

Initiation à l'apprentissage automatique en science des matériaux

4. Classification

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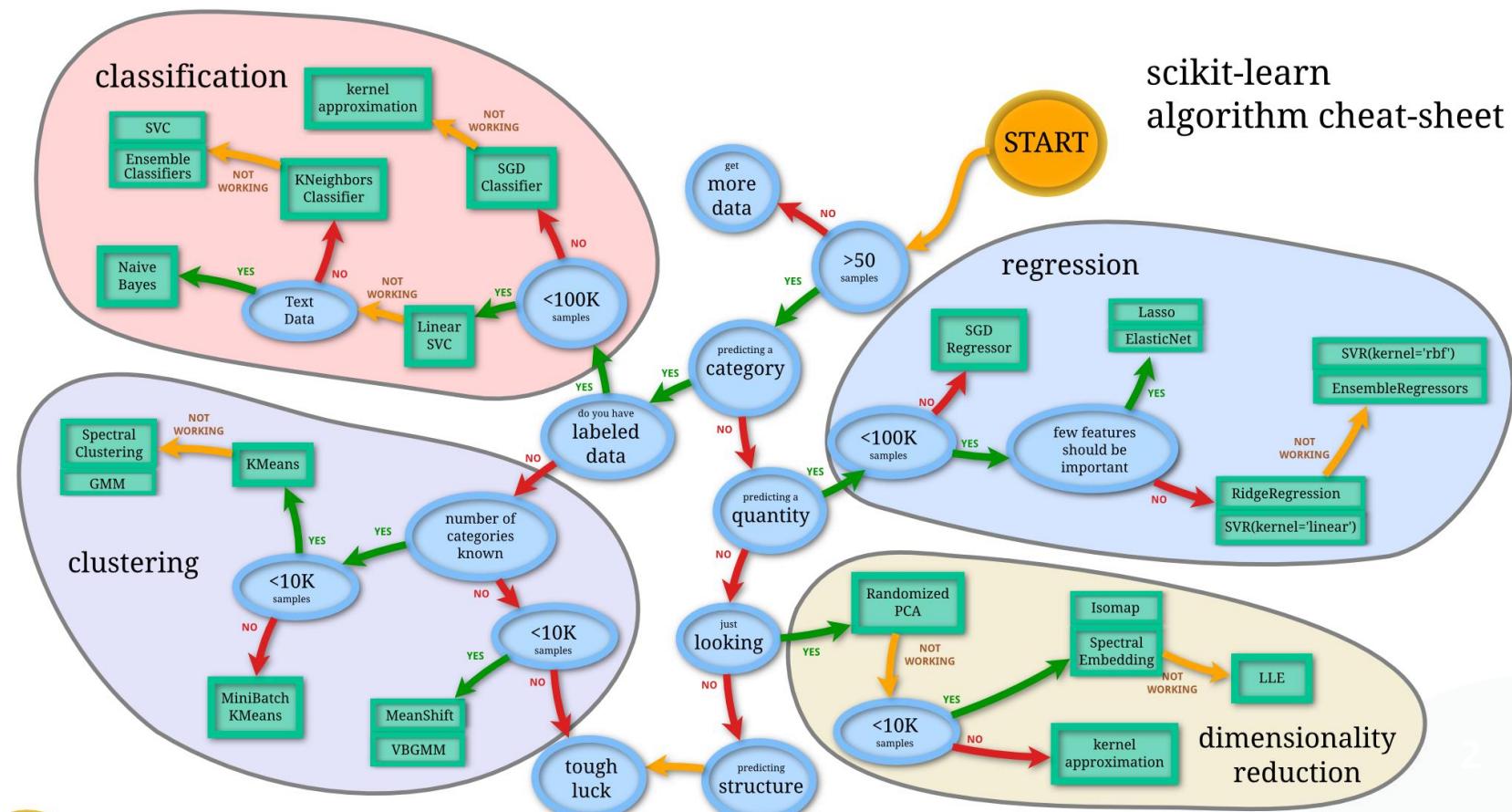
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Several approaches of the data science

- Data-mining algorithms
- Optimization algorithms
- Machine learning algorithms (ML)
 - Reinforcement learning
 - Unsupervised learning (*clustering*)
 - Supervised learning

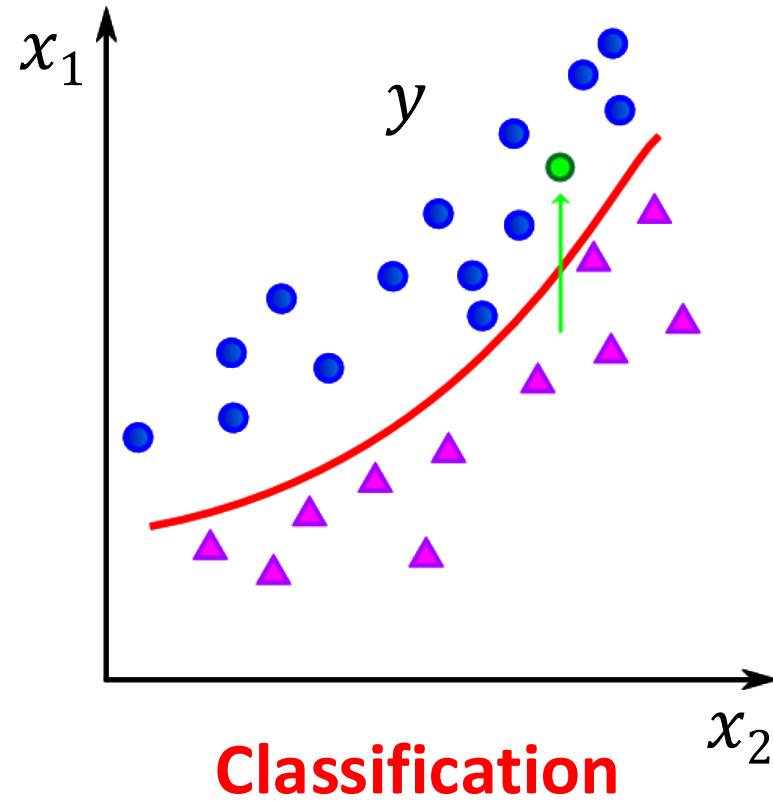
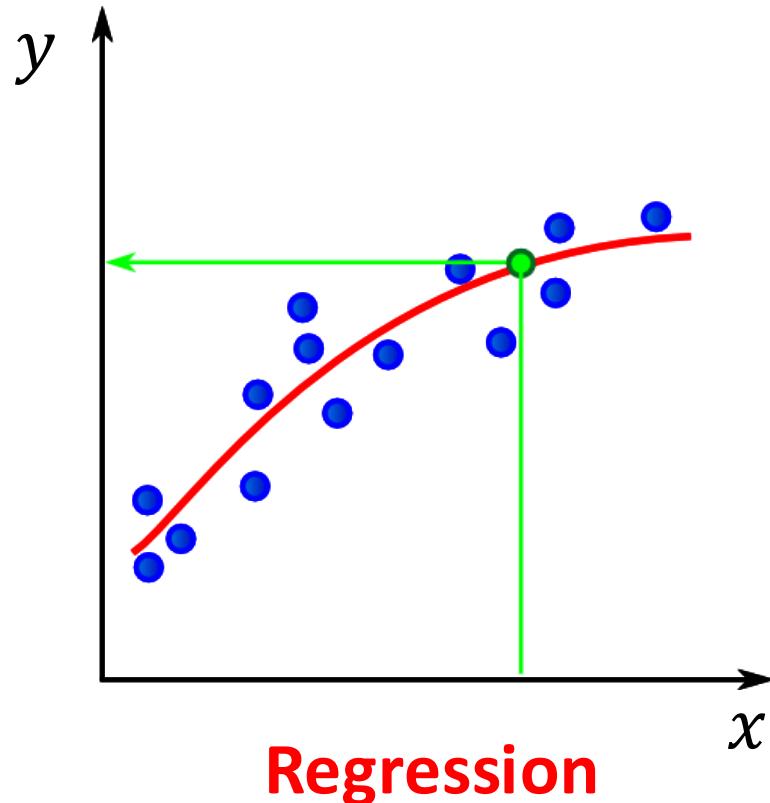
Choosing the right estimator?

