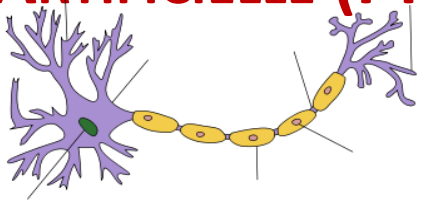
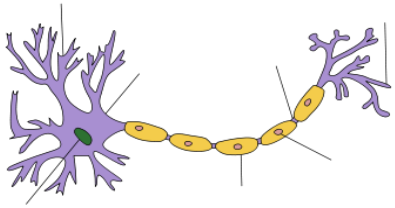
UMONS
Université de Mons

INTELLIGENCE ARTIFICIELLE (I-ILIA-026)



CHAPITRE 05 : L'APPRENTISSAGE PROFOND (DEEP LEARNING)



Sidi Ahmed Mahmoudi

POLYTECH MONS

sidi.mahmoudi@umons.ac.be

24 Fév. 2025

PLAN

PLAN

Introduction

ARTIFICIAL INTELLIGENCE

IS NOT NEW

ARTIFICIAL INTELLIGENCE

Any technique which enables computers to mimic human behavior

MACHINE LEARNING

AI techniques that give computers the ability to learn without being explicitly programmed to do so

DEEP LEARNING

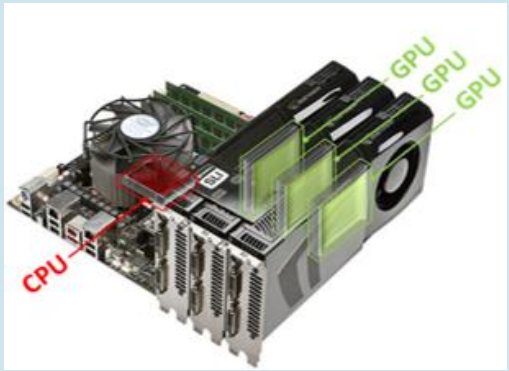
A subset of ML which make the computation of multi-layer neural networks feasible

1950's 1960's 1970's 1980's 1990's 2000's 2010s

ORACLE

Introduction

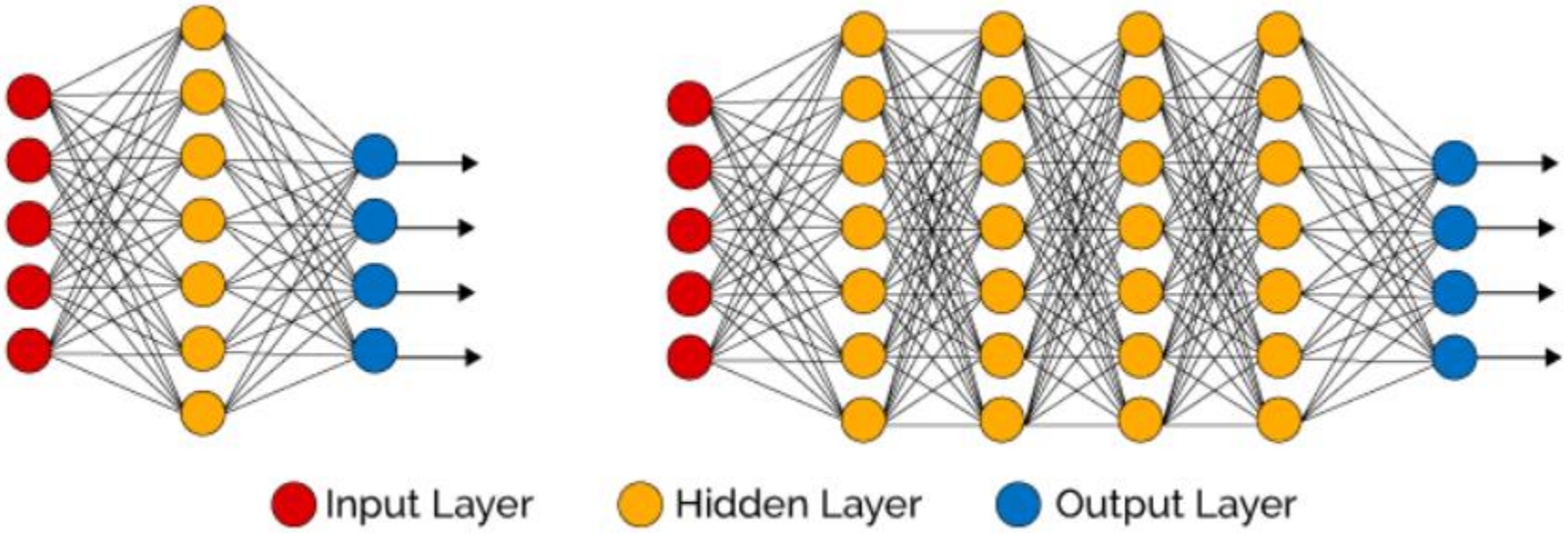
- La forte émergence du Deep Learning est due principalement à :
  - Disponibilité et gestion de très grands jeux de données (Big Data)
  - Enormes capacités de calcul (HPC, GPU, cluster, etc.)
  - Nouveaux modèles d'apprentissage très flexibles permettant de résoudre différents problèmes

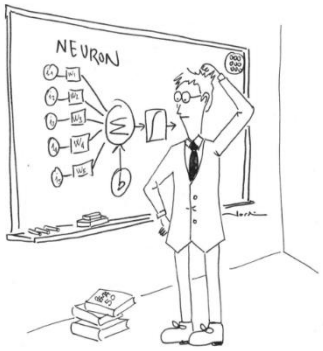


Introduction

Réseau de neurons non profond

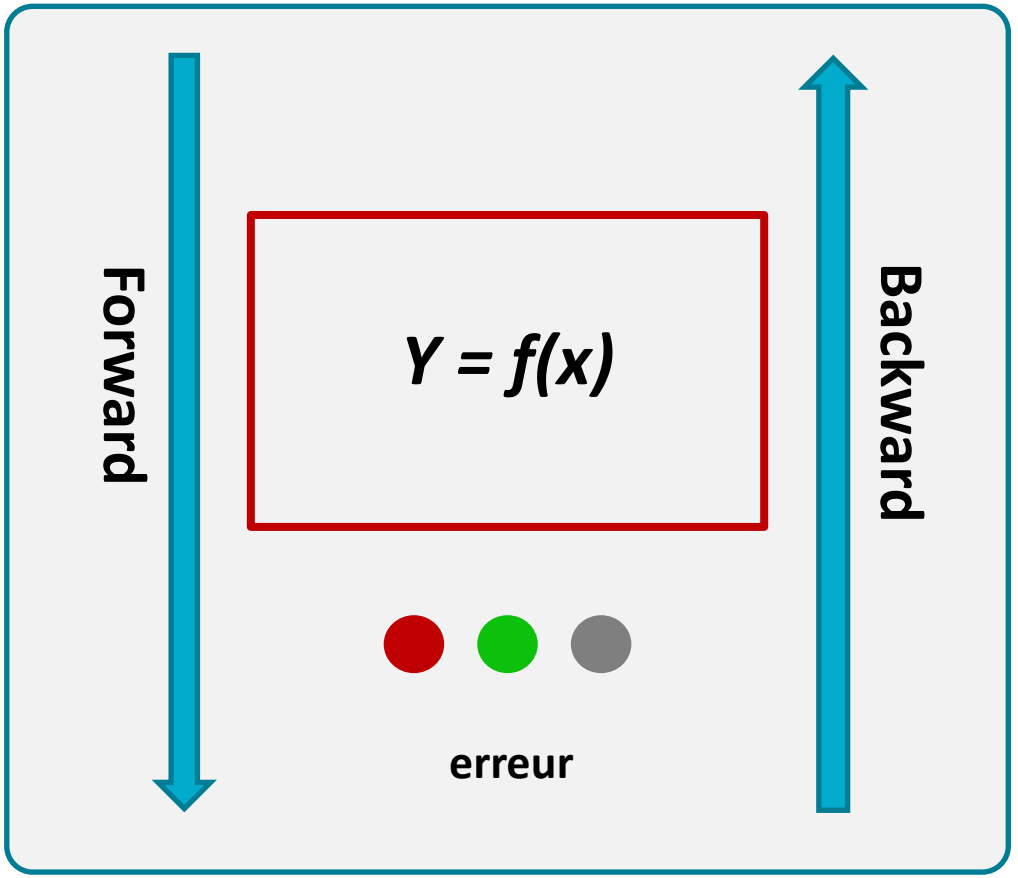
Réseau de neurons profond



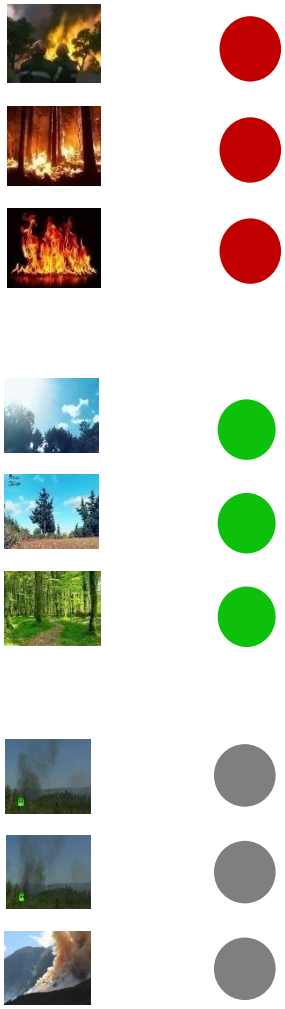


Exemple

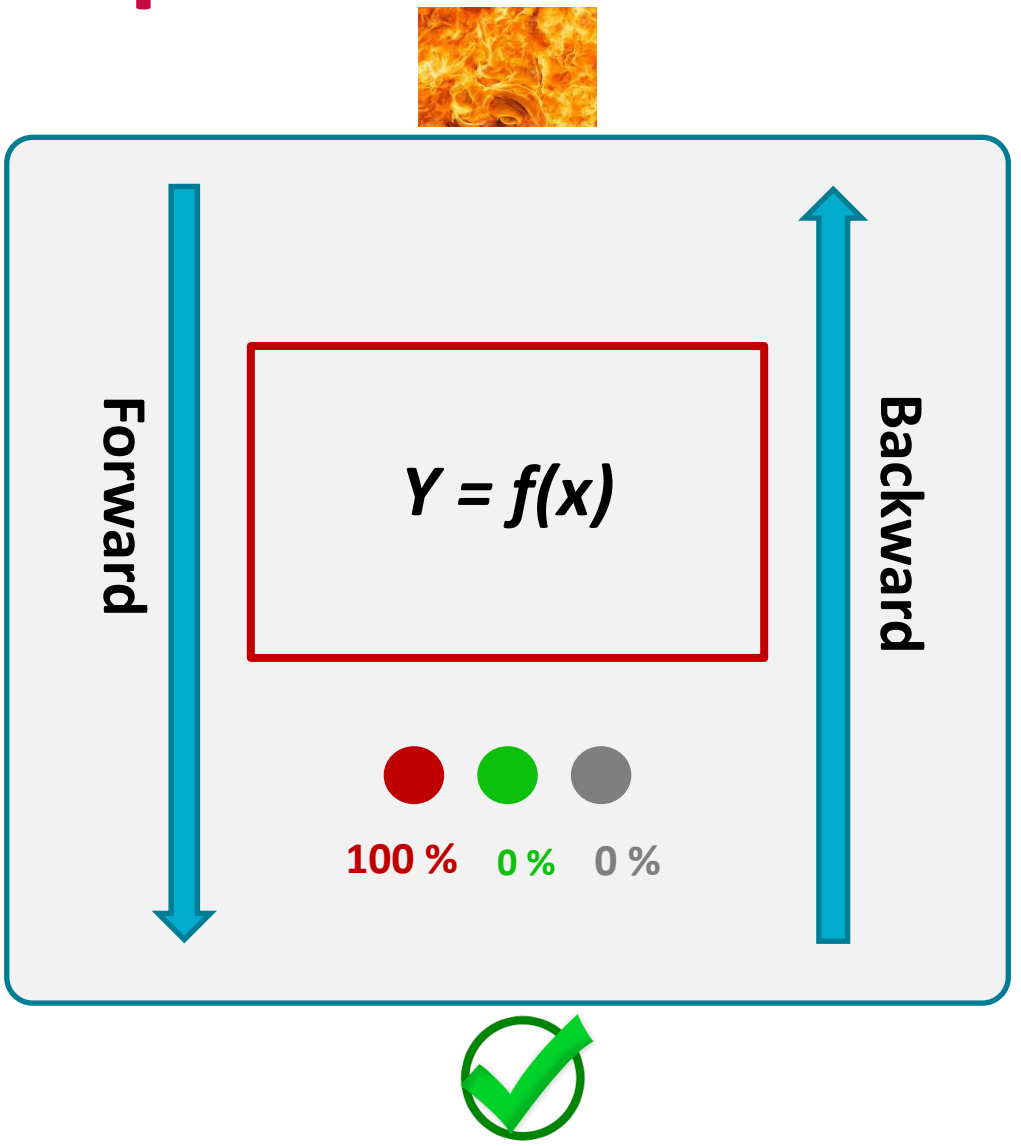
Data



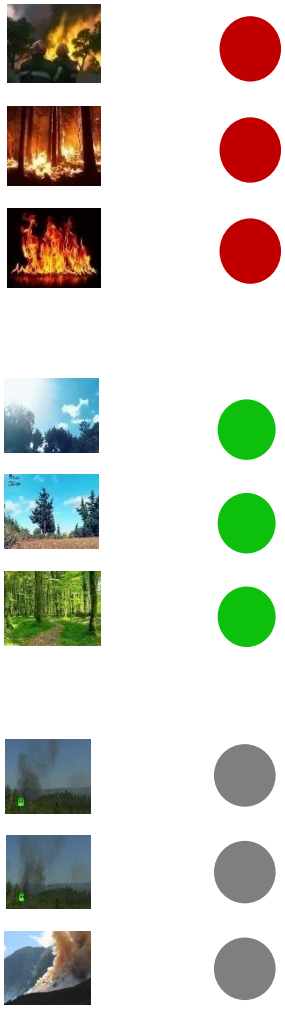
Exemple

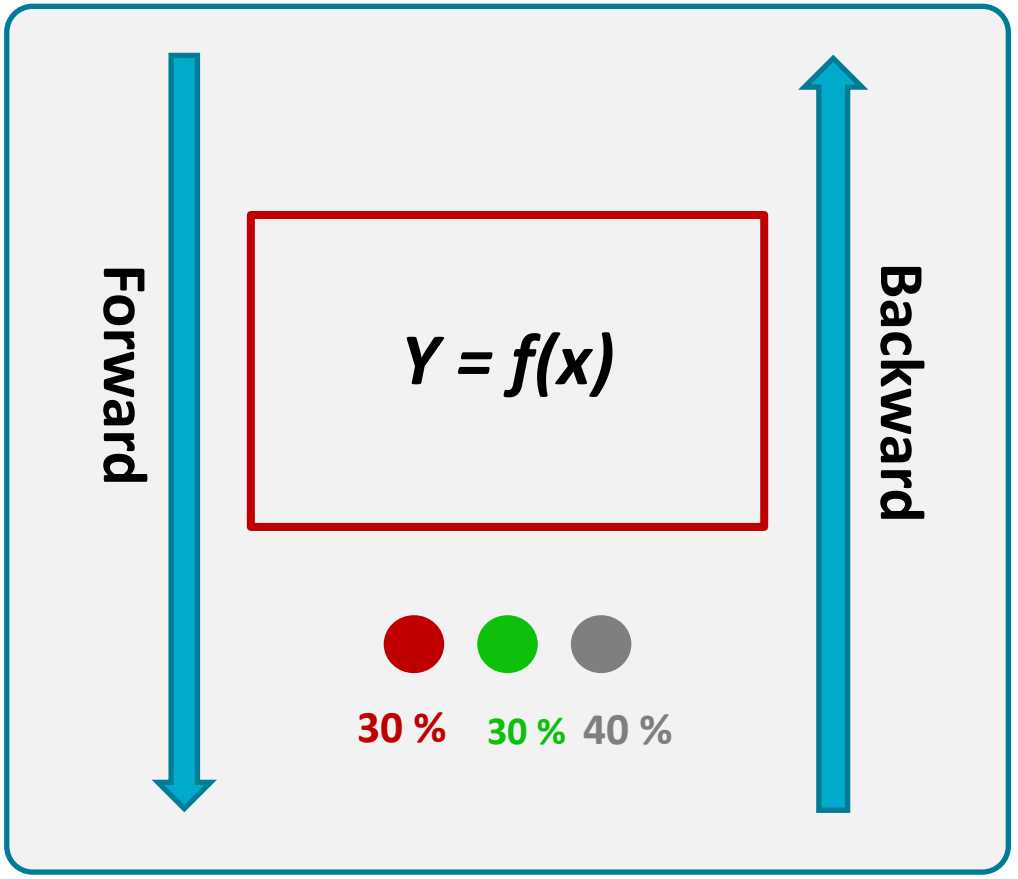


Data



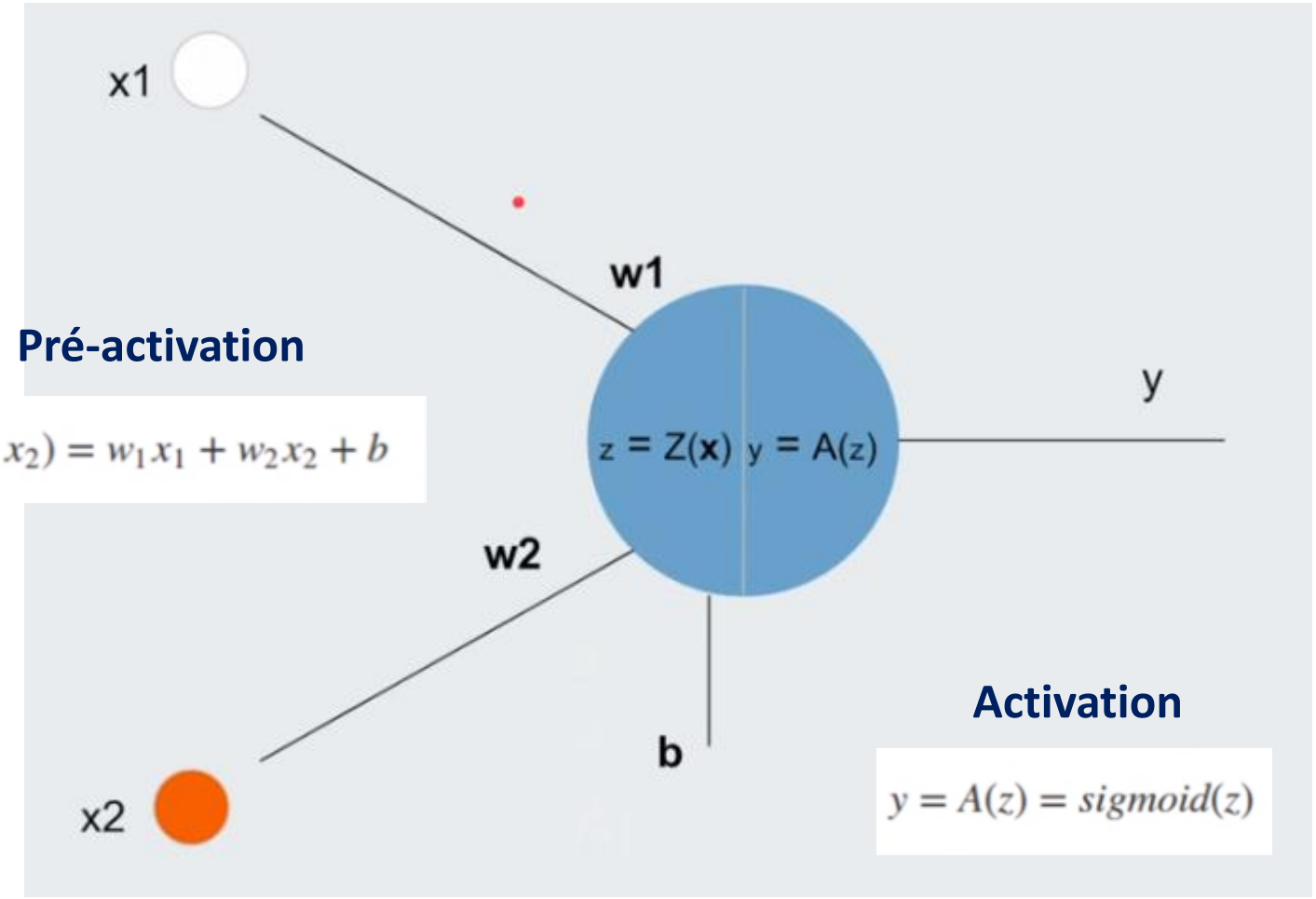
Exemple



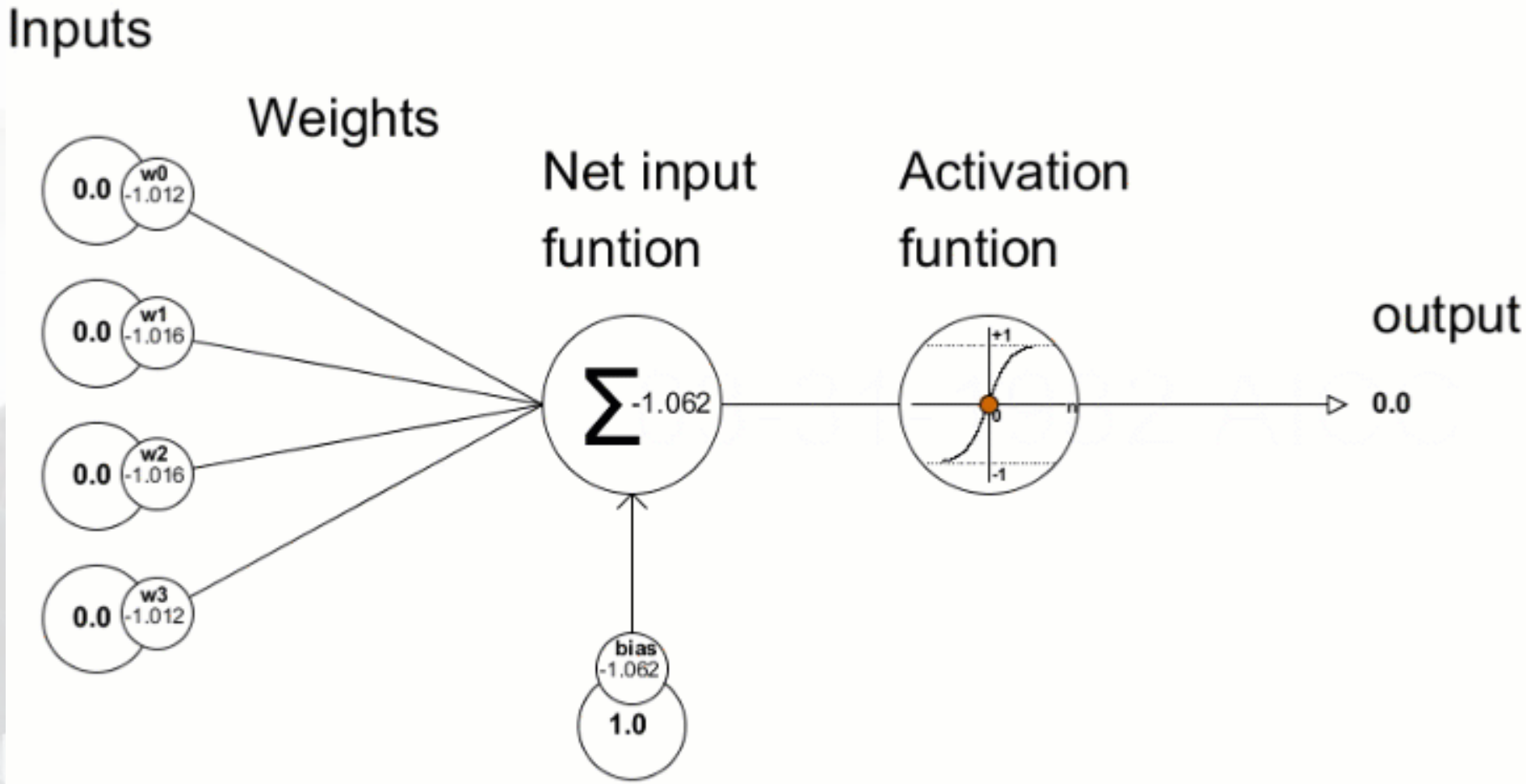


PLAN

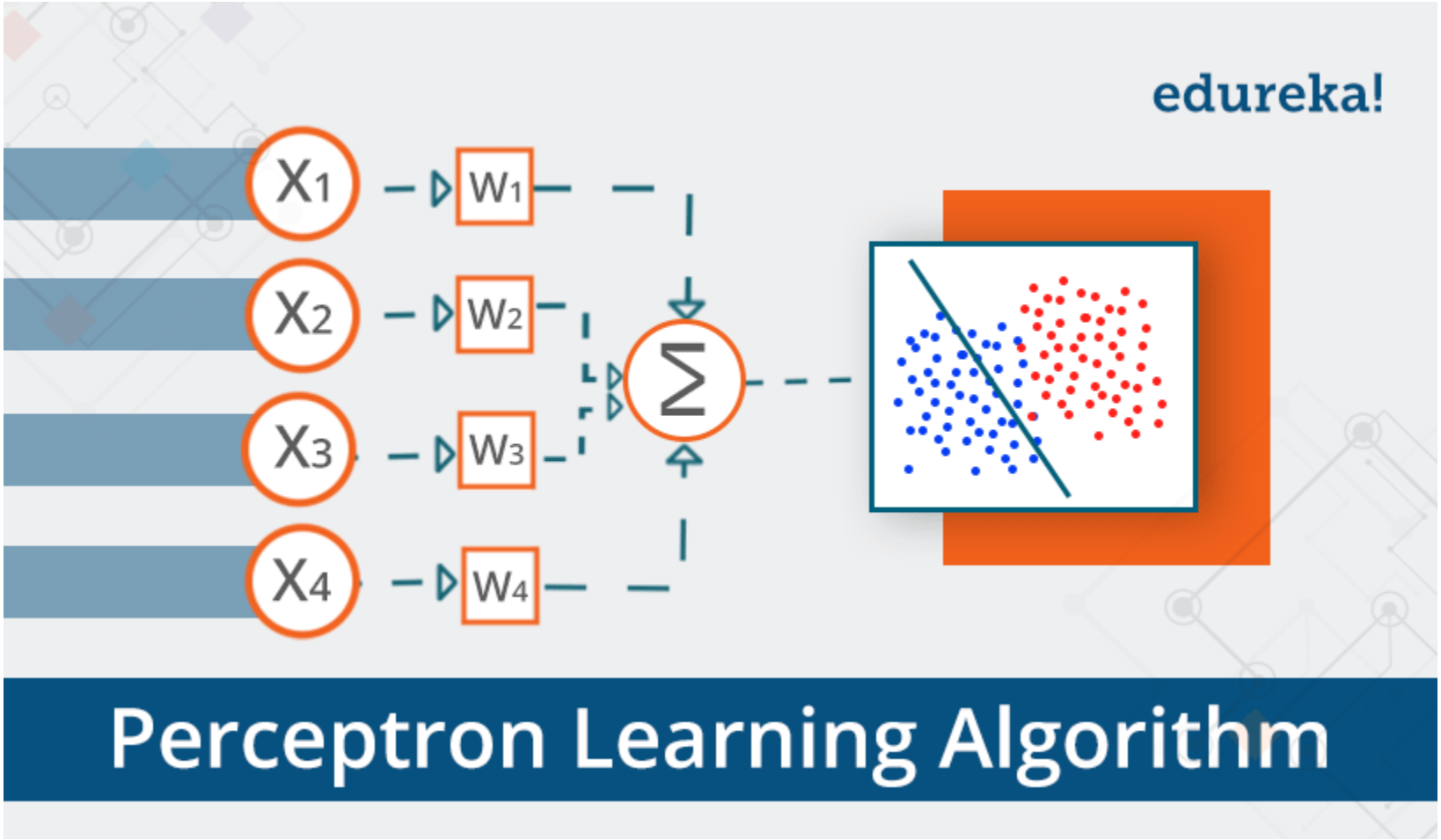
Perceptron


x1
w1
Pré-activation
$Z(x_1, x_2) = w_1 x_1 + w_2 x_2 + b$
z = Z(x)
y = A(z)
y
w2
b
Activation
$y = A(z) = sigmoid(z)$
x2

