Machine Learning for Official Statistics and SDGs

Fourth Live Lecture (Webinar): Starts in **15** minutes

Christophe Bontemps, UN SIAP

UNITED NATIONS siap Statistical Institute for Asia and the Pacific

Machine Learning for Official Statistics and SDGs

Fourth Live Lecture (Webinar):

Starts in **10** minutes

Christophe Bontemps, UN SIAP

UNITED NATIONS
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Asia and the Pacific

Machine Learning for Official Statistics and SDGs

Fourth Live Lecture (Webinar):

Starts in **5** minutes

Christophe Bontemps, UN SIAP

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Machine Learning for Official Statistics and SDGs

Tree-based methods: From Trees to (*random*) Forest

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[- Agenda -]

- Introduction

[- Agenda -]

- Introduction
- Lecture "*From Trees to Forest*"

[- AGENDA -]

- Introduction
- Lecture "*From Trees to Forest*"
- Q&A

[- Agenda -]

- Introduction
- Lecture "*From Trees to Forest*"
- Q&A
- Next week

[From Trees to Forest]

Trees are methods for classification or regression analysis.

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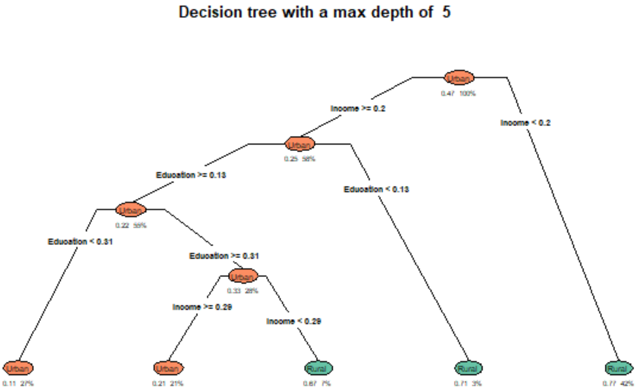
[From Trees to Forest]

Trees are methods for classification or regression analysis.

- Trees are based on recursive binary splits
- The structure is simple and corresponds to regions in the variable's space
- Each node is based on a the value of one variable and a threshold
- Trees can be very detailed and prone to **over fitting**

[Example on a simple tree]

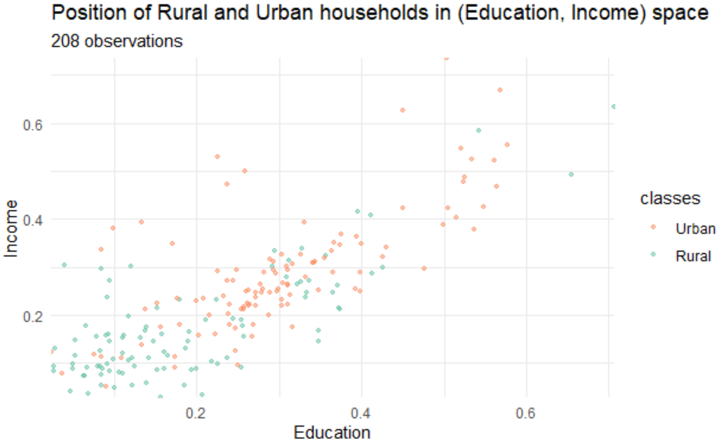
Let us see how this tree is constructed:



4 nodes leading to final leaves $\hookrightarrow$ Depth = 5

[Example on a simple tree]

