





Winter School 24/01/2022



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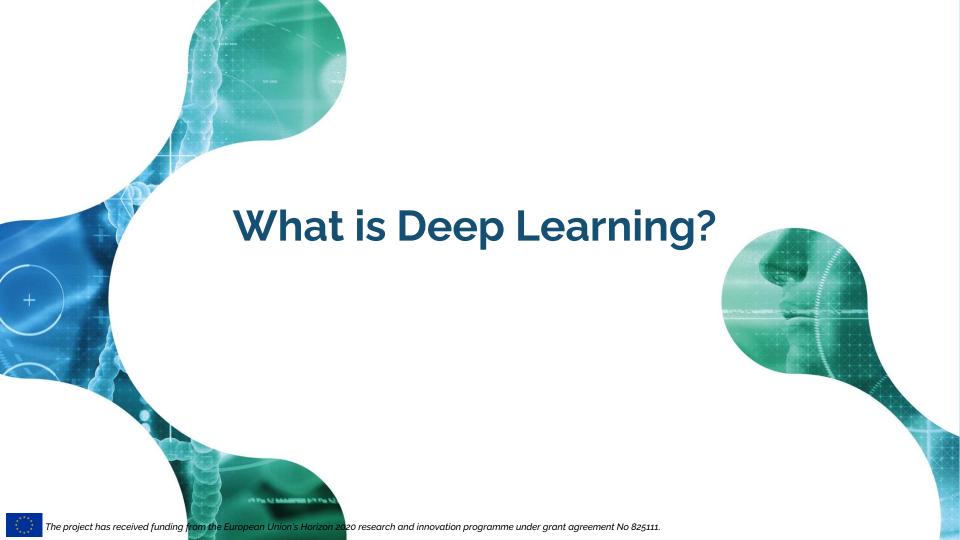




Monday 24 and Tuesday 25

What is Deep Learning?	3
Neural Networks	18
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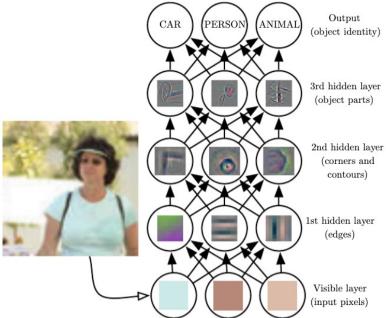
- Machine learning models based on neural networks:
 - Non-linear models
 - Learning by iteratively showing pairs (input,target) examples
 - Topology defined from know-how, hand-crafted
 - Learn the weights (parameters) by gradient descent of a particular loss function, iterative procedure
- Deep means that we stack lot of layers (20, 50, 100, 1000)
- Historically neural nets failed to learn with more than (let's say) 10 layers
- Why we need to go deep? ——> Representation Learning







Going deep



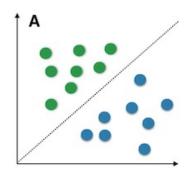


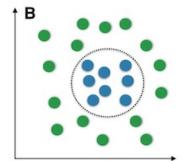




Non-linear models

Linear vs. nonlinear problems



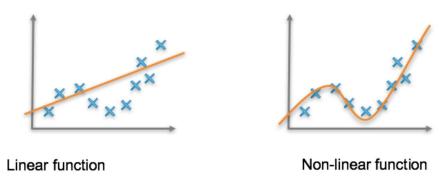






DEEPHEALTH

Non-linear models



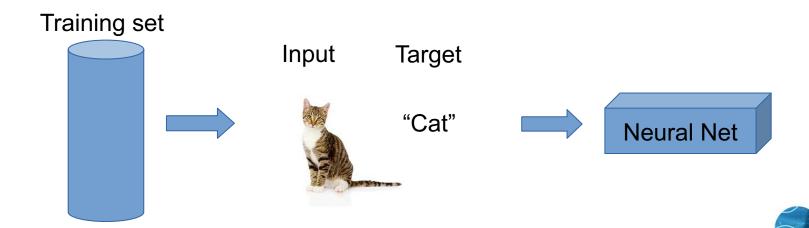
Best fit linear and non-linear models







Learning by iteratively showing pairs (input,target) examples

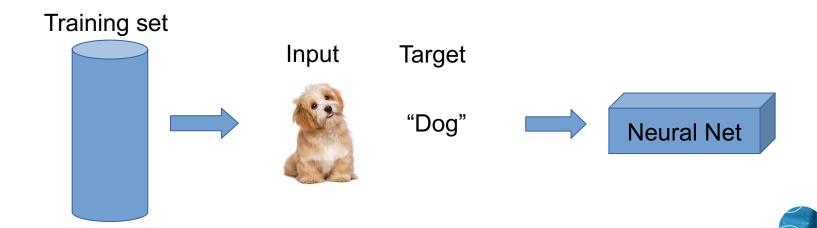








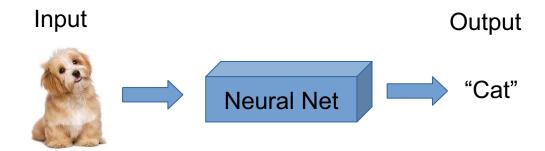
Learning by iteratively showing pairs (input,target) examples







• Learning by iteratively showing pairs (input, target) examples

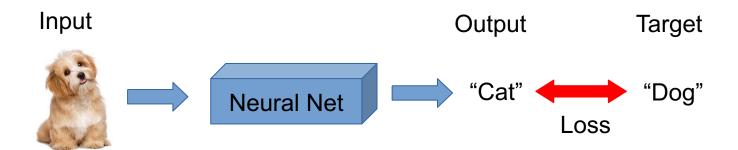








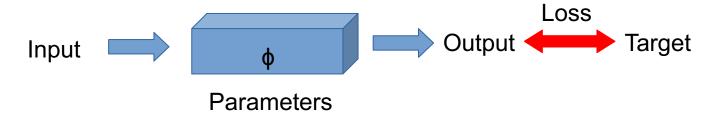
• Learning by iteratively showing pairs (input, target) examples





