AI in Culture and Arts – Tech Crash Course

Introduction to Artificial Intelligence and Machine Learning

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HM

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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 Leaning Machines?

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How to Model Intelligence?

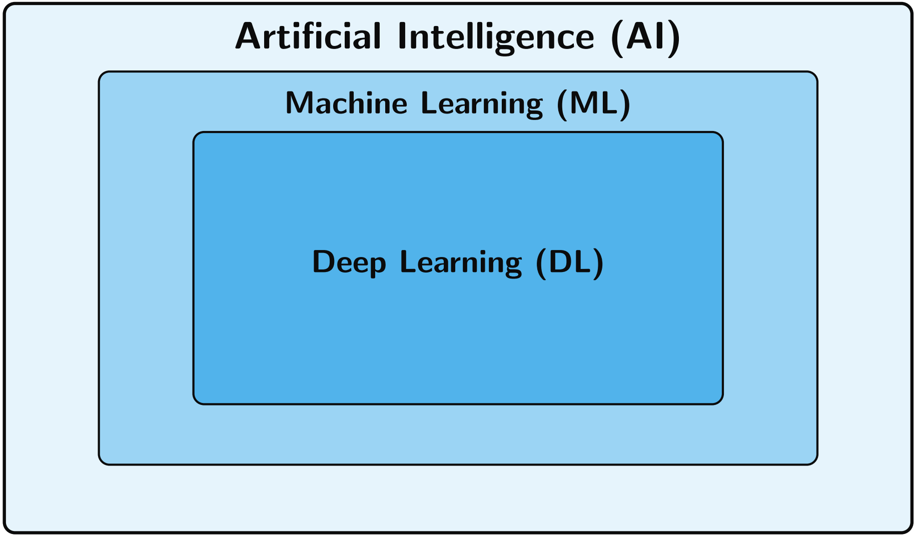
"The ability of an agent to achieve goals in a wide range of environments."
– (Russell, 2019)

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).

How to Model Intelligence?



Most of the hype is based on **Deep Learning**.

How to Model Intelligence?

Symbolism

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

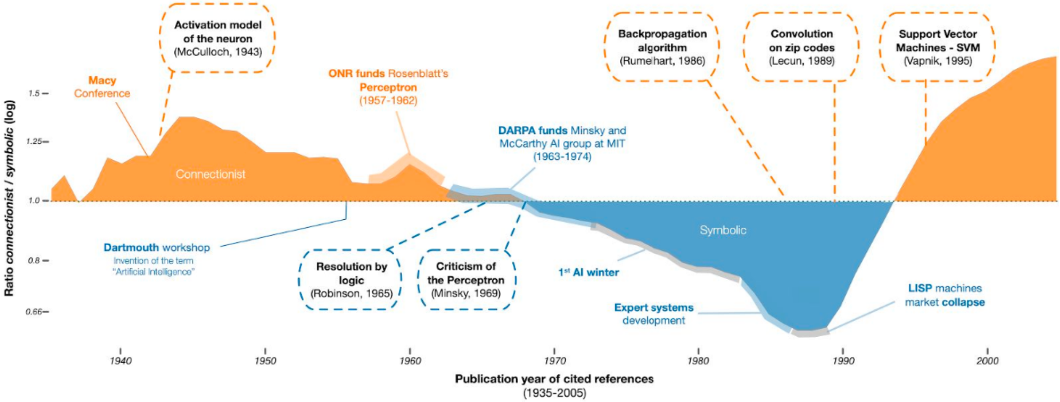
- **Assumption:** Intelligence uses high-level, human-readable symbols to represent problems and logic to solve them.
- **Motivation:** Model the **mind**!

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.
- **Motivation:** Model the **brain**!

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)

010101010101010101010101010101

110011010101110100011100101111

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

$$x_1 = 010101010101010101010101010101$$
$$x_2 = 110011010101110100011100101111$$

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 “often” **suprised** when reading x_2.

When is Learning Possible?

Information entropy measures uncertainty / surprise. It is the **expected value of surprise**.

