

AI in Culture and Arts – Tech Crash Course

Introduction to Artificial Intelligence and Machine Learning

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MUC.DAI
Munich Center for
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müt
Hochschule
für Musik und Theater
München

1. How to Model Intelligence?

2. When is Learning Possible?

3. How Do Machines Learn?

4. How Do Humans Train Machines?

5. How to Interact with Learning Machines?

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How to Model Intelligence?

"The ability of an agent to achieve goals in a wide range of environments."
– (Russell, 2019)

Let E be the space of all computable reward summable environmental measures with respect to the reference machine \mathcal{U} , and let K be the Kolmogorov complexity function. The expected performance of agent π with respect to the universal distribution $2^{K(\mu)}$ over the space of all environments E is given by,

$$\Psi(\pi) := \sum_{\mu \in E} 2^{-K(\mu)} V_\mu^\pi.$$

We call this the **universal intelligence** of agent π (Legg & Hutter, 2007).

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Artificial Intelligence (AI)

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Machine Learning (ML)

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Deep Learning (DL)

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Symbolism

Exploits explicit, rule-based symbolic manipulation, logic, and structured reasoning to represent knowledge and solve problems.

- **Assumption:** Intelligence uses high-level, human-readable symbols to represent problems and logic to solve them.
- **Motivation:** Model the **mind!**

Connectionism

Exploits artificial neural networks & statistics, emphasizing learning from patterns, distributed representations, and emergent behaviors.

- **Assumption:** Intelligence emerges from the interaction of simple and low-level units, i.e. biological neurons.
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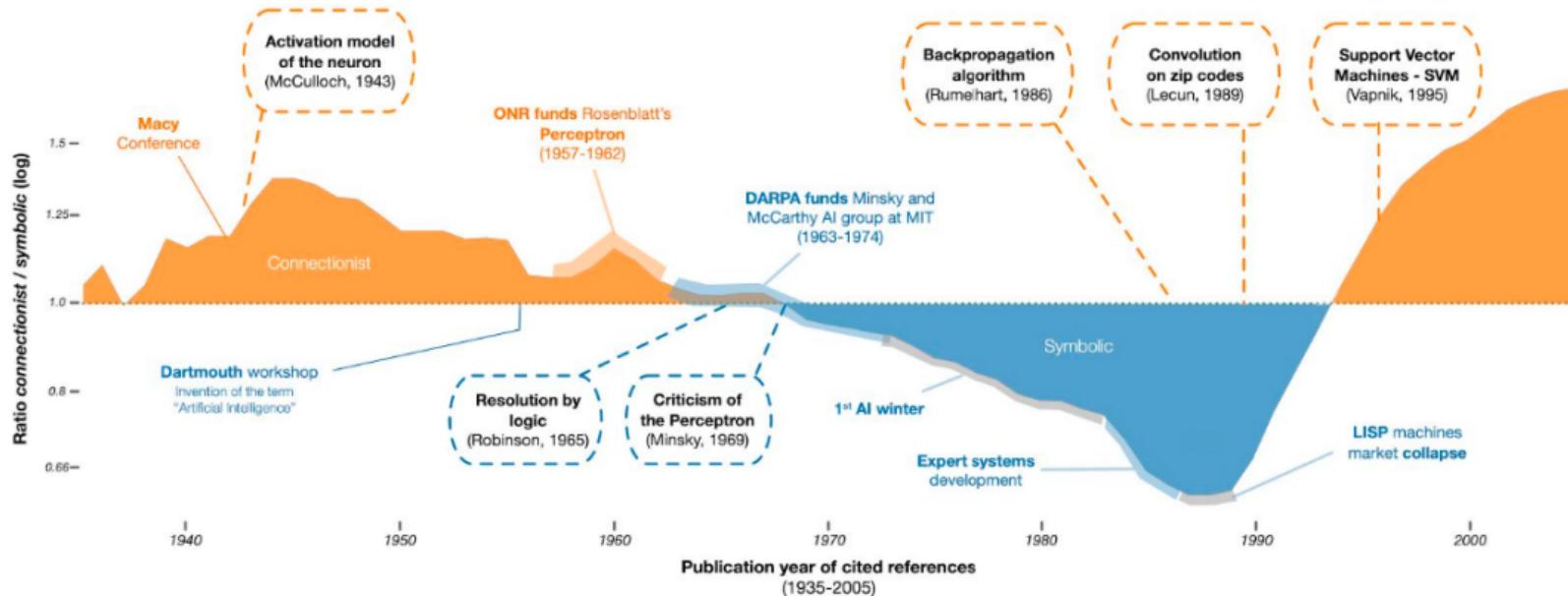
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How to Model Intelligence?



Source: (Cardon et al., 2018)

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When is Learning Possible?

"The organism feeds on negative entropy." – (Schrödinger, 1944)

When is Learning Possible?

0101010101010101010101010101

When is Learning Possible?

1100110101110100011100101111

When is Learning Possible?

Let's say we have the following two 30-bit information:

$$x_1 = 01010101010101010101010101010101$$

$$x_2 = 110011010101110100011100101111$$

Question: Which carries “more” information?

Answer: We say the **entropy** (Shannon, 1948) of x_2 is higher than the entropy of x_1 . If we read the bits from left to right we are more **surprised** when reading x_2 .

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When is Learning Possible?

Information entropy measures uncertainty / surprise.

- High entropy: highly unpredictable, many possible outcomes, each similarly likely
- Low entropy: predictable, only a few likely outcomes

Lerning requires

$$\text{entropy} + \text{structure} \approx \text{complexity}.$$

We have to be surprised but also be able to exploit a structure to compress observations.

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When is Learning Possible?

A physical formula like

$$F = m \cdot a$$

can be thought of a **highly compressed representation** of some aspects of physical reality!

In other words, $F = m \cdot a$ reveals the structure of motion, thus the informational entropy cannot be too high.

When is Learning Possible?

Some neuroscientists (K. Friston, Kilner, & Harrison, 2006; K. J. Friston, 2011) think that organisms try to **minimize surprise** by

1. adjusting expectations (perception, learning)
2. realize expectations (acting)

According to this school of neuroscience,

organisms are their own existence proof.

By acting to keep themselves alive, they continuously generate sensory inputs that confirm their continued existence.

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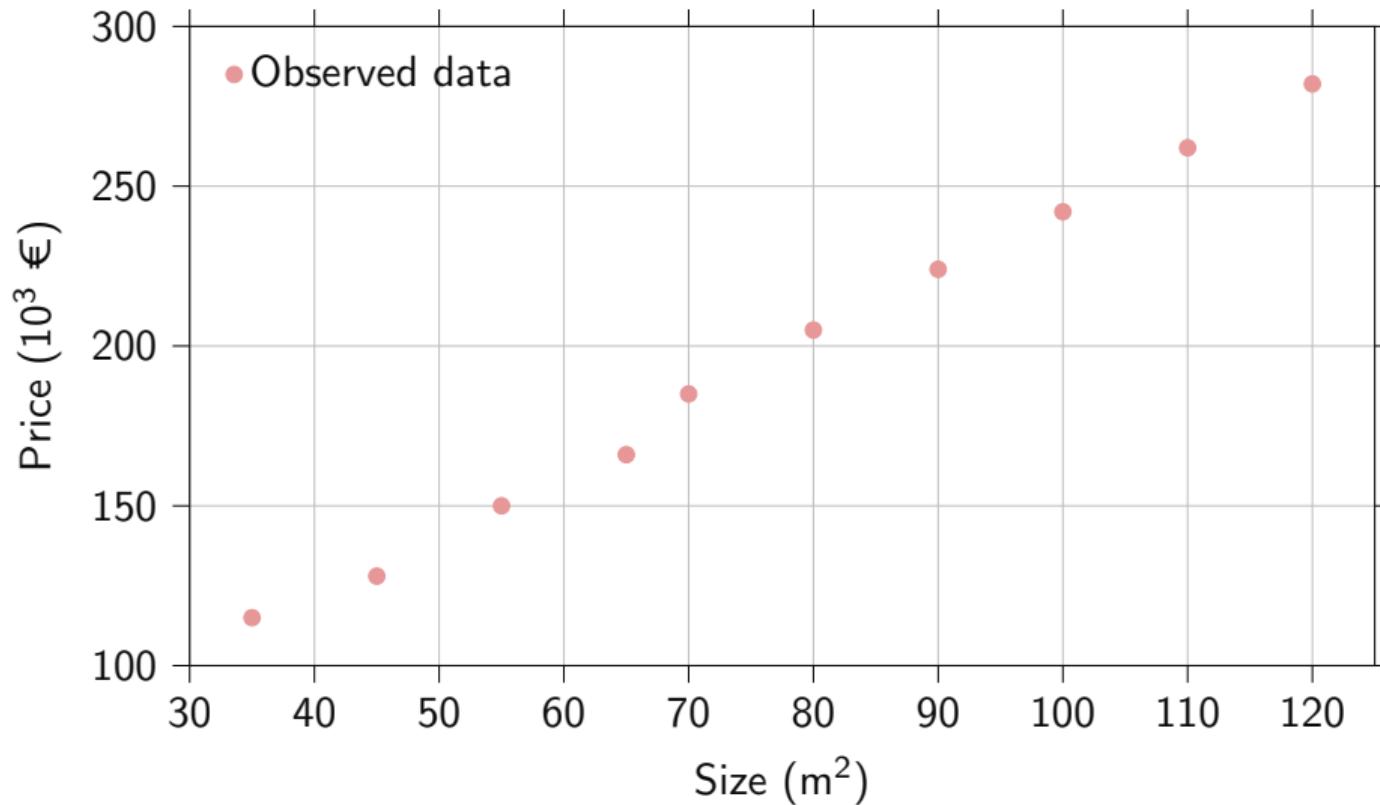
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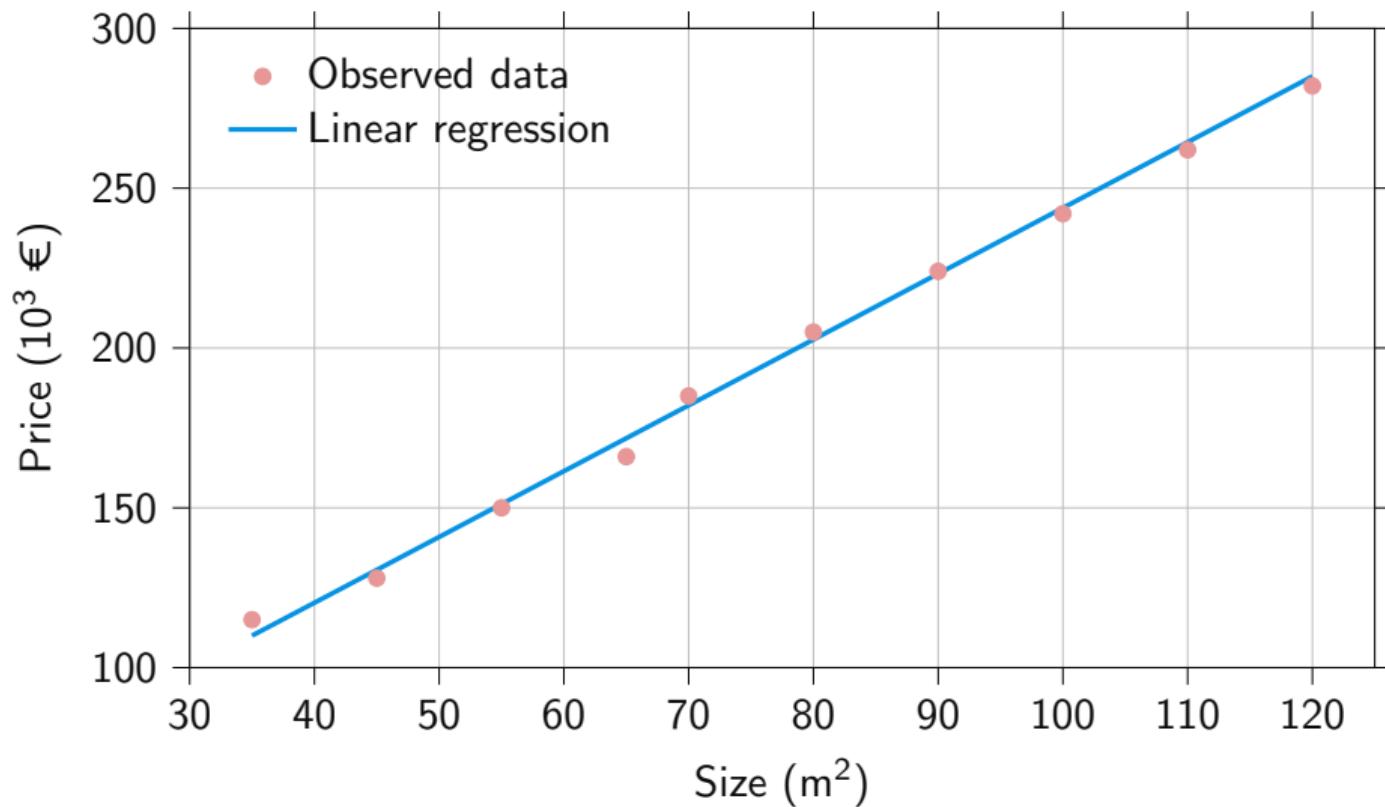
How Do Machines Learn?

