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M2 SIF - DLV

Deep Learning for Vision

Elisa Fromont – Denis Coquenet

UMR IRISA

Who are we?

- Elisa Fromont is professor at Université de Rennes (ISTIC). She works at the IRISA/INRIA Lab in the LACODAM (“Large Scale Collaborative Data Mining”) team.
- Research domain (AI)
  - XAI
  - Machine Learning/Data Mining applied to
    - computer vision,
    - time series analysis,
    - fraud and anomaly detection
- Mail : elisa.fromont@irisa.fr

- Denis Coquenet is associate professor at Université de Rennes (ISTIC). He works at IRISA in the SHADOC team.
- Research domain (AI)
  - Document Analysis
  - Computer vision
- Mail : denis.coquenet@irisa.fr

How will I be graded?

- Final exam 1h30 (E.g. 19/01/2024 at 11h30). Exercises similar to the ones seen during the lectures.

- Oral presentation 15’ (E.g. 17/01/2024 at 16h45). In the last session. A little manipulation of a deep neural network (group of 3 persons). You will be provided with a learned model (Pytorch code) and expected to :
  - Explain/show (10’) to the class, the main parts of the code
  - Test it (5’) on new examples (that you will provide) online in class

  10 pts: you have managed to use the model (install the necessary environment and run it).
  6 pts: your 15’ explanations are clear.

  4 pts: *bonus* if you managed to do additional tasks. E.g. propose another model for the same task, re-train the model on other data, change the output classes, combine it with something else, …..

Which projects?

1) Classification / Vision Transformer / ImageNet

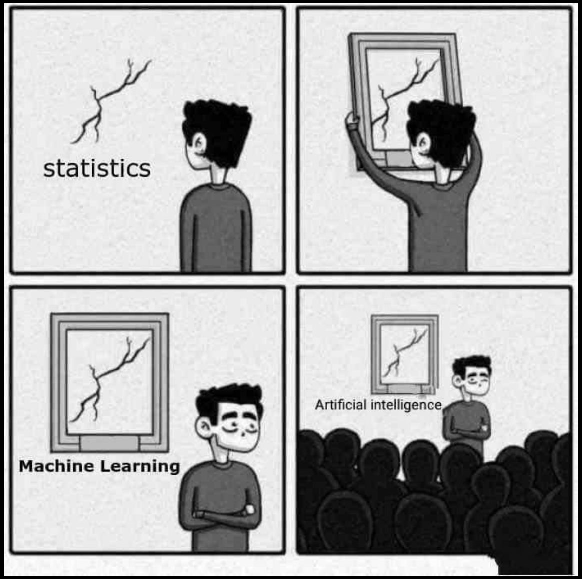
2) Object detection / SSD / COCO

3) Segmentation / FCN / Pascal VOC

4) Text line recognition / FCN / IAM

Each group needs to register now (3 persons per group) on the file indicated here :
https://people.irisa.fr/Denis.Coquenet/courses/DLV.html

Outline



21h 2 parts

Part 1 (7h30)

- Intro ML and main computer vision (learning) problems (1h30)
- NN learning bases (4h00)
  - Perceptron, MLP, Backprop, learning tricks
- Deep learning Basis (2h)
  - Convolutional Neural Networks (CNN)
  - Recurrent Neural Networks (LSTM, GRU)
  - Seq2Seq (CNN + LSTM)

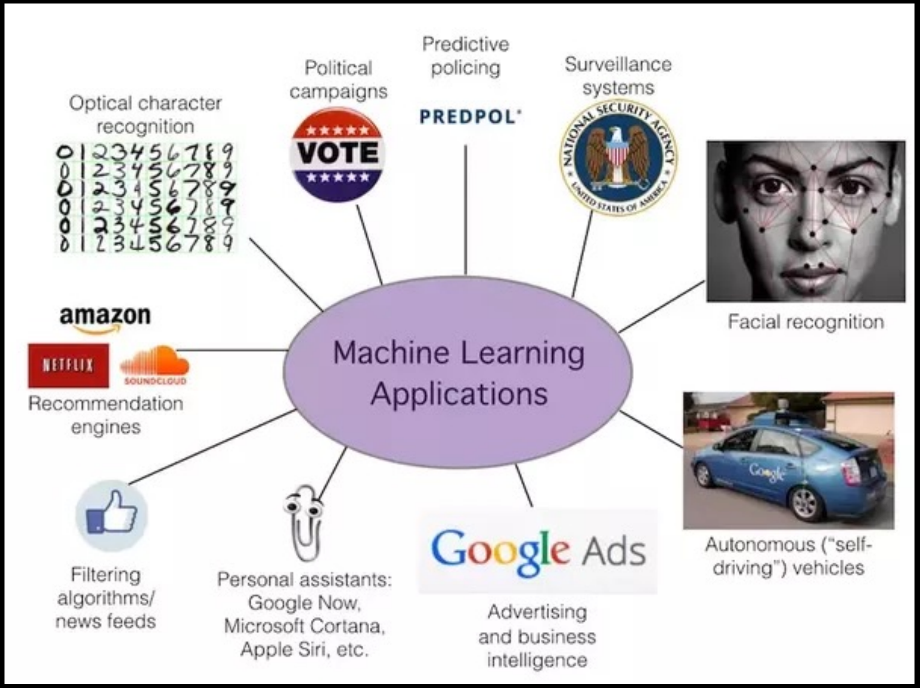
Part 2 (12h00)

- Vision architectures for feature extraction (VGG, Resnet, Vision Transformer) : 3h00
- Object detection dedicated architectures (YOLO, RCNN) : 1h30
- Semantic segmentation architectures (FCN, U-Net, …) : 1h30
- Generative models for vision : 3h
  - GAN & VAE for vision
  - Diffusion Models
- Application (Handwriting recognition) : 1h30

- Oral Presentations : 1h30 (practical session)

Machine Learning?

Machine learning is a sub-field of AI that explores the construction and study of algorithms that enable machines to learn and acquire knowledge from past **data**.



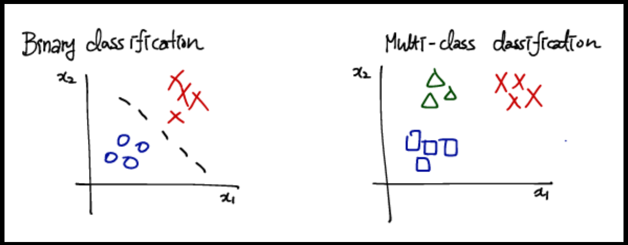
Cf. SML in M2 SIF

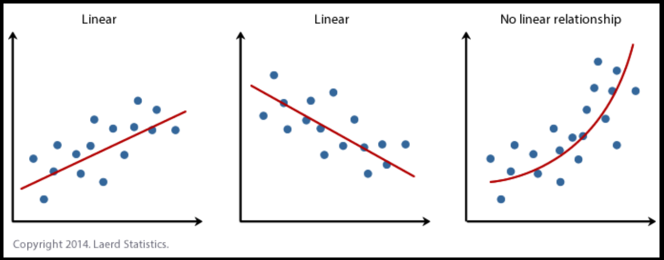
Machine Learning Settings

1. Supervised learning

(classification, regression)

