Introduction to Deep Learning

A course by EuroCC Austria

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Trainer at EuroCC Austria

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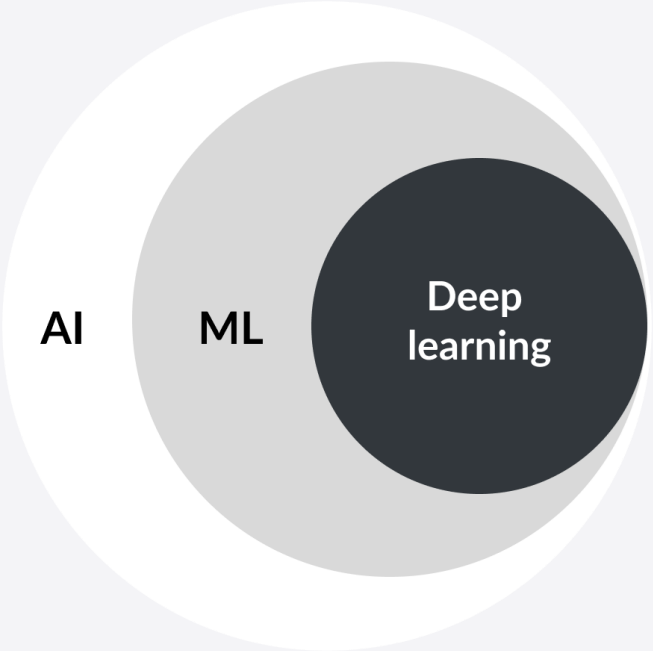
- [ ] Deep Learning is a subset of Machine Learning
- [ ] “Deep” does not mean a deeper understanding of the problem at hand. “Deep” stands for many successive layers of abstract representation
- [ ] Representations are learned via models called artificial neural networks
- [ ] Term “neural network” stems from neural biology. Models were inspired by our understanding of the brain
- [ ] First coined in the 1940



- [ ] Deep Learning is a multi-stage information distillation process. Information goes through successive filters and gets more and more purified
- [ ] Learning happens by exposure to examples i.e. mapping inputs to targets

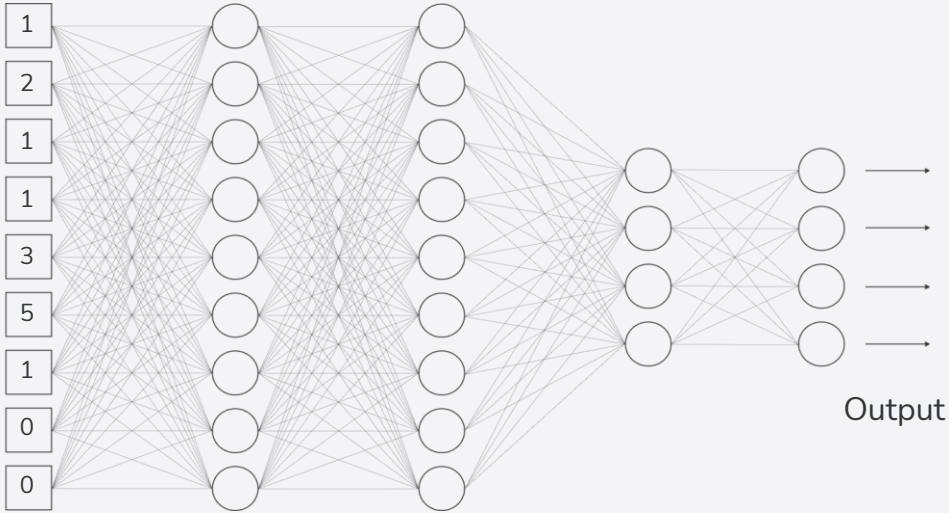
This is a dog

This is (most likely) not a dog

From Input to Output

1	2	1
1	3	5
1	0	0

Flattening



Predictions

Labels

Predictions	Labels
[0.7]	[1]
[0.1]	[0]
[0.1]	[0]
[0.1]	[0]

$$neuron_{layer\ 1,1} = activation\_function(x_1 \times w_{1,1} + x_2 \times w_{1,2} + x_3 \times w_{1,3} + \cdots + x_n \times w_{1,n} + b)$$

1	2	1
1	3	5
1	0	0

Flattening

bias

weights

b

$w_{1,1}$

$w_{1,2}$

$w_{1,9}$

1
2
1
1
3
5
1
0
0

Input

Hidden layers

Output

Predictions

Labels

Predictions	Labels
[0.7]	[1]
[0.1]	[0]
[0.1]	[0]
[0.1]	[0]

Weights & Bias

- Numerical representation of input needs to be “nudged” the right way to result in desired output
- What a layer does to its input data is stored in its weights
- Weights are also called parameters of a model
- Learning means finding the best set of weights for each layer, so that the input is correctly mapped to the corresponding labels
- Bias term is added to each data transformation
- Bias term is not always needed

