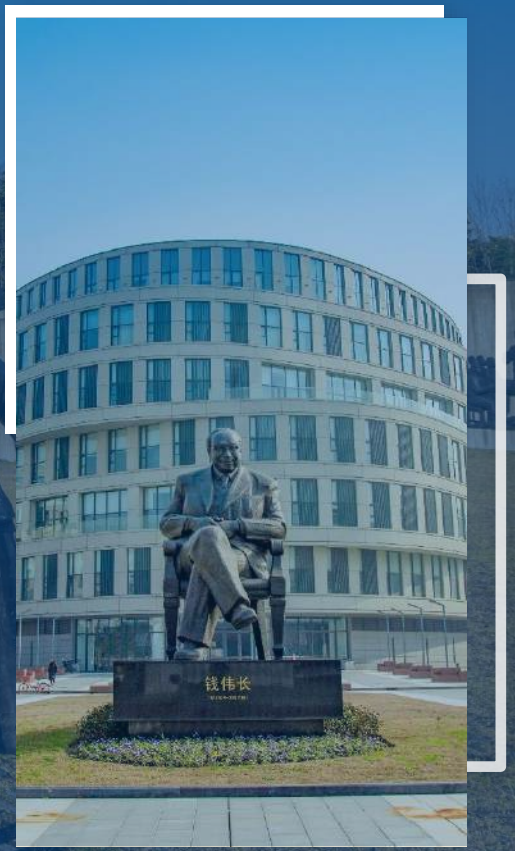
上海大学未来技术学院 SCHOOL OF FUTURE TECHNOLOGY, SHANGHAI UNIVERSITY
上海大学人工智能研究院 INSTITUTE OF ARTIFICIAL INTELLIGENCE, SHANGHAI UNIVERSITY

人工智能导论

——第1课：人工智能基本理论



叶林奇

未来技术学院（人工智能研究院）

2024秋季学期

课程简介

课程内容

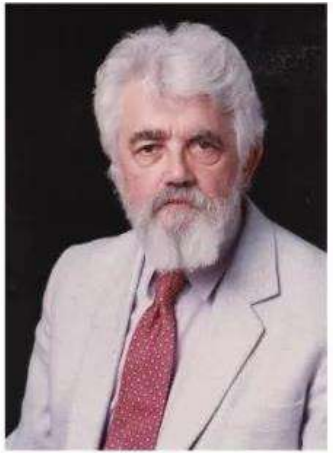
- 第1周，绪论：人工智能基本理论
- 第2周，强化学习
- 第3周，机器人智能控制
- 第4周，生成式AI
- 第5周，大模型
- 第6周，智能体
- 第7周，具身智能
- 第8周，AI for Science
- 第9周，项目汇报，学生分组完成一个人工智能项目。
- 第10周，项目汇报，学生分组完成一个人工智能项目。

考核方式：平时成绩30%+项目汇报70%

人工智能基本理论

1956年：麦卡锡召集哈佛大学、麻省理工学院、IBM公司、贝尔实验室的研究人员召开达特矛斯会议正式提出“人工智能”

2006年达特茅斯会议当事人重聚，左起：摩尔、麦卡锡、明斯基、塞弗里奇、所罗门诺夫。

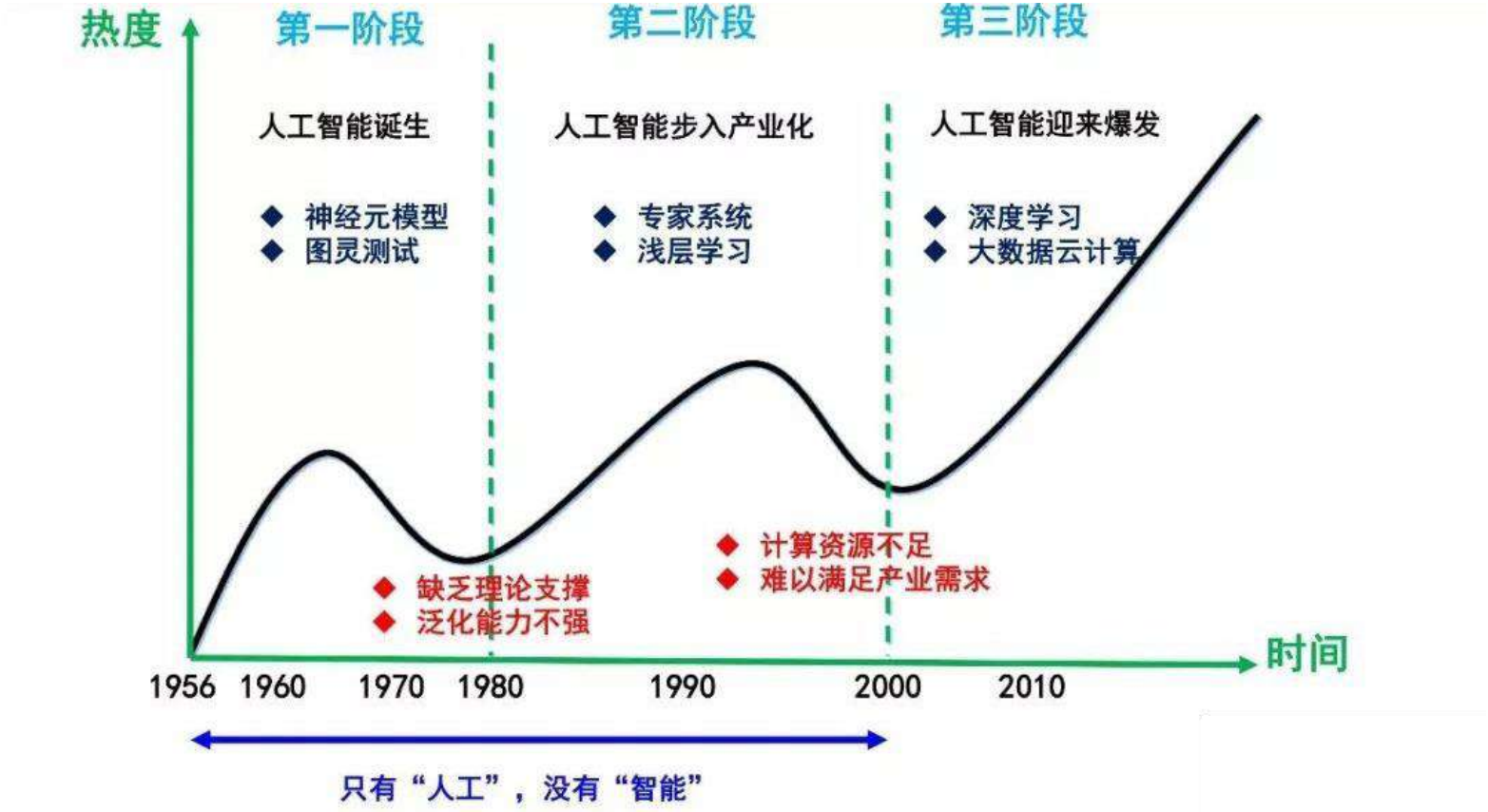


John McCarthy

人工智能之父

制造智能机器的科学和工程，特别是智能计算机程序。它与使用计算机理解人类智能的类似任务有关，但人工智能并不局限于生物学观察。

人工智能基本理论


热度
第一阶段
第二阶段
第三阶段
人工智能诞生
人工智能步入产业化
人工智能迎来爆发
◆ 神经元模型
◆ 图灵测试
◆ 专家系统
◆ 浅层学习
◆ 深度学习
◆ 大数据云计算
◆ 缺乏理论支撑
◆ 泛化能力不强
◆ 计算资源不足
◆ 难以满足产业需求
时间
1956 1960 1970 1980 1990 2000 2010
只有“人工”，没有“智能”

人工智能基本理论

2006年，Hinton和他的学生Salakhutdinov在《科学》上发表了一篇文章，开启了深度学习在学术界和工业界的浪潮。

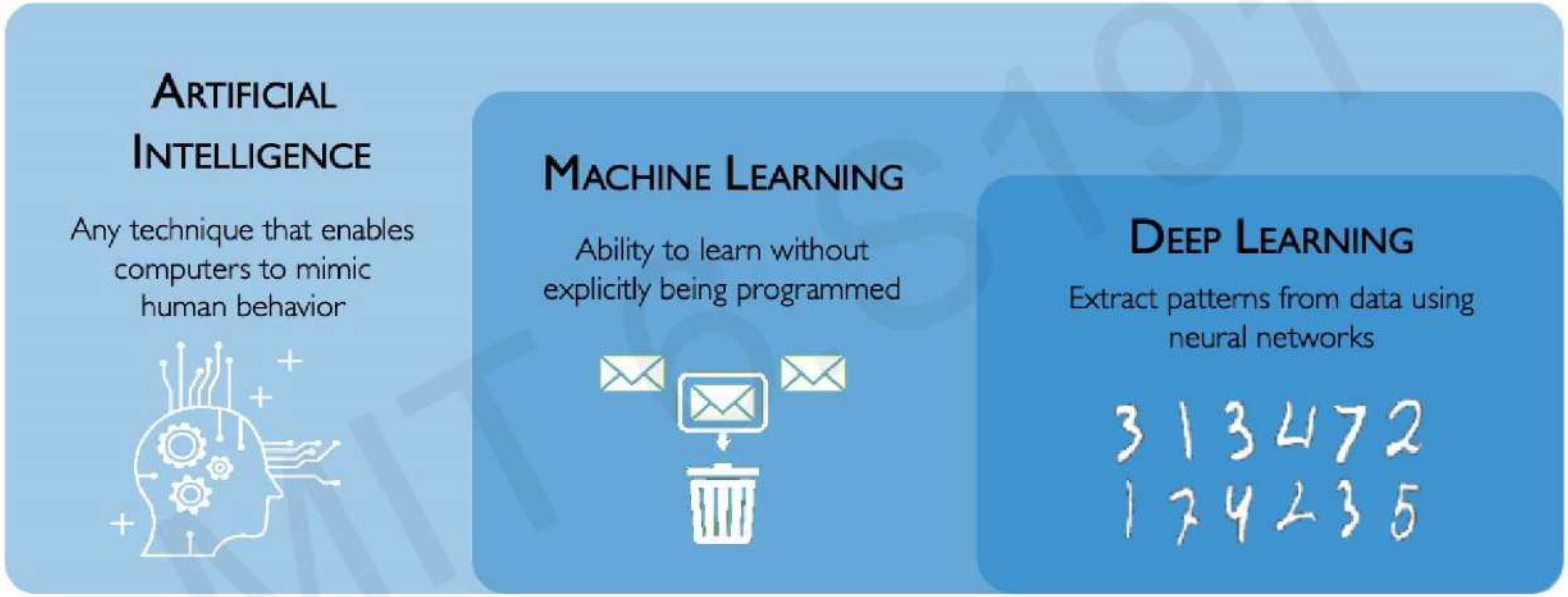
504 28 JULY 2006 VOL 313 SCIENCE

Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov

High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such "autoencoder" networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data

What is Deep Learning?



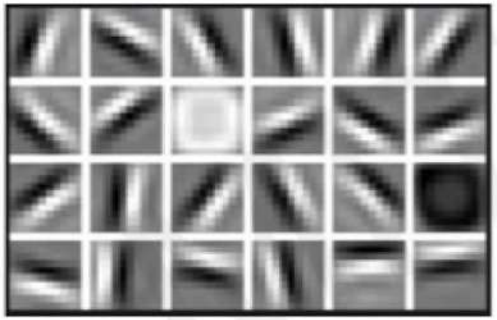
Teaching computers how to **learn a task** directly from **raw data**

Why Deep Learning?

Hand engineered features are time consuming, brittle, and not scalable in practice

Can we learn the **underlying features** directly from data?

Low Level Features



Lines & Edges

Mid Level Features

Eyes & Nose & Ears

High Level Features

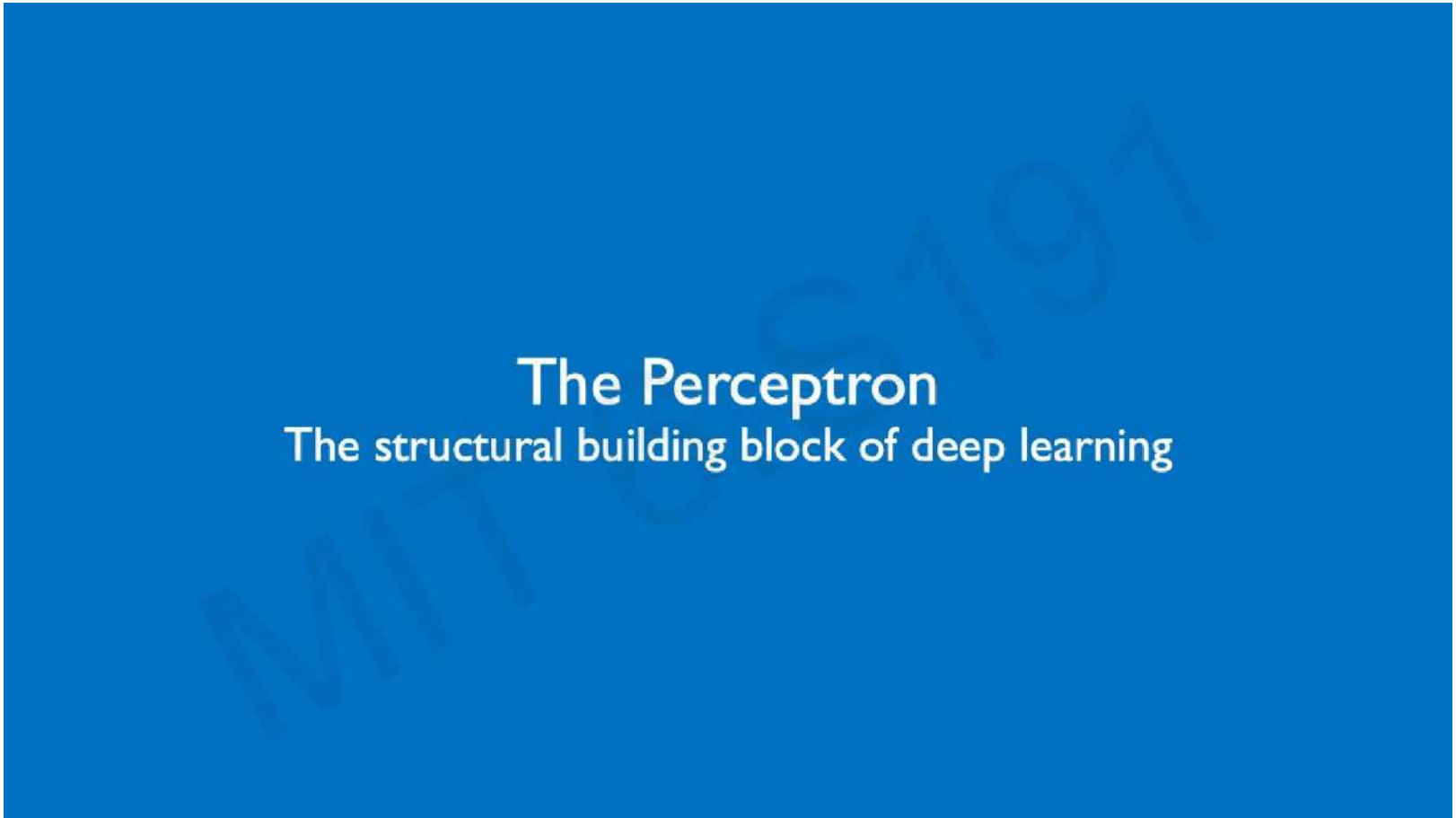
Facial Structure

提纲

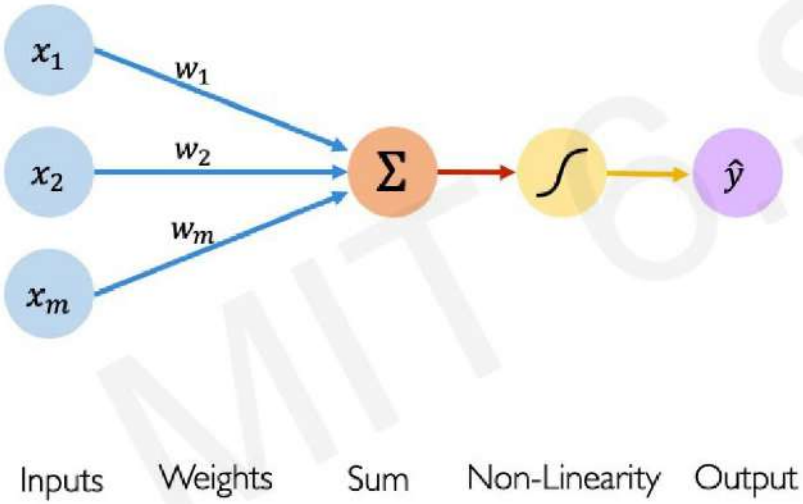
一、前馈网络

二、循环网络

三、卷积网络


The Perceptron
The structural building block of deep learning

The Perceptron: Forward Propagation



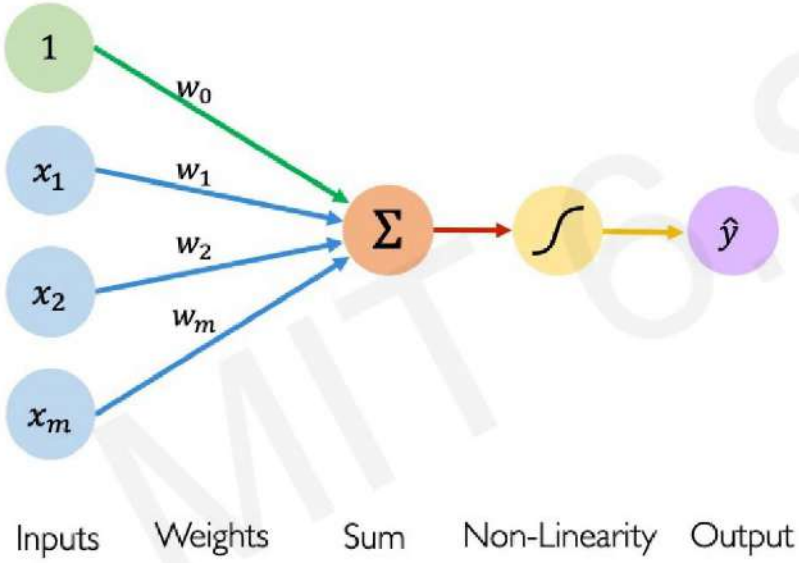
Output

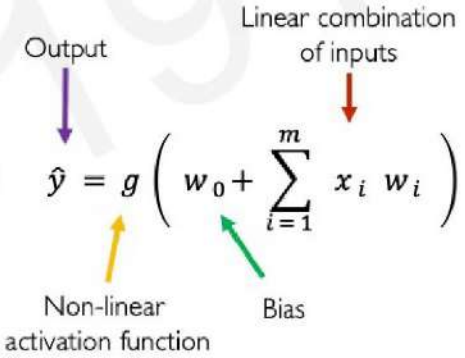
Linear combination of inputs

$$\hat{y} = g\left(\sum_{i=1}^{m} x_i \, w_i\right)$$

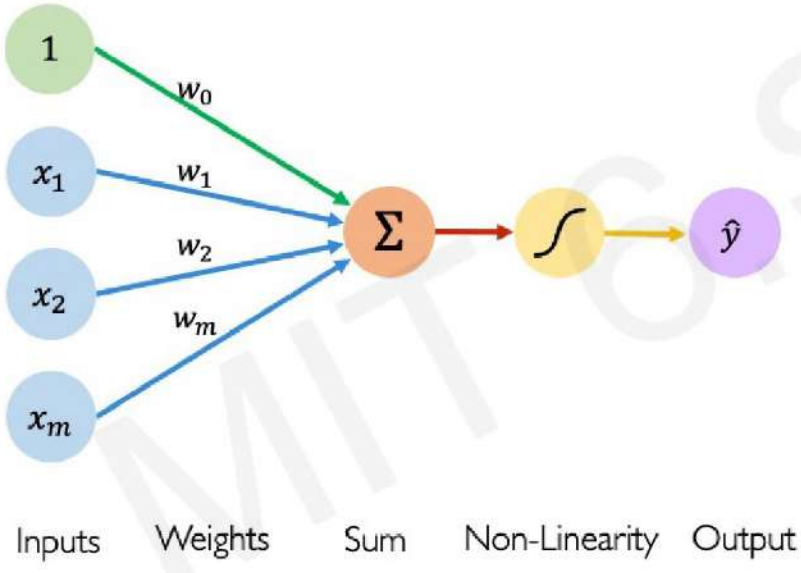
Non-linear activation function

The Perceptron: Forward Propagation





The Perceptron: Forward Propagation

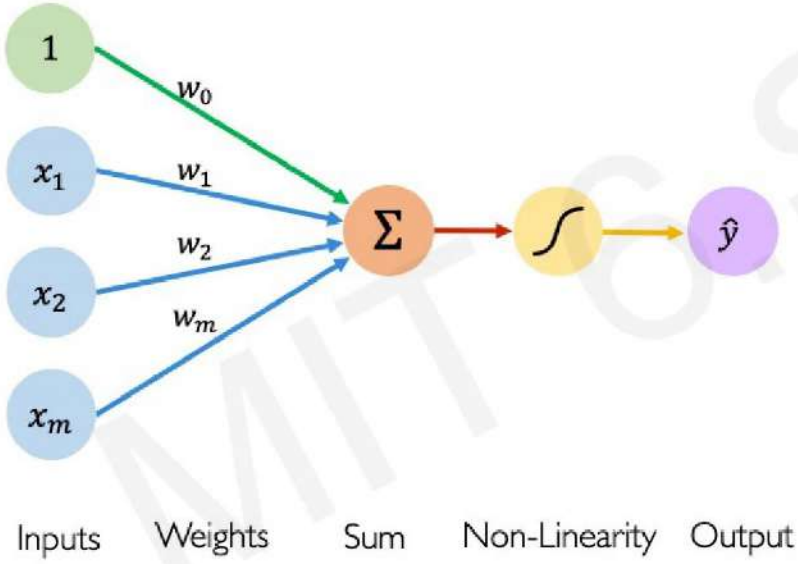


$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i\, w_i\right)$$

$$\hat{y} = g\left(w_0 + \boldsymbol{X}^T \boldsymbol{W}\right)$$

where: $\boldsymbol{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$ and $\boldsymbol{W} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$

The Perceptron: Forward Propagation

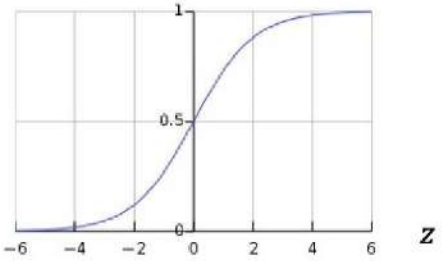


Activation Functions

$$\hat{y} = g(w_0 + \boldsymbol{X}^T \boldsymbol{W})$$

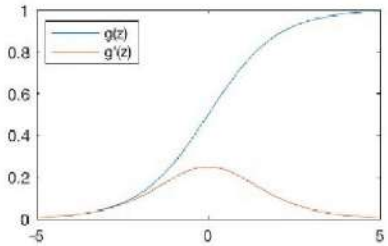
- Example: sigmoid function

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



Common Activation Functions

Sigmoid Function

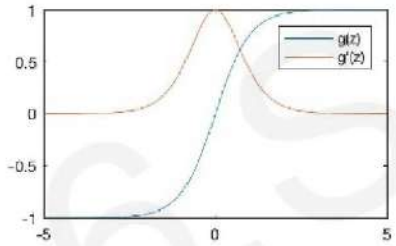


$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

`tf.math.sigmoid(z)`

Hyperbolic Tangent

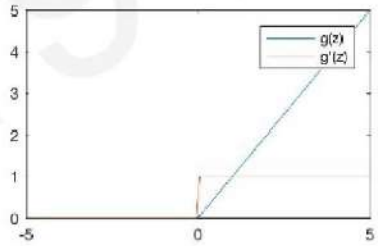


$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

`tf.math.tanh(z)`

Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

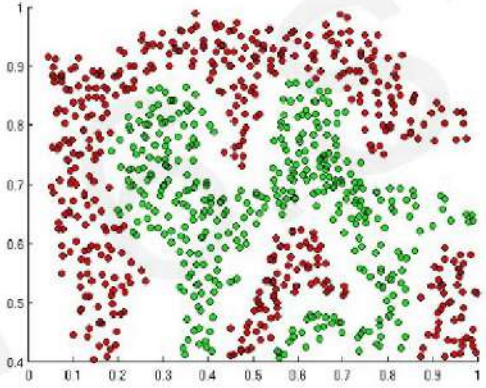
`tf.nn.relu(z)`

TensorFlow code blocks

NOTE: All activation functions are non-linear

Importance of Activation Functions

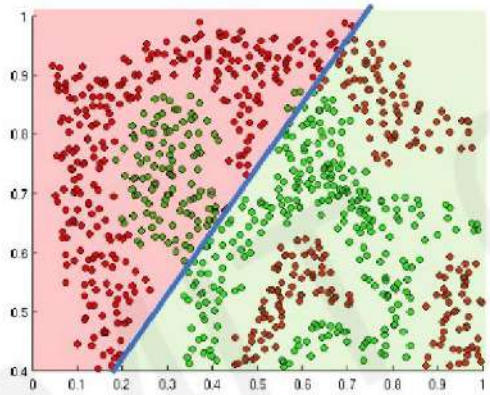
*The purpose of activation functions is to **introduce non-linearities** into the network*



What if we wanted to build a neural network to distinguish green vs red points?

Importance of Activation Functions

*The purpose of activation functions is to **introduce non-linearities** into the network*



Linear activation functions produce linear decisions no matter the network size

Importance of Activation Functions

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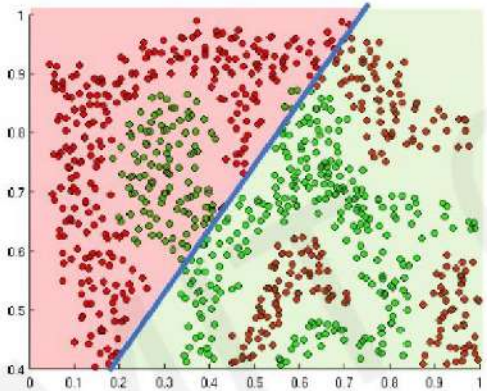
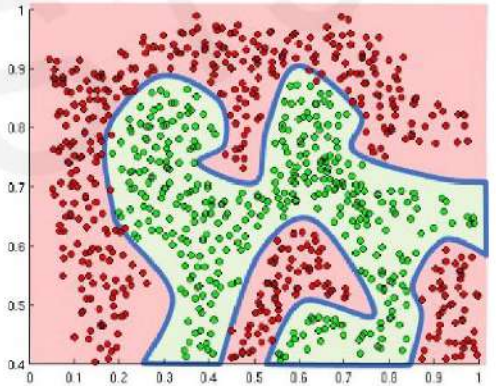
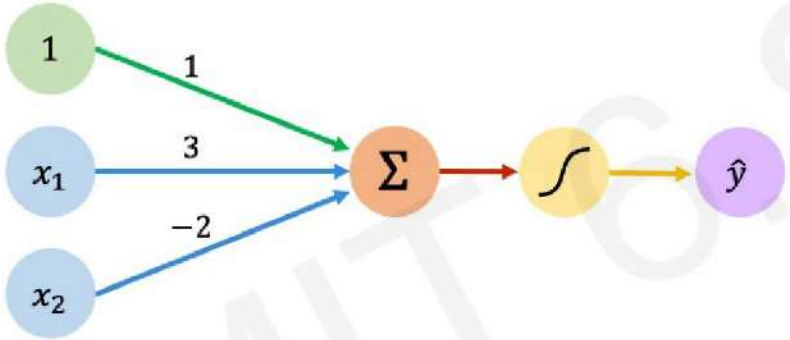


Linear activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

The Perceptron: Example



We have: $w_0 = 1$ and $\boldsymbol{W} = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$

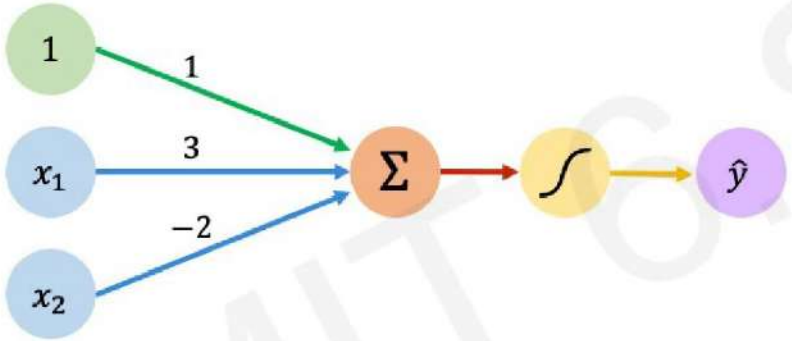
$$\hat{y} = g(w_0 + \boldsymbol{X}^T \boldsymbol{W})$$

$$= g\left(1 + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} 3 \\ -2 \end{bmatrix}\right)$$

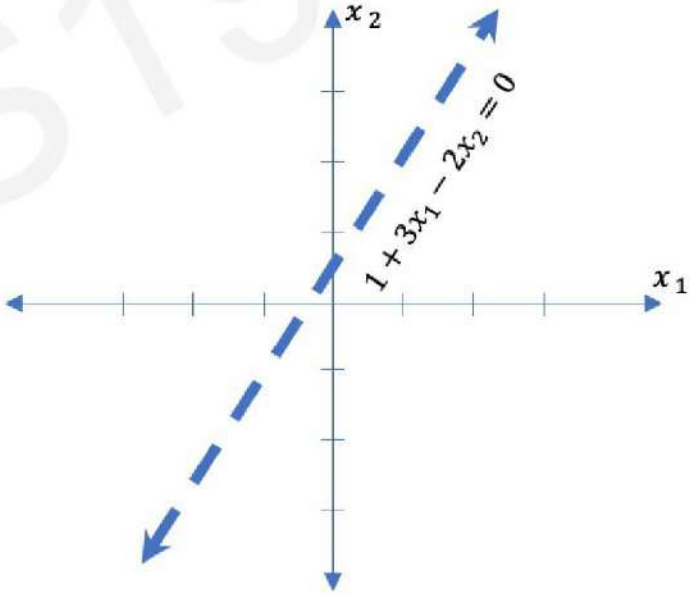
$$\hat{y} = g(1 + 3x_1 - 2x_2)$$

This is just a line in 2D!

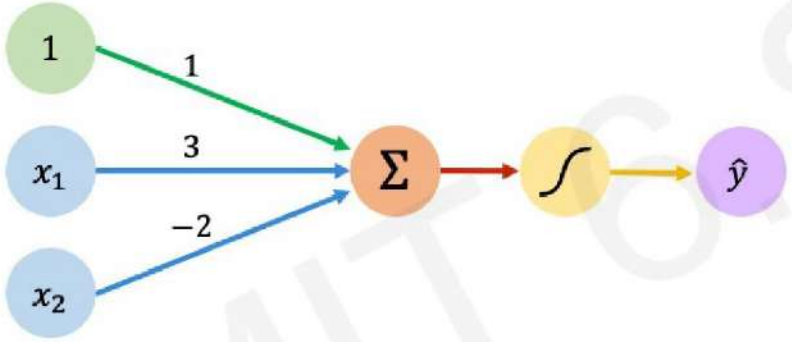
The Perceptron: Example



$$\hat{y} = g(1 + 3x_1 - 2x_2)$$

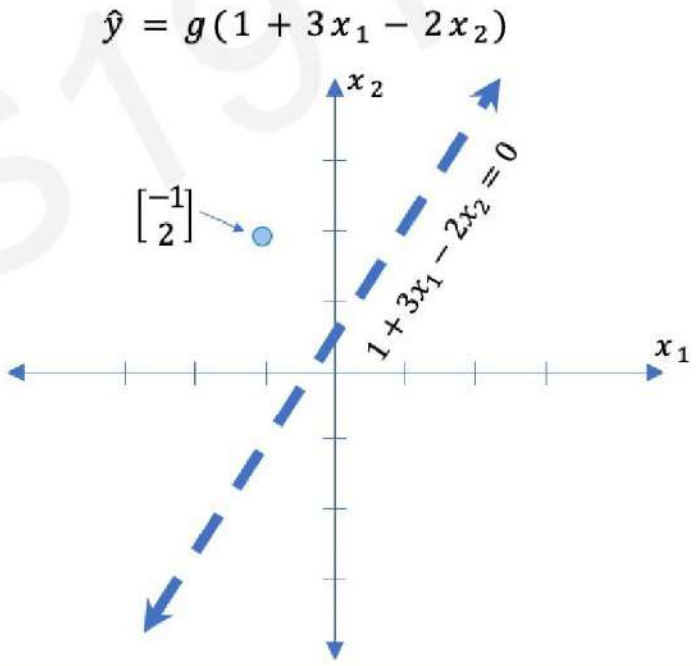


The Perceptron: Example

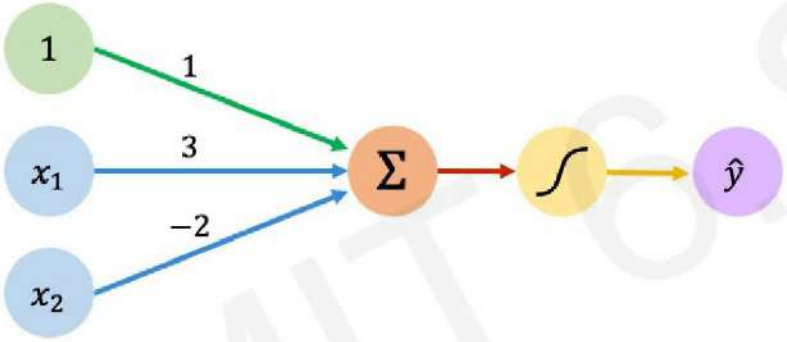


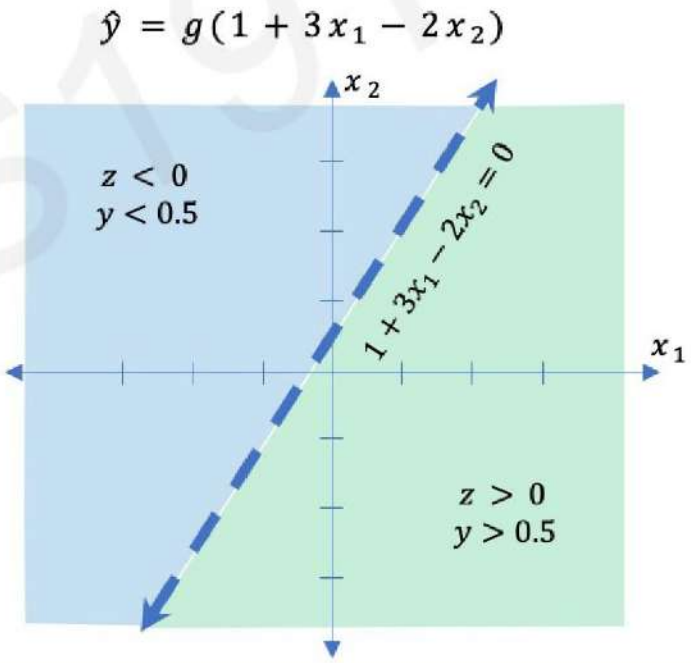
Assume we have input: $\boldsymbol{X} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$

$$\hat{y} = g\left(1 + (3 * -1) - (2 * 2)\right)$$
$$= g(-6) \approx 0.002$$



The Perceptron: Example

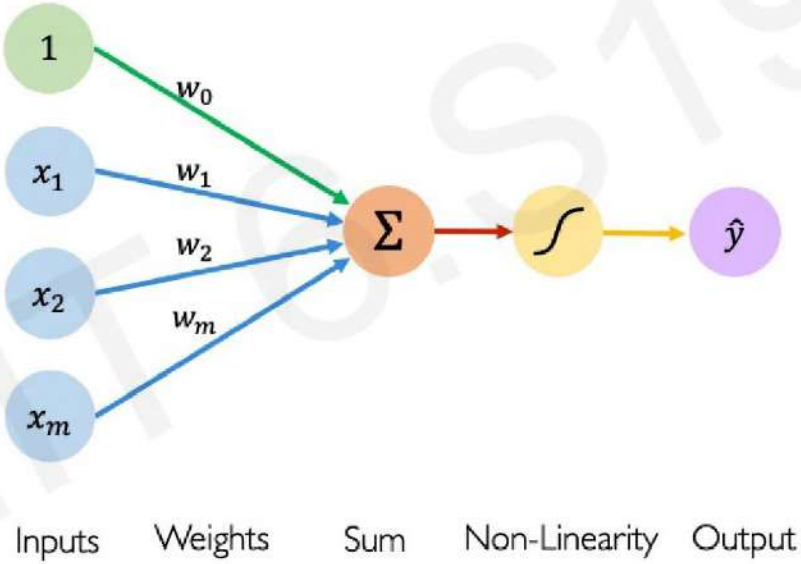




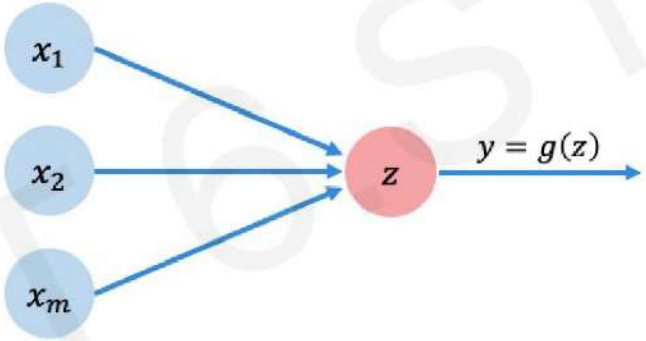
Building Neural Networks with Perceptrons

The Perceptron: Simplified

$$\hat{y} = g\left(w_0 + \boldsymbol{X}^T \boldsymbol{W}\right)$$



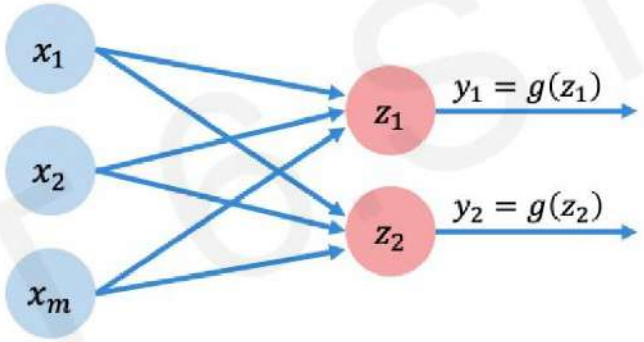
The Perceptron: Simplified



$$z = w_0 + \sum_{j=1}^{m} x_j w_j$$

Multi Output Perceptron

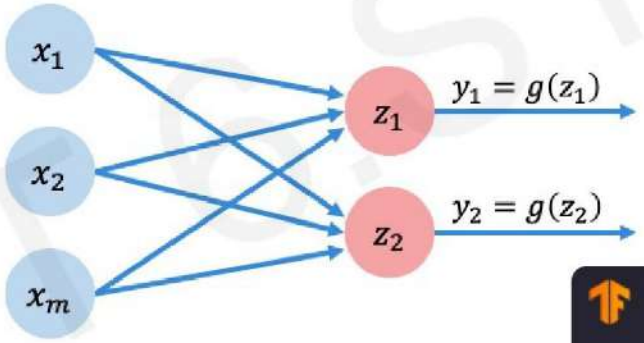
Because all inputs are densely connected to all outputs, these layers are called **Dense** layers



$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j \, w_{j,i}$$

Multi Output Perceptron

Because all inputs are densely connected to all outputs, these layers are called **Dense** layers