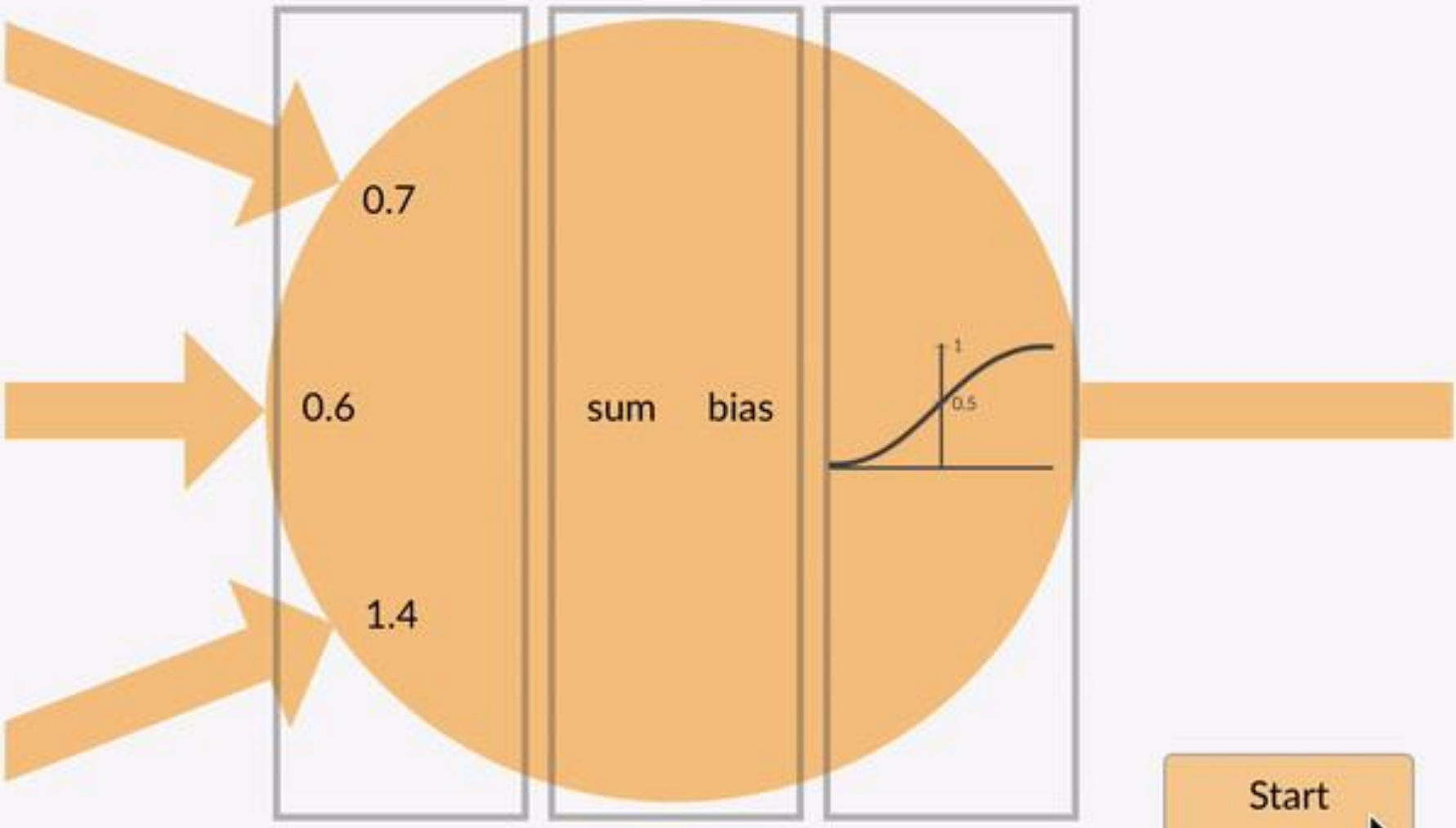
Perceptron


Inputs
Weights
Net input
funtion
Activation
funtion
output
0.0
w0
-1.012
0.0
w1
-1.016
0.0
w2
-1.016
0.0
w3
-1.012
-1.062
bias
-1.062
1.0
+1
0
-1
0.0

Perceptron


edureka!
X1
X2
X3
X4
W1
W2
W3
W4
Σ
Perceptron Learning Algorithm

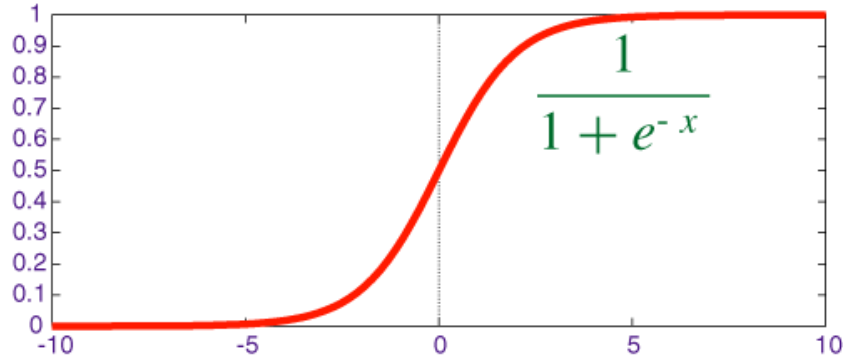
Fonctions d'activation et non linéarité

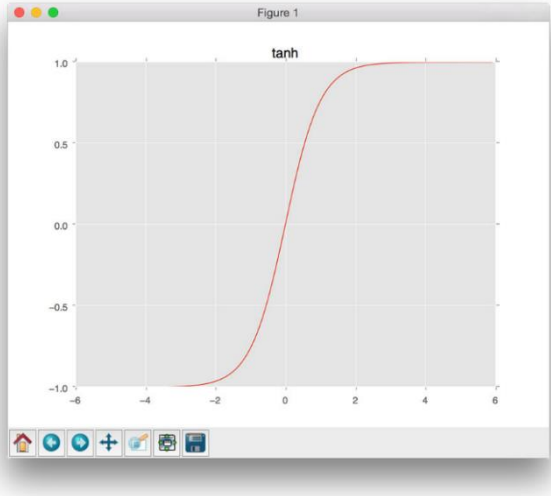


Fonctions d'activation

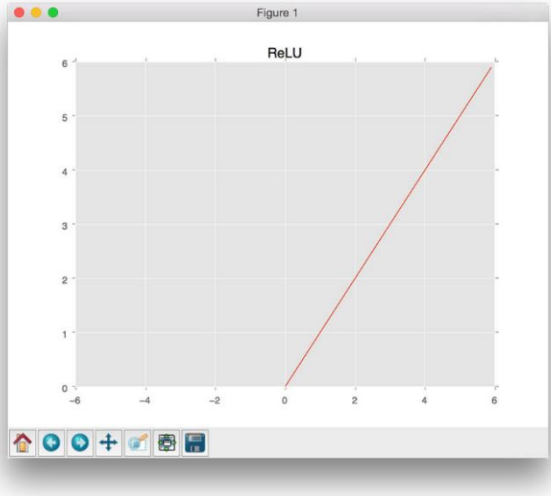
- **Non linéarité:** apprendre des motifs complexes

Sigmoid

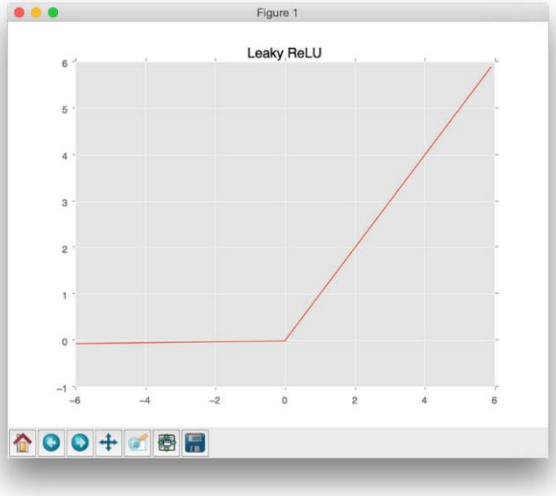




tanh



Relu

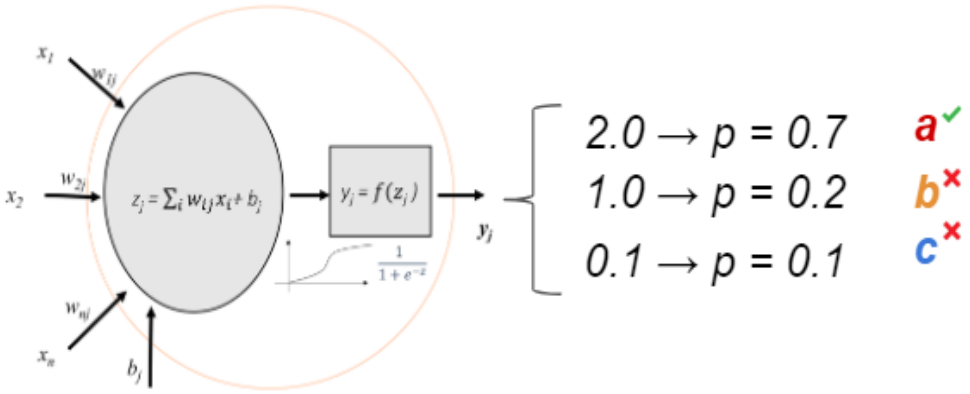


Leaky Relu

Perceptron (fonction softmax)

- **Softmax:** traduire les scores de la dernière couche en probabilités

A



Softmax : $S(y_i) = \frac{e^{y_i}}{\sum_i e^{y_i}}$

- Une entrée ne peut pas avoir qu'un seul label possible (a)
- **But :** avoir une probabilité proche de 1 pour cette classe

  probabilité proche de 0 pour les autres classes

Fonctions d'activation : problèmes rencontrés

Vanishing Gradient:

- gradients deviennent trop petits voire nuls
- Apprentissage très lent voire non évolutif
- Solution : **Relu, Leaky Relu, etc.**

Exploding Gradient:

- gradients trop grands → apprentissage instable
- Solution : **Régularisations, Batch-normalisation, etc.**

Dead neurones (neurones morts) :

- Avec Relu: certaines unités produire que des zéros
- Solution : **Leaky Relu, Parametric Relu.**

Fonctions d'activation : recommandation de choix

Fonction	Formule	Avantages	Inconvénients
Sigmoïde	$\frac{1}{1+e^{-x}}$	Bon pour la probabilité (entre 0 et 1).	Vanishing gradient, non centrée en zéro.
Tanh	$\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$	Centrée en zéro, meilleur que Sigmoïde.	Vanishing gradient.
ReLU	$\max(0,x)$	Rapide, évite en partie le vanishing gradient.	Neurones morts (pour x < 0).
Leaky ReLU	x si $x > 0, 0.01x$ sinon	Corrige le problème des neurones morts	Paramètre α\alphaα à régler
Softmax	$\frac{e^{x_i}}{\sum e^{x_j}}$	Convertit en probabilités (utile pour classification)	Sensible aux valeurs extrêmes.

Comment ça marche ?

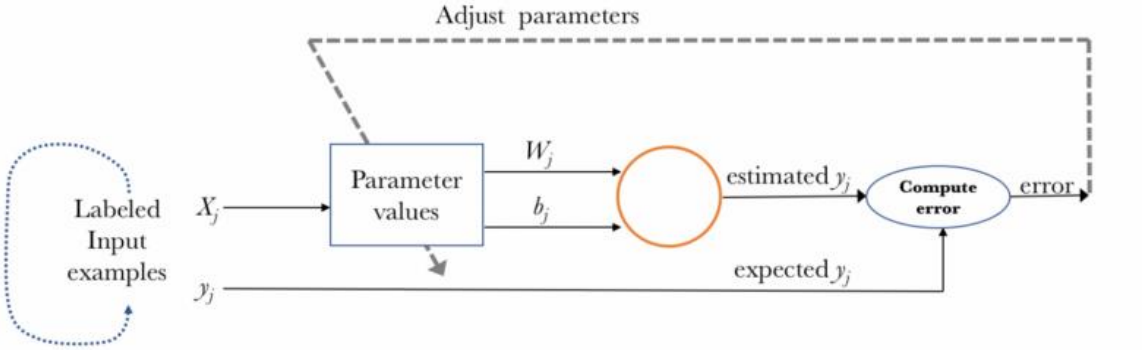
a. **Initialization :** Init weights (W) and bias (b) with random values

b. **Forward Pass :** get predictions using the proposed neural network

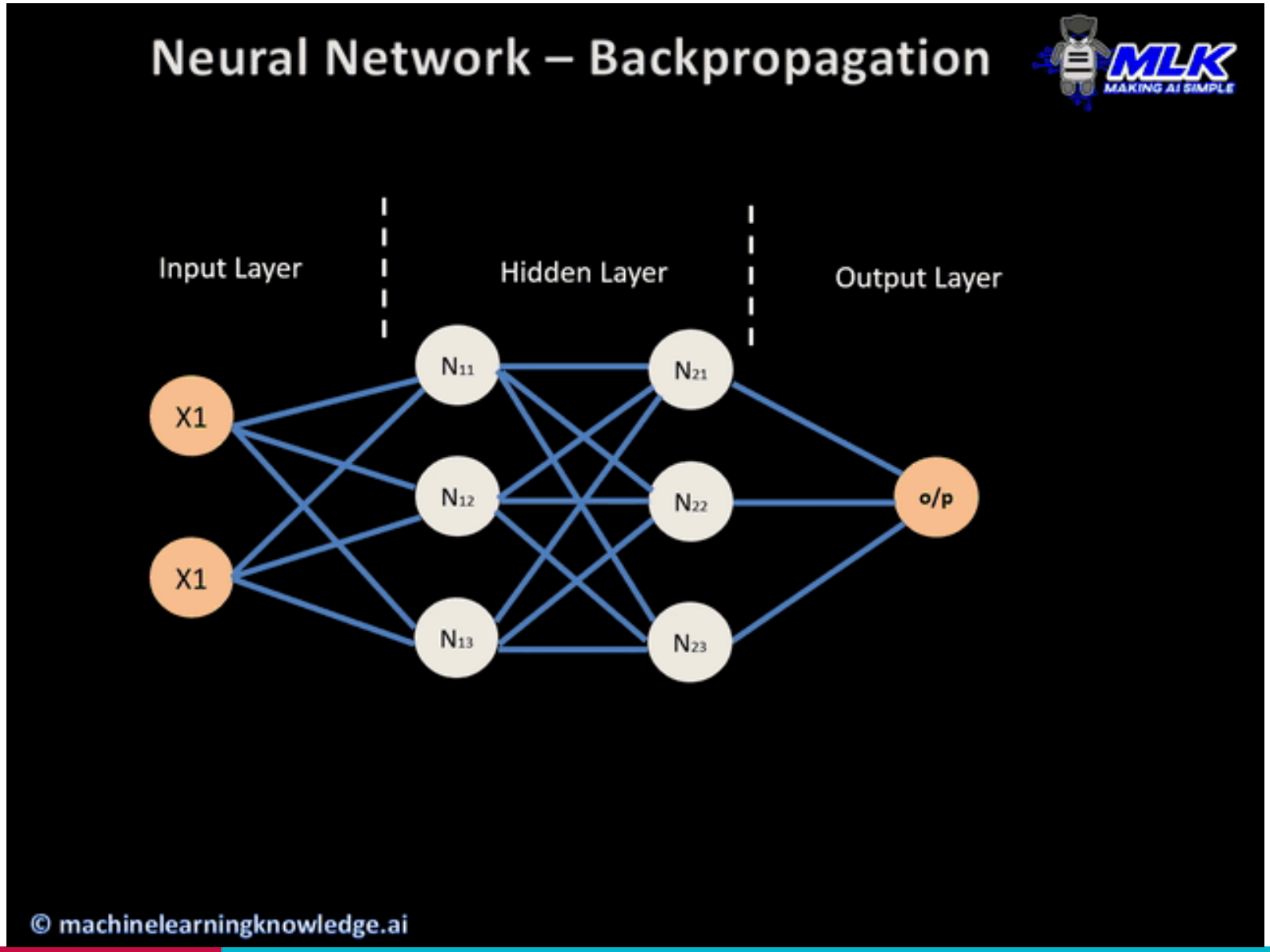
c. **Error calculation :** compare predicted values vs. real values

d. **Backpropagation :** update the weights using gradient descent

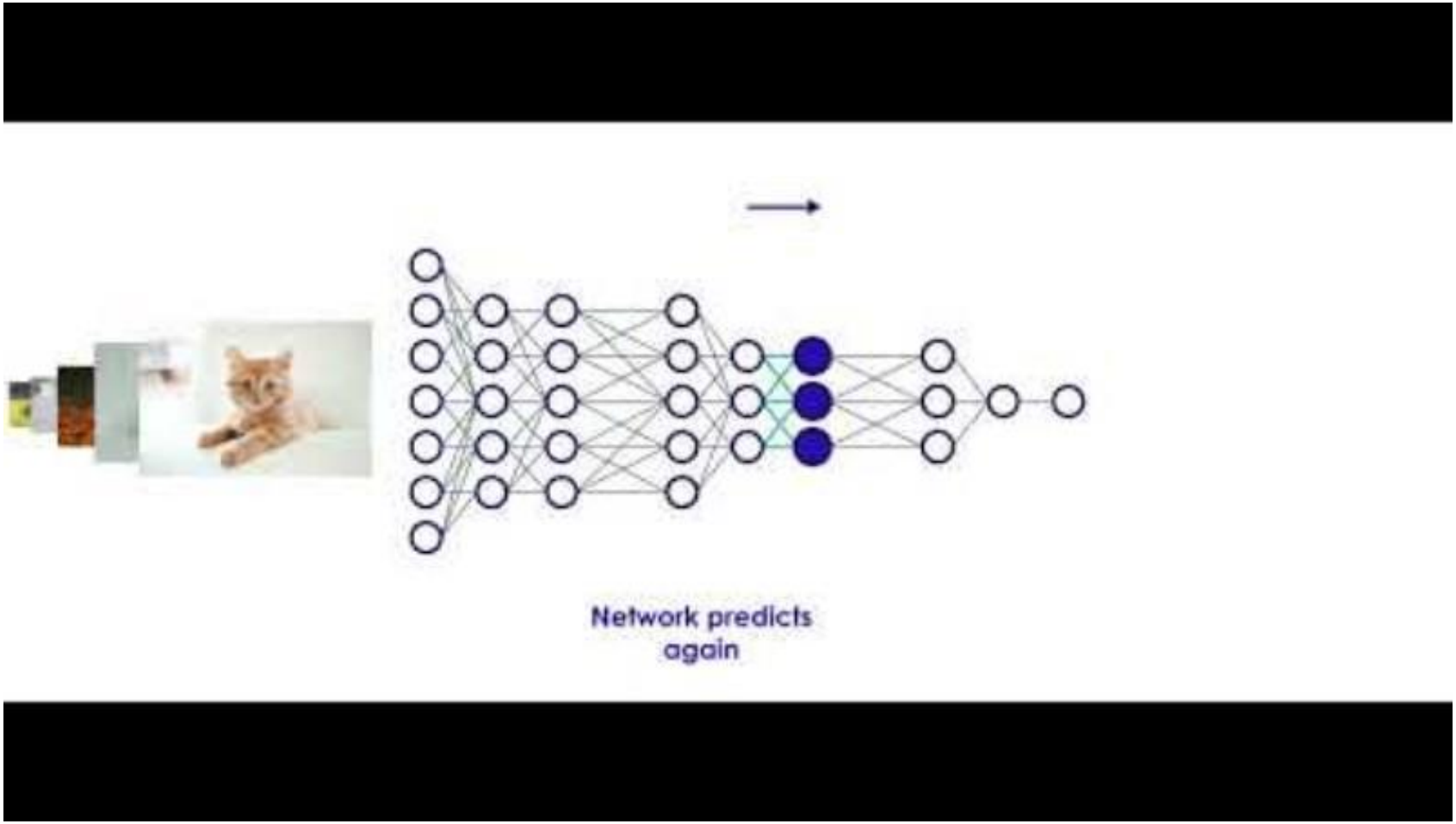
e. **Iterate :** Repeat the previous steps until get efficient model.



Backpropagation process



Neural network training : summary



PLAN

Introduction

I. Le Perceptron

II. **Types de réseaux de neurones profonds (ANN, MLP, CNN, RNN, etc.)**

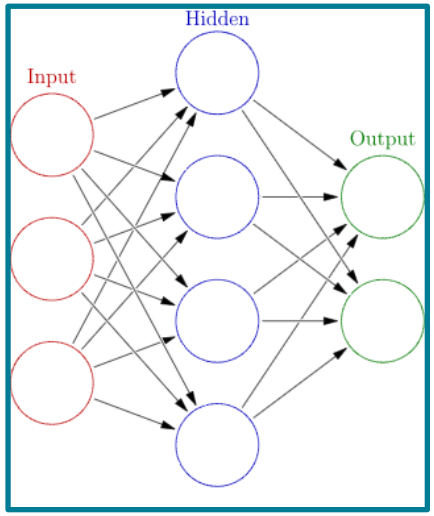
III. Analyse des données et évaluation de modèles

IV. Réseaux de neurones convolutionnels (CNNs)

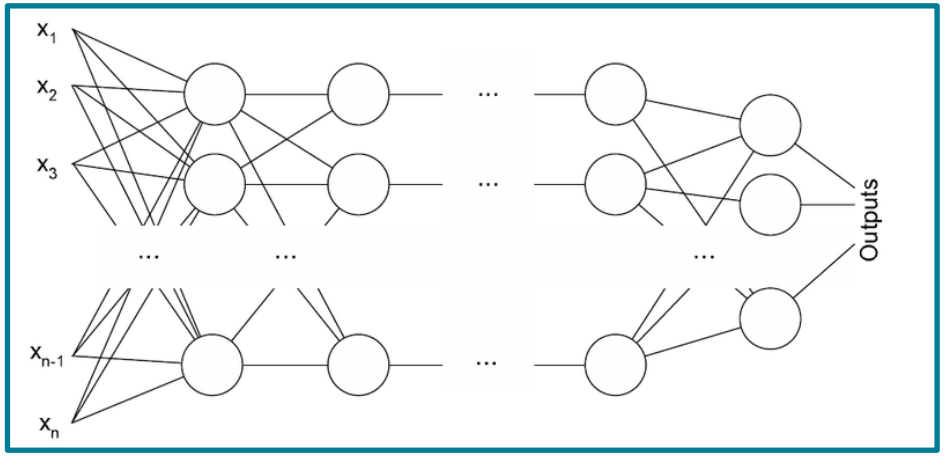
V. Outils de développement et matériel de calcul

Conclusion

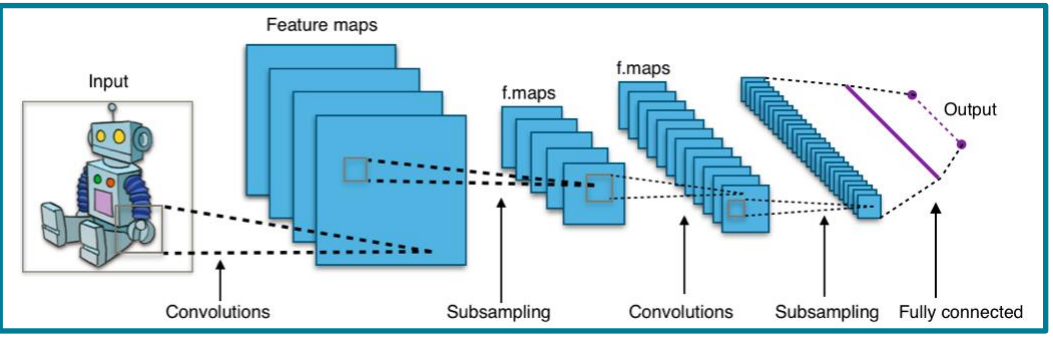
Types de réseaux de neurones profonds



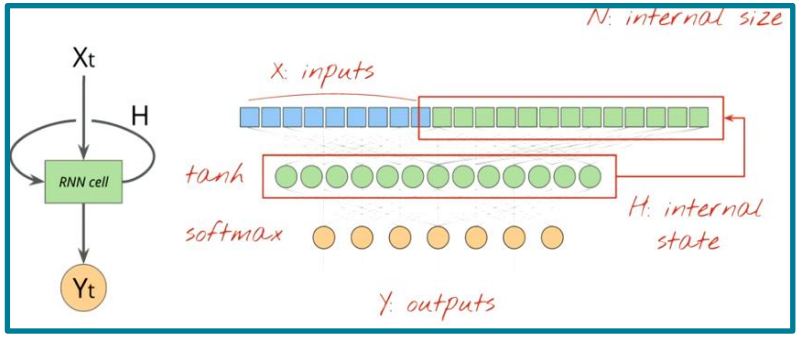
ANN



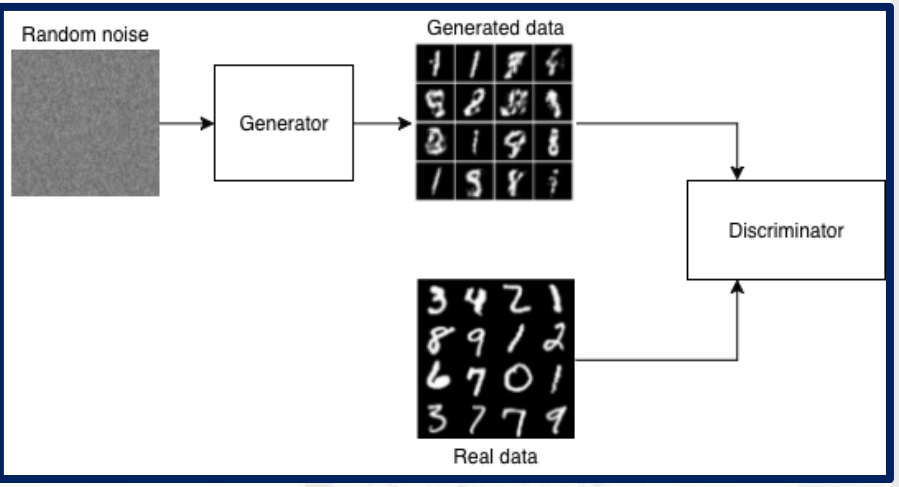
MLP (Multilayer Perceptron)



