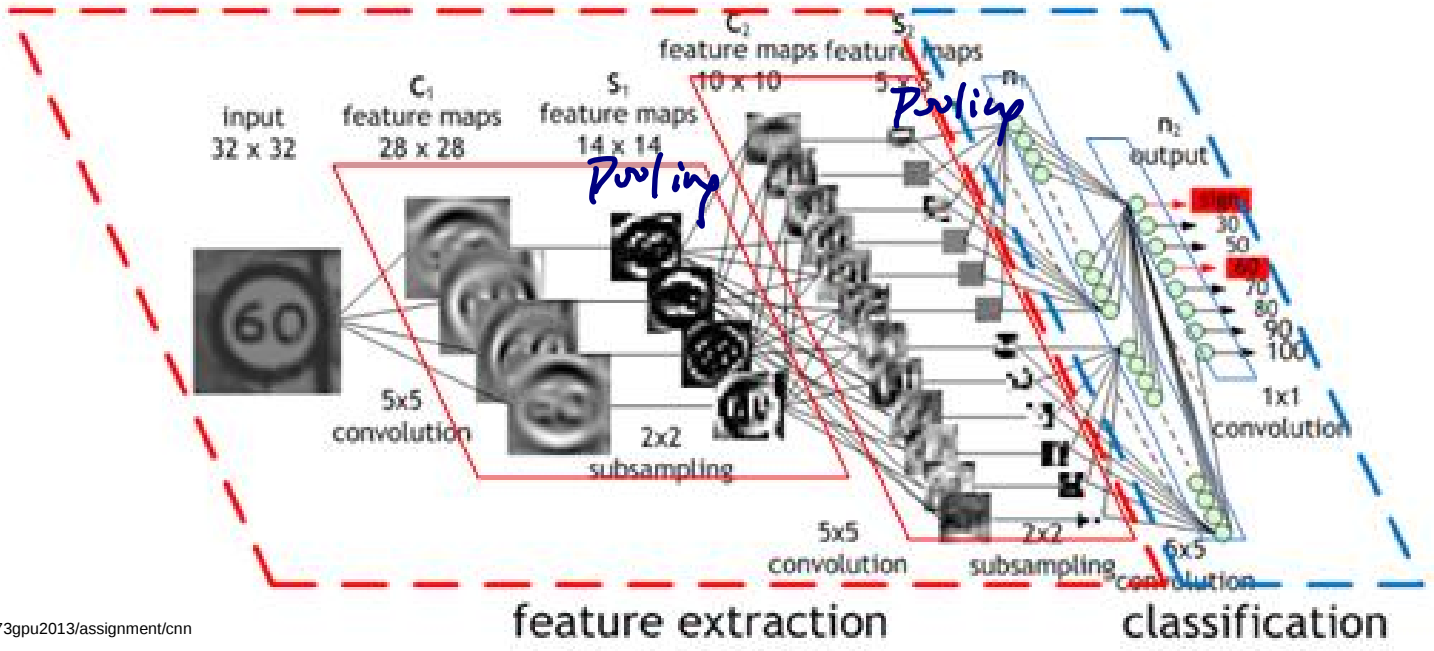
max()



sum()



CNN – example architecture (various layers)

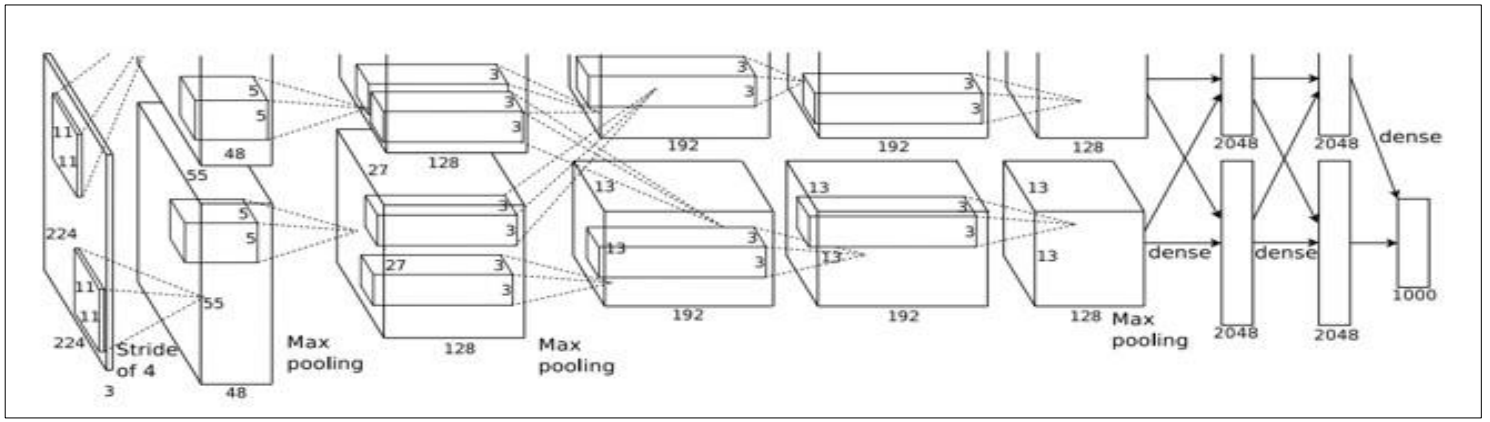


Example CNN design:
https://sites.google.com/site/5kk73gpu2013/assignment/cnn

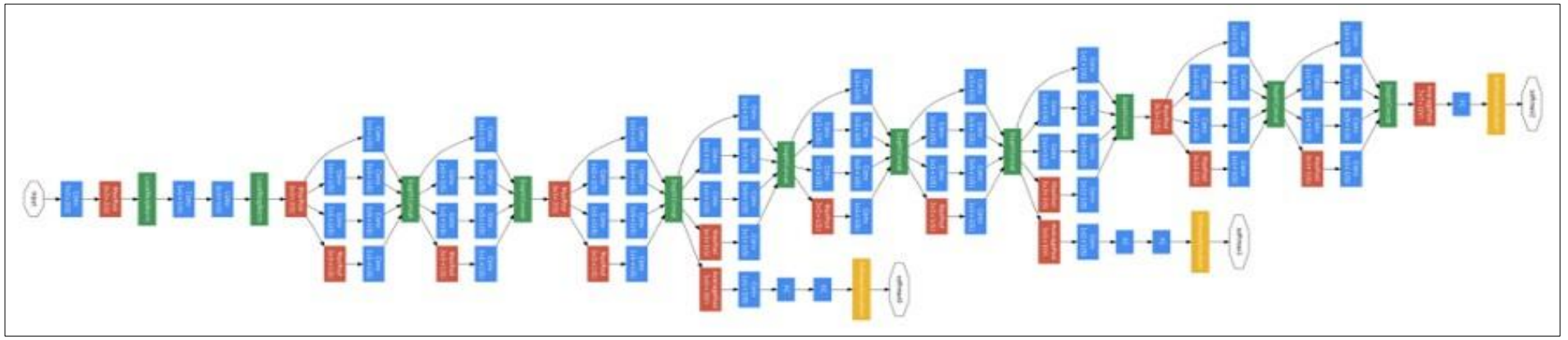
- Number of layers, type of layer, number of nodes/maps per layer – all down to the (human) designer
  - many variants have emerged
- CNN training – efficient **backpropogation**

  as per traditional neural network approaches (with **Dropout**)

Seminal
Deep Learning Architectures



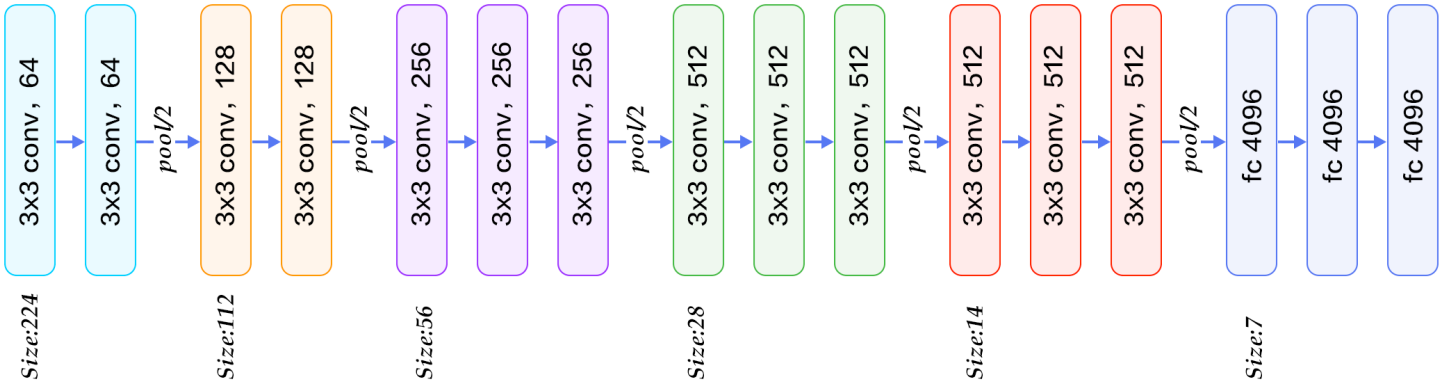
ImageNet Classification with Deep Convolutional Neural Networks
A Krizhevsky I Sutskever, G Hinton (2012) **- "AlexNet"**



Going Deeper with Convolutions, C Szegedy et al (2014) - "**GoogLeNet**"

→ Contemporary architectures ….