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

Lerning requires

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

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

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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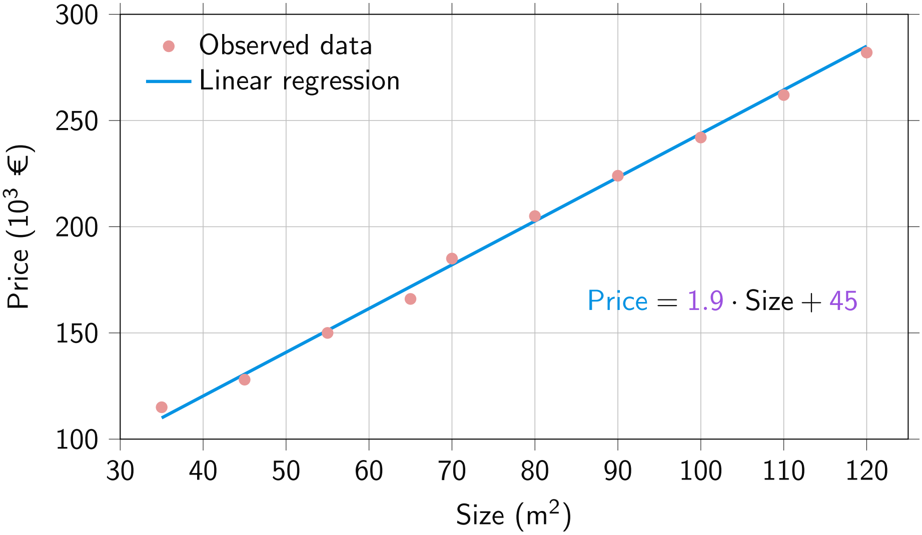
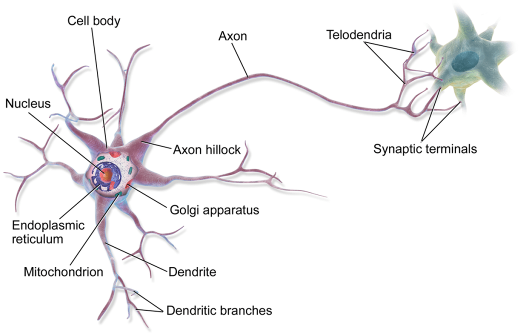
How Do Machines Learn?

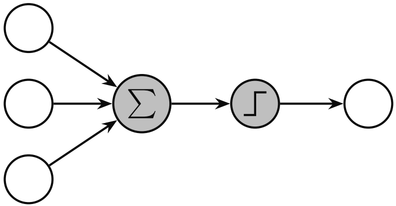
"We do not learn from experience [...] we learn from reflecting on experience." – John Dewey


300
250
200
150
100
Price (10^3 €)
Observed data
Linear regression
Price = 1.9 · Size + 45
30
40
50
60
70
80
90
100
110
120
Size (m^2)

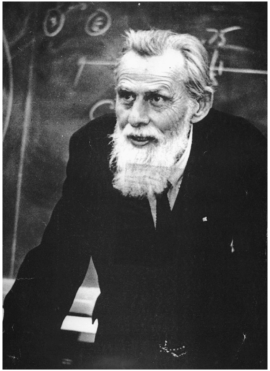
Neuron



Artificial neuron

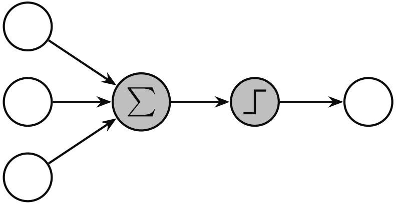


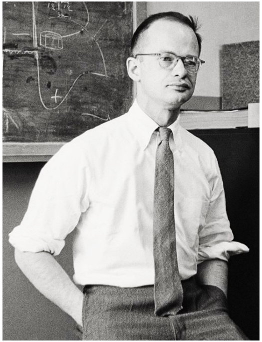
The Mathematical Neuron



Warren S. McCulloch

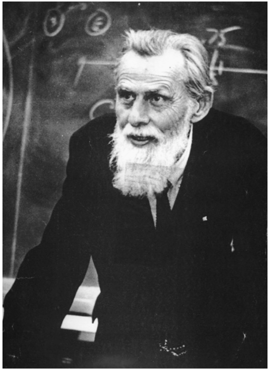
"Because of the 'all-or-none' character of nervous activity, neural events and the relations among them can be treated by means of propositional logic."





