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DEEP LEARNING

A Modern Approach to Artificial Intelligence

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|00 INTRODUCTION

Perceptron
Rosenblatt
1958

Perceptrons
Minsky & Seymour
1958

Boltzmann Machine
Hinton
1985

CNN
LeCun
1989

Contrastive Divergence
Hinton
2002

GAN
Goodfellow
2014

1959
Hubel & Wiesel
Cat Visual Cortex

1979
Fukushima
NeoCognitron

1986
Smolenski
Harmonium
Hinton
RBM
Rumelhart, Hinton & Williams
MLP
Jordan
RNN

1997
Hochreiter & Schmidhuber
LSTM
Schuster & Paliwal
BRNN

2012
Hinton
Dropout

2017
Sabour, Frosst & Hinton
Capsule Network

|00 INTRODUCTION

AlexNet
Krizhevsky, Sutskever & Hinton
2012

ResNet
He, Zhang, Ren & Sun
2015

ResNetXt
Xie, Girshick et al.
2019

2014
Simonyan & Zisserman
VGG
Google
Inception Network

2016
Huang et al.
DenseNet

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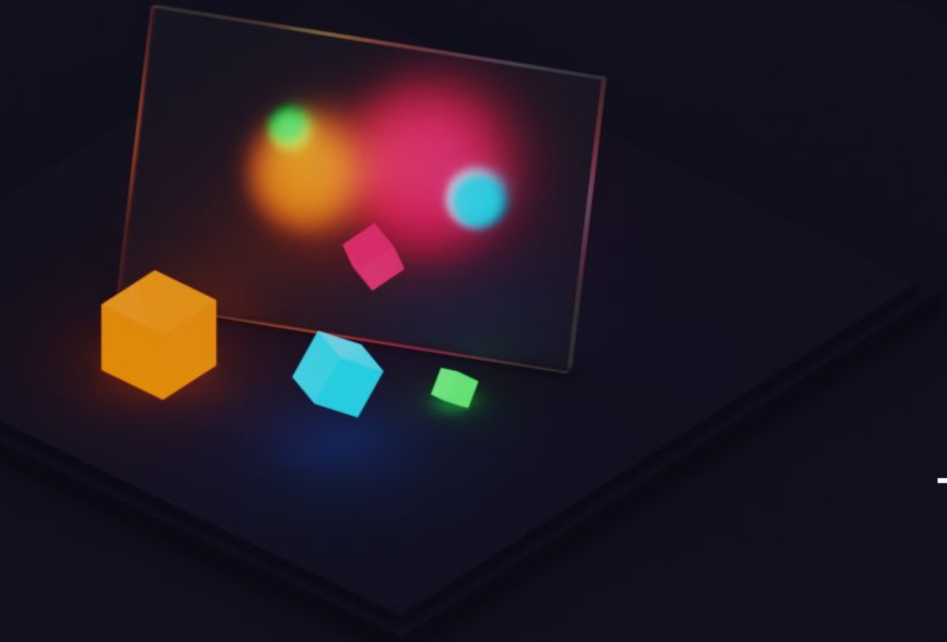

01|

PERCEPTRON

The Beginning and the End

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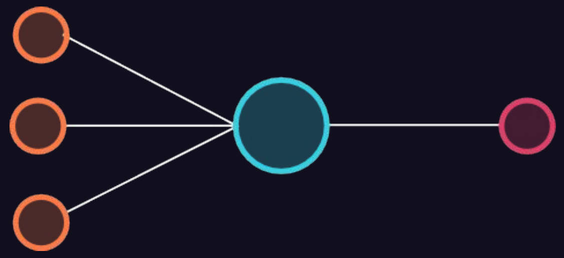
|01 PERCEPTRON



PERCEPTRON

$$\hat{y} = f(wx + b)$$

$$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases}$$

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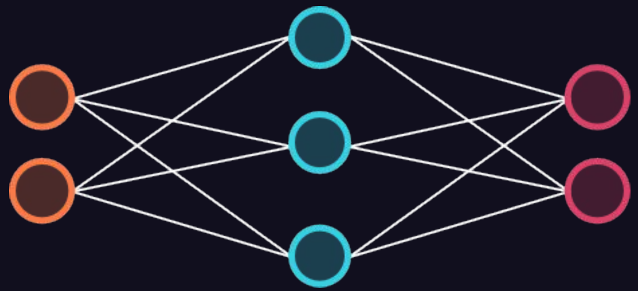
|01 PERCEPTRON