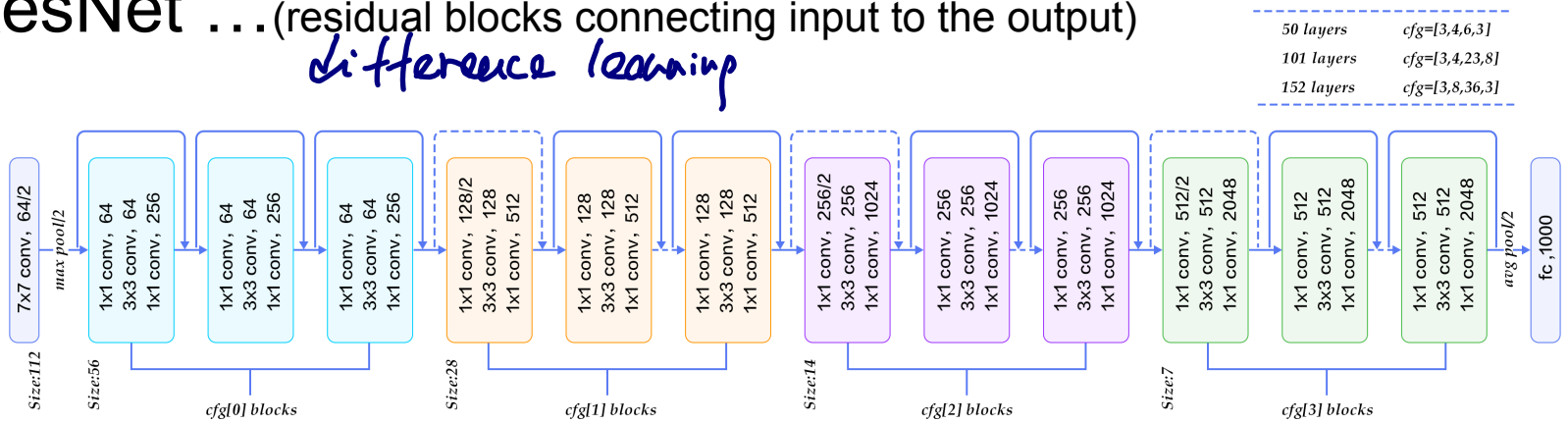
- VGG -16 … (deeper, smaller 3x3 convolutions throughout)



Simonyan Zisserman, 2014: http://www.robots.ox.ac.uk/~vgg/research/very_deep/

- ResNet …(residual blocks connecting input to the output)

difference learning



K. He, X. Zhang, S. Ren, J. Sun. Deep Residual Learning for Image Recognition. CVPR 2016.

Figures: http://book.paddlepaddle.org/03.image_classification/

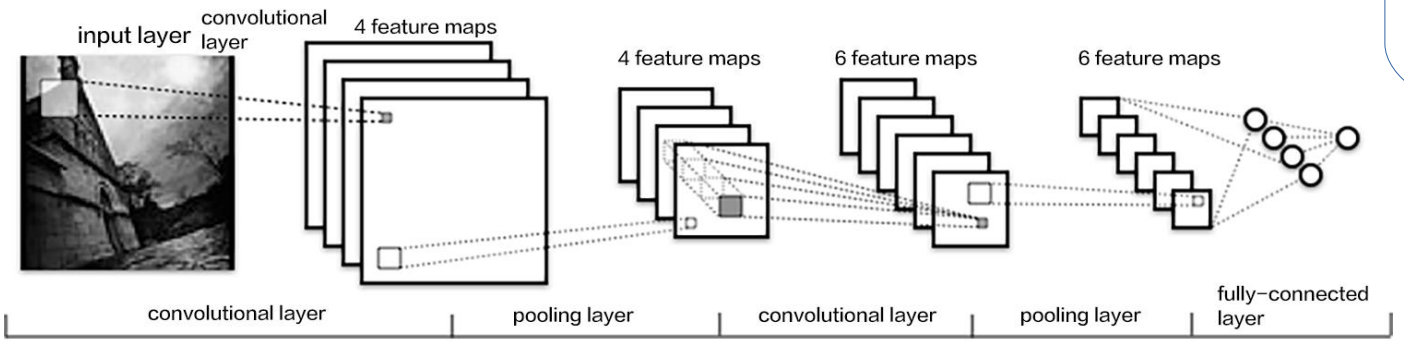
…. and more and more ...

Varying Deep CNN Architectures (and applications) all based on ...

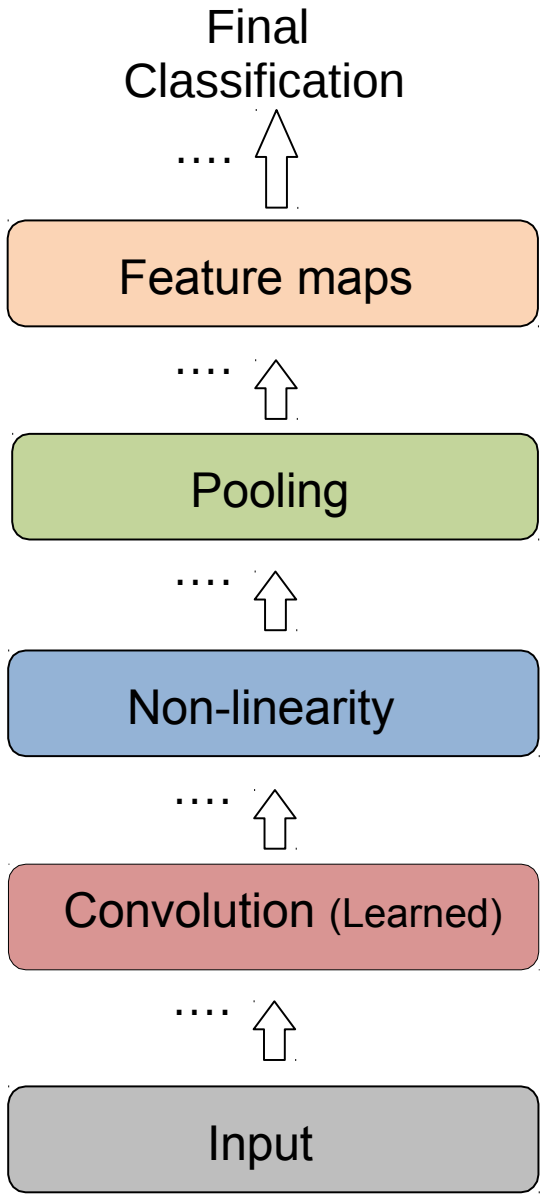
- **Feed-forward network:**
  - Convolve input (feature extraction)
  - Non-linearity (rectified linear)
  - Pooling (local max)

  ... all trained by **backpropogation**

Repeated multiple times over network architecture



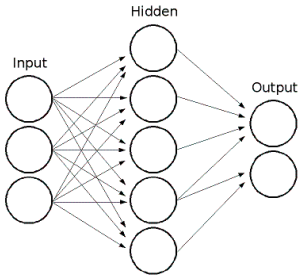
Example: LeNet—5 (http://book.paddlepaddle.org/03.image_classification/)



Train via **Backpropagation**

*Rumelhart, David E.; Hinton, Geoffrey E.; Williams, Ronald J. (8 October **1986**). "Learning representations by back-propagating errors". Nature. 323 (6088): 533–536.*

- **Neural Network Training: weight modifications** are made in the **"backwards" direction**: *from the output layer, through each hidden layer down to the first hidden layer*, hence **"Backpropagation"**



- **Key Algorithmic Steps**
  - **Initialize** weights (to small random values*) in the network
  - **Propagate the inputs forward**
    - (by applying activation function) at each node
  - **Backpropagate the error backwards**
    - (by updating weights and biases)
  - **Terminating** condition
    - when validation error is very small or enough iterations

Backpropogation details beyond scope/time (see accompanying reading)

So overall deep network layers provide …

feature extraction
data de-noising
dimensionality reduction
feature pooling
spatial invariance
non-linear input → output mapping

… specifically optimized towards a given problem*

(* that is represented by a given set of defined examples)

… which really covers *most* desirable aspects for *most* computer vision problems we encounter.

[if you think about it]

Key question – **is it *really* that easy ?**

(images in → results out ?!?)

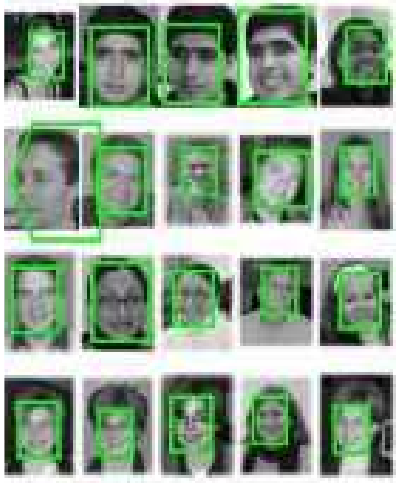
Remember, it's **all about ..**

Learning *from* the Data

- **Training data:** used to train the system
  - i.e. build the rules / learnt target function
  - split into training (back-propogated) and validation (when to stop back-propogating)
  - specific examples (used to learn)

....

- **Test data:** used to test performance of the system
  - *unseen* by the system during training
  - specific examples (used to evaluate)



....

e.g. face gender classification

Simple ? - Well almost .....

provided we avoid
the pitfalls on the way

We must avoid over-fitting …..

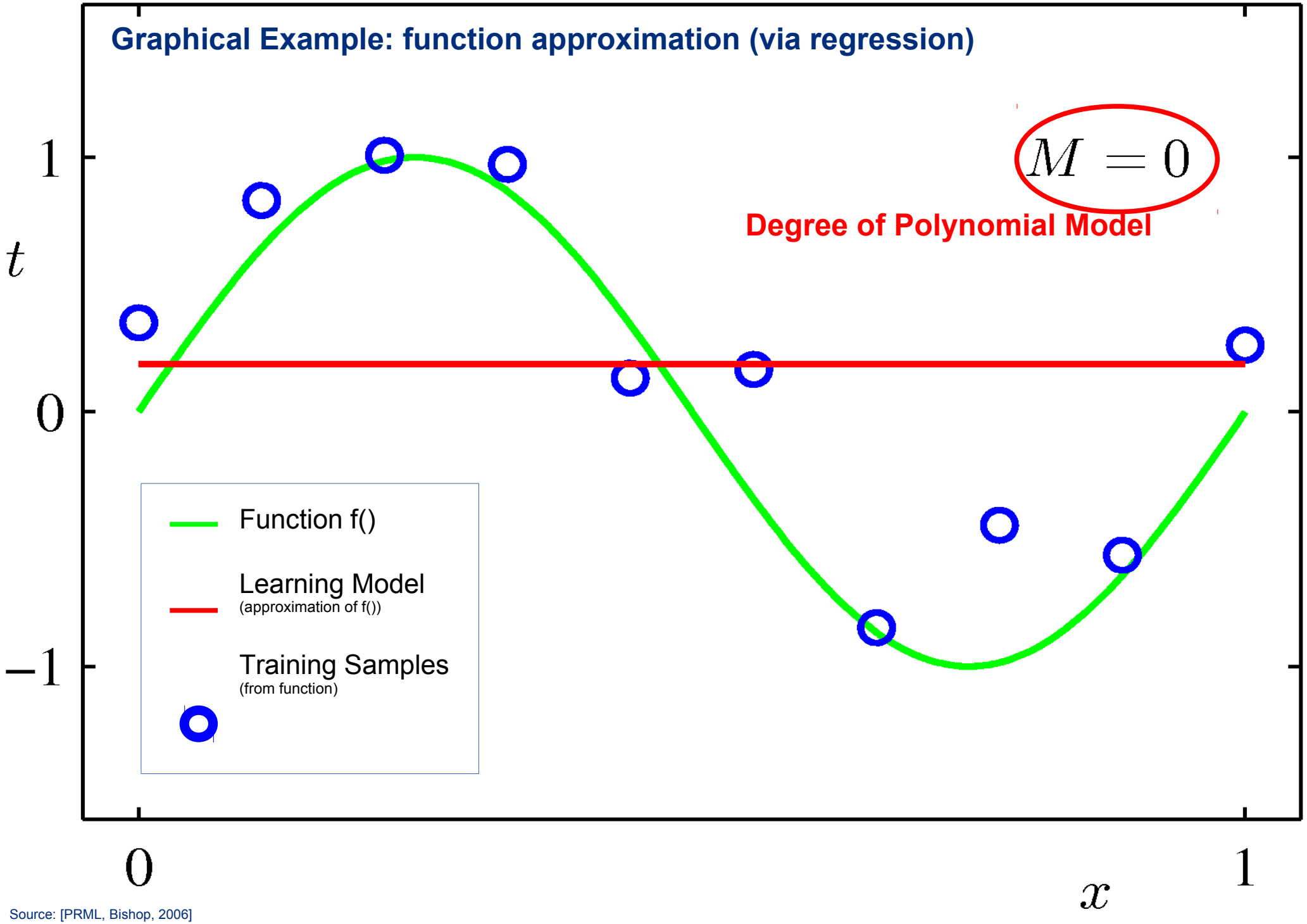
(i.e. over-learning)