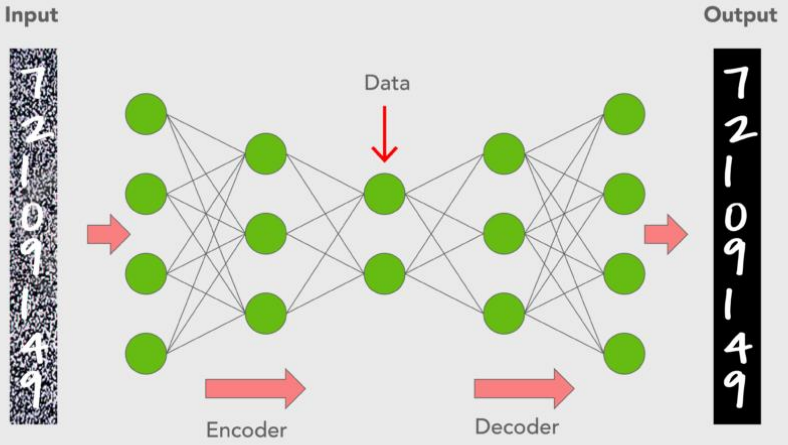
CNN



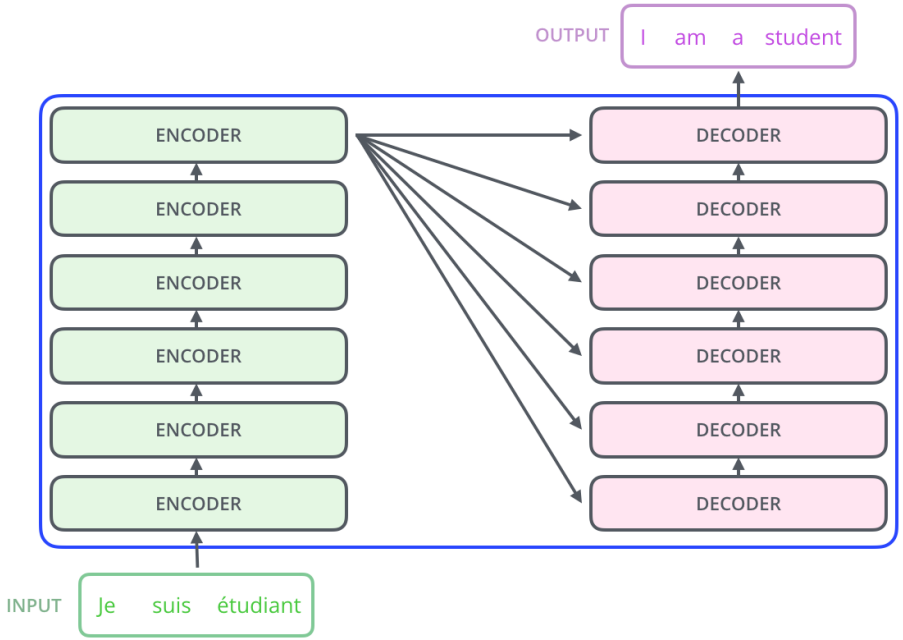
RNN



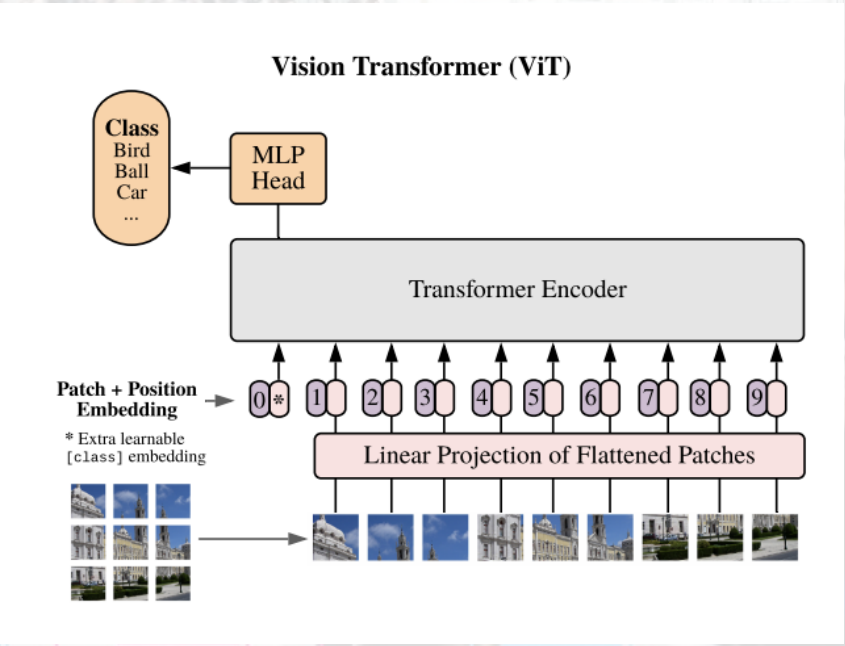
GAN



Auto encoders



Transformers



Vision Transformers

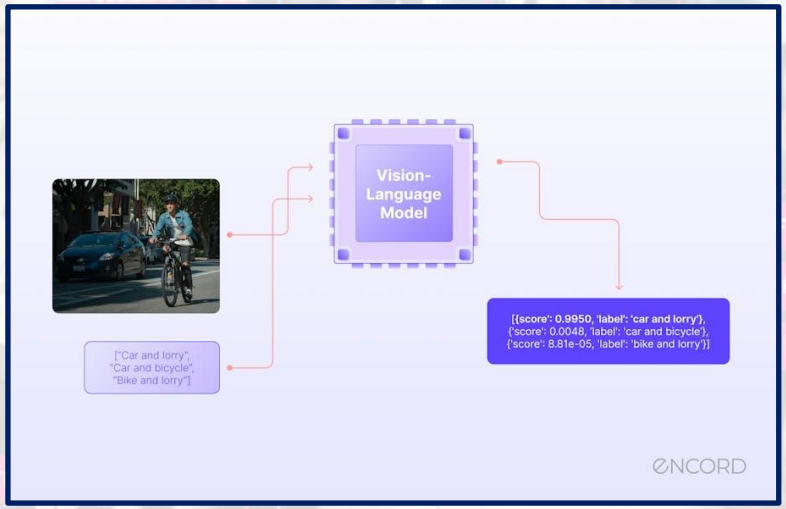
LLMs

Models size comparison of GPT models

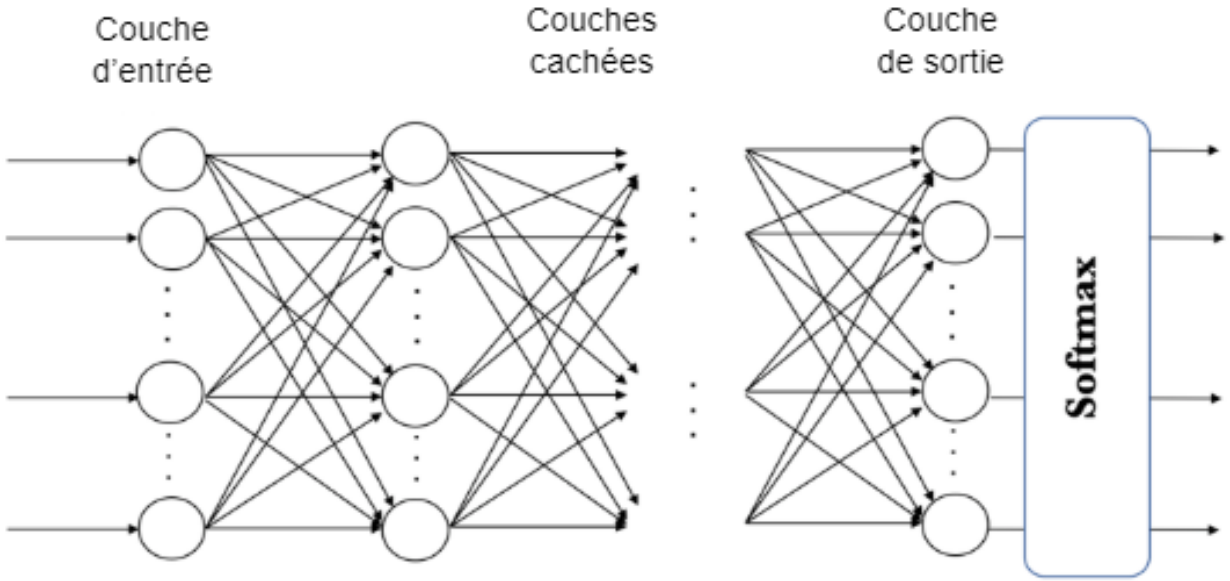
	Parameters	Decoder layers	Context lenght	Hidden layer size
GPT-1	117 million	12	512	768
GPT-2	1.5 billion	48	1024	1600
GPT-3	175 billion	96	2048	12288
GPT-4	1.76 trillion	120	8000*	20k*

*Data subject to confirmation by OpenAI. Last updated: July 2023.

VLMs



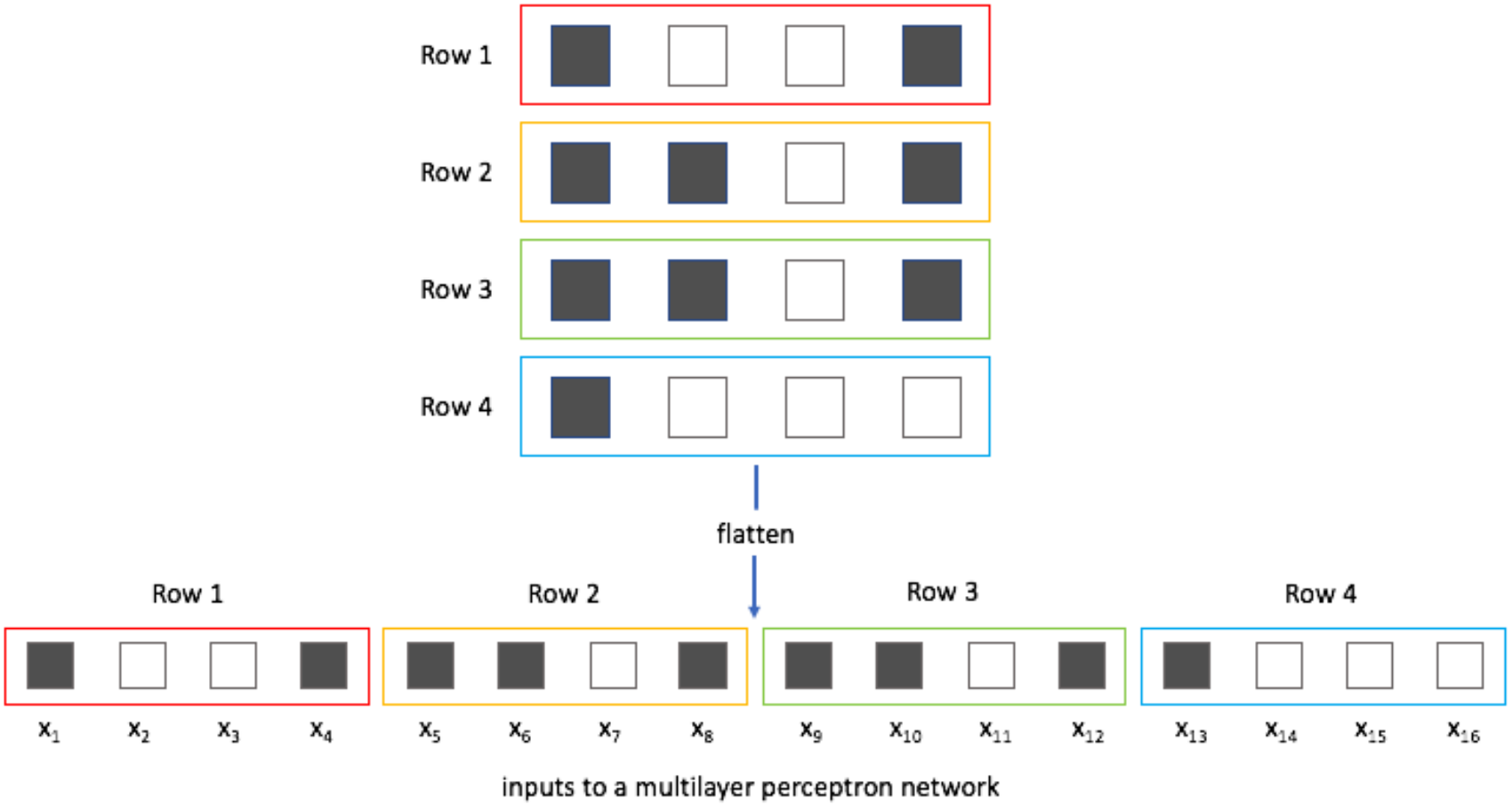
Multilayer Perceptron (MLP)



- **MLP :** Couche d'entrée + 1 ou plusieurs couches cachées + couche de sortie
- 1 couche = plusieurs perceptrons
- Deep Learning => beaucoup de couches cachées

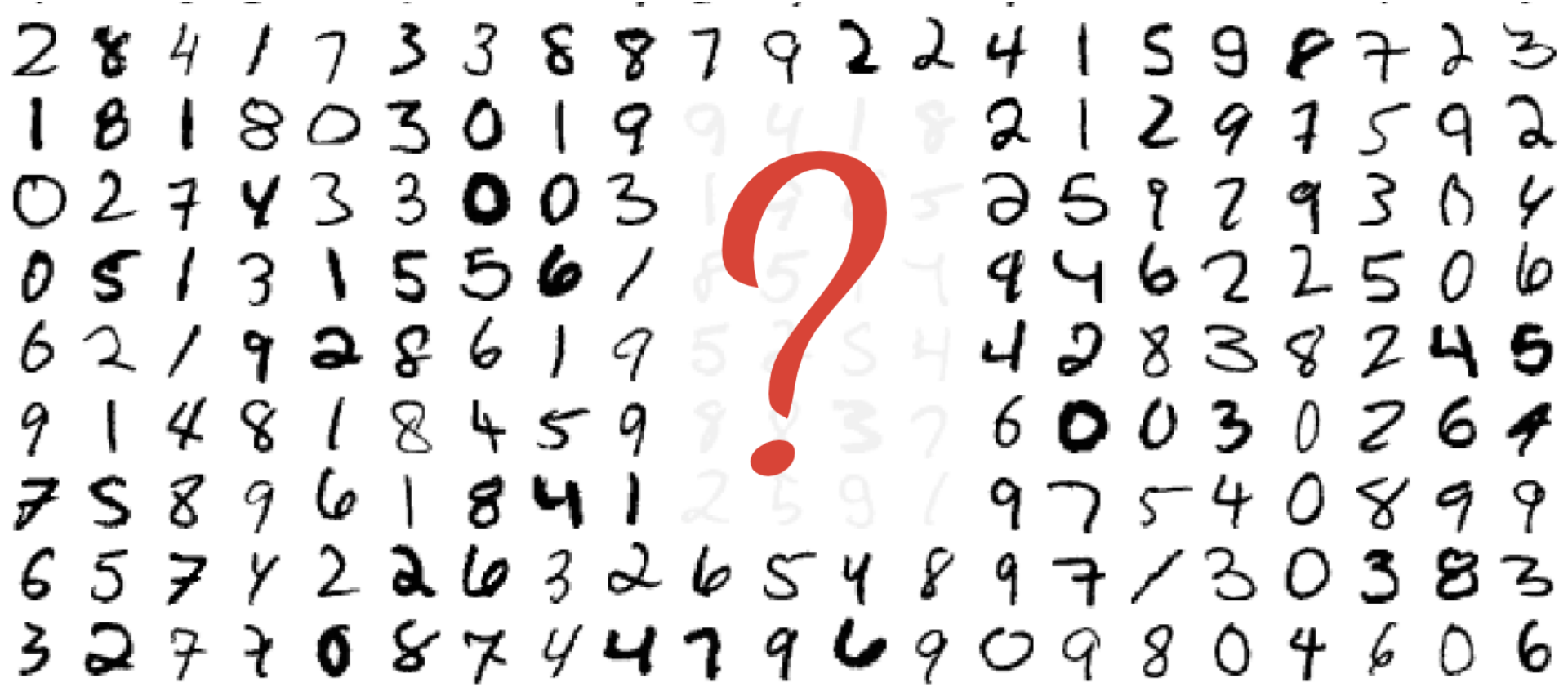
Multilayer Perceptron (MLP)

Une image



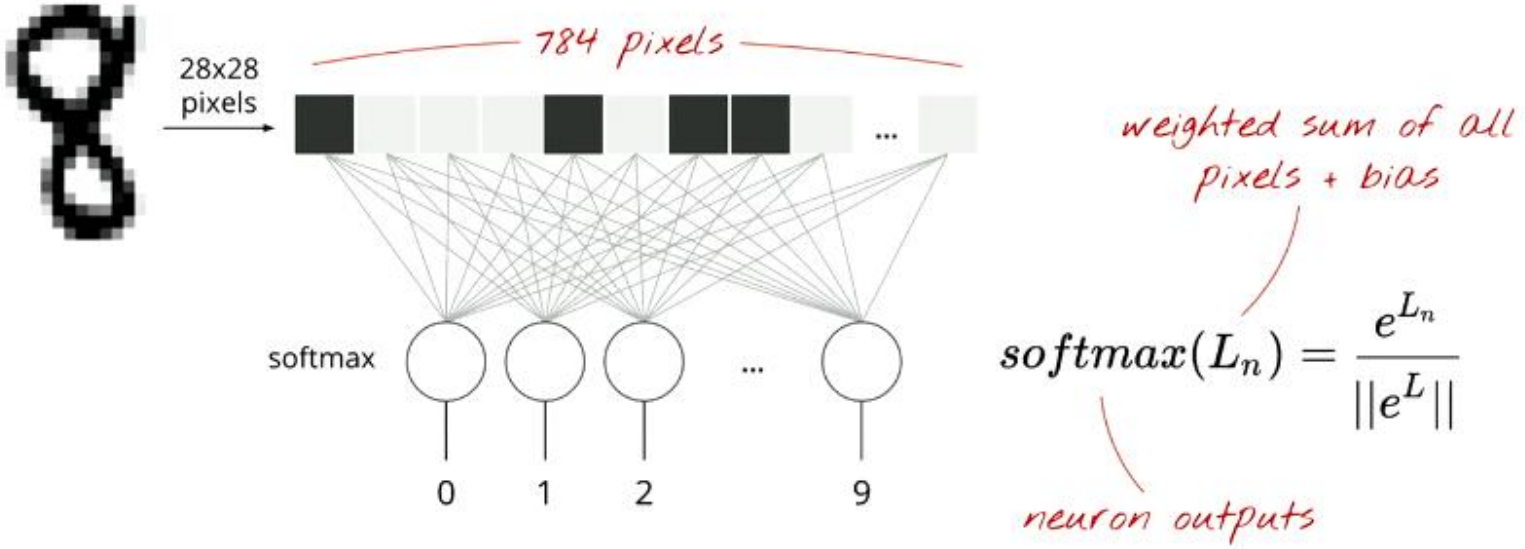
inputs to a multilayer perceptron network

Prenons un exemple



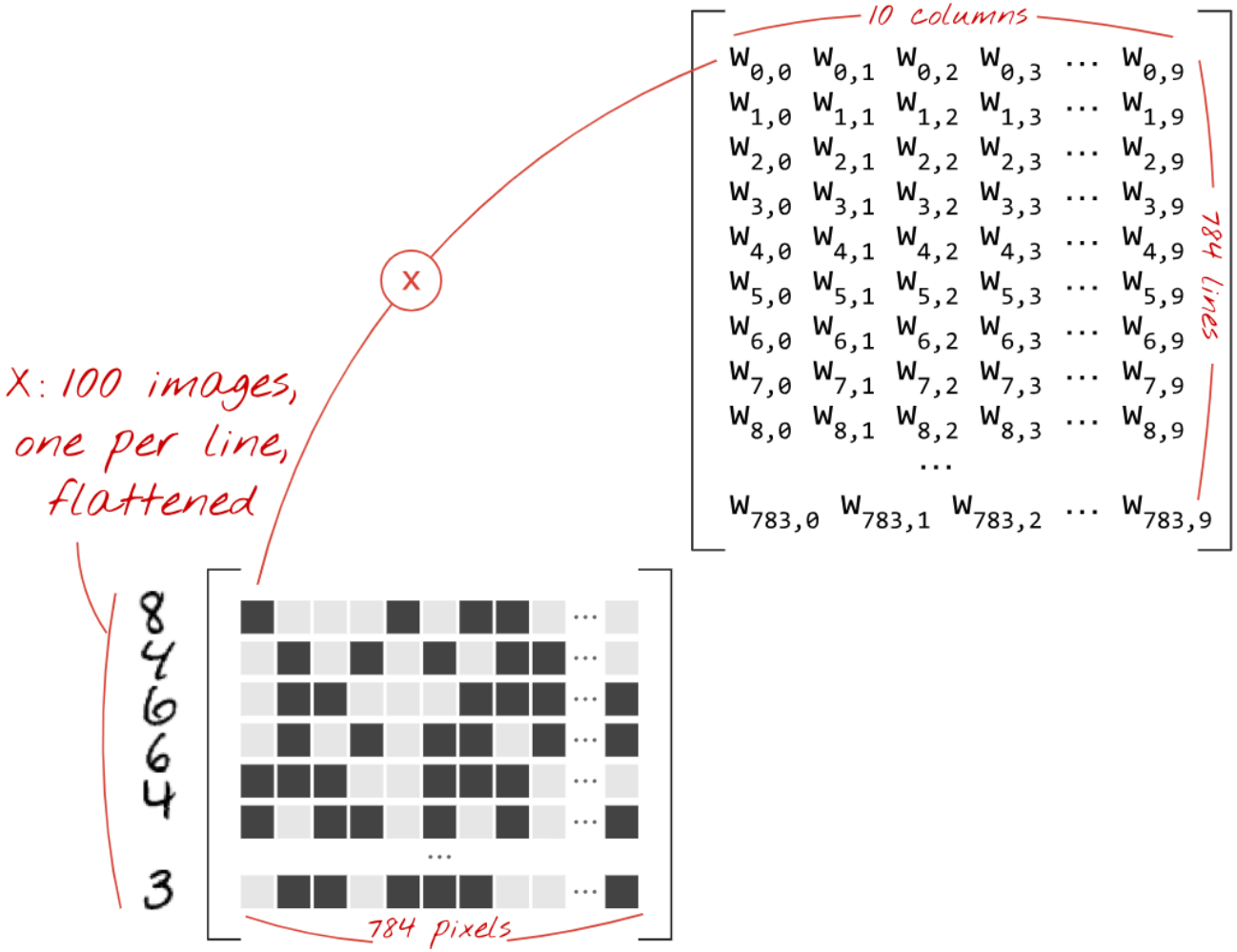
MNIST : Mixed National Institute of Standards and Technology [1]

Prenons un exemple



Modèle simple : classification avec SoftMax [2]

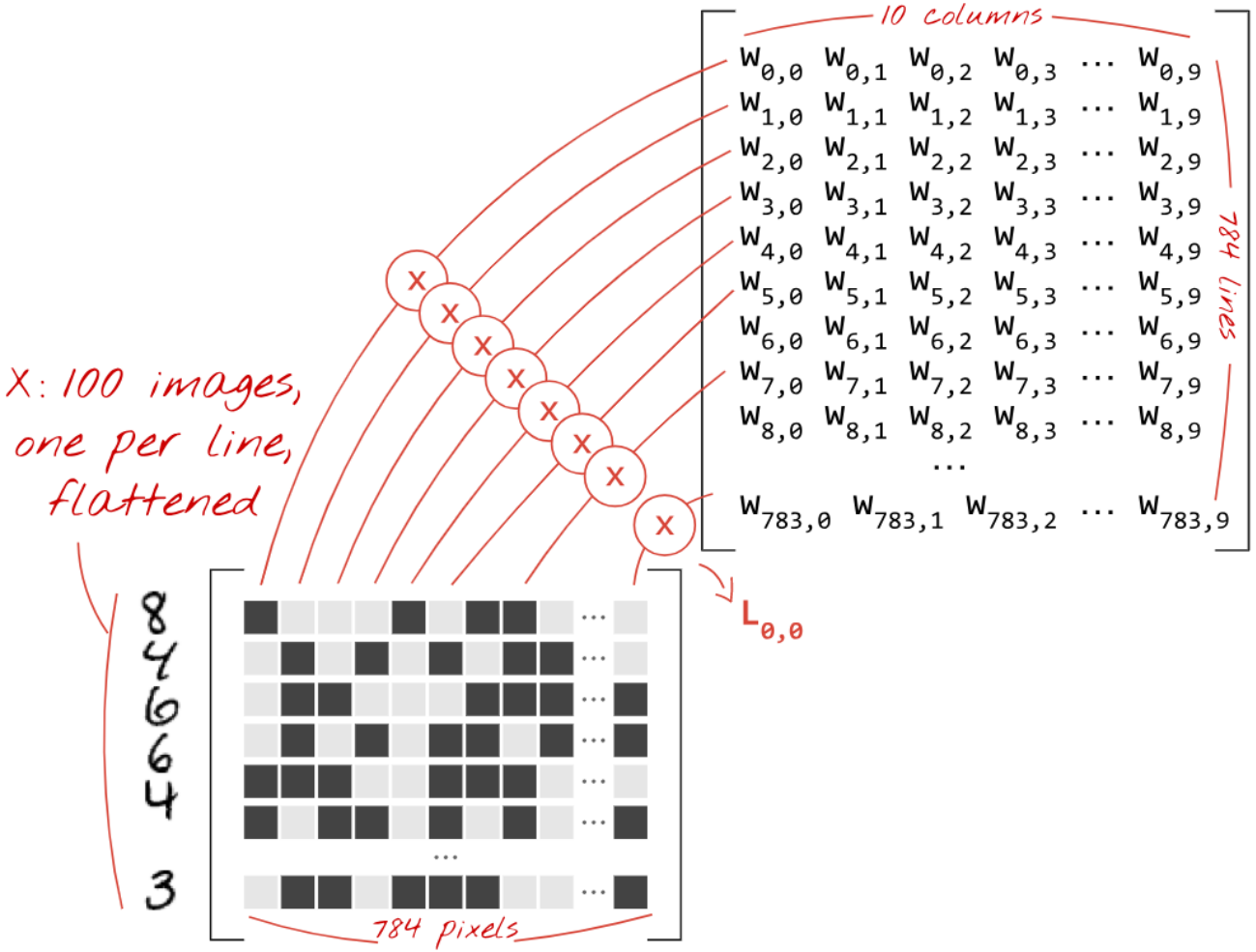
Prenons un exemple



$$L = X.W + b$$

Modèle simple : classification avec SoftMax [2]

