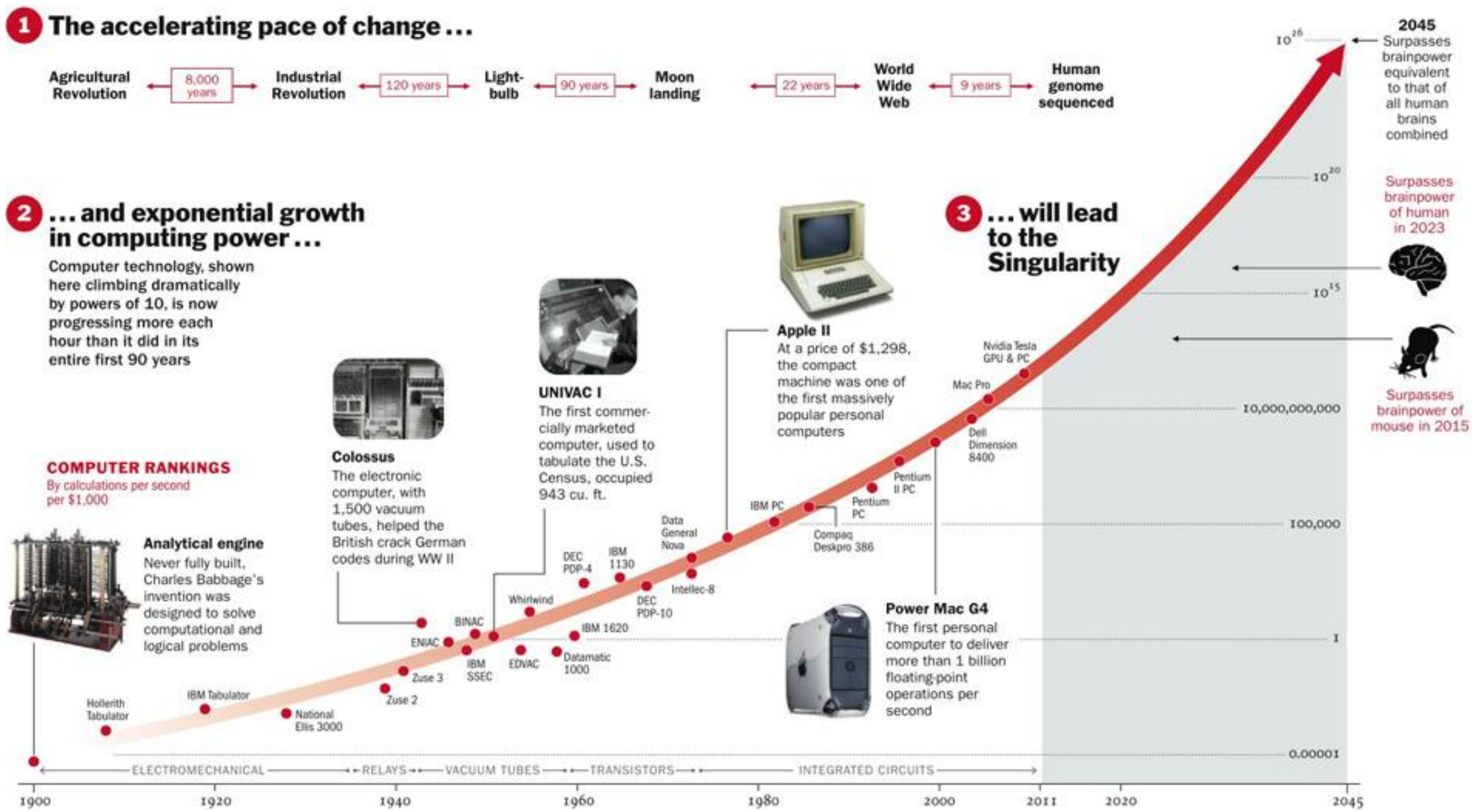
Fundamentals of Deep (Artificial) Neural Networks (DNN)

Greg Tsagkatakis

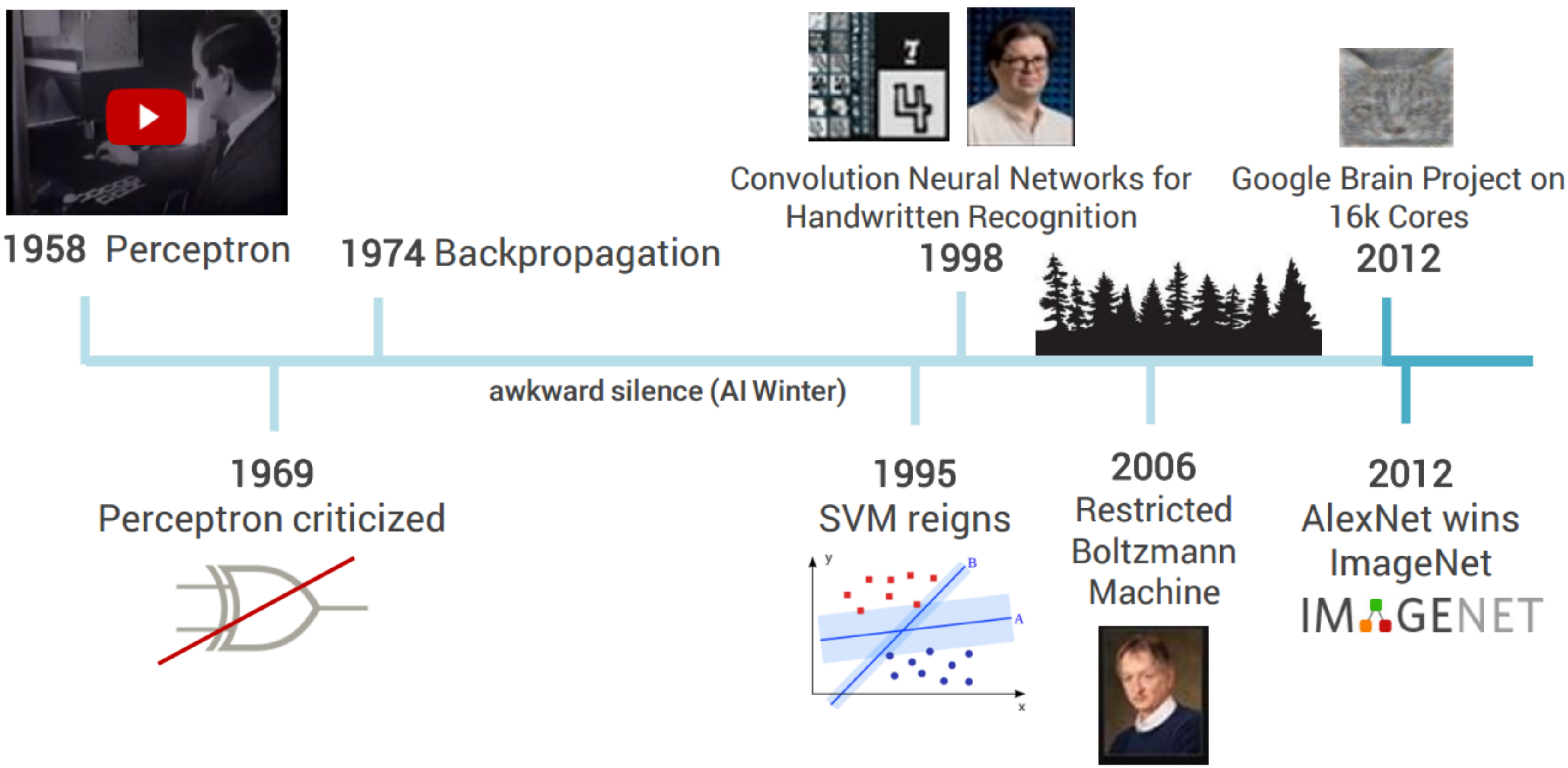
CSD - UOC

ICS - FORTH

Accelerated growth

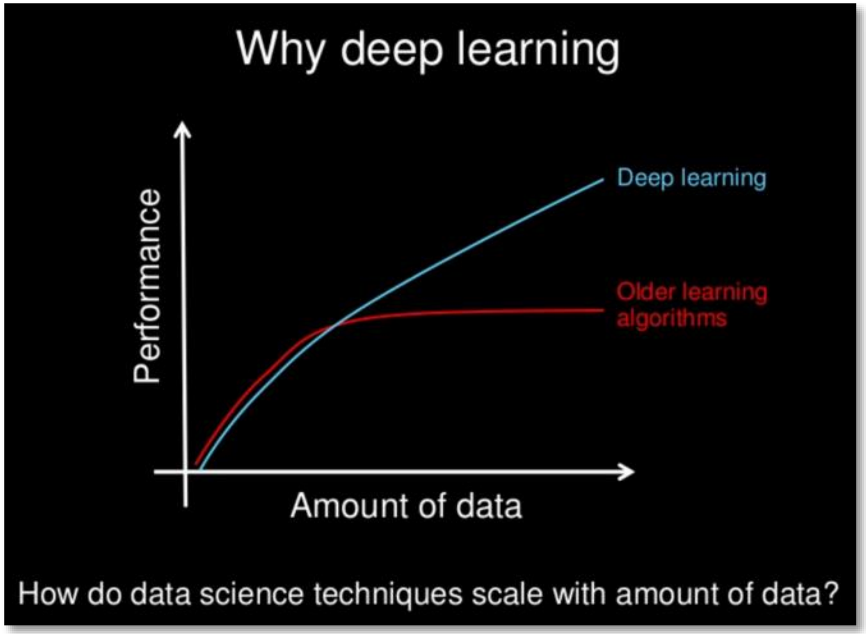


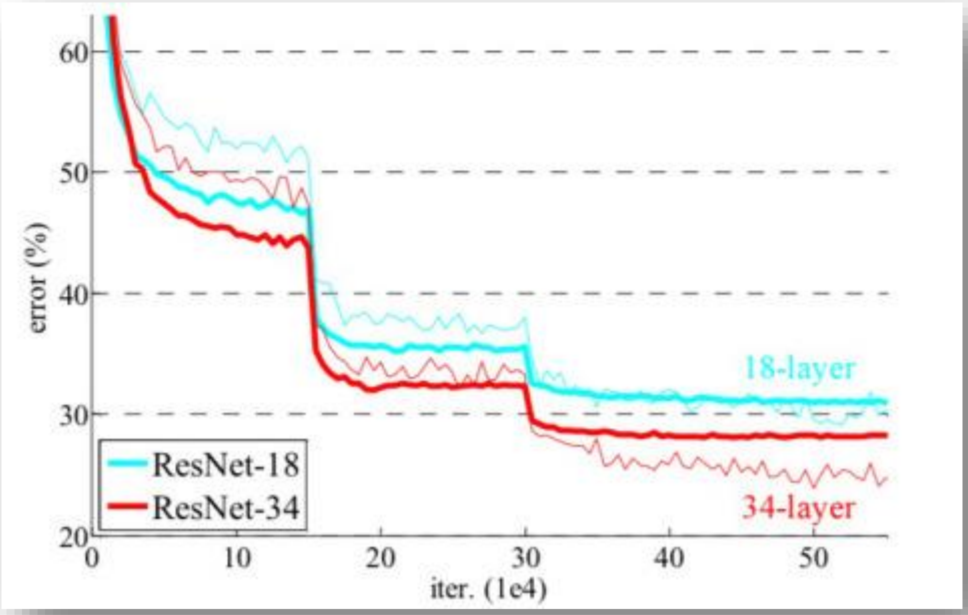
Brief history of DL



Why Today?

Lots of Data

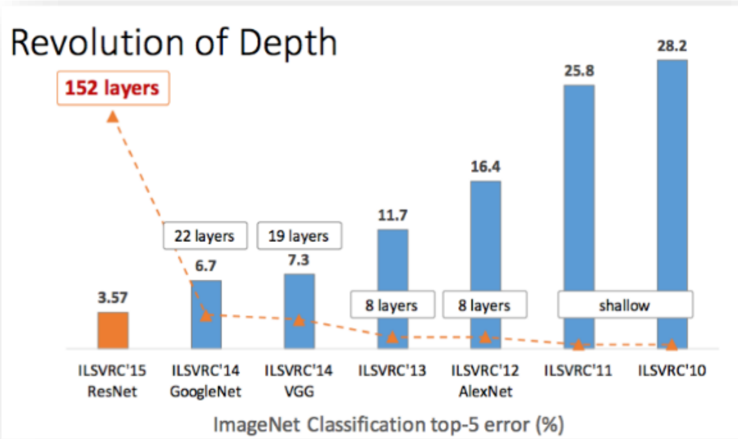


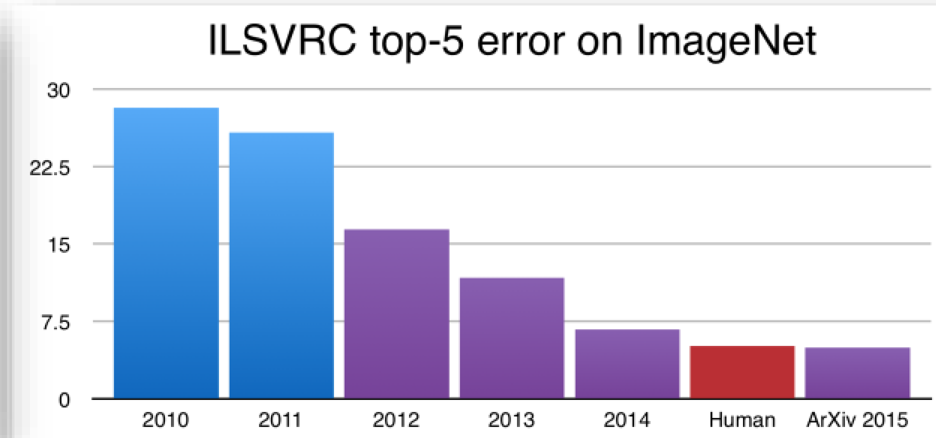


Why Today?

Lots of Data

Deeper Learning



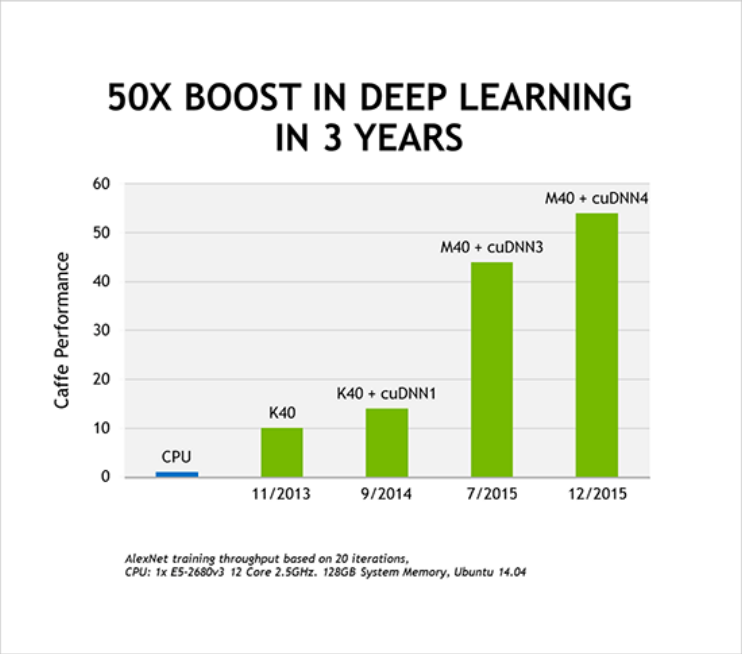


Why Today?

Lots of Data

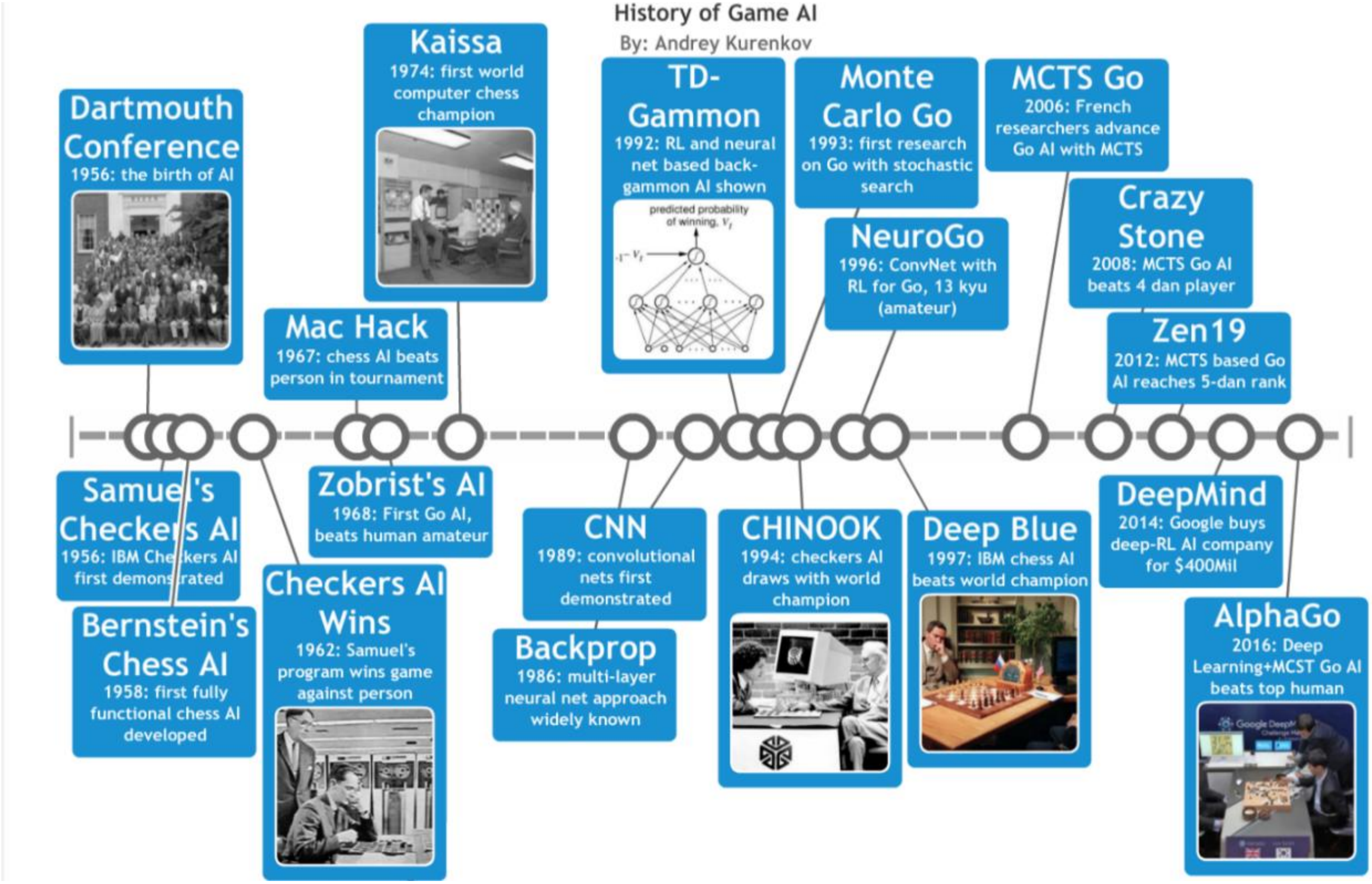
Deep Learning

More Power



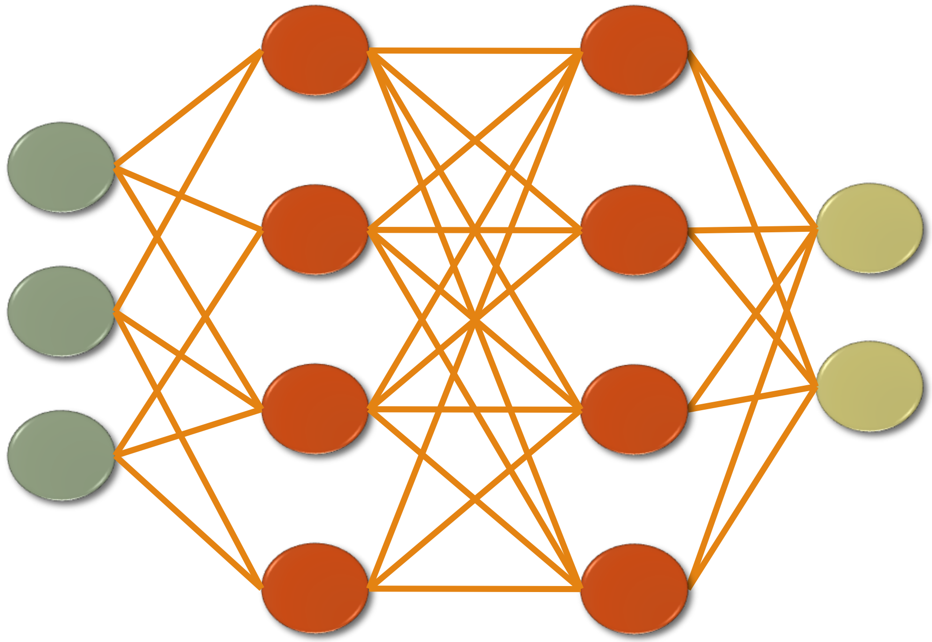
https://blogs.nvidia.com/blog/2016/01/12/accelerating-ai-artificial-intelligence-gpus/
https://www.slothparadise.com/what-is-cloud-computing/

Apps: Gaming


History of Game AI
By: Andrey Kurenkov
Dartmouth Conference
1956: the birth of AI
Kaissa
1974: first world computer chess champion
TD-Gammon
1992: RL and neural net based back-gammon AI shown
predicted probability of winning, V_t
Monte Carlo Go
1993: first research on Go with stochastic search
MCTS Go
2006: French researchers advance Go AI with MCTS
Crazy Stone
2008: MCTS Go AI beats 4 dan player
NeuroGo
1996: ConvNet with RL for Go, 13 kyu (amateur)
Mac Hack
1967: chess AI beats person in tournament
Zen19
2012: MCTS based Go AI reaches 5-dan rank
Samuel's Checkers AI
1956: IBM Checkers AI first demonstrated
Zobrist's AI
1968: First Go AI, beats human amateur
CNN
1989: convolutional nets first demonstrated
CHINOOK
1994: checkers AI draws with world champion
Deep Blue
1997: IBM chess AI beats world champion
DeepMind
2014: Google buys deep-RL AI company for $400Mil
Bernstein's Chess AI
1958: first fully functional chess AI developed
Checkers AI Wins
1962: Samuel's program wins game against person
Backprop
1986: multi-layer neural net approach widely known
AlphaGo
2016: Deep Learning+MCST Go AI beats top human

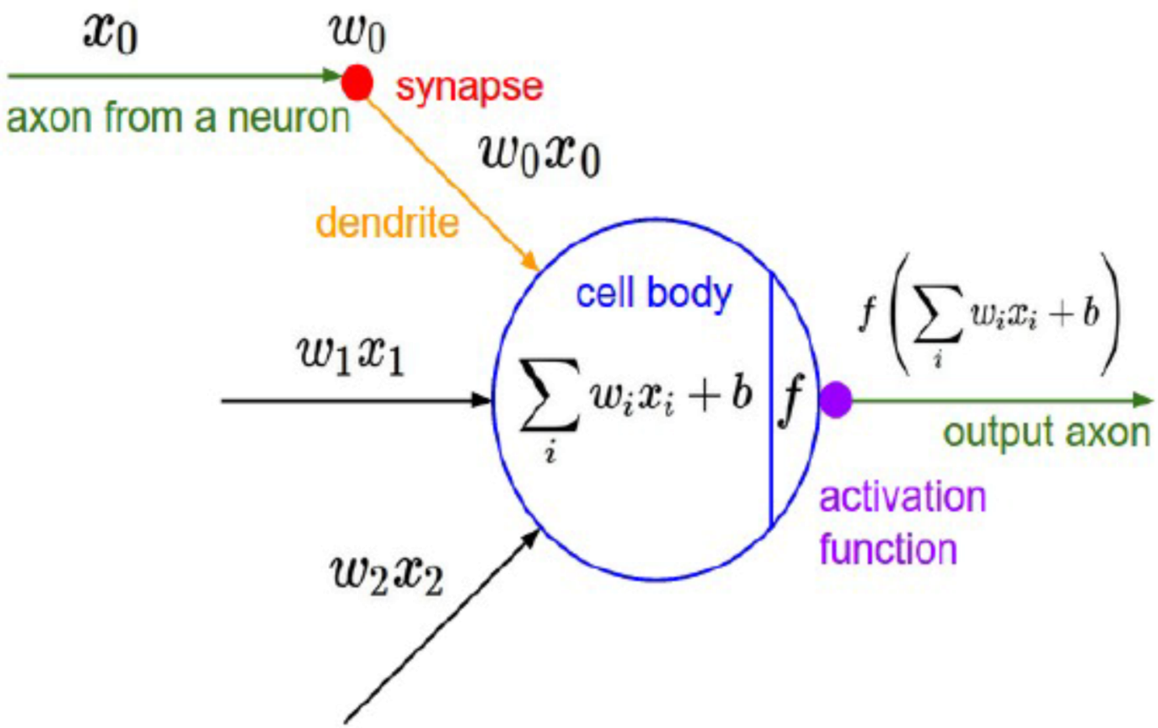
Key components of ANN

- Architecture (input/hidden/output layers)



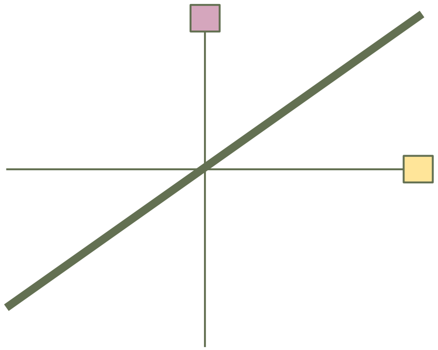
Key components of ANN

- Architecture (input/hidden/output layers)
- Weights

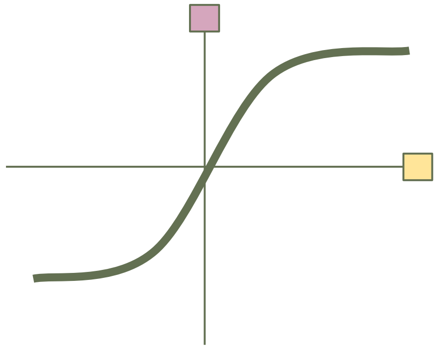


Key components of ANN

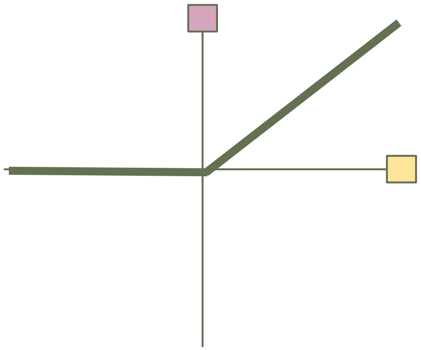
- Architecture (input/hidden/output layers)
- Weights
- Activations



LINEAR



LOGISTIC / SIGMOIDAL / TANH



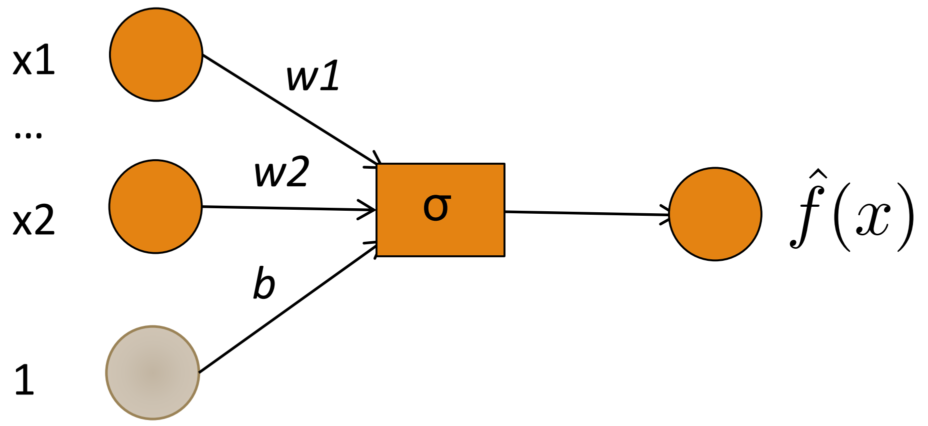
RECTIFIED LINEAR (ReLU)

Perceptron: an early attempt

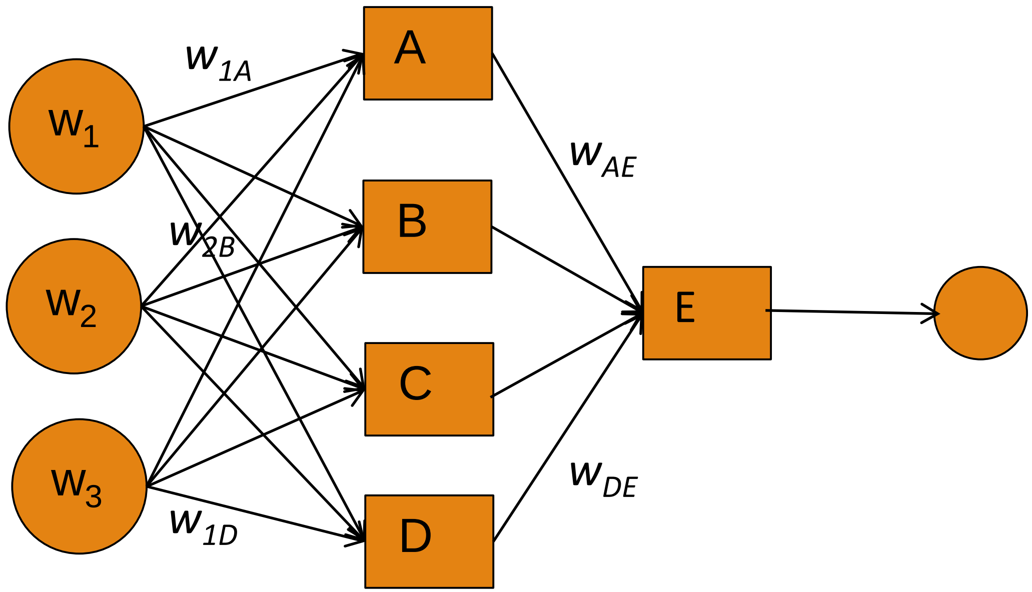
Activation function

$$\hat{f}(x) = \sigma(w \cdot x + b) \qquad \sigma(y) = \begin{cases} 1, & y > 0 \\ 0, & o/w \end{cases}$$

Need to tune w and b



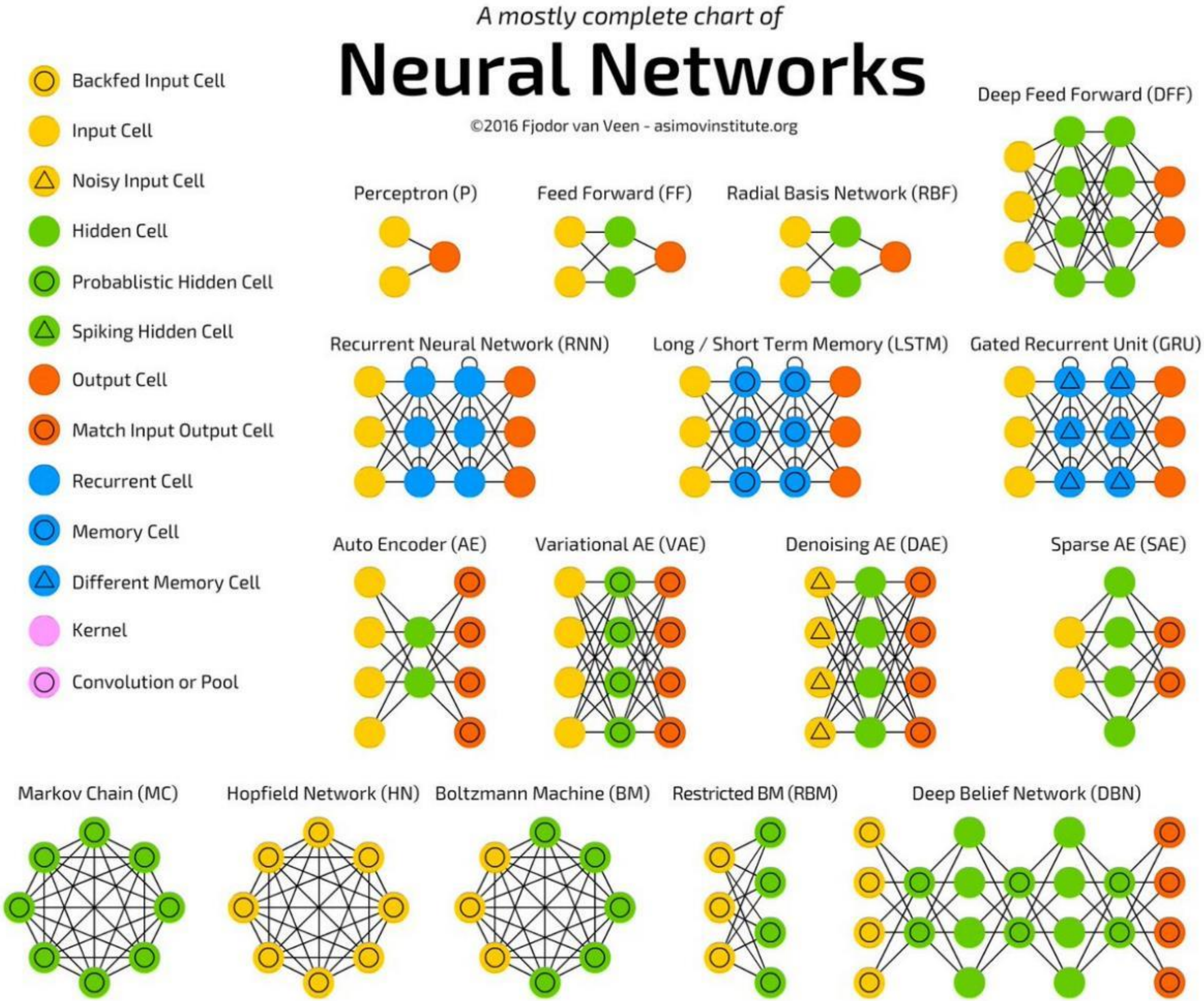
Multilayer perceptron



We just added a neuron layer!

We just introduced non-linearity!

