

Artificial Intelligence day @IRCER Limoges

Deep Learning feedbacks: Reproducibility, Hyperparameters

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Retired from ENSAM Bordeaux,
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Presentation Summary

- Historical way, definitions & concepts of AI & Deep Learning (DL)
- Reproducibility in Deep Learning
- Hyperparameters
- Sharing reproducible DL training



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- Historical way, definitions & concepts of AI & Deep Learning (DL)
- Reproducibility in Deep Learning
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- Sharing reproducible DL training



My professional career

- First industrial career ~10 years (Signal Processing at Thomson-SINTRA then OO C++ development at Capgemini)
- I joined the I2M lab at ENSAM (Bordeaux) as a lecturer, working on "The Contribution of OO to Simulation in Mechanics"
- I taught Scientific & OO programing in Python at ENSAM
- I started to work on AI & Deep Learning in 2015
- Now I go on working on AI as a self-worker...



Presentation Summary

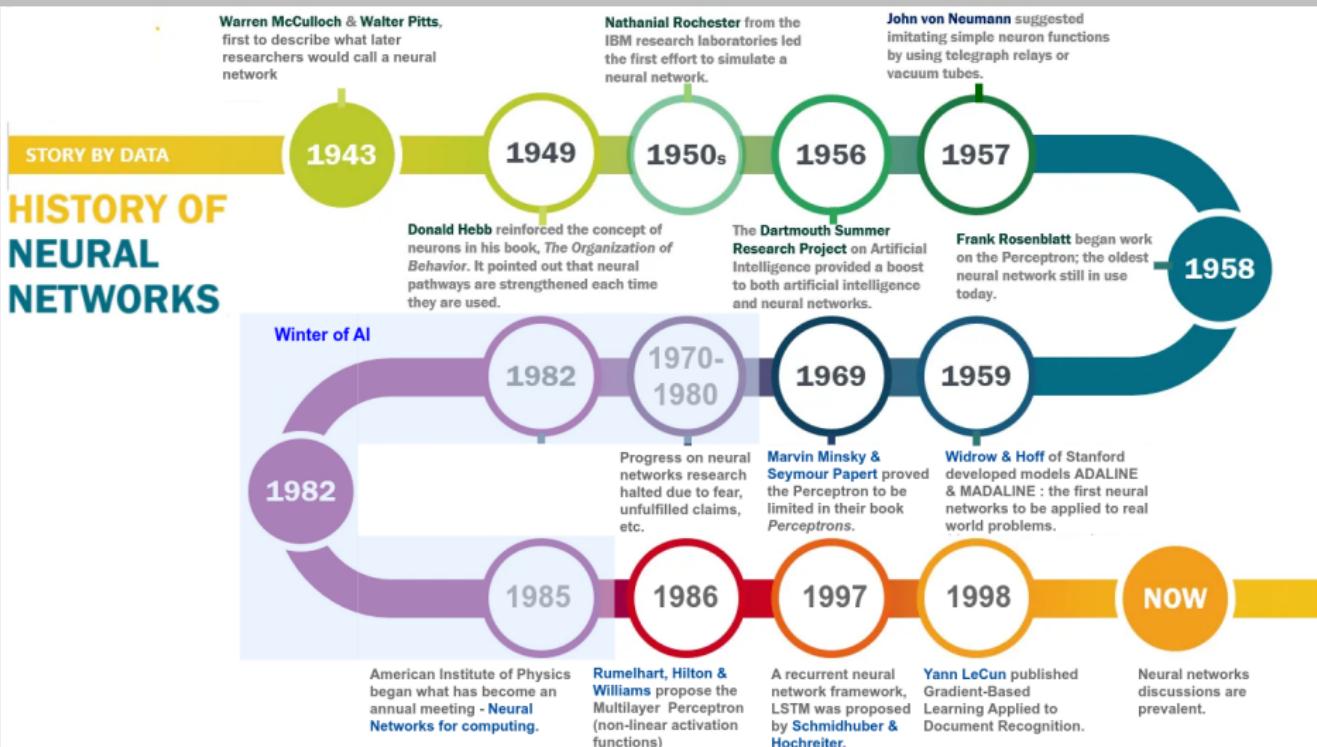
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Ressources

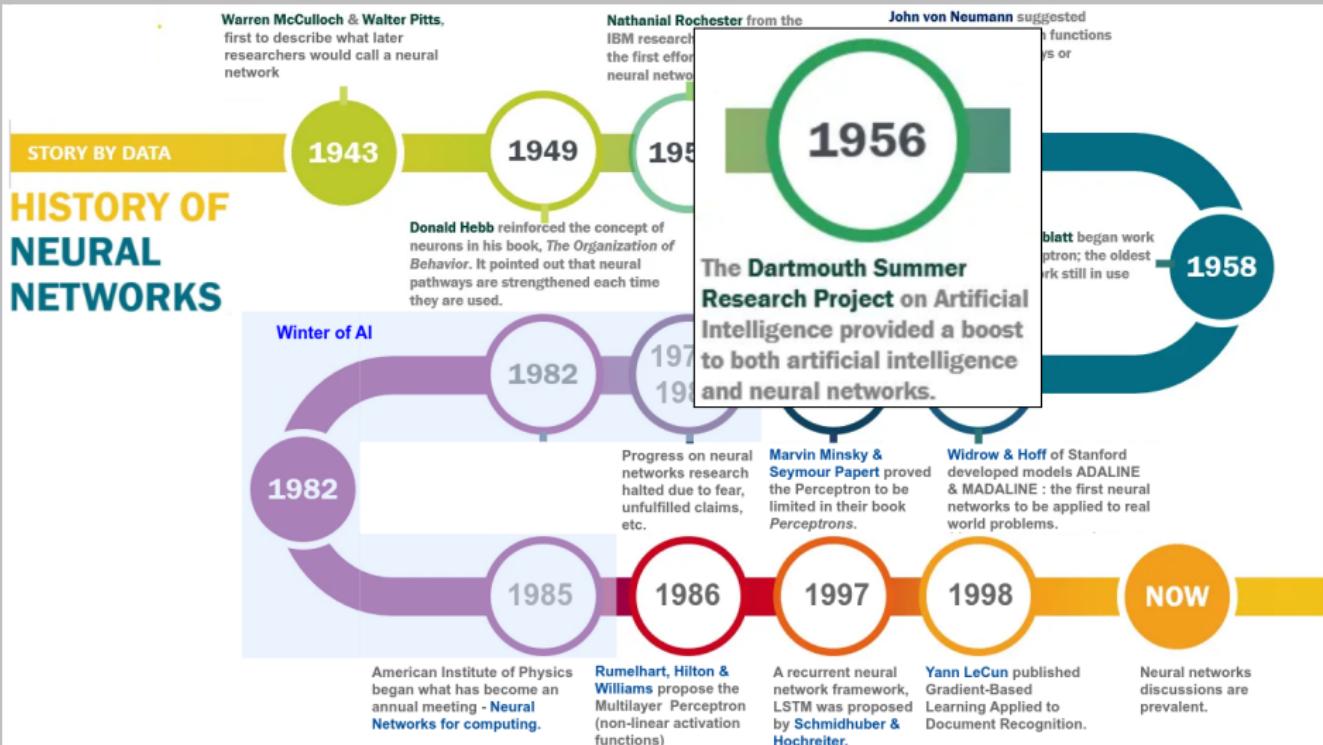
- GitHub repository for the PDF slides:
[DL-Reproducibility-Hyperparams-IA_day_at_IRCER_2025-03-14](#)
- GitHub repository for the example notebooks:
[/Reproducibility-MNIST-DNN-CPU](#) and
[/Reproducibility-MNIST-CNN-GPU](#)

