

# Introduction Deep Learning Séquence 05a

Stratégies d'évaluation des modèles















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This session will be recorded. Find us on our YouTube channel:-)

https://fidle.cnrs.fr/youtube





# Introduction Deep Learning Séquence 05a

Stratégies d'évaluation des modèles













#### Resources

# https://fidle.cnrs.fr

Powered by CNRS CRIC, and UGA DGDSI of Grenoble, Thanks!



Course materials (pdf)



Practical work environment\*



Corrected notebooks



Videos (YouTube)



#### Resources

#### You can also subscribe to:





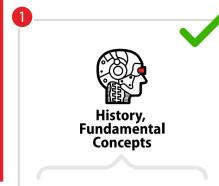
https://listes.services.cnrs.fr/wws/info/devlog1

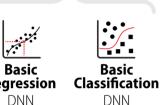


https://listes.math.cnrs.fr/wws/info/calcul<sup>2</sup>

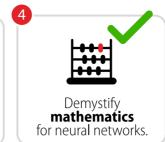
(1) List of ESR\* developers,

(2) List of ESR\* « calcul » group Where ESR is Enseignement Supérieur et Recherche, french universities and public academic research organizations





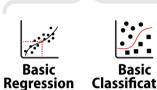












DNN

































### Roadmap







### Training strategies



- 5.1 Training strategies
  - → Basic learning process and bias
  - → Hold-out evaluation
  - → K-fold evaluation

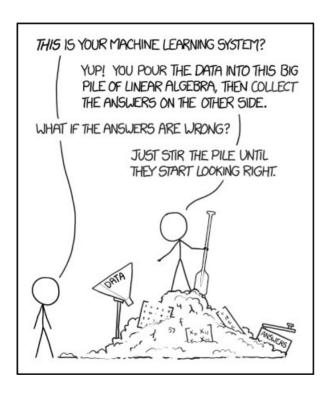
- 5.2 Finding the right metric
  - → Implementation of a simple case

# Training strategies



- 5.1 Training strategies
  - → Basic learning process and bias
  - → Hold-out evaluation
  - → K-fold evaluation

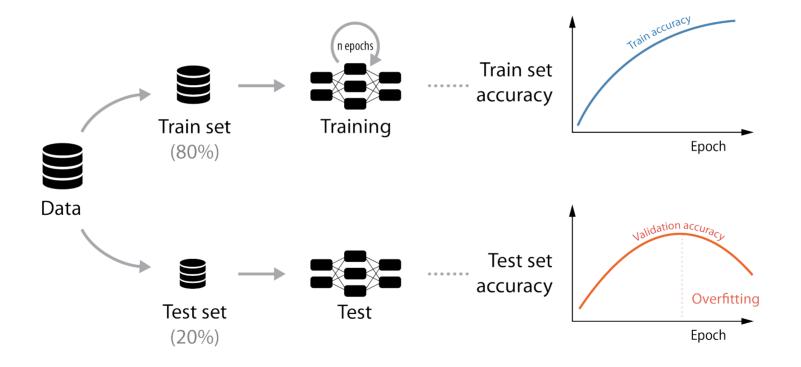
- 522 Finding the right metric
  - → Implementation of a simple case



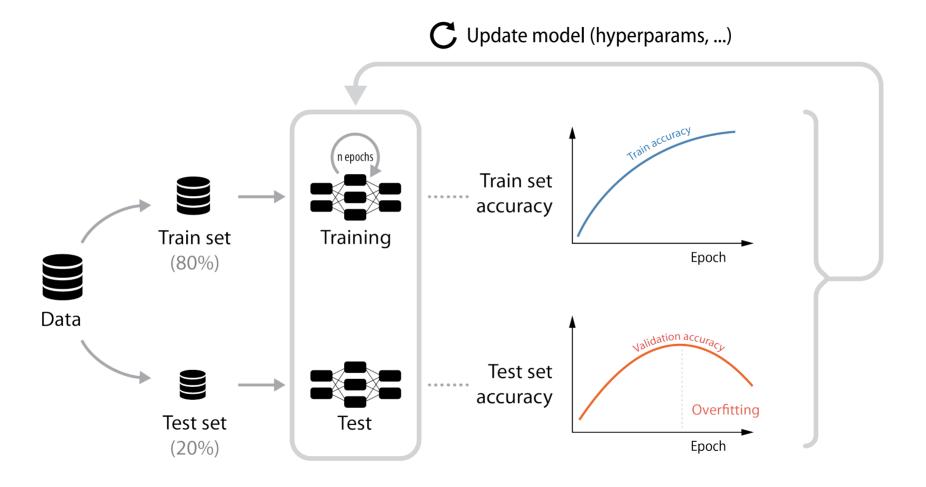
# Learning is not so easy!

