COMPUTER VISION
MEI/1

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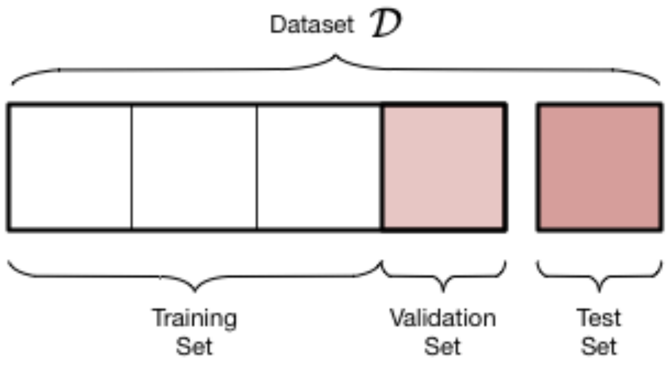
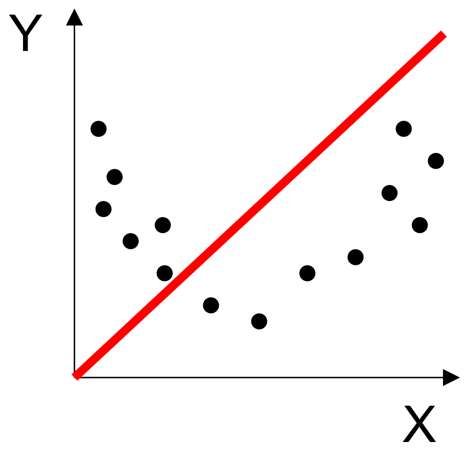
Computer Vision: Experimental Setup

- The design of the experimental procedure to learn/evaluate computer vision/machine learning models is sensitive.
  - Badly designed experiments lead to erroneously optimistic/pessimistic estimates of the system performance
- One of the golden rules in machine learning is that the data should be split in three disjoint subsets:
  - **Learning (Training) set**: this is the set of instances used to fit the parameters of the hypothesis (model).
    - In case of supervised learning, it consists of pairs of a input vectors and the corresponding ground truth, also known as the target or label.
  - **Validation set**. It provides an unbiased evaluation of a model performance during the learning process, while tuning the model **hyper-parameters** (e.g., acceptance/rejection threshold)
  - **Test set**. It is used to provide an unbiased evaluation of a final model.

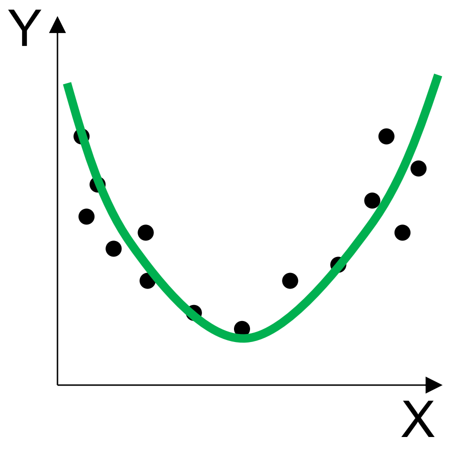


Overfitting

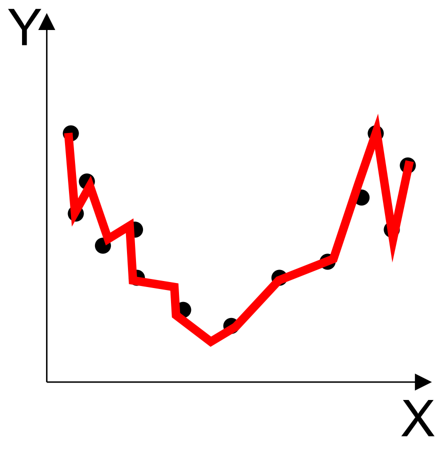
- Overfitting it is one of the most classical problems in Computer Vision/Machine Learning problems.
- It occurs when the our model fits “***too well” the learning data***, but is **fails to generalize to new data**, i.e., the data where we actually want to use the model
- This is particularly probable when the model has a large number of parameters
  - In such case, the model has too many degrees-of-freedom
  - Nowadays, the breakthrough models based in deep-learning frameworks have a huge number of parameters
  - VGG-16 network, proposed in 2014, has 138,000,000 parameters!



Underfitted



OK



Overfitted

Overfitting/Underfitting

- The Occam's razzor is a principle from philosophy that states that:
  - *»Entia non sunt multiplicanda praeter necessitatem»*
- This can be translated to:
  - *"More things should not be used than are necessary"*
- Which in practical terms states that simple models should (in case of **comparable effectiveness**) be preferred over more complex ones.