MULTILAYER PERCEPTRON

$$\hat{y} = f(w_2 h + b_2)$$

$$h = f(w_1 x + b_1)$$

$$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases}$$

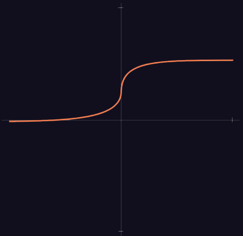
|01 PERCEPTRON

ACTIVATION FUNCTIONS

Step

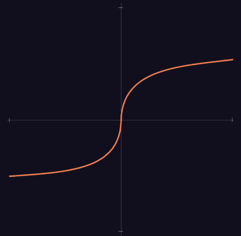
$$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases}$$

Sigmoid



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

Tanh



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

ReLU

$$relu(x) = max(0, x) = x^+$$

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ACTIVATION FUNCTIONS

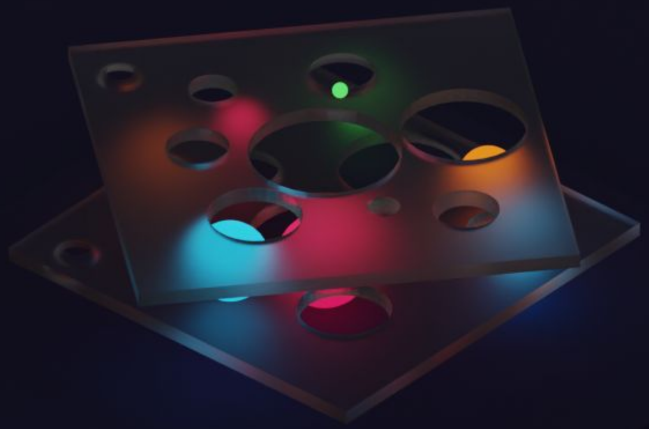
Softmax

$$p_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$$

|02

CONVOLUTION

Signal Processing 101



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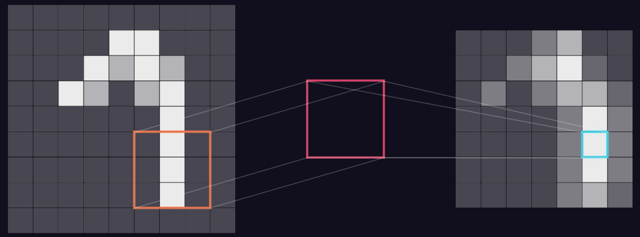