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Activation functions

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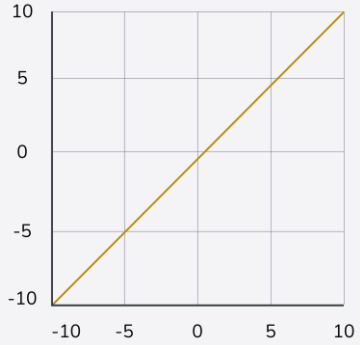
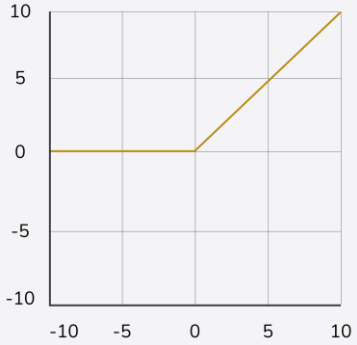
Linear

$$\hat{y} = wx + b$$



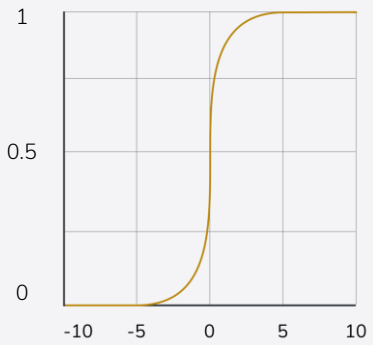
ReLu

$$\hat{y} = \begin{cases} wx + b \; if \; wx + b > 0 \\ 0 \; otherwise \end{cases}$$

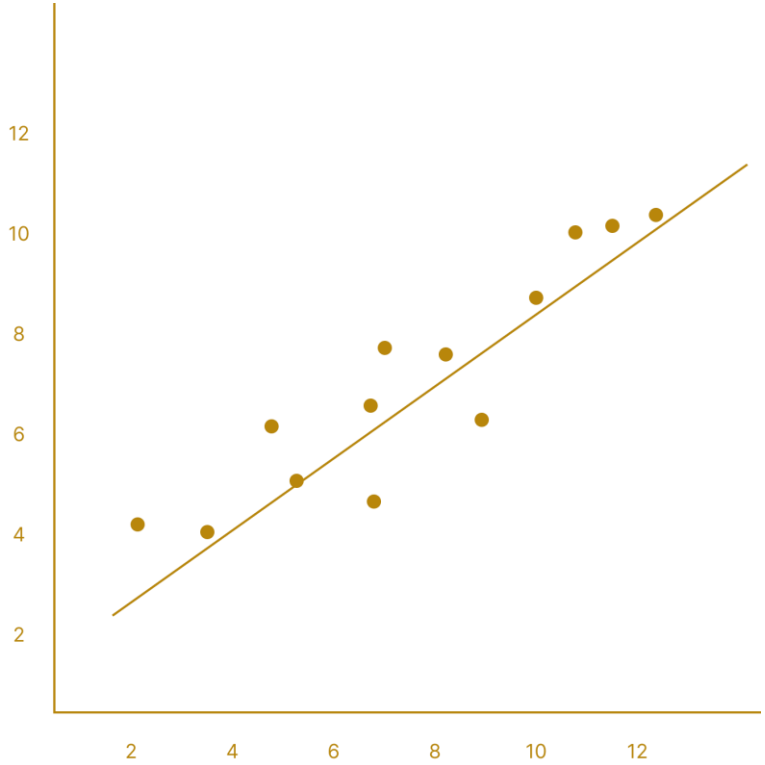


Sigmoid

$$\hat{y} = \frac{1}{1 + e^{-(wx+b)}}$$



Loss function

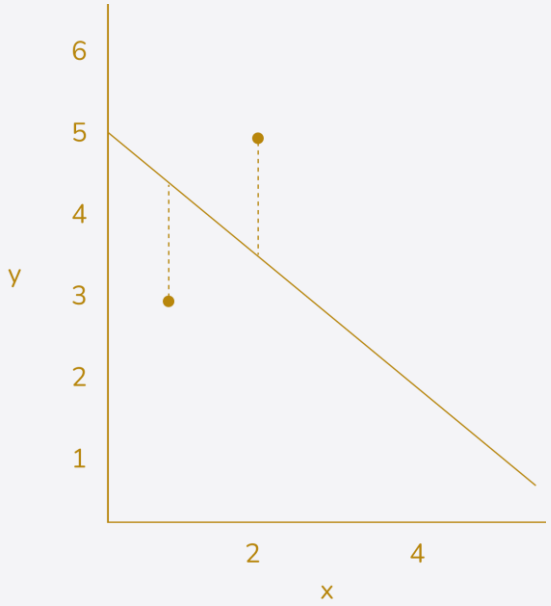


$$MSE = \frac{1}{m}\sum_{i=1}^{m}(\theta^T x^{(i)} - y^{(i)})^2$$

Loss function is some form of averaged difference between the predictions and the true values (e.g. mean squared error)