AI : the historical way... from 1950 to 2000s



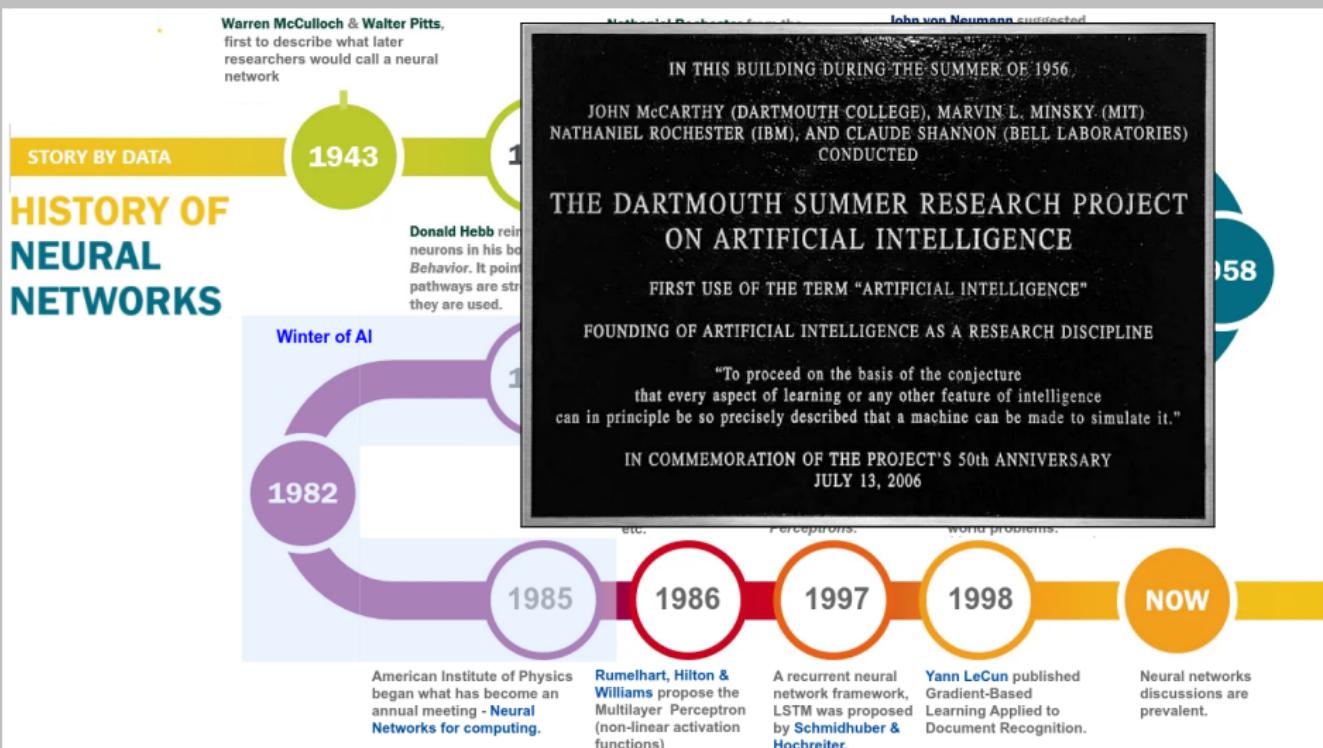
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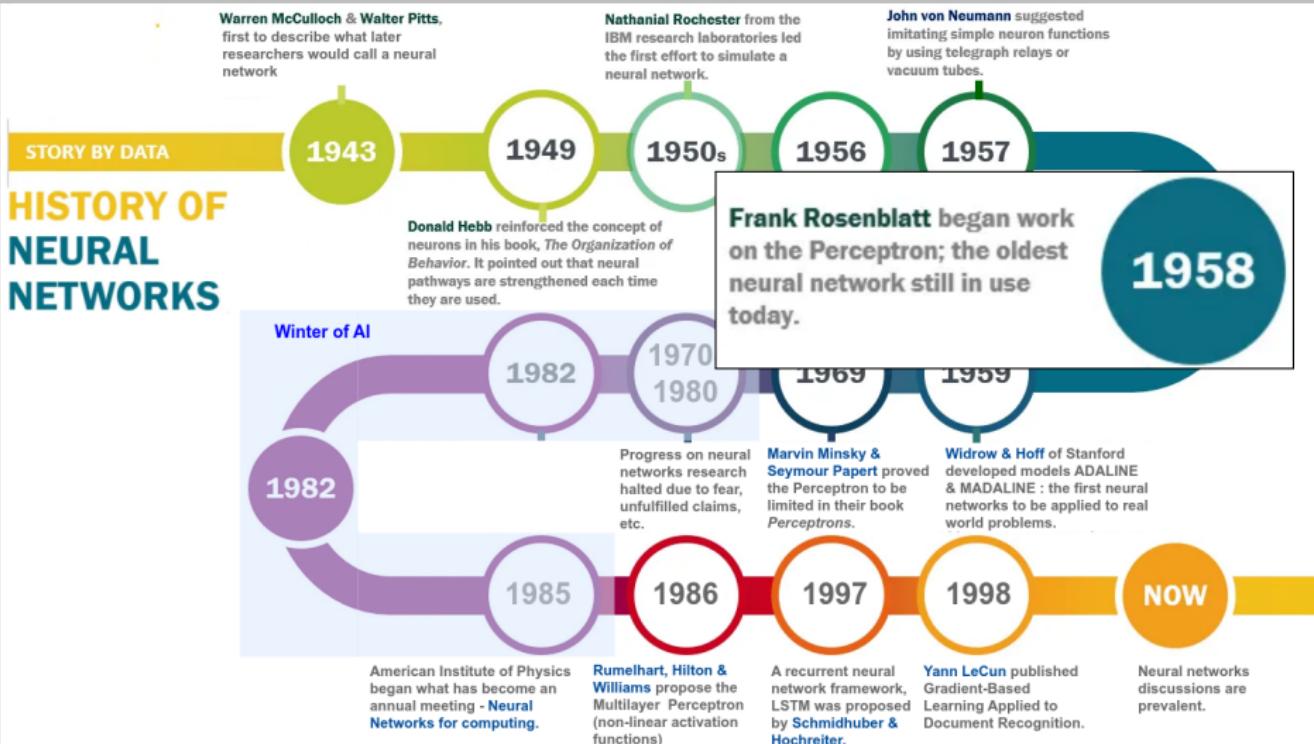
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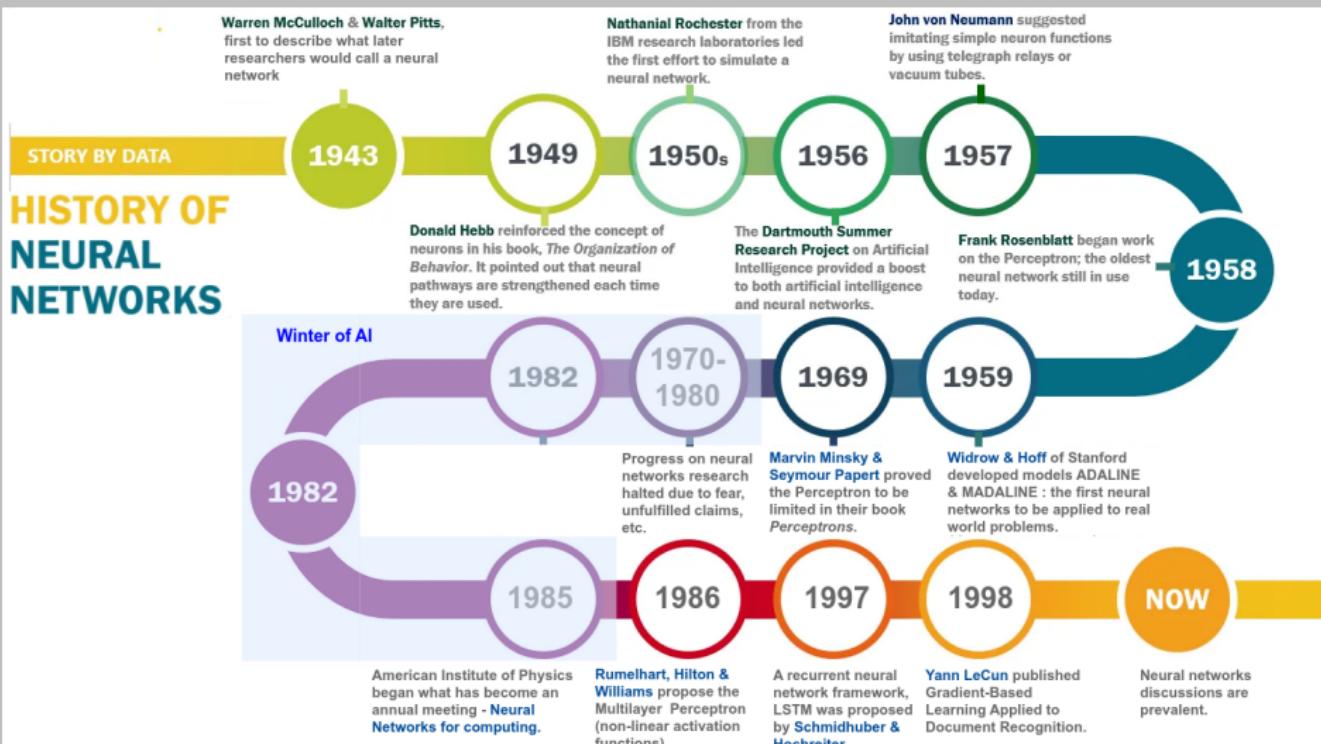
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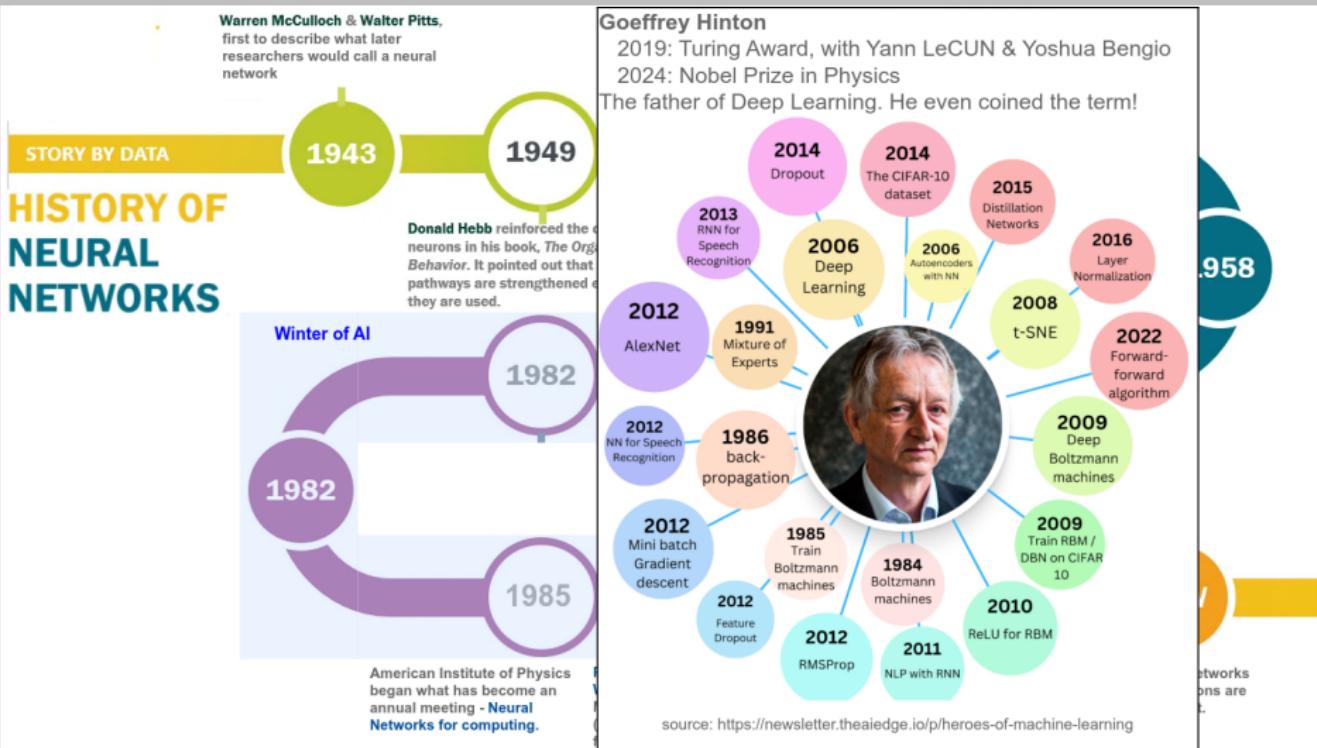
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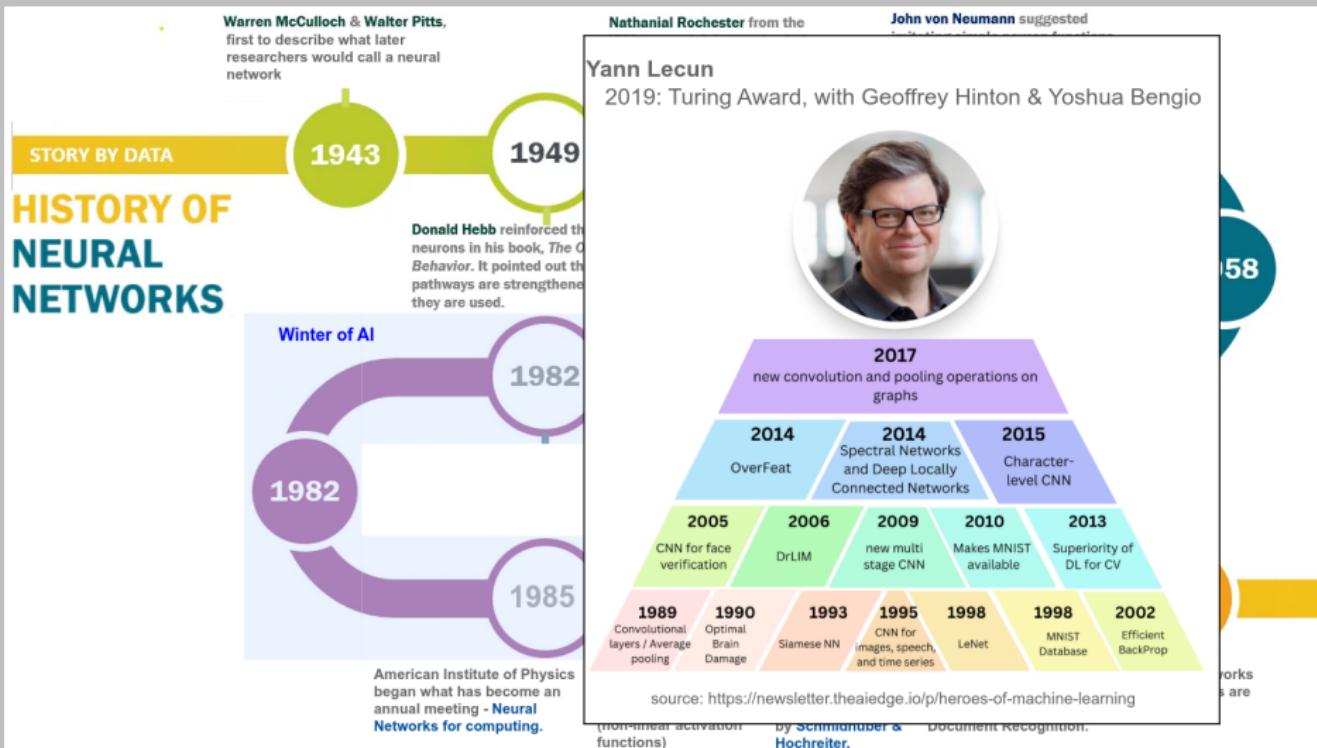
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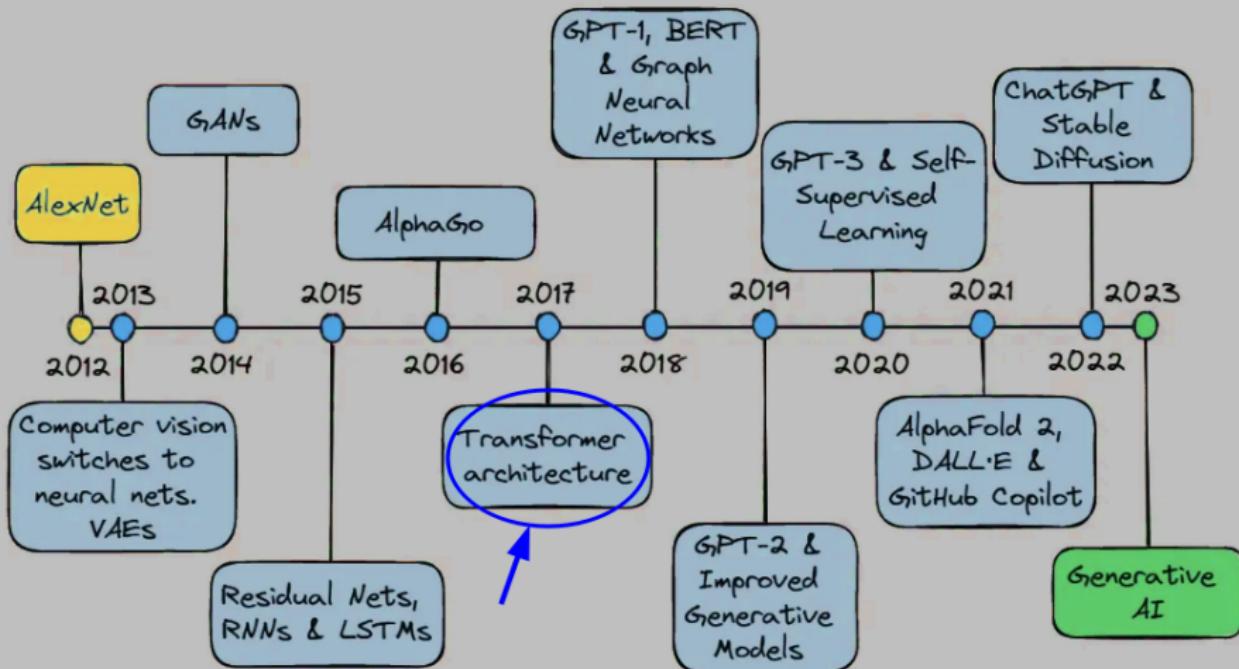
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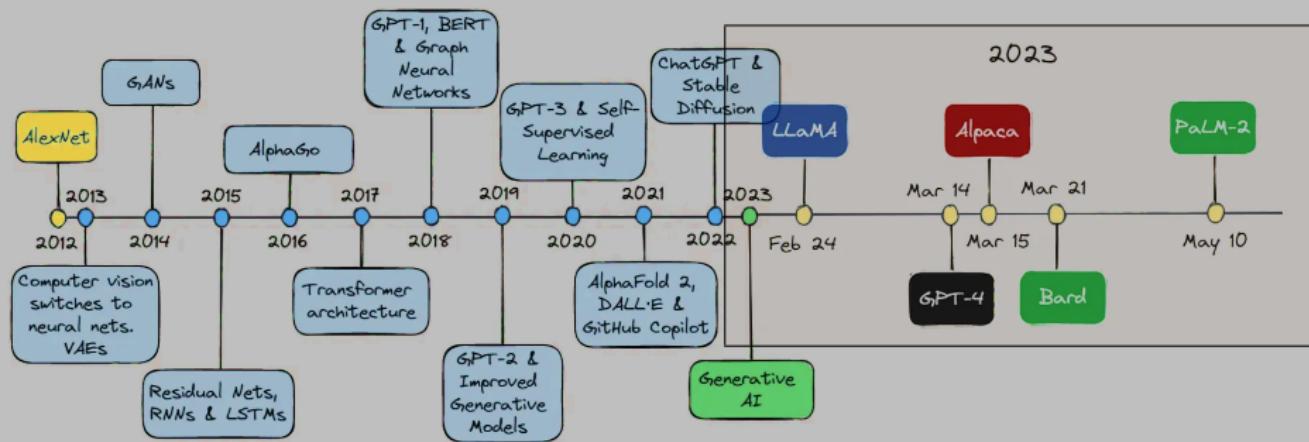
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The historical way... post 2012s: the “coming-of-age” of deep learning



