CORNELL TECH

Deep Learning Clinic

(DLC)

Lecture 4
A Brief Introduction to Deep Learning

Jin Sun

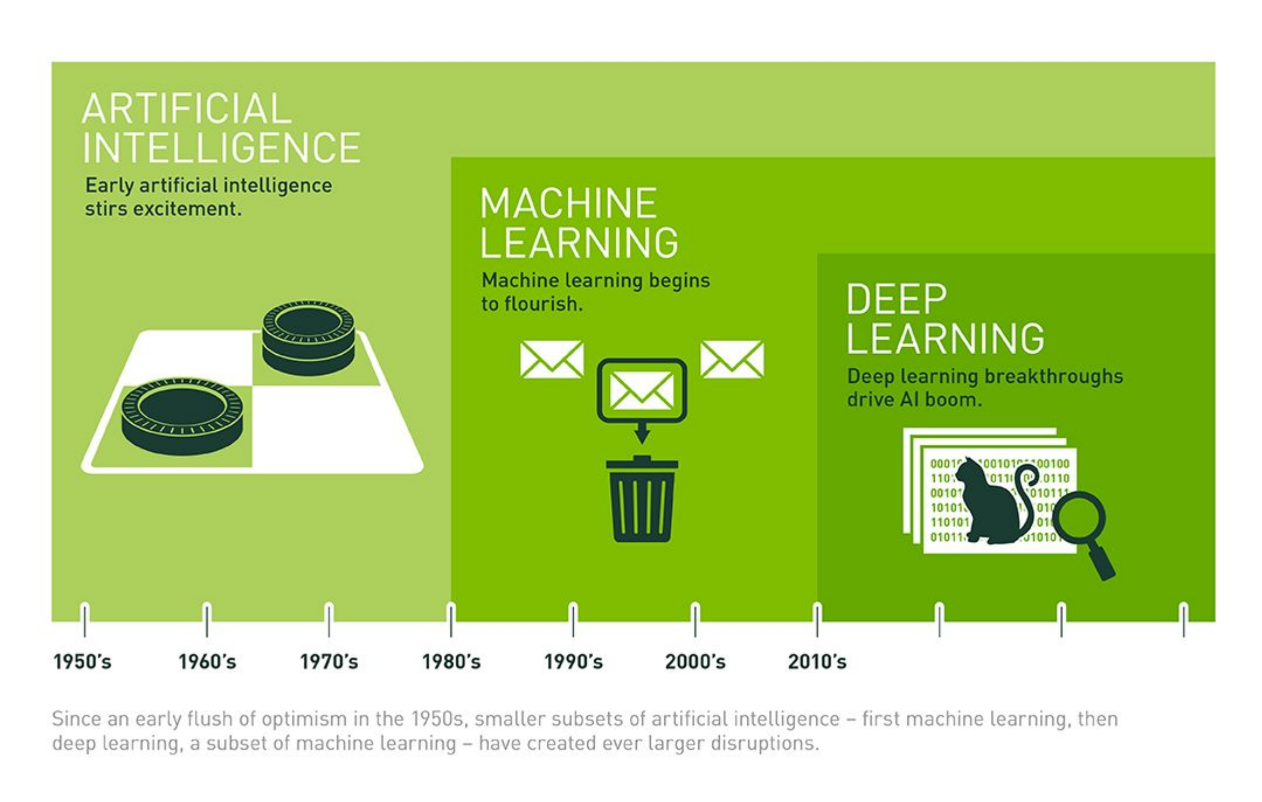
10/19/2018

Today

- **Overview**
- Basic Feedforward Networks and Core Concepts
  - Optimization
  - Regularization
- Convolutional Networks
- Recurrent Networks
- Generative Models
- Research Frontiers

Slides adapted from Ian Goodfellow.

Overview



https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

What is Deep Learning

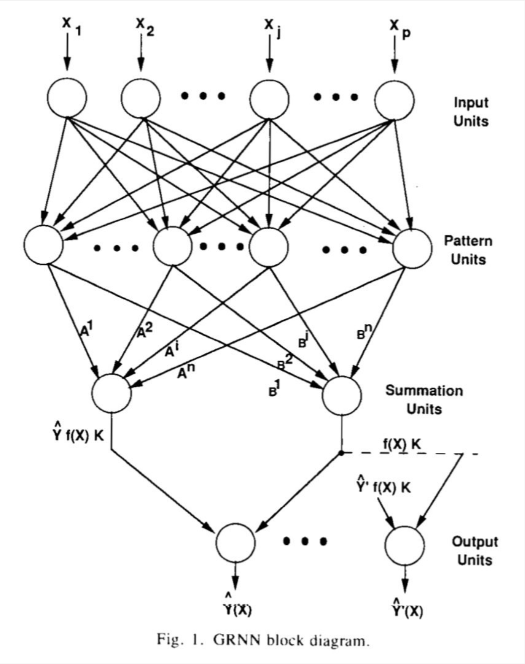
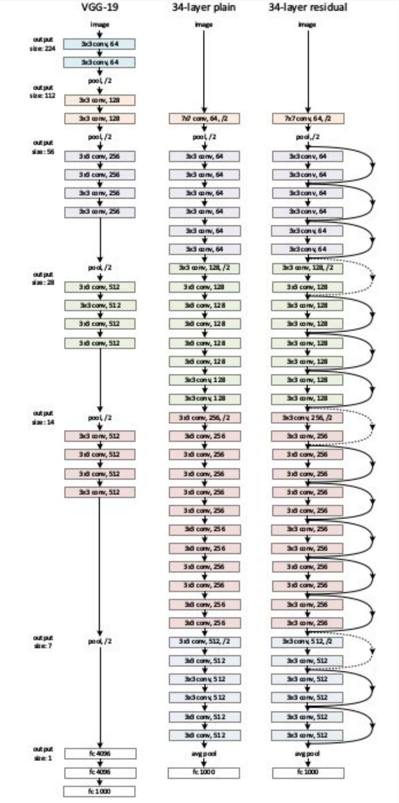


Fig. 1. GRNN block diagram.