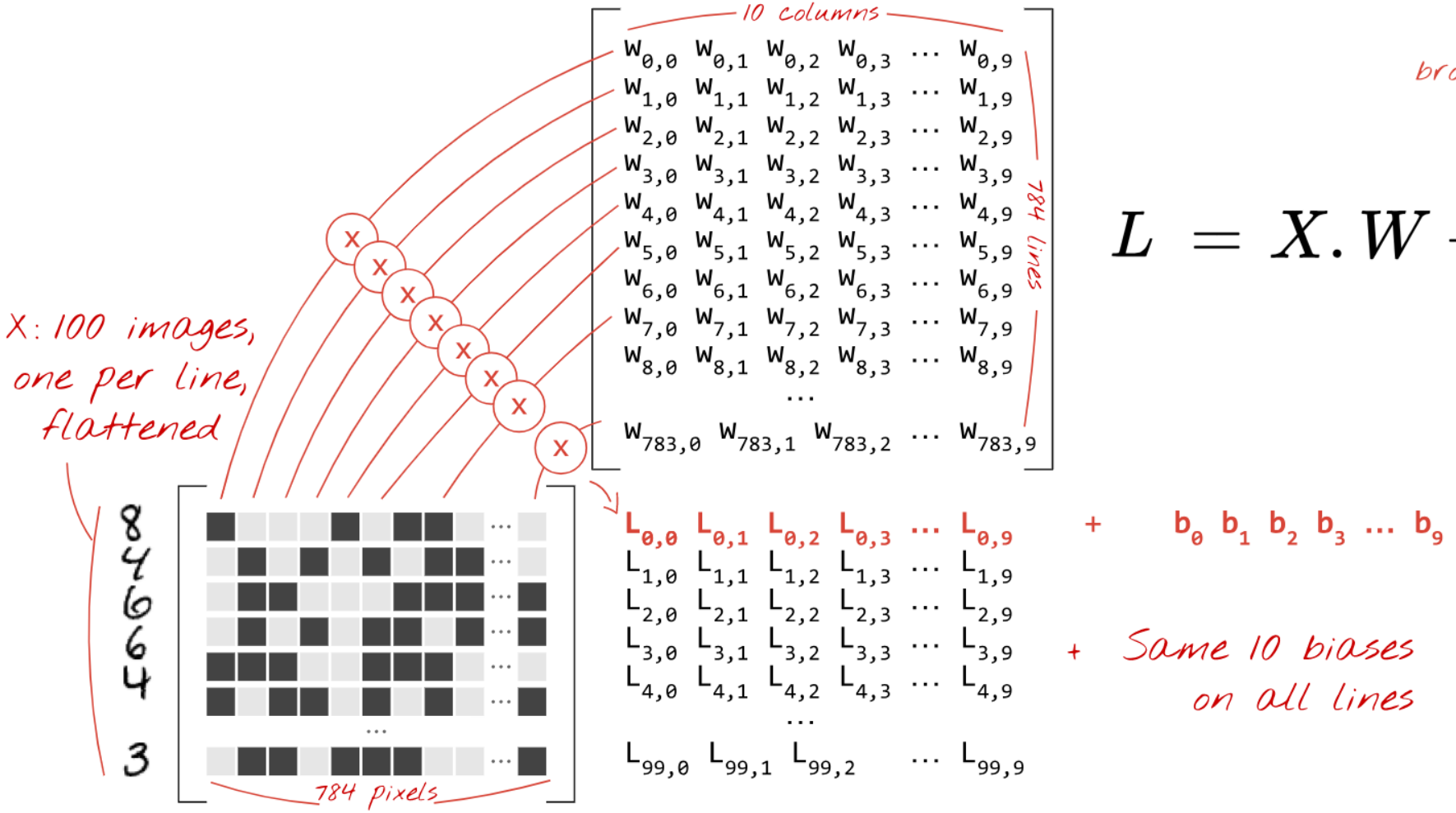
Prenons un exemple



$$L = X.W + b$$

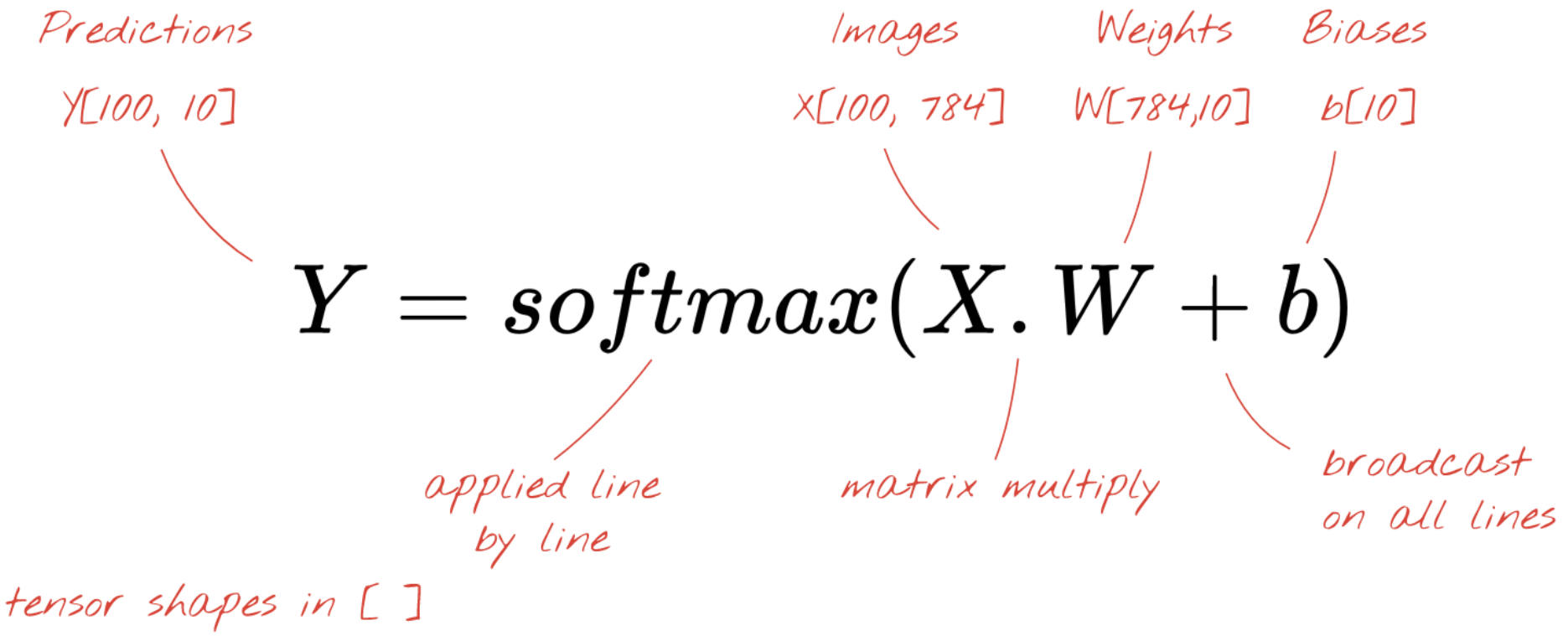
Modèle simple : classification avec SoftMax [2]

Prenons un exemple



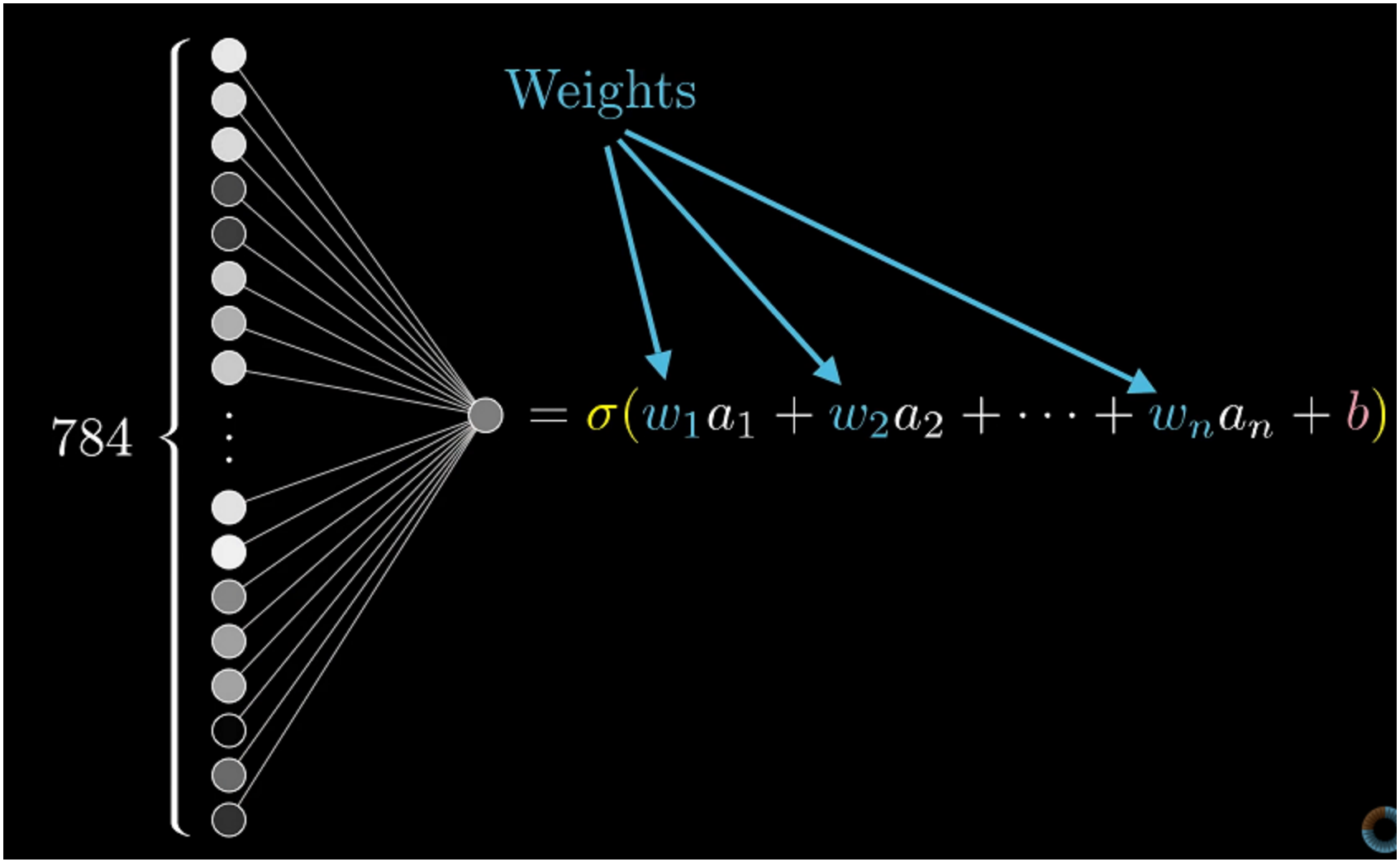
Modèle simple : classification avec SoftMax [2]

Prenons un exemple

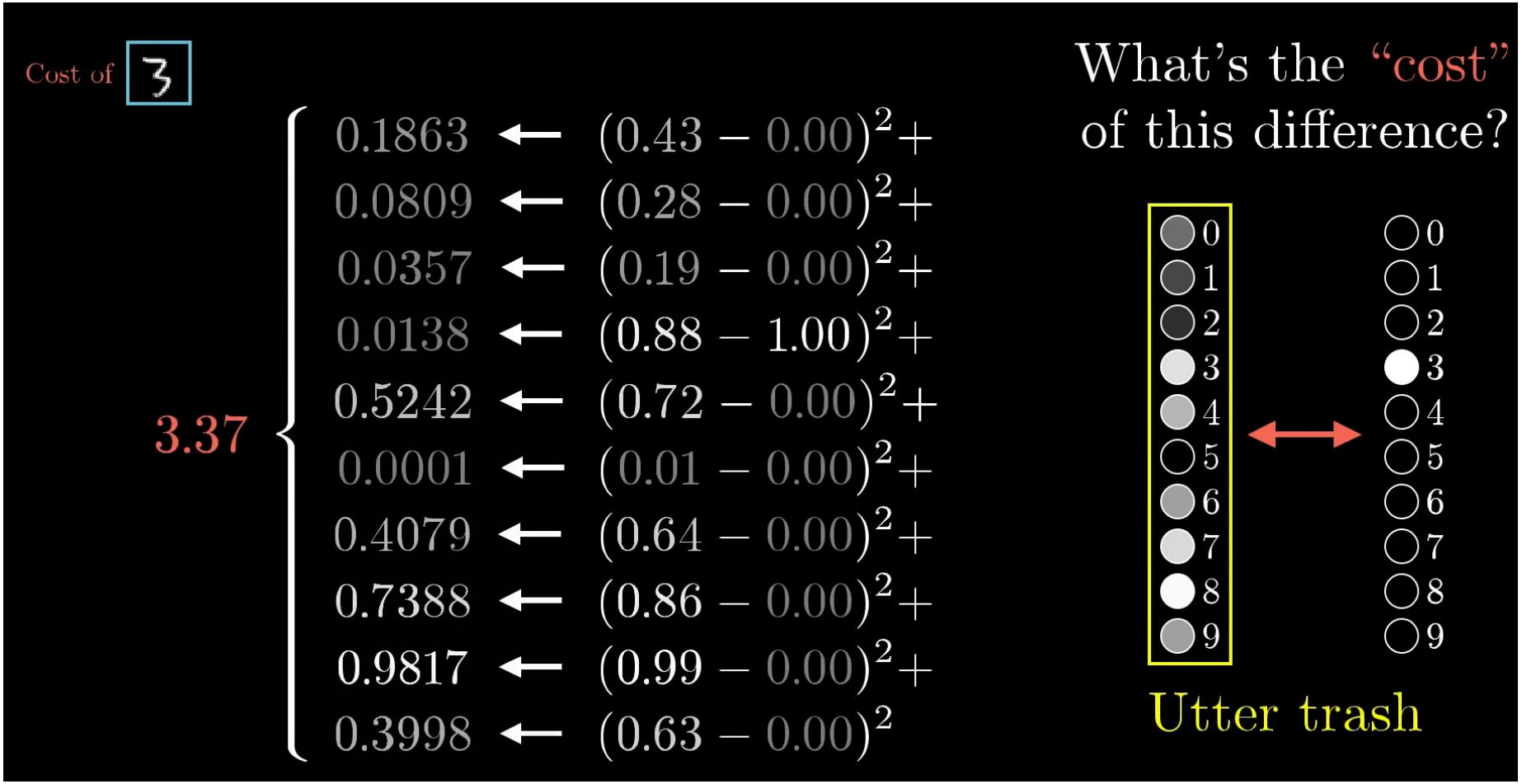


Modèle simple : classification avec SoftMax [2]

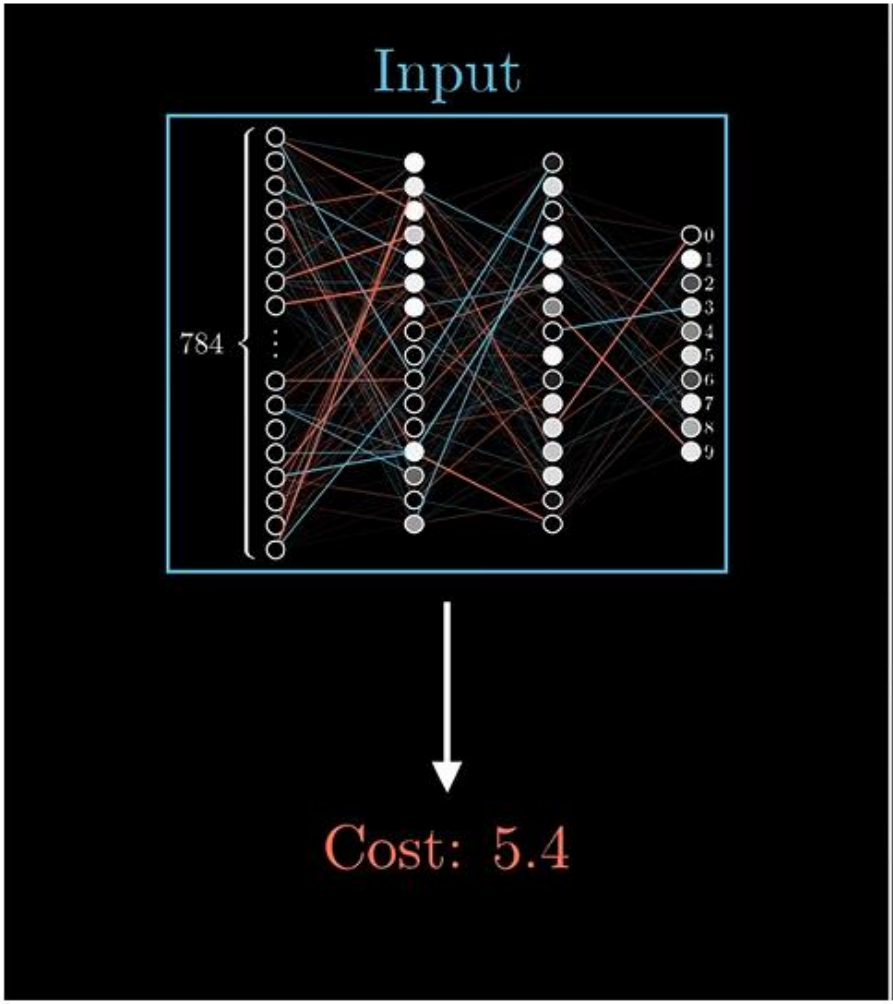
Prenons un exemple

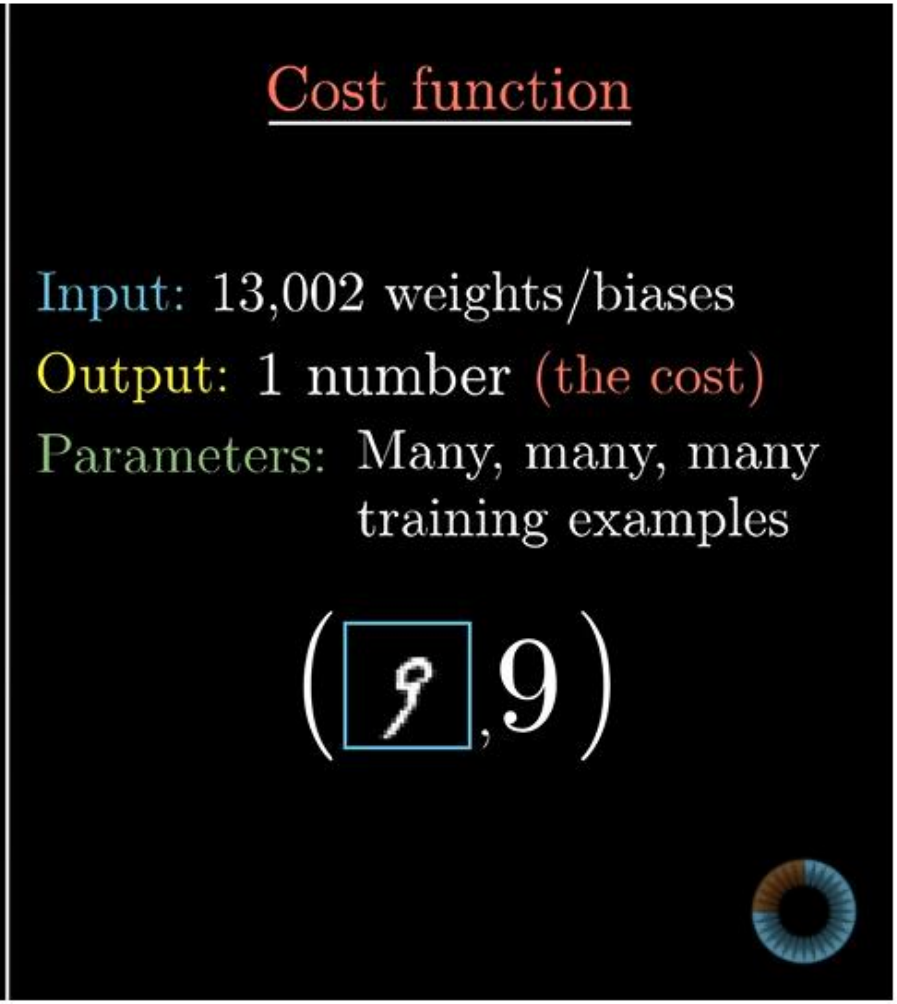


Exemple de calcul d'erreur



Exemple de calcul d'erreur





Descente de gradient et mise à jour des poids

- Problème d'optimisation pouvant être représenté par la formule suivante :

$$\min_{w \in \mathcal{W}} f(w) = \frac{1}{n} \sum_{i=1}^{n} \ell\big(h(x_i, w), y_i\big).$$

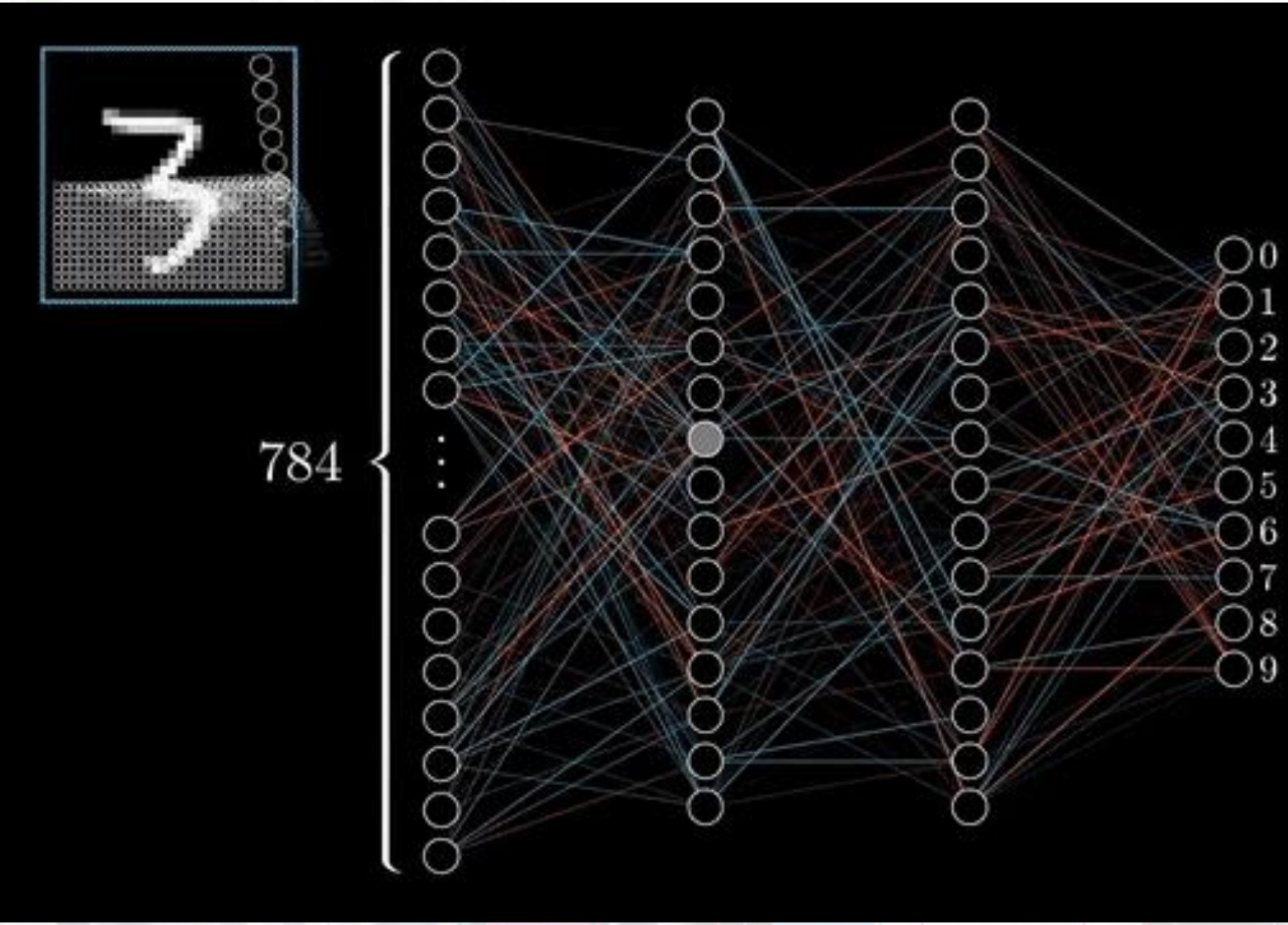
- Ou n : nombre de données,

  Xi : données d'entrainement et Y : labels réels

- Les poids d'un réseau de neurones peuvent être mise à jour comme ceci :

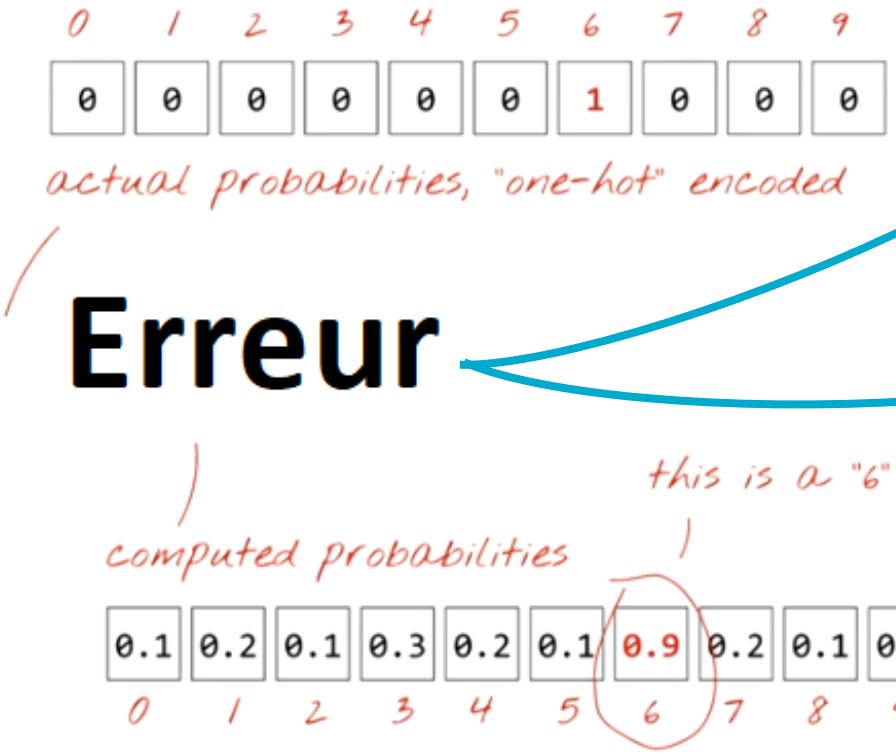
$$w_{t+1} = w_t - \alpha \frac{\partial L}{\partial w_t}$$

Calcul d’erreur



Encodage et calcul d'erreur

```
labels = to_categorical(labels, num_classes=num_classes)
```



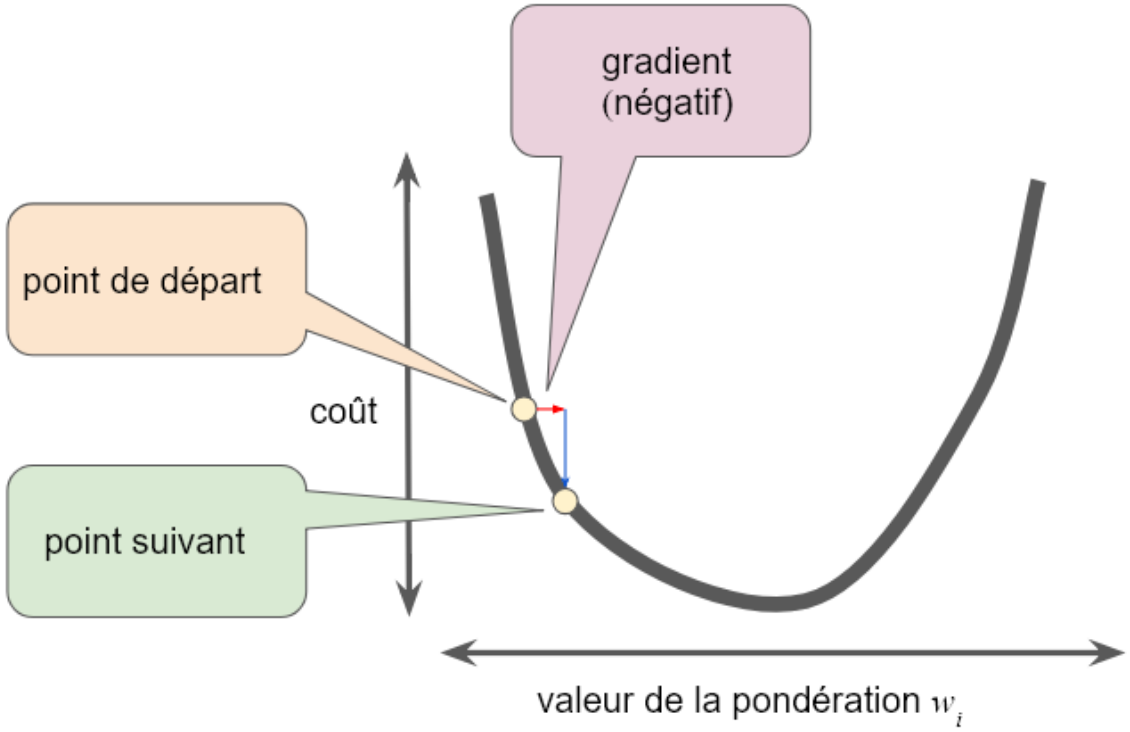
$$L_2 Loss = \sum_{(x,y)\in D} (y - prédiction(x))^2$$

$$MSE = \frac{1}{N} \sum_{(x,y)\in D} (y - prediction(x))^2$$

. . .