https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html

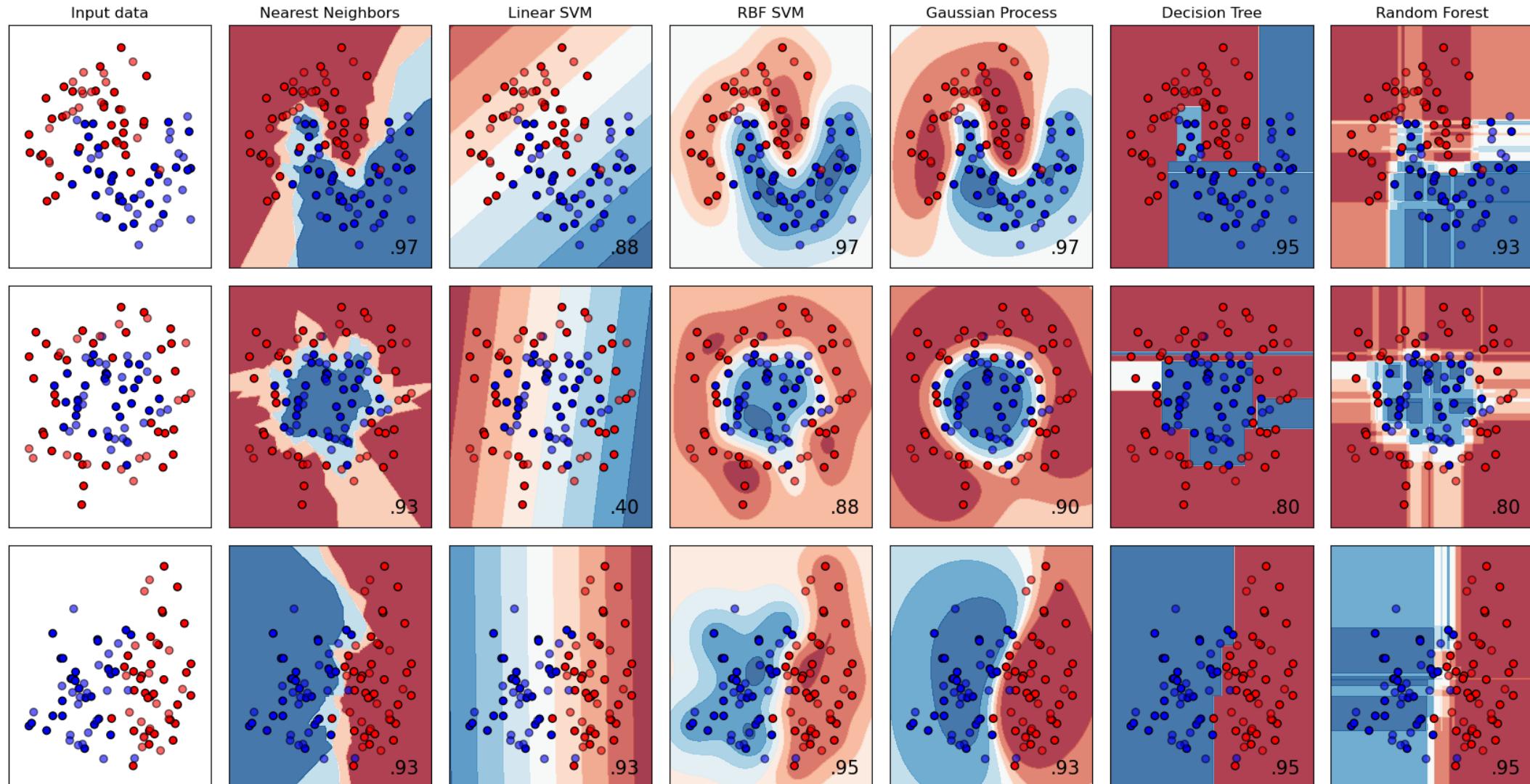


3. Supervised learning

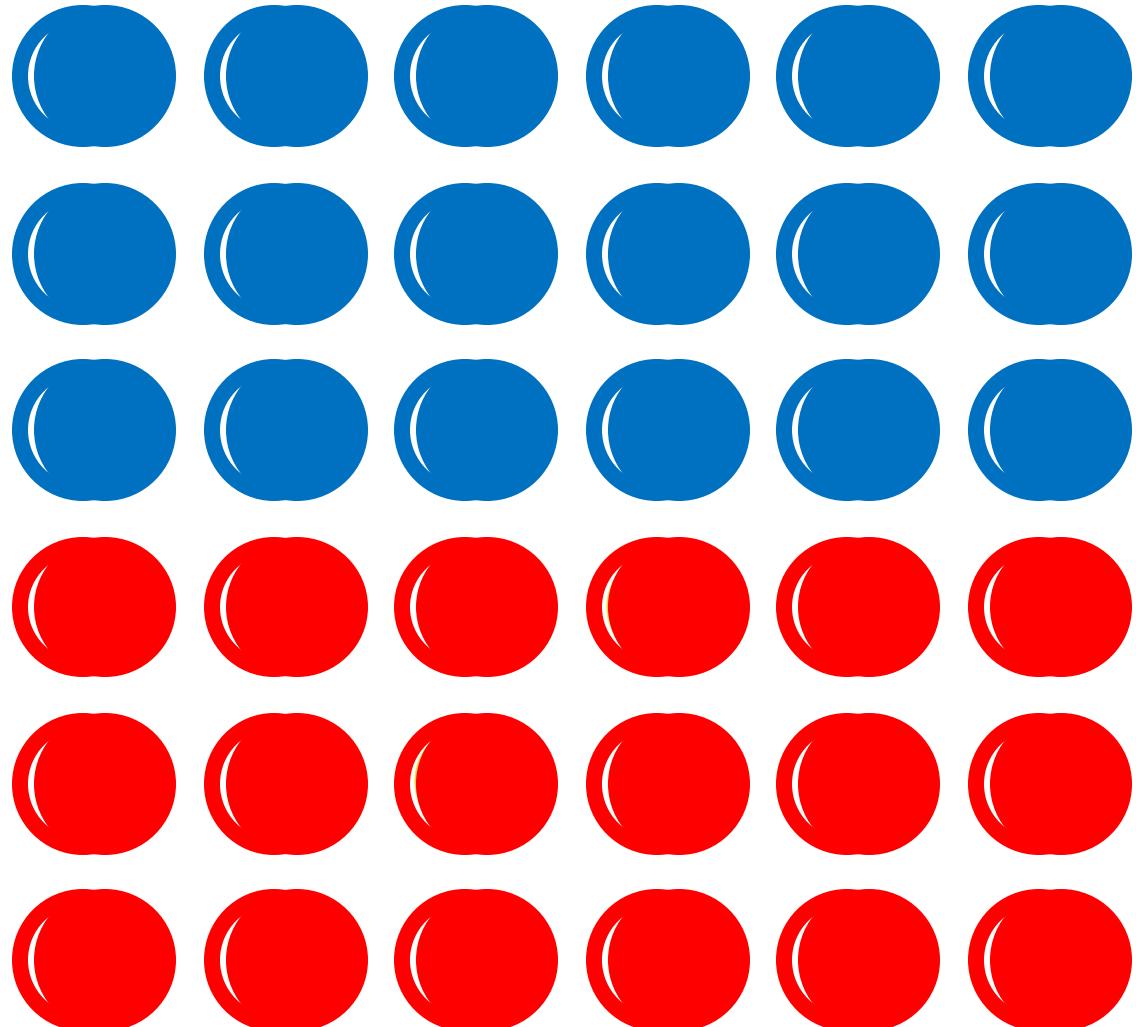
The training dataset often consists of pairs of an input vector (or scalar) and the corresponding output vector (or scalar), the output of the function can be regression or classification.



Binary classifier comparison



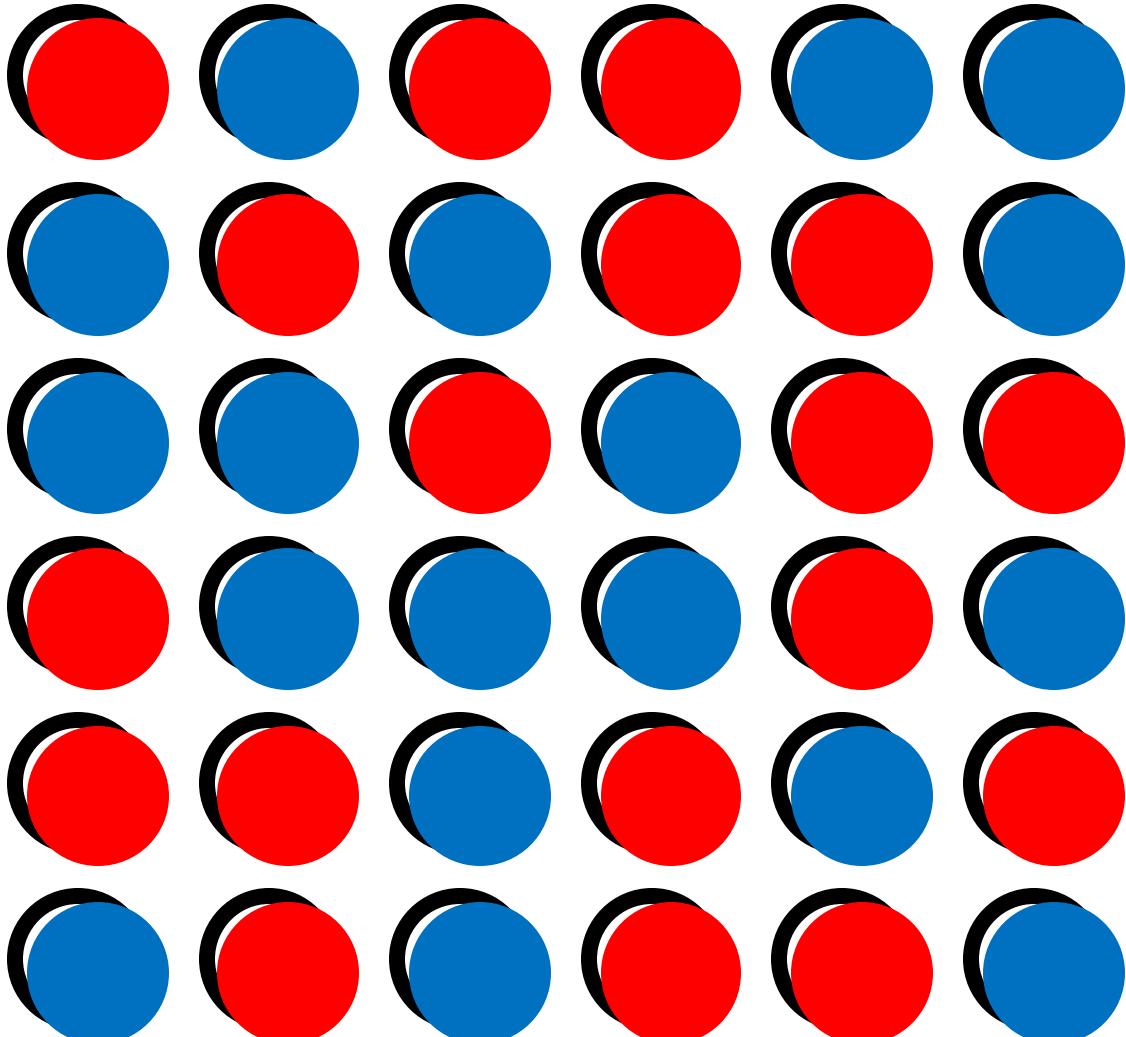
Naïve Bayes Classifier



$p(A|B)?$

Ok if
 $p(B|A)$
known

Naïve Bayes Classifier



$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Independence hypothesis

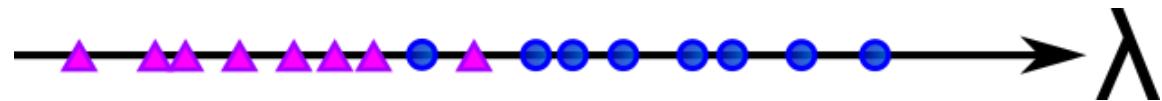
Strengths:

- Good performance
- Even with few data

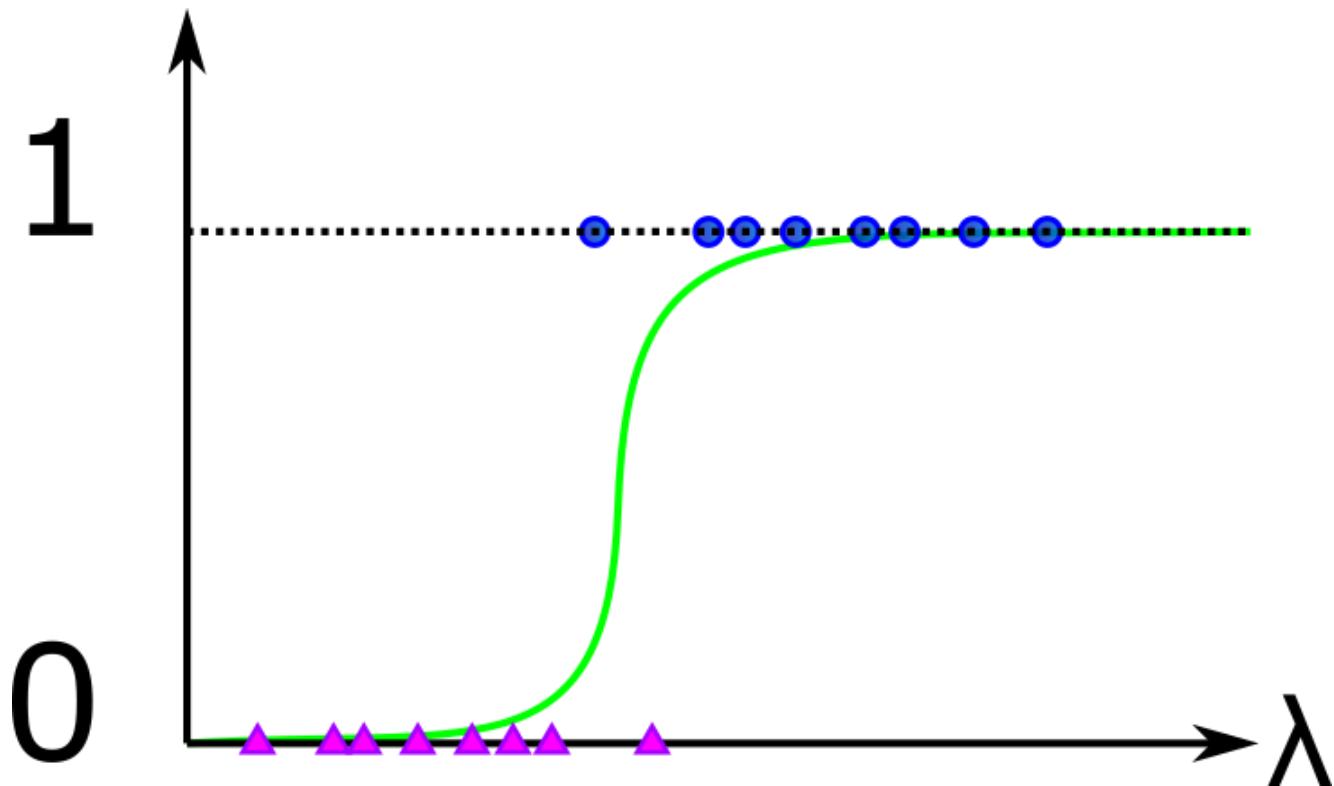
Weaknesses:

- Not valid if condition of independence is not valid

Logistic regression



Is one of most used
Is a part of generalized
linear model (GLM)



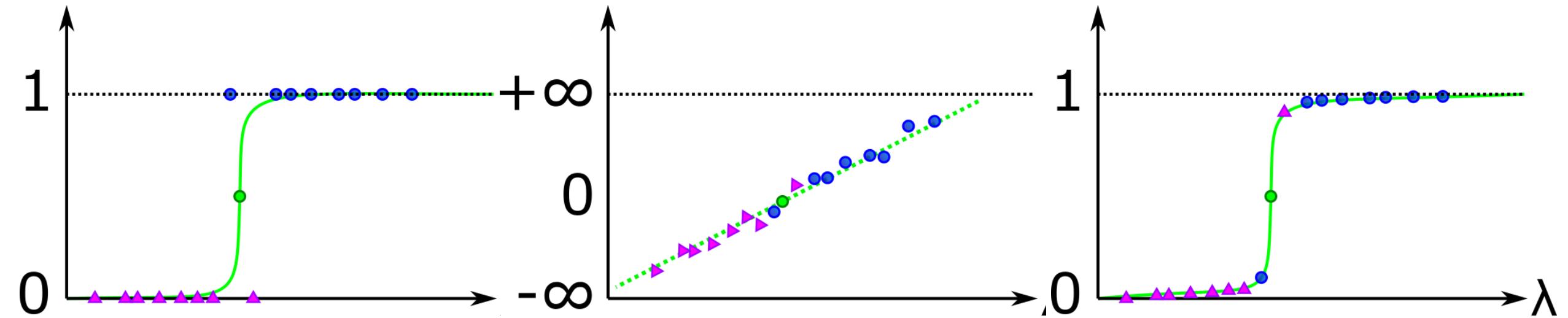
$$p(y = 1|X) = \sigma(w^T X + b)$$

Sigmoid function:

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

as a partition function

Logistic regression

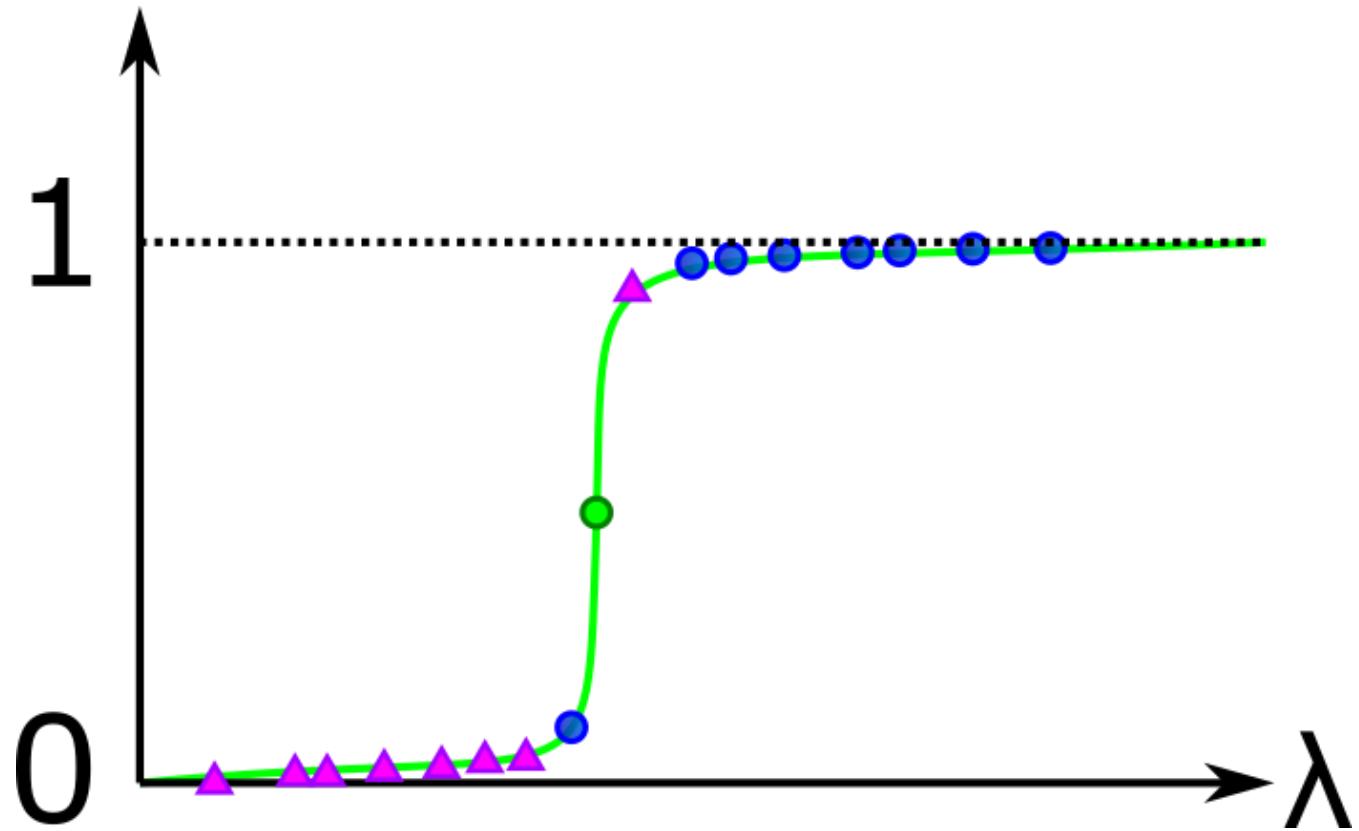


Log odd ratio : $\text{Log}(p/1-p)$

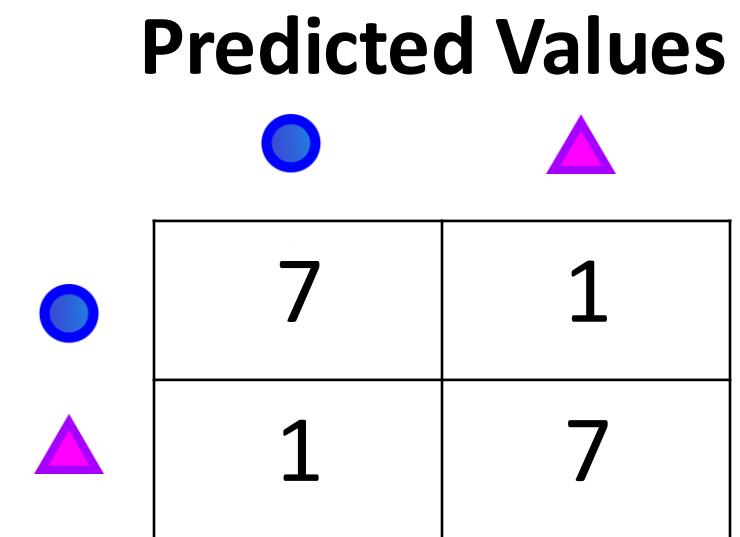
Coefficient ? Similar to a regression

Optimization by Maximum Likelihood estimation

Confusion matrix



Actual Values



Performance evolution metrics

- **True Positives:** outcome correctly predicted as positive class
- **True Negatives:** outcome correctly predicted as negative class
- **False Positives:** outcome incorrectly predicted as positive class
- **False Negatives:** outcome incorrectly predicted as negative class

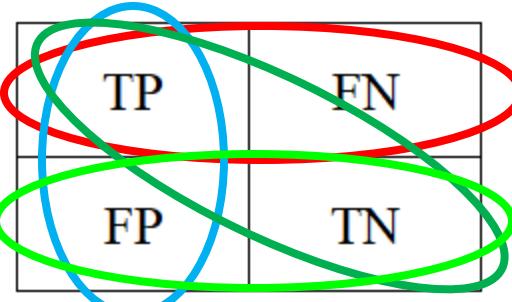
		<i>Predicted Values</i>	
		Positive	Negative
<i>Actual Values</i>	Positive	TP	FN
	Negative	FP	TN

$$\begin{aligned} \text{TP} &= \sum_{i=1}^n 1_{y_i=1, \hat{y}_i=1} \\ \text{TN} &= \sum_{i=1}^n 1_{y_i=-1, \hat{y}_i=-1} \\ \text{FN} &= \sum_{i=1}^n 1_{y_i=1, \hat{y}_i=-1} \\ \text{FP} &= \sum_{i=1}^n 1_{y_i=-1, \hat{y}_i=1} \end{aligned}$$

		Predicted \hat{y}	
		1	-1
True y	1	TP	FN
	-1	FP	TN

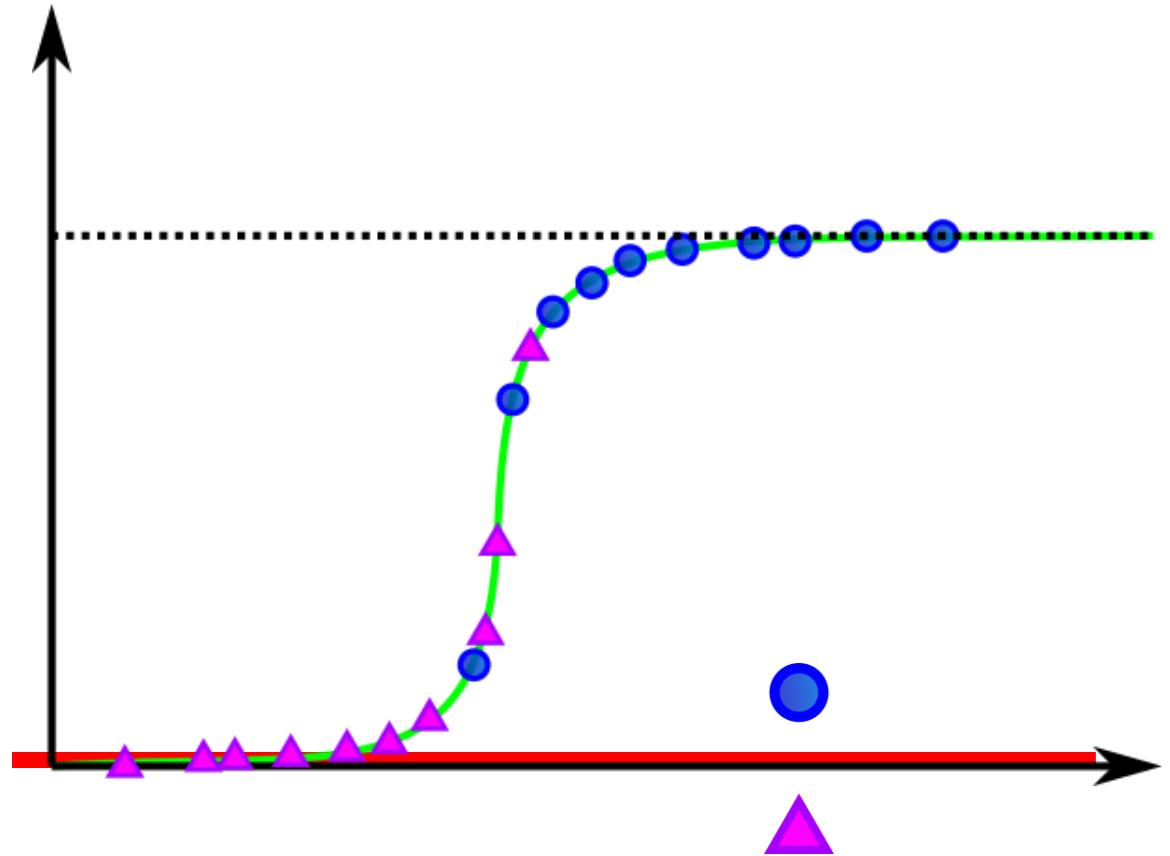
Performance evolution metrics

		<i>Predicted Values</i>		<i>Performance Metric</i>	<i>Formula</i>
<i>Actual Values</i>	Positive	TP	FN	Accuracy	$(TP + TN) / (TP + TN + FP + FN)$
	Negative	FP	TN	Precision	$TP / (TP + FP)$
				Recall (Sensitivity)	$TP / (TP + FN)$
				Specificity	$TN / (FP + TN)$

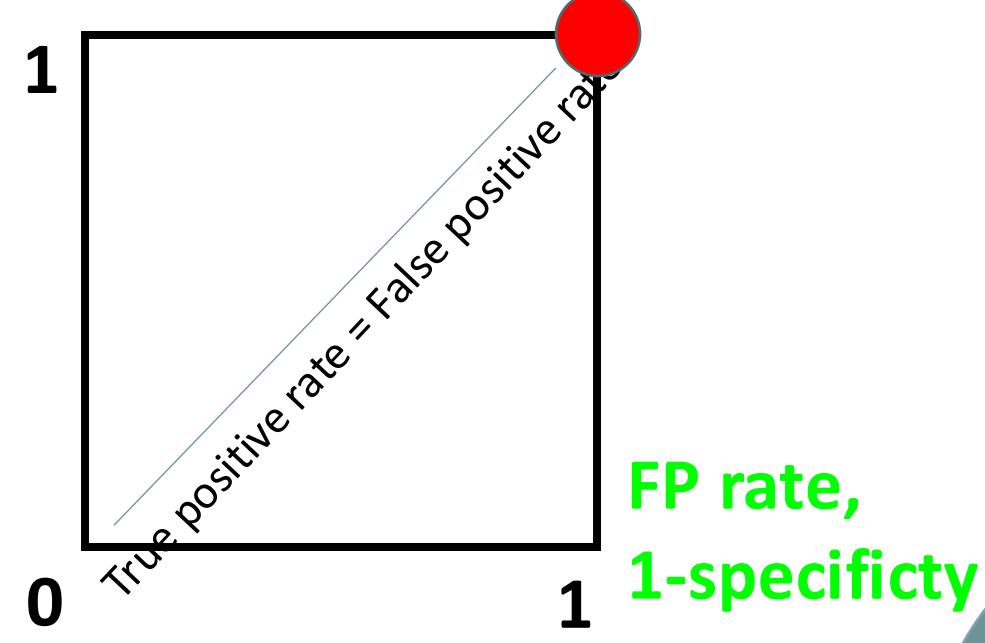


- **Accuracy (*exactitude*)**: test's ability to correctly predict both classes
- **Precision (*précision*)**: test's ability to correctly detect positive classes from all predicted positive classes
- **Recall (*sensitivité*)**: test's ability to correctly detect positive classes from all actual positive classes, true positive rate
- **Specificity**: true negative rate

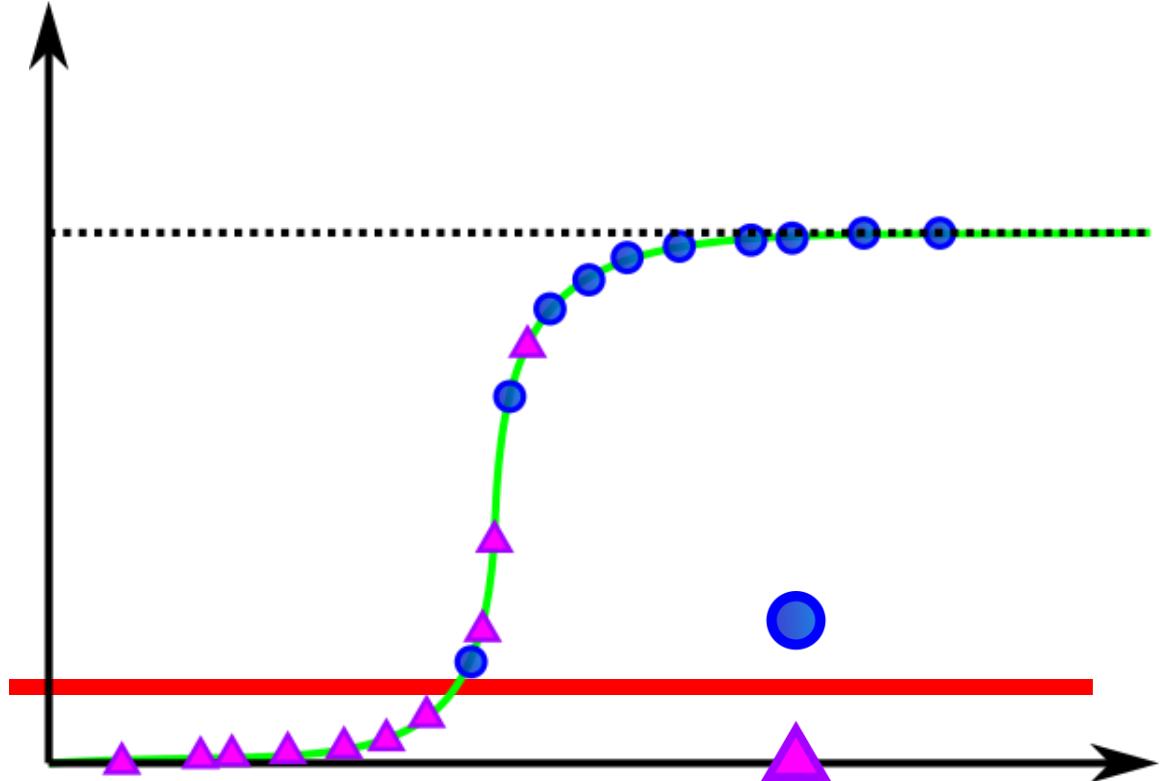
Choice of the threshold (*seuil*)



