

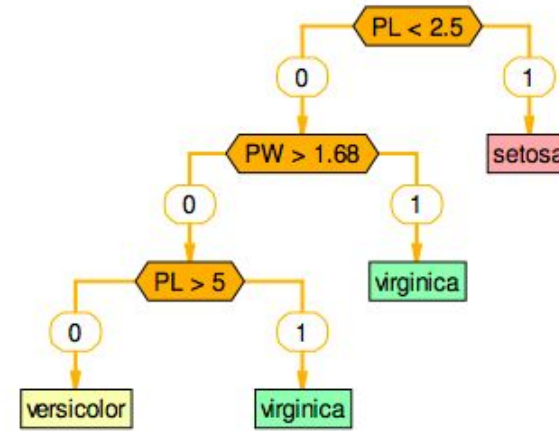
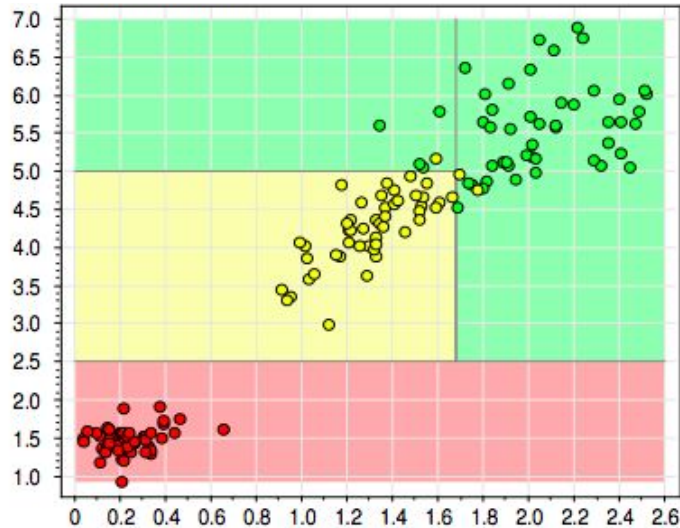
Lecture 7: Decision trees and Ensembles

Outline

1. Decision tree: intuition
2. Decision tree construction procedure
3. Information criteria
4. Pruning
5. Decision trees special highlights
 - Decision tree as linear model
 - Dealing with missing data
 - Categorical features
6. Bootstrap and Bagging
7. Random Forest

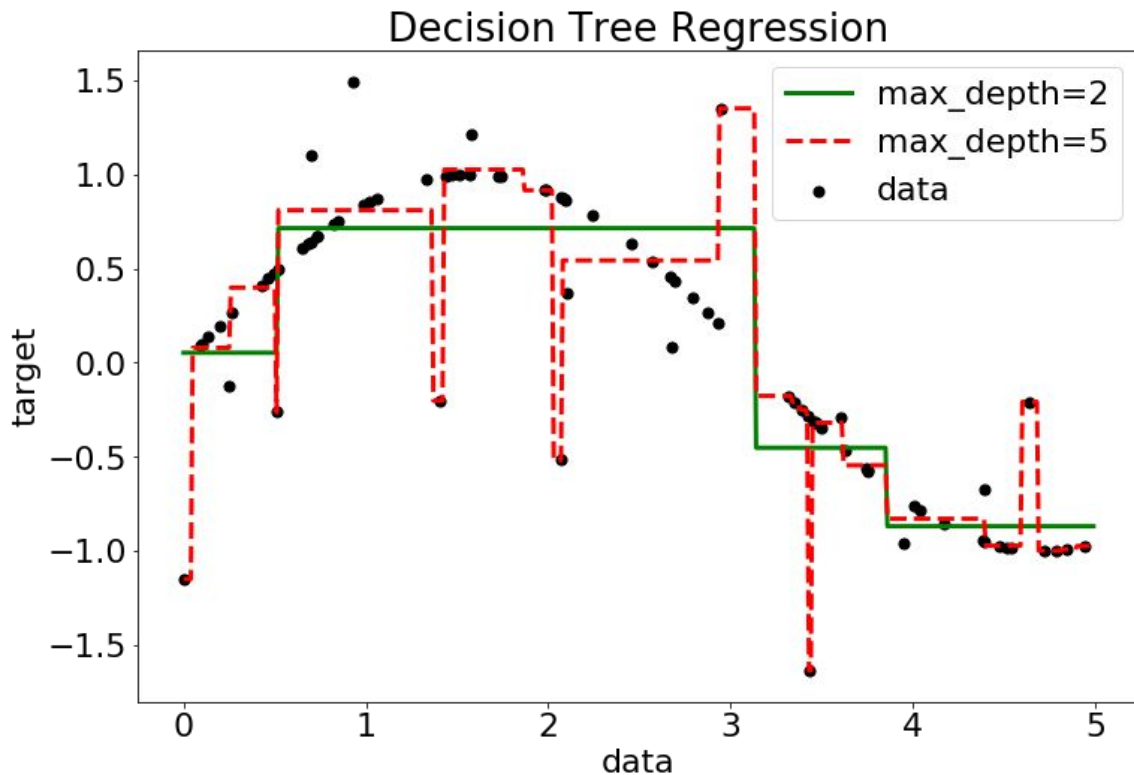
Decision Tree: intuition

Decision tree for Iris data set



setosa	$r_1(x) = [PL \leq 2.5]$
virginica	$r_2(x) = [PL > 2.5] \wedge [PW > 1.68]$
virginica	$r_3(x) = [PL > 5] \wedge [PW \leq 1.68]$
versicolor	$r_4(x) = [PL > 2.5] \wedge [PL \leq 5] \wedge [PW < 1.68]$