Source: Thomas A Dorfe: "Ten Years of AI in Review", kdnuggets.com

The historical way... post 2023s, crazy acceleration



The historical way... post 2023s, crazy acceleration



Artificial Intelligences ?

Narrow/Weak AI

Strong/General AI

Artificial Intelligences ?

Narrow/Weak AI

- AI systems designed for specific, narrow tasks:
AlphaGo, self-driving cars, robot systems in the medical field...
- The most common form of AI that we encounter today.
- Builds systems that **behave like humans**.
- **We already are there...** We use it every day!
anti-spam, facial/voice recognition, language translation...

Strong/General AI

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Strong/General AI

- Builds systems with the ability to reason in general.
- Could explain how humans think?
- **Whe are not yet here...** but closer and closer every day

Machine Learning: a field of AI

ARTIFICIAL INTELLIGENCE

MACHINE LEARNING

SUPERVISED
LEARNING

UNSUPERVISED
LEARNING

DEEP
REINFORCEMENT
LEARNING

SELF-
SUPERVISED
LEARNING

Branches of Machine Learning

Supervised learning

A **labeled dataset** is used to train algorithms (models):

- **Classification**

- Images classification
- Objects detection in images
- Speech recognition...

- **Regression**

- Predict a value...

- **Anomaly detection**

- Spam detection
- Manufacturing: finding known (learned) defects
- Weather prediction
- Diseases classification...

...

Branches of Machine Learning

Unsupervised learning

The algorithm attempts to identify patterns / structures within **unlabeled datasets**:

- **Clustering & Grouping**

- Data mining, web data grouping, news grouping...
- Market segmentation
- Astronomical data analysis...

- **Anomaly Detection**

- Manufacturing: finding defects (even new ones)
- Monitoring abnormal activity: failure, hacker...
- Fraud detection: fake account on Internet...

- **Dimensionality reduction**

- Data compressions...

...

Branches of Machine Learning

Deep Reinforcement Learning DRL

An agent (the model) learns how to drive an environment within a trial and error process by maximising a cumulative **reward**:

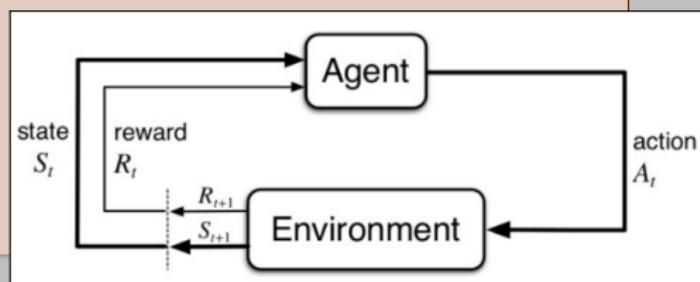
- **Control/command**

- Controlling drones, mechatronic systems, electric VTVL rocket, robots
- Factory optimization
- Financial (stock) trading...

- **Decision making**

- games (video games)
- financial analysis...

...



Branches of Machine Learning

Self-Supervised Learning [LM23]

- Aims to learn features/patterns from **unlabeled data without relying on human annotations.**
- Can extract data features that exhibit robust generalization.
- Technically a subset of Unsupervised Learning.
- But closely related to Supervised Learning
 - ~ optimizes performance against a self-learned ground truth.

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Branches of Machine Learning

Self-Supervised Learning

2 main stages of SSL:

- **Pre-training** (Unsupervised):

- **Fine-Tuning** (Supervised Task):

Branches of Machine Learning

Self-Supervised Learning

2 main stages of SSL:

- **Pre-training** (Unsupervised):

The model learns useful representations from unlabeled data by solving *pretext tasks*:

- Image-Based SSL: Predicting missing parts of an image, similarity between original and augmented images
- Text-Based SSL: Predicting missing words in a sentence
- Audio-Based SSL: Predicting the next segment of audio.

- **Fine-Tuning** (Supervised Task):

Branches of Machine Learning

Self-Supervised Learning

2 main stages of SSL:

- **Pre-training** (Unsupervised):

The model learns useful representations from unlabeled data by solving *pretext tasks*:

- Image-Based SSL: Predicting missing parts of an image, similarity between original and augmented images
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- Audio-Based SSL: Predicting the next segment of audio.

- **Fine-Tuning** (Supervised Task):

The model is adapted to a specific task (image classification, speech recognition) using a smaller labeled dataset.

Various approaches for ML algorithms

Supervised learning:

- Neural Networks
- Bayesian inference
- Random forest
- Decision Tree
- Support Vector Machine (SVM)
- K-Nearest Neighbor (KNN)
- Linear regression
- Logistic regression...

Unsupervised learning:

- Neural Networks
- Principal Composant Analysis (PCA)
- Singular Value Decomposition (SVD)
- K-mean & Prob. clustering...

Reinforcement learning:

- Neural Networks (Q-learning, Actor-Critic, DDPG, PPO...)
- Monte Carlo...

Self-Supervised learning:

- Neural Networks (SimCLR, Dino...)

Various approaches for ML algorithms

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Self-Supervised learning:

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A large variety of possibilities ~ success of **Deep Learning** and **Neural Networks**

Fields & applications of DL

Computer Vision

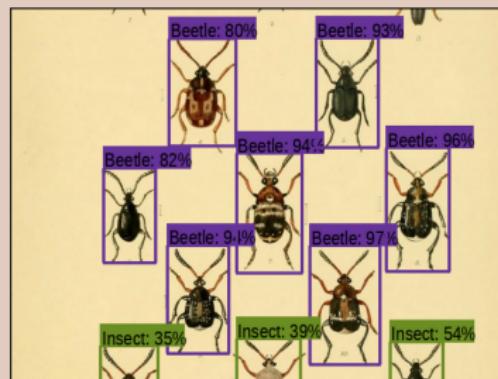
- Image Classification.
- Object Detection .
- (Semantic) Segmentation.
- Pose Estimation.
- Style transfer.
- OCR (Optical Character Recognition)
- Image Generation
- ...



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source : [Tensorflow tutorials object_detection](#)

Fields & applications of DL

Computer Vision

- Image Classification.
- Object Detection .
- (Semantic) Segmentation.

- Pose Estimation
- Style Transfer
- Optical Flow
- Image Enhancement
- Video Processing



source : [Tensorflow](#)

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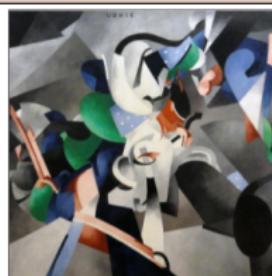


source : [Tensorflow pose_detection](#)

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source : [Tensorflow style_transfer](#)

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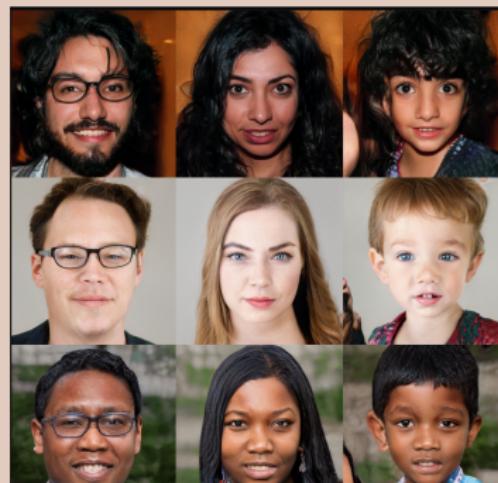


source : pyimagesearch.com

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source : [stylegan](#)

Fields & applications of ML

NLP(Natural Language Processing): some applications...

- Natural Language Understanding (NLU)
- Natural Language Generation (NLG)
- Speech recognition / Speech Synthesis (Text To Speech)
- Machine Translation (languages)
- Virtual agents and ChatBots
- LLM ChatBots
- ...

Societal issues: Explainability

Explainability is becoming an important aspect in research, referred to as

XAI **Explainable Artificial Intelligence** [MM25] [Ali+23]

IML **Interpretable Machine learning** [MCB20] [Mol24] [Rud+21]

Societal issues: Explainability

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Explainability

- **Unexplainability** of the DL results still constitutes an obstacle to their dissemination today.
- Neural Networks are often denigrated as a **Black box** by scientists with a Cartesian approach.
- The growing complexity of NNs (LLM for example) makes the simple explanation of their outputs extremely difficult.

Societal issues: Decision-making, Certification

Decision-making

- **Decisions** in sensible fields (justice, insurance, defense...) are being ceded to ML algorithms to the detriment of human control, raising concern for loss of fairness and equity.
- Decision-making algorithms rely inevitably on assumptions (quality of training data) not always verified

Societal issues: Decision-making, Certification

Decision-making

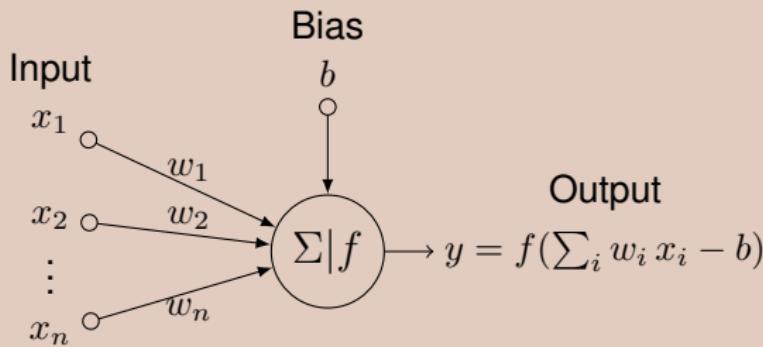
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Certification

- The evaluation and the certification of AI systems remains a major issue for their integration in the industry
- Formal certification of ML algorithms still a subject of research
- Examples:
[LNE: Process certification for AI](#),
[Fraunhofer: Auditing and Certification of AI Systems](#)

NN technical aspects

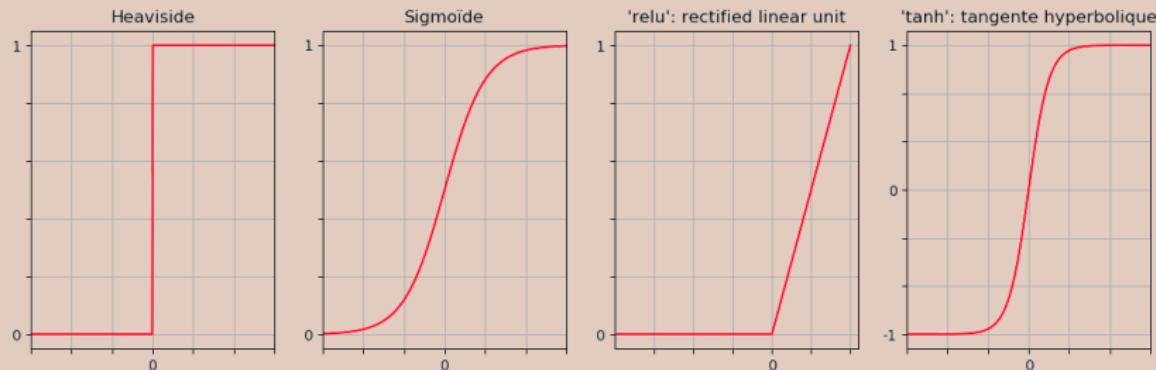
The artificial neurone



- Receives the input stimuli $(x_i)_{i=1..n}$ affected by **weights** (w_i)
- Computes the **weighted sum** of the input: $\sum_i w_i x_i - b$
- Outputs its activation $f(\sum_i w_i x_i - b)$, computed with a non-linear **activation function** f .