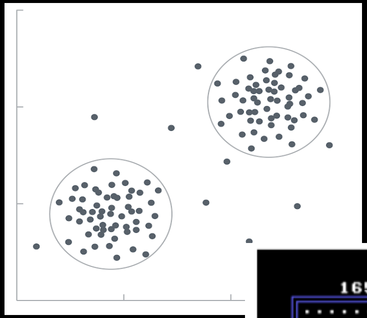
Given a dataset (« training data ») S = $\{(\boldsymbol{x}_i, \boldsymbol{y}_i) | i = 1..n\}$, find a model **h such that**, for any new example **x** (« test data »), we can predict **y** (h(x) = y)





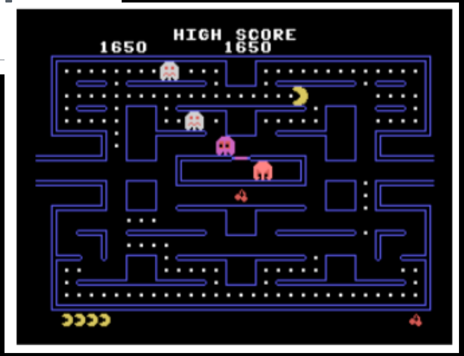
2. Unsupervised learning

Automatically find relevant (to be defined) structural information in the data $\{\boldsymbol{x}_i | i = 1..n\}$

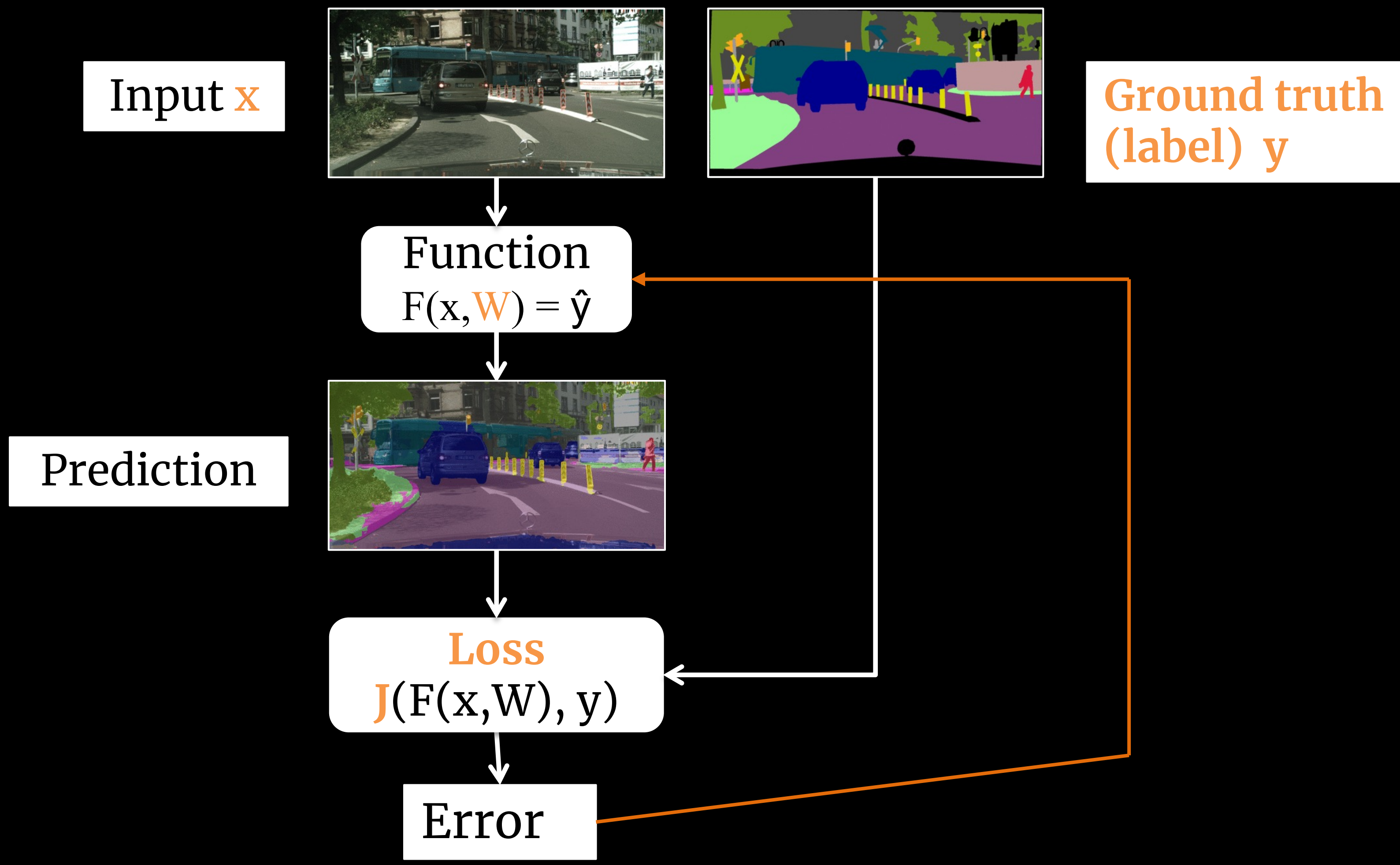


3. Reinforcement learning

Learn from experience what actions to take to optimize a quantitative reward over time