(Root) Mean Square Error

$\hat{y}$	err^2
4	1
3	4
MSE=	2.5
RMSE=	1.6



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

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

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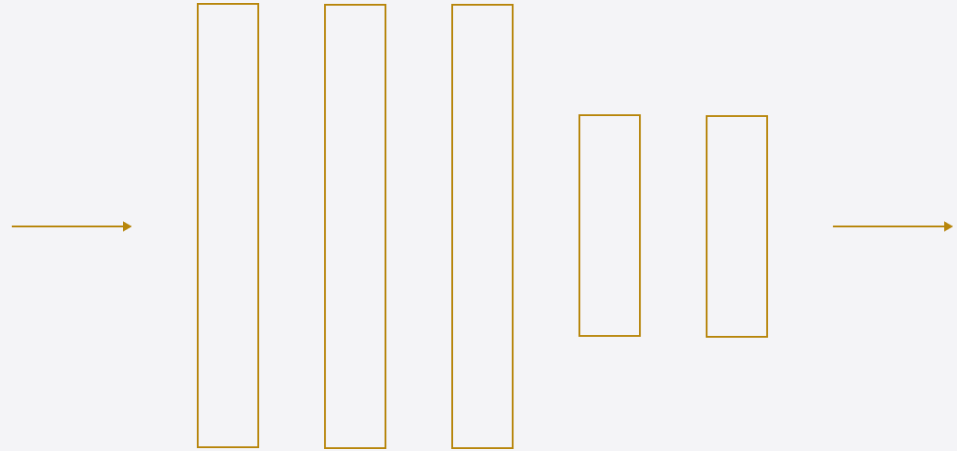
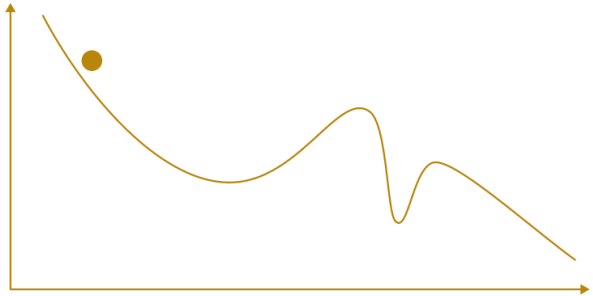
1	2	1
1	3	5
1	0	0



[0.7]	[1]
[0.1]	[0]
[0.1]	[0]
[0.1]	[0]

Gradient Descent

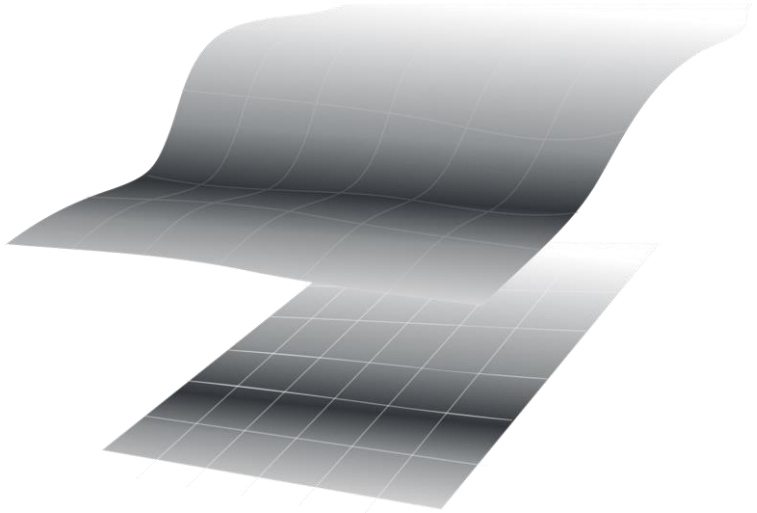
- Optimisation through some form of gradient descent
- Iterative process in small steps (learning rate) in the direction of the negative gradient
- Goal: Find global minimum of loss function



$$\nabla MSE(\theta) = \begin{pmatrix} \frac{\partial}{\partial \theta_0} \\ \frac{\partial}{\partial \theta_1} \\ \vdots \\ \frac{\partial}{\partial \theta_n} \end{pmatrix} MSE(\theta)$$

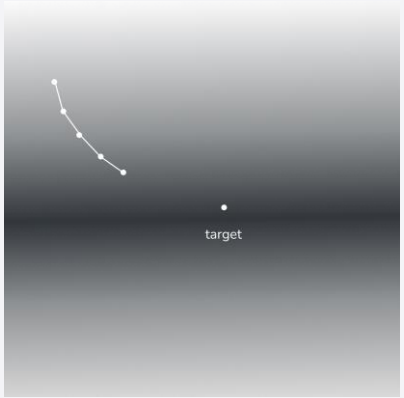
$$\theta^{(next\ step)} = \theta - \lambda \nabla_\theta MSE(\theta)$$