Walter H. Pitts Jr

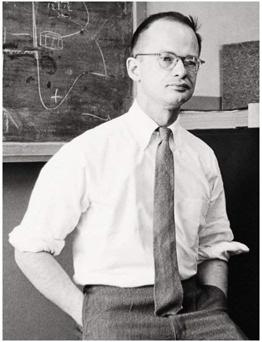
The Mathematical Neuron



Warren S. McCulloch

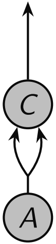
"Because of the 'all-or-none' character of nervous activity, neural events and the relations among them can be treated by means of propositional logic."

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

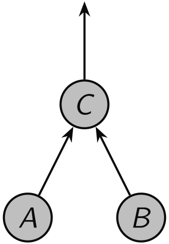


Walter H. Pitts Jr

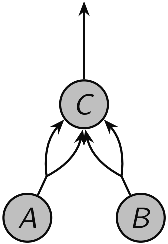
Complex logical operations can be performed using networks of binary neurons.



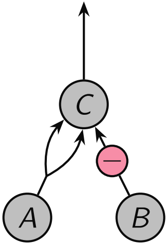
Identity: $C = A$



And: $C = A \wedge B$

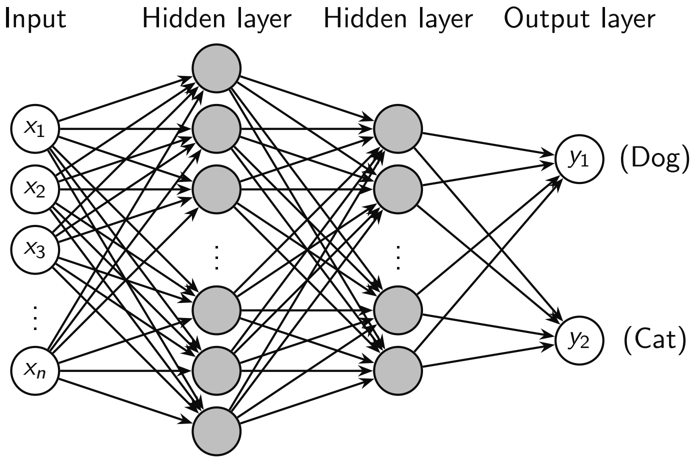


Or: $C = A \vee B$



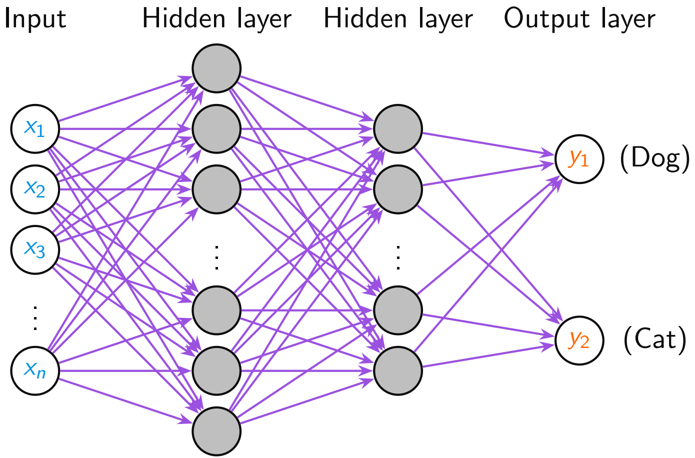
Negation: $C = A \vee \neg B$

Synaptic Plasticity



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

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