1991

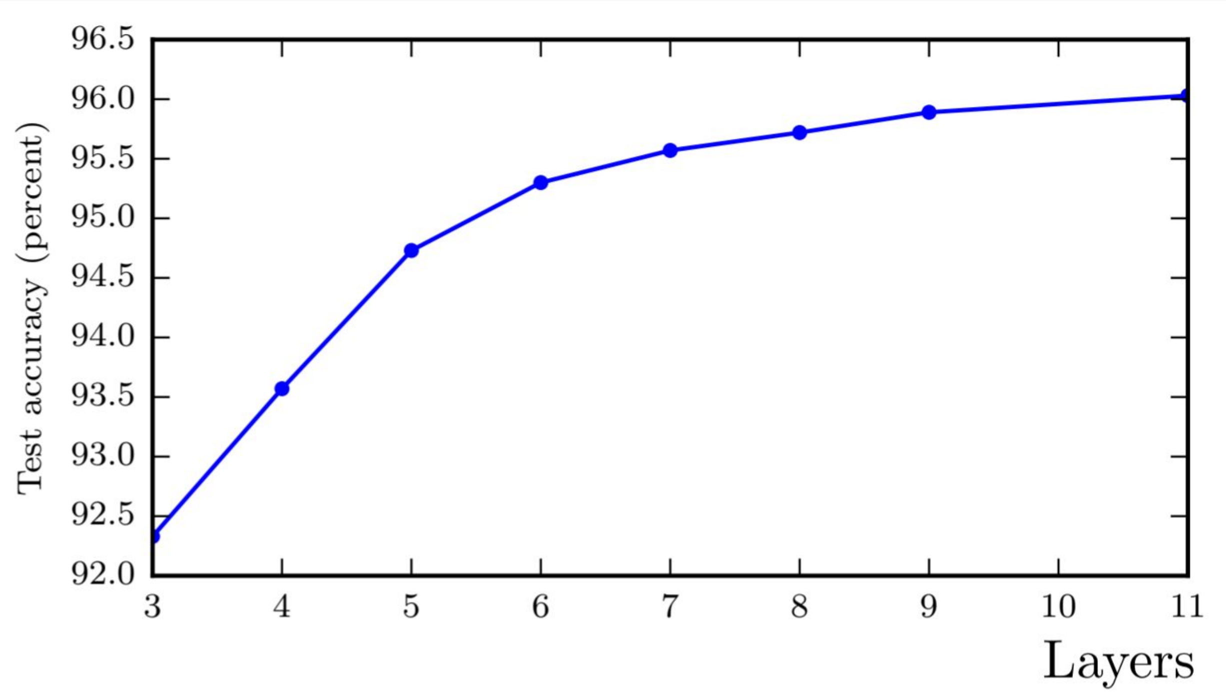
VS



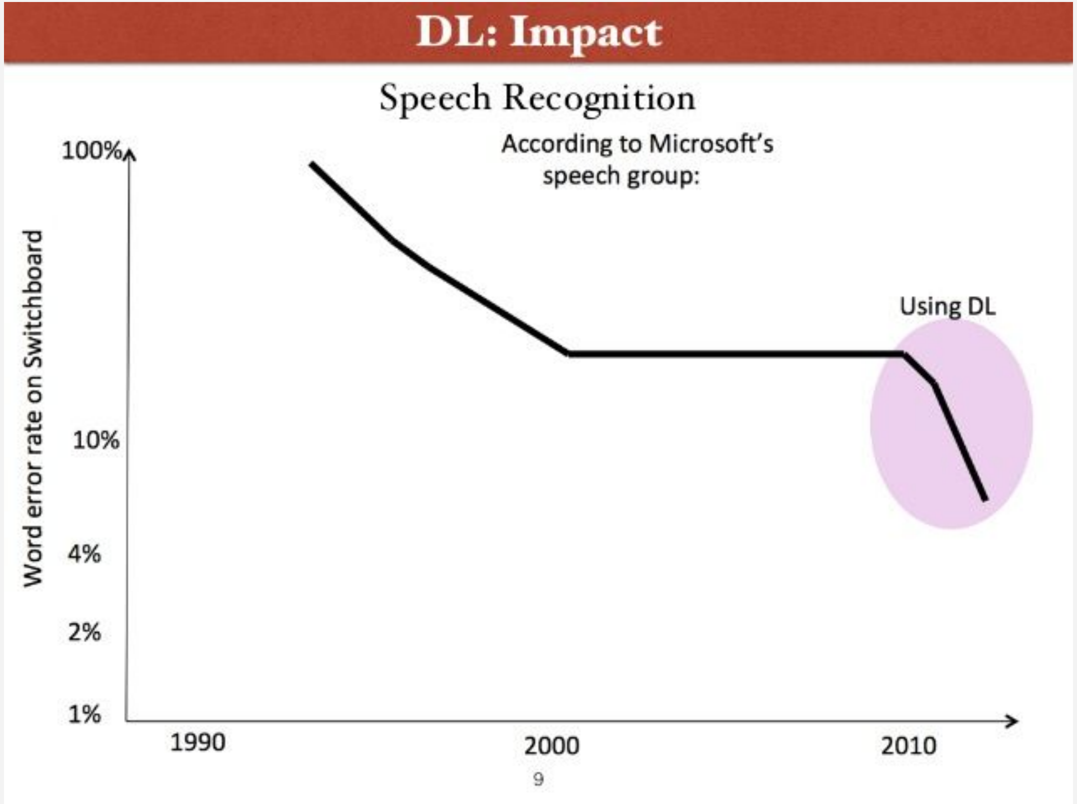
2016

Specht, Donald F. "A general regression neural network." IEEE transactions on neural networks 2.6 (1991): 568-576.

The Benefit of Going Deeper

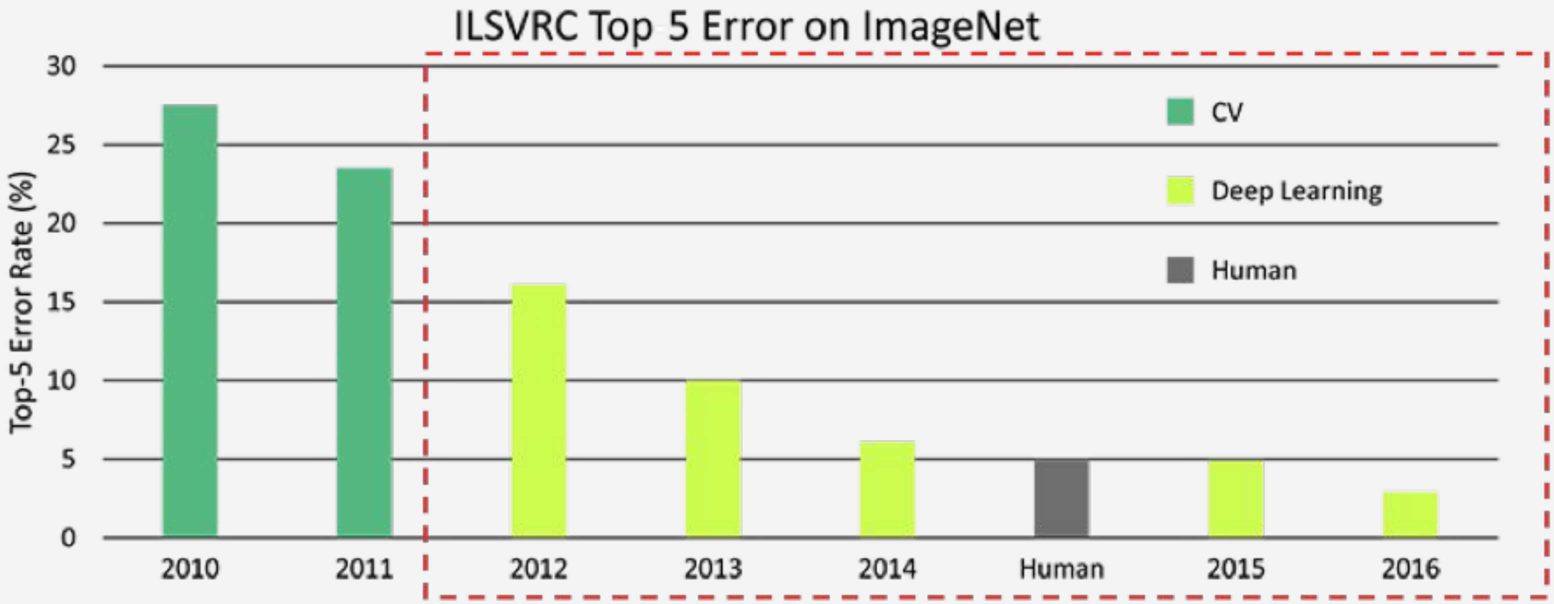


The Dominance of DL



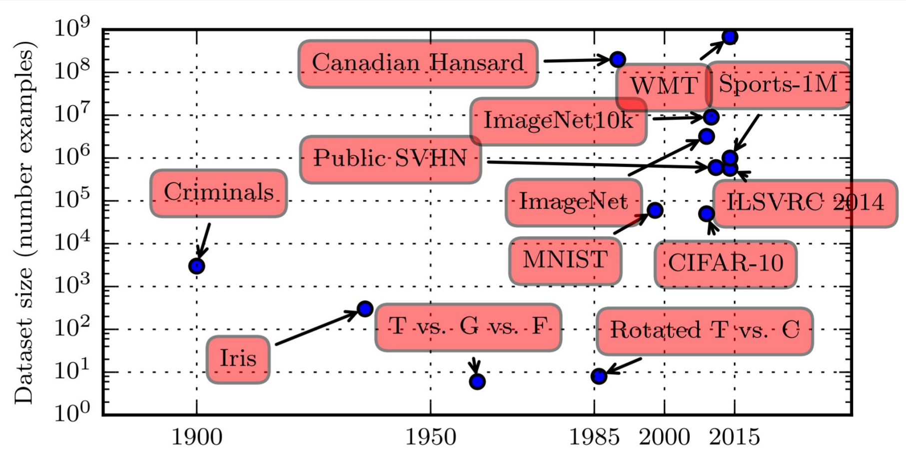
https://www.slideshare.net/roelofp/220115dlmeetup

The Dominance of DL



The introduction of Deep Learning techniques drove performance on image categorization from 30% error rates in 2010, down to <2% in 2017

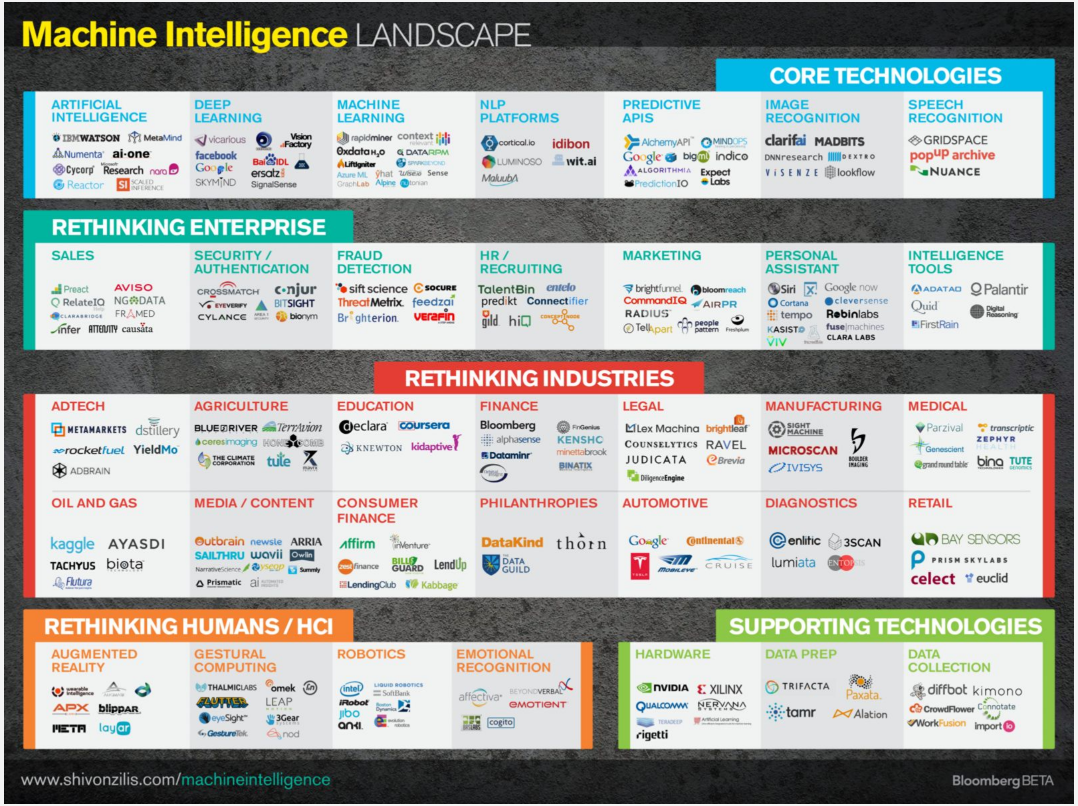
Main Reasons Behind Deep Learning's Success



