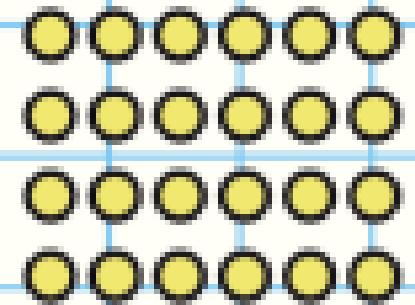
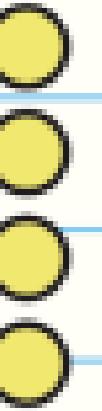


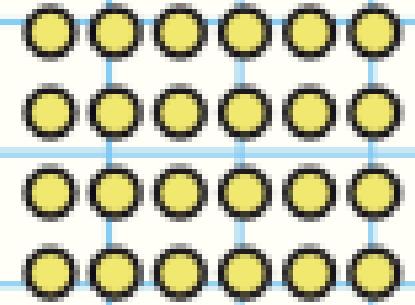


Artificial Intelligence





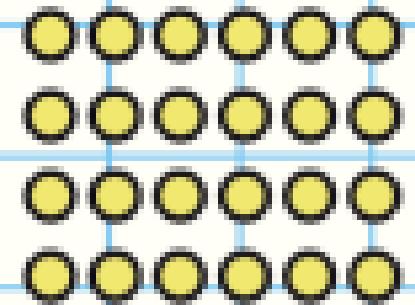
What do you know about AI?





Artificial Intelligence

Artificial Intelligence is the **science** and **art** of making computers **smart!**

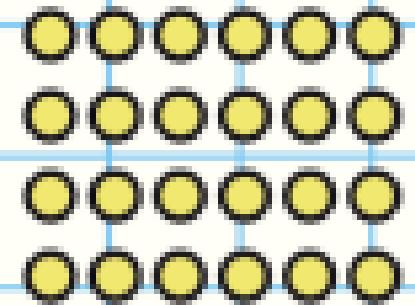


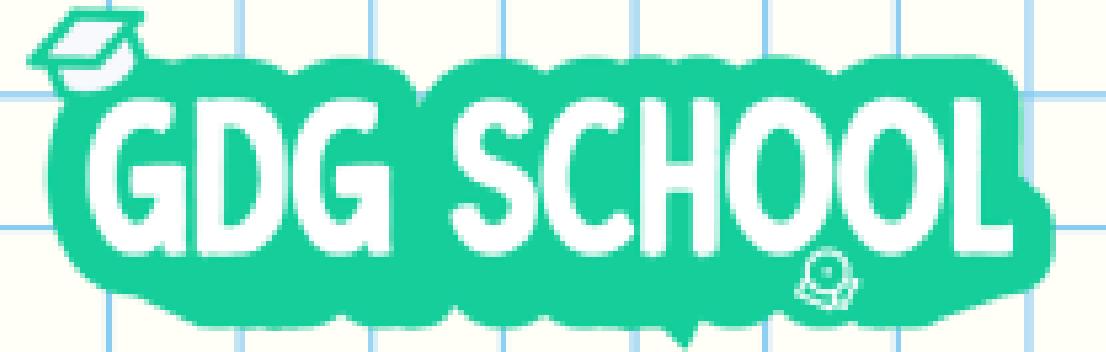


Why now!

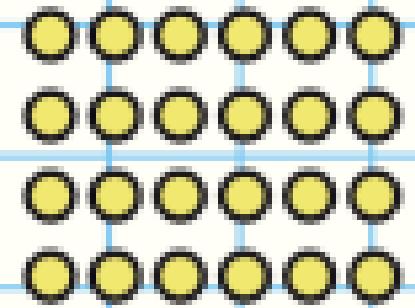
Data is everywhere!

Cool gamers!!





AI is around you!





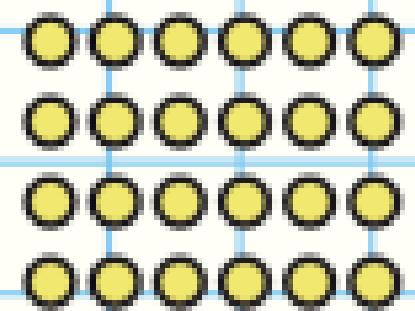
AI Workflow

Problem Statement

Data Collection → Data Pre-processing

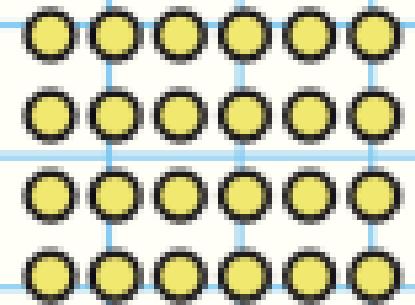
AI Modelling

Tests & Validation → Deployment





Machine Learning





Problem Statement

Study environment

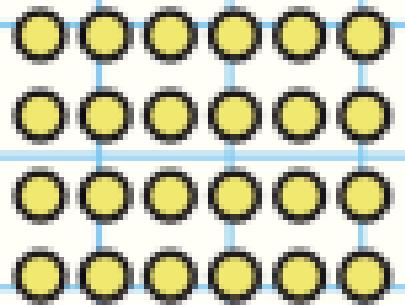
Discipline

Previous score

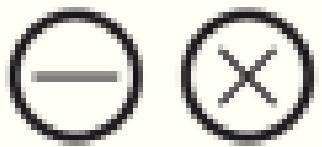
Predict Students' Academic Performance ?/20

Extracurricular Activity

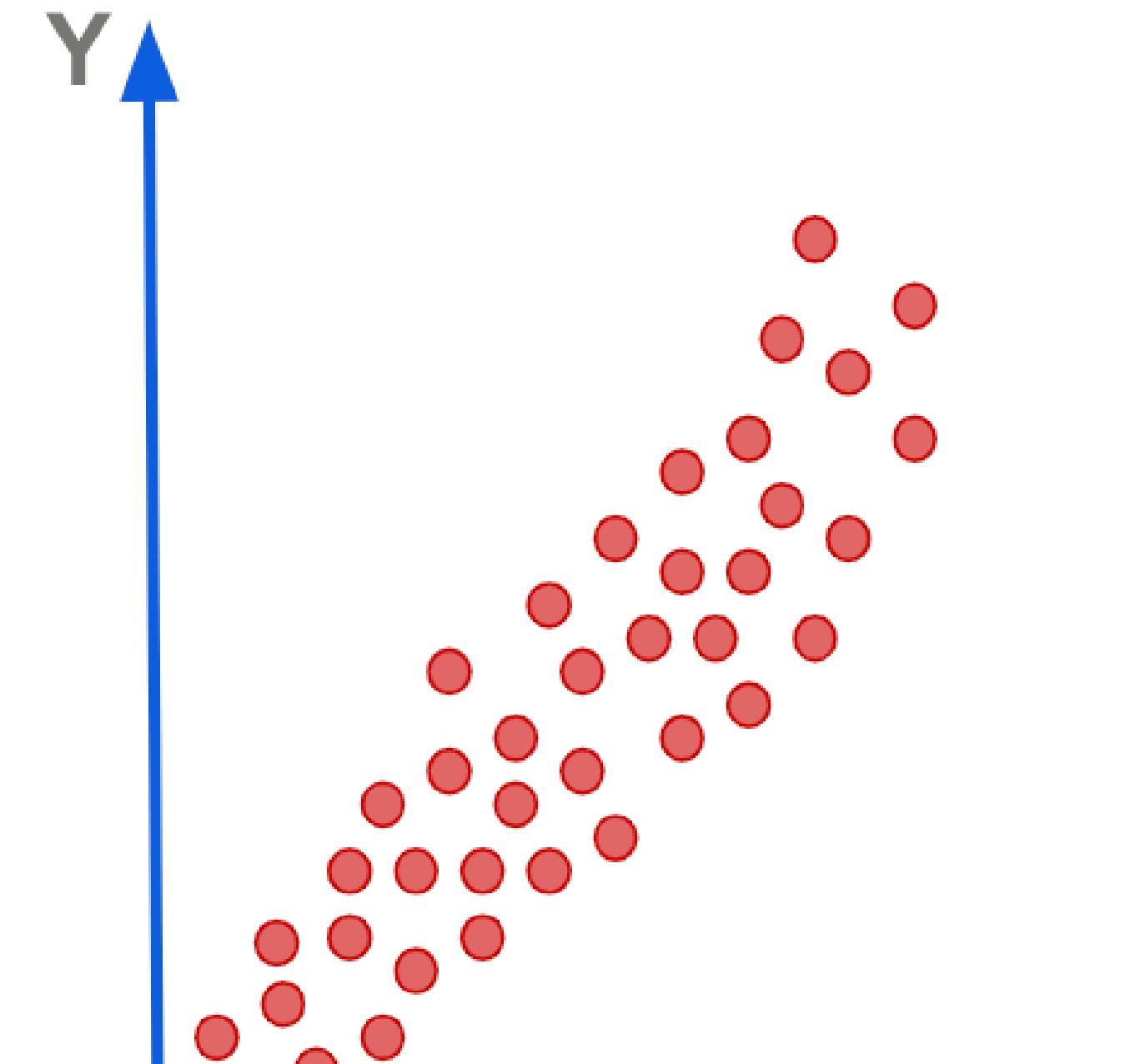
Well-being



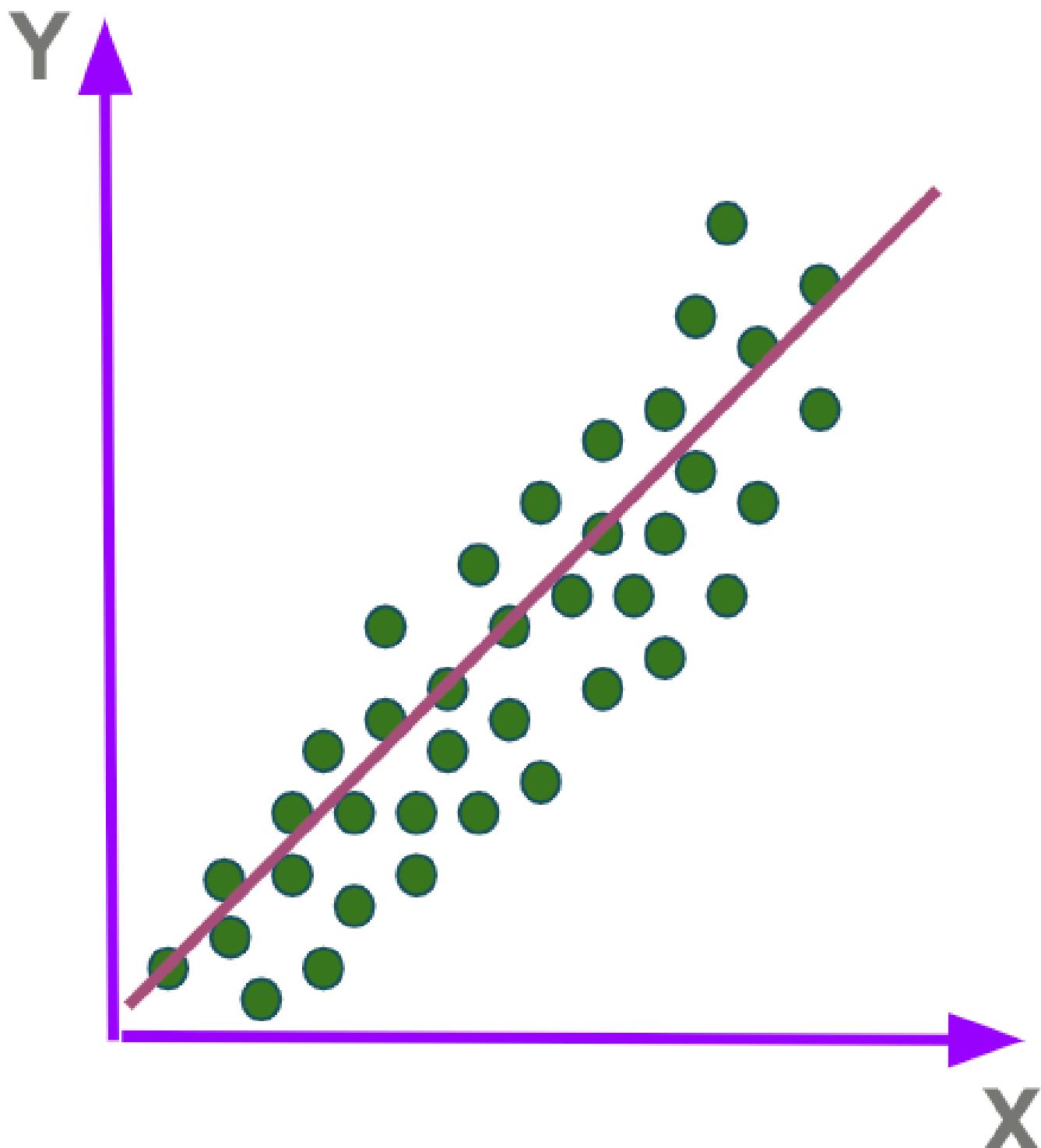
Linear Regression



Correlation



Linear Regression



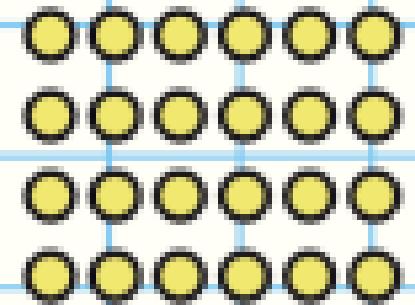


Formulation

Feature Vector (X) = $[x_1, x_2, x_3, \dots, x_n]$

Parameters (W, b) = $[w_1, w_2, w_3, \dots, w_n], b$

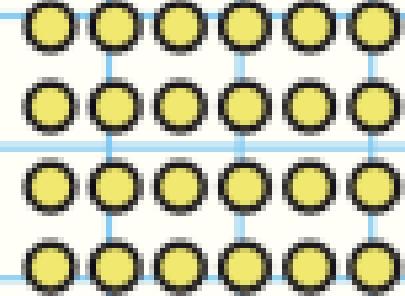
Prediction (y) = $w_1*x_1 + w_2*x_2 + \dots + w_n*x_n + b$





Intuition

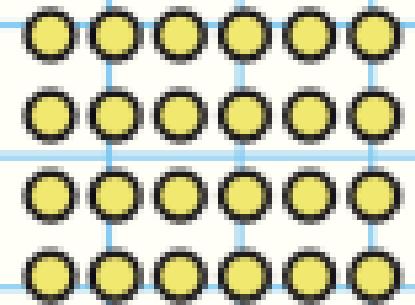
The **prediction** will be evaluated by **weighting** every **feature** in our input additional to a **baseline** value



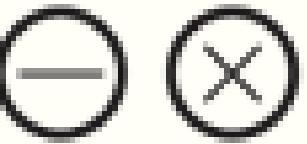


How to become smart ?