Decision tree in regression



Green - decision tree of depth 2

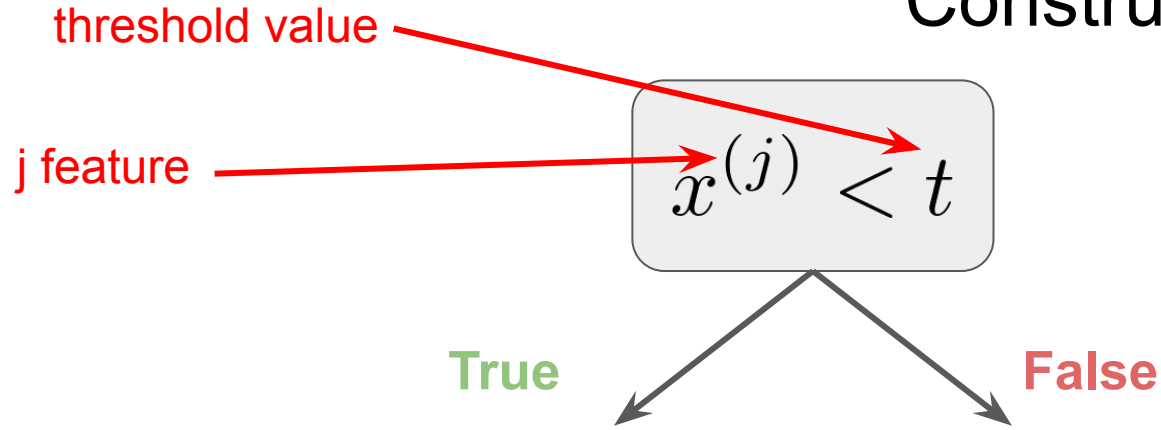
Red - decision tree of depth 5

Every leaf corresponds to some constant.