Gradient Descent



Optimisers

Gradient	Which direction loss decreases the most
λ:The learning rate	How far to travel
Epoch	A model update with full dataset
Batch	A sample of the full dataset
Step	An update to the weight parameters



Optimisers

There are many optimizers out there, but the most common ones are:

- Stochastic Gradient Descent
- Adam
- RMSprop

They all use some form of gradient descent. In addition, some use the adaptive learning rates and momentum

Choosing the right optimizer is very much a trial and error decision

It is advisable to use the default settings of an optimizer (to start with)

Hyperparameters

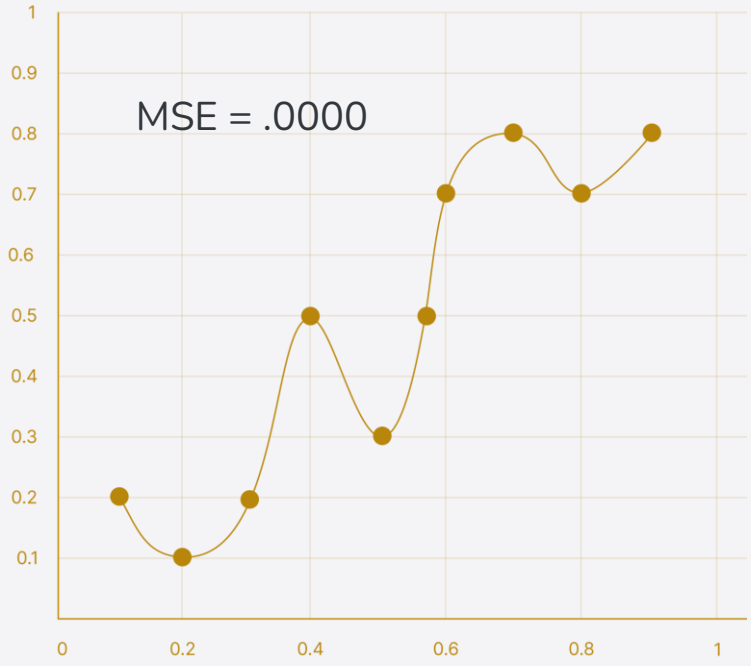
The actual parameters of the model are the weights & biases

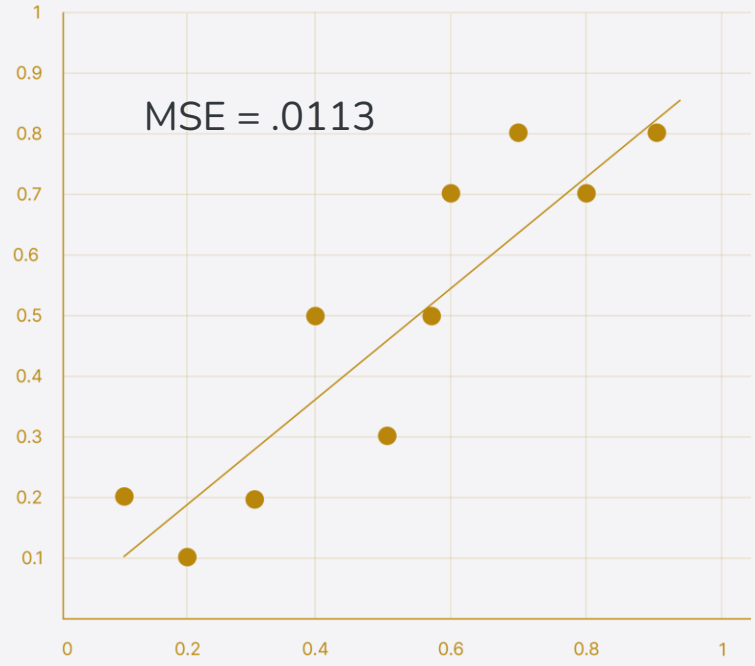
Hyperparameters are set by the programmer to influence the learning outcome

They include:

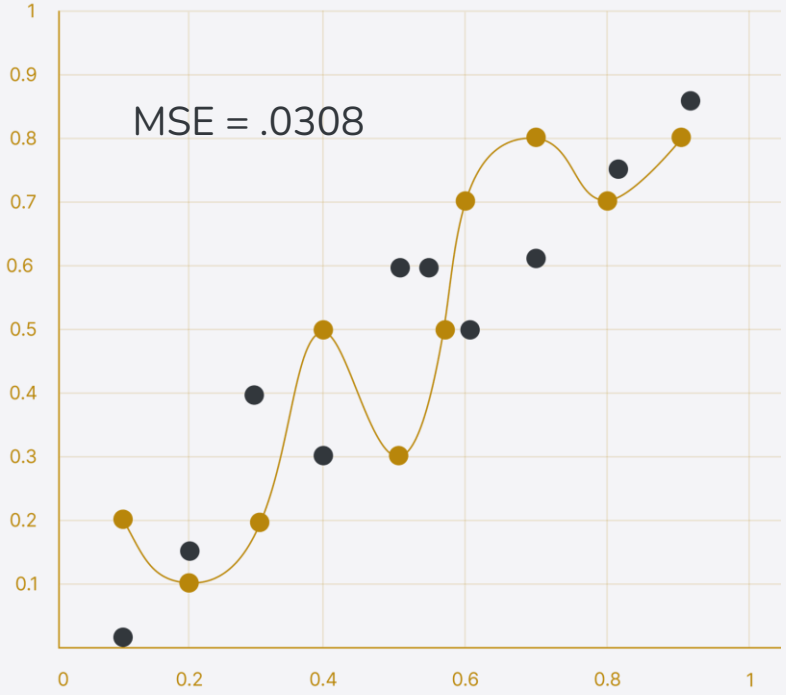
- [ ] Batch size
- [ ] Activation function
- [ ] Optimizer
- [ ] Learning rate
- [ ] Epochs

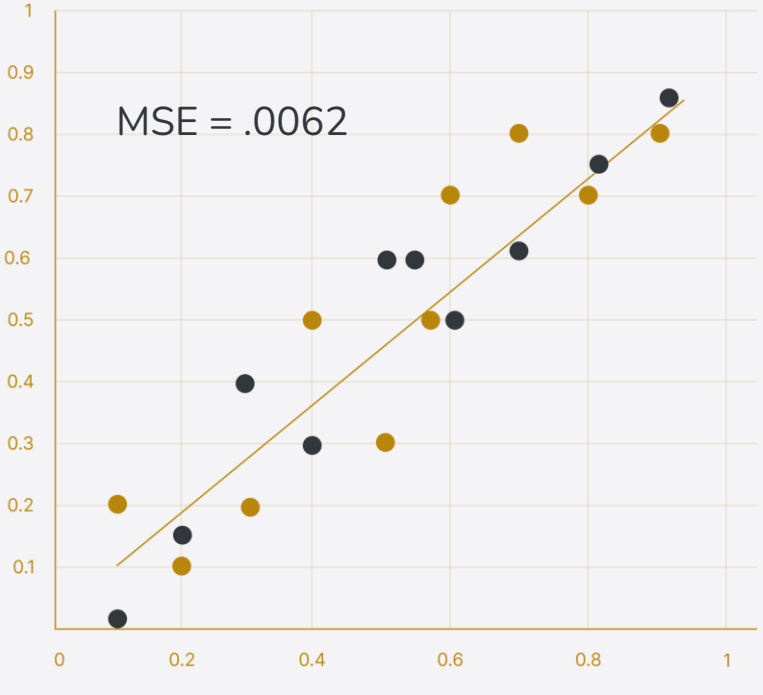
Which trendline is better?





Which trendline is better?





Training data

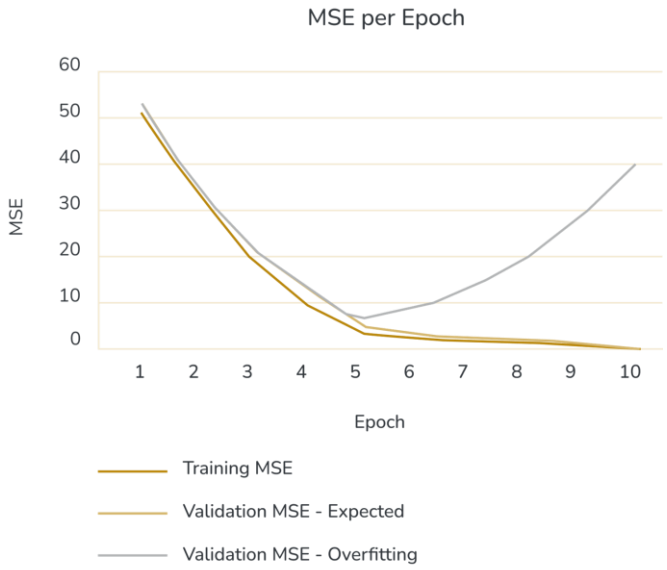
- [ ] Core dataset for the model to learn on