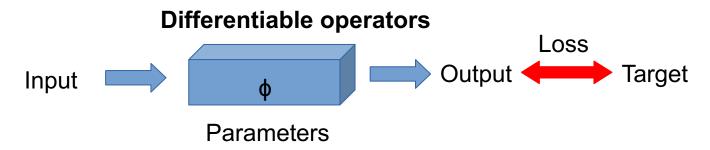






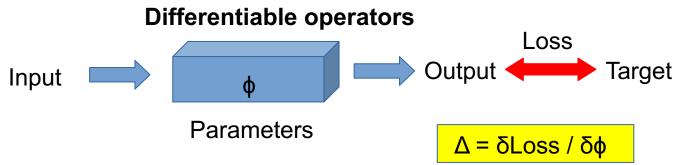
















$$\Delta = \delta Loss / \delta \phi$$

$$\phi = \phi - \mu \Delta$$

μ is what we call learning rate







- Topology defined from know-how
 - Raw Data : Dense Layers
 - Temporal: Recurrent Layers
 - Images: Covolutional Layers







- Topology defined from know-how
 - Raw Data : Dense Layers
 - Temporal: Recurrent Layers
 - Images: Covolutional Layers
 - Classification: resnet, densenet,
 - Segmentation: U-net
 - Detection: FasterRCNN, Yolo, SSD
 - Pixel annotation: MaskRCNN
 - Image Generation: DCGAN, CylceGan
 - Fine grain classification: Bilinear CNN



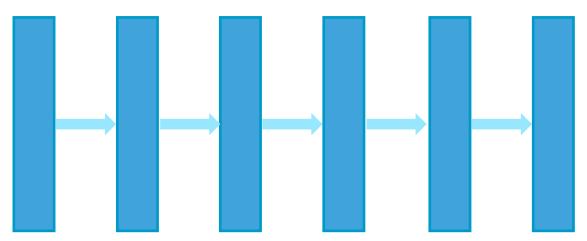






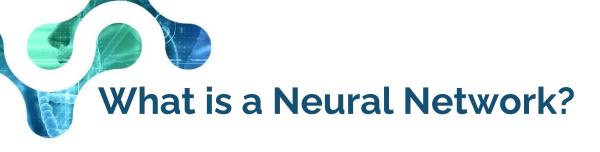




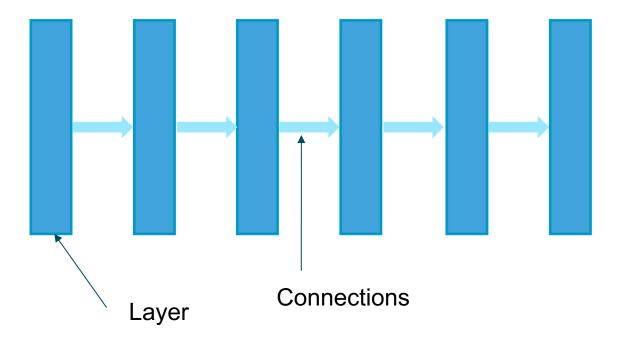


A connectionist model















Layer: Operation over tensors (1D, 2D, 3D ...)

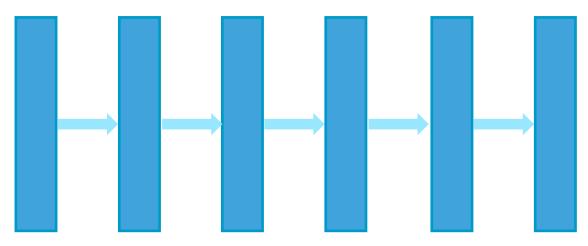
Connection: the output tensor of a layer (result) is used as input tensor of the following layer

We would refer "x" as input and "y" as output









Input Dense Layer Layer ReLu Layer

• • •







Input Layer: Receive the input examples (images of cats)

Dense Layer: Is a **parametric** layer with the following operation:

$$y = Wx + b$$
 W and b are the parameters to learn

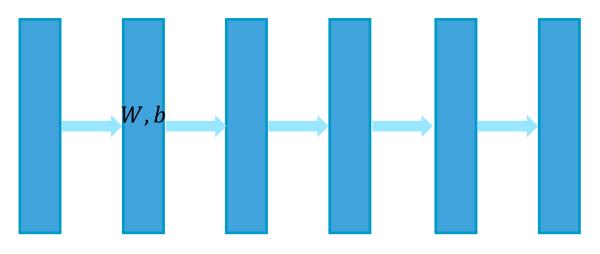
Activation Layer: Normally is a non-parametric layer. In the case of ReLu:

$$y = \begin{cases} x & \text{if } x \ge 0 \\ 0 & \text{if } x < 0 \end{cases}$$









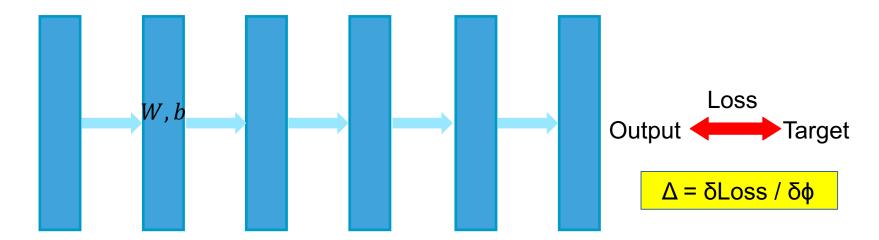
Input Layer Dense Layer ReLu Layer

...









Input Dense Layer Layer

se ReLu r Layer

...









Classification problems. n clases output with n neurons

Output: Softmax

$$y_i = \frac{e^{x_i}}{\sum_{i=1}^n e^{x_j}}$$

$$y_i = p(c = i | \boldsymbol{x})$$

Loss: Categorical cross-entropy

$$ext{Loss} = -\sum_{i=1}^n y_i \cdot \log \hat{y}_i$$

target







Regresion problems. *d* dimensions output with *d* neurons

Output: Linear
$$y_i = x_i$$

Loss: Sum of Quadratic Errors

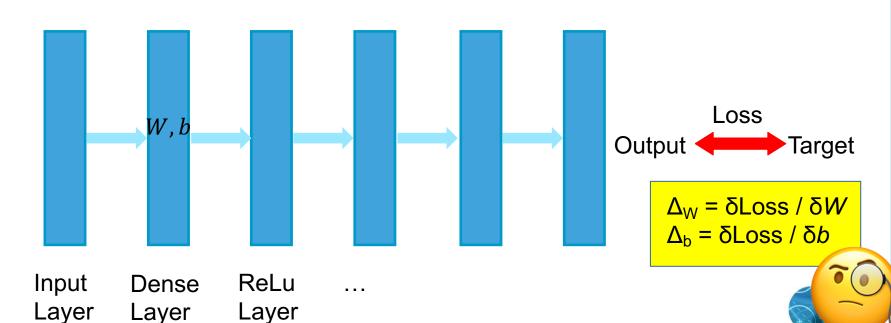
$$Loss = \sum_{i=1}^{d} (y_i - \hat{y}_i)^2$$