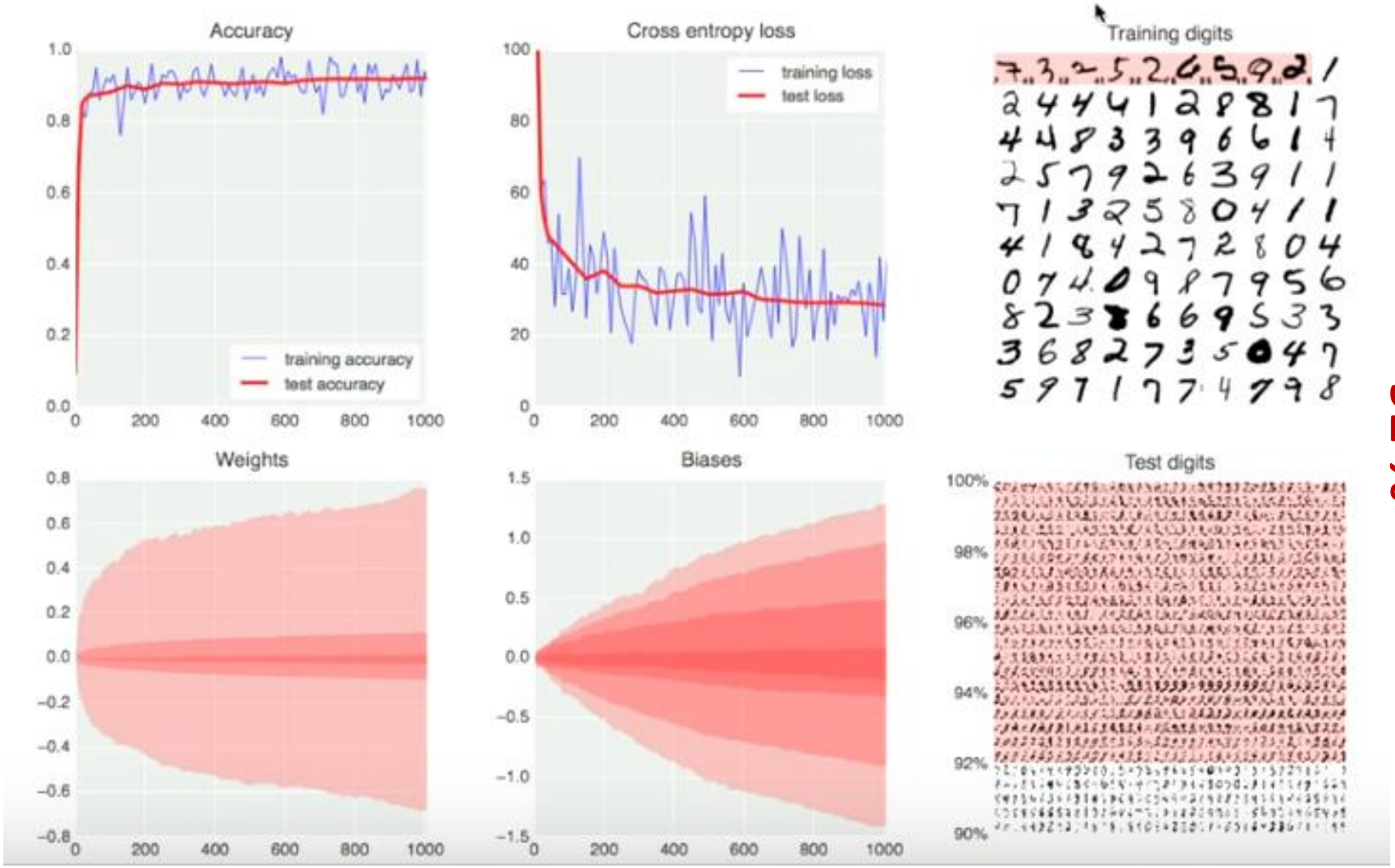
One hot encoding

La descente du gradient



- Pour déterminer le point suivant, l'algorithme de descente de gradient ajoute une fraction de la magnitude du gradient au point de départ
- Processus répété jusqu'à l'arrivée au minimum

Premier résultat



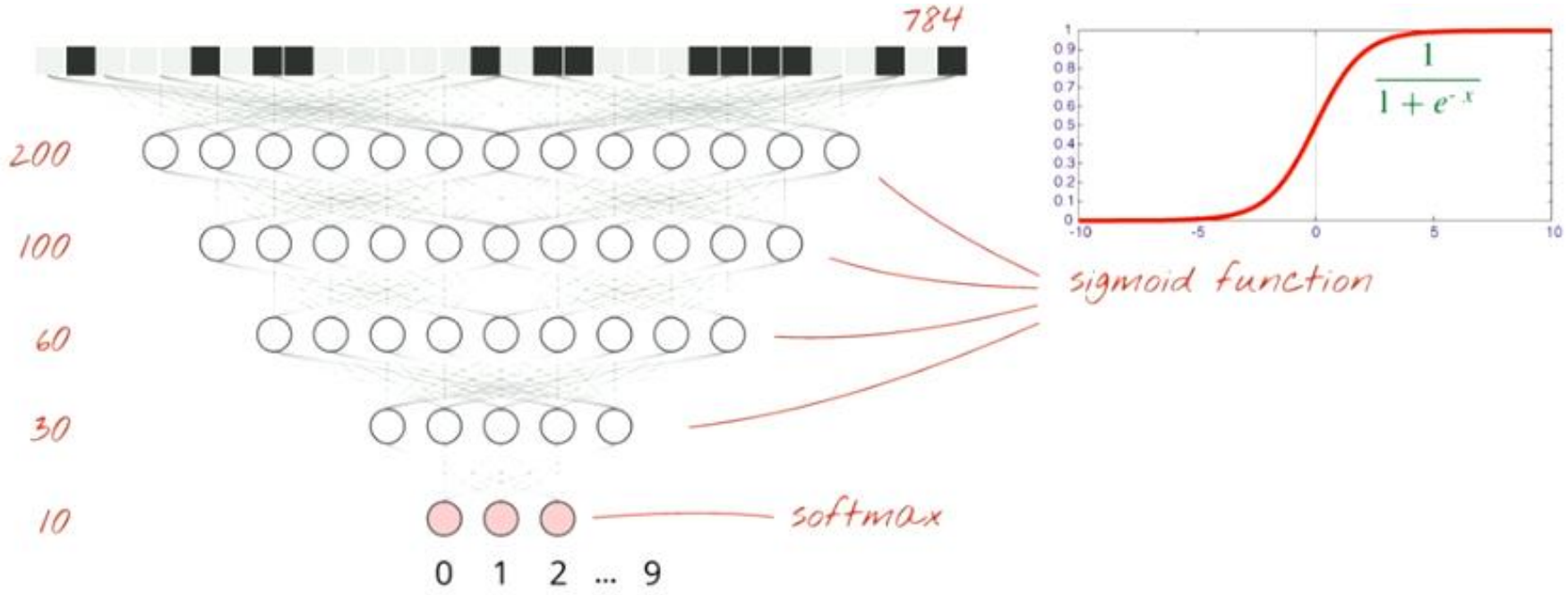
92 %

https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial

Analyse

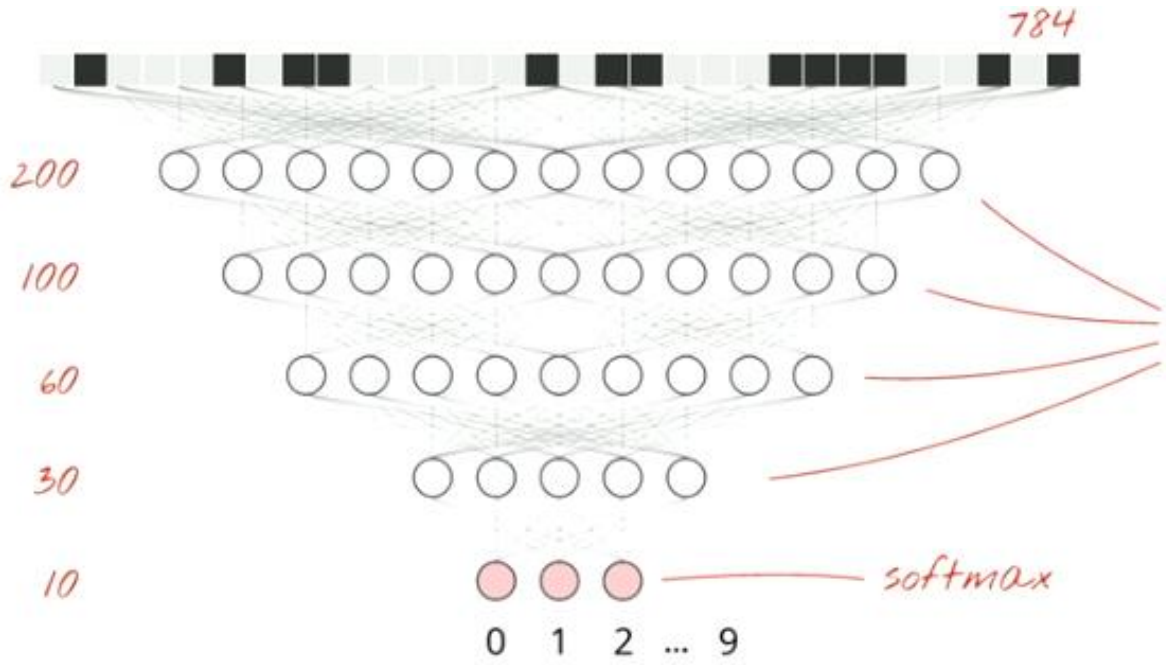
- Peut-on améliorer le score ?
- Si oui, **comment ?**

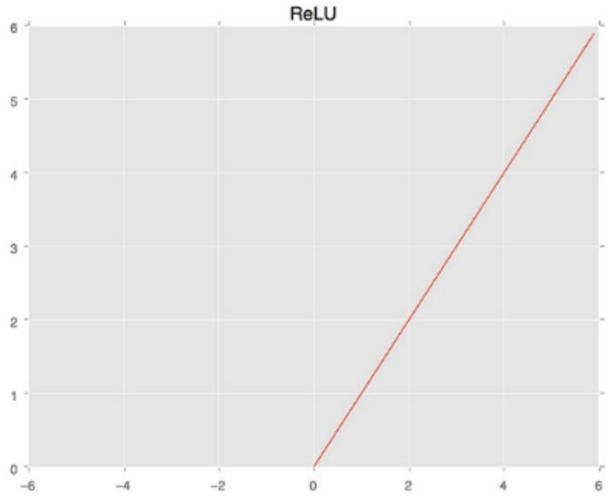
Amélioration N° 01



- Meilleur score mais avec un démarrage d'entrainement plus lent
- Pourquoi ?

Amélioration N° 02



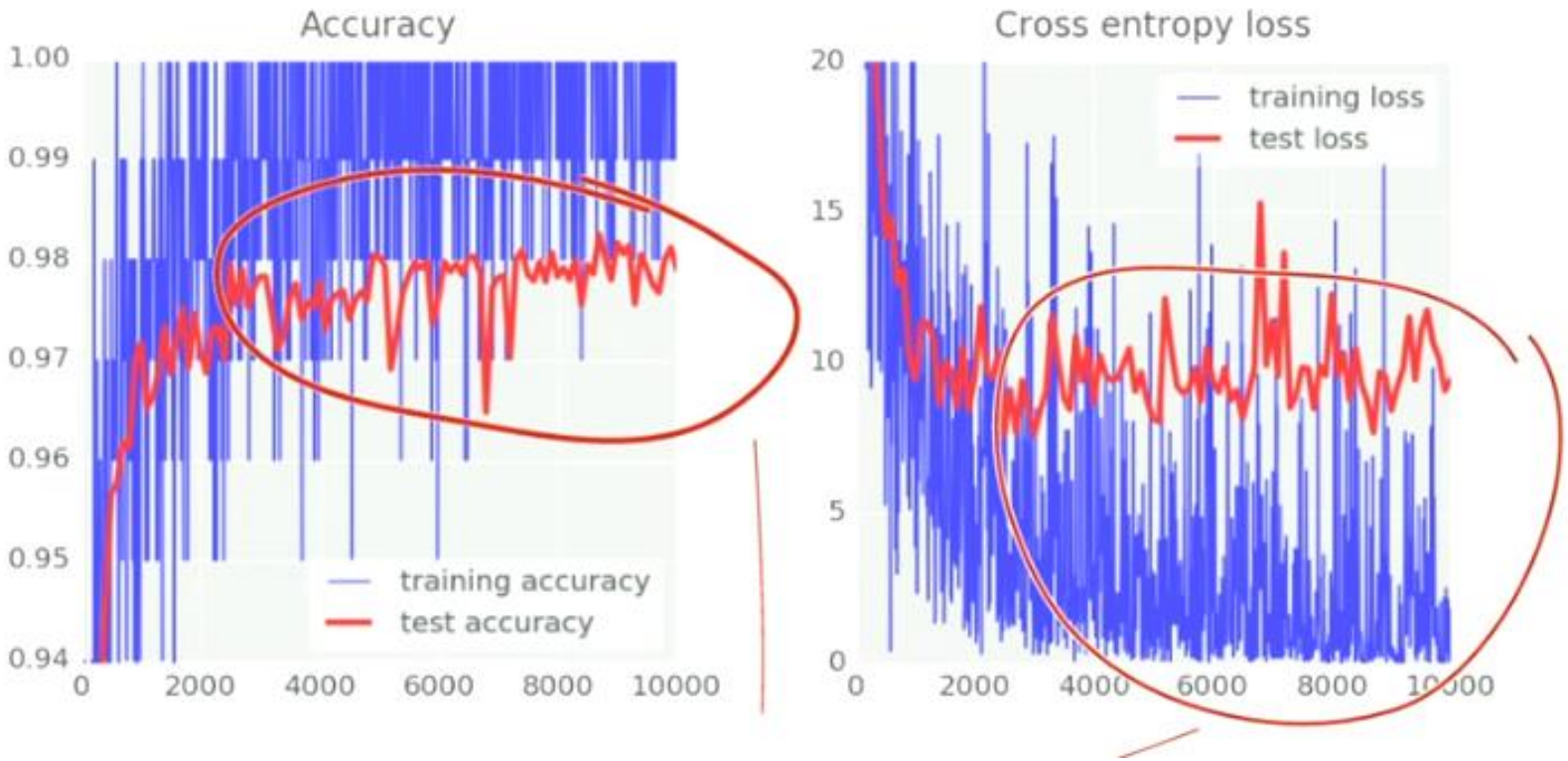


Relu

% 96

- Remplacement de la fonction **Sigmoid** par la fonction **Relu**
- Meilleur score : **96 %** au lieu de **92 %**

98 % mais ?

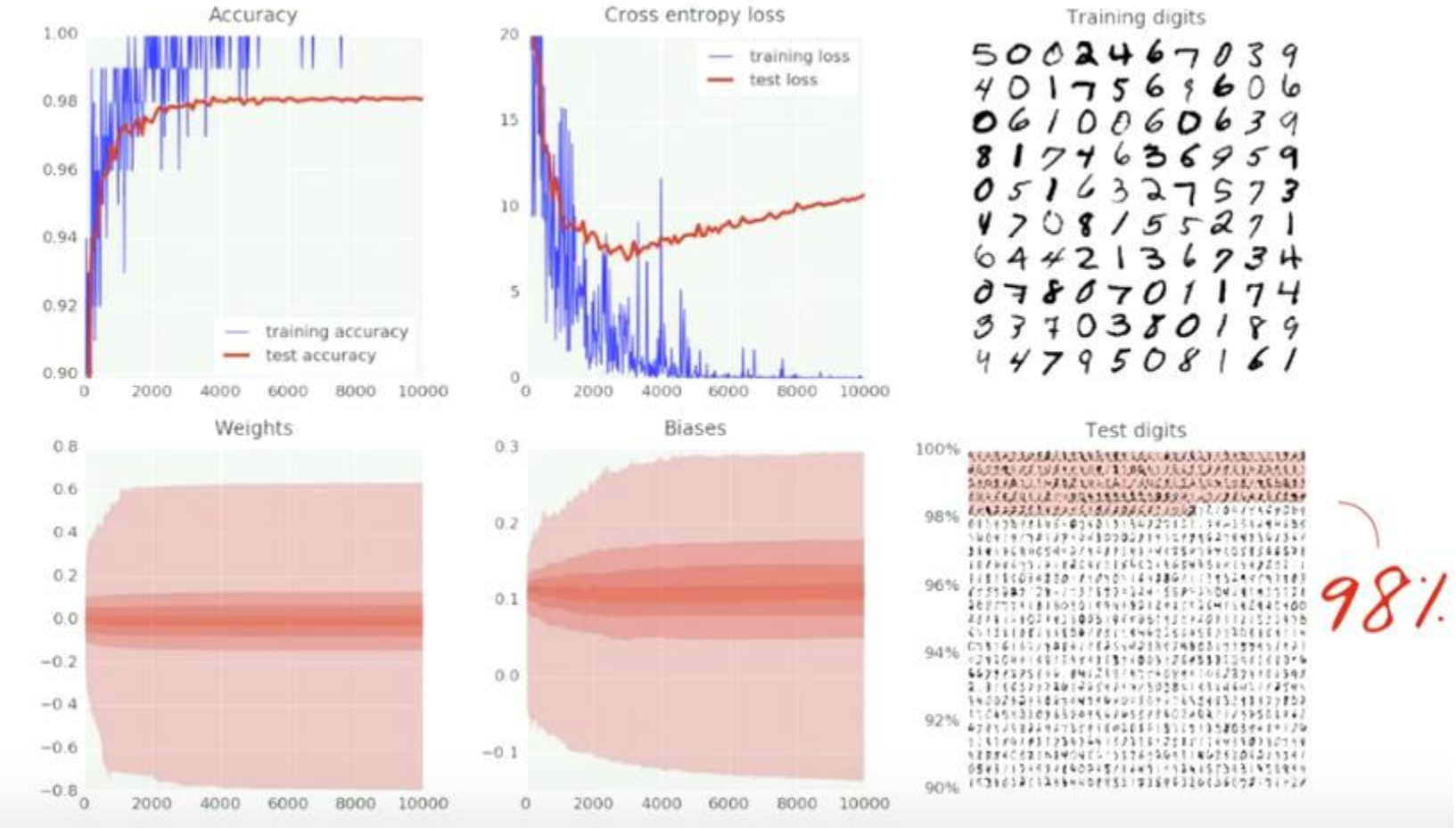


Courbe de precision “Accuracy” bruitée

Réduction progressive du taux d’apprentissage (0,003 à 0,0001)

https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial

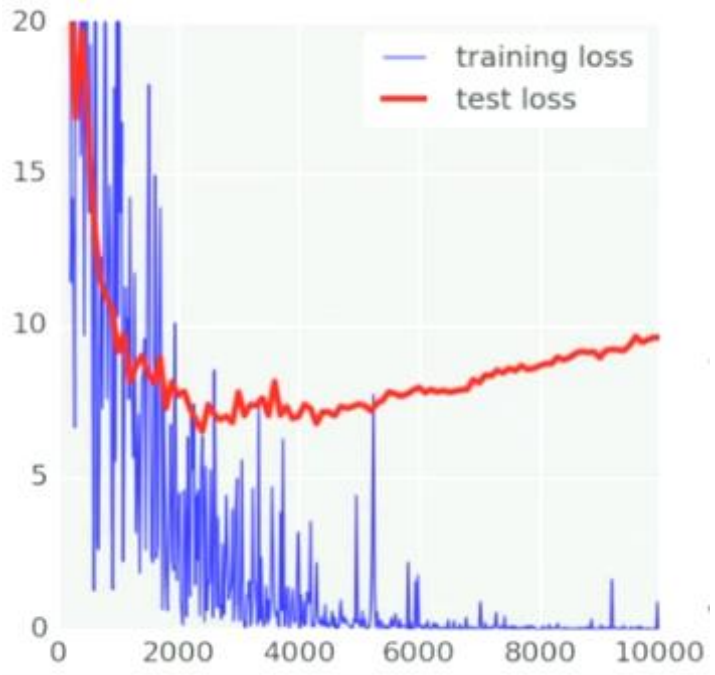
Amélioration N° 03 (rate decay)



https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial

Analysons de nouveau

- Voyez-vous un problème dans les courbes ?
- Si oui, lequel ?



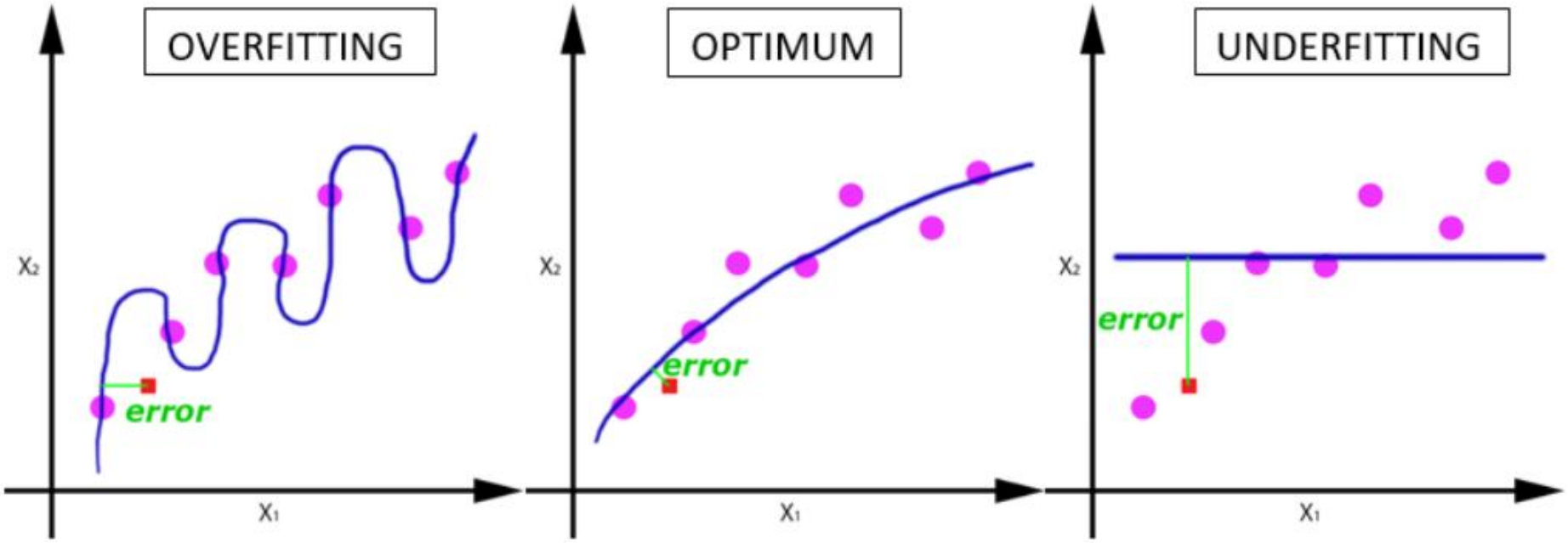
Overtfitting
(sur apprentissage)

https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial

Overfitting

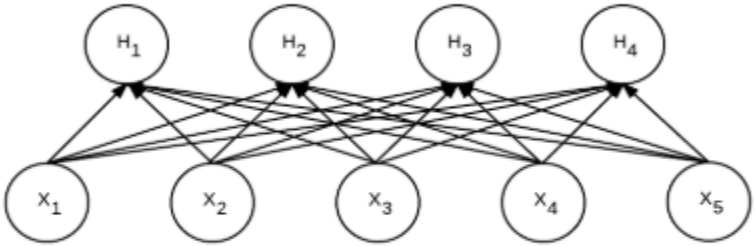
https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial

Overfitting

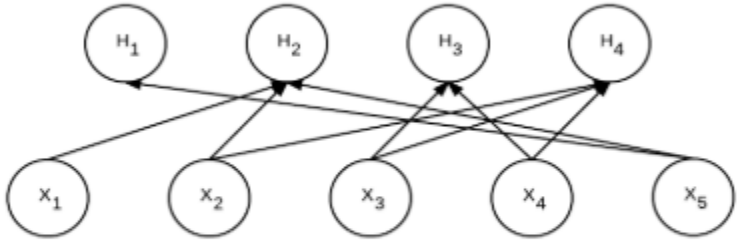


Le modèle apprend les données d'entraînement “par cœur”, et ne peut donc généraliser sur d’autres données.