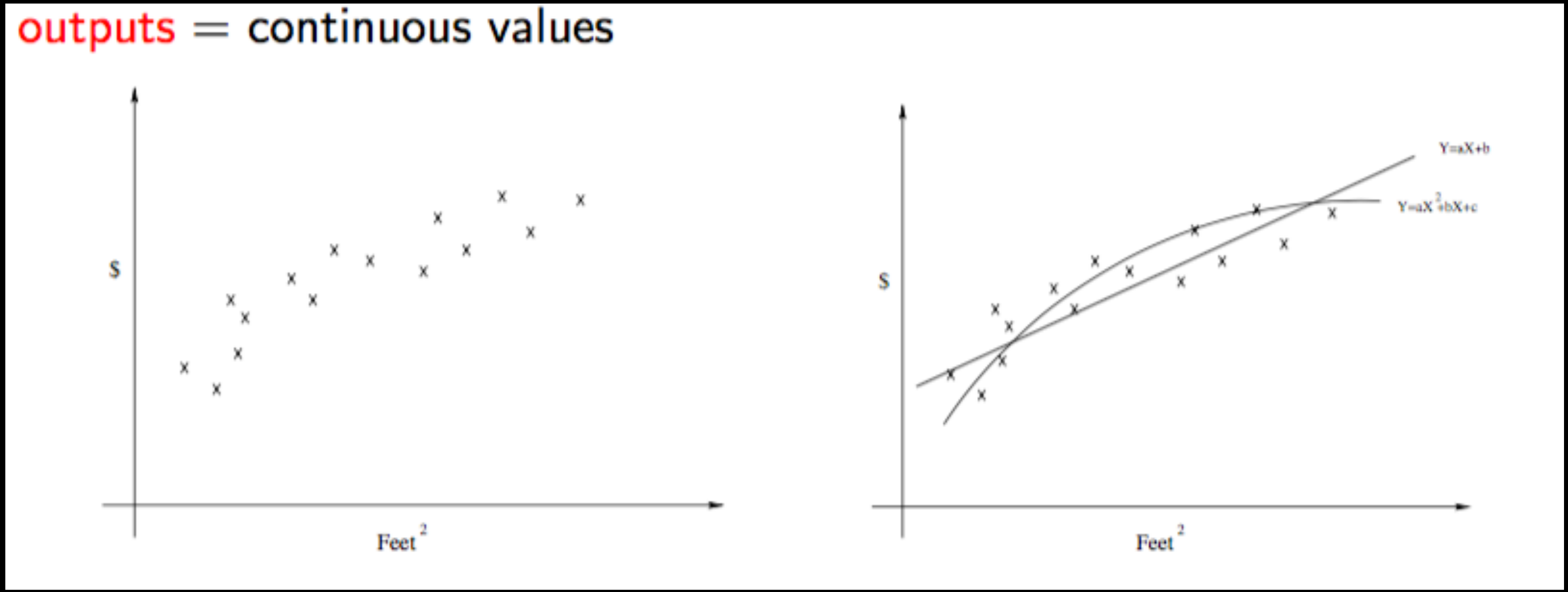


Supervised Machine Learning 101



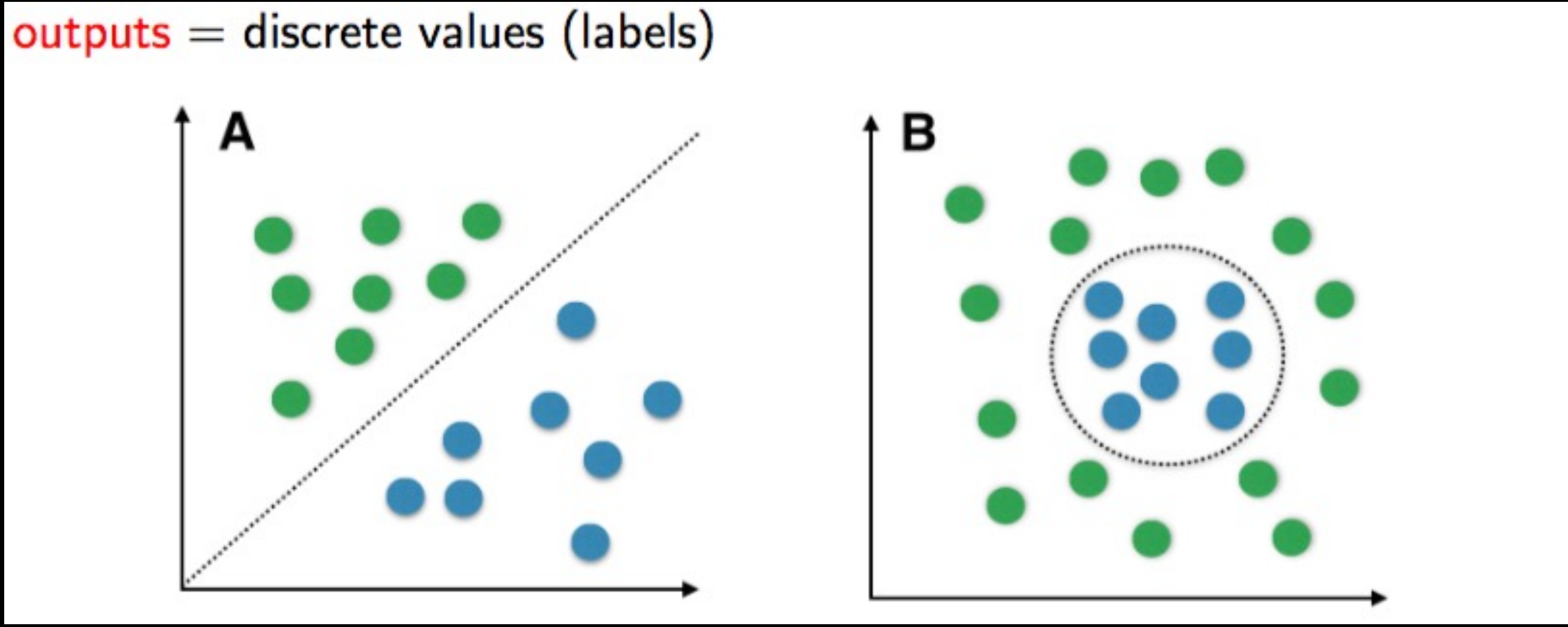
Supervised Learning: **Regression**

The computer has access to training input examples and their desired outputs, given by a teacher or an oracle. The aim is to learn a general rule that maps inputs to outputs. Once learned, the rule can be deployed on test data.



Supervised Learning: Classification

The computer has access to training input examples and their desired outputs, given by a teacher or an oracle. The aim is to learn a general rule that maps inputs to outputs. Once learned, the rule can be deployed on test data.



Supervised learning algorithm

Let S be a set of m training examples $\{z_i = (\boldsymbol{x_i}, y_i)\}_{i=1}^{m}$ independently and identically (i.i.d.) from an unknown joint distribution $D_{\mathcal{Z}}$ over a space $\mathcal{Z} = \mathcal{X} \times \mathcal{Y}$.

1. The x_i values ($\boldsymbol{x_i} \in X$) are typically vectors of the form $< x_{i1}, ..., x_{id} >$, whose components are usually called features.
2. The y values ($y \in Y$) are drawn from a discrete set of classes (typically $Y = \{-1, +1\}$ in binary classification) or are continuous values (regression).
3. We assume that there exists a target function f such that $y = f(\boldsymbol{x})$, $(\boldsymbol{x}, y) \in \mathcal{Z}$.

True Risk (Generalization Error)

In order to pick the best hypothesis h*, we need a criterion to assess the quality of any hypothesis h.

The true risk $\mathcal{R}(h)$ (also called **generalization error**) of a hypothesis h corresponds to the expected error made by h over the entire distribution $D_{\mathcal{Z}}$:

$$\mathcal{R}(h) = \mathbb{E}_{z=(x,y)\sim D_{\mathcal{Z}}} \mathbb{1}_{y \neq h(x)}$$

where $z \sim D_{\mathcal{Z}}$ denotes that z is drawn i.i.d. from $D_{\mathcal{Z}}$.

The goal of supervised learning then becomes **finding a hypothesis h that achieves the smallest true risk**.

Empirical Risk (~ Training Error)

Unfortunately, R(h) cannot be computed because D_Z is unknown. We can only measure it on the training sample S. This is called the **empirical risk.**

Let $S = \{z_i = (\mathbf{x_i}, y_i)\}_{i=1}^{m}$ be a training sample. The empirical risk $\hat{\mathcal{R}}(h)$ (also called empirical error) of a hypothesis $h \in H$ corresponds to the **expected error** suffered by h on the instances in S.

$$\hat{\mathcal{R}}(h) = \mathbb{E}_{\{z_i=(\mathbf{x_i},y_i)\}_{i=1}^{m}} \mathbb{1}_{y \neq h(x)}$$

0/1 Loss or Classification Error

A loss function L : H × Z → R+ measures the degree of agreement between h(x) and y.

$$\mathcal{L}(h(\boldsymbol{x}), y) = \mathbb{1}_{y \neq h(\boldsymbol{x})}$$

corresponds to the proportion of time $h(\boldsymbol{x})$ and y agree, i.e. the proportion of correct predictions.

In binary classification,

$$\mathcal{L}(h(\boldsymbol{x}), y) = \begin{cases} 1 & \textit{if } h(\boldsymbol{x})y < 0 \\ 0 & \textit{otherwise} \end{cases}$$

Surrogate Losses
(Convex Approximations of the 0/1 loss)

Due to the non convexity of the 0/1 loss, minimizing (or approximately minimizing) R(h) is known to be NP-hard even for simple classes of hypotheses (Ben-David et al., 2003).