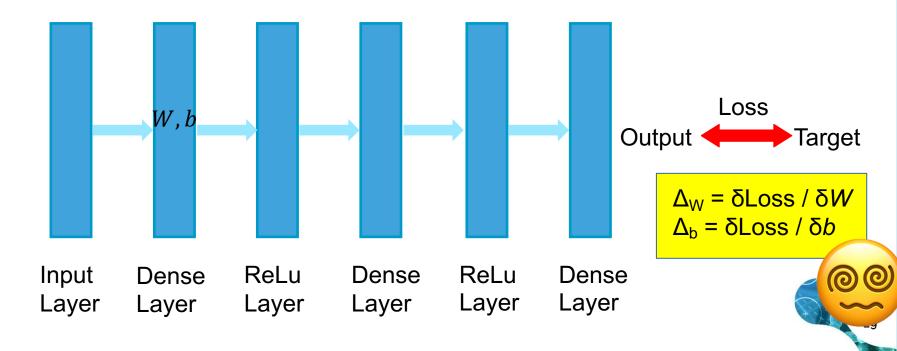






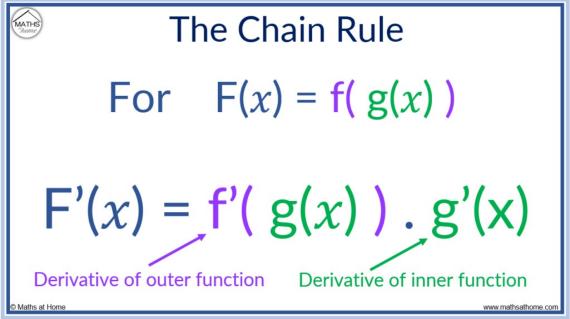
















In order to compute the gradient $\Delta = \delta Loss / \delta \phi$ w.r.t any parameter we can use **the chain rule** to back-propagate the loss

This leads us to the well-know Backpropagation algorithm

Essentially the training phase of a NN is composed by three steps:

- Forward: the output of all the layers are computed
- Backward: the gradient w.r.t all the parameters of all the layers is computed (backpropagation)
- Update: the parameters are updated in the opposite direction of the gradient (optimizer)