Wiliam of Ockham

- In linear and logistic regression, this is equivalent to force the inferred parameters of our model to be small.
- This is done by adding a term to the cost function we want to minimize:
  - It is called the "**regularization term**" (and $\boldsymbol{\lambda}$ the regularization weight)
  - Consider that $\theta = \{\theta_0, \theta_1, \dots, \theta_D\}$

$$J(\boldsymbol{\theta}) = \frac{1}{2N} \sum_{i=1}^{N} \left(h_{\theta}(x^{(i)}) - y^{(i)}\right)^2 + \lambda \sum_{i=1}^{D} {\theta_i}^2$$

Overfitting/Underfitting

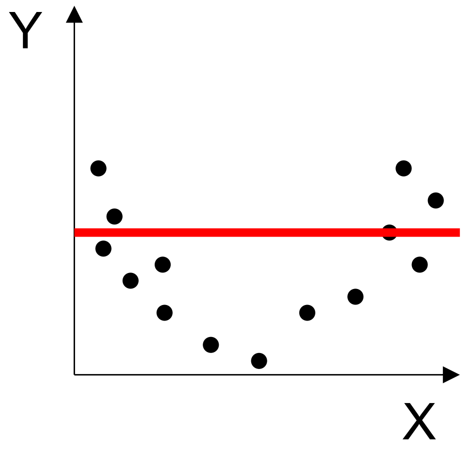
- Consider the following model:

$$h_\theta(x) = \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$

- Suppose that we set λ too large. What happens?
- Minimizing the J() function, it will force that $\theta_1 \ldots \theta_4$ will be approximately 0

$$\mathrm{J}(\boldsymbol{\theta}) = \frac{1}{2N}\sum_{i=1}^{N}\left(h_{\theta}\left(x^{(i)}\right) - y^{(i)}\right)^2 + \lambda \sum_{i=1}^{D} \theta_i^{\,2}$$

- Hence, the inferred model will be given by:



Poor Fitting!!
(Underfitted)

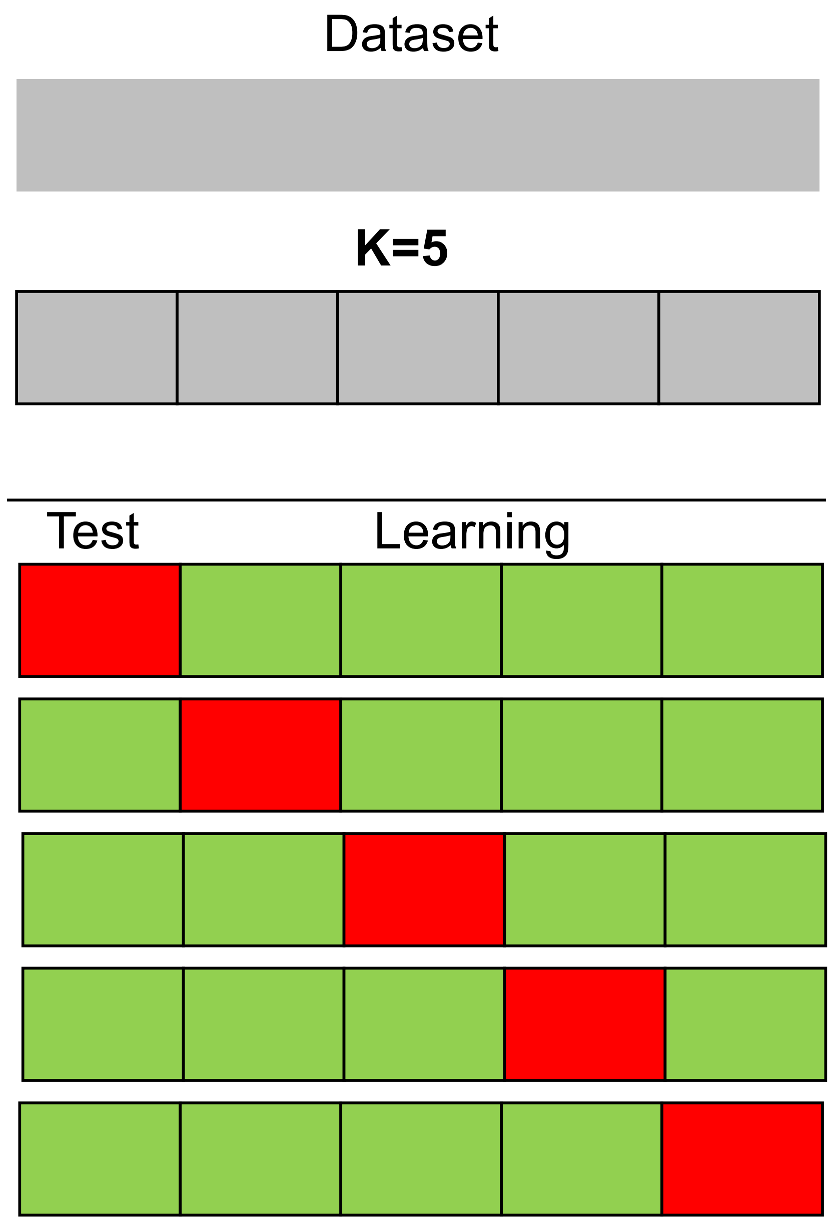
Overfitting/Underfitting

- In practice terms, this adds one extra-parameter λ to our problem.
  - This parameter is not part of the model, but instead, it is used during the learning process
  - These are called "**hyper-parameters**"
- We saw that:
  - Too large values will lead to underfitted models
  - Too small values will lead to overfitted models
- Typically, the choice of λ can be made according to the performance in the validation set.
- To adapt the linear and logistic regression learning processes, in order to obtain regularized models, one just have to consider that:

$$\frac{\int}{\int \theta_i} \lambda \sum_{i=1}^{D} \theta_i{}^2 = 2\lambda\theta_i$$

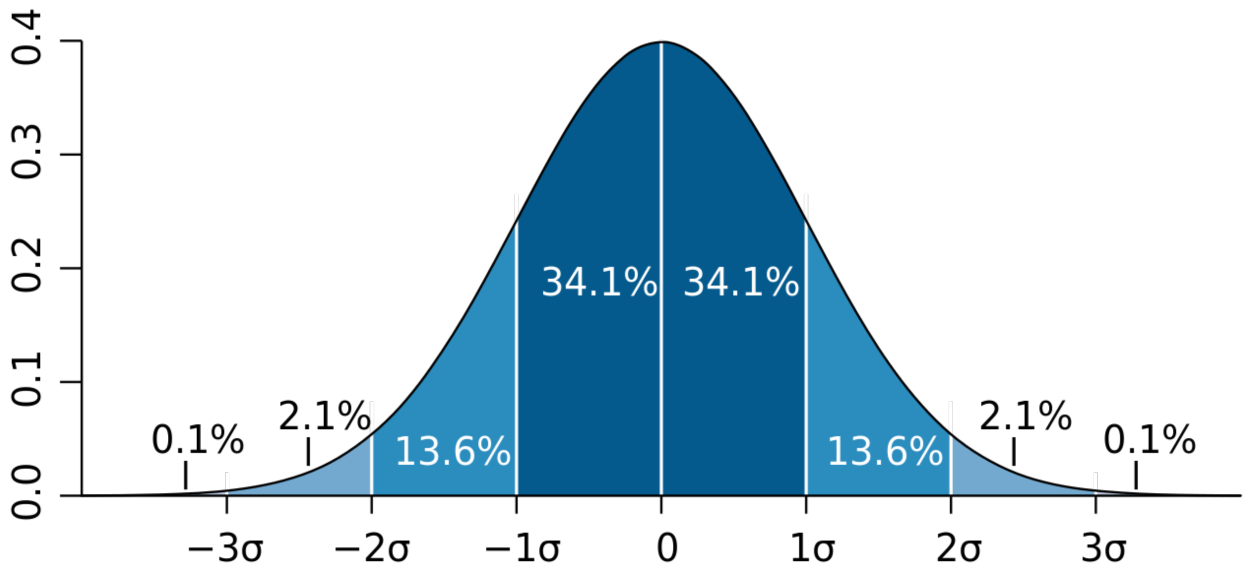
K-Fold Cross Validation

- It is a statistical method used to estimate the performance of machine learning hypotheses (models).
- It is one of the most commonly used, being easy to understand and to implement, with estimates generally having comparable bias than other more sophisticated methods (e.g., bootstrapping)
- It is a **resampling** technique.
  - The value for "K" is defined at the beginning
  - The available data is randomly split at K samples (groups)
  - The model is fitted "K" times, each time using 1 group as **test set** and the remaining (k-1) groups as **learning data**
  - Performance is obtained for the test set
  - The final performance is given by the mean value of the "K" performance values.



K-Fold Cross Validation

- Also, typically results are given in a (“mean” ∓ “standard deviation”) performance values
  - E.g.: “0.70 ∓0.02” means that it is expected that the model performs well 70% of the times, with “typical” variations of more or less 2%
- It has roots in the “***law of big numbers***” and in the “***theorem of the central limit***”
- Considering that repeated observed performance values will approach their “true mean” and that they follow a Gaussian distribution, one can conclude that about 68.2% of the times, the model performance will lie in the “mean ∓ standard deviation” interval.



Bootstrapping

- It is closely related to K-fold cross validation and follows the same idea:
  - Generates multiple subsets, by sampling from a single, original dataset.
  - Each of the "*new*" sets can be used to estimate performance.
  - Since there are multiple sets (and therefore multiple estimates), one can also obtain the mean, standard deviation or a confidence interval for the estimate.
- The key difference is that bootstrapping **resamples the data *with replacement***.
  - Given a dataset containing N points, bootstrap picks a data point uniformly at random, adds it to the bootstrapped set, *puts that data point back into the dataset*, and repeats.
  - Why put the data point back?
  - In a real setting, data would come from the "real distribution of the data".
  - But all we have is a dataset (i.e., a sample), we don't have the real distribution of the data. Out set is supposed to represent the underlying distribution, i.e., **it is an *empirical* distribution of data**.
  - The rule is to simulate sub-sets by drawing from the empirical distribution.
  - Hence, the data point must be put back, because otherwise the empirical distribution would change after each draw.