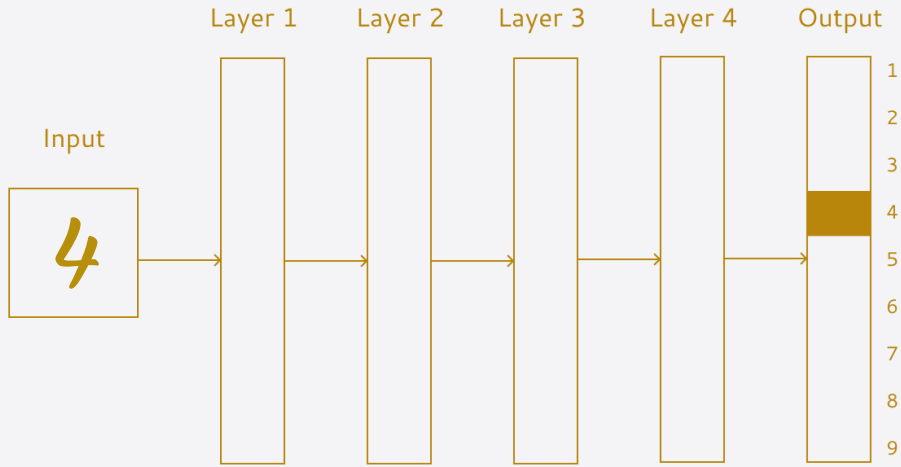
Validation data

- [ ] New data for model to see if it truly understands

Test data

- [ ] When model performs well on training data, but not the validation data (evidence of memorization)