A neuron is of the form **σ(w.x + b)** where **σ** is an *activation* function



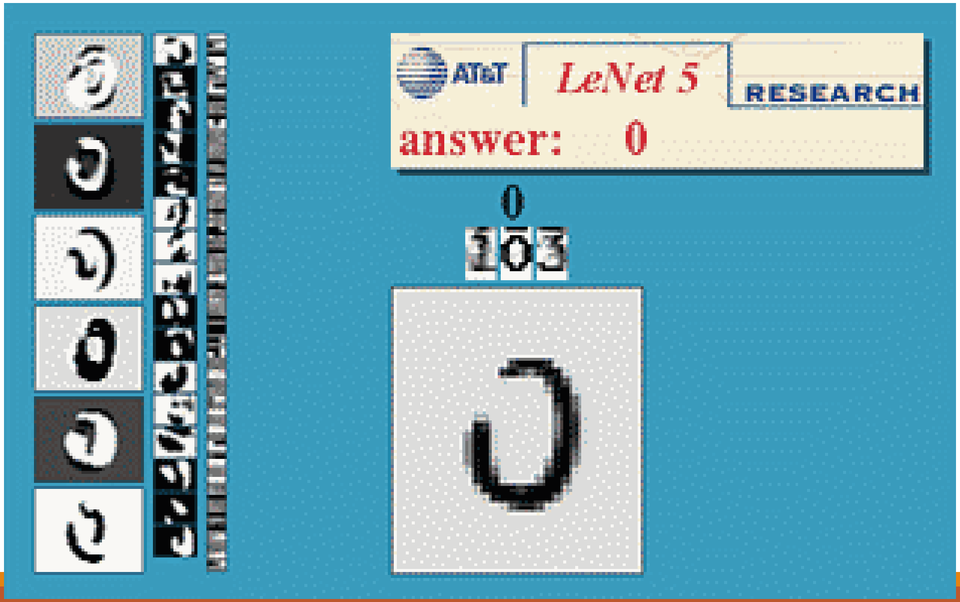
[Sasen Cain (@spectralradius)]

Training & Testing

Training: determine weights

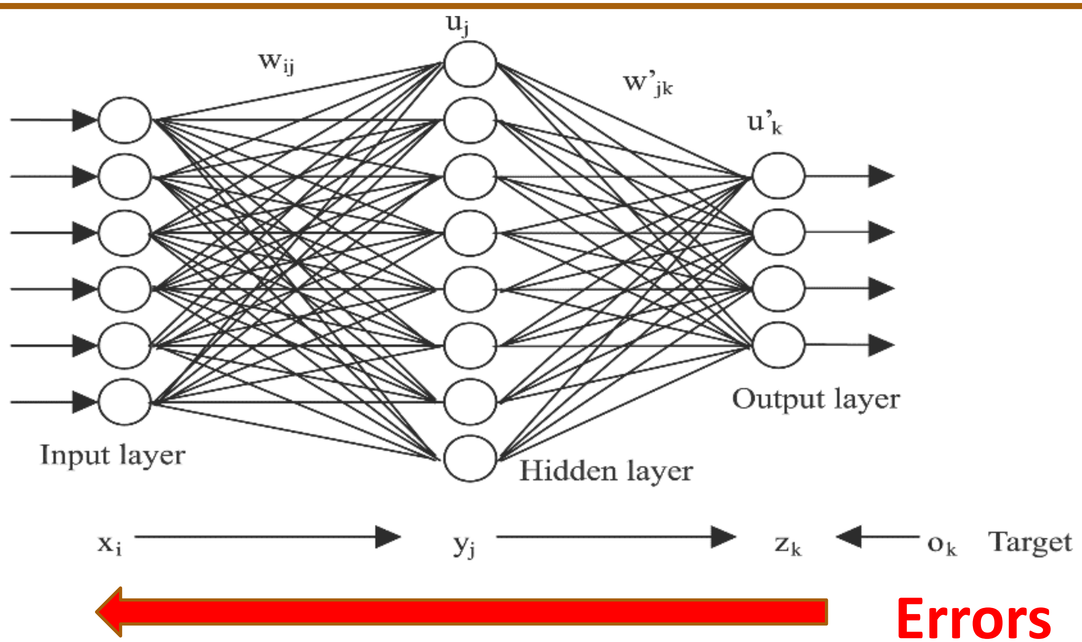
- Supervised: labeled training examples
- Unsupervised: no labels available
- Reinforcement: examples associated with rewards

Testing (Inference): apply weights to new examples



Training DNN

1. Get batch of data
2. Forward through the network -> estimate loss
3. Backpropagate error
4. Update weights based on gradient



Backpropagation

Chain Rule in Gradient Descent: Invented in 1969 by Bryson and Ho

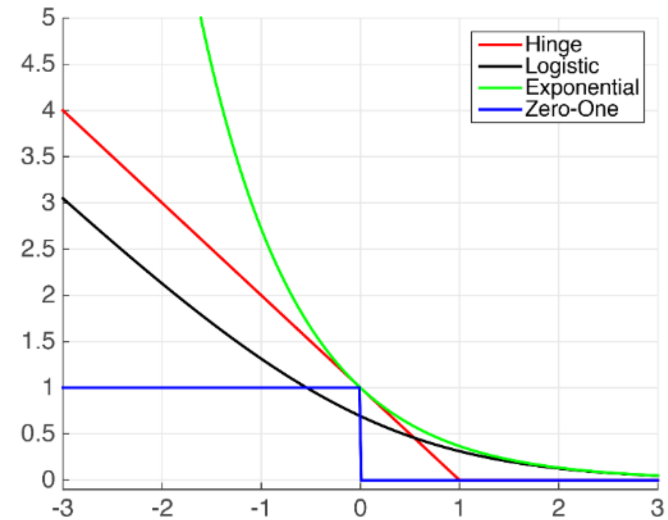
Defining a loss/cost function $$J(x, y; \theta) = \frac{1}{2} \sum (y - f(x; \theta))^2$$

Assume a function

$$f(x; \theta) = w^T x + b \quad , \quad \theta = \{w, b\}$$

Types of Loss function

- Hinge $J(x, y) = max\{0, 1 - xy\}$
- Exponential $J(x, y) = exp(-xy)$
- Logistic $J(x, y) = log_2(1 + exp(-xy))$



Gradient Descent

- Minimize function J w.r.t. parameters θ

New weights

$$\theta^* = \theta - n * \nabla J(y, x; \theta)$$

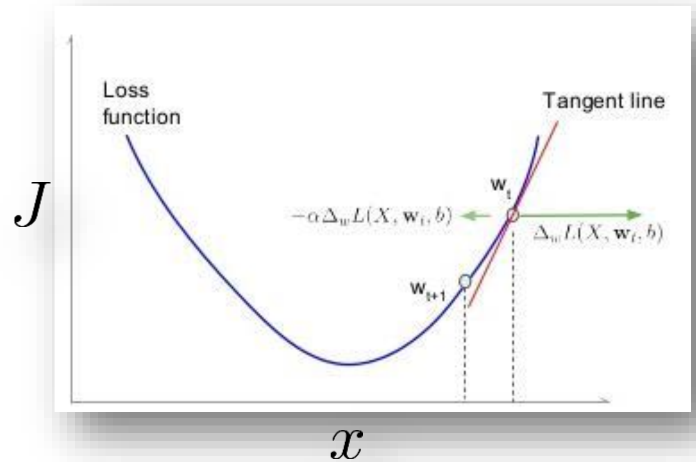
Gradient

Old weights

Learning rate

- Gradient

$$\nabla J(x) = \left(\frac{\partial J(x)}{\partial x_1}, \frac{\partial J(x)}{\partial x_2}, \ldots, \frac{\partial J(x)}{\partial x_n}\right)$$

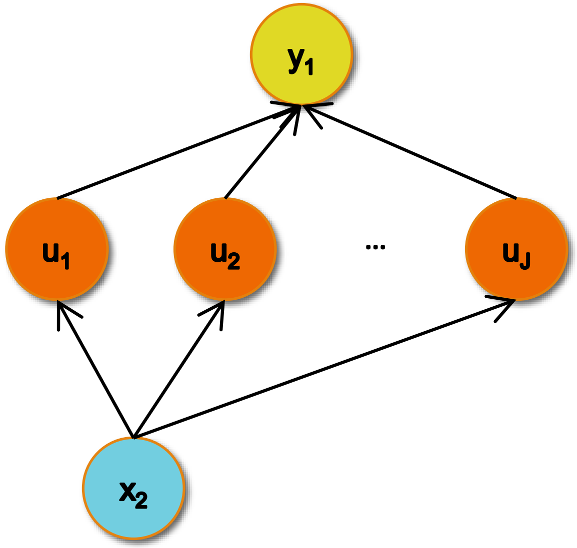


Backpropagation

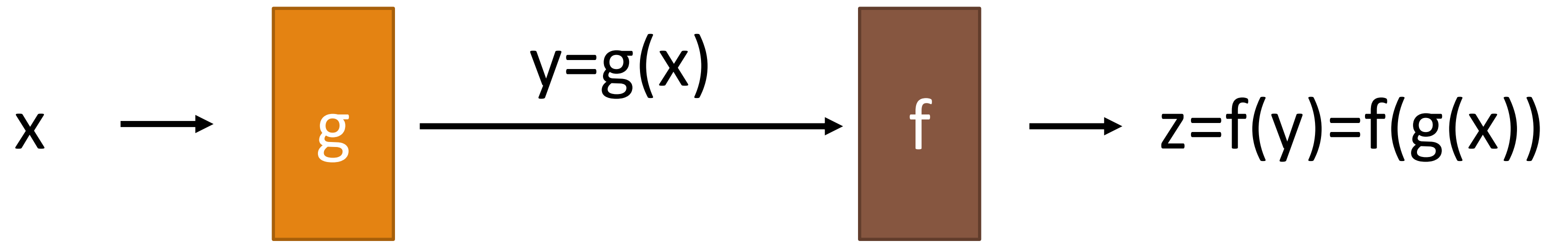
Given: $\boldsymbol{y} = g(\boldsymbol{u})$ and $\boldsymbol{u} = h(\boldsymbol{x})$.

Chain Rule:

$$\frac{dy_i}{dx_k} = \sum_{j=1}^{J} \frac{dy_i}{du_j}\frac{du_j}{dx_k}, \quad \forall i, k$$



Backpropagation



Chain rule:

- **Single variable**

$$\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}.$$

- **Multiple variables**

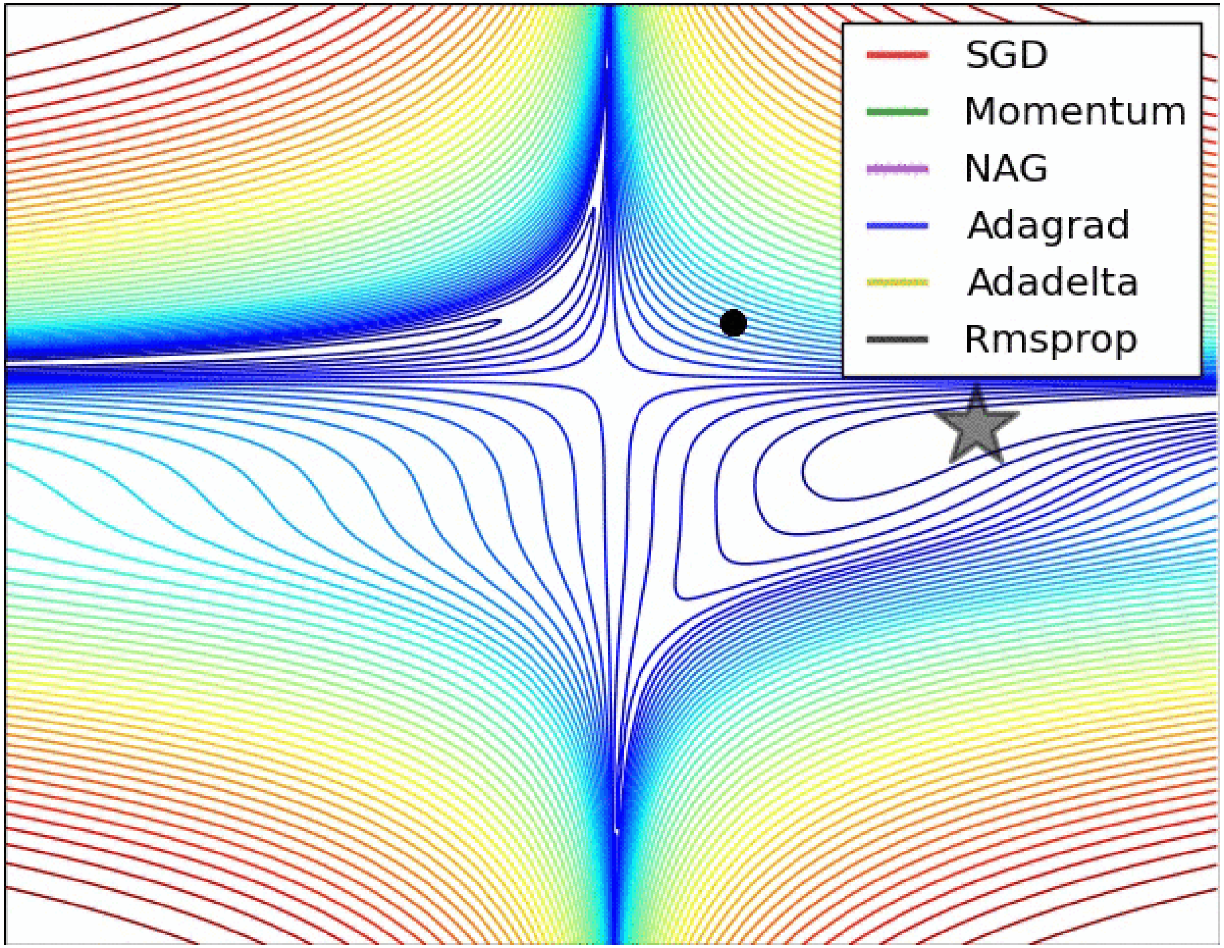
$$\frac{\partial z}{\partial x_i} = \sum_j \frac{\partial z}{\partial y_j}\frac{\partial y_j}{\partial x_i}.$$

https://google-developers.appspot.com/machine-learning/crash-course/backprop-scroll/

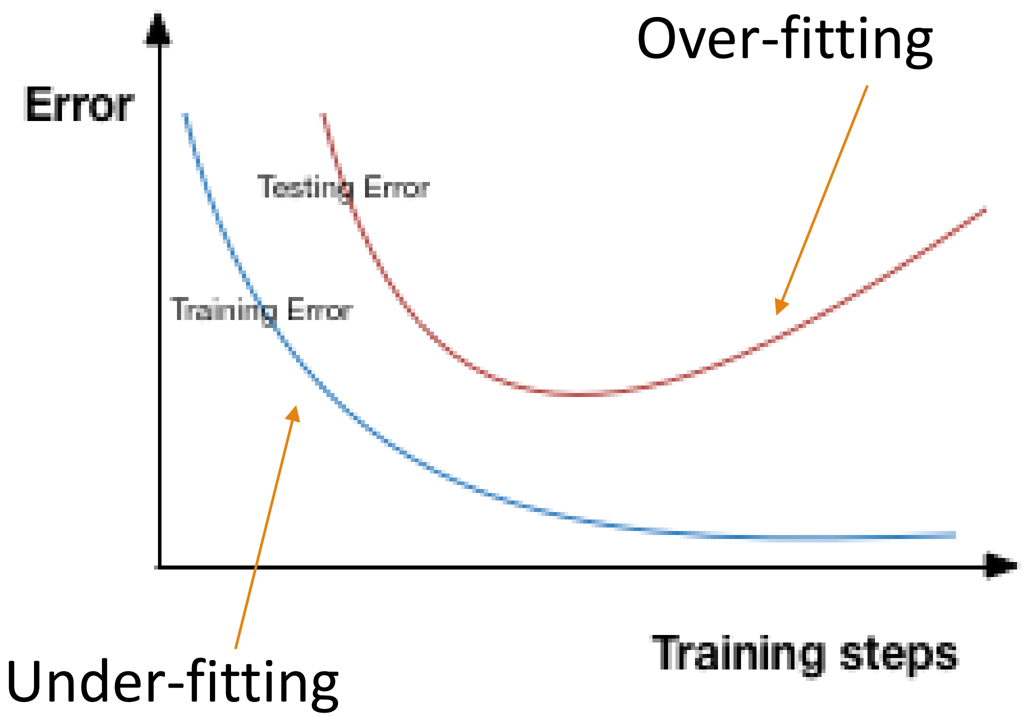
Optimization algorithms

Optimization algorithm	Core idea	Pros	Cons
SGD [140]	Computes the gradient of mini-batches iteratively and updates the parameters	• Easy to implement	• Setting a global learning rate required • Algorithm may get stuck on saddle points or local minima • Slow in terms of convergence • Unstable
Nesterov's momentum [125]	Introduces momentum to maintain the last gradient direction for the next update	• Stable • Faster learning • Can escape local minima	• Setting a learning rate needed
Adagrad [126]	Applies different learning rates to different parameters	• Learning rate tailored to each parameter • Handle sparse gradients well	• Still requires setting a global learning rate • Gradients sensitive to the regularizer • Learning rate becomes very slow in the late stages
Adadelta [141]	Improves Adagrad, by applying a self-adaptive learning rate	• Does not rely on a global learning rate • Faster speed of convergence • Fewer hyper-parameters to adjust	• May get stuck in a local minima at late training
RMSprop [140]	Employs root mean square as a constraint of the learning rate	• Learning rate tailored to each parameter • Learning rate do not decrease dramatically at late training • Works well in RNN training	• Still requires a global learning rate • Not good at handling sparse gradients
Adam [127]	Employs a momentum mechanism to store an exponentially decaying average of past gradients	• Learning rate stailored to each parameter • Good at handling sparse gradients and non-stationary problems • Memory-efficient • Fast convergence	• It may turn unstable during training

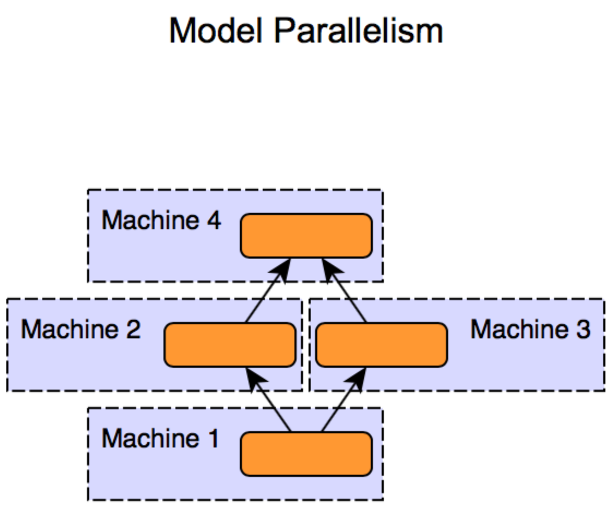
Visualization

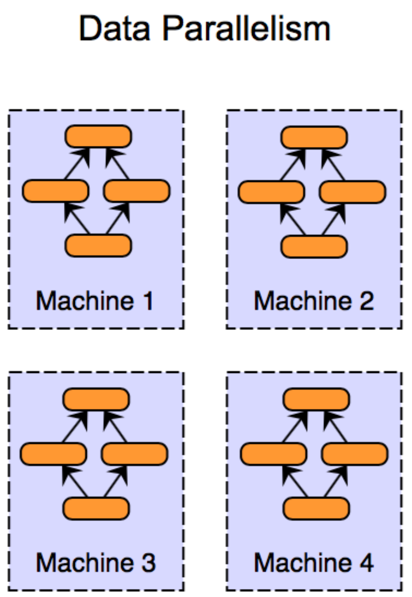


Training Characteristics

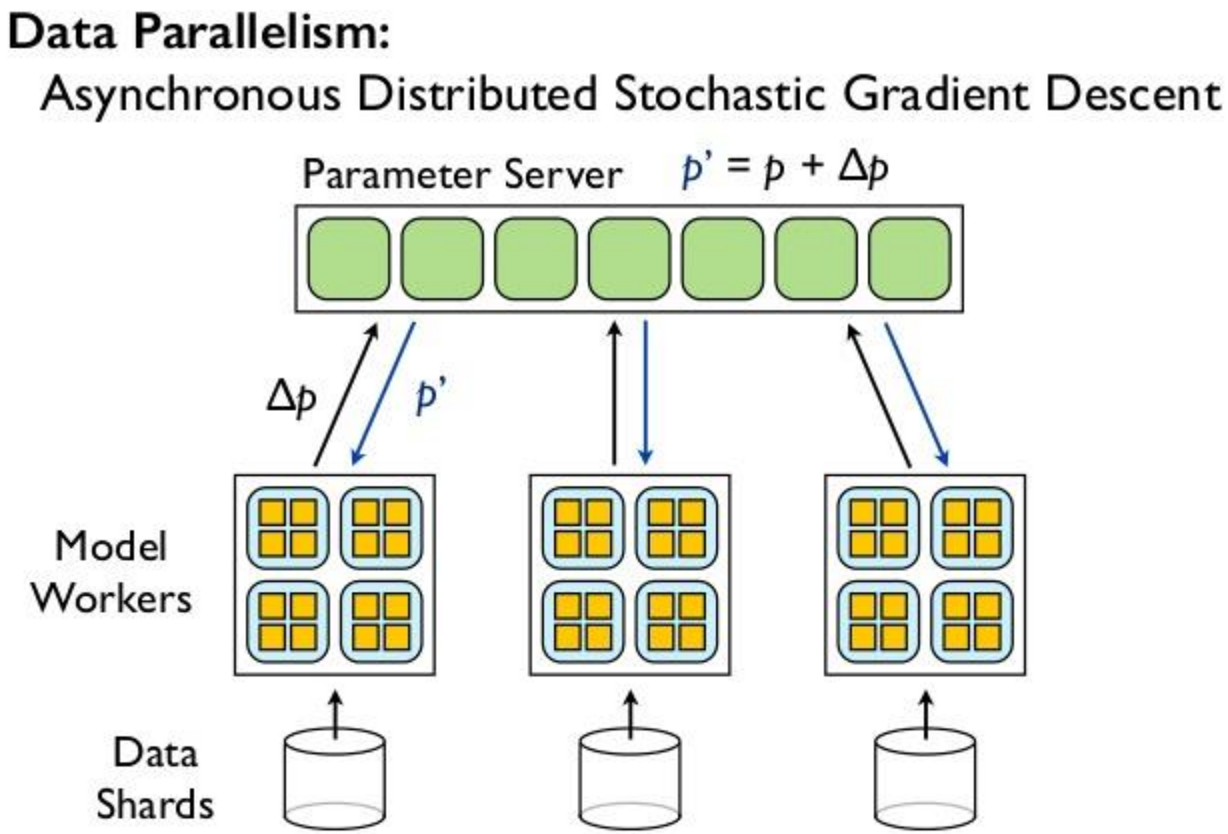


Model vs Data parallelism





Parameter server approach

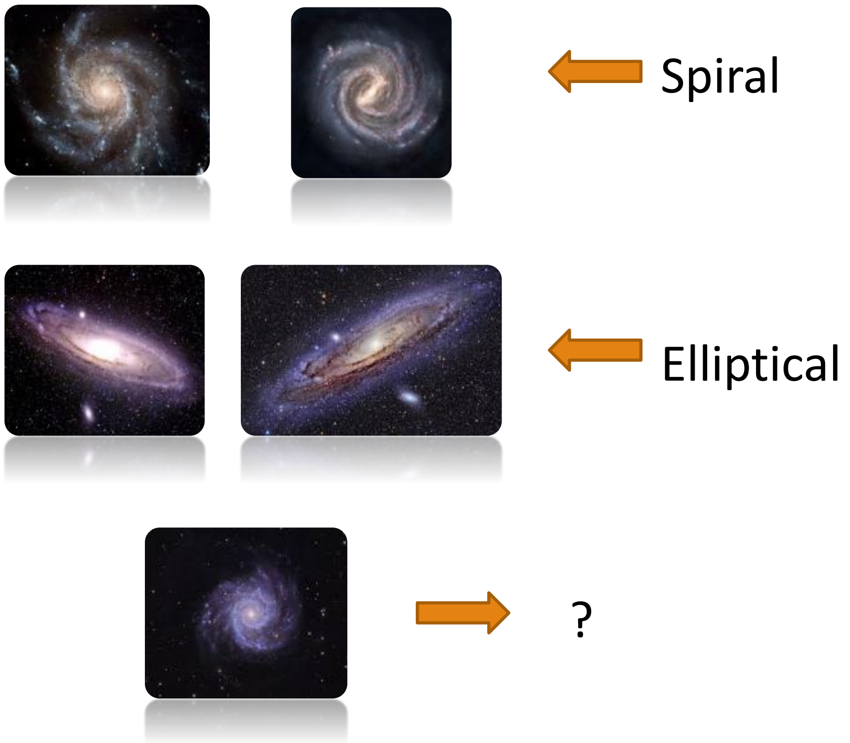


Supervised Learning

Supervised Learning

Data
Labels

Model
Prediction



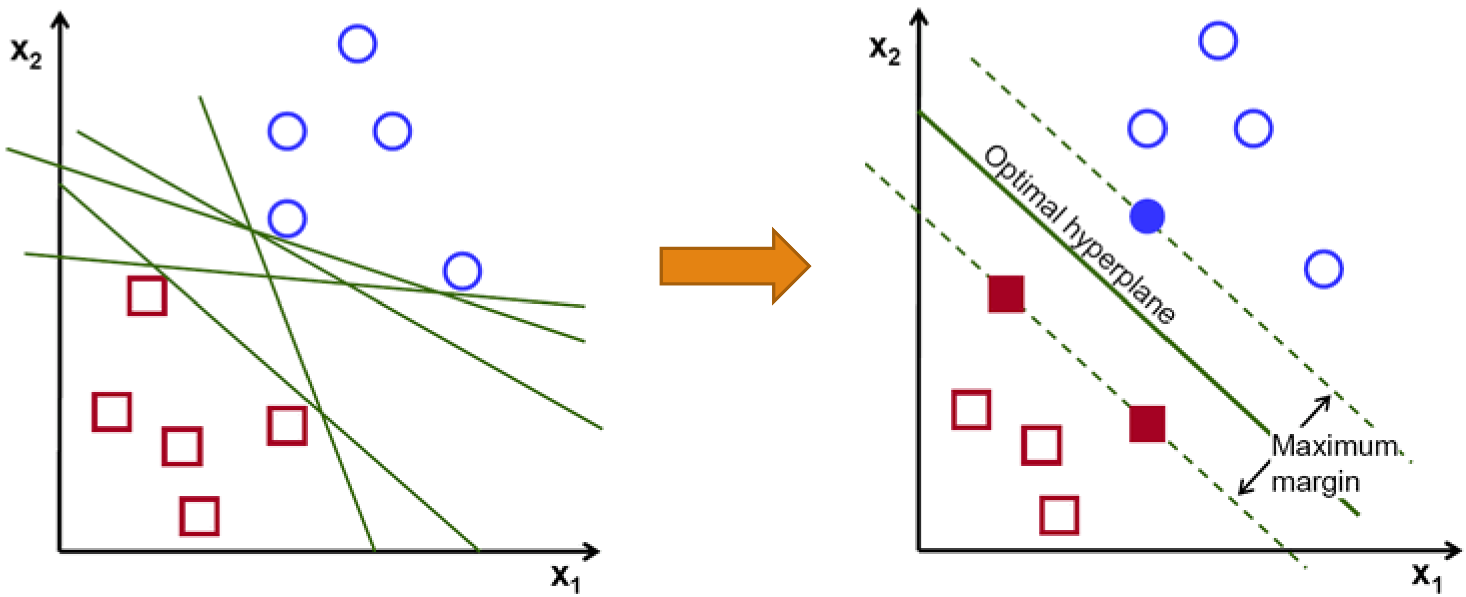
Exploiting prior knowledge

- Expert users
- Crowdsourcing
- Other instruments

State-of-the-art (before Deep Learning)

Support Vector Machines

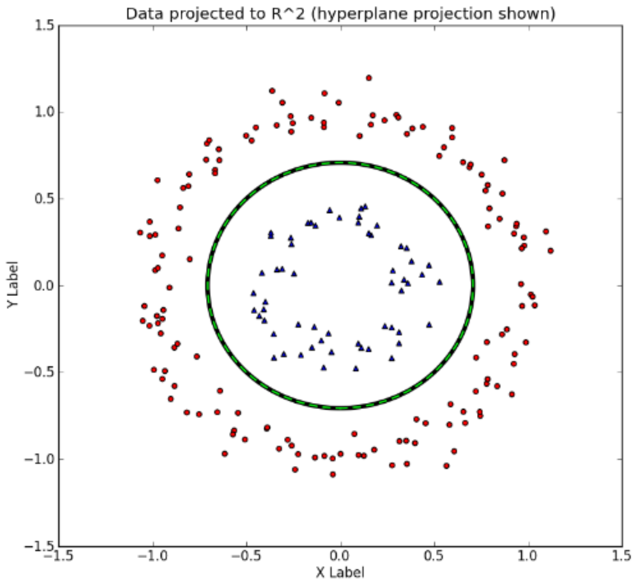
- Binary classification

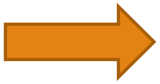


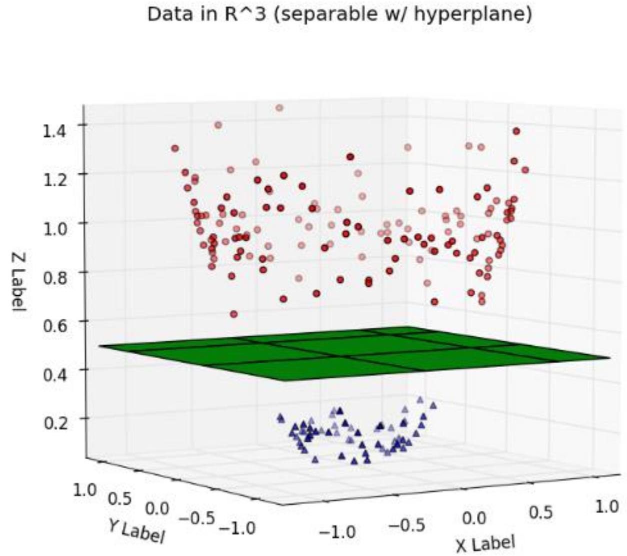
State-of-the-art (before Deep Learning)

Support Vector Machines

- Binary classification
- Kernels <-> non-linearities







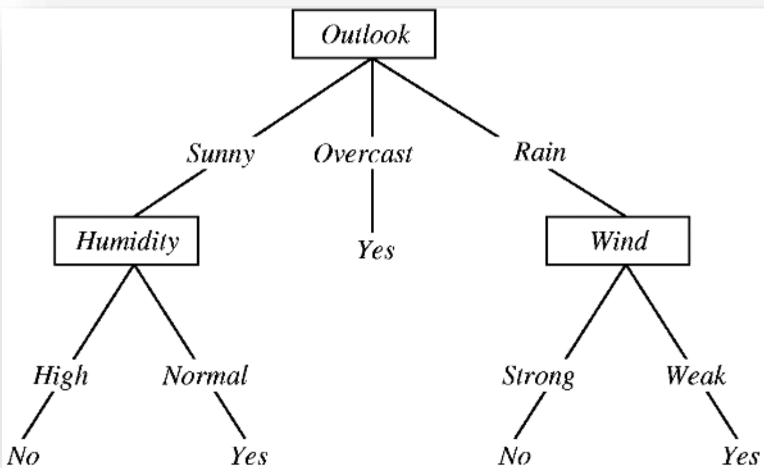
State-of-the-art (before Deep Learning)

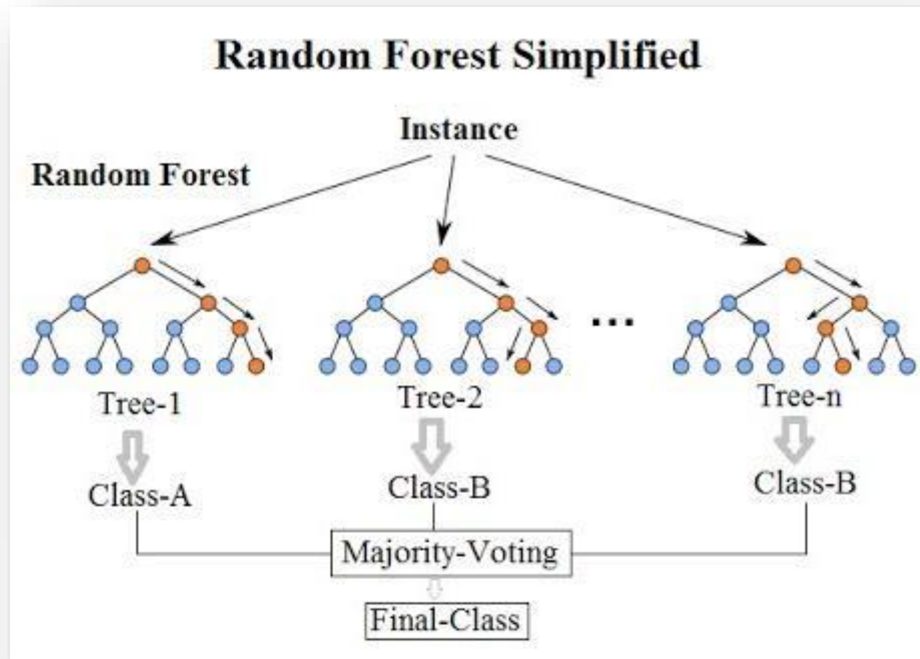
Support Vector Machines

- Binary classification
- Kernels <-> non-linearities

Random Forests

- Multi-class classification





State-of-the-art (before Deep Learning)