Principle of Occam's Razor

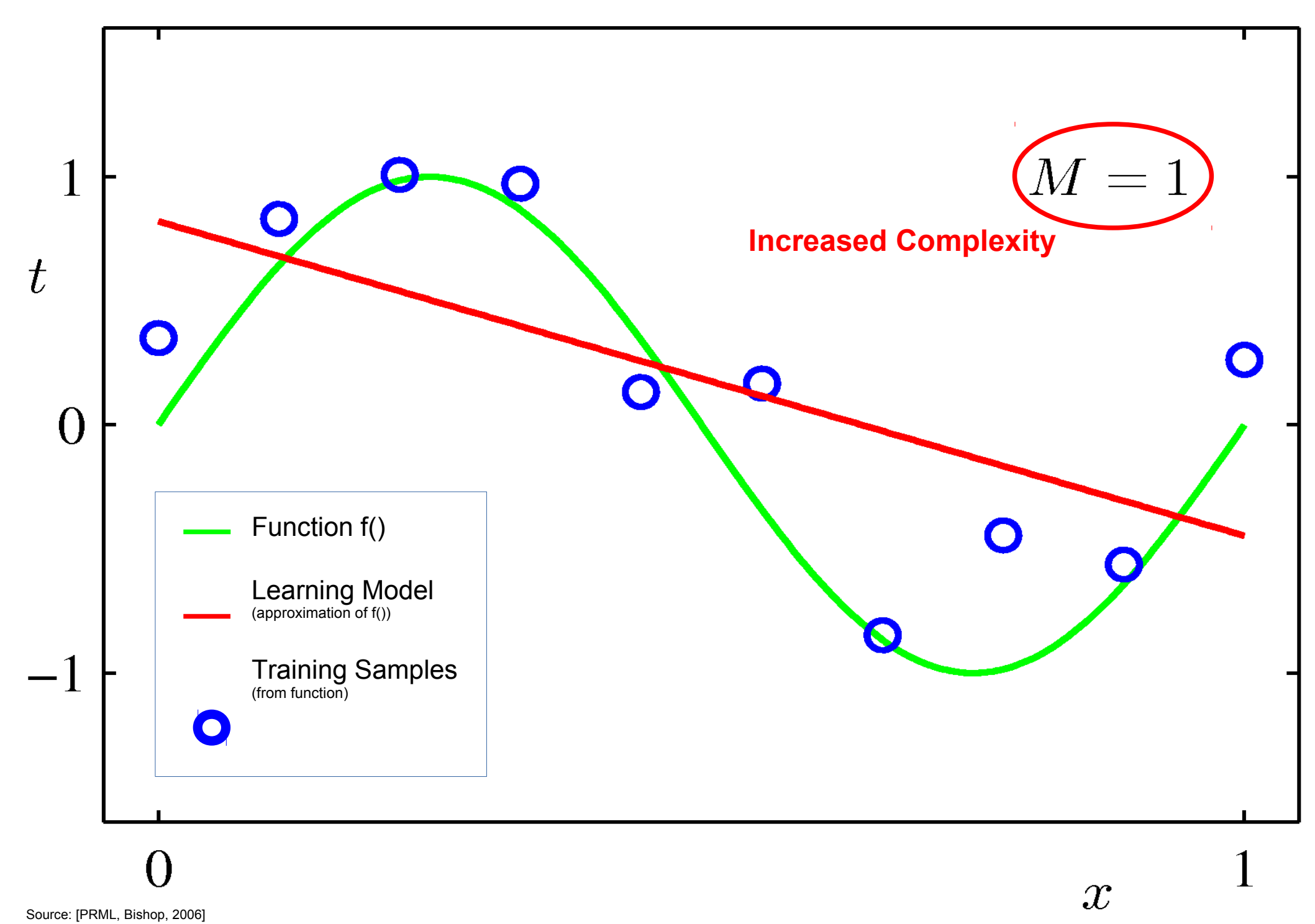
- Occam's Razor
  - "entia non sunt multiplicanda praeter necessitatem" **(latin!)**
  - "entities should not be multiplied beyond necessity" **(english)**
  - **"All things being equal, the simplest solution tends to be the best one"**
- **For Machine Learning :** prefer the simplest {model | hypothesis | …. tree | projection | network } that fits the data

14th-century English logician William of Ockham

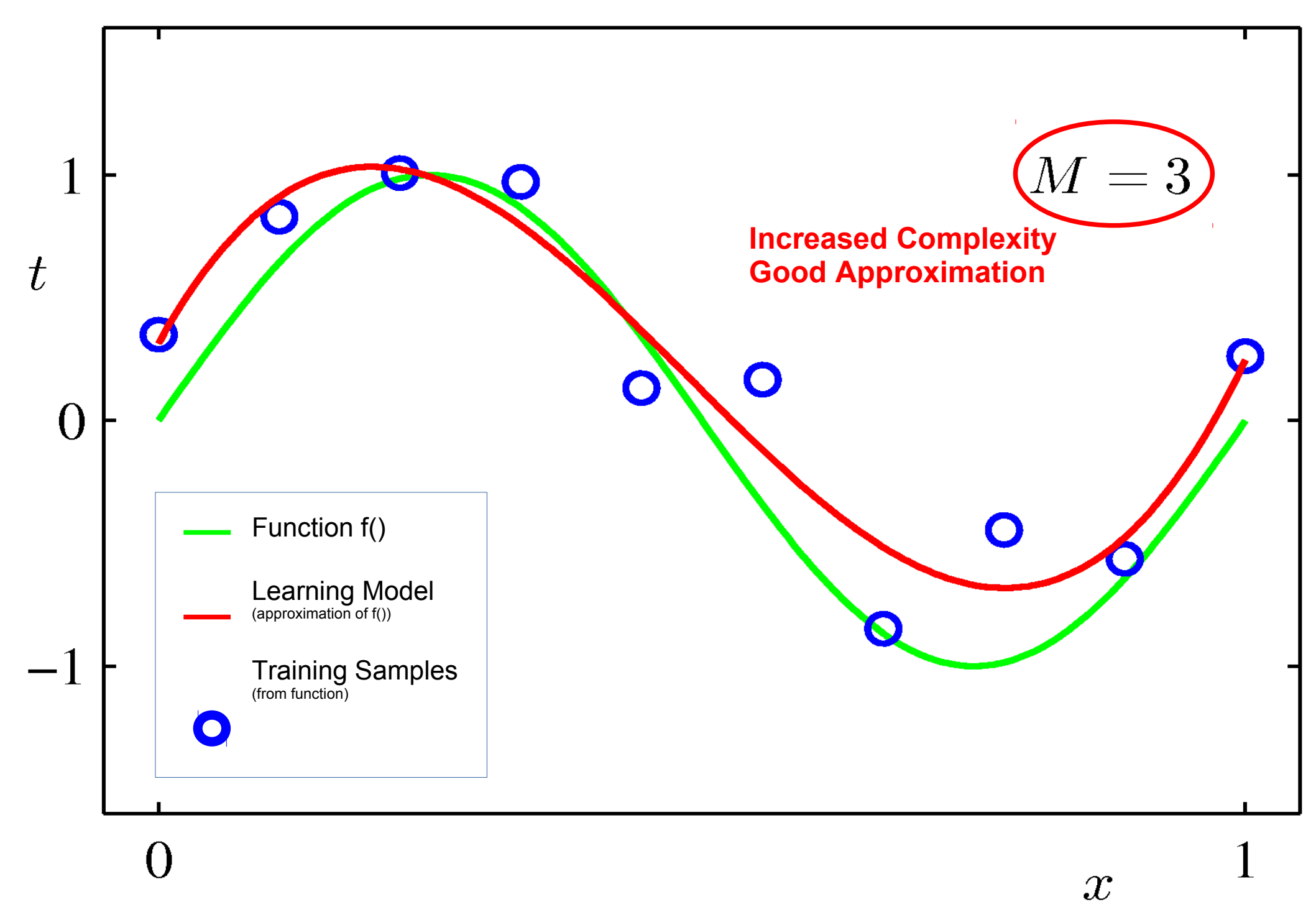
Graphical Example: function approximation (via regression)