- [ ] Ideally, the accuracy and loss should be similar between both datasets




Input
4
Layer 1
Layer 2
Layer 3
Layer 4
Output
1
2
3
4
5
6
7
8
9

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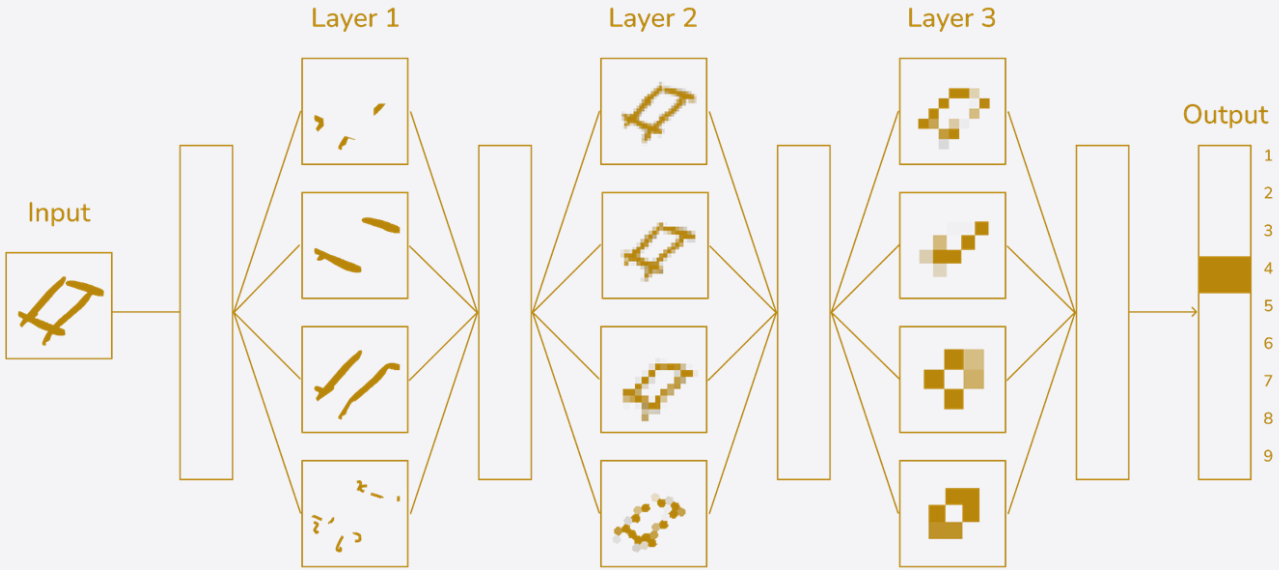
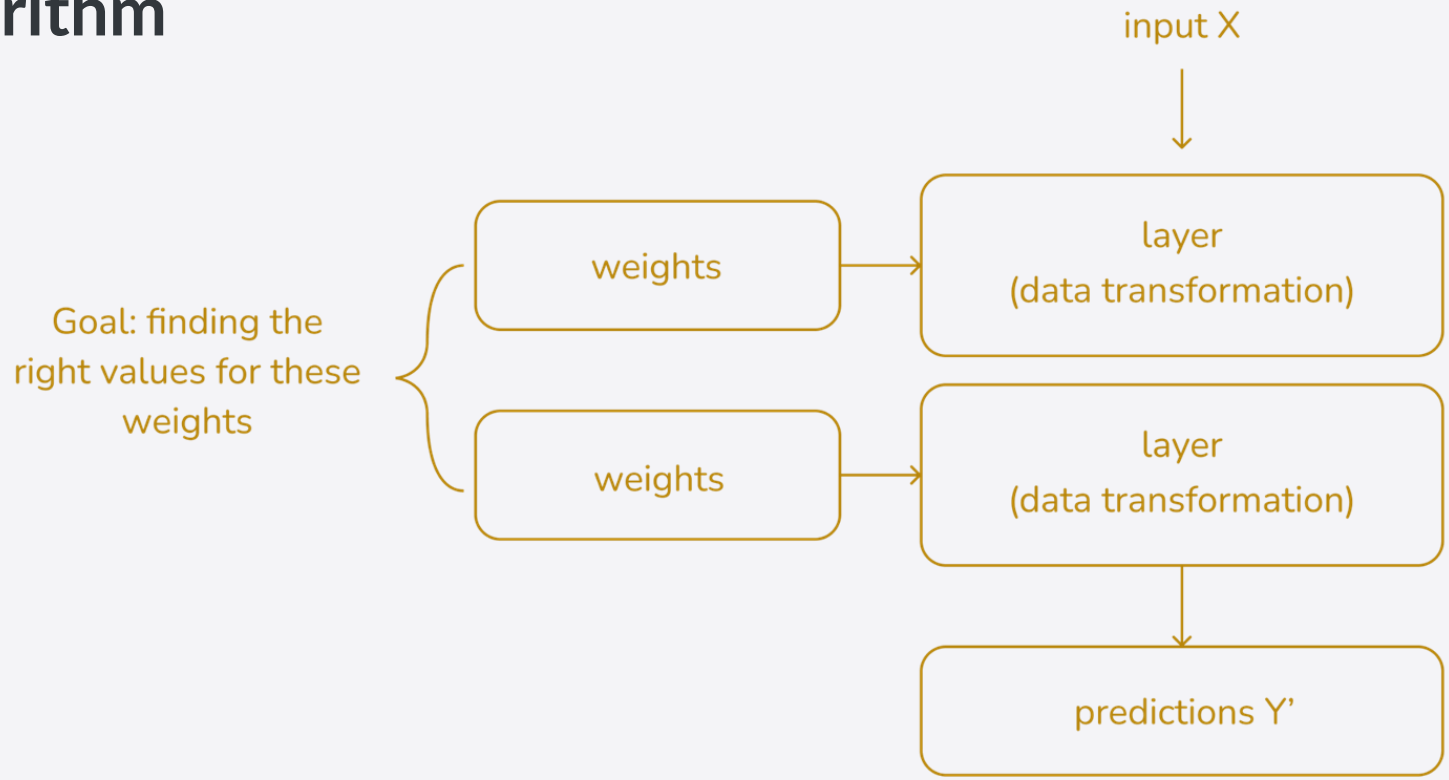