Decision Tree

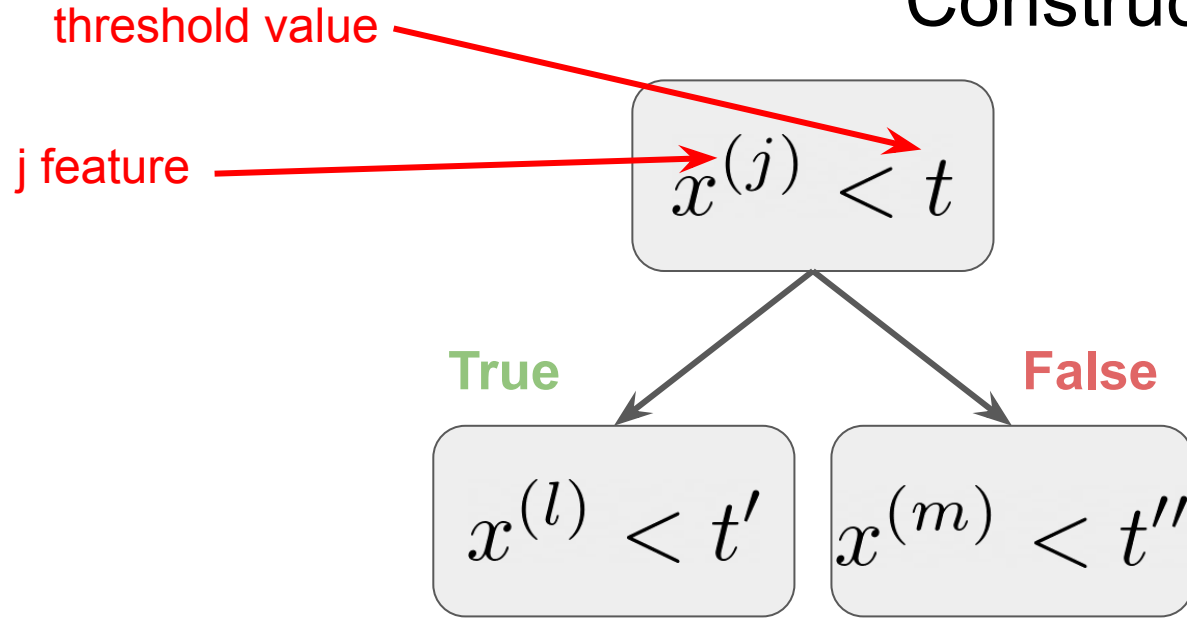
construction procedure

Constructing decision trees



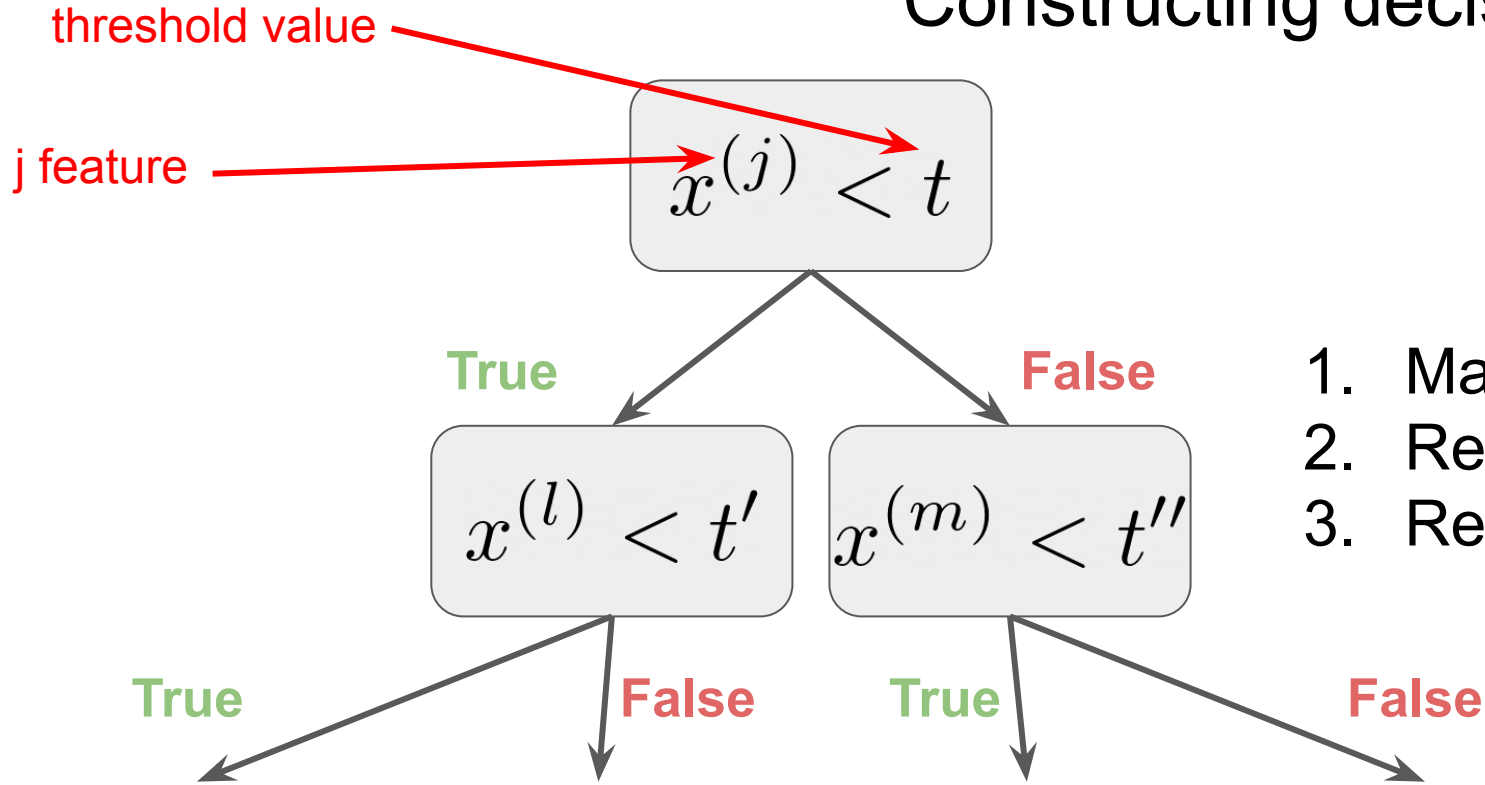
1. Make a split

Constructing decision trees



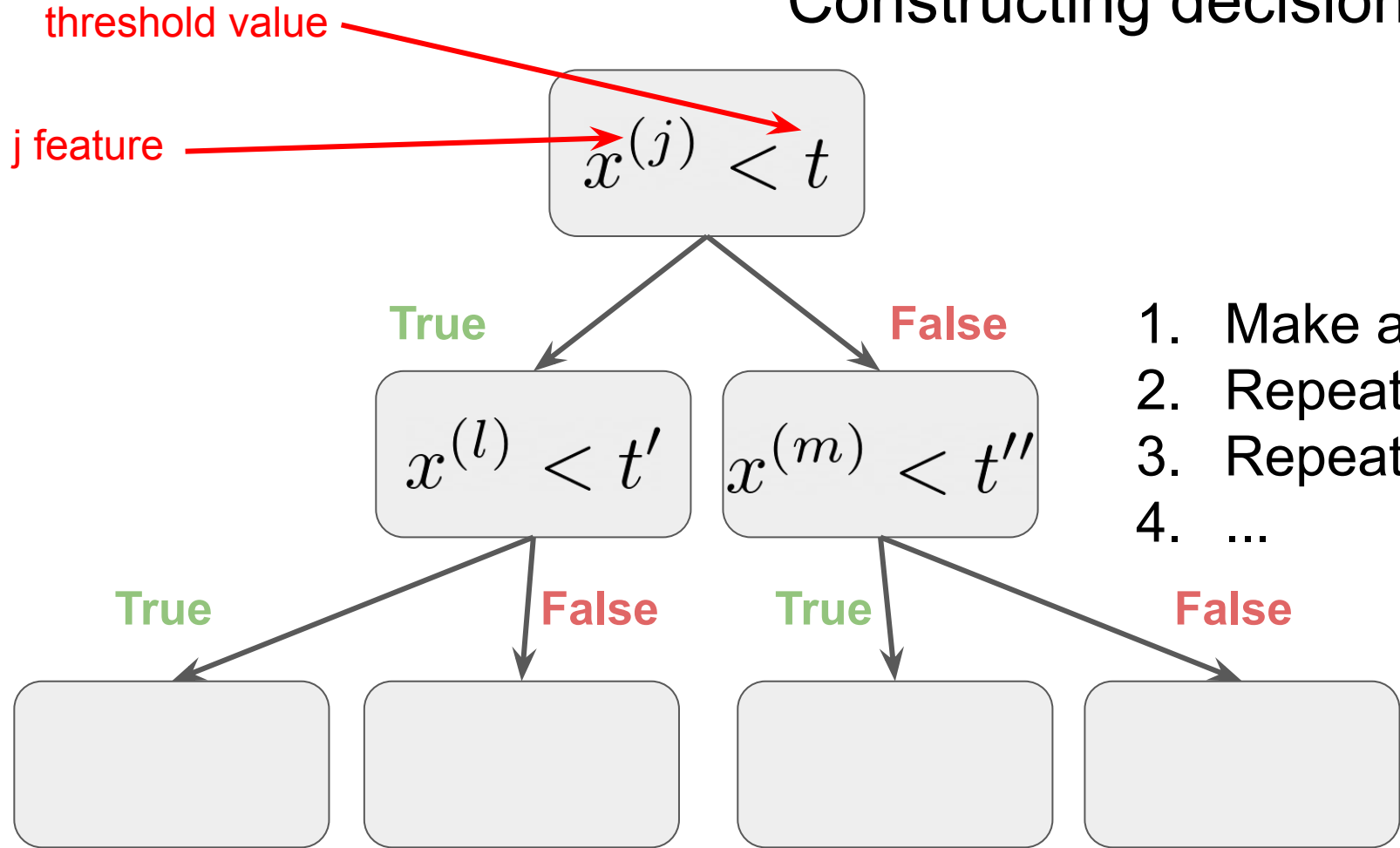
1. Make a split
2. Repeat

Constructing decision trees



1. Make a split
2. Repeat
3. Repeat

Constructing decision trees



1. Make a split
2. Repeat
3. Repeat
4. ...

Constructing decision trees

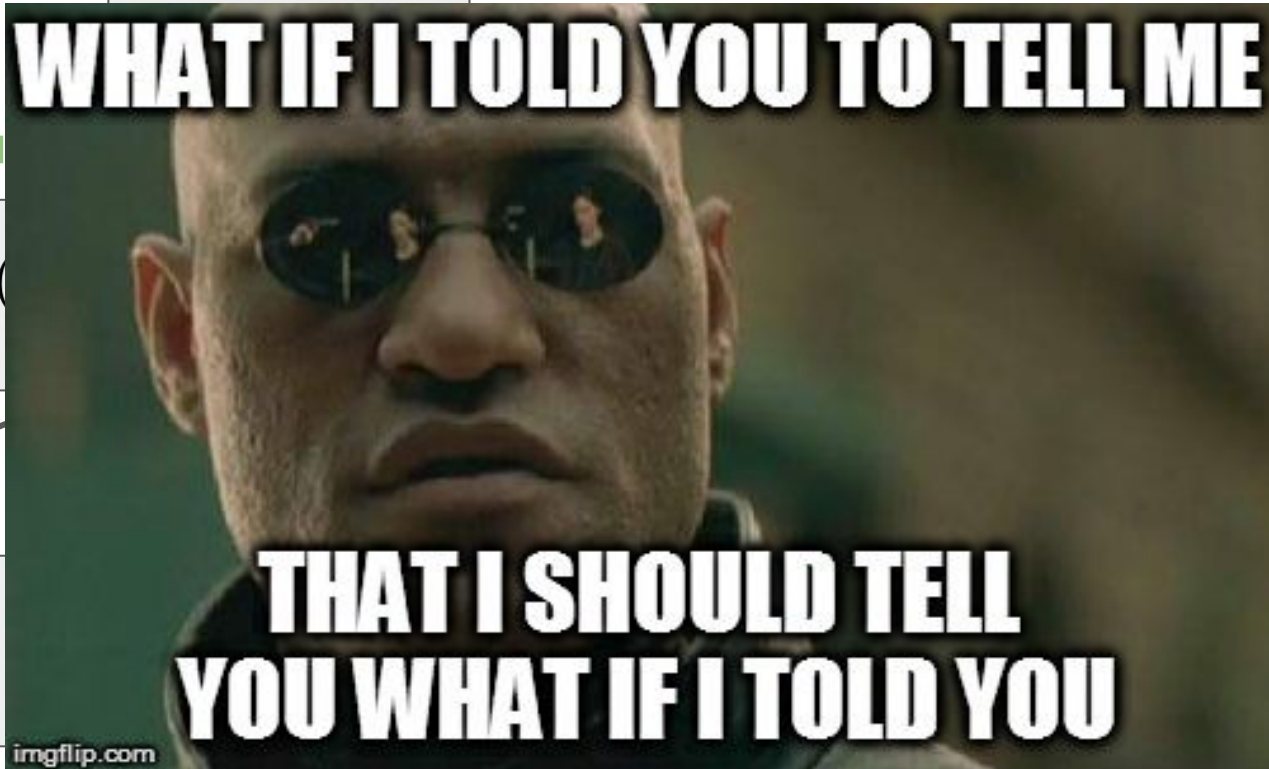