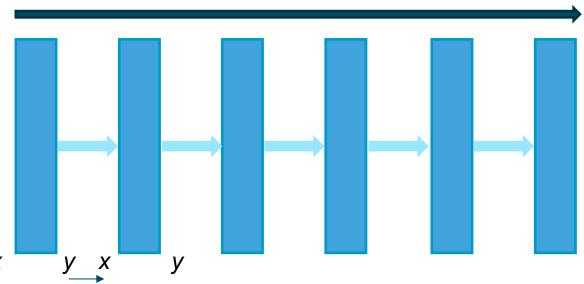








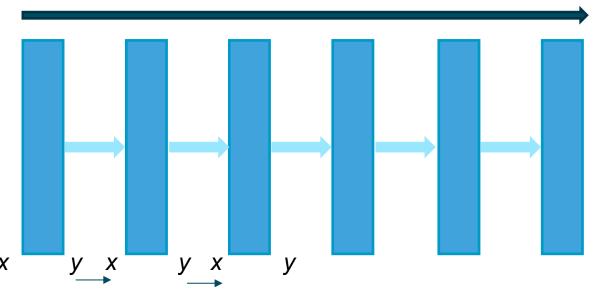






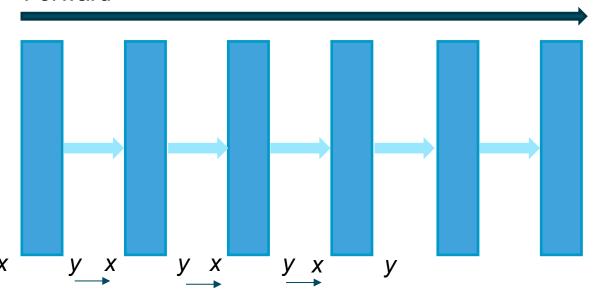






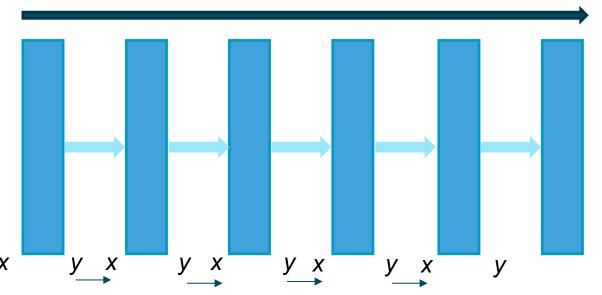










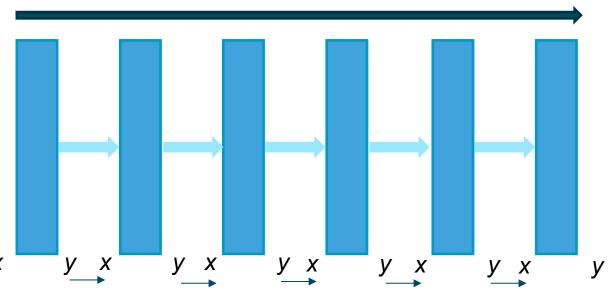








Forward





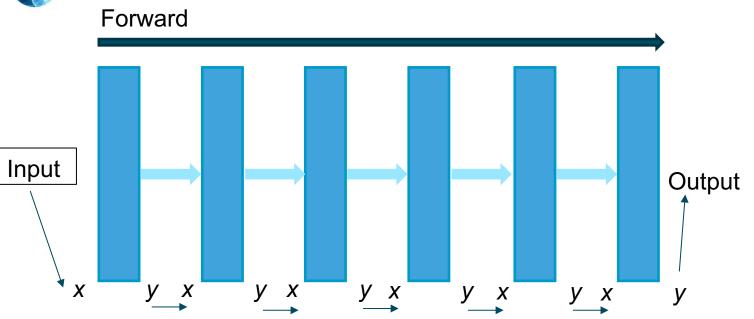


Forward Output

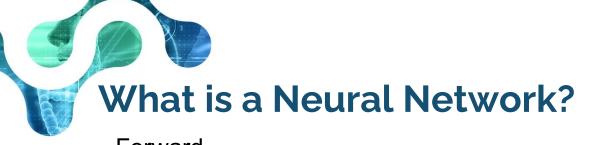




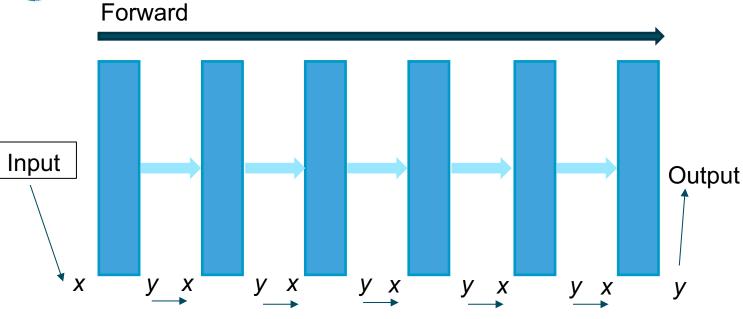










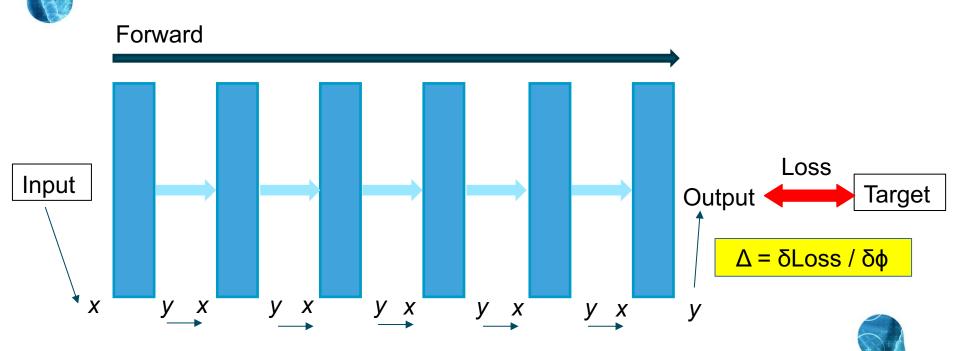


Target



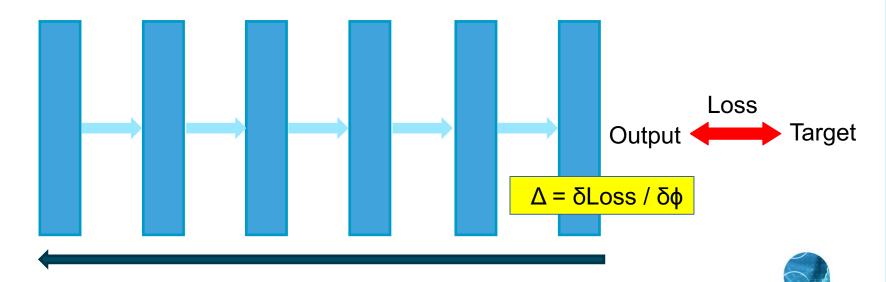




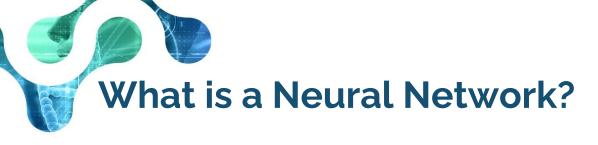




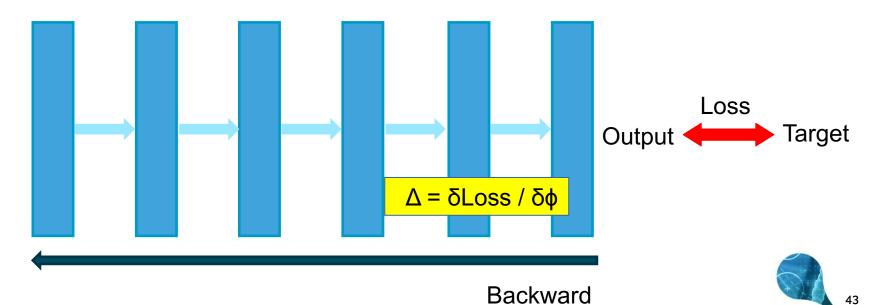




Backward

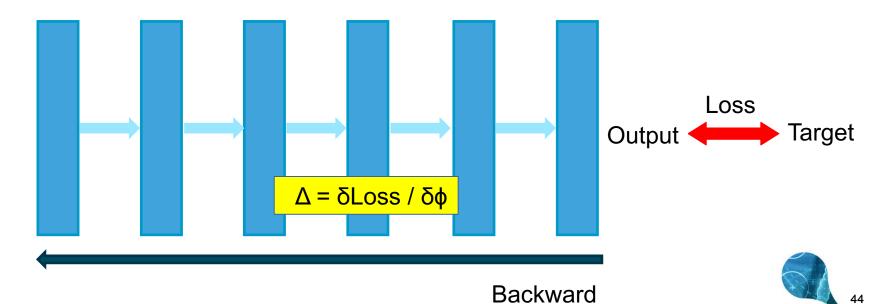


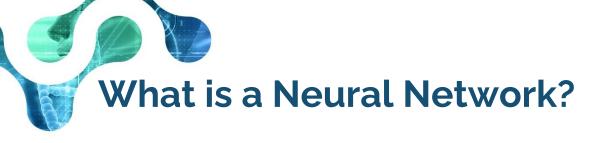