TP rate, sensitivity



Choice of the threshold (*seuil*)

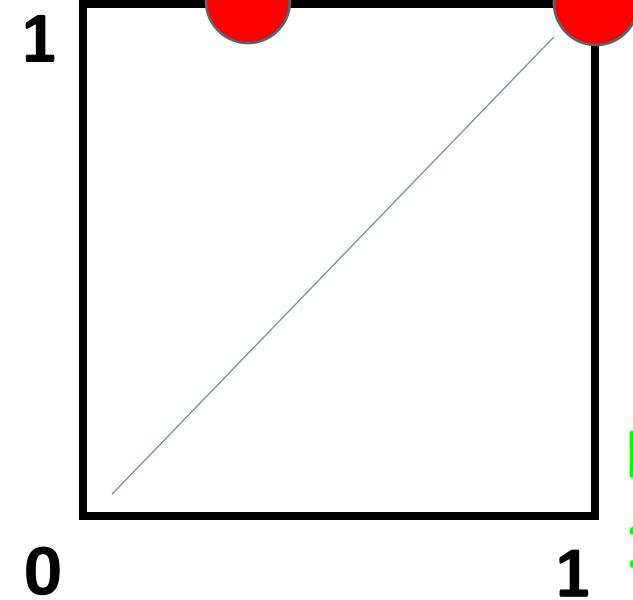


TP rate, sensitivity

Actual
Values

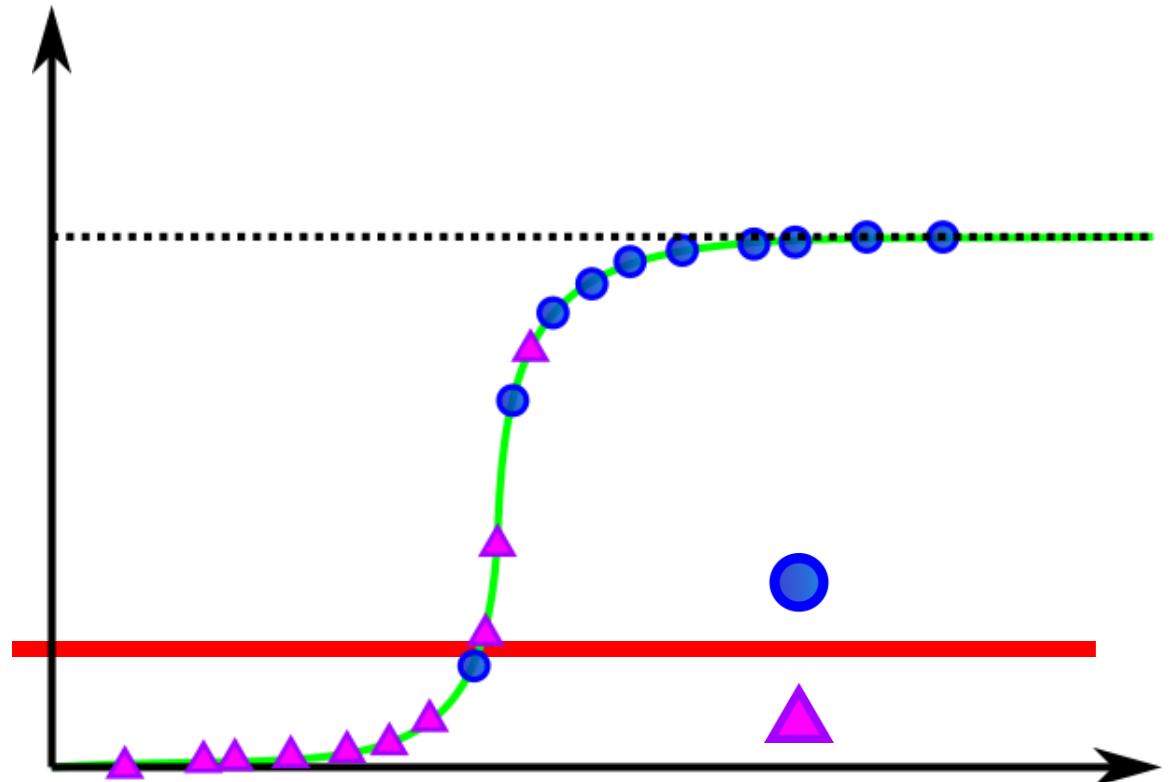
Predicted Values	
0	1
0	10
1	3

Actual Values

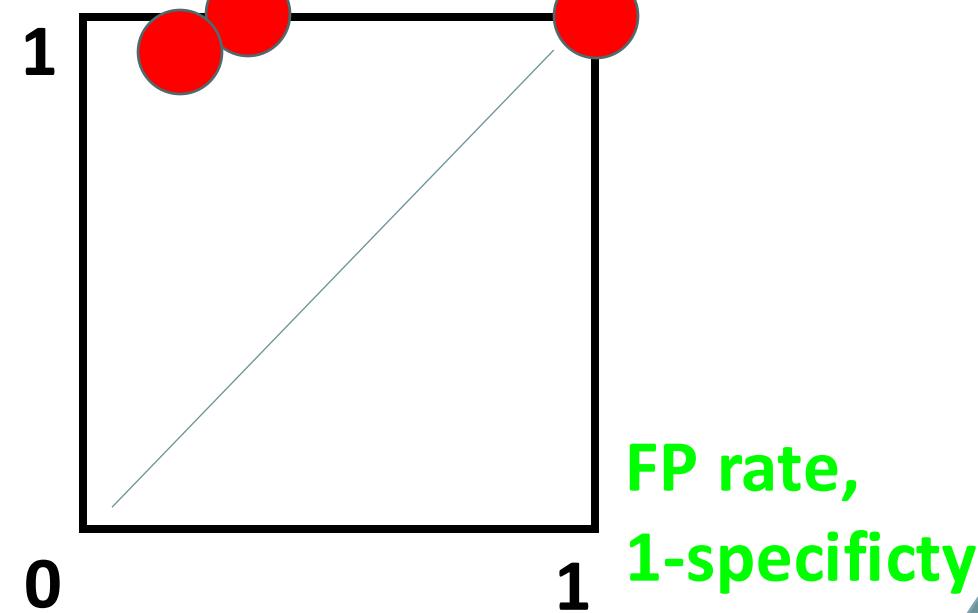


FP rate,
1-specificity

Choice of the threshold (*seuil*)



TP rate, sensitivity

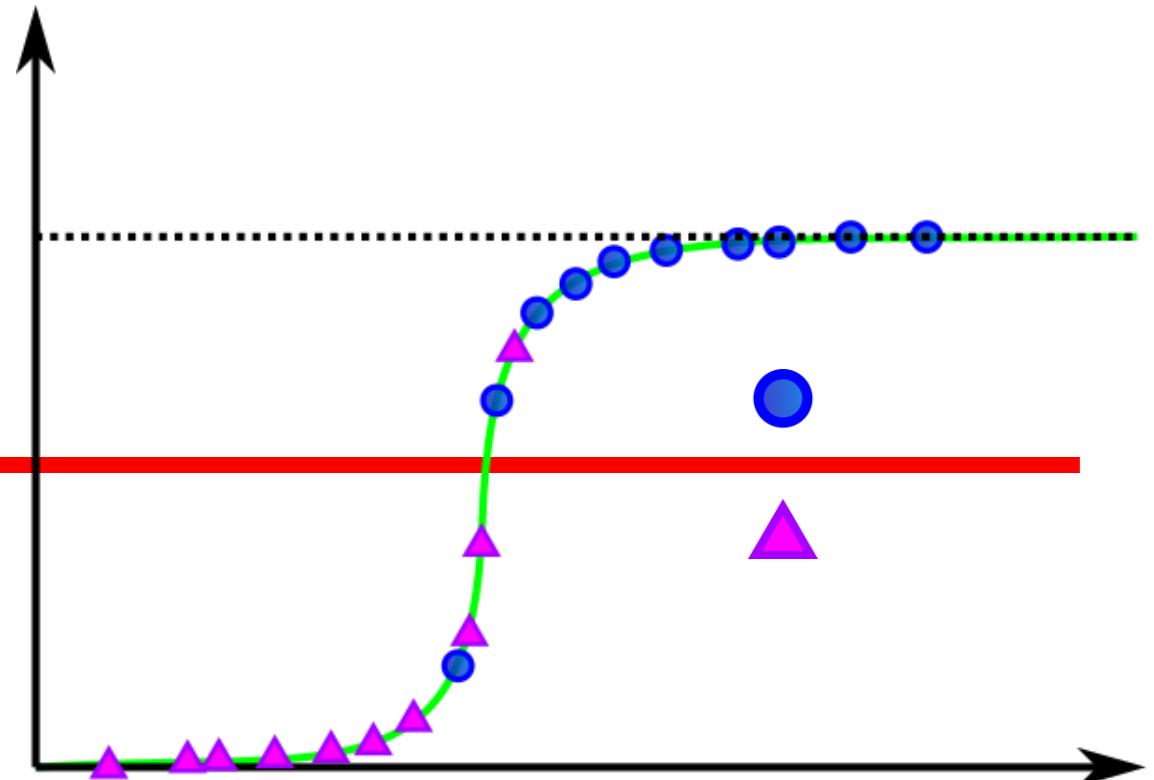


Predicted Values

Actual
Values

Predicted Values	
Actual Value 1	Actual Value 0
9	1
3	7

Choice of the threshold (*seuil*)



TP rate, sensitivity

Actual
Values

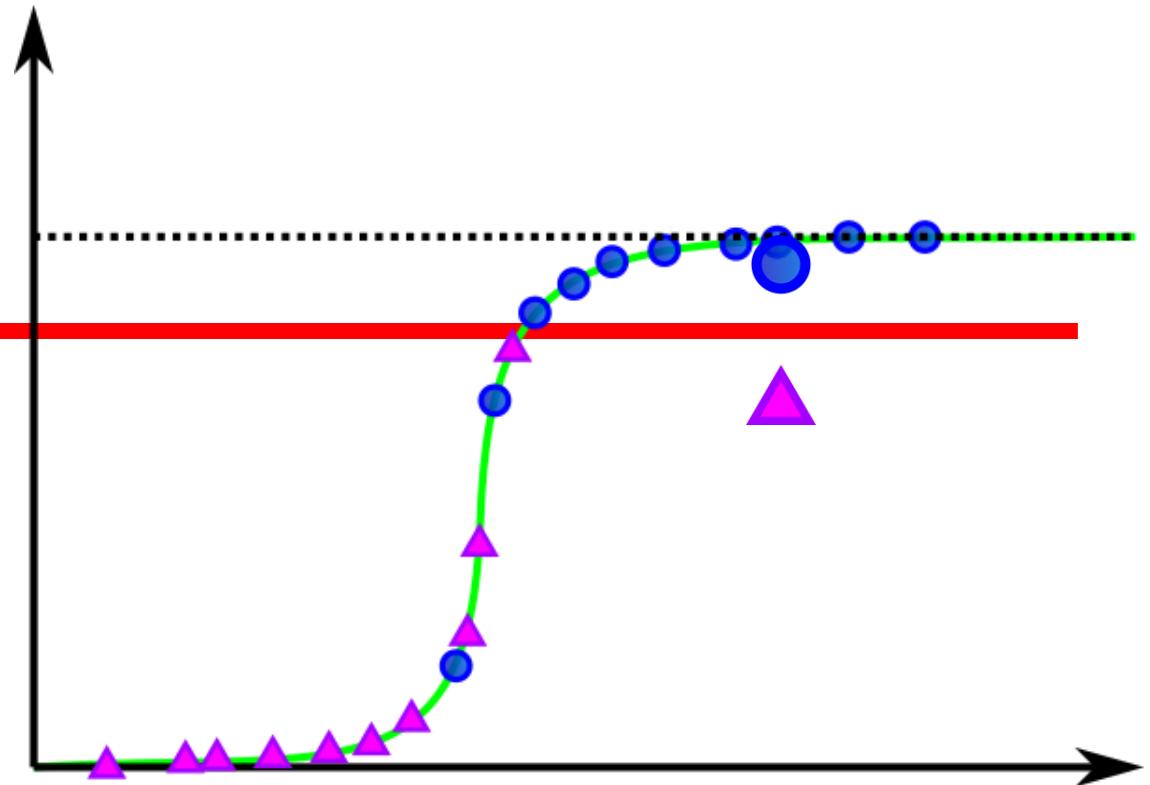
Predicted Values	
Actual Value	Predicted Value
9	1
1	9