Data

Hardware

Deep Learning Landscape



https://medium.com/@shivon/the-current-state-of-machine-intelligence-f76c20db2fe1

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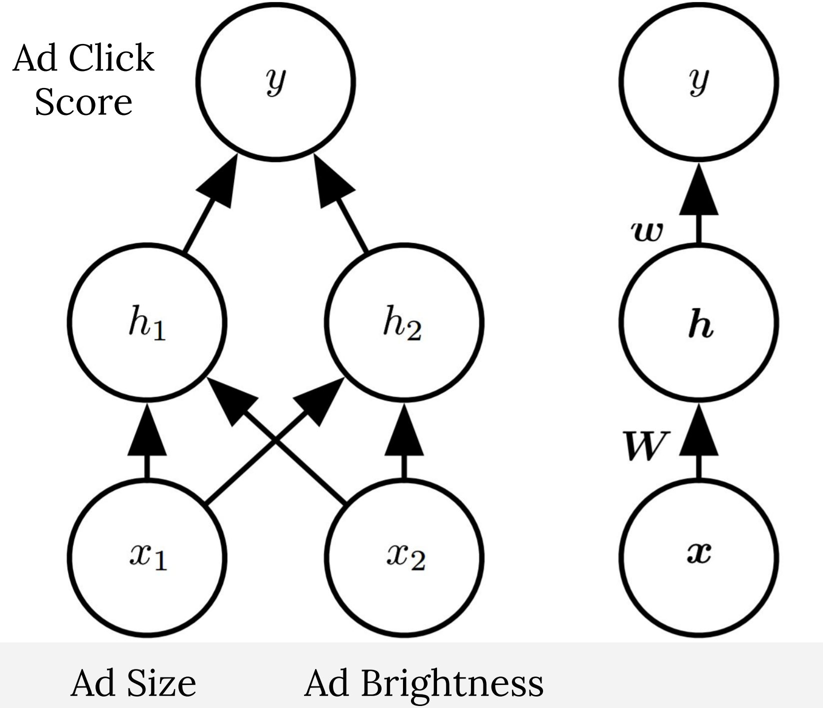
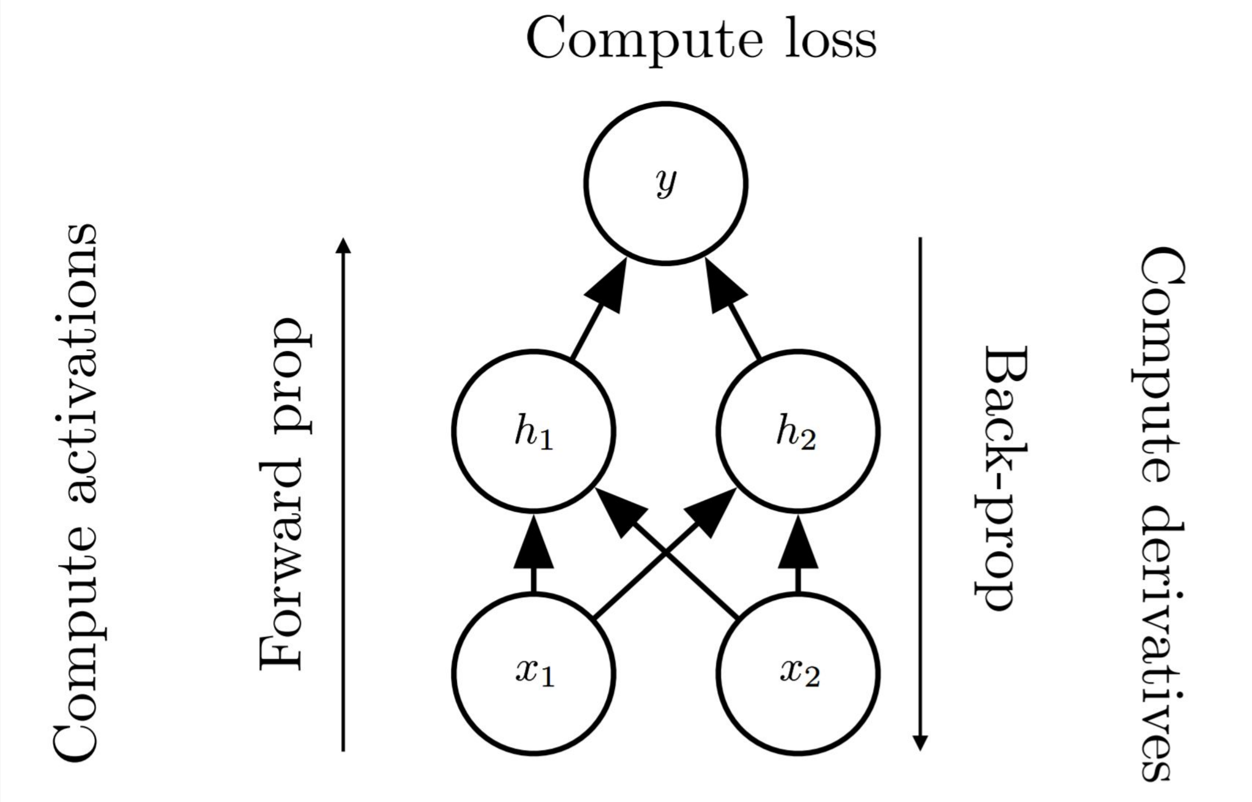
Basic Feedforward Networks

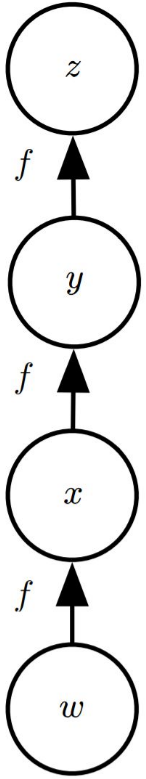
$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^\top \max\{0, \boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c}\} + b.$$



Backpropagation



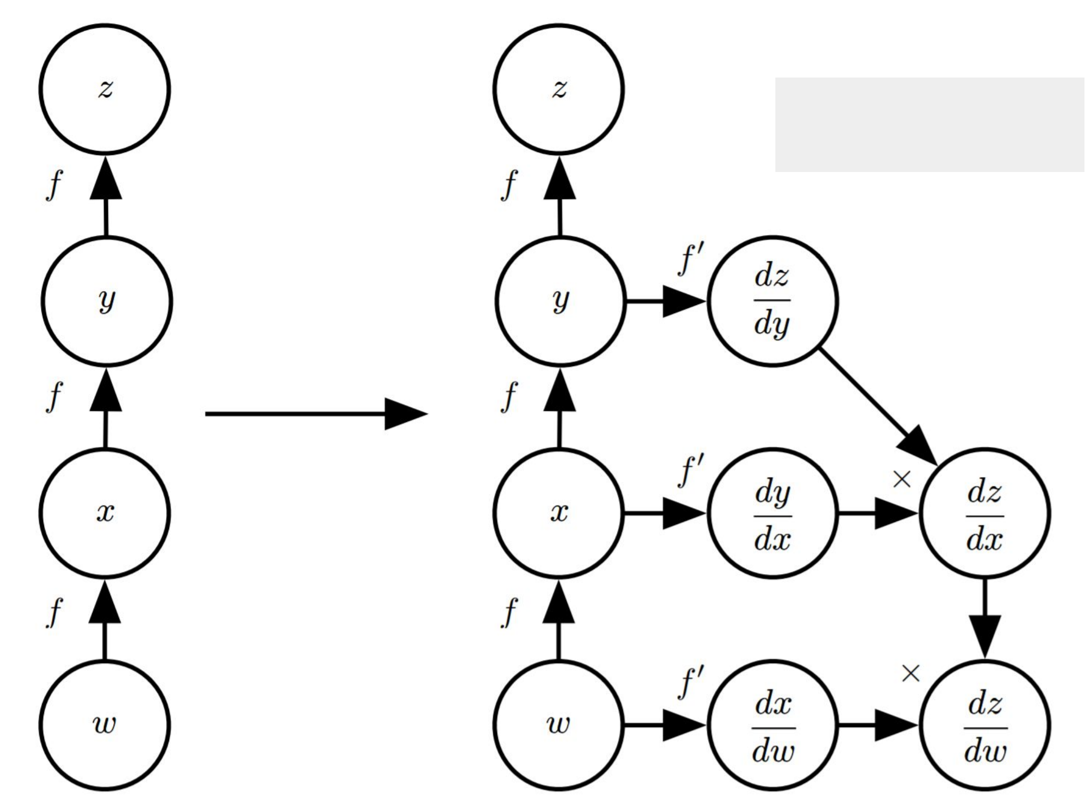
Backpropagation



$$
\begin{aligned}
&\frac{\partial z}{\partial w} \\
=&\frac{\partial z}{\partial y}\frac{\partial y}{\partial x}\frac{\partial x}{\partial w} \\
=&f'(y)f'(x)f'(w) \\
=&f'(f(f(w)))f'(f(w))f'(w)
\end{aligned}
$$