BY MAKING MISTAKES 😊



Loss function

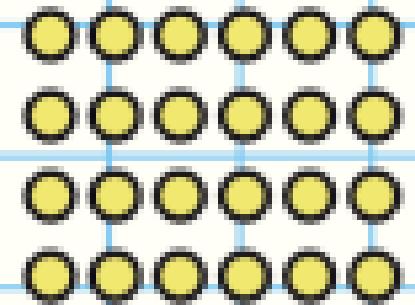


$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

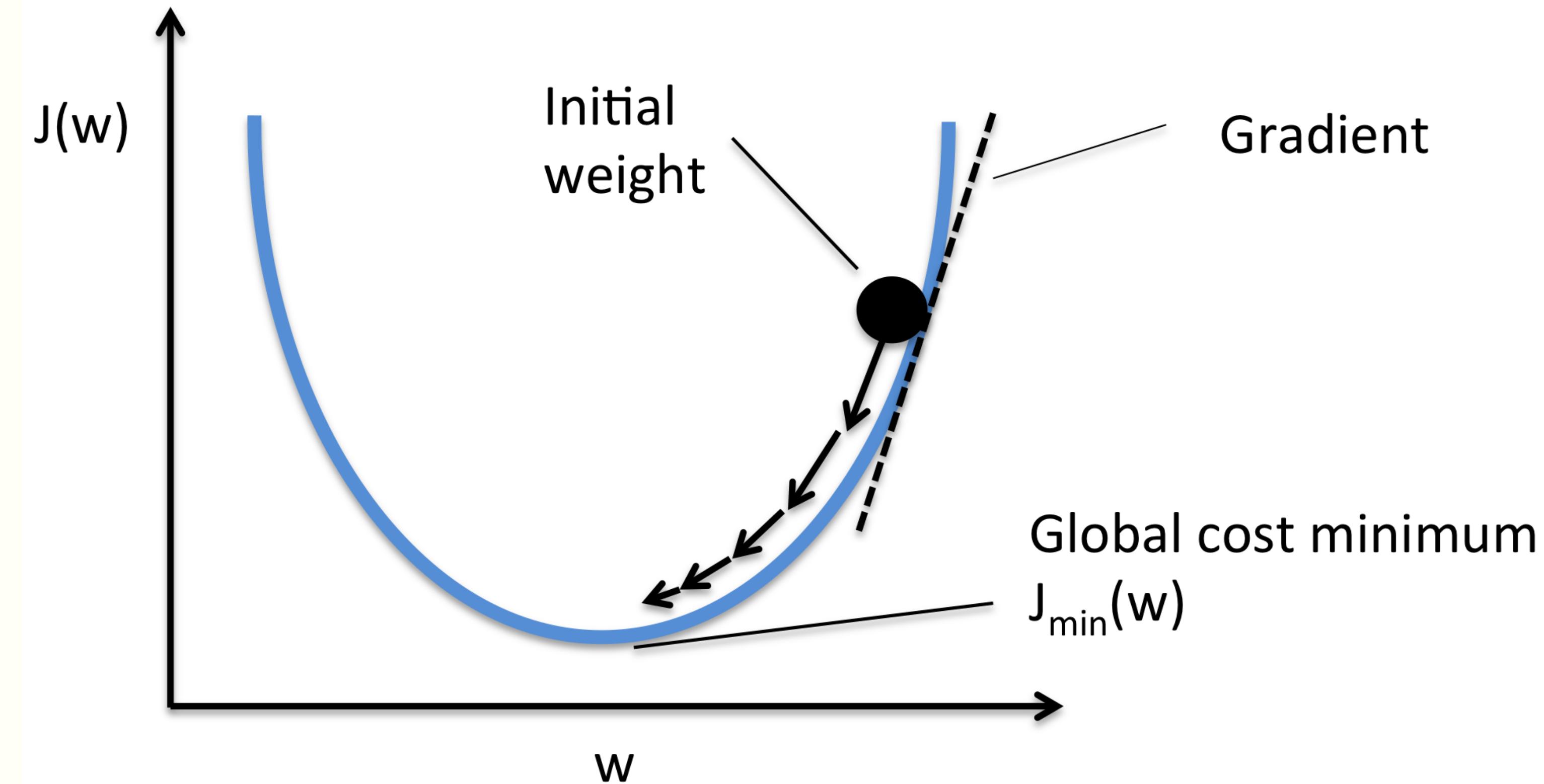
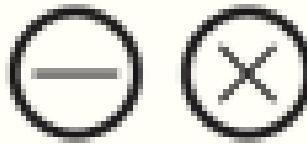


How to become really smart ?

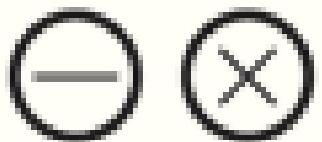
BY RUNNING DOWN THE HILL 😊



Gradient Descent



Everything together



- **W, b initialized randomly, learning_rate**
- **For every epoch:**
 - **For every pair (X,y):**
 - **Prediction = WX + b**
 - **Loss = MSE(Y, Prediction)**
 - **Param(i) -= learning_rate x gradient**



Problem Statement

Study environment

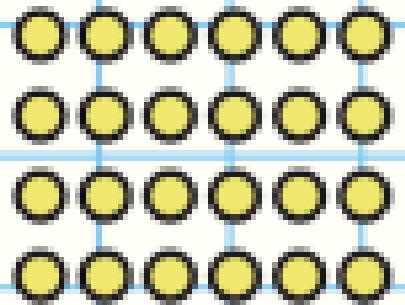
Discipline

Previous score

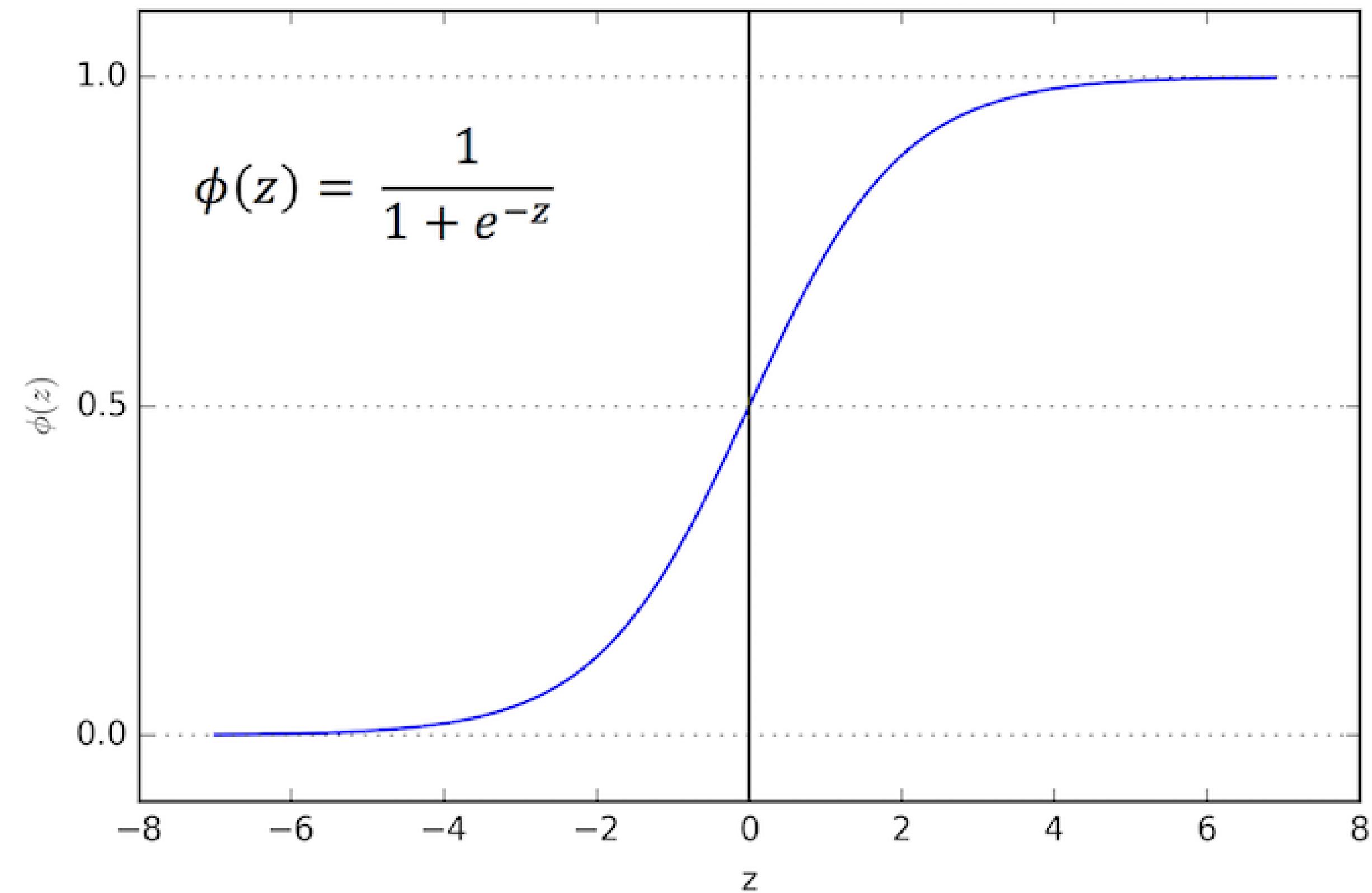
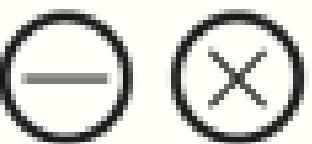
Predict Success/Failure of a Student

Extracurricular Activity

Well-being



Logistic Regression



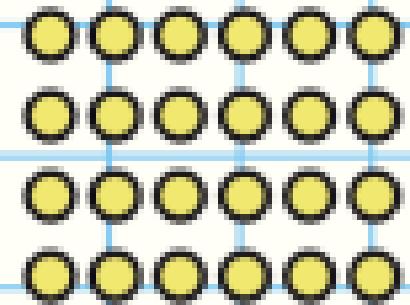


Formulation

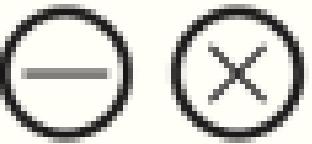
Feature Vector (X) = $[x_1, x_2, x_3, \dots, x_n]$

Parameters (W, b) = $[w_1, w_2, w_3, \dots, w_n], b$

Prediction (y) = sigmoid($w_1*x_1 + w_2*x_2 + \dots + w_n*x_n + b$)

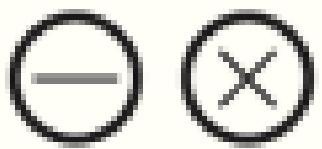


Loss function

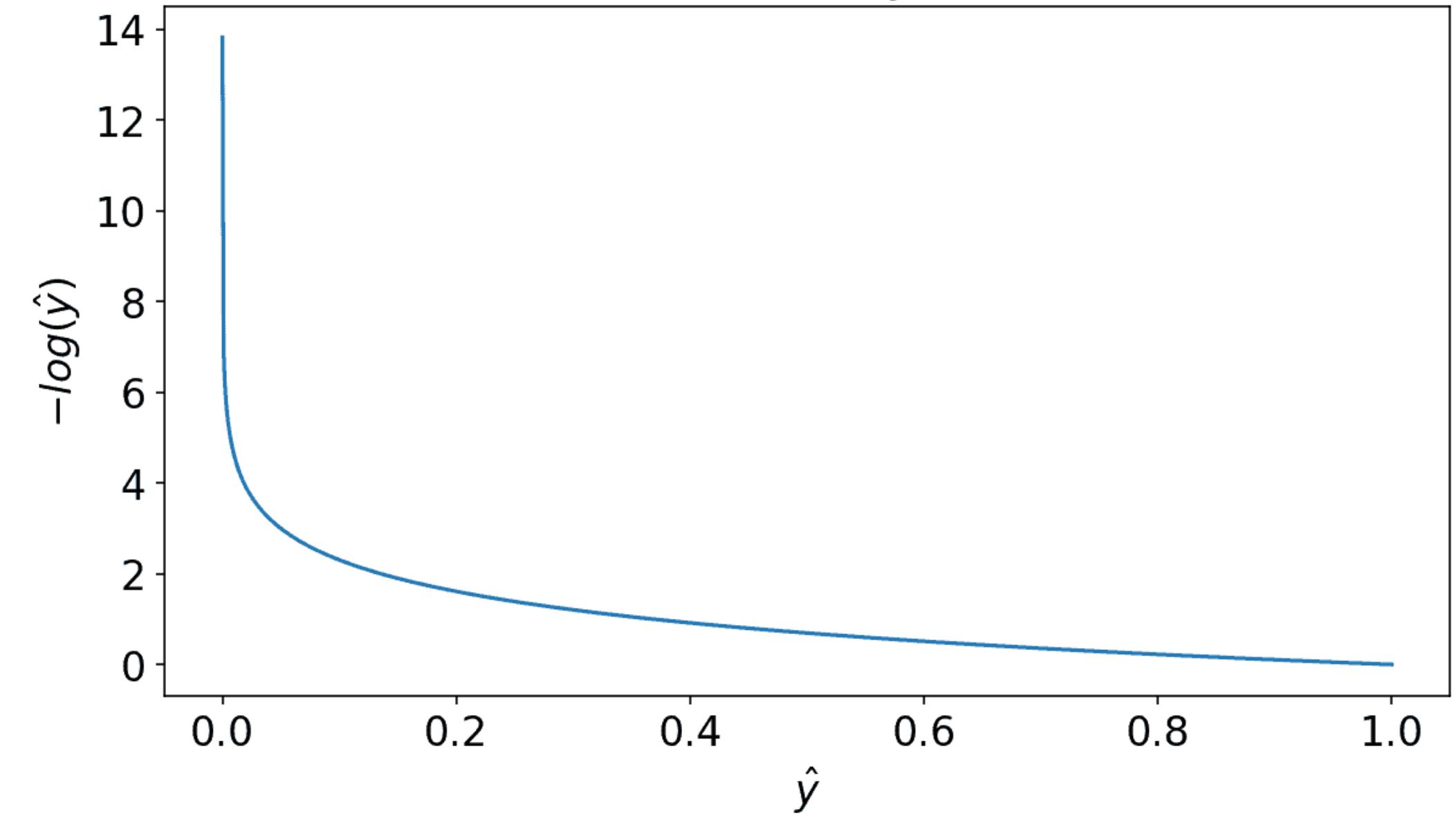


$$L_{BCE} = -\frac{1}{n} \sum_{i=1}^n (Y_i \cdot \log \hat{Y}_i + (1 - Y_i) \cdot \log (1 - \hat{Y}_i))$$