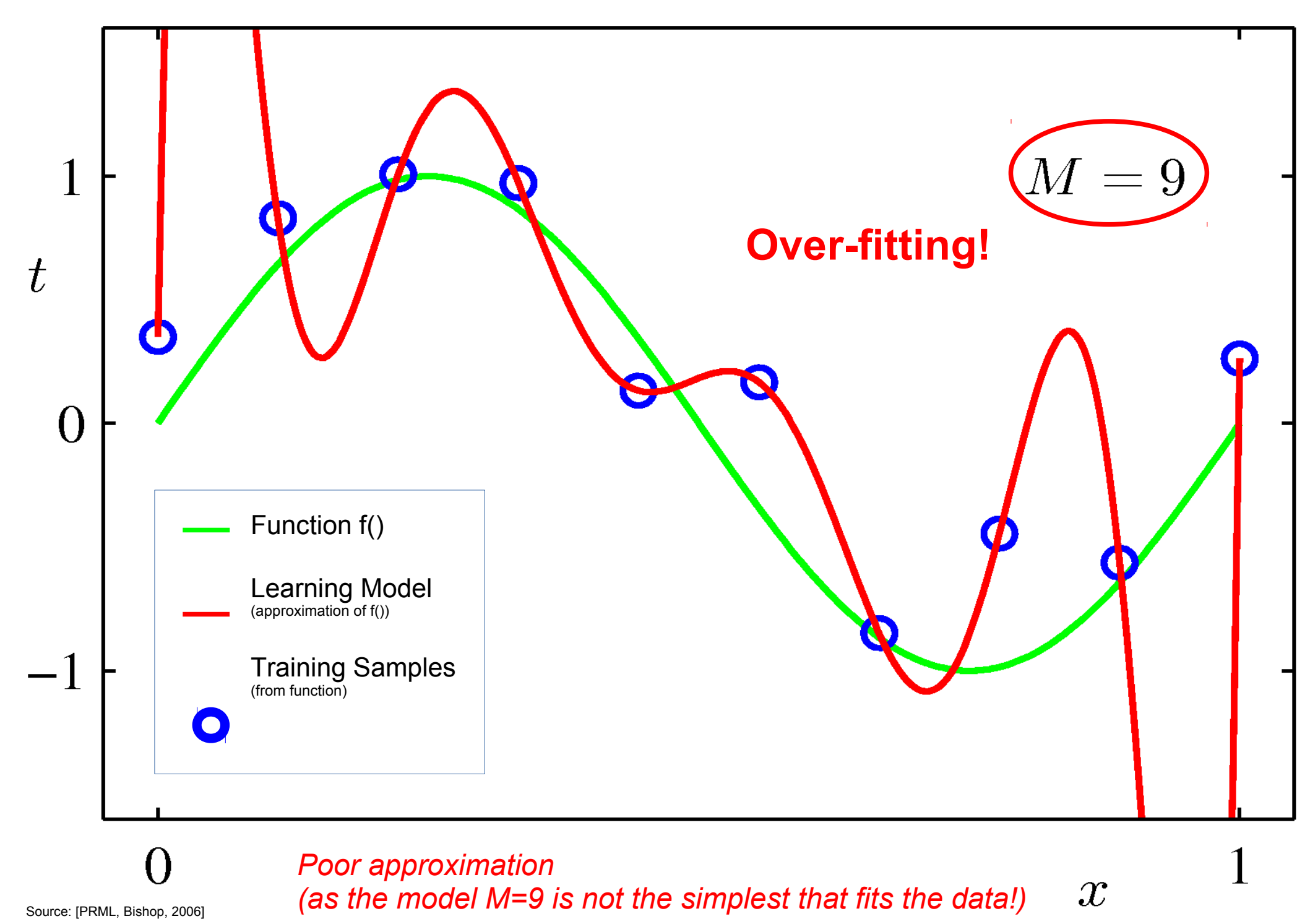
Source: [PRML, Bishop, 2006]



Source: [PRML, Bishop, 2006]



Source: [PRML, Bishop, 2006]

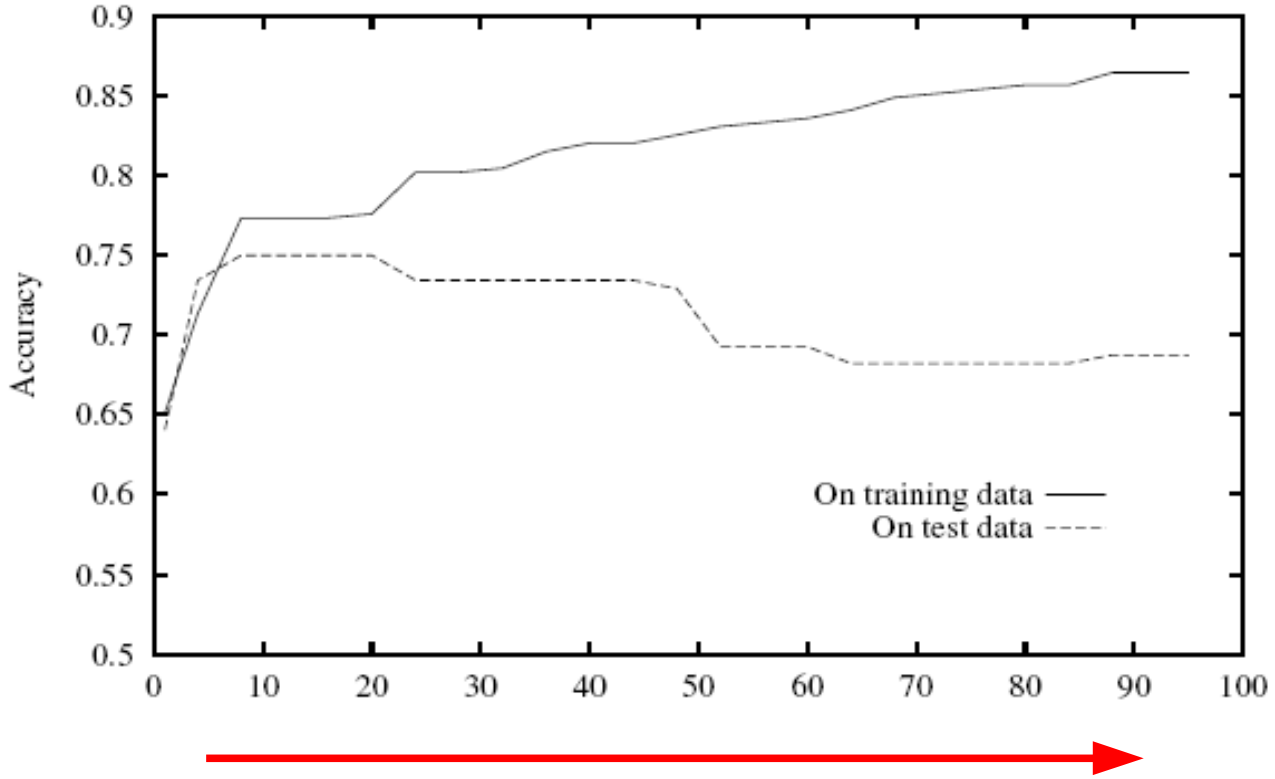


Poor approximation
(as the model M=9 is not the simplest that fits the data!)

Source: [PRML, Bishop, 2006]

How to spot over-fitting ...

- **Performance** on the **training** data **improves**
- **Performance** on the unseen **test** data **decreases**



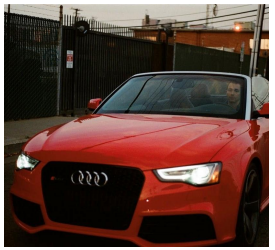
Increasing model complexity or training iterations

Loss *what* ?

Loss Functions: how good is our net ?

Suppose: 3 training examples, 3 classes.
With some parameters, W the scores

$f(x, W) = Wx$ are:


cat	**3.2**	1.3	2.2
car	5.1	**4.9**	2.5
frog	-1.7	2.0	**-3.1**

A **loss function** tells how good our current classifier is

Given a dataset of examples

$$\{(x_i, y_i)\}_{i=1}^{N}$$

Where x_i is image and
y_i is (integer) label

Loss over the dataset is a sum of loss over examples:

$$L = \frac{1}{N} \sum_i L_i(f(x_i, W), y_i)$$

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Softmax(): mapping output activation scores to probabilities

Want to interpret raw CNN output scores as **probabilities:**

scores → **probabilities**

$$s = f(x_i; W)$$

$$P(Y = k|X = x_i) = \frac{e^{s_k}}{\sum_j e^{s_j}}$$

use softmax() function

Probabilities must be >= 0

Probabilities must sum to 1

		exp		normalize	
cat	**3.2**	→	**24.5**	→	**0.13**
car	5.1	→	164.0	→	0.87
frog	-1.7	→	0.18	→	0.00

probabilities

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Softmax(): mapping output activation scores to probabilities

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cat	**3.2**	exp →	**24.5**	normalize →	**0.13**
car	5.1		164.0		0.87
frog	-1.7		0.18		0.00

compare ← **1.00** / 0.00 / 0.00

probabilities

Correct (probabilities)

Cross-entropy loss (diff. in correct probabilities)

$$L_i = -\log P(Y = y_i|X = x_i)$$

$$L_i = -\log\left(\frac{e^{sy_i}}{\sum_j e^{s_j}}\right)$$

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Regularization: prevent the net over-fitting

λ = regularization strength (hyperparameter)

$$L(W) = \underbrace{\frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, W), y_i)}_{\text{Data loss}} + \underbrace{\lambda R(W)}_{\text{Regularization}}$$

Data loss: Model predictions should match training data

Regularization: Prevent the model from doing *too* well on training data (i.e. overfitting)

→ Occam's Razor

Simple examples

L2 regularization: $R(W) = \sum_k \sum_l W_{k,l}^2$

L1 regularization: $R(W) = \sum_k \sum_l |W_{k,l}|$

Elastic net (L1 + L2): $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Regularization: prevent the net over-fitting

λ = regularization strength (hyperparameter)

avoid too large/small weights

$$L(W) = \frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, W), y_i) + \lambda R(W)$$

Data loss: Model predictions should match training data

Regularization: Prevent the model from doing *too* well on training data (i.e. overfitting)

Why regularize?

- Express preferences over weights
- Make the model *simple* so it works on test data
- Improve optimization by adding curvature

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

e.g. **L2 Regularization**: how and why ?