Back-prop avoids computing this twice

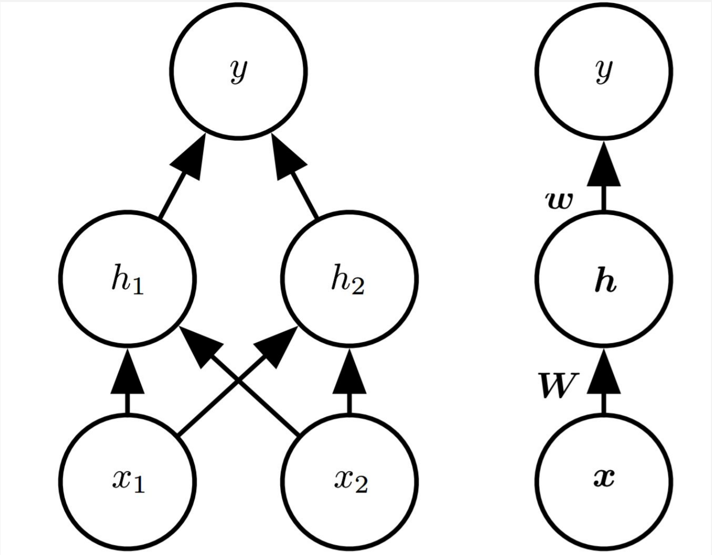
Backpropagation - How It Is Done



Backpropagation - PyTorch Example

```
import torch
from torch.autograd import Variable

x = Variable(torch.ones(2), requires_grad=True)

W = Variable(torch.ones(2), requires_grad=True)
c = Variable(torch.ones(2), requires_grad=True)

w = Variable(torch.ones(2,1), requires_grad=True)
b = Variable(torch.ones(1), requires_grad=True)

h = torch.relu(x*W + c)
y = torch.matmul(w.t(),h) + b

y_target = Variable(torch.zeros(1))
loss  = (y - y_target)**2

loss.backward()
```

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{c}, \boldsymbol{w}, b) = \boldsymbol{w}^\top \max\{0, \boldsymbol{W}^\top \boldsymbol{x} + \boldsymbol{c}\} + b.$$



Optimization

Why backpropagation is useful?

It helps us to calculate the gradient of a model’s parameters, so we can use gradient based optimization techniques.

Recap from last lecture:

$$\text{minimize}_\theta \ e \doteq \mathbb{E}_{(x,y)\sim D}[L(y, f(x;\theta))]$$

Find the best θ that minimizing the expected loss.

Common Optimization Algorithms in DL

Stochastic Gradient Descent (SGD)

Instead of calculating the gradient over the whole training set, only do it over a few examples (called a minibatch).

No need to fit the whole data into memory; Enables online learning.

Adam

A more advanced SGD extension. Works well with noisy gradient and large data problems.

Optimization - PyTorch Example

```
optimizer = optim.SGD(model.parameters(), lr = 0.01, momentum=0.9)

or

optimizer = optim.Adam([var1, var2], lr = 0.0001)


for input, target in dataset:

    optimizer.zero_grad()

    output = model(input)
    loss = loss_fn(output, target)
    loss.backward()

    optimizer.step()
```