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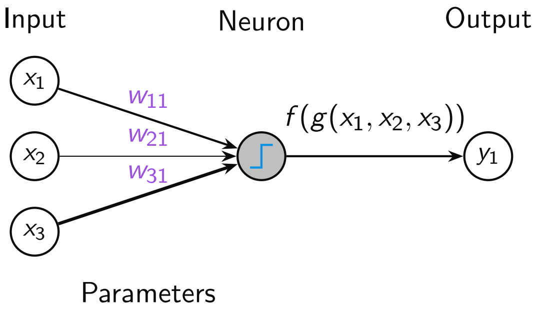
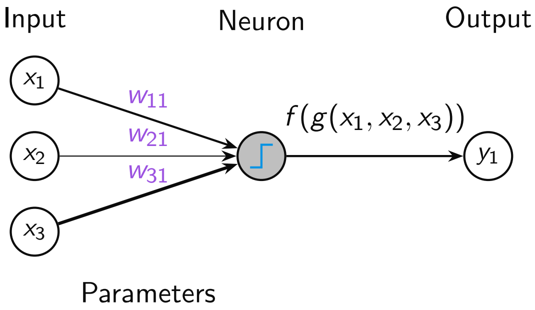
Synaptic Plasticity



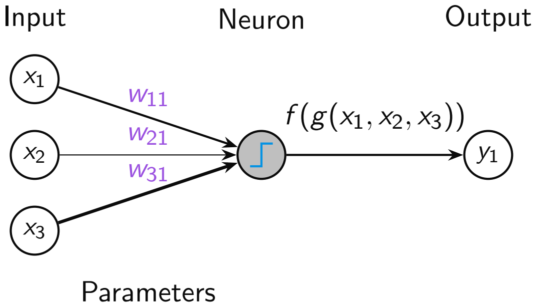
Parameters determine how strong neurons are wired together:

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



"Neurons that fire together, wire together."

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

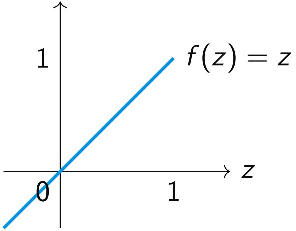


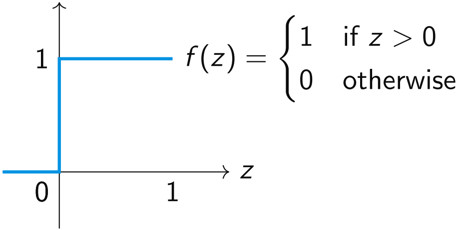
"Neurons that fire together, wire together."

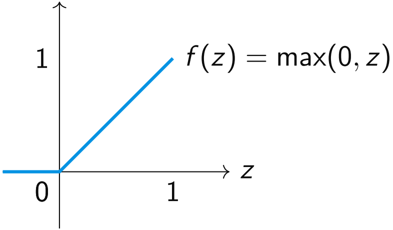
$$\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t)$$

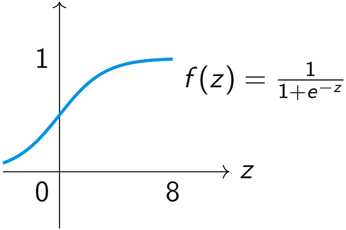
In this case $\theta_t = (w_{11}, w_{21}, w_{31})$.

Activation Functions

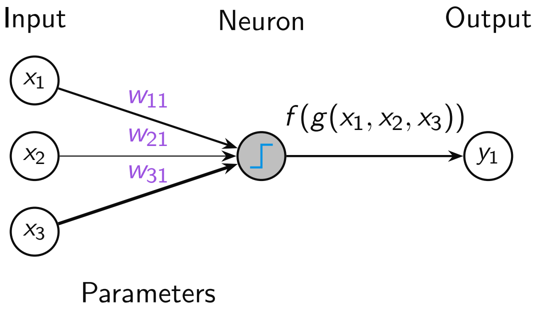








Synaptic Plasticity



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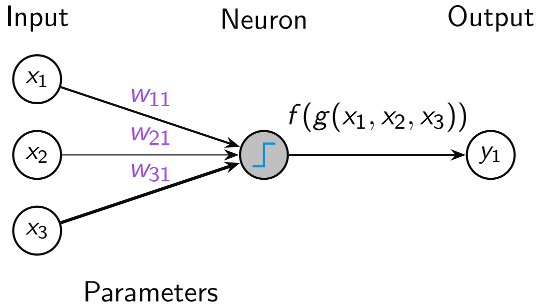
$$w_{ij} = w_{ij} - \eta \cdot x_i \cdot y_j$$