- the **hinge loss** (used in SVM):

$$\mathcal{L}_{hinge}(h(\boldsymbol{x}), y) = [1 - yh(\boldsymbol{x})]_+ = \max(0, 1 - yh(\boldsymbol{x}))$$

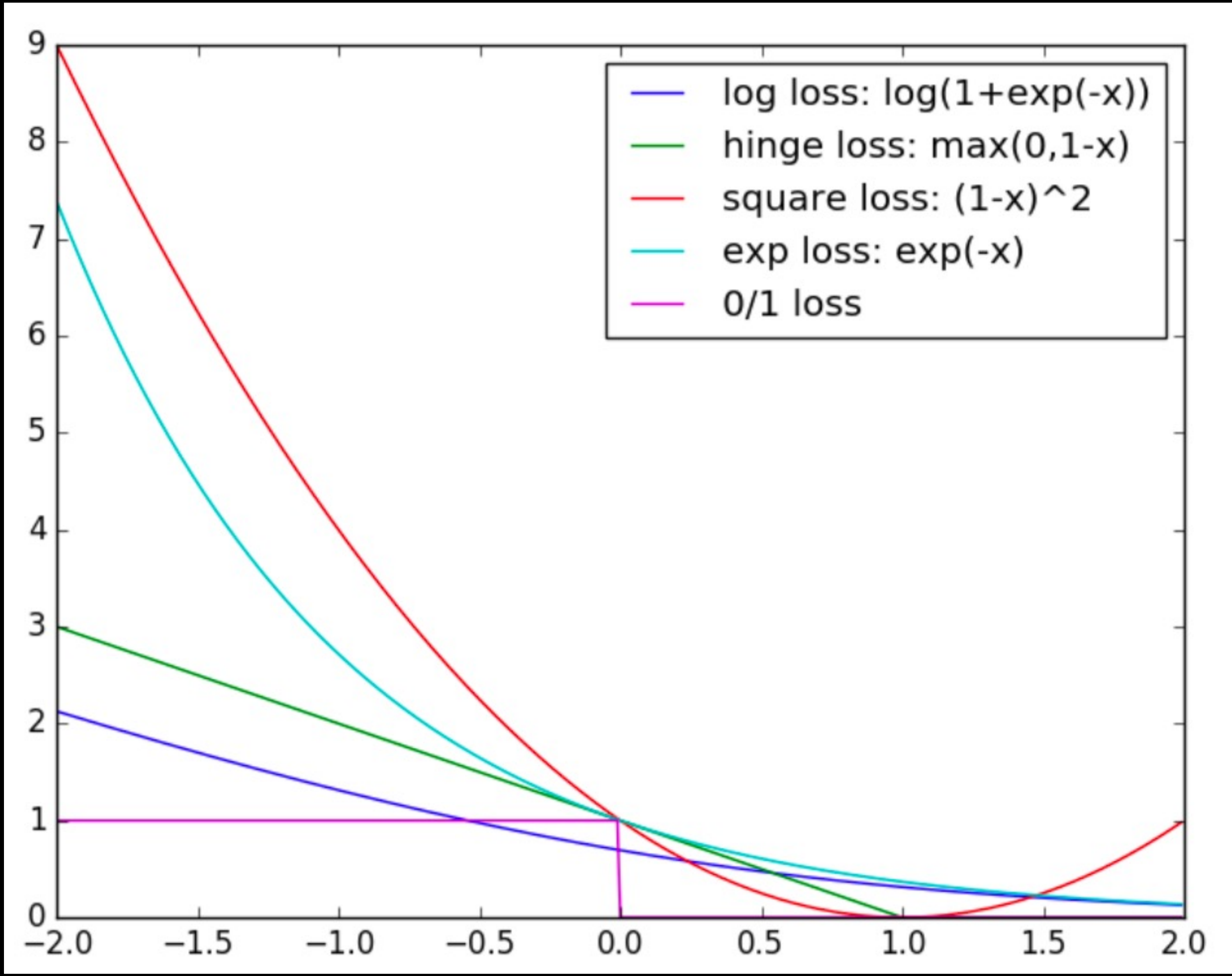
- the **exponential loss** (used in boosting):

$$\mathcal{L}_{exp}(h(\boldsymbol{x}), y) = \exp(yh(\boldsymbol{x}))$$

- the **logistic loss** (used in logistic regression):

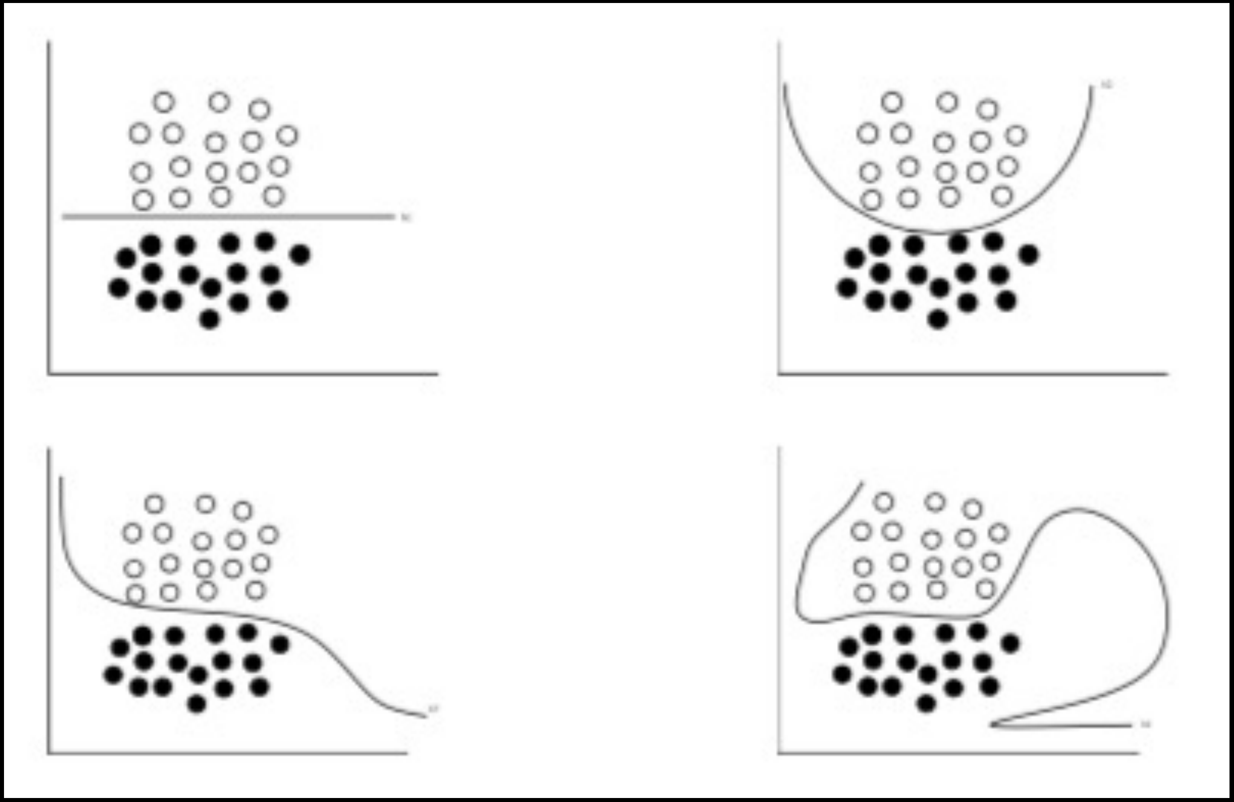
$$\mathcal{L}_{log}(h(\boldsymbol{x}), y) = \log(1 + \exp(yh(\boldsymbol{x})))$$