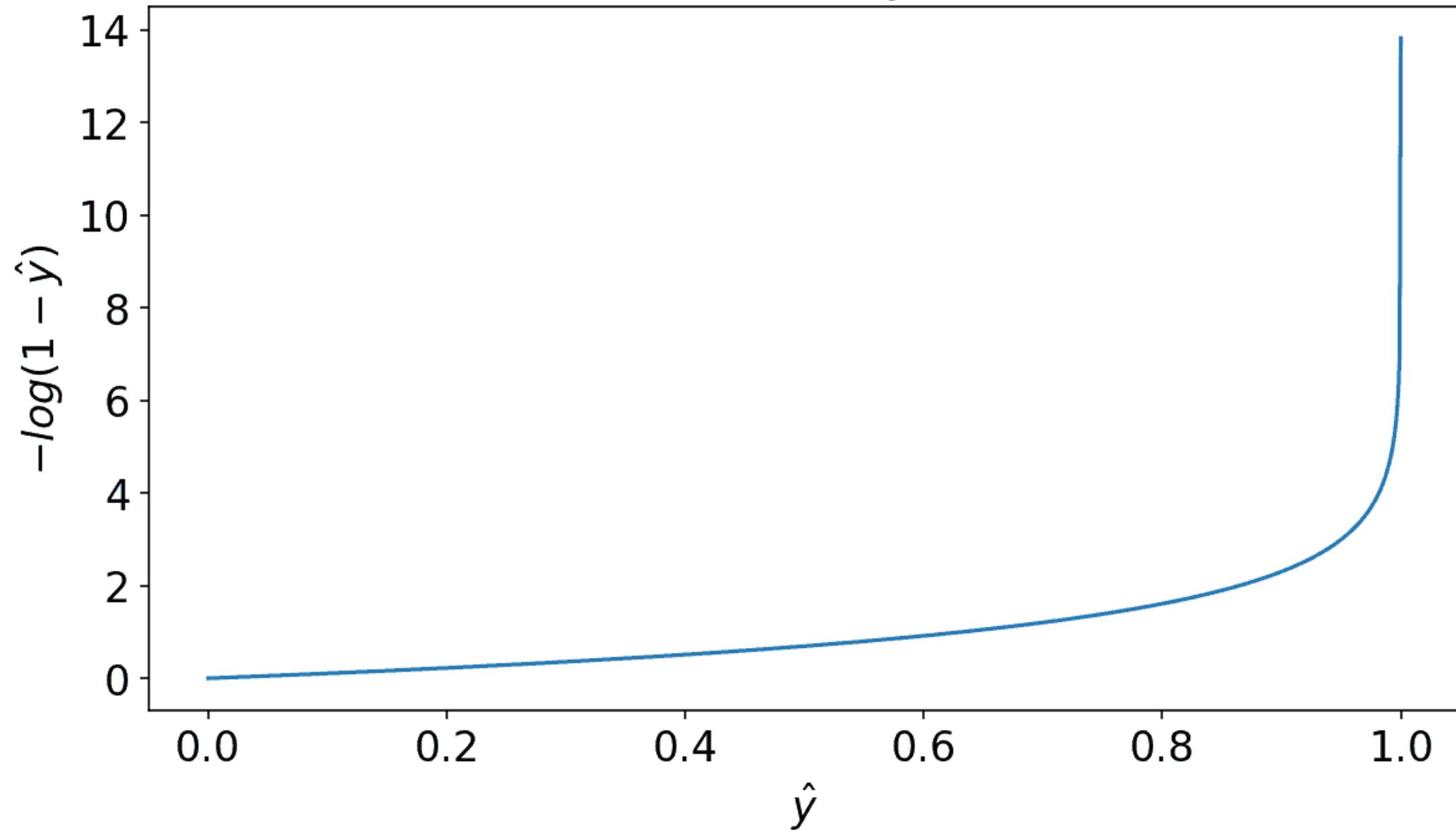
Loss function



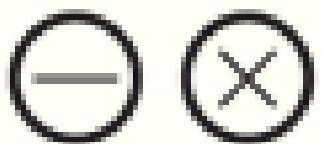
BCE loss when $y == 1$



BCE loss when $y == 0$

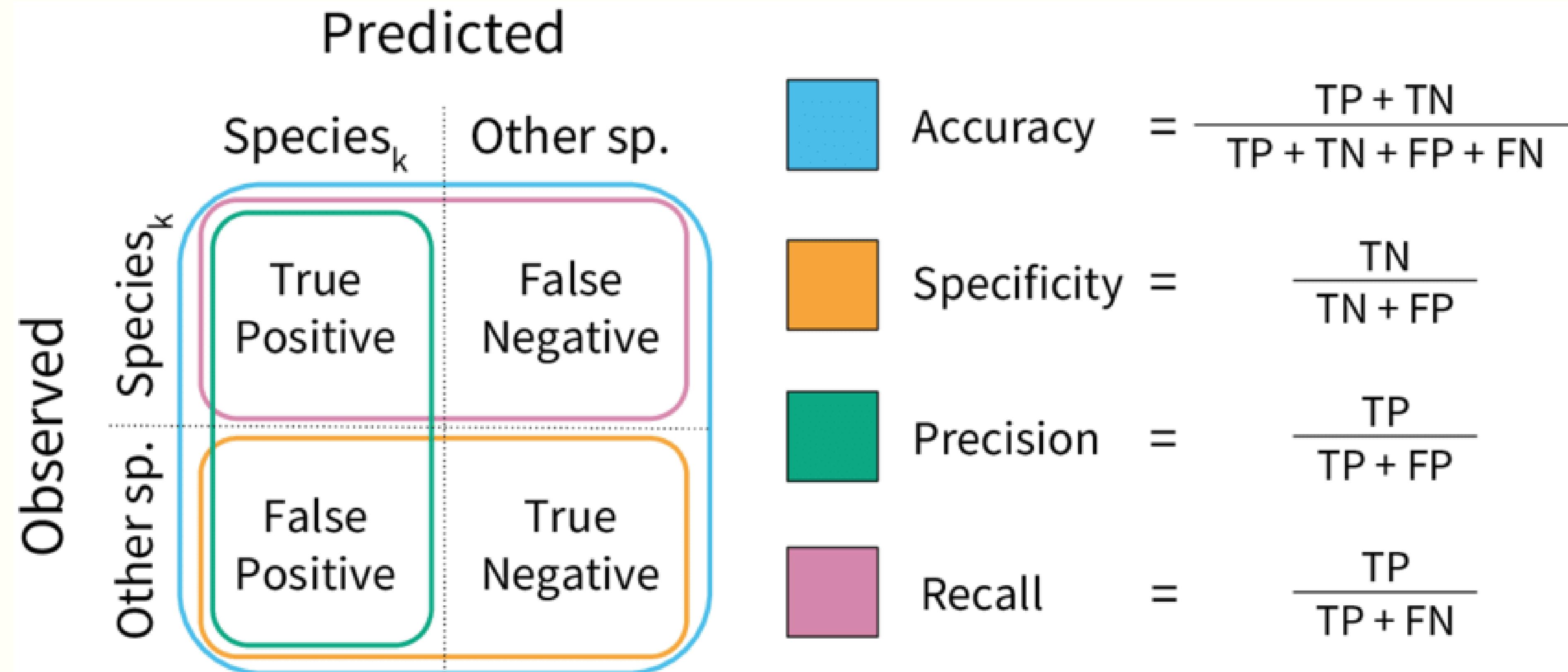
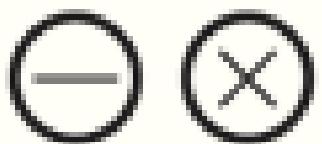


Gradient



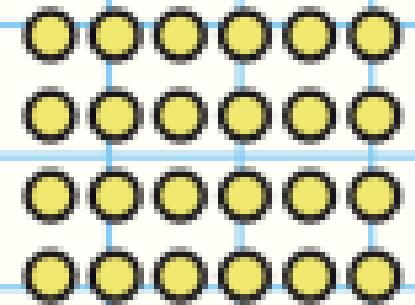
$$\frac{\partial L(W)}{\partial W} = \frac{\hat{y} - y}{\hat{y}(1 - \hat{y})} \hat{y}(1 - \hat{y})X = (\hat{y} - y)X \quad (12)$$

Classification Evaluation





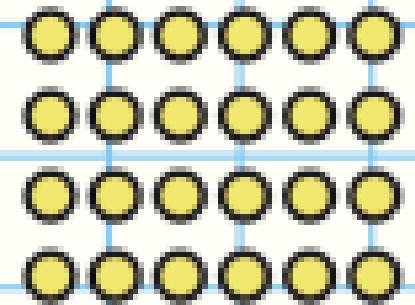
Deep Learning



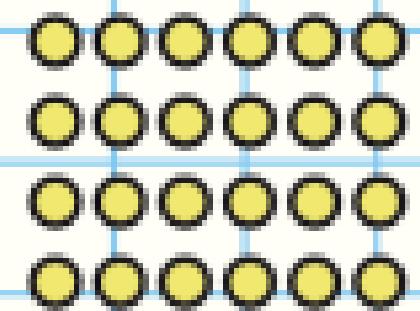
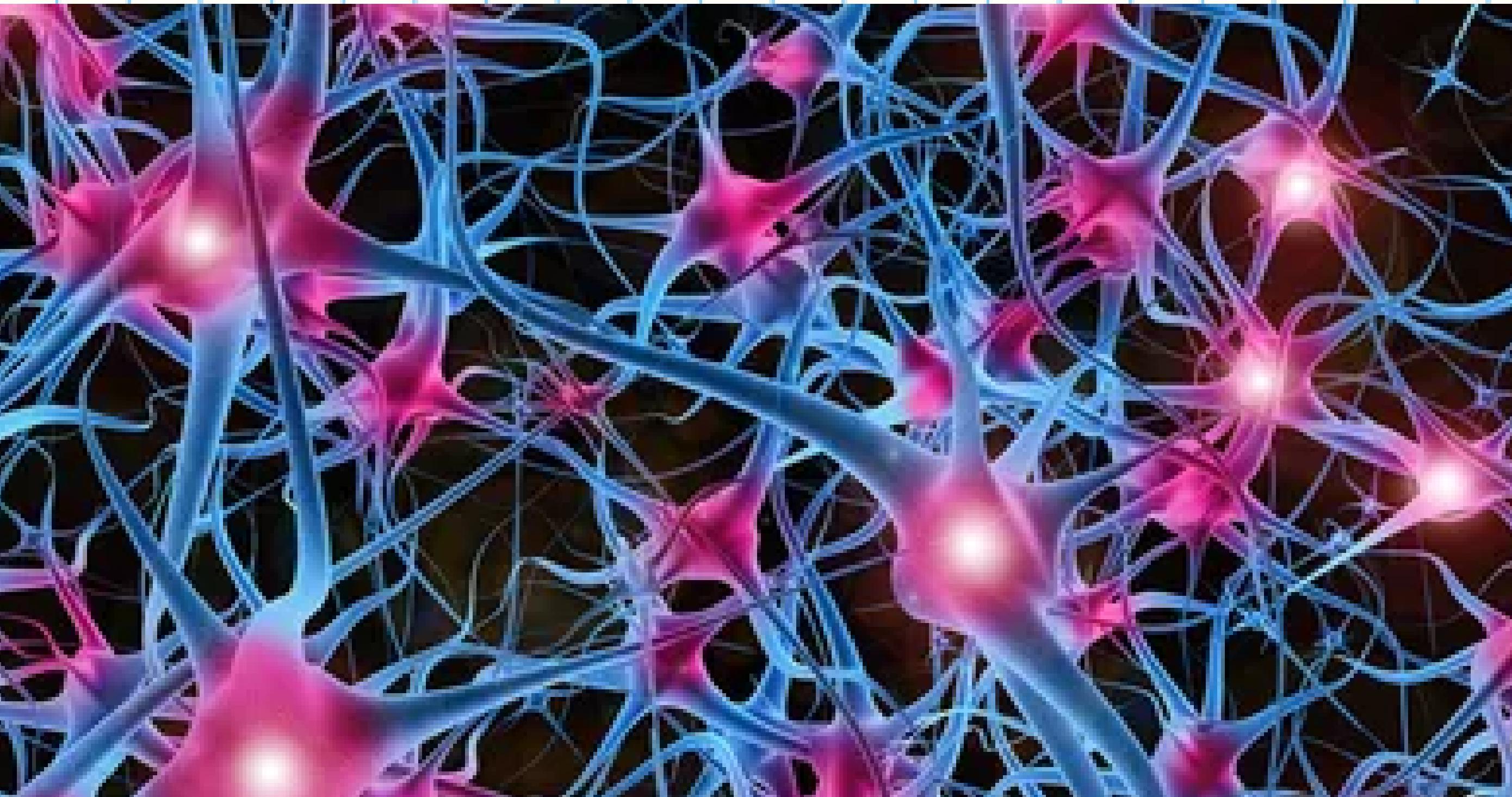


Deep Learning

**Problems can become harder implying
complex data patterns**

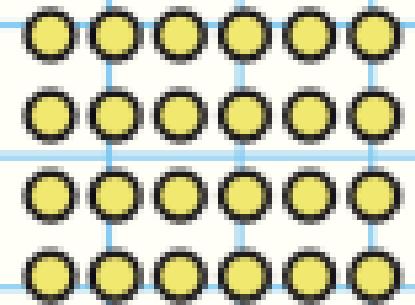


Biology ?!