“We do not learn from experience [...] we learn from reflecting on experience.” – John Dewey

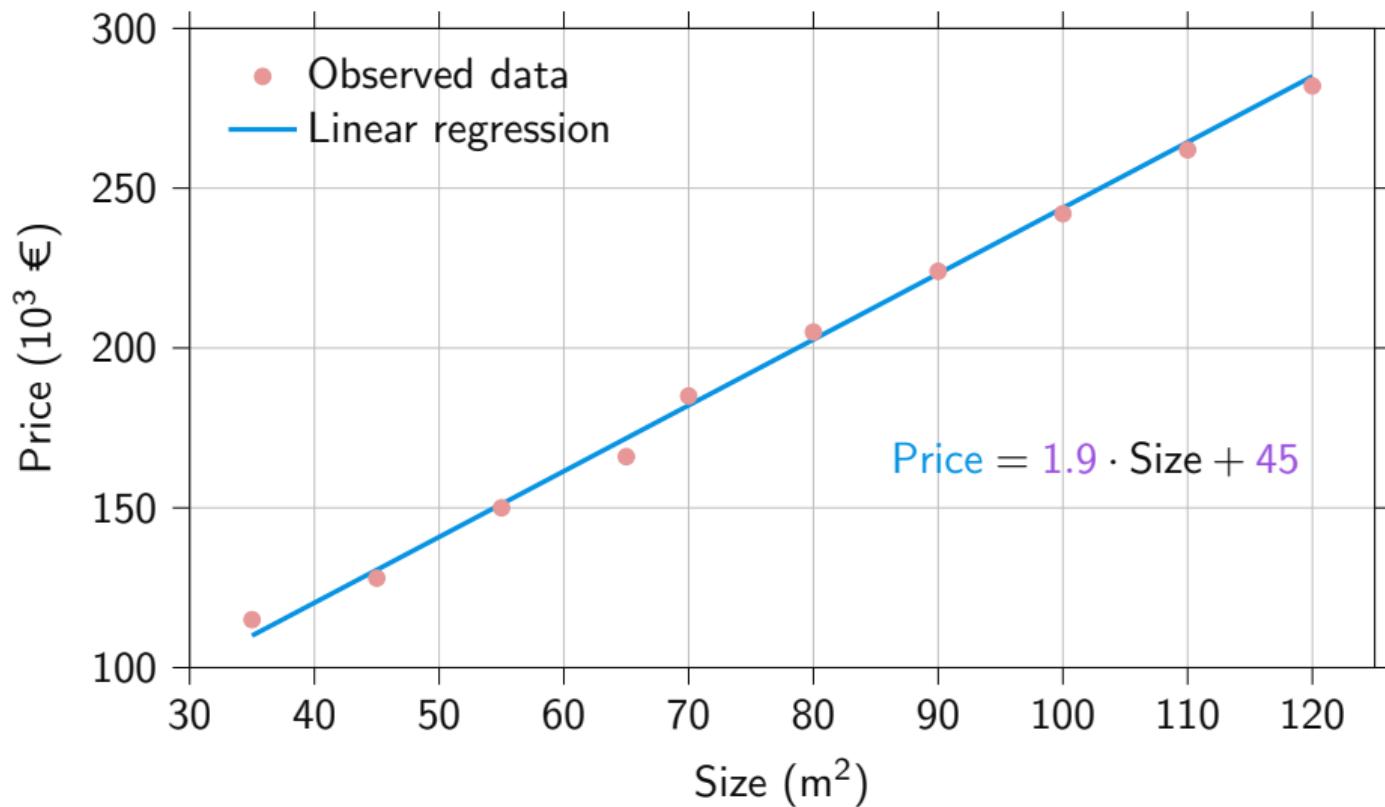
Learning a model of “the world”



Learning a model of “the world”

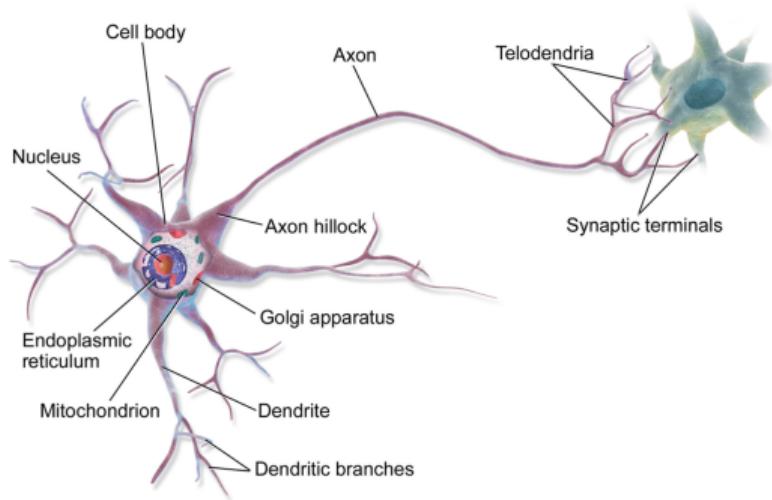


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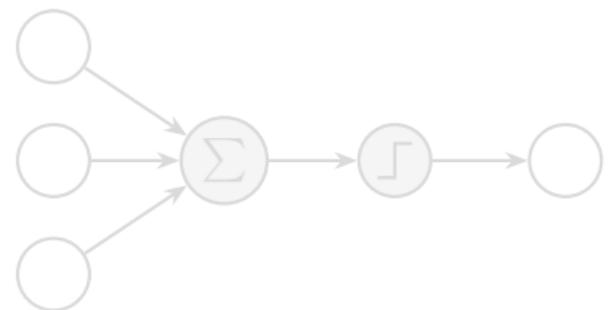


The Mathematical Neuron

Neuron

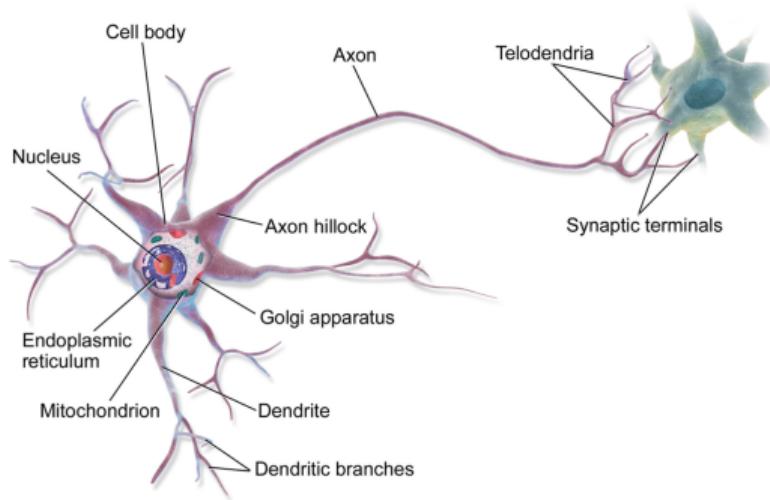


Artificial neuron

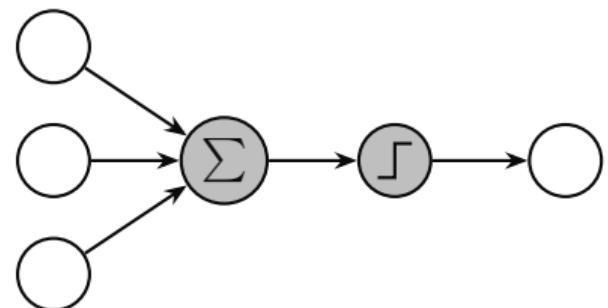


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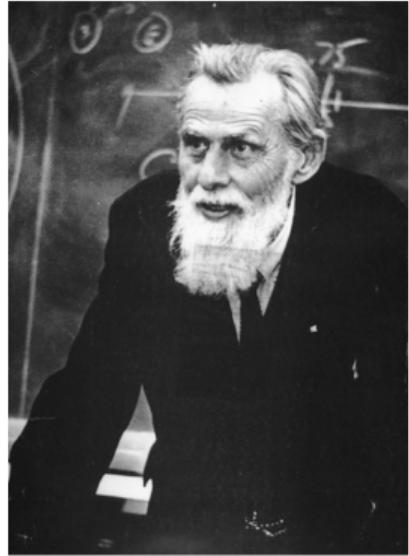
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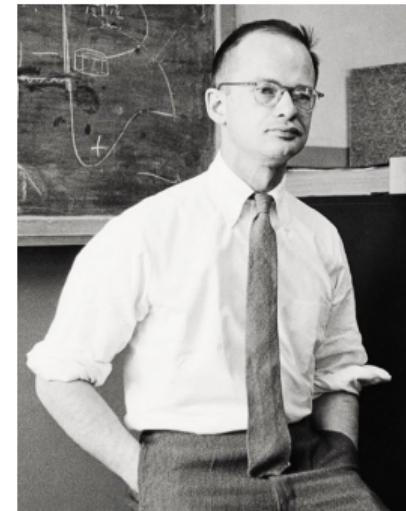


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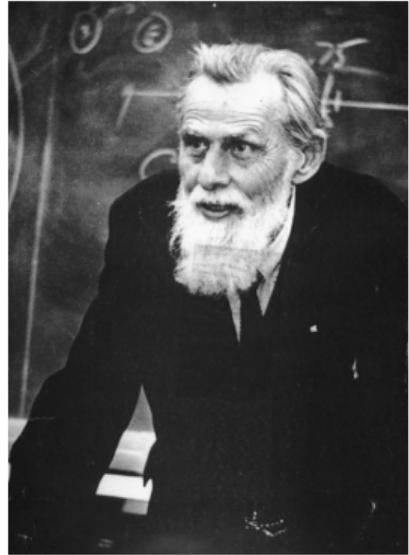
Warren S. McCulloch

- Communication takes place when an electro-chemical signal gets transferred from one neuron to another.
- All the processing then happens in the cell body.
- The processed information then travels to the synaptic terminal which “decides” whether the information should be passed to the next neuron or not.
- The same information passes to millions of neurons.



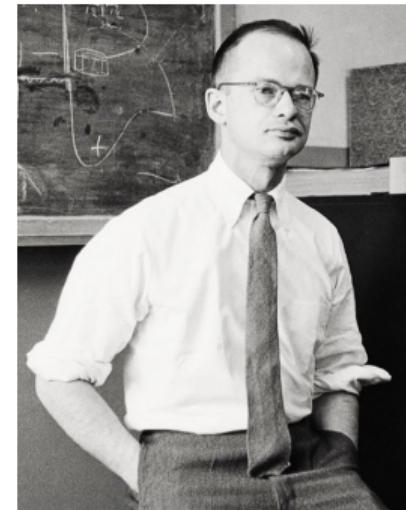
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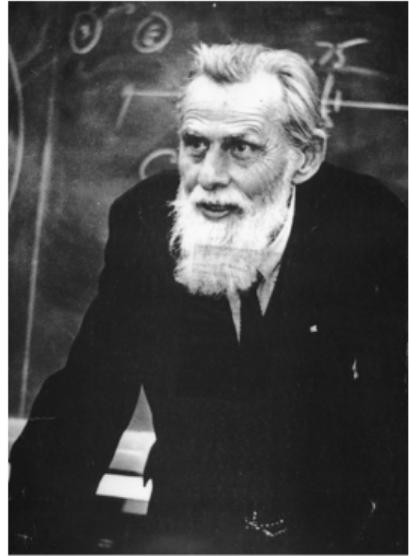
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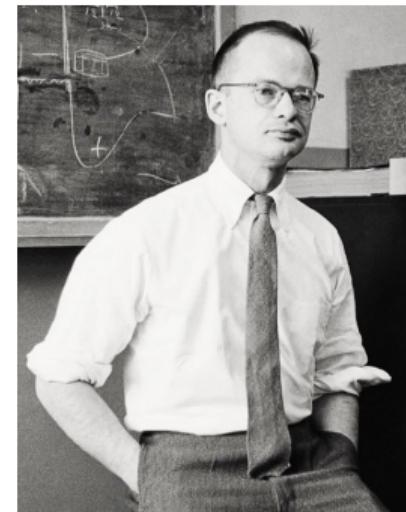
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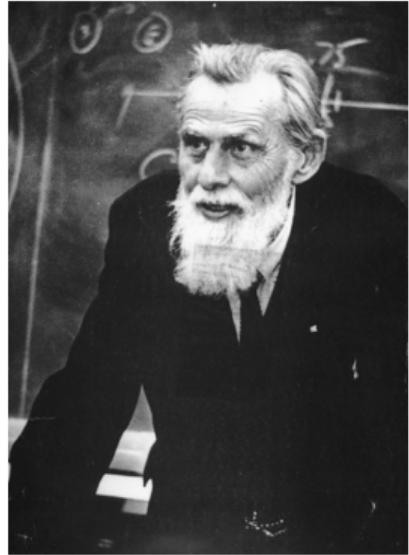
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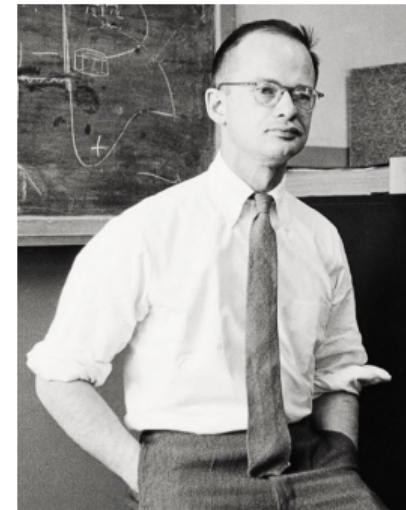
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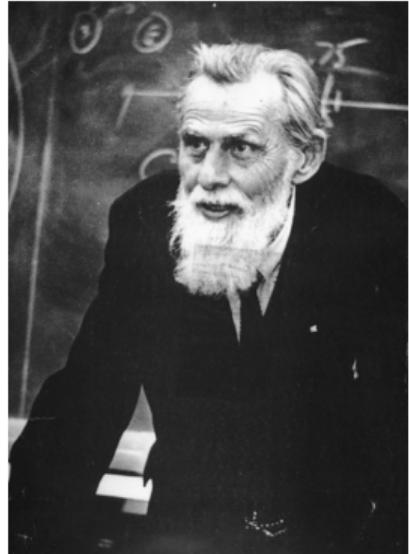
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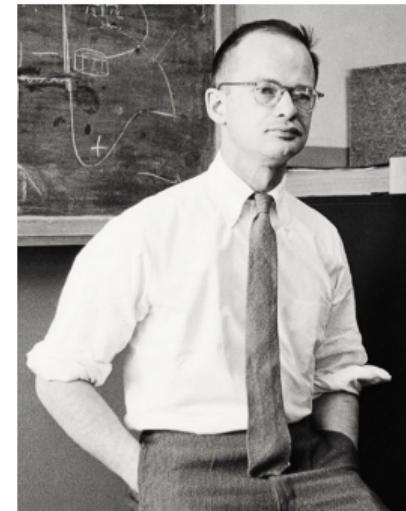
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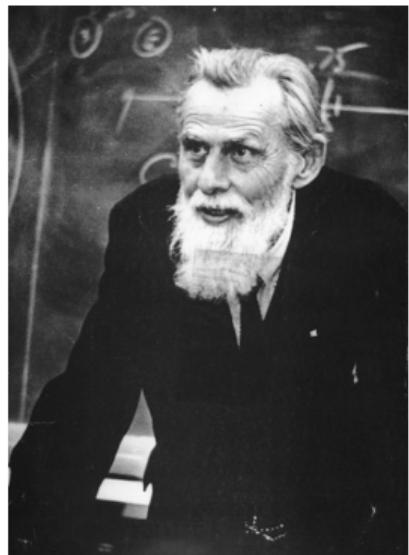
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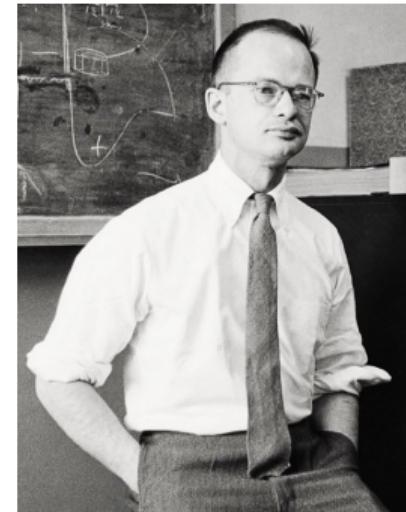
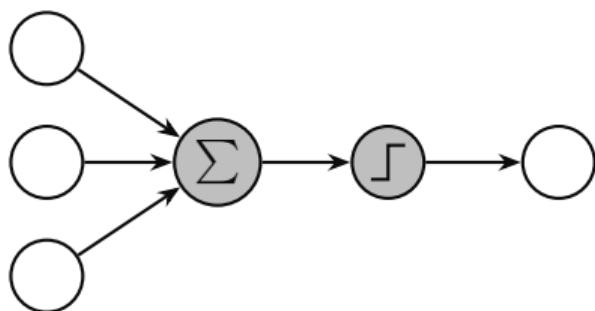
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The Mathematical Neuron