Surrogate Losses



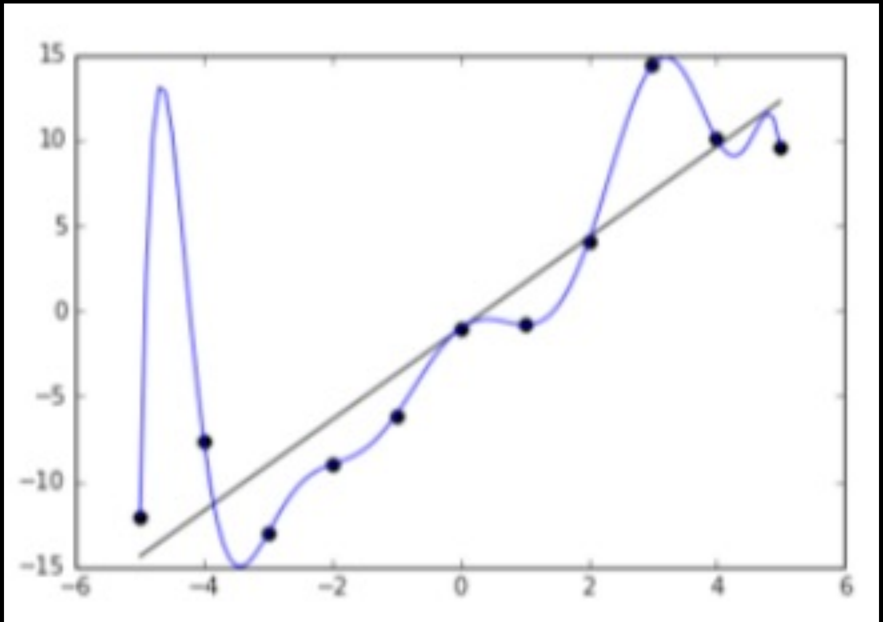
What is a good classifier?

From a same machine learning problem, several class of classifiers can be used leading to the same empirical rate.



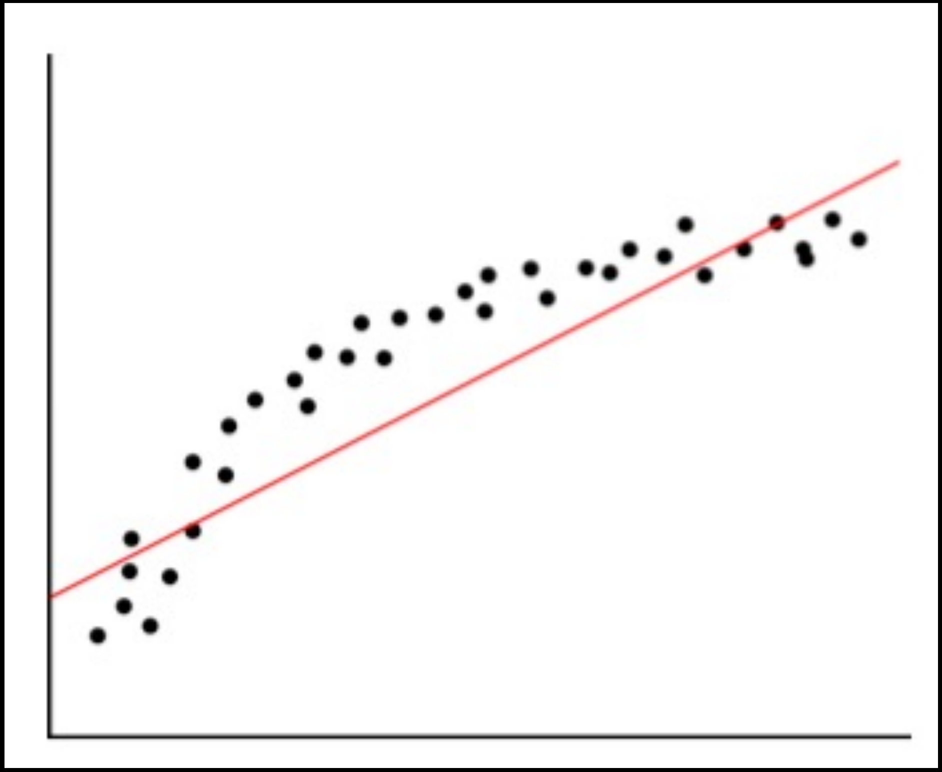
Overfitting

In statistics, overfitting occurs when **a model describes random error or noise** instead of the underlying relationship. In ML: when a **model is excessively complex** or **the size of the training dataset is small** (too many degrees of freedom w.r.t. the amount of available data).

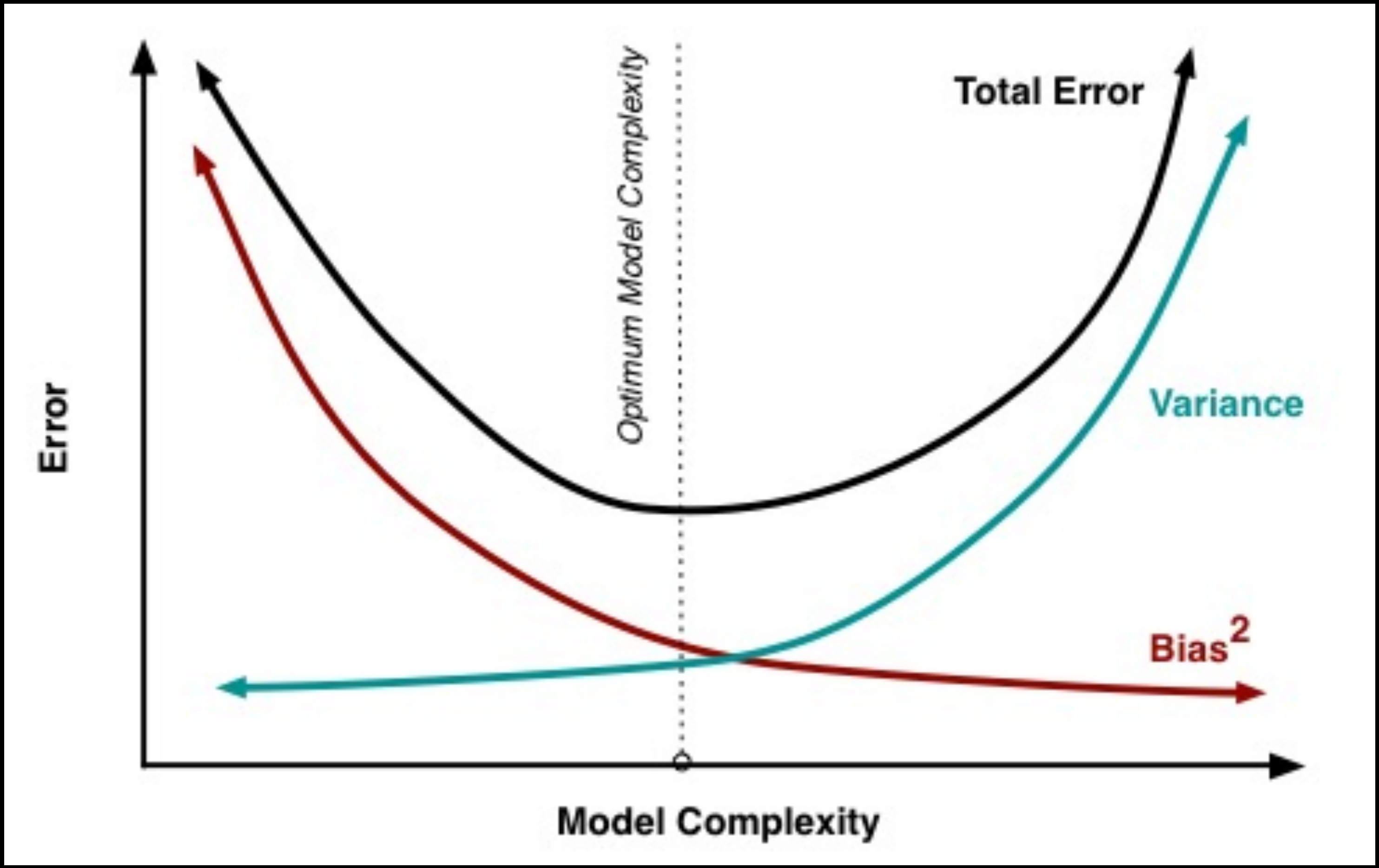


Underfitting

Underfitting occurs when a statistical model or ML algorithm cannot capture the underlying trend of the data = when a model is **excessively simple**.



