VIP Cheatsheet: Machine Learning Tips

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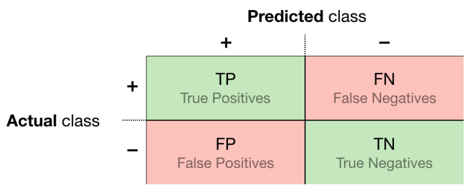
Metrics

In a context of a binary classification, here are the main metrics that are important to track to assess the performance of the model.

❒ **Confusion matrix** – By noting True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN), the confusion matrix is defined as follows:



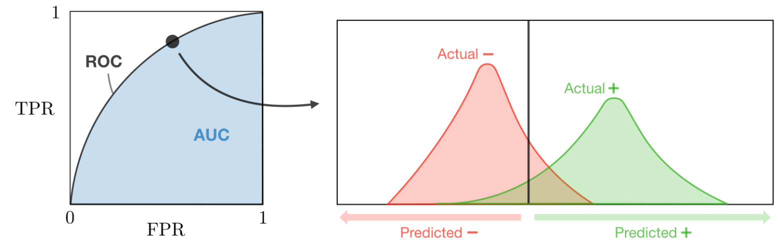
❒ **Main metrics** – Here are the main metrics to track:

Metric	Formula	Interpretation
Accuracy	$\dfrac{\textrm{TP}+\textrm{TN}}{\textrm{TP}+\textrm{TN}+\textrm{FP}+\textrm{FN}}$	Overall performance of model
Precision	$\dfrac{\textrm{TP}}{\textrm{TP}+\textrm{FP}}$	How accurate the positive predictions are
Recall Sensitivity	$\dfrac{\textrm{TP}}{\textrm{TP}+\textrm{FN}}$	Coverage of actual positive sample
Specificity	$\dfrac{\textrm{TN}}{\textrm{TN}+\textrm{FP}}$	Coverage of actual negative sample
F1 score	$\dfrac{2\textrm{TP}}{2\textrm{TP}+\textrm{FP}+\textrm{FN}}$	Hybrid metric useful for unbalanced classes

❒ **ROC** – The receiver operating curve, also noted ROC, is the plot of TPR versus FPR by varying the threshold. These metrics are are summed up in the table below:

Metric	Formula	Equivalent
True Positive Rate TPR	$\dfrac{\textrm{TP}}{\textrm{TP}+\textrm{FN}}$	Recall, sensitivity
False Positive Rate FPR	$\dfrac{\textrm{FP}}{\textrm{TN}+\textrm{FP}}$	1-specificity

❒ **AUC** – The area under the receiving operating curve, also noted AUC or AUROC, is the area below the ROC as shown in the following figure:



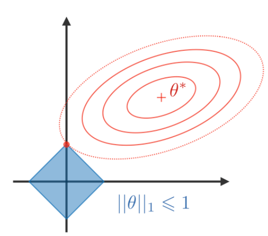
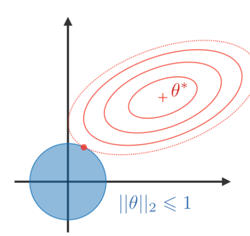
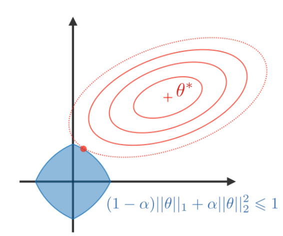
Model selection

❒ **Vocabulary** – When selecting a model, we distinguish 3 different parts of the dataset as follows:

- Training set: this is the part of the dataset on which the model is trained.
- Validation set: also called hold-out, development set or dev set, it is used to assess the performance of the previously trained model.
- Test set: once the model has been chosen, it is trained on the training+validation set and tested on the unseen test set.

❒ **Cross-validation** – Cross-validation is a model selection technique aimed at assessing which model would generalize well. While several types of cross-validation exist, the most common one is the k-fold cross-validation where the dataset is split into k parts and where the model is used as follows:

❒ **Regularization** – The regularization procedure aims at avoiding the model to overfit the data and thus deals with high variance issues. The following table sums up the different types of commonly used regularization techniques:

LASSO	Ridge	Elastic Net
- Shrinks coefficients to 0 - Good for variable selection	Makes coefficients smaller	Tradeoff between variable selection and small coefficients
		
$...+\lambda\|\|\theta\|\|_1$ $\lambda\in\mathbb{R}$	$...+\lambda\|\|\theta\|\|_2^2$ $\lambda\in\mathbb{R}$	$...+\lambda\Big[(1-\alpha)\|\|\theta\|\|_1+\alpha\|\|\theta\|\|_2^2\Big]$ $\lambda\in\mathbb{R},\quad\alpha\in[0,1]$

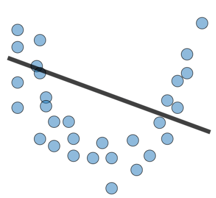
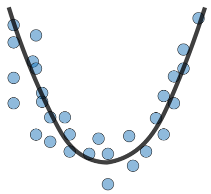
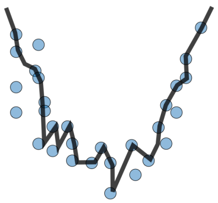
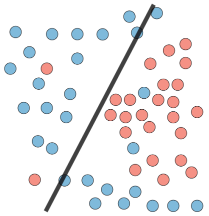
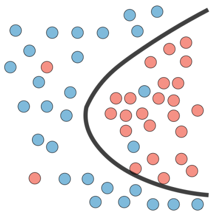
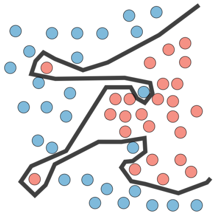
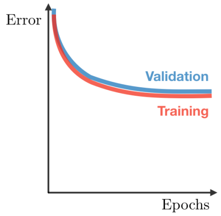
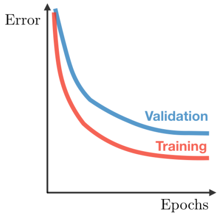
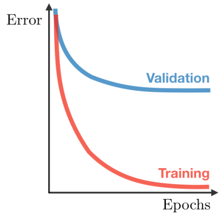
❒ **Model selection** – Train model on training set, then evaluate on the development set, then pick best performance model on the development set, and retrain all of that model on the whole training set.

Diagnostics

❒ **Bias** – The bias of a model is the difference between the expected prediction and the correct model that we try to predict for given data points.

❒ **Variance** – The variance of a model is the variability of the model prediction for given data points.

❒ **Bias/variance tradeoff** – The simpler the model, the higher the bias, and the more complex the model, the higher the variance.

	Underfitting	**Just right**	**Overfitting**
Symptoms	- High training error - Training error close to test error	- Training error slightly lower than test error - High bias	- Low training error - Training error much lower than test error - High variance
Regression			
Classification			
Deep learning			
Remedies	- Complexify model - Add more features - Train longer		- Regularize - Get more data

❒ **Error analysis** – Error analysis is analyzing the root cause of the difference in performance between the current and the perfect models.

❒ **Ablative analysis** – Ablative analysis is analyzing the root cause of the difference in performance between the current and the baseline models.