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“Because of the ‘all-or-none’ character of nervous activity, neural events and the relations among them can be treated by means of propositional logic.”



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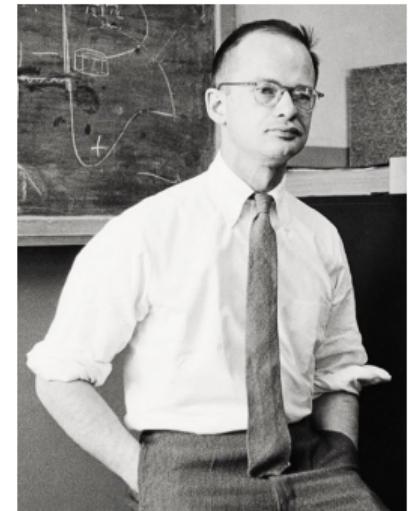
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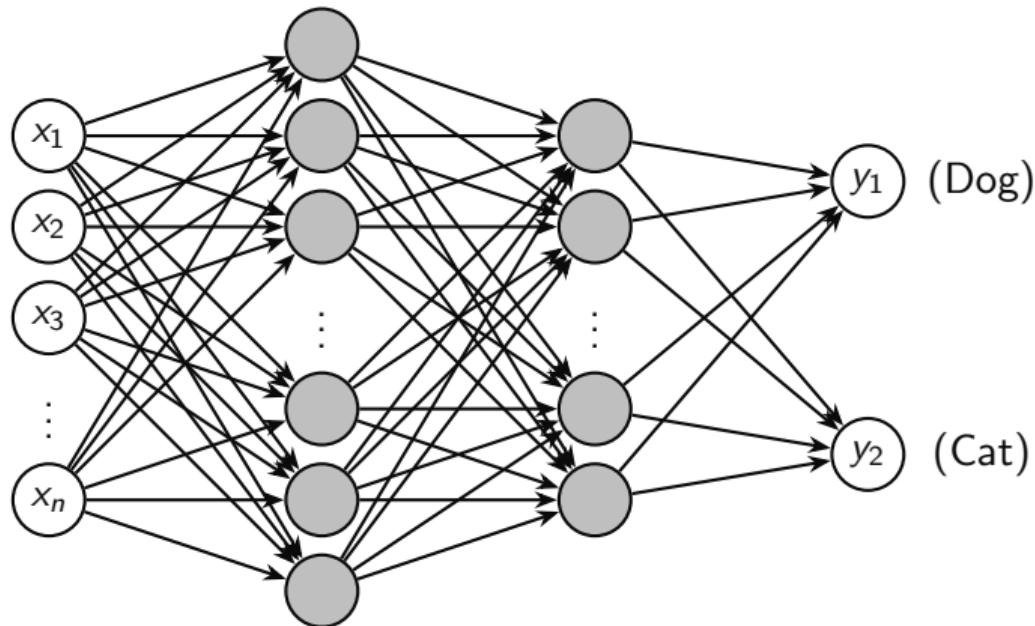
$$f(x_1, \dots, x_n) = \begin{cases} 1 & \text{if } \sum_{k=1}^n x_k > 1 \\ 0 & \text{otherwise.} \end{cases}$$



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Synaptic Plasticity

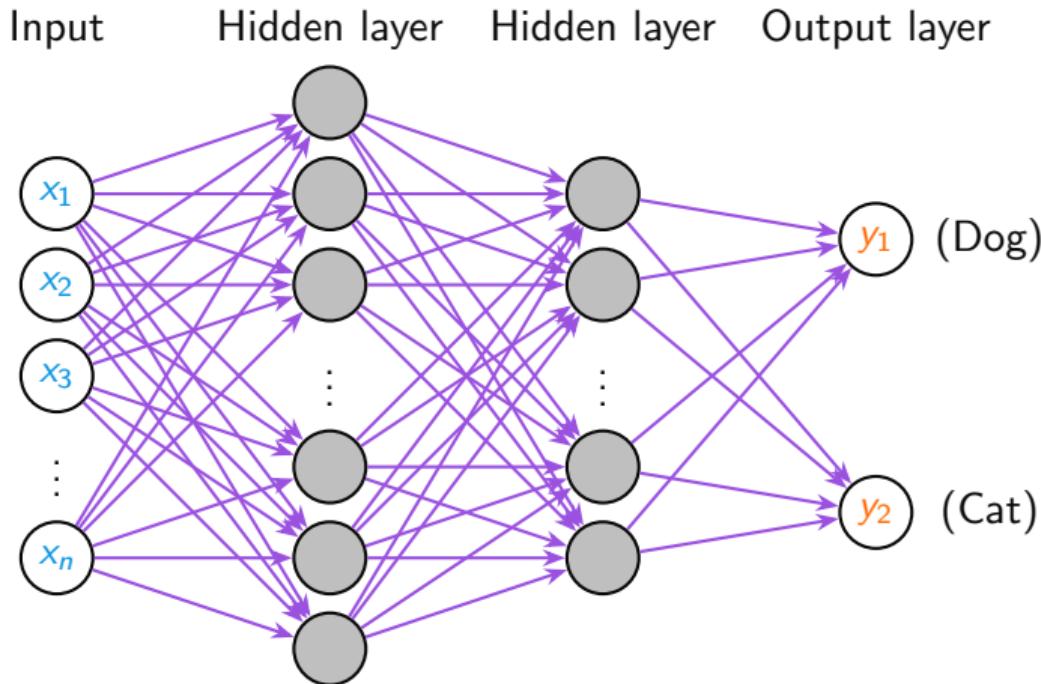
Input Hidden layer Hidden layer Output layer



$$h_{\theta}(\mathbf{x}) = \mathbf{y},$$

where $\mathbf{x} = (x_1, \dots, x_n)$ and $\mathbf{y} = (y_1, \dots, y_k)$

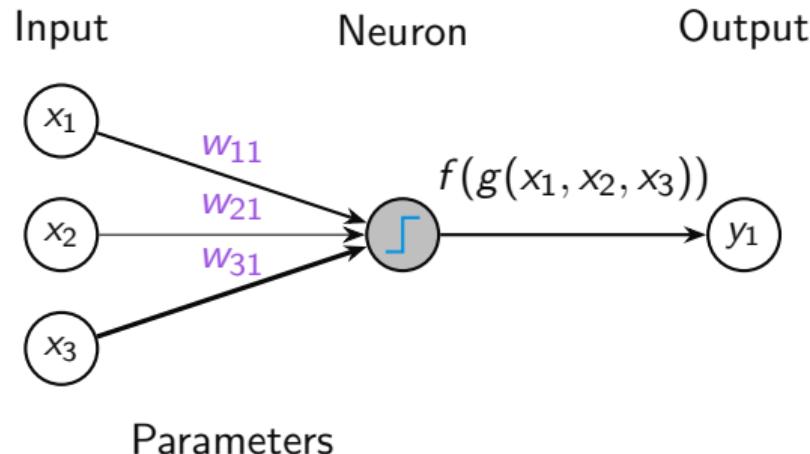
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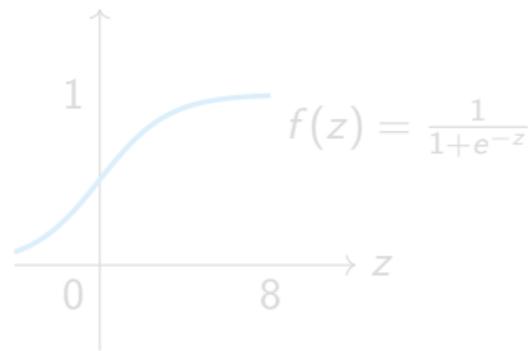
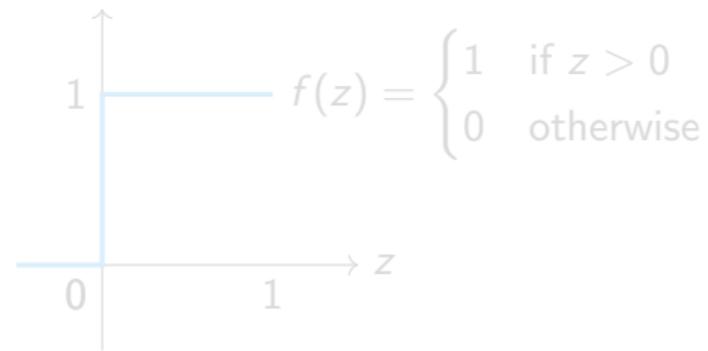
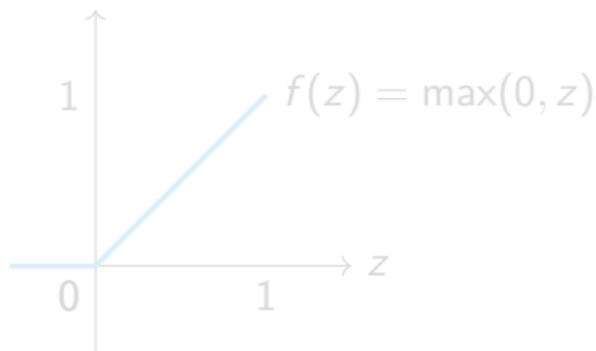
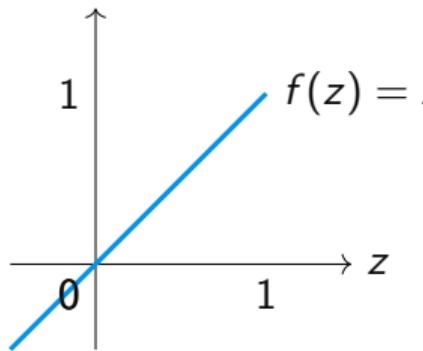
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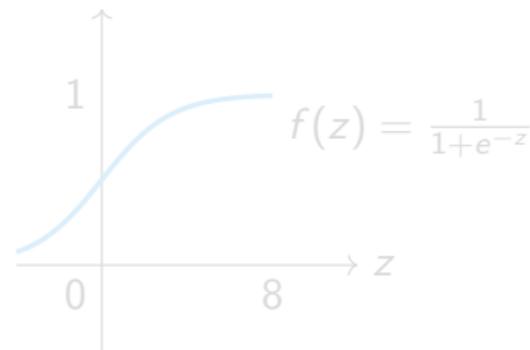
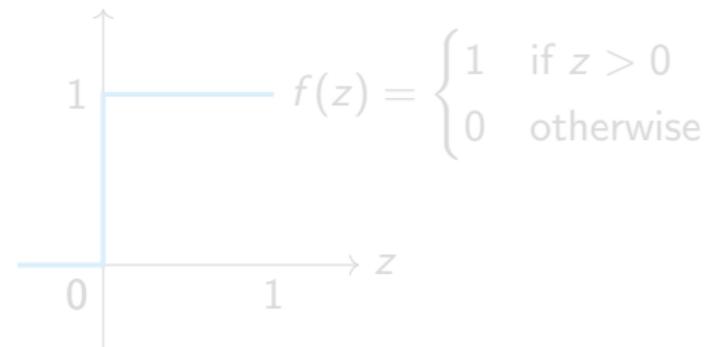
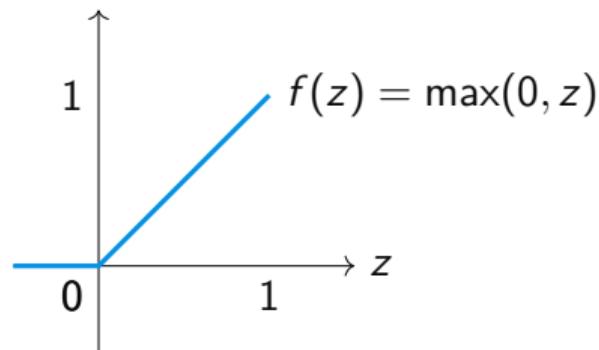
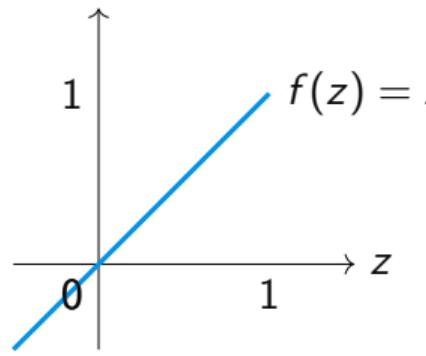
Parameters determine how strong neurons are wired together:

$$g(x_1, x_2, x_3) = x_1 \cdot w_{11} + x_2 \cdot w_{21} + x_3 \cdot w_{31}$$

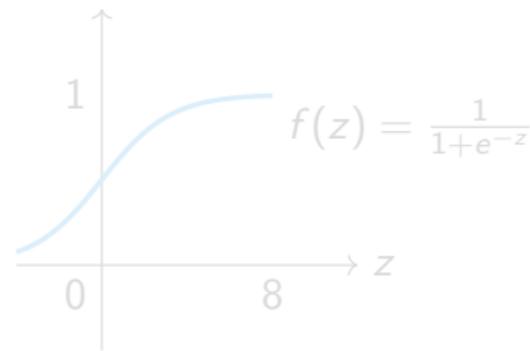
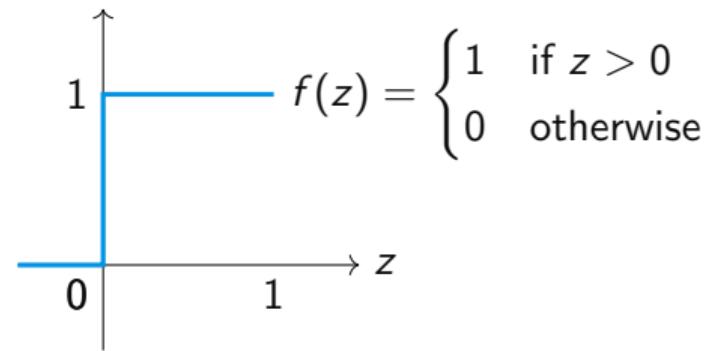
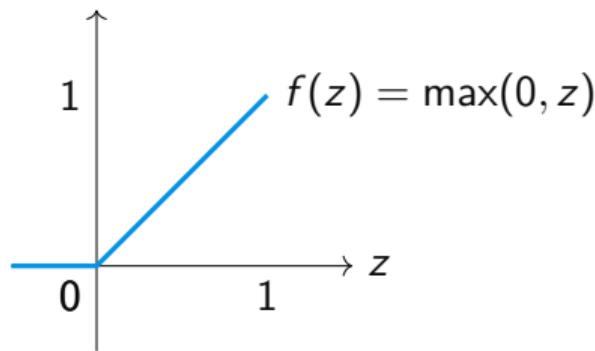
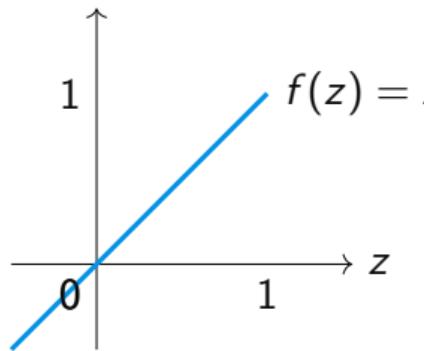
Activation Functions



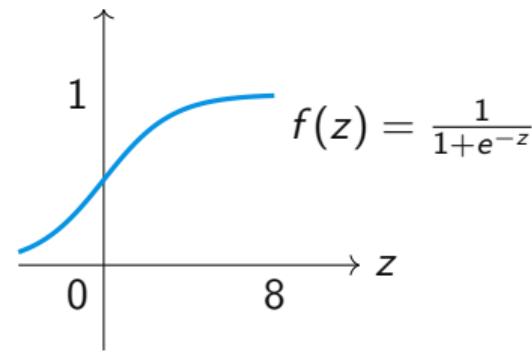
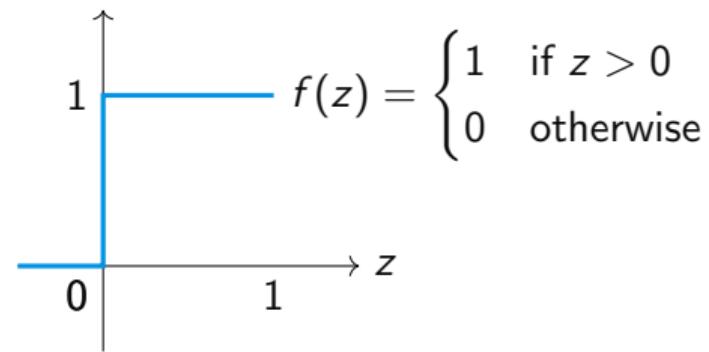
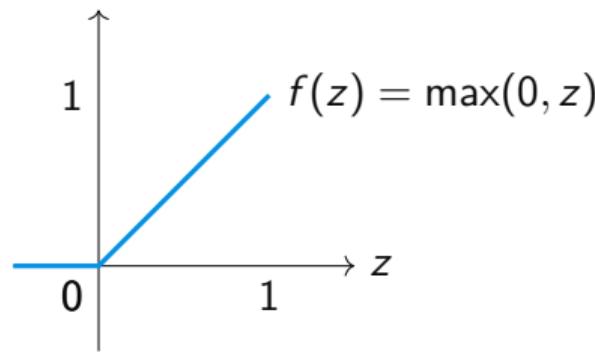
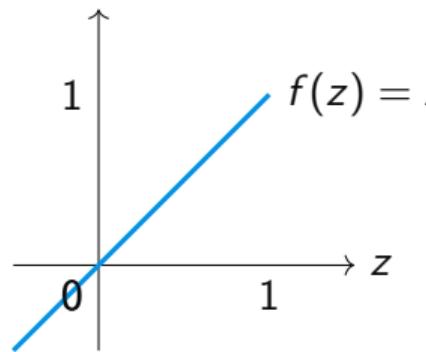
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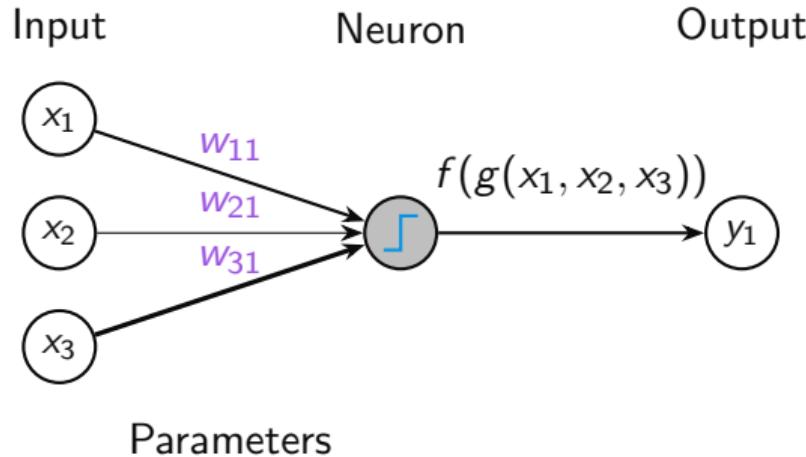
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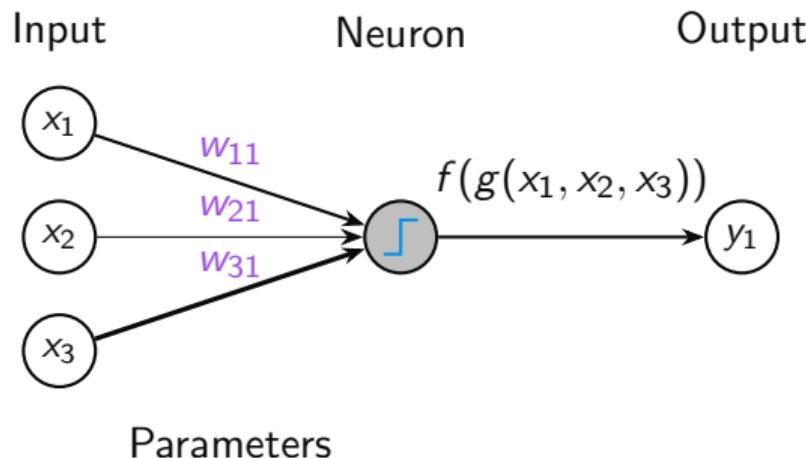
Synaptic Plasticity



“Neurons that fire together, wire together.”

$$w_{ij} = w_{ij} - \eta \cdot x_i \cdot y_j$$

Synaptic Plasticity



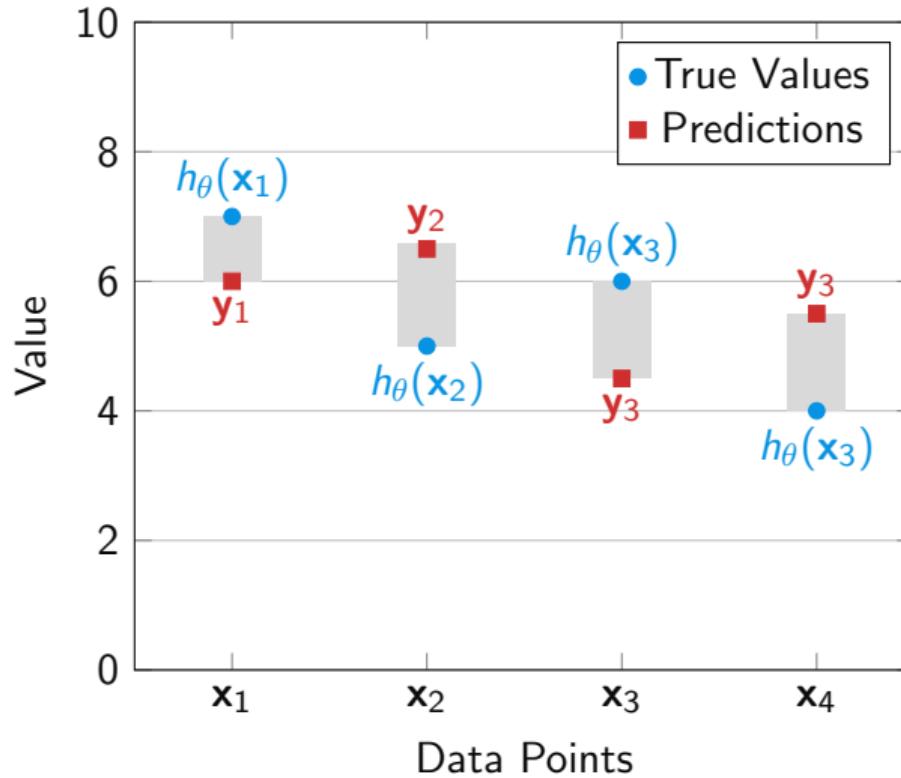
“Neurons that fire together, wire together.”

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t)$$

In this case $\theta_t = (w_{11}, w_{21}, w_{31})$.

Cost Function (Regression)

Mean Squared Error (MSE):



Cost Function (Regression)

Mean Squared Error (MSE):

$$J(\theta) = \frac{1}{N} \sum_{i=1}^N (\mathbf{y}_i - h_\theta(\mathbf{x}_i))^2$$

where \mathbf{y}_i is the correct label of a data point $\mathbf{x}_i = (x_1, \dots, x_n)$ in our training data.

Cost Function (Regression)

Example: Let us suppose $h_{\theta}(x_1, x_2) = w_{11} \cdot x_1 + w_{21} \cdot x_2$ and let us assume $w_{11} = 2$, $w_{21} = 0.5$ and we have two data points $\mathbf{x}_1 = (1, 1)$, $y_1 = 1$ and $\mathbf{x}_2 = (-1, -2)$, $y_2 = -3$. Then our mean squared error is:

$$\begin{aligned} J(w_{11}, w_{21}) &= \frac{1}{2} [(1 - (w_{11} \cdot 1 + w_{21} \cdot 1))^2 + (-3 - (w_{11} \cdot (-1) + w_{21} \cdot (-2)))^2] \\ &= \frac{1}{2} [(1 - (2 \cdot 1 + 0.5 \cdot 1))^2 + (-3 - (2 \cdot (-1) + 0.5 \cdot (-2)))^2] \end{aligned}$$

The gradient would be:

$$\nabla J(w_{11}, w_{21}) = \begin{bmatrix} -4 + 2w_{11} + 3w_{21} \\ -7 + 3w_{11} + 5w_{21} \end{bmatrix}$$

Categorical Cross Entropy Cost:

$$J(\theta) = -\frac{1}{N} \sum_{i=1}^N [\mathbf{y}_i \cdot \log(h_\theta(\mathbf{x}_i))]$$

where \mathbf{y}_i is interpreted as the probability distribution of categories for $\mathbf{x}_i = (x_1, \dots, x_n)$, i. e. a data point.

To improve the model's prediction, we try to minimize the cost function. One way to do this is **gradient decent**:

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t)$$

Condition: $\nabla J(\theta_t)$ exists!