Support Vector Machines

- Binary classification
- Kernels <-> non-linearities

Random Forests

- Multi-class classification

Markov Chains/Fields

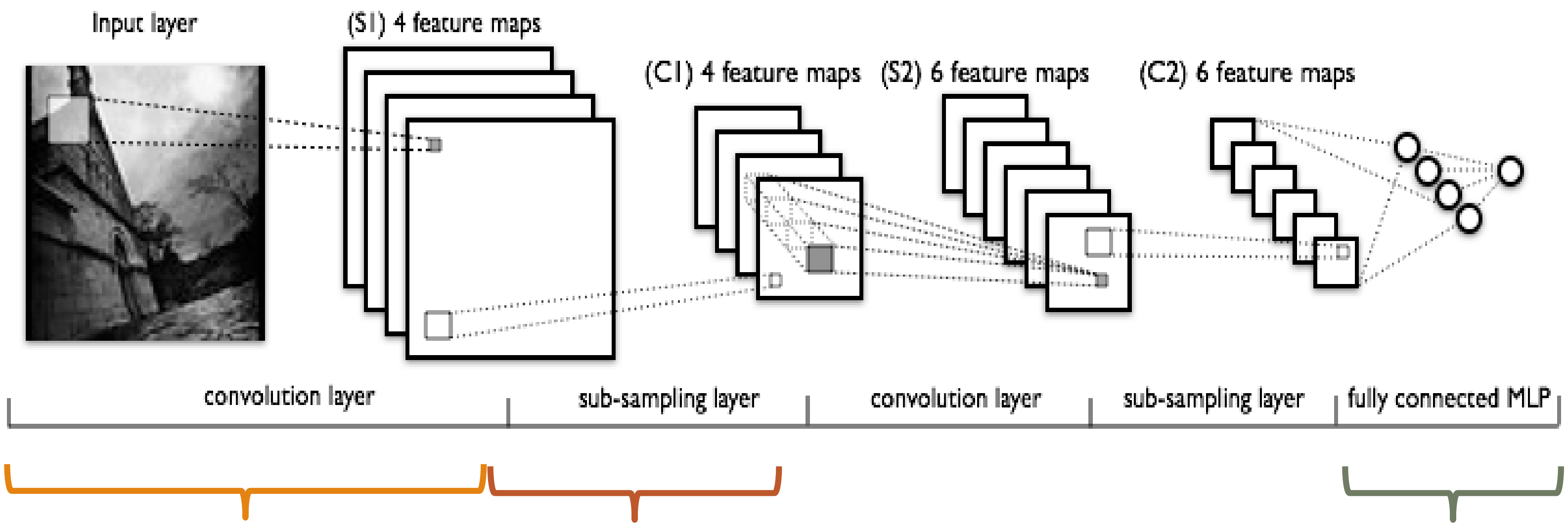
- Temporal data

State-of-the-art (since 2015)

Deep Learning (DL)

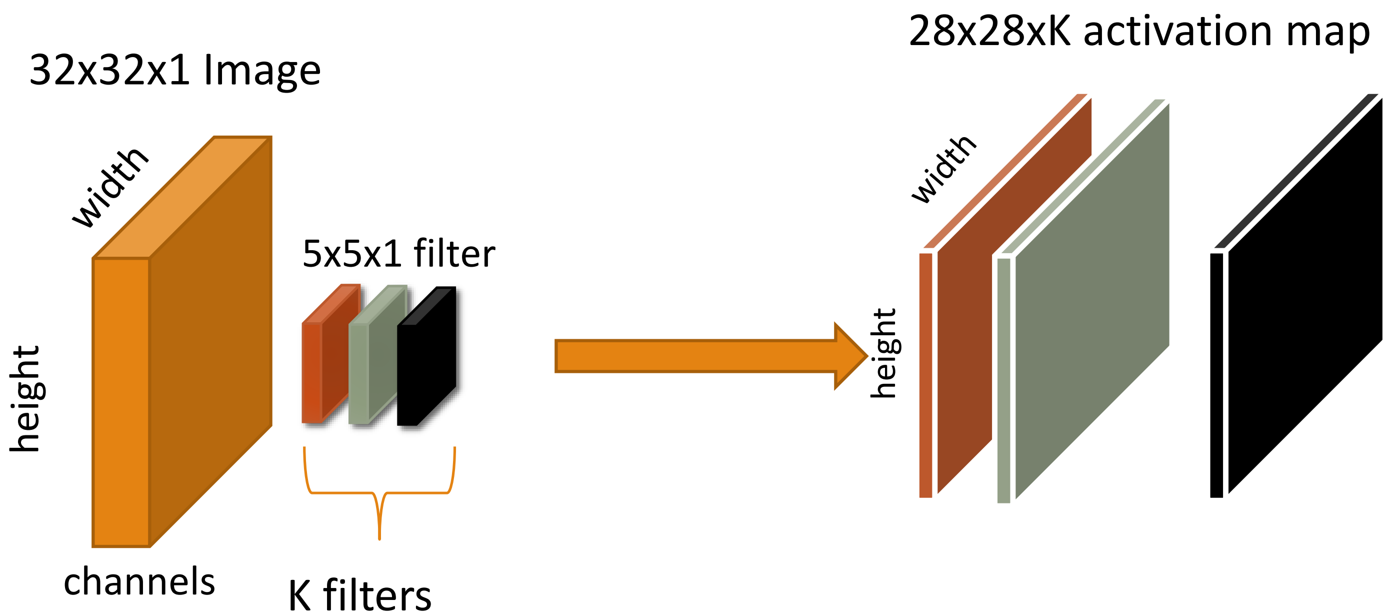
- Convolutional Neural Networks (CNN) <-> Images
- Recurrent Neural Networks (RNN) <-> Audio

Convolutional Neural Networks



(Convolution + Subsampling) + () … + Fully Connected

Convolutional Layers



$$(I * K)_{ij} = \sum_{m=0}^{k_1-1} \sum_{n=0}^{k_2-1} I(i-m, j-n) K(m,n)$$

$$= \sum_{m=0}^{k_1-1} \sum_{n=0}^{k_2-1} I(i+m, j+n) K(-m,-n)$$

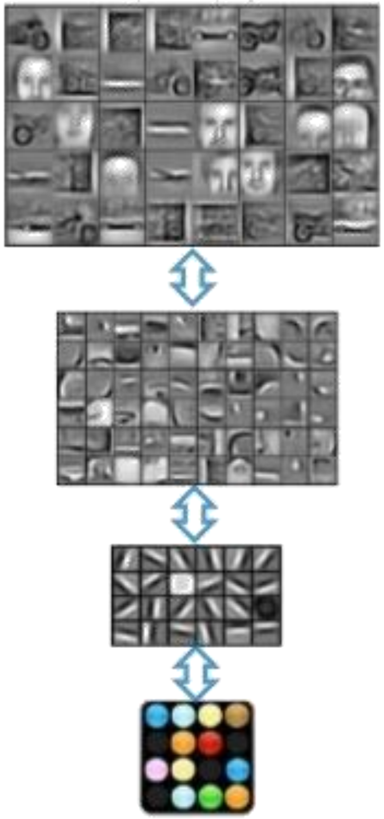
Convolutional Layers

Characteristics

- Hierarchical features
- Location invariance

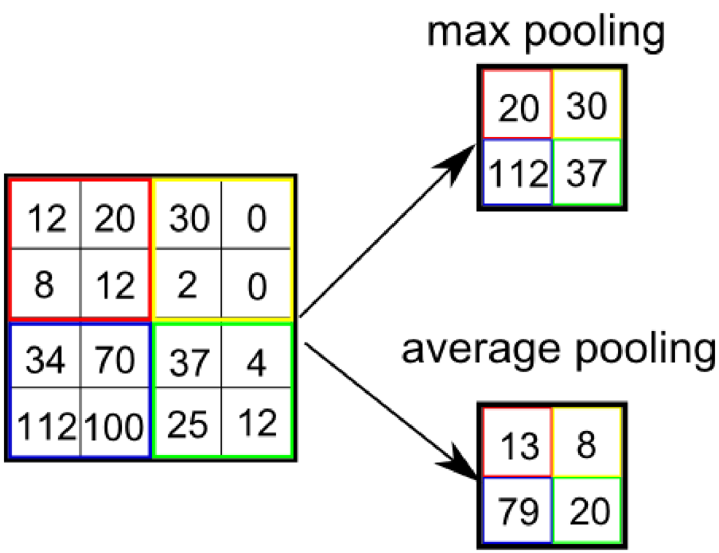
Parameters

- Number of filters (32,64…)
- Filter size (3x3, 5x5)
- Stride (1)
- Padding (2,4)



"Machine Learning and AI for Brain Simulations" – Andrew Ng Talk, UCLA, 2012

Subsampling (pooling) Layers



<-> downsampling

➢ Scale invariance

Parameters

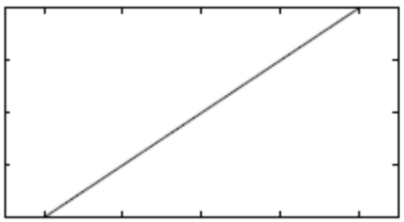
- Type
- Filter Size
- Stride

Activation Layer

Introduction of non-linearity

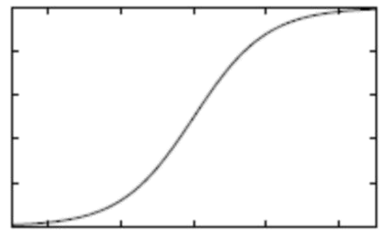
- Brain: thresholding -> spike trains

Identity (Linear)



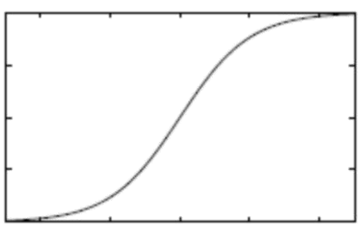
$$identity(x) = x$$

Sigmoid



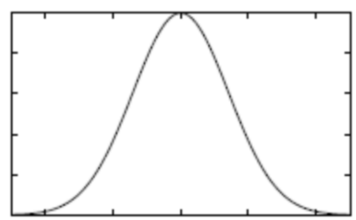
$$sigmoid(x) = \frac{1}{1 + e^{-x}}$$

Tanh (Hypertangent)



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

Gaussian



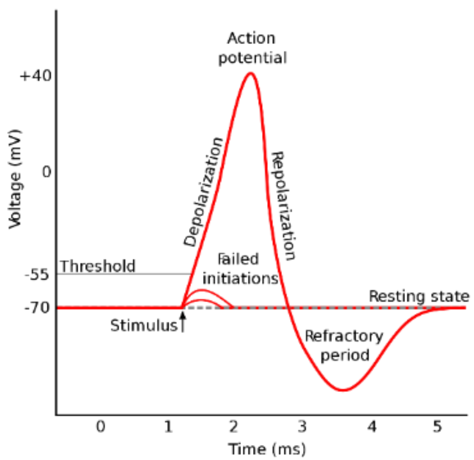
$$gaussian(x) = e^{-x^2/\sigma^2}$$

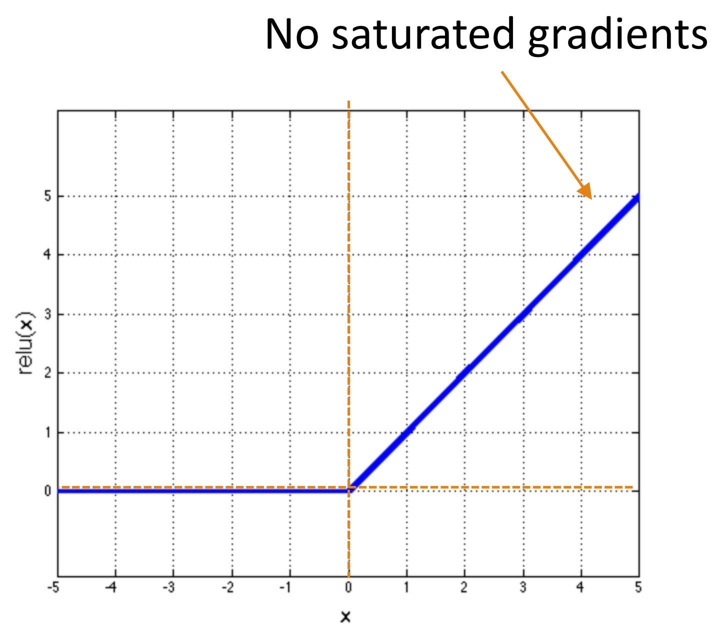
Activation Layer

ReLU: x=max(0,x)

- ✓ Simplifies backprop
- ✓ Makes learning faster
- ✓ Avoids saturation issues
- ✓ ~ non-negativity constraint

(Note: The brain)



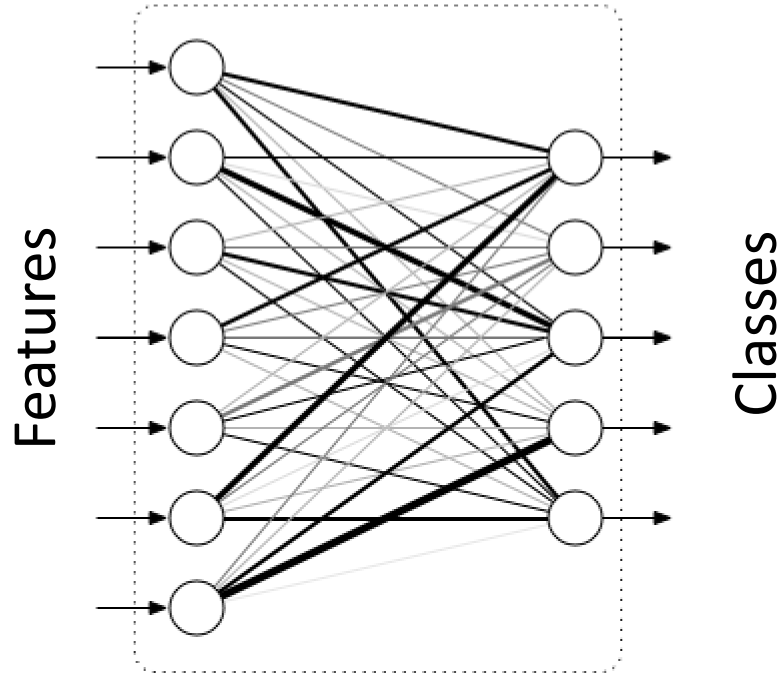


Fully Connected Layers

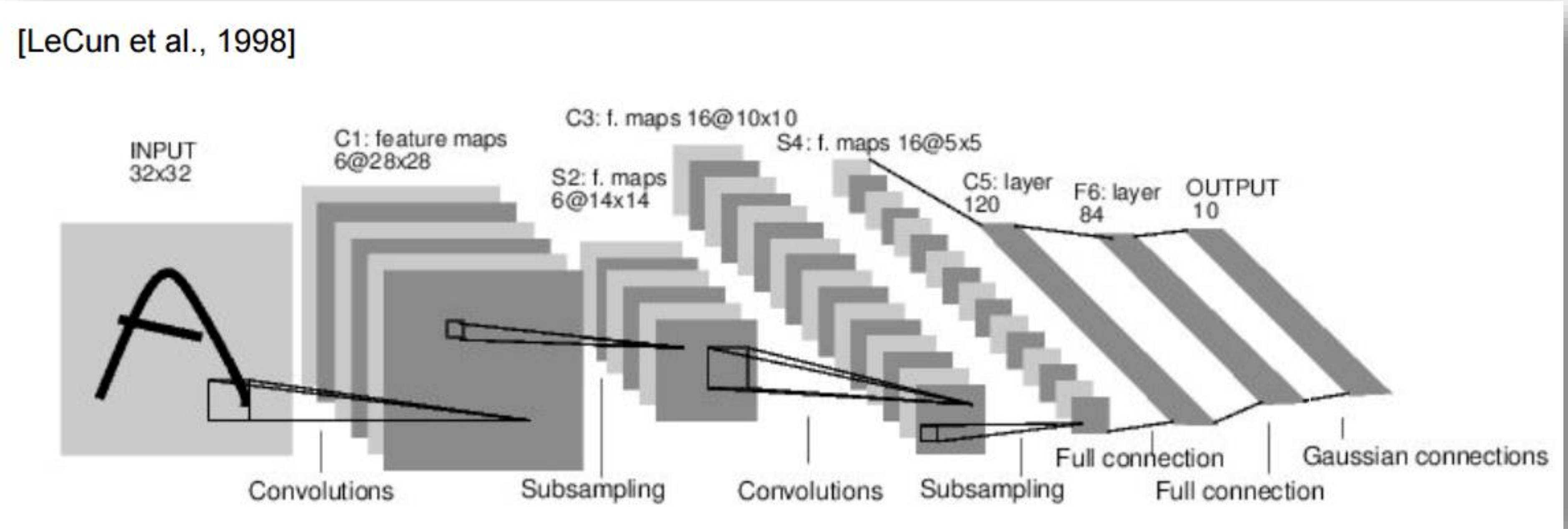
Full connections to all activations in previous layer

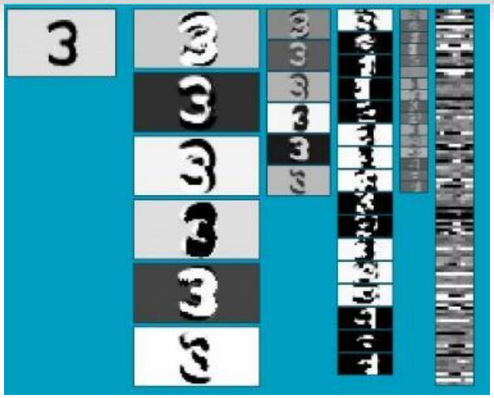
Typically at the end

Can be replaced by conv

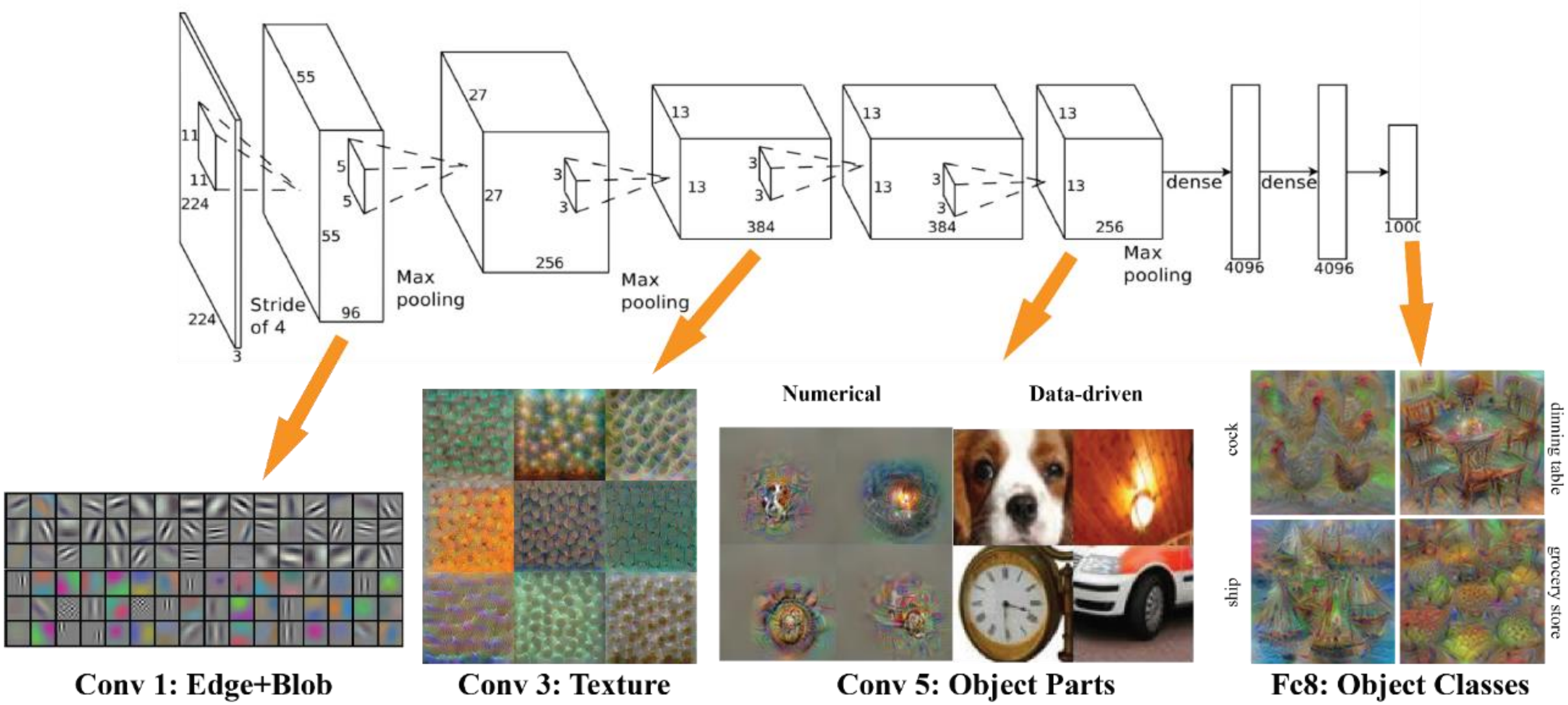


LeNet [1998]


[LeCun et al., 1998]
INPUT
32x32
C1: feature maps
6@28x28
S2: f. maps
6@14x14
C3: f. maps 16@10x10
S4: f. maps 16@5x5
C5: layer
120
F6: layer
84
OUTPUT
10
Convolutions
Subsampling
Convolutions
Subsampling
Full connection
Full connection
Gaussian connections

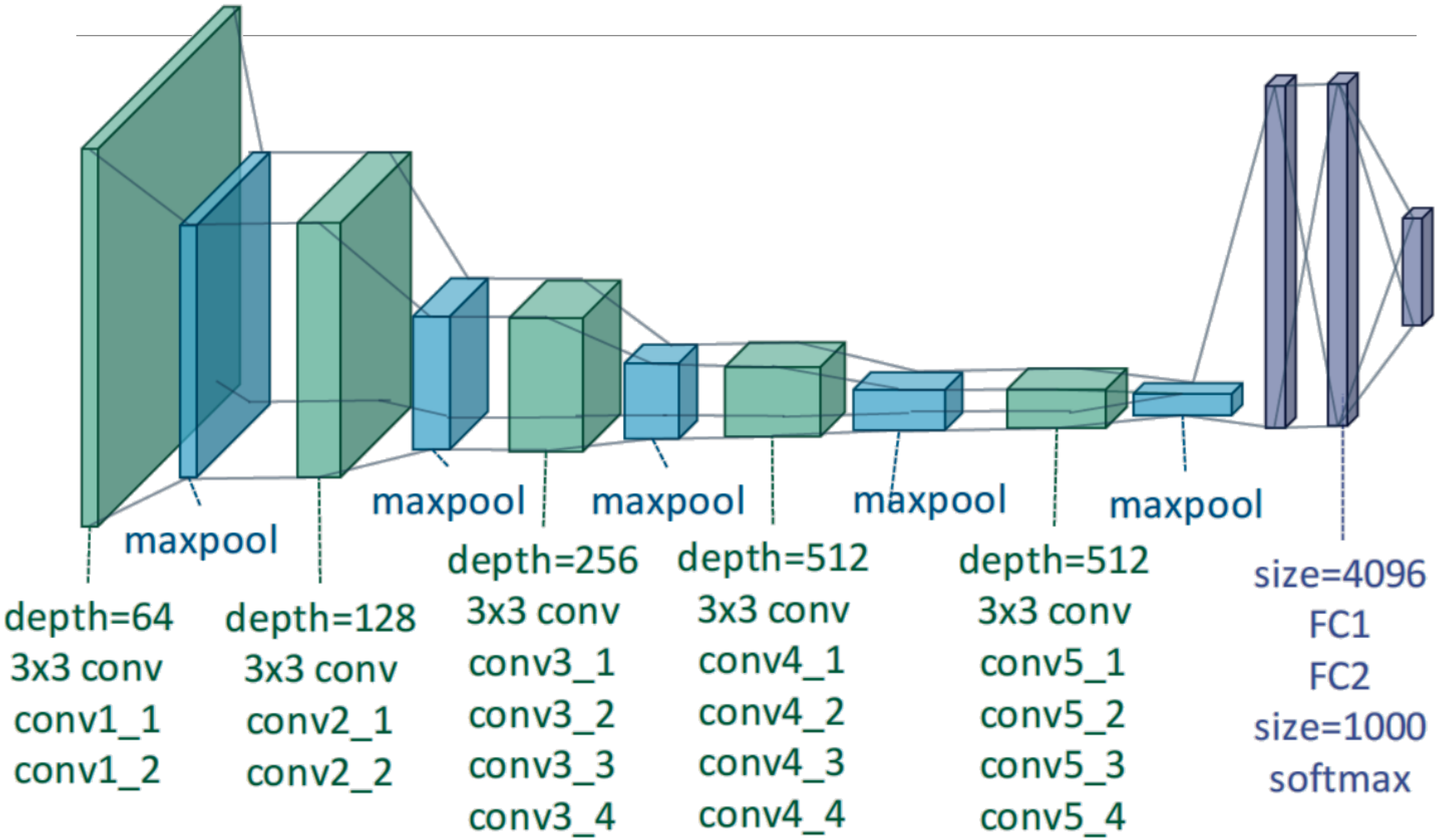


AlexNet [2012]



Alex Krizhevsky, Ilya Sutskever and Geoff Hinton, [ImageNet ILSVRC challenge] in 2012
http://vision03.csail.mit.edu/cnn_art/data/single_layer.png

VGGnet [2014]



K. Simonyan, A. Zisserman Very Deep Convolutional Networks for Large-Scale Image Recognition, arXiv technical report, 2014

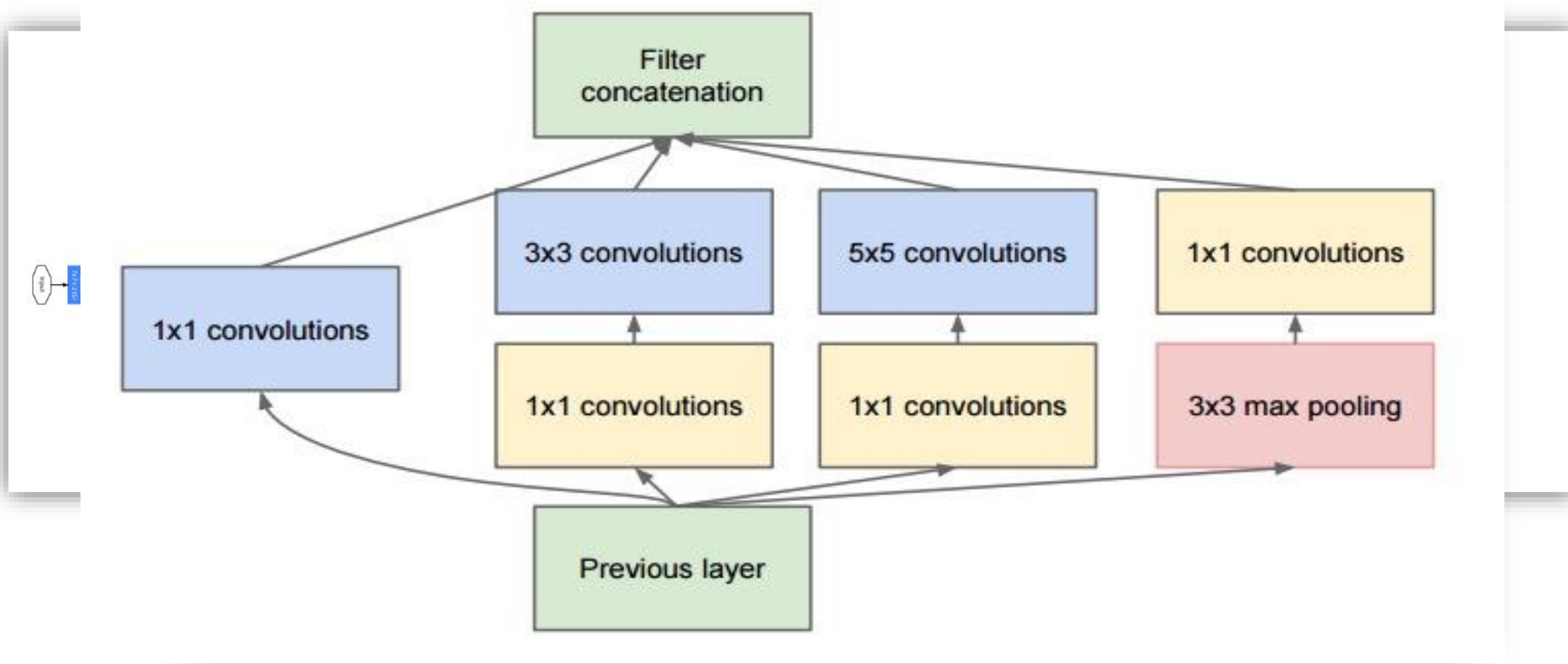
VGGnet

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

D: VGG16
E: VGG19
All filters are 3x3

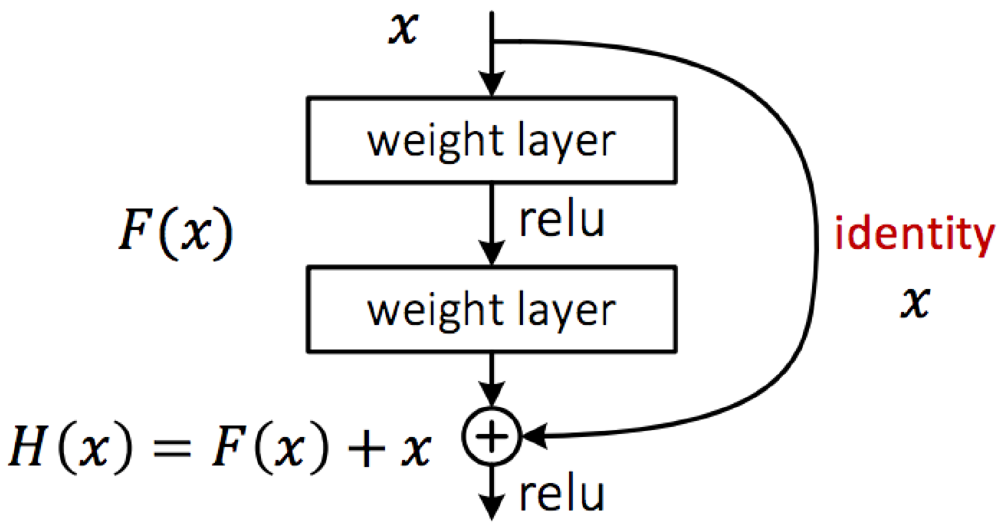
More layers
smaller filters

Inception (GoogLeNet, 2014)

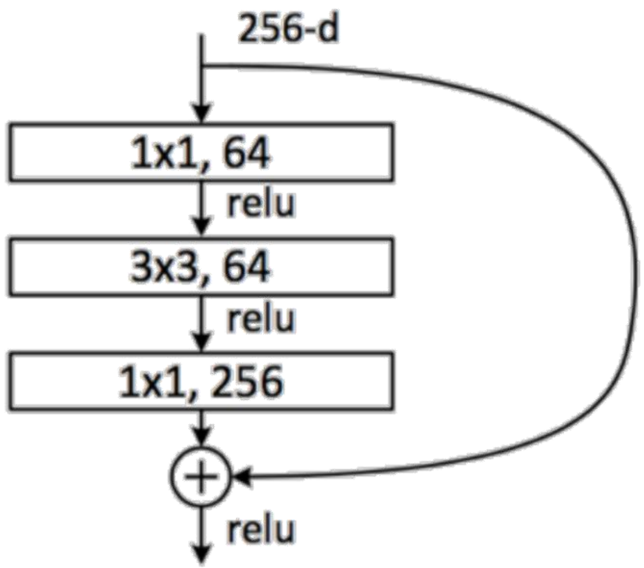


Inception module with dimensionality reduction

Residuals

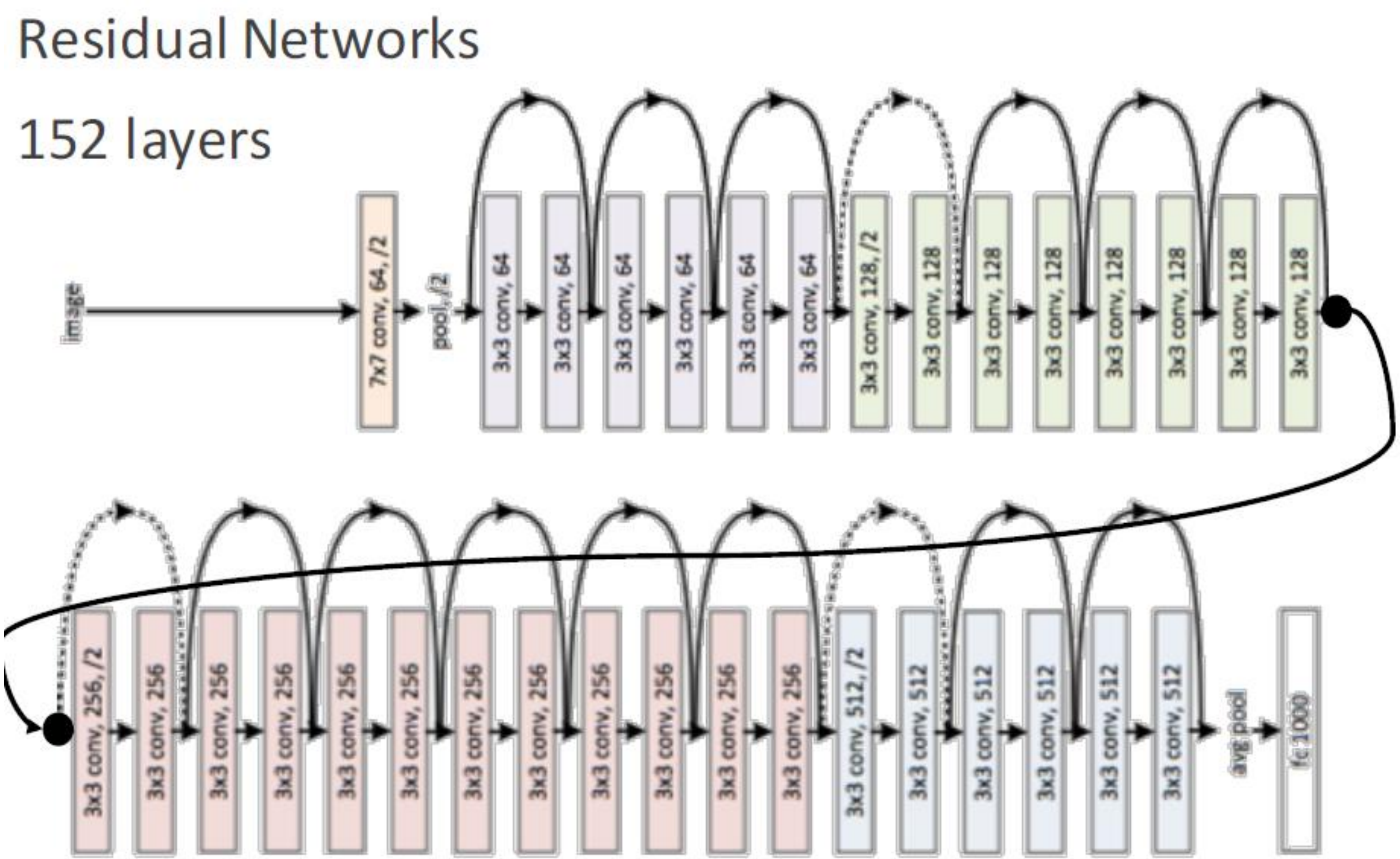


x
weight layer
relu
weight layer
$F(x)$
identity
x
$H(x) = F(x) + x$
relu



256-d
1x1, 64
relu
3x3, 64
relu
1x1, 256
relu

ResNet, 2015



He, Kaiming, et al. "Deep residual learning for image recognition." *IEEE CVPR*. 2016.