The problem is a 2D space



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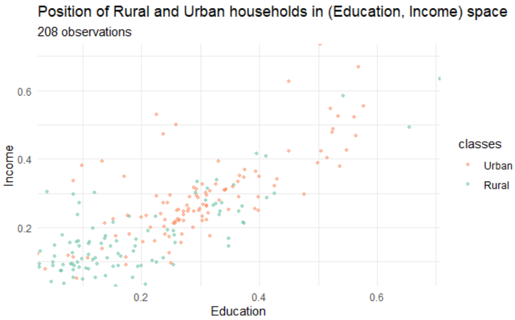
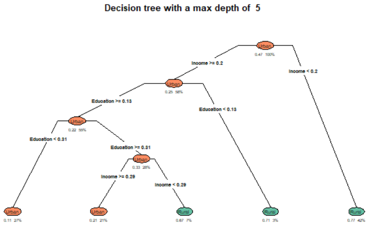
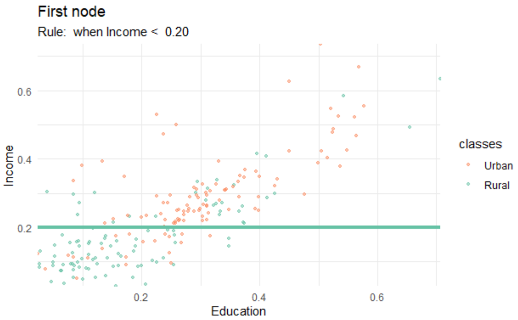
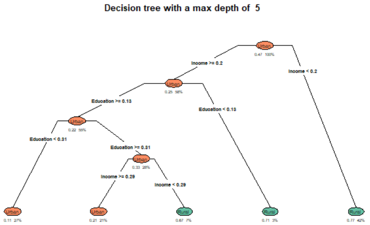




How to split the (Education, Income) space?

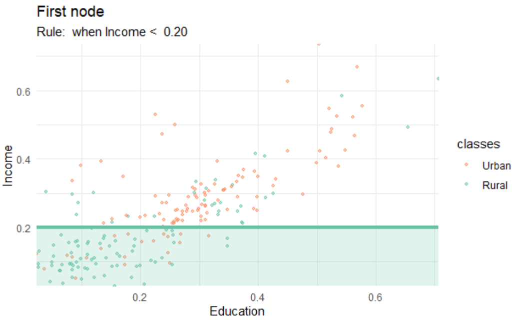
[Example on a simple tree]

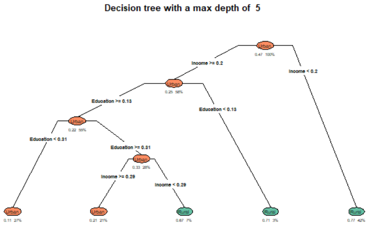




The first boundary decision line

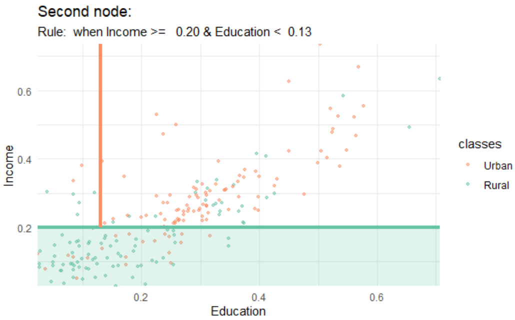
[Example on a simple tree]

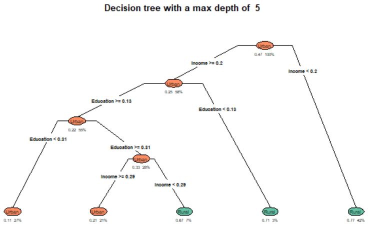




The space below the line is classified as rural

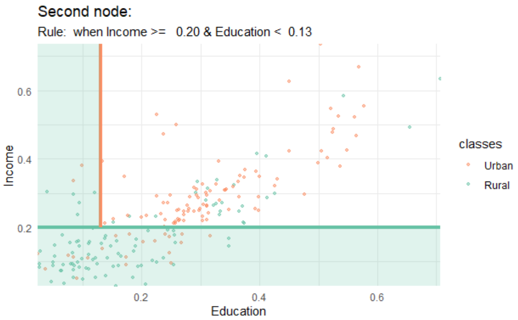
[Example on a simple tree]