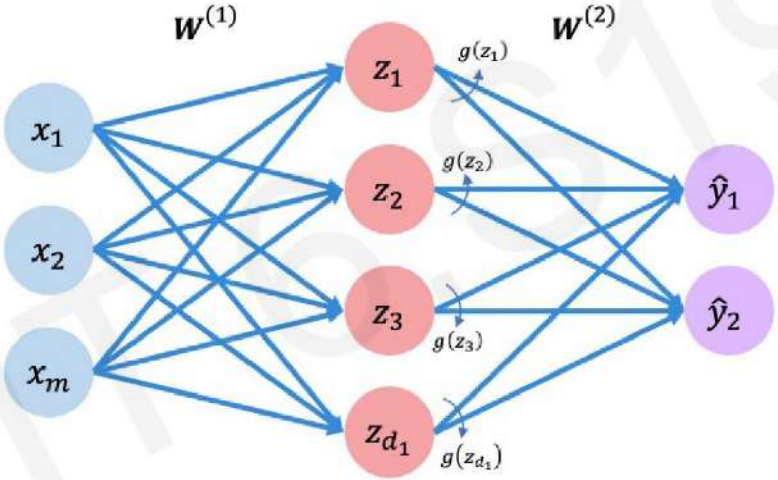



```
import tensorflow as tf

layer = tf.keras.layers.Dense(
    units=2)
```

$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j \, w_{j,i}$$

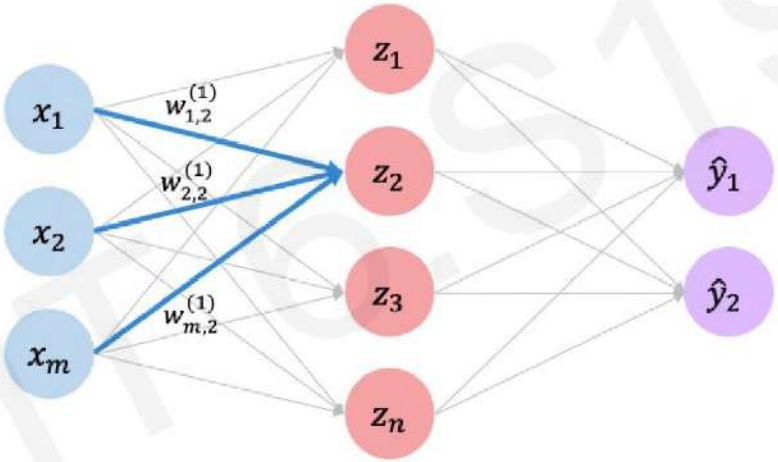
Single Layer Neural Network



$$z_i = w_{0,i}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,i}^{(1)}$$

$$\hat{y}_i = g\left(w_{0,i}^{(2)} + \sum_{j=1}^{d_1} g(z_j) \, w_{j,i}^{(2)}\right)$$

Single Layer Neural Network



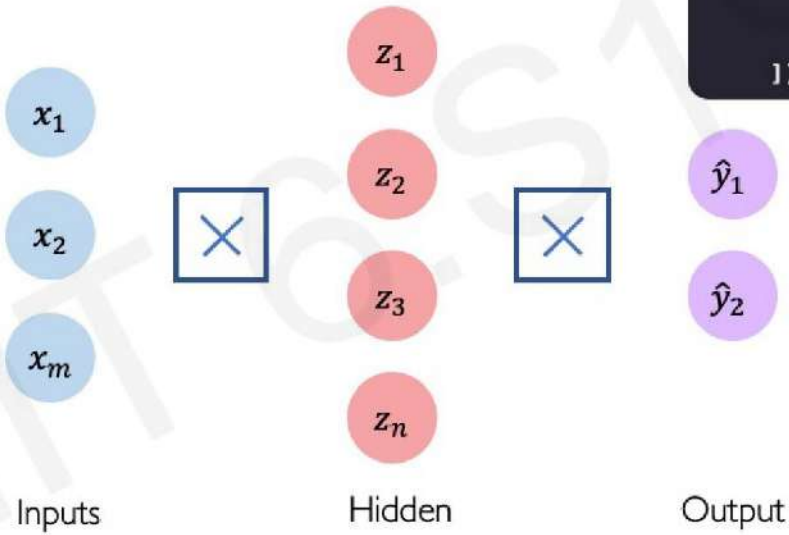
$$z_2 = w_{0,2}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,2}^{(1)}$$

$$= w_{0,2}^{(1)} + x_1 \, w_{1,2}^{(1)} + x_2 \, w_{2,2}^{(1)} + x_m \, w_{m,2}^{(1)}$$

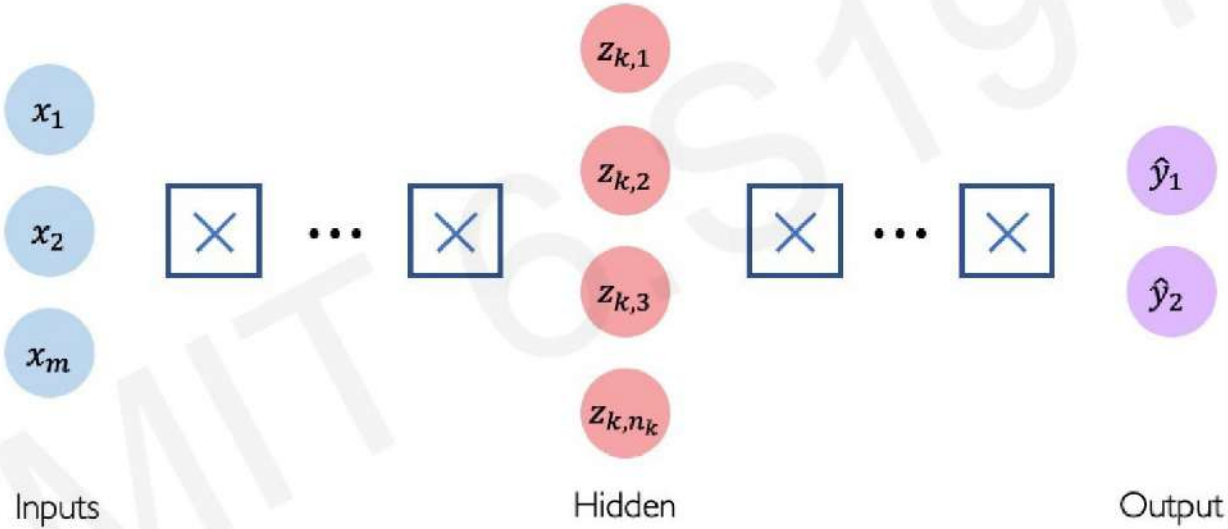
Multi Output Perceptron

```
import tensorflow as tf

model = tf.keras.Sequential([
    tf.keras.layers.Dense(n),
    tf.keras.layers.Dense(2)
])
```

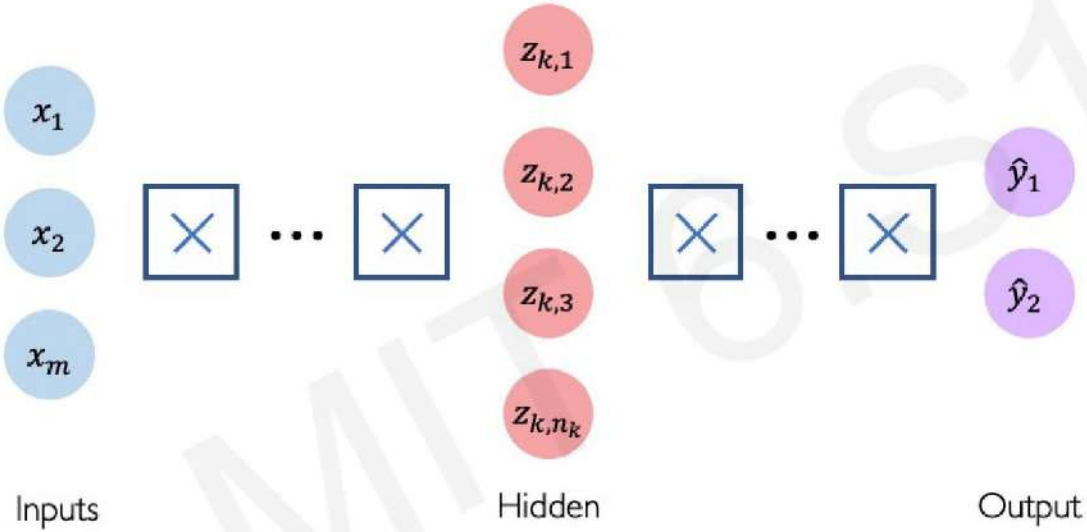


Deep Neural Network



$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

Deep Neural Network




```python
import tensorflow as tf

model = tf.keras.Sequential([
  tf.keras.layers.Dense(n_1),
  tf.keras.layers.Dense(n_2),
  ⋮
  tf.keras.layers.Dense(2)
])
```

$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

Applying Neural Networks

Example Problem

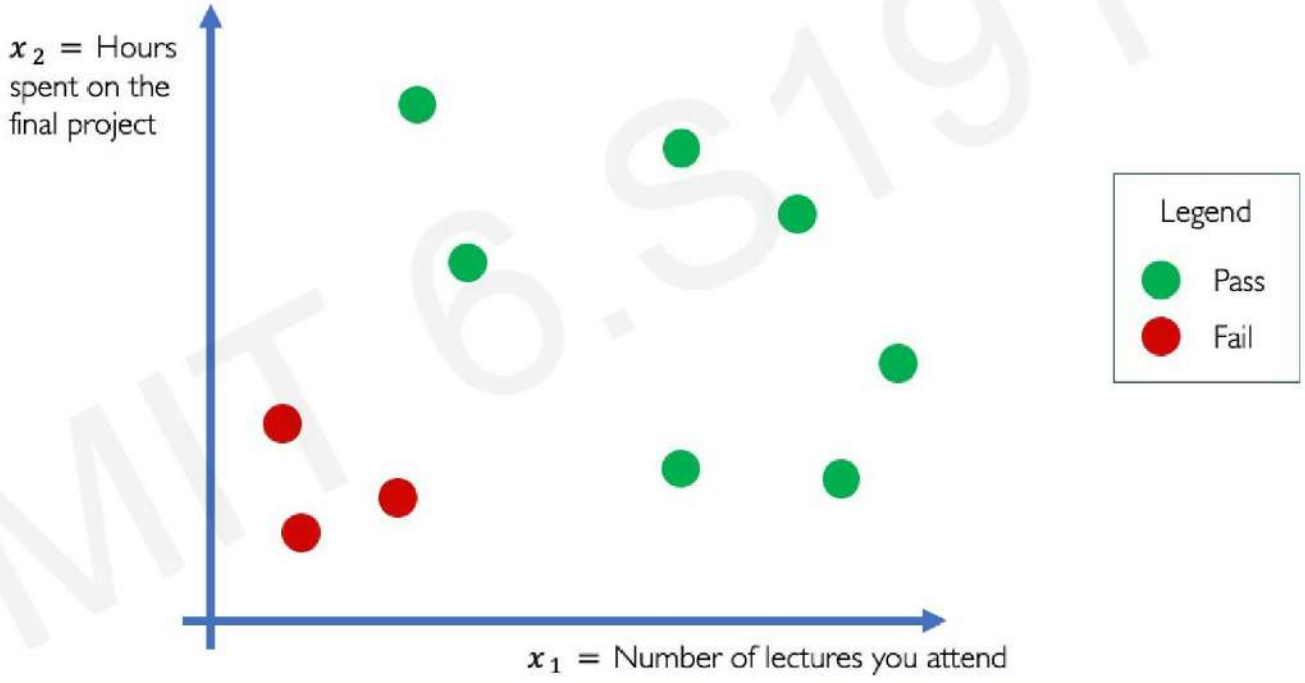
Will I pass this class?

Let's start with a simple two feature model

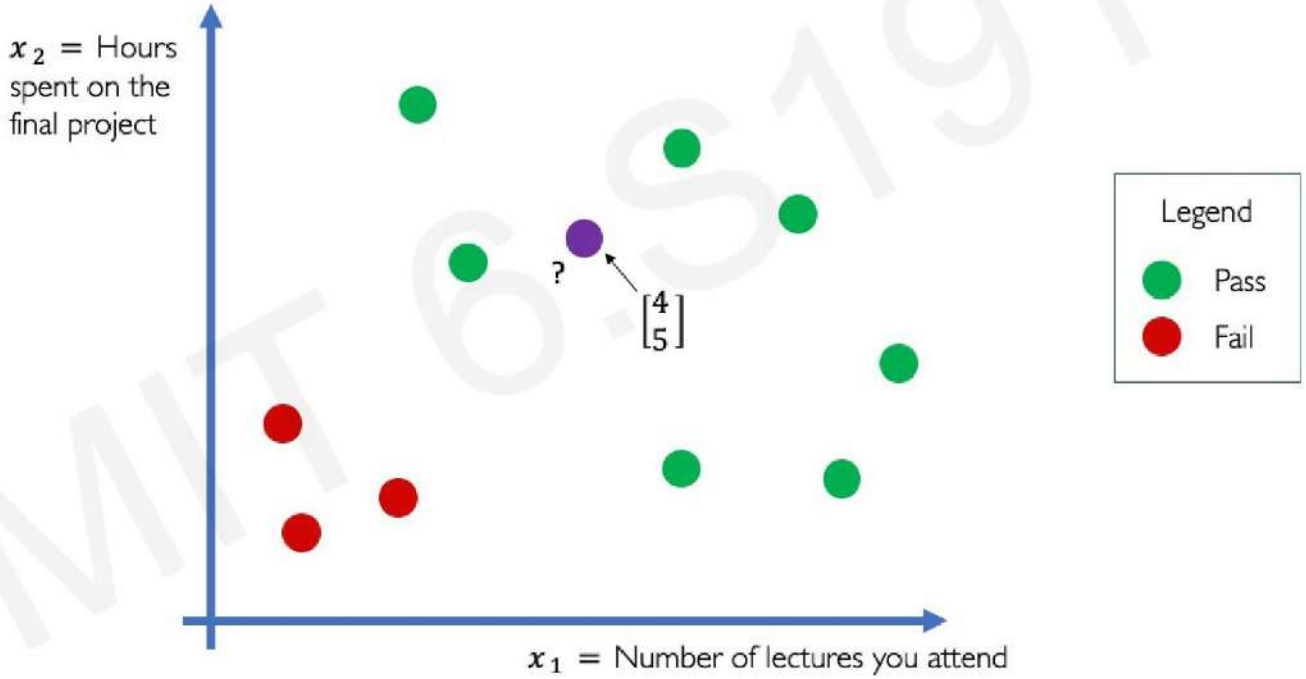
x_1 = Number of lectures you attend

x_2 = Hours spent on the final project

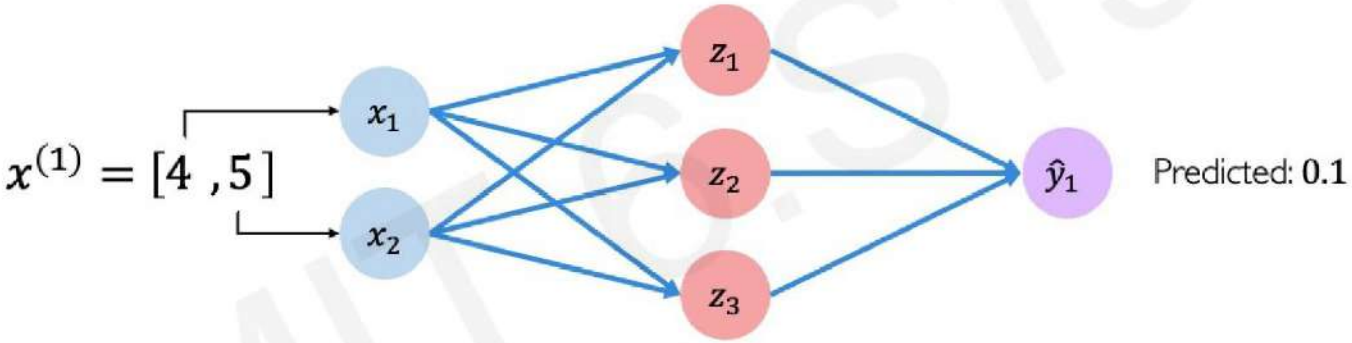
Example Problem: Will I pass this class?



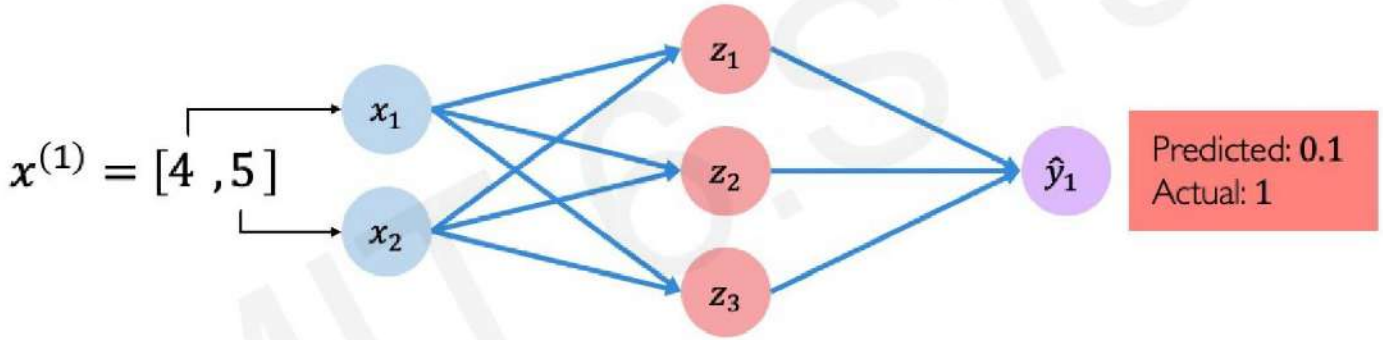
Example Problem: Will I pass this class?



Example Problem: Will I pass this class?

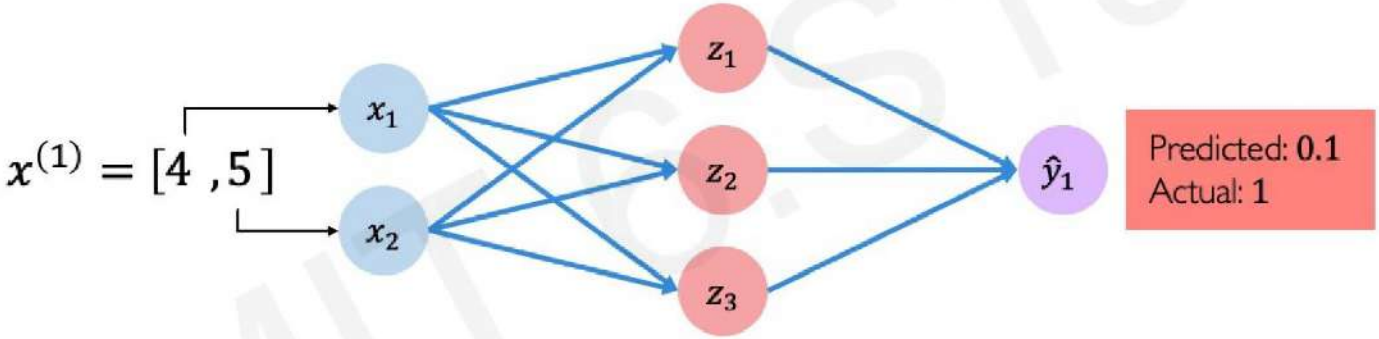


Example Problem: Will I pass this class?



Quantifying Loss

*The **loss** of our network measures the cost incurred from incorrect predictions*

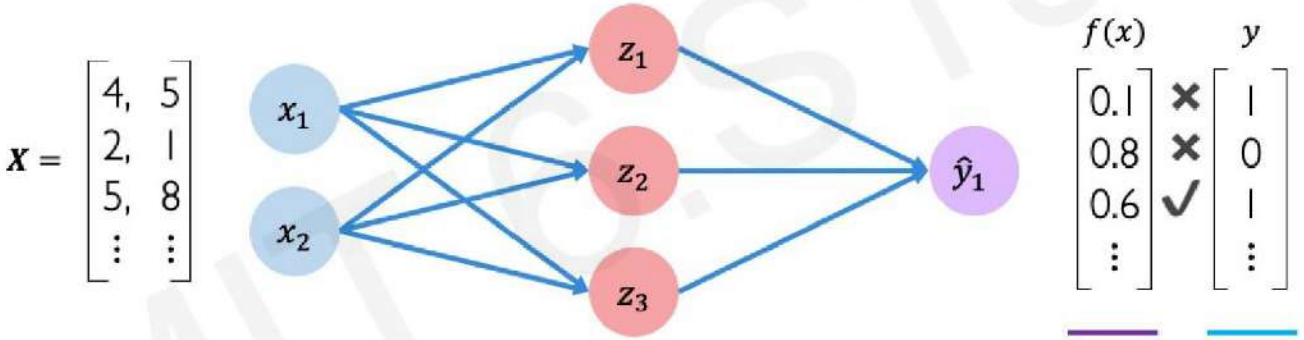


$$\mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

Empirical Loss

*The **empirical loss** measures the total loss over our entire dataset*



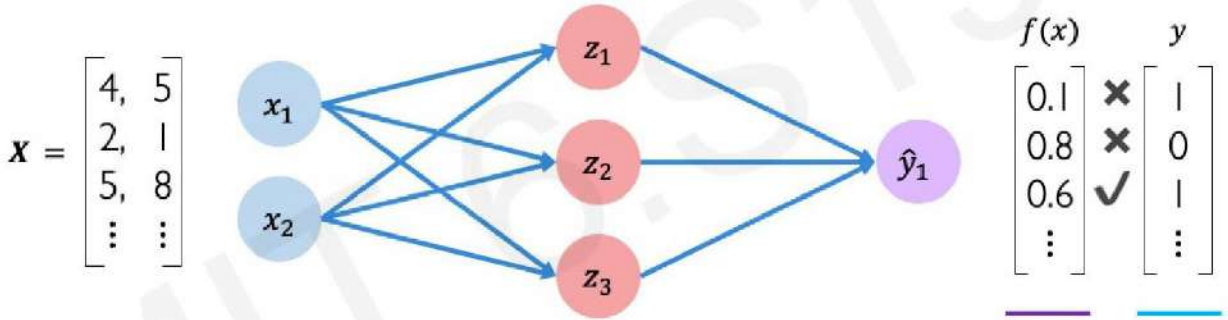
$$J(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted　　Actual

Also known as:
- Objective function
- Cost function
- Empirical Risk

Binary Cross Entropy Loss

Cross entropy loss *can be used with models that output a probability between 0 and 1*



$$J(W) = -\frac{1}{n}\sum_{i=1}^{n} y^{(i)} \log\left(f\left(x^{(i)}; W\right)\right) + \left(1 - y^{(i)}\right) \log\left(1 - f\left(x^{(i)}; W\right)\right)$$

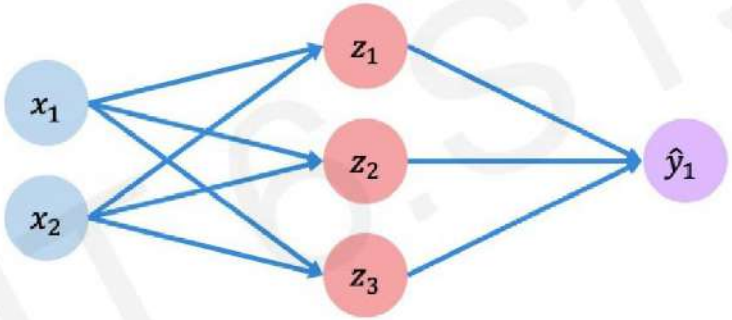
Actual Predicted Actual Predicted

```
loss = tf.reduce_mean( tf.nn.softmax_cross_entropy_with_logits(y, predicted) )
```

Mean Squared Error Loss

Mean squared error loss *can be used with regression models that output continuous real numbers*

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



$f(x)$		y
30	✗	90
80	✗	20
85	✓	95
⋮		⋮

Final Grades (percentage)

$$J(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n}\left(y^{(i)} - f\left(x^{(i)}; \boldsymbol{W}\right)\right)^2$$

Actual Predicted

```
loss = tf.reduce_mean( tf.square(tf.subtract(y, predicted)) )
loss = tf.keras.losses.MSE( y, predicted )
```

Training Neural Networks

Loss Optimization

We want to find the network weights that ***achieve the lowest loss***

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} J(\boldsymbol{W})$$

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$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} J(\boldsymbol{W})$$

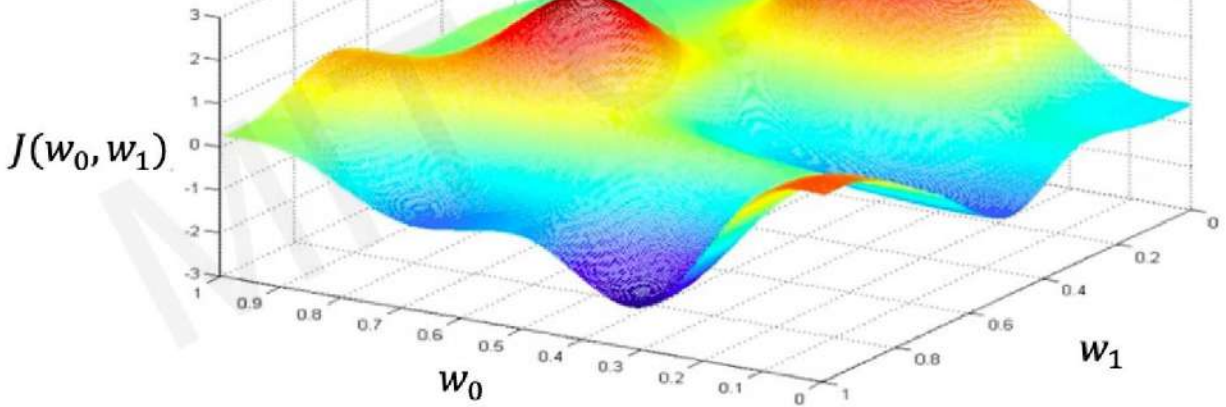
Remember:

$$\boldsymbol{W} = \left\{\boldsymbol{W}^{(0)}, \boldsymbol{W}^{(1)}, \ldots\right\}$$

Loss Optimization

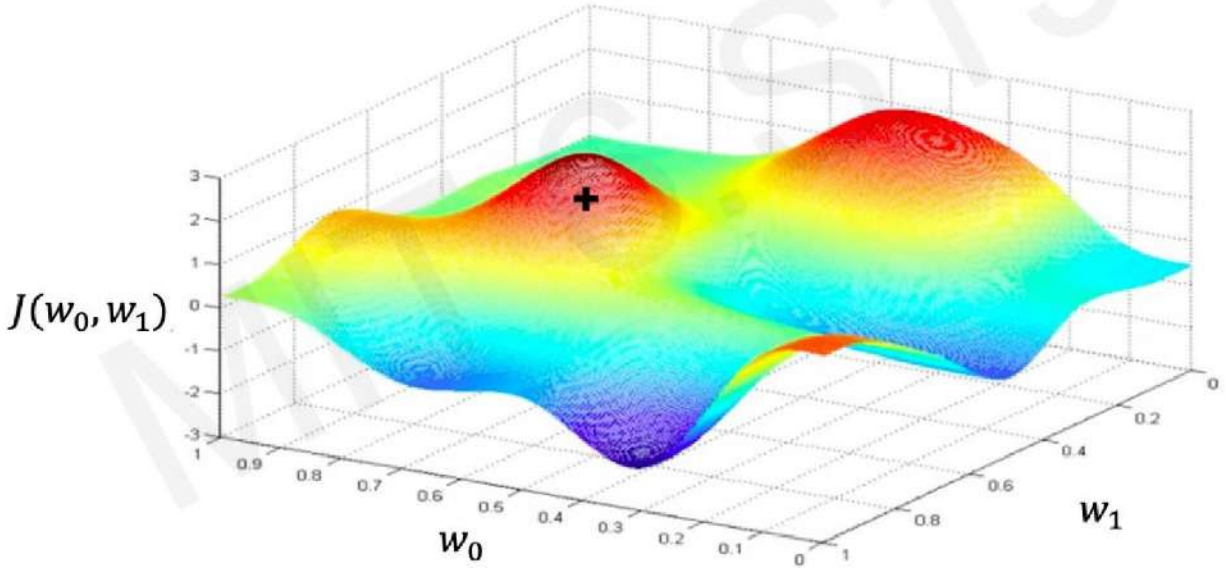
$$W^* = \underset{W}{\operatorname{argmin}} J(W)$$

Remember:
Our loss is a function of the network weights!



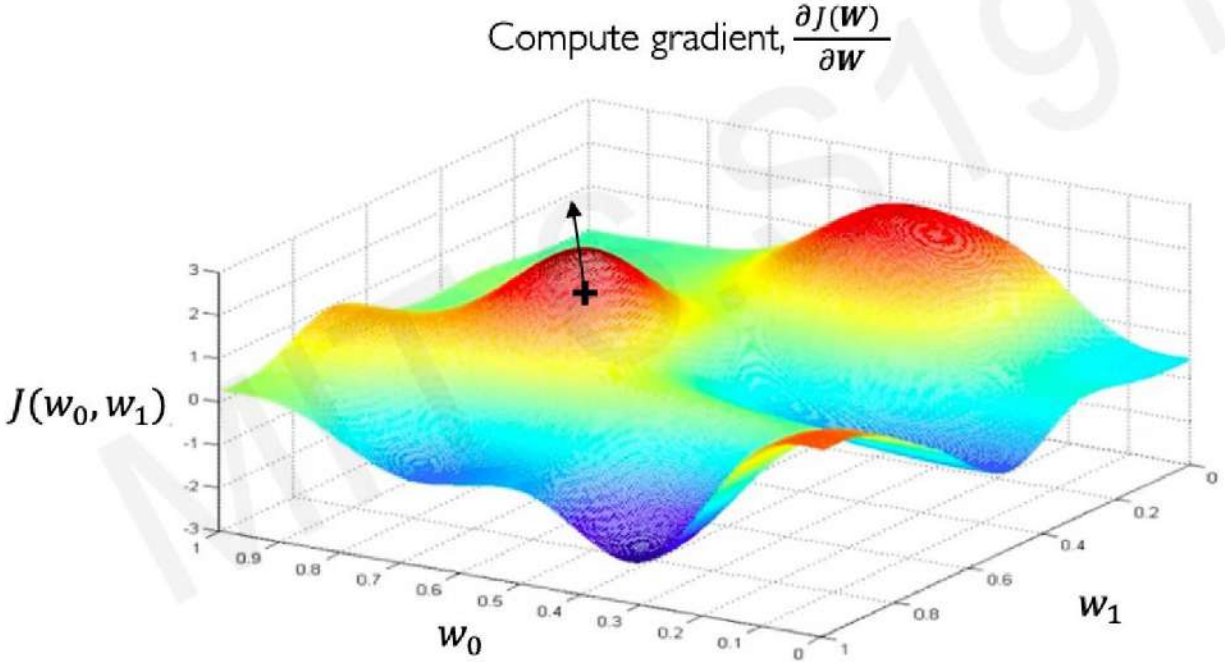
Loss Optimization

Randomly pick an initial (w_0, w_1)



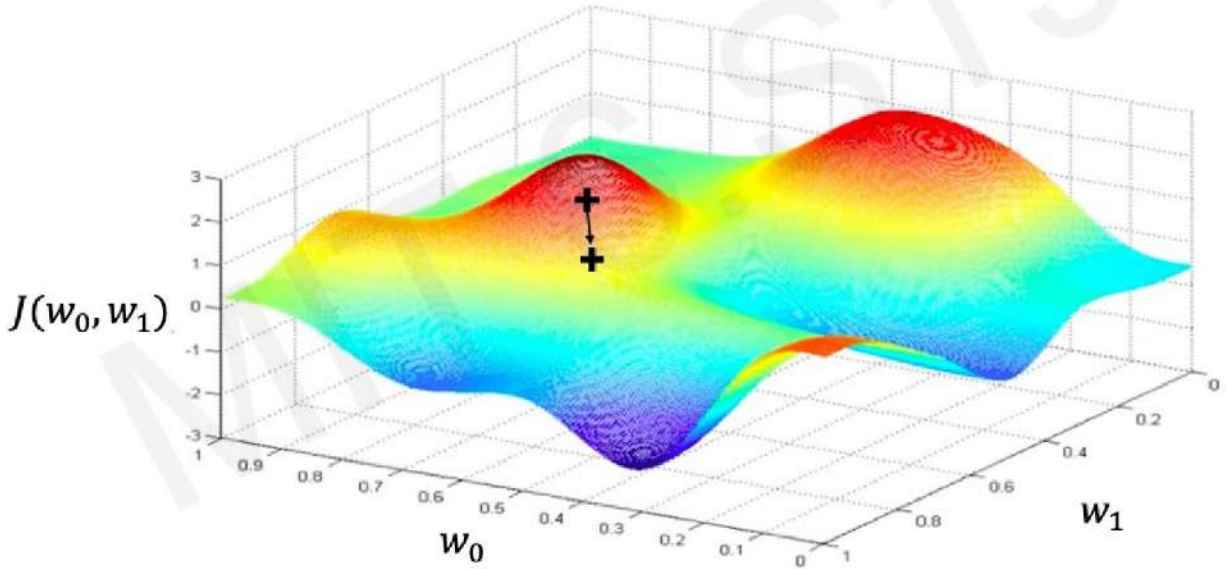
Loss Optimization

Compute gradient, $\frac{\partial J(W)}{\partial W}$



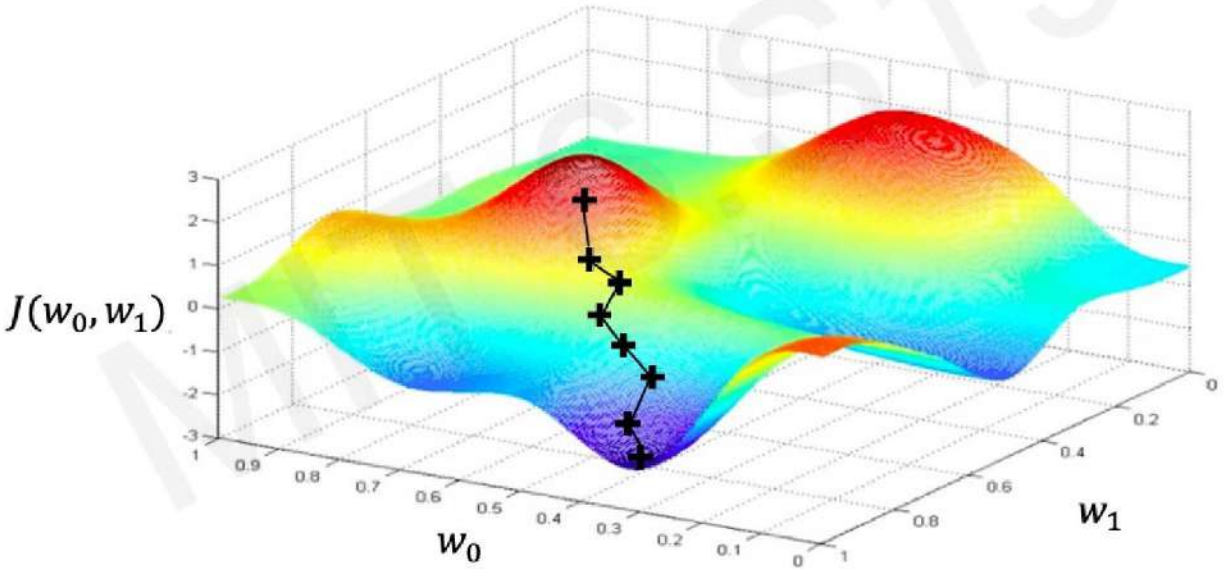
Loss Optimization

Take small step in opposite direction of gradient



Gradient Descent

Repeat until convergence



Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights

Gradient Descent

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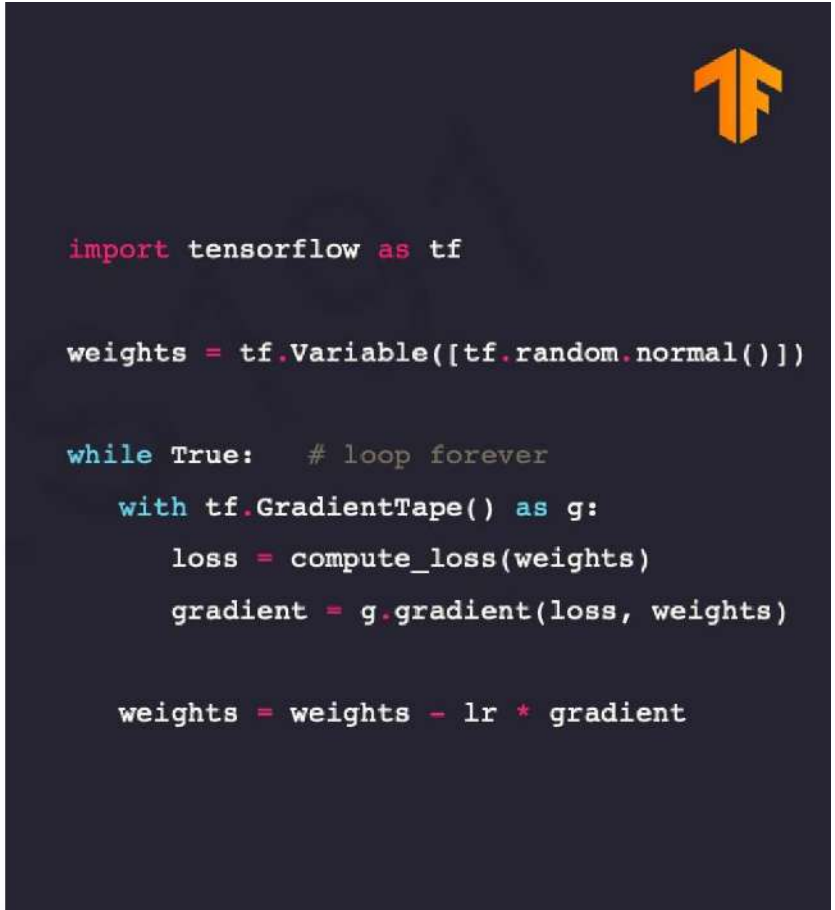

```
import tensorflow as tf

weights = tf.Variable([tf.random.normal()])

while True:    # loop forever
    with tf.GradientTape() as g:
        loss = compute_loss(weights)
        gradient = g.gradient(loss, weights)

    weights = weights - lr * gradient
```

Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
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    weights = weights - lr * gradient
```

Computing Gradients: Backpropagation

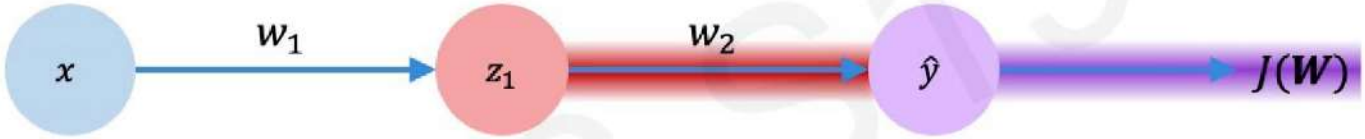
How does a small change in one weight (ex. $\boldsymbol{w_2}$) affect the final loss $\boldsymbol{J(W)}$?

Computing Gradients: Backpropagation

$$\frac{\partial J(W)}{\partial w_2} =$$

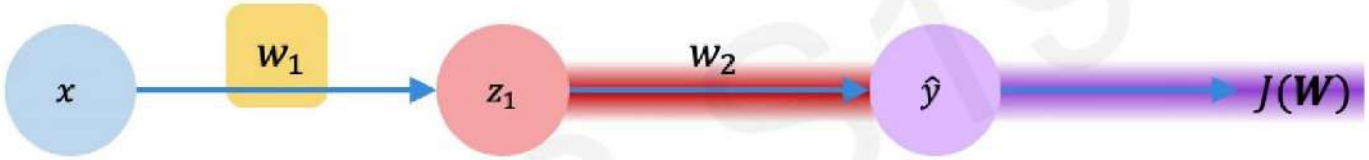
Let's use the chain rule!

Computing Gradients: Backpropagation



$$\frac{\partial J(W)}{\partial w_2} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_2}$$

Computing Gradients: Backpropagation

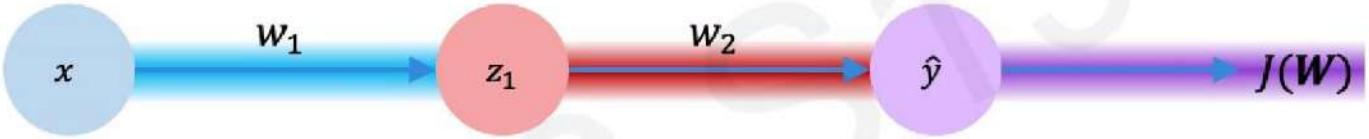


$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_1}$$

Apply chain rule!

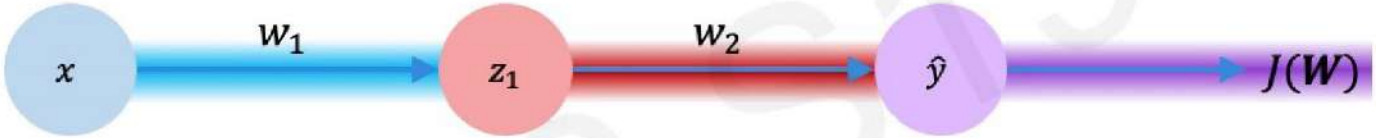
Apply chain rule!

Computing Gradients: Backpropagation



$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

Computing Gradients: Backpropagation

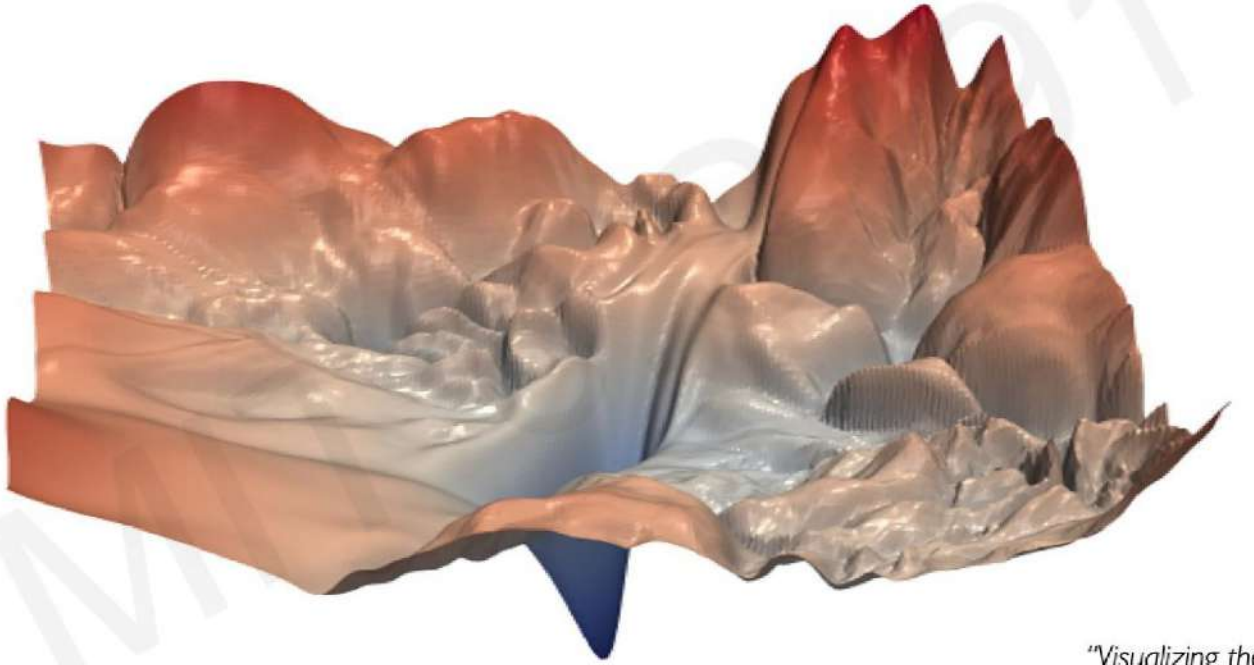


$$\frac{\partial J(W)}{\partial w_1} = \frac{\partial J(W)}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

Repeat this for ***every weight in the network*** *using gradients from later layers*

Neural Networks in Practice: Optimization

Training Neural Networks is Difficult



"Visualizing the loss landscape of neural nets". Dec 2017.

Loss Functions Can Be Difficult to Optimize

Remember:

Optimization through gradient descent

$$\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$$

Loss Functions Can Be Difficult to Optimize

Remember:

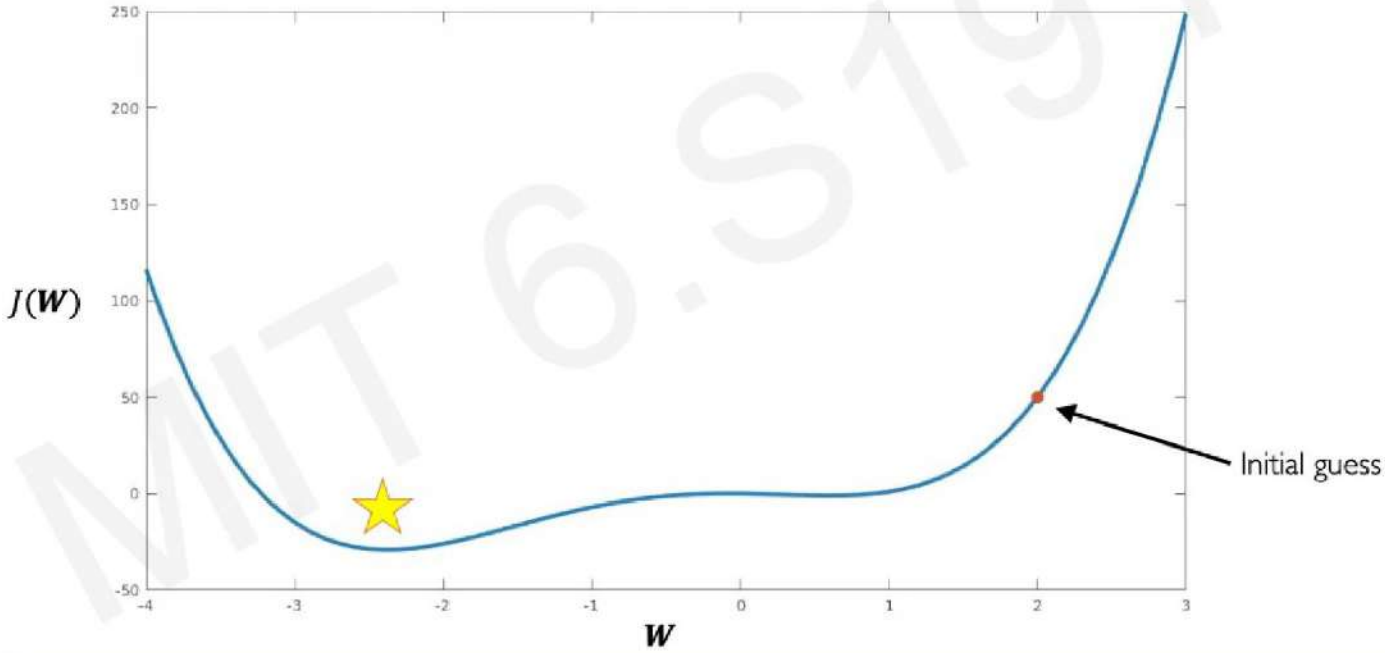
Optimization through gradient descent

$$\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$$

How can we set the learning rate?

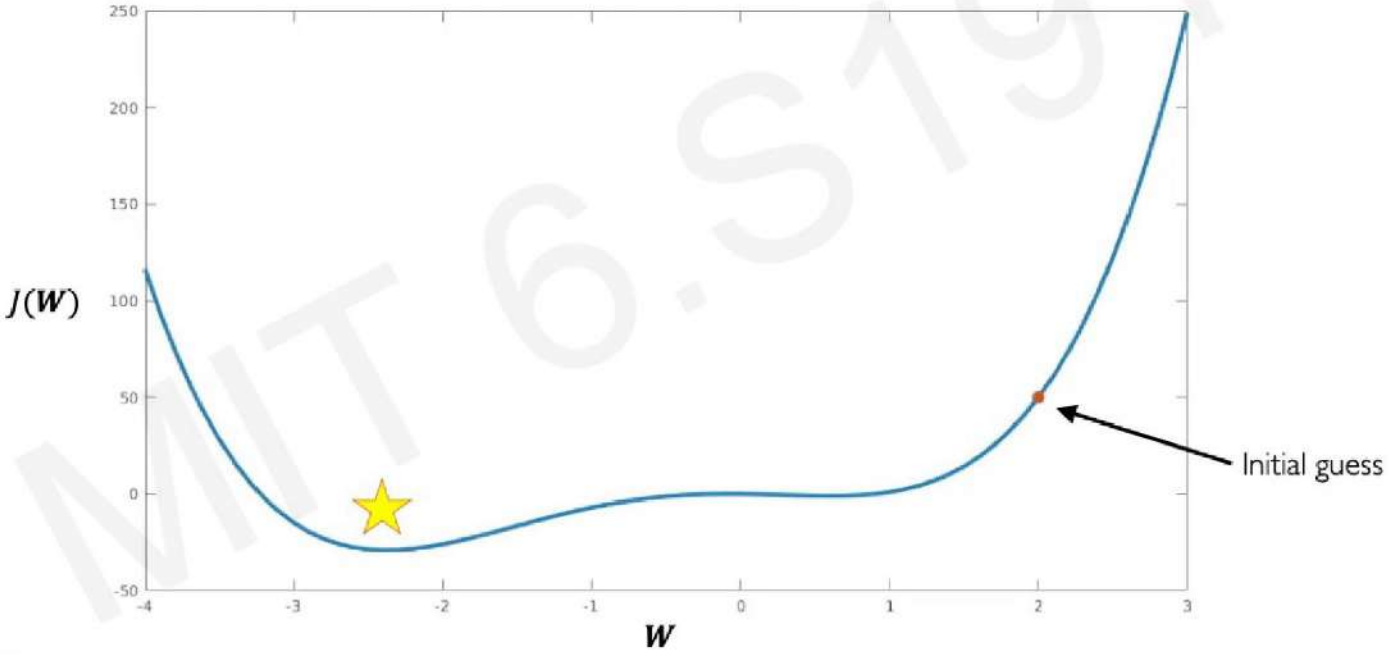
Setting the Learning Rate

Small learning rate *converges slowly and gets stuck in false local minima*



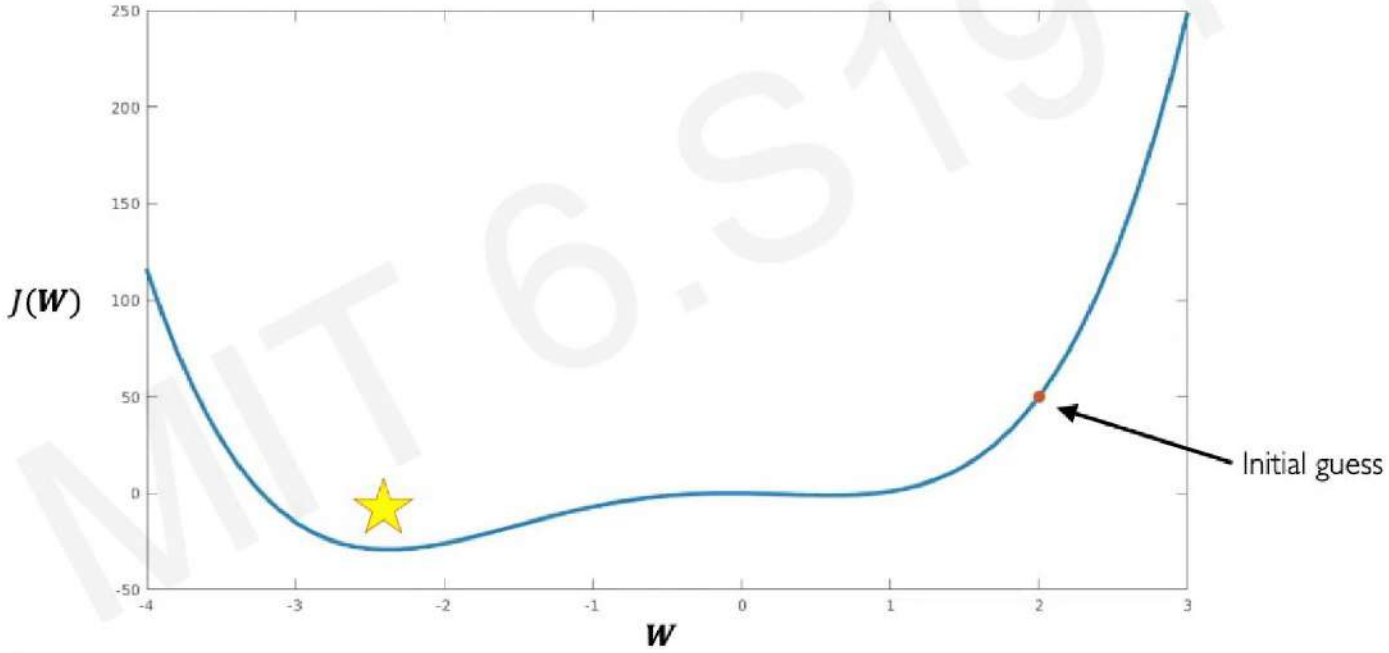
Setting the Learning Rate

Large learning rates overshoot, become unstable and diverge



Setting the Learning Rate

Stable learning rates *converge smoothly and avoid local minima*



How to deal with this?

Idea 1:

Try lots of different learning rates and see what works "just right"

How to deal with this?

Idea 1:

Try lots of different learning rates and see what works "just right"

Idea 2:

Do something smarter!
Design an adaptive learning rate that "adapts" to the landscape

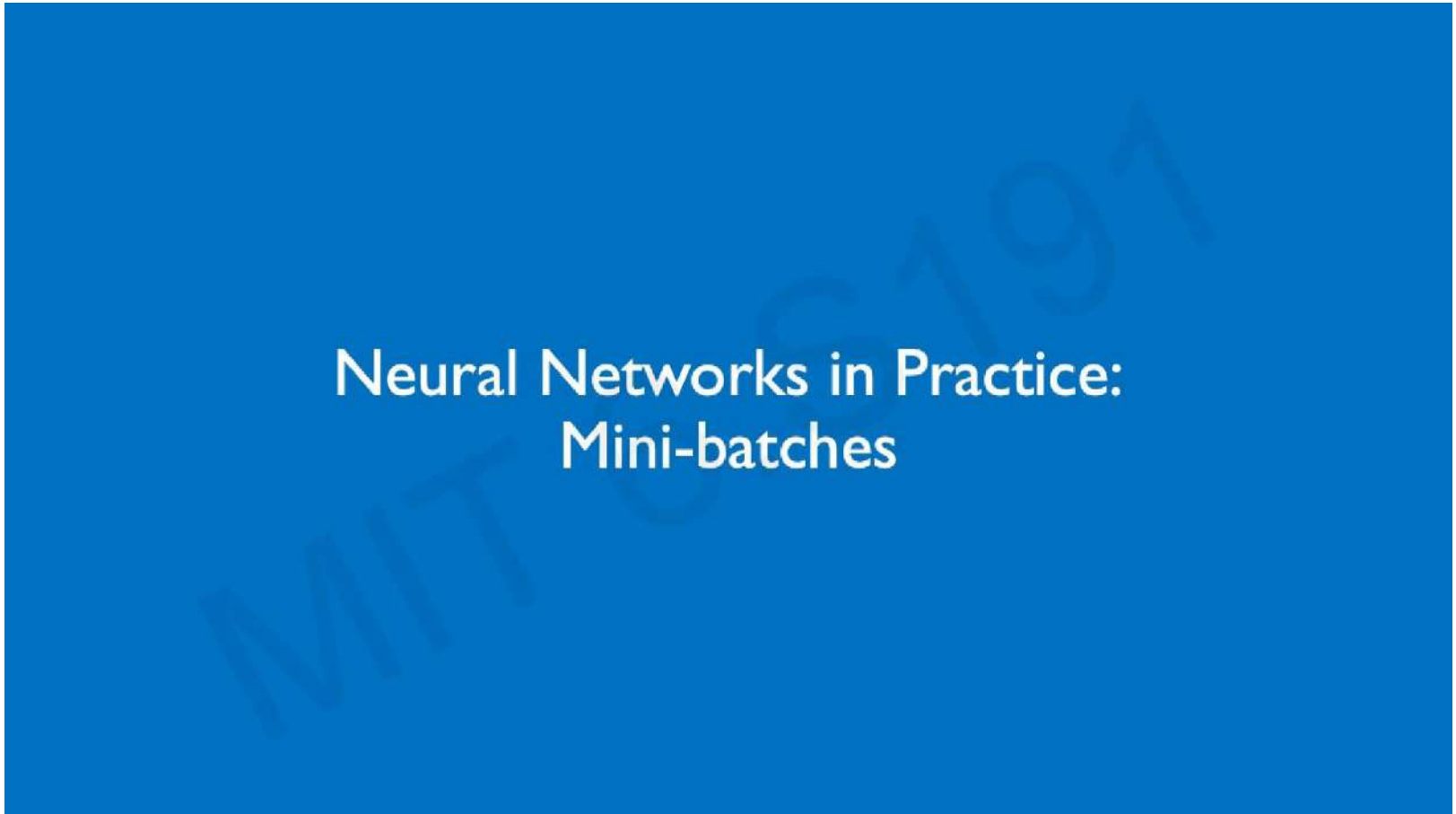
Adaptive Learning Rates

- Learning rates are no longer fixed
- Can be made larger or smaller depending on:
  - how large gradient is
  - how fast learning is happening
  - size of particular weights
  - etc...

Gradient Descent Algorithms

Algorithm	TF Implementation	Reference
• SGD	tf.keras.optimizers.SGD	Kiefer & Wolfowitz. "Stochastic Estimation of the Maximum of a Regression Function." 1952.
• Adam	tf.keras.optimizers.Adam	Kingma et al. "Adam: A Method for Stochastic Optimization." 2014.
• Adadelta	tf.keras.optimizers.Adadelta	Zeiler et al. "ADADELTA: An Adaptive Learning Rate Method." 2012.
• Adagrad	tf.keras.optimizers.Adagrad	Duchi et al. "Adaptive Subgradient Methods for Online Learning and Stochastic Optimization." 2011.
• RMSProp	tf.keras.optimizers.RMSProp	

Additional details: http://ruder.io/optimizing-gradient-descent/


Neural Networks in Practice:
Mini-batches

Gradient Descent

Algorithm

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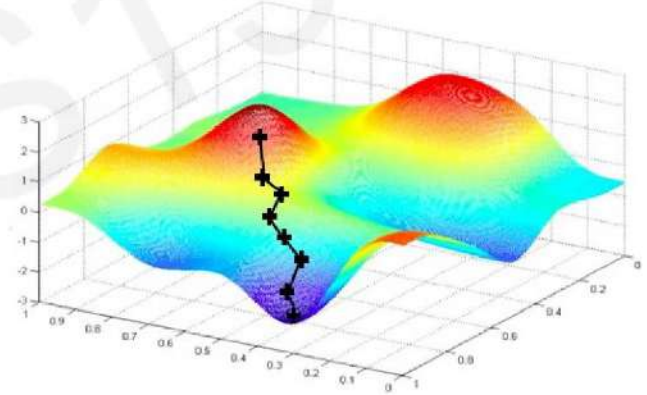

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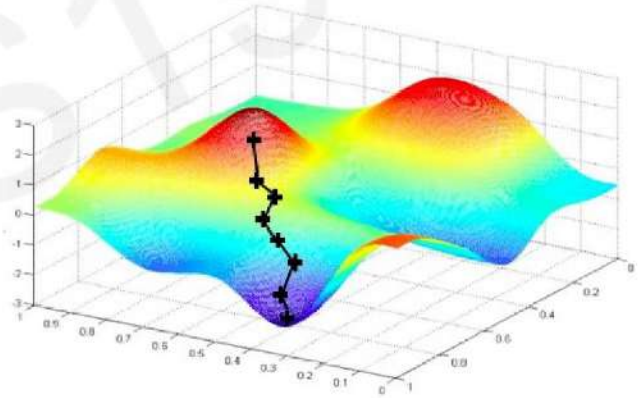
Can be very **computationally intensive** to compute!



Stochastic Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick single data point i
4. Compute gradient, $\frac{\partial J_i(W)}{\partial W}$
5. Update weights, $W \leftarrow W - \eta \frac{\partial J(W)}{\partial W}$
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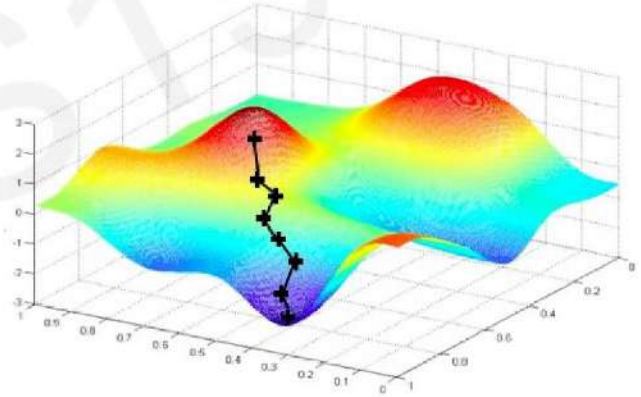

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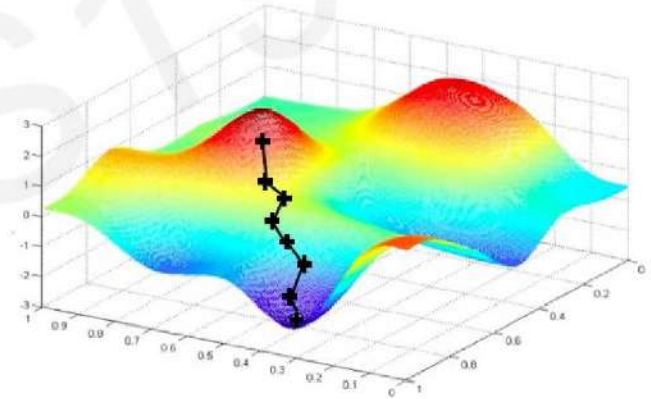
Easy to compute but **very noisy** (stochastic)!



Stochastic Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick batch of B data points
4. Compute gradient, $\frac{\partial J(W)}{\partial W} = \frac{1}{B}\sum_{k=1}^{B}\frac{\partial J_k(W)}{\partial W}$
5. Update weights, $W \leftarrow W - \eta\frac{\partial J(W)}{\partial W}$
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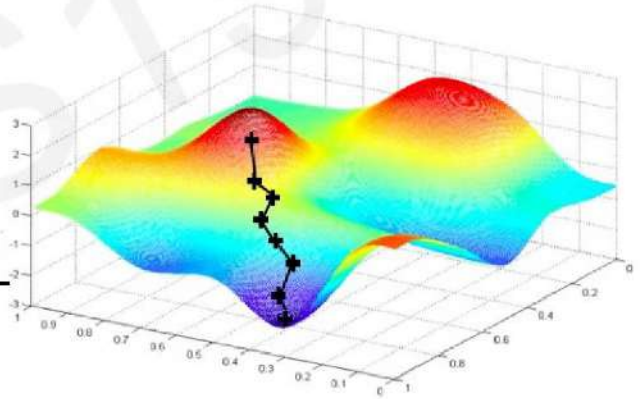

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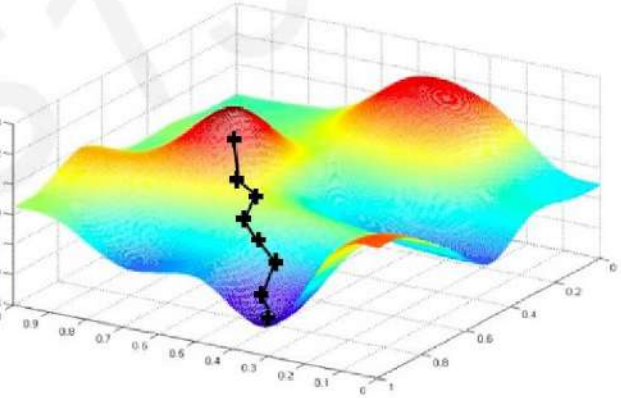


Fast to compute and a much better estimate of the true gradient!

Mini-batches while training

More accurate estimation of gradient

Smoother convergence

Allows for larger learning rates

Mini-batches while training

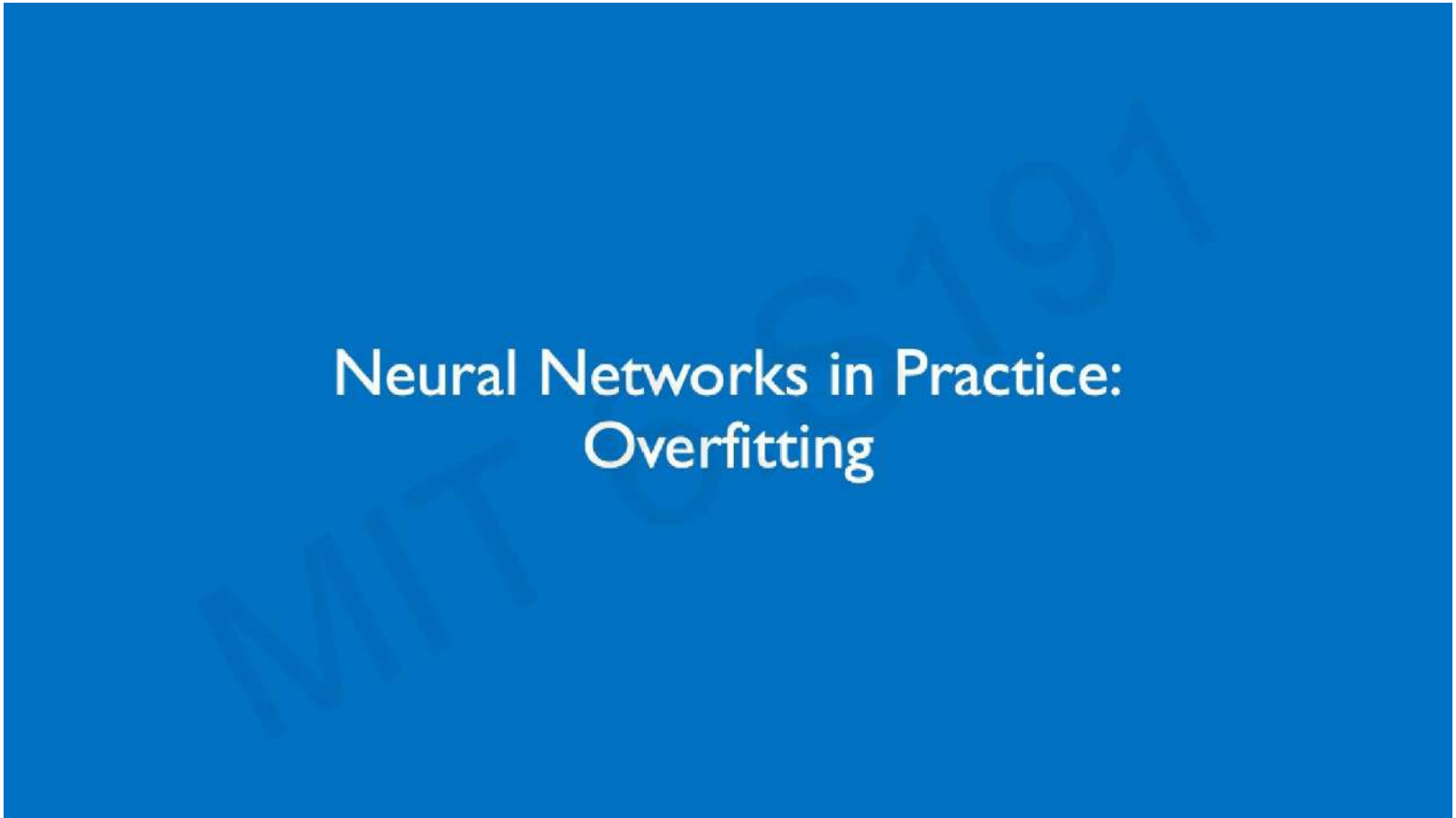
More accurate estimation of gradient

Smoother convergence

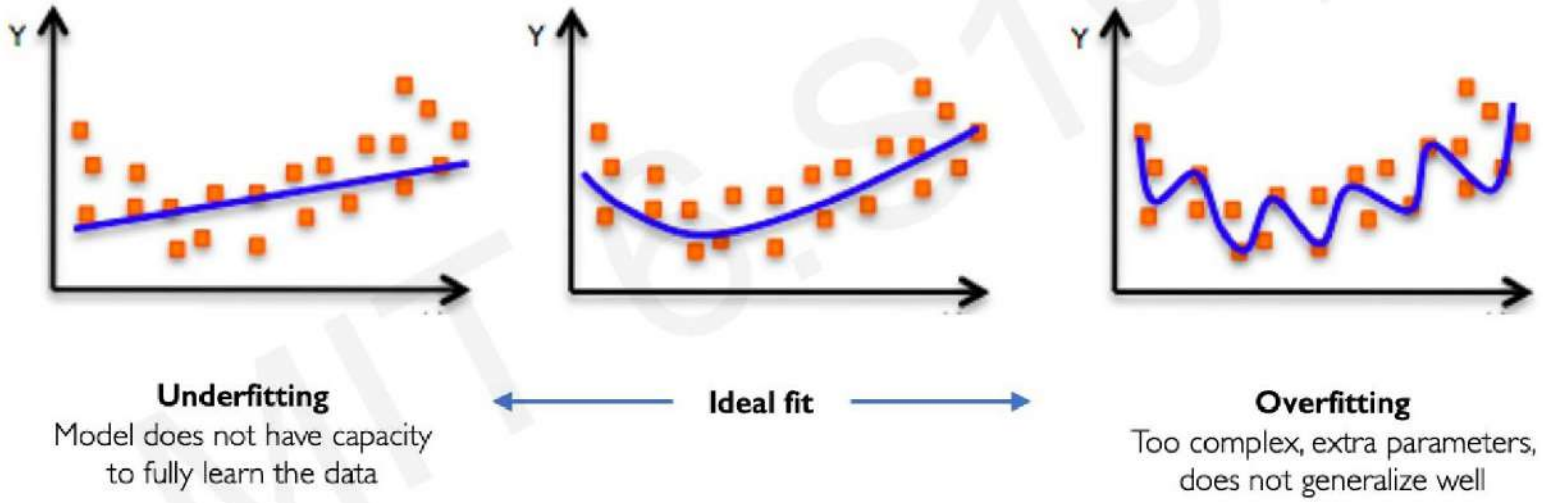
Allows for larger learning rates

Mini-batches lead to fast training!

Can parallelize computation + achieve significant speed increases on GPU's


Neural Networks in Practice:
Overfitting

The Problem of Overfitting



Regularization

What is it?

Technique that constrains our optimization problem to discourage complex models

Regularization

What is it?

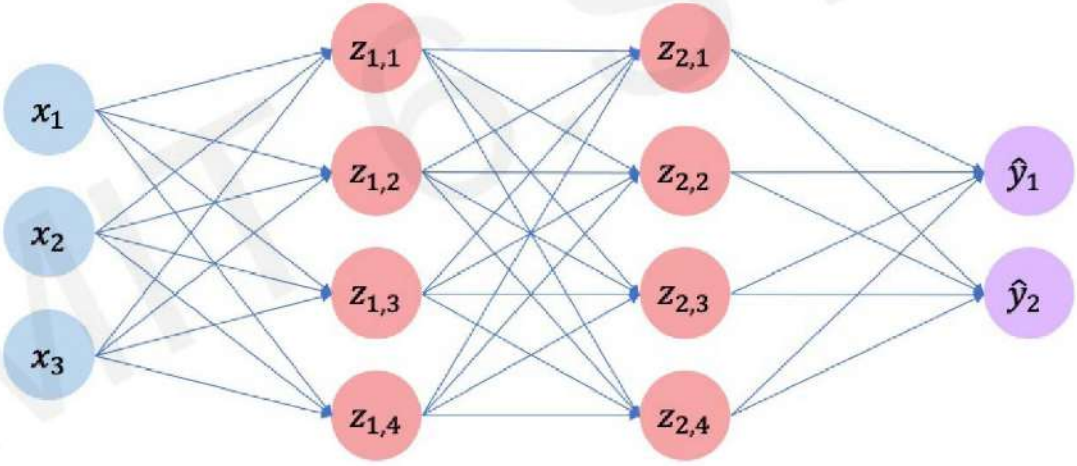
Technique that constrains our optimization problem to discourage complex models

Why do we need it?

Improve generalization of our model on unseen data

Regularization 1: Dropout

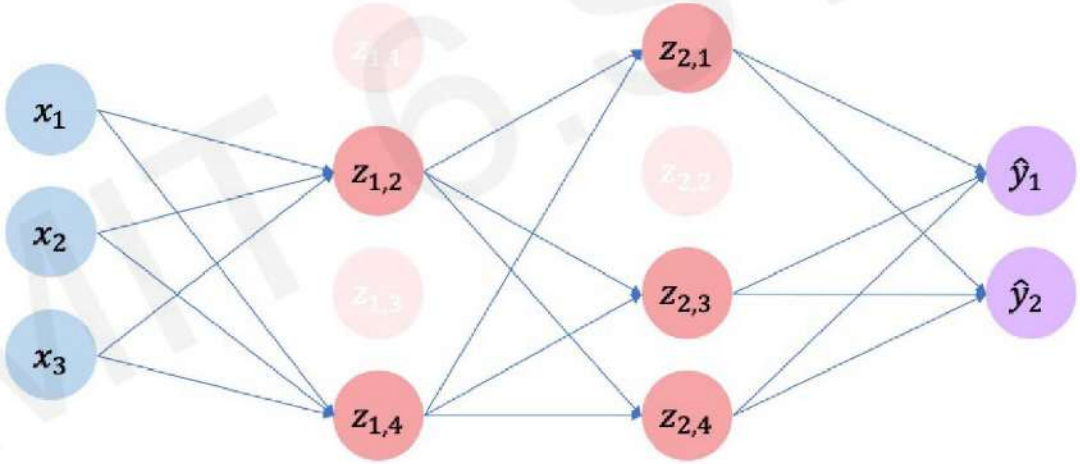
- During training, randomly set some activations to 0



Regularization 1: Dropout

- During training, randomly set some activations to 0
  - Typically 'drop' 50% of activations in layer
  - Forces network to not rely on any 1 node