Interactive Tutorial

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Interactive Tutorial

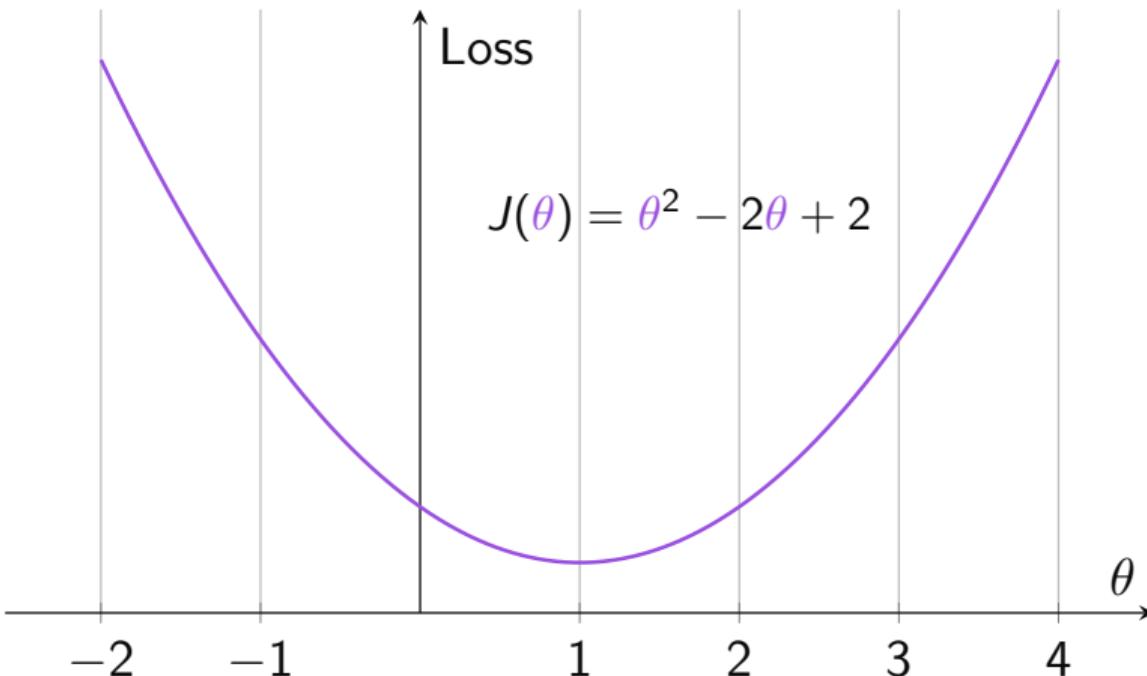
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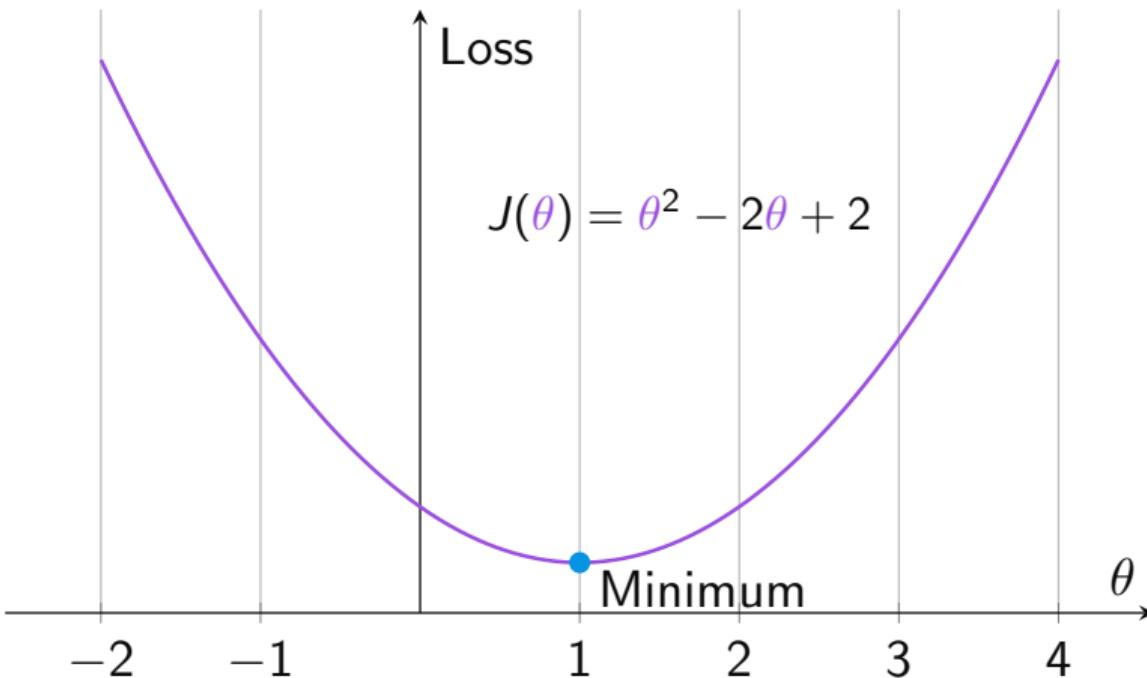
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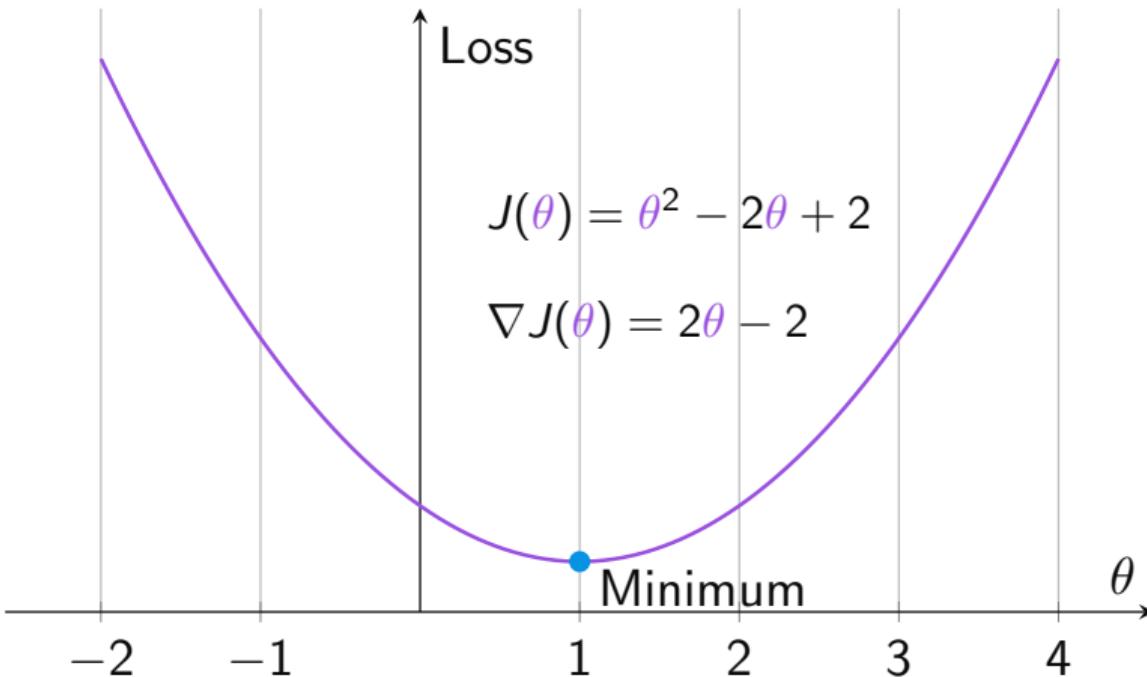
Gradient Decent