Expresses a preference for weight equality:

$$x = [1, 1, 1, 1]$$

$$w_1 = [1, 0, 0, 0]$$

$$w_2 = [0.25, 0.25, 0.25, 0.25]$$

L2 Regularization

$$R(W) = \sum_k \sum_l W_{k,l}^2$$

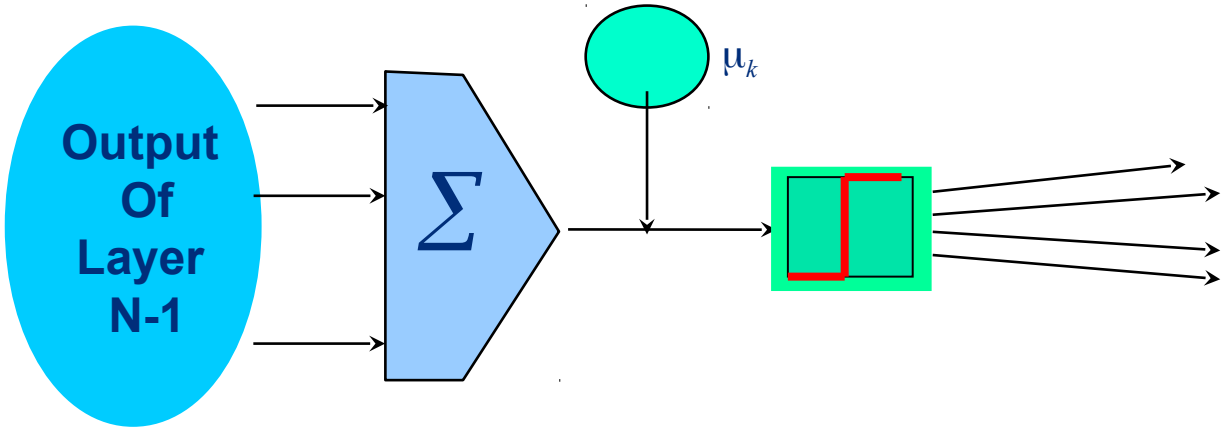
L2 regularization likes to "spread out" the weights

Where several W may have same classification result:

$$w_1^T x = w_2^T x = 1$$

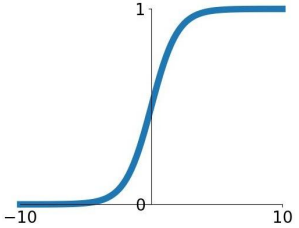
[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

… **in every node:** activation functions



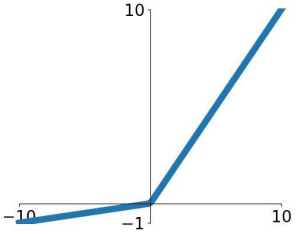
Sigmoid

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



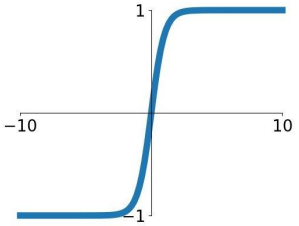
Leaky ReLU

$$\max(0.1x, x)$$



tanh

$$\tanh(x)$$

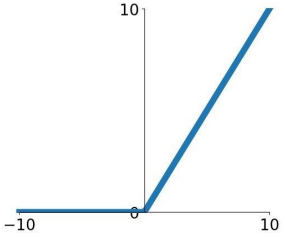


Maxout

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

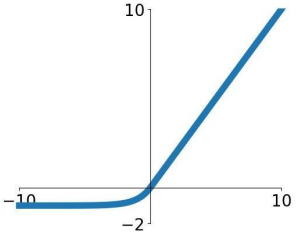
ReLU

$$\max(0, x)$$



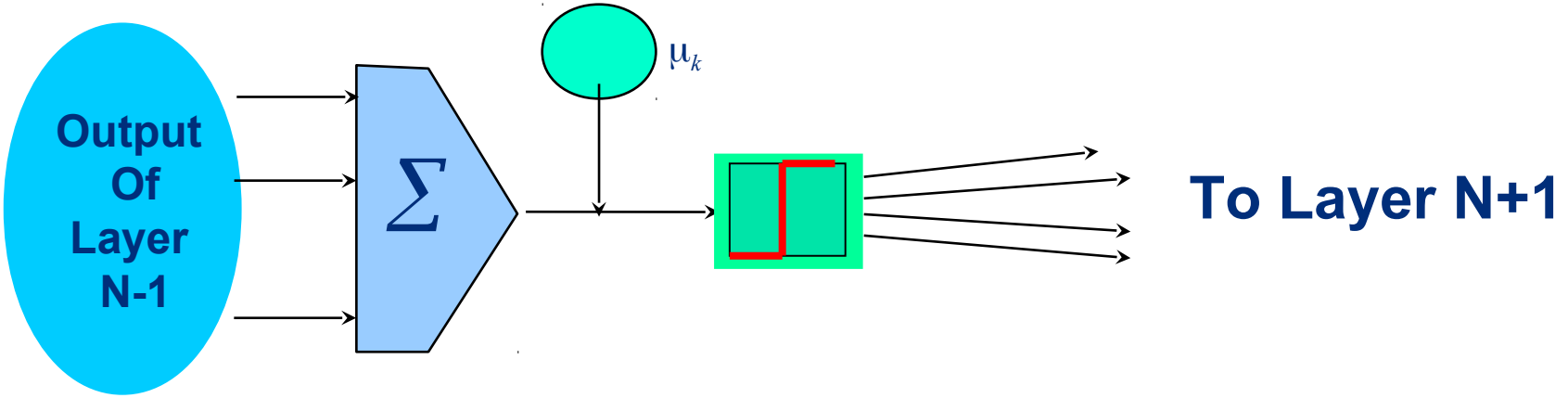
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

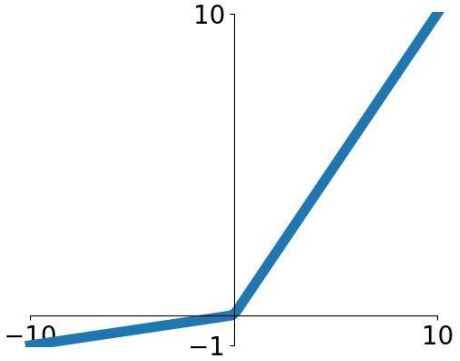
… in every node: activation functions



- Use ReLU. Be careful with your learning rates
- Try out Leaky ReLU / Maxout / ELU
- Try out tanh but don't expect much
- Don't use sigmoid

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Activation Functions – **ReLU variations**



Leaky ReLU

$$f(x) = \max(0.01x, x)$$

[Mass et al., 2013]
[He et al., 2015]

- Does **not saturate**
- Computationally **efficient**
- **Converges** much **faster** than sigmoid/tanh in practice! (e.g. 6x)
- **will not "die"** (like ReLU → 0 output)

also **Parametric Rectifier (PReLU)**

$$f(x) = \max(\alpha x, x)$$

backprop parameter

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

… but how **many network architectures** are we training?

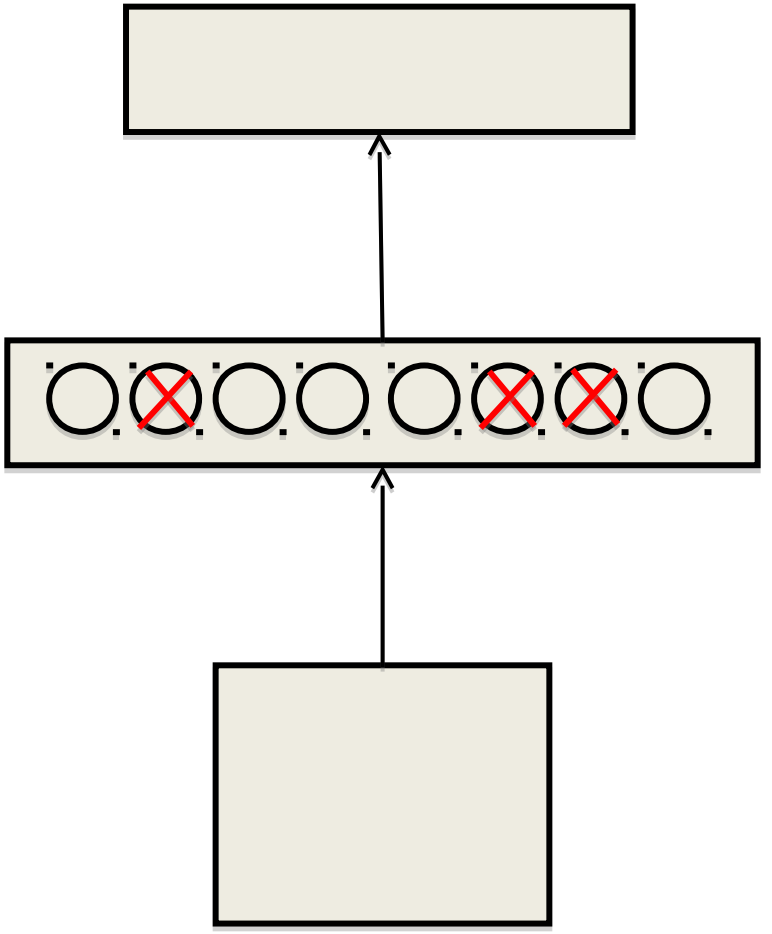
(are all the node weights updated in each backpropogation cycle?)

Dropout: efficient and robust training for large neural nets (Hinton et al., 2012 http://arxiv.org/abs/1207.0580)

- Consider a neural net with H hidden units
- Each time we present a **training** example within backpropogation, we **randomly omit each hidden unit** in *{all | some}* layers with probability 0.5.

  → we are randomly sampling from 2^H different architectures

- At **test time** – use all hidden units but **halve all the outgoing weights**
  - computes an approximate mean of the predictions of all 2^H models.



[This slide – adapted from: G. Hinton]

Get the **setup correct ...**

Input **pre-processing** – image data

e.g. consider CIFAR-10

dataset with [32,32,3] images

Zero-centre all the image pixel data inputs so backpropogation gradients are both +ve and -ve

Otherwise – major issue!