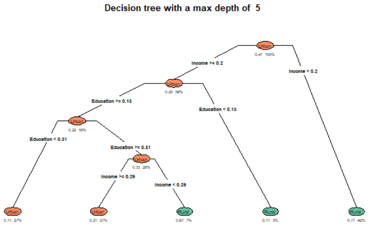




Second boundary decision line

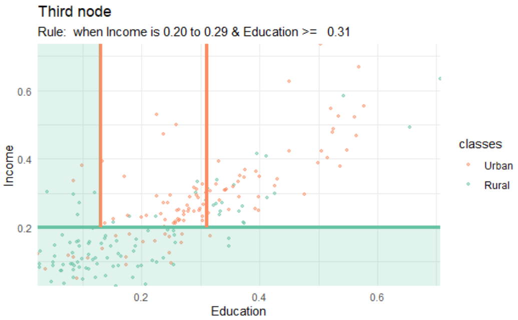
[Example on a simple tree]

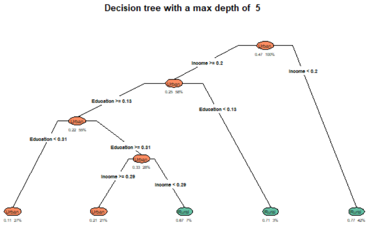




The space on the left of the line is classified as rural

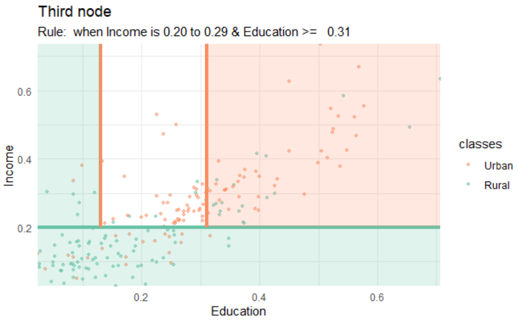
[Example on a simple tree]

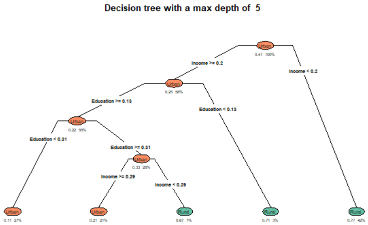




Third boundary decision line

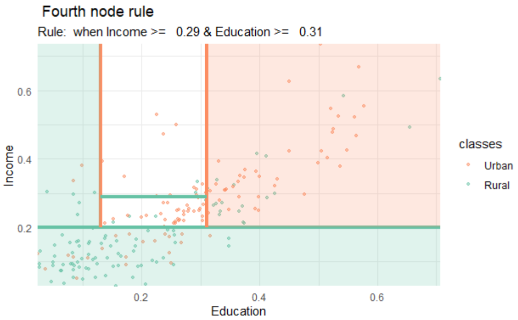
[Example on a simple tree]

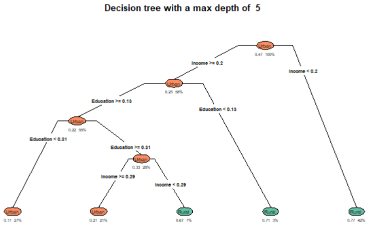




The space on the right of the line is classified as Urban

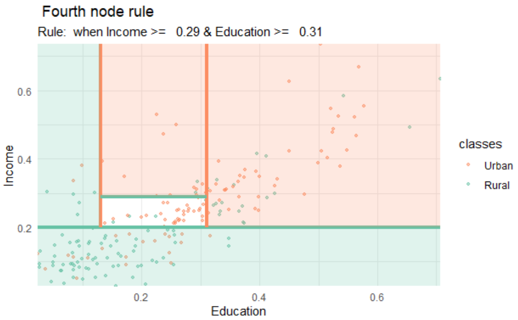
[Example on a simple tree]

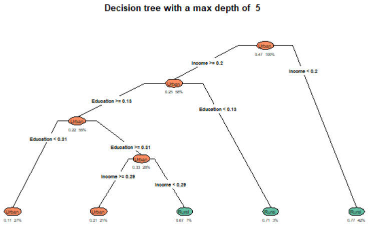




Fourth boundary decision line

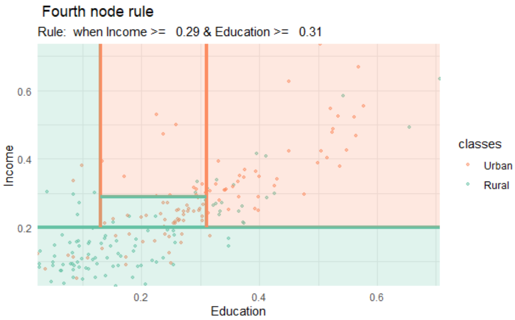
[Example on a simple tree]