Training protocols

Fully Supervised

- Random initialization of weights
- Train in supervised mode (example + label)

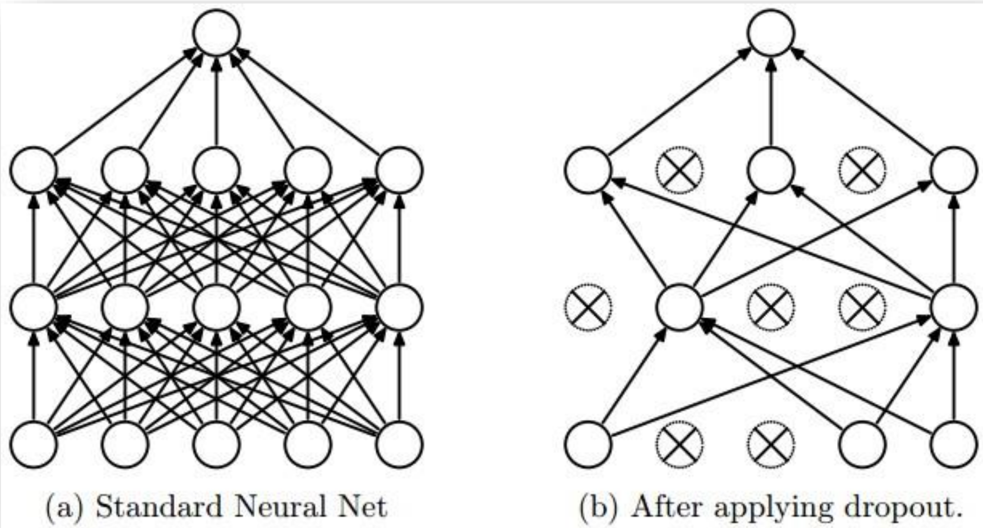
Unsupervised pre-training + standard classifier

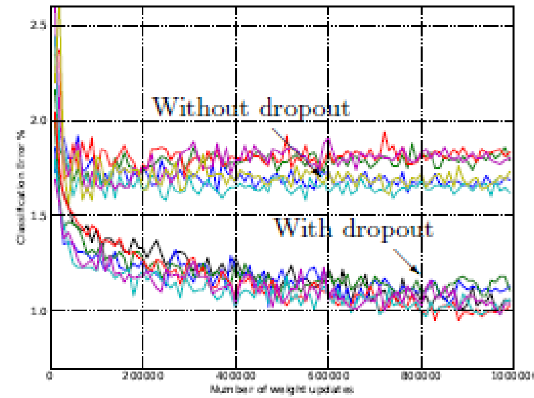
- Train each layer unsupervised
- Train a supervised classifier (SVM) on top

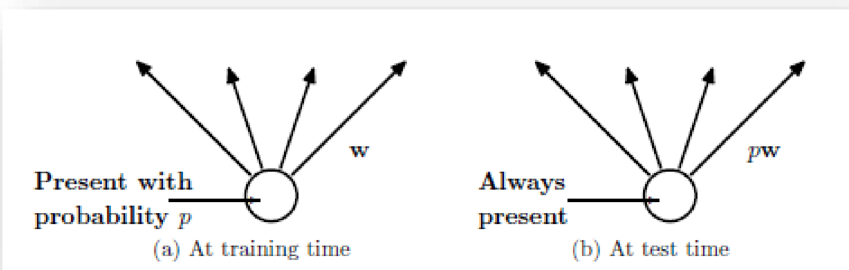
Unsupervised pre-training + supervised fine-tuning

- Train each layer unsupervised
- Add a supervised layer

Dropout







Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." *Journal of machine learning research*15.1 (2014): 1929-1958.

Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

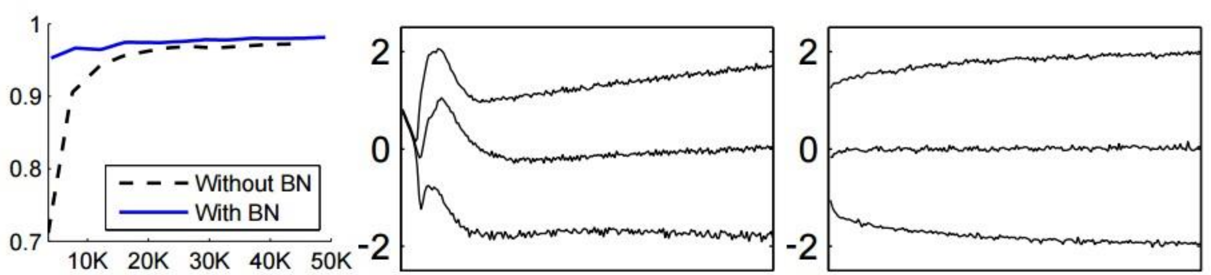
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

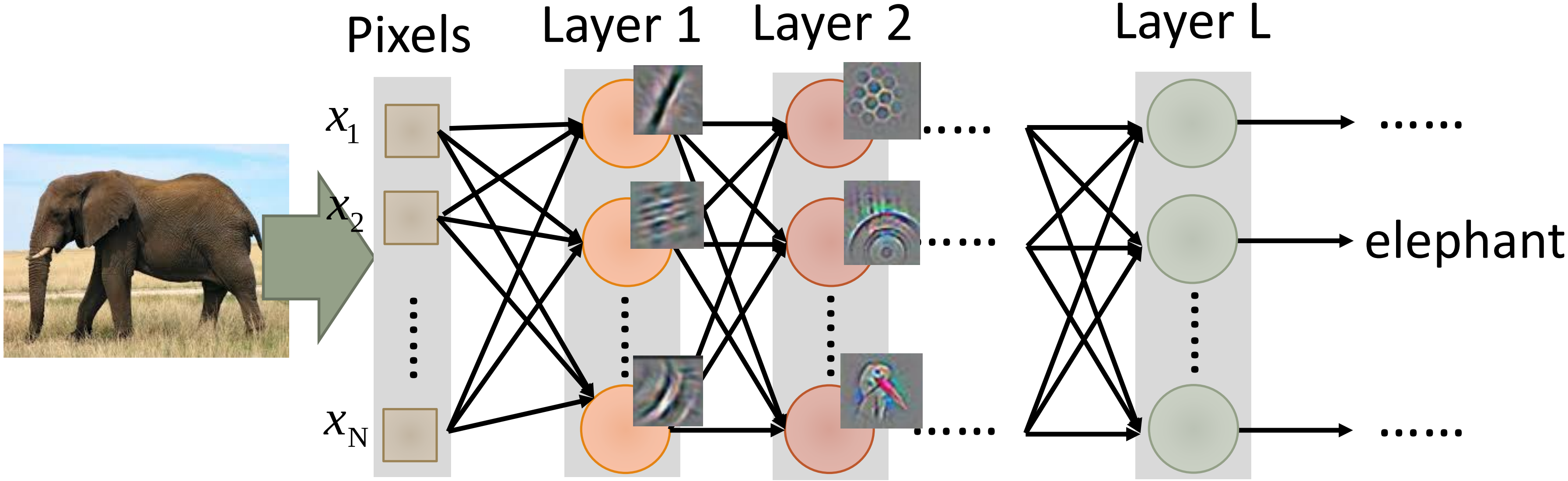
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$



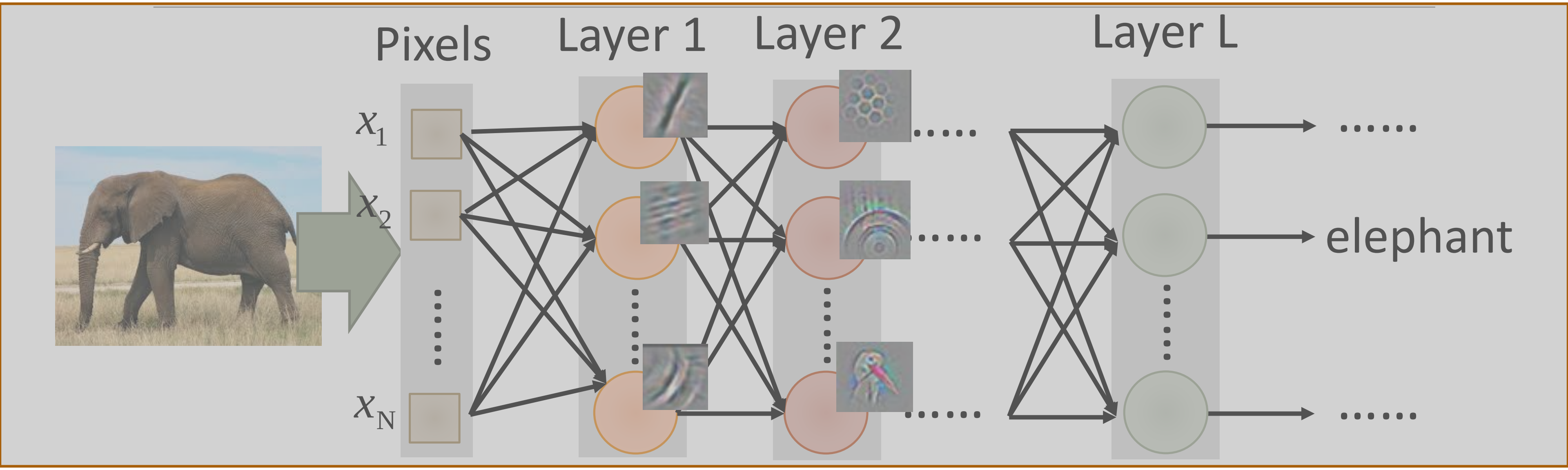
(a) (b) Without BN (c) With BN

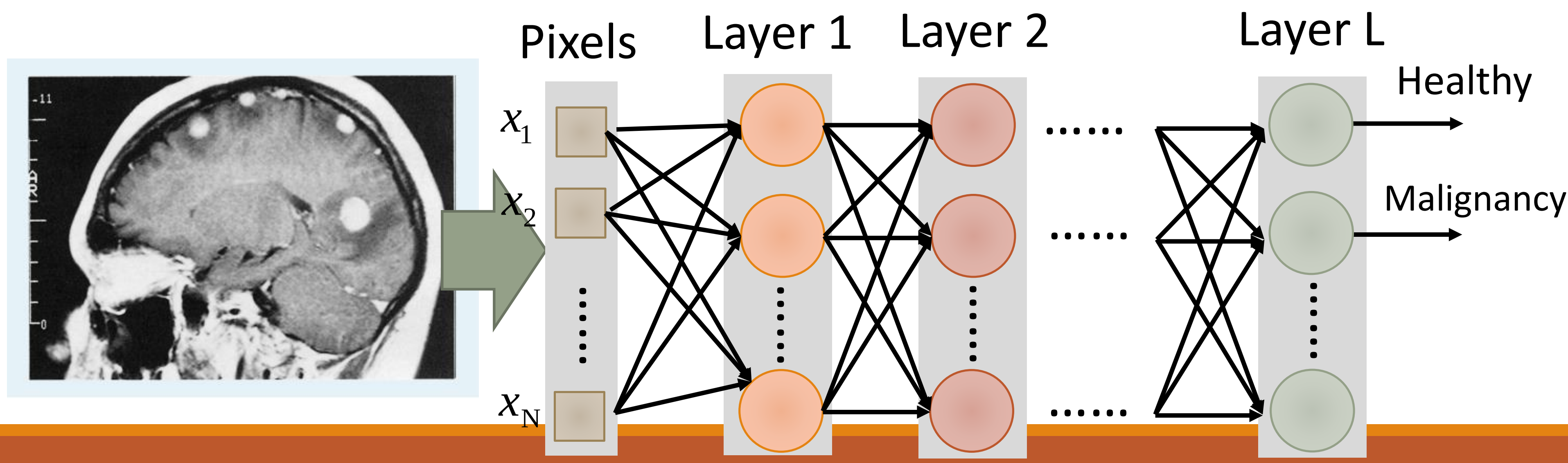
Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift [Ioffe and Szegedy 2015]

Transfer Learning

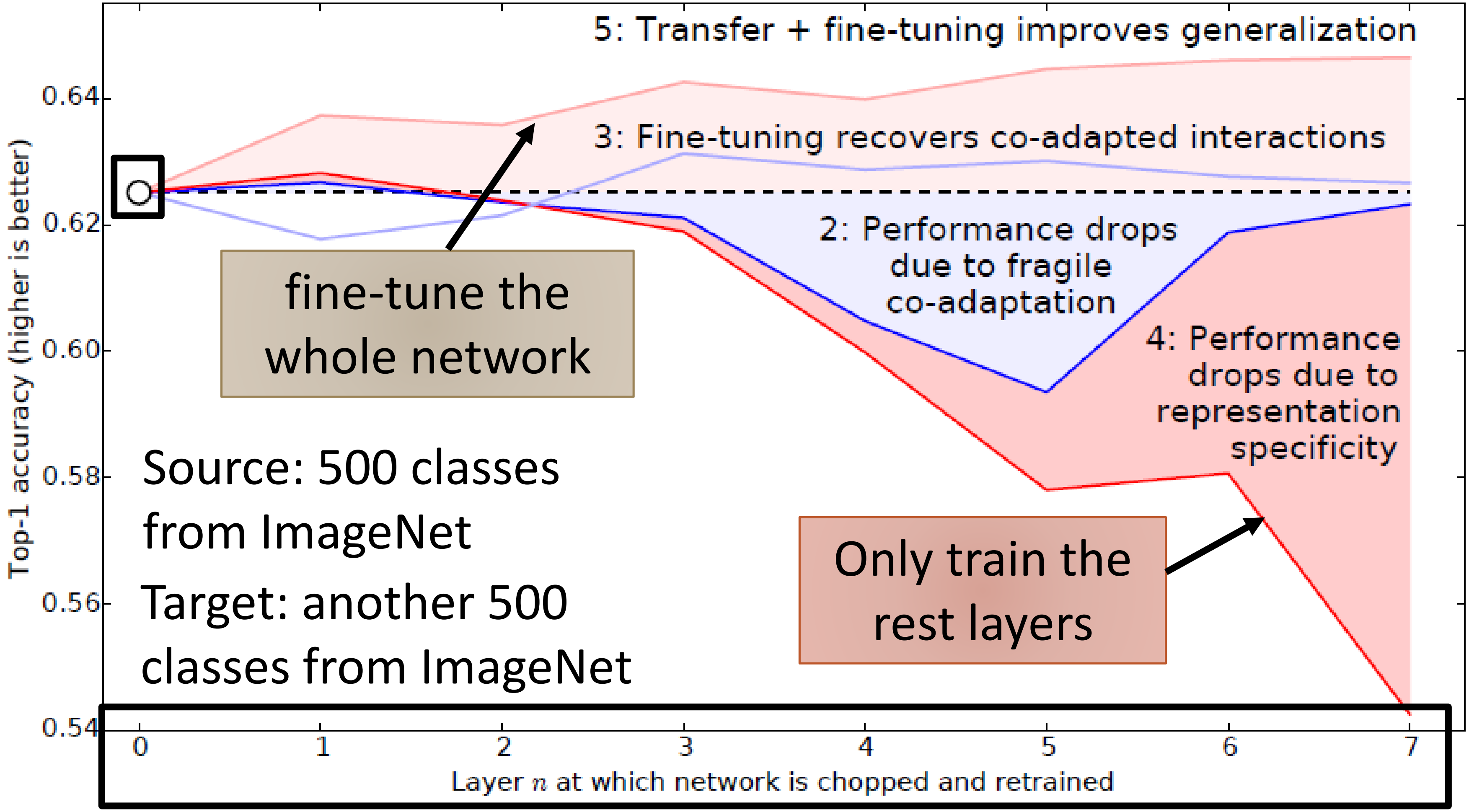


Transfer Learning





Layer Transfer - Image



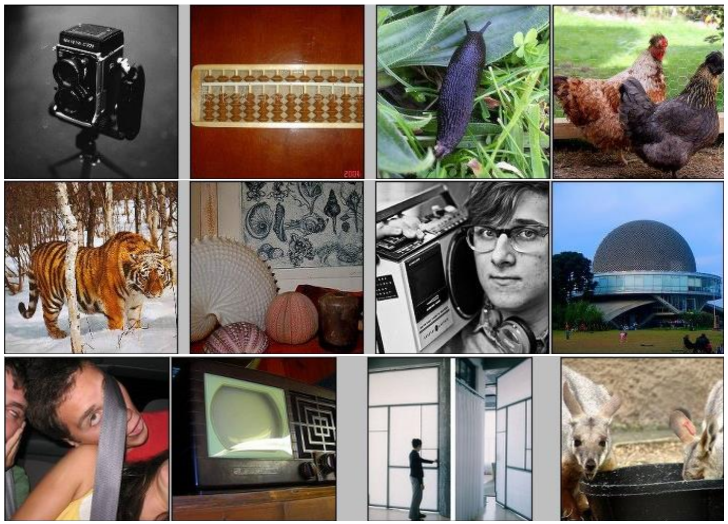
Source: 500 classes from ImageNet

Target: another 500 classes from ImageNet

Jason Yosinski, Jeff Clune, Yoshua Bengio, Hod Lipson, "How transferable are features in deep neural networks?", NIPS, 2014

ImageNET

IMAGENET



- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- ImageNet Large-Scale Visual Recognition Challenge (ILSVRC):
  1.2 million training images, 1000 classes

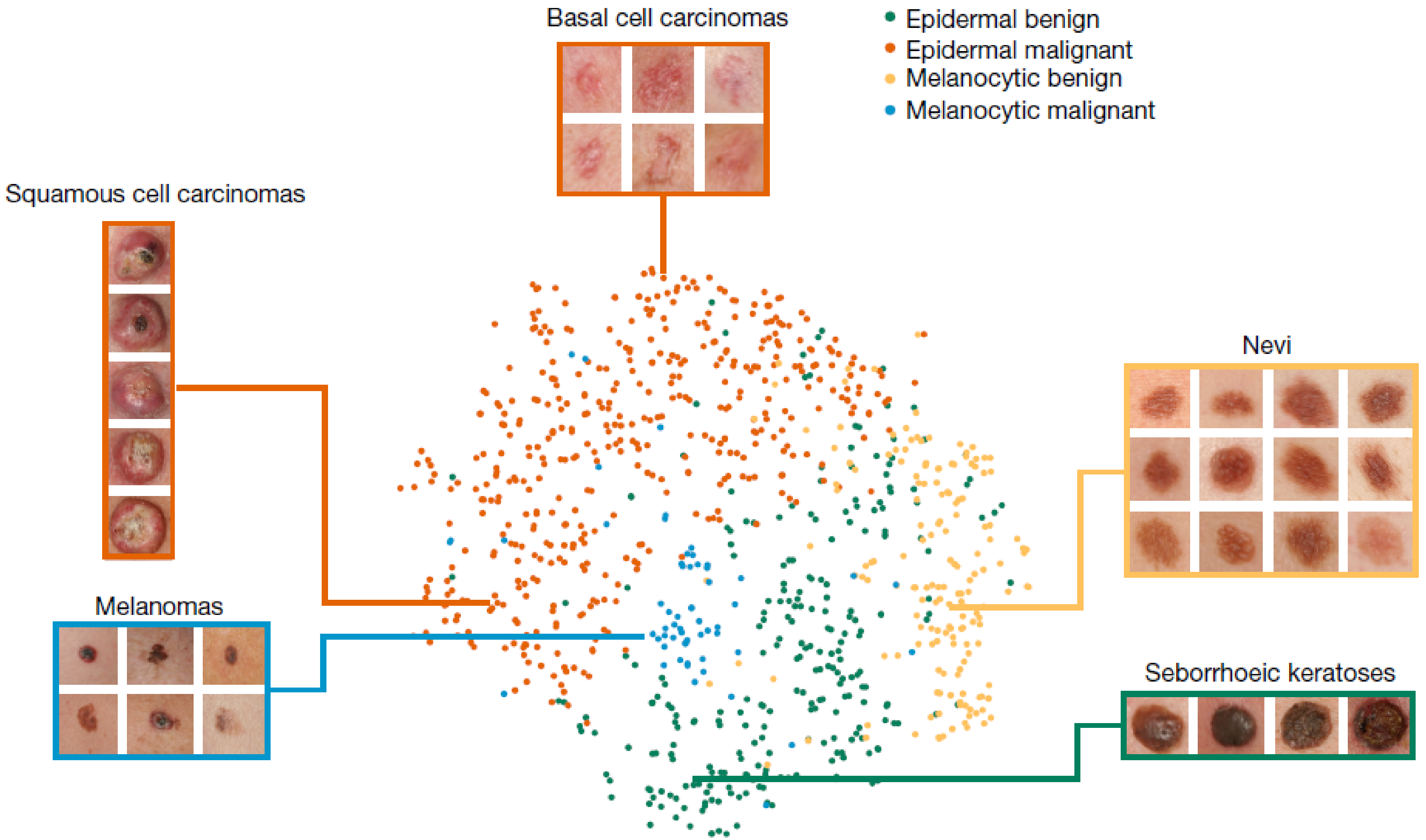
www.image-net.org/challenges/LSVRC/

Summary: ILSVRC 2012-2015

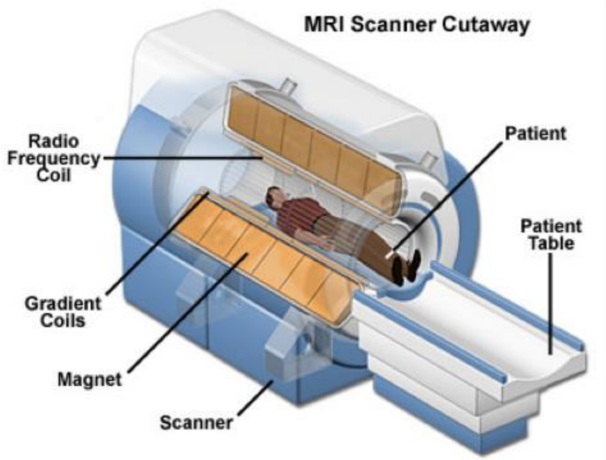
Team	Year	Place	Error (top-5)	External data
(AlexNet, 7 layers)	2012	-	16.4%	no
SuperVision	2012	1st	15.3%	ImageNet 22k
Clarifai – NYU (7 layers)	2013	-	11.7%	no
Clarifai	2013	1st	11.2%	ImageNet 22k
VGG – Oxford (16 layers)	2014	2nd	7.32%	no
GoogLeNet (19 layers)	2014	1st	6.67%	no
ResNet (152 layers)	2015	1st	3.57%	
Human expert*			5.1%	

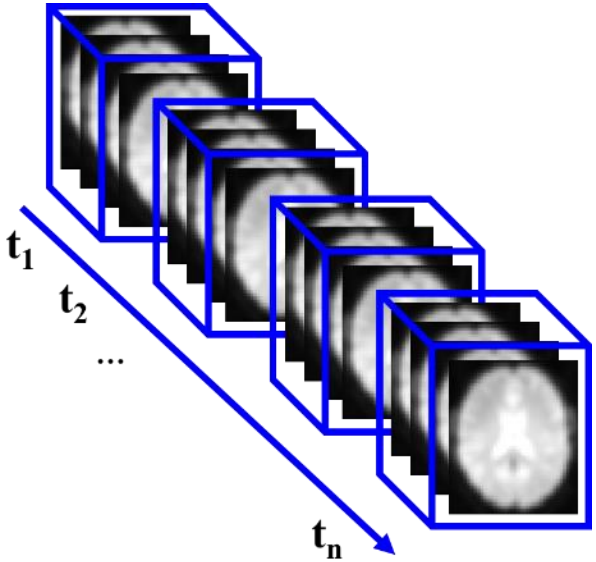
http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/

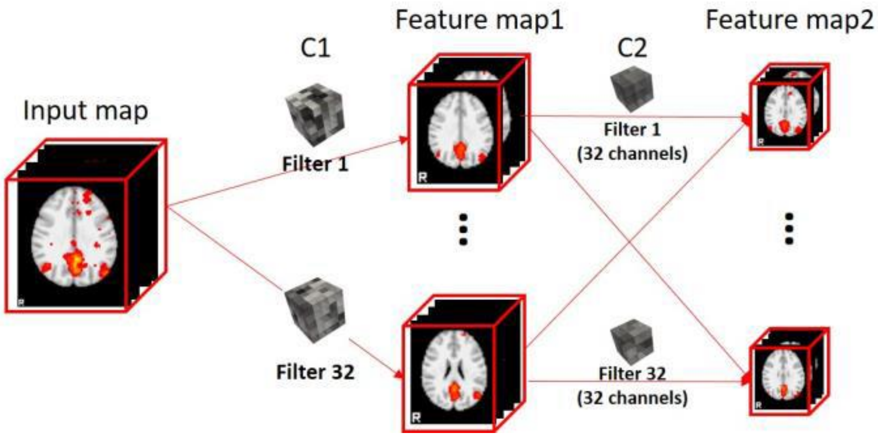
Skin cancer detection



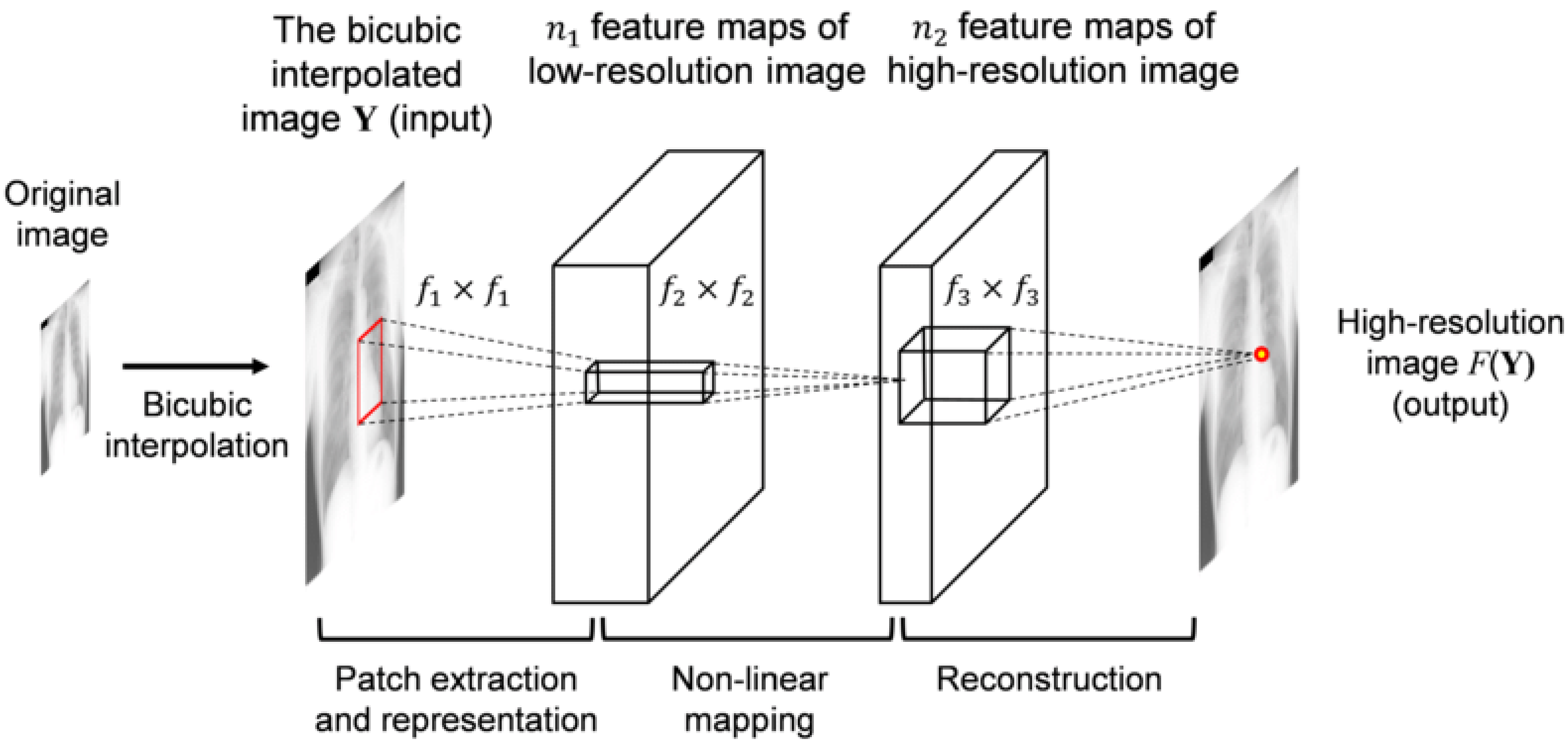
CNN & FMRI


MRI Scanner Cutaway
Radio Frequency Coil
Patient
Patient Table
Gradient Coils
Magnet
Scanner

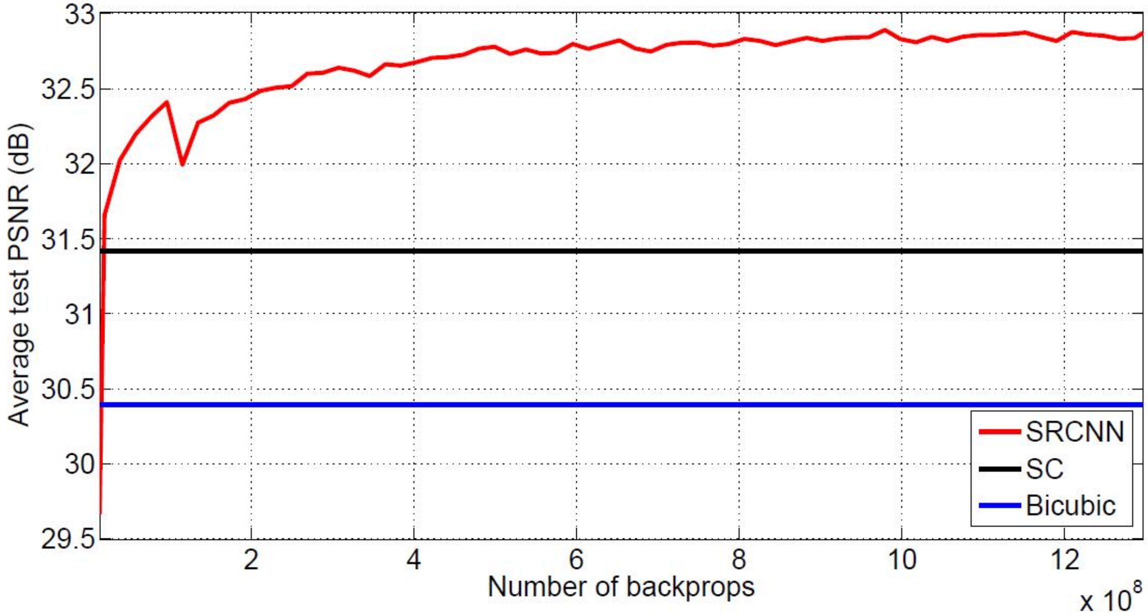

t_1
t_2
...
t_n

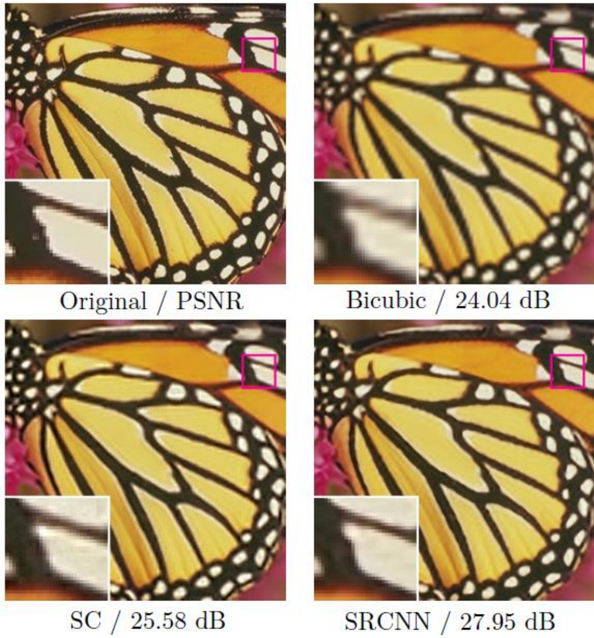

Input map
C1
Filter 1
Filter 32
Feature map1
C2
Filter 1 (32 channels)
Filter 32 (32 channels)
Feature map2

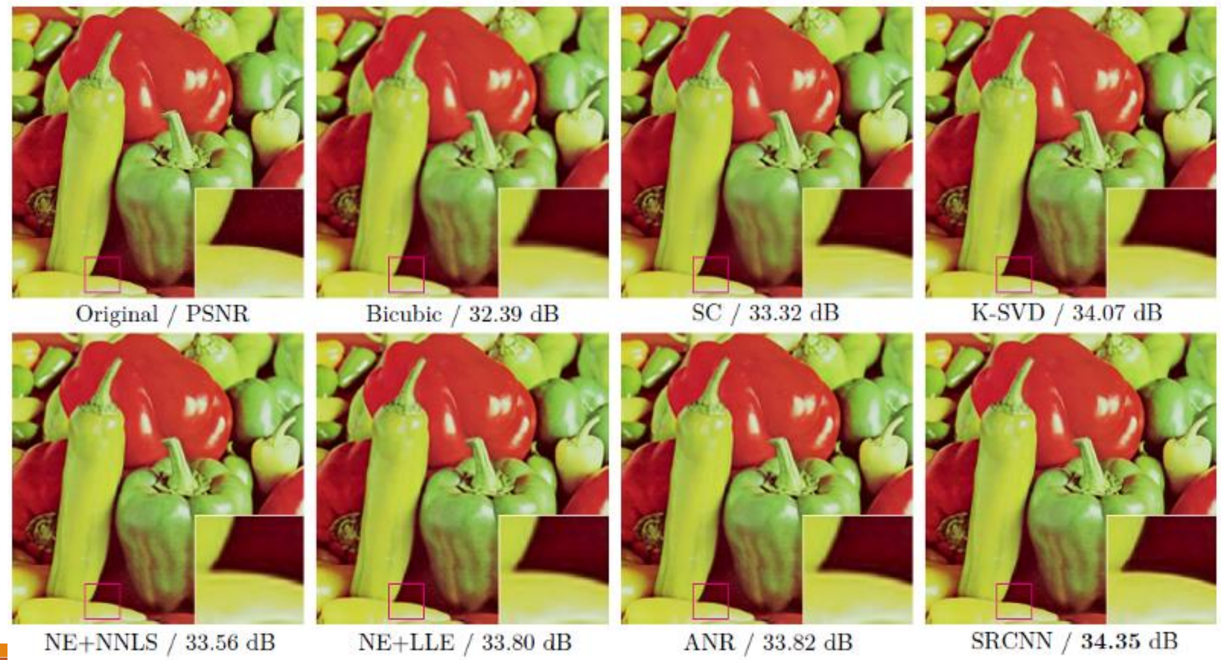
Super-Resolution Convolutional Neural Network (SRCNN)



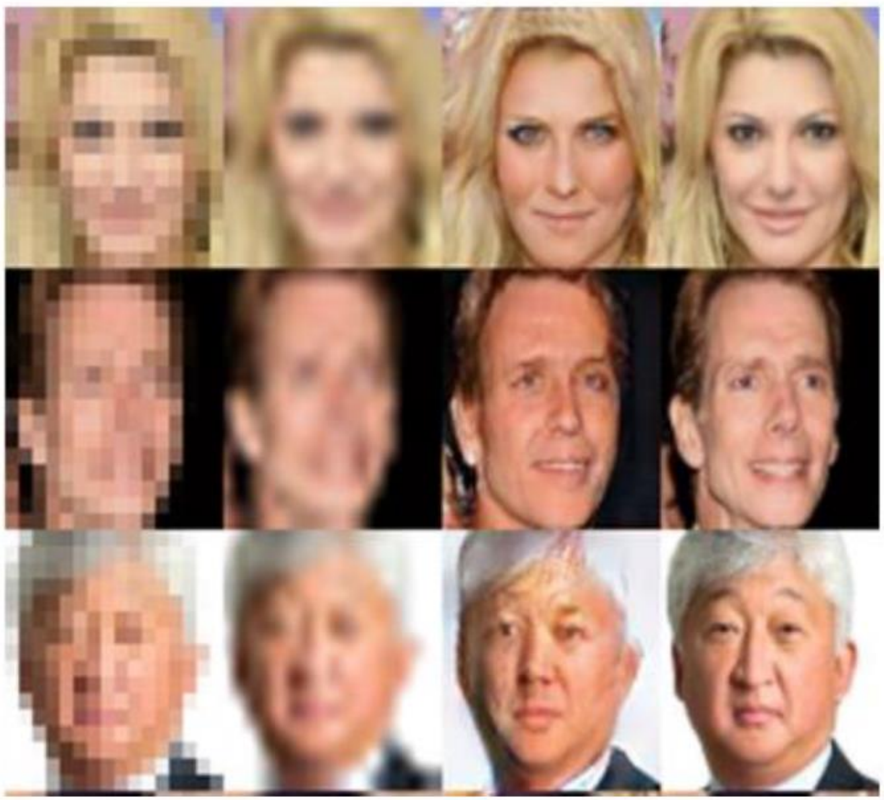
Dong, Chao, et al. "Image super-resolution using deep convolutional networks." *IEEE transactions on pattern analysis and machine intelligence* 38.2 (2015): 295-307.