NN technical aspects

Common activation functions

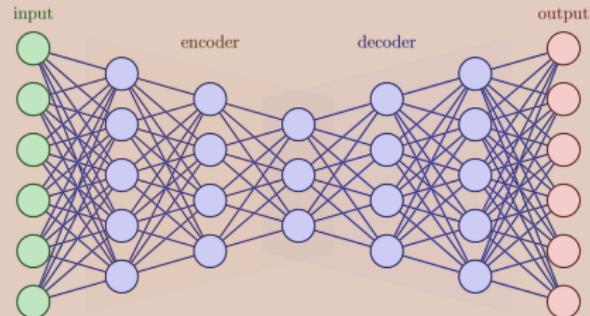
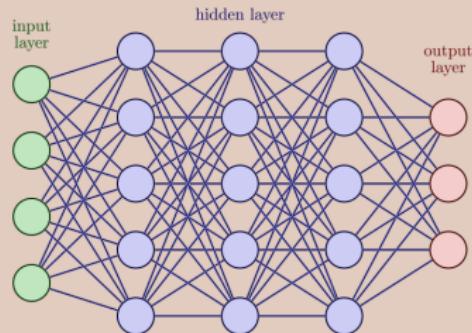


- Introduces a non-linear behavior.
- Sets the range of the neuron output: $[-1, 1]$, $[0, 1]$, $[0, \infty[$...
- The bias b sets the activation threshold of the neuron.

NN Computing aspects

Neural network

Neurons are grouped by layers to form a **Neural Network**



Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list)

- **Dense Neural Network**

the simplest architecture made of successive layers of neurones, with *FeedForward Neural Network (FNN)* and *Back Propagation* algorithms.

- **Convolutional (CNN)**

- **Recurrent (RNN)**

- **Auto Encoder (AEN)**

- **Generative Adversarial (GAN)**

- **Transformers**

- **Large Language Model (LLM)**

- ...

Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list)

- **Dense Neural Network**
- **Convolutional (CNN)** - Mostly used for analyzing and classifying images.
- **Recurrent (RNN)**
- **Auto Encoder (AEN)**
- **Generative Adversarial (GAN)**
- **Transformers**
- **Large Language Model (LLM)**
- ...

Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list)

- **Dense Neural Network**
- **Convolutional (CNN)**
- **Recurrent (RNN)** - Used for time series, like the Long Short-Term Memory (LSTM) algorithm.
- **Auto Encoder (AEN)**
- **Generative Adversarial (GAN)**
- **Transformers**
- **Large Language Model (LLM)**
- ...

Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list)

- **Dense Neural Network**
- **Convolutional (CNN)**
- **Recurrent (RNN)**
- **Auto Encoder (AEN)**- Dimensionality reduction, Feature extraction, Denoising of data/images, Inputting missing data...
- **Generative Adversarial (GAN)**
- **Transformers**
- **Large Language Model (LLM)**
- ...

Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list)

- **Dense Neural Network**
- **Convolutional (CNN)**
- **Recurrent (RNN)**
- **Auto Encoder (AEN)**
- **Generative Adversarial (GAN)**
to generate text, images, music...
- **Transformers**
- **Large Language Model (LLM)**
- ...

Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list)

- **Dense Neural Network**
- **Convolutional (CNN)**
- **Recurrent (RNN)**
- **Auto Encoder (AEN)**
- **Generative Adversarial (GAN)**
- **Transformers**
(2017) Natural language processing, and also image classification
- **Large Language Model (LLM)**
- ...

Neural Network Architectures

Many NN architectures for many applications (non-exhaustive list)

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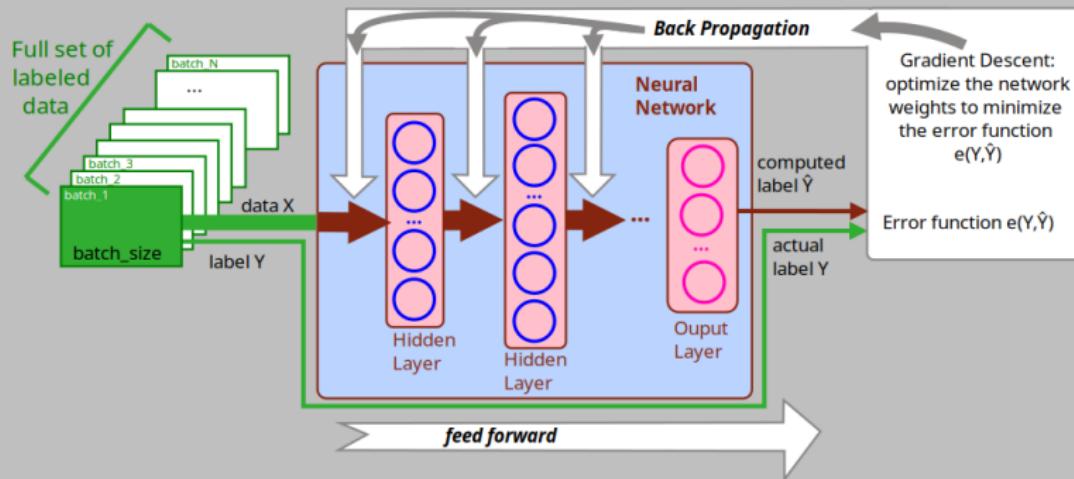
read text, sound, write books, images, speak, make music ...

*OpenAI: ChatGPT - Anthropic: Claude, Sonnet - Google: Gemini -
Mistral: mistral - Meta: LLama...*

- ...

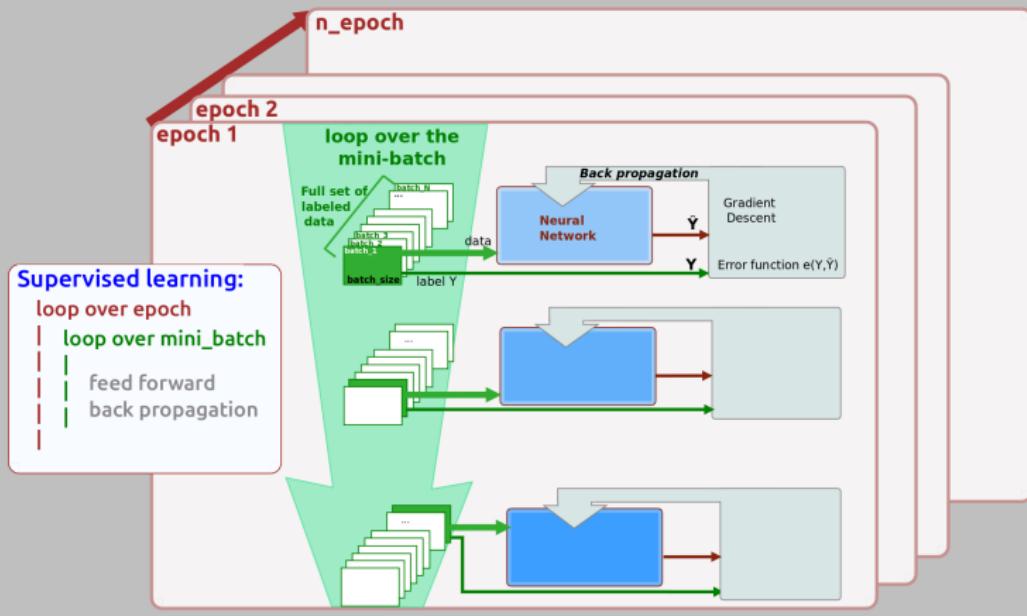
NN Computing aspects

Supervised learning : Feed Forward and Back Propagation



- The dataset is split into (mini) **batches** of size **batch_size**
- After each *feed forward* the *Back Propagation* algorithm modifies the neurons weights to minimize the error e .

NN Computing aspects



- Training with the whole dataset is repeated n_epoch times,
- The network state after epoch n becomes the initial state for epoch $n+1$.

Reproducibility

The reproducibility crisis in AI & ML is not new...

- *1500 scientists lift the lid on reproducibility*
Nature, volume 533, pages 452–454 (2016)
- *Artificial intelligence faces reproducibility crisis*
Science, 16 Feb 2018, Vol 359, Issue 6377, pp. 725-726
- *Reproducibility Workshops* at major AI conferences:
 - NeurIPS NeurIPS Reproducibility Challenge 2018, 2019, 2020...
 - ICML International Conference on Machine Learning: 2017, 2018, 2019...
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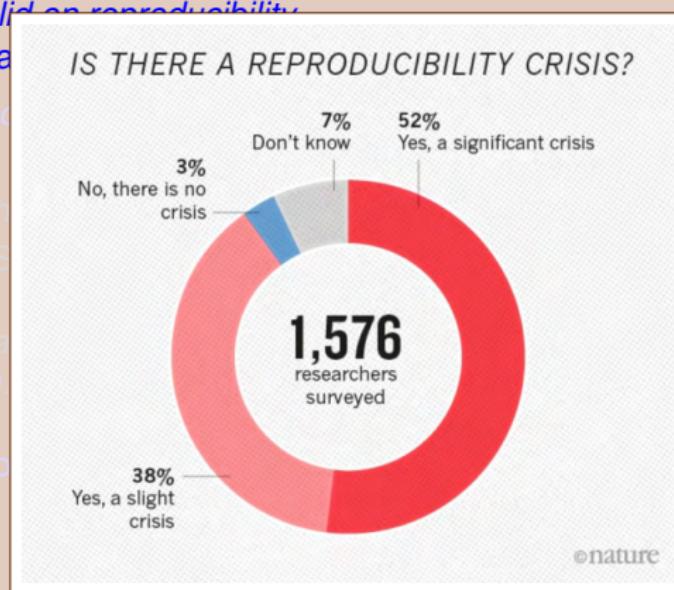
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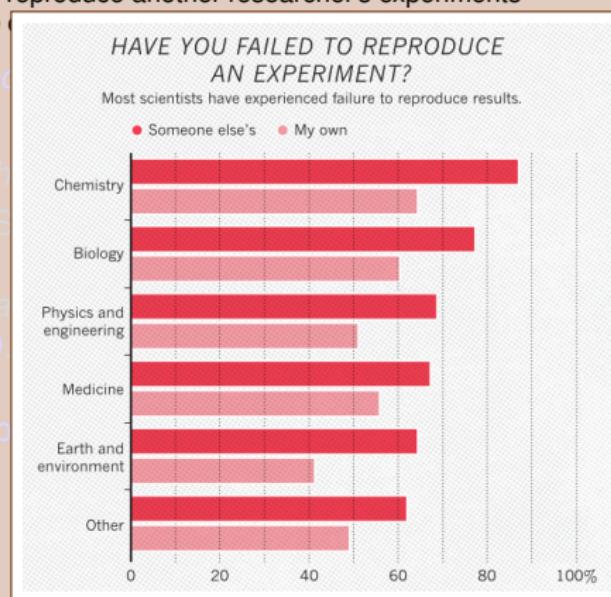
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70% of researchers failed to reproduce another researcher's experiments
50% failed to reproduce one of their own

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NeurIPS 2019, 2020...
ICML International Conference
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 - ICML *International Conference on Machine Learning*: [2017](#), [2018](#), [2019](#)...
 - AAAI *Association for the Advancement of Artificial Intelligence*: [reproducibility checklist](#)
- Many papers relate the reproducibility question in AI & ML:
[\[Bak16\]](#)[\[Alb+23\]](#)[\[Pin+20\]](#)[\[TVD18\]](#)[\[Sha19\]](#)[\[eal20\]](#)[\[GK18\]](#)[\[Hut18\]](#)..
- Currently still a problem for trusting ML outputs.