threshold value

j feature

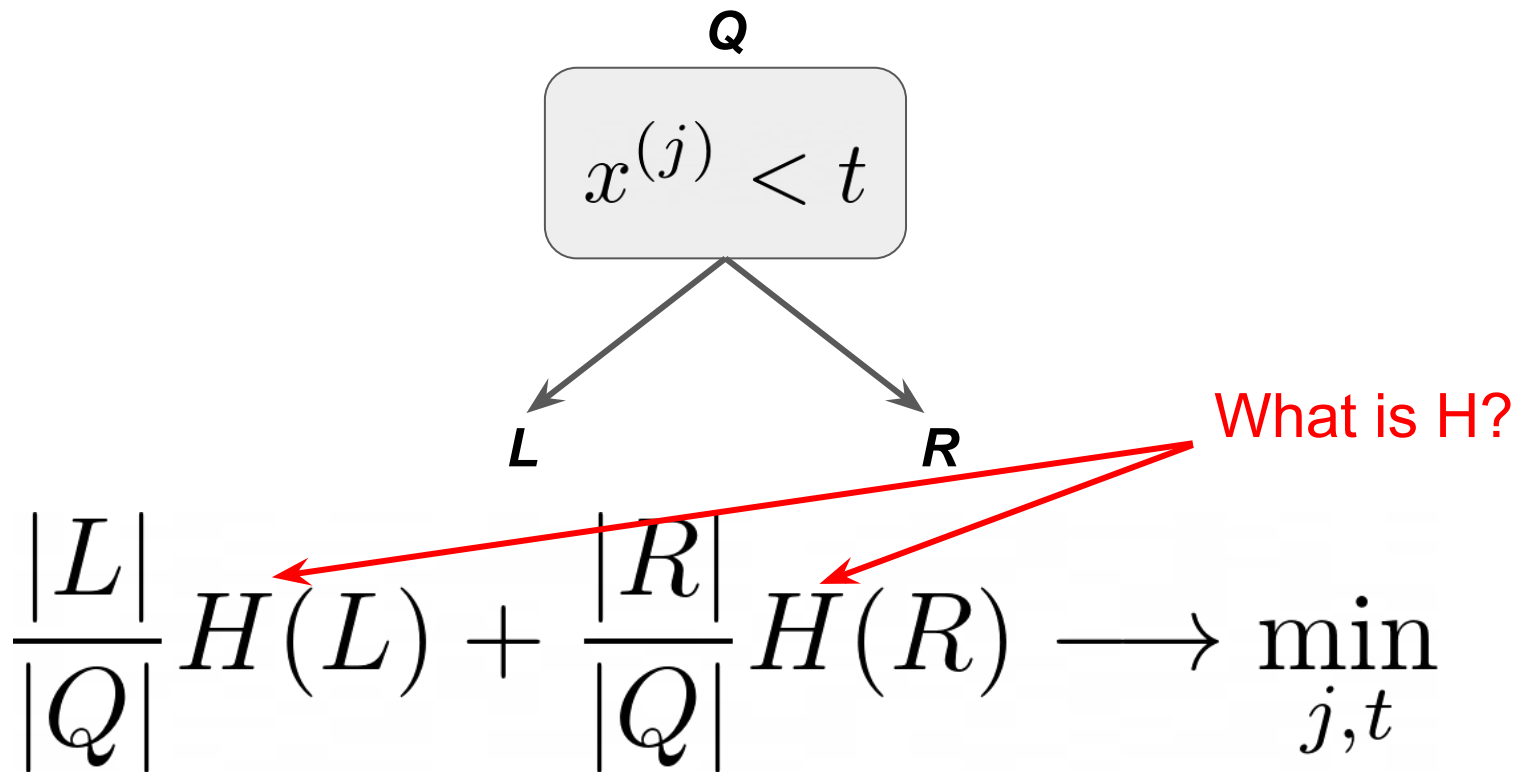
$$x^{(j)} < t$$

True

True

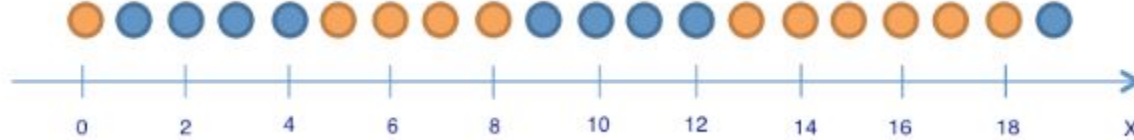


How to split data properly?

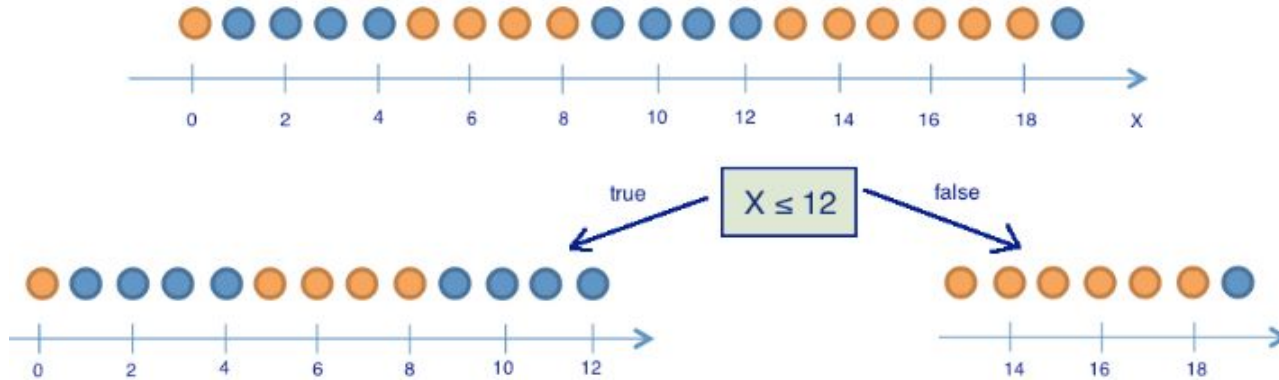


Information criteria

$H(R)$ is measure of “heterogeneity” of our data.
Consider binary classification problem:



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Consider **binary classification** problem:

Obvious way: Misclassification criteria: $H(R) = 1 - \max\{p_0, p_1\}$

1. Entropy criteria: $H(R) = -p_0 \log p_0 - p_1 \log p_1$

2. Gini impurity: $H(R) = 1 - p_0^2 - p_1^2 = 1 - 2p_0p_1$

$H(R)$ is measure of “heterogeneity” of our data.

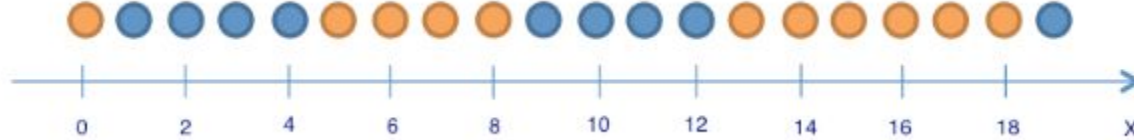
Consider **multiclass classification** problem:

Obvious way: Misclassification criteria: $H(R) = 1 - \max_k \{p_k\}$

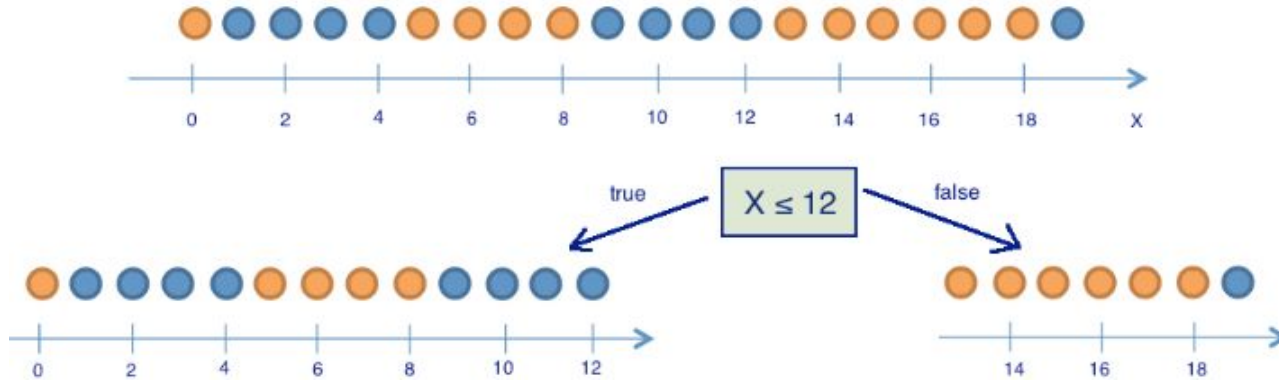
1. Entropy criteria:
$$H(R) = - \sum_{k=0}^K p_k \log p_k$$