https://imgs.xkcd.com/comics/machine\_learning.png

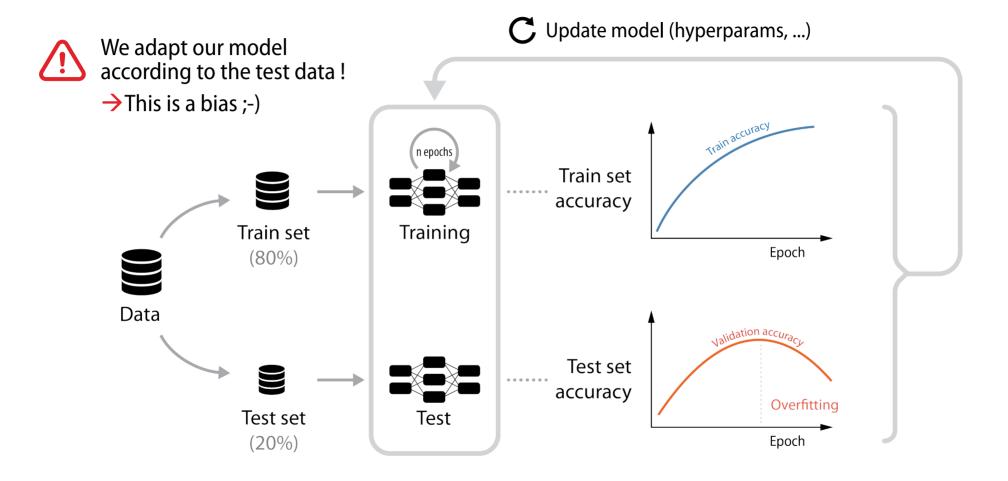
# Basic learning process



### Basic learning process

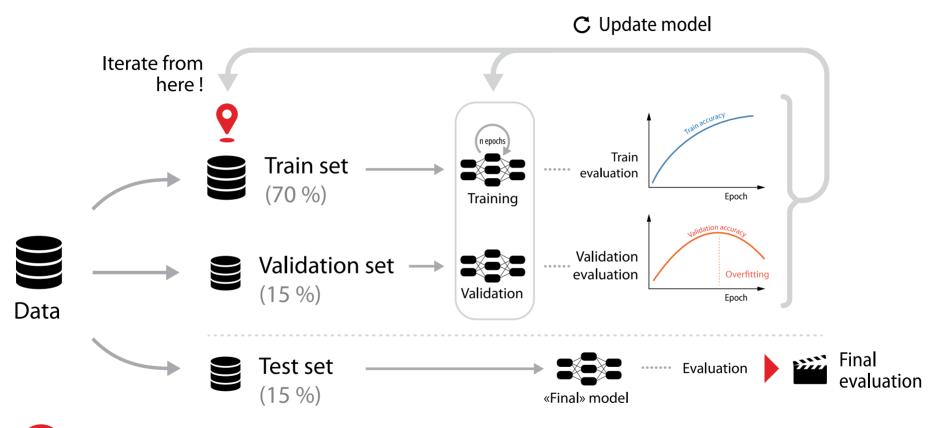


### Basic learning process



#### Hold-out evaluation

Validation simple

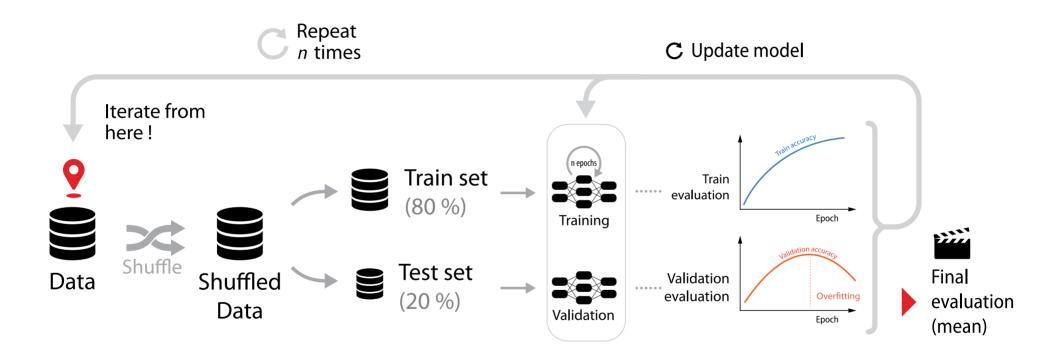


Suitable for large datasets, allowing for large Validation and Test sets.

If the Validation/Test sets are too small, the final evaluation will be statistically unstable.

#### Iterative hold-out evaluation with shuffling

Validation simple, itérative avec brassage des données



Suitable for medium sized datasets: generating a shuffled dataset can be expensive...
The number of iterations depends on the data.

#### K-fold cross validation

Validation croisée