Dropout



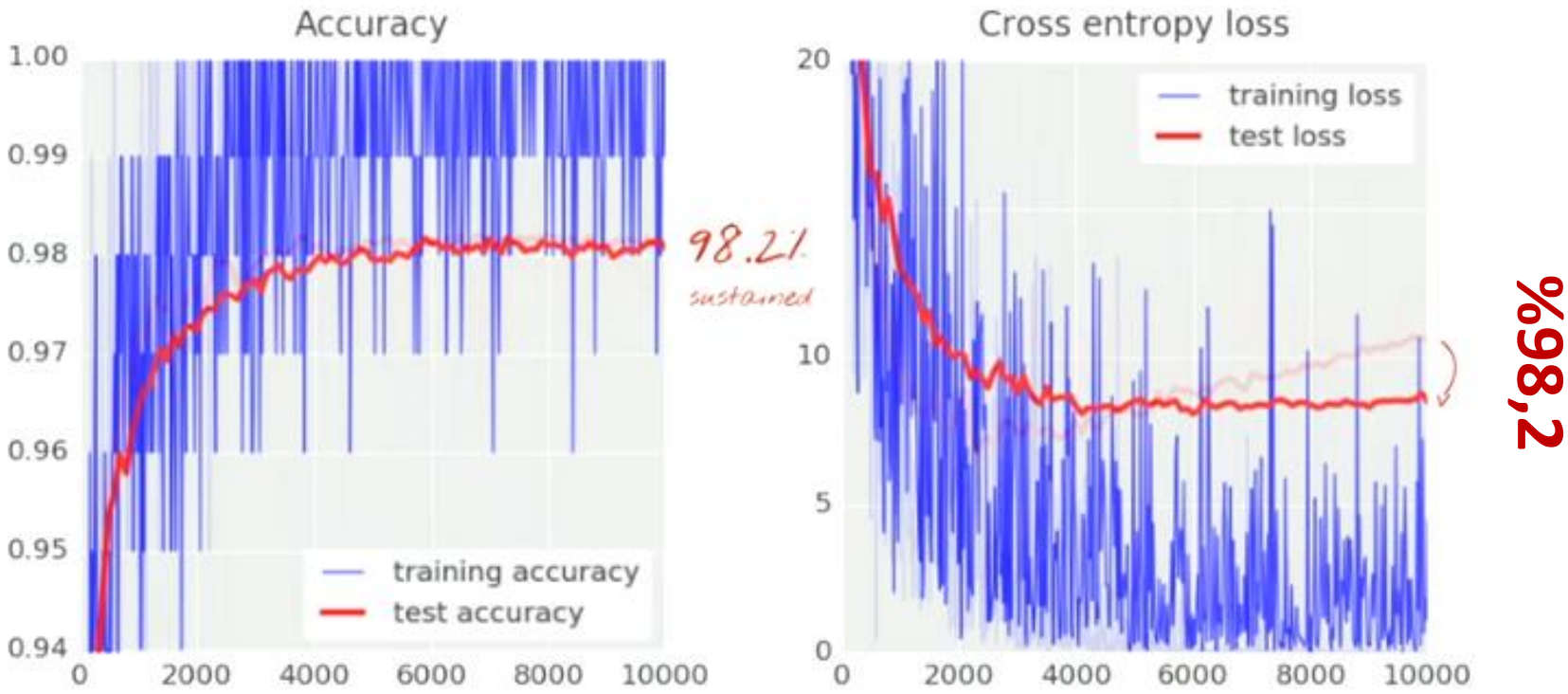
FC



FC with 50% dropout

Utilisé pour éviter l'Overfitting en **supprimant aléatoirement** des connexions entre deux couches pendant l'entrainement

Amélioration N° 04



05 couches + Relu + réduction progressive du taux d'apprentissage + Dropout (75%)

https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial

PLAN

Introduction

I. Le Perceptron

II. Types de réseaux de neurones profonds (ANN, MLP, CNN, RNN, etc.)

III. **Paramètres d'entrainement, syntaxe et et évaluation de modèles**

IV. Réseaux de neurones convolutionnels (CNNs)

V. Outils de développement et matériel de calcul

Conclusion

Paramètres d'entrainement

Epocs

- 1 époque : l'ensemble entier des données est passé dans le réseau 1 fois

Batch_size

- Nombre de données d'entrainement présents dans un batch
- Données divisées en plusieurs batchs

Itérations

- Nombre de batchs par époques : tailles des données/batch_size

Paramètres d'entrainement « Torch Lightning »

trainer.fit

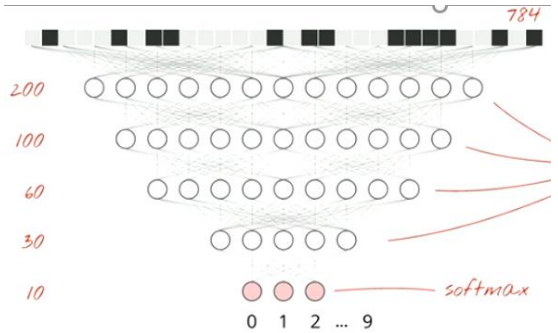
```
model1   = MNISTModel(mlp1)

# Initialize a trainer
trainer = pl.Trainer(
    accelerator=ACCELERATOR,
    max_epochs=EPOCHS,
    logger=csv_logger,
    callbacks=[checkpoint_callback]
)
# Train the model ⚡
trainer.fit(model1, train_loader,val_loader)
```

Préparation et division des données

Préparation, division des données et entrainement

Training Set

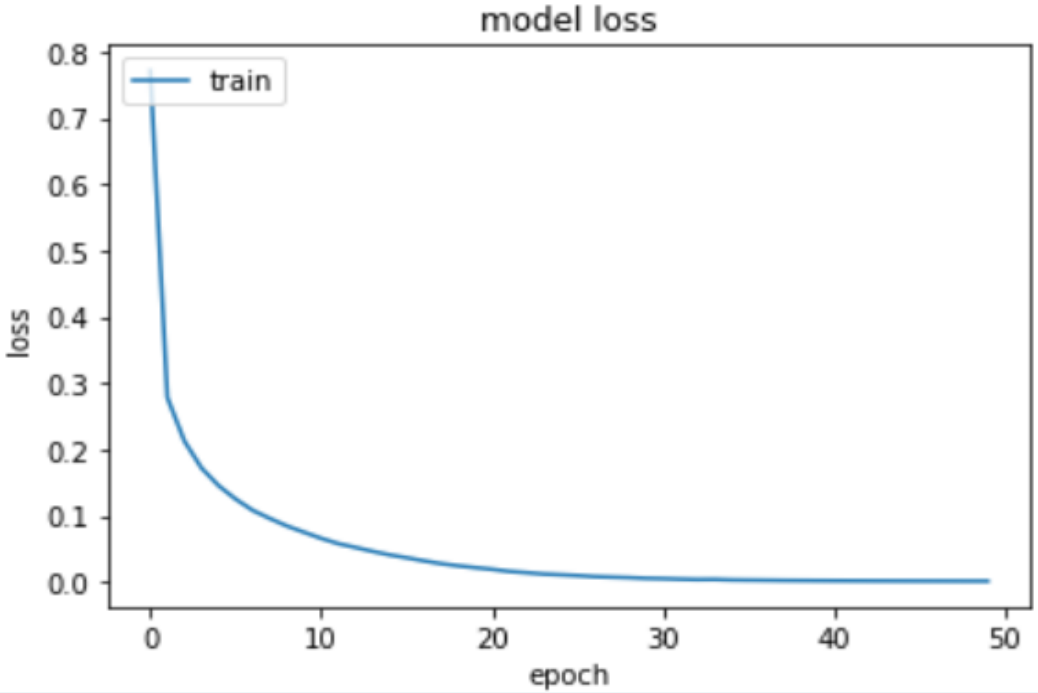
```
class MLP2(nn.Module):
    def __init__(self):
        super(MLP2, self).__init__()
        self.fc1 = nn.Linear(28 * 28, 200)
        self.fc2 = nn.Linear(200, 100)
        self.fc3 = nn.Linear(100, 60)
        self.fc4 = nn.Linear(60, 30)
        self.fc5 = nn.Linear(30, 10)

    def forward(self, x):
        # Flatten the input (28x28 -> 784)
        x = x.view(x.size(0), -1)
        # Hidden layers with sigmoid activations
        x = torch.sigmoid(self.fc1(x))
        x = torch.sigmoid(self.fc2(x))
        x = torch.sigmoid(self.fc3(x))
        x = torch.sigmoid(self.fc4(x))
        x = self.fc5(x)
        return x
```



Préparation, division des données et entrainement

Training Set

```
trainer.fit(model, train_loader)
```

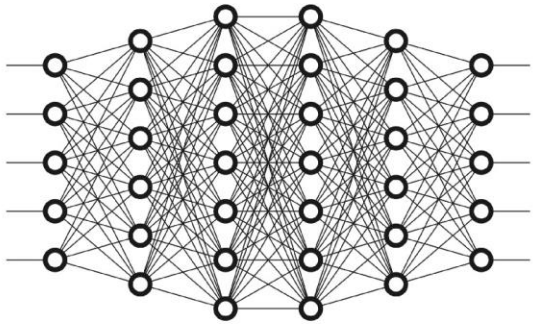


- Peut-on évaluer ce modèle ?

Préparation, division des données et entrainement

Training Set

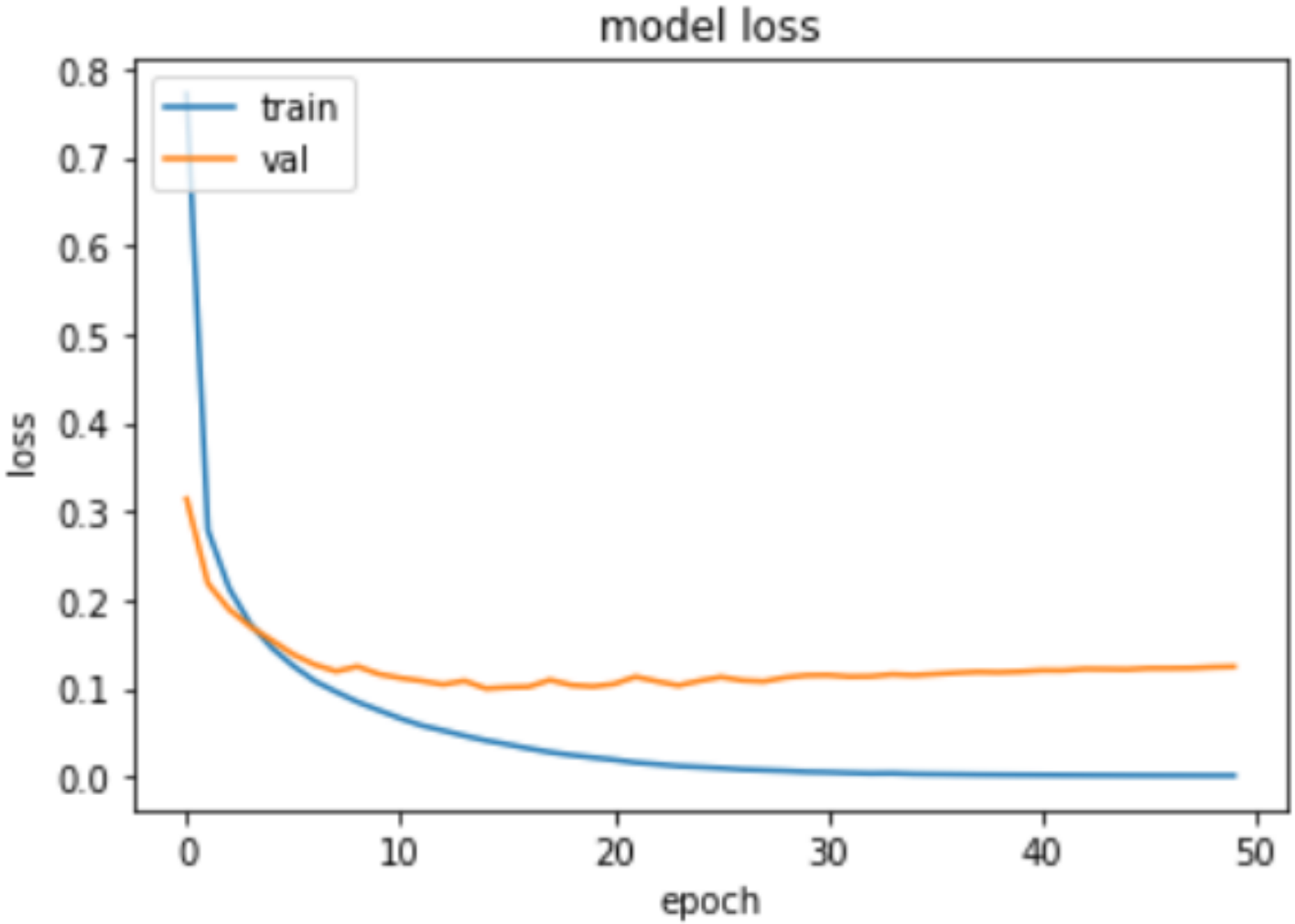
Validation Set



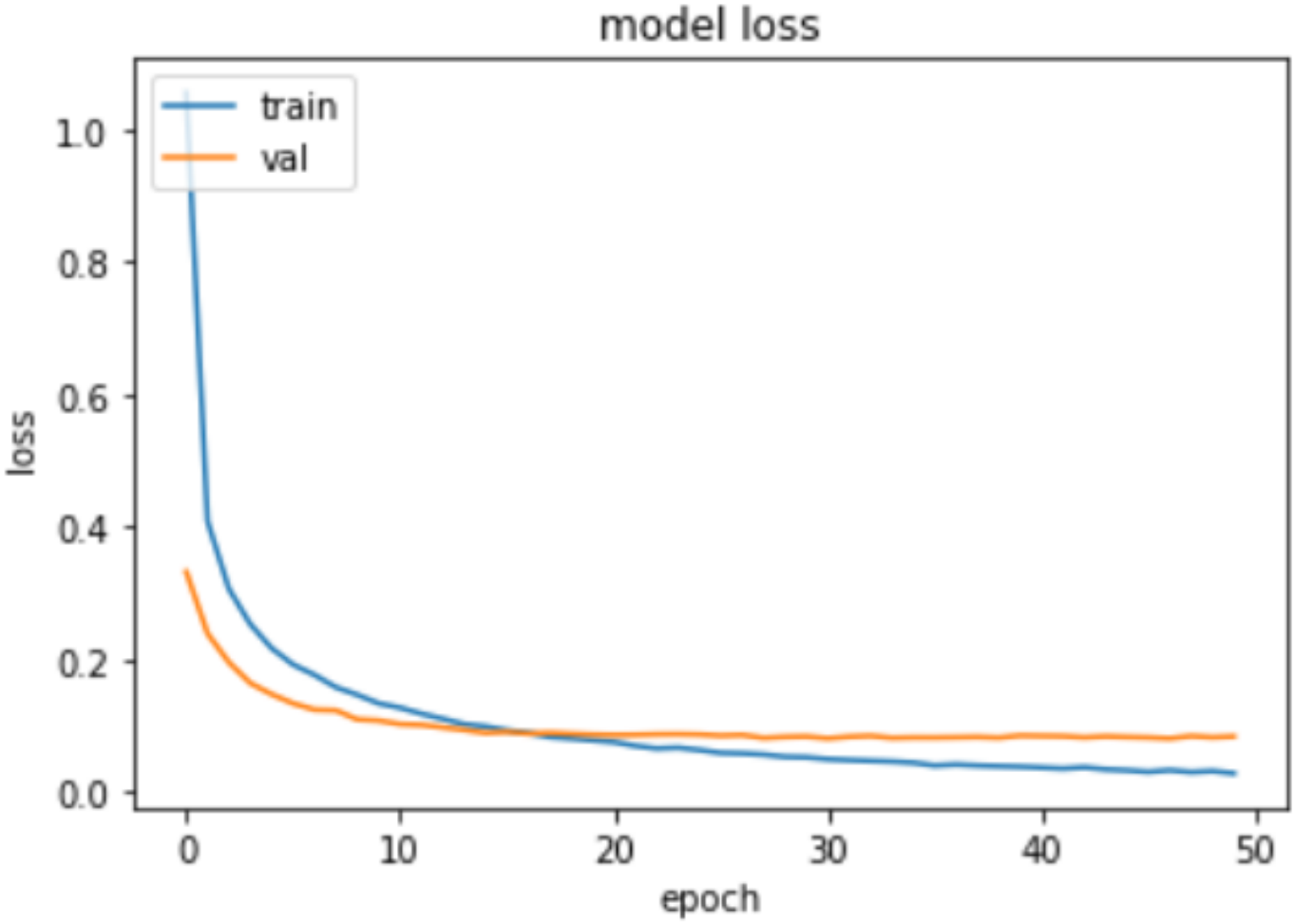
```
trainer.fit(model, train_loader,val_loader)
```

- Ou se trouve la différence ? Est-ce suffisant ?

Préparation, division des données et entrainement



Avec le Dropout



Préparation, division des données et entrainement

Training Set | **Validation Set** | **Test Set**

- Données de test: soit téléchargés au début
- Données de test : split des données d'entrainement

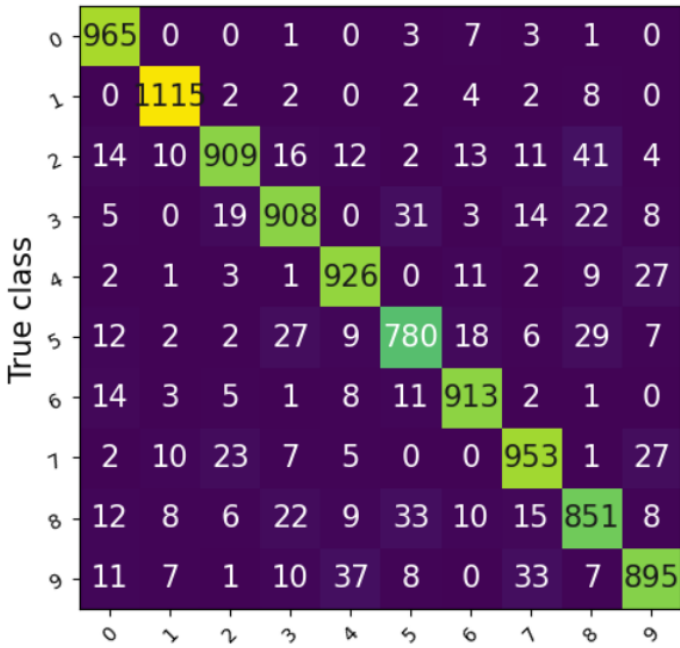
```
trainX, testX, trainY, testY=train_test_split(x_train, y_train, test_size=0.25, random_state=42)
```

Préparation, division des données et entrainement

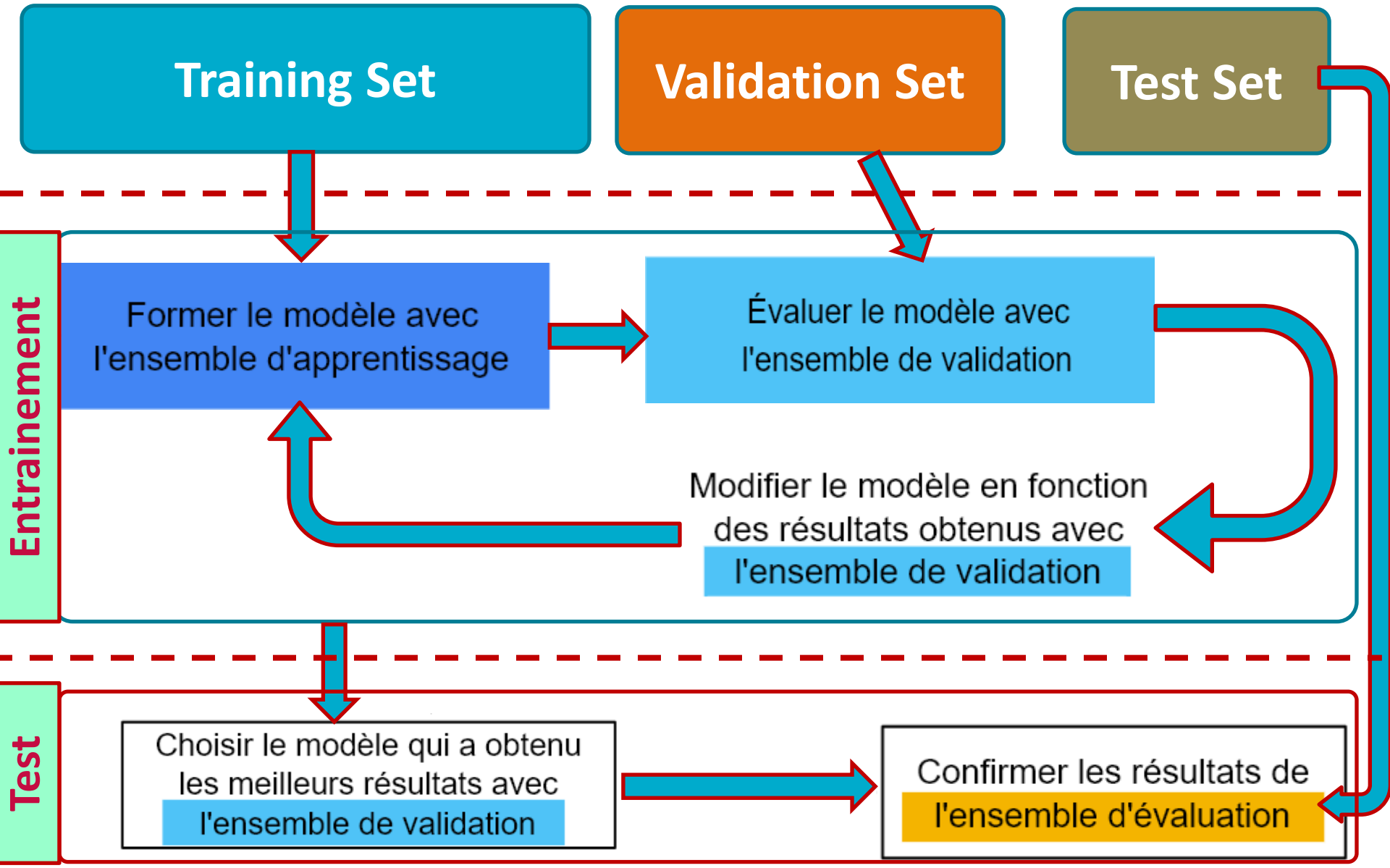

```
trainer.test(dataloaders=train_loader,ckpt_path="./mlp1.ckpt")

trainer.test(dataloaders=val_loader,ckpt_path="./mlp1.ckpt")

trainer.test(dataloaders=test_loader,ckpt_path="./mlp1.ckpt")
```

Test metric	DataLoader 0
test_acc	0.921500027179718
test_loss	0.2809731364250183

```
[{'test_loss': 0.2809731364250183, 'test_acc': 0.9215000271797
```



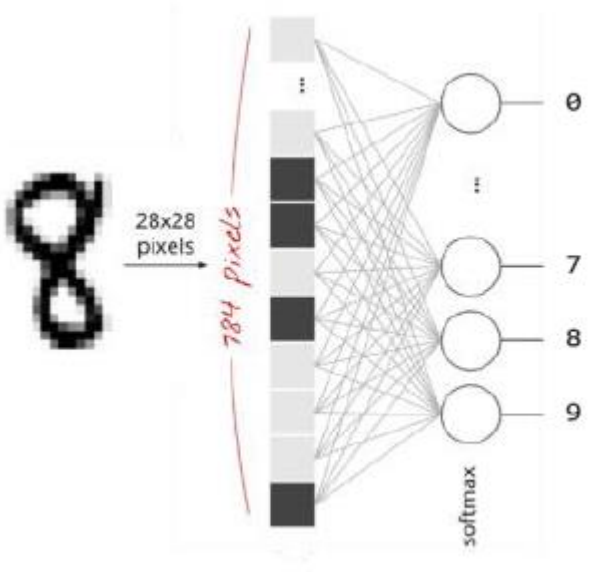
Processus d'entraînement



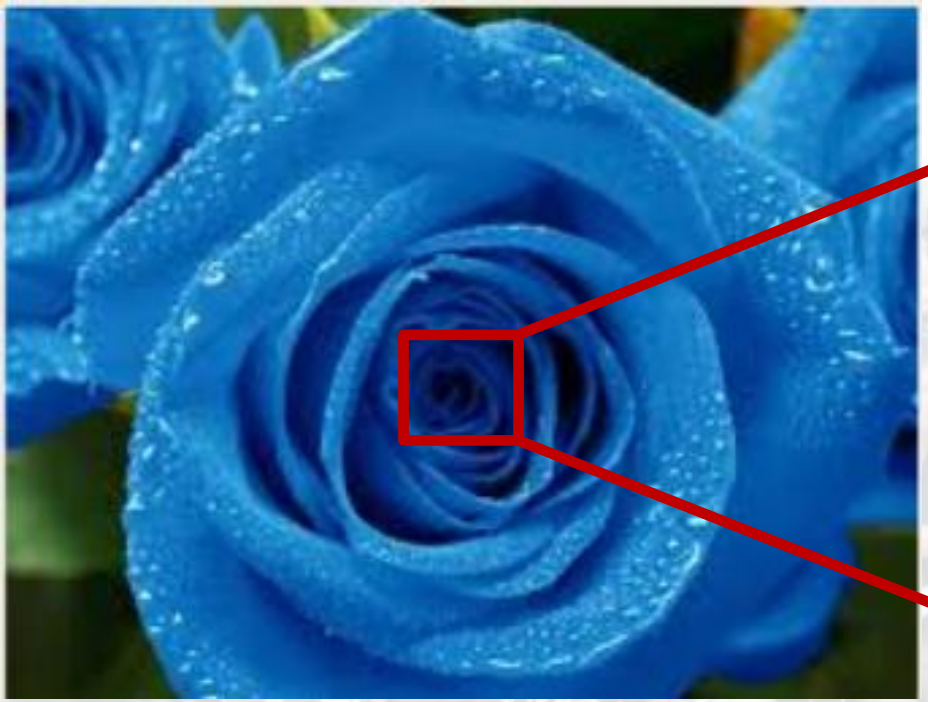
PLAN

Encore

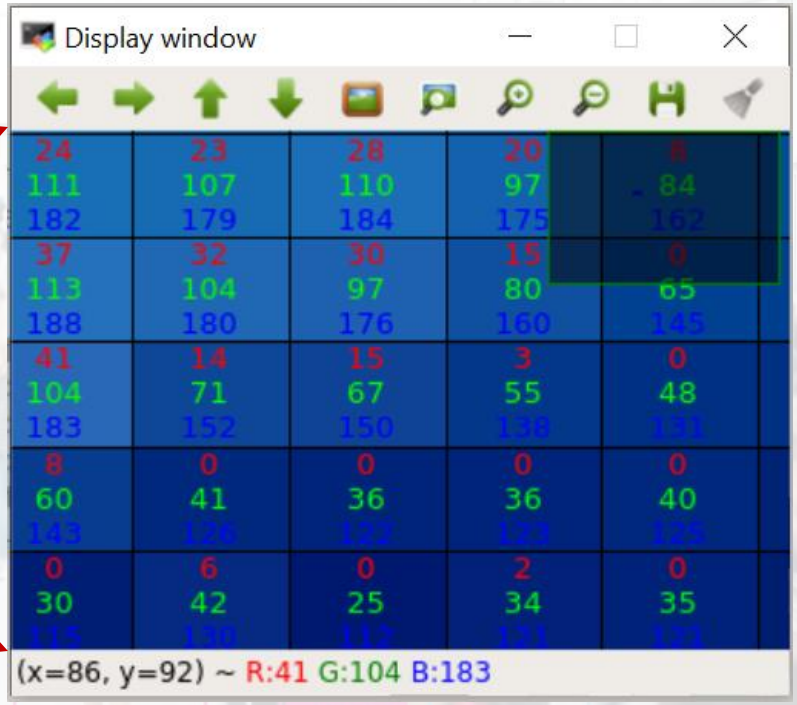
- Peut-on aller plus loin ?
- Pourquoi ?