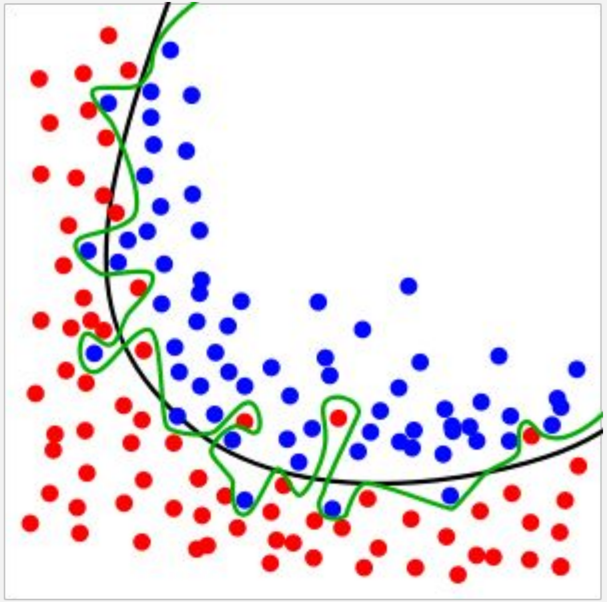
Regularization

L1 Norm

Prefer sparse weights

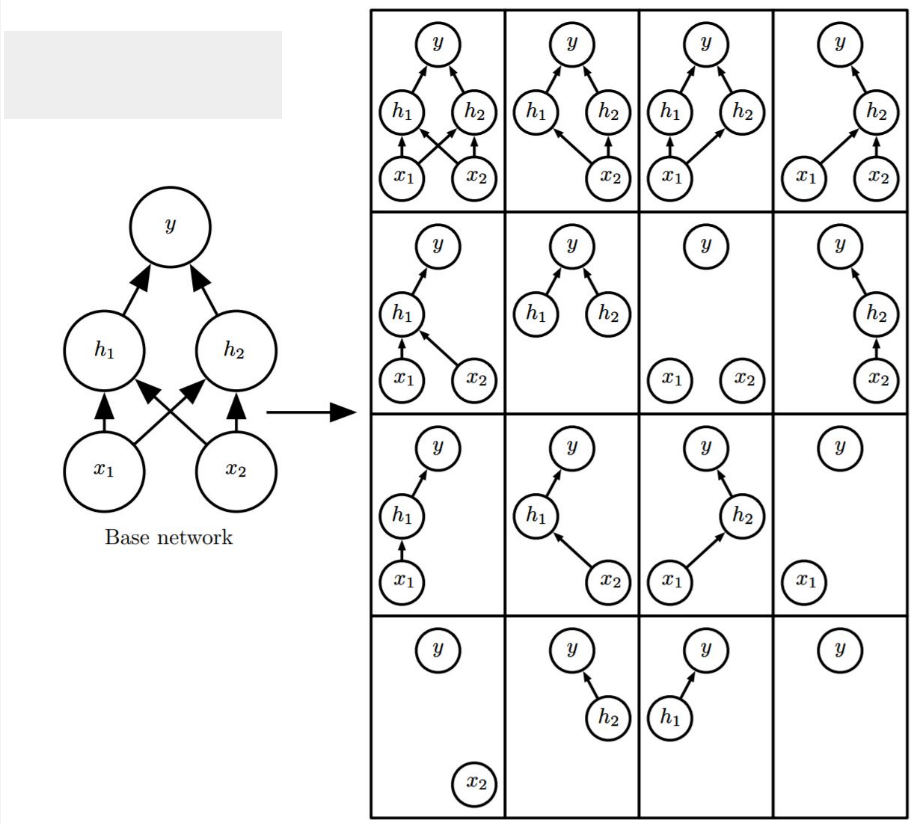
L2 Norm

Prefer smaller weights



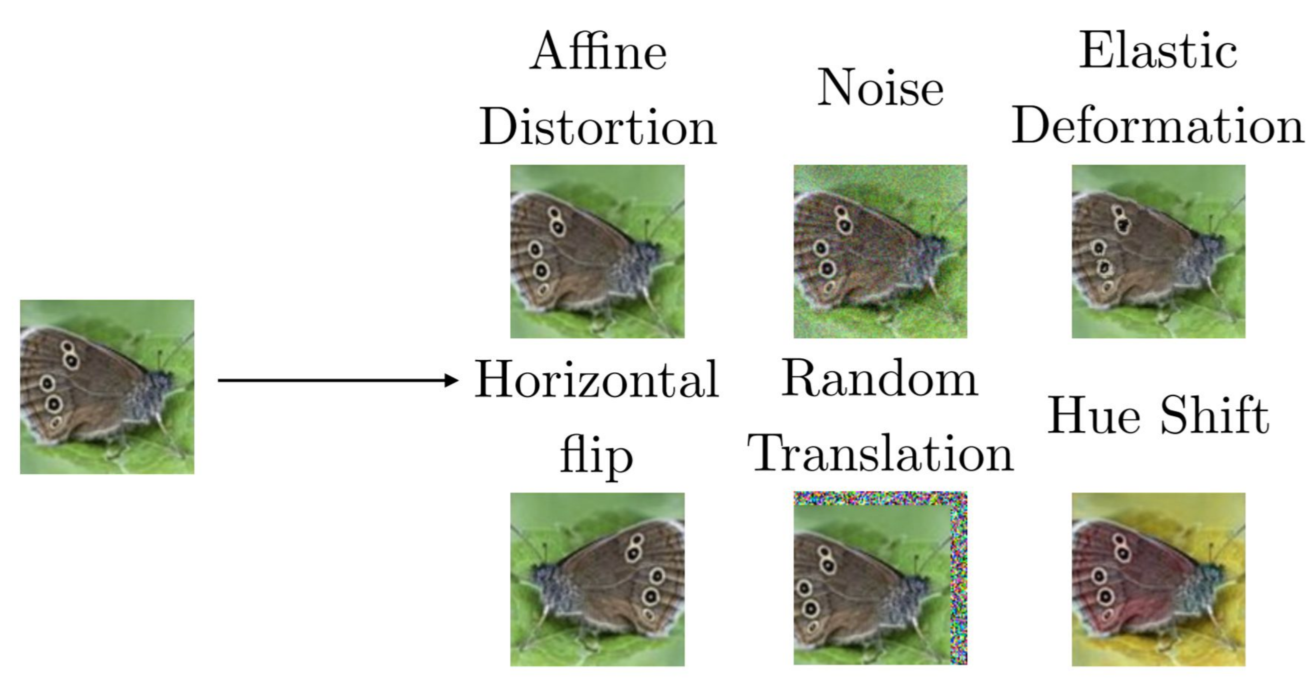
Regularization

Dropout



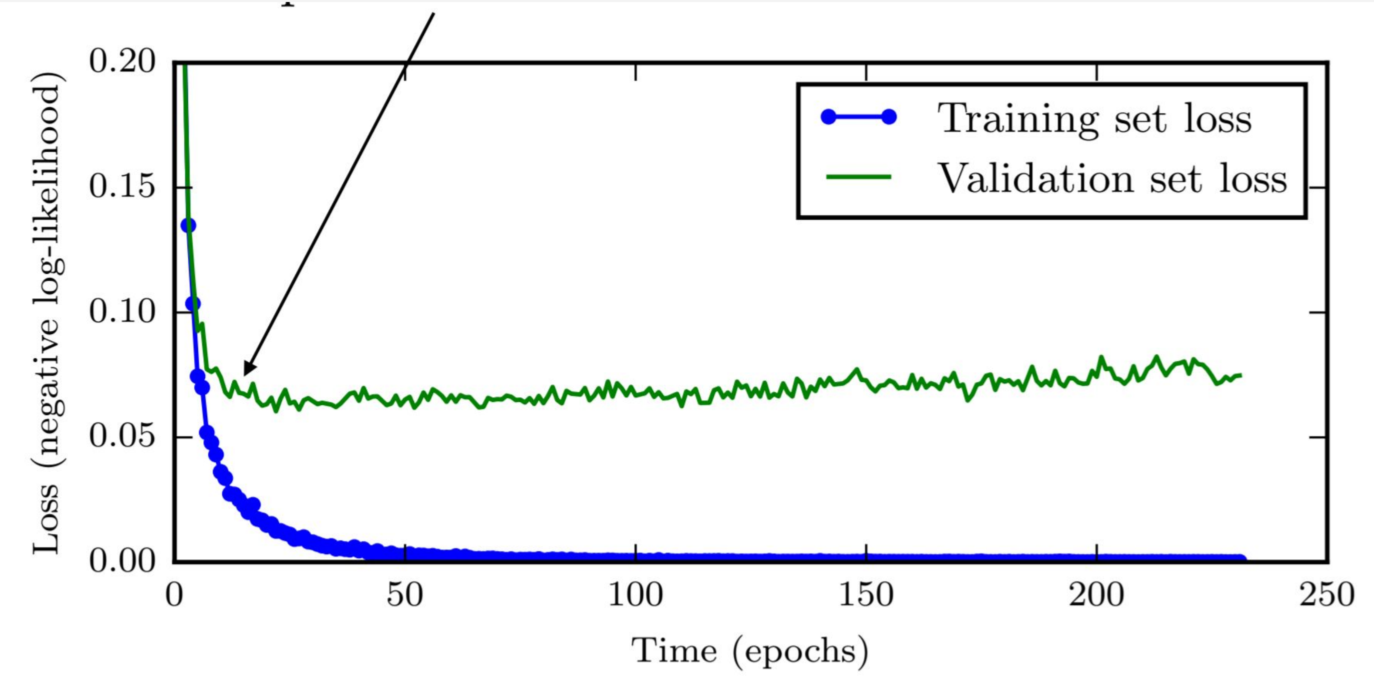
Regularization

Data Augmentation



Regularization

Early Stopping



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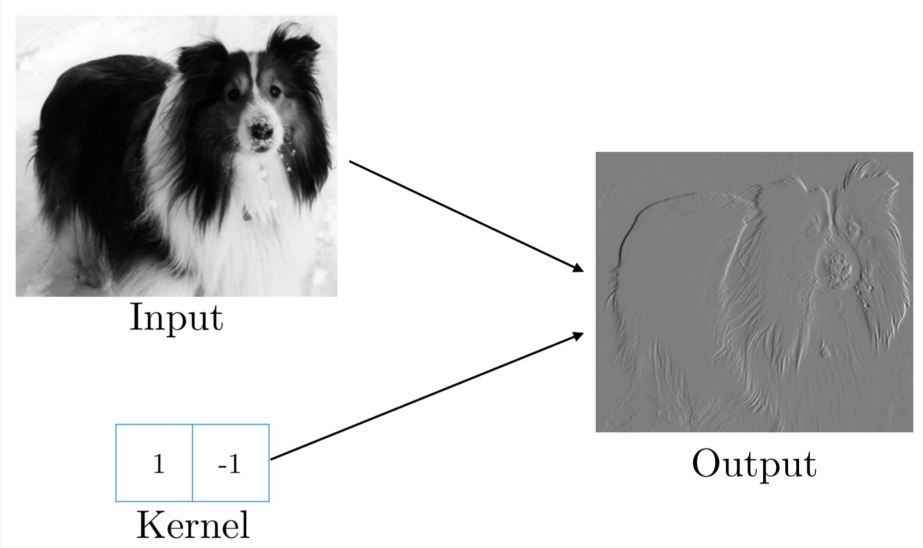
Data and Neural Network Models

Static Data	Dynamic Data	Unsupervised Data
Convolutional Neural Networks	Recurrent Neural Networks	Generative Neural Networks

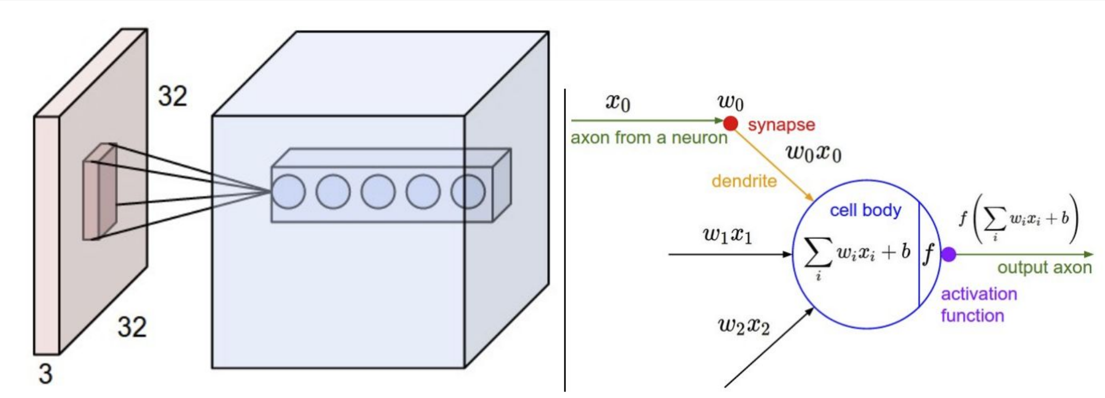
Convolutional Networks

Convolution

A local operation that extracts information from data.