1

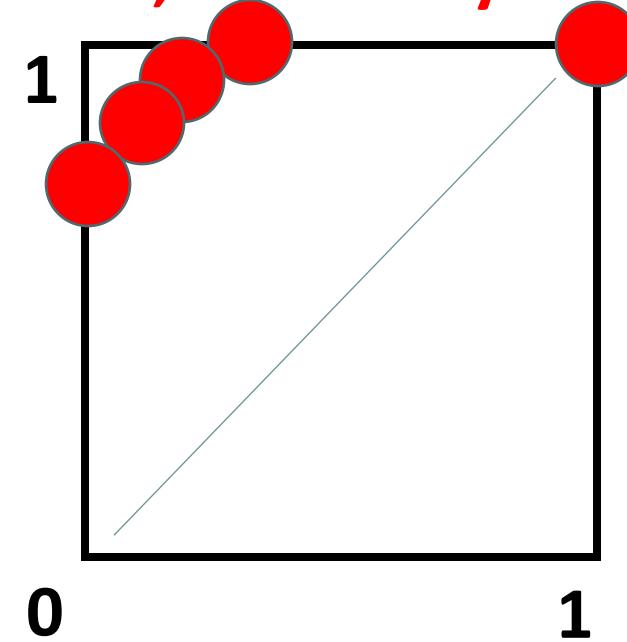
0

FP rate,
1-specificity

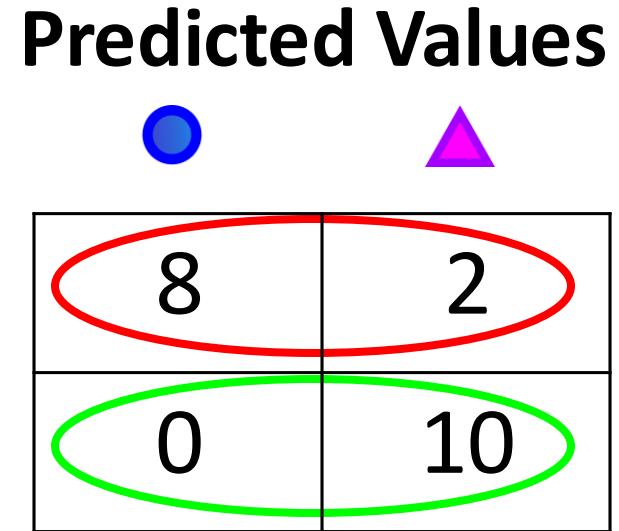
Choice of the threshold (*seuil*)



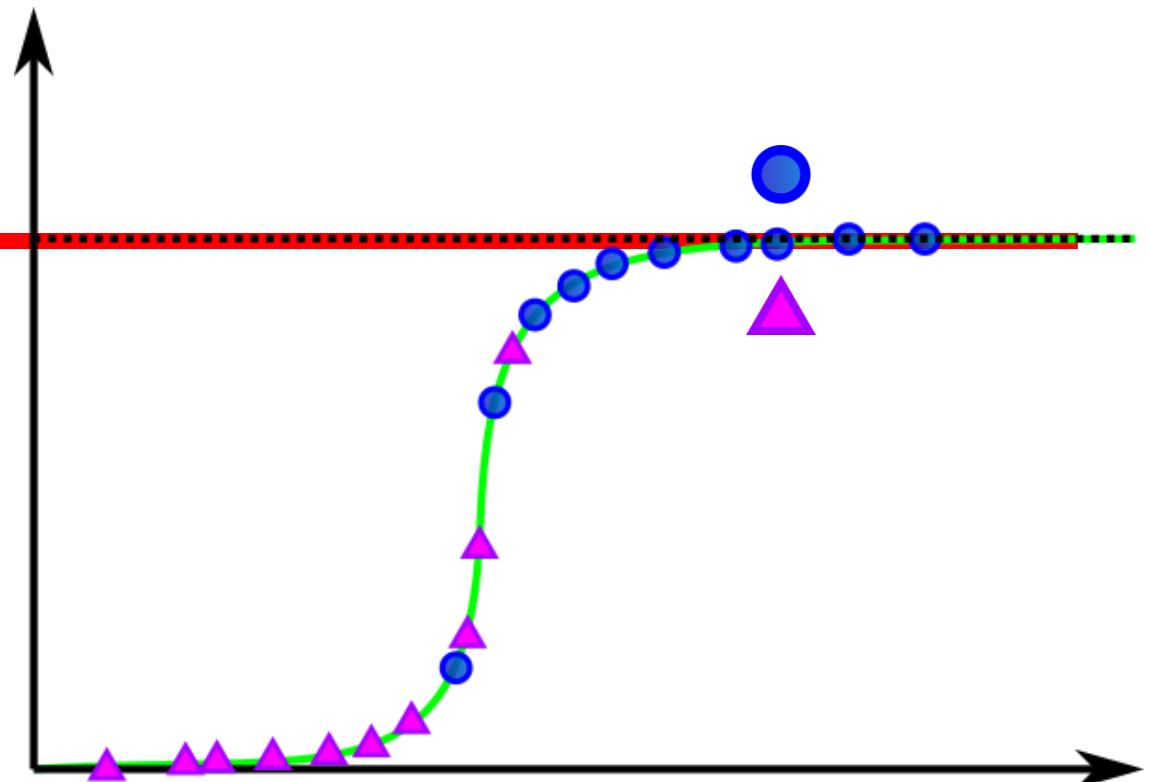
TP rate, sensitivity



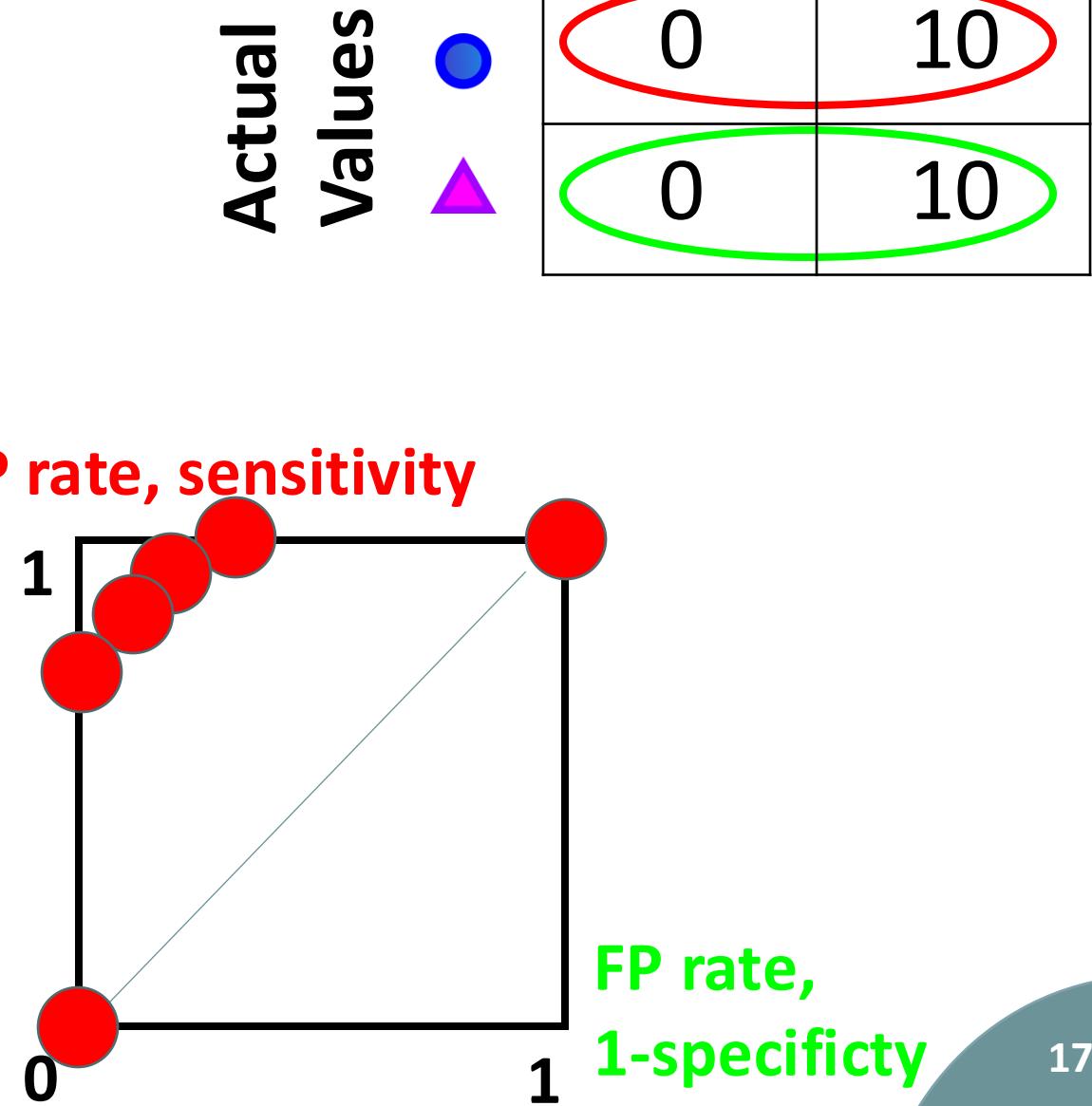
FP rate,
1-specificity



Choice of the threshold (*seuil*)

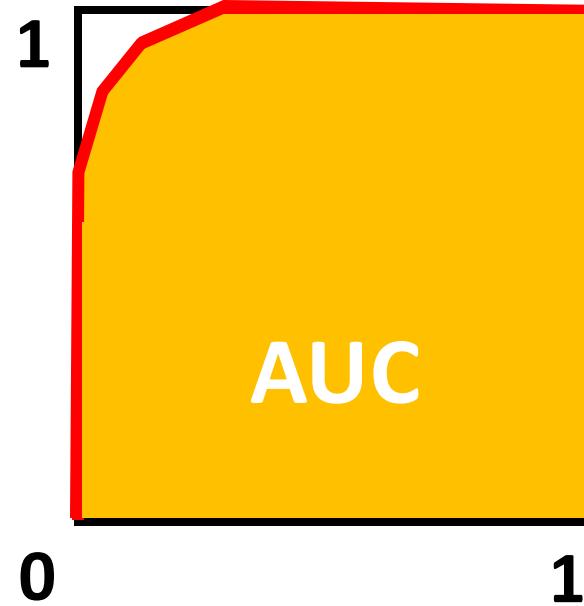


TP rate, sensitivity



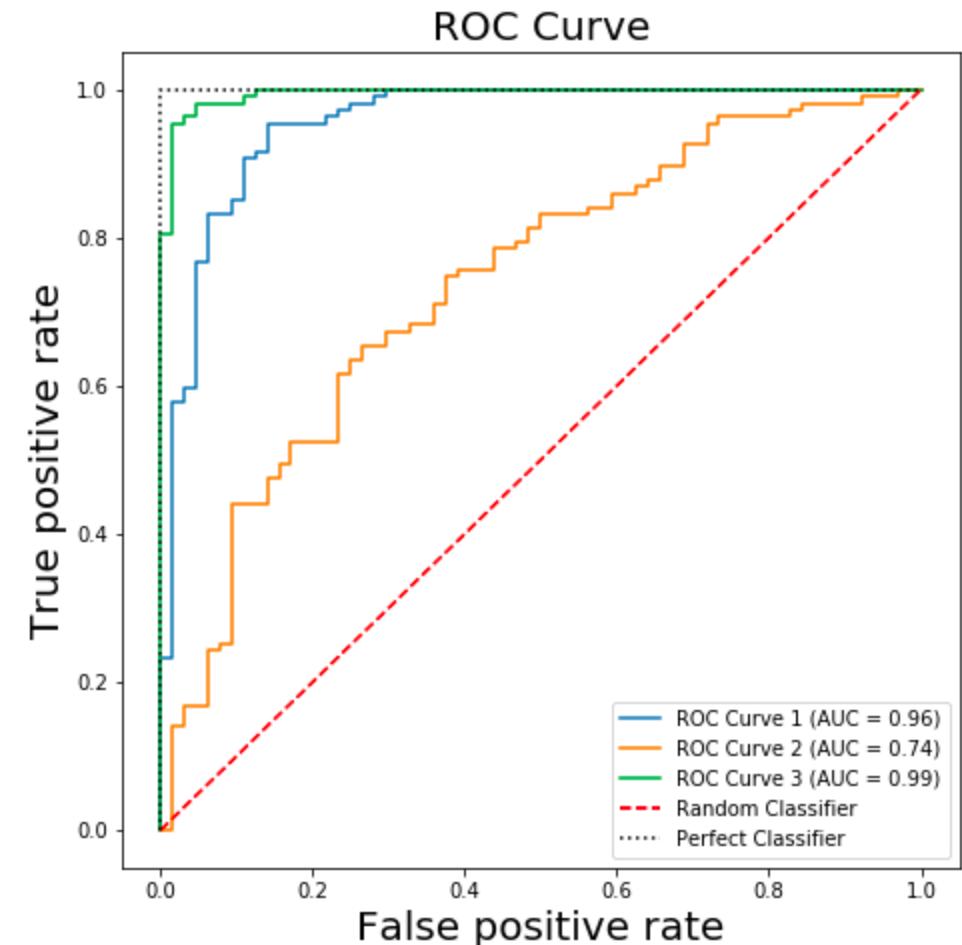
ROC graph (Receiver Operating Characteristic)