Bias vs Variance



Regularization

- A way of avoiding overfitting
- Regularization, in mathematics and statistics and particularly in ML, refers to a process of **introducing additional information in order to** solve an ill-posed problem or to **prevent overfitting**.
  This information is usually of the form of a **penalty for complexity**, such as restrictions for smoothness or bounds on the vector space norm.

Regularized Risk Minimization

New optimization problem:

$$h = \arg\min_{h_i \in \mathcal{H}} \hat{\mathcal{R}}(h_i) + \lambda ||h_i||$$

where

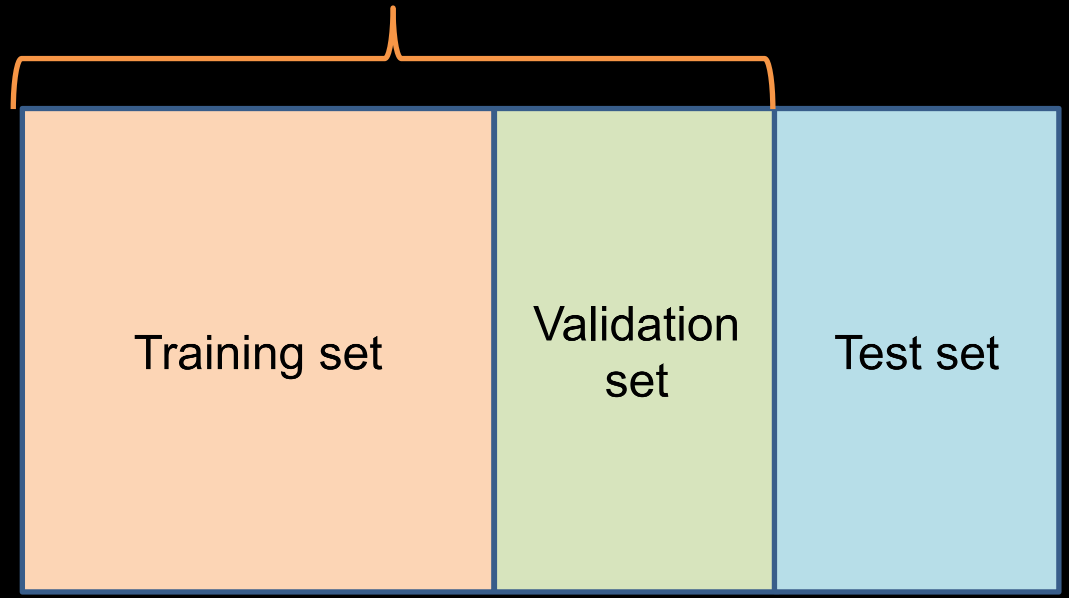
- λ is the regularization parameter (or hyper-parameter)
- $||.||$ is a norm function

We select a hypothesis h that achieves the best trade-off between empirical risk minimization and regularization.

Empirical estimation of the generalization error (true risk)

= how good your model is

1. Estimation using the learning set S
2. Estimation using a test set T
3. Estimation by cross-validation



Estimation using the learning set S 😱

Minimize the empirical risk over the m examples of S to choose the hypothesis h ∈ H:

with

$$h = \underset{h_i \in \mathcal{H}}{\arg\min}\, \hat{\mathcal{R}}(h_i)$$

$$\hat{\mathcal{R}}^{\mathcal{L}}(h(\boldsymbol{x}), y) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(h(\boldsymbol{x_i}), y)$$

Drawback: **too optimistic** because it tends to overestimate the generalization ability of h, and does not allow us to detect overfitting situations (Breiman 84).

Estimation using the test set T

Split in two subsets such that $S = S^* \cup T$. S^* is used to build h, while T is used to test h on examples that have not been used for its inference, but for which the label y is known.

$$h = \arg\min_{h_i \in \mathcal{H}} \hat{\mathcal{R}}(h_i)$$

with

$$\hat{\mathcal{R}}^{\mathcal{L}}(h(\boldsymbol{x}), y) = \frac{1}{|T|} \sum_{(\mathbf{x_i}, y_i) \in T} \mathcal{L}(h(\boldsymbol{x_i}), y)$$

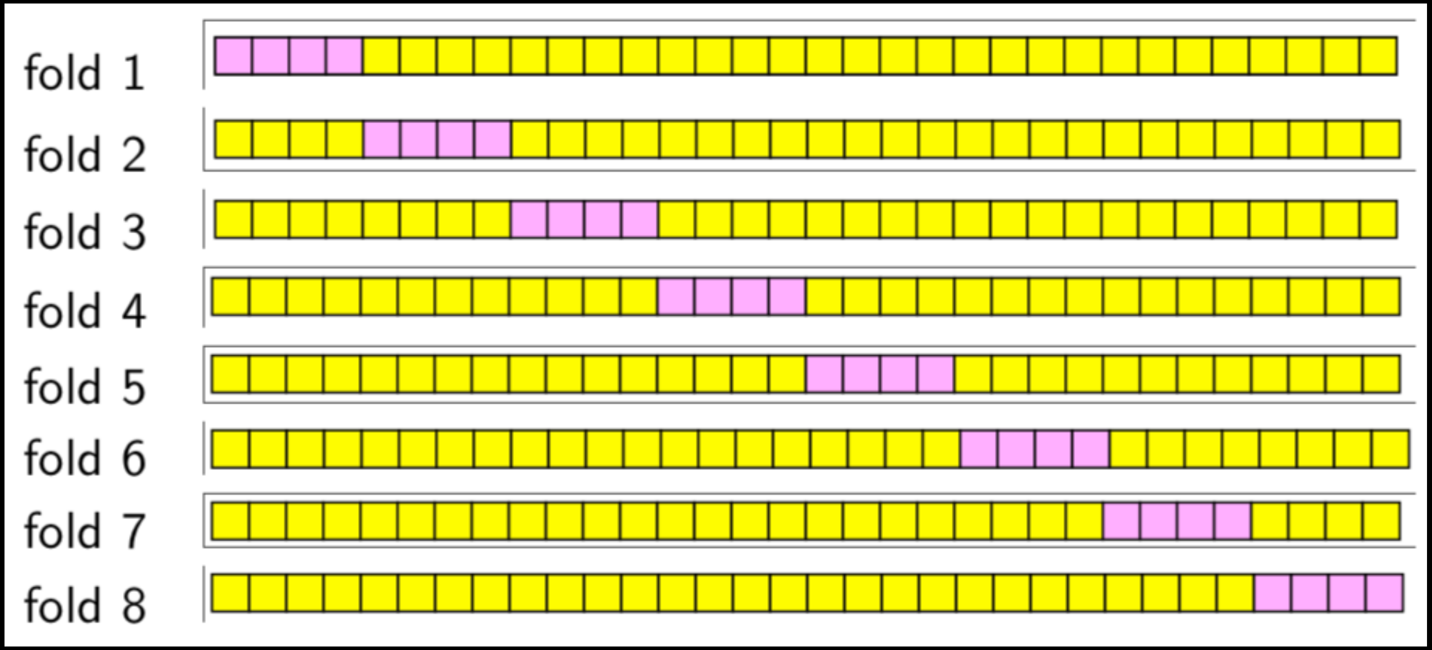
<u>Drawback</u>: reduces the number of examples available for learning h.