Reproducibility - The DL context

Reproducibility - The DL context

Reproducibility for Deep Learning

refers to the ability to achieve the **same or similar results**:

- Using the same **training dataset**
- Using the same **algorithms**
model architecture, parameters and hyperparameters, and other code
- Within the same computing **environment**
software (Python modules) used to run the algorithm,
data-preprocessing... and all pieces of code.

Reproducibility - The DL context

Reproducibility: an important issue for confidence in DL

- Necessary to trust DL outputs
- Required for the validation of published results & claims
- Helps to promote open and accessible research
- Makes published matter an educational tool for students

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Reproducibility - The DL context

2 main reasons why DL training is not reproducible

- NN training involves random draws at many stages:
- Non-determinism in hardware operations
(floating-point ops are sensitive to computation order...)
 - Most of these cases occur on GPUs
auto-tuning: libraries CUDA and cuDNN auto-select the optimal primitive operations at runtime ~ different ops may occur on subsequent run
 - Forcing deterministic ops possible but ~ slower computation 😬

Reproducibility - The DL context

2 main reasons why DL training is not reproducible

- NN training involves random draws at many stages:
 - Data augmentation [SK19]
 - Shuffling training data
 - Batch ordering at each epoch
 - Initialisation of the NN weights
 - Exploration noise during training (DRL)
 - Specific algorithm treatments: *dropout* [Sri+14]
 - Optimisation algorithms: *stochastic gradient* (adam)...
- Non-determinism in hardware operations
(floating-point ops are sensitive to computation order...)
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Reproducibility - The DL context

2 main reasons why DL training is not reproducible

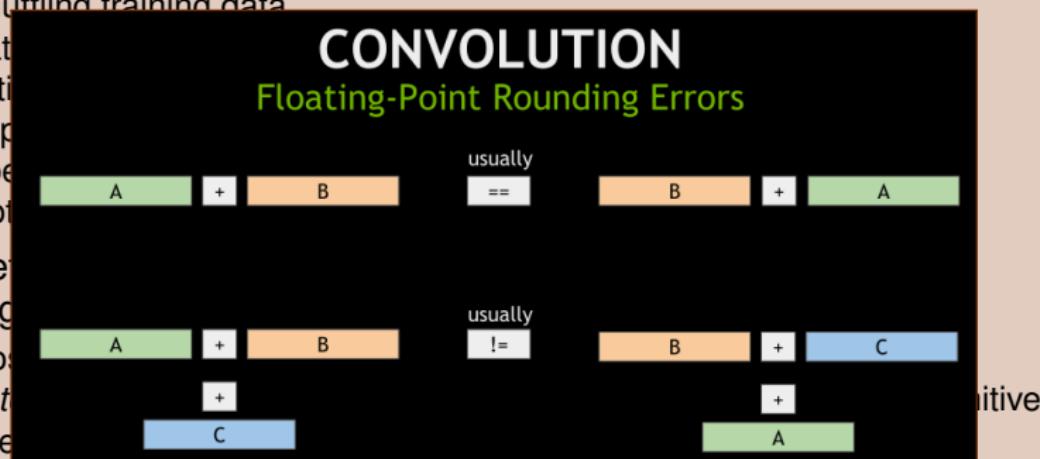
- NN training involves random draws at many stages:
 - Data augmentation [[SK19](#)]
 - Shuffling training data
 - Batch ordering at each epoch
 - Initialisation of the NN weights
 - Exploration noise during training (DRL)
 - Specific algorithm treatments: *dropout* [[Sri+14](#)]
 - Optimisation algorithms: *stochastic gradient* (adam)...
- Non-determinism in hardware operations
(floating-point ops are sensitive to computation order...)
 - Most of these cases occur on GPUs
 - auto-tuning:* libraries CUDA and cuDNN auto-select the optimal primitive operations at runtime \leadsto different ops may occur on subsequent run
 - Forcing deterministic ops possible but \sim slower computation 😊

Reproducibility - The DL context

2 main reasons why DL training is not reproducible

- NN training involves random draws at many stages:

- Data augmentation [SK19]
- Shuffling training data
- Batching
- Initialization
- Experiments
- Special cases
- Optimizations



- Forcing deterministic ops possible but ~ slower computation 😊

Reproducibility - The DL context

2 main reasons why DL training is not reproducible

- NN training involves random draws at many stages:
 - Data augmentation [SK19]
 - Shuffling training data
 - Batch ordering at each epoch
 - Initialisation of the NN weights
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Reproducibility - The DL context

Some practices to make DL reproducible

1/ set the **SEED** ↪ makes random generators reproducible

- tensorflow
- pytorch

[ten24a][ten24c][ten24b]

[Pyt24][PyT24]

Reproducibility - The DL context

Some practices to make DL reproducible

1/ set the **SEED** ↳ makes random generators reproducible

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[ten24a][ten24c][ten24b]

```
tf.keras.utils.set_random_seed(<SEED>) # sets Python, NumPy and TensorFlow seed
```

- pytorch

[Pyt24][PyT24]

Reproducibility - The DL context

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● tensorflow

[ten24a][ten24c][ten24b]

```
tf.keras.utils.set_random_seed(<SEED>) # sets Python, NumPy and TensorFlow seed
```

● pytorch

[Pyt24][PyT24]

```
import random
import numpy as np
import torch

random.seed(<SEED>)           # Sets the seed for Python built-in random module
np.random.seed(<SEED>)         # Sets the seed for NumPy random number generator

torch.manual_seed(<SEED>)      # Sets the seed for PyTorch CPU random number generator

torch.cuda.manual_seed(<SEED>)  # Sets the seed for the current GPU device
torch.cuda.manual_seed_all(<SEED>) # Sets the seed for all available GPU devices
```

Reproducibility - The DL context

Some practices to make DL reproducible

2/ Set the operations deterministic \rightsquigarrow makes GPU ops deterministic at the cost of performance

- tensorflow [ten24a][ten24c][ten24b]
- pytorch [Pyt24][PyT24]

Reproducibility - The DL context

Some practices to make DL reproducible

2/ Set the operations deterministic \rightsquigarrow makes GPU ops deterministic at the cost of performance

- tensorflow

[ten24a] [ten24c] [ten24b]

```
tf.config.experimental.enable_op_determinism()  
# this will make GPU ops as deterministic as possible,  
# but it will affect the overall performance
```

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[Pyt24] [PyT24]

Reproducibility - The DL context

Some practices to make DL reproducible

2/ Set the operations deterministic \rightsquigarrow makes GPU ops deterministic at the cost of performance

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tf.config.experimental.enable_op_determinism()  
# this will make GPU ops as deterministic as possible,  
# but it will affect the overall performance
```

- pytorch

[PyT24] [PyT24]

```
# try this:  
import torch.backends.cudnn  
torch.backends.cudnn.deterministic = True  
torch.backends.cudnn.benchmark = False
```

but it can be more tricky... seed [PyT24].

Reproducibility - Simple examples

Simple example: Dense NN to classify MNIST hand-written digits [GitHub](#)



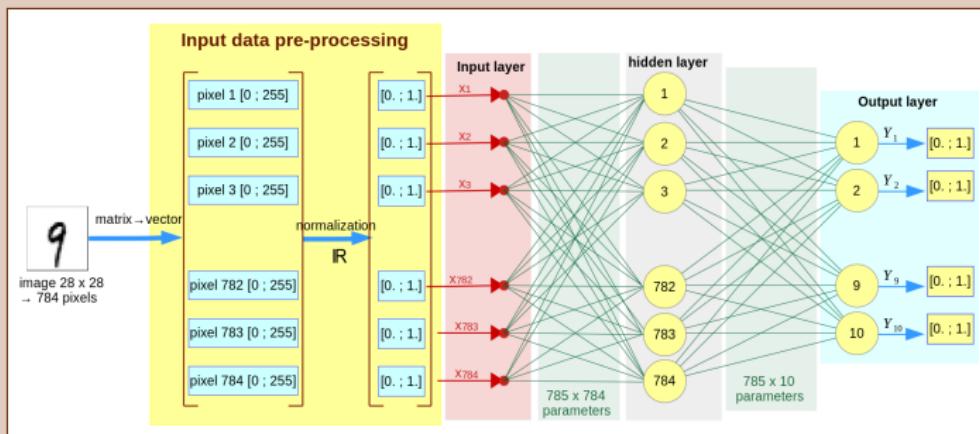
[MNIST dataset](#): 70 000 labeled grayscale images 28×28 pixels (60000 training, 10000 validation)

Reproducibility - Simple examples

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MNIST dataset: 70 000 labeled grayscale images 28×28 pixels (60000 training, 10000 validation)



Dense NN: 784 inputs, 1 hidden layer (784 neurones, *relu*), 1 output layer (10 neurones, *softmax*)

Reproducibility - Simple examples

Simple example: Dense NN

tensorflow/keras snippet to build the model:

```
def build_DNN(seed=None):
    if seed is not None:
        #####
        # Deterministic training #
        #####
        # 1/ sets the Python seed, the NumPy seed, and the TensorFlow seed:
        tf.keras.utils.set_random_seed(seed)

        # 2/ make the tf ops deterministic
        # this will make GPU ops as deterministic as possible, but it will affect
        # the overall performance:
        tf.config.experimental.enable_op_determinism()

    # 5 keras lines to build the dense network.
    model = Sequential()
    model.add(Input(shape=(NB_INPUT,), name='input'))                      # INPUT layer
    model.add(Dense(NB_NEURON, activation='relu', name='c1'))                 # First hidden layer
    model.add(Dense(NB_CLASS, activation='softmax', name='c2'))                # OUTPUT layer
    model.compile(loss='categorical_crossentropy',
                  optimizer='adam',
                  metrics=['accuracy'])
    return model
```

Reproducibility - Simple examples

Simple example: Dense NN **no seed fixed**

Simple experiment: write a loop where the model is built **without setting seed**, trained & evaluated once at each iteration (*epochs=1*) :

Reproducibility - Simple examples

Simple example: Dense NN **no seed fixed** \leadsto **not reproducible**

Simple experiment: write a loop where the model is built **without setting seed**, trained & evaluated once at each iteration (*epochs=1*) :

```
print(get_cpu_info()['brand_raw'])
for _ in range(5):
    model = build_DNN() # Build a new model without setting seed
    hist = model.fit(x_train, y_train, epochs=1, batch_size=16, validation_data=(x_valid, y_valid), verbose=2)

Intel(R) Xeon(R) W-1390P @ 3.50GHz
3750/3750 - 8s - 2ms/step - accuracy: 0.9448 - loss: 0.1822 - val_accuracy: 0.9582 - val_loss: 0.1349
3750/3750 - 8s - 2ms/step - accuracy: 0.9468 - loss: 0.1789 - val_accuracy: 0.9690 - val_loss: 0.0936
3750/3750 - 8s - 2ms/step - accuracy: 0.9459 - loss: 0.1800 - val_accuracy: 0.9754 - val_loss: 0.0798
3750/3750 - 8s - 2ms/step - accuracy: 0.9462 - loss: 0.1771 - val_accuracy: 0.9690 - val_loss: 0.1082
3750/3750 - 8s - 2ms/step - accuracy: 0.9469 - loss: 0.1777 - val_accuracy: 0.9698 - val_loss: 0.0956
```

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```

\leadsto Same behaviour on Google Collab platform (Xeon processor):

```
1 print(get_cpu_info()['brand_raw'])
2 for _ in range(5):
3     model = build_DNN() # Build a new model without setting seed
4     hist = model.fit(x_train[:1000], y_train[:1000], epochs=1, batch_size=16,
5                       validation_data=(x_valid[:200], y_valid[:200]), verbose=2)

Intel(R) Xeon(R) CPU @ 2.20GHz
63/63 - 2s - 27ms/step - accuracy: 0.7410 - loss: 0.8808 - val_accuracy: 0.8550 - val_loss: 0.5447
63/63 - 2s - 27ms/step - accuracy: 0.7470 - loss: 0.8468 - val_accuracy: 0.8150 - val_loss: 0.5601
63/63 - 2s - 34ms/step - accuracy: 0.7520 - loss: 0.8321 - val_accuracy: 0.8350 - val_loss: 0.5183
63/63 - 2s - 39ms/step - accuracy: 0.7490 - loss: 0.8592 - val_accuracy: 0.8600 - val_loss: 0.4838
63/63 - 2s - 28ms/step - accuracy: 0.7360 - loss: 0.8955 - val_accuracy: 0.8150 - val_loss: 0.5690
```

Reproducibility - Simple examples

Simple example: Dense NN **no seed fixed** \leadsto **not reproducible**

Non-reproducibility worsens if the dataset is reduced:

```
print(get_cpu_info()['brand_raw'])
for _ in range(5):
    model = build_DNN() # Build a new model without setting seed
    hist = model.fit(x_train[:1000], y_train[:1000], epochs=1, batch_size=16,
                      validation_data=(x_valid[:200], y_valid[:200]), verbose=2)