#### K-Fold / Cross validation Fold #1: Evaluation #1 train train test Final Fold #2: Evaluation #2 evaluation train train test Data (mean) Fold #3: Evaluation #3 train train

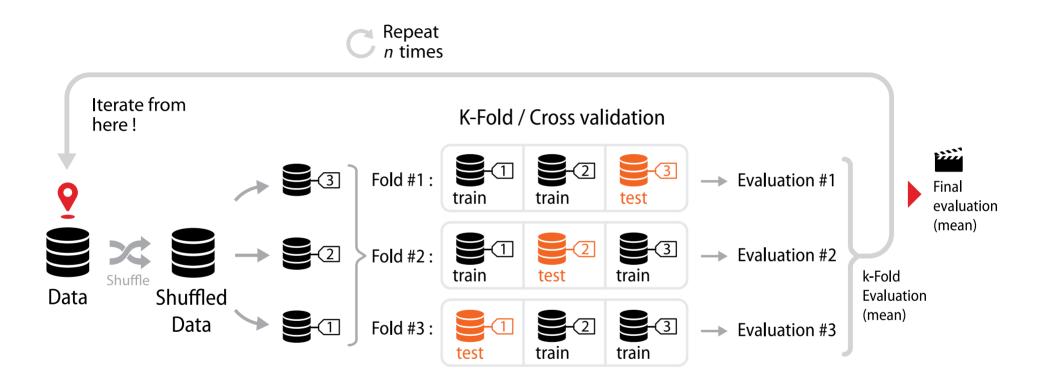
In this example, k=3 In practice, we will rather use a k=5, k=8, ...

Very interesting strategy for small datasets.

If the amount of data is small, however, the result can remain unstable...

#### Iterated K-fold cross validation with shuffling

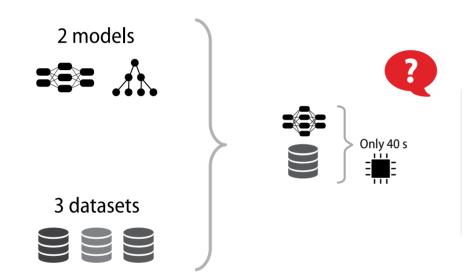
Validation croisée, itérative avec brassage des données



Probably the best strategy for small datasets...

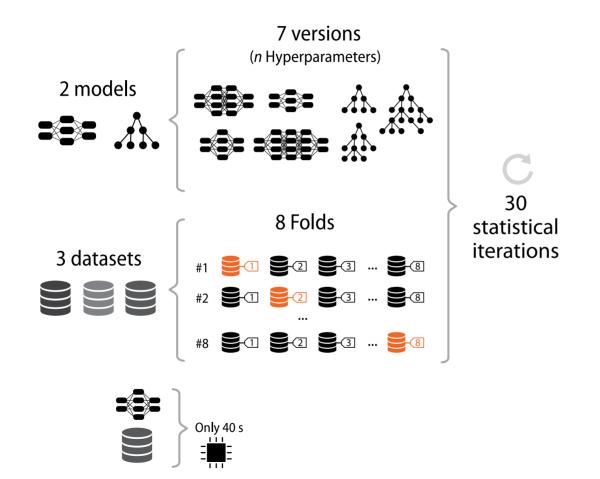
...but if K and n are important, the combination can become very expensive!