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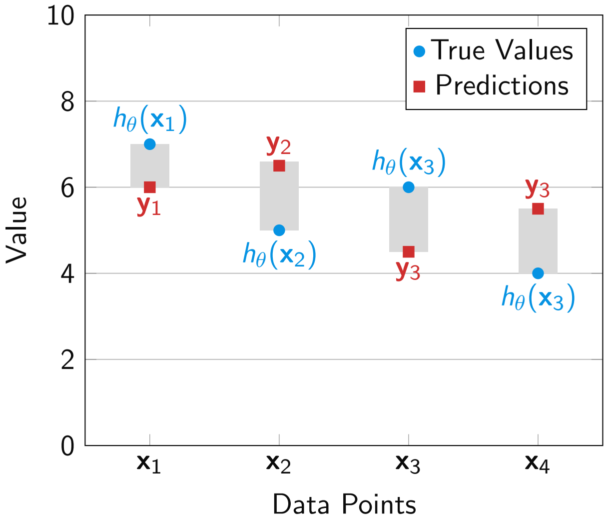
In this case $\theta_t = (w_{11}, w_{21}, w_{31})$.

Mean Squared Error (MSE):



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:

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

The gradient would be:

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

Cost Function (Classification)

Categorical Cross Entropy Cost:

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

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

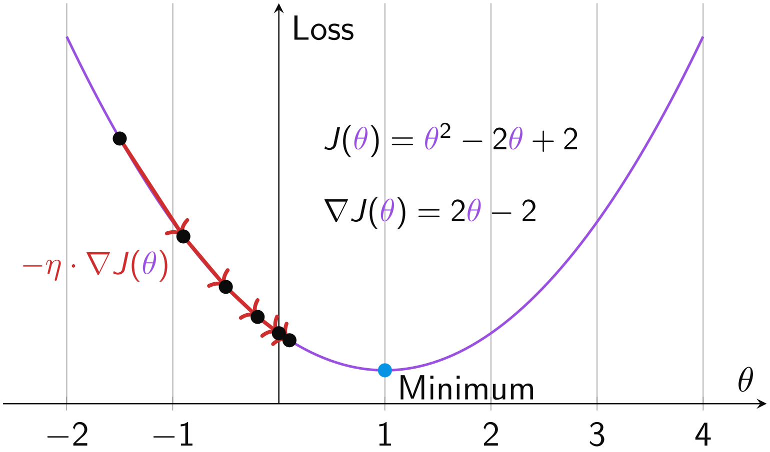
Gradient Decent

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

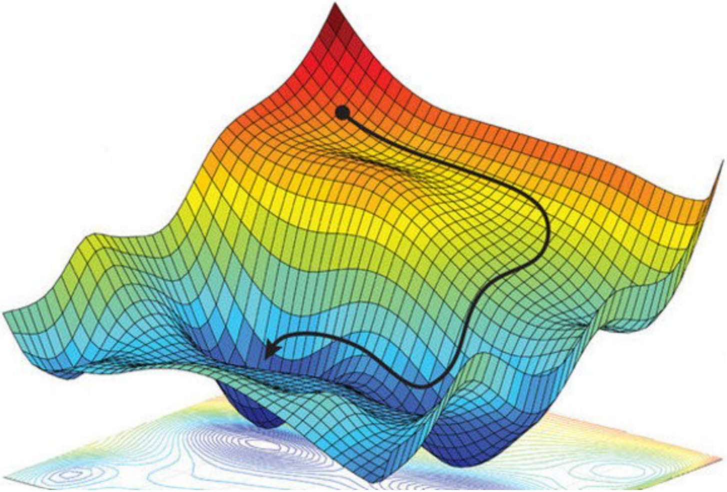
$$\theta_{t+1} = \theta_t - \eta \cdot \nabla J(\theta_t)$$