How -

- Subtract the mean image (e.g. AlexNet)
  (CIFAR - mean image = [32,32,3] array)
- Subtract per-channel mean (e.g. VGGNet)

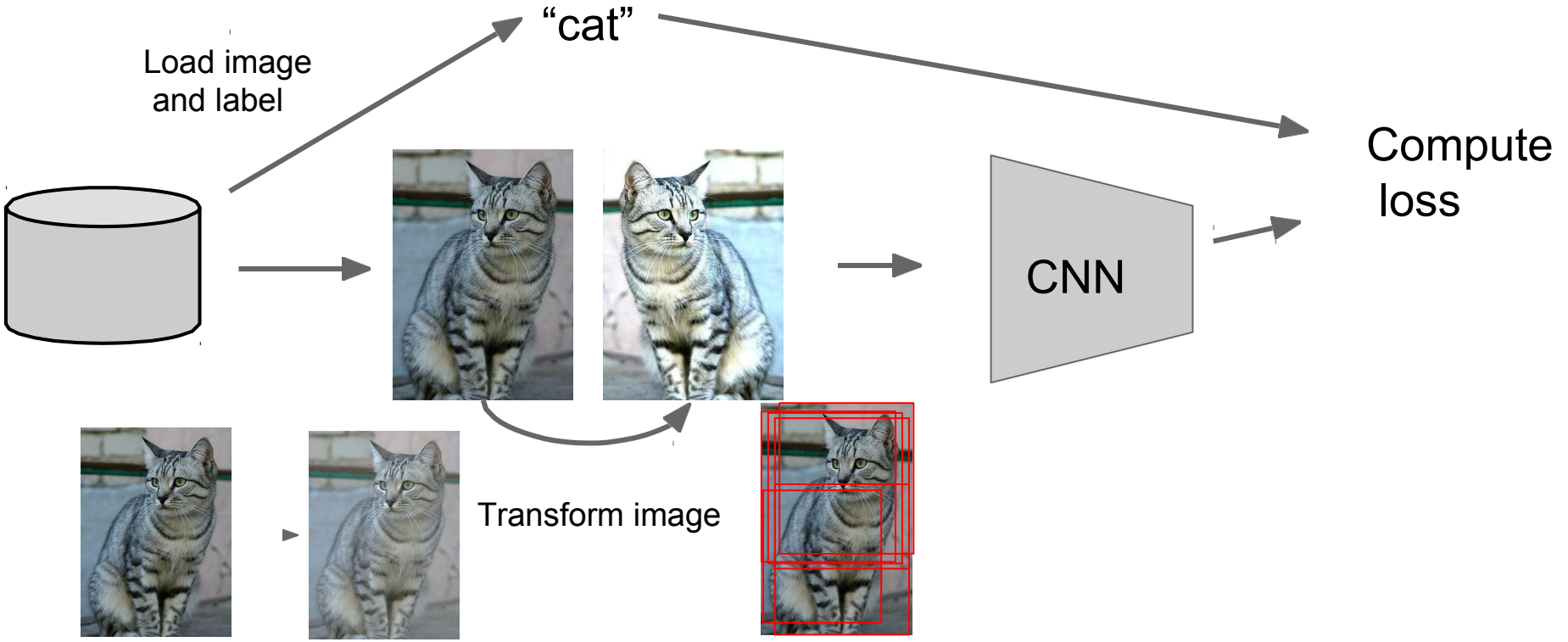
  (CIFAR - mean along each channel = 3 numbers)

Not common to normalize variance, to do PCA or whitening

Remember t**o zero-centre inputs at run-time (test) also!**

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Data **Augmentation** – *generate more data!*



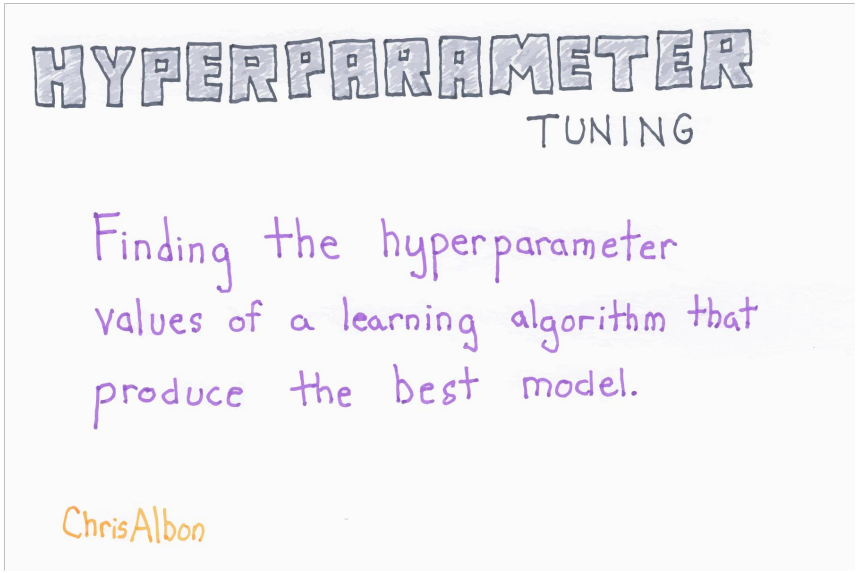
- Use random mix/combinations of : flipping, translation, rotation, stretching, shearing, illumination changes (log/exp/gamma transform), lens distortions, …(go crazy!)

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

And **finally ...**

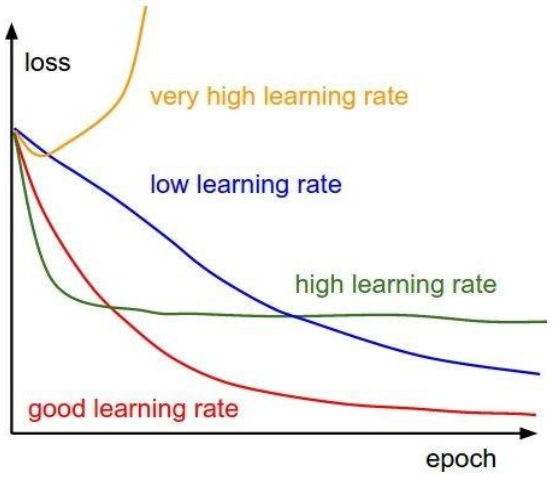
Hyper-parameters: within deep learning

- choices about the algorithm that we set rather than learn
  - e.g.
    - **drop-out** rate
    - **weight initialization**
    - **Backprop parameters ...**
    - …
    - **cross-validation** folds (?)



https://chrisalbon.com/machine_learning/model_selection/hyperparameter_tuning_using_grid_search/

- Highly problem-dependent.
  - must explore the hyper-parameter space (via glorified **"trial and error"**) to find optimal set



Key **Enablers**

(i.e. what changed to make all this happens)

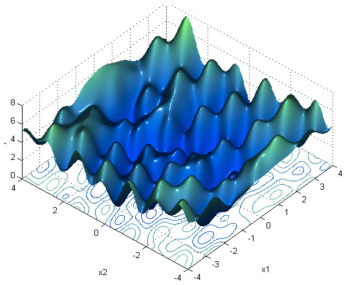
- As of now (~2012 → 2016+) we now have three key things that made deep learning possible:
  - **data** *(lots of it available)*

~14 million labeled images, 20k classes

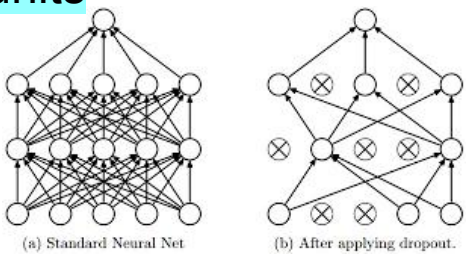
  - low-cost, **high-performance GPU hardware**
    (to train larger networks than before)
  - **key algorithmic insights** to backpropogation **training**
    (to train networks more efficiently + guard against local minima and overfitting)

Neural Networks – *a deep reprize*

- Recent work shows **local minima are less of a problem than thought**
  (Pascanu et al., 2014, Dauphin et. al., 2014, Choromanska et al., 2015)
  - local minima dominate low dimensions but saddle points (ridges) dominate high dimensions
  - most local minima are close to global minima in high dimensions
    - … *and* **deep neural networks use a very high dimensional weight space**



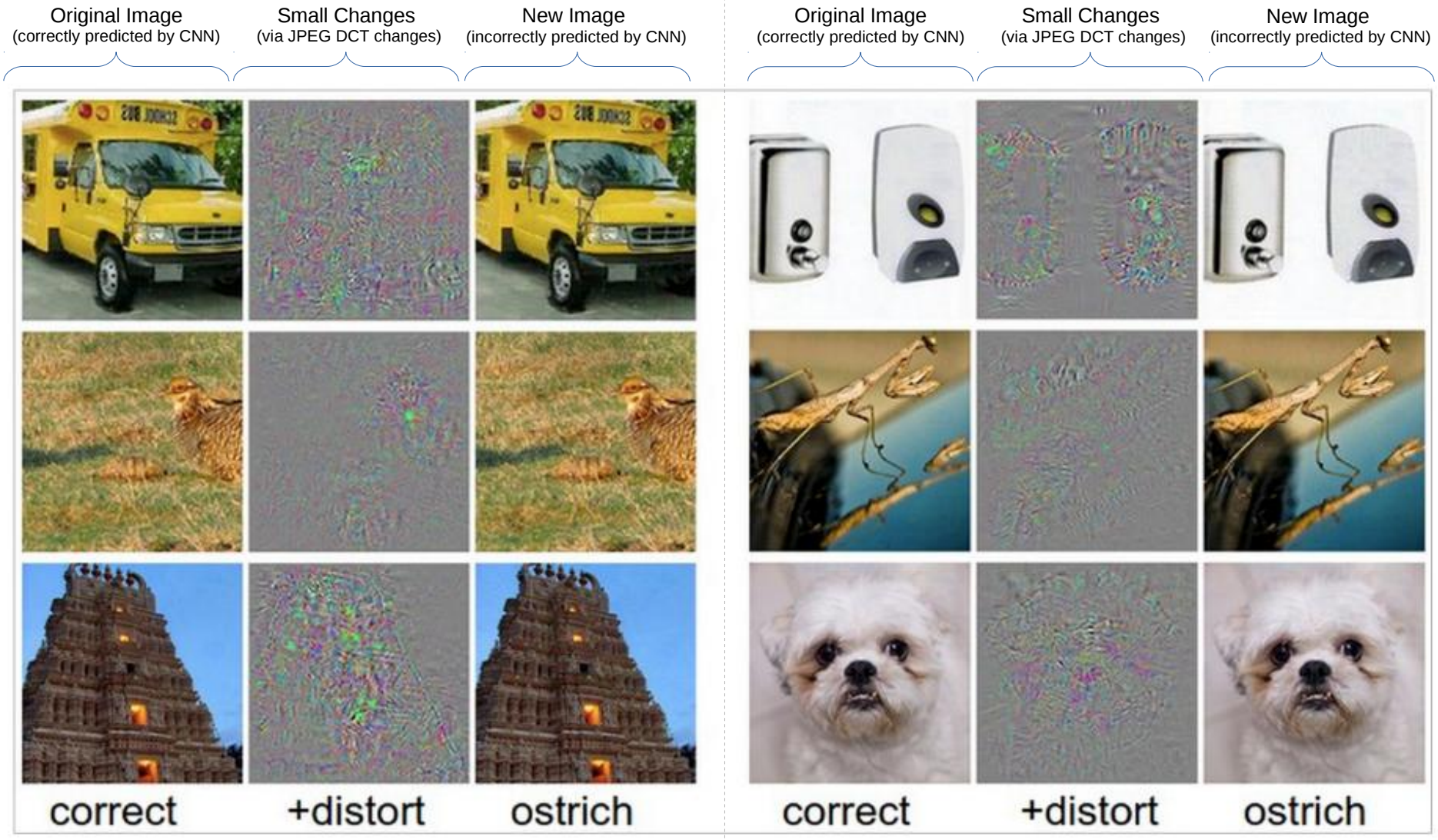
- **Advances in training:** use of **drop-out** to regularize the weights in the globally connected layers (which contain most of the parameters)
  - **dropout:** half of the hidden units in a layer are randomly removed for each training example.
  - **effect:** stops hidden units from relying too much on other hidden units (hence **reduces likelihood of over-fitting**)



Beyond Classification ...