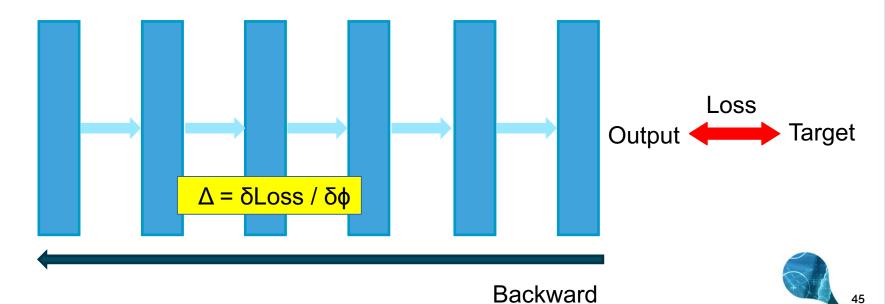


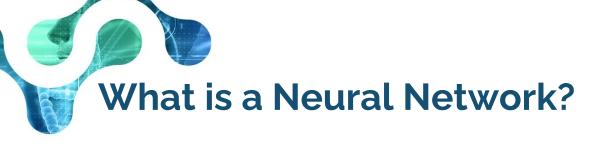




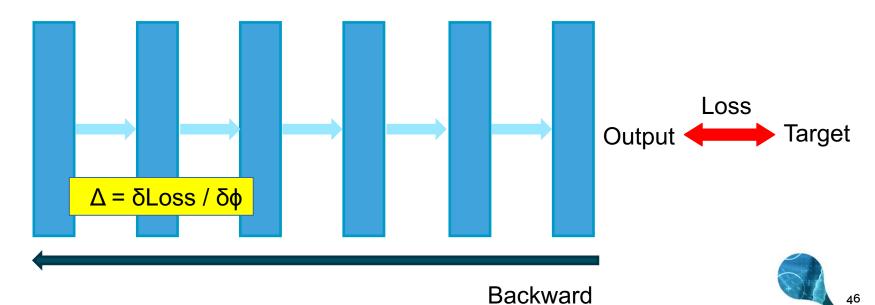






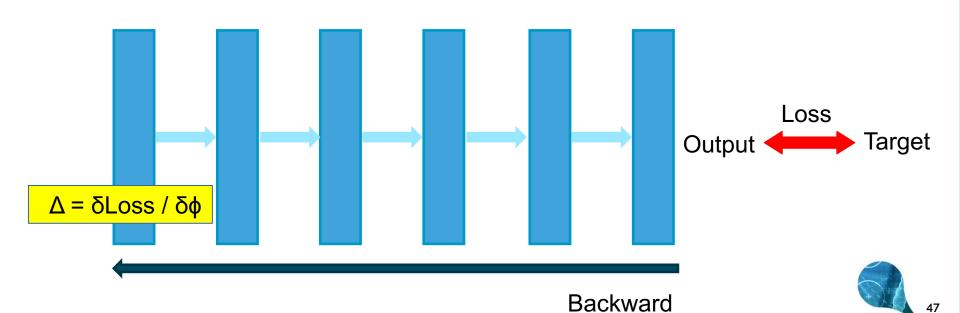






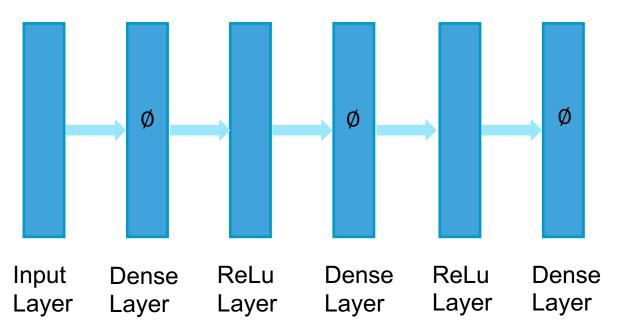








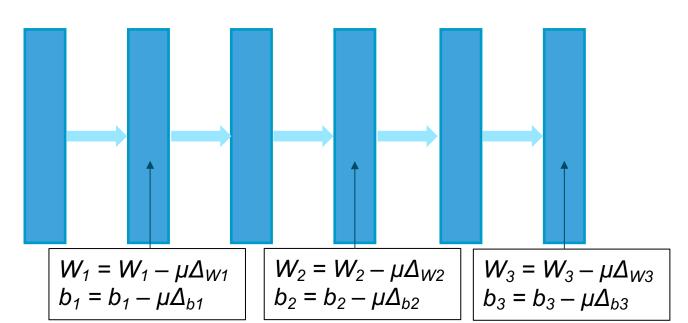








Update









- Forward
- Backward
- Update

Inference:

Forward







- Forward
- Backward
- Update

EDDL: model.fit(input, target)

Inference:

Forward

EDDL: output = model.predict(input)







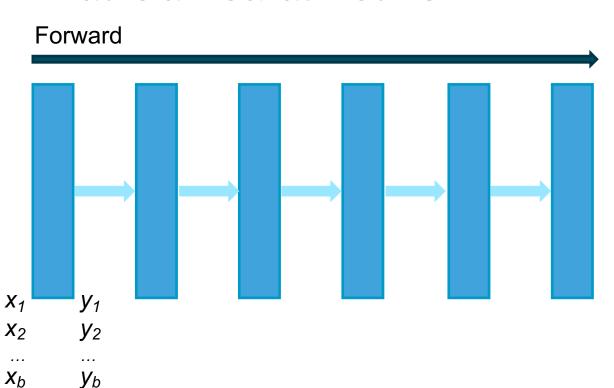
- Forward
- Backward
- Update

The samples (input,target) are presented in batch, then the gradient is computed for all the samples in a **batch**