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

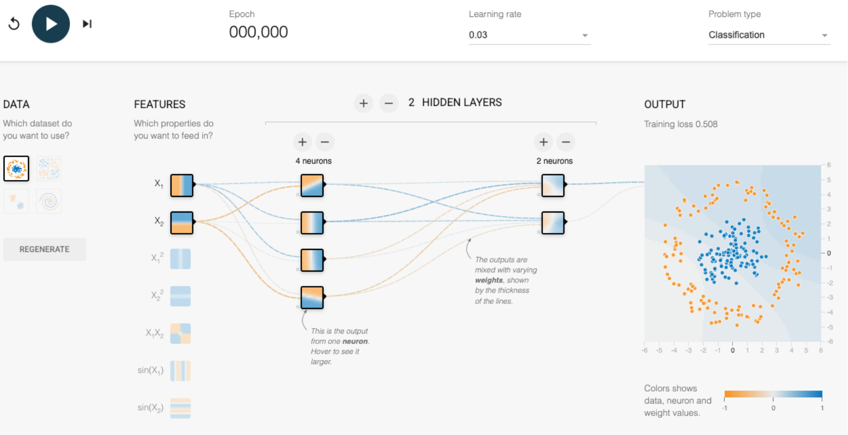
Interactive Tutorial


Loss
$J(\theta) = \theta^2 - 2\theta + 2$
$\nabla J(\theta) = 2\theta - 2$
$-\eta \cdot \nabla J(\theta)$
Minimum
θ
-2
-1
1
2
3
4

Gradient Decent



Design and Try Your Perceptron

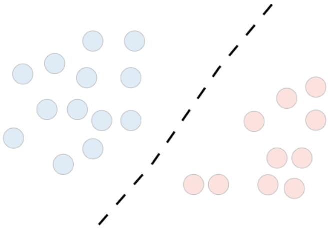


Simplified Tensorflow Playground

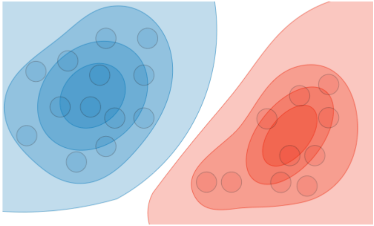
Extended Tensorflow Playground

Modeltypes

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



Discriminative modelling



Generative modelling

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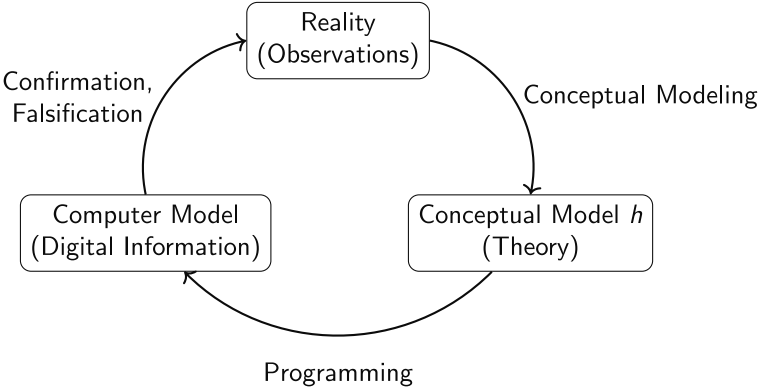
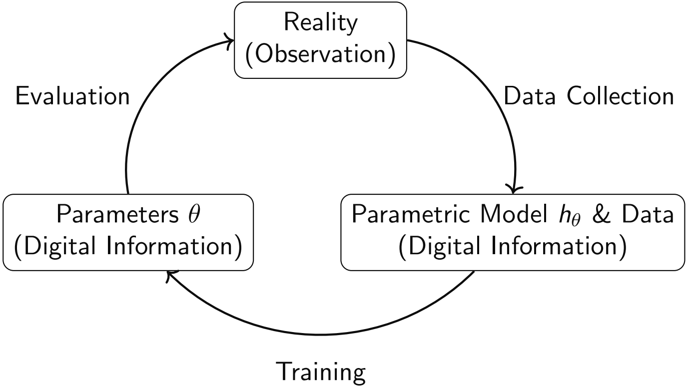
Theory-driven Modeling