TP rate, sensitivity

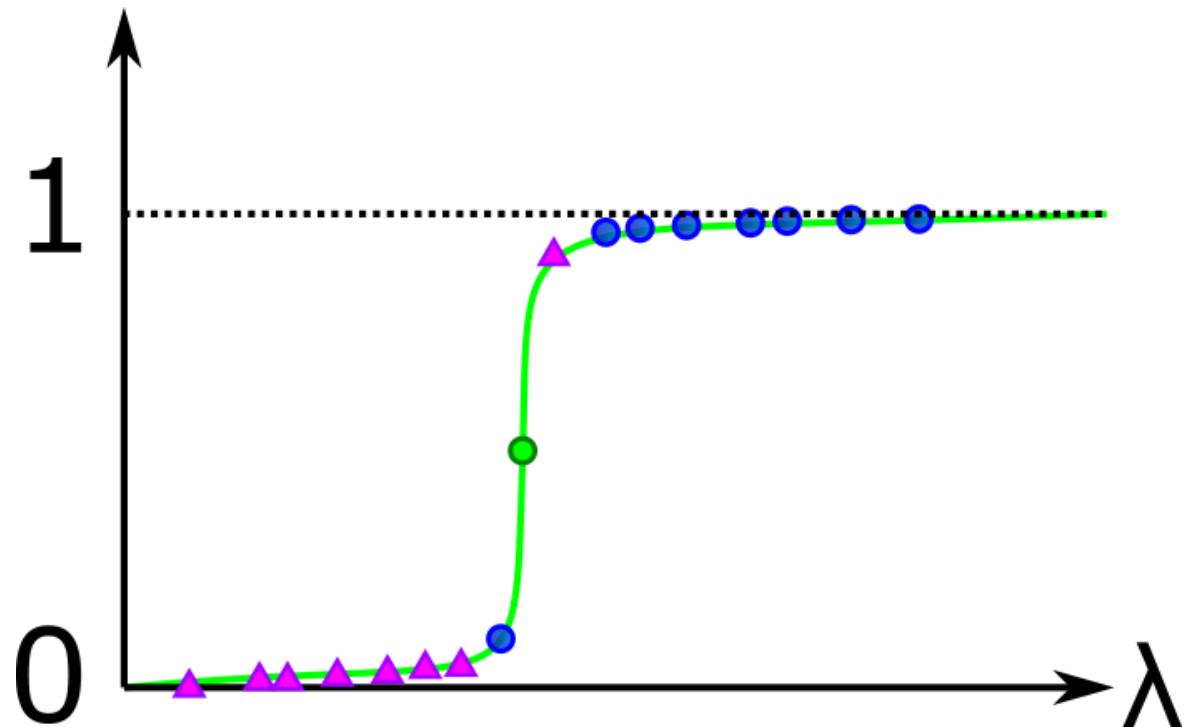


FP rate,
1-specificity

AUC score:
Area Under the ROC Curve



Logistic regression



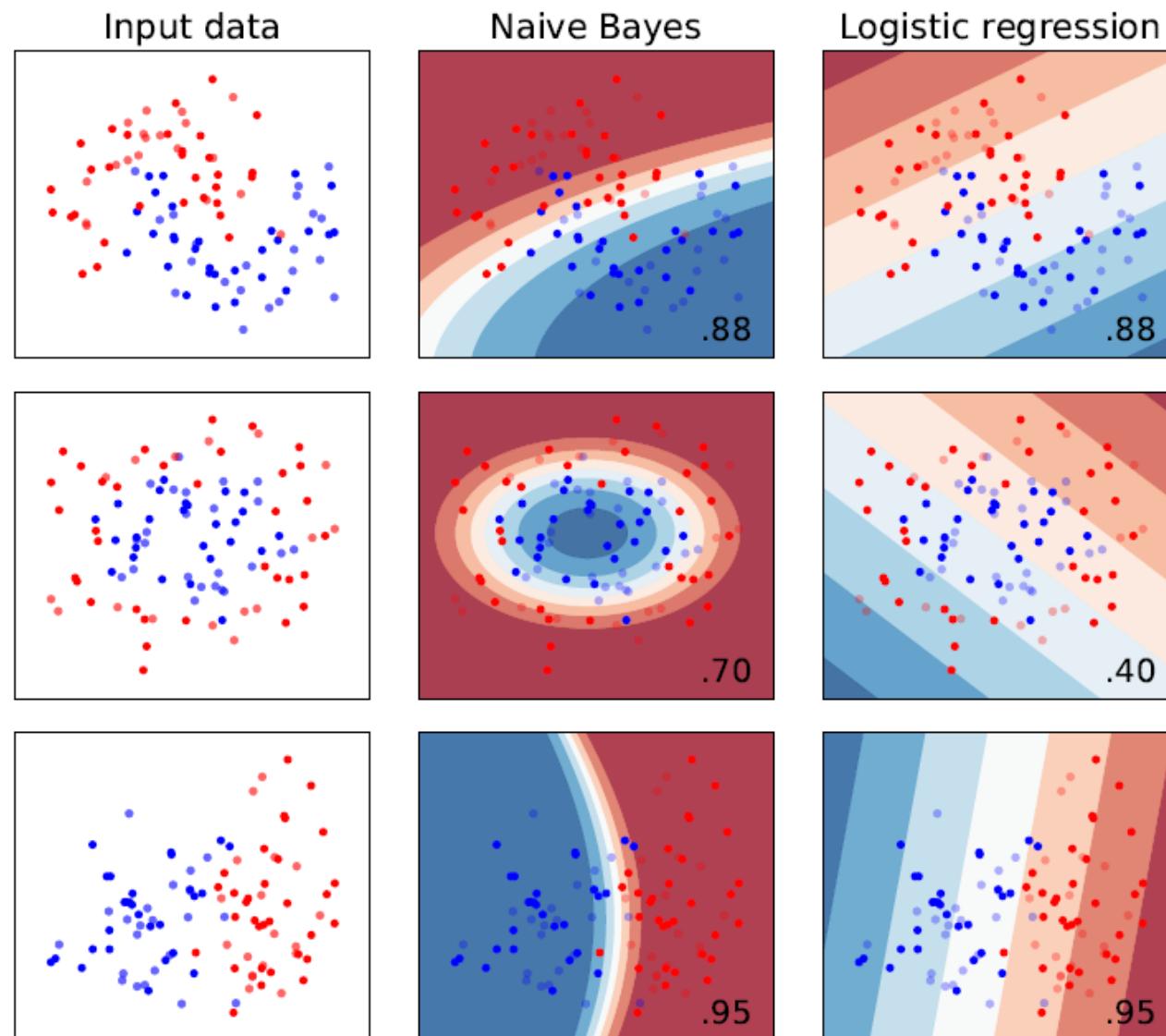
Strengths:

- Quick evaluation
- Easy interpretation of parameters

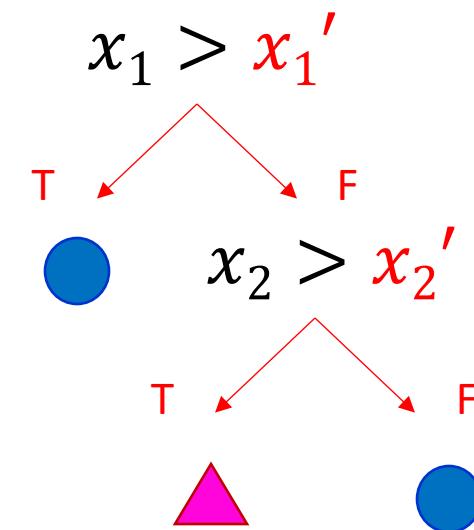
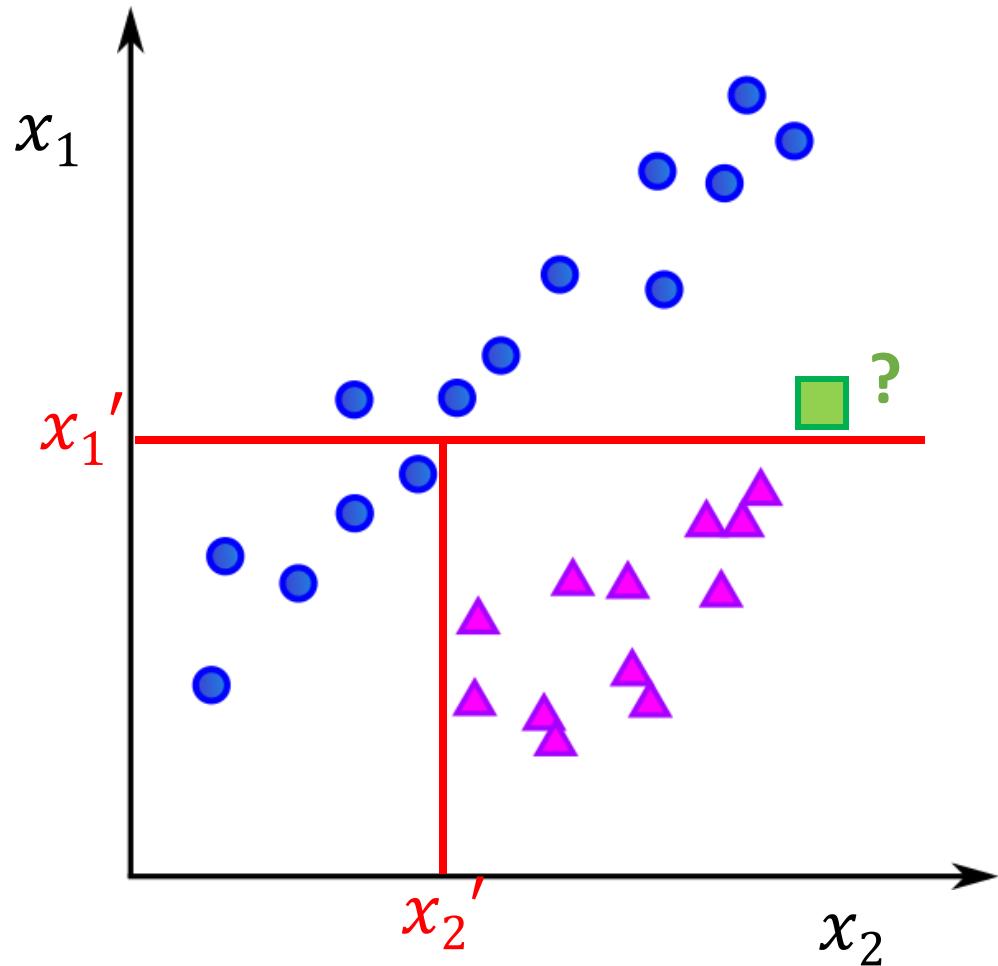
Weaknesses:

- Limited to binary classes
- Linearity hide interactions between variables
- Sensitive to outliers