Confusion Matrix

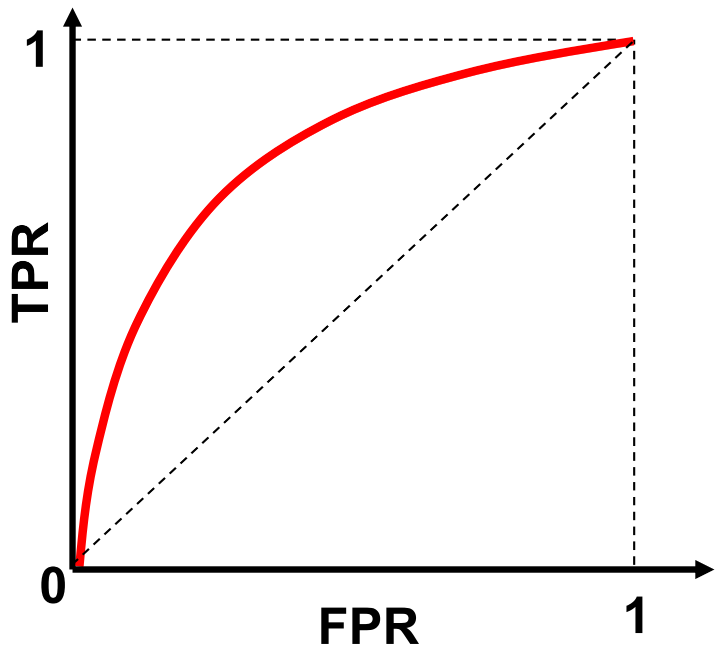
- Also known as an error matrix, this table summarizes the model performance, providing more information that the simple “accuracy” value.
- For a binary classification problem, it is a table with two rows and two columns, reporting the number of *false positives*, *false negatives*, *true positives*, and *true negatives*.
    - Each row corresponds to one predicted outcome (class)
    - Each column corresponds to one actual (ground-truth) class

		Prediction outcome		
		positive	negative	
Actual value	positive	TP	FN	$TP+FN$
	negative	FP	TN	$FP+TN$
		$TP+FP$	$FN+TN$	

- The model **accuracy** is given by: $\frac{TP+TN}{TP+TN+FP+FN}$
- **Precision**: $\frac{TP}{TP+FP}$ (*when it predicts “yes”, how likely it is correct?*)
- **Recall**: $\frac{TP}{TP+FN}$ (*what is the proportion of “yes” that are actually detected?*)

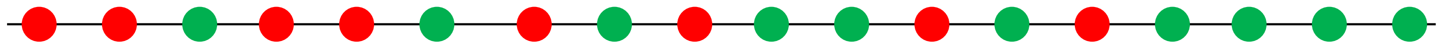
ROC: Receiver Operating Characteristic

- A **R**eceiver **O**perating **C**haracteristic curve (**ROC)**, is a graphical plot that illustrates the performance of a binary classifier system, with respect to changes in its discrimination threshold.
- This curve shows the relationship between two measures:
  - True Positive Rate
  - False Positive Rate
- The **T**rue **P**ositive **R**ate (**TPR**) is also known as recall and is given by:
  - $TPR = \frac{TP}{TP+FN}$
- The **F**alse **P**ositive **R**ate (**FPR**) (1 – specificity) is given by:
  - $FPR = \frac{FP}{FP+TN}$
- This plot gives the TPR vs. FPR at different acceptance thresholds.
  - Low thresholds classify more items as positive, which increases both the TPR and FPR
  - High thresholds classify less items as positive, which decreases both the TPR and FPR

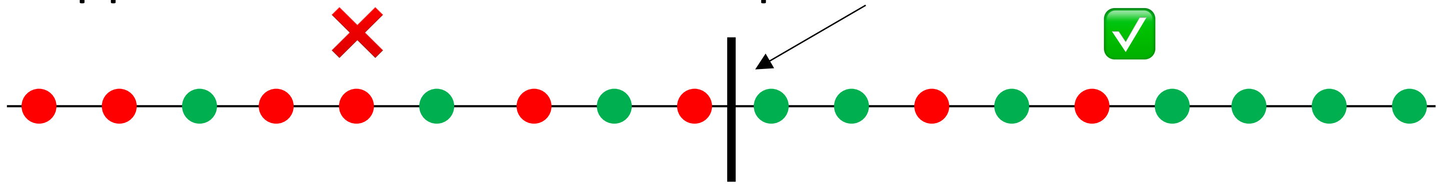


ROC: Receiver Operating Characteristic

- To obtain the data for a ROC curve, we start by sorting the output scores, obtained for the evaluation set:
  - Consider that red dots correspond to class “0” (the *negative* class), and green dots to class “1” (the positive class)