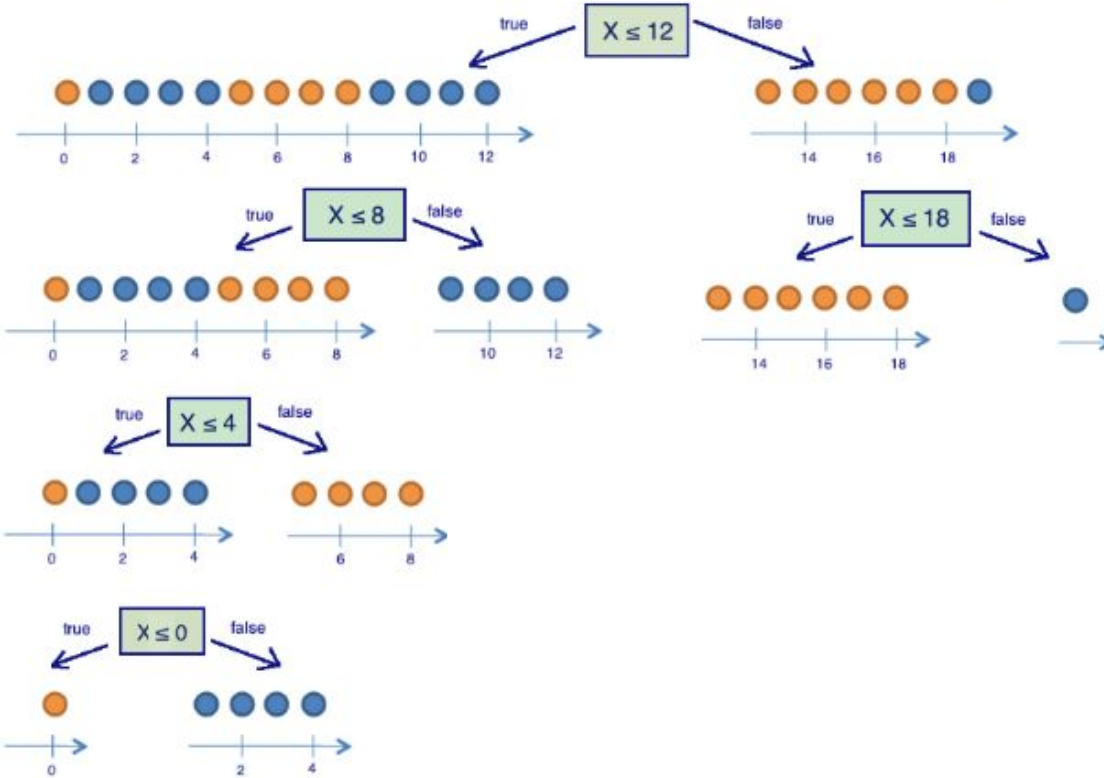
2. Gini impurity:
$$H(R) = 1 - \sum_k (p_k)^2$$

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$H(R)$ is measure of “heterogeneity” of our data.
Consider binary classification problem:





$$S = -M \sum_{k=0}^K p_k \log p_k$$

In binary case $N = 2$

$$S = -p_+ \log_2 p_+ - p_- \log_2 p_- = -p_+ \log_2 p_+ - (1 - p_+) \log_2 (1 - p_+)$$

Information criteria: Gini impurity

$$G = 1 - \sum_k (p_k)^2$$

In binary case $N = 2$

$$G = 1 - p_+^2 - p_-^2 = 1 - p_+^2 - (1 - p_+)^2 = 2p_+(1 - p_+)$$

$H(R)$ is measure of “heterogeneity” of our data.

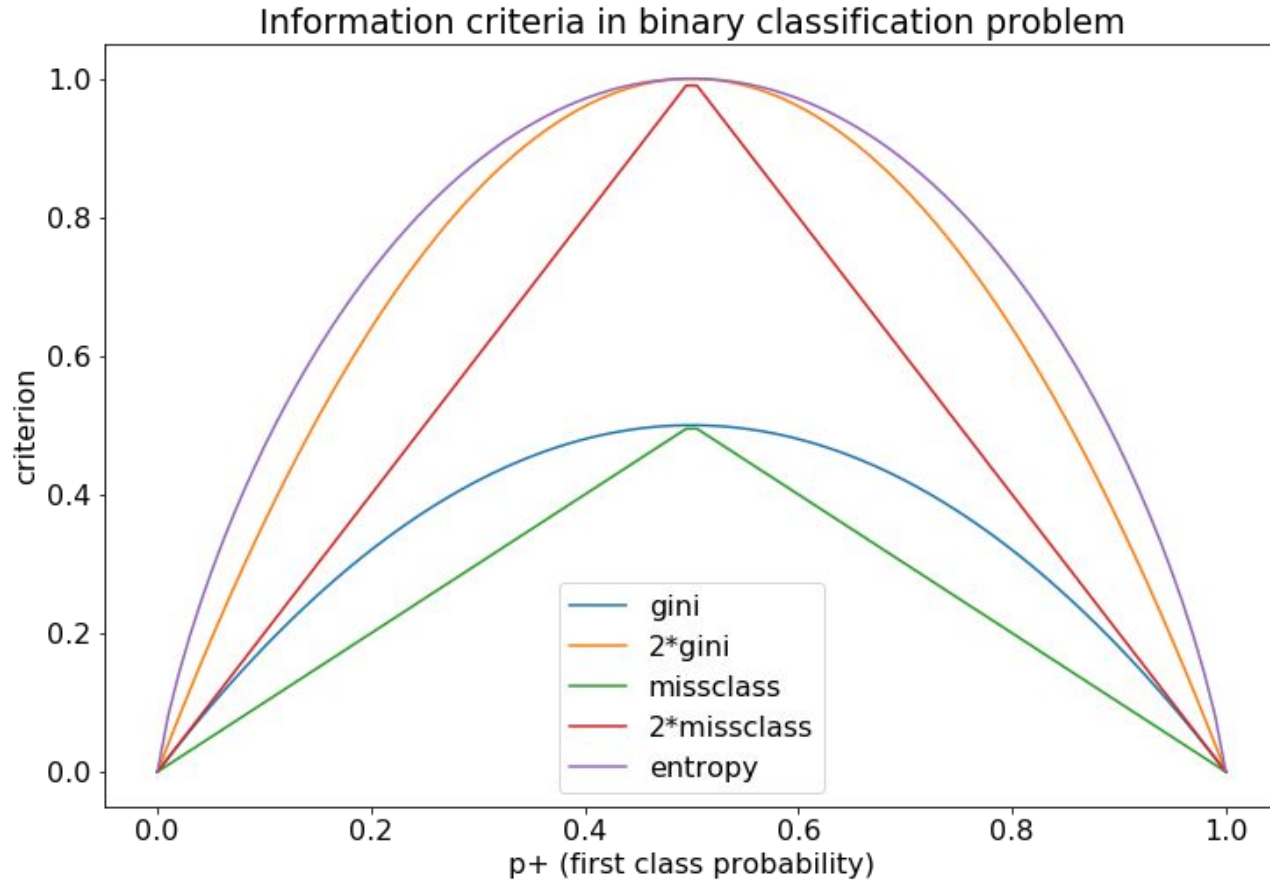
Consider **multiclass classification** problem:

Obvious way: Misclassification criteria: $H(R) = 1 - \max_k \{p_k\}$

1. Entropy criteria: $H(R) = - \sum_k p_k \log_2 p_k$

2. Gini impurity: $H(R) = 1 - \sum_k (p_k)^2$

Information criteria



$H(R)$ is measure of “heterogeneity” of our data.

Consider **regression** problem:

1. Mean squared error

$$H(R) = \min_c \frac{1}{|R|} \sum_{(x_i, y_i) \in R} (y_i - c)^2$$

What is the constant?

$$c^* = \frac{1}{|R|} \sum_{y_i \in R} y_i$$

Pruning

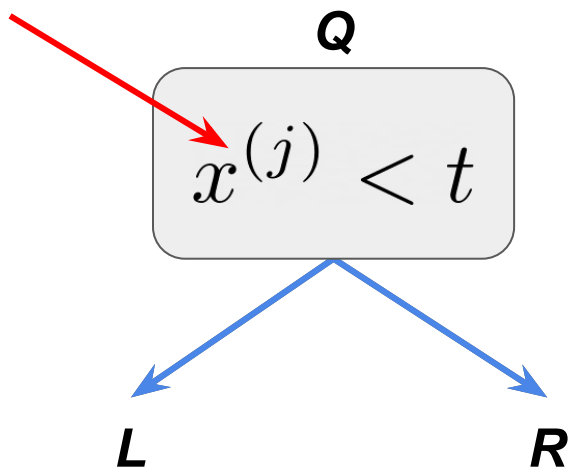
- Pre-pruning:
 - Constrain the tree before construction
- Post-pruning:
 - Simplify constructed tree

Special highlights

Missing values in Decision Trees

- If the value is missing, one might use both sub-trees and average their predictions

Missing value



$$\hat{y} = \frac{|L|}{|Q|} \hat{y}_L + \frac{|R|}{|Q|} \hat{y}_R$$

Bootstrap and Bagging

Consider dataset X containing m objects.

Pick m objects with return from X and repeat in N times to get N datasets.

Error of model trained on X_j : $\varepsilon_j(x) = b_j(x) - y(x), \quad j = 1, \dots, N,$

Then $\mathbb{E}_x(b_j(x) - y(x))^2 = \mathbb{E}_x \varepsilon_j^2(x).$

The mean error of N models: $E_1 = \frac{1}{N} \sum_{j=1}^N \mathbb{E}_x \varepsilon_j^2(x).$

Bootstrap

Consider the errors unbiased and uncorrelated:

$$\mathbb{E}_x \varepsilon_j(x) = 0;$$

$$\mathbb{E}_x \varepsilon_i(x) \varepsilon_j(x) = 0, \quad i \neq j.$$

The final model averages all predictions:

$$a(x) = \frac{1}{N} \sum_{j=1}^N b_j(x).$$

Error decreased by N times!

$$\begin{aligned} E_N &= \mathbb{E}_x \left(\frac{1}{N} \sum_{j=1}^n b_j(x) - y(x) \right)^2 = \\ &= \mathbb{E}_x \left(\frac{1}{N} \sum_{j=1}^N \varepsilon_j(x) \right)^2 = \\ &= \frac{1}{N^2} \mathbb{E}_x \left(\sum_{j=1}^N \varepsilon_j^2(x) + \underbrace{\sum_{i \neq j} \varepsilon_i(x) \varepsilon_j(x)}_{=0} \right) = \\ &= \frac{1}{N} E_1. \end{aligned}$$

Bootstrap

Consider the errors ~~unbiased and uncorrelated~~:

This is a lie

$$\mathbb{E}_x \varepsilon_j(x) = 0;$$

$$\mathbb{E}_x \varepsilon_i(x) \varepsilon_j(x) = 0, \quad i \neq j.$$

The final model averages all predictions:

$$a(x) = \frac{1}{N} \sum_{j=1}^N b_j(x).$$

Error decreased by N times!

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Bagging = Bootstrap aggregating

Decreases the variance if the basic algorithms are not correlated.