Estimation by cross-validation

Input: A learning algorithm L, a set of training examples S
Output: an estimate $\hat{\epsilon}'_h$
Divide randomly S in k subsets $S_1, \ldots, S_k$;
for *i=1 to k* **do**
  Run L on the sample $S - S_i$ and generate the classifier h_i;
Deduce the estimate of the real risk such that $\hat{\epsilon}'_h = \frac{1}{k} \sum_{i=1}^{k} \hat{\epsilon}'_{h_i}$ where $\hat{\epsilon}'_{h_i}$ is the error rate of h_i on the subset S_i;

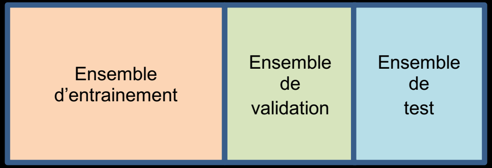
Drawback: costly from a complexity point of view.
Tricky when needed for nested cross-validation to tune hyperpameters too (cf. later)

Ex: 8-fold cross validation



- For each fold i: learn from yellow, test on pink → get $\hat{e}_i$
- $\hat{e}$ = somme ($\hat{e}_i$) / 8
- variant for small dataset: **leave-one-out** = 1 example in test

Tuning hyperparameters



Ex: lambda

- **Bad idea**: choose the one with the lowest training error (problem of overfitting).
- **Worst idea**: choose the best parameter on the test set
- **Good idea**:
  - Use a validation set !
  - k-fold cross-validation + select the value for hyper-parameter with the lowest cross-validation error.

Hyperparameter tuning is different from model performance estimation

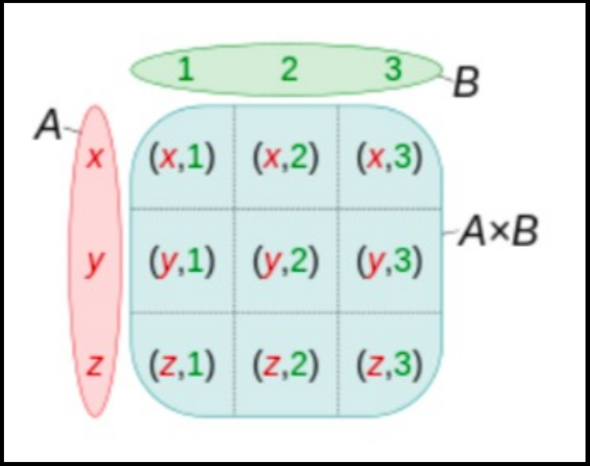
(without test set, may need 2 loops of cross-val to do both)

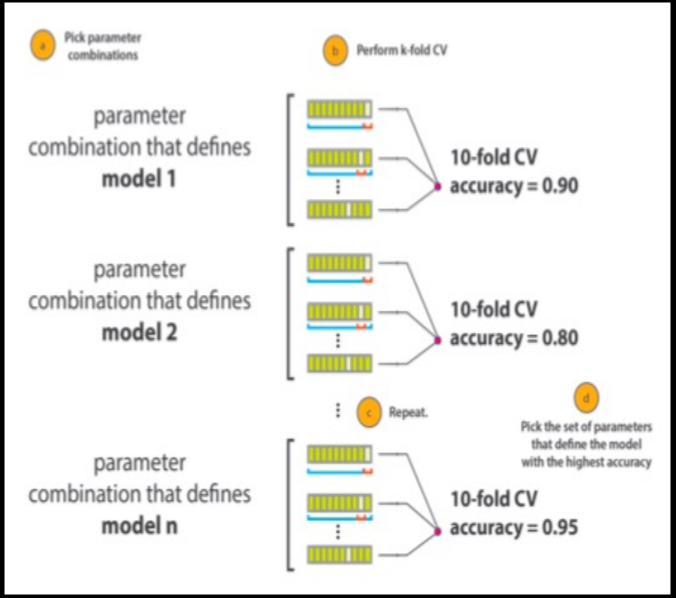
Which hyperparameters values to test?

A way to choose the combinations of values for multiple hyper-parameter tuning (p):

1. fix the set s_z of possible values per hyper-parameter λ_z (ex. $s_1 = \{0.001, 0.01, 0.1, 1, 10, 100\}$);
2. compute a cross-validation for each combination of values $(\lambda_1, \lambda_2, ...)$;
3. select the combination of values $(\lambda_1, \lambda_2, ...)$ that gives the best error.
4. Total number of cross-validations:

$$\prod_{z=1}^{p} |s_z|$$



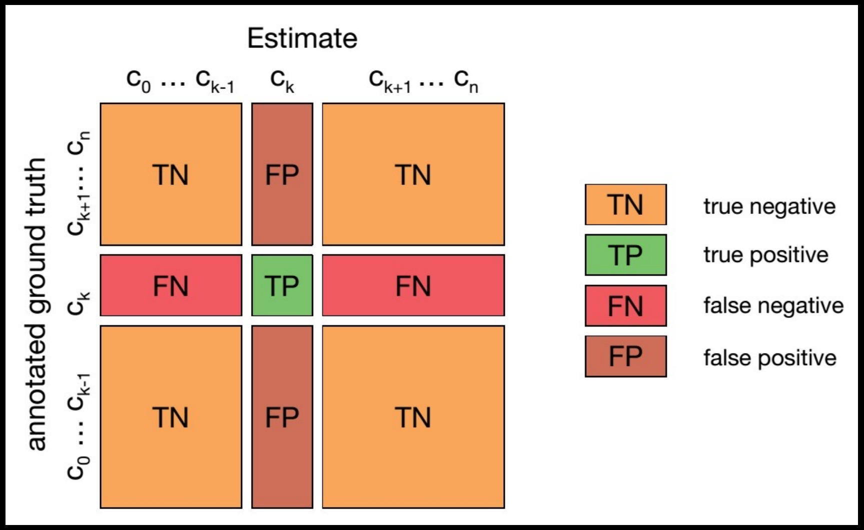


Types of errors = Confusion Matrix

		Prediction	
		(in class *c*)	(not in class *c*)
Ground Truth	(in class *c*)	True Positive (TP)	False Negative (FN)
	(not in class *c*)	False Positive (FP)	True Negative (TN)