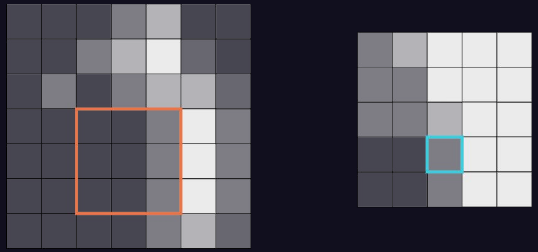
CONVOLUTION
CROSS CORRELATION

$$(f * g)(x) = \int_{-\infty}^{+\infty} f(x)g(x-t)dt$$

Weight Sharing

|02 CONVOLUTION

POOLING



Dimensionality Reduction

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|02 CONVOLUTION

CONVOLUTIONAL NEURAL NETWORK

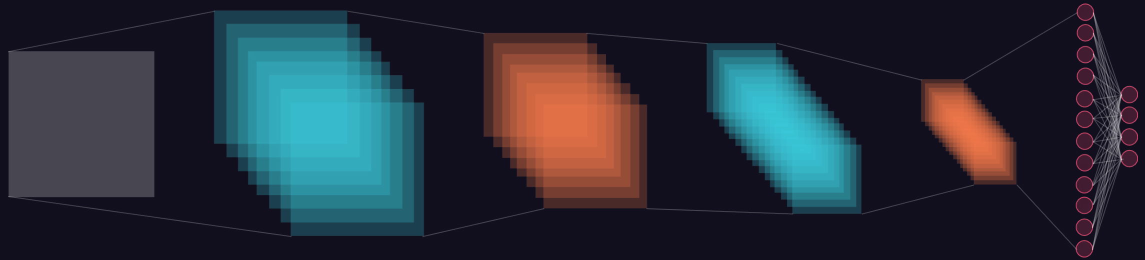

Image Input | Convolution & Pooling | MLP

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03|

RECURRENT

Backprop Through Time

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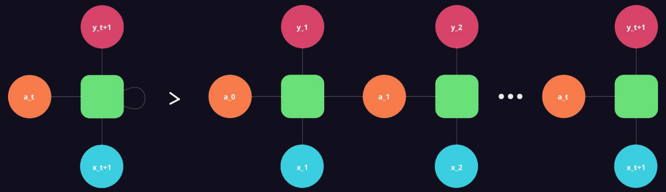
RECURRENT CELLS



Weight Sharing & Backprop Through Time

$$a_t = g_1(W_{aa} a_{t-1} + W_{ax} x_t + b_a)$$

$$y_t = g_2(W_{ya} a_t + b_y)$$

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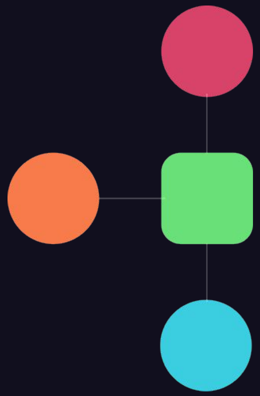
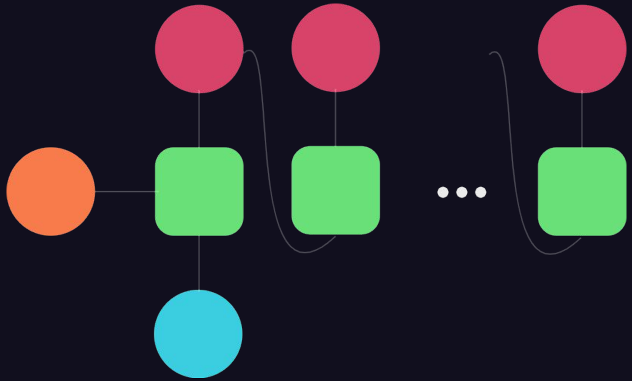