Petit rappel : une image



Une image



Une région de l'image

Extraction de caractéristiques et filtrage d'image convolutions

0	0	0	0	0	0	0
0	60	113	56	139	85	0
0	73	121	54	84	128	0
0	131	99	70	129	127	0
0	80	57	115	69	134	0
0	104	126	123	95	130	0
0	0	0	0	0	0	0

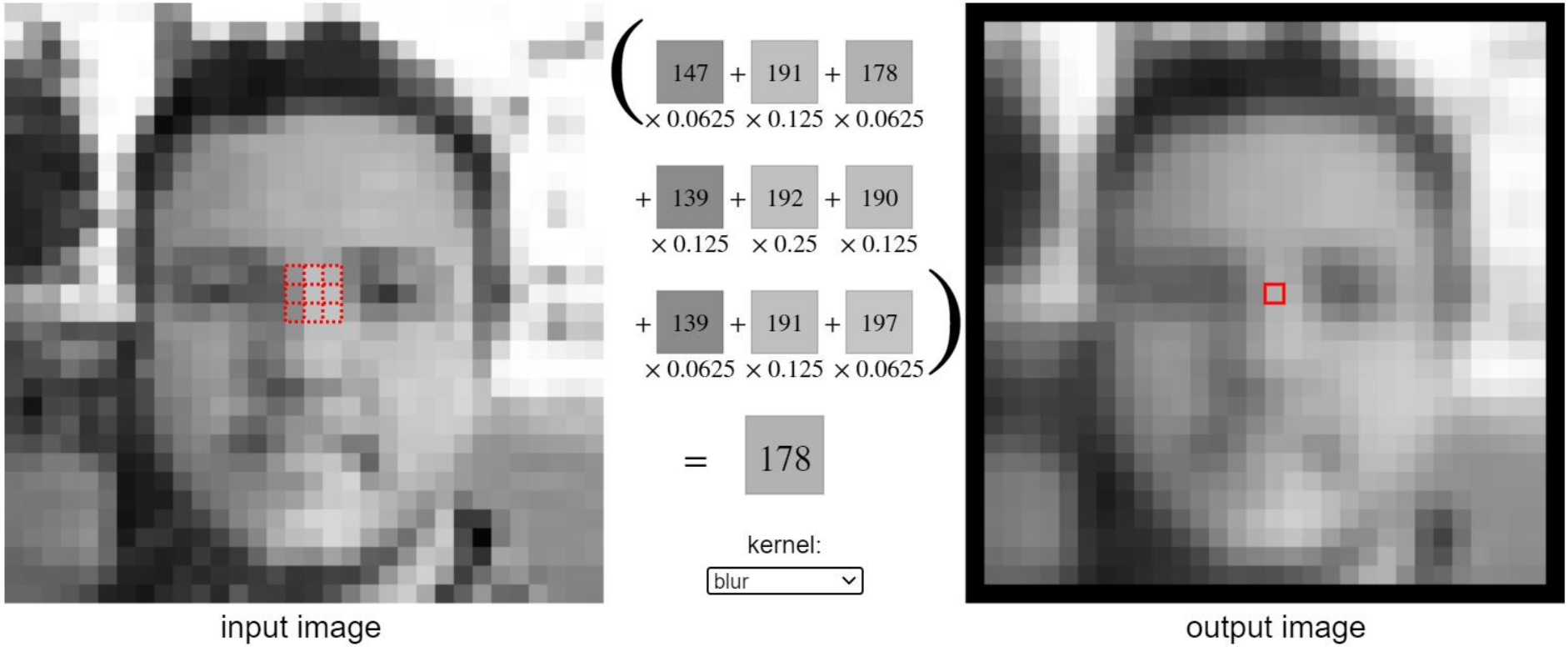
Kernel

0	-1	0
-1	5	-1
0	-1	0

114				

Exemple de convloution

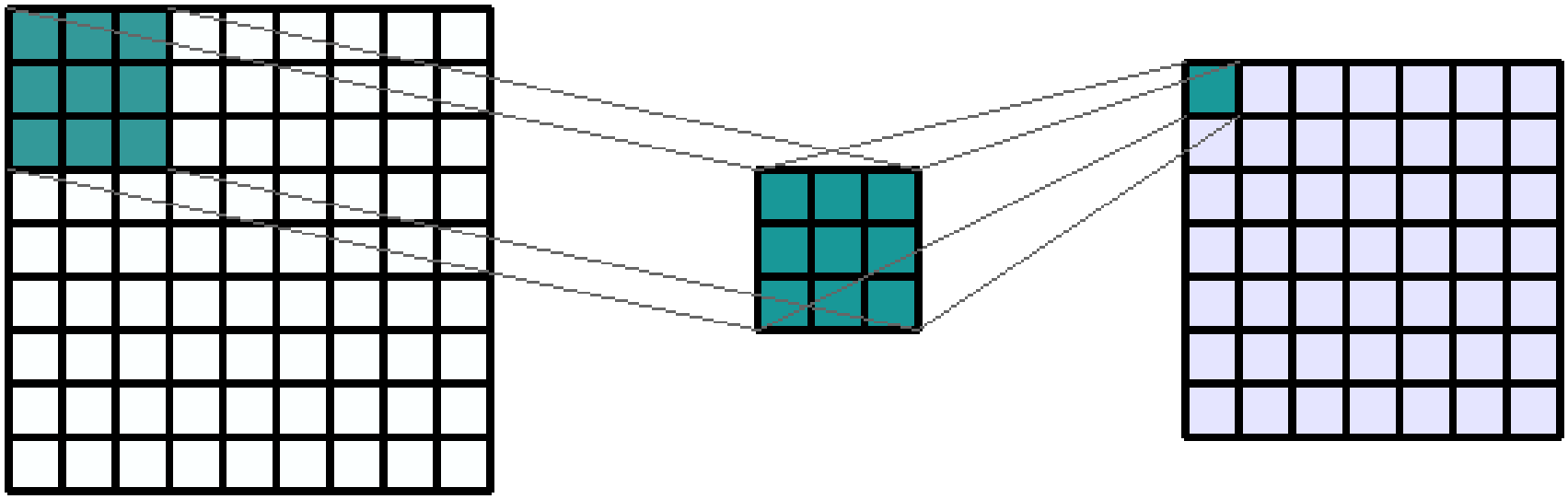
Extraction de caractéristiques et filtrage d'image convolutions



https://setosa.io/ev/image-kernels/

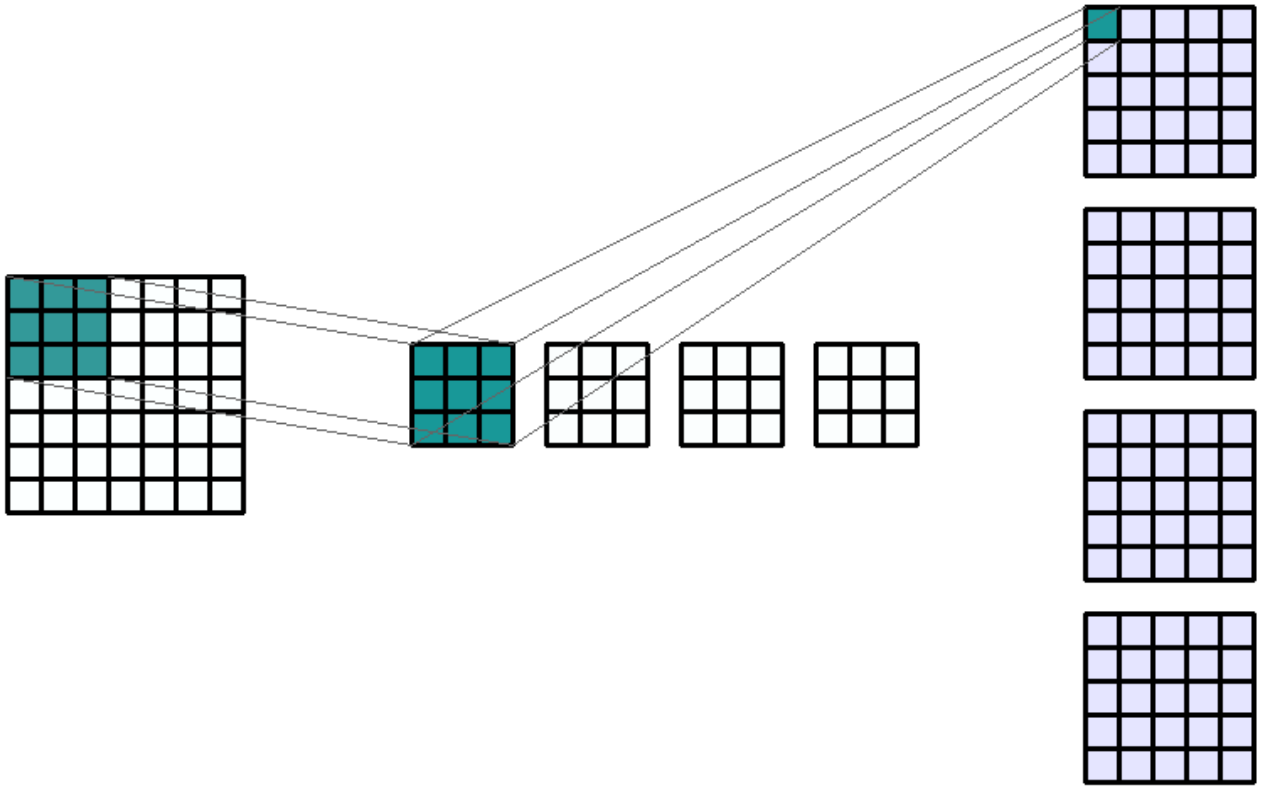
Exemple de convolution

Extraction de caractéristiques et filtrage d'image convolutions



Un filtre de convolution

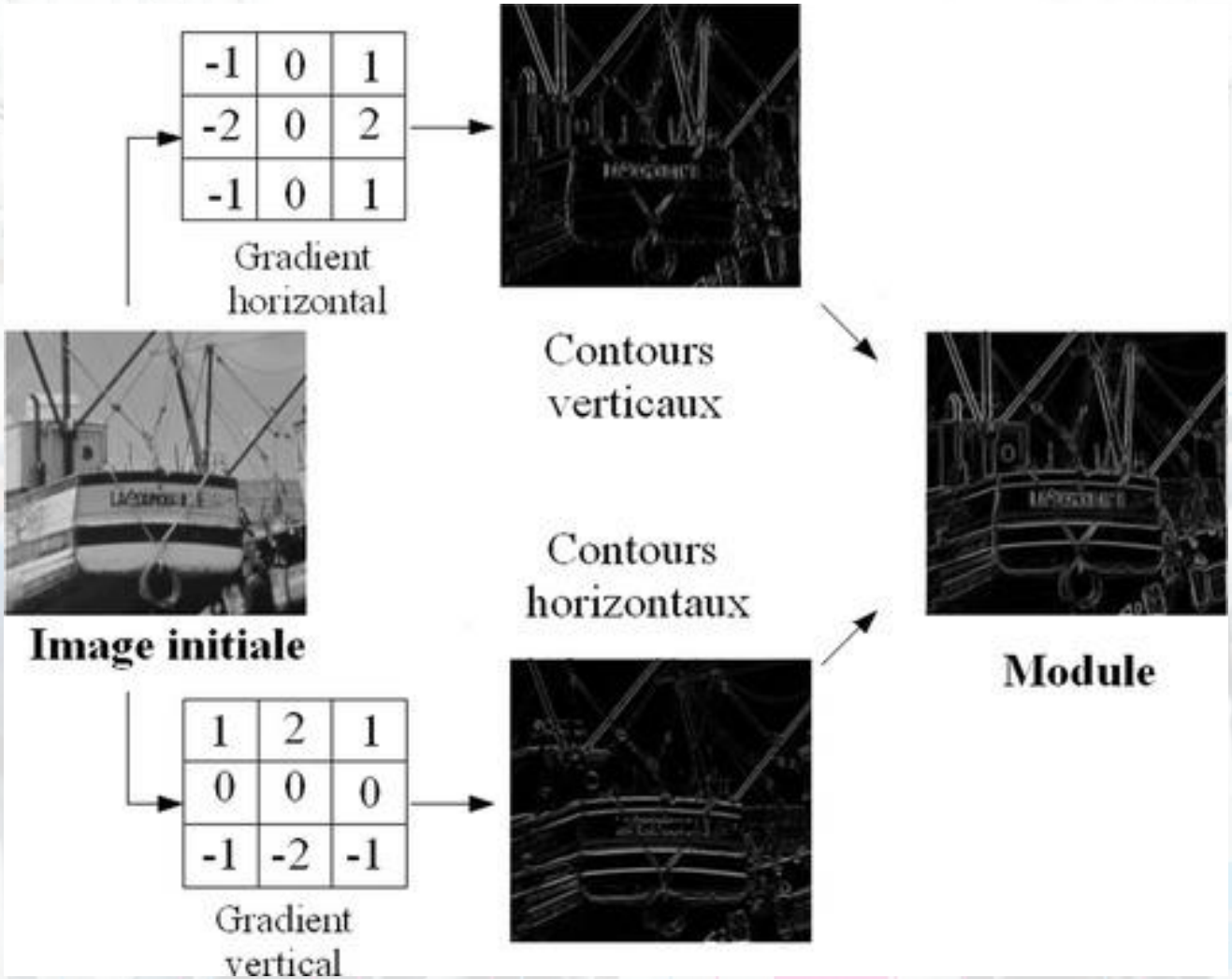
Extraction de caractéristiques et filtrage d'image convolutions



4 filtres de convolution

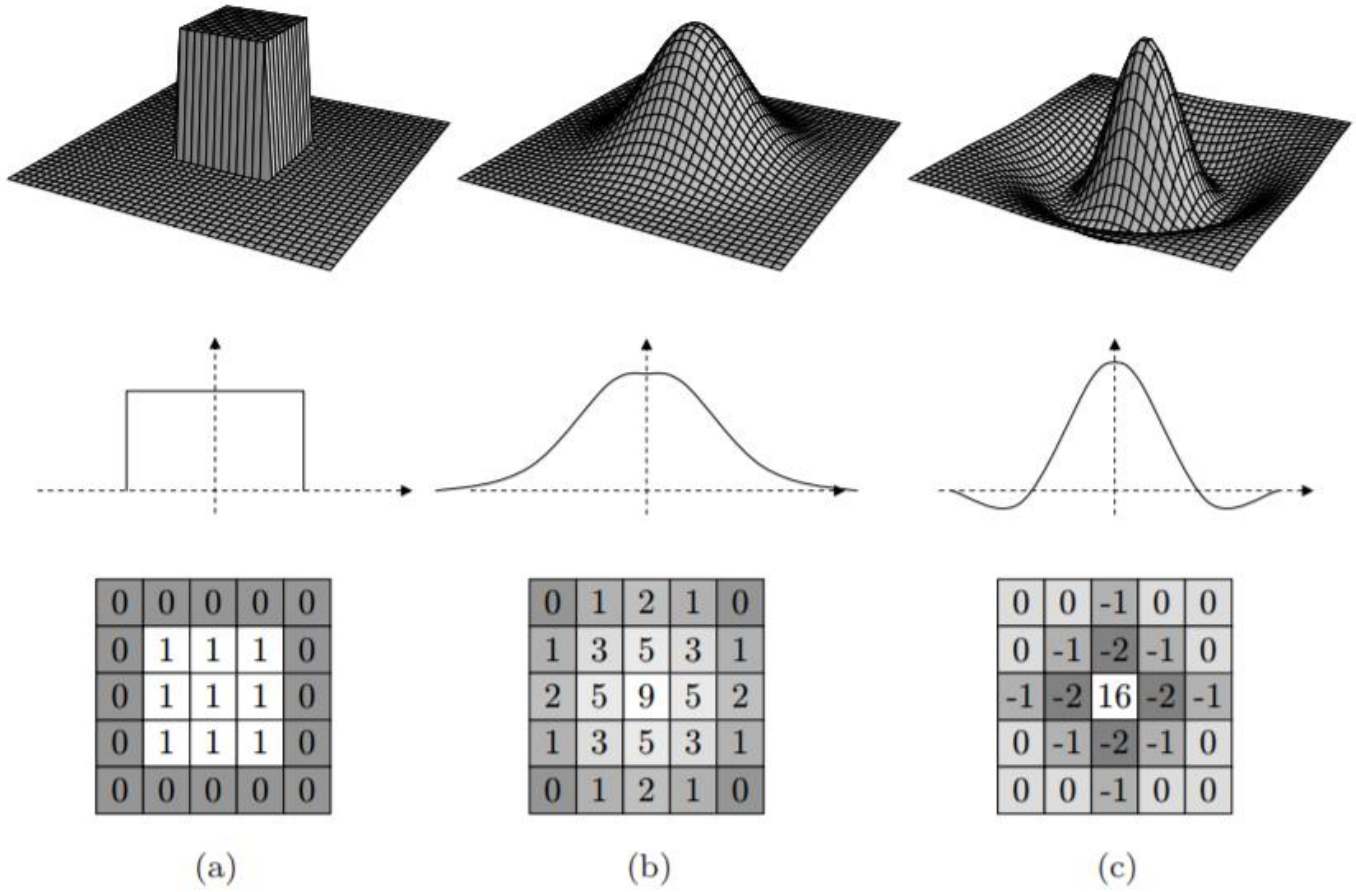
Extraction de caractéristiques et filtrage d'image

convolutions



Exemples de filtres

Extraction de caractéristiques et filtrage d'image convolutions



0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

(a)

0	1	2	1	0
1	3	5	3	1
2	5	9	5	2
1	3	5	3	1
0	1	2	1	0

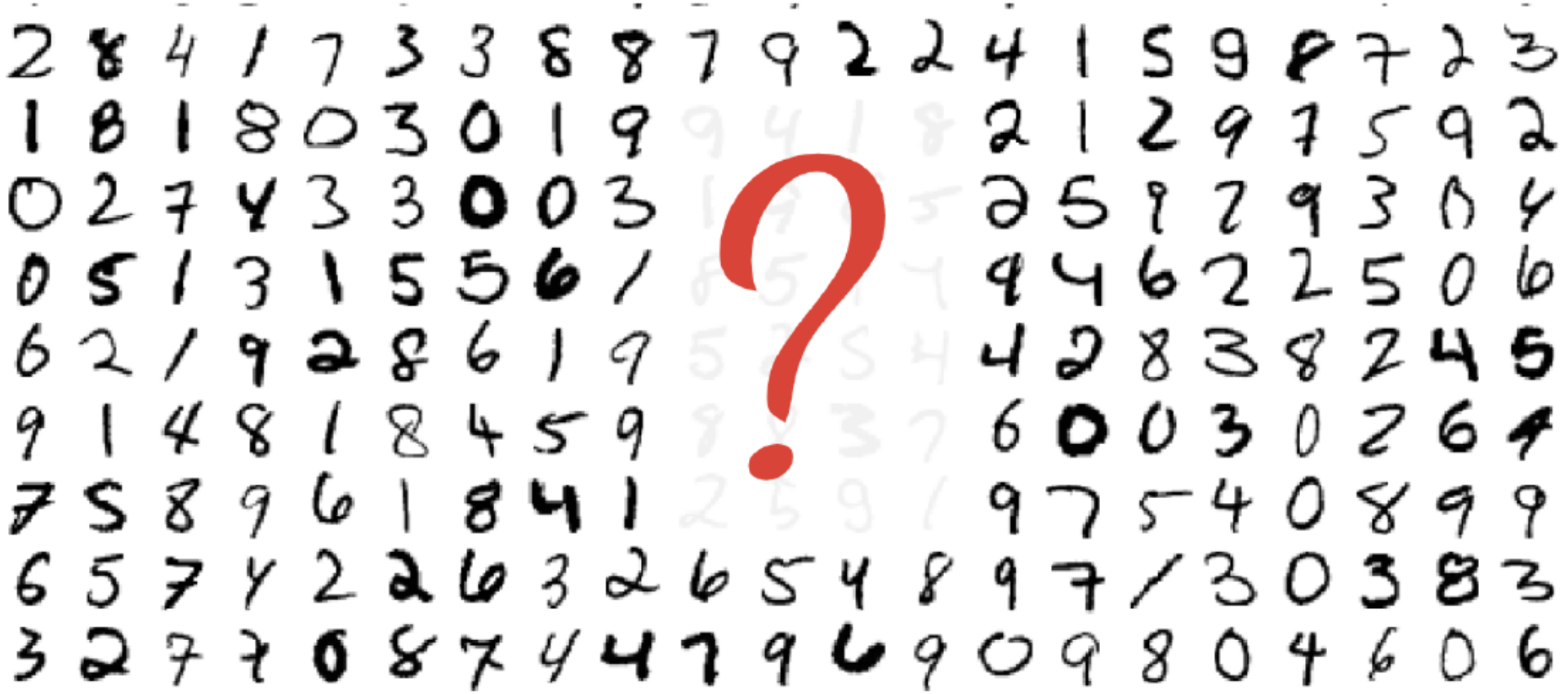
(b)

0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

(c)

Exemples de convloution

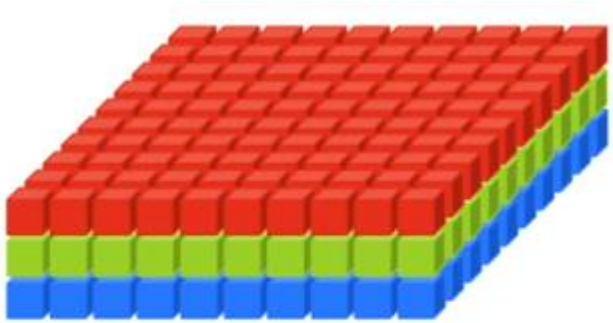
Premier classifieur d'images



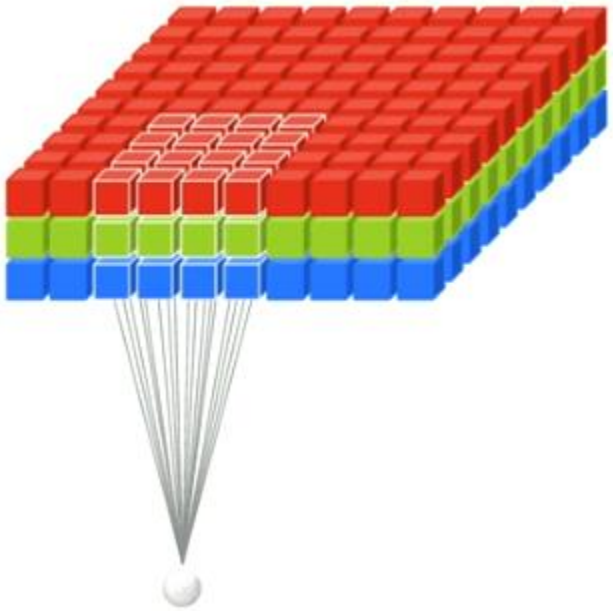
MNIST : Mixed National Institute of Standards and Technology [1]

Réseaux de neurones convolutionnels (CNNs)

Image 2D



Réseaux de neurones convolutionnels (CNNs)



-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

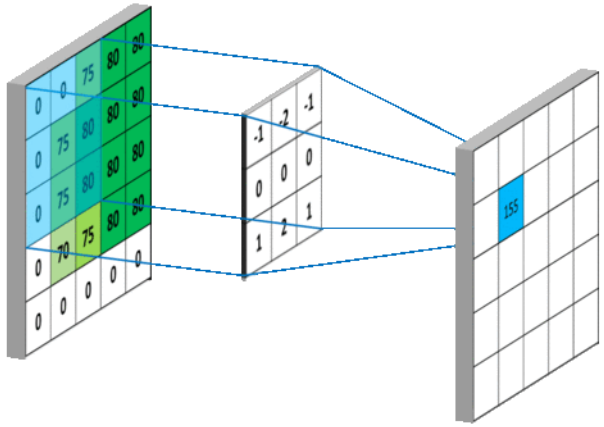
Gy

1_{x1}	1_{x0}	1_{x1}	0	0
0_{x0}	1_{x1}	1_{x0}	1	0
0_{x1}	0_{x0}	1_{x1}	1	1
0	0	1	1	0
0	1	1	0	0

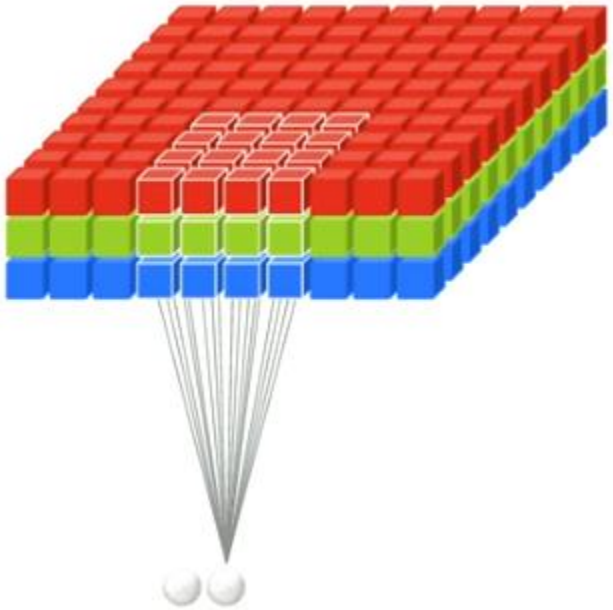
Image

4		

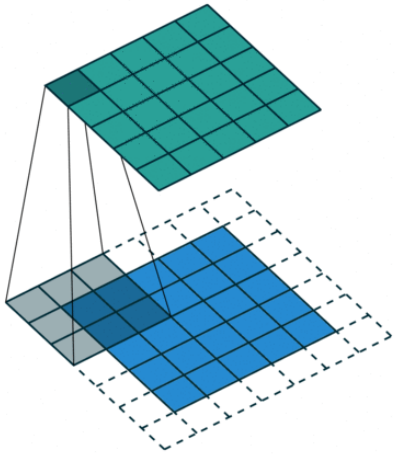
Convolved Feature

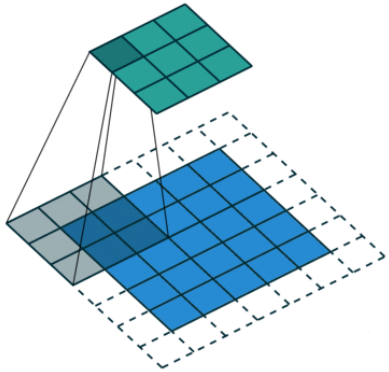


Réseaux de neurones convolutionnels (CNNs)

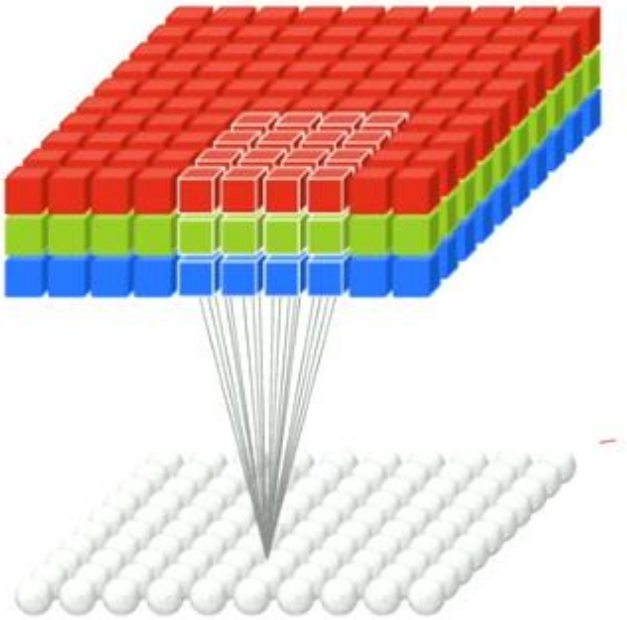


Stride = 2





Réseaux de neurones convolutionnels (CNNs)