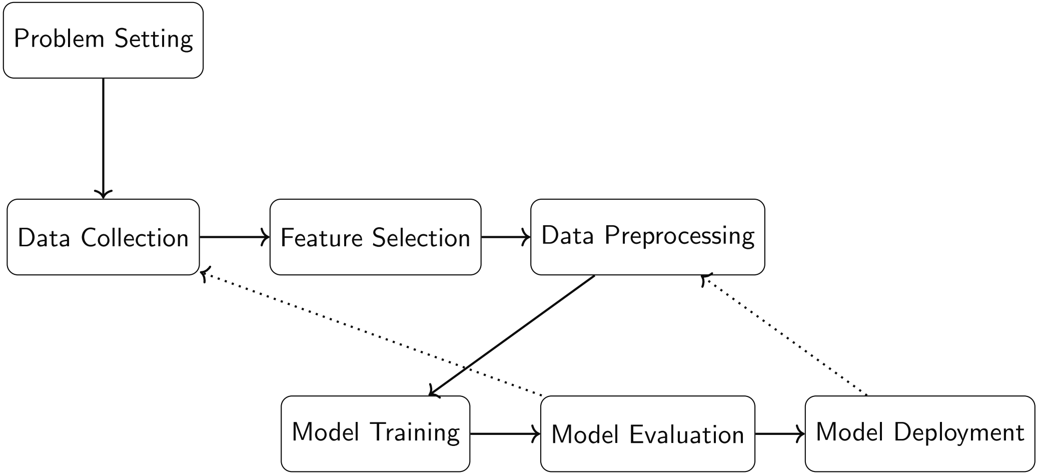


Minds contructs a (falsifiable) theory or hypothesis about reality to test against.

Data-driven Modeling



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


Problem Setting
Data Collection
Feature Selection
Data Preprocessing
Model Training
Model Evaluation
Model Deployment

Programming Libraries

```python
class fast_qlinear(torch.autograd.Function):
    def forward(ctx, a, b, scales, zeros):

        m, k = a.shape
        _, n = b.shape

        quant_groupsize = 128
        block_size_m = 16
        block_size_n = 32 # [N = 4096 // 32] = 128 blocks
        block_size_k = 256
        group_size_m = 8
        num_warps = 4
        num_stages = 8
        total_blocks_m = triton.cdiv(m, block_size_m)
        total_blocks_n = triton.cdiv(n, block_size_n)
```

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

Train a Model with Python

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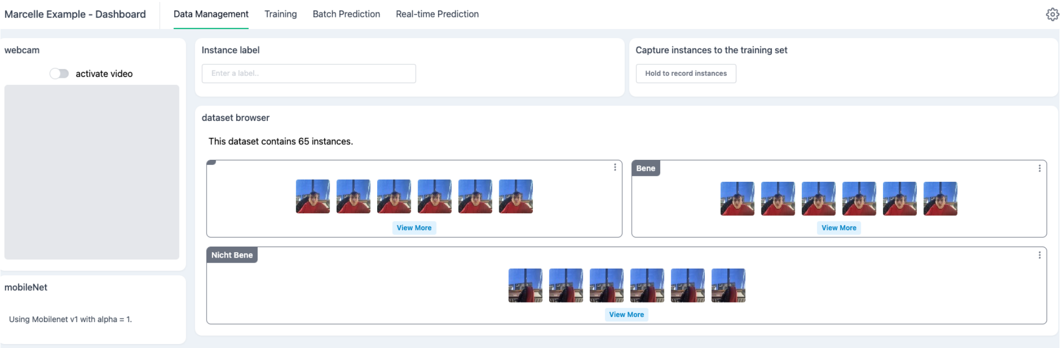
Marcelle: composing interactive machine learning workflows and interfaces (Françoise, Caramiaux, & Sanchez, 2021).

https://marcelle.dev/

The Marcelle Toolkit



Any questions?

References I

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References II

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