ARCHITECTURES

One to One

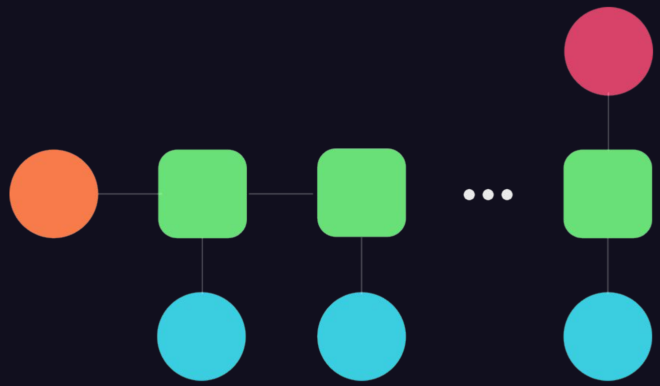
Traditional Neural Network



ARCHITECTURES

One to Many

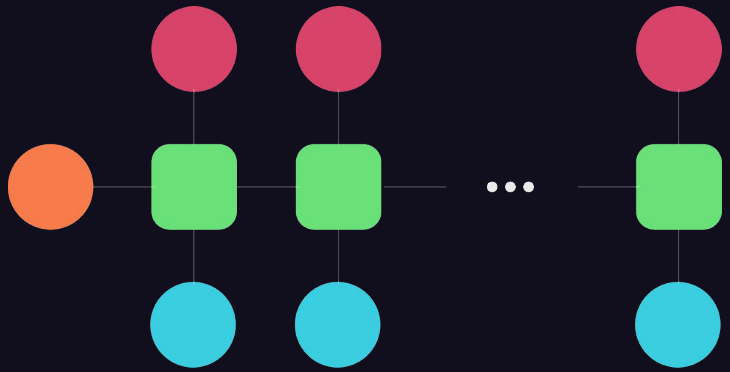
Music Generation



ARCHITECTURES

Many to One

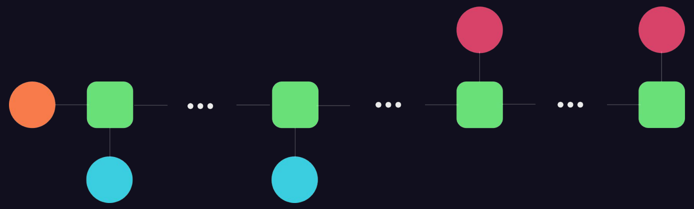
Sentiment Classification



ARCHITECTURES

Many to Many

Name Entity Recognition



ARCHITECTURES

Many to Many

Machine Translation

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|03 RECURRENT

ADVANTAGES

Infinite Input Length
Model **Size Invariant**
Historical Information
Weight Sharing Through Time

DRAWBACKS

Computationally **Slow**
Long Time **Dependency Lost** Over Time
Future Input not Considered
Vanishing/Exploding Gradient

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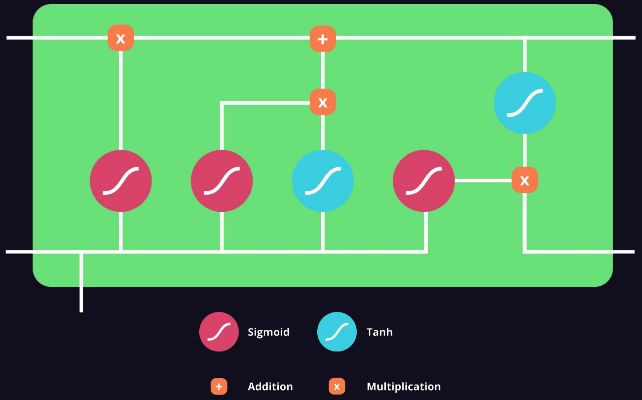
|03 RECURRENT



LSTM

Gates

Forget Gate
Update Gate
Output Gate

I/O

Previous Input
Cell State
Output State

Still **Suffers** from **Exploding Gradient**

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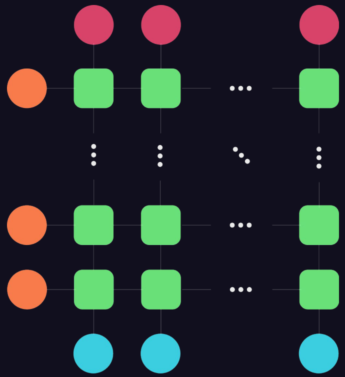
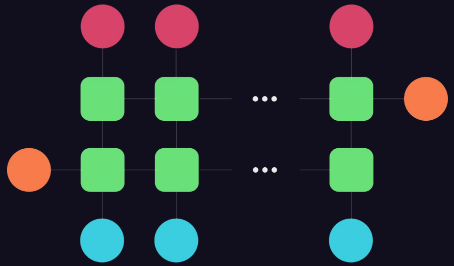
|03 RECURRENT

STACKED



BIDIRECTIONAL



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|04

AUTO-ENCODER

Hierarchical Compression is Key

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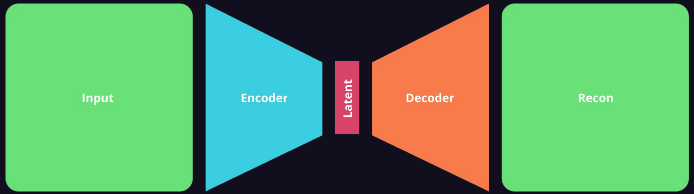
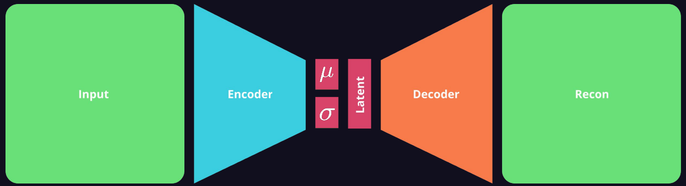
AUTO-ENCODER