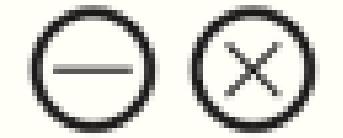




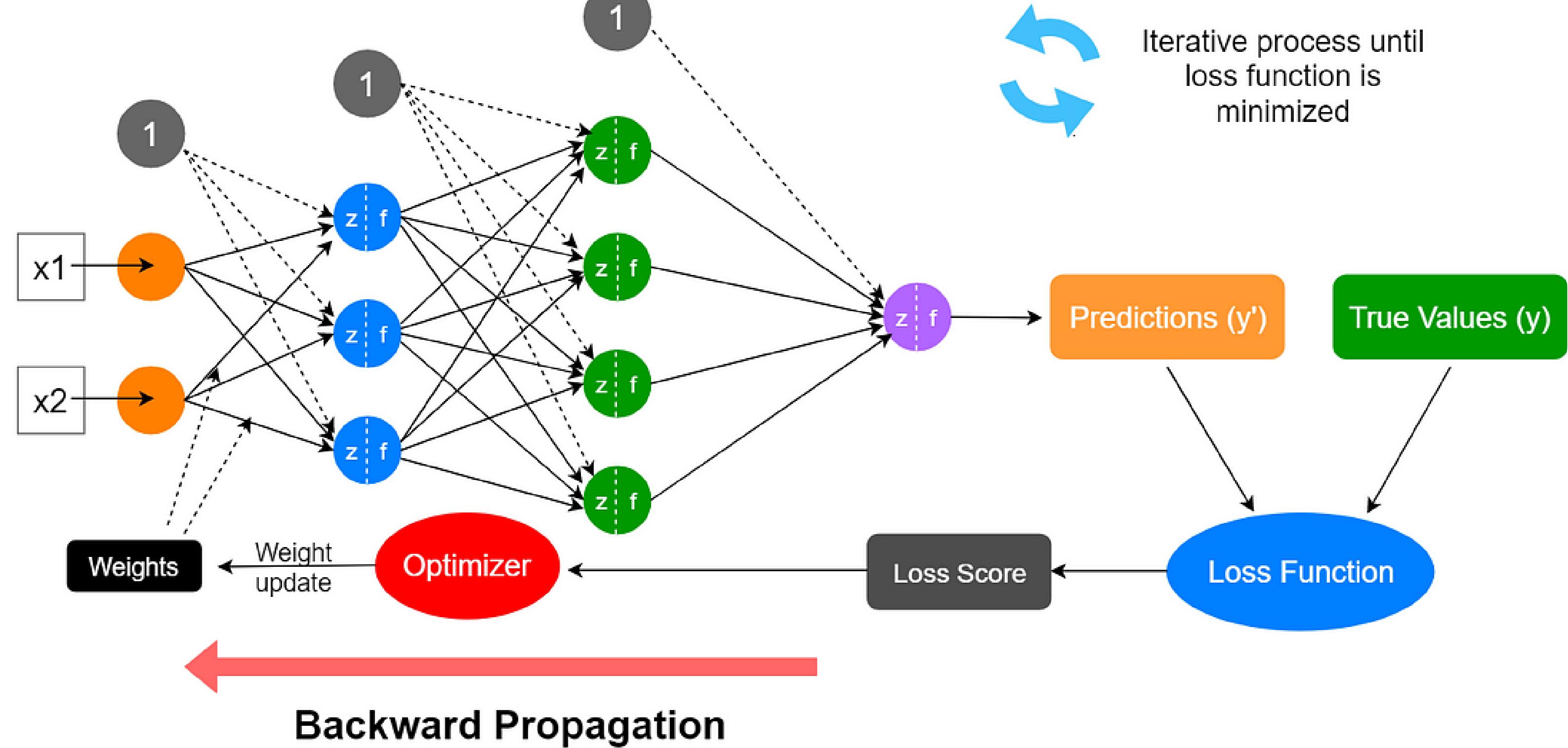
Neural Networks



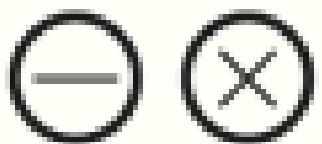
Neural Networks



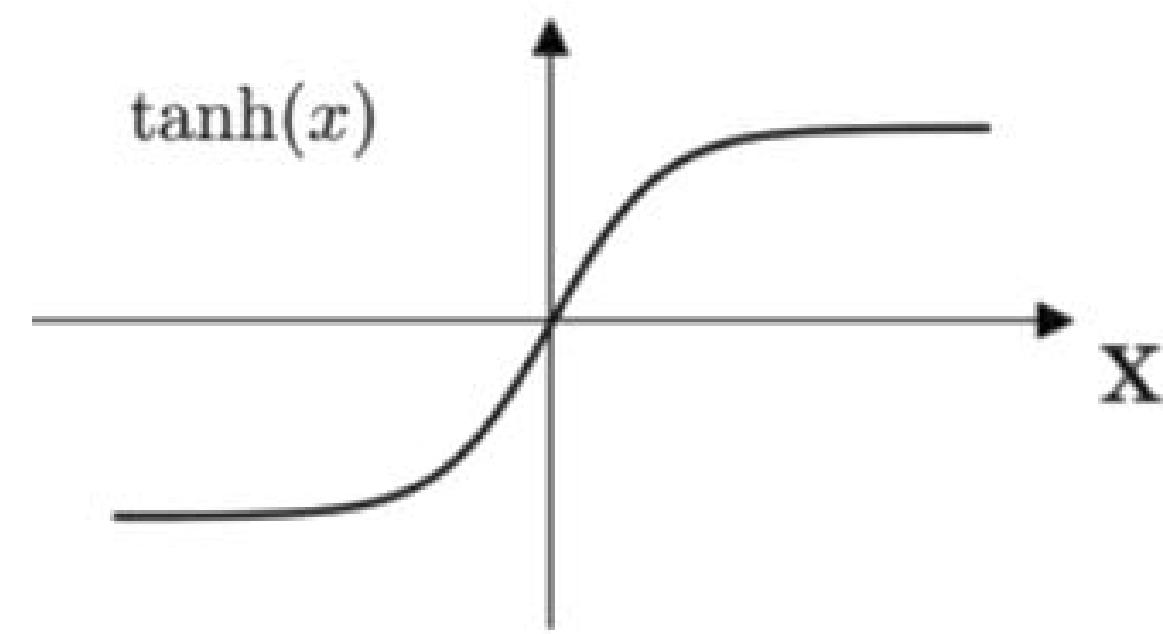
Forward Propagation



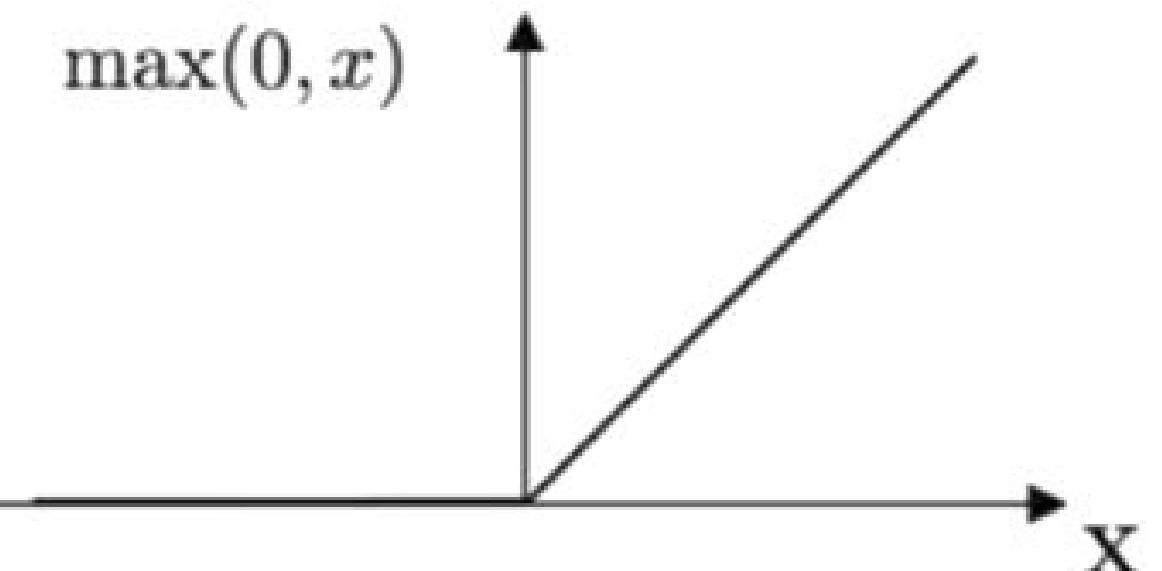
Activation functions



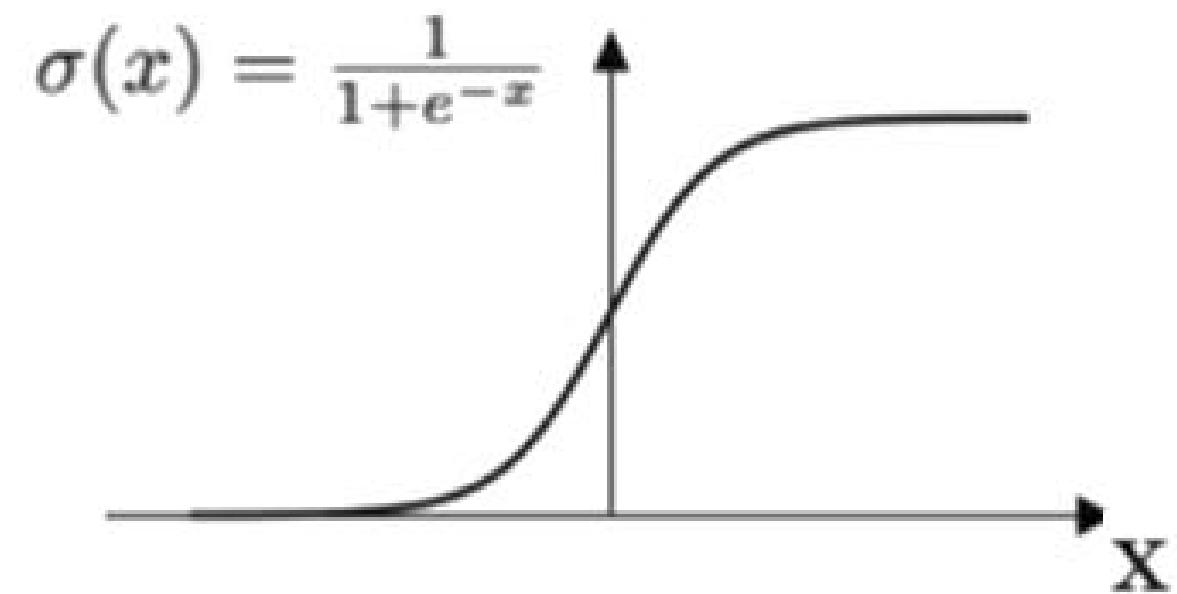
Tanh



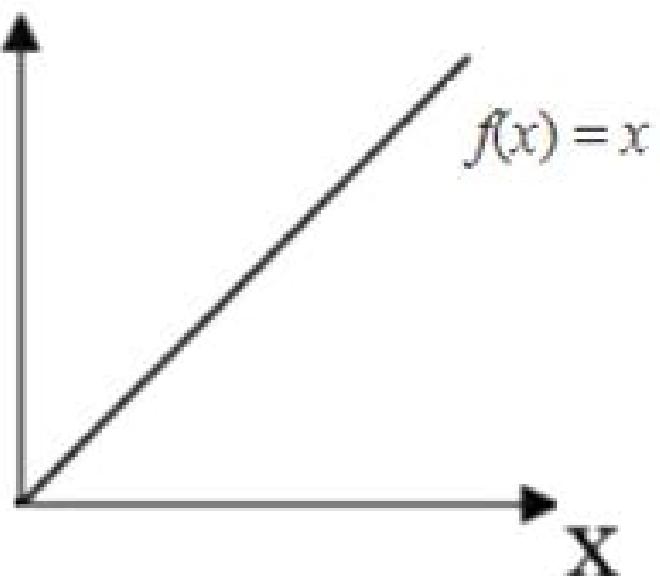
ReLU



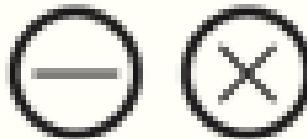
Sigmoid



Linear



Chain rule

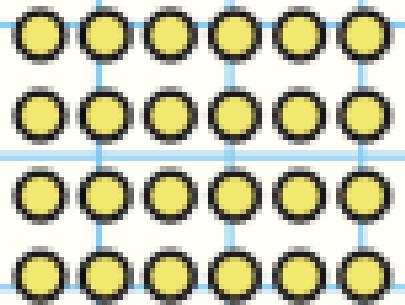


$$\frac{dy}{dx} = \frac{dy}{du} \cdot \frac{du}{dx}$$



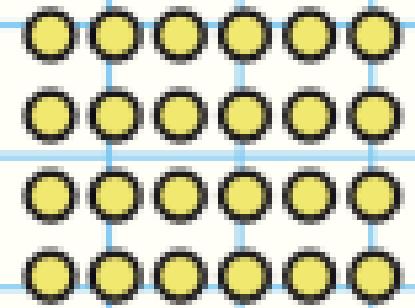
Intuition

With deeper networks, computers can model very complex functions. Hence, they can understand the world!





Computer Vision





Computer Vision

Computers can now see!

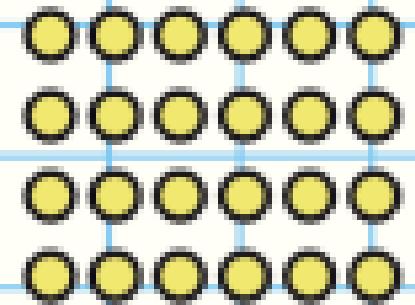
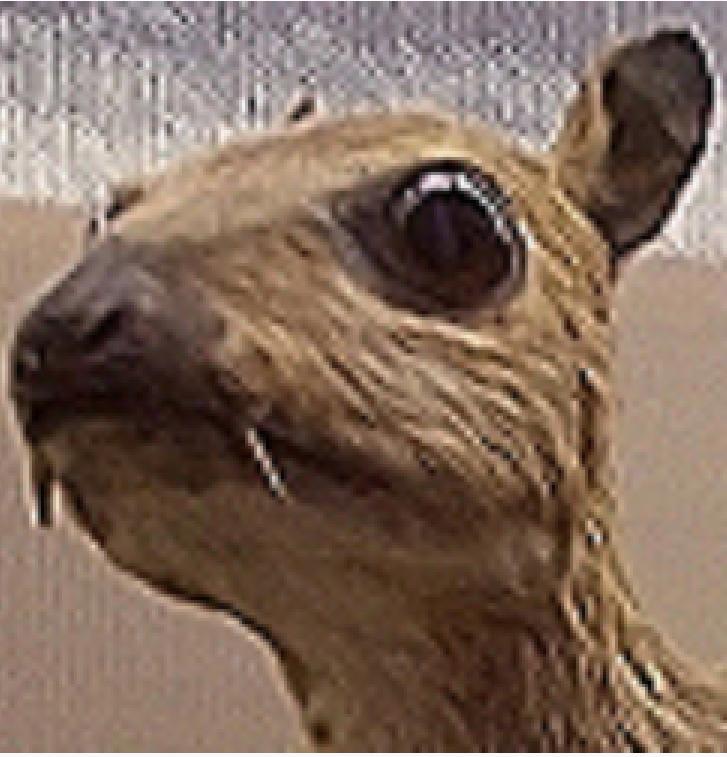


Image filters

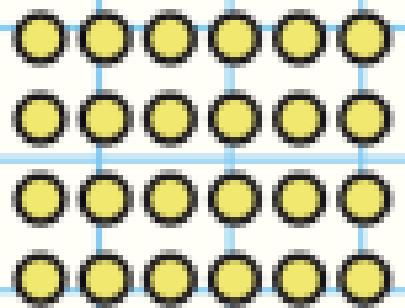
Sharpen

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



Box blur
(normalized)

$$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$



Convolution Operation



Source layer

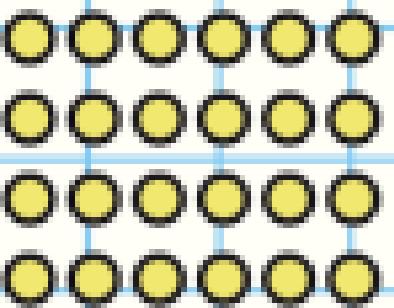
5	2	6	8	2	0	1	2
4	3	4	5	1	9	6	3
3	9	2	4	7	7	6	9
1	3	4	6	8	2	2	1
8	4	6	2	3	1	8	8
5	8	9	0	1	0	2	3
9	2	6	6	3	6	2	1
9	8	8	2	6	3	4	5

Convolutional
kernel

-1	0	1
2	1	2
1	-2	0

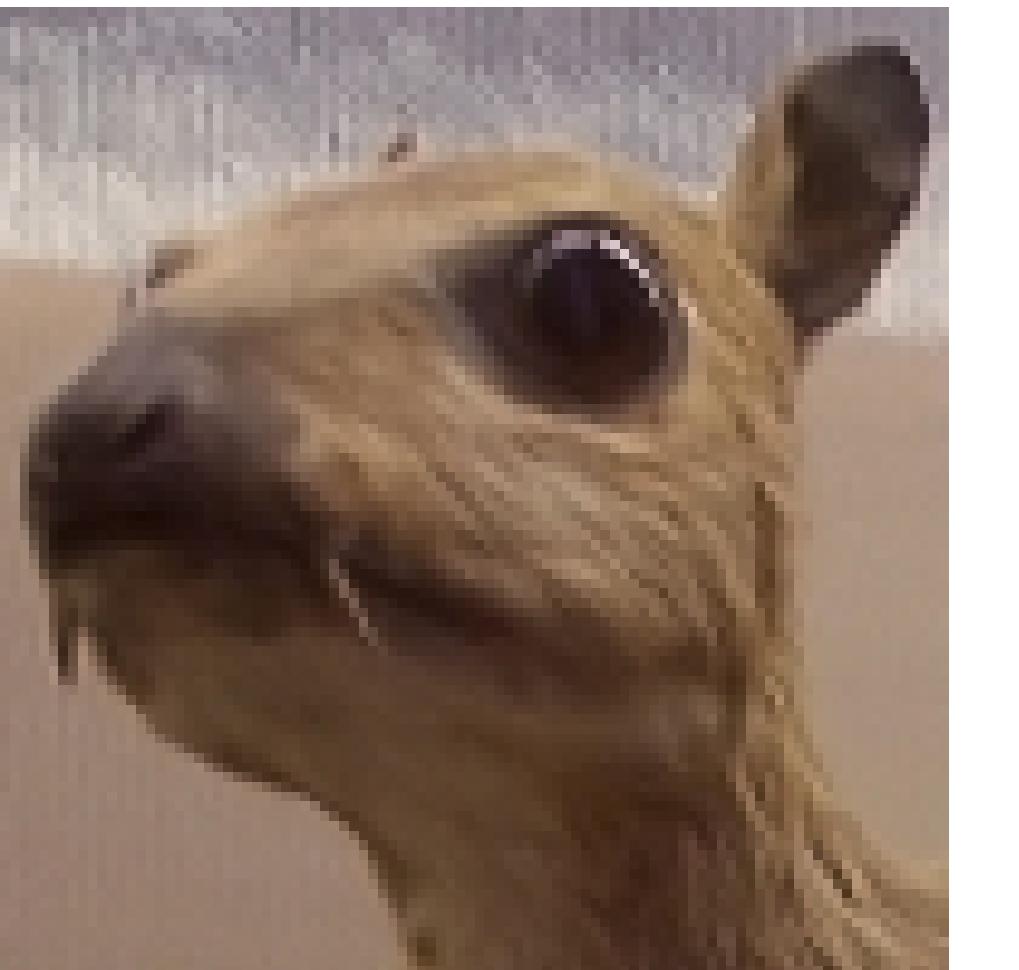
Destination layer

$$(-1 \times 5) + (0 \times 2) + (1 \times 6) + \\ (2 \times 4) + (1 \times 3) + (2 \times 4) + \\ (1 \times 3) + (-2 \times 9) + (0 \times 2) = 5$$