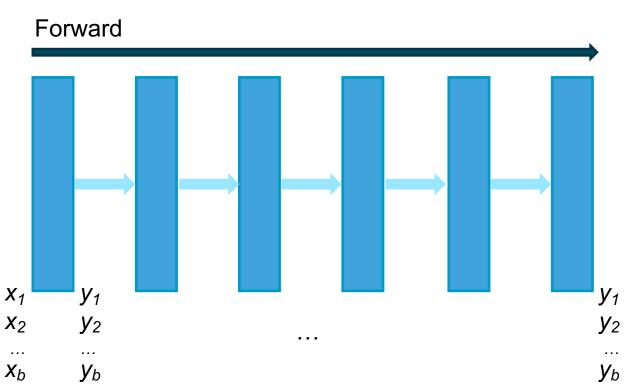








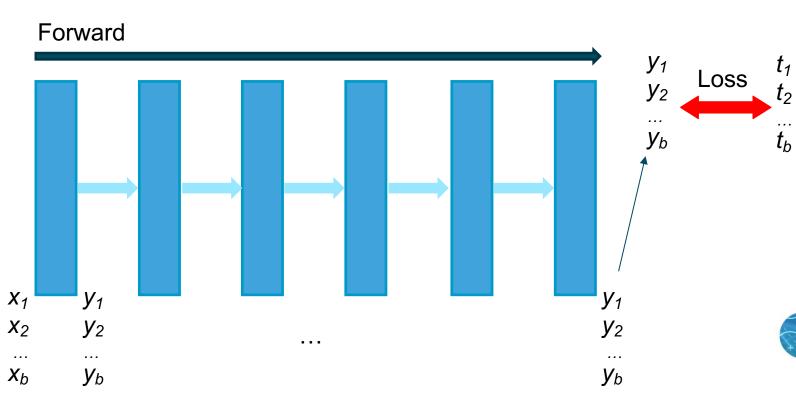






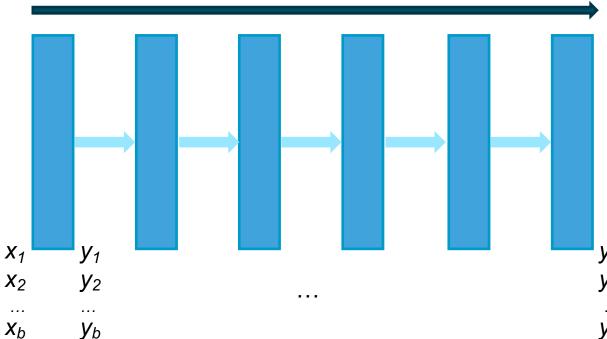


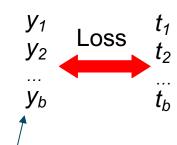


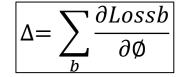




Forward







У₁ У₂ ... У_b







- Forward
- Backward
- Update

EDDL: model.fit(input, target, batch_size)

Inference:

Forward

EDDL: output = model.predict(input)







Training

Definition of **epoch**: train all the samples, then is to train the number of batches that fit in your training set.

Training set of 50.000 samples Batch_size= 100

Epoch means to train 500 batches (randomly selected) covering all the samples of the training set





- Forward
- Backward
- Update

EDDL: model.fit(input, target, batch_size, epochs)

Inference:

Forward

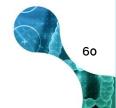
EDDL: output = model.predict(input)







EDDL Basic







EDDL is an open source library for Distributed Deep Learning and Tensor Operations in C++ for **CPU**, **GPU** and **FPGA**. EDDL is developed inside the DeepHealth project.

EDDL provides a high level API to develop Deep learning projects in C++

PyEDDL is a Python wrapper for the EDDL







EDDL is like Keras in the way the models are defined and the training is carried out. The main difference between EDDL and other toolkits is the introduction of the Computing Service (CS) object.

The DL model created with EDDL has a CS attached where this model will be deployed. This CS could be CPU, GPU or FPGA and even we could define a distributed CS.

This CS definition only affects to a single line in your programs.







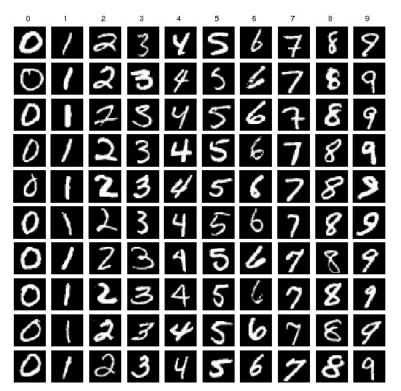
```
download_mnist();
// Define network
layer in = Input(\{784\});
layer 1 = in;
1 = LeakyReLu(Dense(1, 1024));
1 = LeakyReLu(Dense(1, 1024));
1 = LeakyReLu(Dense(1, 1024));
layer out = Softmax(Dense(1, 10), -1);
model net = Model({in}, {out});
// Computing service
compserv cs = CS_CPU();
// cs = CS_GPU(\{1\},"low_mem"); // one GPU
// cs = CS_GPU(\{1,1\},100); // two GPU
// cs = CS_FPGA(\{1\});
```







EDDL Basic MNIST Digits Classification



28x28 images (2D)

stored as 784 pixels (1D)

10 classes









```
eddl.download mnist()
# Load the dataset
x_train = Tensor.load('mnist_trX.bin')
y_train = Tensor.load('mnist_trY.bin')
x_test = Tensor.load('mnist_tsX.bin')
y_test = Tensor.load('mnist_tsY.bin')
# Preprocess the images. From [0-255] to [0-1]
x train.div (255.0)
x test.div (255.0)
# Show data shape
print('Dataset shape:')
print(f'Train split images: {x_train.shape}')
print(f'Train split labels: {y_train.shape}')
print(f'Test split images: {x_test.shape}')
print(f'Test split labels: {v_test.shape}')
```







EDDL Basic Model

```
# Define the model topology
num_classes = 10
in_ = Input([784])
layer = Reshape(in_, [1, 28, 28]) # EDDL needs channel first images
layer = ReLu(BatchNormalization(Conv(layer, 32, [3, 3]), affine=True))
layer = MaxPool(layer, [2, 2])
layer = ReLu(BatchNormalization(Conv(layer, 64, [3, 3]), affine=True))
layer = MaxPool(layer, [2, 2])
layer = ReLu(BatchNormalization(Conv(layer, 128, [3, 3]), affine=True))
layer = MaxPool(layer, [2, 2])
layer = ReLu(BatchNormalization(Conv(layer, 256, [3, 3]), affine=True))
layer = GlobalAveragePool(layer)
layer = Flatten(layer)
out_ = Softmax(Dense(layer, num_classes))
# Create the model
model = eddl.Model([in_], [out_])
```







EDDL Basic Learning

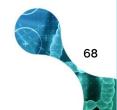
```
# Build the model to prepare it for training or inference
eddl.build(model,
                                            # Optimizer
           opt,
            ['categorical_cross_entropy'], # Losses
            ['accuracy'],
                                          # Metrics
                                            # Computing Service
            cs)
# Show the model layers
eddl.summary(model)
eddl.fit(model, [x_train], [y_train], batch_size, epochs)
                                                          # Train
eddl.evaluate(model, [x_test], [y_test], args.batch_size) # Validation
```







Layers and Tensors







Dense

- Input a 1D Tensor (d)
- Output a 1D Tensor (d')
- Operation: y = Wx + b
- Parameters: W,b
 - W is a (d',d) 2D Tensor
 - B is a (d') 1D Tensor

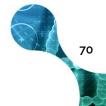






Activation

- Input any D Tensor
- Output the same dim as input Tensor
- Operation: depends on activation function
- Parameters: NO

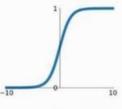




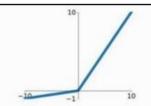


Sigmoid

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



Leaky ReLU max(0.1x, x)



tanh

tanh(x)