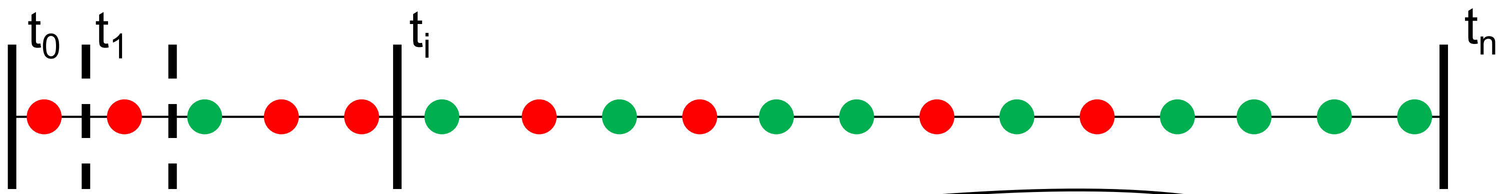
- What happens when we set the acceptance threshold at?



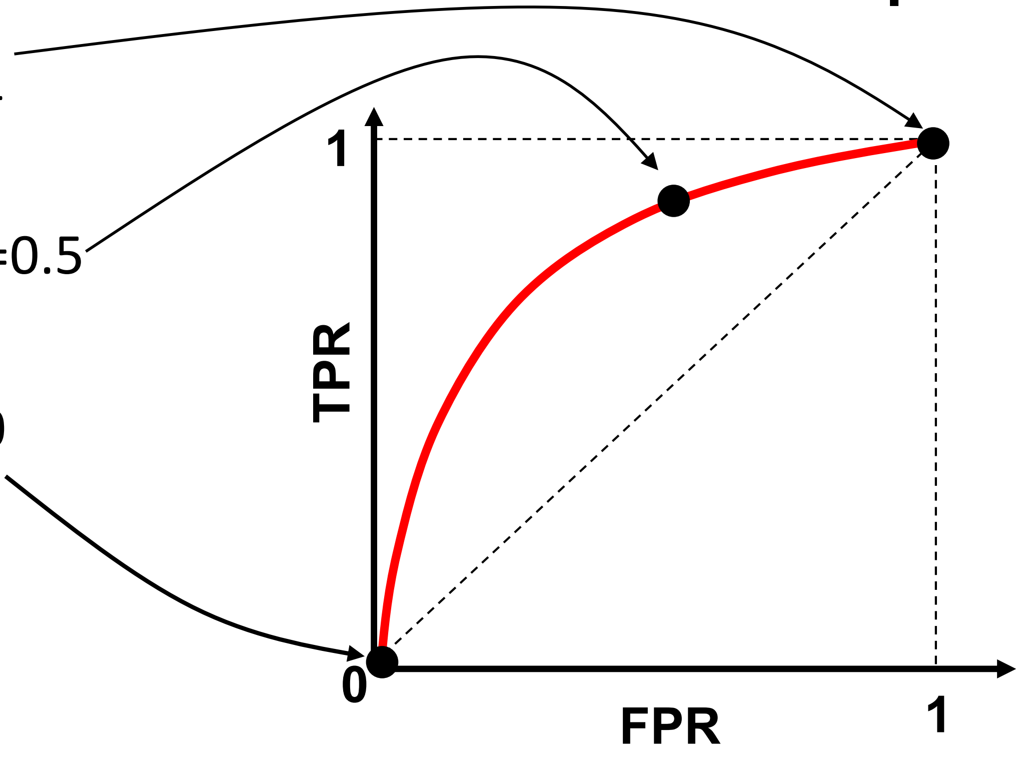
  - 6 (out of 8) negative samples are correctly rejected. TNR=6/8
  - 2 (out of 8) negative samples are erroneously considered as positive. FPR = 2/8
  - 7 (out of 10) positive samples are correctly accepted. TPR = 7/10
  - 3 (out of 10) positive samples are erroneously considered as negative. FNR = 3/10

ROC: Receiver Operating Characteristic

- Next, we obtain the TPR/FPR values for all possible acceptance thresholds:

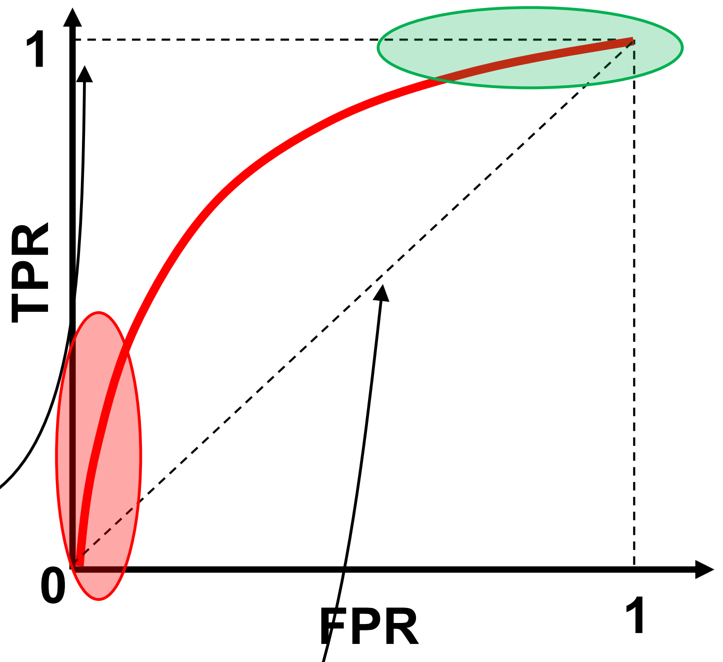


- At t_0, we have TPR=1, FPR=1
- At t_1, …
- At t_i, we have TPR=0.9, FPR=0.5
- …
- At t_n, we have TPR=0, FPR=0



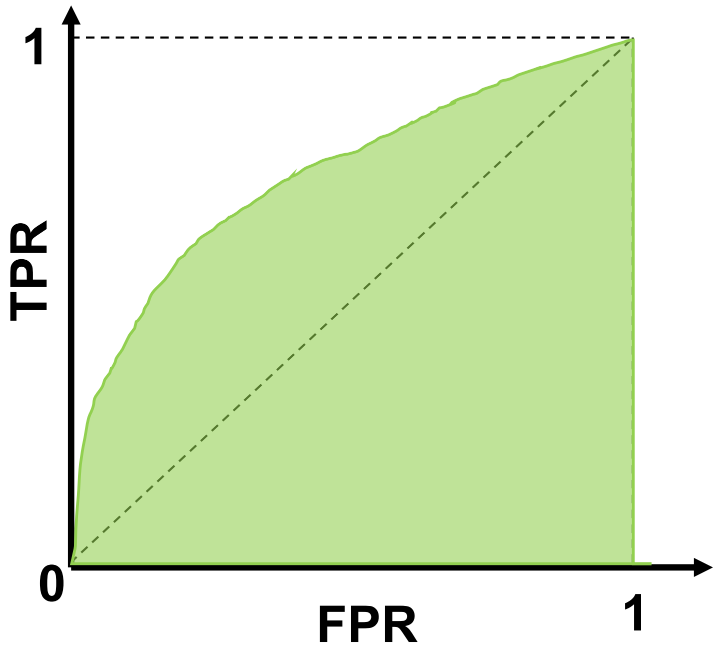
ROC: Receiver Operating Characteristic

- The ROC curve reports all the possible performance parameterizations of our model:
  - Either tuned for security or convenience
- When comparing two models, the best one would have the ROC curve above the other most times
- The optimal performance will correspond to the (0,1) point in the plot
- The $x_i = y_i$ line corresponds to the worst possible model, with performance equal of a random number generator.



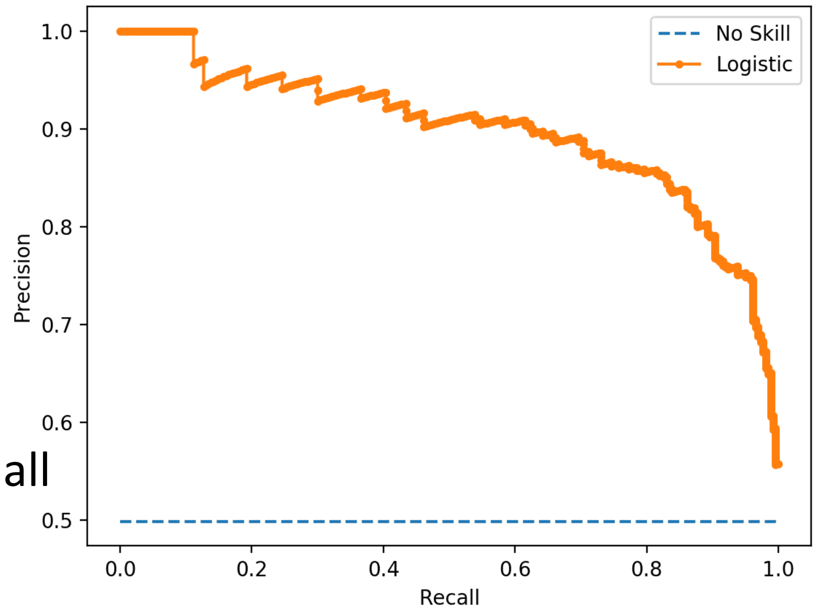
AUC: Area Under Curve

- The ROC curve shows all possible parameterization, and it is given as a plot
- To obtain a numeric value that sumarizes the effectiveness of a model, it is typically used the **A**rea **U**nder **C**urve metric.
- It is given by:
    - $\int_0^1 f(x)dx$
- with $f(x)$ corresponding to the ROC curve values.
- AUC = 1 is the **perfect system** that obtains optimal performance with all possible acceptance thresholds
- AUC = 0.5 is the “random number” generator (**worst possible system**)