Binary classifier comparison



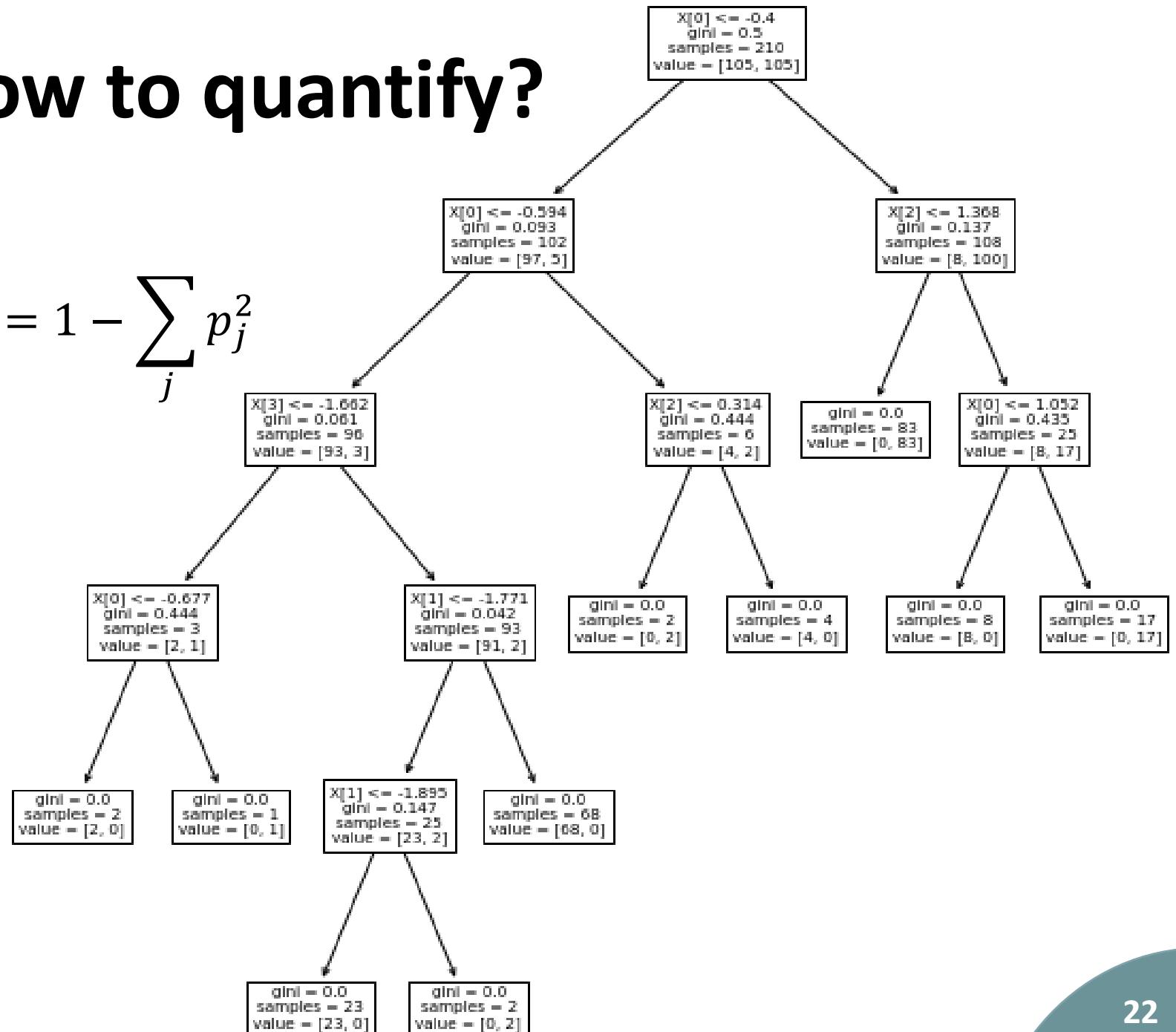
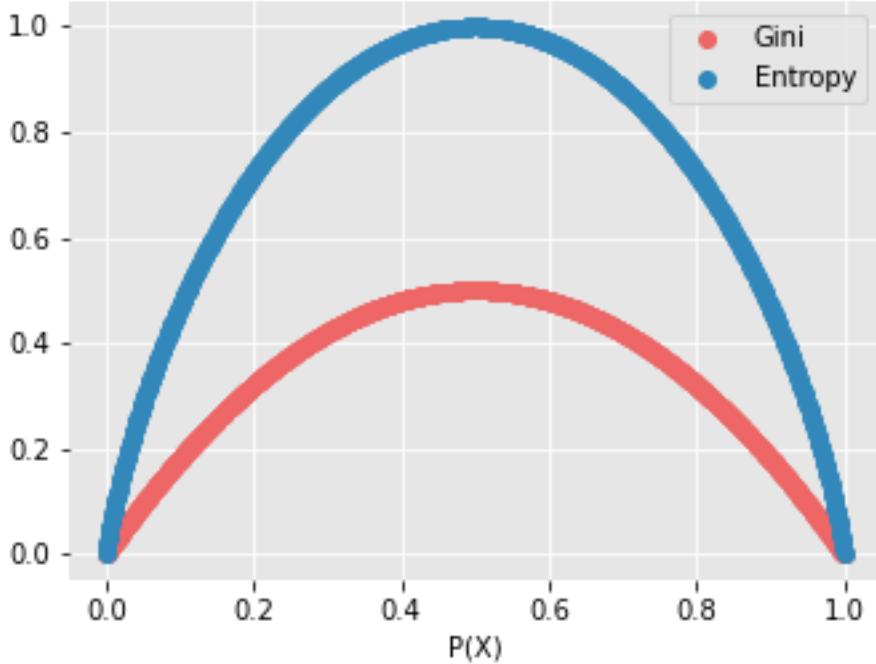
Decision Tree



Decision Tree: How to quantify?

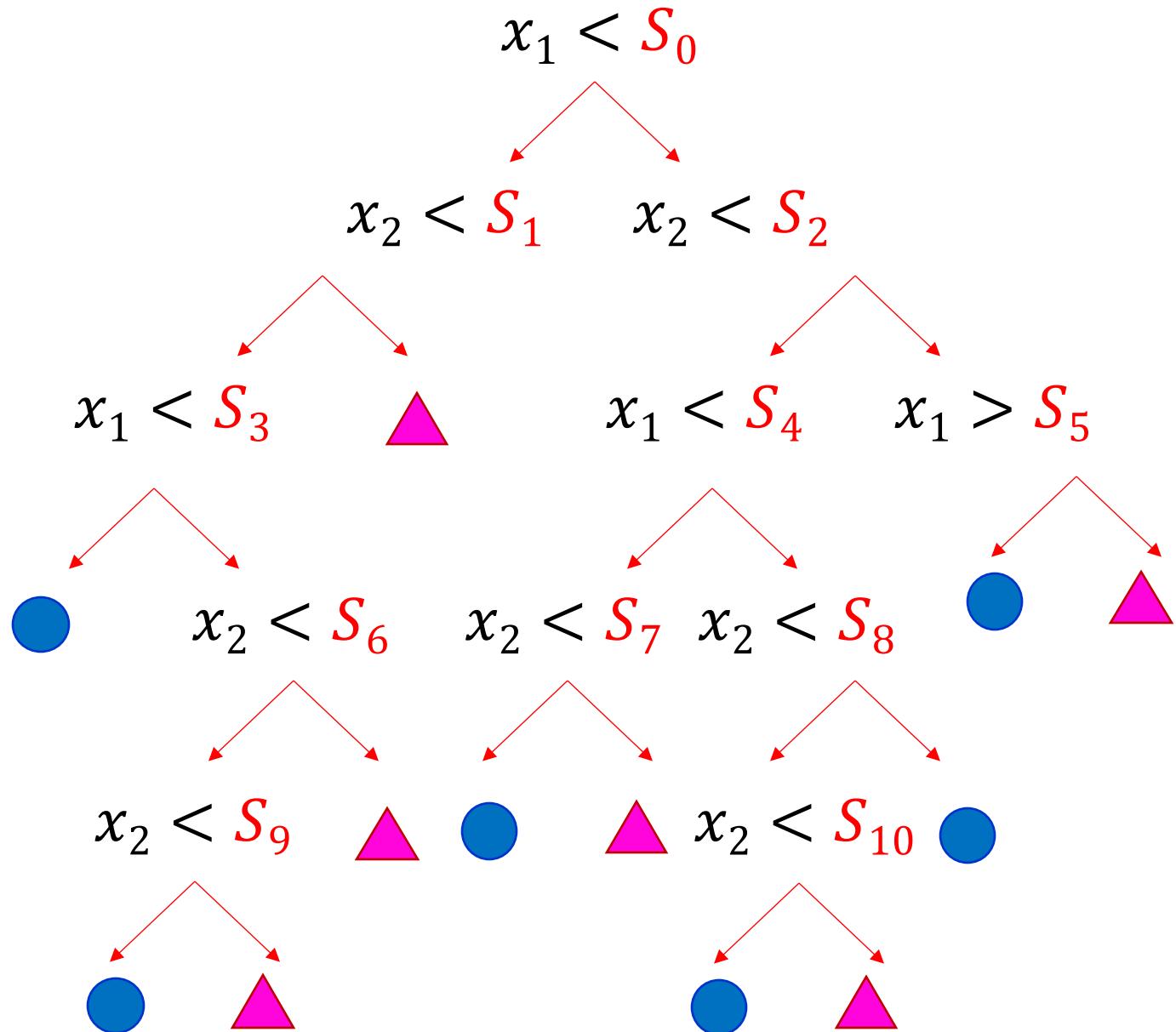
Classification in j class:

$$\text{entropy} = - \sum_j p_j \log_2 p_j \quad \text{gini} = 1 - \sum_j p_j^2$$



Regression: variance

Decision Tree



Strengths:

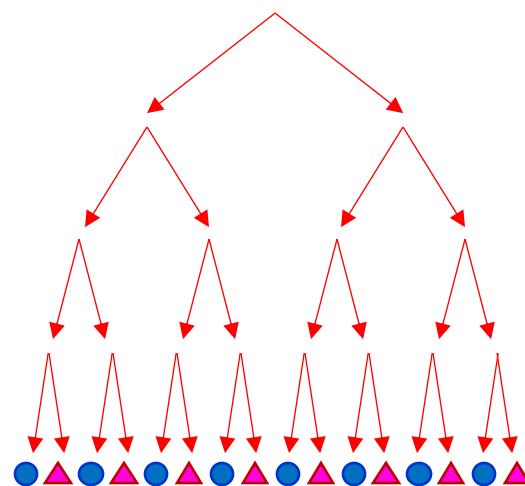
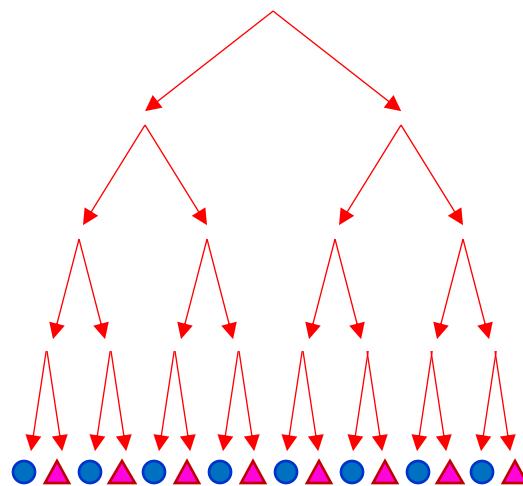
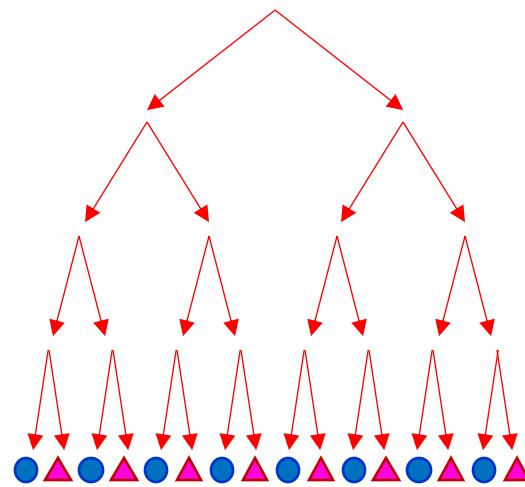
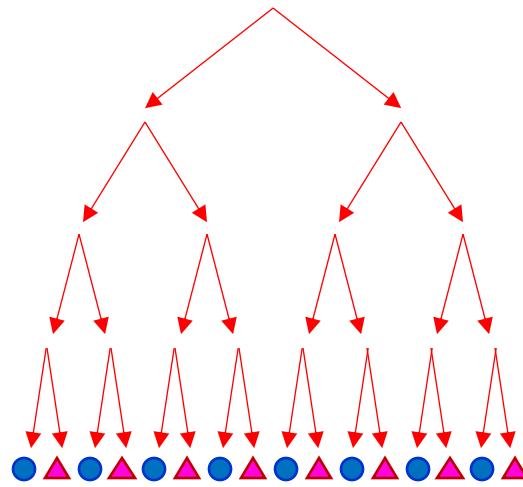
- visibility
 - multiclassess

Weaknesses:

- No correlation
 - Greedy approach, no regret
 - Overfitting

Random forest

stochastic discrimination based on averaging multiple decision trees, trained on different parts



Strengths:

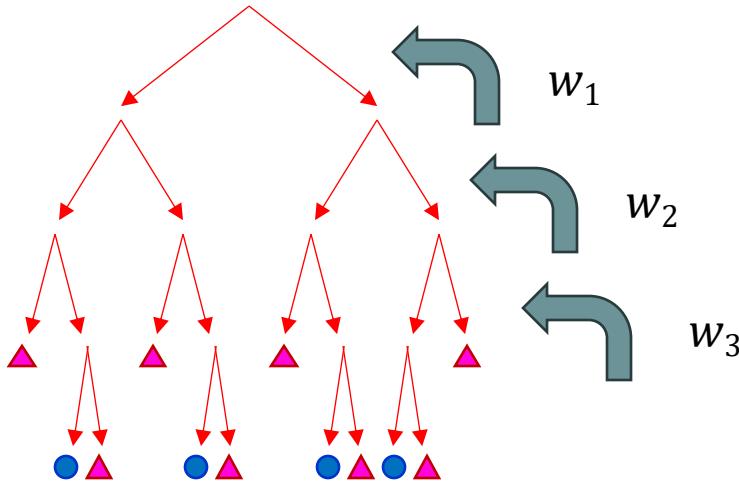
- Very accurate
- Overcomes the DT overfitting
- Efficient even if missing data

Weaknesses:

- Loss of the easy reading of DT (black box)
- Several parameters

[sklearn.ensemble.RandomForestClassifier](#)