33
32.5
32
31.5
31
30.5
30
29.5
Average test PSNR (dB)
2
4
6
8
10
12
Number of backprops
x 10^8
SRCNN
SC
Bicubic


Original / PSNR
Bicubic / 24.04 dB
SC / 25.58 dB
SRCNN / 27.95 dB

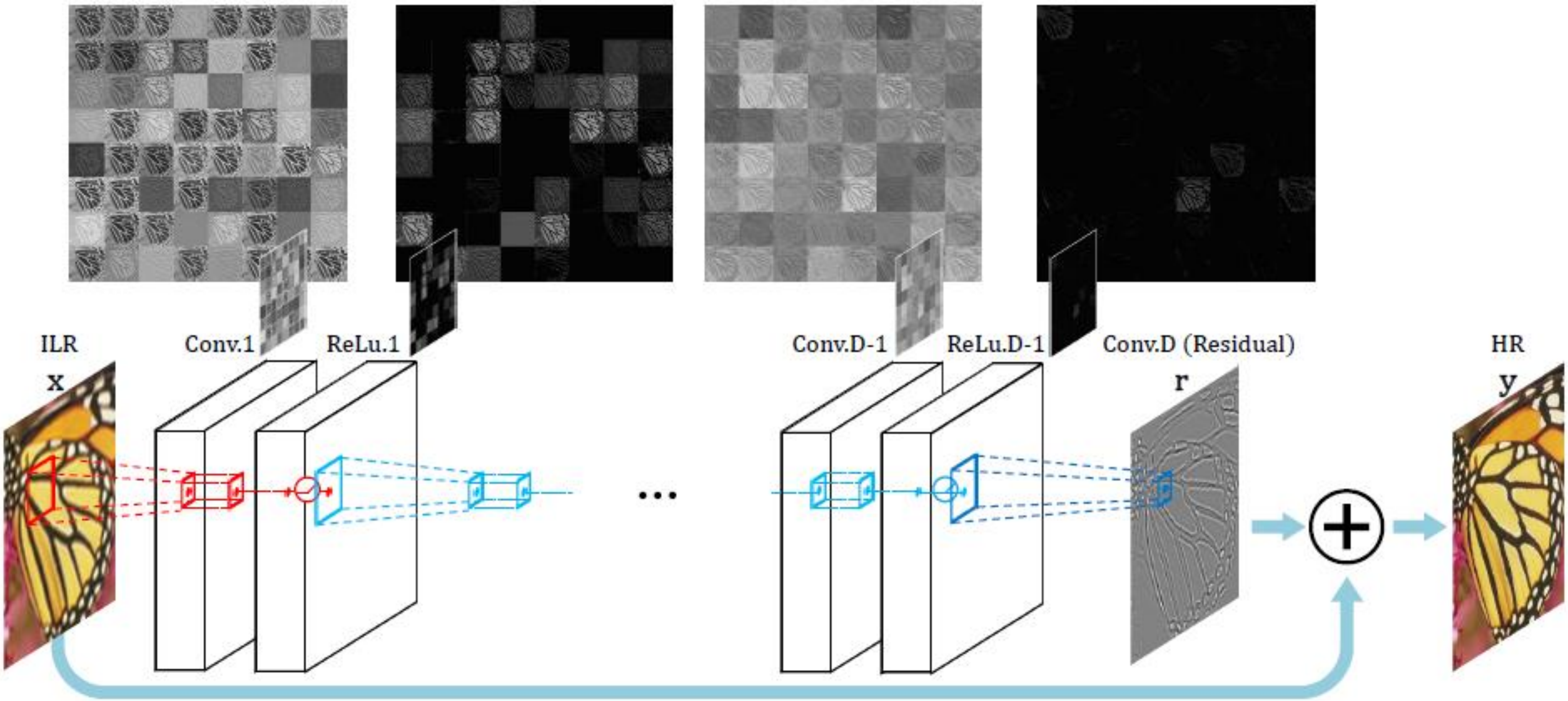

Original / PSNR
Bicubic / 32.39 dB
SC / 33.32 dB
K-SVD / 34.07 dB
NE+NNLS / 33.56 dB
NE+LLE / 33.80 dB
ANR / 33.82 dB
SRCNN / **34.35** dB

Source | Bicubic Interpolation | CNN | Reference

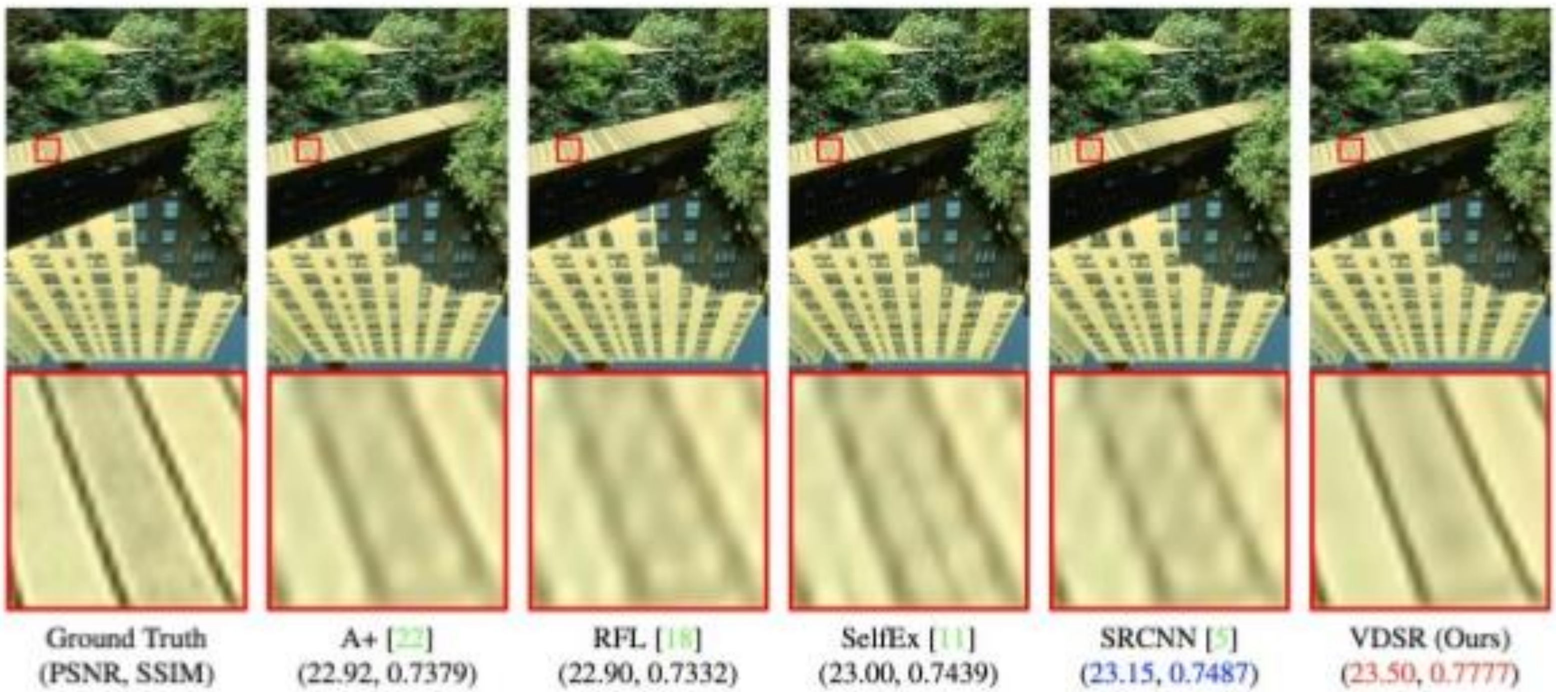


Source | Bicubic Interpolation | CNN | Reference

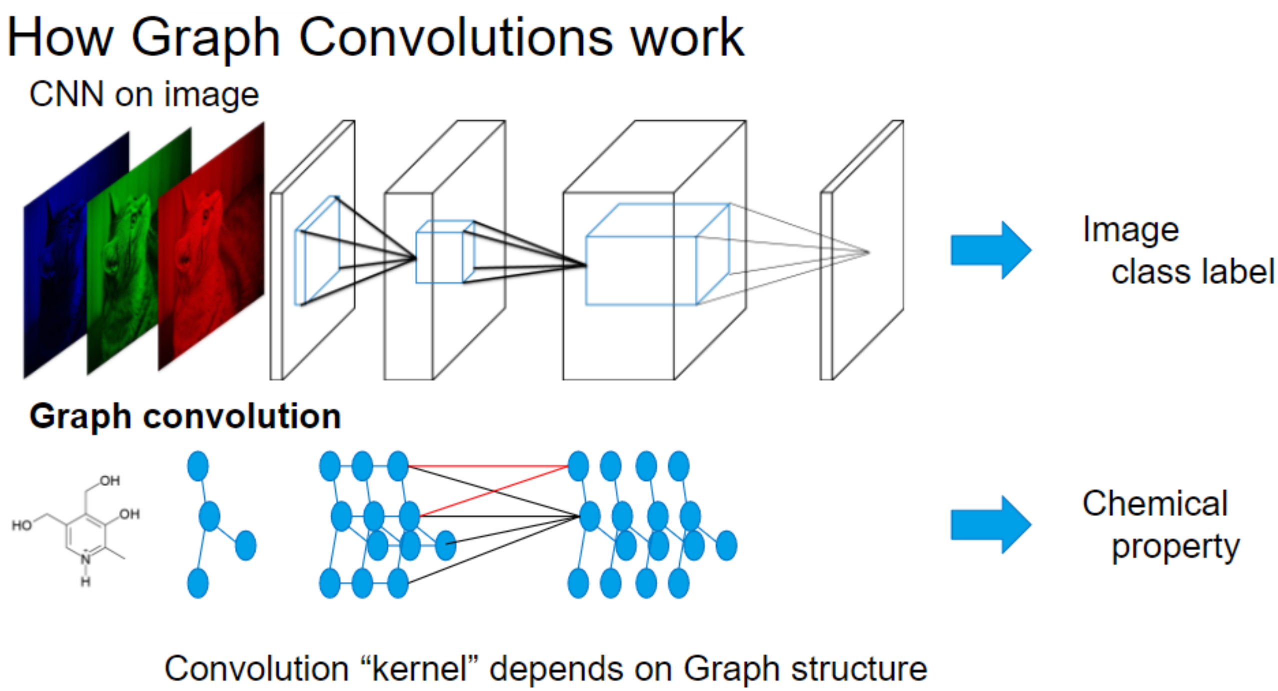
Very Deep Super Resolution

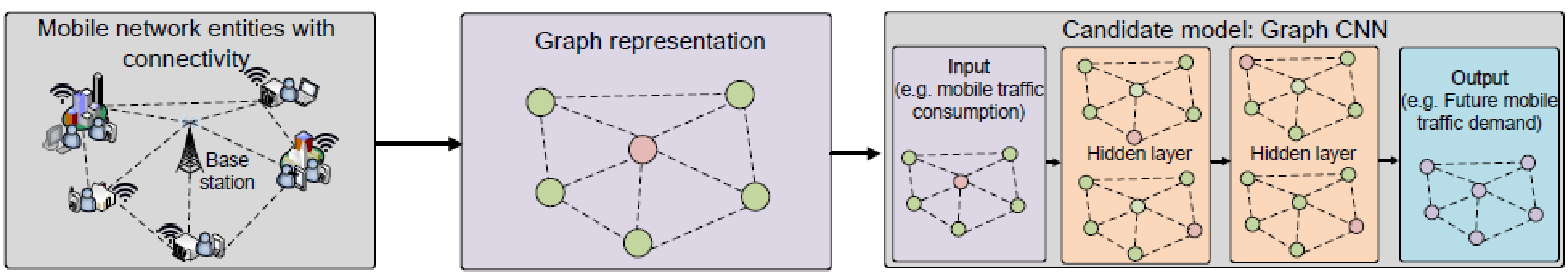


Kim, Jiwon, Jung Kwon Lee, and Kyoung Mu Lee. "Accurate image super-resolution using very deep convolutional networks." *IEEE computer vision and pattern recognition*. 2016.

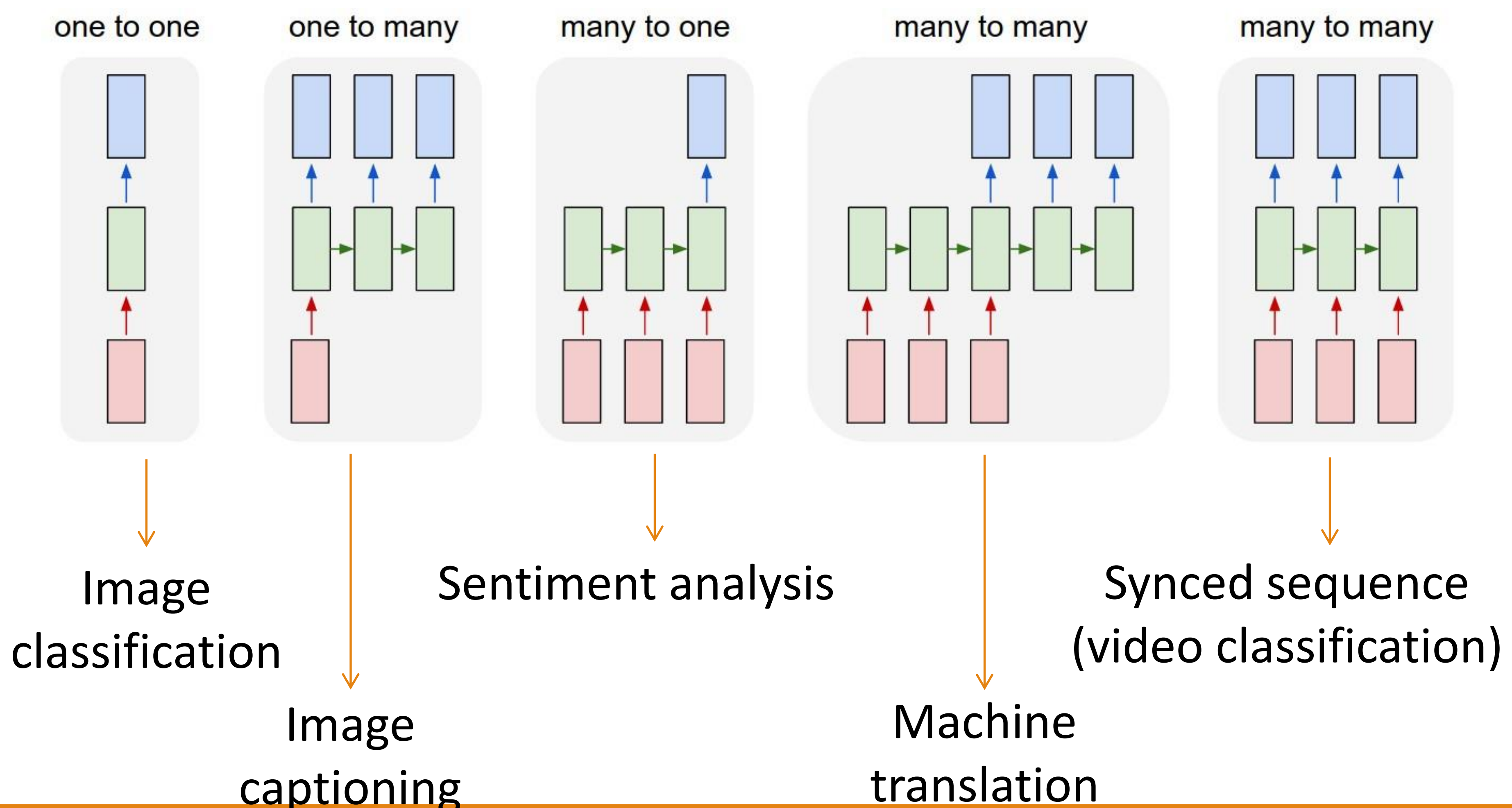

Ground Truth
(PSNR, SSIM)
A+ [22]
(22.92, 0.7379)
RFL [18]
(22.90, 0.7332)
SelfEx [11]
(23.00, 0.7439)
SRCNN [5]
(23.15, 0.7487)
VDSR (Ours)
(23.50, 0.7777)

Graph CNN


How Graph Convolutions work
CNN on image
Image
class label
Graph convolution
Chemical
property
Convolution “kernel” depends on Graph structure


Mobile network entities with
connectivity
Base
station
Graph representation
Candidate model: Graph CNN
Input
(e.g. mobile traffic
consumption)
Hidden layer
Hidden layer
Output
(e.g. Future mobile
traffic demand)

Different types of mapping



Recurrent Neural Networks

Motivation

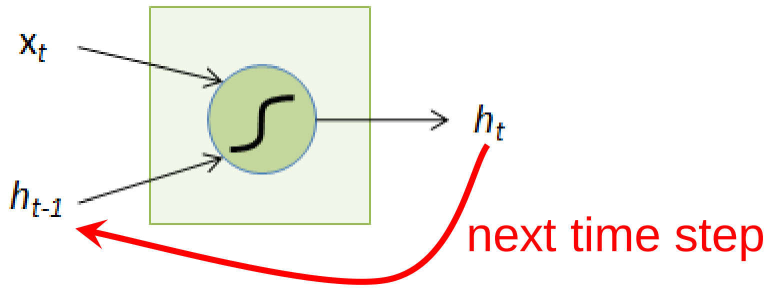
- Feed forward networks accept a fixed-sized vector as input and produce a fixed-sized vector as output
- fixed amount of computational steps
- recurrent nets allow us to operate over *sequences* of vectors

Use cases

- Video: sequence understanding
- Audio: speech transcription
- Text: natural language processing

Recurrent neuron

- x_t: Input at time t
- h_{t-1}: State at time t-1



$$h_t = f(W_h h_{t-1} + W_x x_t)$$

Recurrent Neural Networks

Feed-forward NN

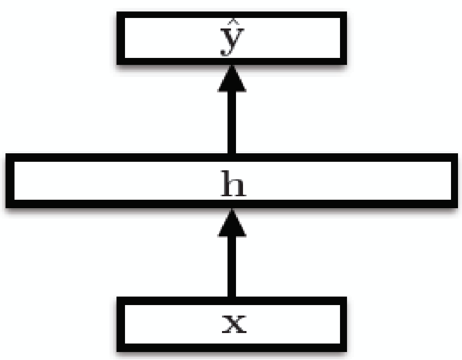
$$\mathbf{h} = g(\mathbf{V}\mathbf{x} + \mathbf{c})$$

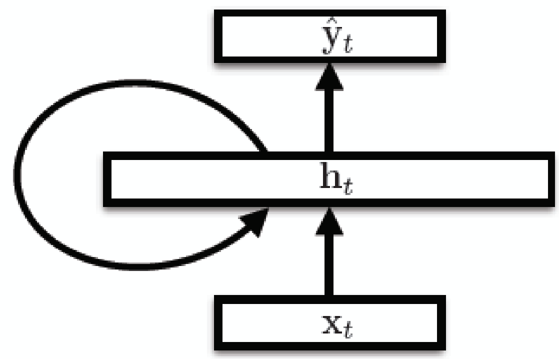
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h} + \mathbf{b}$$

Recurrent NN

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$

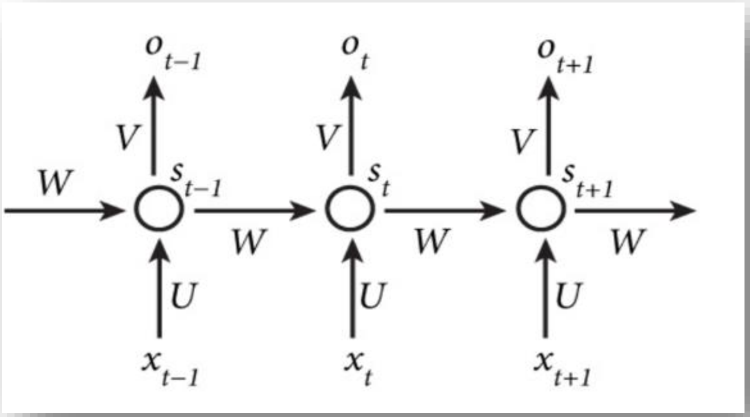
$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$

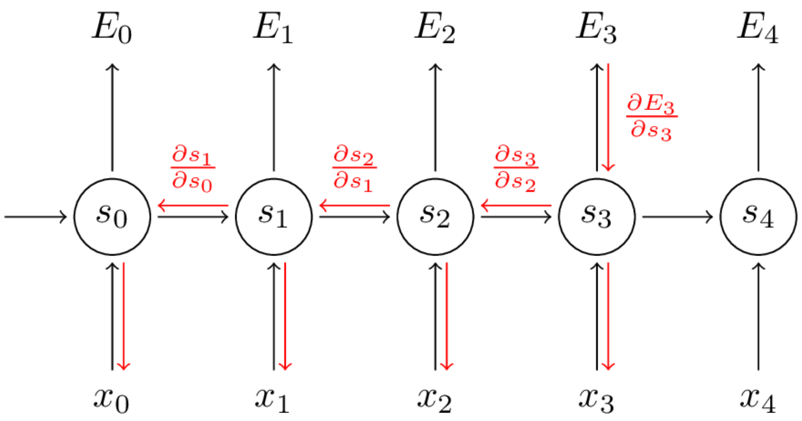




Unfolding RNNs

- Each node represents a layer of network units at a single time step.
- The same weights are reused at every time step.





Domain adaptation

Dog/Cat Classifier

cat

dog

Data ***<u>not directly related to</u>*** the task considered

elephant

tiger

dog

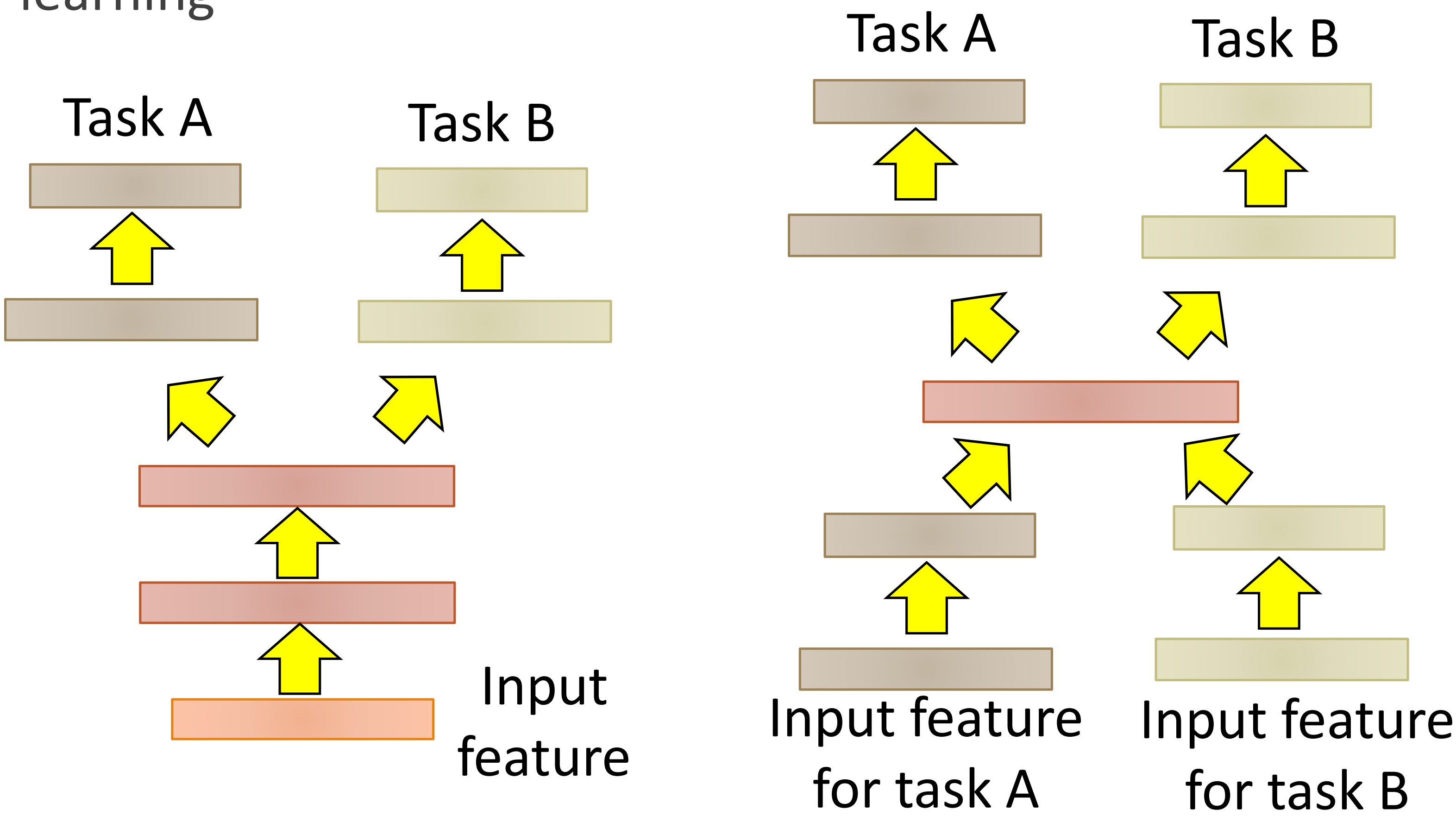
cat

Similar domain, different tasks

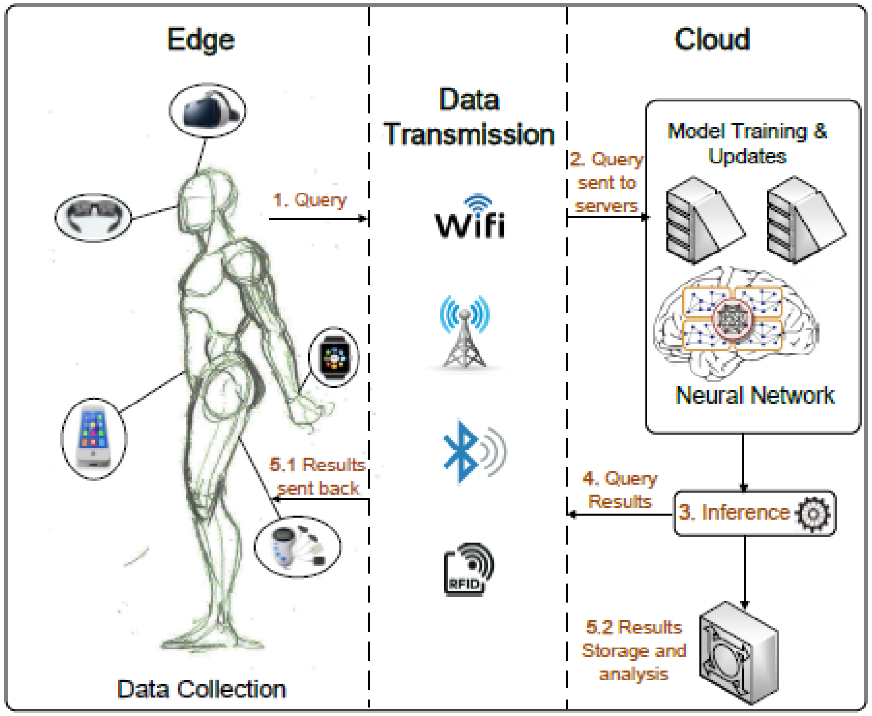
Different domains, same task

Multitask Learning

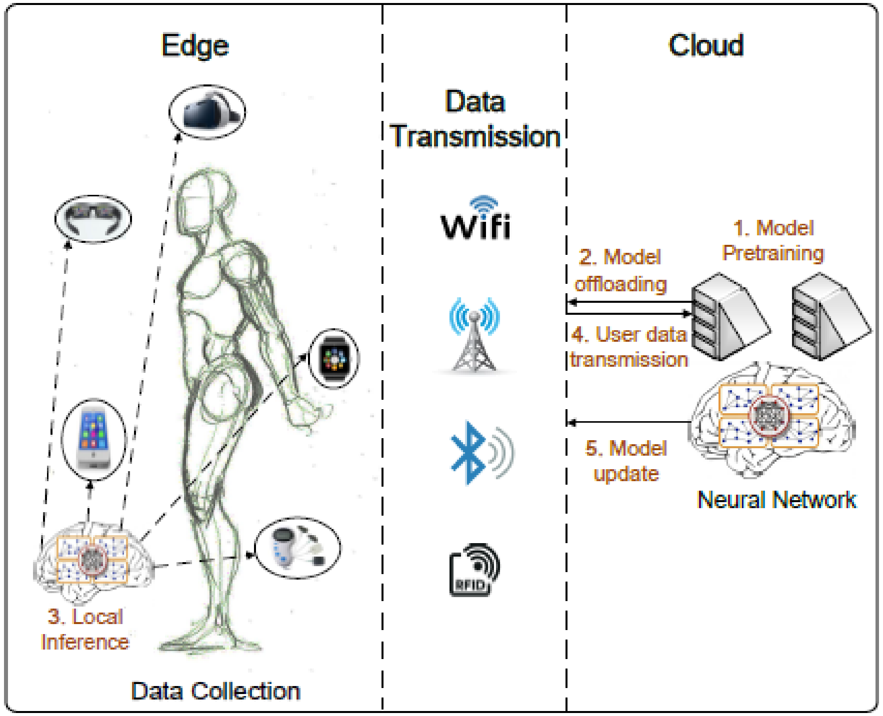
The multi-layer structure makes NN suitable for multitask learning



app-level mobile data analysis



Cloud-based



Edge-based

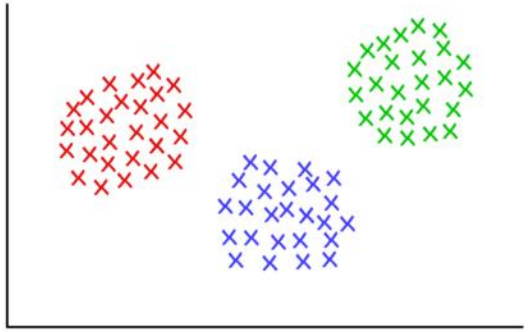
Unsupervised Learning

Why unsupervised?