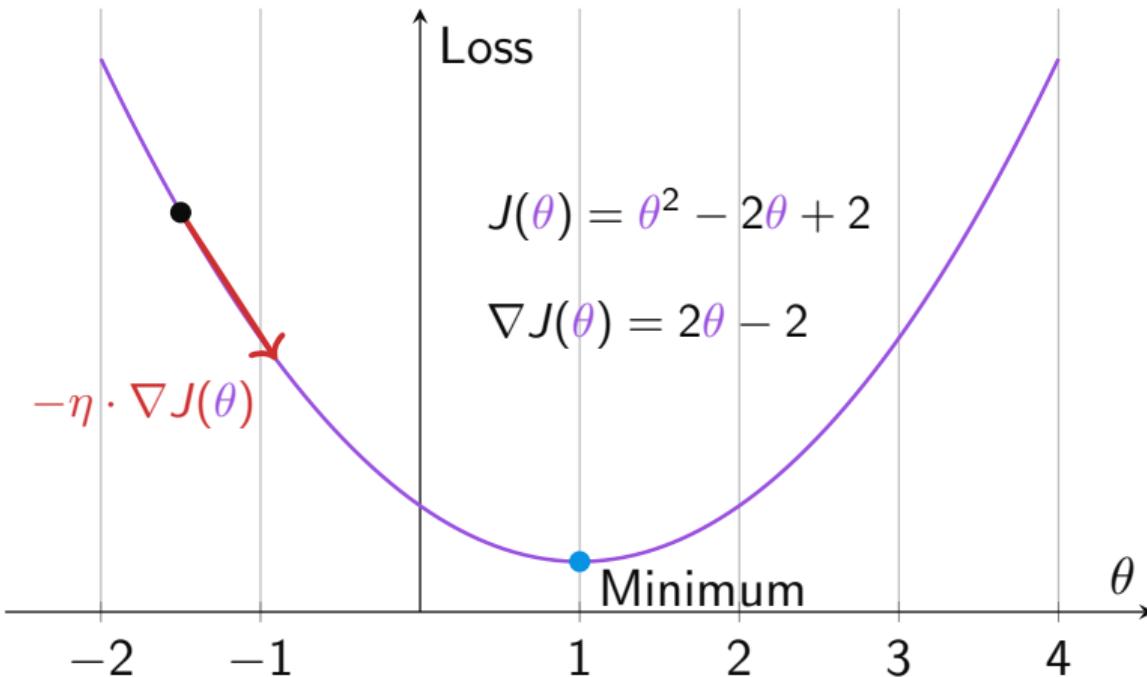
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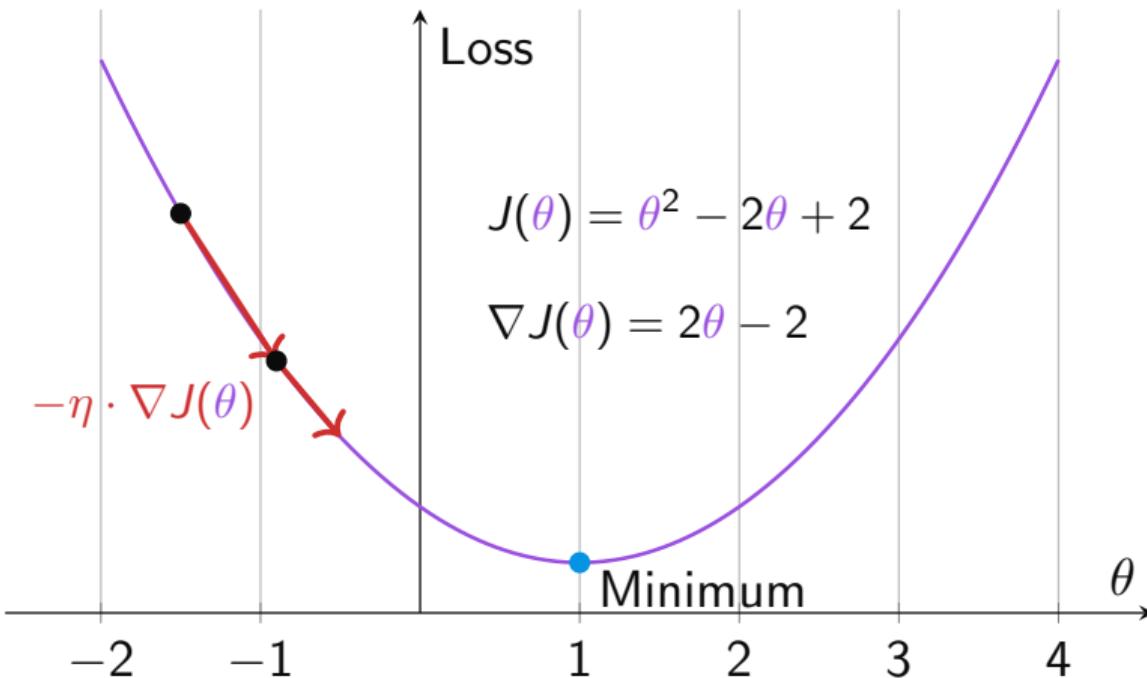
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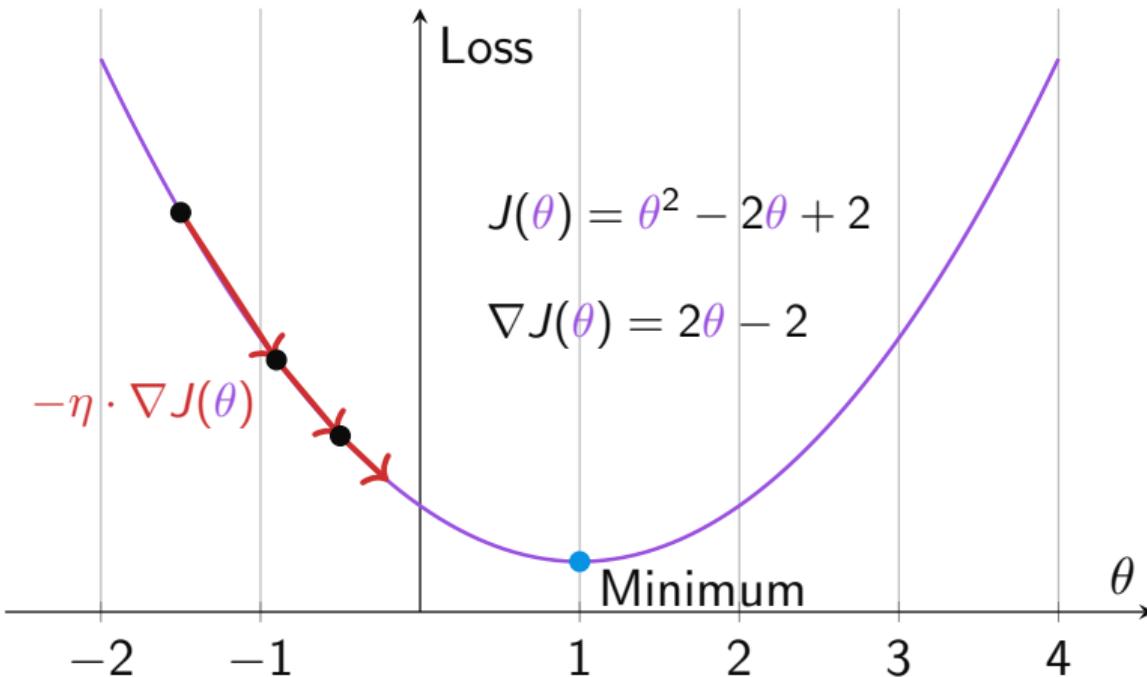
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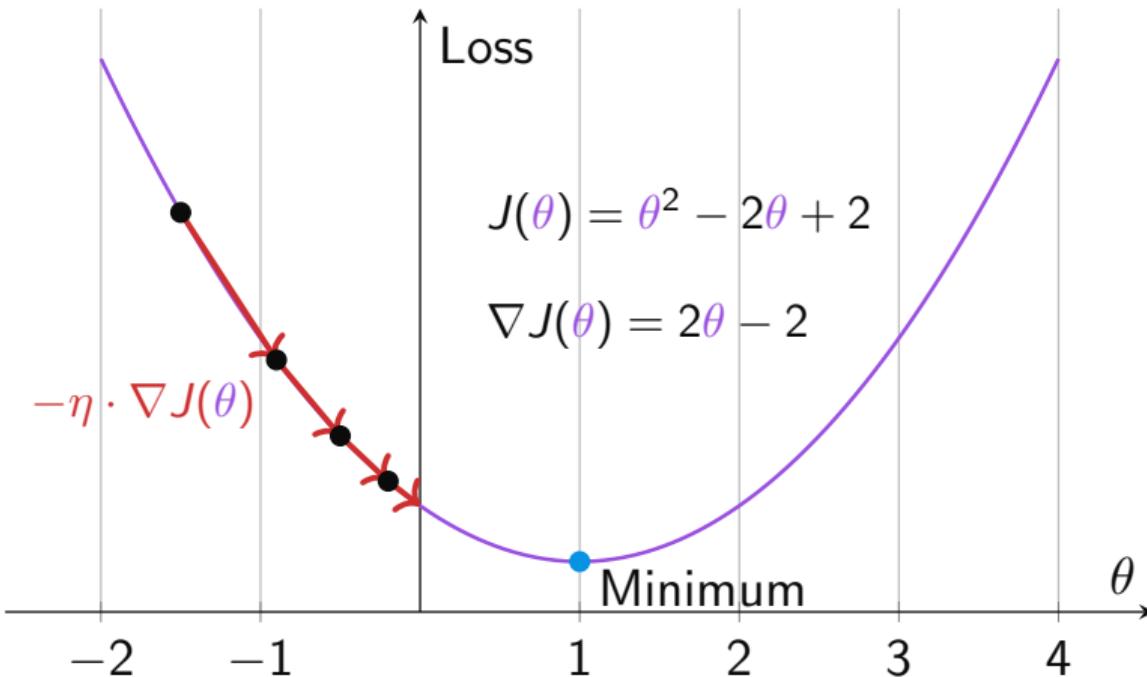
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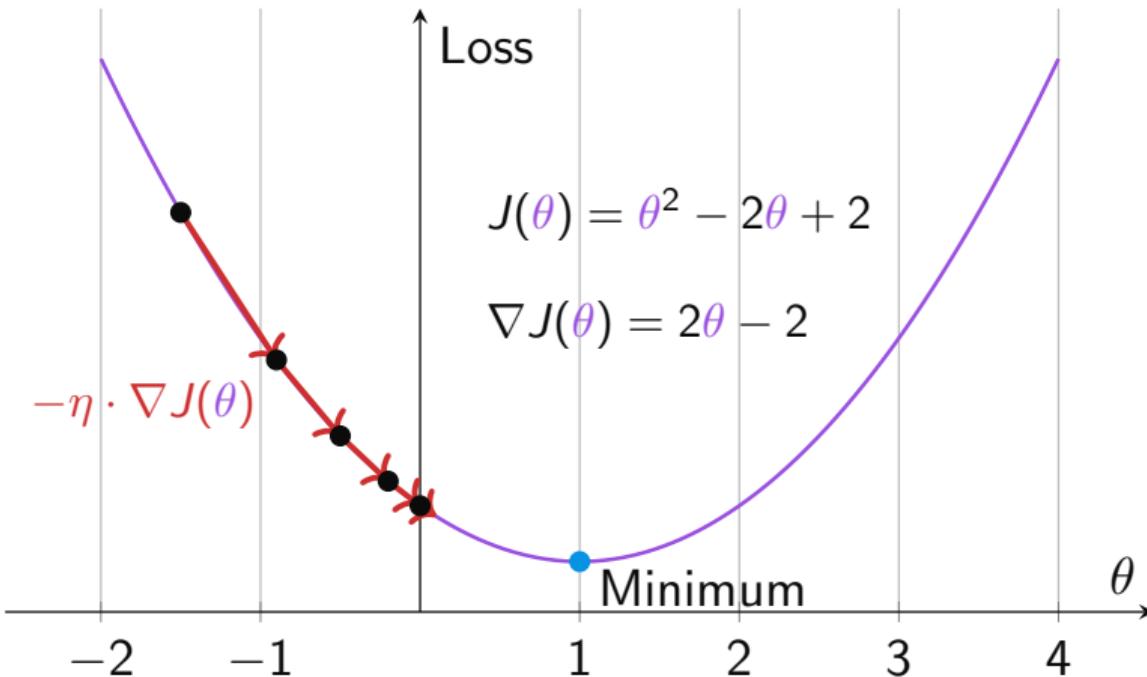
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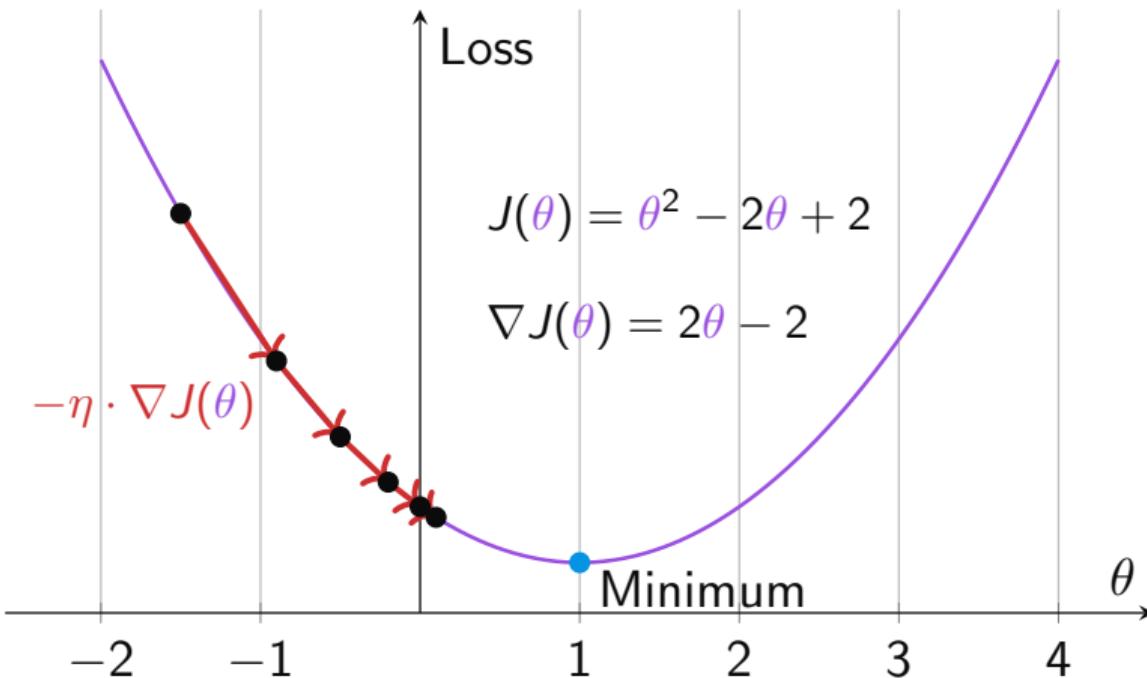
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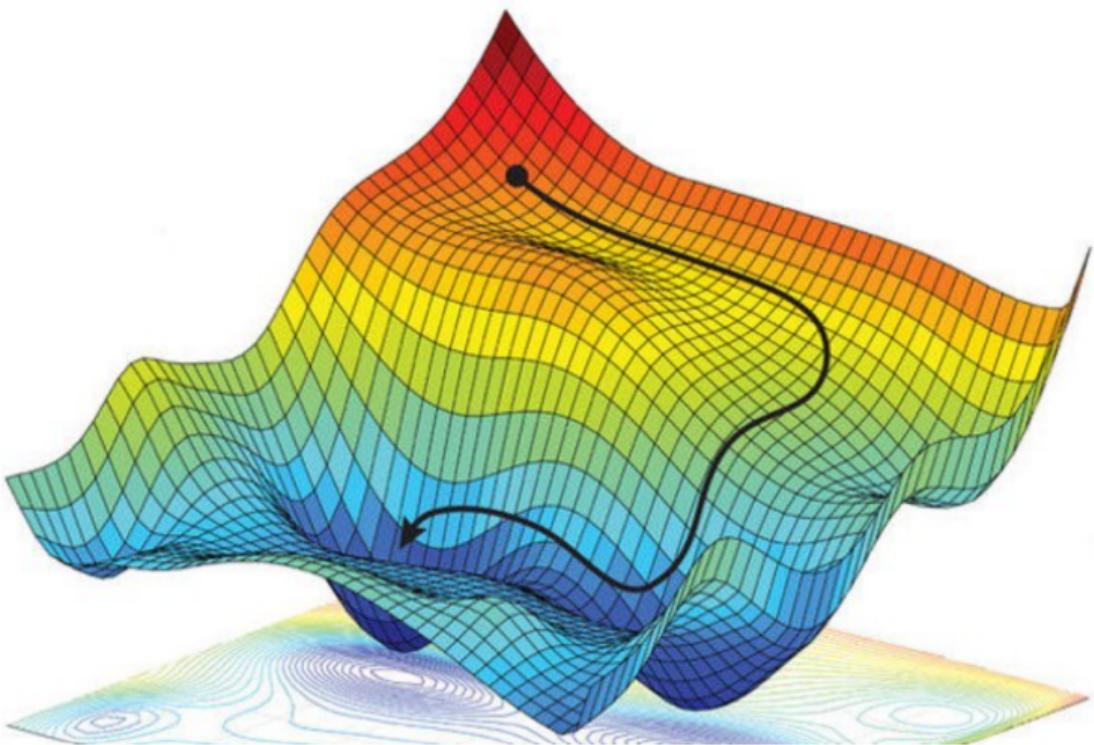
Gradient Decent



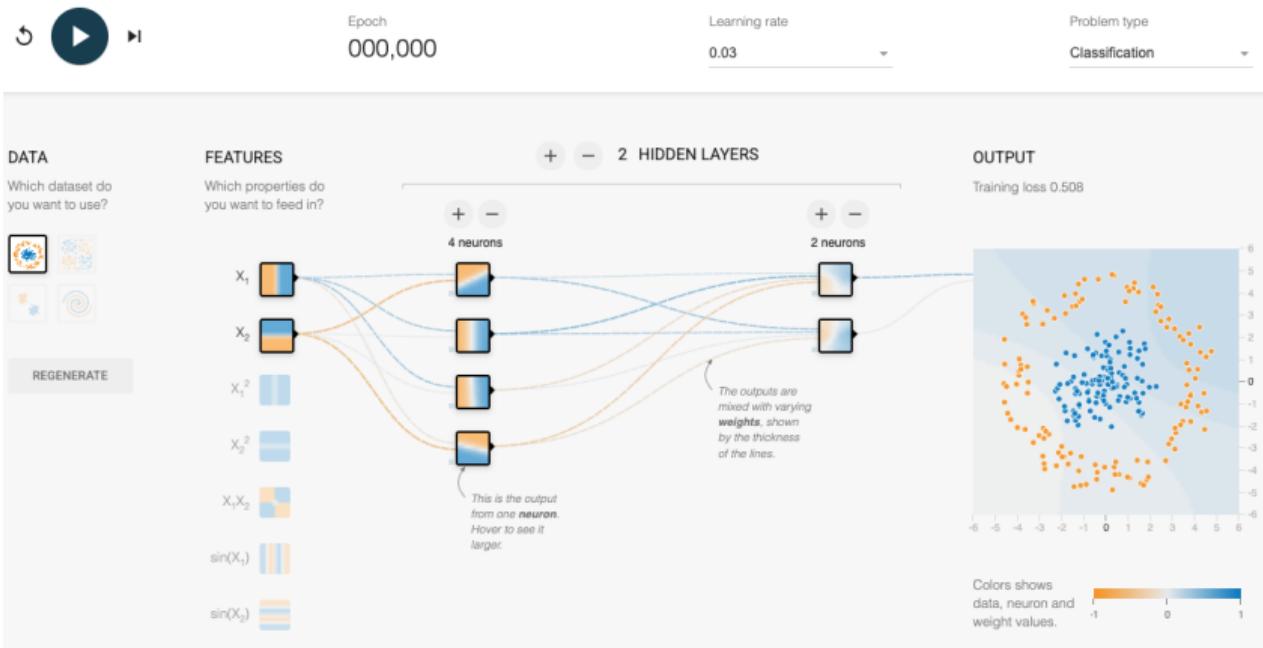
Gradient Decent



Gradient Decent



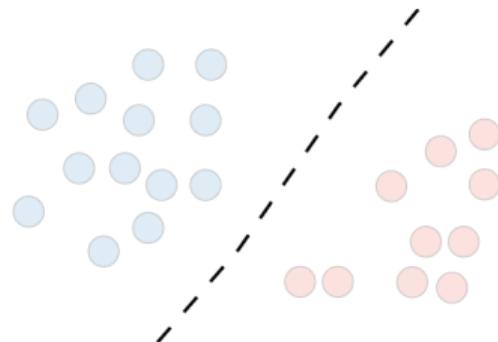
Design and Try Your Perceptron



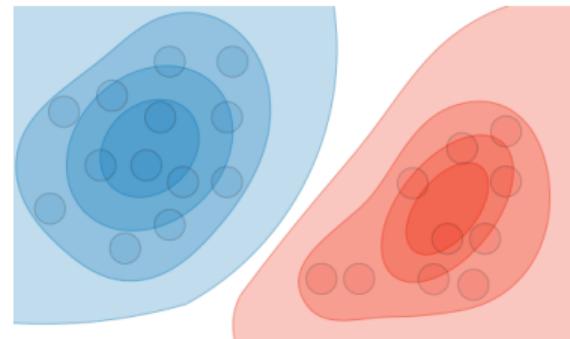
Simplified Tensorflow Playground

Extended Tensorflow Playground

- **Discriminative models:** Learn the boundaries of decisions.
- **Generative models:** Learn the whole distribution of the data.