Convolution kernels

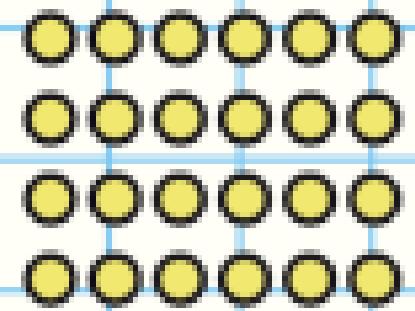
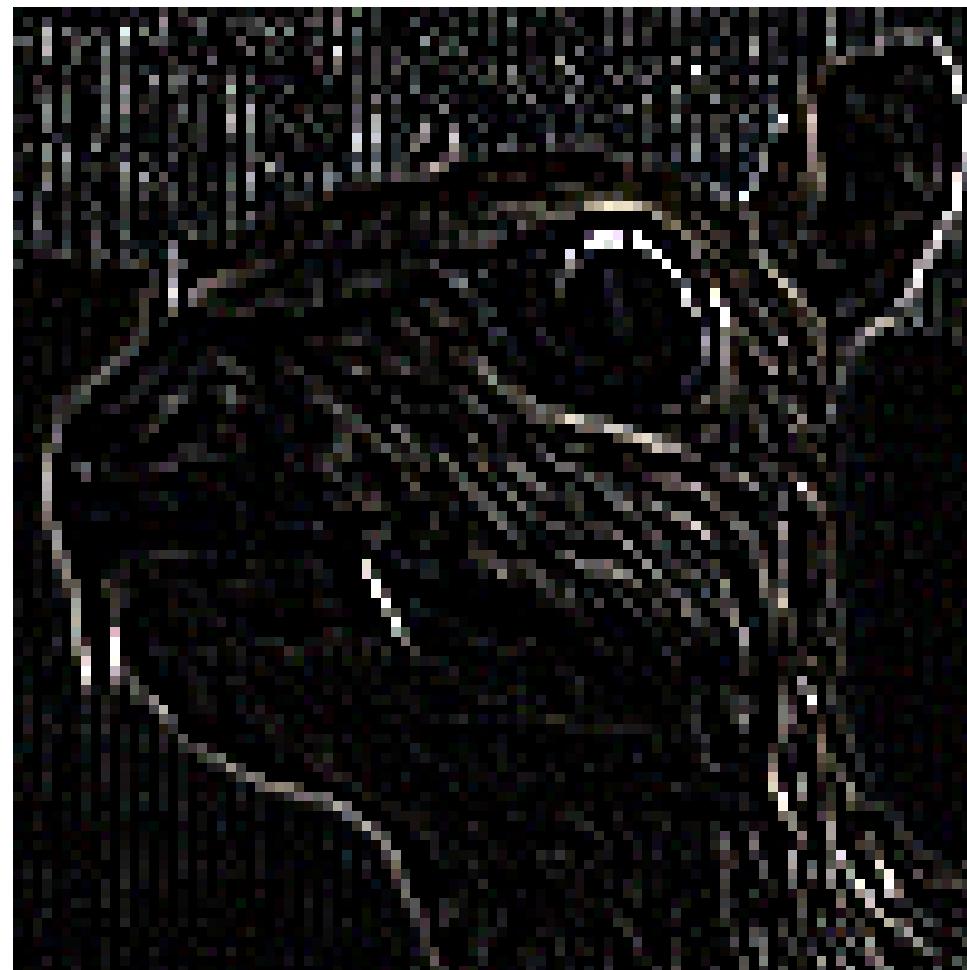
Input image



Convolution
Kernel

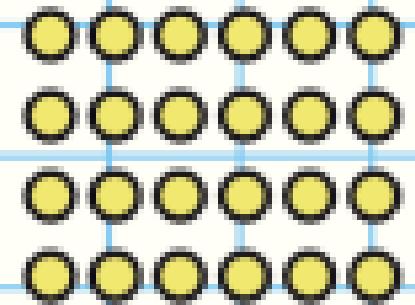
$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Feature map

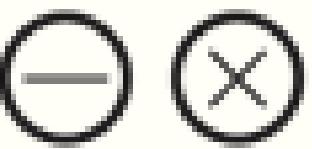




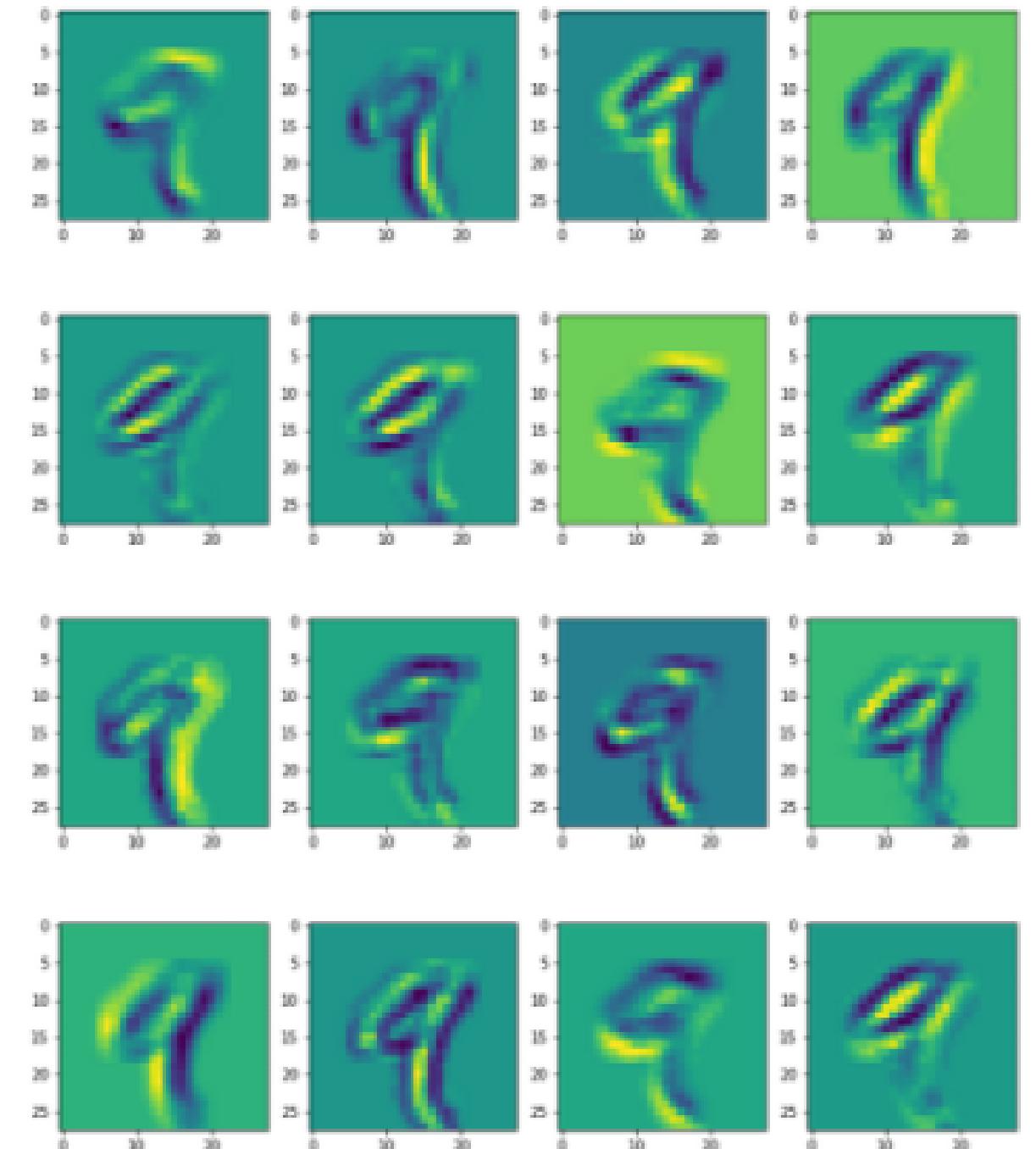
Convolutional Layers



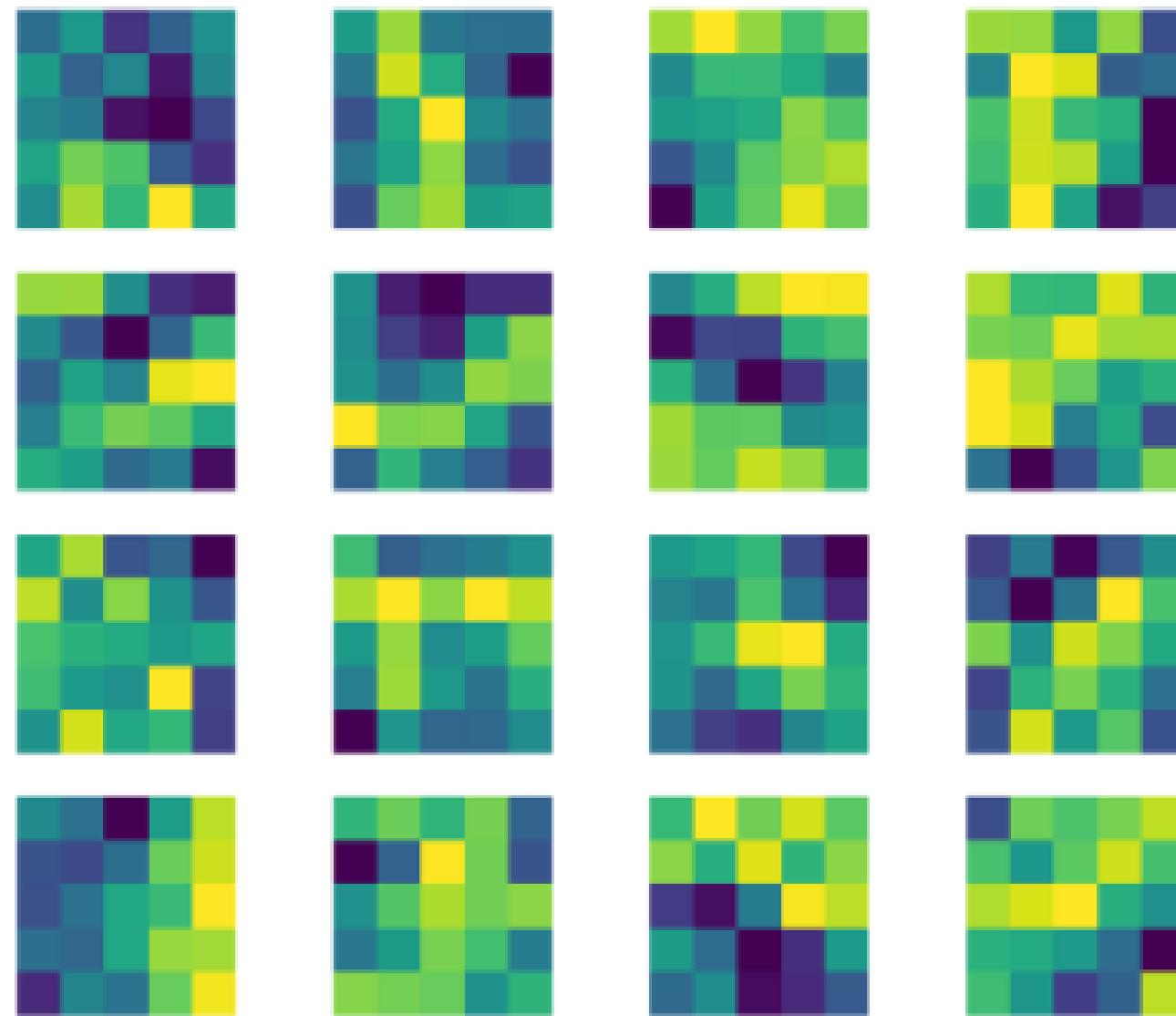
Convolutional layers



Feature map



Filters

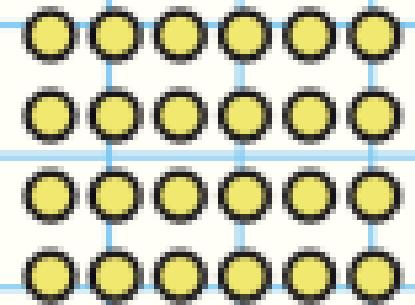


Pooling layers

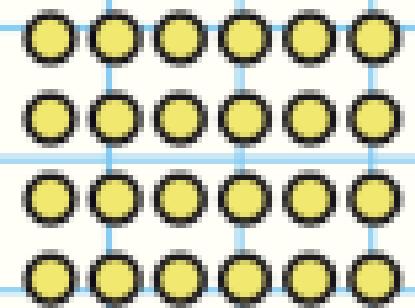
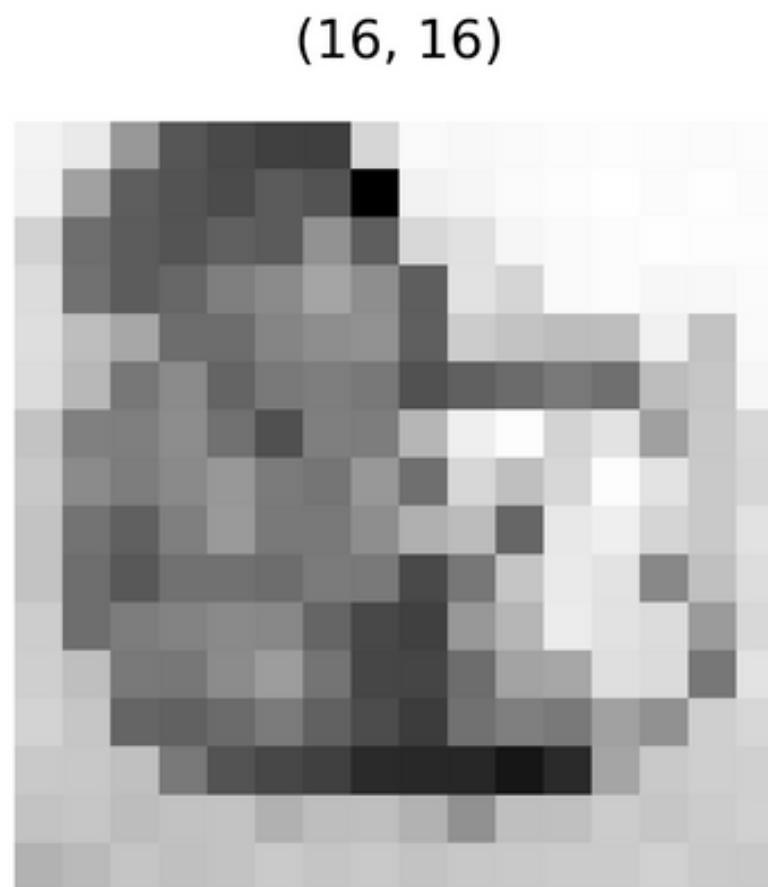
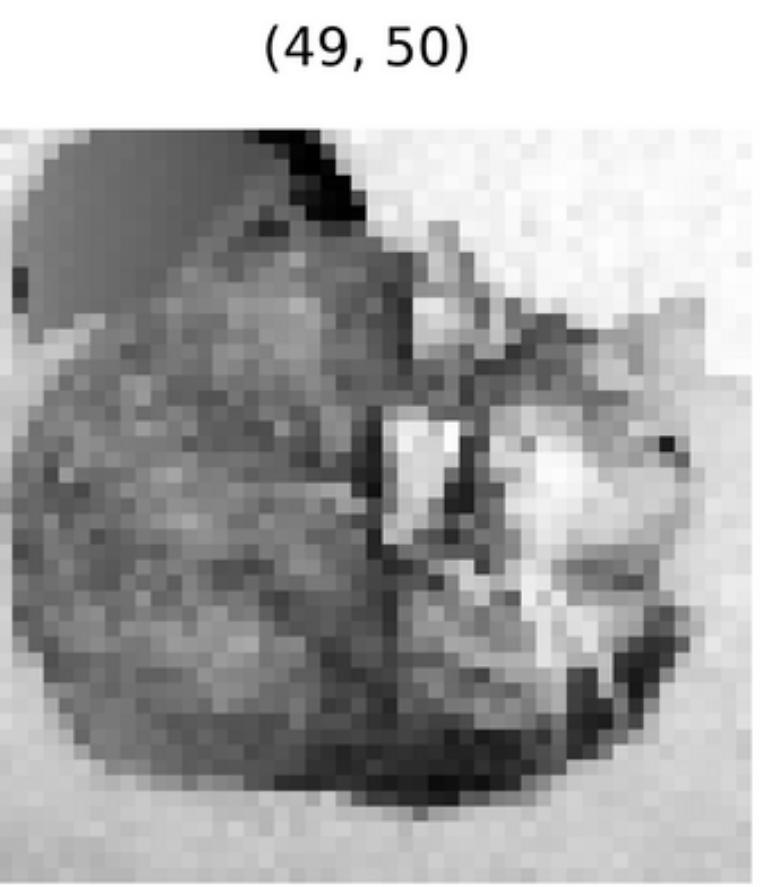