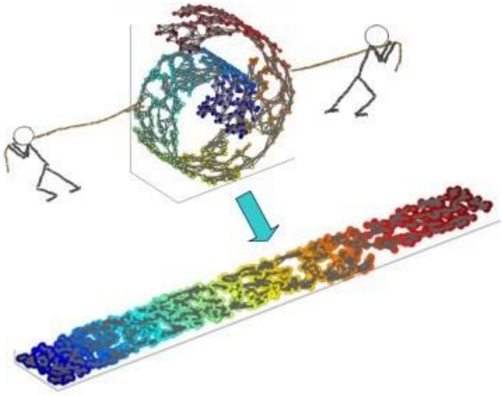
➢ Challenges

- Massive volumes of observations
- No user-introduced annotations

➢ Applications

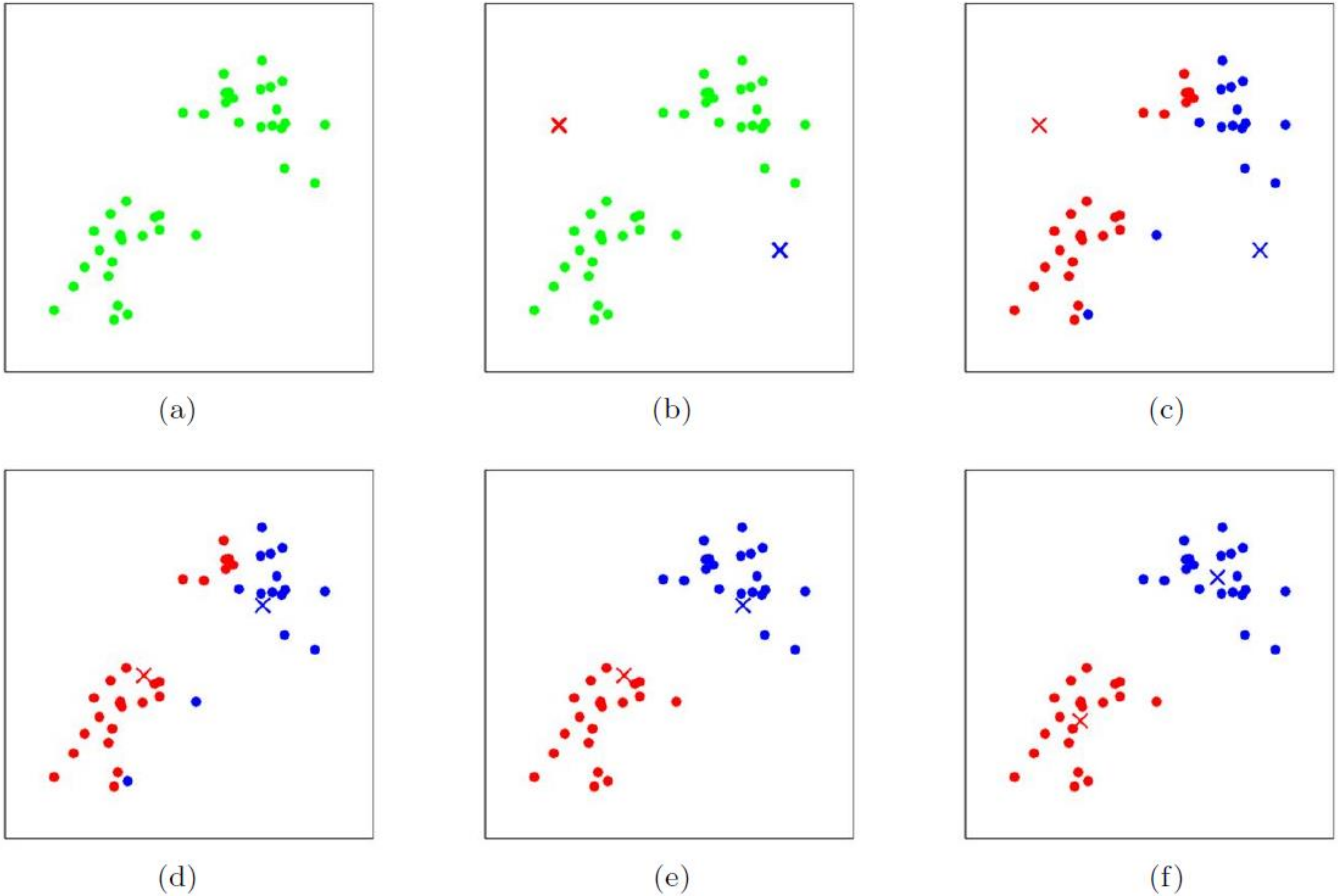


Clustering

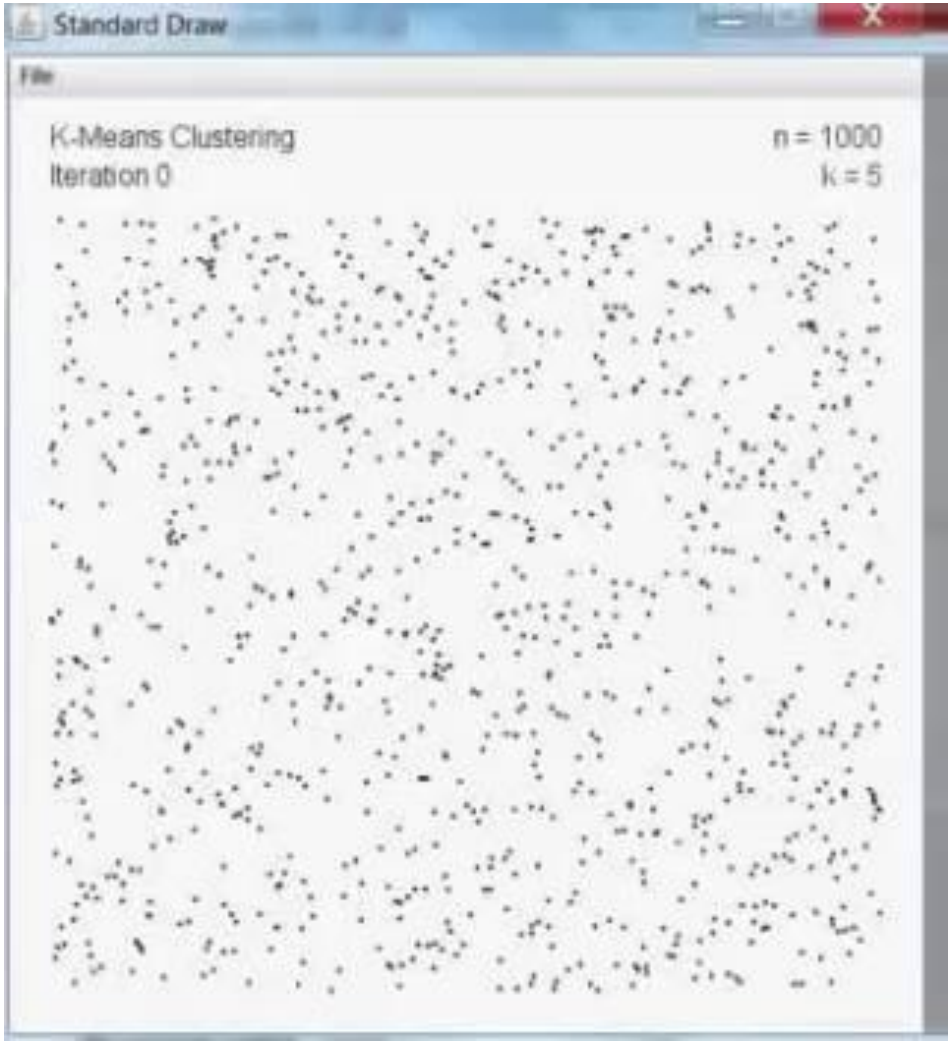


Dimensionality reduction

K-means



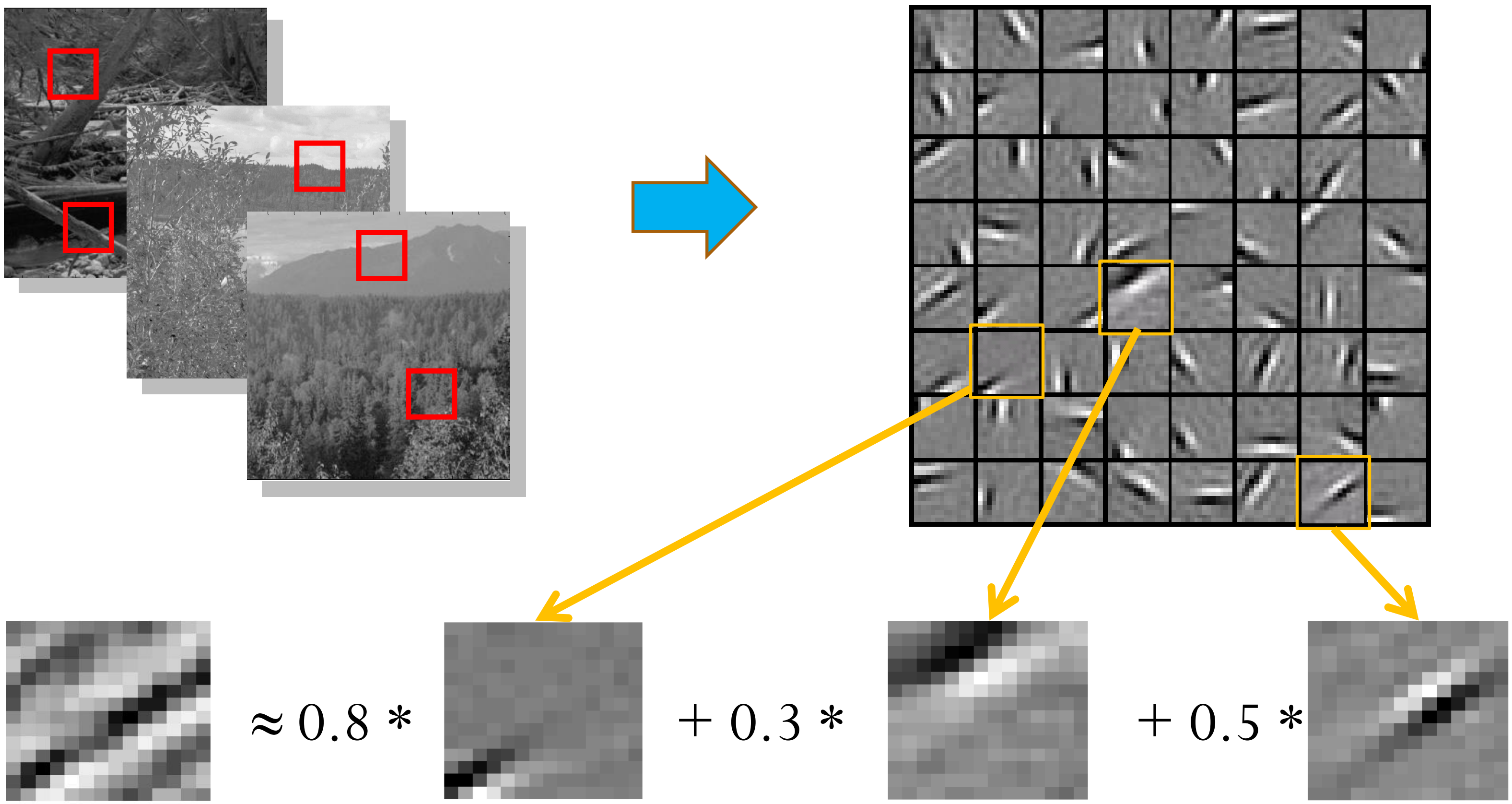
K-means



Topics

- Sparse coding
- Autoencoders
- Generative Adversarial Networks

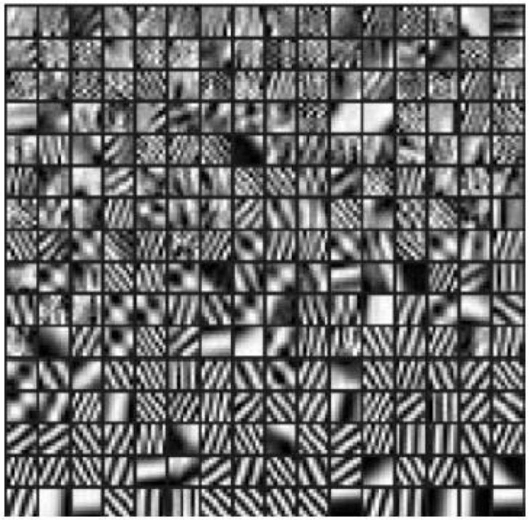
Sparse Coding



$$\min \left\| x - Ds \right\|_2 \quad \text{s.t.} \quad \left\| s \right\|_1 \leq K$$

Deep Models

Applications of SC

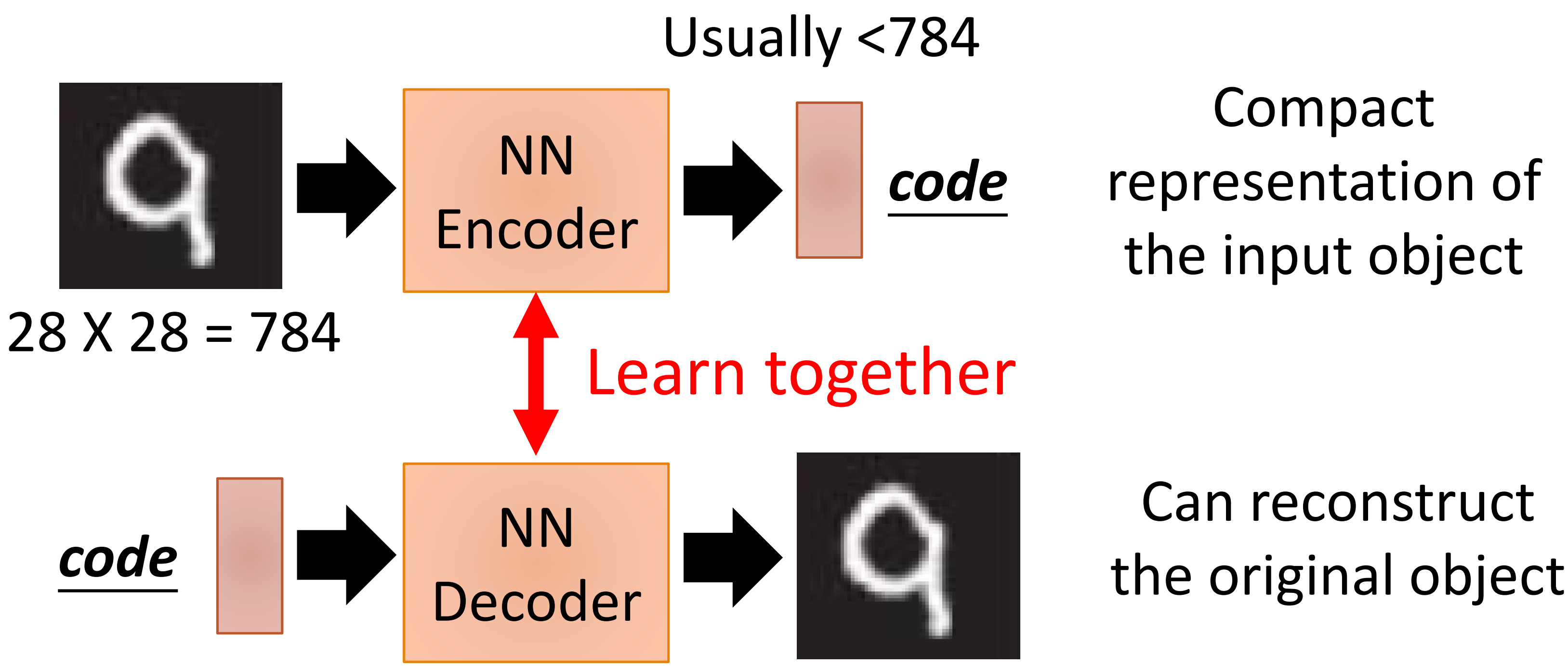


[M. Elad, Springer 2010]

Shortcoming

- Shallow model <-> single level of representation
- Complexity <-> dictionary size
- Task specific

AutoEncoders (AE)



AutoEncoders (AE)

Unsupervised feature learning

Network is trained to output the input (learn identify function).

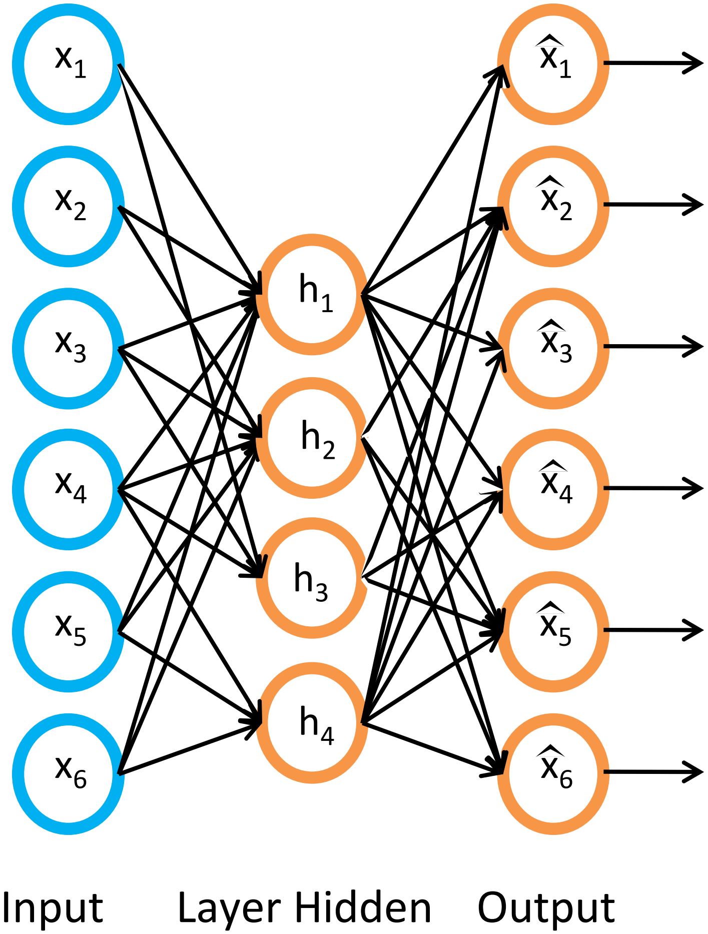
$$J = \frac{1}{m} \sum_{i=1}^{m} \|\hat{x} - x\|_2$$

Encoder

$$f(x) = \mathbf{h} = z(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1)$$

Decoder

$$g(f(x)) = \hat{\mathbf{x}} = z(\mathbf{W}_2 \mathbf{h} + \mathbf{b_2})$$

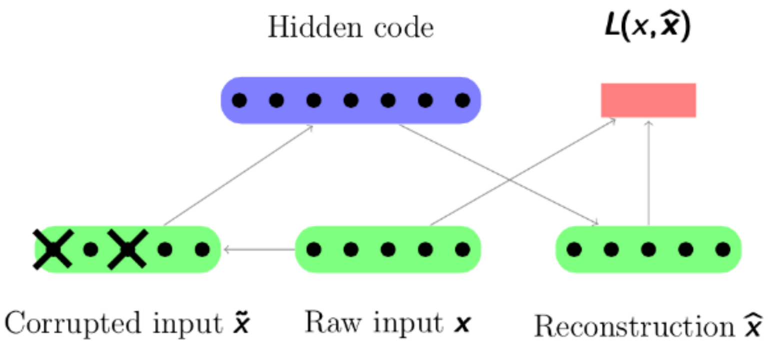


Regularized Autoencoders

Sparse neuron activation

$$J_{sparse} = \sum \|\hat{\mathbf{x}} - \mathbf{x}\|_2 + \beta \sum KL(p, \hat{p})$$

Denoising auto-encoders



Convolutional AE

$$f(x) = \mathbf{h} = z(\mathbf{W}_1 * \mathbf{x} + \mathbf{b}_1)$$

Stacked AutoEncoders (SAE)

Extended AE with multiple layers of hidden units

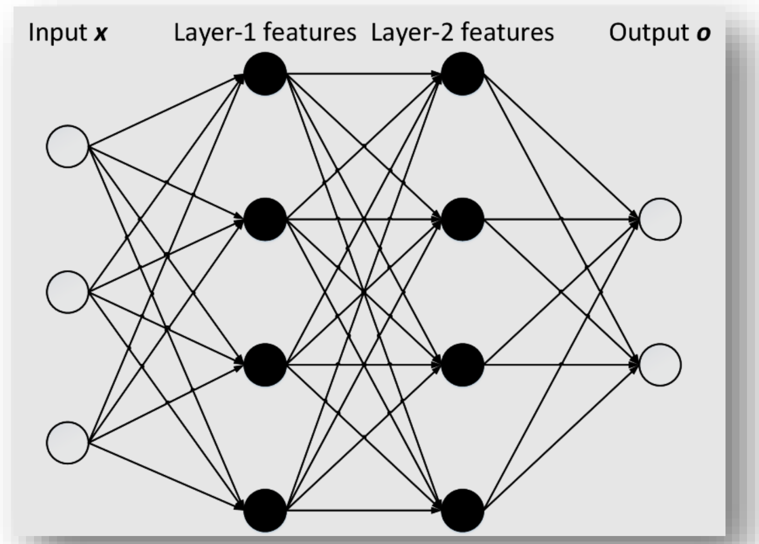
Challenges of Backpropagation

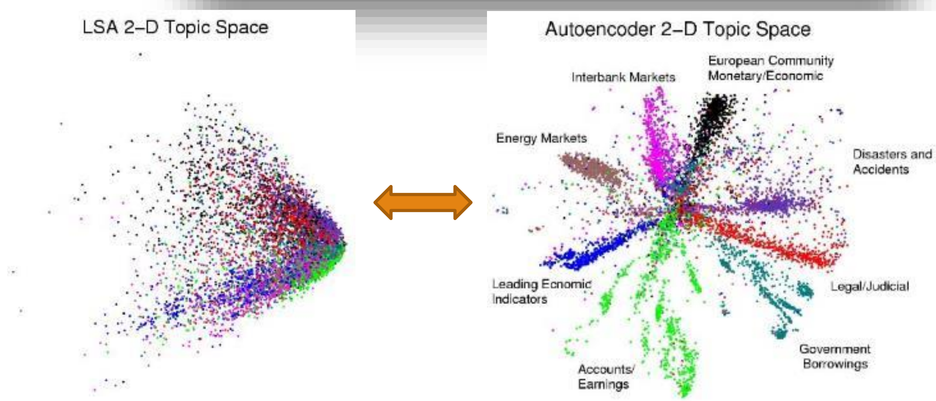
Efficient training

- Normalization of input

Unsupervised pre-training

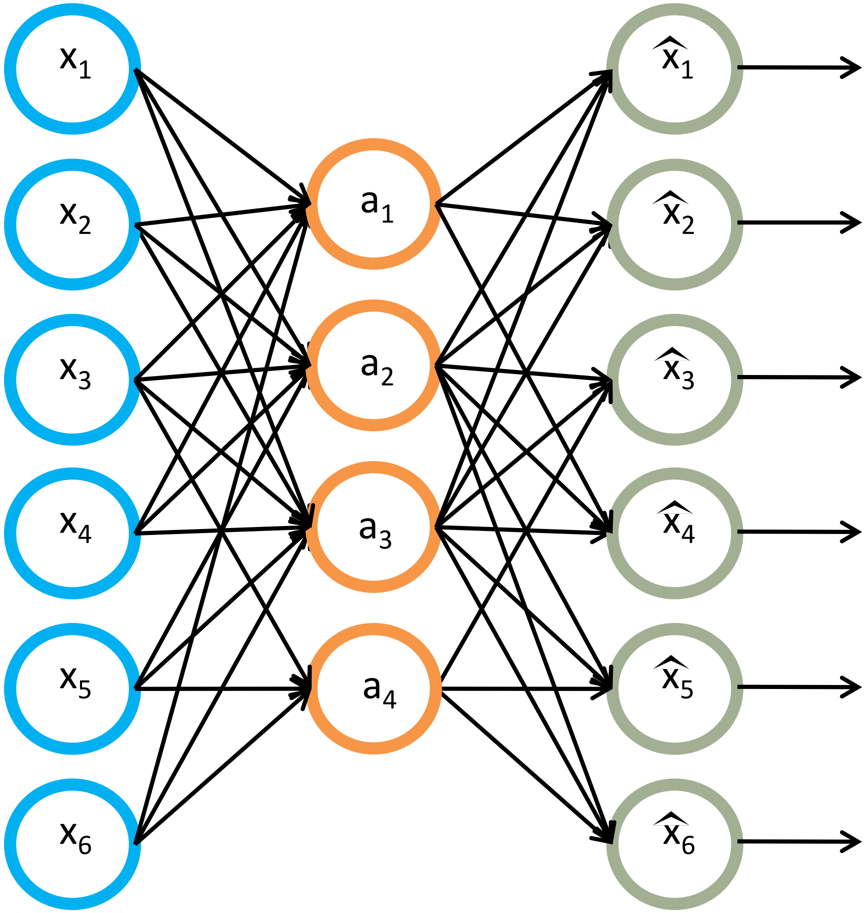
- Greedy layer-wise training
- Fine-tune w.r.t criterion





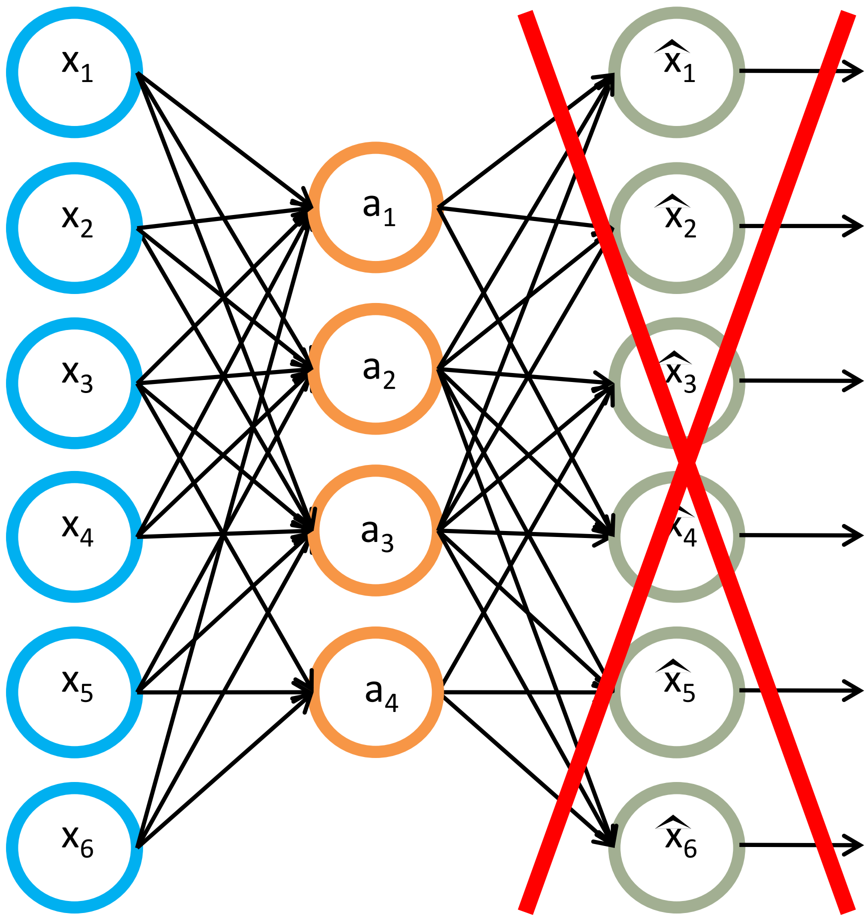
Bengio, Learning deep architectures for AI, Foundations and Trends in Machine Learning ,2009

SAE



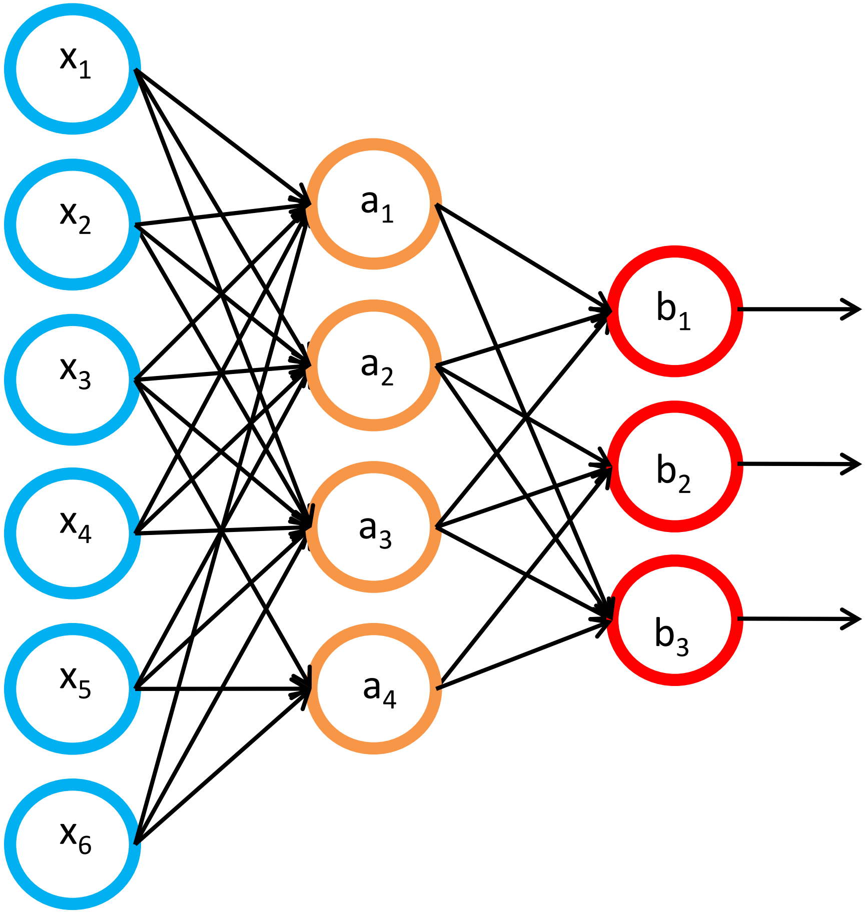
$$loss = \frac{1}{m}\sum_{i=1}^{m} \|\hat{x}_i - x_i\|_2$$