(applications in computer vision beyond classification include : Detection Segmentation, Regression, Pose estimation, Image Synthesis ...)

Are they always right ? - fooling CNNs



Take a correctly classified image (left image in both columns), and add a tiny distortion (middle) to fool the ConvNet with the resulting image (right).

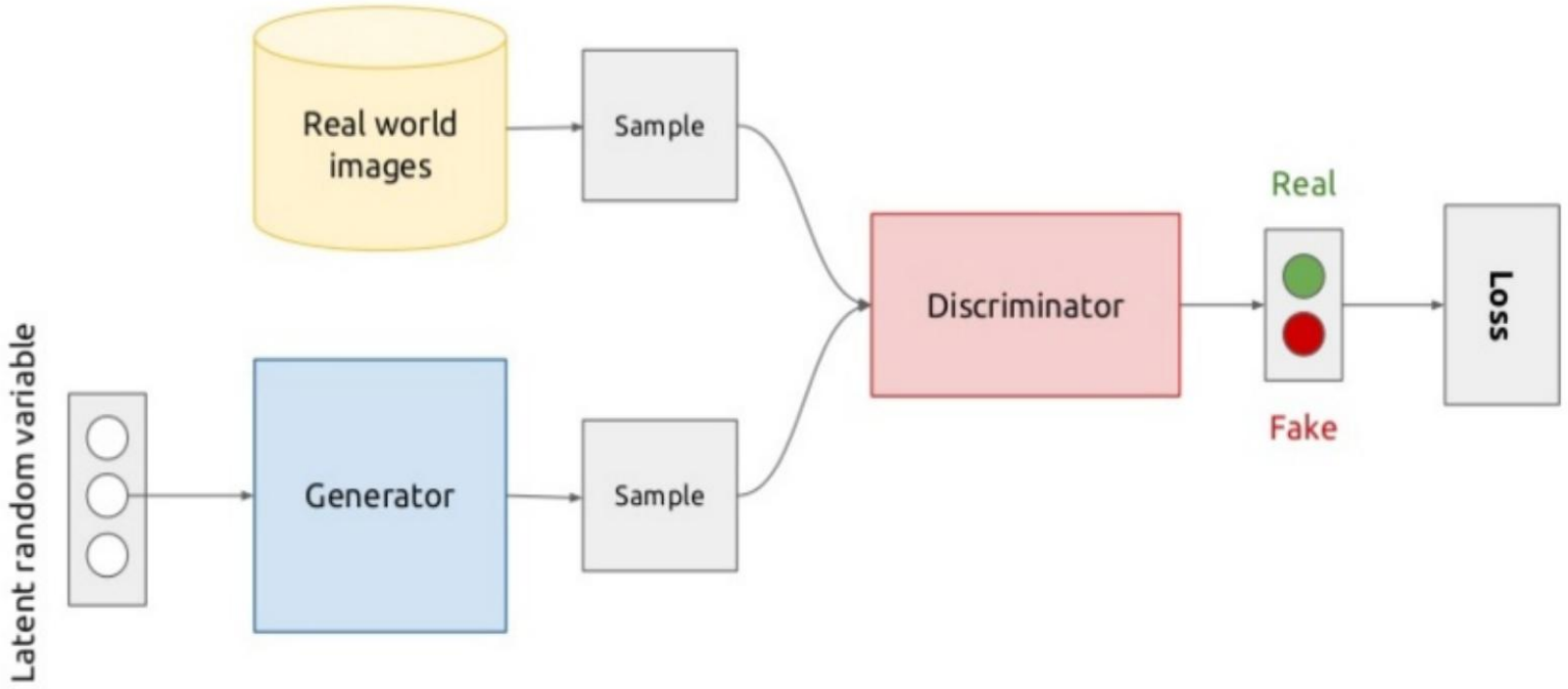
Reference: Intriguing properties of neural networks [Szegedy ICLR 2014]

Press article: http://www.i-programmer.info/news/105-artificial-intelligence/7352-the-flaw-lurking-in-every-deep-neural-net.html

… in today's terminology we call these **adversarial examples**

… which brings us on to a whole new sub-topic of deep learning

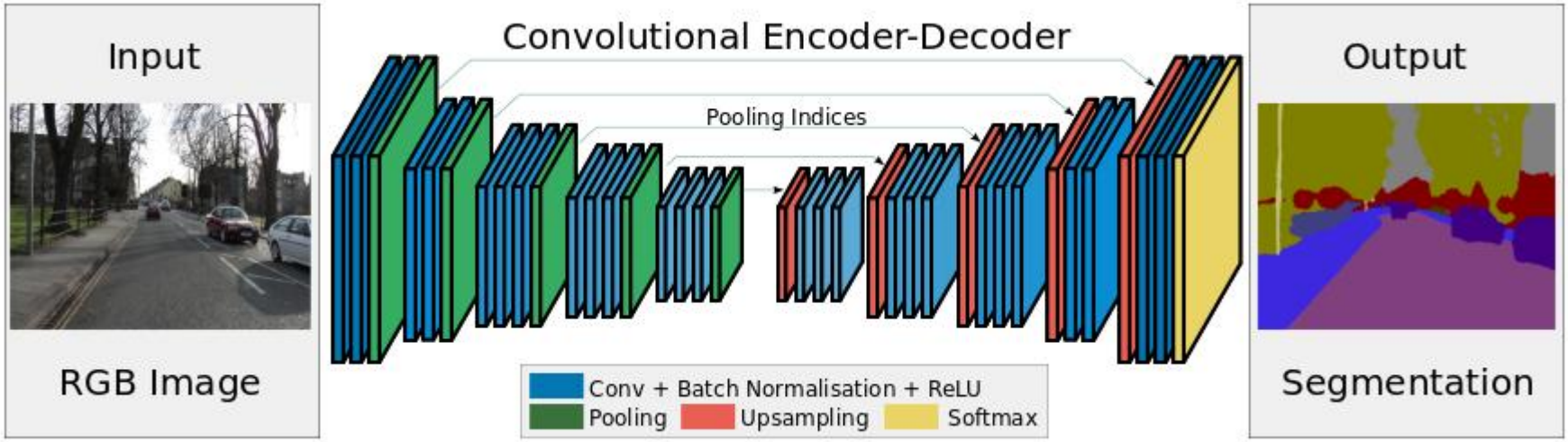
Generative Adversarial Networks (GAN)



[Goodfellow et al., 2014
https://arxiv.org/abs/1406.2661]

- train two models:
  - one to generate some sort of fake examples from random noise (or some conditioned distribution)
  - one to discern fake model examples from real examples
- **Many applications** in improving deep network performance

Example: semantic pixel labelling via SegNet ….



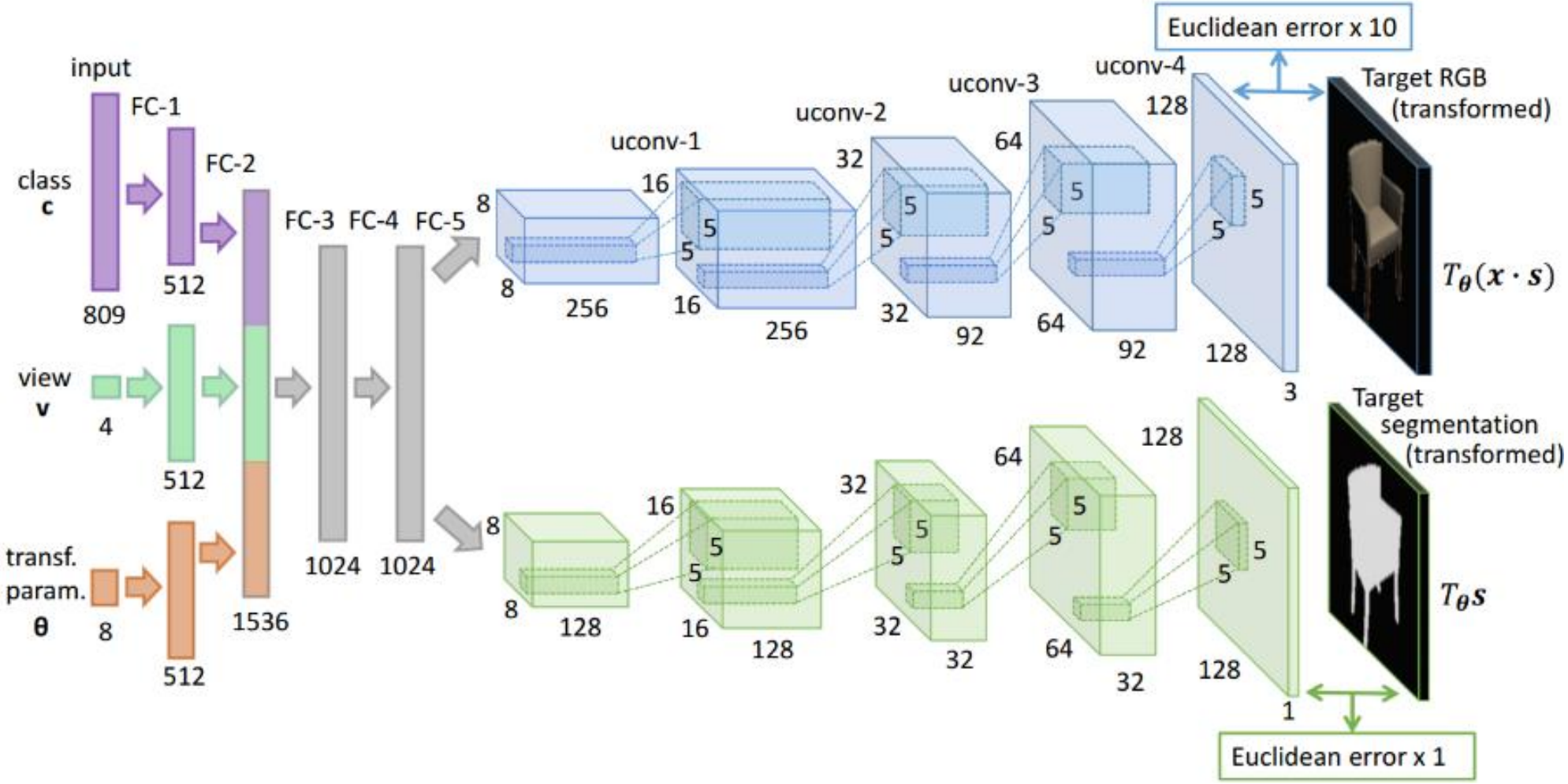
- Application to Semantic Image Segmentation via CNN
  - use of per complex network to perform per-pixel classification by object type (i.e. semantic pixel labelling)
  - Encoder ↔ Decoder architecture (but same concepts of layer types)