```
tf.keras.layers.Dropout(p=0.5)
```



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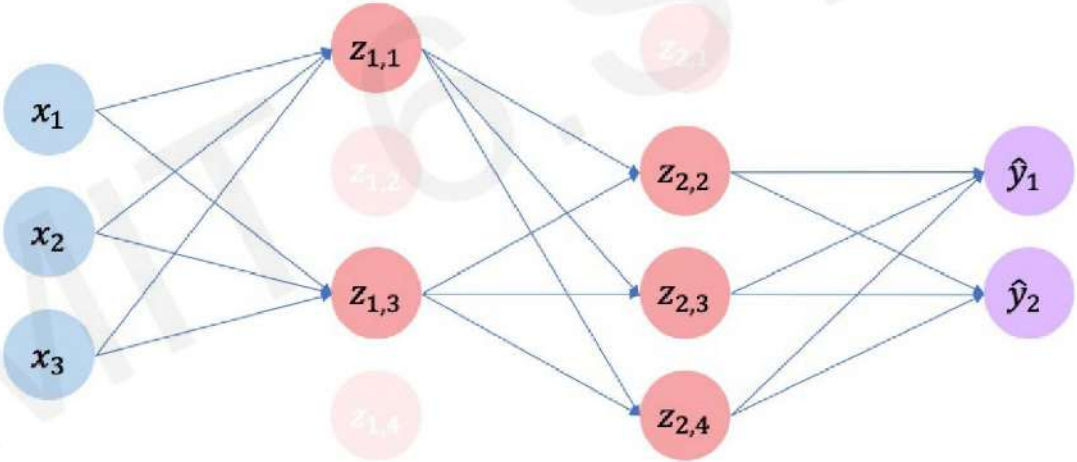

Regularization 2: Early Stopping

- Stop training before we have a chance to overfit

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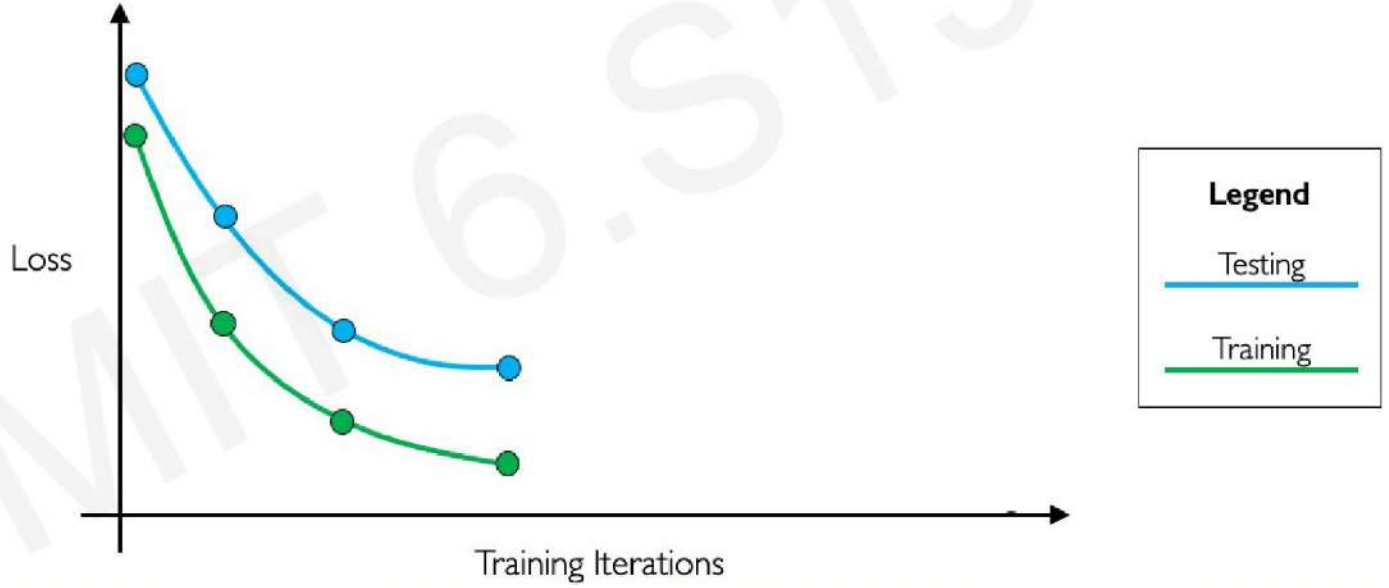

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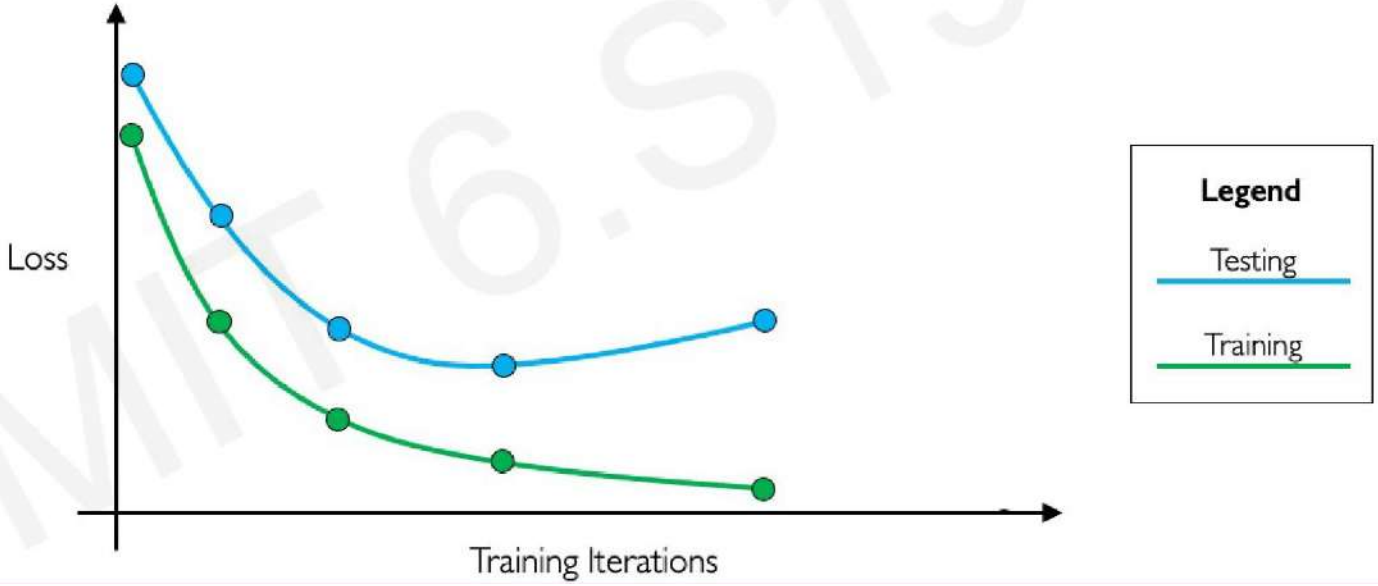

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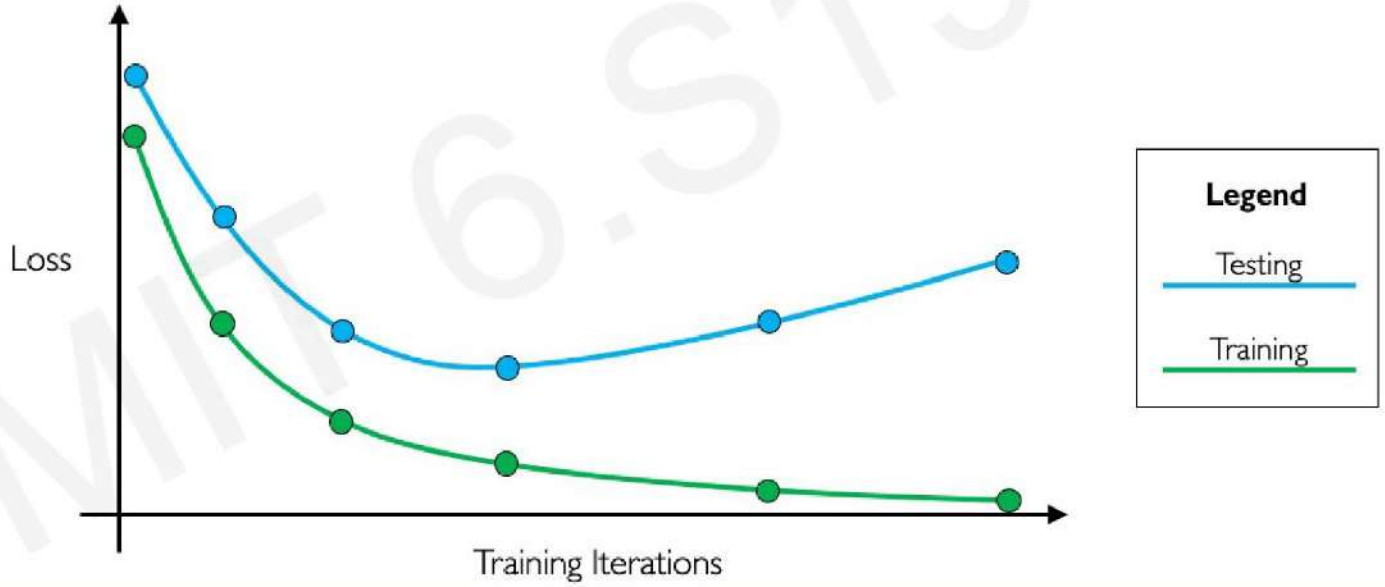

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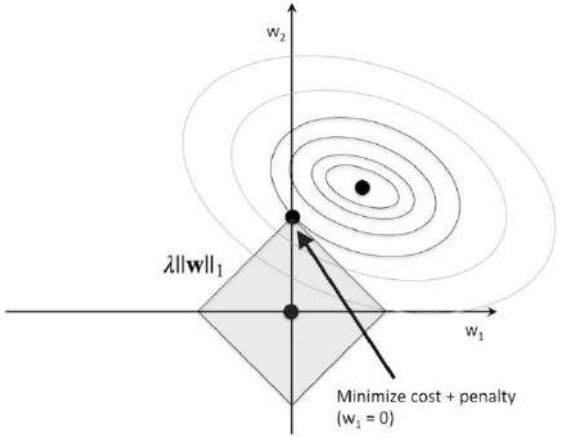
Regularization

L1 Regularization

loss(truth, predictions) + λ |W|

Or, if we number each individual weight w in the model with a number $i = 0, 1, 2, \ldots, n$:

loss(truth, predictions) + $\lambda \sum_{i=0}^{n} |w_i|$

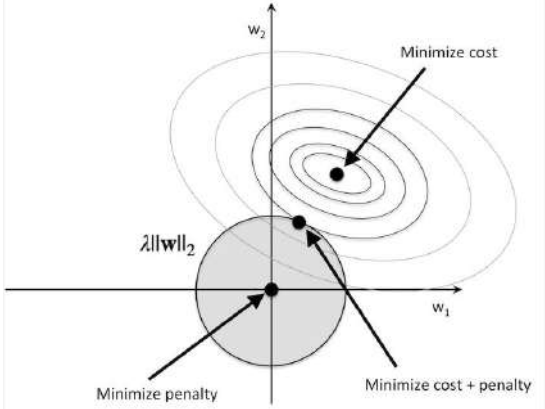


L2 Regularization

loss(truth, predictions) + λ W^2

Or, if we number each individual weight w in the model with a number $i = 0, 1, 2, \ldots, n$:

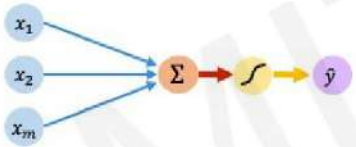
loss(truth, predictions) + $\lambda \sum_{i=0}^{n} w_i^2$



Core Foundation Review

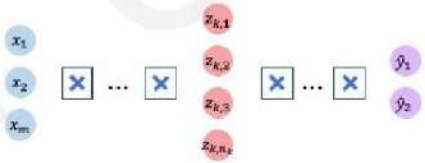
The Perceptron

- Structural building blocks
- Nonlinear activation functions



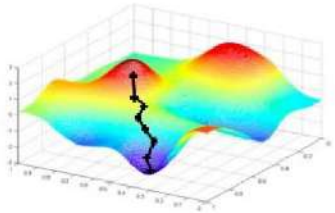
Neural Networks

- Stacking Perceptrons to form neural networks
- Optimization through backpropagation



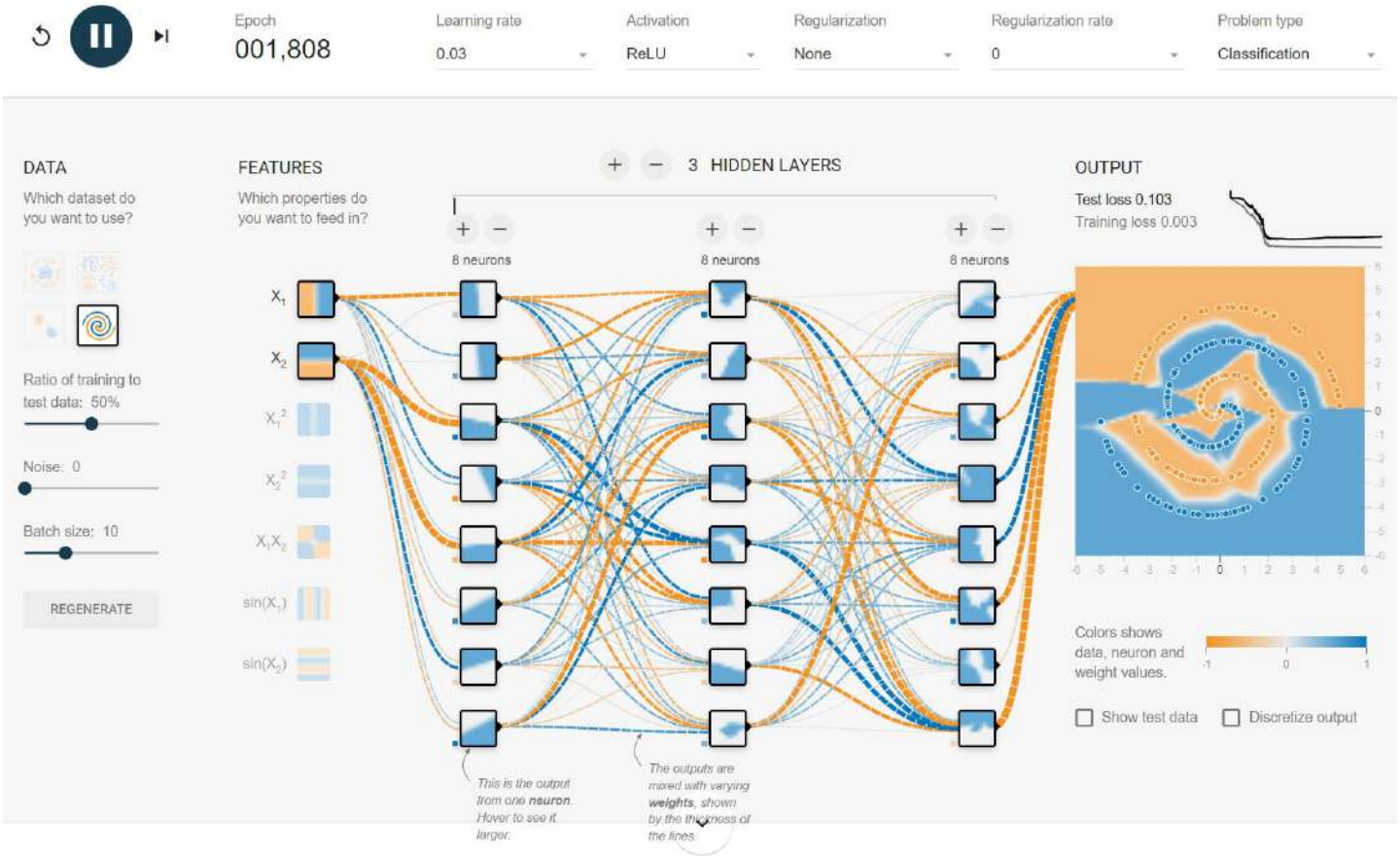
Training in Practice

- Adaptive learning
- Batching
- Regularization



人工智能基本理论

https://playground.tensorflow.org/

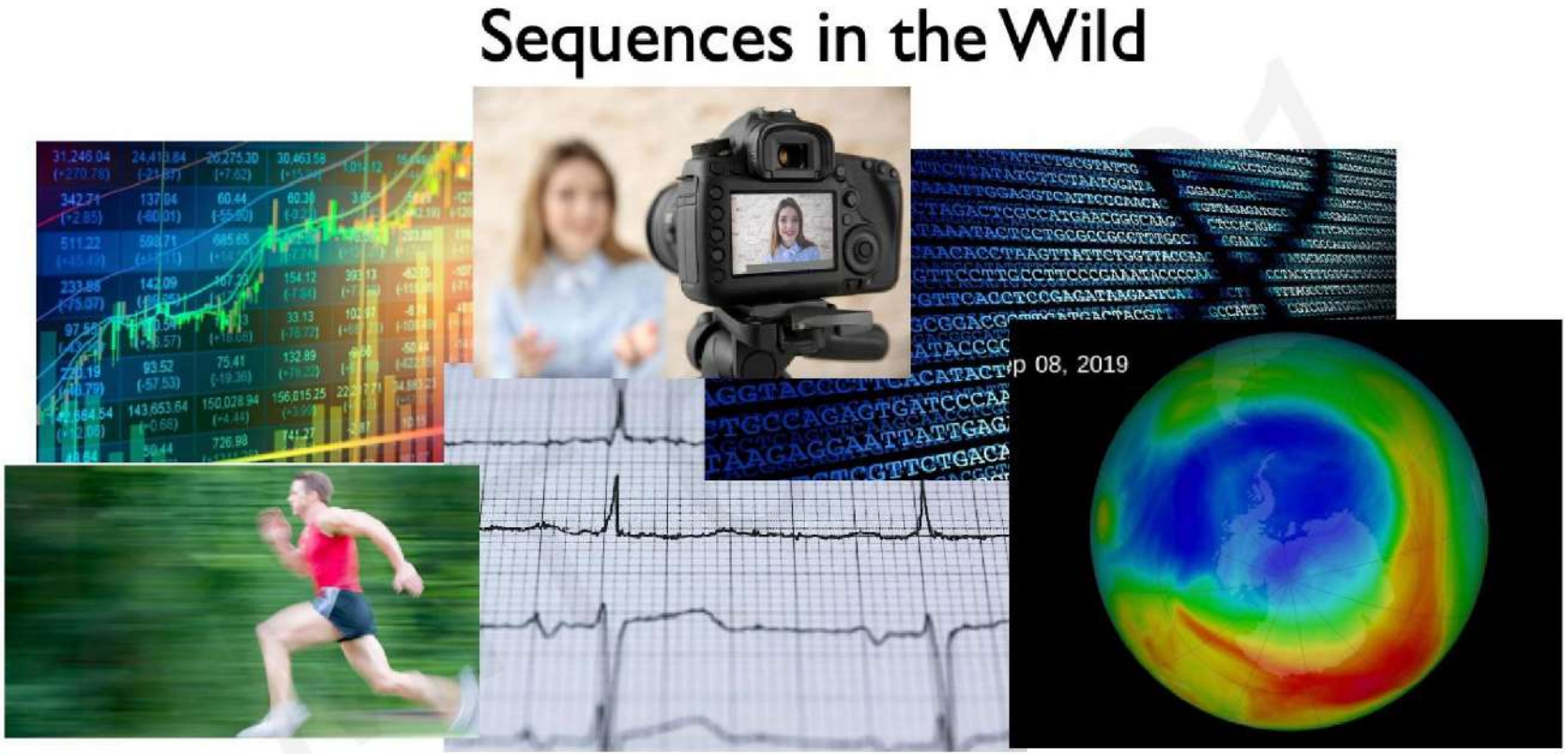


提纲

一、前馈网络

二、循环网络

三、卷积网络


Sequences in the Wild
p 08, 2019

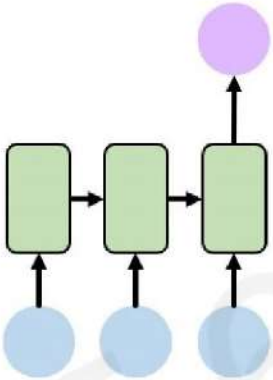
Sequence Modeling Applications

One to One

Binary Classification

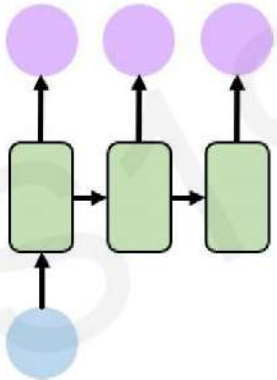
"Will I pass this class?"

Student → Pass?



Many to One

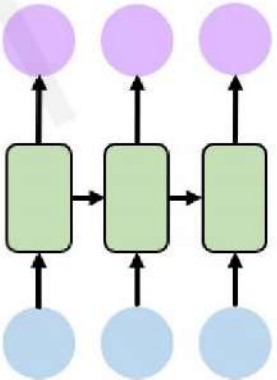
Sentiment Classification



One to Many

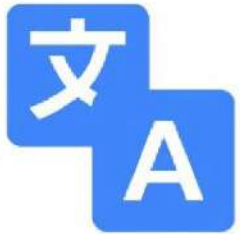
Image Captioning

"A baseball player throws a ball."

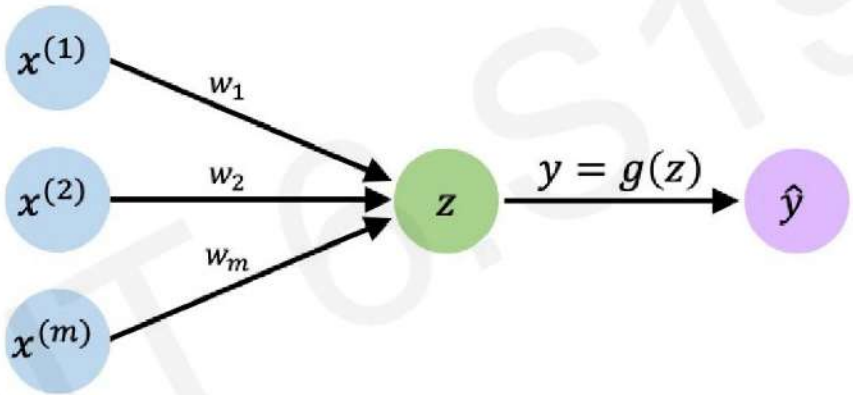


Many to Many

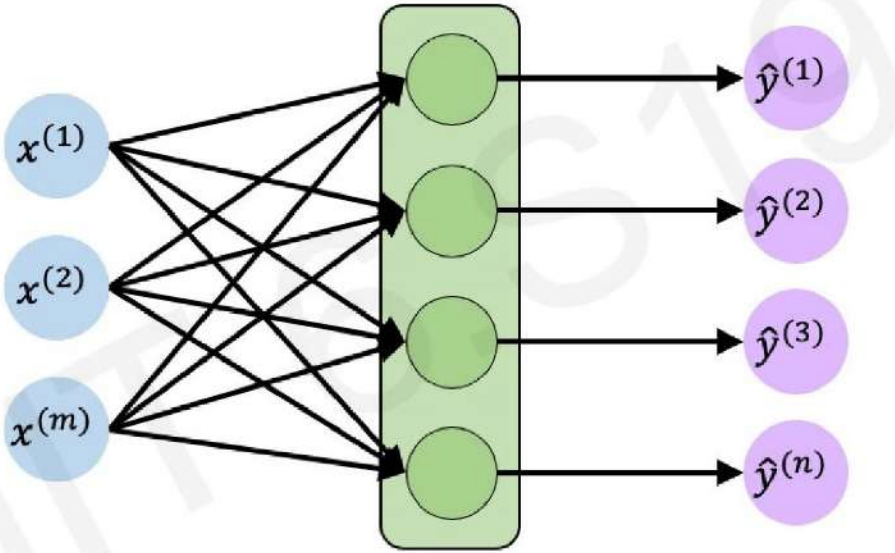
Machine Translation



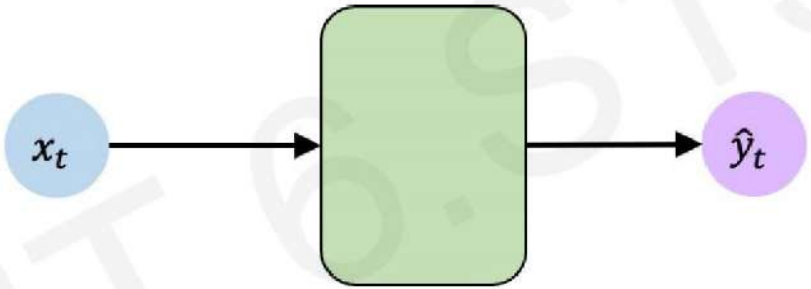
The Perceptron Revisited



Feed-Forward Networks Revisited

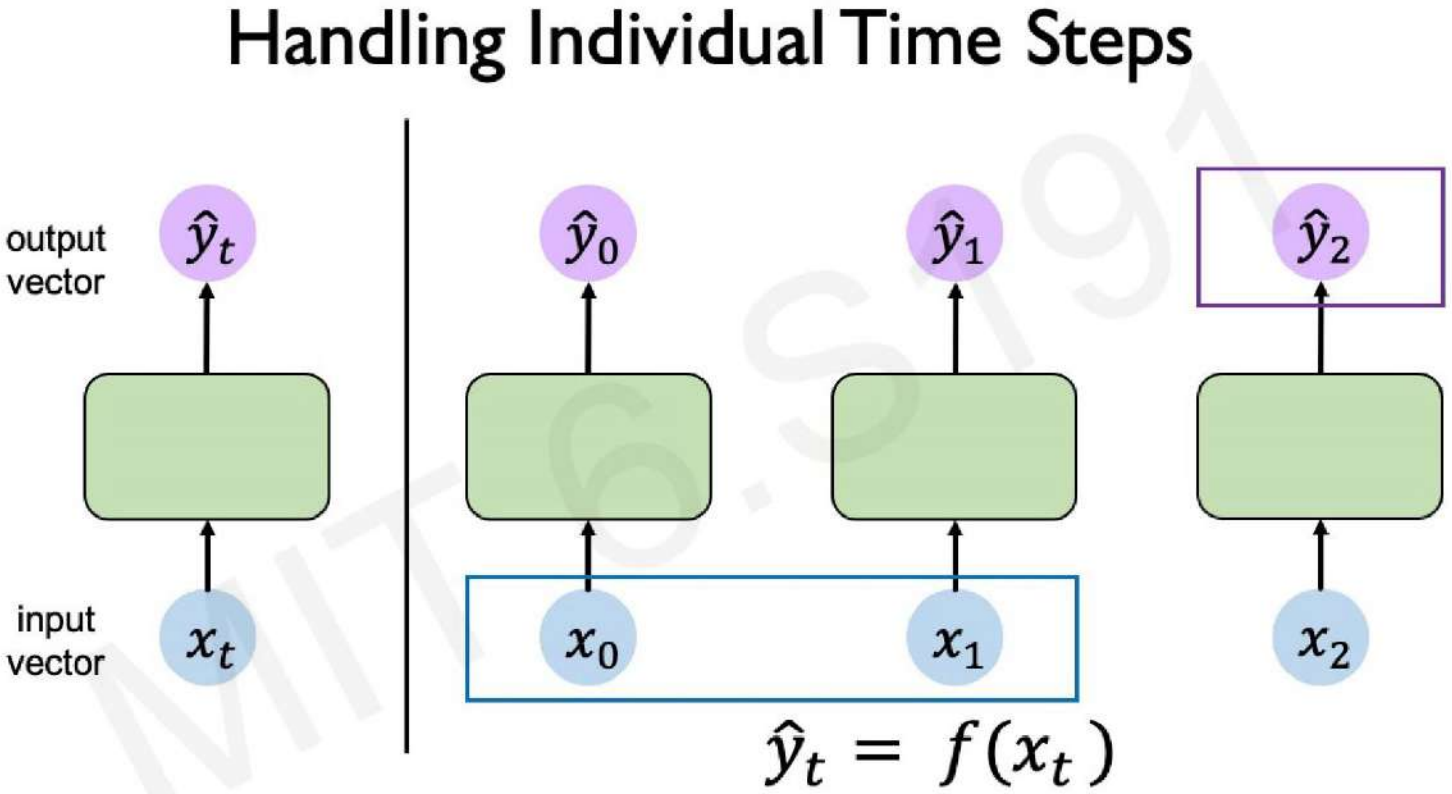


Feed-Forward Networks Revisited

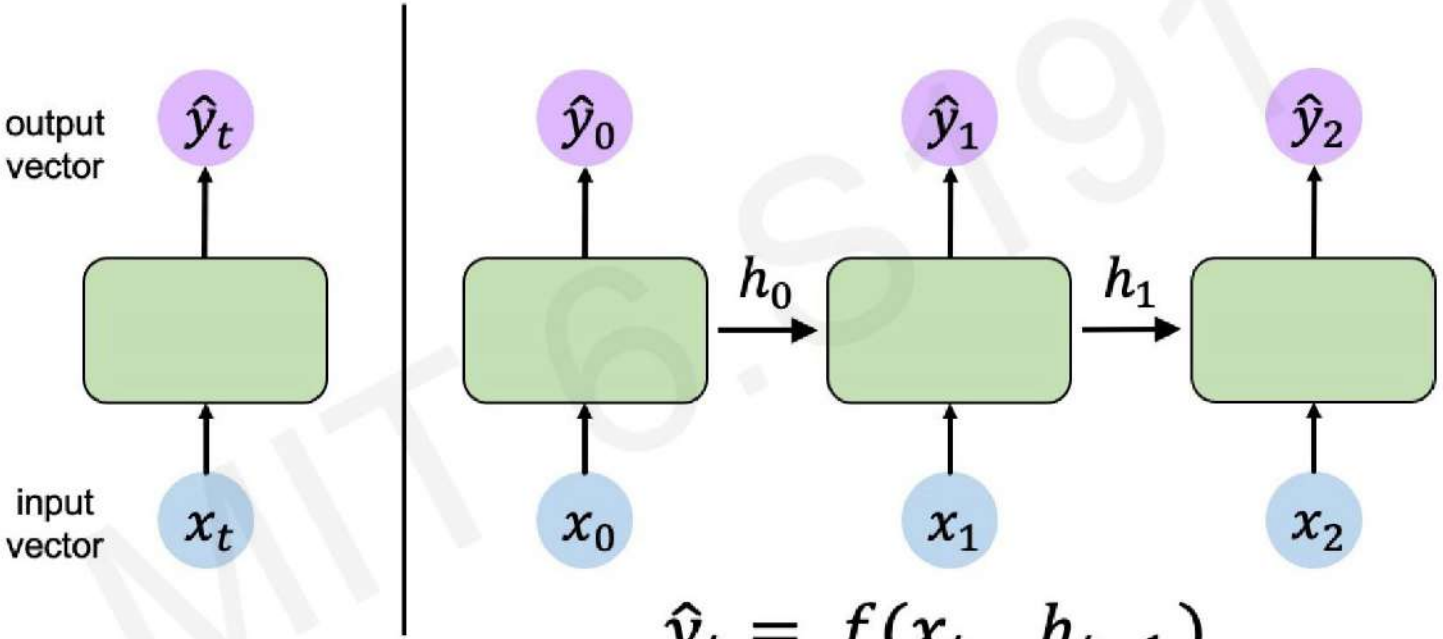


$\boldsymbol{x_t} \in \mathbb{R}^m$

$\hat{\boldsymbol{y}}_t \in \mathbb{R}^n$

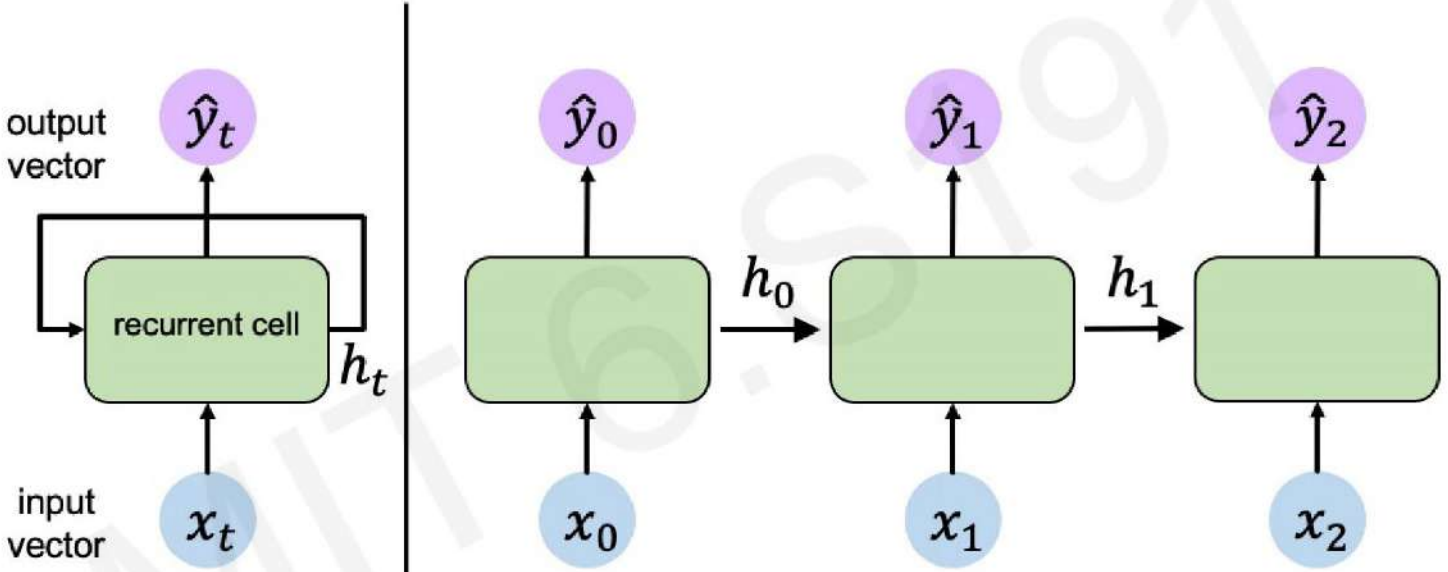

Handling Individual Time Steps
output vector
$\hat{y}_t$
input vector
x_t
$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
x_0
x_1
x_2
$\hat{y}_t = f(x_t)$

Neurons with Recurrence



$$\underbrace{\hat{y}_t}_{\text{output}} = f(\underbrace{x_t}_{\text{input}}, \underbrace{h_{t-1}}_{\text{past memory}})$$

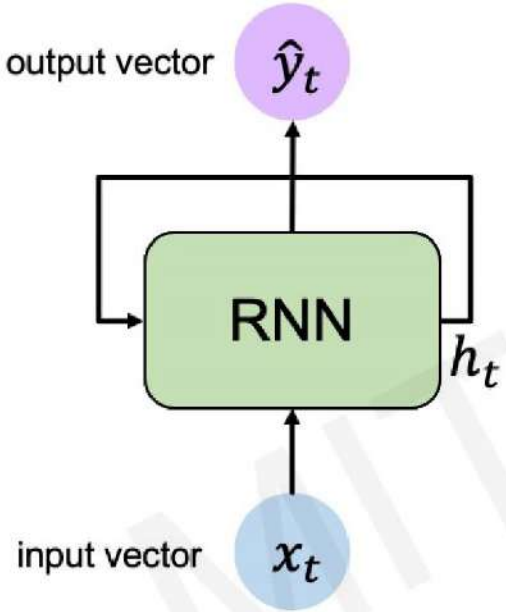
Neurons with Recurrence



$$\underbrace{\hat{y}_t}_{\text{output}} = f(\underbrace{x_t}_{\text{input}}, \underbrace{h_{t-1}}_{\text{past memory}})$$

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs)



Apply a **recurrence relation** at every time step to process a sequence:

$$h_t = f_W(x_t, h_{t-1})$$

cell state

function with weights W

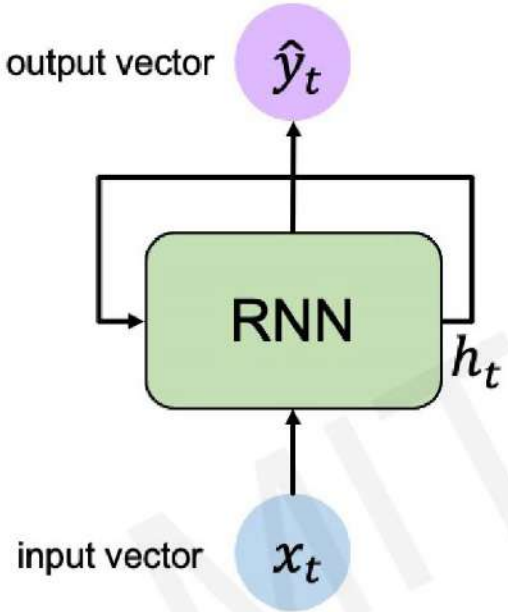
input

old state

Note: the same function and set of parameters are used at every time step

RNNs have a **state**, h_t, that is updated **at each time step** as a sequence is processed

RNN State Update and Output



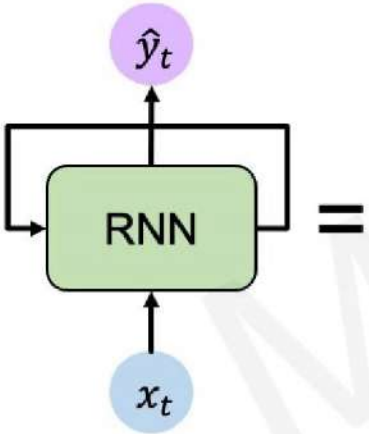
Update Hidden State

$$h_t = \tanh(\boldsymbol{W}_{\boldsymbol{hh}}^{\boldsymbol{T}} h_{t-1} + \boldsymbol{W}_{\boldsymbol{xh}}^{\boldsymbol{T}} x_t)$$

Input Vector

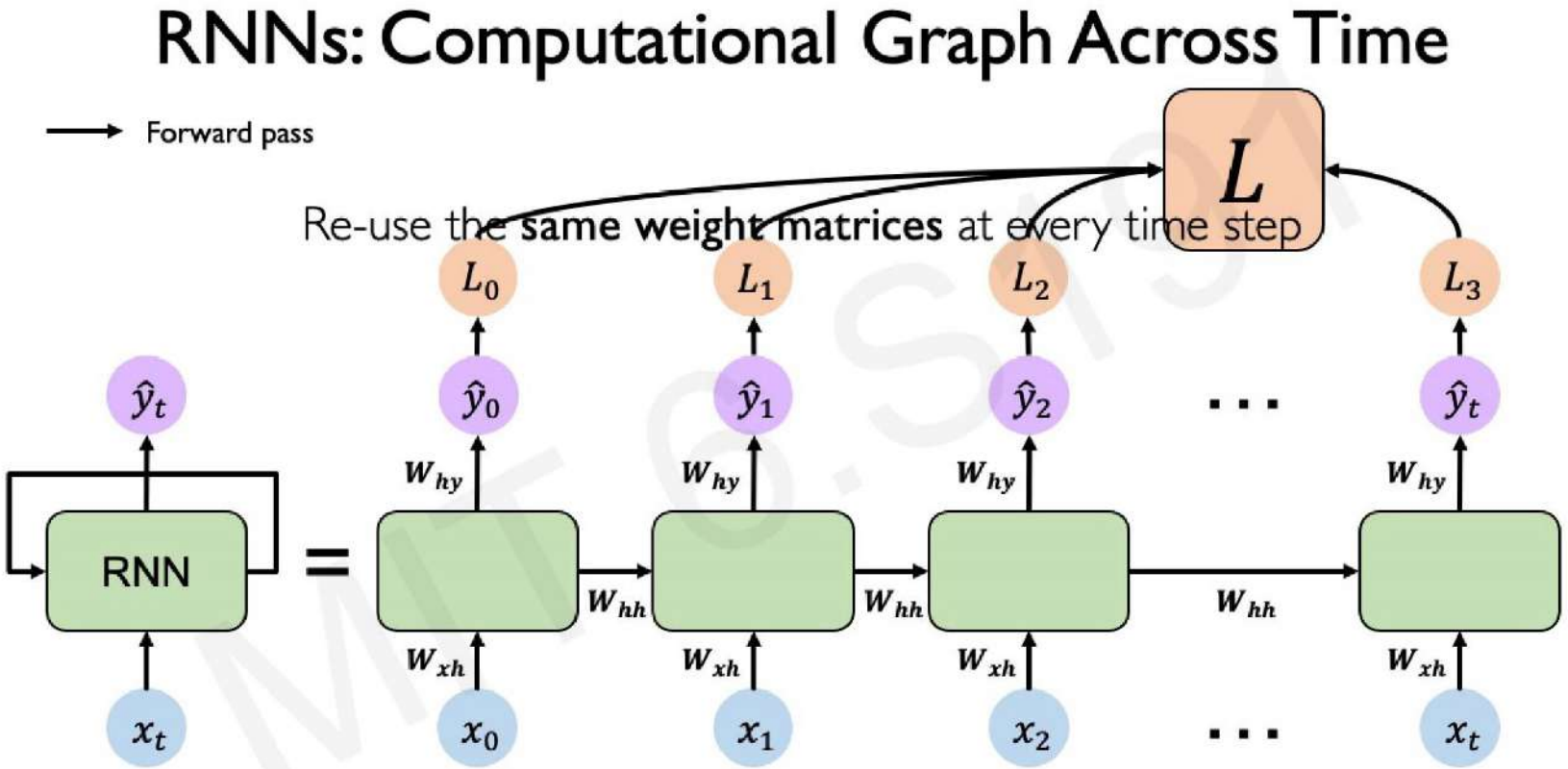
x_t

RNNs: Computational Graph Across Time



=

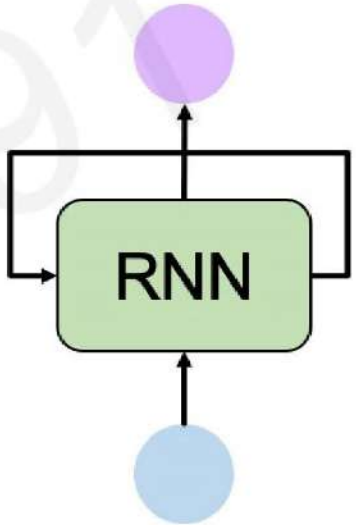
Represent as computational graph unrolled across time


RNNs: Computational Graph Across Time
Forward pass
L
Re-use the same weight matrices at every time step
RNN
=
L_0
L_1
L_2
L_3
$\hat{y}_t$
$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_t$
W_{hy}
W_{hh}
W_{xh}
x_t
x_0
x_1
x_2
x_t

Sequence Modeling: Design Criteria

To model sequences, we need to:

1. Handle **variable-length** sequences
2. Track **long-term** dependencies
3. Maintain information about **order**
4. **Share parameters** across the sequence



Recurrent Neural Networks (RNNs) meet these sequence modeling design criteria

A Sequence Modeling Problem:
Predict the Next Word

A Sequence Modeling Problem: Predict the Next Word

"This morning I took my cat for a walk."

A Sequence Modeling Problem: Predict the Next Word

"This morning I took my cat for a walk."

given these words

A Sequence Modeling Problem: Predict the Next Word

"This morning I took my cat for a walk."

given these words

predict the next word

A Sequence Modeling Problem: Predict the Next Word

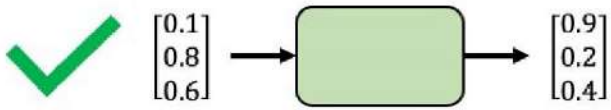
"This morning I took my cat for a walk."

given these words

predict the next word

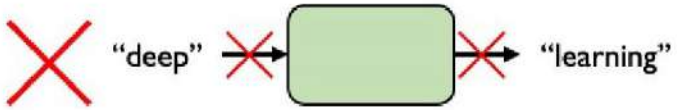
Representing Language to a Neural Network

Neural networks cannot interpret words

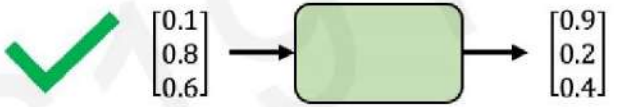


Neural networks require numerical inputs

Encoding Language for a Neural Network

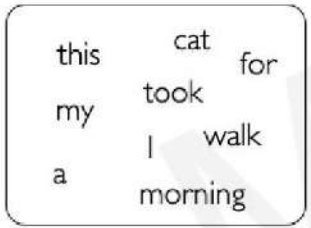


Neural networks cannot interpret words

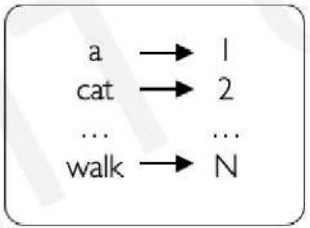


Neural networks require numerical inputs

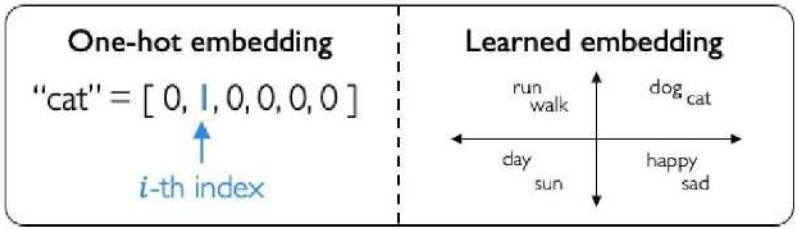
Embedding: transform indexes into a vector of fixed size.



1. Vocabulary:
Corpus of words



2. Indexing:
Word to index



3. Embedding:
Index to fixed-sized vector

Handle Variable Sequence Lengths

The food was great

vs.

We visited a restaurant for lunch

vs.

We were hungry but cleaned the house before eating

Model Long-Term Dependencies

"**France** is where I grew up, but I now live in Boston. I speak fluent ____."

We need information from **the distant past** to accurately predict the correct word.

Capture Differences in Sequence Order

The food was good, not bad at all.

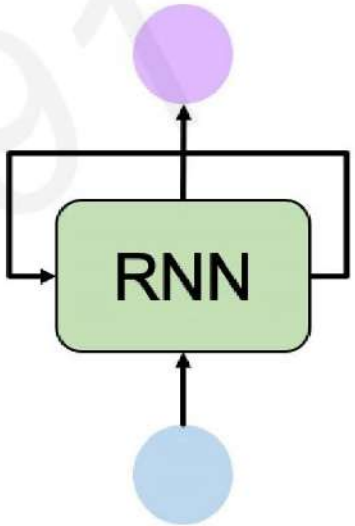
vs.

The food was bad, not good at all.

Sequence Modeling: Design Criteria

To model sequences, we need to:

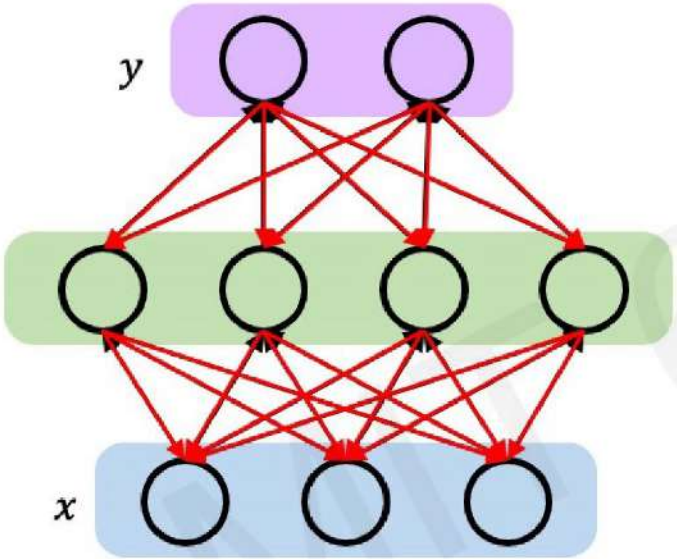
1. Handle **variable-length** sequences
2. Track **long-term** dependencies
3. Maintain information about **order**
4. **Share parameters** across the sequence



Recurrent Neural Networks (RNNs) meet these sequence modeling design criteria

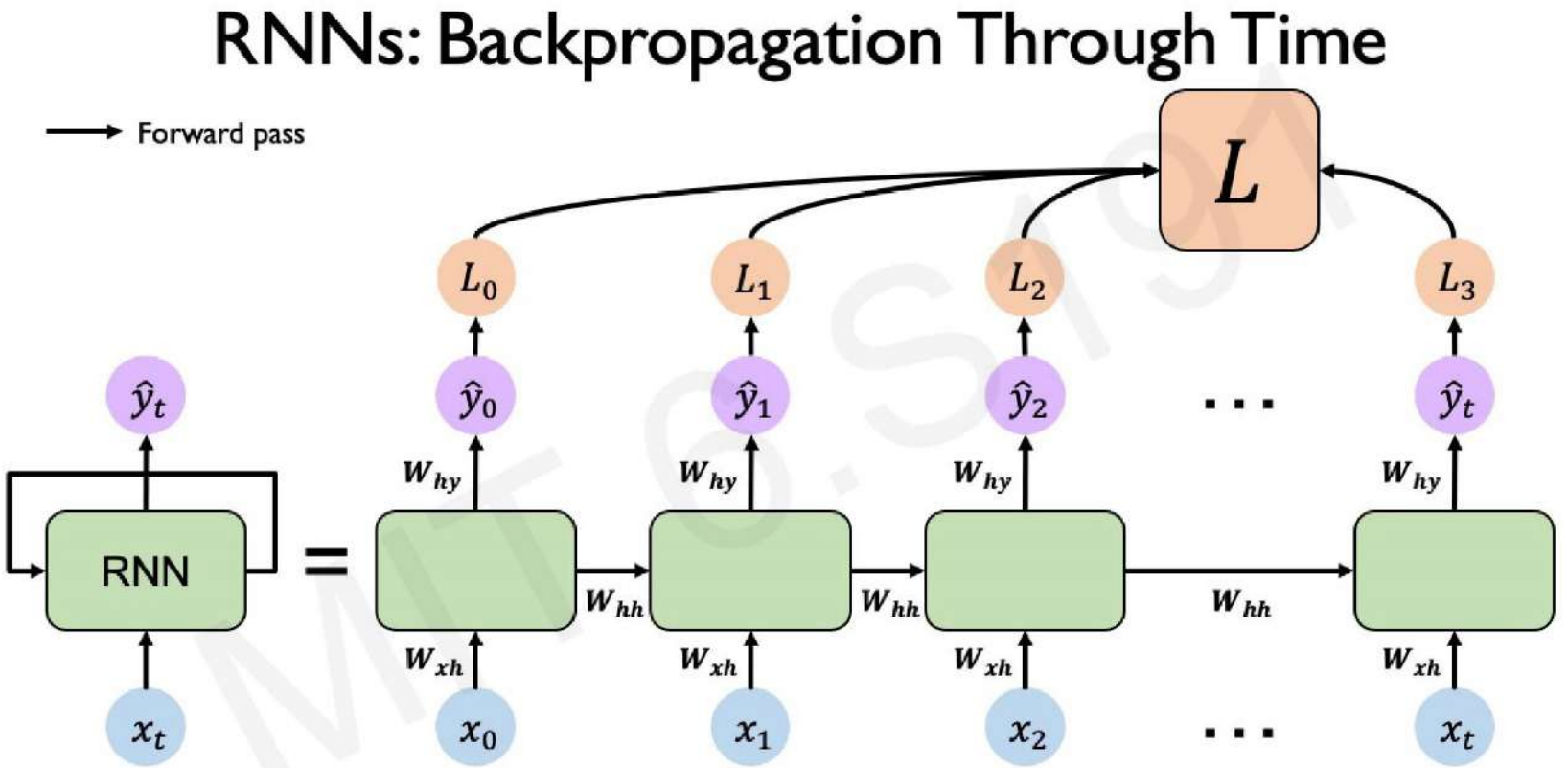
Backpropagation Through Time (BPTT)

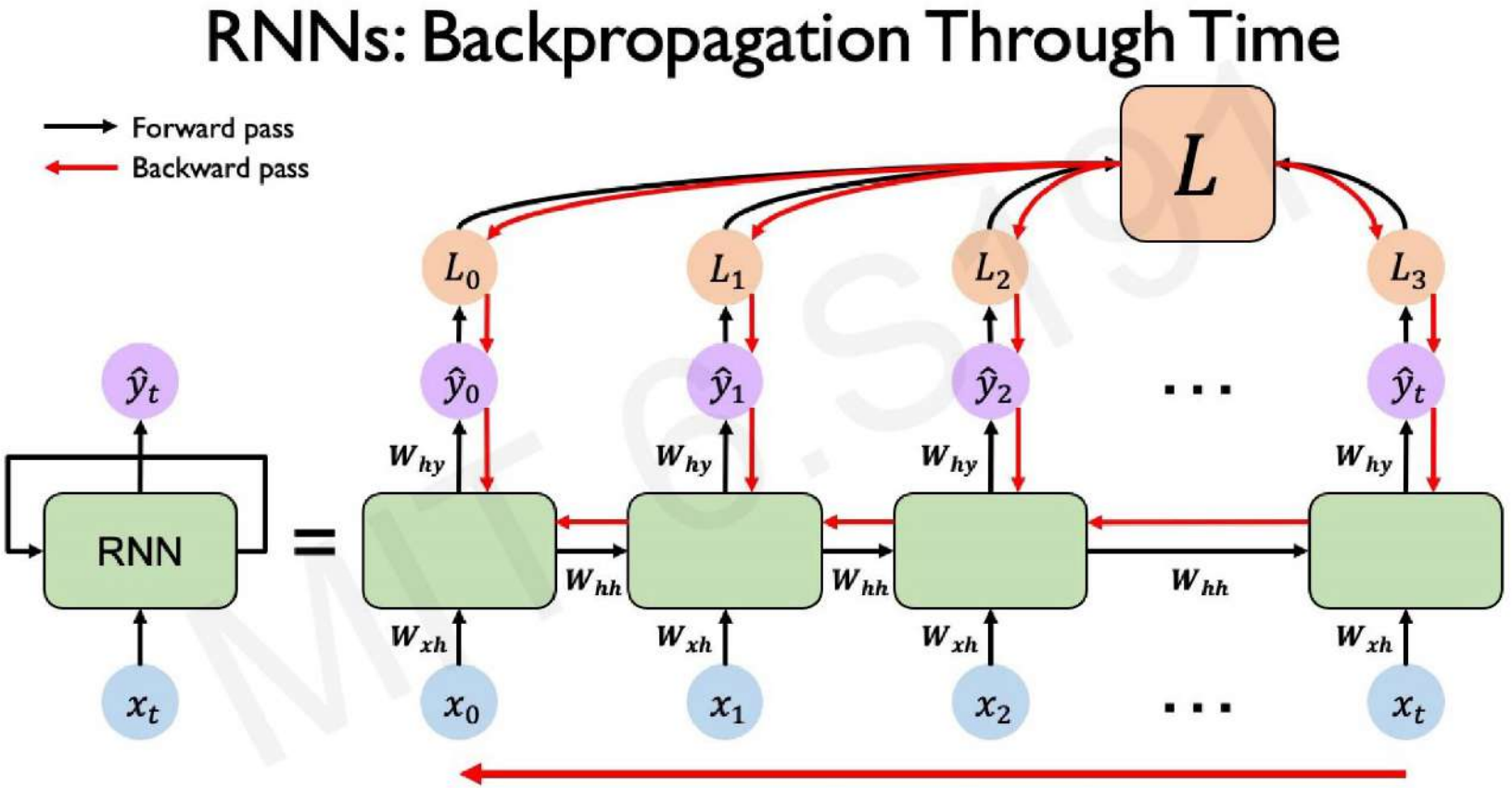
Recall: Backpropagation in Feed Forward Models

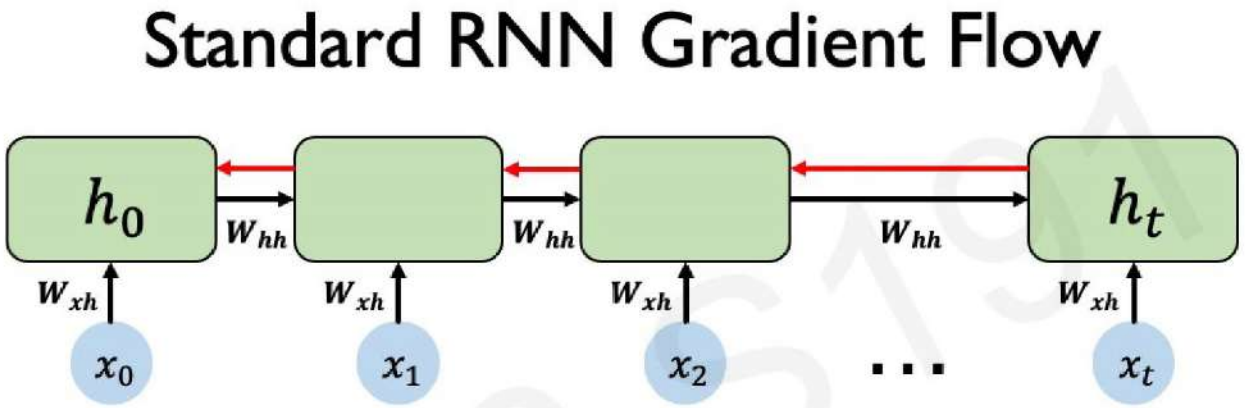


Backpropagation algorithm:

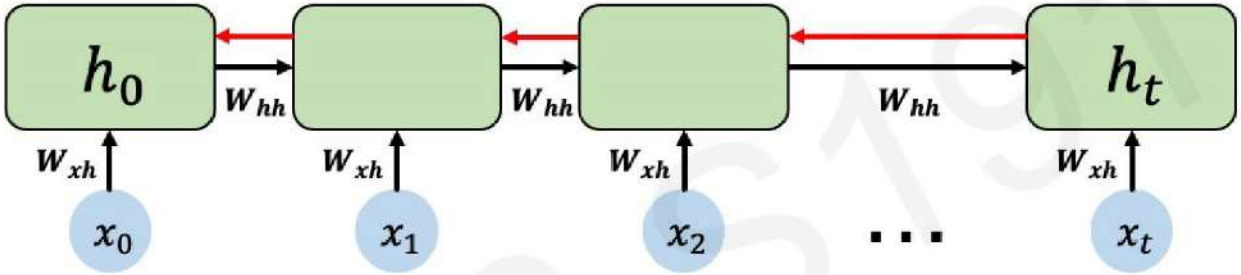
1. Take the derivative (gradient) of the loss with respect to each parameter
2. Shift parameters in order to minimize loss


RNNs: Backpropagation Through Time
Forward pass
L
L_0
L_1
L_2
L_3
$\hat{y}_t$
$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_t$
RNN
=
W_{hy}
W_{hh}
W_{xh}
x_t
x_0
x_1
x_2
x_t


RNNs: Backpropagation Through Time
Forward pass
Backward pass
L
L_0
L_1
L_2
L_3
$\hat{y}_t$
$\hat{y}_0$
$\hat{y}_1$
$\hat{y}_2$
$\hat{y}_t$
RNN
=
W_{hy}
W_{hh}
W_{xh}
x_t
x_0
x_1
x_2
x_t

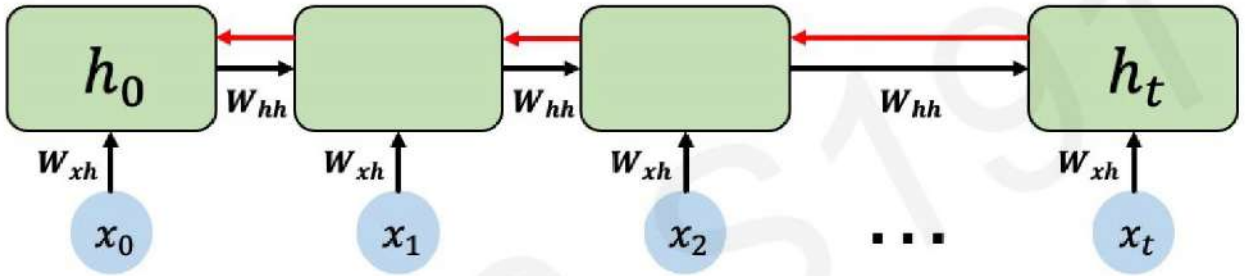

Standard RNN Gradient Flow
h_0
h_t
W_{hh}
W_{hh}
W_{hh}
W_{xh}
W_{xh}
W_{xh}
W_{xh}
x_0
x_1
x_2
x_t
...

Standard RNN Gradient Flow



Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

Standard RNN Gradient Flow: Exploding Gradients

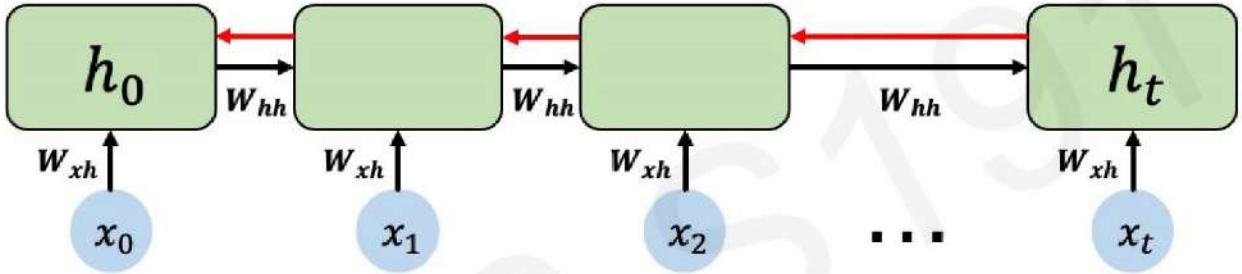


Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

Many values > 1:
exploding gradients

Gradient clipping to scale big gradients

Standard RNN Gradient Flow: Vanishing Gradients



Computing the gradient wrt h_0 involves **many factors of W_{hh} + repeated gradient computation!**

Many values > 1:
exploding gradients

Gradient clipping to scale big gradients

Many values < 1:
vanishing gradients

1. Activation function
2. Weight initialization
3. Network architecture

The Problem of Long-Term Dependencies

Why are vanishing gradients a problem?

Multiply many **small numbers** together

↓

Errors due to further back time steps have smaller and smaller gradients

↓

Bias parameters to capture short-term dependencies

The Problem of Long-Term Dependencies

"The clouds are in the ___"

Why are vanishing gradients a problem?

Multiply many **small numbers** together

↓

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Bias parameters to capture short-term dependencies

The Problem of Long-Term Dependencies

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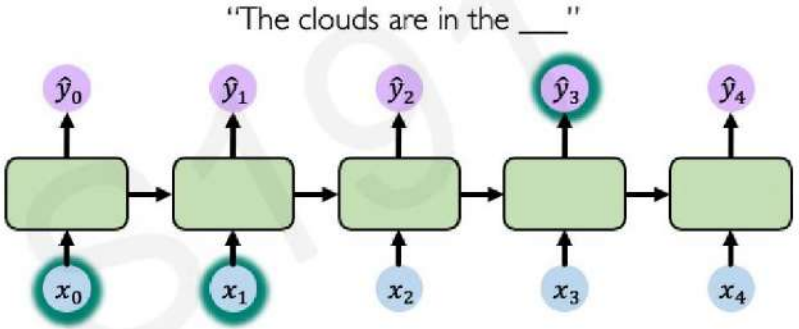
Bias parameters to capture short-term dependencies



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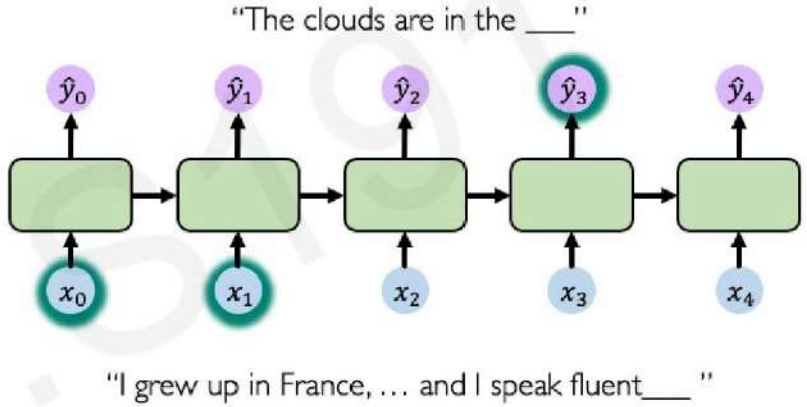

The Problem of Long-Term Dependencies

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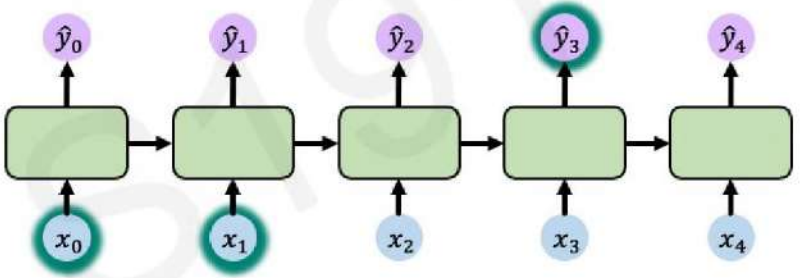
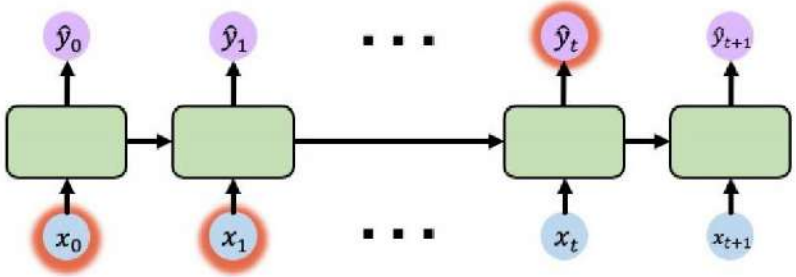
Bias parameters to capture short-term dependencies

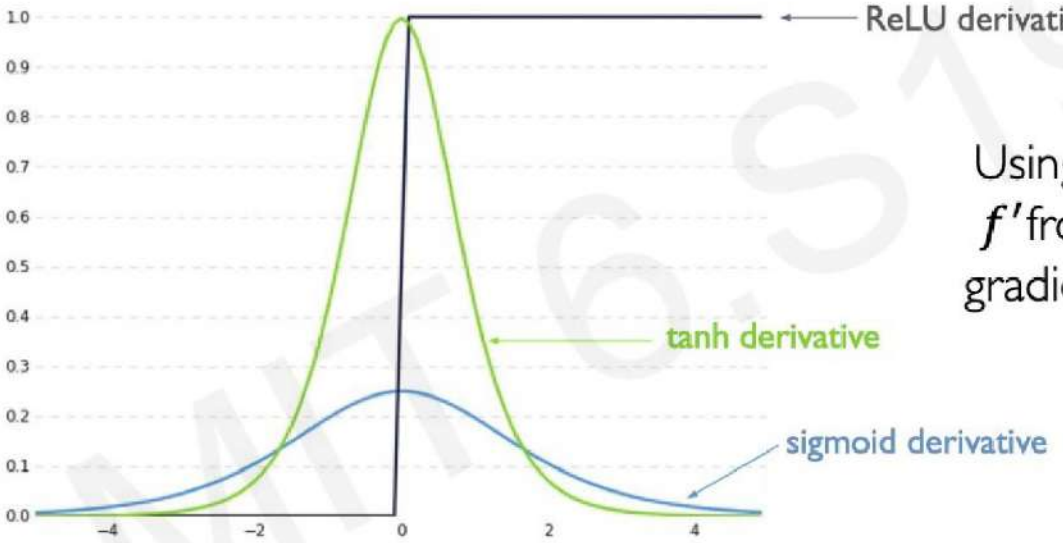
"The clouds are in the ___"



"I grew up in France, … and I speak fluent___"



Trick #1: Activation Functions



Using ReLU prevents f' from shrinking the gradients when $x > 0$

Trick #2: Parameter Initialization

Initialize **weights** to identity matrix

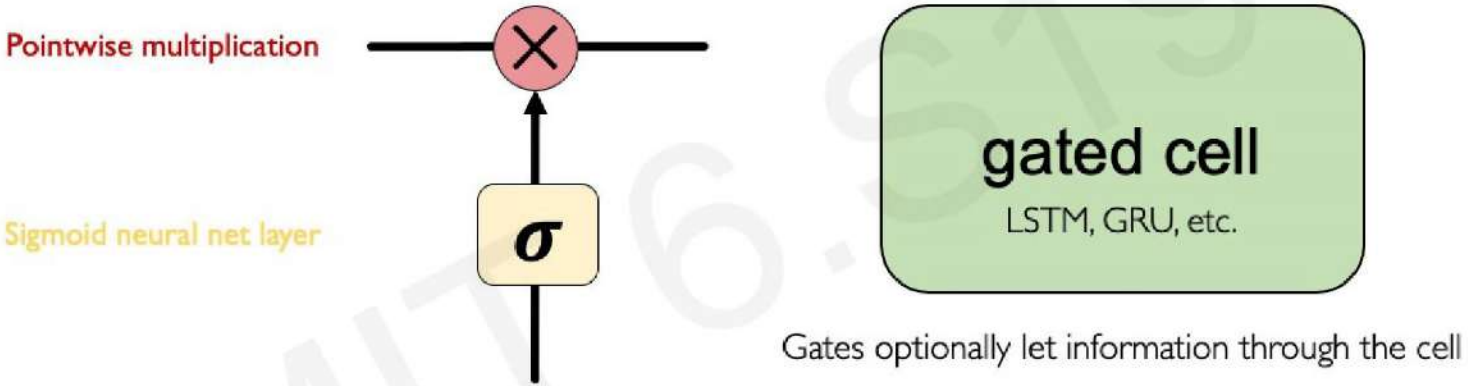
Initialize **biases** to zero

$$I_n = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}$$

This helps prevent the weights from shrinking to zero.

Trick #3: Gated Cells

Idea: use **gates** to selectively **add** or **remove** information within **each recurrent unit with**



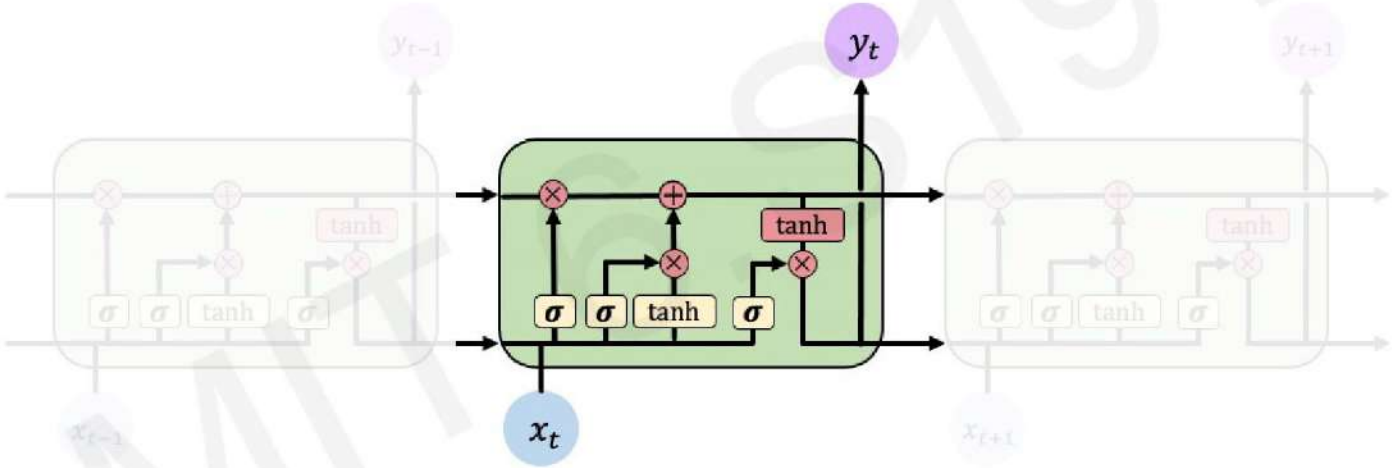
Gates optionally let information through the cell

Long Short Term Memory (LSTMs) networks rely on a gated cell to track information throughout many time steps.

Long Short Term Memory (LSTMs)

Gated LSTM cells **control information flow:**

1) Forget 2) Store 3) Update 4) Output



LSTM cells are able to track information throughout many timesteps

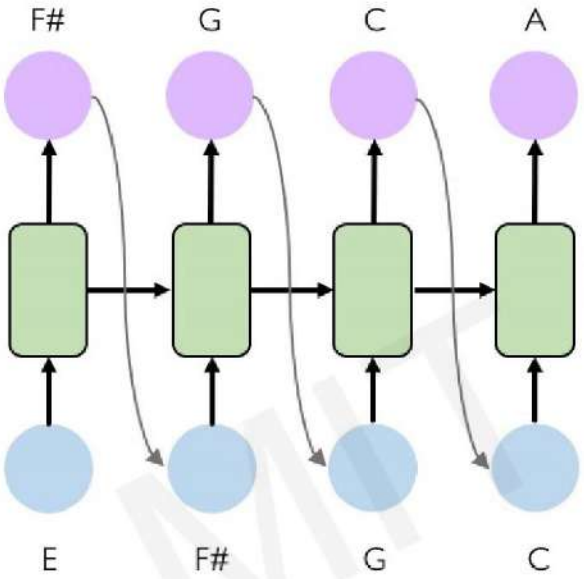
```
tf.keras.layers.LSTM(num_units)
```

LSTMs: Key Concepts

1. Maintain a **cell state**
2. Use **gates** to control the **flow of information**
   - **Forget** gate gets rid of irrelevant information
   - **Store** relevant information from current input
   - Selectively **update** cell state
   - **Output** gate returns a filtered version of the cell state
3. Backpropagation through time with partially **uninterrupted gradient flow**

RNN Applications & Limitations

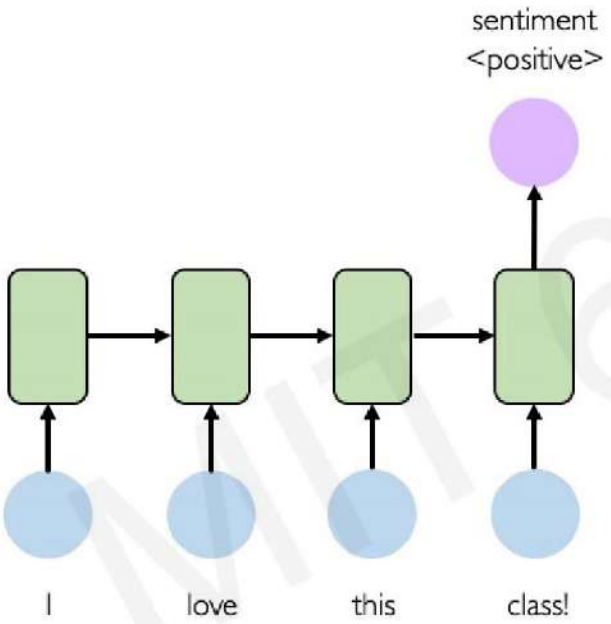
Example Task: Music Generation



Input: sheet music

Output: next character in sheet music

Example Task: Sentiment Classification

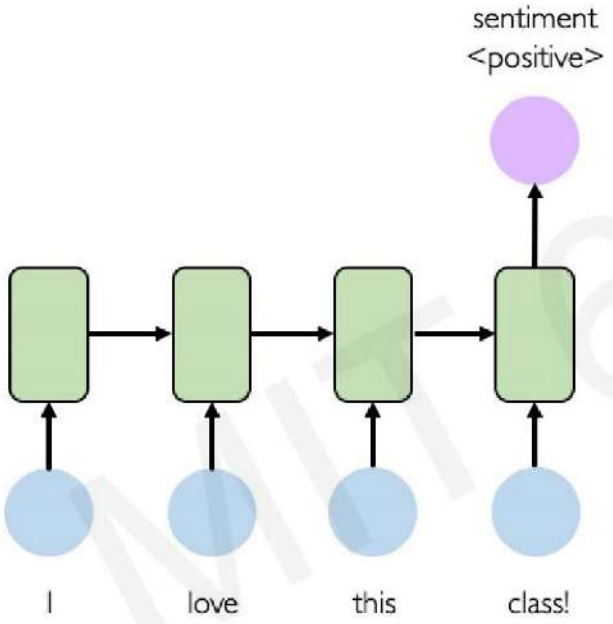


Input: sequence of words

Output: probability of having positive sentiment