Convolutional Networks

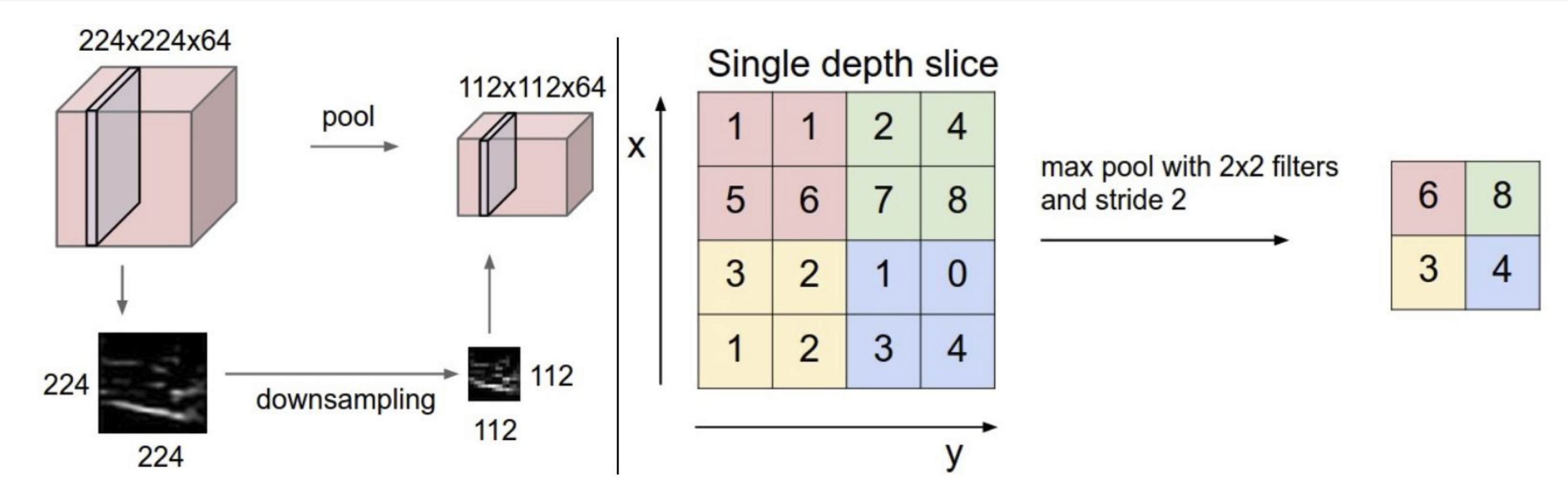


Convolution in action:

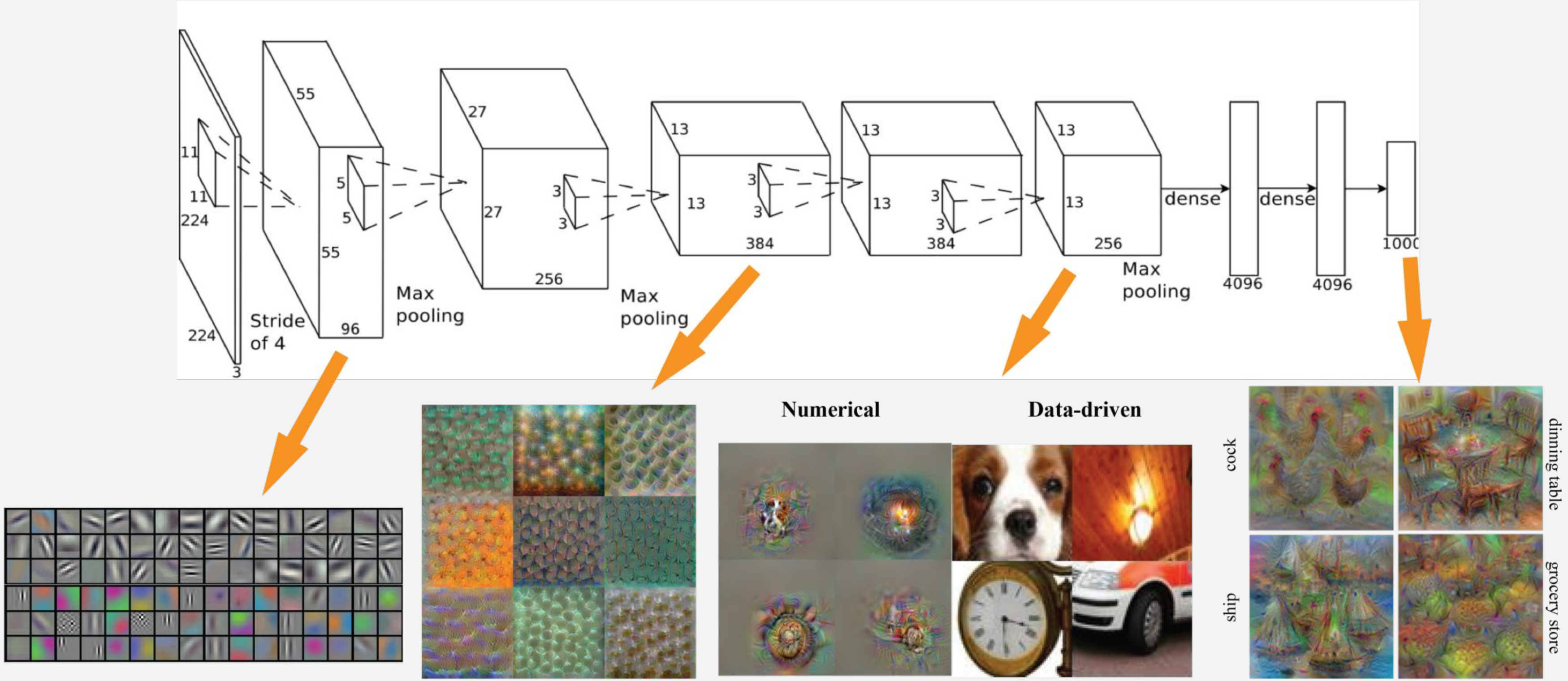
http://cs231n.github.io/convolutional-networks/

Convolutional Networks

Pooling



Convolutional Networks



Conv 1: Edge+Blob

Conv 3: Texture

Conv 5: Object Parts

Fc8: Object Classes

Convolutional Networks

Good for:

Data with translation invariance and shared statistics.

Data that can benefitted from different levels of abstraction.

Not so good for:

Dynamic data.

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Recurrent Networks

Dynamic Data

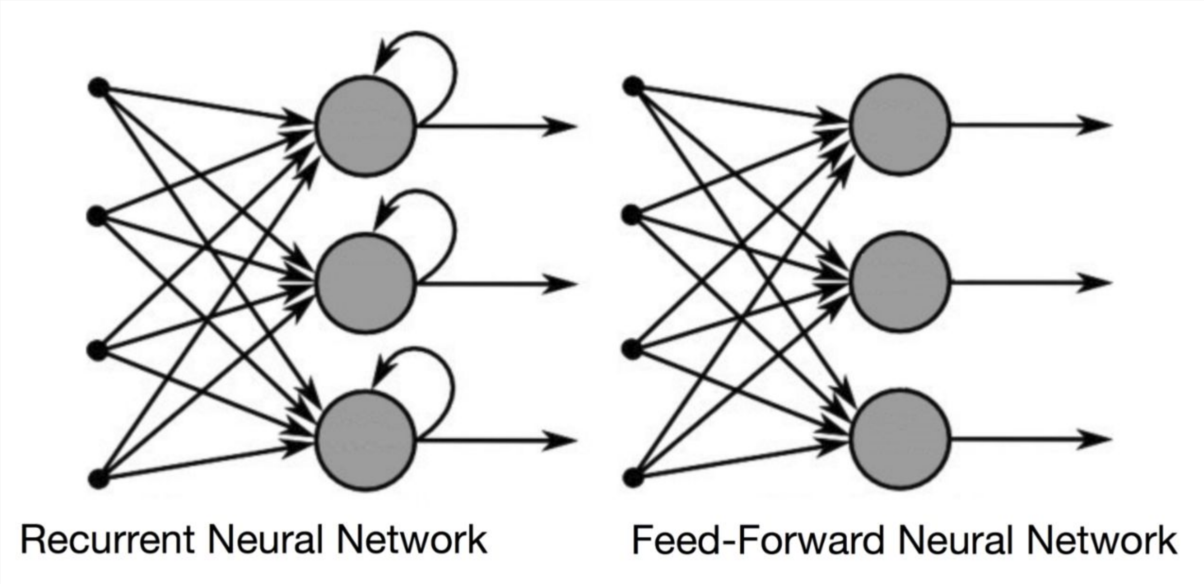
Data changes over time.