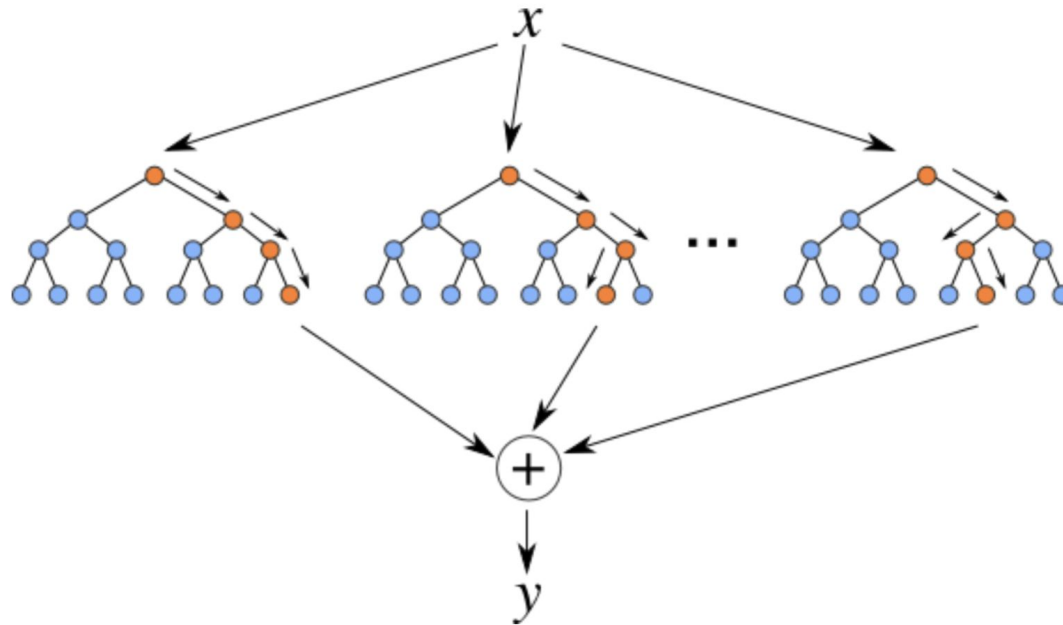
Random Forest

RSM - Random Subspace Method

Same approach, but with features.

Random Forest

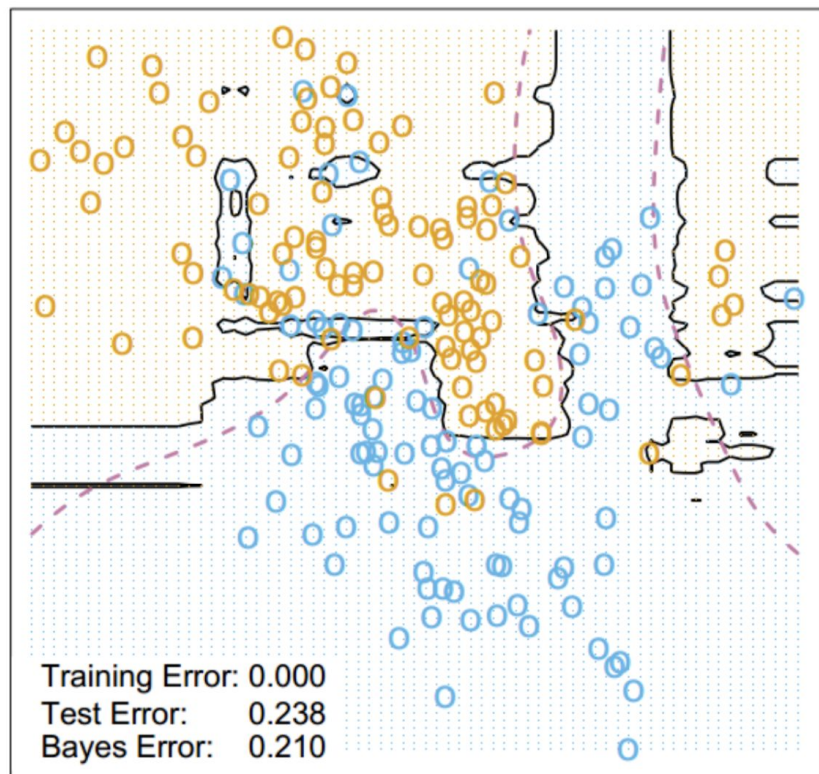
Bagging + RSM = Random Forest



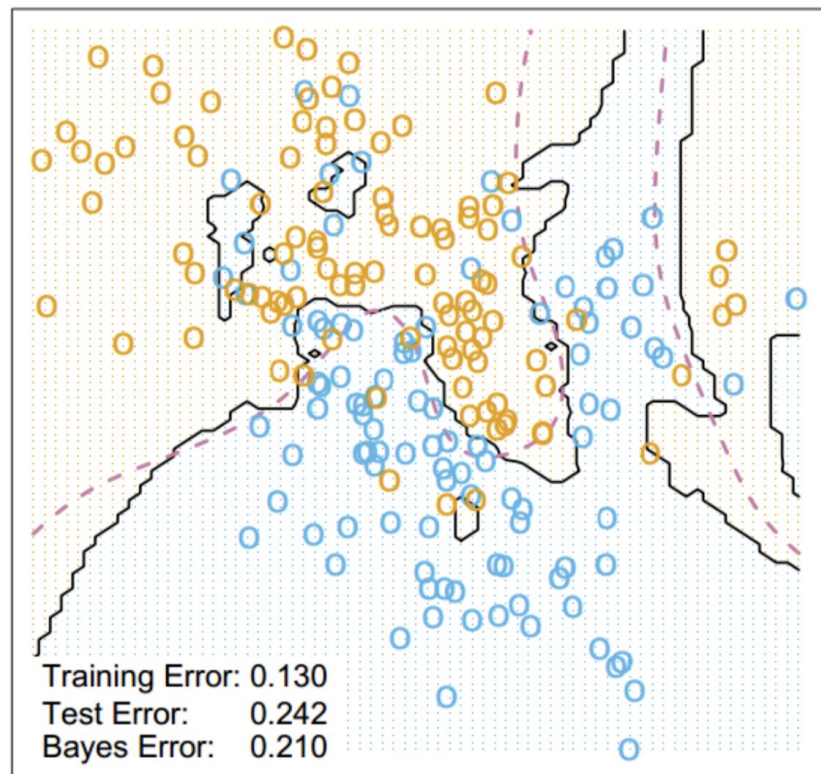
- One of the greatest “universal” models.
- There are some modifications: Extremely Randomized Trees, Isolation Forest, etc.
- Allows to use train data for validation: OOB

$$\text{OOB} = \sum_{i=1}^{\ell} L \left(y_i, \frac{1}{\sum_{n=1}^N [x_i \notin X_n]} \sum_{n=1}^N [x_i \notin X_n] b_n(x_i) \right)$$

Random Forest Classifier



3-Nearest Neighbors



Q & A