Max Pool
→

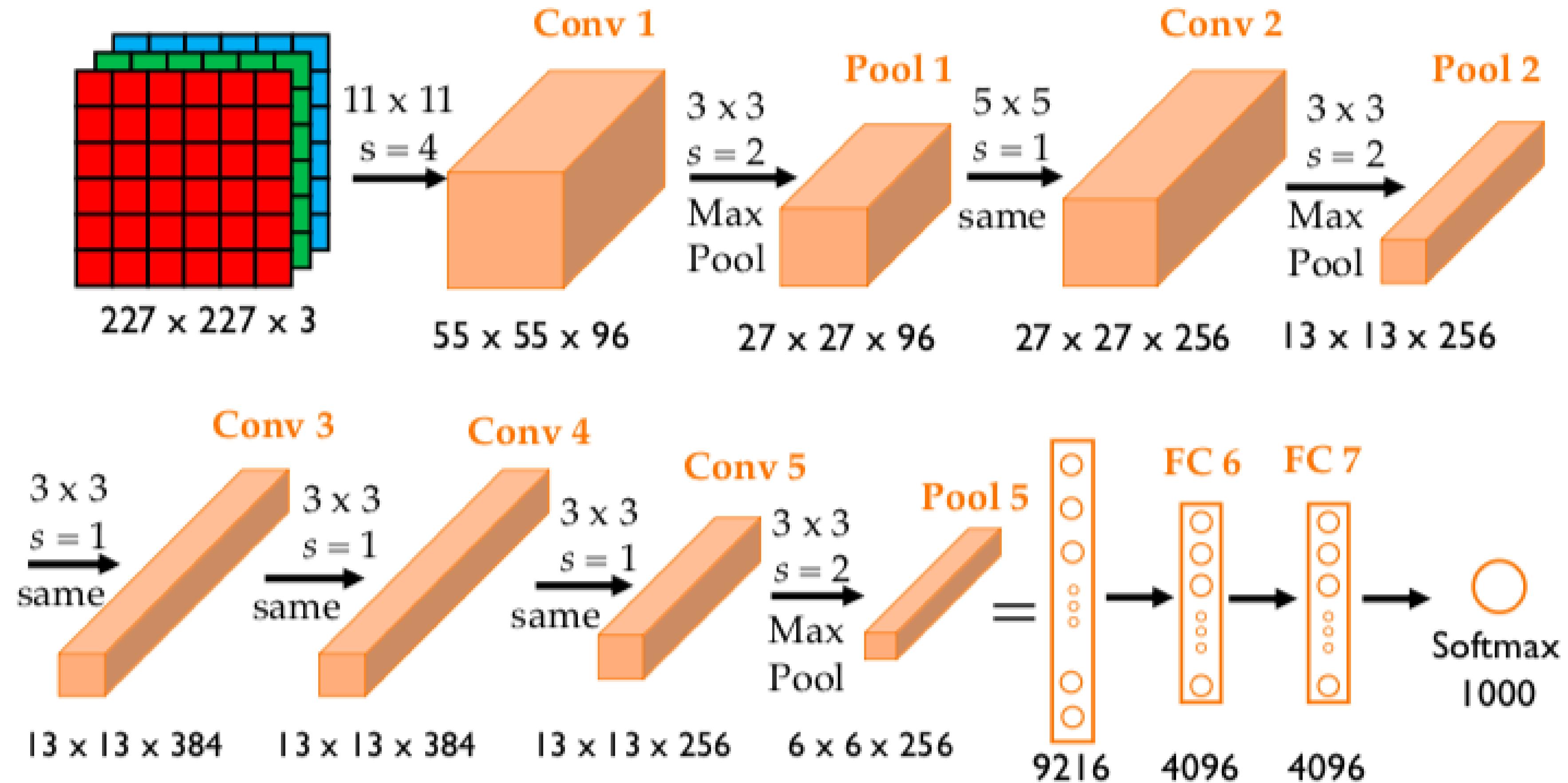
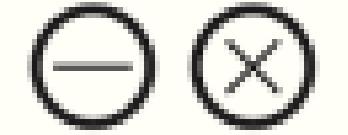
Filter - (2 x 2)
Stride - (2, 2)



Pooling layers



Convolutional Networks



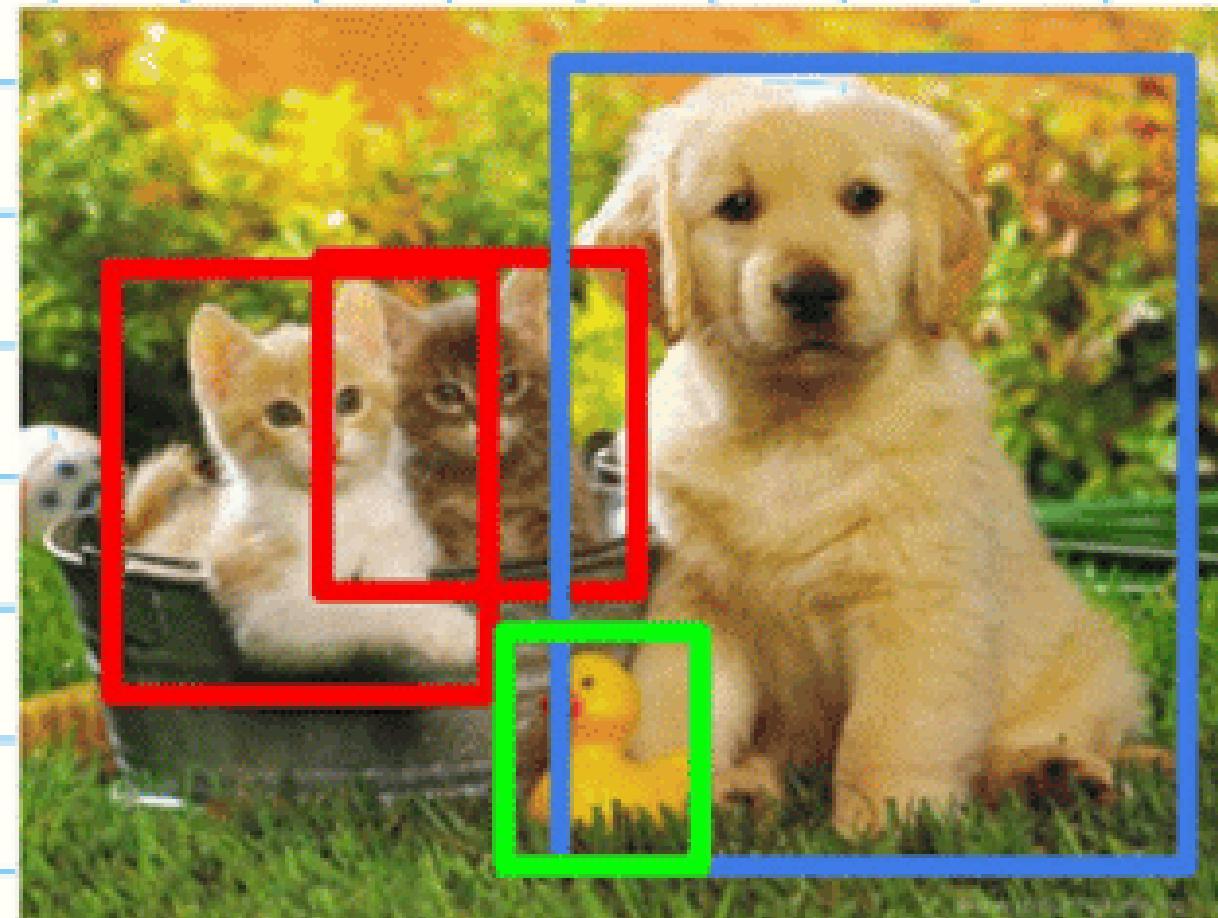
Use cases

Classification

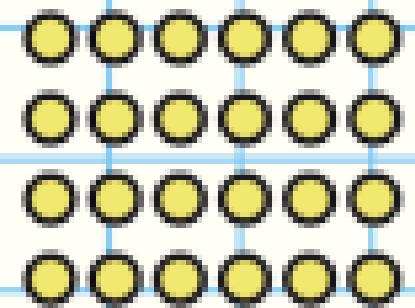


CAT

Object Detection

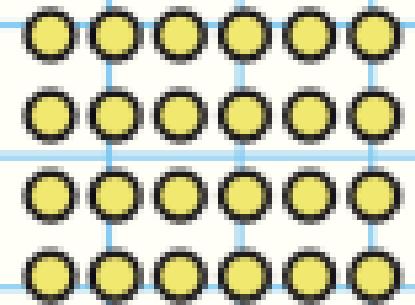


CAT, DOG, DUCK





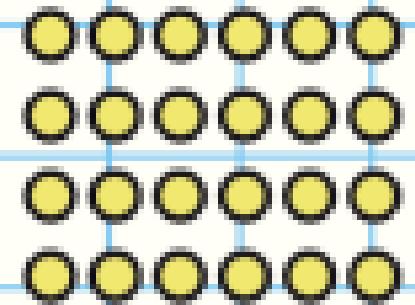
Natural Language Processing





Natural Language Processing

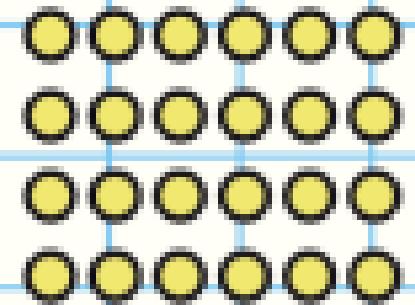
Computers can now understand and talk with us!





Language

This is an Artificial Intelligence workshop!





Language

Tokens

7

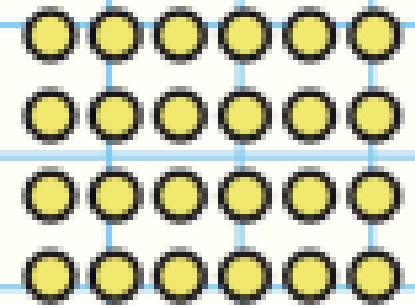
Characters

44

This is an Artificial Intelligence workshop!

TEXT

TOKEN IDS



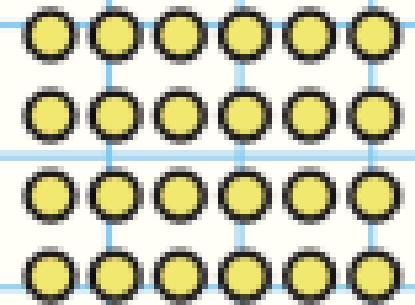
GDG Algiers



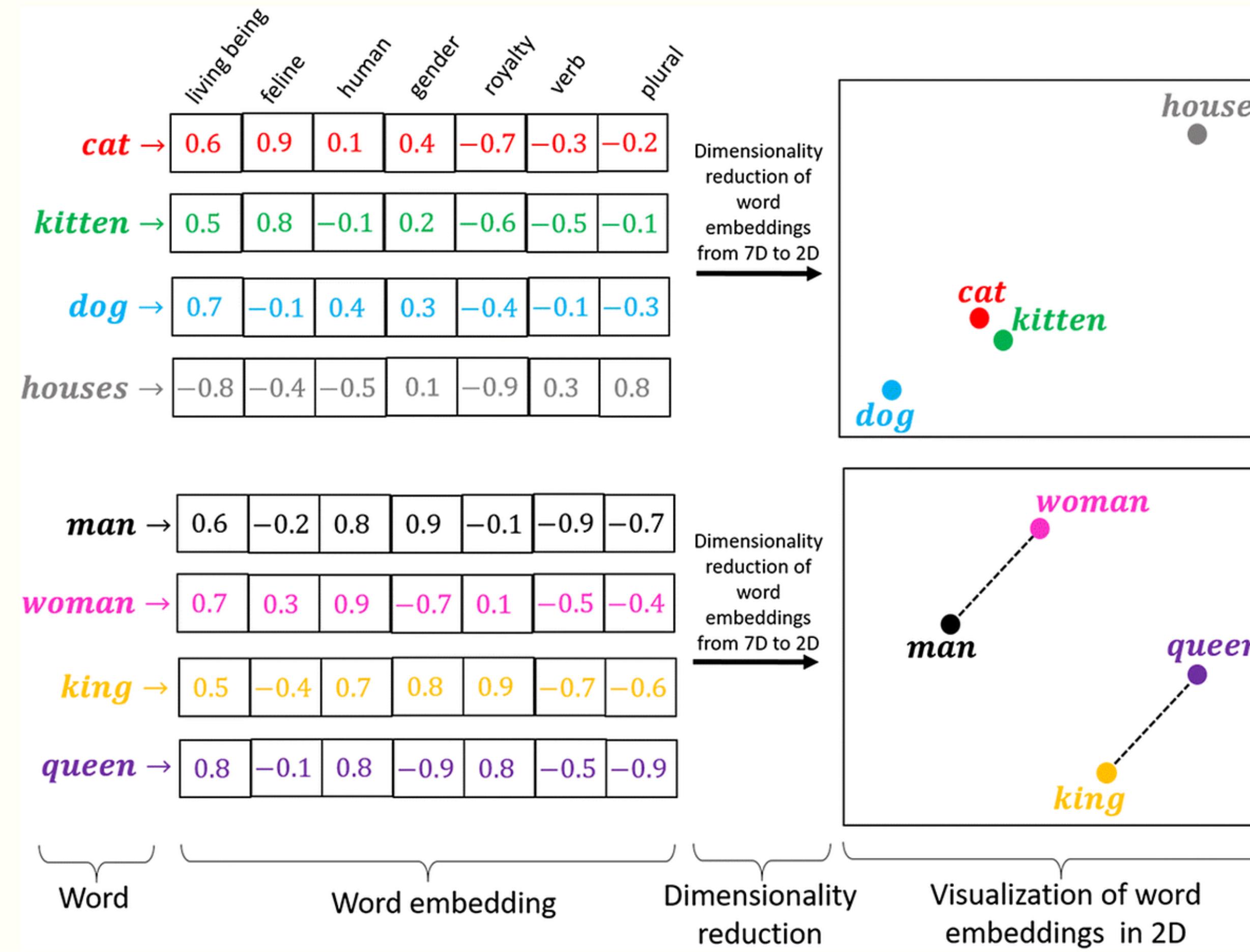
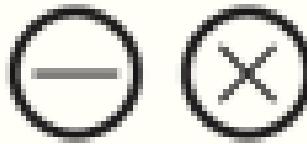


Meaning

How to make meaning out of language?