Language

Video

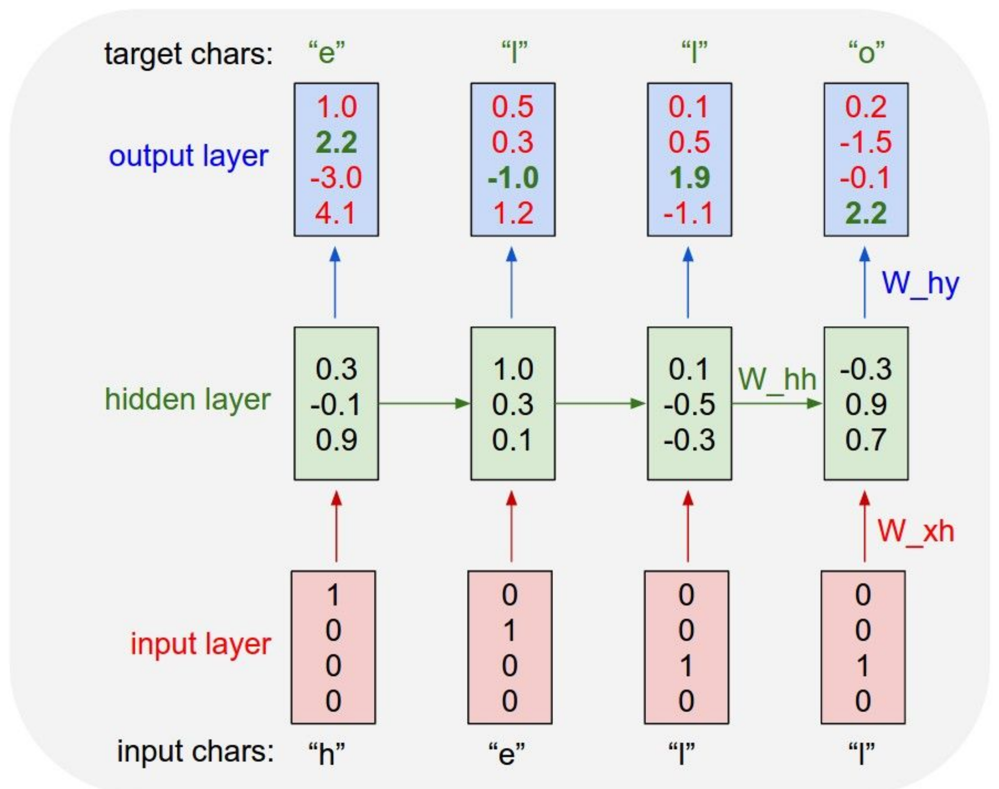
Recurrent Networks

A model's output is not just depending on the current input



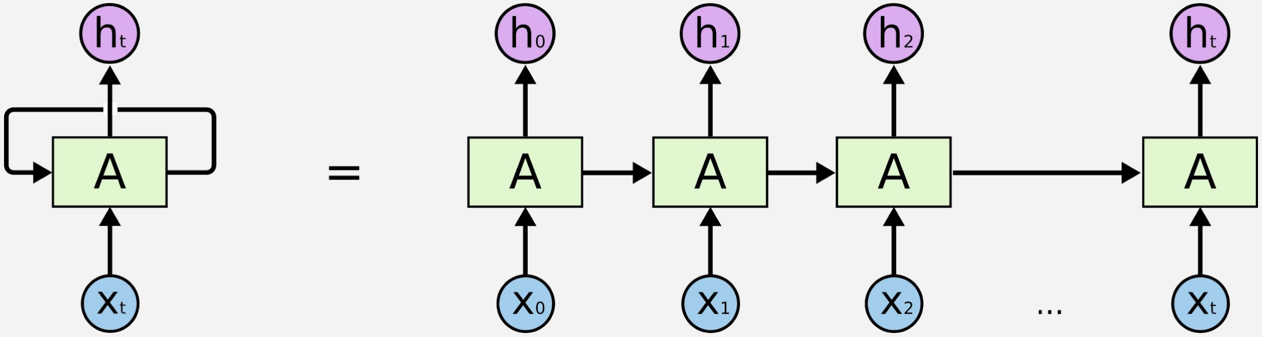
https://towardsdatascience.com/recurrent-neural-networks-and-lstm-4b601dd822a5

Recurrent Networks

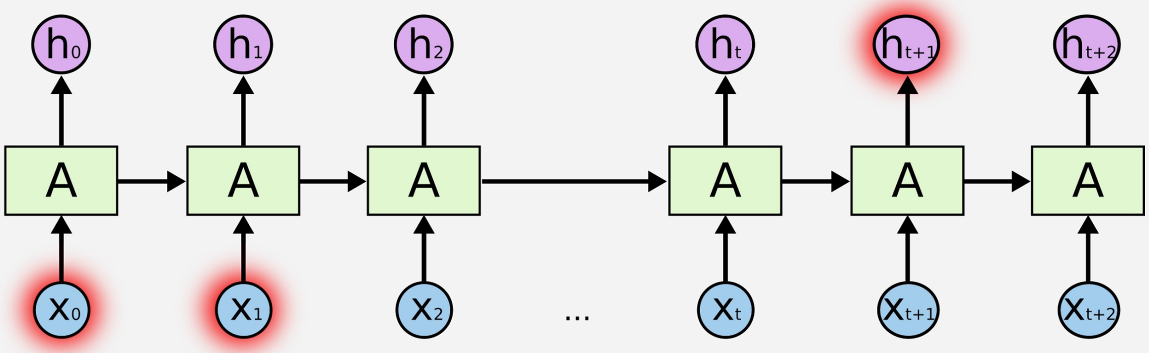


http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Unrolled RNNs



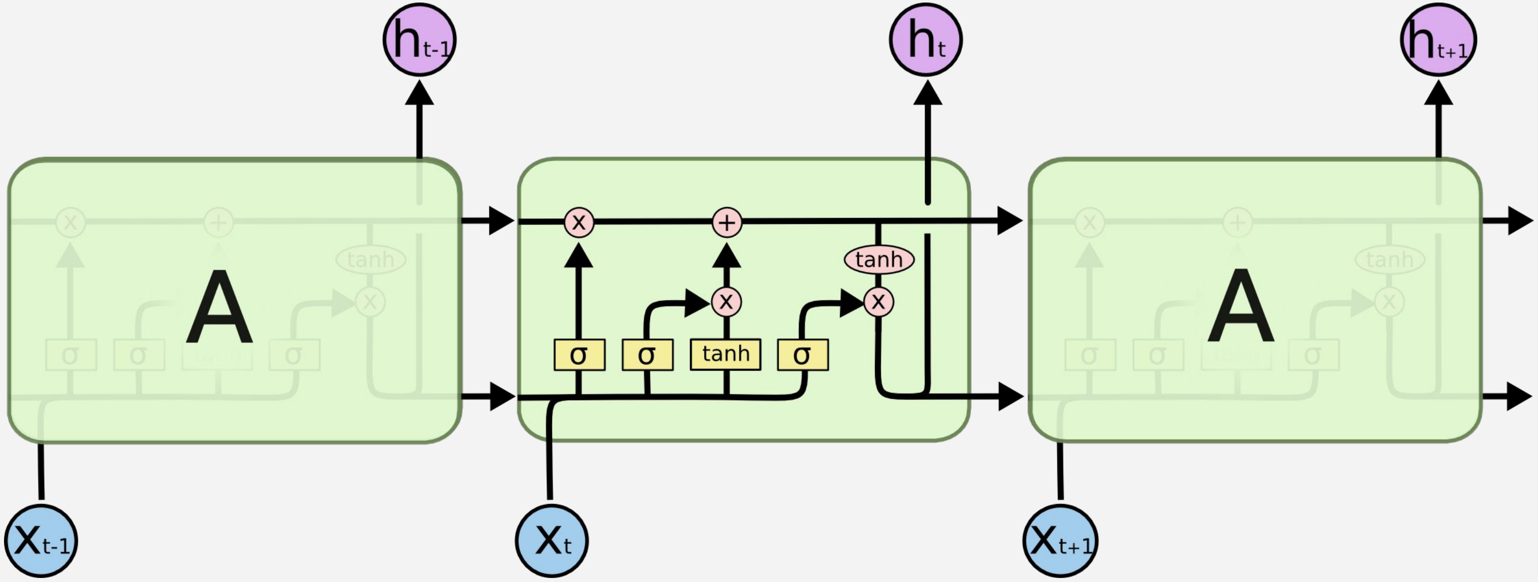
Long term relations



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short-Term Memory (LSTM) Networks

Being able to remember… and forget!



Recurrent Networks

Good for:

Dynamic data.

Not so good:

Might be tricky to train.

An interesting read.

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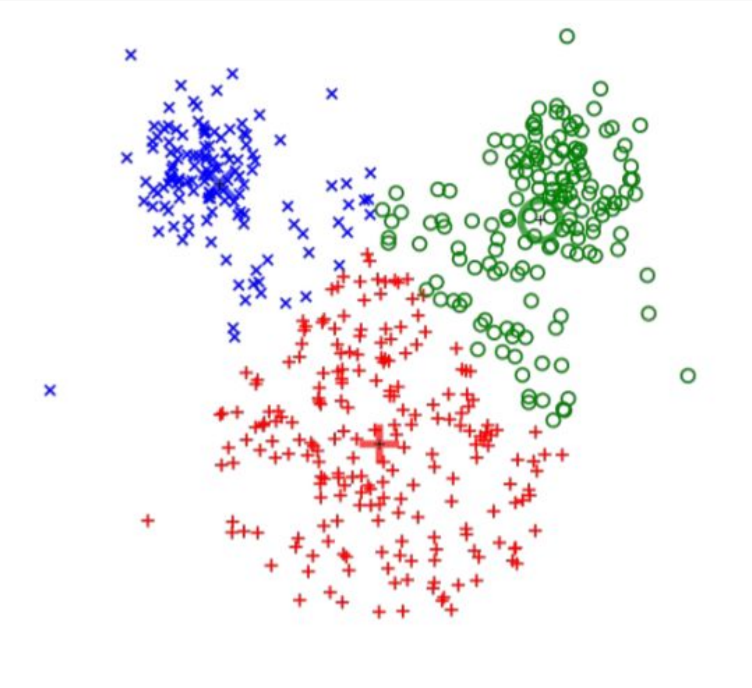
Generative Models

We have data, but no labels.

Goal

Recover underlying structures of the data.