Discriminative modelling



Generative modelling

1. How to Model Intelligence?

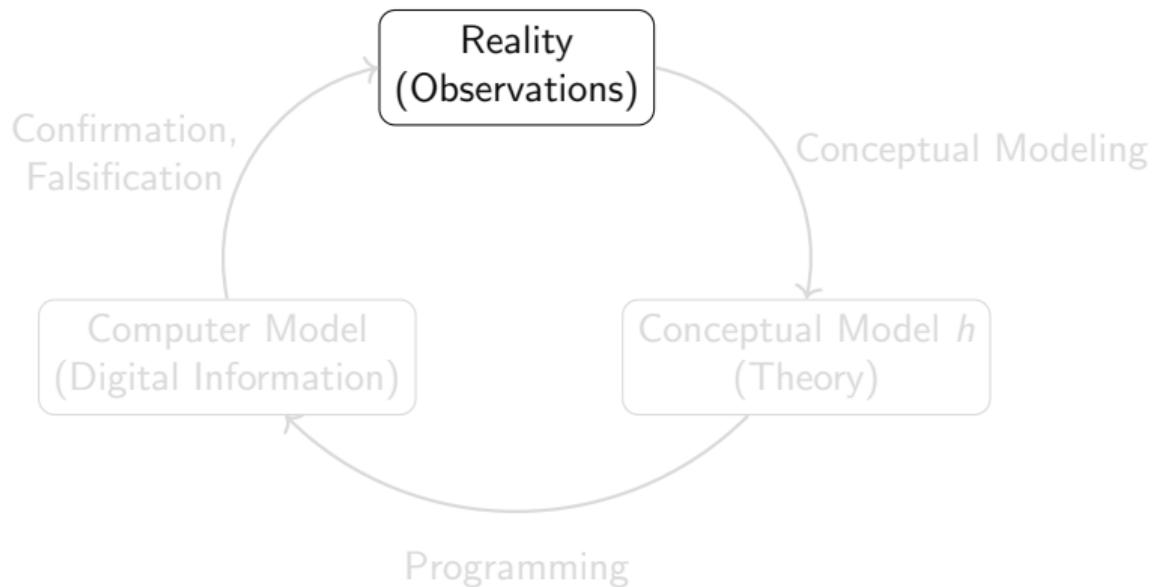
2. When is Learning Possible?

3. How Do Machines Learn?

4. How Do Humans Train Machines?

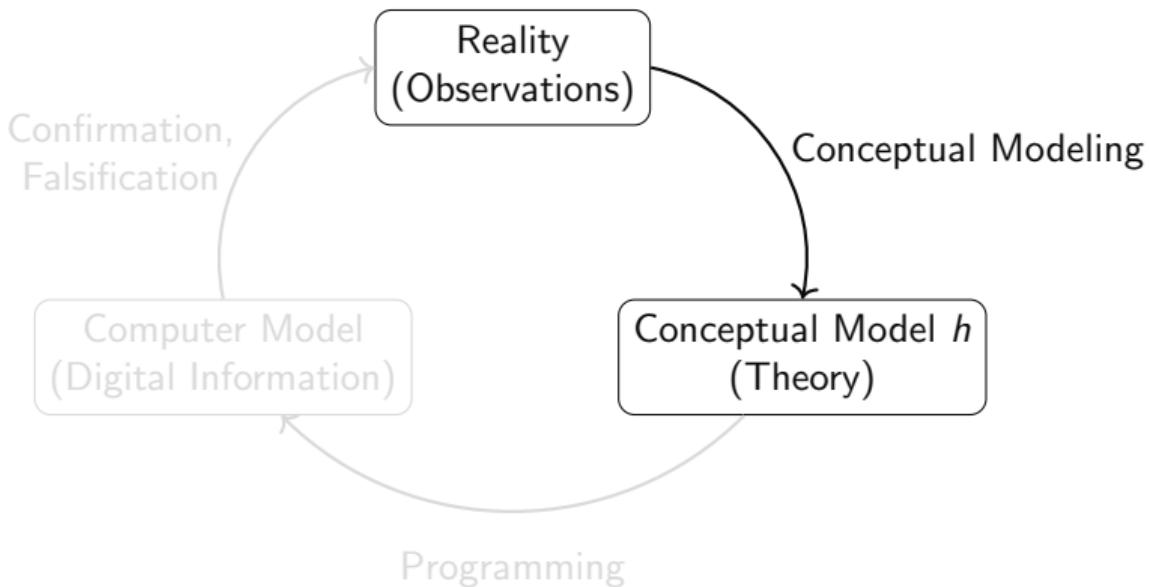
5. How to Interact with Learning Machines?

Theory-driven Modeling



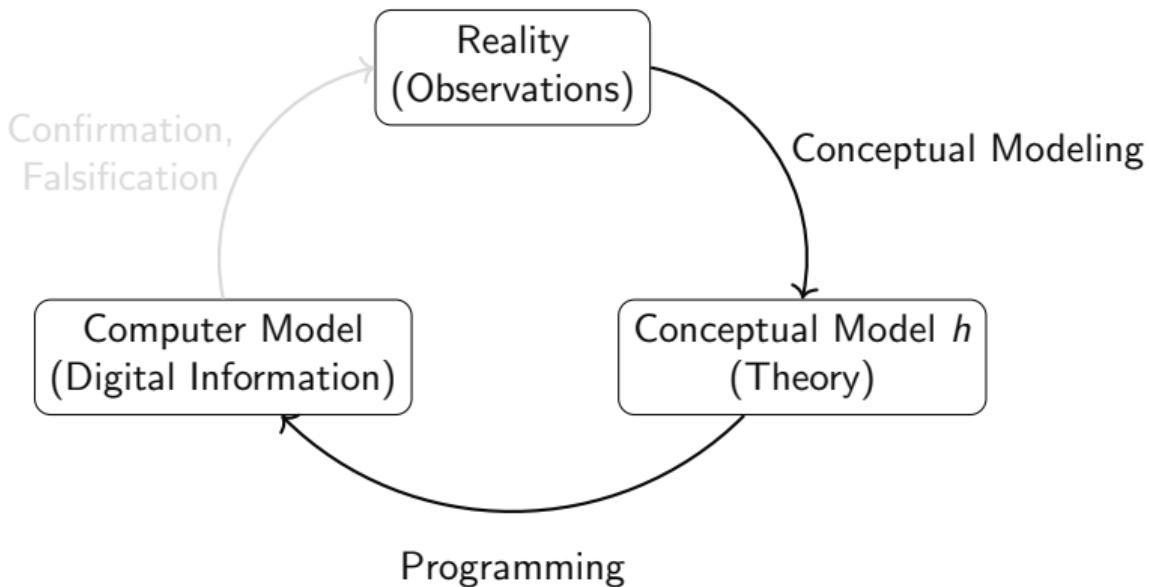
Minds constructs a (falsifiable) theory or hypothesis about reality to test against.

Theory-driven Modeling



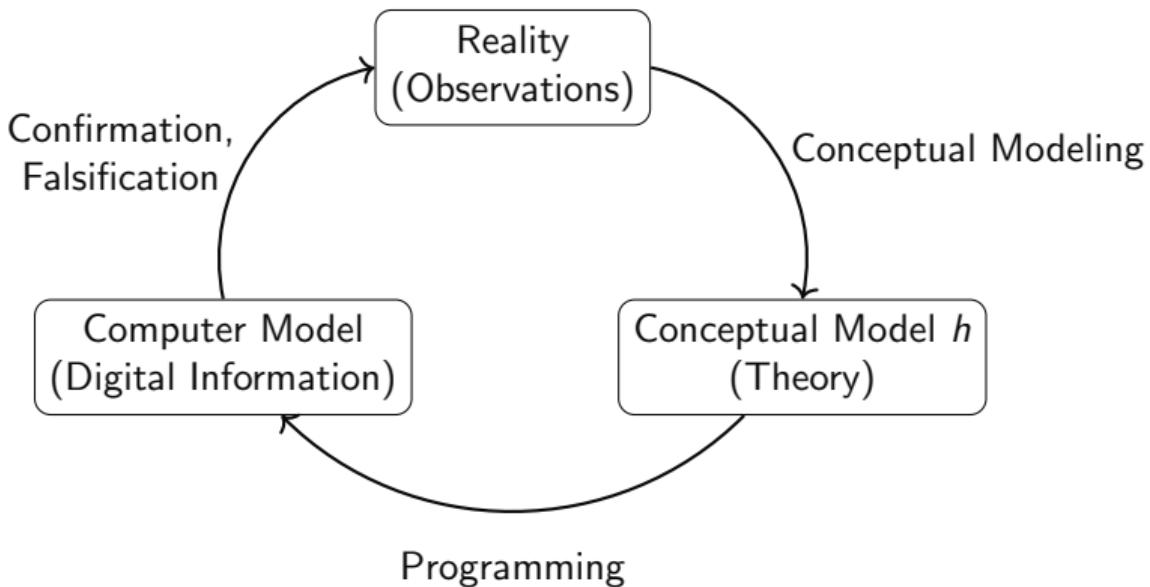
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Theory-driven Modeling



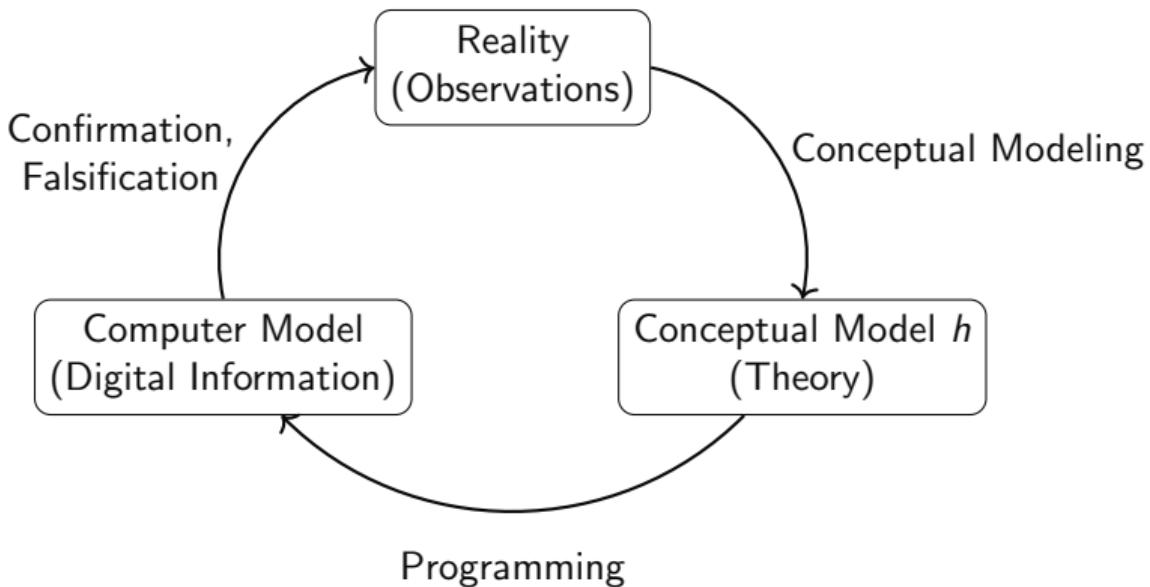
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Theory-driven Modeling



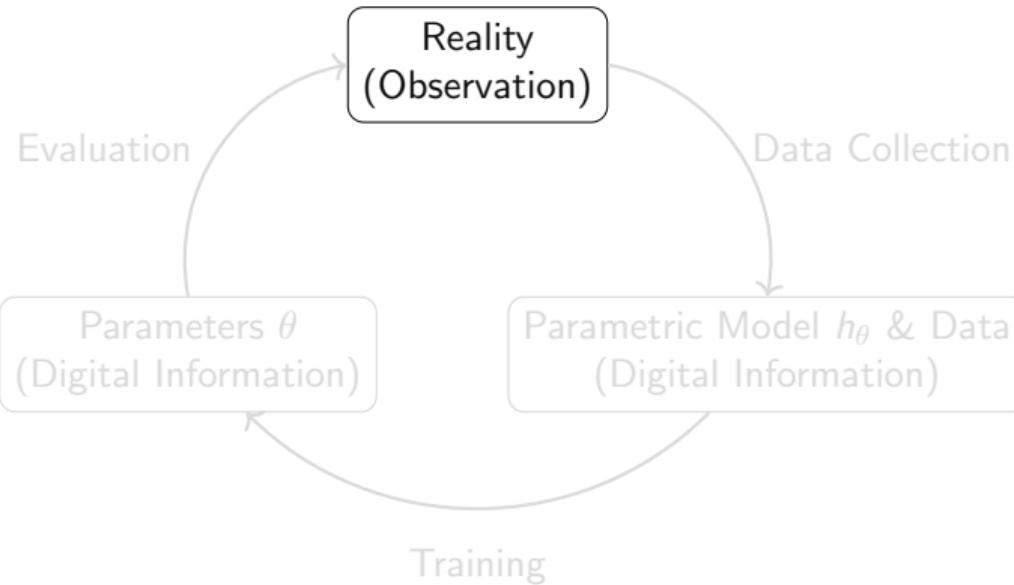
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Theory-driven Modeling