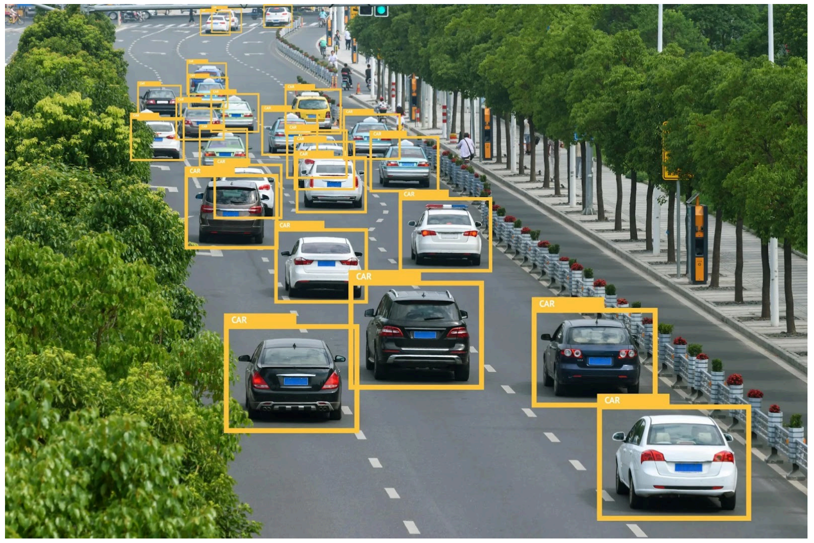


Precision/Recall Plots

- Precision-Recall is particularly suitable when the classes are very imbalanced.
    - In information retrieval, precision is the fraction of relevant items among actually returned items. Recall is a measure of the fraction of items that were returned among all items that should have been returned.



- Precision/Recall plots are mostly used for detection purposes.
    - In this type of problems, there are typically much more positions where one object isn't than the positions that actually contain the object.



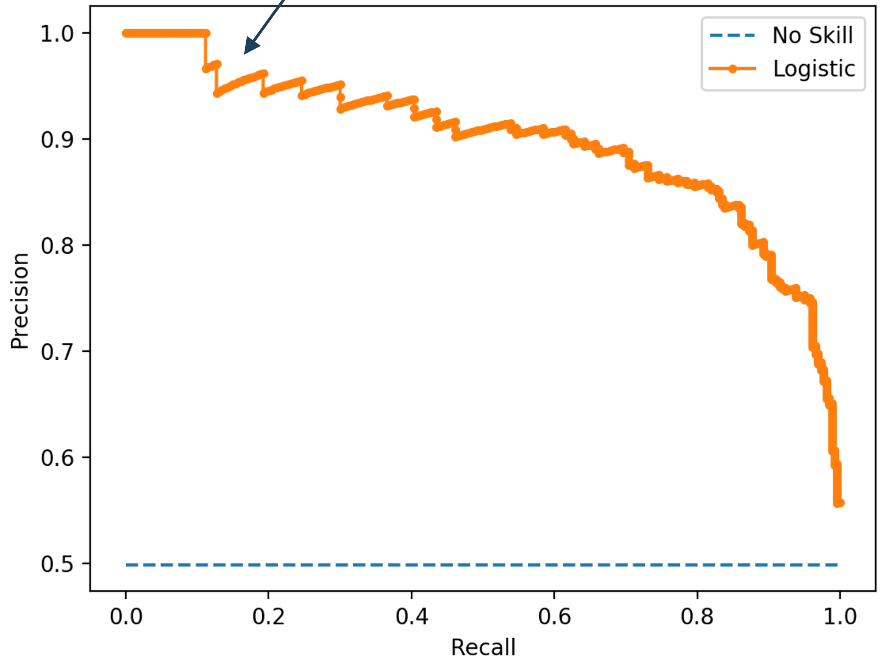
Precision/Recall Plots

Precision (P) is defined as the number of true positives (T_p) over the number of true positives plus the number of false positives (F_p).

$$P = \frac{T_p}{T_p + F_p}$$

"Every time one object is detected, how likely it is actually a match?"