```
loss = tf.nn.softmax_cross_entropy_with_logits(y, predicted)
```

Example Task: Sentiment Classification



Tweet sentiment classification

Ivar Hagendoorn
@IvarHagendoorn
Follow

The @MIT Introduction to #DeepLearning is definitely one of the best courses of its kind currently available online introtodeeplearning.com

12:45 PM - 12 Feb 2018

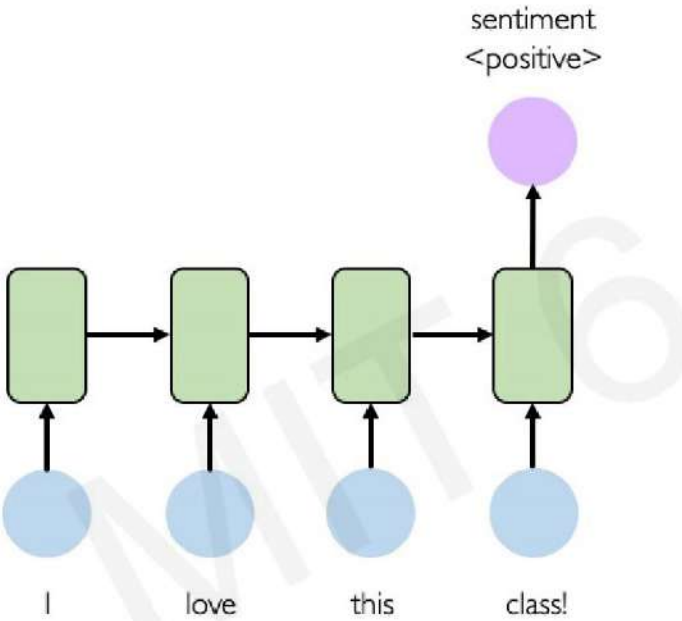
Angels-Cave
@AngelsCave
Follow

Replying to @Kazuki2048

I wouldn't mind a bit of snow right now. We haven't had any in my bit of the Midlands this winter! :(

2:19 AM - 25 Jan 2019

Limitations of Recurrent Models

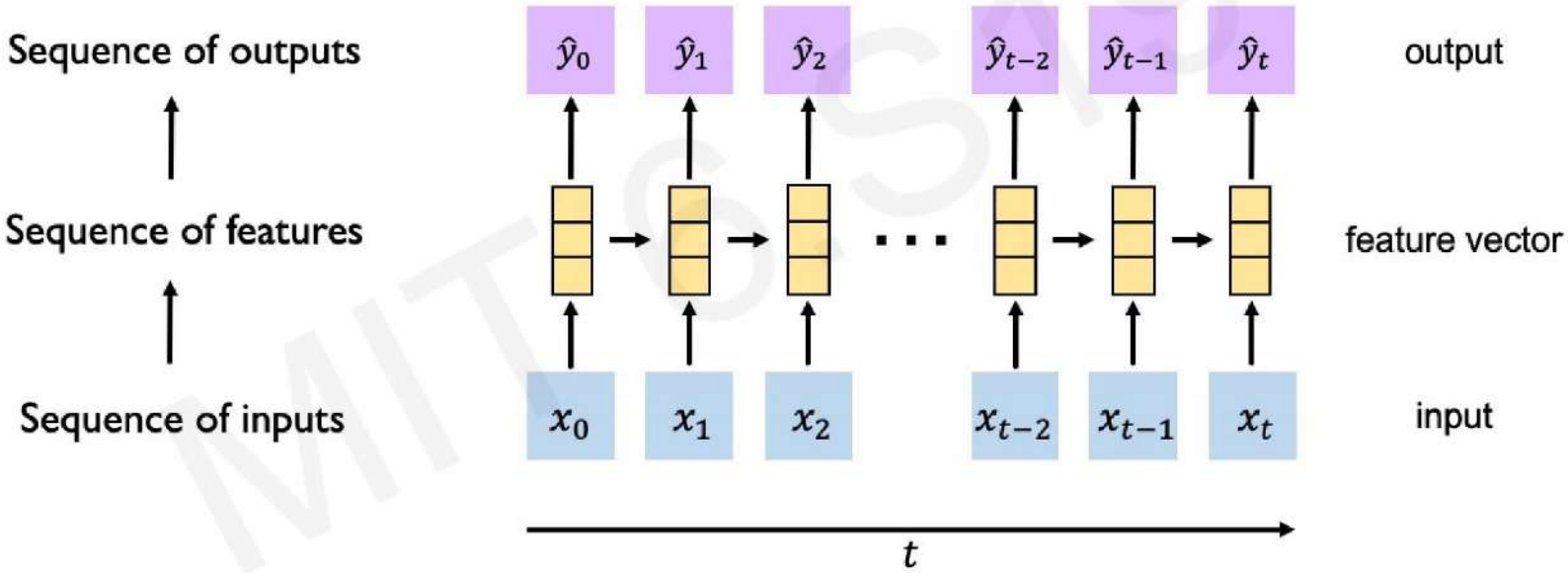


Limitations of RNNs

- Encoding bottleneck
- Slow, no parallelization
- Not long memory

Goal of Sequence Modeling

RNNs: recurrence to model sequence dependencies

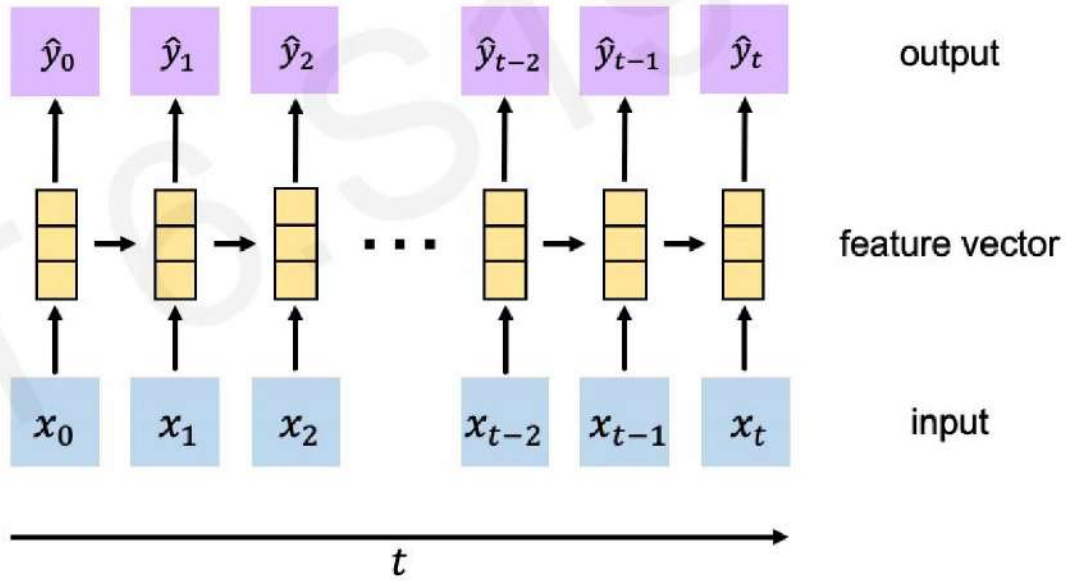


Goal of Sequence Modeling

RNNs: recurrence to model sequence dependencies

Limitations of RNNs

- Encoding bottleneck
- Slow, no parallelization
- Not long memory

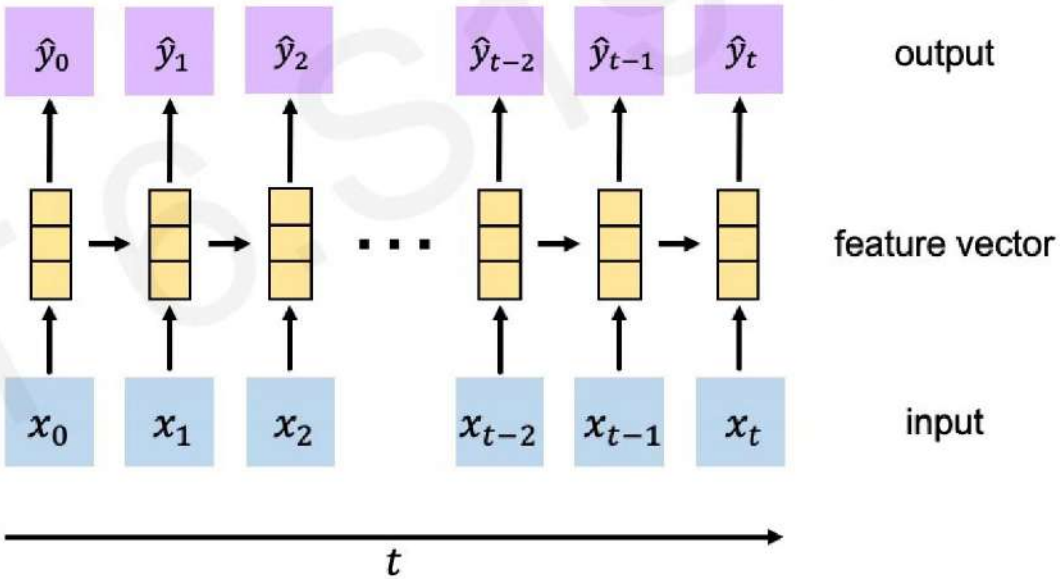


Goal of Sequence Modeling

Can we eliminate the need for recurrence entirely?

Desired Capabilities

- Continuous stream
- Parallelization
- Long memory



Goal of Sequence Modeling

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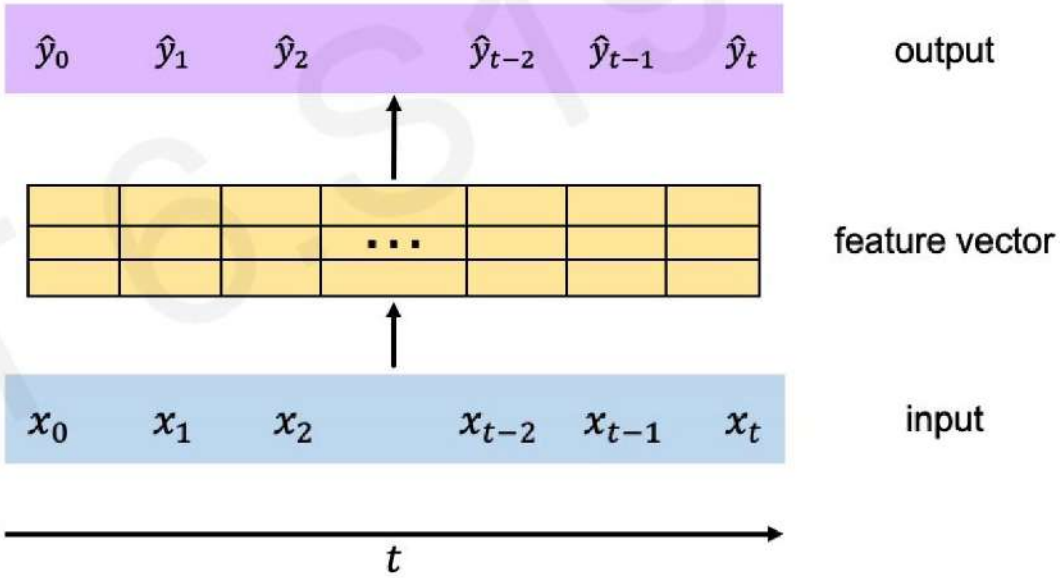
- Continuous stream
- Parallelization
- Long memory



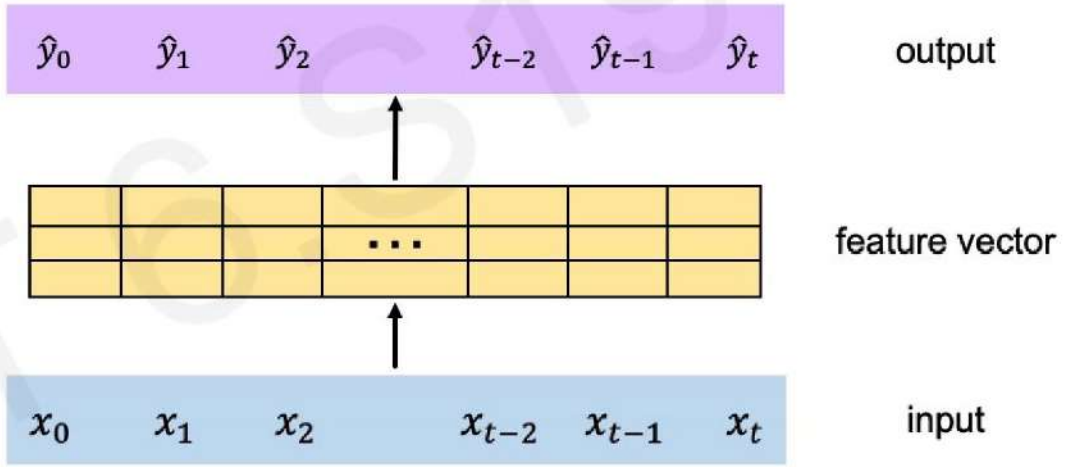
Goal of Sequence Modeling

Idea 1: Feed everything into dense network

- ✓ No recurrence
- ✗ Not scalable
- ✗ No order
- ✗ No long memory

Idea: Identify and attend to what's important

Can we eliminate the need for recurrence entirely?



Attention Is All You Need

Intuition Behind Self-Attention

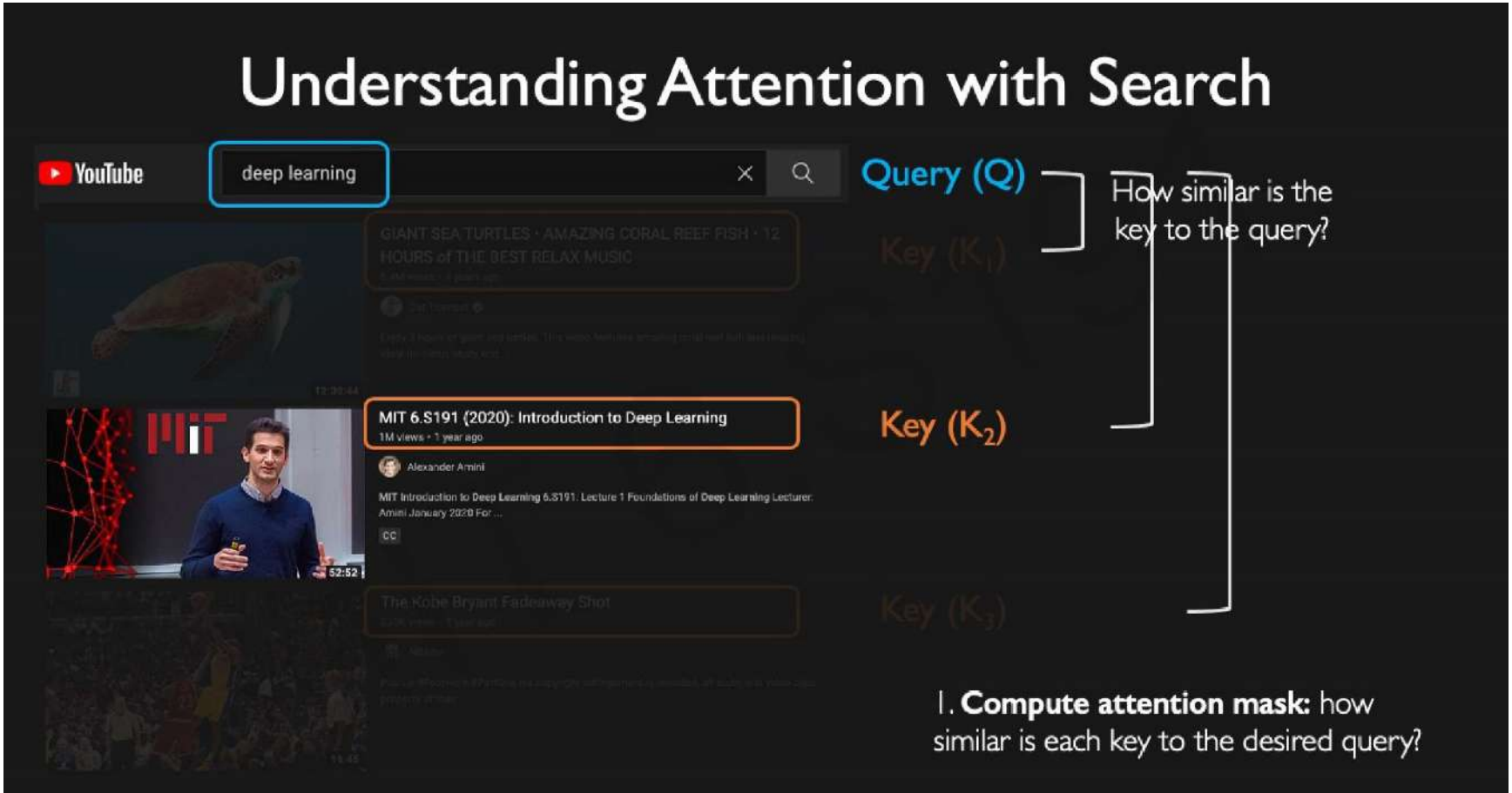
Attending to the most important parts of an input.

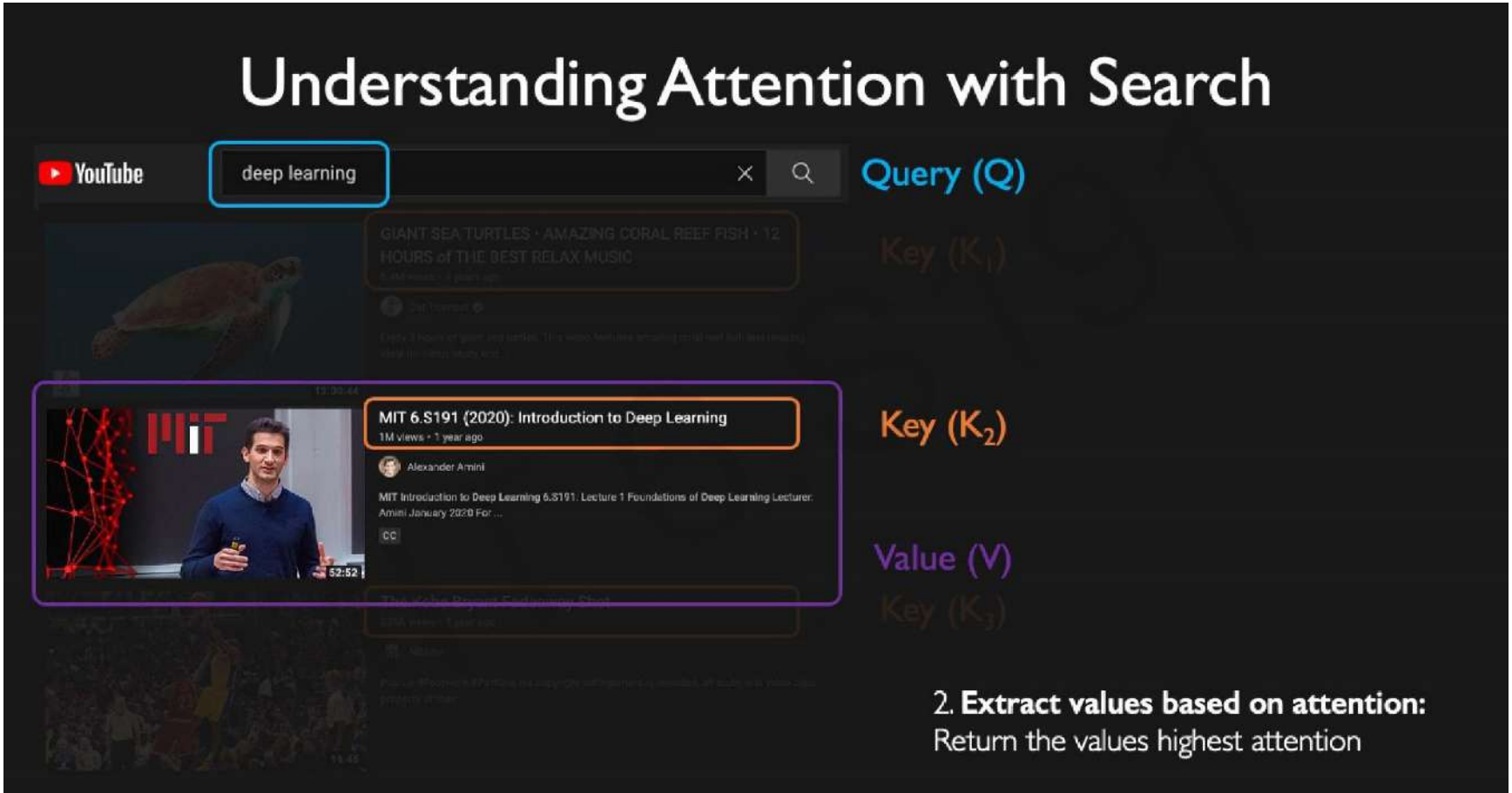
1. Identify which parts to attend to

Similar to a search problem!

2. Extract the features with high attention

A Simple Example: Search


Understanding Attention with Search
YouTube
deep learning
Query (Q)
How similar is the key to the query?
GIANT SEA TURTLES • AMAZING CORAL REEF FISH • 12 HOURS of THE BEST RELAX MUSIC
Key (K_1)
MIT 6.S191 (2020): Introduction to Deep Learning
1M views • 1 year ago
Alexander Amini
MIT Introduction to Deep Learning 6.S191: Lecture 1 Foundations of Deep Learning Lecturer: Amini January 2020 For ...
CC
52:52
Key (K_2)
The Kobe Bryant Fadeaway Shot
Key (K_3)
1. Compute attention mask: how similar is each key to the desired query?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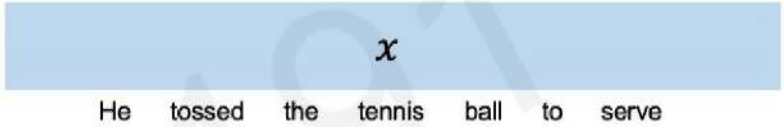
1M views • 1 year ago
Alexander Amini
MIT Introduction to Deep Learning 6.S191: Lecture 1 Foundations of Deep Learning Lecturer: Amini January 2020 For ...
CC
52:52
Key (K_2)
Value (V)
Key (K_3)
2. Extract values based on attention:
Return the values highest attention

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.



1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract features with high attention

Data is fed in all at once! Need to encode position information to understand order.

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract query, key, value for search
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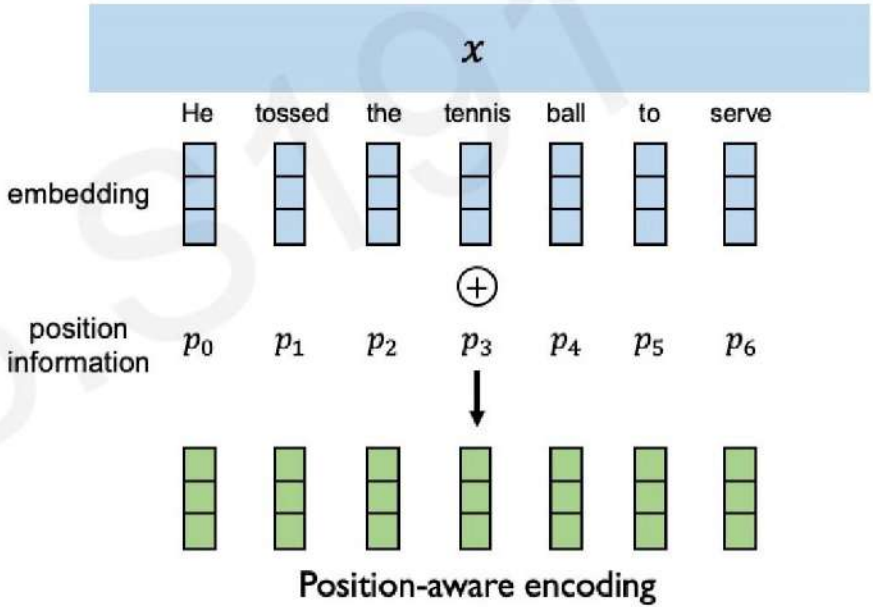

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Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract **query, key, value** for search
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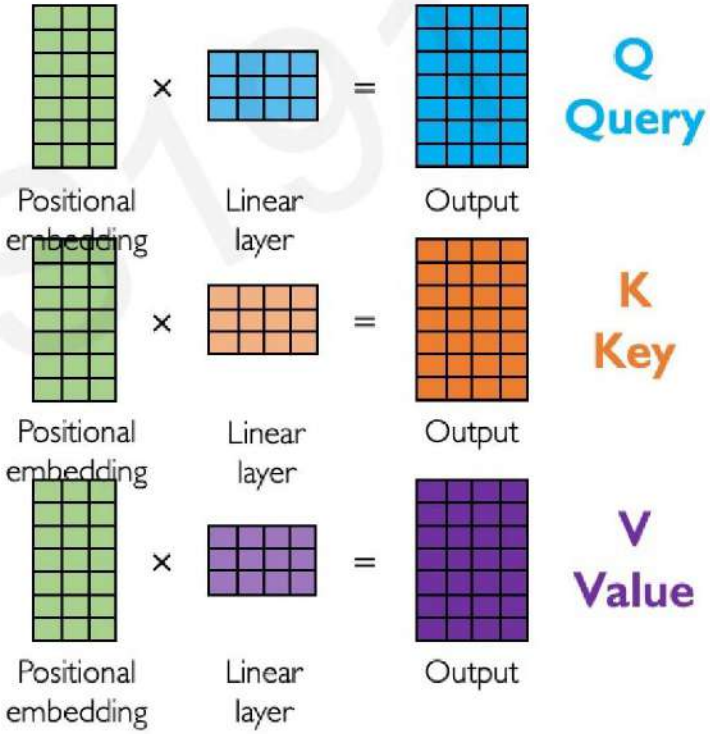


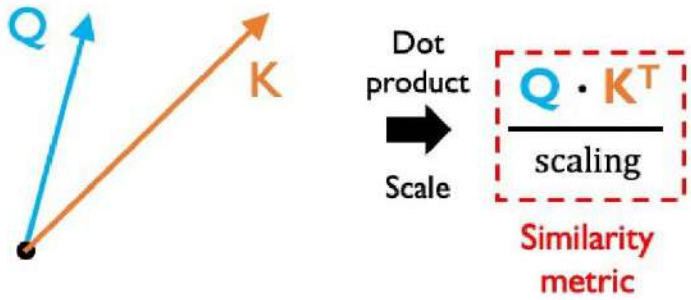
Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract features with high attention

Attention score: compute pairwise similarity between each query and key

How to compute similarity between two sets of features?



Also known as the "cosine similarity"

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract features with high attention

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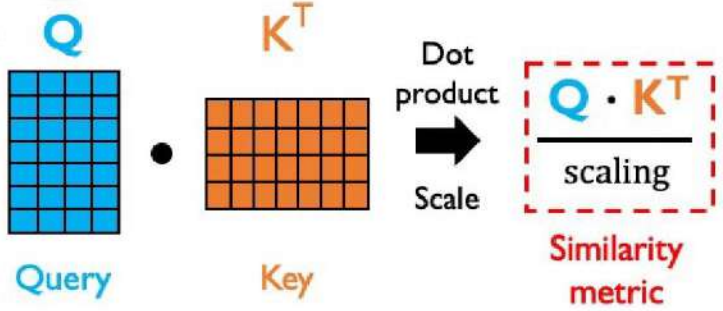


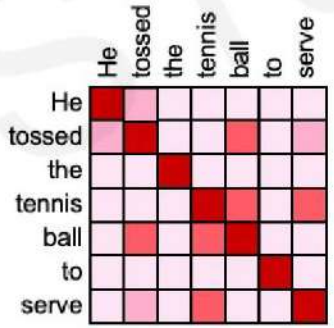
Also known as the "cosine similarity"

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract features with high attention

Attention weighting: where to attend to! How similar is the key to the query?



$$softmax\left(\frac{Q \cdot K^T}{scaling}\right)$$

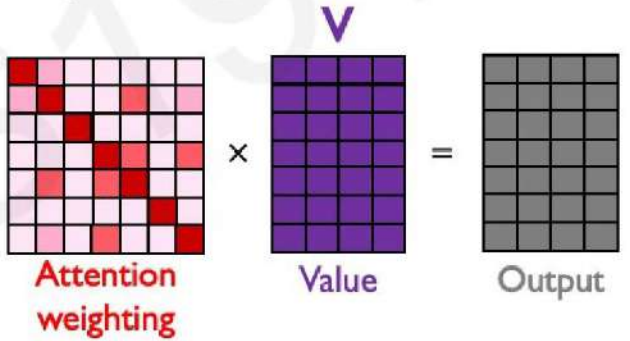
Attention weighting

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract **features with high attention**

Last step: self-attend to extract features



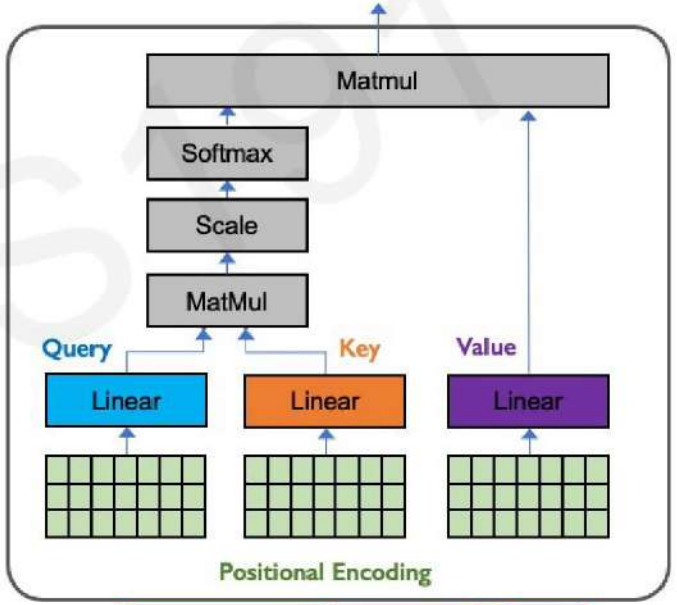
$$softmax\left(\frac{Q \cdot K^T}{scaling}\right) \cdot V = A(Q, K, V)$$

Learning Self-Attention with Neural Networks

Goal: identify and attend to most important features in input.

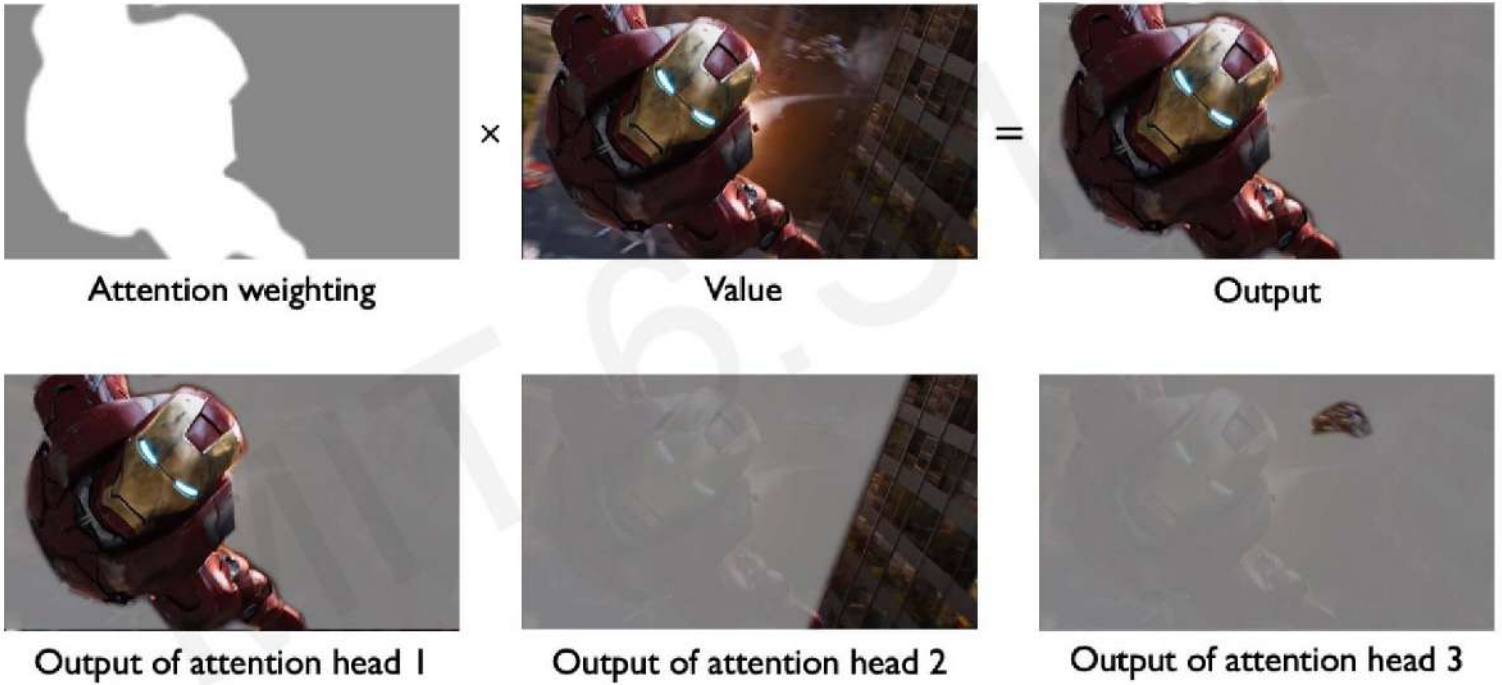
1. Encode **position** information
2. Extract **query, key, value** for search
3. Compute **attention weighting**
4. Extract **features with high attention**

These operations form a self-attention head that can plug into a larger network.
Each head attends to a different part of input.



$$softmax\left(\frac{Q \cdot K^T}{scaling}\right) \cdot V$$

Applying Multiple Self-Attention Heads



Self-Attention Applied

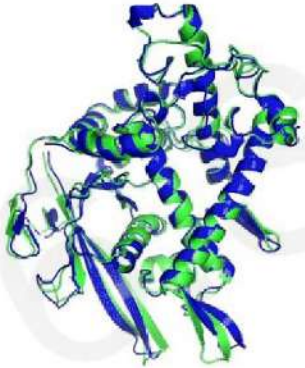
Language Processing

An armchair in the shape of an avocado

BERT, GPT-3

Devlin et al., *NAACL* 2019
Brown et al., *NeurIPS* 2020

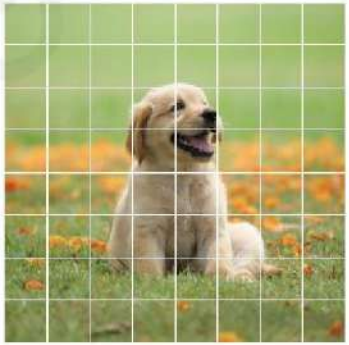
Biological Sequences



AlphaFold2

Jumper et al., *Nature* 2021

Computer Vision



Vision Transformers

Dosovitskiy et al., *ICLR* 2020

Deep Learning for Sequence Modeling: Summary

1. RNNs are well suited for **sequence modeling** tasks
2. Model sequences via a **recurrence relation**
3. Training RNNs with **backpropagation through time**
4. Models for **music generation**, classification, machine translation, and more
5. Self-attention to model **sequences without recurrence**

提纲

一、前馈网络

二、循环网络

三、卷积网络

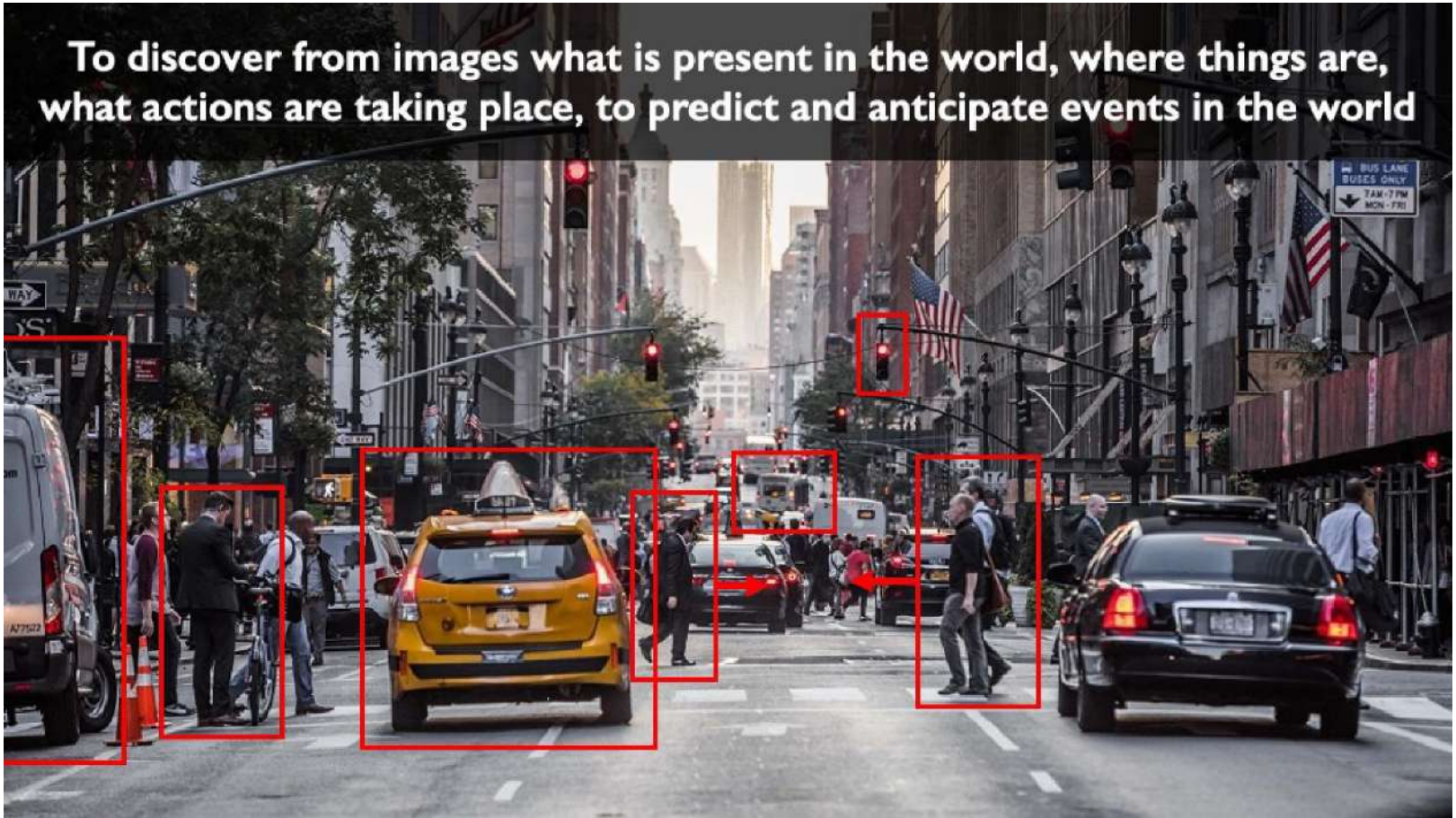
人工智能基本理论

从一个故事讲起……

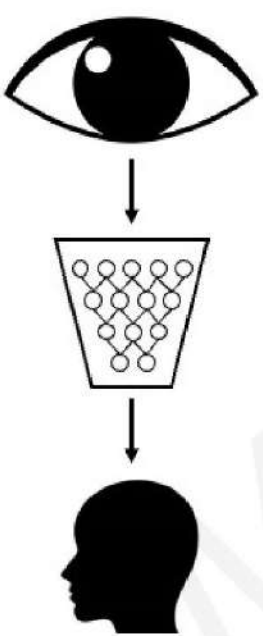
人工智能基本理论

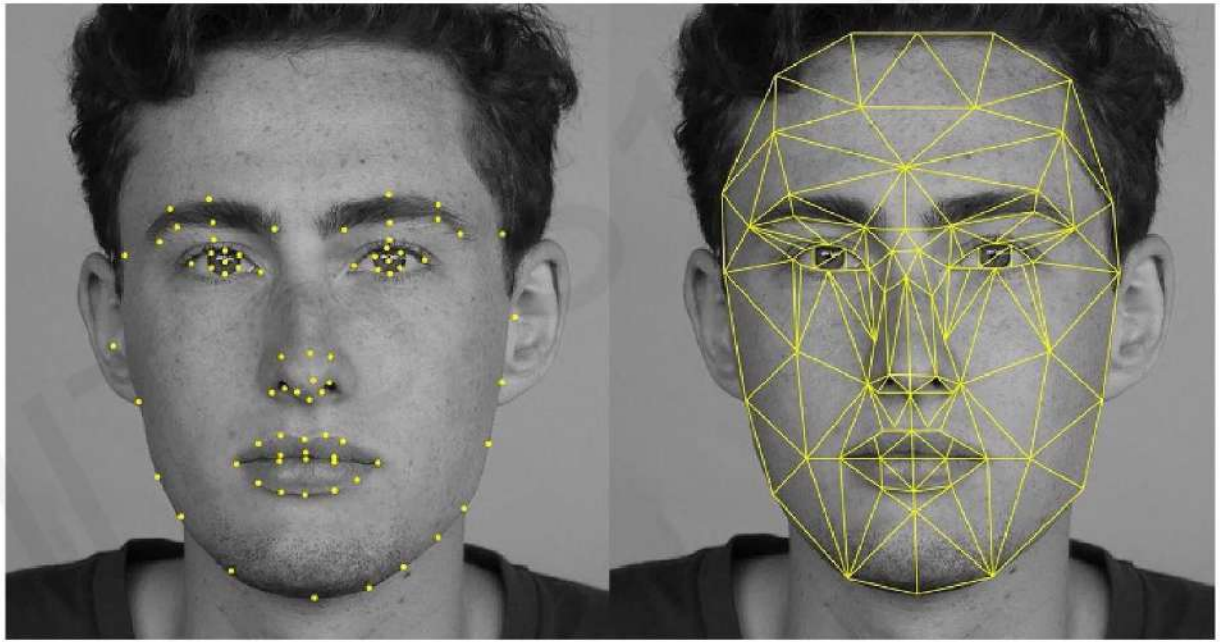

15:38
懂鸟·全球鸟类识别
拍摄地点: 未指定
yè lù
夜鹭
Black-crowned Night Heron
Nycticorax nycticorax
识别可信度: 92.8%
拍照识别
相册识别
群图片
听音辨鸟
浏览搜索

人工智能基本理论

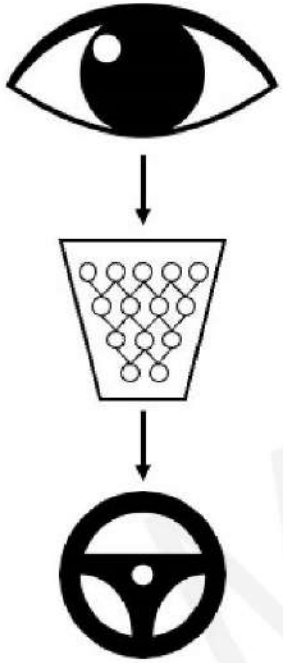

To discover from images what is present in the world, where things are,
what actions are taking place, to predict and anticipate events in the world
BUS LANE
BUSES ONLY
7AM-7PM
MON-FRI

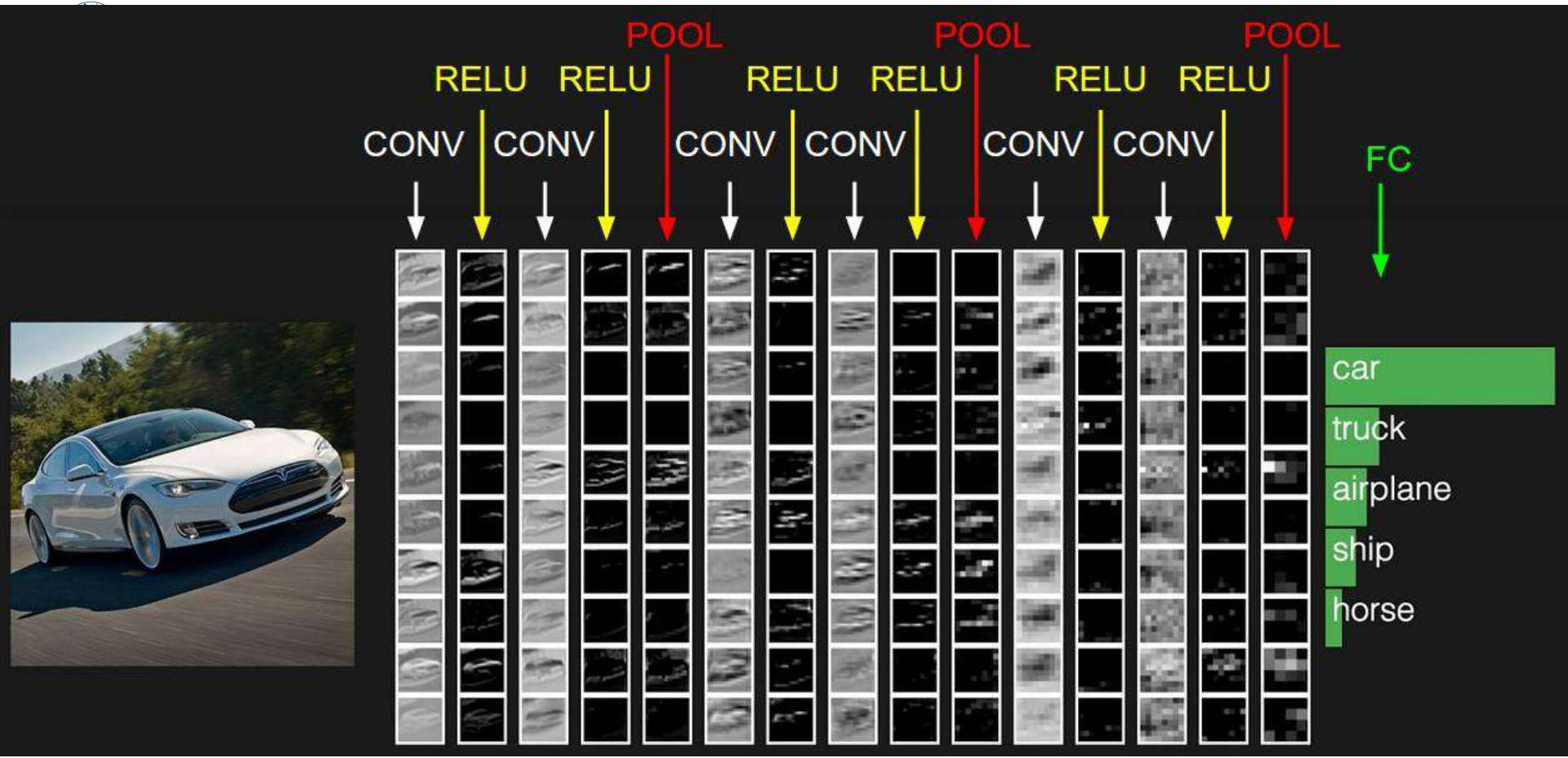
Impact: Facial Detection & Recognition



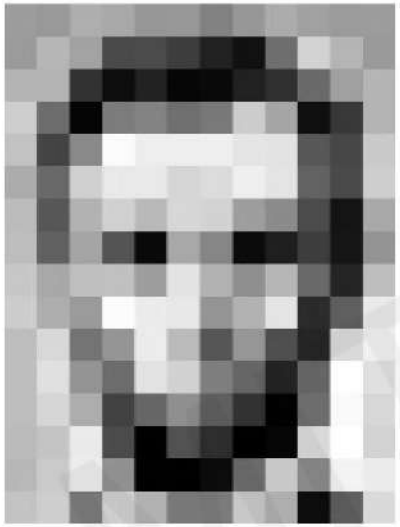


Impact: Self-Driving Cars




POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

Images are Numbers



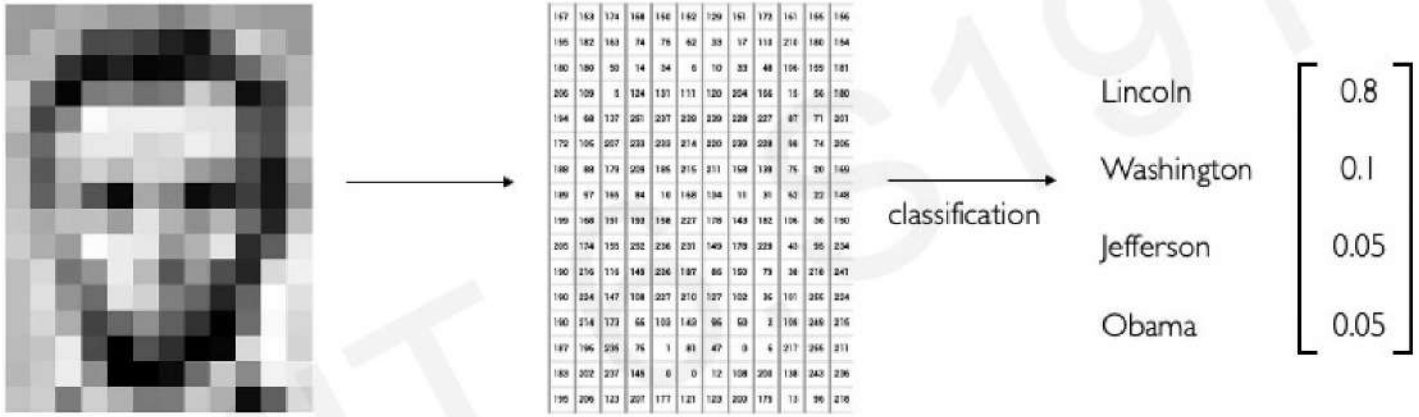
157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

What the computer sees

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

An image is just a matrix of numbers [0,255]!
i.e., 1080x1080x3 for an RGB image

Tasks in Computer Vision



- **Regression**: output variable takes continuous value
- **Classification**: output variable takes class label. Can produce probability of belonging to a particular class