SAE

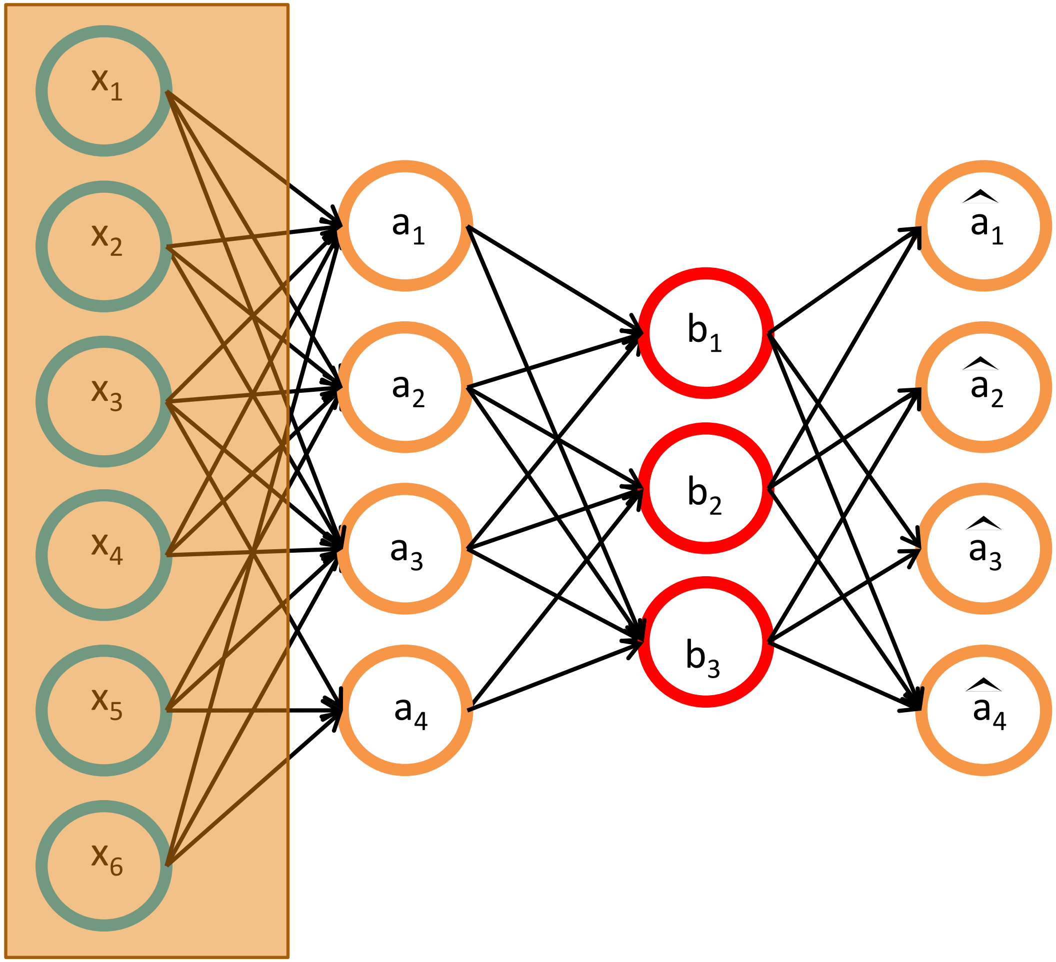


$$loss = \frac{1}{m}\sum_{i=1}^{m} \|\hat{x}_i - x_i\|_2$$

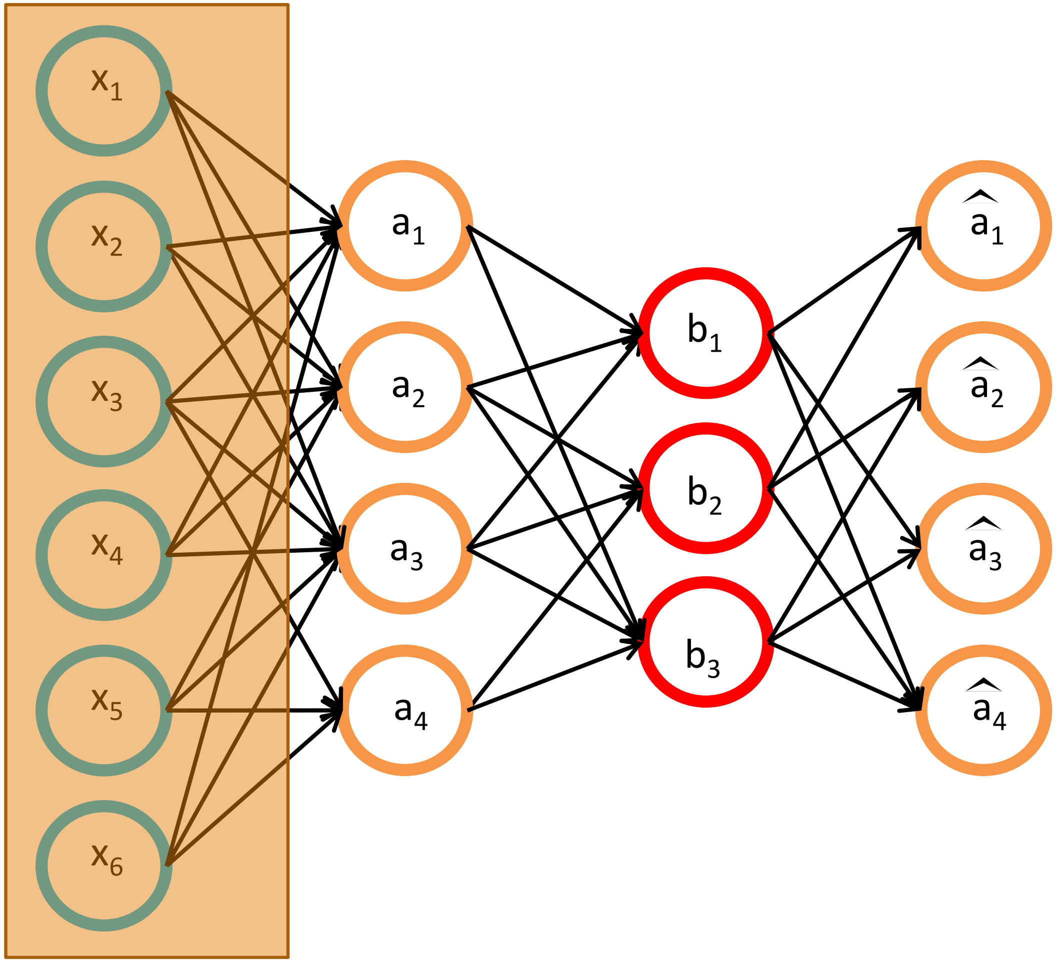
SAE



SAE

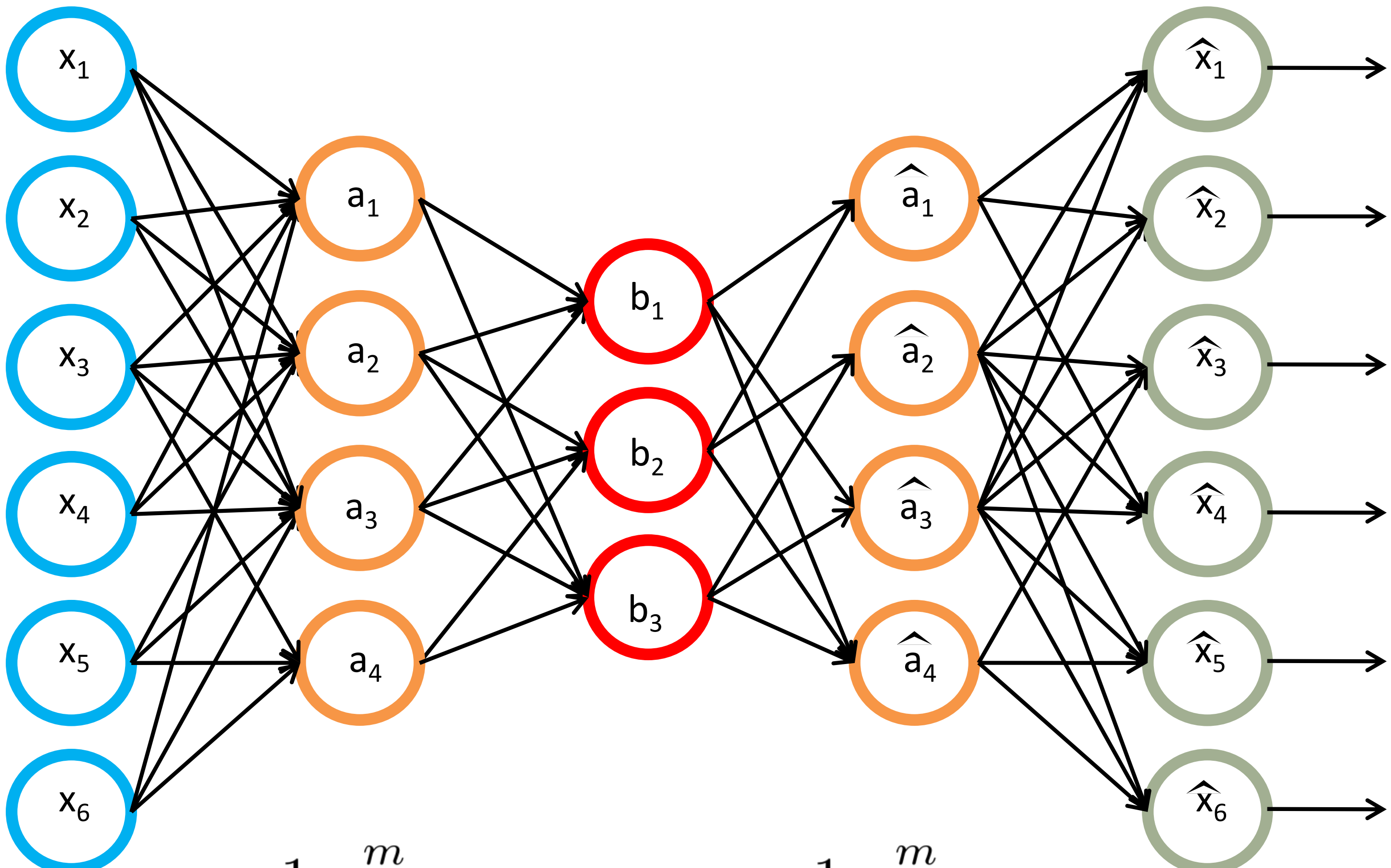


SAE



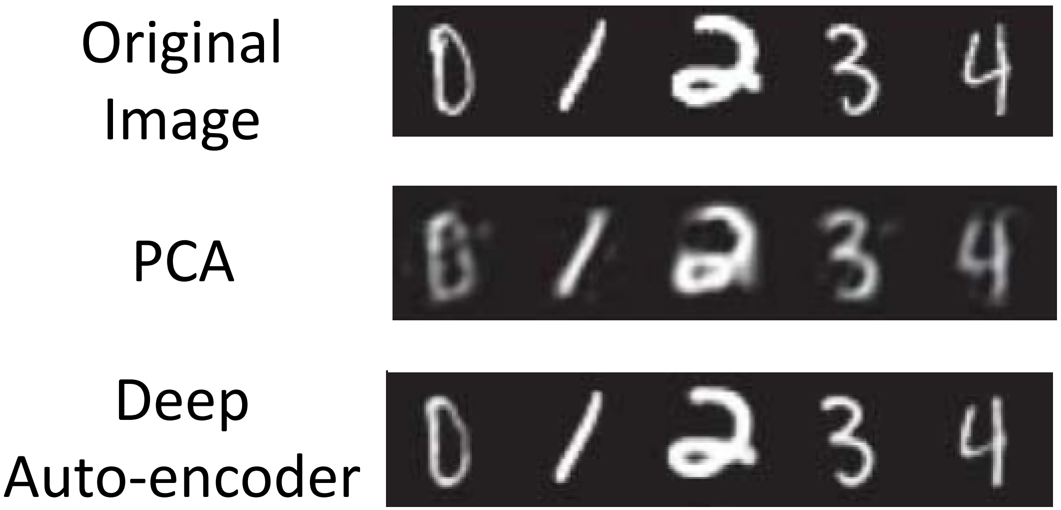
$$loss = \frac{1}{m}\sum_{i=1}^{m}\|\hat{a}_i - a_i\|_2$$

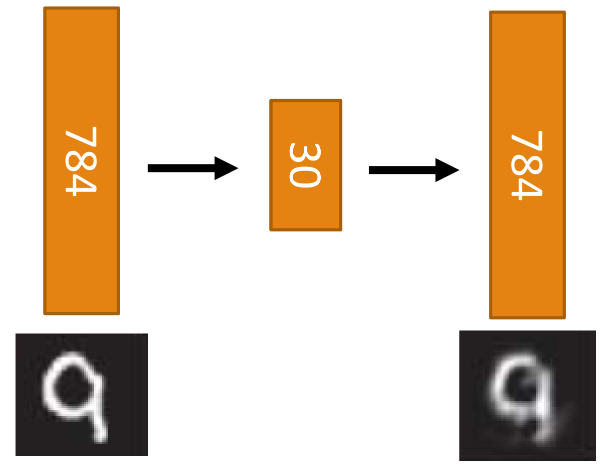
SAE

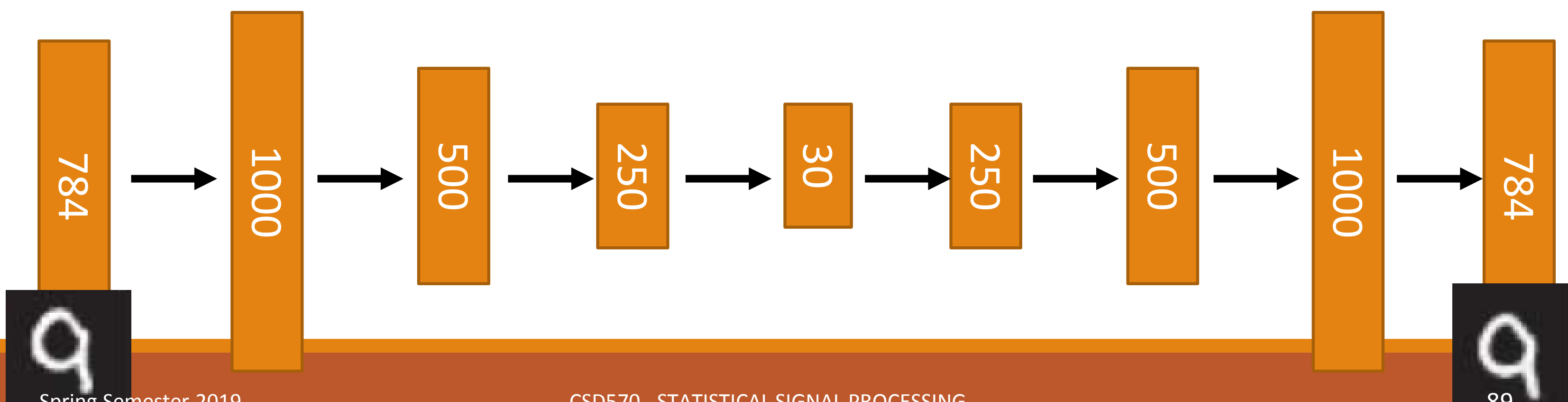


$$loss = \frac{1}{m}\sum_{i=1}^{m} \|\hat{x}_i - x_i\|_2 = \frac{1}{m}\sum_{i=1}^{m} \|\hat{a}_1(b_1(a_1(\hat{x}_i))) - x_i\|_2$$

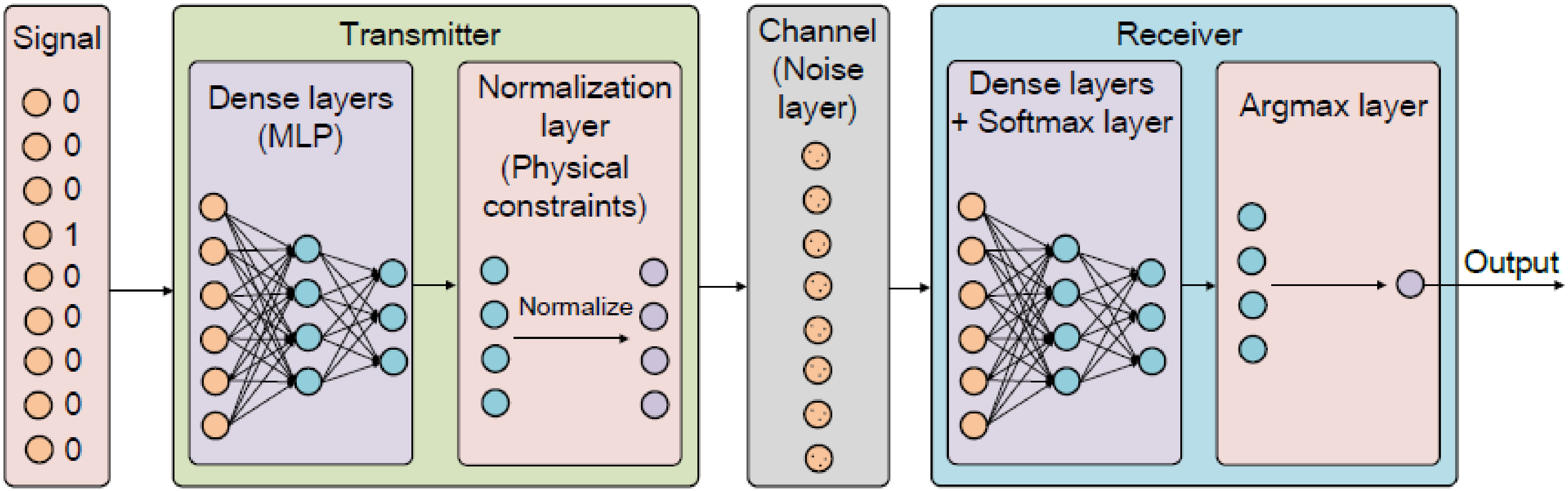
Deep Auto-encoder





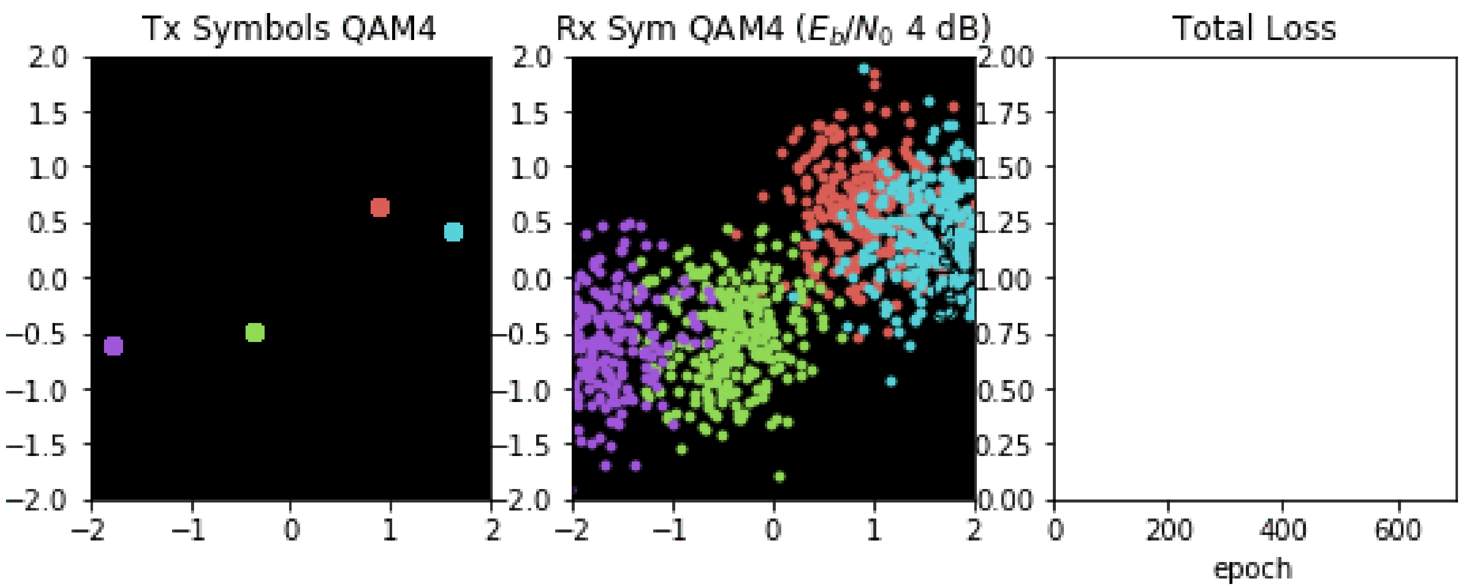


AWGN channel modeling



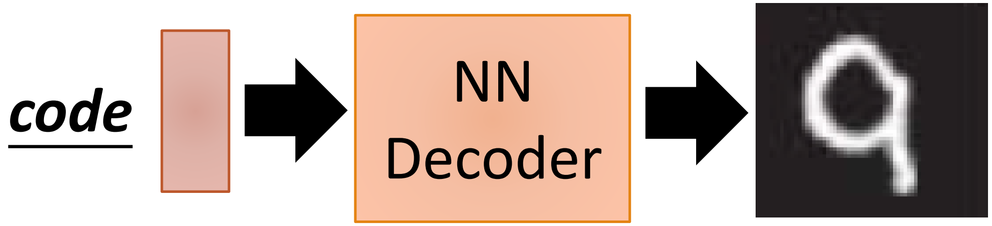
Application in modulation

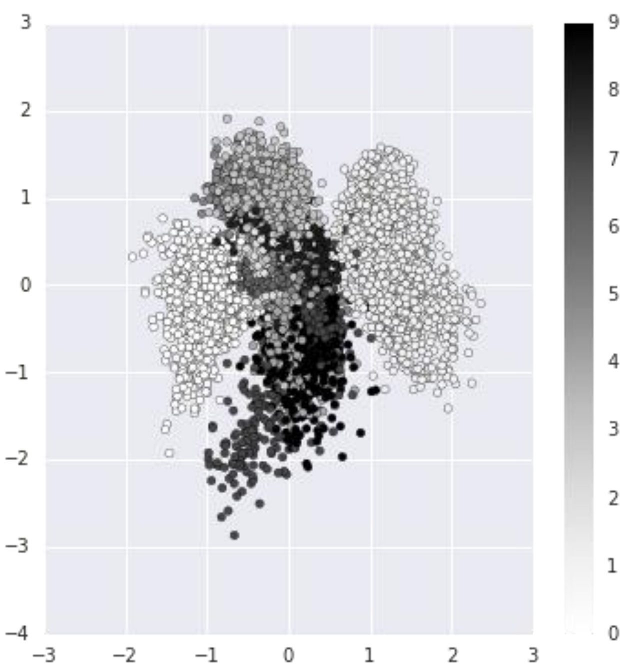
training a *learned physical layer*, where a channel autoencoder learns how to optimize BER for two bits of information over a simple Additive White Gaussian Noise (AWGN) effect.

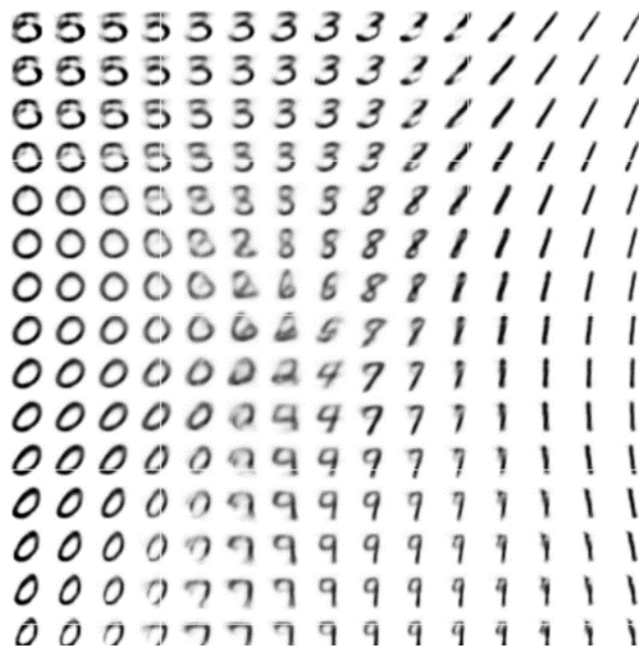



AND NOW FOR SOMETHING COMPLETELY DIFFERENT

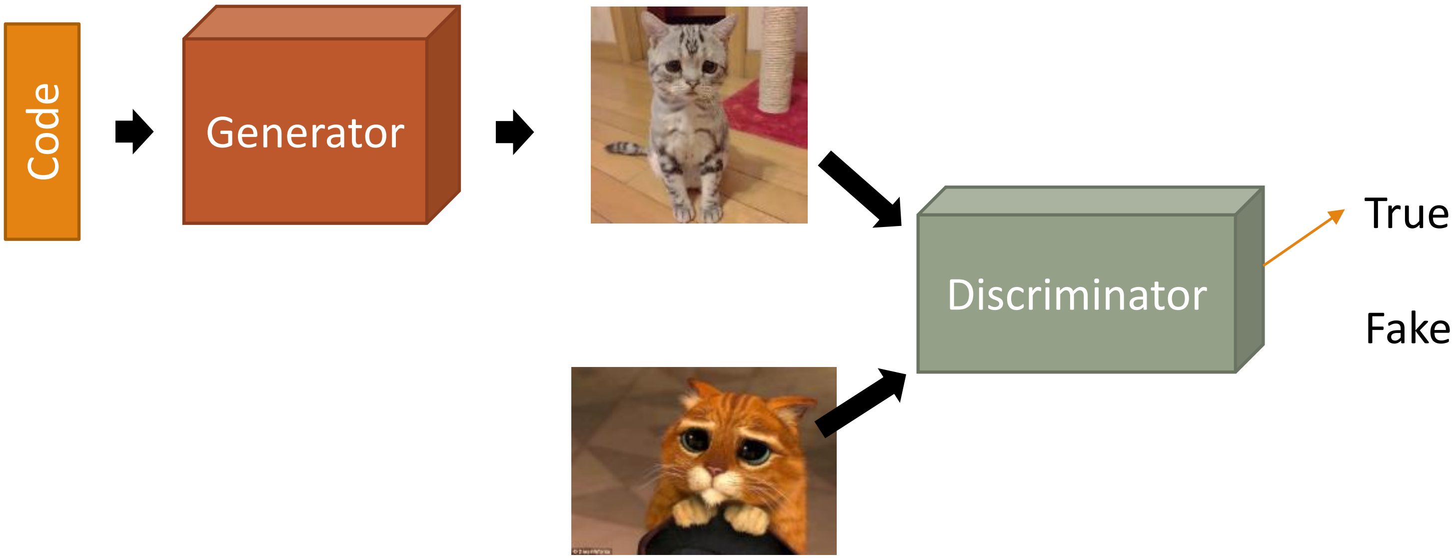
Generators?







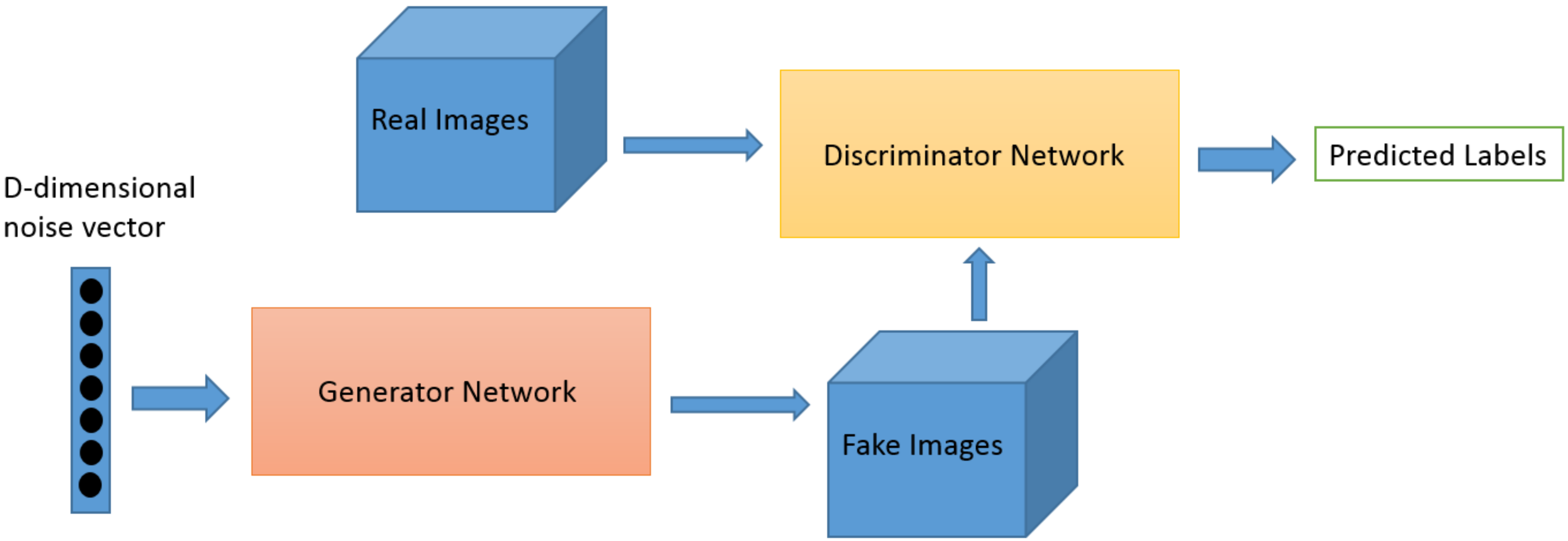
Generative Adversarial Networks



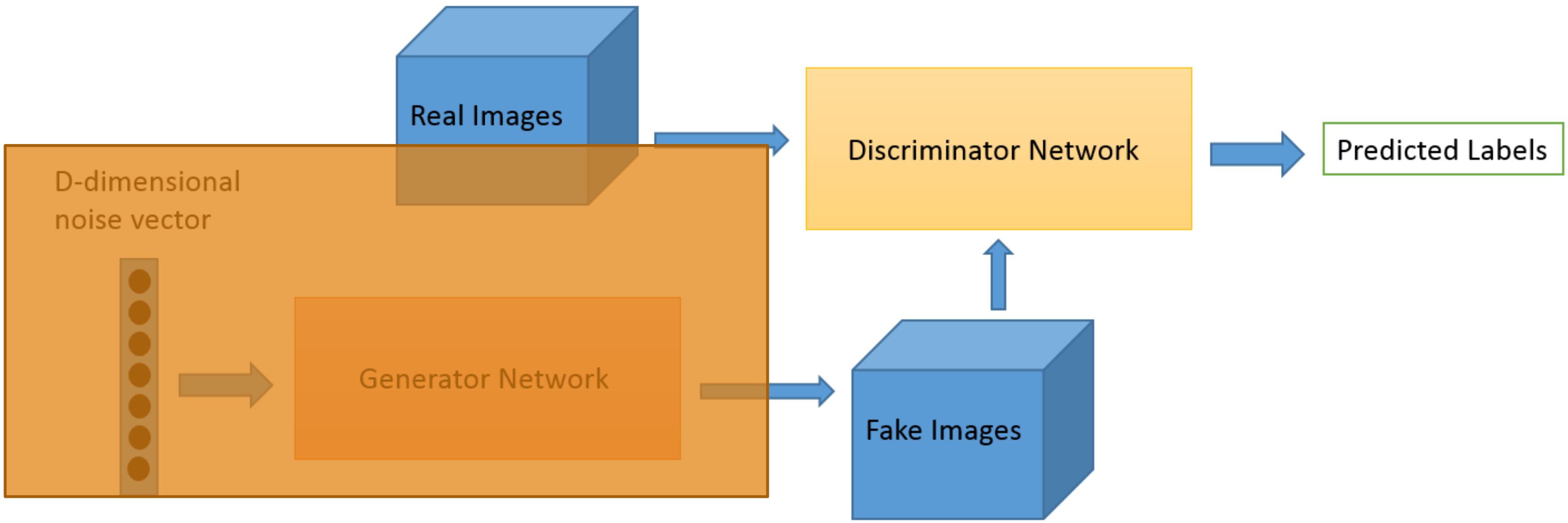
Goodfellow, Ian, et al. "Generative adversarial nets." NIPS 2014

Yann LeCun, “adversarial training is the coolest thing since sliced bread.”

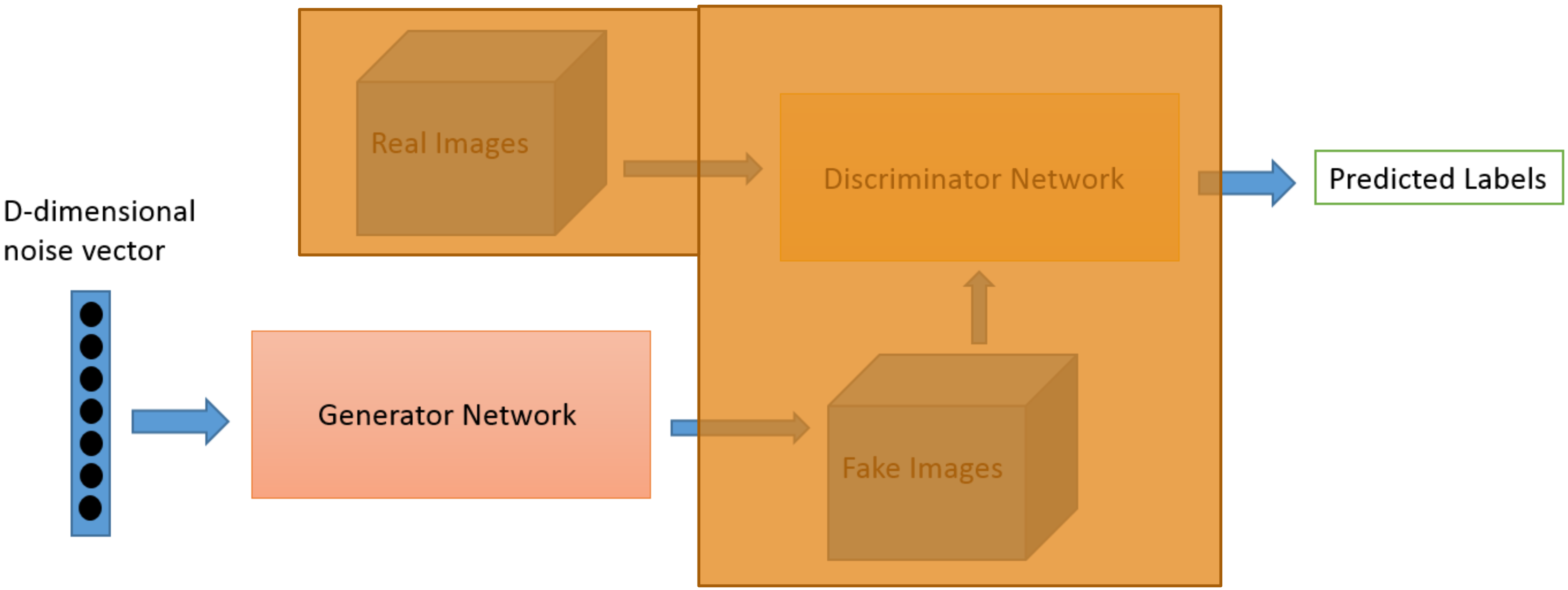
GANs


Real Images
Discriminator Network
Predicted Labels
D-dimensional noise vector
Generator Network
Fake Images

GANs

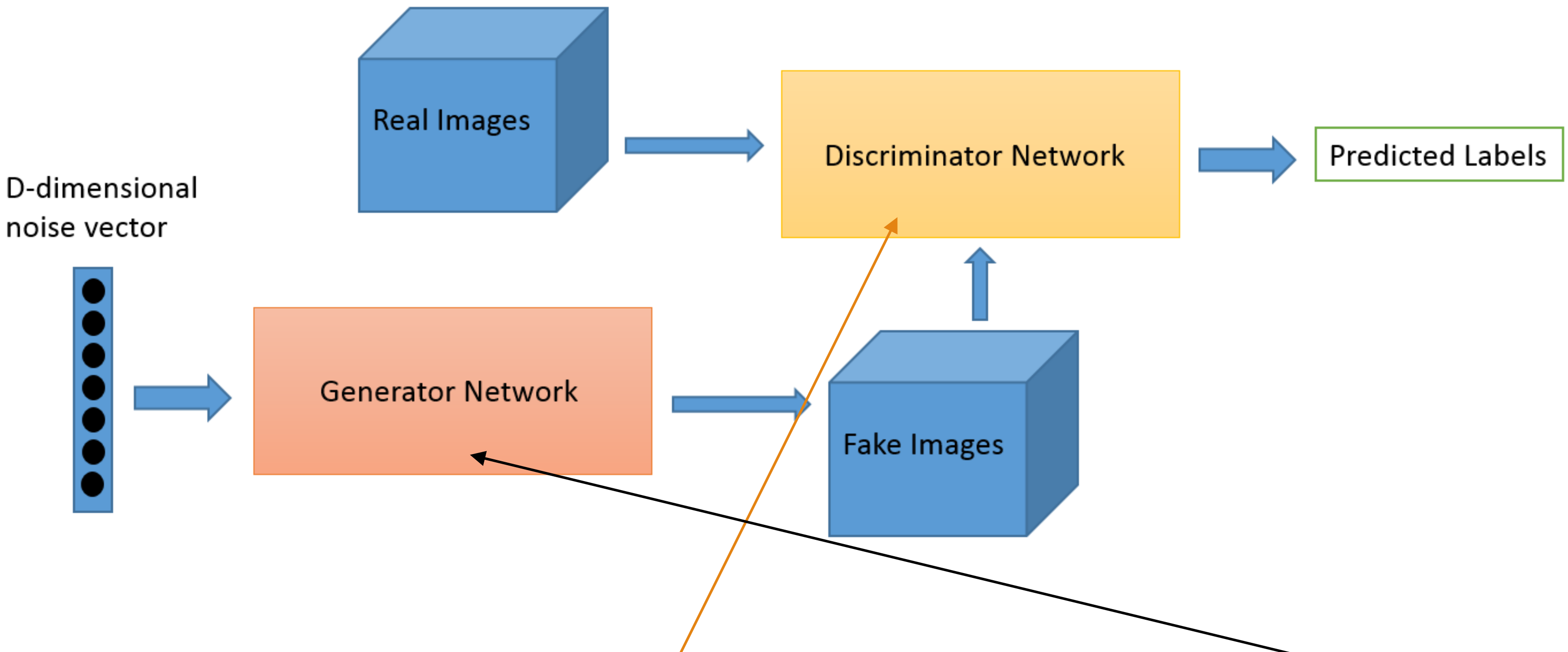

Real Images
Discriminator Network
Predicted Labels
D-dimensional noise vector
Generator Network
Fake Images

GANs



Real Images
Discriminator Network
Predicted Labels
D-dimensional noise vector
Generator Network
Fake Images

GANs



$$\min_{G} \max_{D} = \mathbb{E}_{\mathbf{x}\sim p_{data}(\mathbf{x})}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(z)}[1 - \log D(G(\mathbf{x}))]$$

Training Procedure: Basic Idea

G tries to fool D

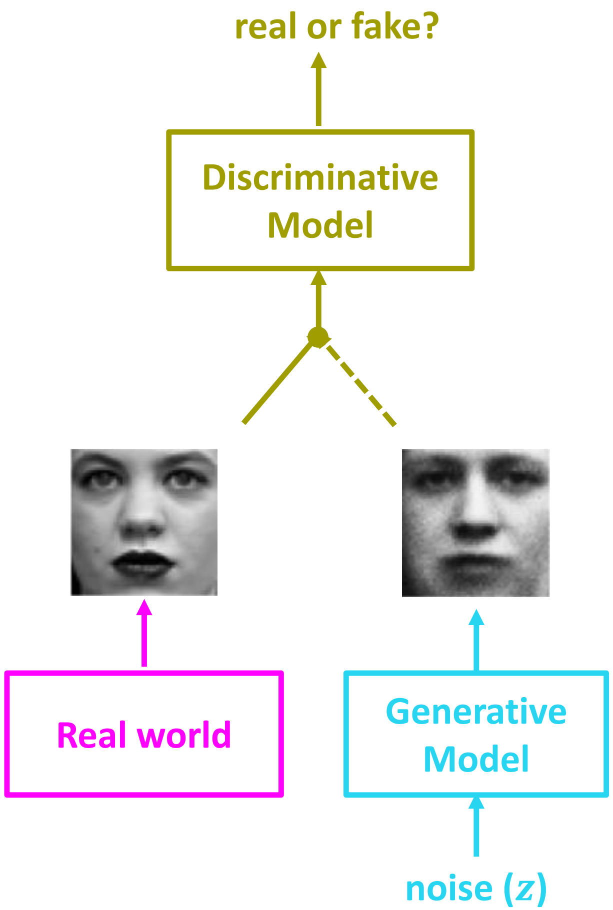
D tries not to be fooled

Models are trained simultaneously

- As G gets better, D has a more challenging task
- As D gets better, G has a more challenging task