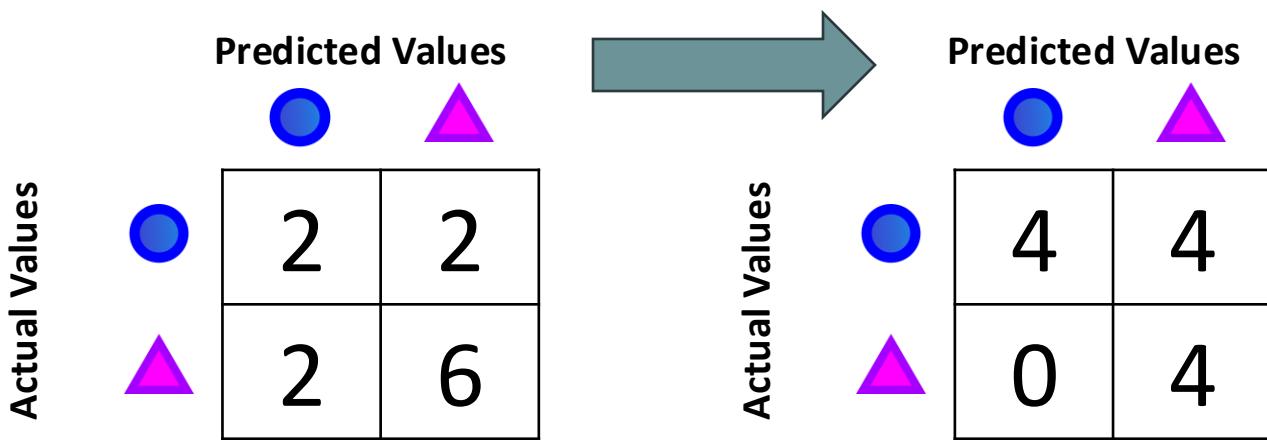
Gradient boosting



$$\text{Hyperparameters : } w_i = \frac{N_{\Delta}}{N_{\bullet} \times \mu}$$

Strengths:

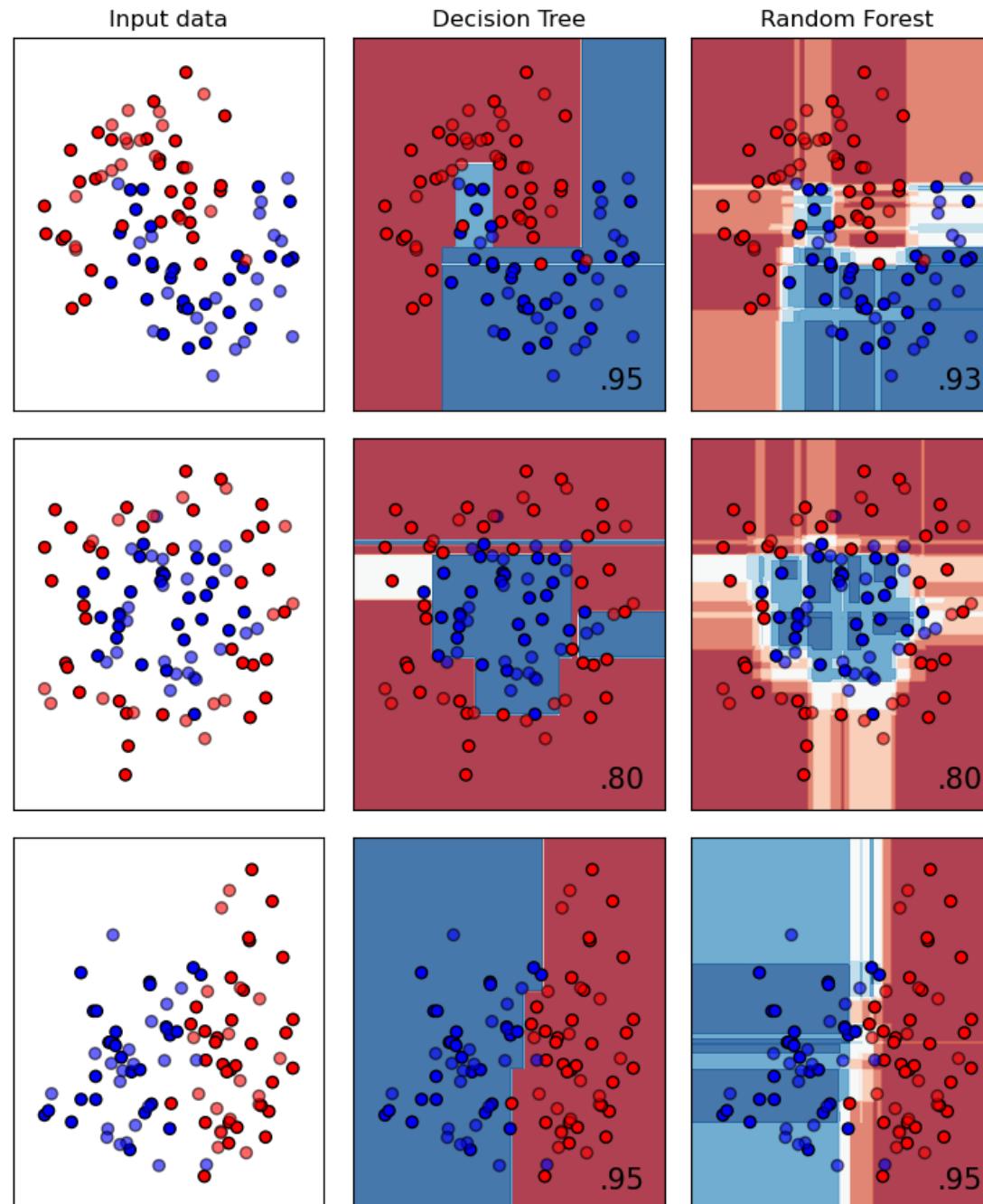
- Very efficient
- flexible



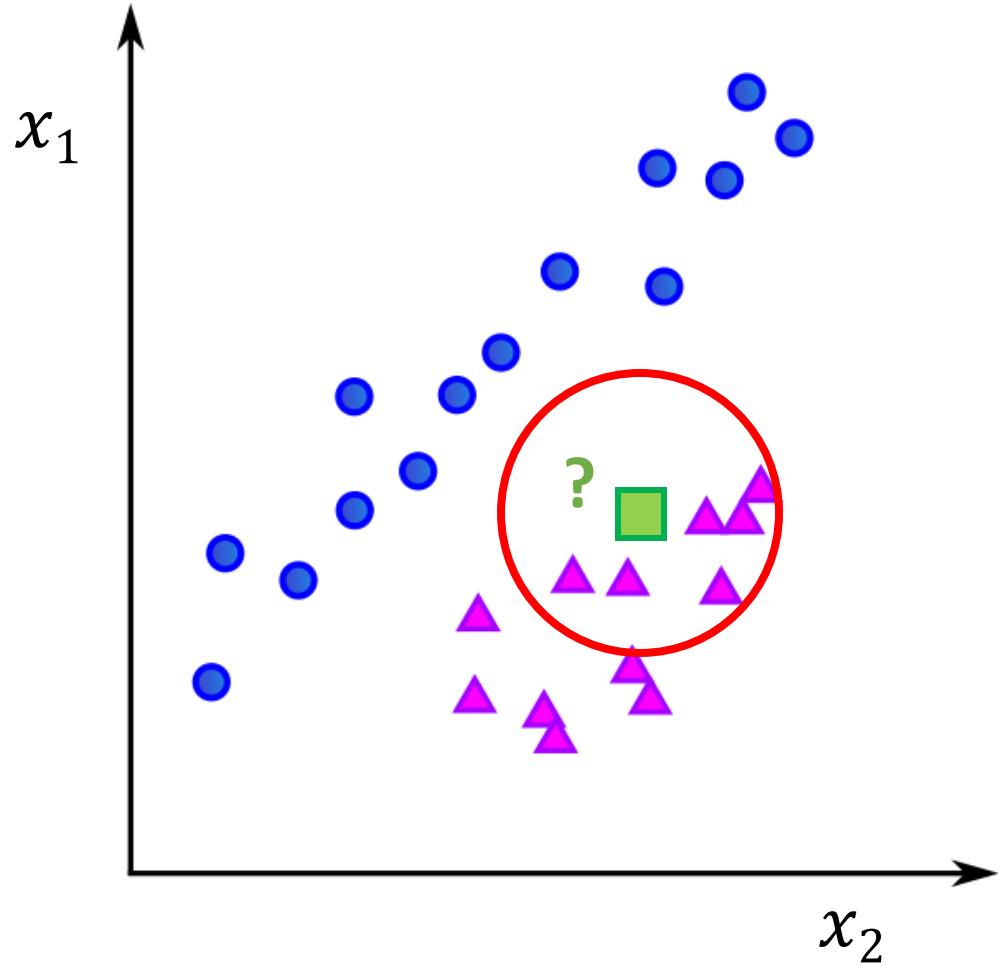
Weaknesses:

- Slow to train
- Sensitive to hyperparameters

Tree VS Forest



K-nearest neighbors



Find portion of N in k cluster for which sum of squared distance is minimum

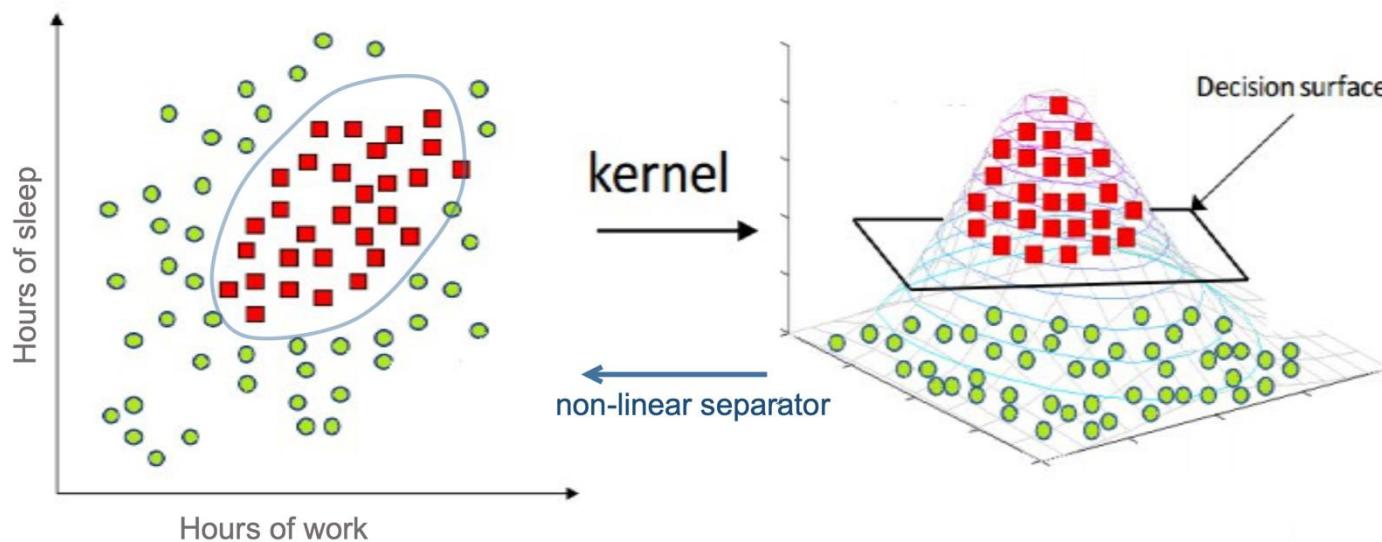
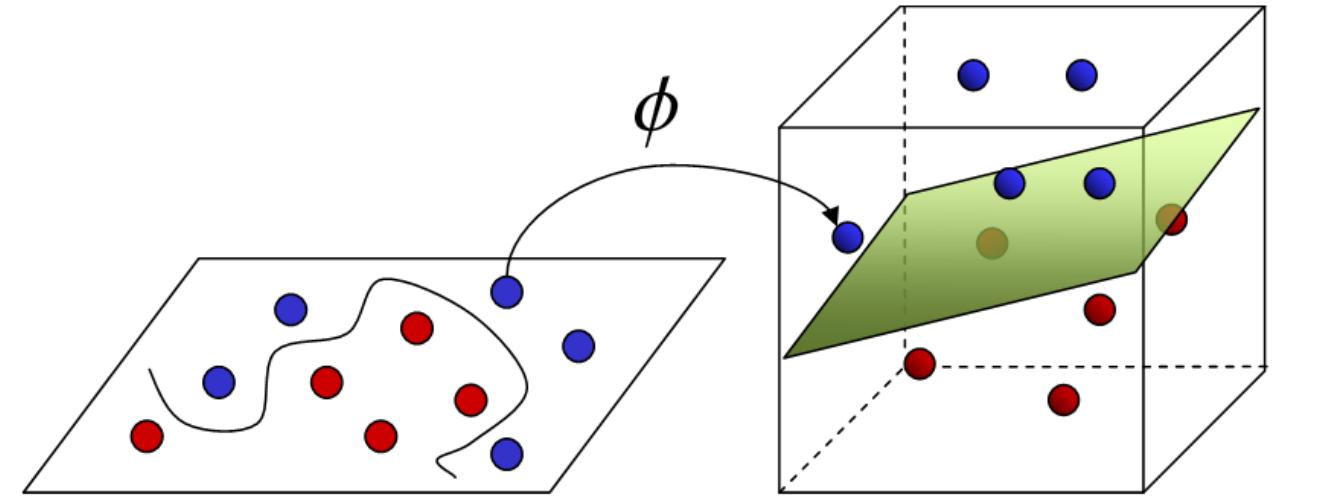
Strengths:

- Efficient, flexible
- Easy to understand

Weaknesses:

- Sensible to noise
- Too local
- Slow if many data
- Sensitive to outliers

Support Machine Vector (SVM)



Separation by a linear plan : find the hyper space (higher degree) easy to separate data

Strengths:

- Large dimension data
- Faster than NN

Weaknesses:

- Complexity in N^3
- Less efficient than RF
- Interpretability

Classification is a regression ?