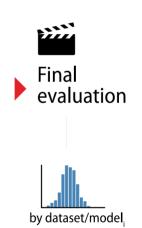
#### Be careful with combinatories ;-)



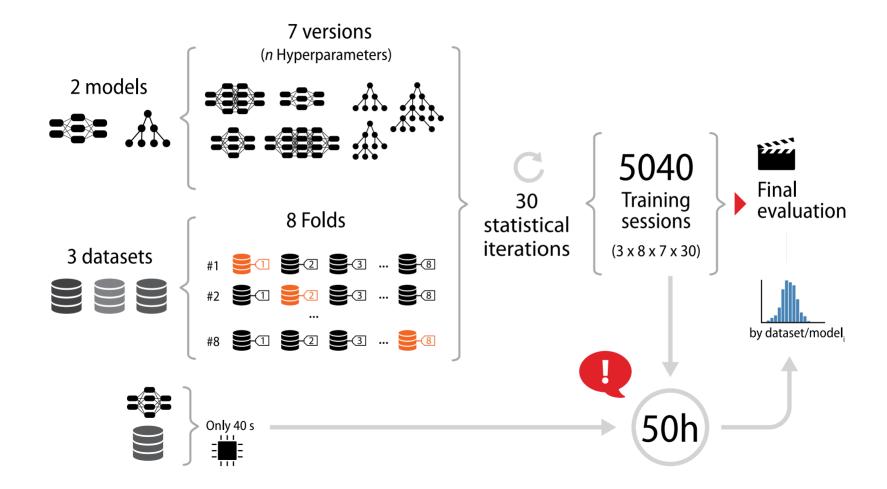
Which model is the best?
Which hyperparameters should I use?
Which dataset is the most usable?
Are my results significant?

#### Be careful with combinatories ;-)





#### Be careful with combinatories ;-)



# A few questions to keep in mind!



Are my data subsets (train, test, ...) representative of my data?

Can I or should I shuffle my data? (time sequences, ordered data, ...)

Within the dataset, what is the share and impact of outliers?

Mes résultats sont-ils significatifs?

How many folds, how many iterations do I need?

How much data do I need?

How much will it cost?



# Training strategies



- 5.1 Training strategies
  - → Basic learning process and bias
  - → Hold-out evaluation
  - → K-fold evaluation

- 5.2 Finding the right metric
  - → Implementation of a simple case

TYPE I ERROR: FALSE POSITIVE

TYPE II ERROR: FALSE NEGATIVE

TYPE III ERROR: TRUE POSITIVE FOR

INCORRECT REASONS

TYPE IV ERROR: TRUE NEGATIVE FOR

INCORRECT REASONS

TYPE I ERROR: INCORRECT RESULT WHICH

LEADS YOU TO A CORRECT

CONCLUSION DUE TO UNRELATED ERRORS

TYPE I ERROR: CORRECT RESULT WHICH

YOU INTERPRET WRONG

TYPE VII ERROR: INCORRECT RESULT WHICH

PRODUCES A COOL GRAPH

TYPE VIII ERROR: INCORRECT RESULT WHICH

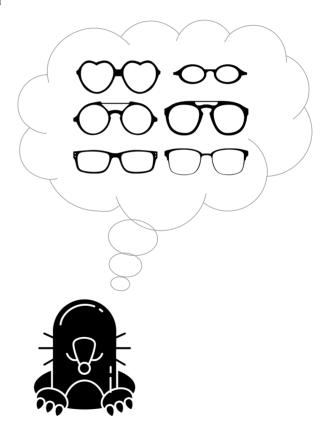
SPARKS FURTHER RESEARCH AND THE DEVELOPMENT OF NEW TOOLS WHICH REVEAL THE FLAW IN THE ORIGINAL

RESULT WHILE PRODUCING

NOVEL CORRECT RESULTS

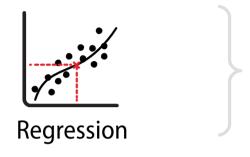
TYPE IX ERROR: THE RISE OF SKYWALKER

Evaluating a result is not easy!