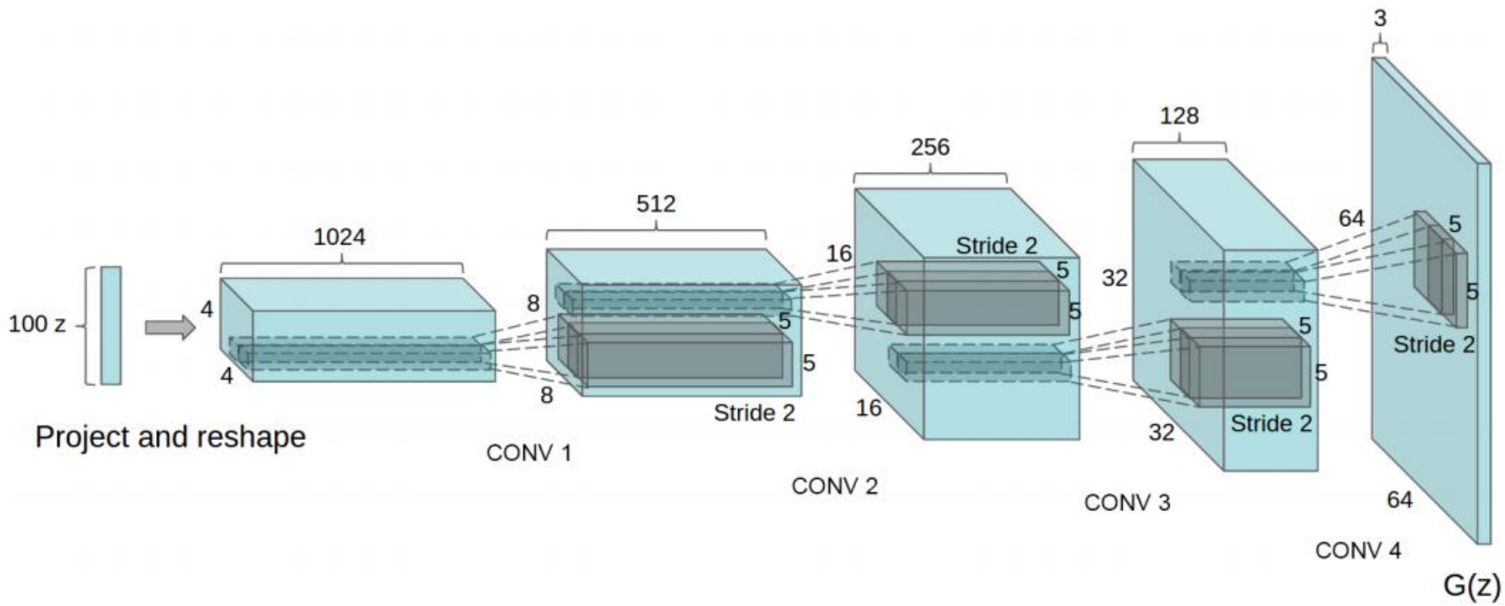
Ultimately, we don't care about the D

- Its role is to force G to work harder



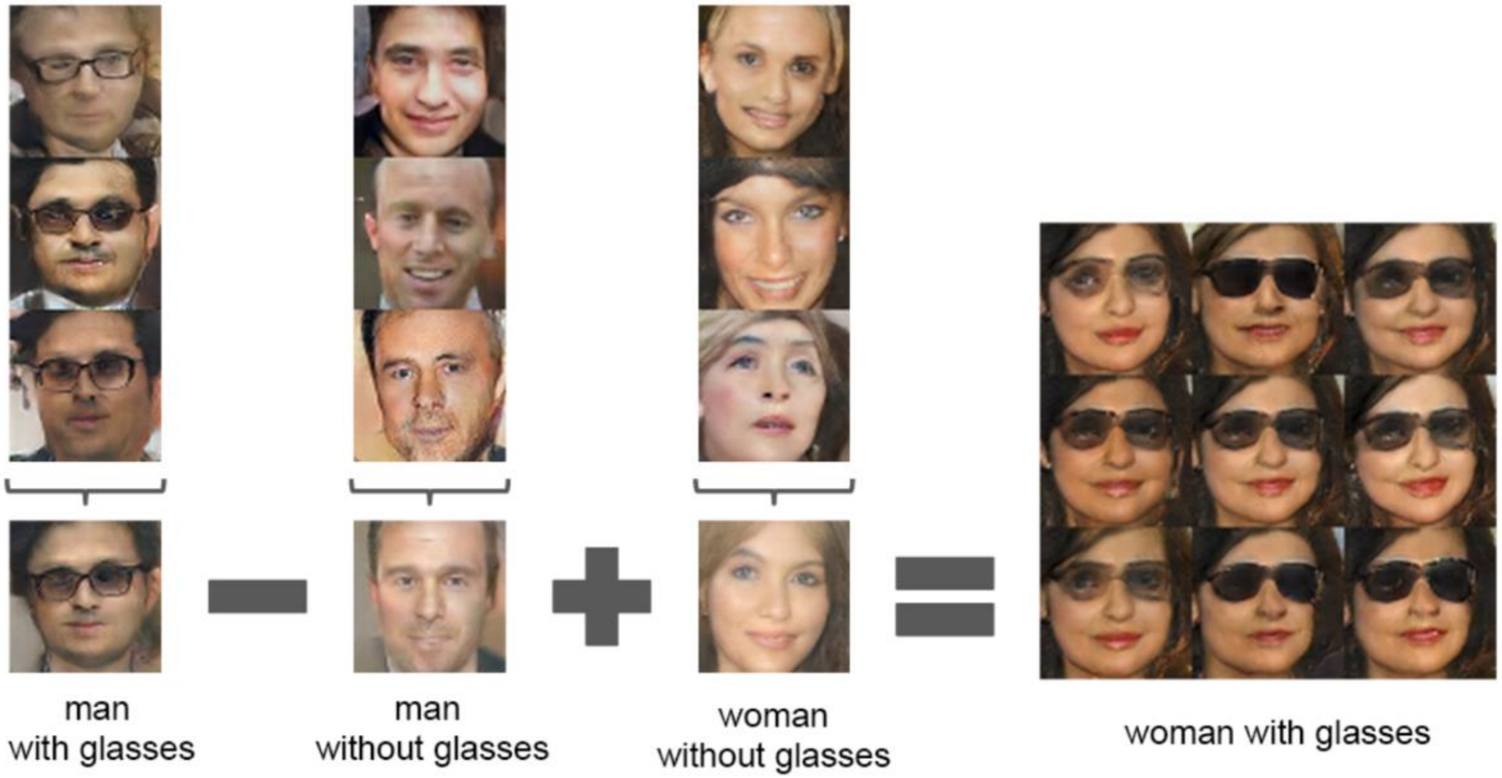
DCGANs

Deep Convolutional Generative Adversarial Networks

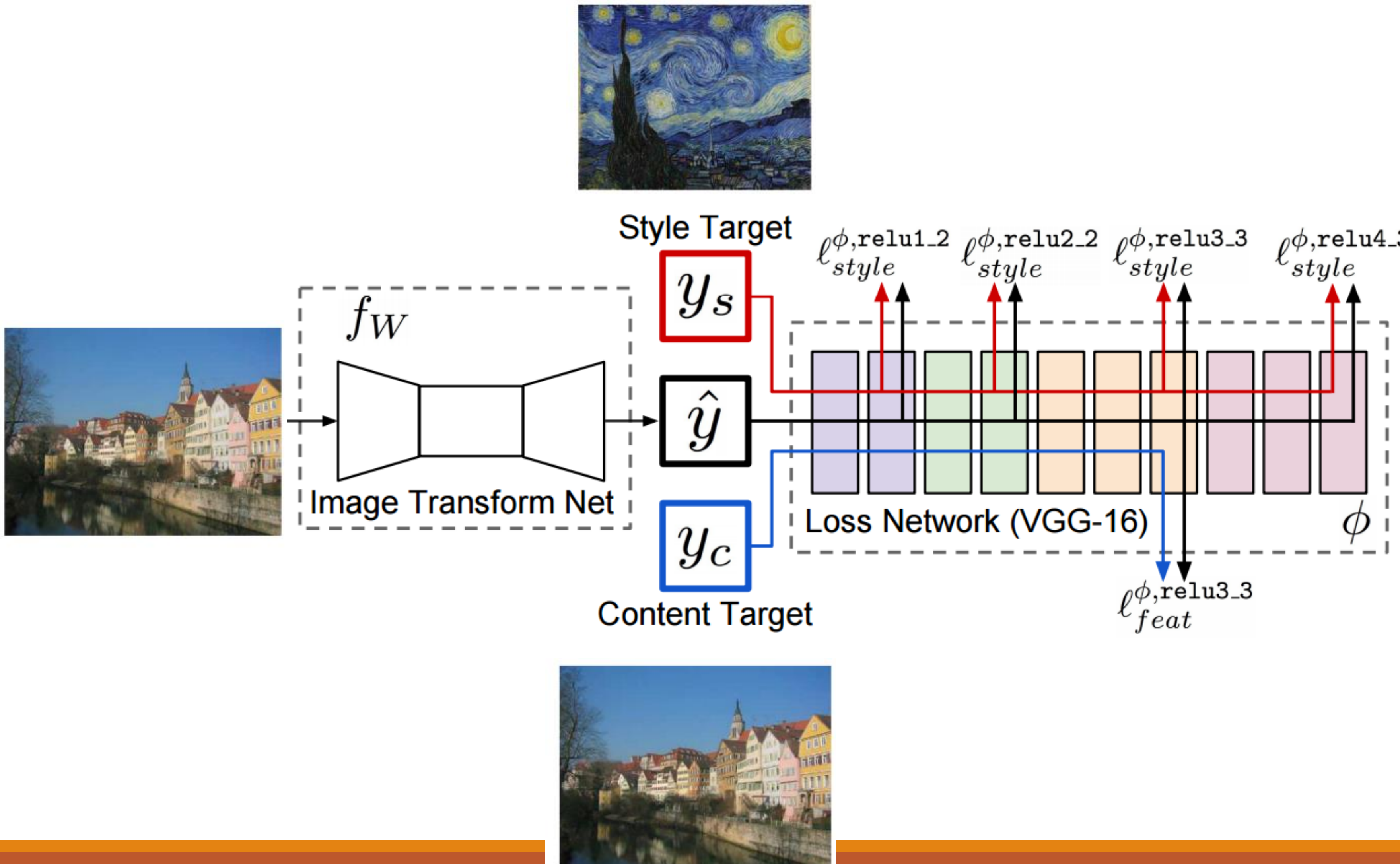


Radford et. al. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. ICLR 2016

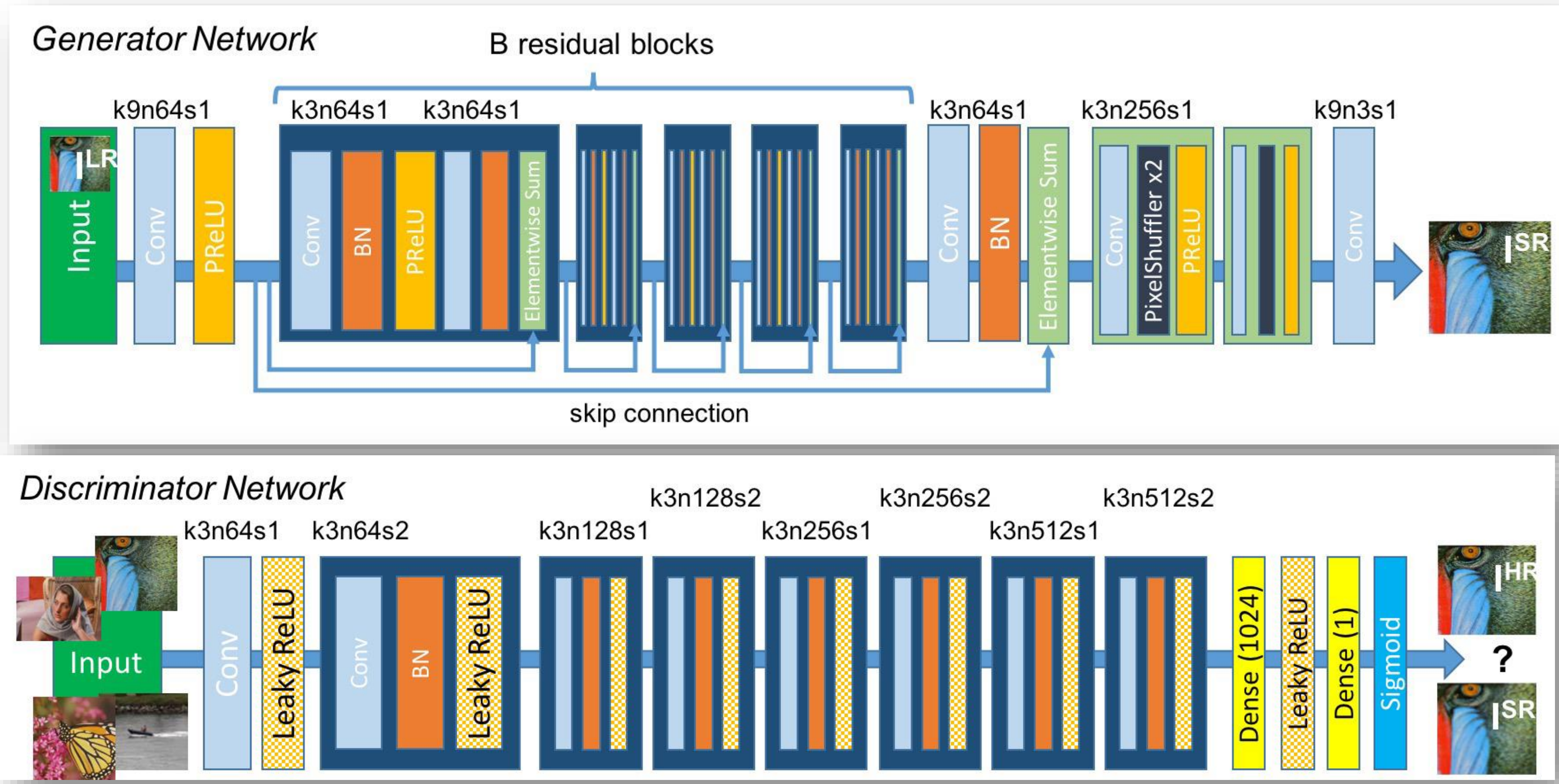
Image arithmetic



GAN based Style Transfer



GANs for Super Resolution



Ledig, Christian, et al. "Photo-realistic single image super-resolution using a generative adversarial network." *arXiv preprint arXiv:1609.04802* (2016).

GANs for Super Resolution

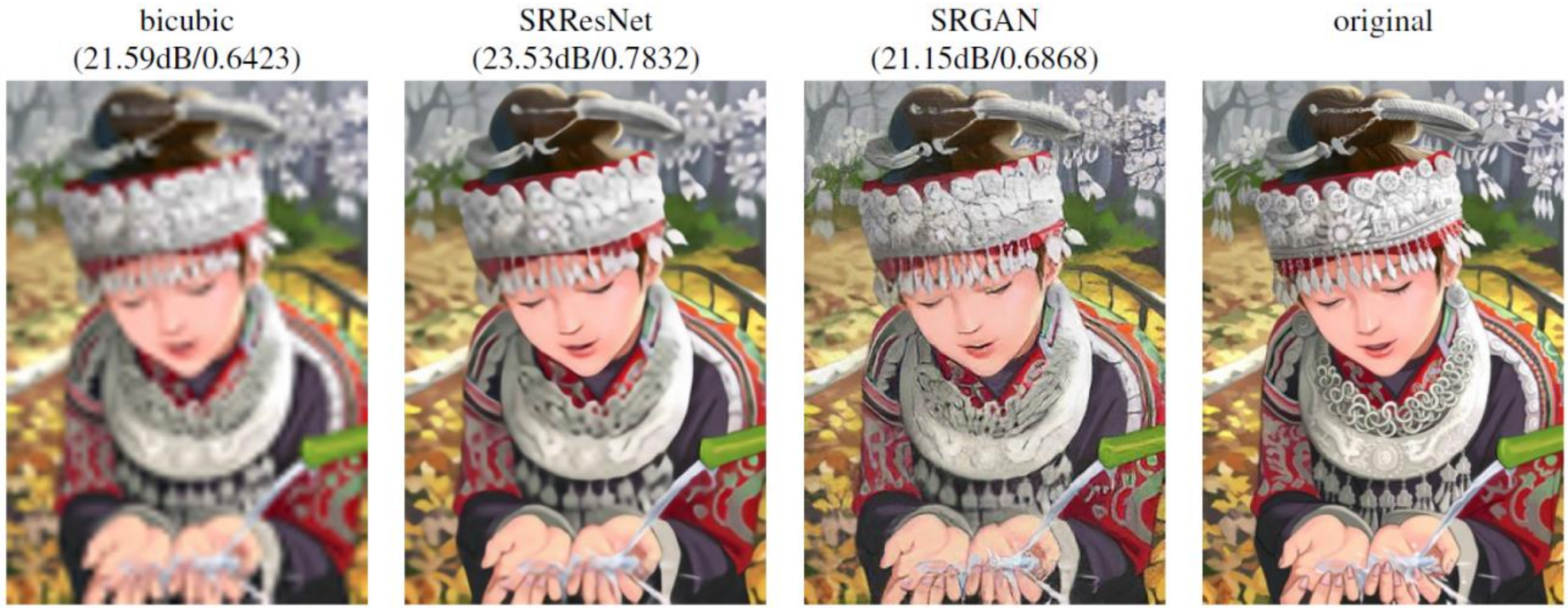


Figure 2: From left to right: bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception, original HR image. Corresponding PSNR and SSIM are shown in brackets. [$4\times$ upscaling]

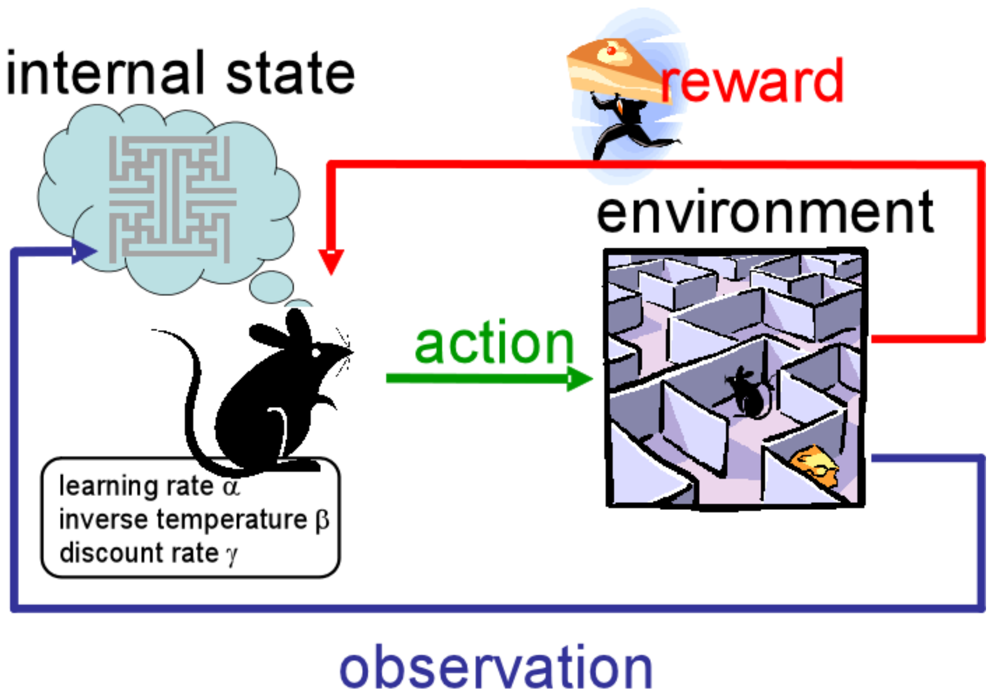
Fake news

https://youtu.be/8siezzLXbNo

https://www.youtube.com/watch?v=DIZf7eRlD4w&t=108s

Reinforcement learning

Reinforcement learning: system interacts with environment and must perform a certain goal without explicitly telling it whether it has come close to its goal or not.



Types of Reinforcement Learning

Search-based: evolution directly on a policy

- E.g. genetic algorithms

Model-based: build a model of the environment

- Then you can use dynamic programming
- Memory-intensive learning method

Model-free: learn a policy without any model

- Temporal difference methods (TD)
- Requires limited episodic memory (though more helps)

Q-learning

- The TD version of Value Iteration
- This is the most widely used RL algorithm

Q-Learning

Define **Q*(s,a):** "Total reward if an agent in state **s** takes action **a**, then acts optimally at all subsequent time steps"

Optimal policy: $\boldsymbol{\pi^*(s)=\text{argmax}_a Q^*(s,a)}$

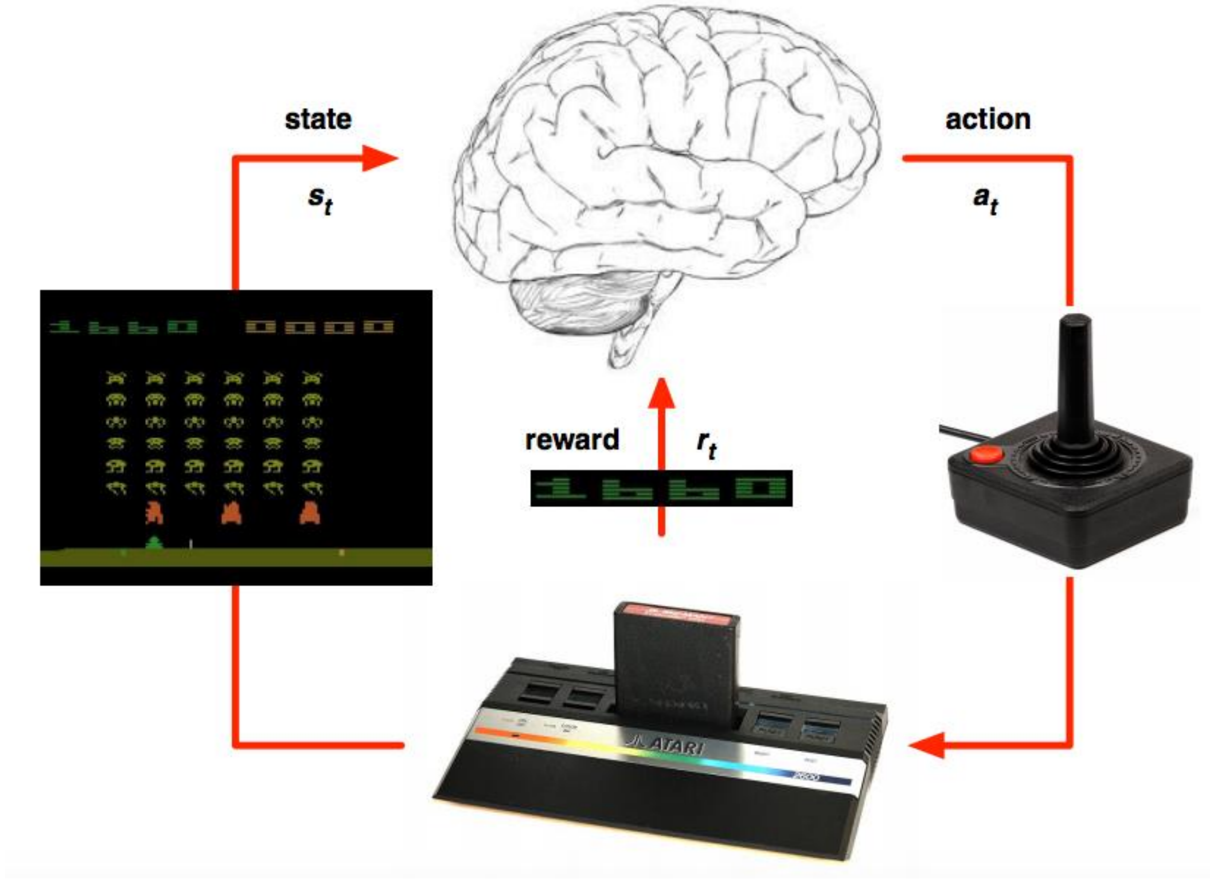
Q(s,a) is an estimate of **Q*(s,a)**

Q-learning motion policy: $\boldsymbol{\pi(s)=\text{argmax}_a Q(s,a)}$

Update Q recursively:

$$Q(s,a) = r + \gamma \max_{a'} Q(s',a') \qquad 0 < \gamma < 1$$

Deep Q-Learning



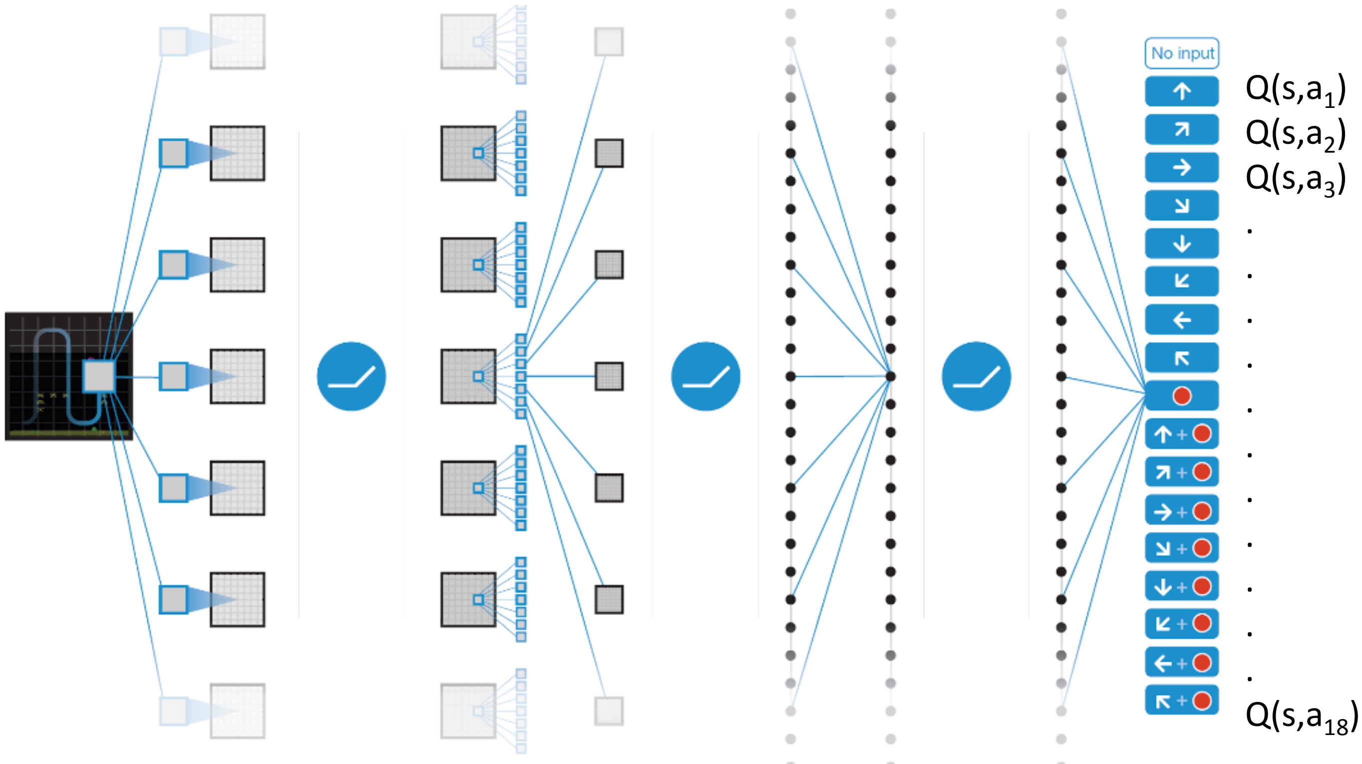
Mnih et al. Human-level control through deep reinforcement learning, *Nature* 2015

Deep Q learning in Atari

End-to-end learning of Q(s,a) from pixels s

Output is Q(s,a) for 18 joystick/button configurations

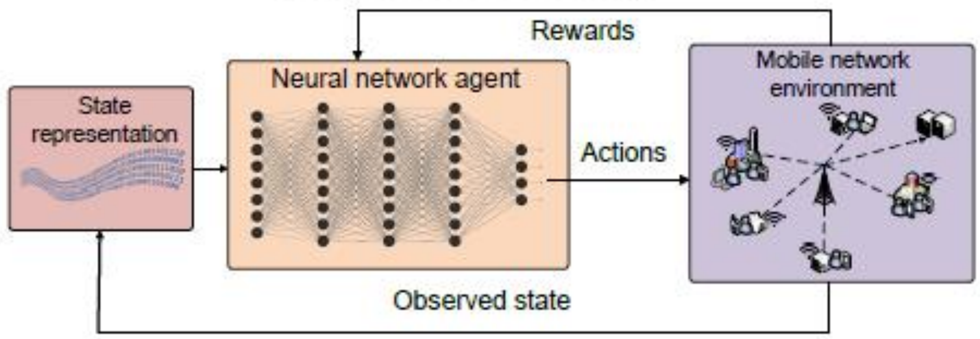
Reward is change in score for that step



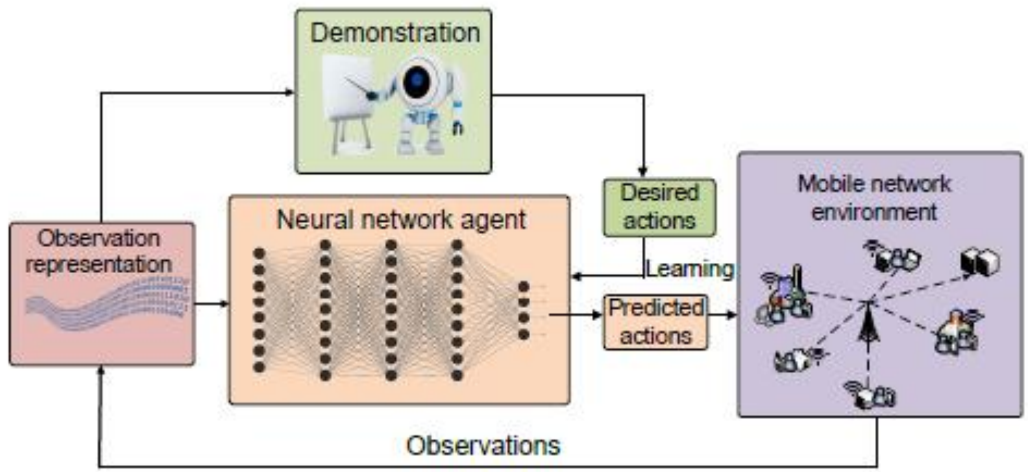
Breakout demo

https://www.youtube.com/watch?v=TmPfTpjtdgg

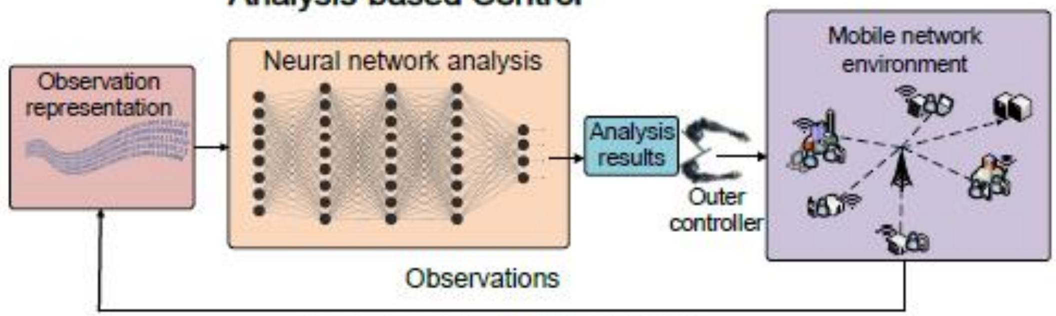
Reinforcement Learning



Imitation Learning



Analysis-based Control



TensorFlow

Deep learning library, open-sourced by Google (11/2015)

TensorFlow provides primitives for

- defining functions on tensors
- automatically computing their derivatives

What is a tensor

What is a computational graph

Material from lecture by Bharath Ramsundar, March 2018, Stanford

Introduction to Keras

Official high-level API of TensorFlow

- Python
- 250K developers

Same front-end <-> Different back-ends

- TensorFlow (Google)
- CNTK (Microsoft)
- MXNet (Apache)
- Theano (RIP)

Hardware

- GPU (Nvidia)
- CPU (Intel/AMD)
- TPU (Google)

Companies: Netflix, Uber, Google, Nvidia…

Material from lecture by Francois Chollet, 2018, Stanford

Keras models

Installation

- Anaconda -> Tensorflow -> Keras

Build-in

- Conv1D, Conv2D, Conv3D…
- MaxPooling1D, MaxPooling2D, MaxPooling3D…
- Dense, Activation, RNN…

The Sequential Model

- Very simple
- Single-input, Single-output, sequential layer stacks

The functional API

- Mix & Match
- Multi-input, multi-output, arbitrary static graph topologies

Sequential

>>**from** keras.models **import** Sequential

>>model = Sequential()

>> **from** keras.layers **import** Dense

>> model.add(Dense(units=64, activation='relu', input_dim=100))

>> model.add(Dense(units=10, activation='softmax'))

>> model.compile(loss='categorical_crossentropy', optimizer='sgd', metrics=['accuracy'])

>> model.fit(x_train, y_train, epochs=5, batch_size=32)

>> loss_and_metrics = model.evaluate(x_test, y_test, batch_size=128)

>> classes = model.predict(x_test)

Functional

```
>> from keras.layers import Input, Dense
>> from keras.models import Model
>> inputs = Input(shape=(784,))
>> x = Dense(64, activation='relu')(inputs)
>> x = Dense(64, activation='relu')(x)
>> predictions = Dense(10, activation='softmax')(x)
>> model = Model(inputs=inputs, outputs=predictions)
>> model.compile(optimizer='rmsprop',
loss='categorical_crossentropy', metrics=['accuracy'])
>> model.fit(data, labels)
```

References

Stephens, Zachary D., et al. "Big data: astronomical or genomical?." *PLoS biology* 13.7 (2015): e1002195.

LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning.“ *Nature* 521.7553 (2015): 436-444.

Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.

Kietzmann, Tim Christian, Patrick McClure, and Nikolaus Kriegeskorte. "Deep Neural Networks In Computational Neuroscience. " *bioRxiv* (2017): 133504.

https://playground.tensorflow.org/#activation=tanh&batchSize=10&dataset=circle&regDataset=reg-plane&learningRate=0.03&regularizationRate=0&noise=0&networkShape=3,2&seed=0.57693&showTestData=false&discretize=true&percTrainData=50&x=true&y=true&xTimesY=false&xSquared=true&ySquared=false&cosX=false&sinX=false&cosY=false&sinY=false&collectStats=false&problem=classification&initZero=false&hideText=false