Maxout

 $\max(w_1^T x + b_1, w_2^T x + b_2)$

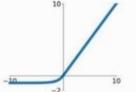
ReLU

 $\max(0, x)$



ELU

$$x$$
 $x \ge 0$ $\alpha(e^x - 1)$ $x < 0$







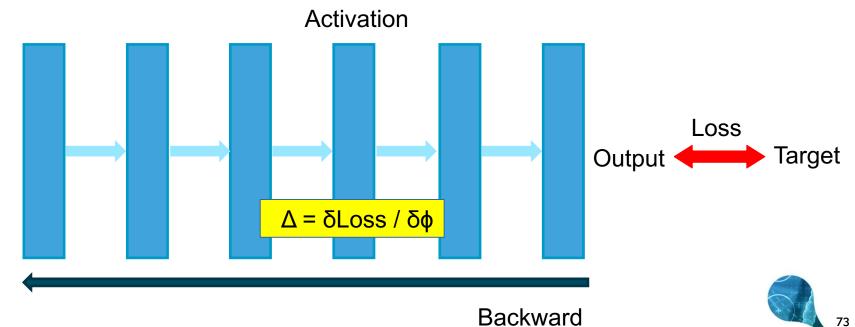
Activation

 The backpropagated gradient is multiply by the derivative of the activation function



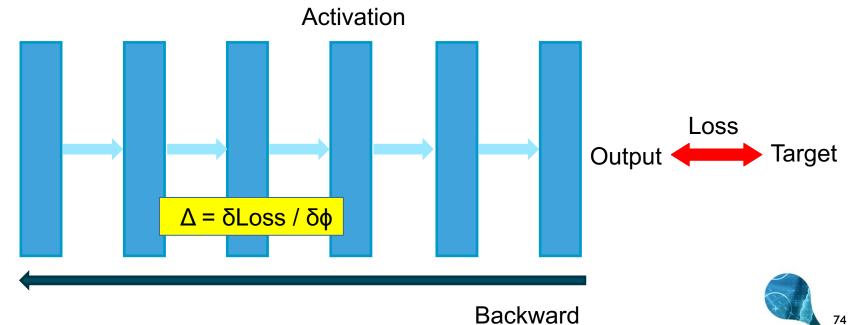
















Activation

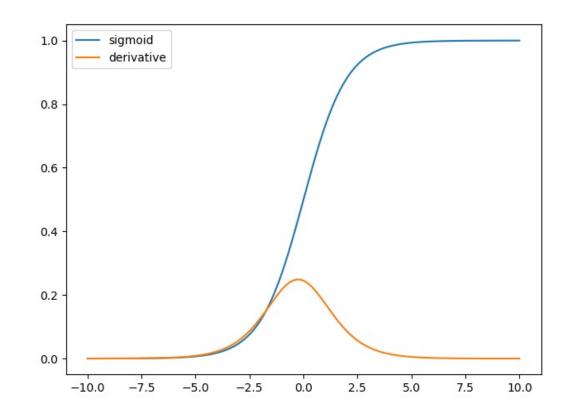
- The backpropagated gradient is multiply by the derivative of the activation function
- Vanishing gradient problem with some activation functions
- Most used: ReLu, ELU and similar







Activation



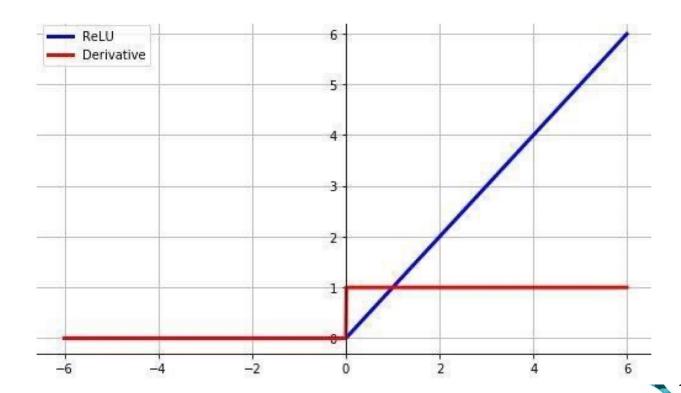








Activation

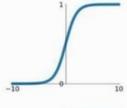






Sigmoid

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

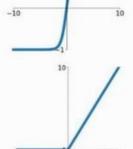


tanh

tanh(x)

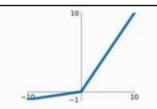
ReLU

 $\max(0,x)$



Leaky ReLU

 $\max(0.1x, x)$



Maxout

 $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$









Activation - Softmax

$$y_i = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}}$$

$$y_i = p(c = i | \boldsymbol{x})$$





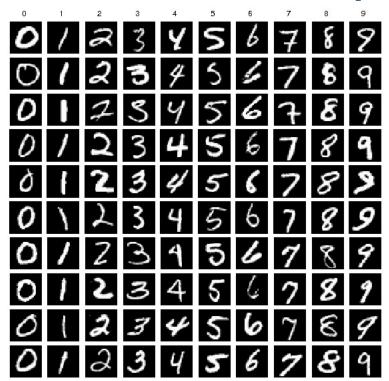


More Layers?

Deep Learning features







28x28 images (2D)

stored as 784 pixels (1D)

10 classes







num_classes = 10

in = eddl.Input([784])

layer = eddl.ReLu(eddl.Dense(in, 1024))

layer = eddl.ReLu(eddl.Dense(layer, 512))

out = eddl.Softmax(eddl.Dense(layer, num_classes))

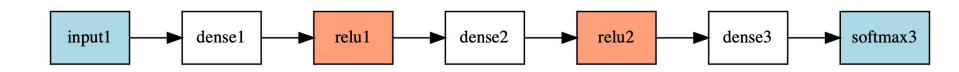
net = eddl.Model([in], [out])















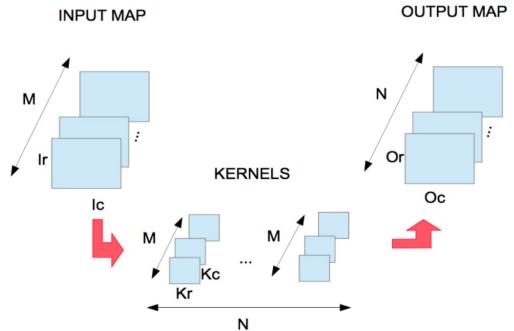
Conv2D

- Input a 3D Tensor (channels_in, height_in, width_in)
- Output a 3D Tensor (channels_out, height_in, width_out)
- Operation: y = K * x + b
- Parameters: K,b
 - K is a (num_filters, channels_in, kernel_height, kernel_width) 4D
 Tensor
 - B is a (num_filters) 1D Tensor