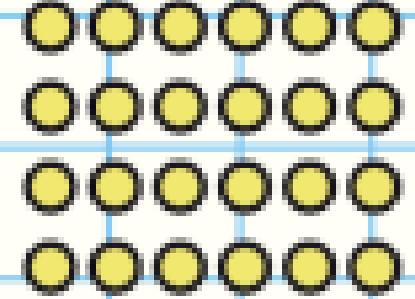
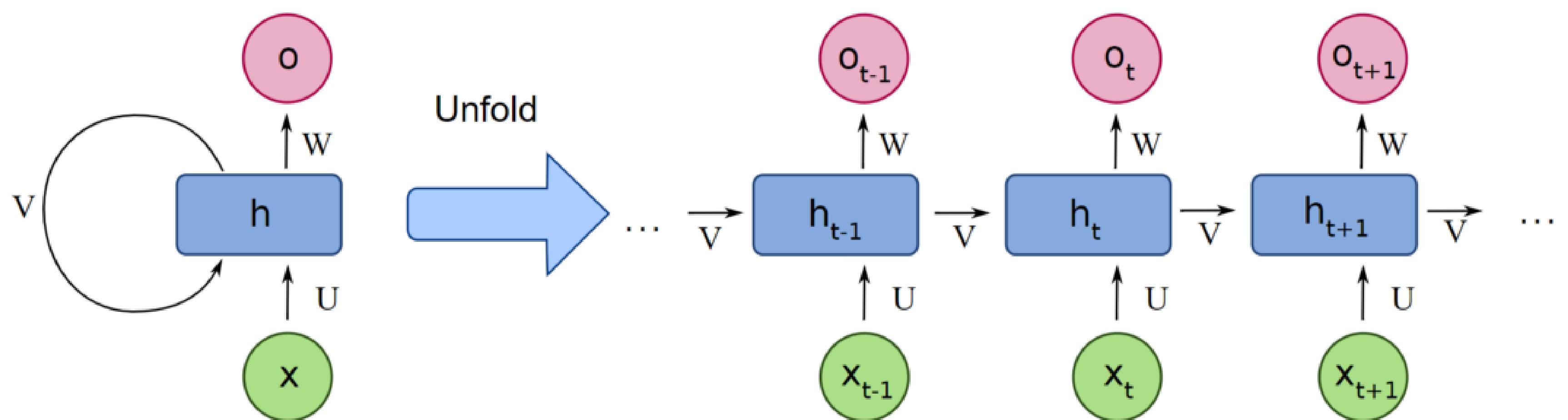


Word Embedding





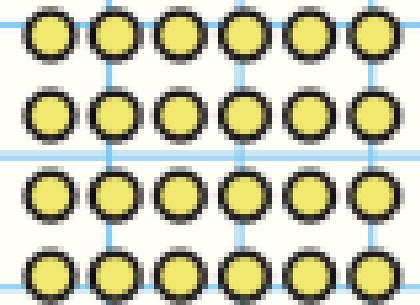
Recurrent Layers





LLMs

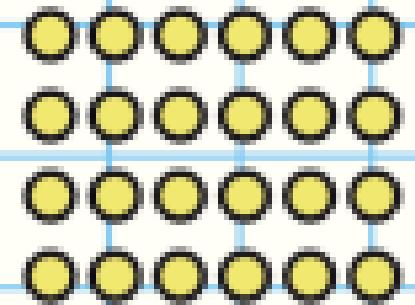
Every AI revolution starts with a paper





Attention

Every AI revolution starts with a paper





Attention Is All You Need

Ashish Vaswani*
Google Brain
avaswani@google.com

Noam Shazeer*
Google Brain
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Niki Parmar*
Google Research
nikip@google.com

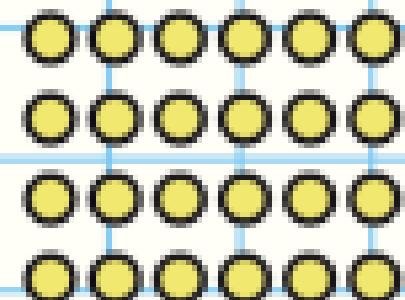
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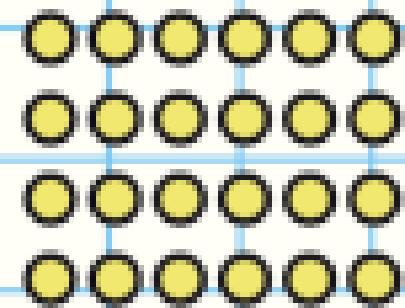
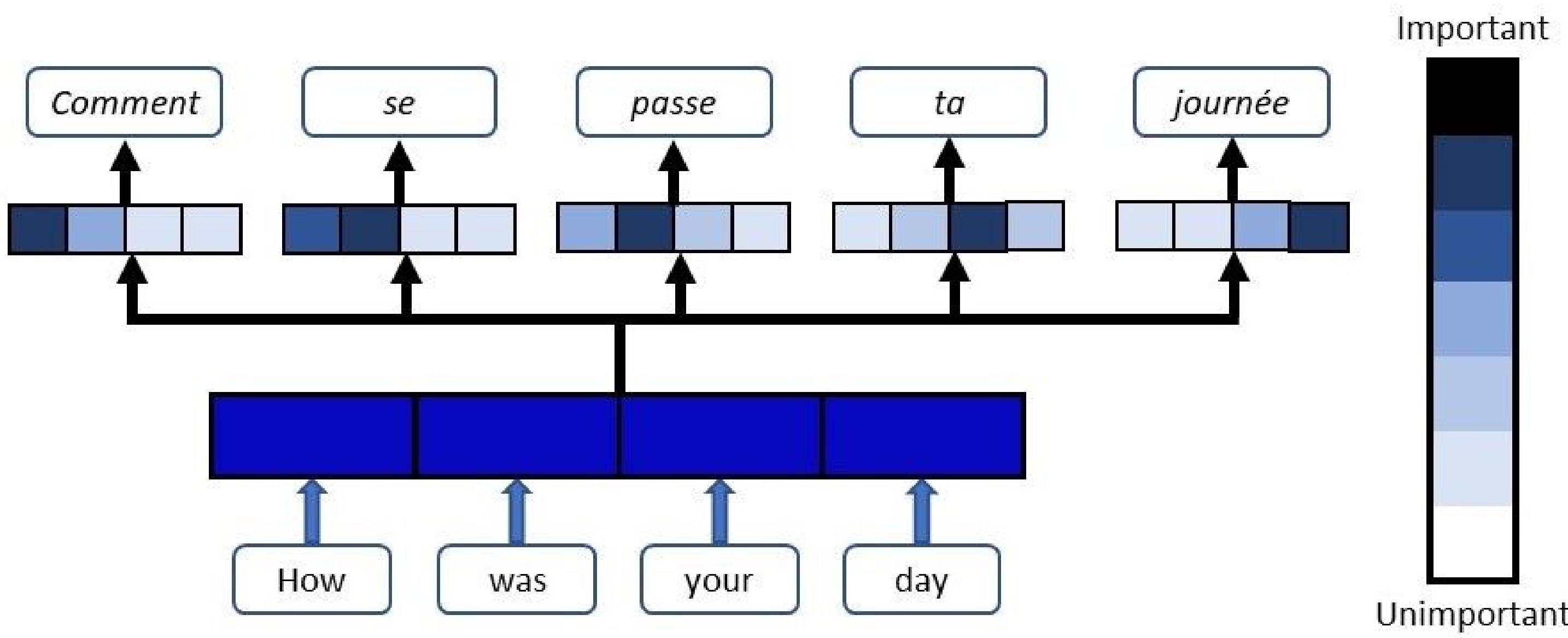
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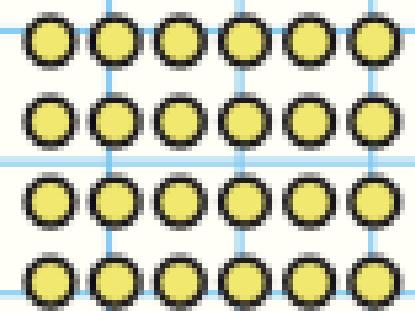
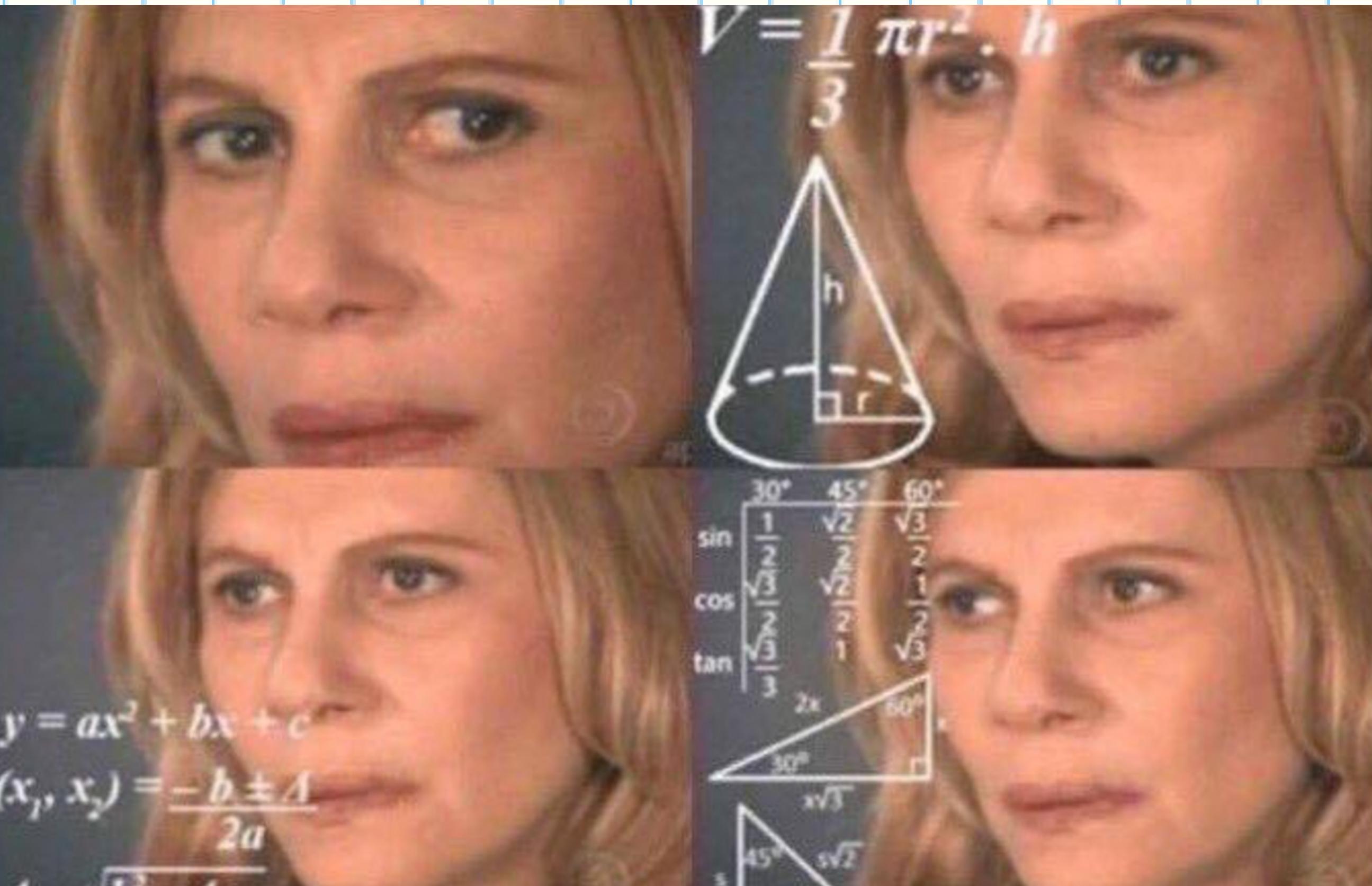


Attention Mechanism



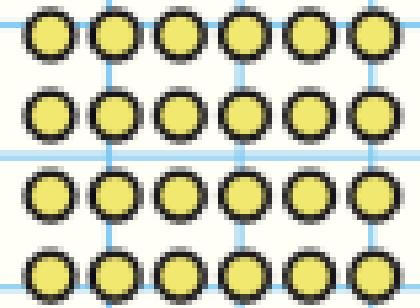


pov: your lunch break





Tensorflow



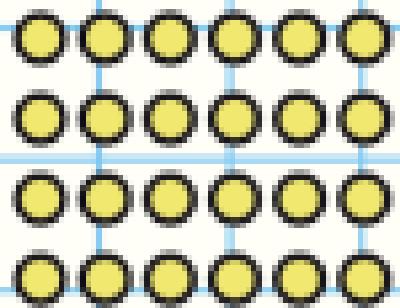


Tensorflow

TensorFlow is an open-source machine learning framework developed by Google that facilitates the creation and deployment of deep learning models.