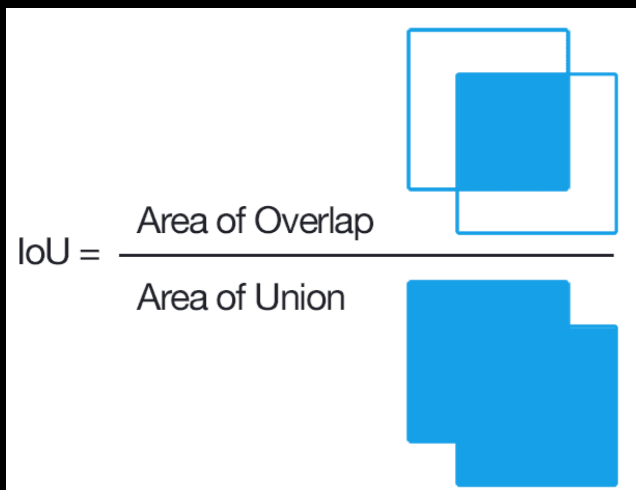
Evaluation (measures) of a classifier

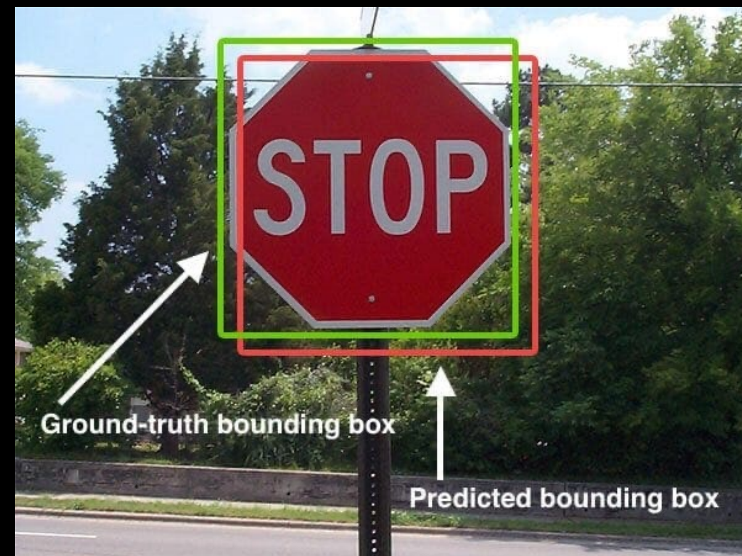
- Accuracy = fraction of correct classifications on unseen data (test set, cross validation, bootstrap, ...) $$\frac{TN + TP}{TN + FP + FN + TP}$$
- Error rate = 1 − Accuracy
- Precision = $\frac{TP}{FP + TP}$
- Recall = $\frac{TP}{FN + TP}$



Typical measures in CV

- Intersection over Union (IoU) for *object detection*





(confusion matrix depends on the IoU threshold)

- Mean Average Precision (mAP)
- Average Precision(AP) is the area under the Precision/Recall curve

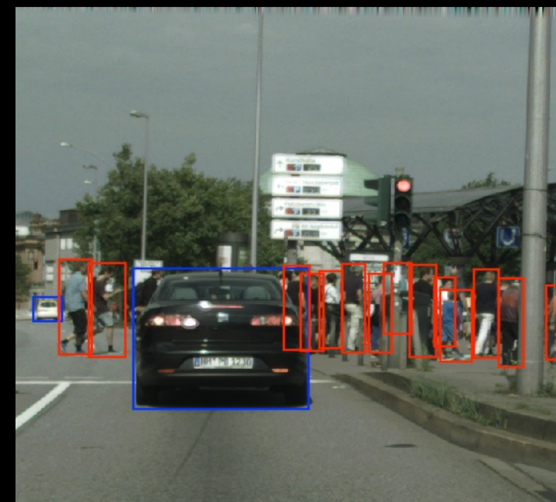
$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i$$

Mean Average Precision Formula

i = class

Computer Vision: Supervised Problems

Object classification



Object detection

Semantic segmentation

Instance segmentation

CV Tasks for Generative Algorithms

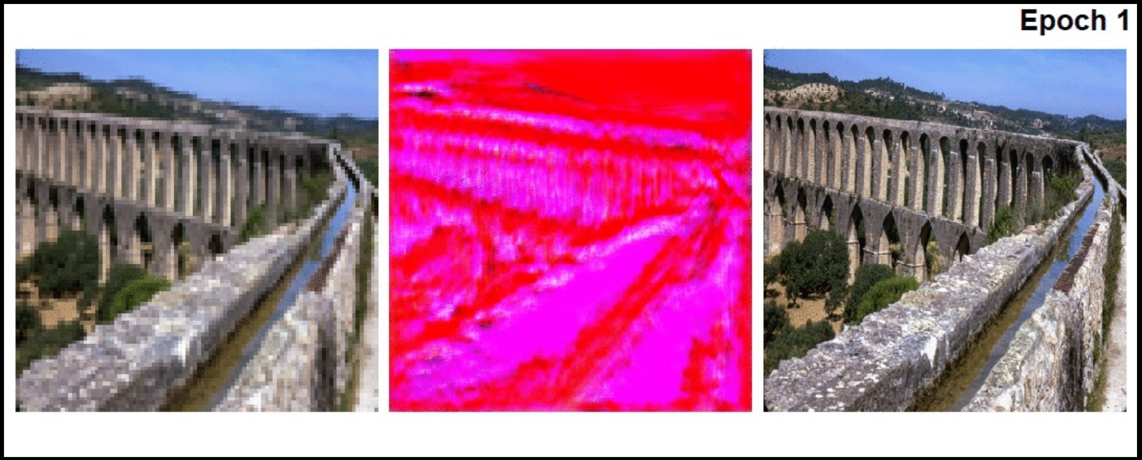


Image generation using Super Resolution GAN architecture

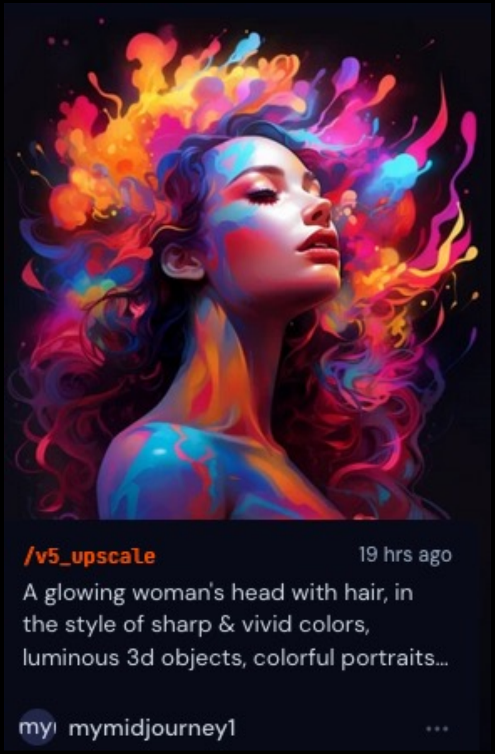


Image generation from multimodal deep architechtures

- Dall-E (https://openai.com/dall-e-2)
- Mid-Journey

(https://www.midjourney.com/)

…

Unsupervised learning?

- E.g. Dimensionality reduction, clustering, pattern mining
- Optimization or combinatorial enumeration (when working on discrete structures)
- Also uses regularizations (or heuristics)
- Also used in CV but
  - As a preprocessing step for the previous tasks
  - As a basis for generative models
  - For anomaly detection
- No clear target y:
  - No general loss to optimize (different for each problem, ex: clustering)
  - No clear way to evaluate the outcome (be creative)

Reinforcement Learning?

- Learn more here : http://ivg.au.tsinghua.edu.cn/DRLCV/
- And (David Silver course on RL) https://www.youtube.com/watch?v=2pWv7GOvuf0