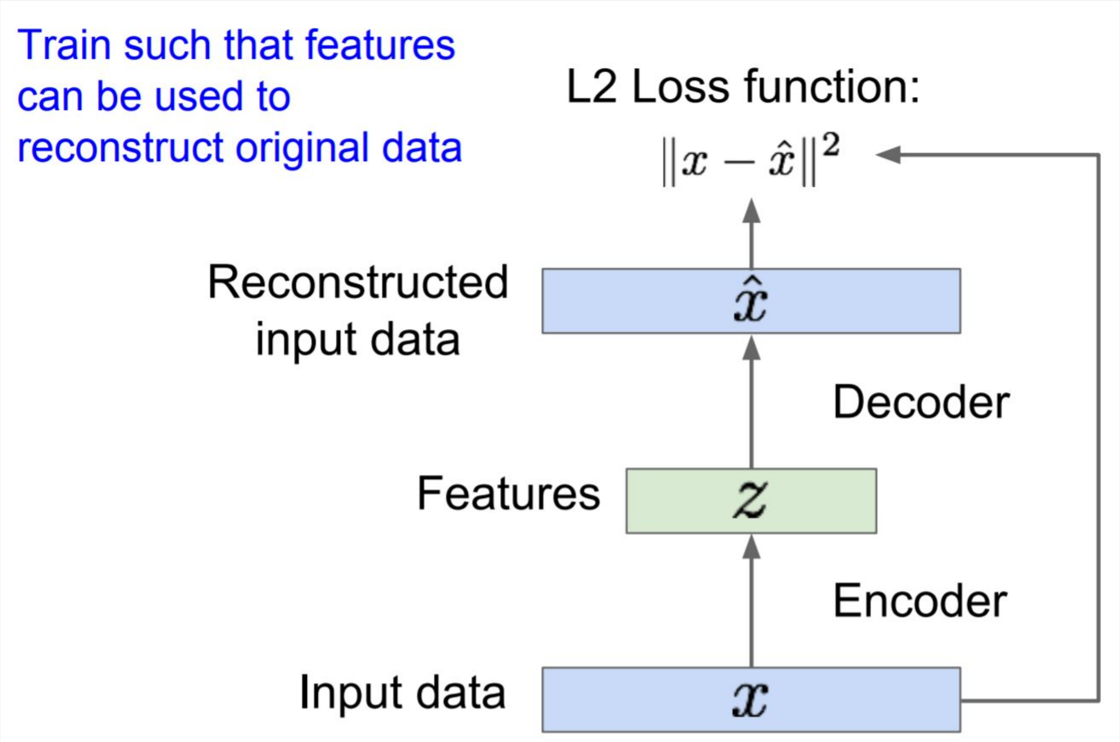


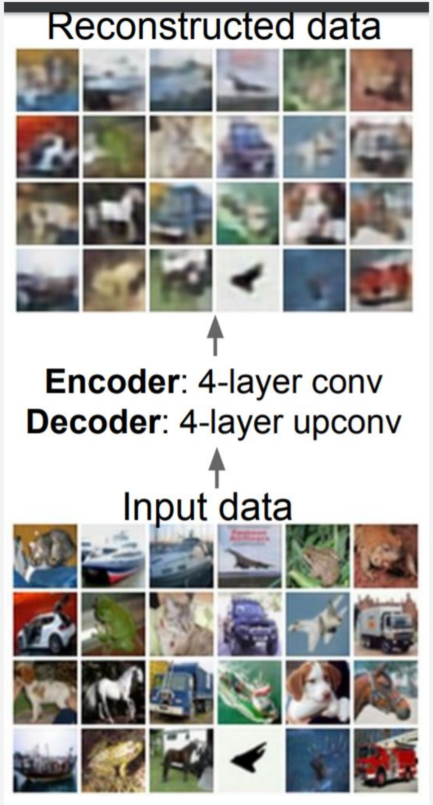
Generative Models

- Realistic samples for artwork, super-resolution, colorization, etc.

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture13.pdf

Autoencoder

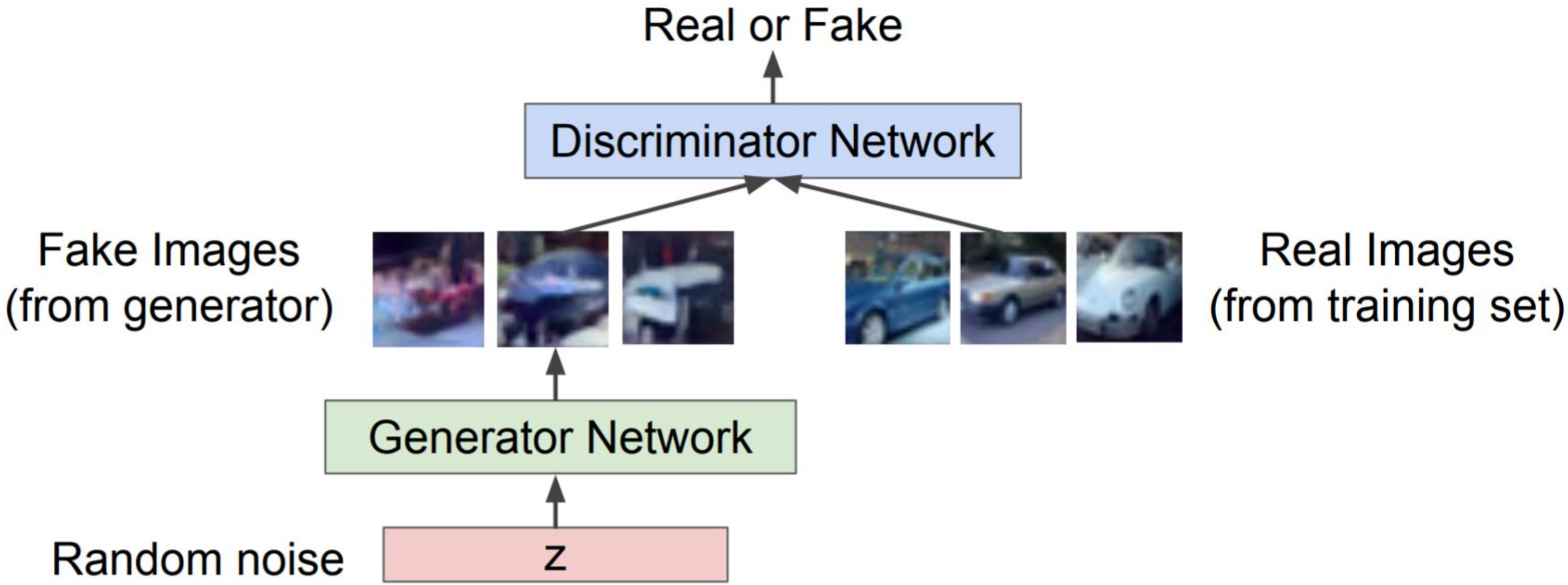




http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture13.pdf

Generative Adversarial Networks

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture13.pdf

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Research Frontiers

Deeper Networks

Vanishing gradient, instability -> ResNet

More Efficient Networks

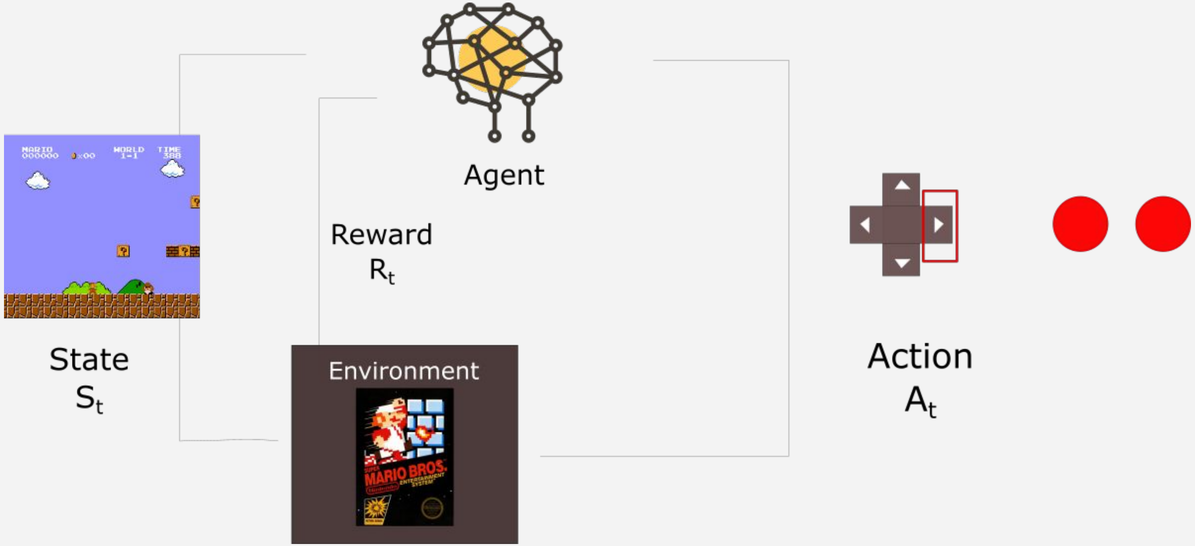
Network compression / Binary networks

Understanding Networks

The explainability of neural networks

Research Frontiers

Reinforcement Learning is trying to solve a very different problem than standard ML: instead of supervision, we are given a vague signal called ‘reward’.



https://medium.freecodecamp.org/an-introduction-to-reinforcement-learning-4339519de419

Summary

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Further Readings:

Deep Learning by Ian Goodfellow and Yoshua Bengio and Aaron Courville link