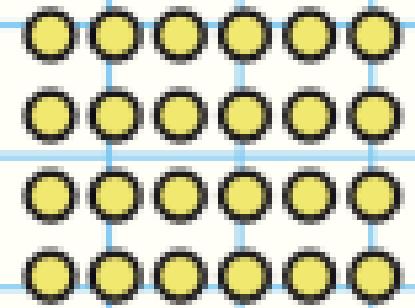


TensorFlow



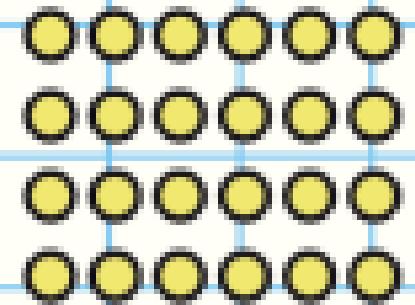


Labs





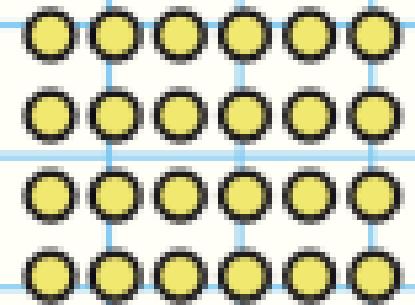
Reinforcement Learning





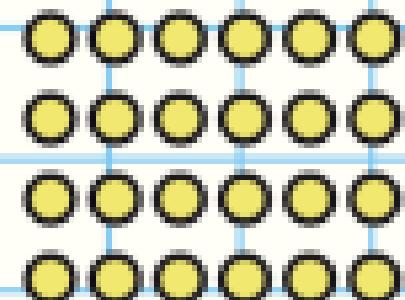
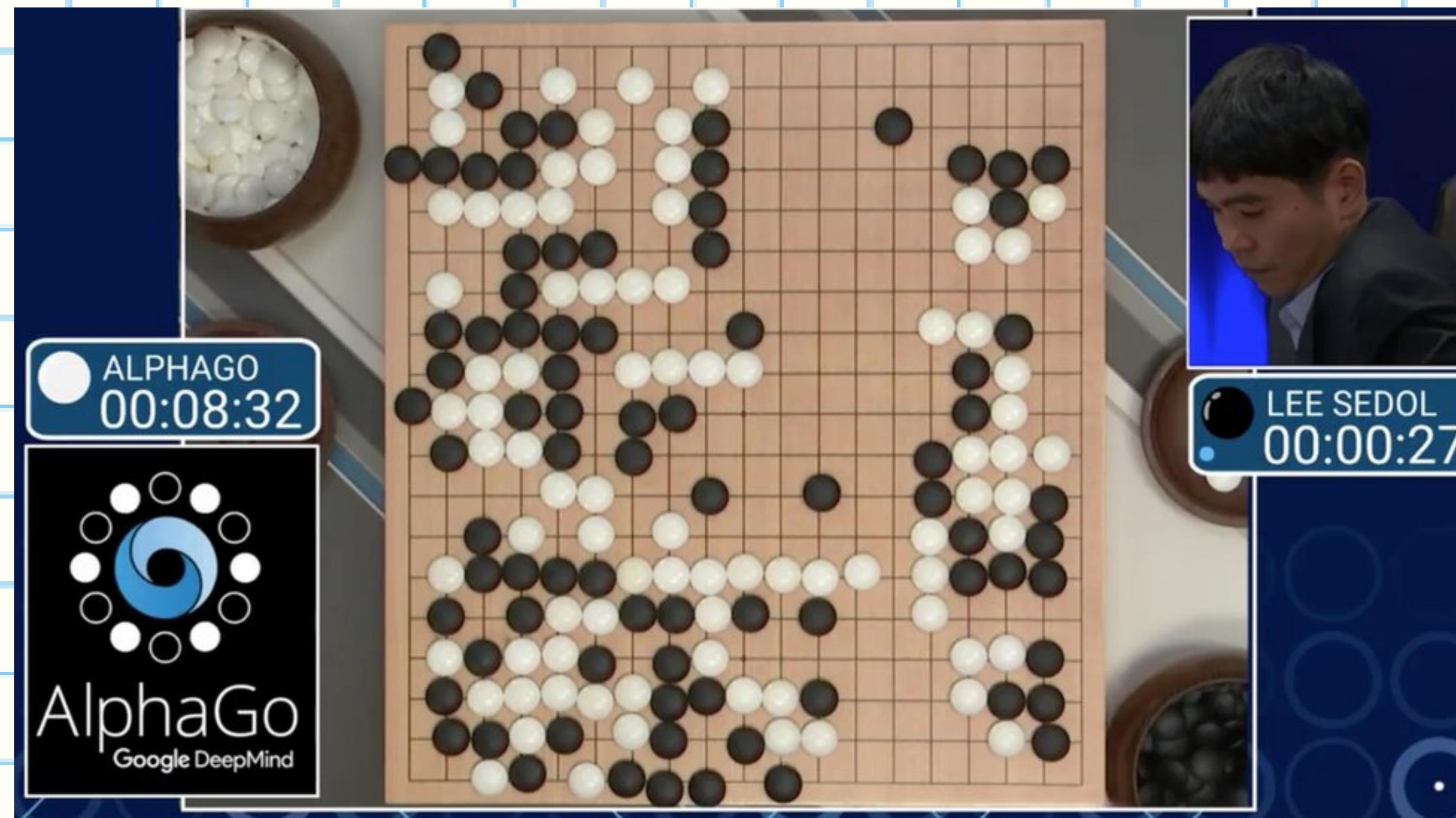
Reinforcement Learning

Computers can now play games beyond human level!



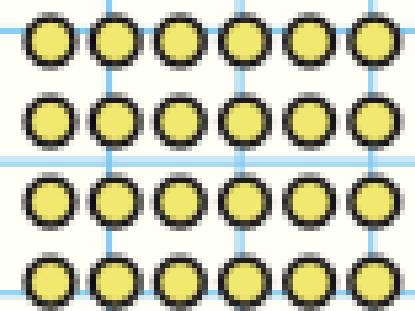
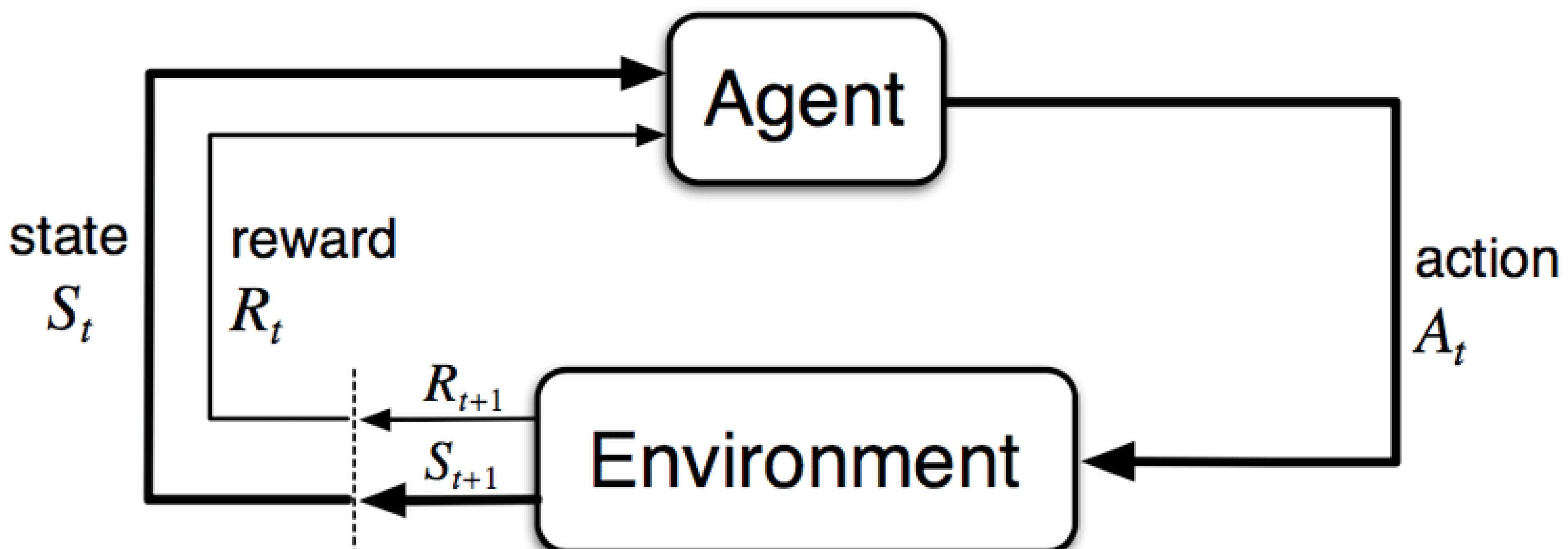


Reinforcement Learning



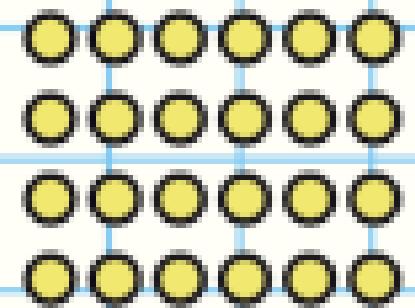


RL Framework





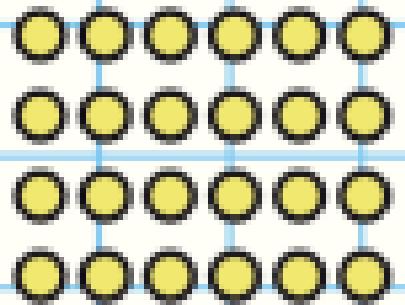
RL Framework





Reward Hypothesis

**Every goal can be described as the maximization
of an expected cumulative reward.**





Return: Cumulative Reward

$$R(\tau) = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \gamma^3 r_{t+4} + \dots$$

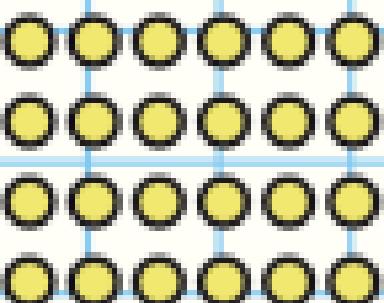


Return: cumulative reward

Gamma: discount rate

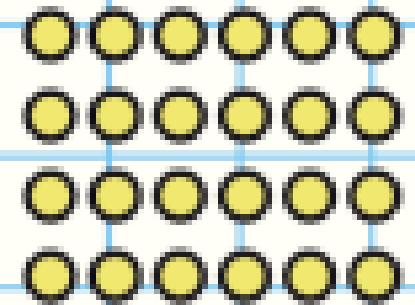
Trajectory (read Tau)

Sequence of states and actions





Value Based Solution: Q-Learning



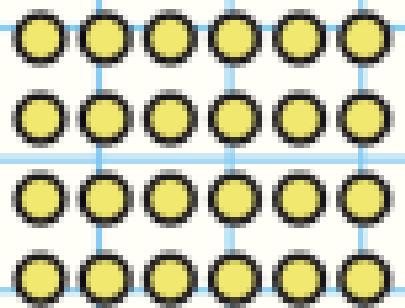


State-Action Value

$$Q^\pi(s, a) = \mathbb{E}_\pi \left[\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s, a_t = a \right]$$

(math-ignore)

How good is it to be in state (s_t) and take action (a_t)





Getting Smart

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha [R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)]$$

New
Q-value
estimation

Former
Q-value
estimation

Learning
Rate

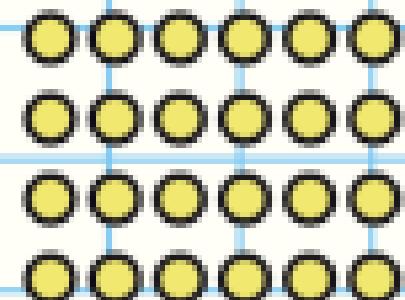
Immediate
Reward

Discounted Estimate
optimal Q-value
of next state

Former
Q-value
estimation

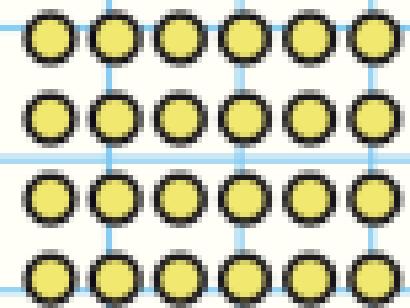
TD Target

TD Error



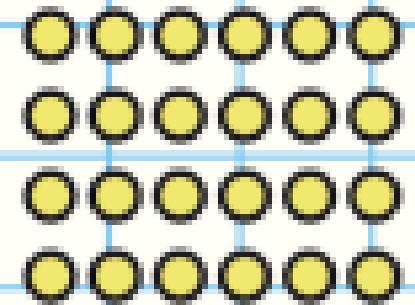
Q-Learning

- **epsilon, learning_rate**
- **For every episode:**
 - **While S_t is not terminal:**
 - **Observe state S_t**
 - **Take action A_t (e-greedy)**
 - **Observe S_{t+1}, R_{t+1}**
 - **Correct $Q(S_t, A_t)$**



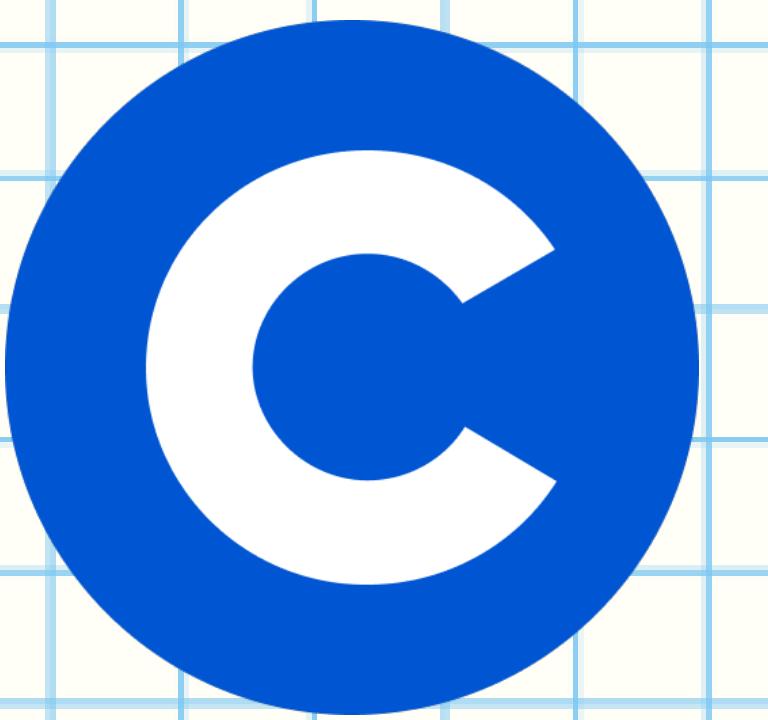


Discussion

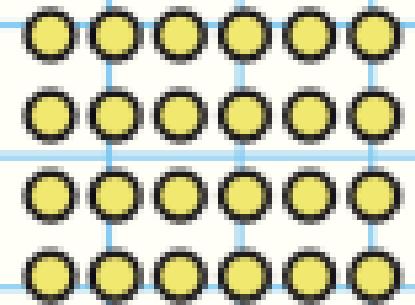
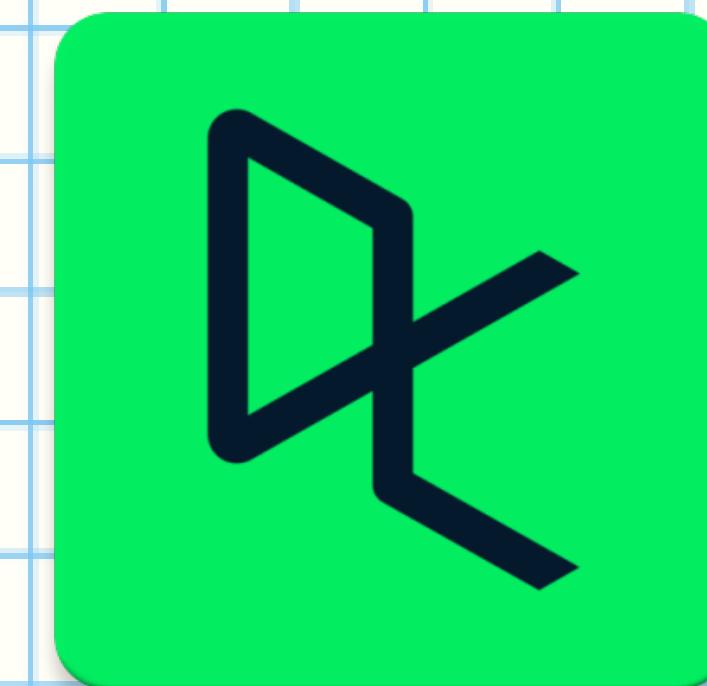




Ressources

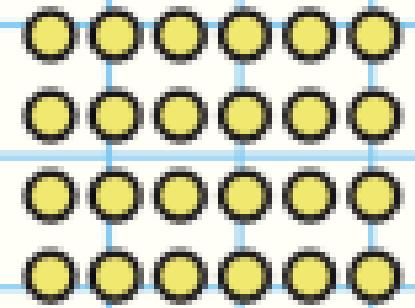


kaggle





Q/A





Thank you!