Intel(R) Xeon(R) W-1390P @ 3.50GHz
63/63 - 1s - 10ms/step - accuracy: 0.7490 - loss: 0.8607 - val_accuracy: 0.8300 - val_loss: 0.5360
63/63 - 1s - 10ms/step - accuracy: 0.7510 - loss: 0.8562 - val_accuracy: 0.8300 - val_loss: 0.5765
63/63 - 1s - 10ms/step - accuracy: 0.7490 - loss: 0.8049 - val_accuracy: 0.8600 - val_loss: 0.4851
63/63 - 1s - 9ms/step - accuracy: 0.7250 - loss: 0.8943 - val_accuracy: 0.8550 - val_loss: 0.4981
63/63 - 1s - 11ms/step - accuracy: 0.7500 - loss: 0.8424 - val_accuracy: 0.8300 - val_loss: 0.5456
```

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Reproducibility - Simple example

Simple example: Dense NN no seed fixed

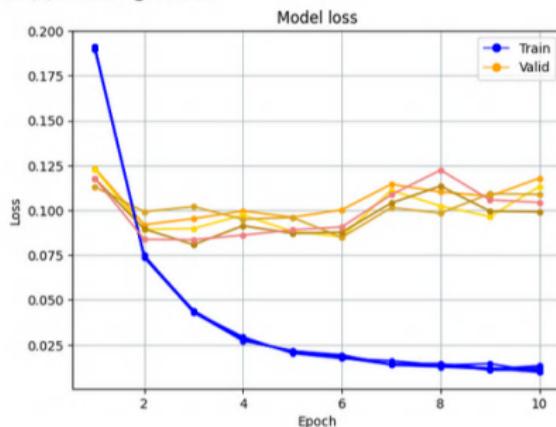
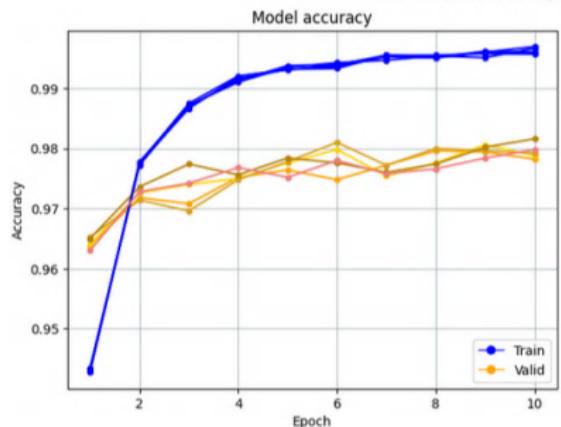
```
for i in range(5):
    model = build_DNN()                      # build a new mode without setting seed
    hist  = model.fit(x_train, y_train,          # images, labels
                       epochs=10,                 # the total number of successive trainings
                       batch_size=32,              # input images by batch of <batche_size> images
                       validation_data=(x_valid, y_valid), # validation after each epcoh
                       verbose=0)
```

Reproducibility - Simple example

Simple example: Dense NN no seed fixed \leadsto not reproducible

```
for i in range(5):
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Model trained on Intel(R) Xeon(R) W-1390P @ 3.50GHz

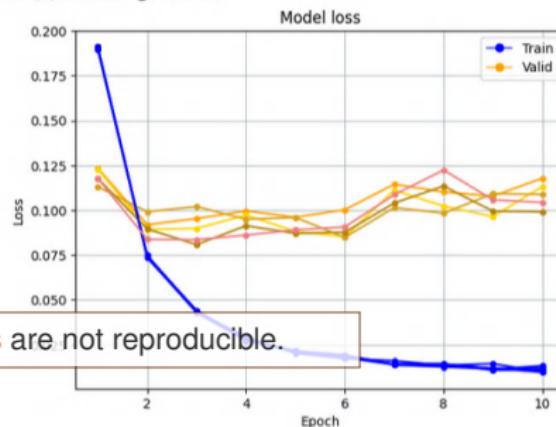
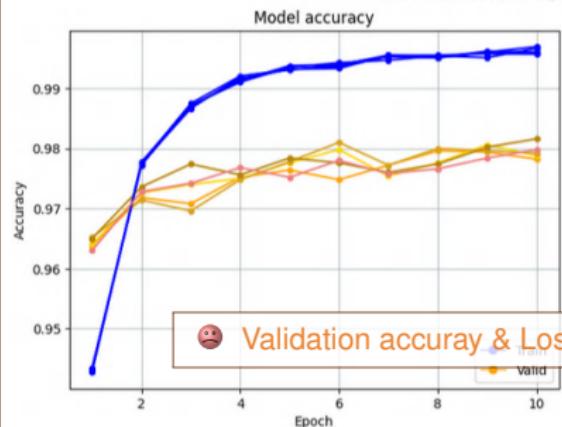


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for i in range(5):
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Model trained on Intel(R) Xeon(R) W-1390P @ 3.50GHz



Validation accuracy & Loss are not reproducible.

Reproducibility - Simple examples

Simple example: Dense NN **seed set** \leadsto reproducible

A model is built with **seed set** at each iteration:

```
print(get_cpu_info()['brand_raw'])
for _ in range(5):
    model = build_DNN(seed=1234) # Build a new model with seed set
    hist = model.fit(x_train, y_train, epochs=1, batch_size=16, validation_data=(x_valid, y_valid), verbose=2)

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```

Reproducibility - Simple examples

Simple example: reload model structure & weights \sim **reproducible**

The model built once with **seed set** is saved and then just re-loaded (structure & weights) at each iteration:

```
model = build_DNN(seed=1234)
model.save('models/DNN_relu_seed1234.keras')

print(get_cpu_info()['brand_raw'])
for _ in range(5):
    model = tf.keras.models.load_model('models/DNN_relu_seed1234.keras') # reload the model structure & weights
    hist = model.fit(x_train, y_train, epochs=1, batch_size=16, validation_data=(x_valid, y_valid), verbose=2)

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`print(get` \sim Same behaviour on Google Collab platform (Xeon processor):

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Reproducibility - Simple example

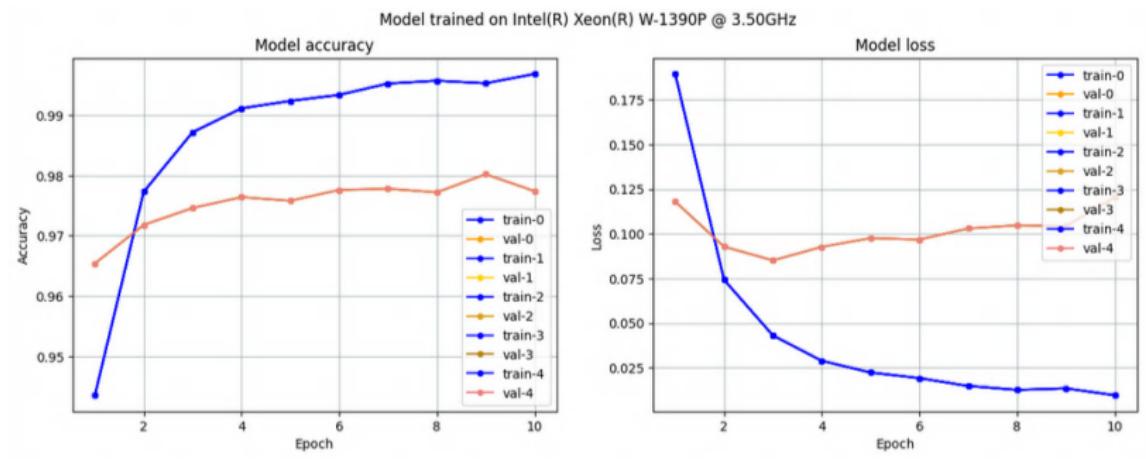
Simple example: Dense NN **seed fixed**

```
for i in range(5):
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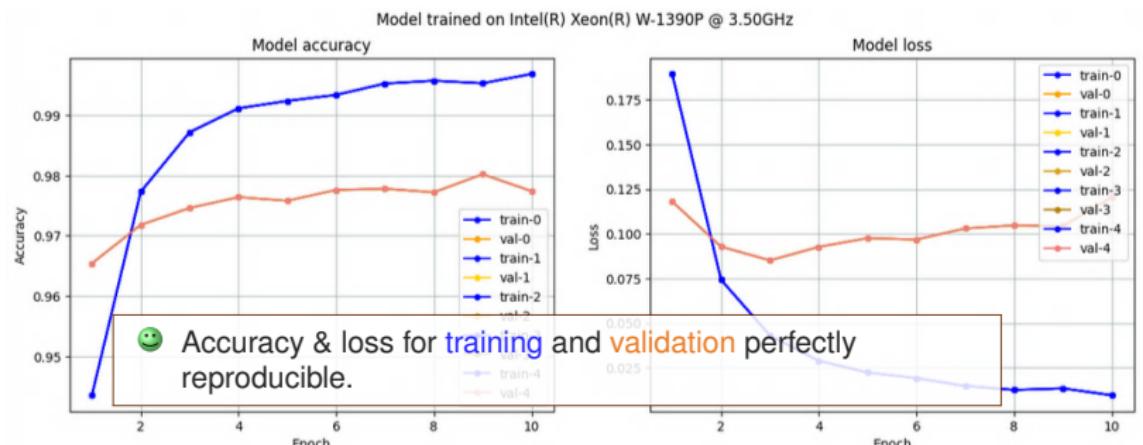
```
for i in range(5):
```



Reproducibility - Simple example

Simple example: Dense NN **seed fixed** \leadsto reproducible

```
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```

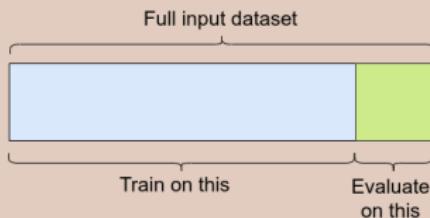


Training & Evaluation strategy

Validation techniques are essential for assessing how well a model generalizes to unseen data.

Split the input Dataset

Common practice: Simple hold-out validation split



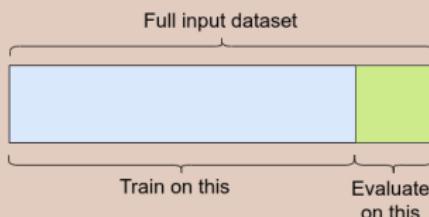
Input Dataset ~ **Train** and **Valid** (test) datasets

Training & Evaluation strategy

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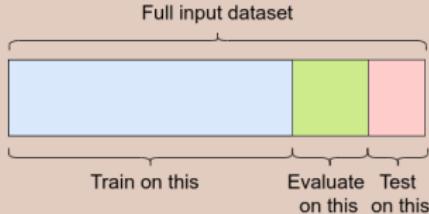
Split the input Dataset

Common practice: Simple hold-out validation split



Input Dataset \leadsto **Train** and **Valid** (test) datasets

State of the art: Train/Validation/Test



Input Dataset \leadsto **Train**, **Valid** and **test** datasets.

Training & Evaluation strategy

Split the input Dataset

Random Split: most used method
unless dealing with ordered data like time-series

- **Training Dataset**
- **Validation Dataset**
- **Test Dataset**

Training & Evaluation strategy

Split the input Dataset

Random Split: most used method
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- **Training Dataset** ~ to train the model
- **Validation Dataset**

- **Test Dataset**

Training & Evaluation strategy

Split the input Dataset

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- **Training Dataset** → to train the model
- **Validation Dataset** → to get unbiased evaluation (loss function...) of the model during training , used to tune:
 - **model hyper-parameters**: nb layers, nb neurons/layer, activation function/layer, optimisation algorithm...
 - **training hyper-parameters**: split ratio, batch size, nb epochs, learning rate
 - But training and validation dataset are known to the trained DL model
- **Test Dataset**

Training & Evaluation strategy

Split the input Dataset

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 - **training hyper-parameters**: split ratio, batch size, nb epochs, learning rate
 - But training and validation dataset are known to the trained DL model
- **Test Dataset** completely new to the model → to get performance of the trained model.

Training & Evaluation strategy

Split the input Dataset: different strategies

● Random Splitting

- Randomly shuffle dataset and assign samples to train, valid or test sets according to given ratios
- Supervised Learning ~ may not be indicated with *imbalanced dataset* (some classes have significantly fewer items than others)

● Stratified Splitting (Supervised Learning)

- The dataset is divided while preserving the relative proportions of each class across the subsets

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- The dataset is divided while preserving the relative proportions of each class across the subsets

Training & Evaluation strategy

Split the input Dataset: different strategies

● Random Splitting

- Randomly shuffle dataset and assign samples to train, valid or test sets according to given ratios
- Supervised Learning \leadsto may not be indicated with *imbalanced dataset* (some classes have significantly fewer items than others)

● Stratified Splitting (Supervised Learning)

- The dataset is divided while preserving the relative proportions of each class across the subsets
- For example : [scikit train_test_split](#) function \leadsto random & stratified split.