In opposition to ROCs, it can be non-monotonous



Recall (R) is defined as the number of true positives (T_p) over the number of true positives plus the number of false negatives (F_n).

$$P = \frac{T_p}{T_p + F_n}$$

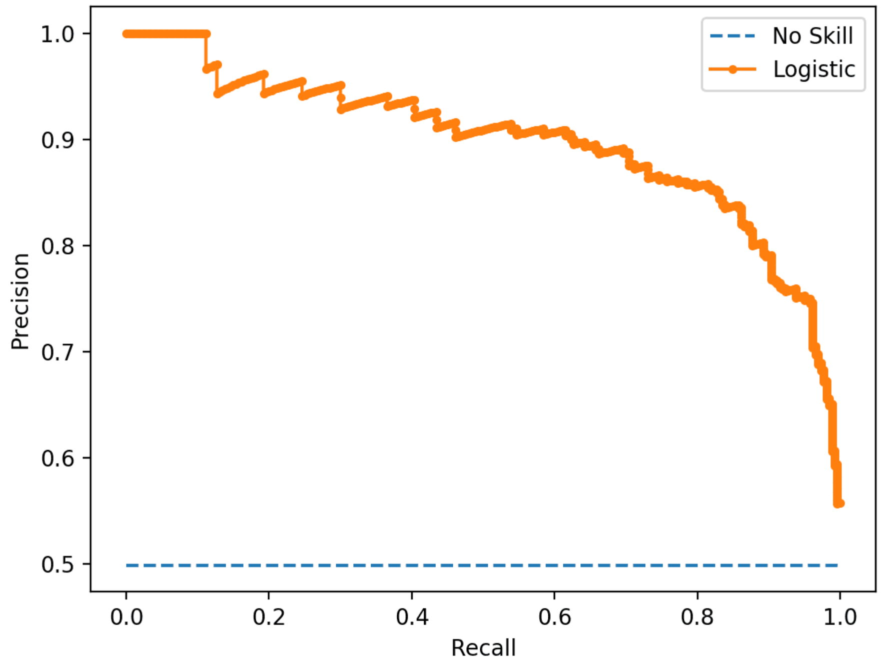
"What is the proportion of objects detected?"

Average Precision (AP) and mAP

Average precision (AP) summarizes such a plot as the weighted mean of precisions achieved at each threshold, with the increase in recall from the previous threshold used as the weight:

$$AP = \sum_i (R_i - R_{i-1}) \, P_i$$

In practice, it can be seen as the equivalent of AUC for ROC plots



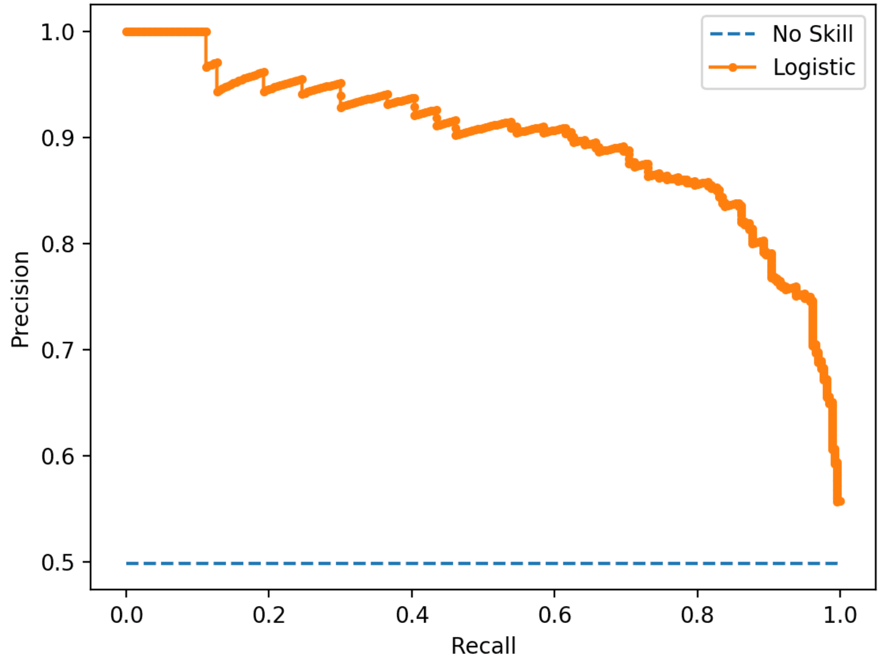
Upon this metric, (measured for single class), we obtain the “Mean Average Precisoon”, which is the harmonic mean for all classes.

$$mAP = \frac{1}{k} \sum_k AP_k$$

F1 Score

The F1 score can be interpreted as a harmonic mean of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal.

$$F1 = \frac{2 \times P \times R}{P + R}$$



Precision and recall are a trade-off, i.e., one metric comes at the cost of another. Typically, more precision implies less recall values and vice-versa.

The F1 score combines precision and recall using their harmonic mean, and maximizing the F1 score implies simultaneously maximizing both precision and recall. Thus, the F1 score has become one of the most popular choices of researchers for evaluating their models