#### Finding the right metric?



We try to predict a quantity (scalar, vector, ...)

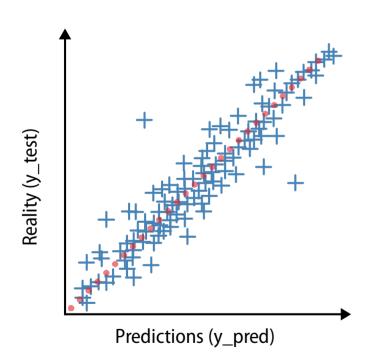
→ Is my predicted value "good"?



We try to predict a quality (class membership, ...)

→ Is my prediction "correct"?

#### **Evaluation of a regression**



MSE = 
$$\frac{1}{n} \sum_{i=1}^{n} \left[ \hat{y}^{(i)} - y^{(i)} \right]^{2}$$

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

MAE = 
$$\frac{1}{n} \sum_{i=1}^{n} |\hat{y}^{(i)} - y^{(i)}|$$

$$\mathsf{MAPE} = \frac{1}{n} \sum_{i=0}^{n} \frac{|y_i - \hat{y}_i|}{max(\epsilon, |y_i|)}$$

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (y_{i} - \hat{y_{i}})^{2}}{\sum_{i=1}^{n} (y_{i} - \bar{y})^{2}}$$

# Mean Squared Error Differentiable

Can be use as lost function Increases very quickly

#### **Root Mean Squared Error**

Same unit as *y*Robust to outliers
Humans understandable

#### Mean absolute error

Same unit as *y*More robust to outliers
Humans understandable

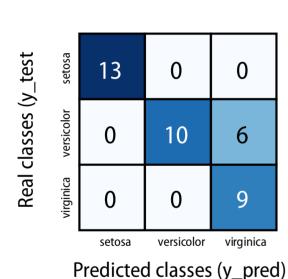
#### Mean Absolute Percentage Error

Humans understandable (%)
Problem when *y* is null!

# R<sup>2</sup> score, coefficient of determination Result in [0, 1]

Measures a correlation between 2 series, nothing else..

#### Evaluation of a classification



$$accuracy = \frac{Total\ number\ of\ correct\ predictions}{Total\ number\ of\ prédictions}$$

Ability to make correct predictions

« exactitude » en fr

 $HammingLoss = \frac{Total number of wrong predictions}{Total number of prédictions}$ 

Ability to make wrong predictions

 $precision_{class i} = \frac{Number of correct predictions for class i}{Total number of predictions for class i}$ 

Ability to identify without error, the elements of the class i

 $recall_{class\,i} = \frac{Number\ of\ correct\ predictions\ for\ class\ i}{Total\ number\ of\ real\ class\ i}$ 

Ability to identify all the elements of the class i

«sensibilité» en fr

F1 is the harmonic mean of the model's precision and recall.

$$F1_{classi} = 2 * \frac{recall_{classi} \cdot precision_{classi}}{recall_{classi} + precision_{classi}}$$

#### Next, on Fidle:



#### Jeudi 15 décembre

Séquence 5b:

Données creuses/textuelles de dimensions variables

Spécificités et gestion des données creuses/textuelles Principes de l'Embedding (Keras, CBOW, Skip-Gram) ...ou comment réduire les dimensions!

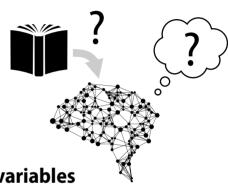
Exemple proposé:

Analyse de sentiment avec une analyse de critique de films.









#### Next on Fidle:



#### Jeudi 15 décembre, 14h00

Séquence 5b:

Données creuses/textuelles de dimensions variables



To be continued...