$$z = e(x) \qquad \hat{y} = d(z)$$

$$loss = \frac{1}{N} \sum_i^N (\hat{y}_i - y_i)^2$$

VARIATIONAL AUTO-ENCODER



$$< \mu, \sigma >= e(x)$$

$$z = \mu \cdot \epsilon + \sigma$$

$$\hat{y} = d(z)$$

$$\epsilon \sim \mathcal{N}(0,1)$$

$$z \sim \mathcal{N}(\mu, \sigma)$$

$$loss = \frac{1}{N}\sum_i^N (\hat{y}_i - y_i)^2 + KL(\mathcal{N}(\mu_i, \sigma_i)||\mathcal{N}(0,1))$$

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05|

GENERATIVE ADVERSARIAL NETWORK

Min Max for the Win

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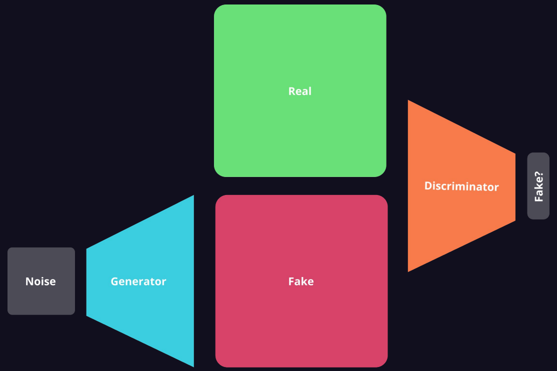
|05 GENERATIVE ADVERSARIAL NETWORK



GENERATIVE ADVERSARIAL NETWORK

$$\underset{G}{min}\,\underset{D}{max} = \mathbb{E}_{x\sim p_r}[log(D(x))] + \mathbb{E}_{x\sim p_g}[1 - log(D(x))]$$

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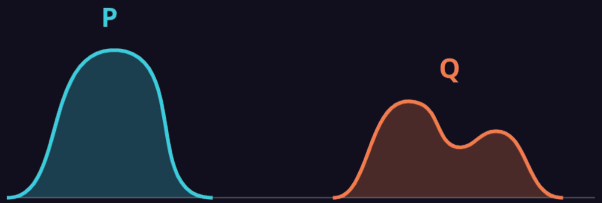
|05 GENERATIVE ADVERSARIAL NETWORK

WASSERSTEIN



$$W_{(p_r,p_g)} = \underset{\gamma \sim \pi(p_r,p_g)}{inf} \mathbb{E}_{(x,y)\sim\gamma}[||x-y||]$$

|06

ATTENTION

It is All You Need

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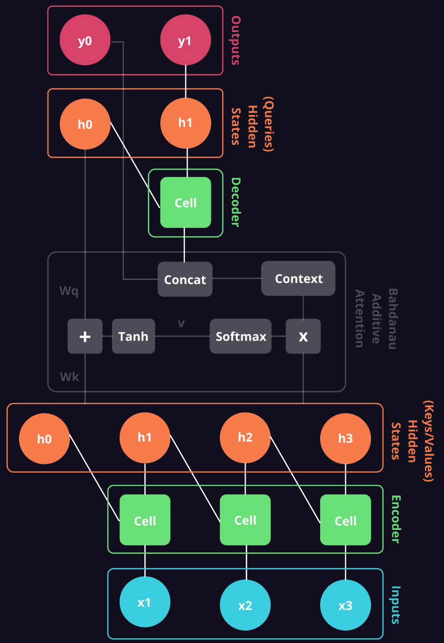
|06 ATTENTION



BAHDANAU ATTENTION

$$score(k,q) = V^T tanh(W_k k + W_q q)$$

$$attention(k,q) = softmax(score(k,q))$$

$$context = v \cdot attention(k,q)$$

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SELF ATTENTION