Training & Evaluation strategy

Split the input Dataset: strategies

- **K-fold Cross-Validation** K-Fold CV
- **Stratified K-Fold Cross-Validation**
- And yet other strategies depending on the dataset...

Training & Evaluation strategy

Split the input Dataset: strategies

● **K-fold Cross-Validation** K-Fold CV

- Recommended with small datasets
- One of the ways to reduce training overfit
- Shuffle then split the input dataset into K (often 10) partitions (*folds*)
- Loop over K :
 - fold $k \sim$ validation and the $k - 1$ remaining folds \sim training
 - At the end, compute average metrics (val loss, val accuracy...) over k

● **Stratified K-Fold Cross-Validation**

- And yet other strategies depending on the dataset...

Training & Evaluation strategy

Split the input Dataset: strategies

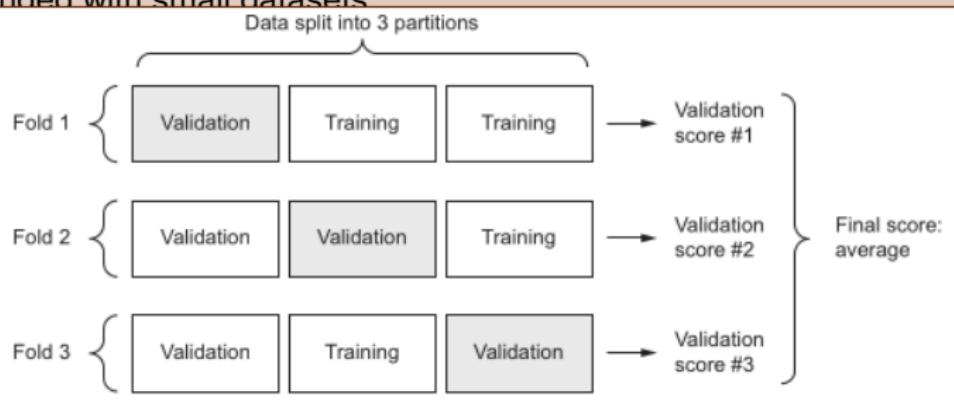
● K-fold Cross-Validation K-Fold CV

- Recommended with small datasets
- One of the
- Shuffle the
- Loop over fold k

At the end

● Stratified K-F

● And yet other



source: [Cho18] p. 99

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● **Stratified K-Fold Cross-Validation**

- K-Fold CV + stratifying \sim each fold has the same proportion of classes as the entire dataset.
- And yet other strategies depending on the dataset...

Training & Evaluation strategy

Split the input Dataset: strategies

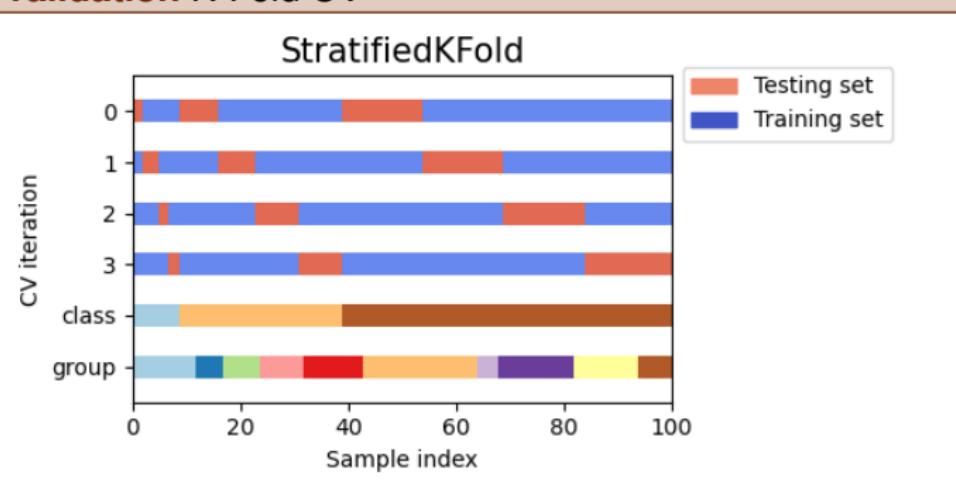
● K-fold Cross-Validation K-Fold CV

- Recommended
- One of the best
- Shuffle the data
- Loop over fold k
- At the end

● Stratified K-Fold CV

- K-Fold CV as the entire process

● And yet other



source: [scikit-learn Cross-validation pages](#)

Training & Evaluation strategy

Split the input Dataset: strategies

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● Stratified K-Fold Cross-Validation

- K-Fold CV + stratifying \sim each fold has the same proportion of classes as the entire dataset.
- And yet other strategies depending on the dataset...
 - Exple Python : **scikit** **KFold** function \sim random, stratified, grouped...

Training & Evaluation strategy

Split the input Dataset: strategies

● K-fold Cross-Validation K-Fold CV

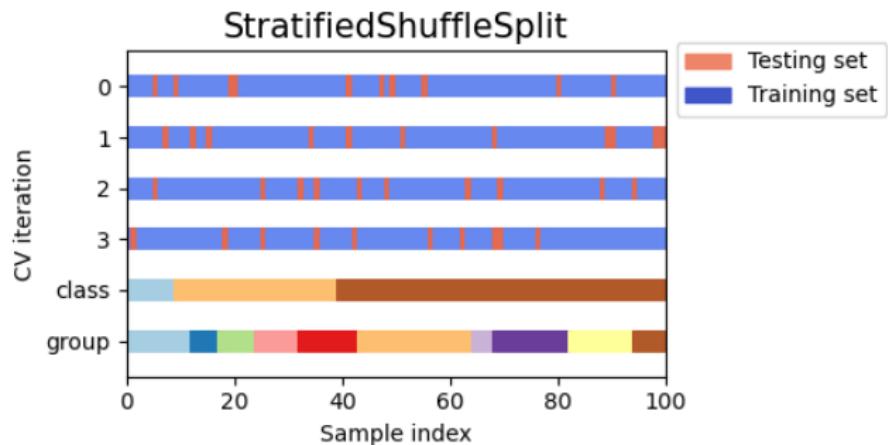
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- Exple Pyth



source: [Cho18] p. 99

Hyper parameters

The training Hyper-Parameters

- Have a determinant influence on:
 - the whole training process
 - the performance of the trained network
- Many hyper-parameters are involved in the training of a Neural Network
 - Some are *well known* and clearly visible in the computer code:
 - the `ratios` used to split the input Dataset into train/valid/test sets
 - `epochs` ~ the number of epochs
 - `batch_size` ~ the size of the mini-batch
 - `learning_rate` ~ the learning rate of the optimizer (SGD, ADAM...)
 - Some are less *highlighted* in published papers &tutos

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Hyper parameters

The training Hyper-Parameters

- Have a determinant influence on:

- the whole training process
- the performance of the learning network

- Many hyper-parameters in a Neural Network**

- Some are visible in the computer code:
- the **ratio** of training / validation data
- epoch** size
- batch** size
- learning rate** of the optimizer (SGD, ADAM...)
- Some are hidden papers &tutos

```
fit(
    x=None,
    y=None,
    batch_size=None,
    epochs=1,
    verbose='auto',
    callbacks=None,
    validation_split=0.0,
    validation_data=None,
    shuffle=True,
    class_weight=None,
    sample_weight=None,
    initial_epoch=0,
    steps_per_epoch=None,
    validation_steps=None,
    validation_batch_size=None,
    validation_freq=1
)
tensorflow model fit
```

well known

and in the training of a Neural

visible in the computer code:

Dataset into train/valid/test sets

mini-batch

size of the optimizer (SGD, ADAM...)

hidden papers &tutos

Hyper parameters

The training Hyper-Parameters

- Have a determinant influence on:
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 - the performance of the trained network

- Many hyper-parameters** involved in the training of a Neural Network

- Some are
 - the **rate**
 - epoch**
 - batch**
 - learning_rate**
- Some are

```
tf.keras.optimizers.Adam(
    learning_rate=0.001, well known
    beta_1=0.9,
    beta_2=0.999,
    epsilon=1e-07,
    amsgrad=False,
    weight_decay=None,
    clipnorm=None,
    clipvalue=None,
    global_clipnorm=None,
    use_ema=False,
    ema_momentum=0.99,
    ema_overwrite_frequency=None,
    loss_scale_factor=None,
    gradient_accumulation_steps=None,
    name='adam',
    **kwargs
)
```

tensorflow optimizers Adam

visible in the computer code:

Dataset into train/valid/test sets

mini-batch

type of the optimizer (SGD, ADAM...)

published papers &tutos

Hyper parameters

The training Hyper-Parameters

- Have a determinant influence on:
 - the whole training process
 - the performance of the trained network
- Many hyper-parameters are involved in the training of a Neural Network
 - Some are
 - the **rate**
 - **epoch**
 - **batch**
 - **learning_rate**
 - Some are

```
tf.keras.optimizers.SGD(  
    learning_rate=0.01, well known  
    momentum=0.0,  
    nesterov=False,  
    weight_decay=None,  
    clipnorm=None,  
    clipvalue=None,  
    global_clipnorm=None,  
    use_ema=False,  
    ema_momentum=0.99,  
    ema_overwrite_frequency=None,  
    loss_scale_factor=None,  
    gradient_accumulation_steps=None,  
    name='SGD',  
    **kwargs  
)
```

tensorflow optimizers SGD

visible in the computer code:

Dataset into train/valid/test sets

mini-batch

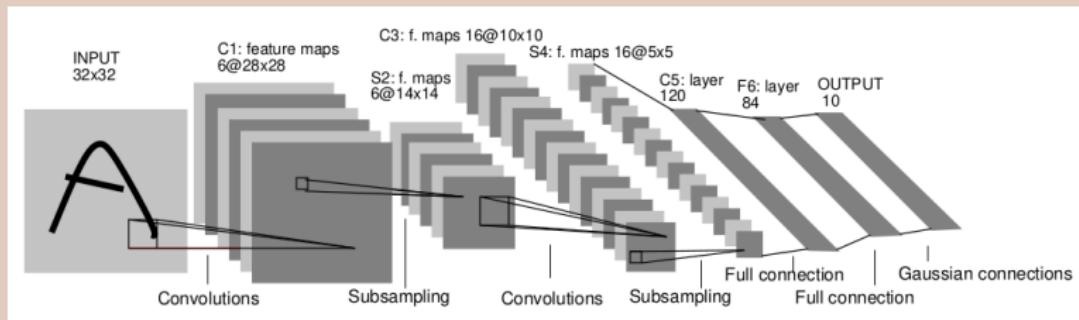
type of the optimizer (SGD, ADAM...)

published papers &tutos

Hyper parameters

The **batch_size** hyper-parameter

- Exemple: MNIST dataset, CNN model LeNet5 build with SEED set [GitHub]



LeNet5 from LeCun

Hyper parameters

The `batch_size` hyper-parameter

- Example: MNIST dataset, CNN model LeNet5 build with SEED set
- 6 trainings with `batch_size` in (16, 32, 64, 128, 256, 512, 1024)

Hyper parameters

The `batch_size` hyper-parameter

- Example: MNIST dataset, CNN model LeNet5 build with SEED set
- 6 trainings with `batch_size` in (16, 32, 64, 128, 256, 512, 1024)

tensorflow/keras snippet:

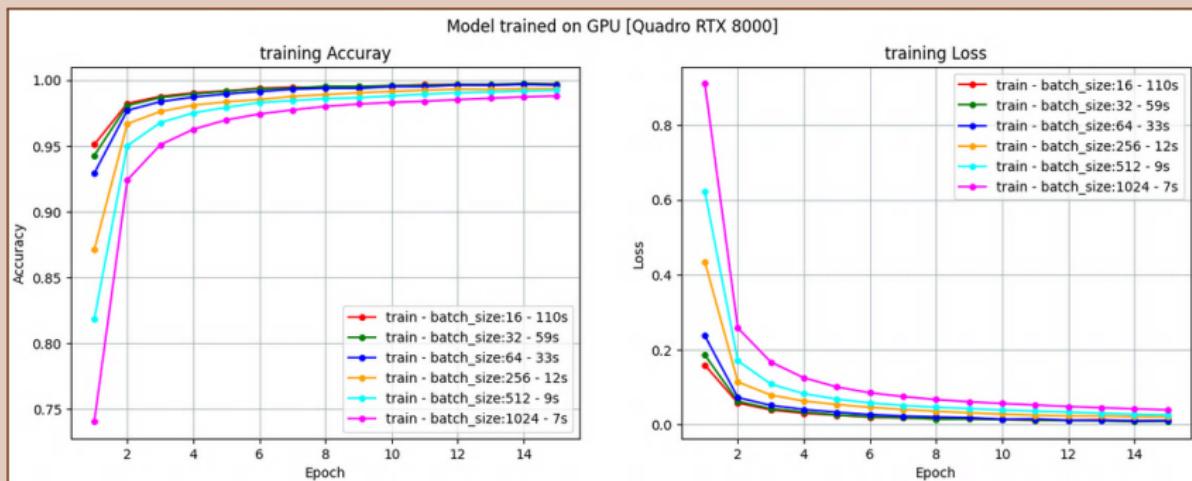
```
nb_epoch = 15
for bs in (16, 32, 64, 256, 512, 1024):
    print(f'batch_size={bs}, {SEED=}')

    ...
    # Build a new model at each lopp lap, with seed set:
    model = build_CNN(IM_SHAPE, seed=SEED)

    hist = model.fit(x_train, y_train, # images, labels
                      epochs=nb_epoch, # the total number of successive trainings
                      batch_size=bs,   # split the train dataset in multiple batches
                      validation_data=(x_valid, y_valid),
                      verbose=0)
    ...
```