High Level Feature Detection

Let's identify key features in each image category

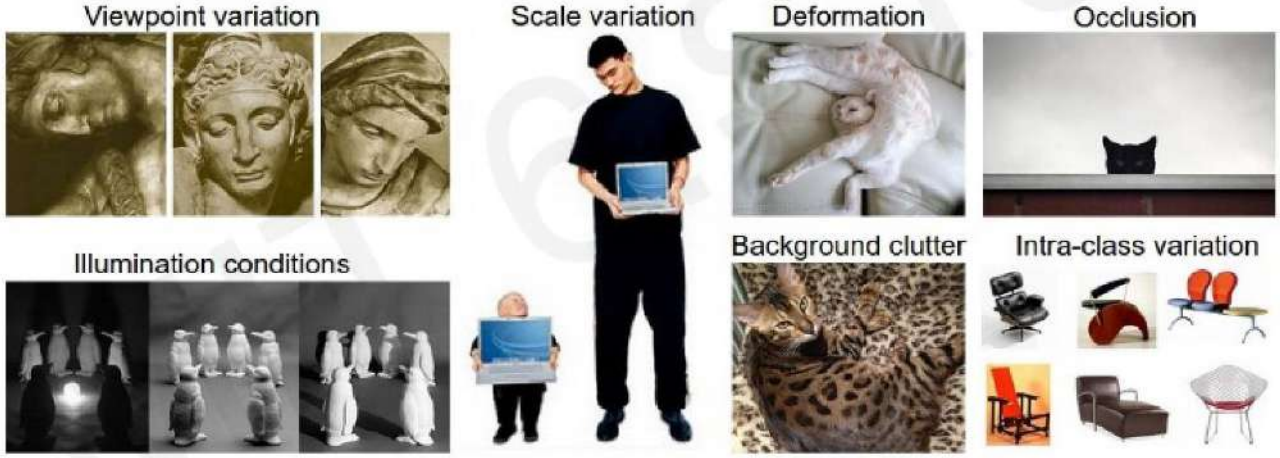
Nose,
Eyes,
Mouth

Wheels,
License Plate,
Headlights

Door,
Windows,
Steps

Manual Feature Extraction

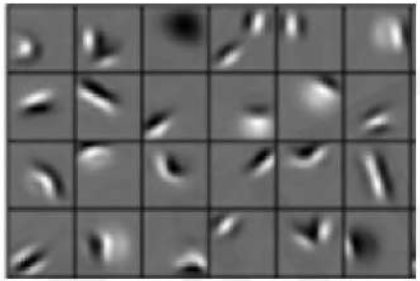
Domain knowledge → Define features → Detect features to classify



Learning Feature Representations

Can we learn a **hierarchy of features** directly from the data instead of hand engineering?

Low level features



Edges, dark spots

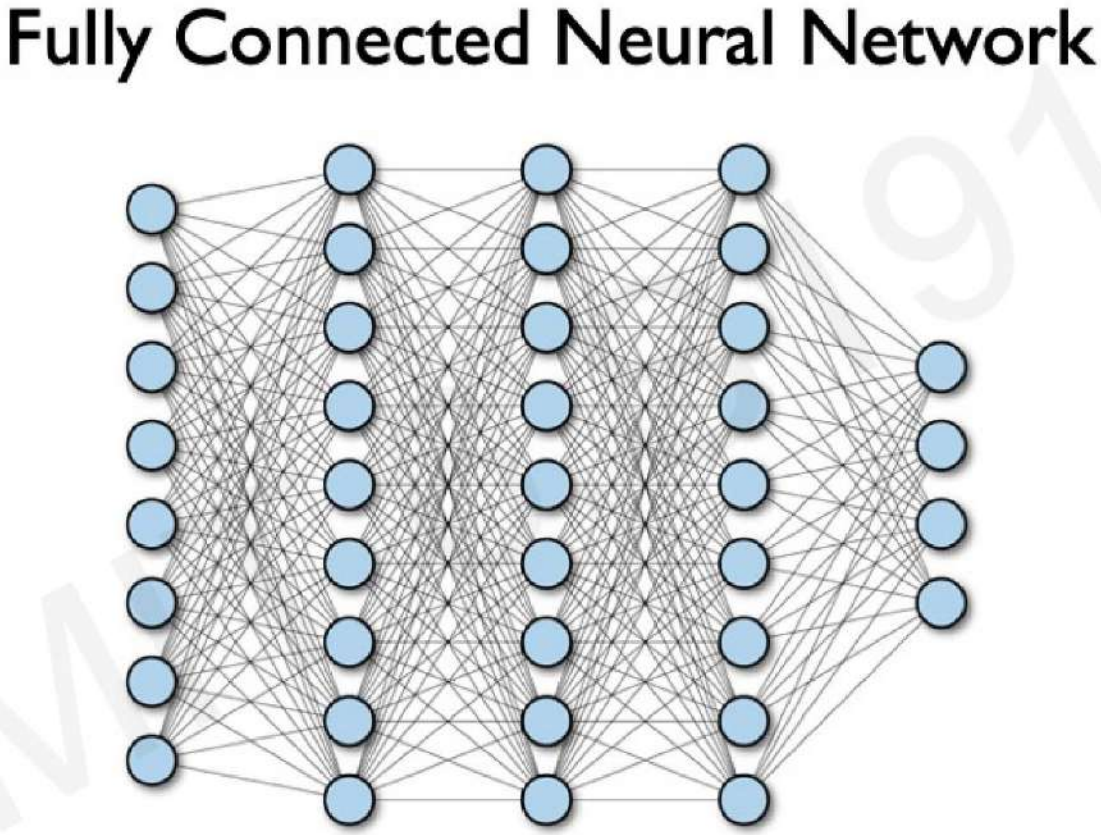
Mid level features

Eyes, ears, nose

High level features

Facial structure

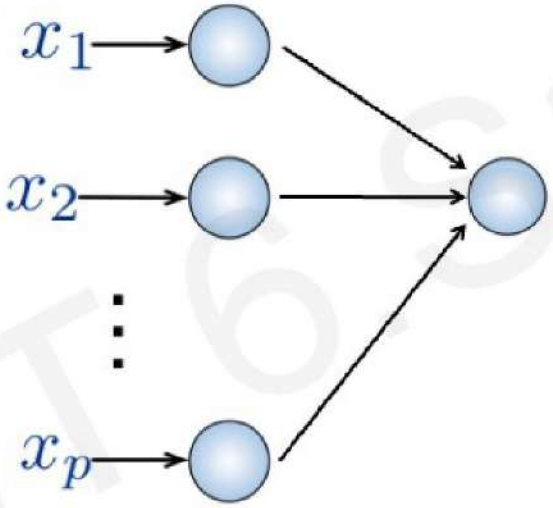
Learning Visual Features


Fully Connected Neural Network

Fully Connected Neural Network

Input:

- 2D image
- Vector of pixel values



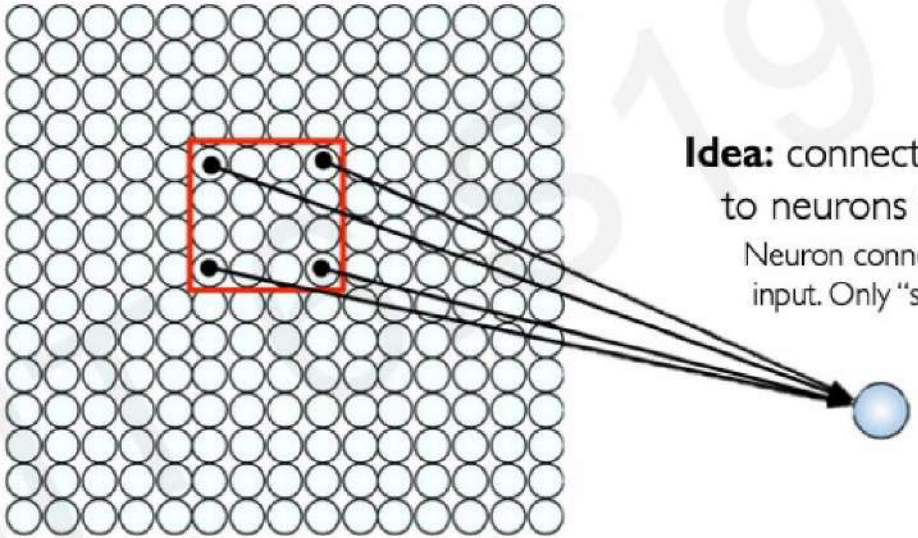
Fully Connected:

- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

How can we use **spatial structure** in the input to inform the architecture of the network?

Using Spatial Structure

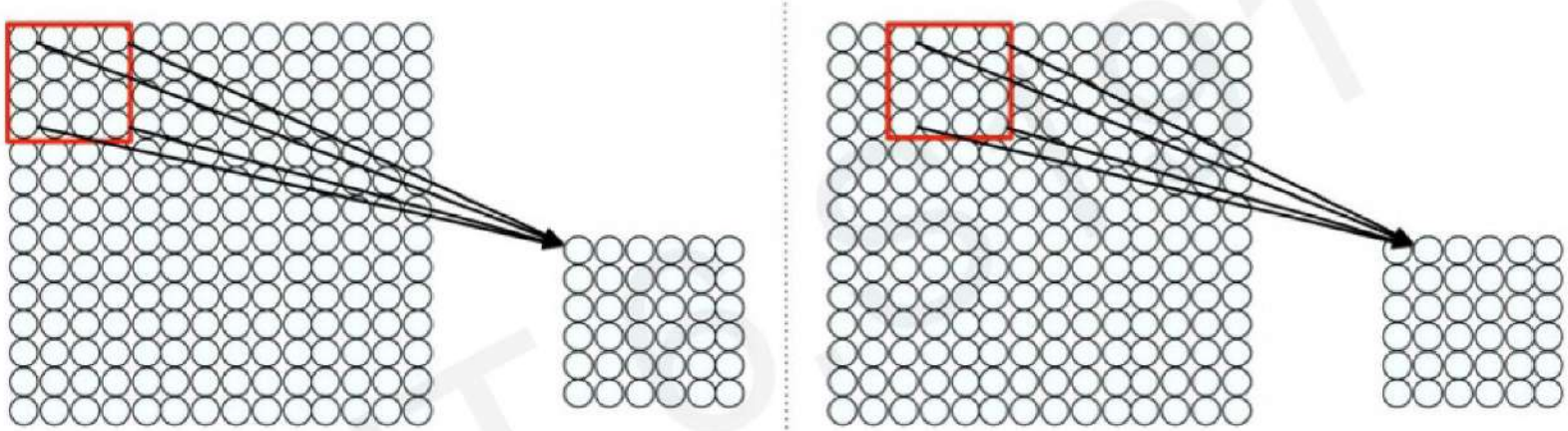
Input: 2D image.
Array of pixel values



Idea: connect patches of input to neurons in hidden layer.

Neuron connected to region of input. Only "sees" these values.

Using Spatial Structure



Connect patch in input layer to a single neuron in subsequent layer.
Use a sliding window to define connections.
How can we **weight** *the patch to detect particular features?*

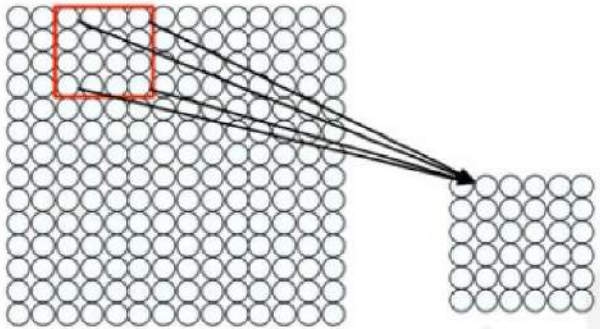
Applying Filters to Extract Features

1) Apply a set of weights – a filter – to extract **local features**

2) Use **multiple filters** to extract different features

3) Spatially **share** parameters of each filter
(features that matter in one part of the input should matter elsewhere)

Feature Extraction with Convolution



- Filter of size 4x4 : 16 different weights
- Apply this same filter to 4x4 patches in input
- Shift by 2 pixels for next patch

This "patchy" operation is **convolution**

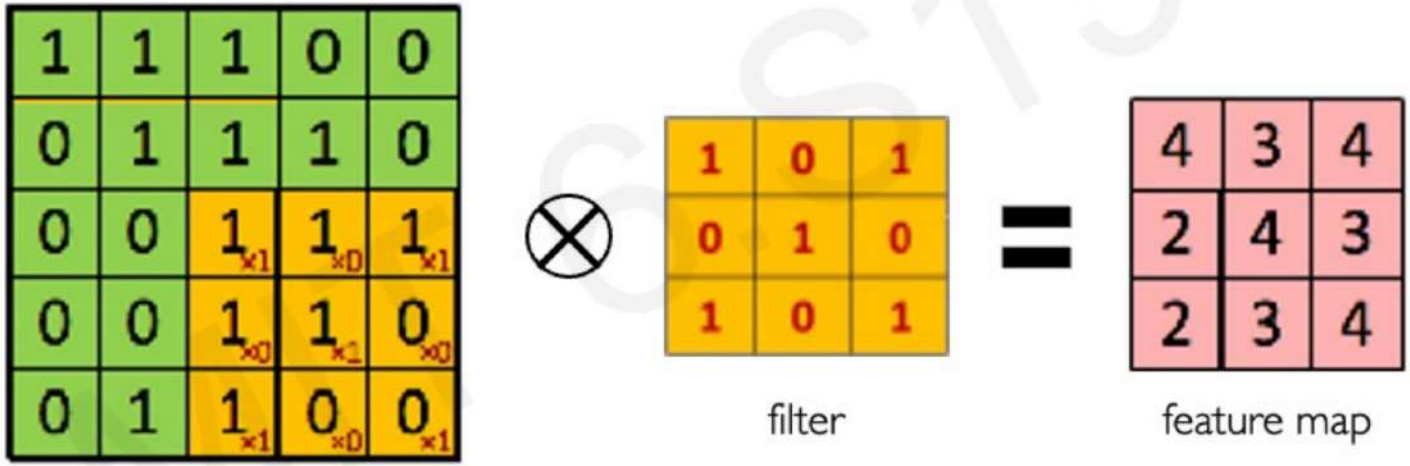
1) Apply a set of weights – a filter – to extract **local features**

2) Use **multiple filters** to extract different features

3) **Spatially share** parameters of each filter

The Convolution Operation

We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs:



Producing Feature Maps

Original

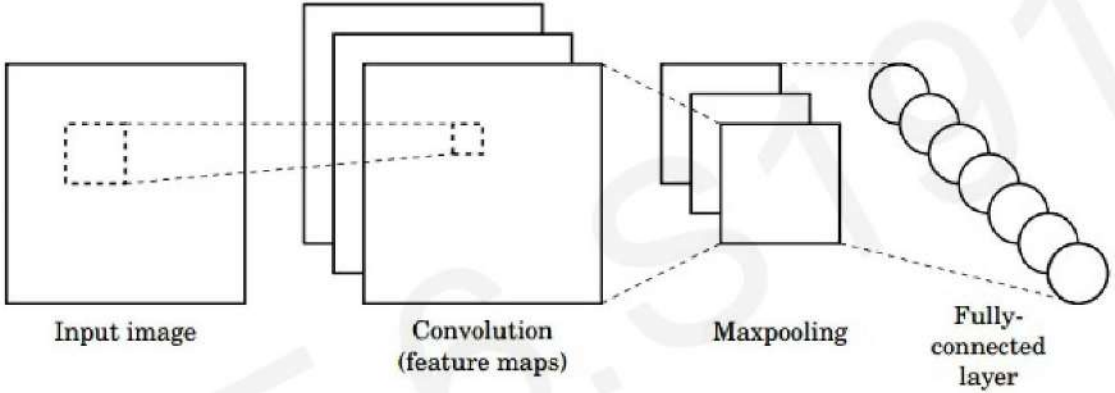
Sharpen

Edge Detect

"Strong" Edge Detect

Convolutional Neural Networks (CNNs)

CNNs for Classification



1. **Convolution**: Apply filters to generate feature maps.
2. **Non-linearity**: Often ReLU.
3. **Pooling**: Downsampling operation on each feature map.

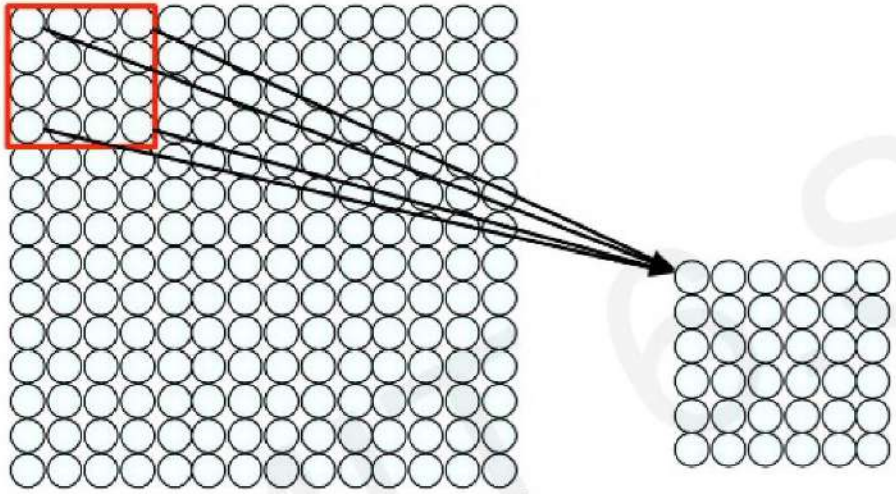
`tf.keras.layers.Conv2D`

`tf.keras.activations.*`

`tf.keras.layers.MaxPool2D`

Train model with image data.
Learn weights of filters in convolutional layers.

Convolutional Layers: Local Connectivity



tf.keras.layers.Conv2D

For a neuron in hidden layer:

- Take inputs from patch
- Compute weighted sum
- Apply bias

4x4 filter: matrix of weights w_{ij}

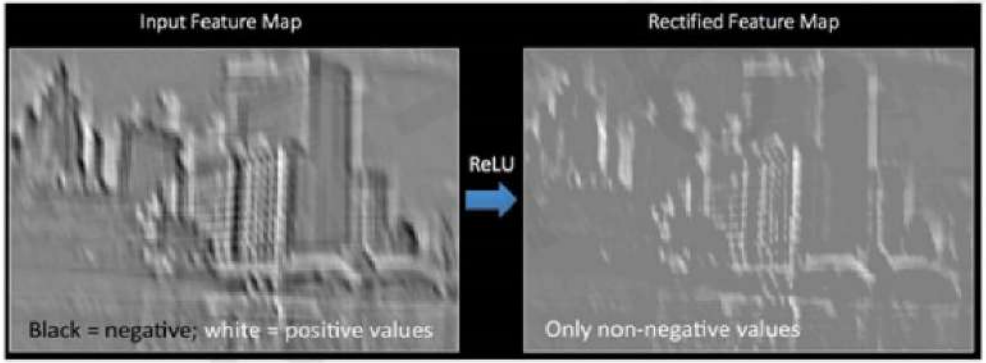
$$\sum_{i=1}^{4}\sum_{j=1}^{4} w_{ij}\, x_{i+p,j+q} + b$$

for neuron (p,q) in hidden layer

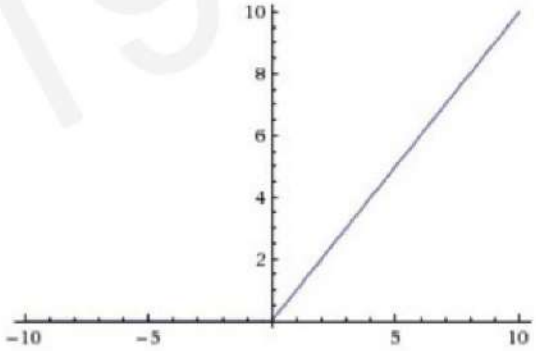
1) applying a window of weights
2) computing linear combinations
3) activating with non-linear function

Introducing Non-Linearity

- Apply after every convolution operation (i.e., after convolutional layers)
- ReLU: pixel-by-pixel operation that replaces all negative values by zero. **Non-linear operation!**



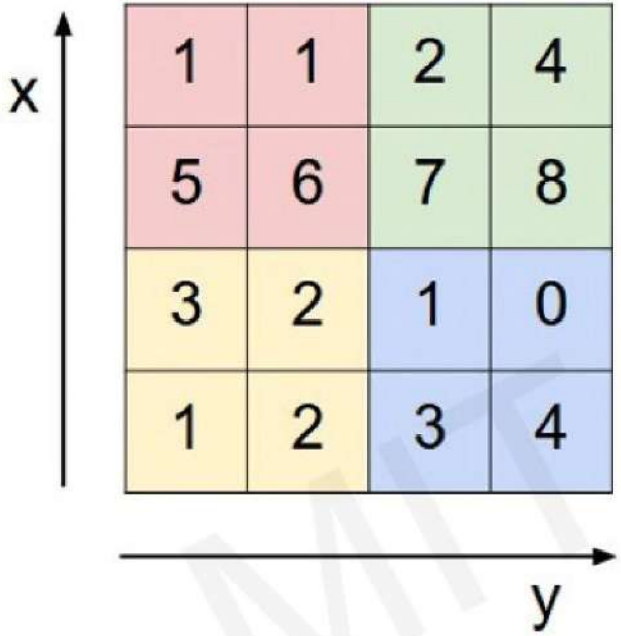
Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

`tf.keras.layers.ReLU`

Pooling



max pool with 2x2 filters
and stride 2

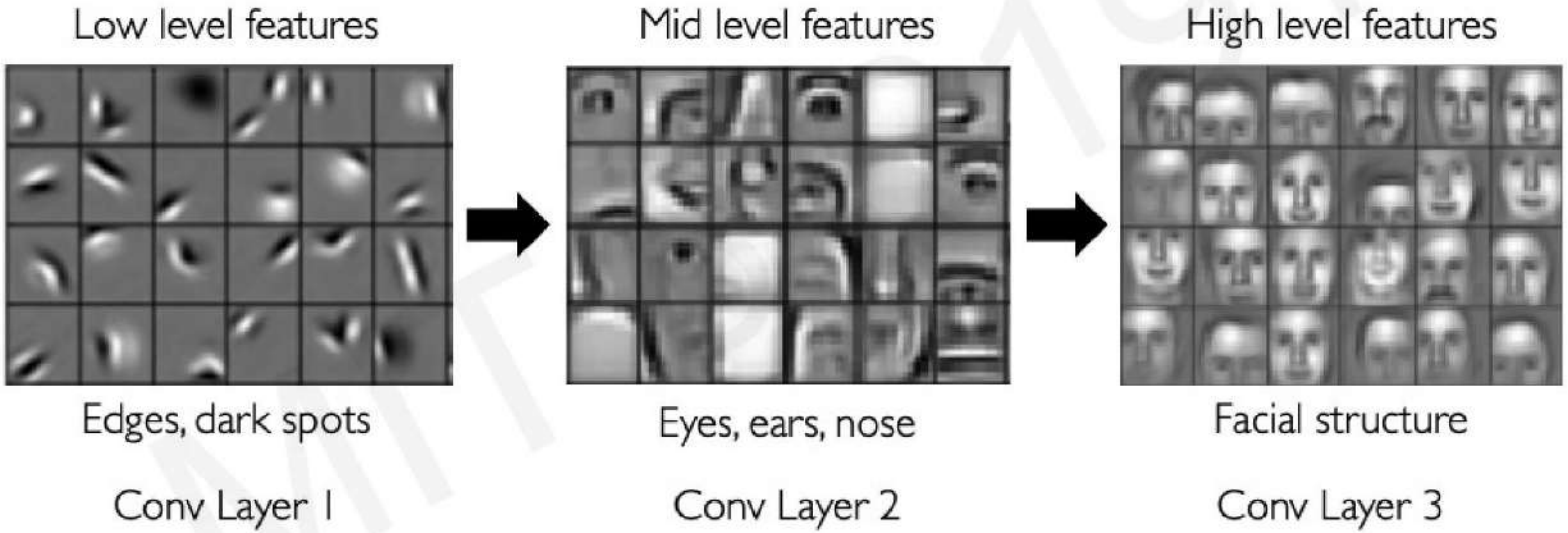
```
tf.keras.layers.MaxPool2D(
    pool_size=(2,2),
    strides=2
)
```

6	8
3	4

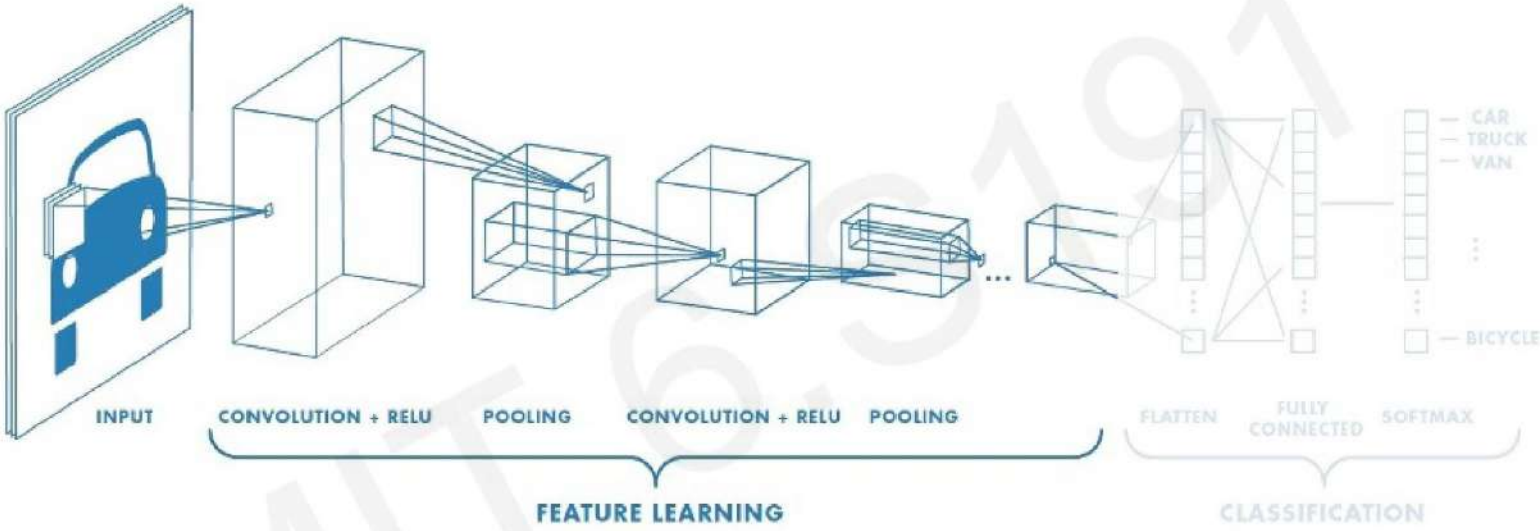
1) Reduced dimensionality
2) Spatial invariance

How else can we downsample and preserve spatial invariance?

Representation Learning in Deep CNNs

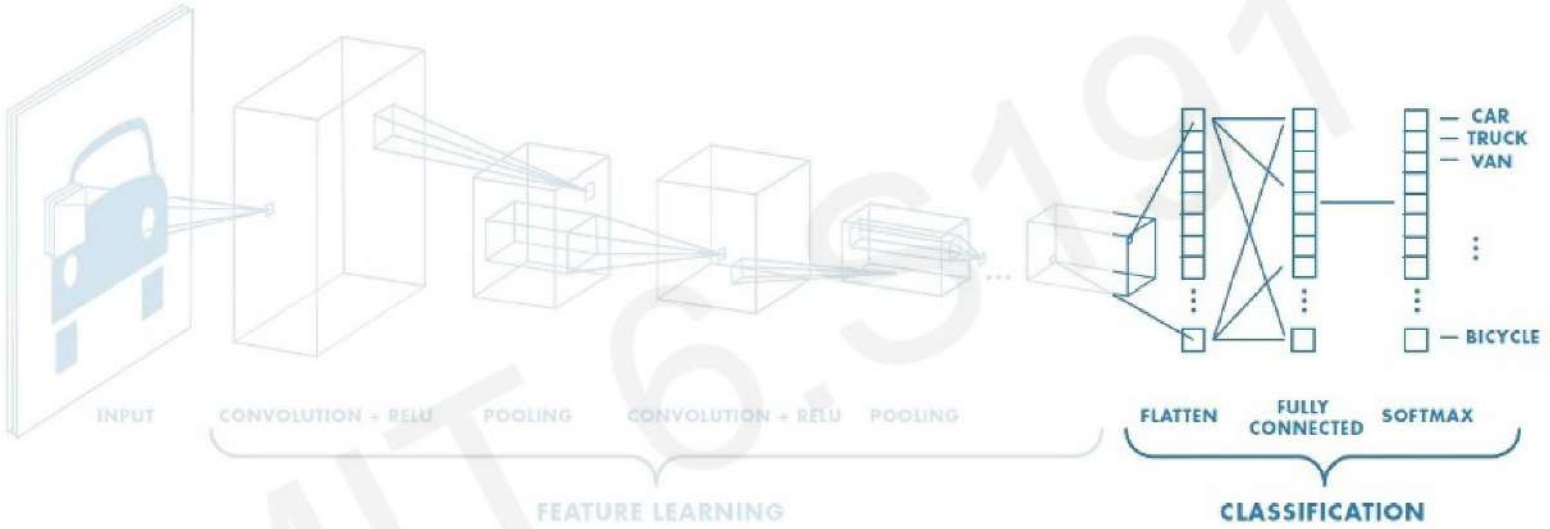


CNNs for Classification: Feature Learning



1. Learn features in input image through **convolution**
2. Introduce **non-linearity** through activation function (real-world data is non-linear!)
3. Reduce dimensionality and preserve spatial invariance with **pooling**

CNNs for Classification: Class Probabilities

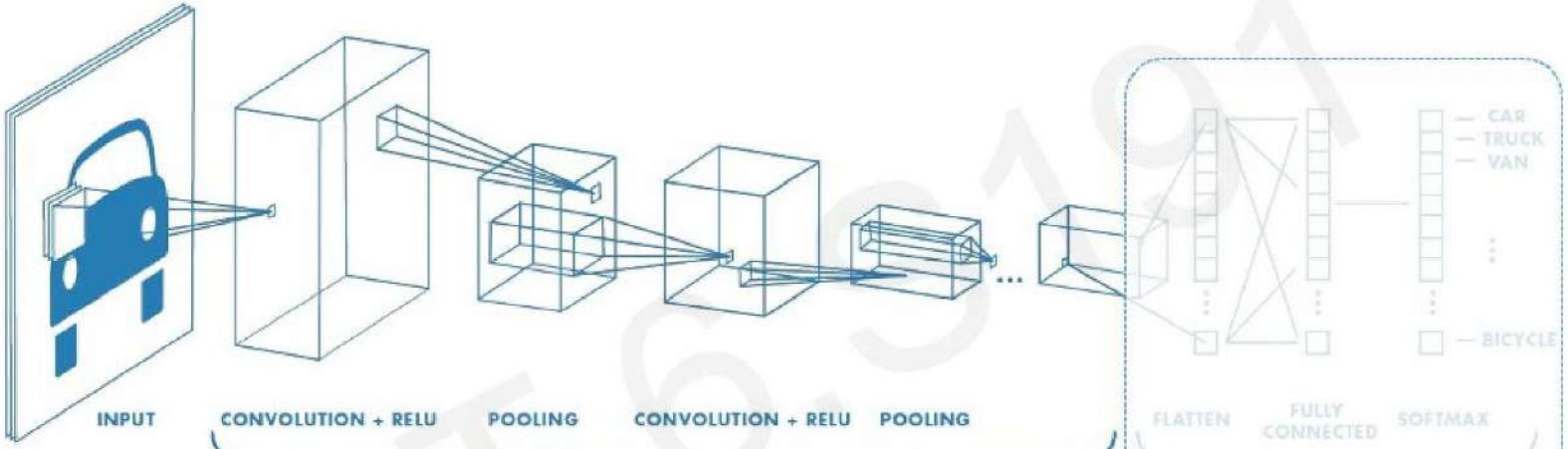


- CONV and POOL layers output high-level features of input
- Fully connected layer uses these features for classifying input image
- Express output as **probability** of image belonging to a particular class

$$\text{softmax}(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

An Architecture for Many Applications

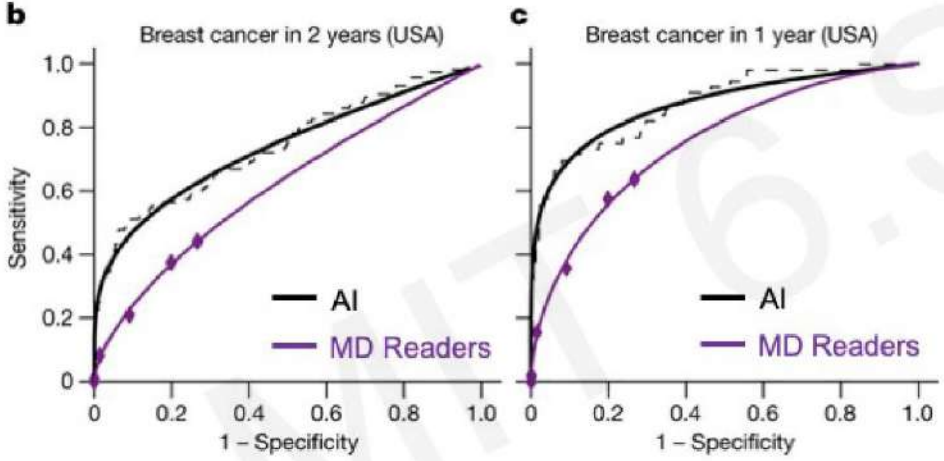
An Architecture for Many Applications



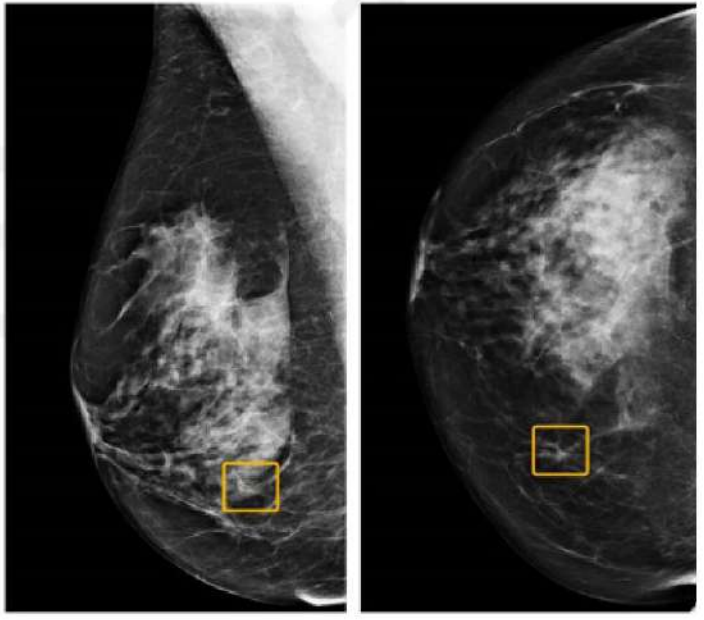
Classification
Object detection
Segmentation
Probabilistic control

Classification: Breast Cancer Screening

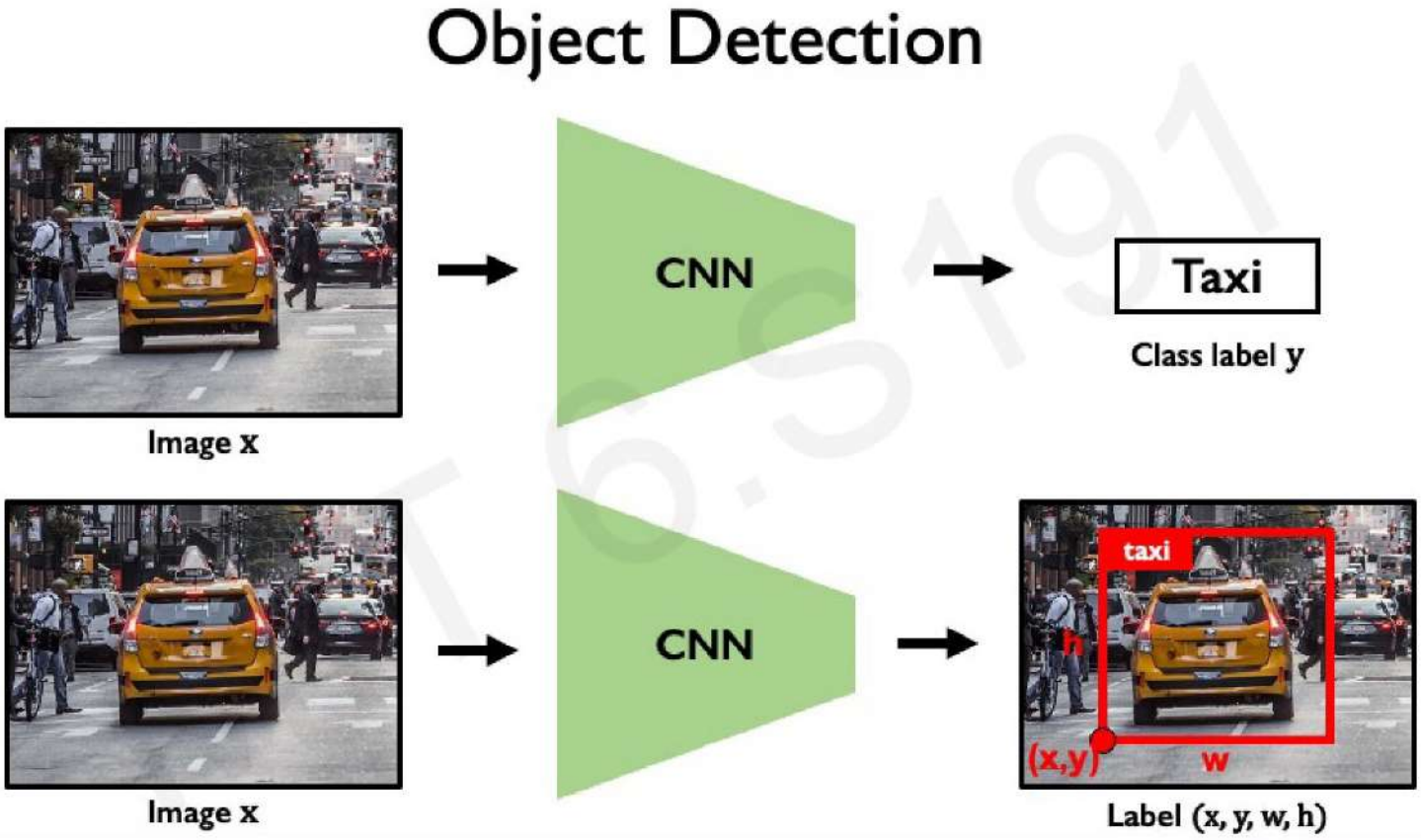
International evaluation of an AI system for breast cancer screening nature



CNN-based system outperformed expert radiologists at detecting breast cancer from mammograms

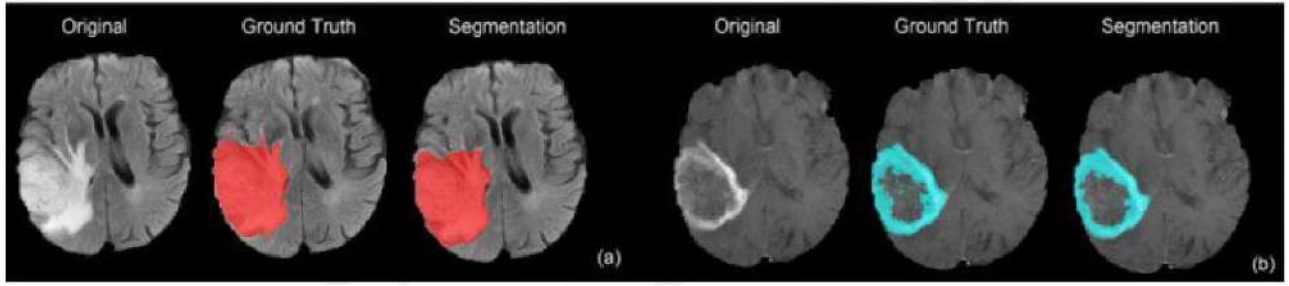


Breast cancer case missed by radiologist but detected by AI

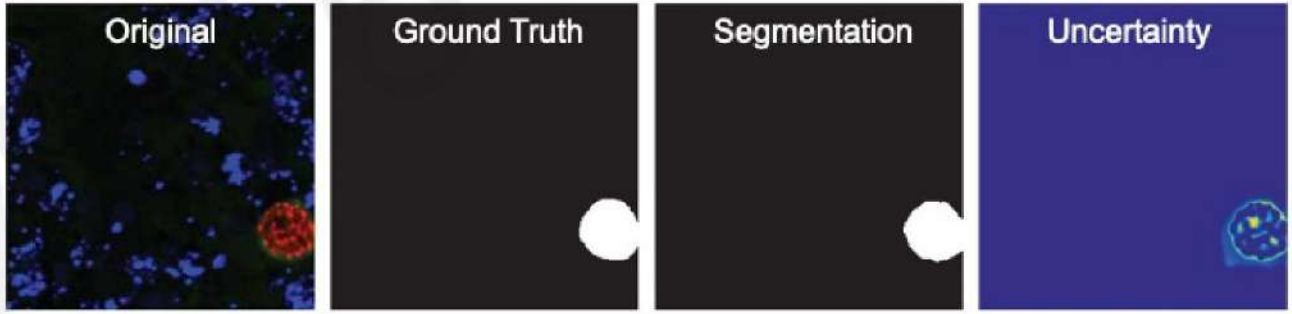

Object Detection
CNN
Taxi
Class label y
Image x
CNN
taxi
h
(x,y)
w
Image x
Label (x, y, w, h)

Semantic Segmentation: Biomedical Image Analysis

Brain Tumors
Dong+ *MIUA* 2017.



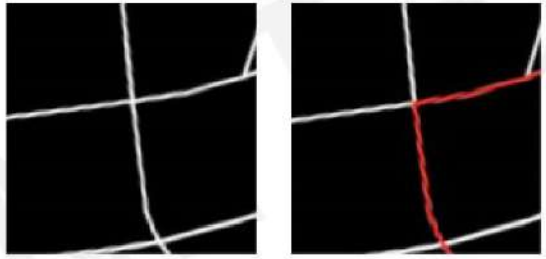
Malaria Infection
Soleimany+ *arXiv* 2019.

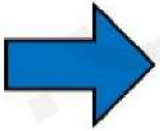


Continuous Control: Navigation from Vision

Raw Perception
I
(ex. camera)

Coarse Maps
M
(ex. GPS)

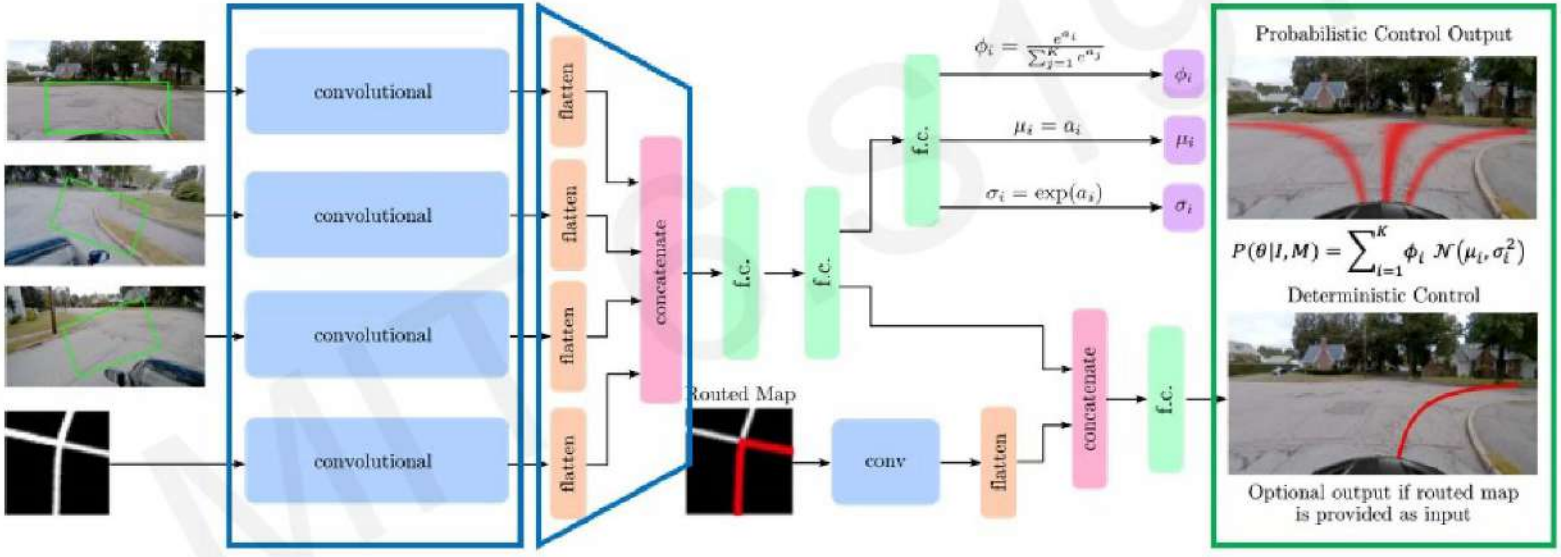




Possible Control Commands

End-to-End Framework for Autonomous Navigation

Entire model is trained end-to-end **without any human labelling or annotations**



$$L = -\log(P(\theta|I,M))$$

ImageNet： 深度学习热潮的关键推动者之一

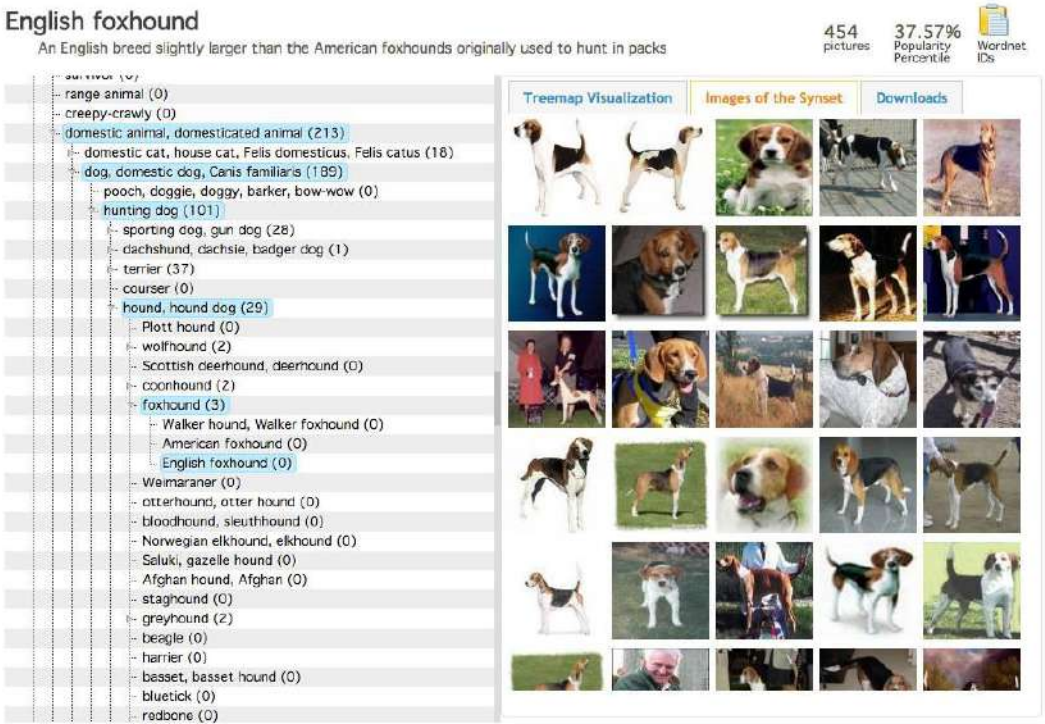
ImageNet 可以说是计算机视觉研究人员进行大规模物体识别和检测时，最先想到的视觉大数据来源。ImageNet 数据集最初由斯坦福大学李飞飞等人在 CVPR 2009 的一篇论文中推出。

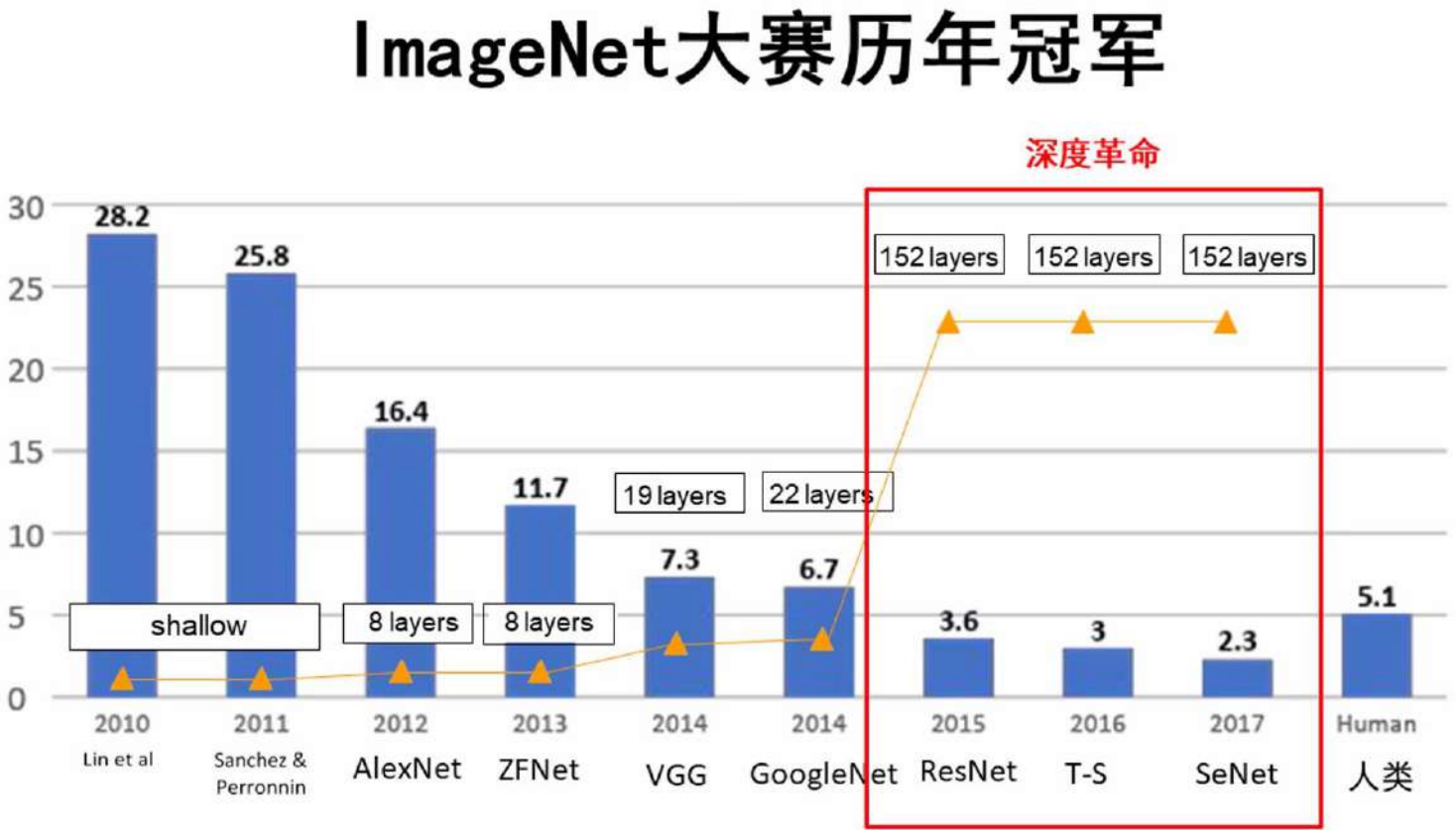
ImageNet Dataset

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., ... & Fei-Fei, L. (2015). Imagenet large scale visual recognition challenge. *arXiv preprint arXiv:1409.0575*. [web]

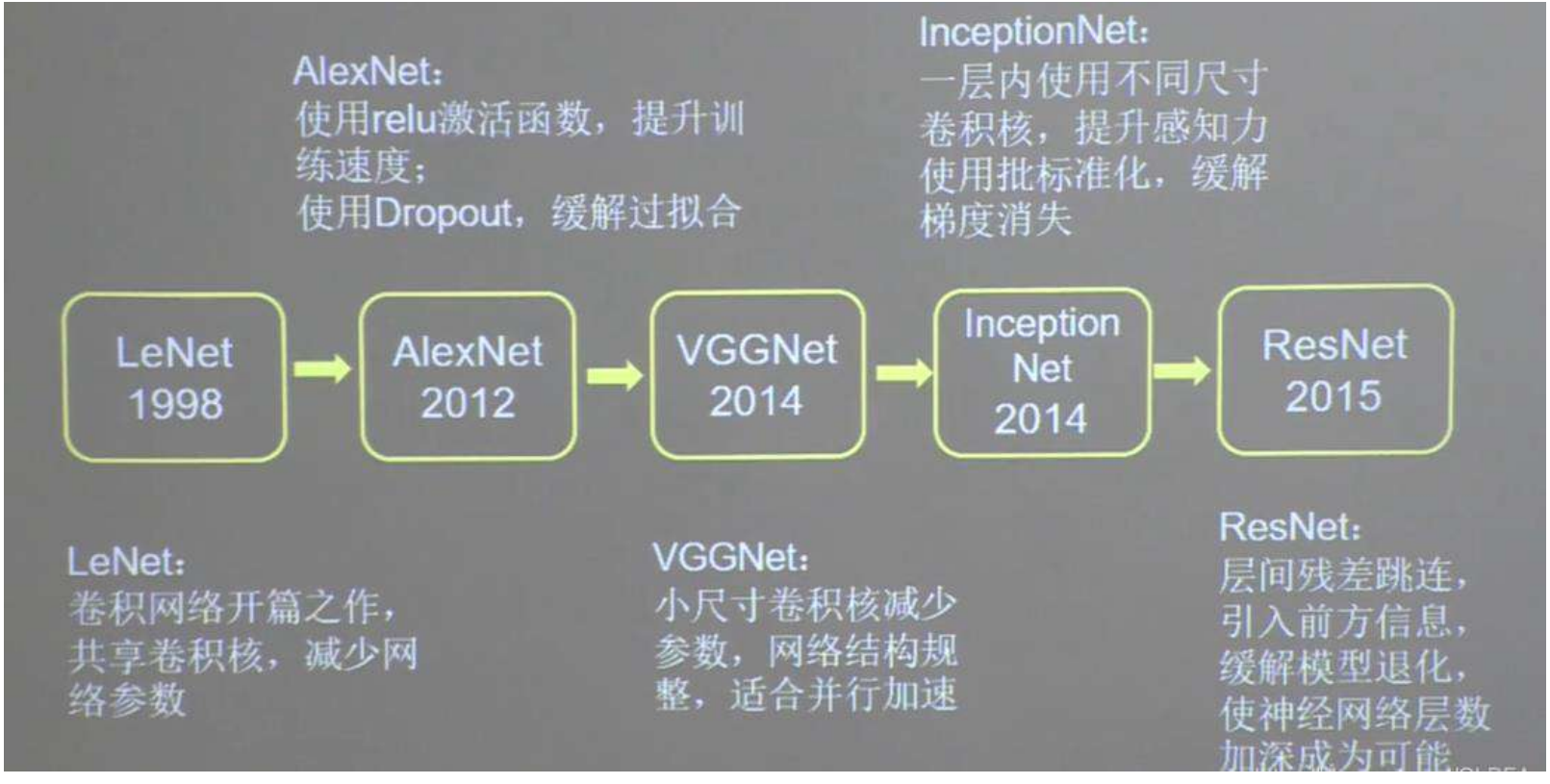
人工智能基本理论

截至 2016 年，ImageNet 中含有超过 1500 万由人手工注释的图片网址，也就是带标签的图片，标签说明了图片中的内容，超过 2.2 万个类别。




ImageNet大赛历年冠军
深度革命
30
25
20
15
10
5
0
28.2
25.8
16.4
11.7
7.3
6.7
3.6
3
2.3
5.1
shallow
8 layers
8 layers
19 layers
22 layers
152 layers
152 layers
152 layers
2010
Lin et al
2011
Sanchez & Perronnin
2012
AlexNet
2013
ZFNet
2014
VGG
2014
GoogleNet
2015
ResNet
2016
T-S
2017
SeNet
Human
人类

经典的卷积网络


AlexNet:
使用relu激活函数，提升训练速度；
使用Dropout，缓解过拟合
InceptionNet:
一层内使用不同尺寸卷积核，提升感知力
使用批标准化，缓解梯度消失
LeNet 1998
AlexNet 2012
VGGNet 2014
Inception Net 2014
ResNet 2015
LeNet:
卷积网络开篇之作，共享卷积核，减少网络参数
VGGNet:
小尺寸卷积核减少参数，网络结构规整，适合并行加速
ResNet:
层间残差跳连，引入前方信息，缓解模型退化，使神经网络层数加深成为可能

LeNet

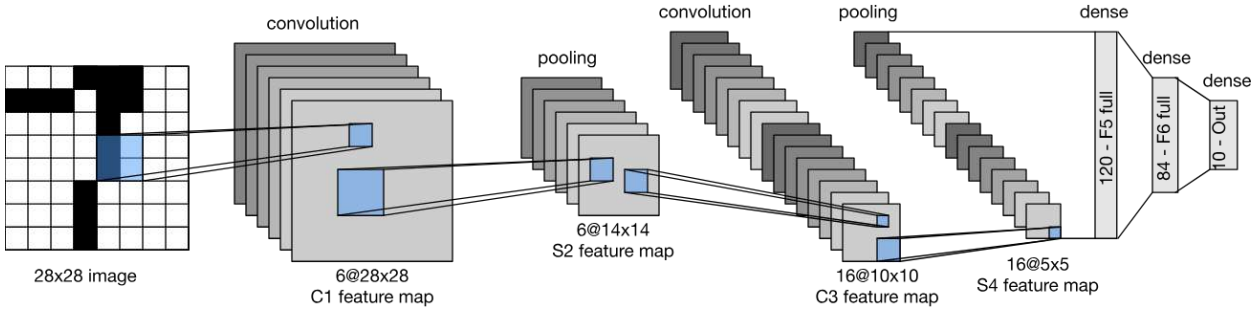
LeNet是最早的CNN架构之一,由Yann LeCun等人于1998年提出,用于手写数字识别。
它的结构如下:

```
INPUT => CONV => POOL => CONV => POOL => FC => FC => OUTPUT
```

其中:

- CONV: 卷积层,提取局部特征
- POOL: 池化层,降低特征维度
- FC: 全连接层,进行分类

LeNet的创新之处在于引入了卷积层和池化层,极大地减少了网络参数,提高了模型的泛化能力。



AlexNet

AlexNet是2012年ImageNet大赛的冠军模型,由Alex Krizhevsky等人提出,被认为是深度学习在计算机视觉领域的开端。它的结构如下:

```
INPUT => CONV => POOL => CONV => POOL => CONV => CONV => CONV => POOL => FC => FC => FC => OUTPUT
```

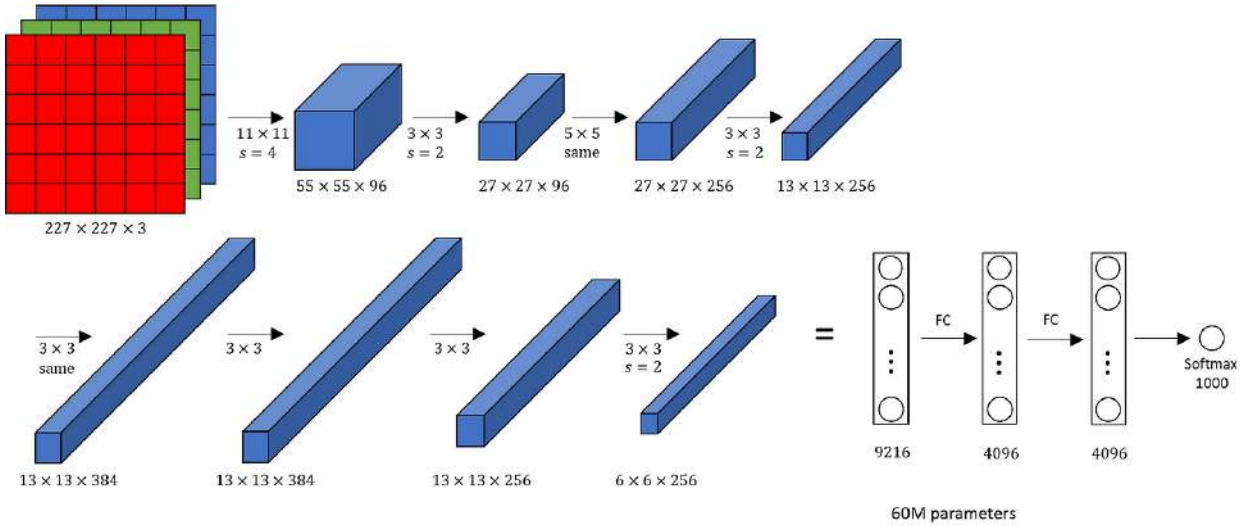
AlexNet的主要创新点包括:

1.使用了ReLU激活函数,提高了训练效率。

2.引入了Dropout技术,有效缓解了过拟合问题。

3.利用GPU并行计算,大大加快了训练速度。

4.数据增强技术,如翻转、裁剪等,增加了训练数据的多样性。

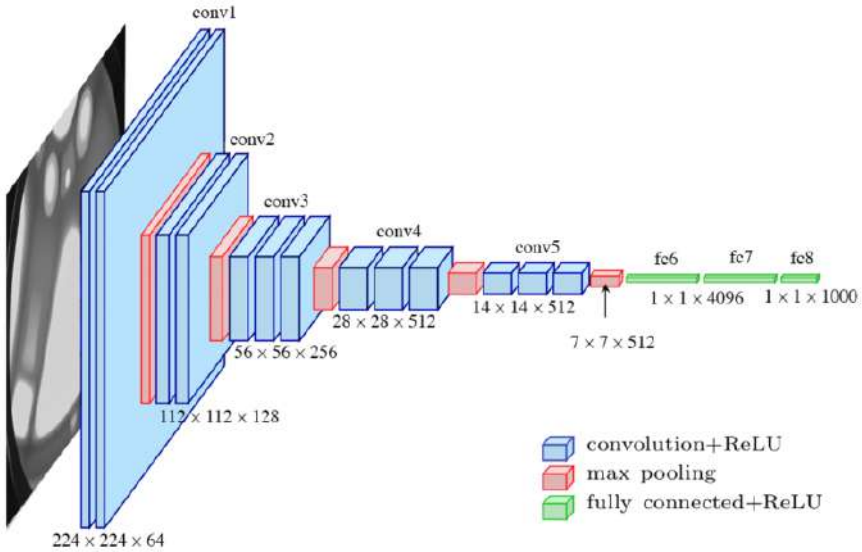


VGGNet

VGGNet是2014年ImageNet大赛的亚军模型,由Karen Simonyan和Andrew Zisserman提出。它的结构如下:

```
INPUT => CONV => CONV => POOL => CONV => CONV => POOL => CONV => CONV => CONV => POOL =>
CONV => CONV => CONV => POOL => CONV => CONV => CONV => POOL => FC => FC => FC => OUTPUT
```

VGGNet的特点是使用了连续的3x3小卷积核,代替了AlexNet中的大卷积核,提高了非线性表达能力。同时,VGGNet也探索了不同深度的网络结构,发现深度对提高性能至关重要。



VGGNet

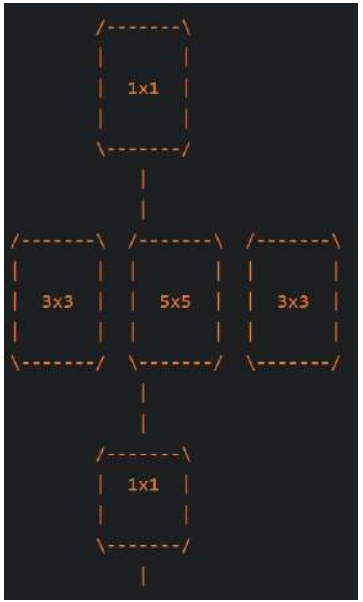
```
INPUT: [224x224x3]        memory:  224*224*3=150K   weights: 0
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*64)*64 = 36,864
POOL2: [112x112x64]  memory:  112*112*64=800K   weights: 0
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*128)*128 = 147,456
POOL2: [56x56x128]  memory:  56*56*128=400K   weights: 0
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
POOL2: [28x28x256]  memory:  28*28*256=200K   weights: 0
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512]  memory:  14*14*512=100K   weights: 0
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512]  memory:  7*7*512=25K  weights: 0
FC: [1x1x4096]  memory:  4096  weights: 7*7*512*4096 = 102,760,448
FC: [1x1x4096]  memory:  4096  weights: 4096*4096 = 16,777,216
FC: [1x1x1000]  memory:  1000 weights: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters
```

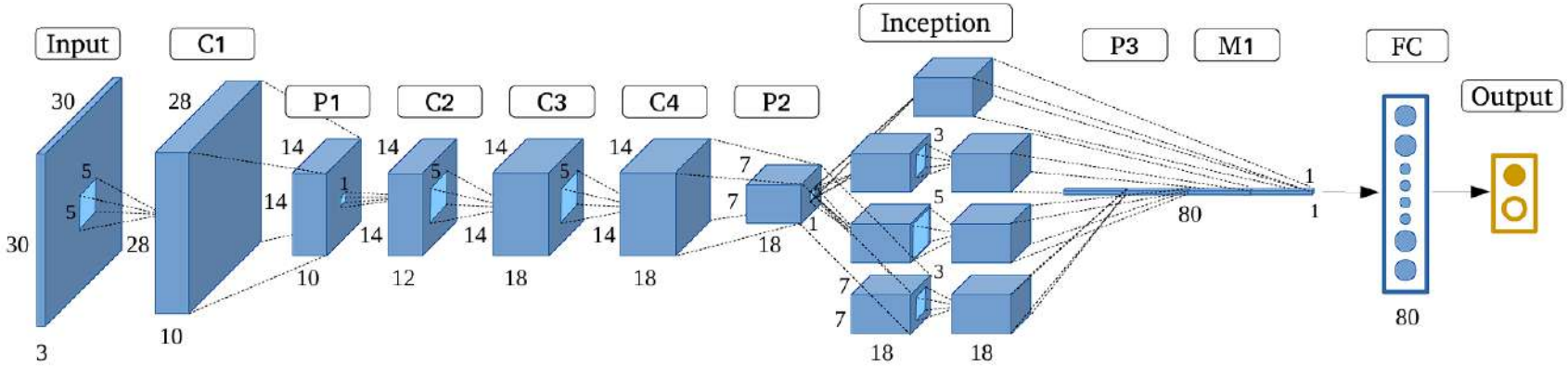
人工智能基本理论

GoogLeNet(Inception)

GoogLeNet是2014年ImageNet大赛的冠军模型,由Christian Szegedy等人提出。它的核心是Inception模块,如下所示:

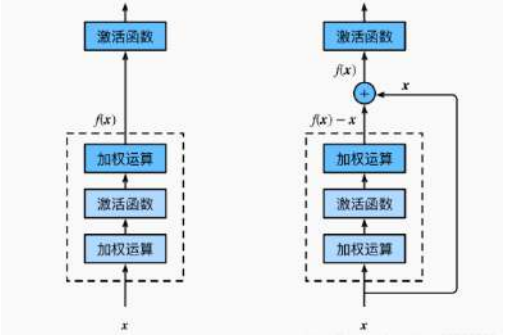


Inception模块通过并行的卷积核组合,提高了网络的表达能力,同时控制了参数数量。GoogLeNet还引入了辅助分类器,缓解了梯度消失问题。

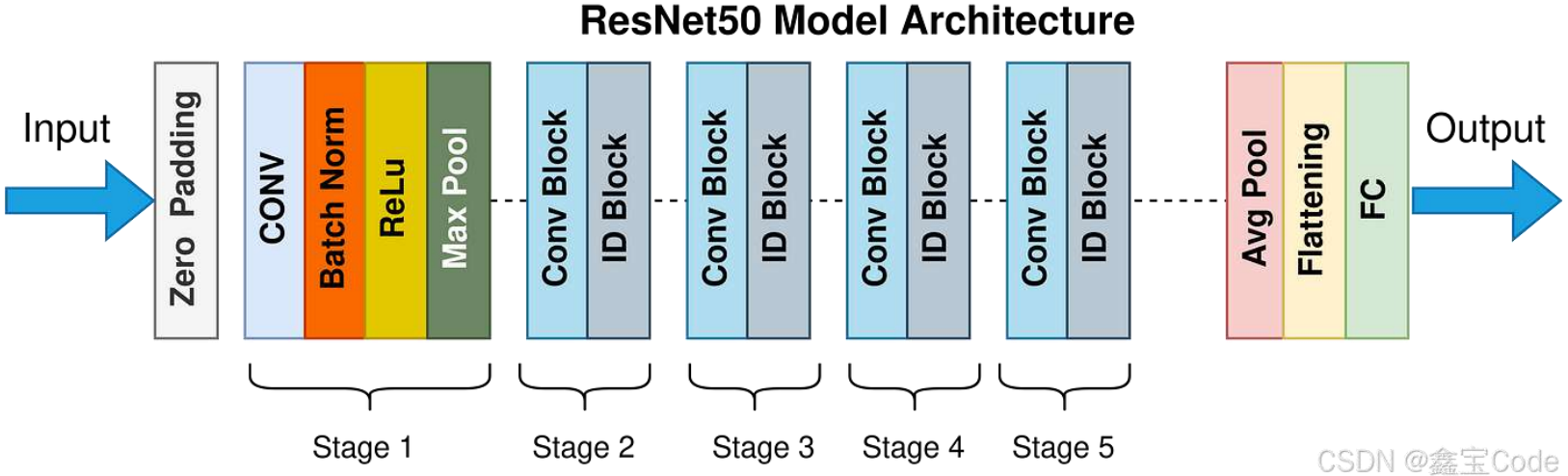


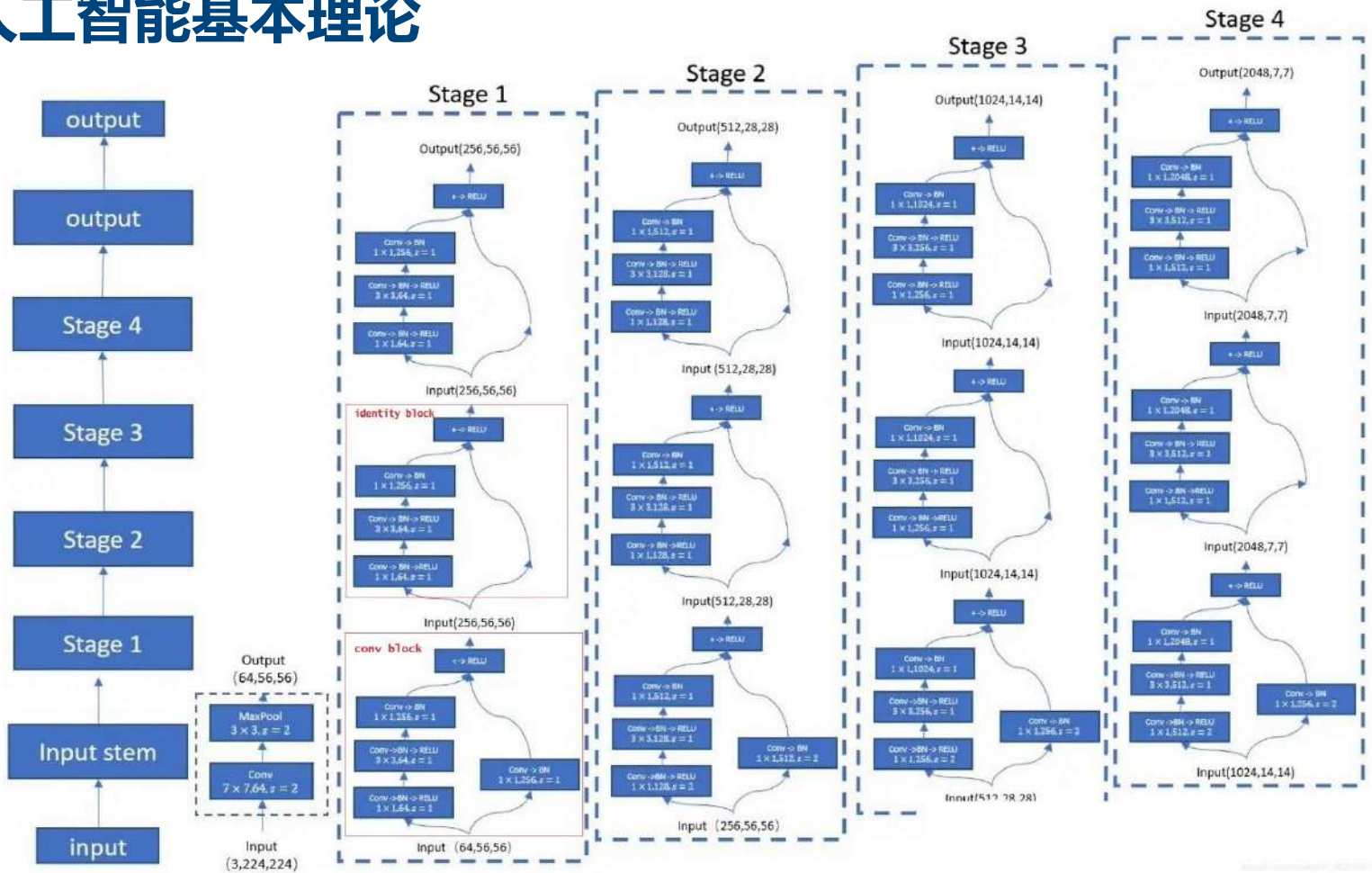
ResNet

ResNet是2015年ImageNet大赛的冠军模型,由Kaiming He等人提出。它的核心是残差模块(Residual Block),如下所示:



残差模块通过引入shortcut connection,使得梯度可以直接传递到较浅层,有效缓解了梯度消失/爆炸问题,从而可以训练出更深的网络。ResNet在ImageNet数据集上取得了极高的分类精度。




output
output
Stage 4
Stage 3
Stage 2
Stage 1
Input stem
input
Output
(64,56,56)
MaxPool
3 × 3, s = 2
Conv
7 × 7,64, s = 2
Input
(3,224,224)
Stage 1
Output(256,56,56)
Input(256,56,56)
identity block
Input(256,56,56)
conv block
Input (64,56,56)
Stage 2
Output(512,28,28)
Input (512,28,28)
Input(512,28,28)
Input (256,56,56)
Stage 3
Output(1024,14,14)
Input(1024,14,14)
Input(1024,14,14)
Stage 4
Output(2048,7,7)
Input(2048,7,7)
Input(2048,7,7)
Input(1024,14,14)

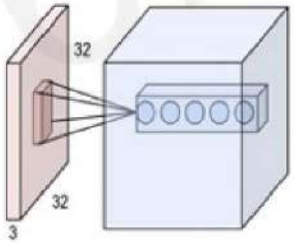
Deep Learning for Computer Vision: Summary

Foundations

- Why computer vision?
- Representing images
- Convolutions for feature extraction

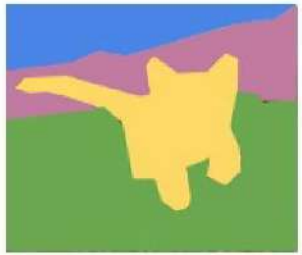
CNNs

- CNN architecture
- Application to classification
- ImageNet

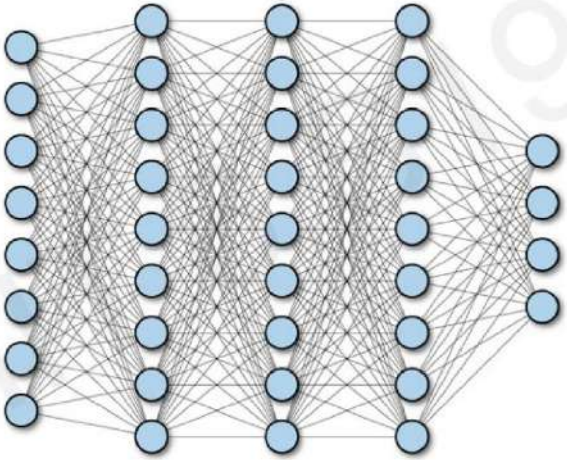


Applications

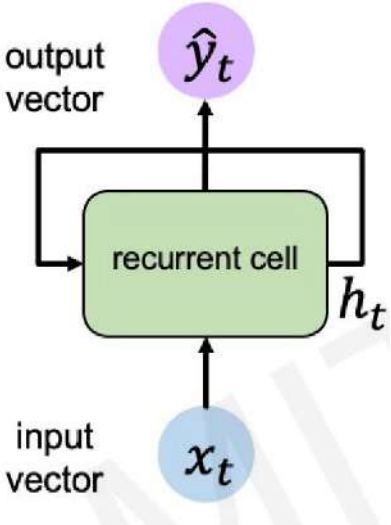
- Segmentation, image captioning, control
- Security, medicine, robotics



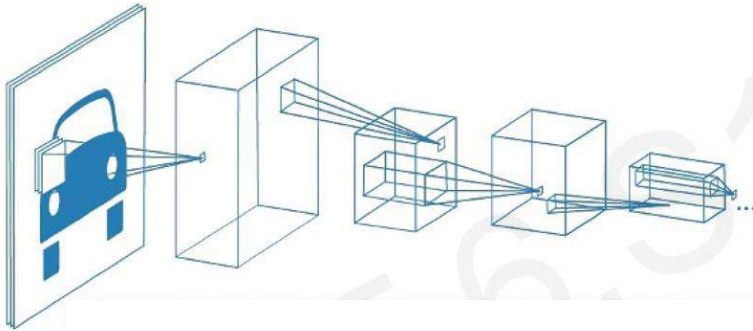
人工智能基本理论



前馈神经网络
MLP



循环神经网络
RNN



卷积神经网络
CNN

谢谢大家