http://www.youtube.com/embed/e9bHTlYFwhg?rel=0

Vijay Badrinarayanan, Alex Kendall and Roberto Cipolla "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation." arXiv preprint arXiv:1511.00561, 2015. http://arxiv.org/abs/1511.00561

http://mi.eng.cam.ac.uk/projects/segnet/

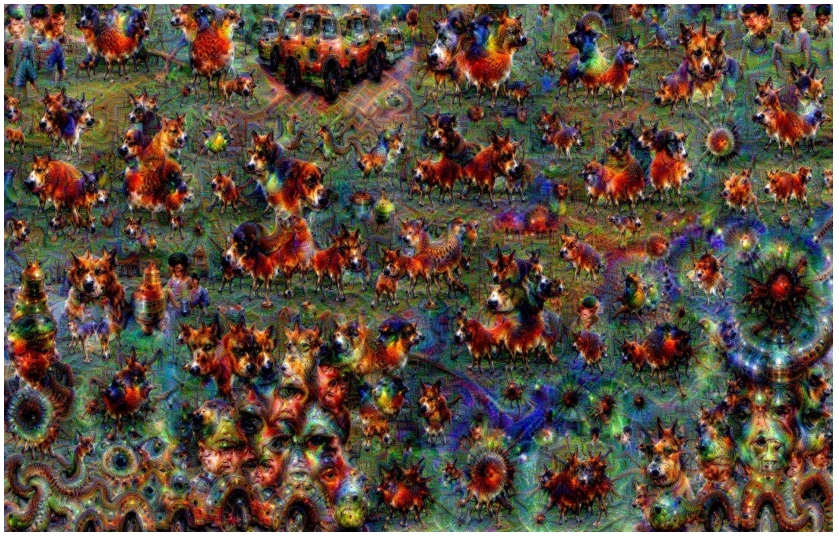
CNN for Image Generation (synthesis)

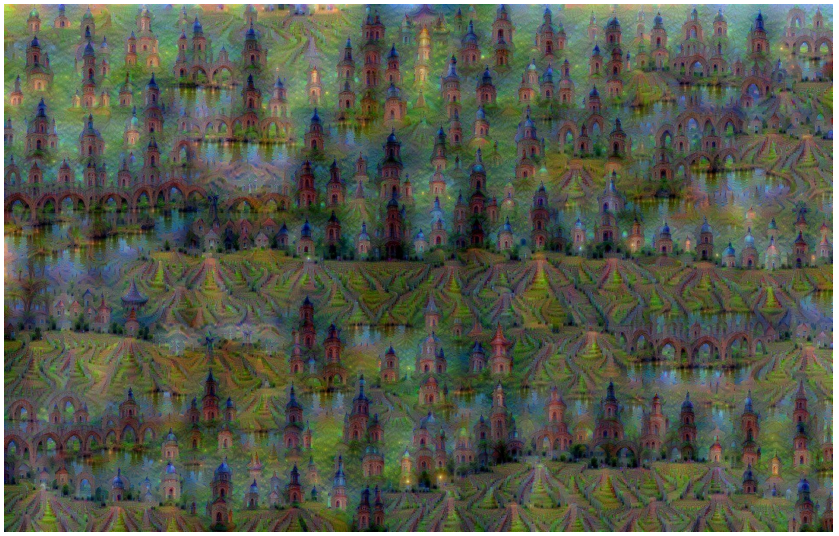


Video: http://lmb.informatik.uni-freiburg.de/Publications/2015/DB15/Generate_Chairs_mov_morphing.avi

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

Style Transfer ….





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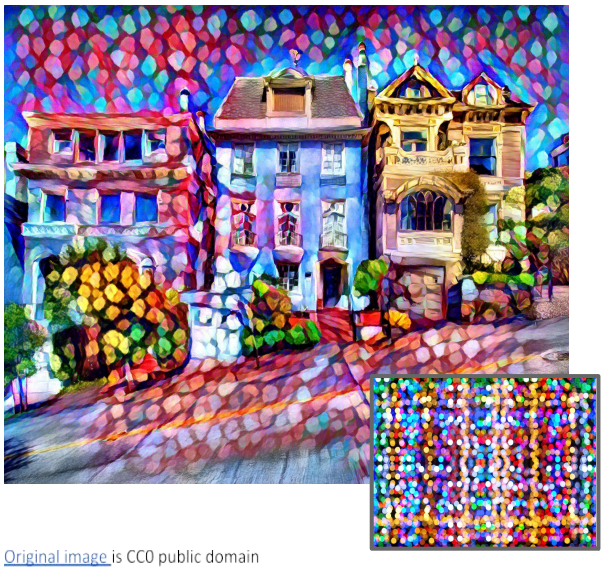

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Starry Night and Tree Roots by Van Gogh are in the public domain
Bokeh image is in the public domain
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Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016
Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Images ↔ text ….

No errors

A white teddy bear sitting in the grass

Minor errors

A man in a baseball uniform throwing a ball

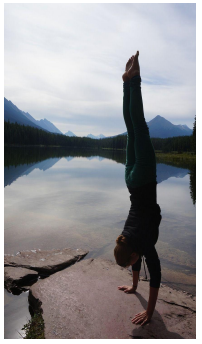
Somewhat related

A woman is holding a cat in her hand

[Vinyals et al., 2015]
[Karpathy and Fei-Fei, 2015]

A man riding a wave on top of a surfboard

A cat sitting on a suitcase on the floor



A woman standing on a beach holding a surfboard

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https://pixabay.com/en/luggage-antique-cat-1643010/
https://pixabay.com/en/teddy-plush-bears-cute-teddy-bear-1623436/
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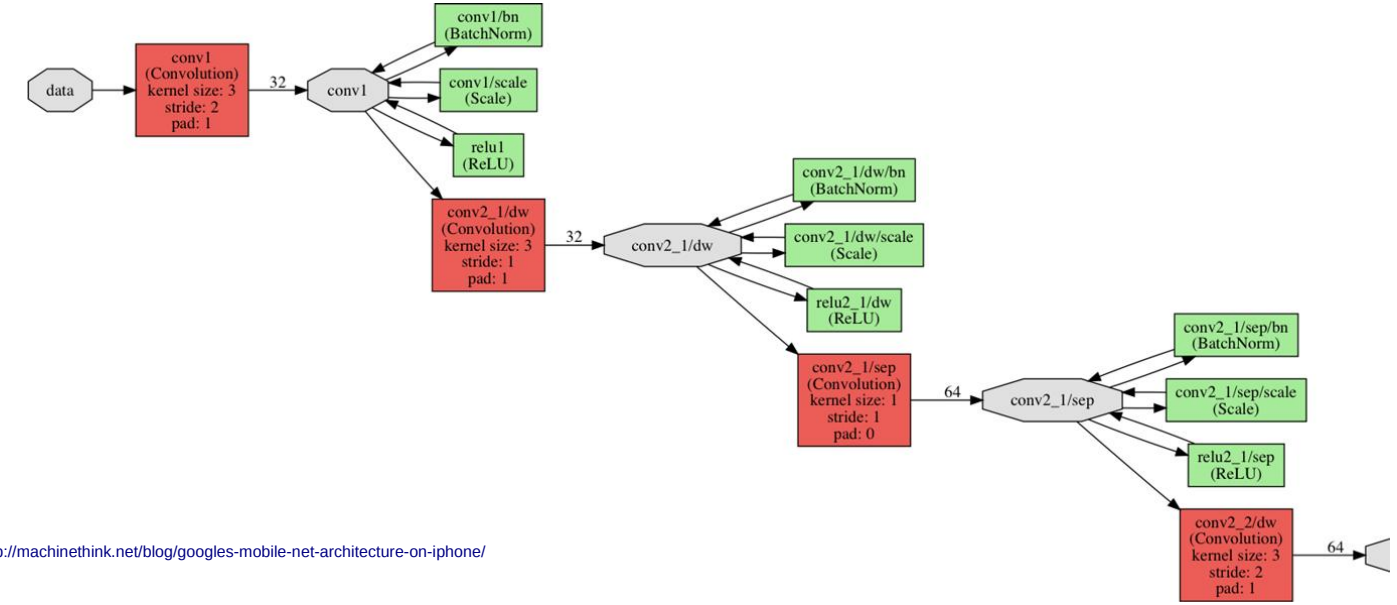
Captions generated by Justin Johnson using Neuraltalk2

[This slide – adapted from: Fei-Fei Li & Justin Johnson & Serena Yeung]

Efficient Networks – *MobileNets* (et al.)

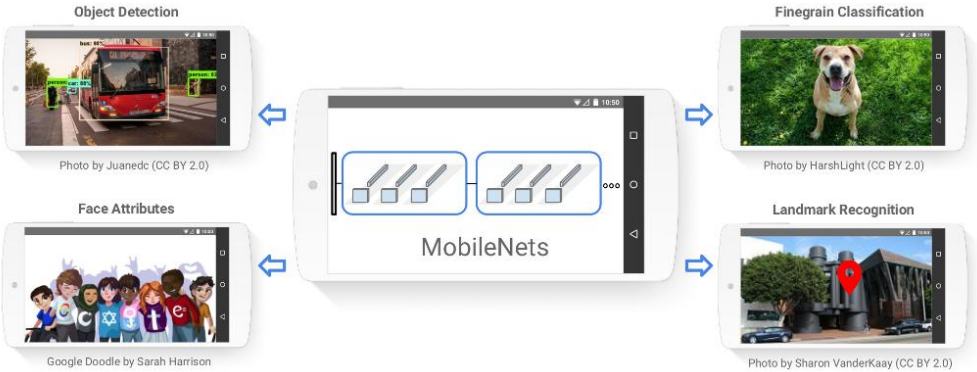


http://machinethink.net/blog/googles-mobile-net-architecture-on-iphone/

- **MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications**

  Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, Hartwig Adam (Google)

  https://arxiv.org/abs/1704.04861



- **MobileNetV2: Inverted Residuals and Linear Bottlenecks**

  Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, Liang-Chieh Chen

  CVPR 2018

  https://openaccess.thecvf.com/content_cvpr_2018/CameraReady/3427.pdf