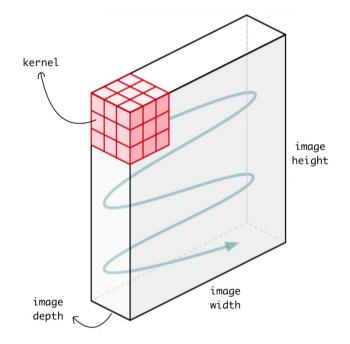








Conv2D









0	0	0	0	0	0	
0	156	155	156	158	158	
0	153	154	157	159	159	
0	149	151	155	158	159	
0	146	146	149	153	158	
0	145	143	143	148	158	

0	0	0	0	0	0	
0	167	166	167	169	169	
0	164	165	168	170	170	
0	160	162	166	169	170	
0	156	156	159	163	168	
0	155	153	153	158	168	

0	0	0	0	0	0	
0	163	162	163	165	165	
0	160	161	164	166	166	
0	156	158	162	165	166	
0	155	155	158	162	167	
0	154	152	152	157	167	

Input Channel #1 (Red)

Input Channel #2 (Green)

Input Channel #3 (Blue)

-1	-1	1
0	1	-1
0	1	1

Kernel Channel #2

Kernel Channel #3

Bias = 1

	(Outp	ut	
-25				
	1	ı	1	

308

-498





Conv2D

- Input a 3D Tensor (channels_in, height_in, width_in)
- Output a 3D Tensor (channels_out, height_in, width_out)
- channels_out = num_filters
- with padding="same"
 - height_out= height_in
 - width_out= width_in







Maxpool2D

- Input a 3D Tensor (channels_in, height_in, width_in)
- Output a 3D Tensor (channels_in, height_in/s, width_in/s)
 Normally s=2

Parameters: None







Maxpool2D

12	20	30	0
8	12	2	0
34	70	37	4
112	100	25	12

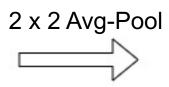
2×2 Max-Pool	20	30
	112	37





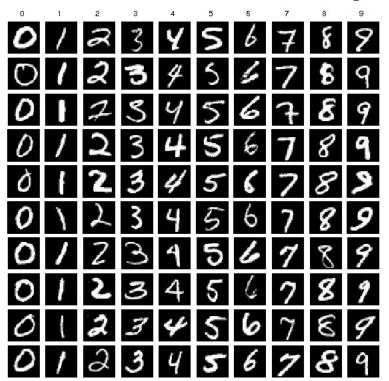
AveragePool2D

4	3	1	5
1	3	4	8
4	5	4	3
6	5	9	4



2.8	4.5	
5.3	5.0	



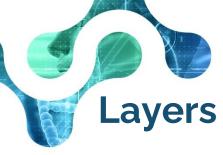


28x28 images (2D)

stored as 784 pixels (1D)

10 classes







num_classes = 10

```
in = eddl.Input([784]) # 784 components vector layer = eddl.Reshape(in, [1, 28, 28]) # 28 x 28 gray-level image layer = eddl.MaxPool(eddl.ReLu(eddl.Conv(layer, 32, [3, 3]))) #(32,14,14) layer = eddl.MaxPool(eddl.ReLu(eddl.Conv(layer, 64, [3, 3]))) #(64,7,7) layer = eddl.MaxPool(eddl.ReLu(eddl.Conv(layer, 128, [3, 3]))) #(128,3,3) layer = eddl.MaxPool(eddl.ReLu(eddl.Conv(layer, 256, [3, 3]))) #(256,1,1) layer = eddl.Reshape(layer, [-1]) # 256 components vector out = eddl.Softmax(eddl.Dense(layer, num_classes))
```





eddl.summary(net)

```
model
input1
            (784)
                                      (784)
reshape1 | (784)
                                     (1, 28, 28)
conv2d1
                                     (32, 28, 28)
                                                          320
            (1, 28, 28)
relu1
            (32, 28, 28)
                                => (32, 28, 28)
                                => (32, 14, 14)
maxpool2d2|
            (32, 28, 28)
conv2d2
            (32, 14, 14)
                                => (64, 14, 14)
                                                          18496
relu2
            (64, 14, 14)
                                => (64, 14, 14)
maxpool2d41
            (64, 14, 14)
                                     (64, 7, 7)
conv2d3
             (64, 7, 7)
                                     (128, 7, 7)
                                                          73856
relu3
            (128, 7, 7)
                                     (128, 7, 7)
maxpool2d6|
            (128, 7, 7)
                                     (128, 3, 3)
            (128, 3, 3)
                                                          295168
conv2d4
                                      (256, 3, 3)
relu4
            (256, 3, 3)
                                      (256, 3, 3)
maxpool2d8|
            (256, 3, 3)
                                      (256, 1, 1)
reshape2 |
            (256, 1, 1)
                                      (256)
dense1
            (256)
                                      (10)
                                                          2570
softmax5
             (10)
                                      (10)
```















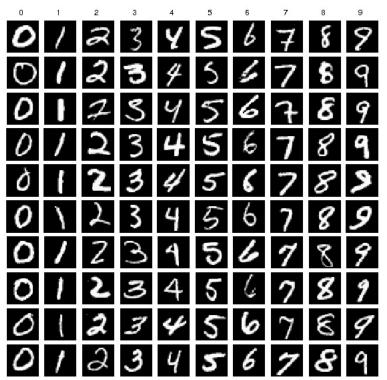
Recurrent Layers:

- Vanilla RNN
- LSTM
- GRU

All accept a 1D tensor (vector) as Input and returns 1D vector as Output







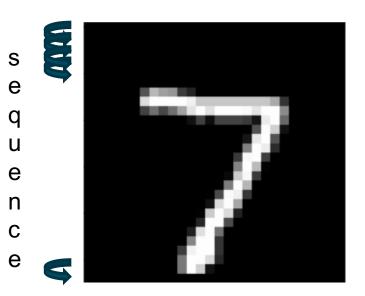
28x28 images (2D)

stored as 784 pixels (1D)

10 classes



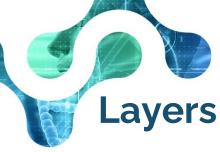




We are going to consider the digits as a sequence of 28 rows of 28 pixels

Then the recurrent layers expect to receive a 1D tensor of 28 components







```
num_classes = 10

in = eddl.Input([28])
  layer = eddl.ReLu(eddl.Dense(in, 32))
  layer = eddl.LSTM(layer, 128)
  out = eddl.Softmax(eddl.Dense(layer, num_classes))
.
```

90

(N, sequence length, dim)

x_train.reshape_([x_train.shape[0], 28, 28]).