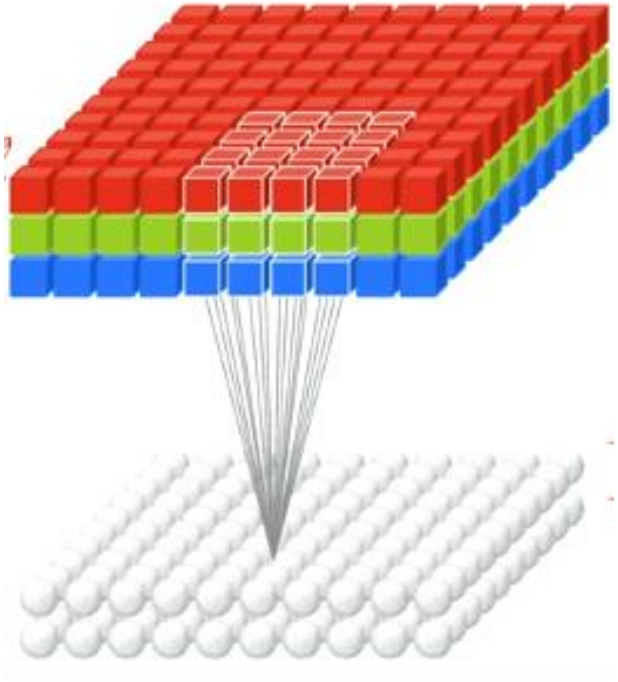


Padding =1

Matrices de poids

W [4, 4, 3]

Réseaux de neurones convolutionnels (CNNs)



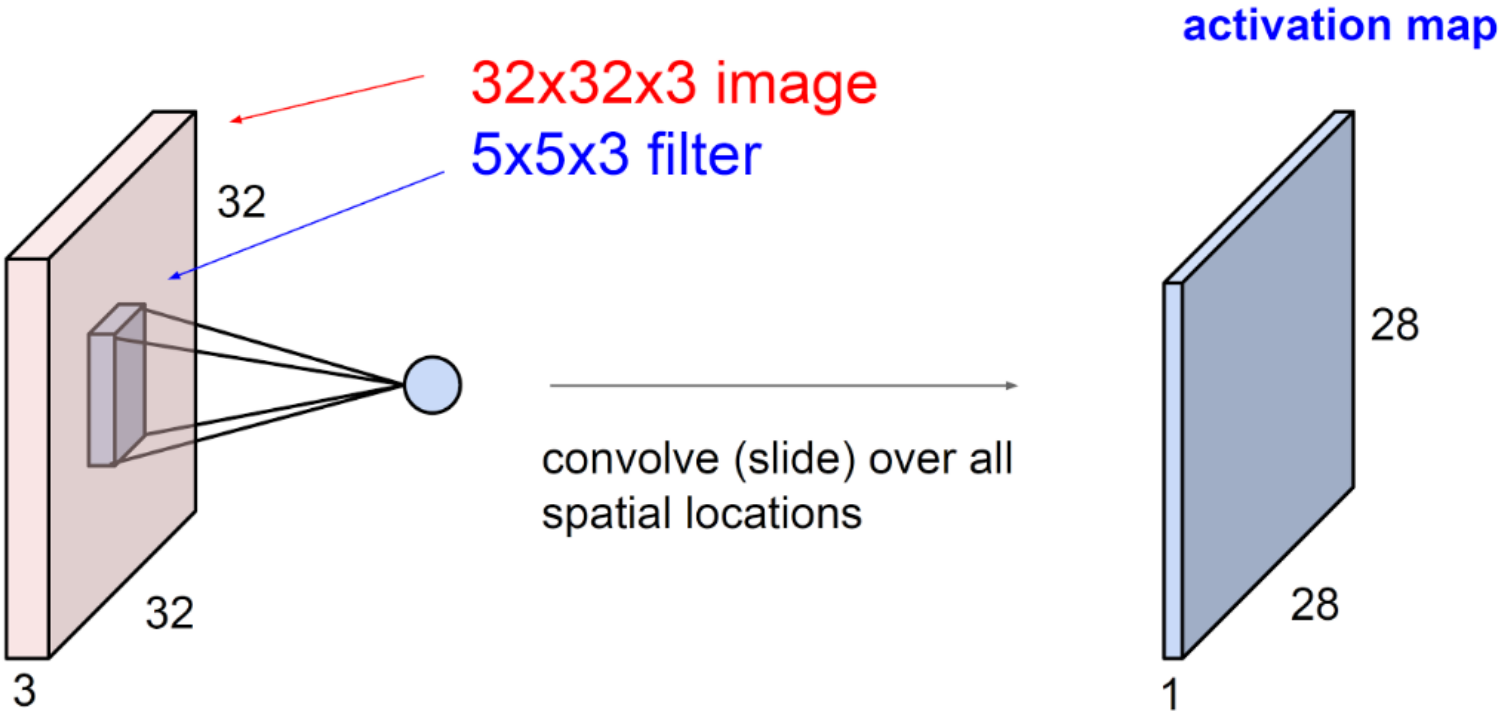
Matrices de poids

W [4, 4, 3]

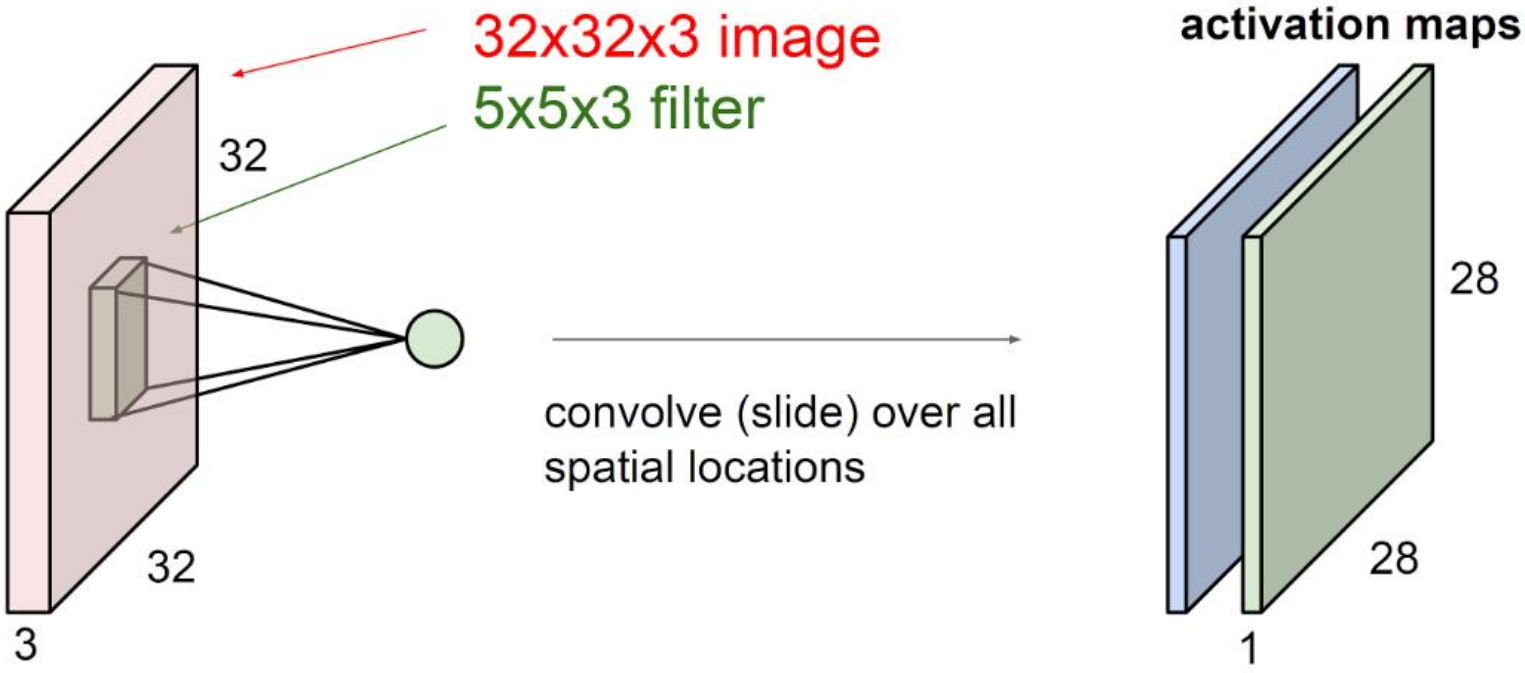
W [4, 4, 3]

W [4, 4, 3, 2]

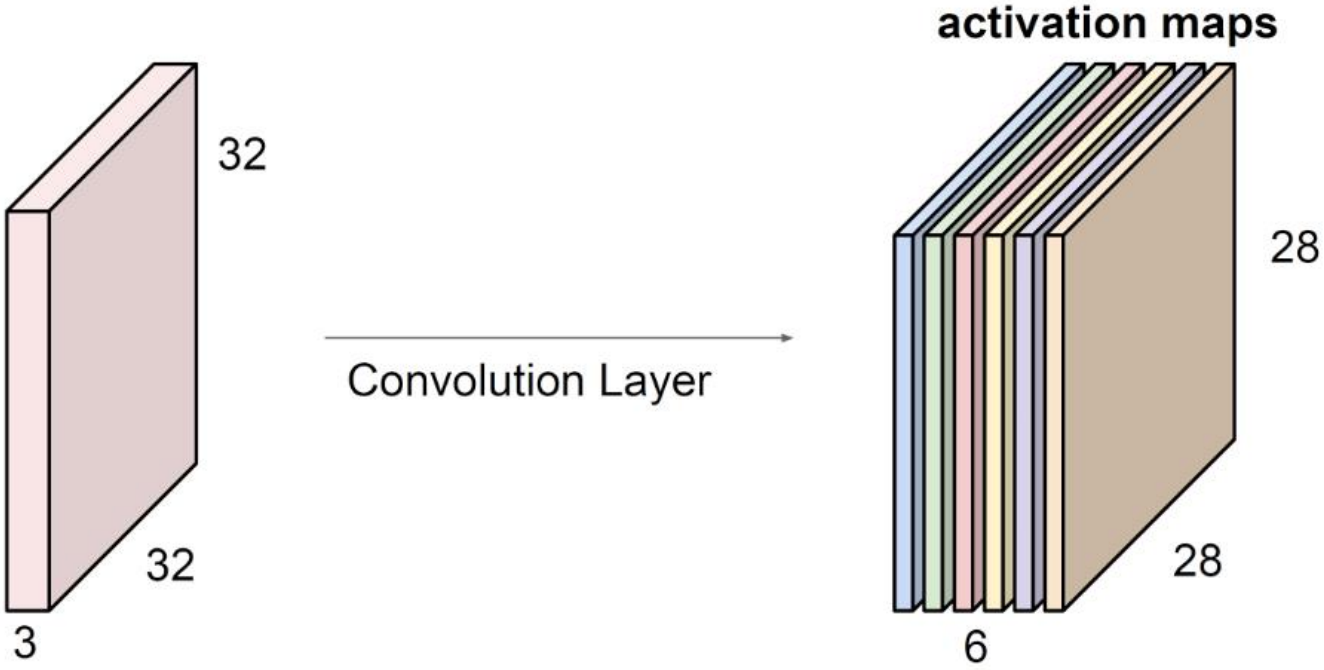
CNN : couches de convolution



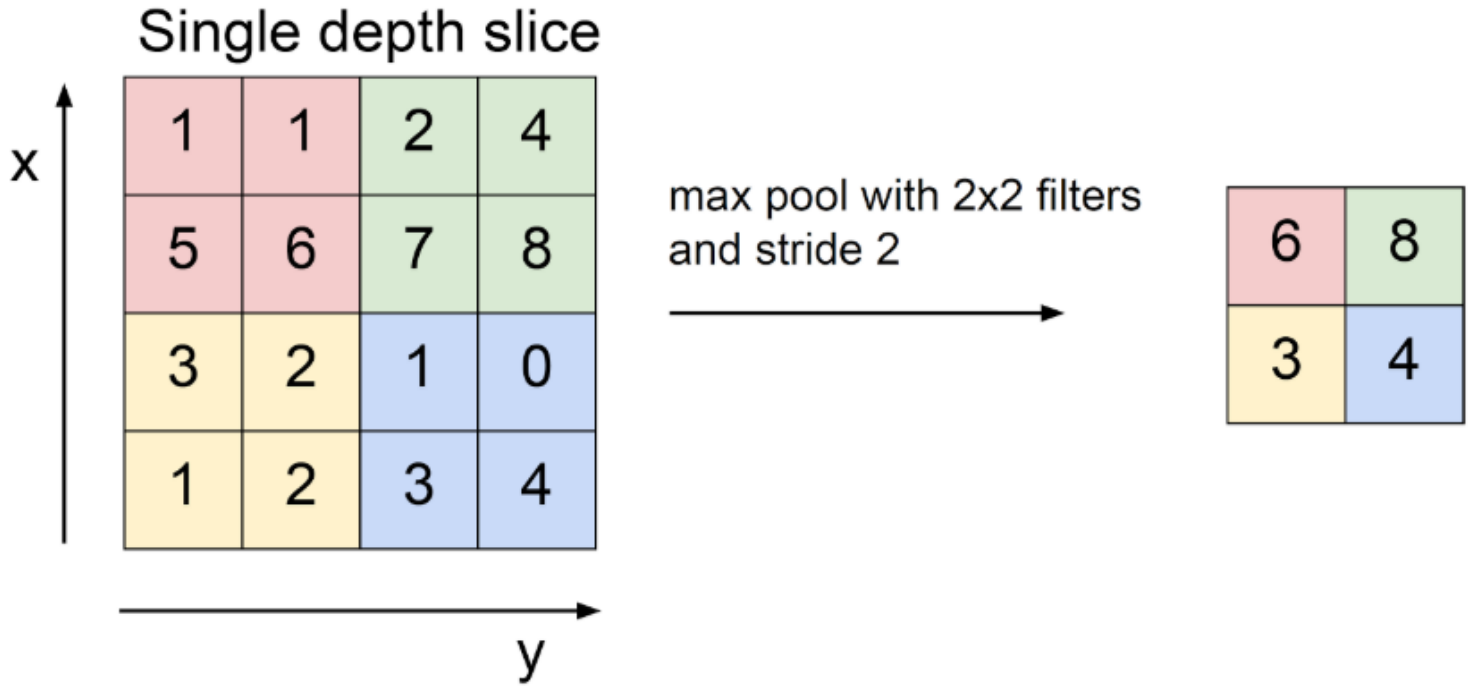
CNN : couches de convolution



CNN : couches de convolution

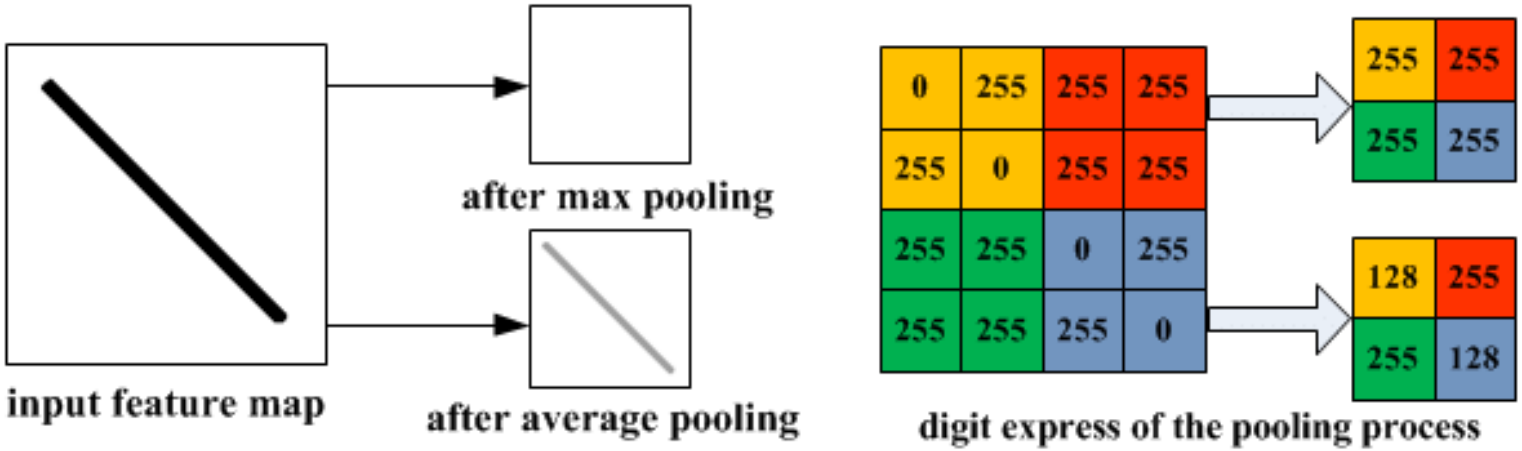


CNN : pooling

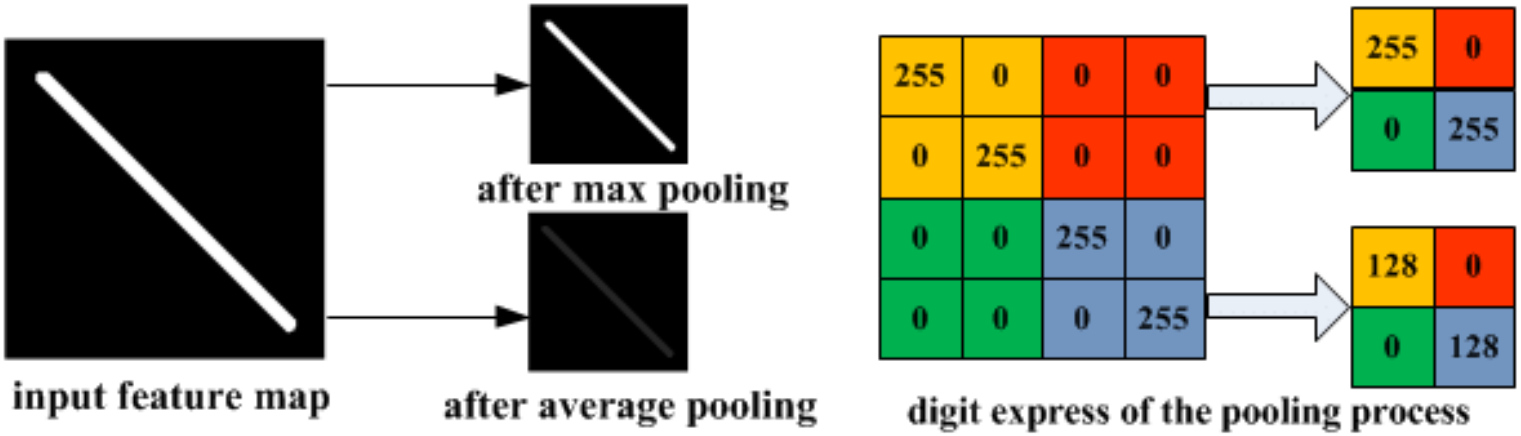


- Inséré entre deux convolutions successives
- Réduit la taille spatiale progressivement ainsi que le nombre de paramètres
- Aider au contrôle du sur apprentissage (overfitting)

CNN : pooling

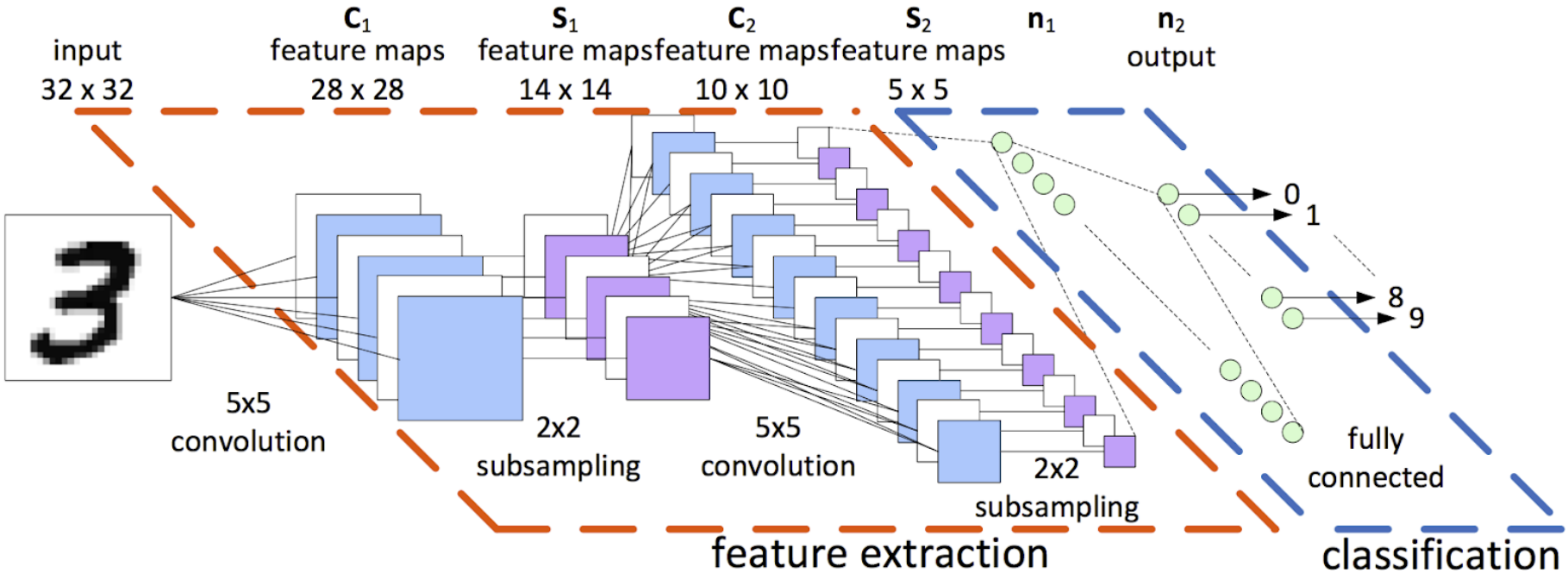


(a) Illustration of max pooling drawback

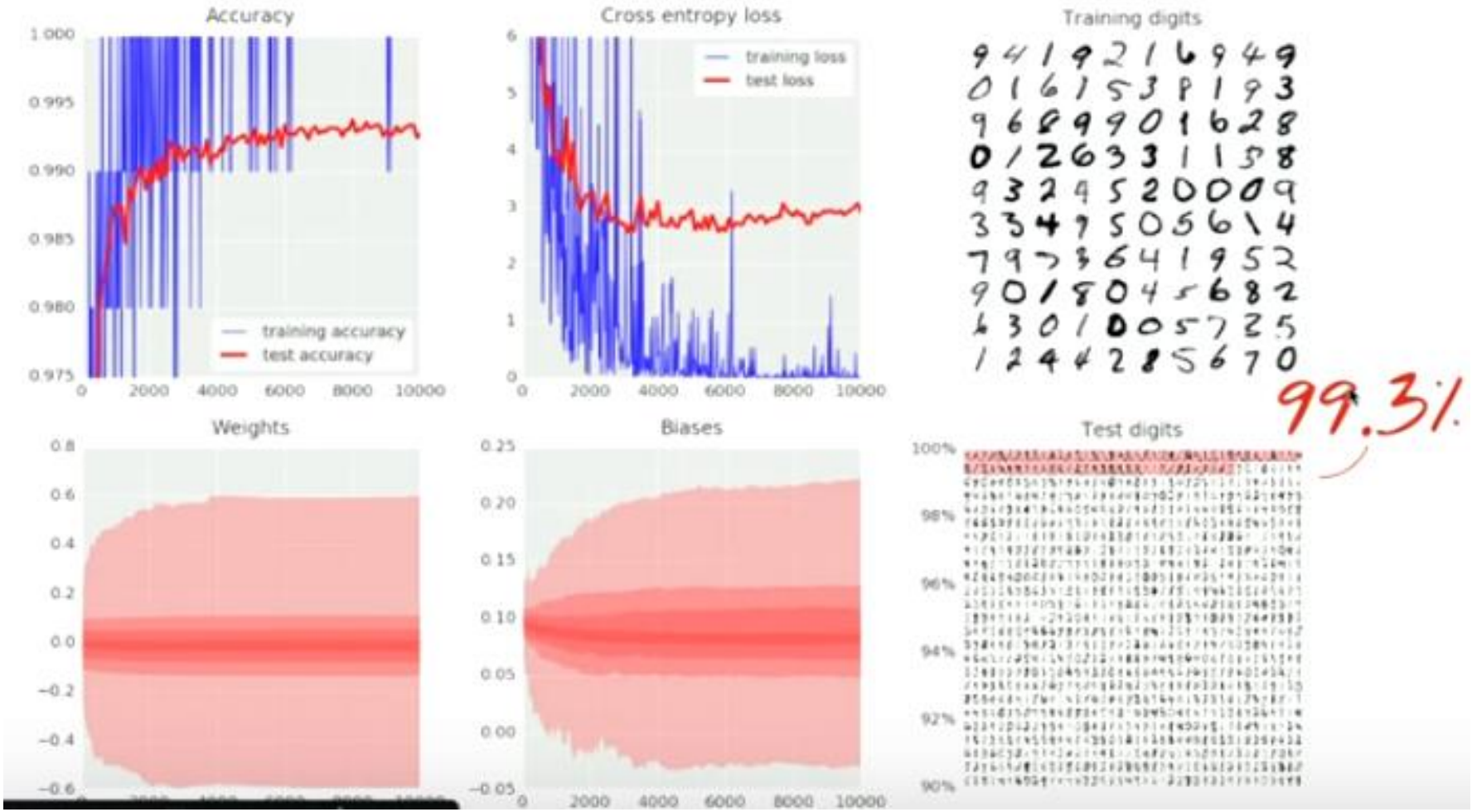


(b) Illustration of average pooling drawback

Réseaux de neurones convolutionnels (CNNs)



Réseaux de neurones convolutionnels (CNNs)



https://github.com/GoogleCloudPlatform/tensorflow-without-a-phd/tree/master/tensorflow-mnist-tutorial

Initiation aux outils : Torch Lightning

Définition du modèle

```python
class MyModel(L.LightningModule):
    def __init__(self, input_size, output_size):
        super().__init__()
        self.model = nn.Sequential(
            nn.Linear(input_size, 128),
            nn.ReLU(),
            nn.Linear(128, output_size)
        )
        self.loss_fn = nn.CrossEntropyLoss()

    def forward(self, x):
        return self.model(x)

    def training_step(self, batch, batch_idx):
        x, y = batch
        y_hat = self(x)
        loss = self.loss_fn(y_hat, y)
        self.log("train_loss", loss)
        return loss

    def configure_optimizers(self):
        return optim.Adam(self.parameters(), lr=1e-3)
```

Initiation aux outils : Torch Lightning

Préparation/chargement des données

```
class MyDataModule(L.LightningDataModule):
    def __init__(self, batch_size=32):
        super().__init__()
        self.batch_size = batch_size

    def prepare_data(self):
        X = torch.randn(1000, 10)
        y = torch.randint(0, 2, (1000,))
        dataset = TensorDataset(X, y)
        self.train_data, self.val_data = random_split(dataset, [800, 200])

    def train_dataloader(self):
        return DataLoader(self.train_data, batch_size=self.batch_size, shuffle=True)

    def val_dataloader(self):
        return DataLoader(self.val_data, batch_size=self.batch_size)
```

MERCI