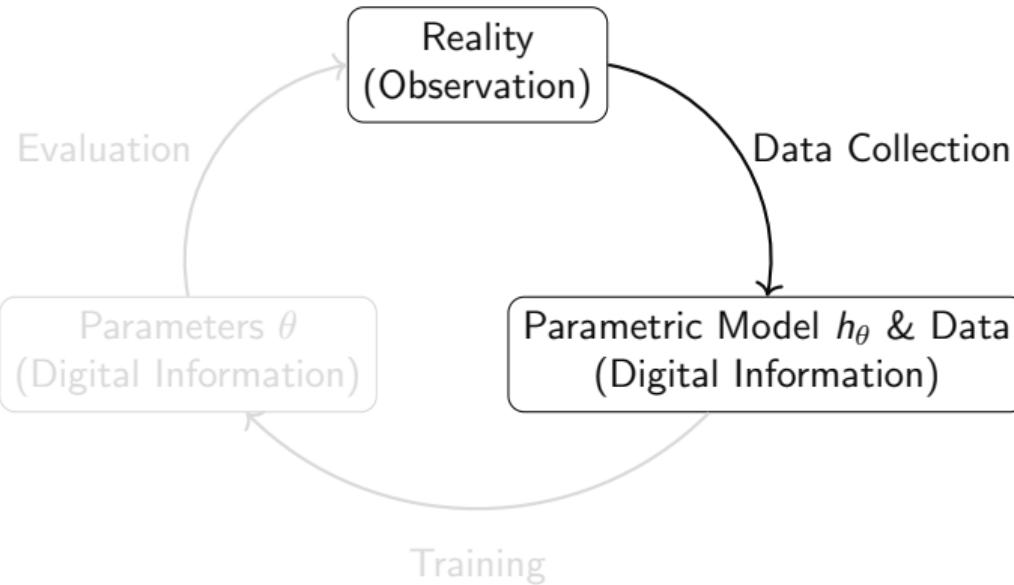
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Data-driven Modeling



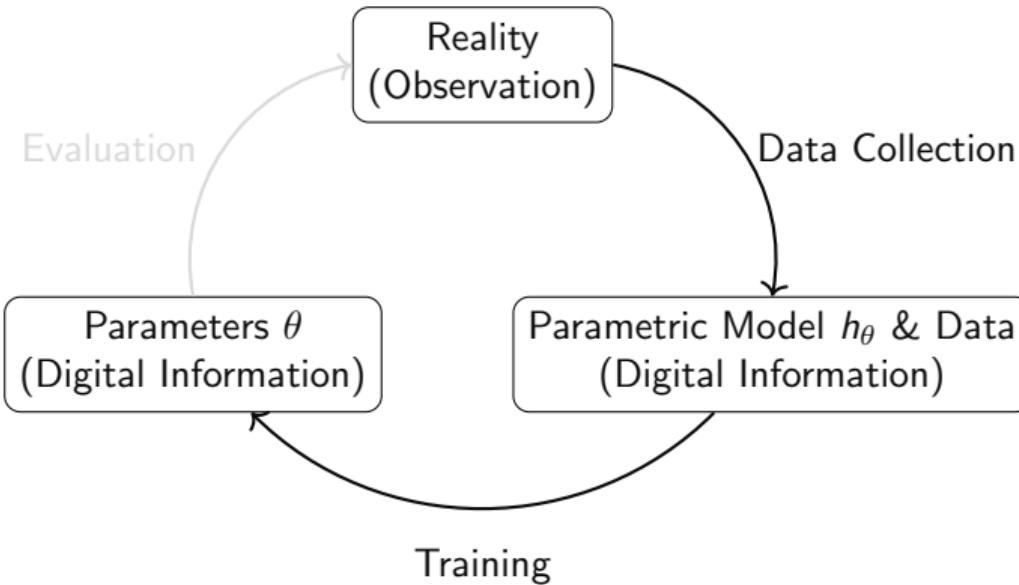
Algorithms (directly) fit a parametric model to the data. **Minds** are usually unable to conceptualize the trained model.

Data-driven Modeling



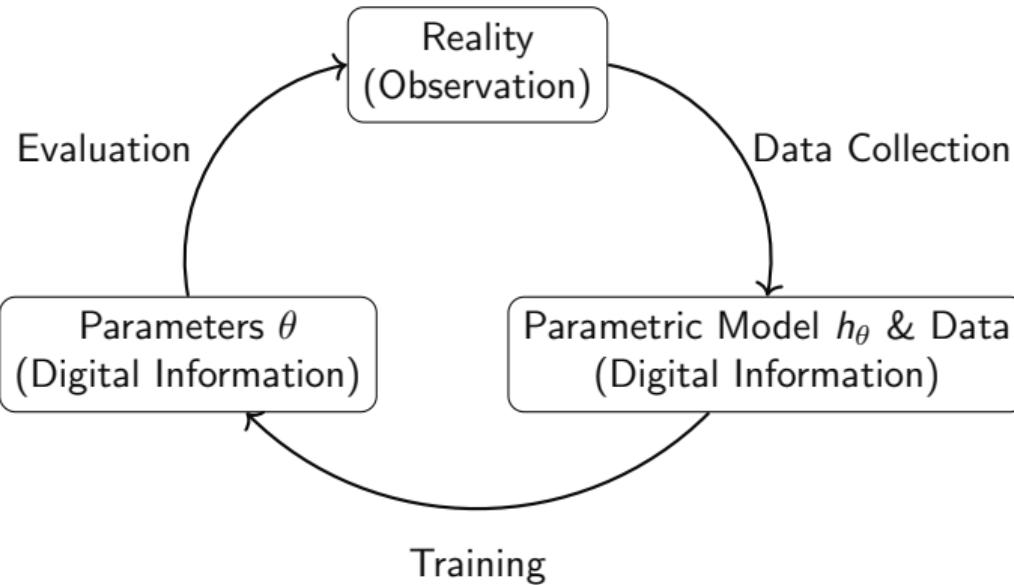
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Data-driven Modeling



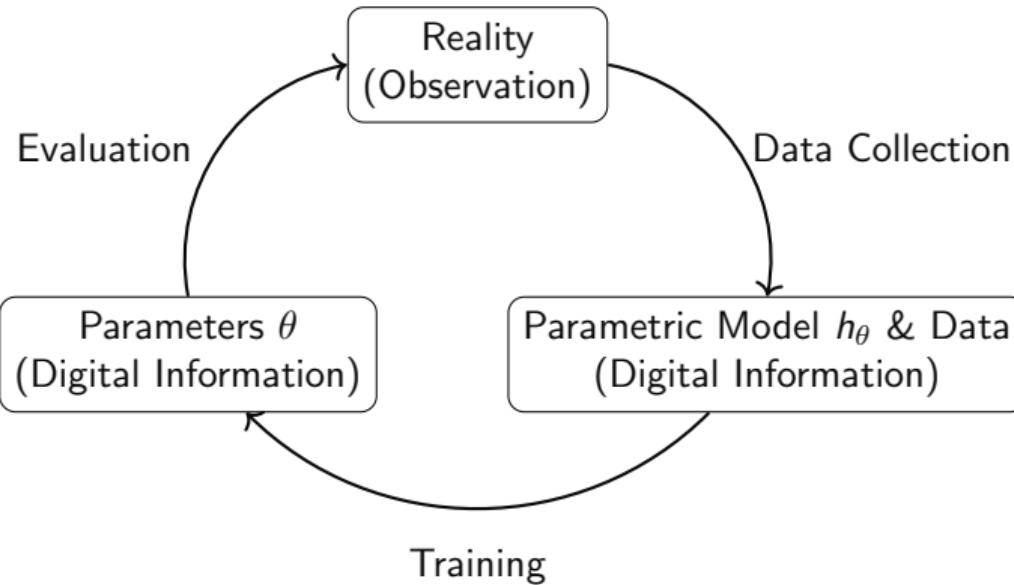
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Data-driven Modeling



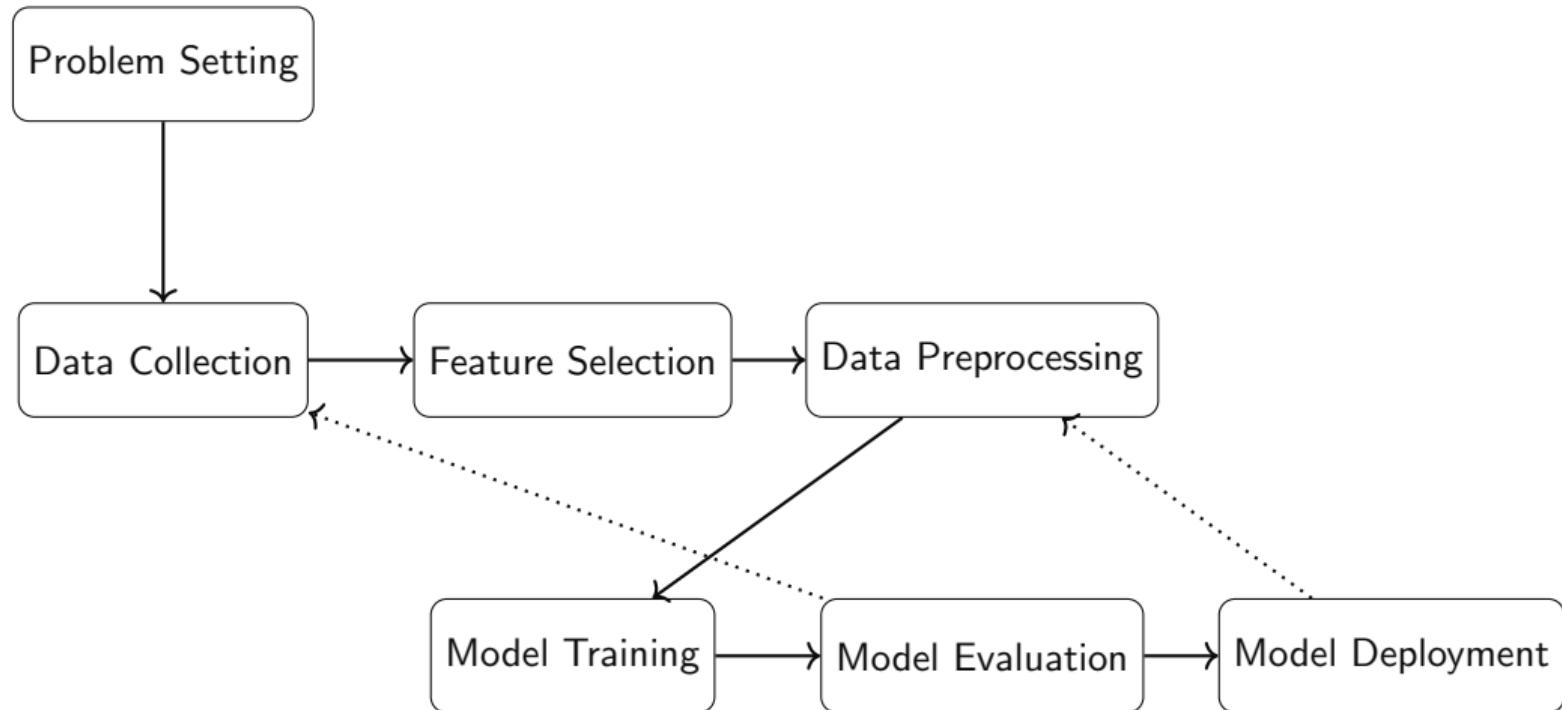
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Data-driven Modeling



Algorithms (directly) fit a parametric model to the data. **Minds** are usually unable to conceptualize the trained model.

Development Cycle



Programming Libraries

```
100 class fast_qlinear(torch.autograd.Function):
101     def forward(ctx, a, b, scales, zeros):
102         m, k = a.shape
103         _, n = b.shape
104
105         quant_groupsize = 128
106         block_size_m = 16
107         block_size_n = 32 # [N = 4096 // 32] = 128 blocks
108         block_size_k = 256
109         group_size_m = 8
110         num_warps = 4
111         num_stages = 8
112         total_blocks_m = triton.cdiv(m, block_size_m)
113         total_blocks_n = triton.cdiv(n, block_size_n)
```

Python and ML libraries (PyTorch,
tensorflow, JAX etc.)

Train a Model with Python

1. How to Model Intelligence?

2. When is Learning Possible?

3. How Do Machines Learn?

4. How Do Humans Train Machines?

5. How to Interact with Learning Machines?

The Marcelle Toolkit

Marcelle: composing interactive machine learning workflows and interfaces (Françoise, Caramiaux, & Sanchez, 2021).

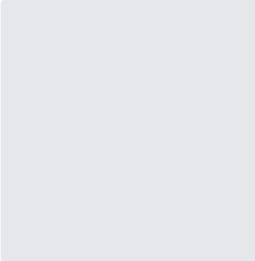
<https://marcelle.dev/>

The Marcelle Toolkit

Marcelle Example - Dashboard Data Management Training Batch Prediction Real-time Prediction 

webcam

activate video



dataset browser

This dataset contains 65 instances.

Instance label

Enter a label...

Capture instances to the training set

Hold to record instances

Bene

Nicht Bene

View More

View More

mobileNet

Using Mobilenet v1 with alpha = 1.

Any questions?

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