Training algorithm



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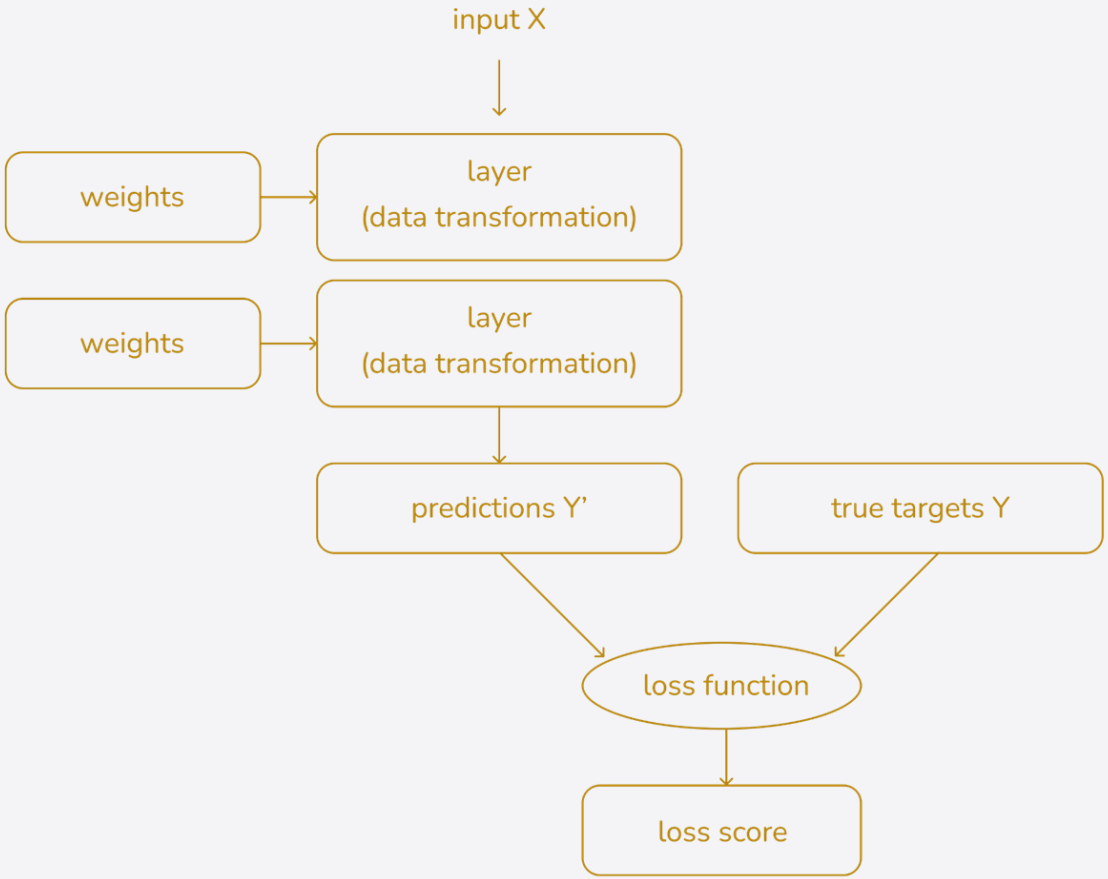
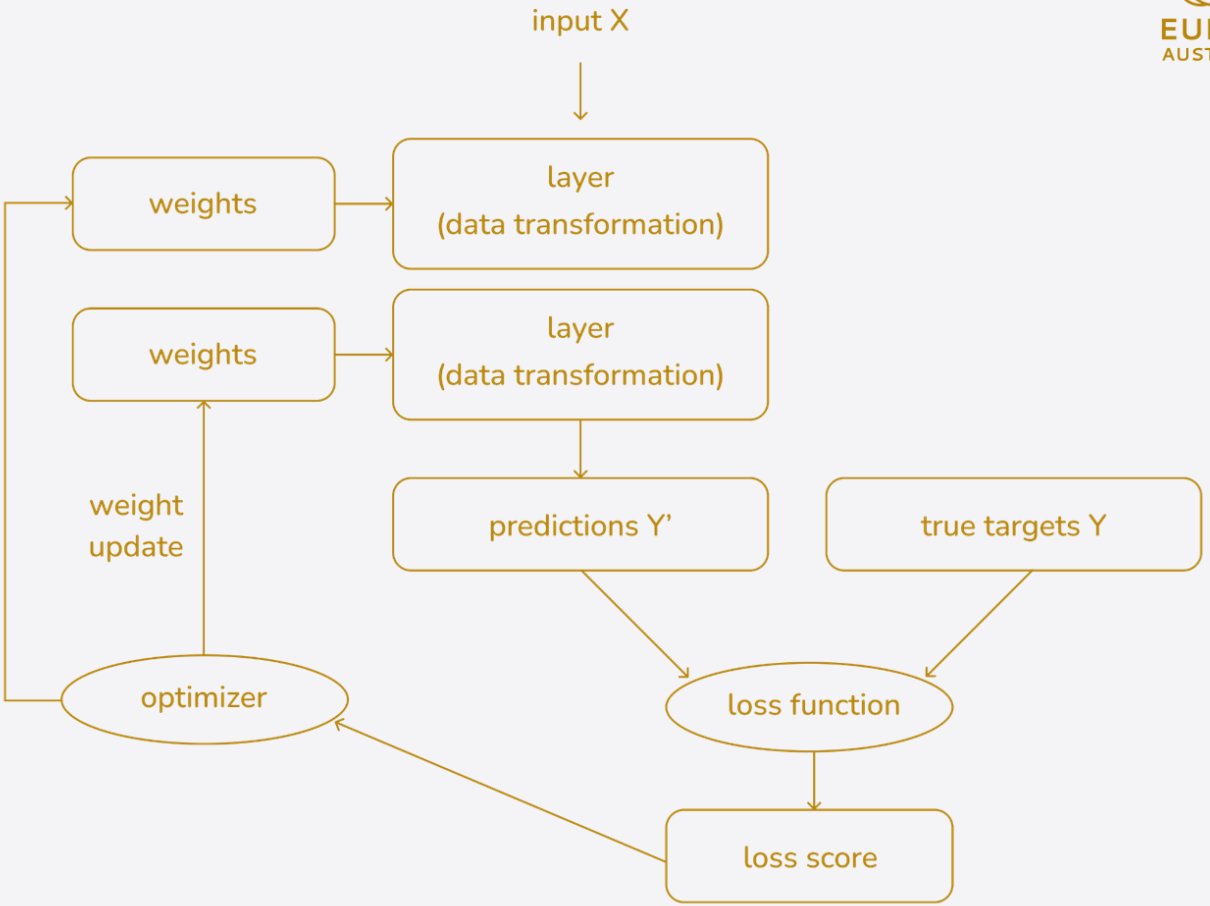


Training algorithm



THANK YOU

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