Hyper parameters

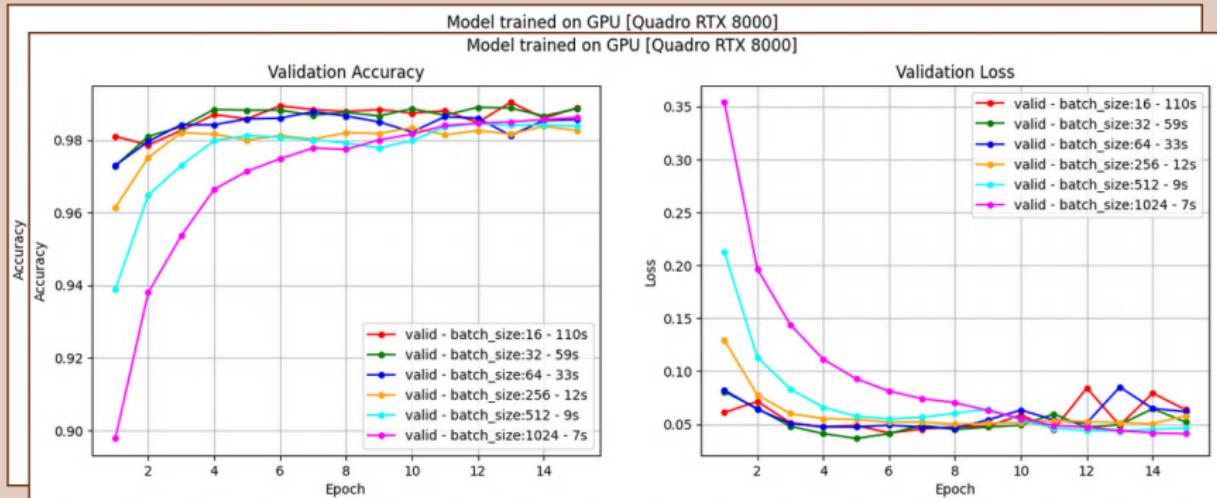
The **batch_size** hyper-parameter



- Training metrics (accuracy & loss) \leadsto right shape but not relevant.
- Validation metrics \leadsto interesting minimum loss for batch_size=32 at epoch=5

Hyper parameters

The **batch_size** hyper-parameter



- Training metrics (accuracy & loss) \leadsto right shape but not relevant.
- Validation metrics \leadsto interesting minimum loss for **batch_size**=32 at **epoch**=5

Hyper parameters

The **patience** hyper-parameter in the **EarlyStopping** algorithm

- Given the previous Validation Loss curves, it should be wise to stop the training for `batch_size=32` at `epoch=5` because the validation loss increases.
- `tensorflow` & `PyTorch` offer such mechanism known as **Early Stopping**

Hyper parameters

The **patience** hyper-parameter in the **EarlyStopping** algorithm

- Given the previous Validation Loss curves, it should be wise to stop the training for `batch_size=32` at `epoch=5` because the validation loss increases.
- `tensorflow` & `PyTorch` offer such mechanism known as **Early Stopping**

`tensorflow/keras` snippet: using `EarlyStopping` *callback* to stop the training

```
for bs in (16, 32, 64, 256, 512, 1024):
    ...
    # Build a new model at each lopp lap, with seed set:
    model = build_CNN(IM_SHAPE, seed=SEED)
    callbacks_list = [
        EarlyStopping(monitor='val_loss', # The parameter to monitor
                      patience=1,           # accept that 'val_loss' increases 1 time
                      restore_best_weights=True, # important !!!
                      verbose=1) ]
    hist = model.fit(x_train, y_train, # images, labels
                      epochs=nb_epoch, # the total number of successive trainings
                      batch_size=bs,   # split the train dataset in multiple batches
                      validation_data=(x_valid, y_valid),
                      verbose=0,
                      callbacks = callbacks_list)
```

Hyper parameters

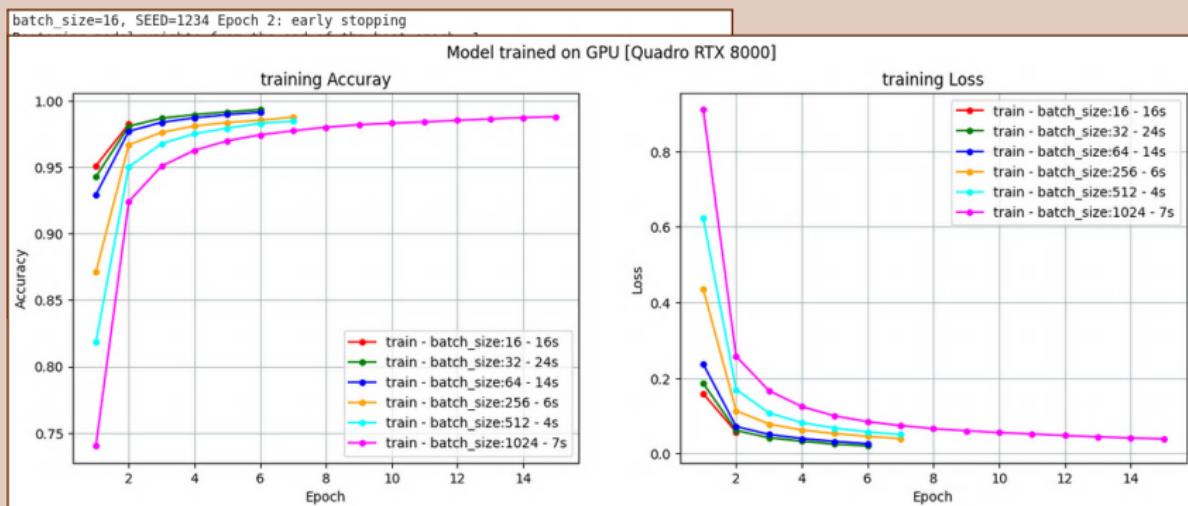
The **patience** hyper-parameter in the **EarlyStopping** algorithm

```
batch_size=16, SEED=1234 Epoch 2: early stopping
Restoring model weights from the end of the best epoch: 1.
Train Elapsed time 17s -> 00:00:17
batch_size=32, SEED=1234 Epoch 6: early stopping
Restoring model weights from the end of the best epoch: 5. ←
Train Elapsed time 27s -> 00:00:27
batch_size=64, SEED=1234 Epoch 6: early stopping
Restoring model weights from the end of the best epoch: 5.
Train Elapsed time 15s -> 00:00:15
batch_size=256, SEED=1234 Epoch 7: early stopping
Restoring model weights from the end of the best epoch: 6.
Train Elapsed time 6s -> 00:00:06
batch_size=512, SEED=1234 Epoch 7: early stopping
Restoring model weights from the end of the best epoch: 6.
Train Elapsed time 5s -> 00:00:05
batch_size=1024, SEED=1234 Restoring model weights from the end of the best epoch: 15.
Train Elapsed time 7s -> 00:00:07
```

- Training for **batch_size**=32 stopped at **epoch**=6 (model is saved for **epoch**=5)

Hyper parameters

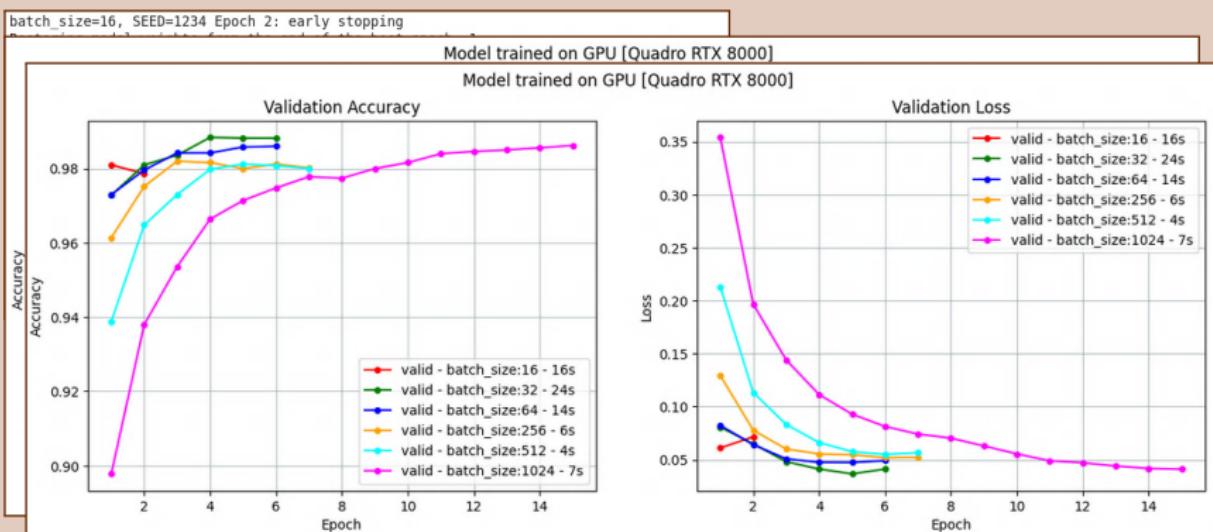
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Hyper parameters

The patience hyper-parameter in the EarlyStopping algorithm



- Training for `batch_size=32` stopped at `epoch=6` (model is saved for `epoch=5`)

Hyper parameters

The **patience** hyper-parameter in the **EarlyStopping** algorithm

```
batch_size: 16 time:16s test acc: 0.981 test_loss:0.064
batch_size: 32 time:25s test acc: 0.990 test loss:0.035
batch_size: 64 time:16s test_acc: 0.986 test_loss:0.044
batch_size: 256 time:6s test_acc: 0.983 test_loss:0.050
batch_size: 512 time:5s test_acc: 0.981 test_loss:0.054
batch_size:1024 time:7s test_acc: 0.987 test_loss:0.040
```

- The model performance for **batch_size**=32 at **epoch**=5 has the best score when tested with the **test Dataset**.
- The training elapsed time is now only 25 sec.
- The whole notebook is reproducible.

Hyper parameters

The **patience** hyper-parameter in the **EarlyStopping** algorithm

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Sharing reproducible DL training

Use a **Python Virtual Environment** (PVE)

- A PVE defines a dedicated file tree where to store the Python modules & tools of a DL project
- Ensures that different projects do not interfere with each other
- Isolate project dependencies
- Protects the Python modules from system updates or from modules updates in other projects
- Provides tools to easily delete/duplicate/reproduce it
- Allows efficient sharing
- Use a dedicated PVE for each DL project, even if small project

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Sharing reproducible DL training

Use a tool to manage your DL projects & PVEs

- Minimalist: `venv`, `virtualenv`...
- More efficient: `conda`, `poetry`...
- And more recently (more powerful) : `uv`

Sharing reproducible DL training

Use a tool to manage your DL projects & PVEs

- Minimalist: `venv`, `virtualenv`...
- More efficient: `conda`, `poetry`...
- And more recently (more powerful) : `uv`
 - From the Web page of `uv`:
 - A single tool to replace pip, pipx, poetry, pyenv, virtualenv...
 - 10-100x faster than pip !
 - Provides comprehensive project management, with a universal lockfile.
 - Installs and manages Python versions.
 - Includes a pip-compatible interface for a performance boost with a familiar CLI.
 - Disk-space efficient, with a global cache for dependency deduplication.
 - Supports macOS, Linux, and Windows....

Sharing reproducible DL training

Use an **Integrated Development Environment (IDE) aware of PVE**

- VSCode
- PyCharm
- Atom
- PyDev
- Jupyter notebook
- Jupyter Lab
- ...

Sharing reproducible DL training

Use a **versionning** tool

- To keep track of **code** and **data** versions
- To share **code** and **data**
- Example: **git** repository for code and data (< 5 GB)
 - Maintain the repository !
 - If your data files are too big, use the **Git Large File** (GLF) extension to version the data with Git.

Thank you for your attention.

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Deep Learning (DL)

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Reproducibility

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