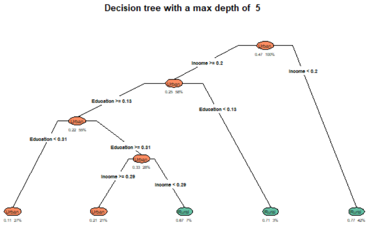




The space above the line is classified as Urban

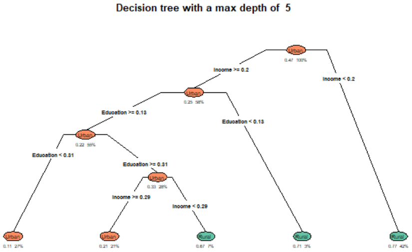
[Example on a simple tree]

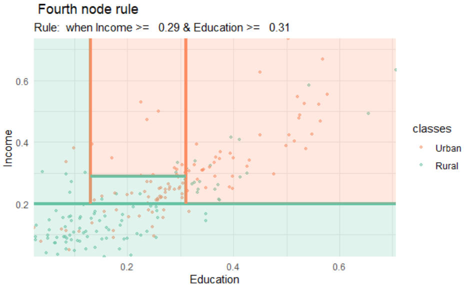




Finally, the remaining space is classified as rural

[Problems with trees]





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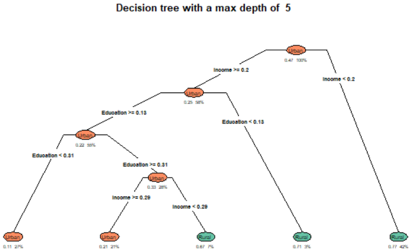

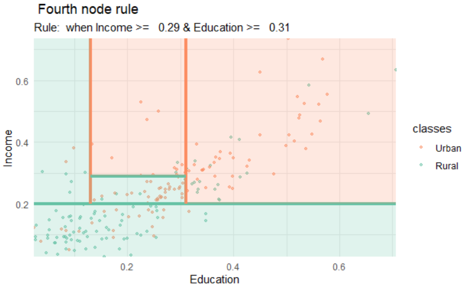

By structure:

- Trees are splitting the variable's space into "rectangles"

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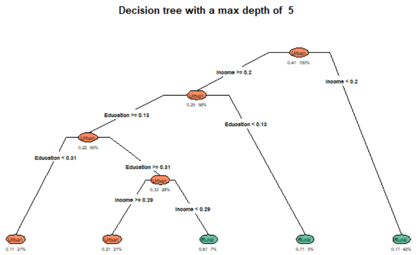

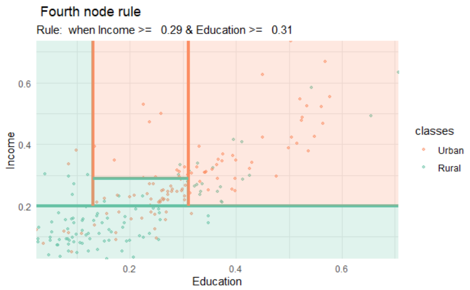

By structure:

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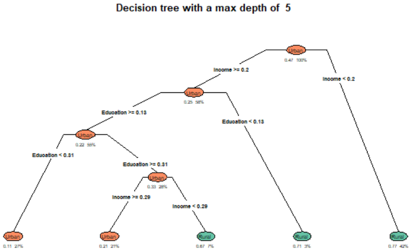
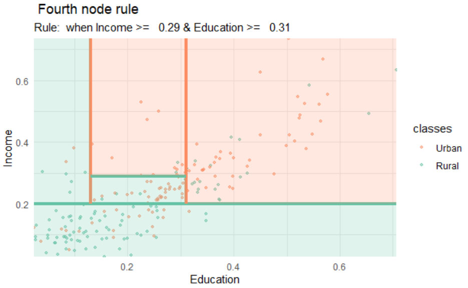
[Problems with trees]





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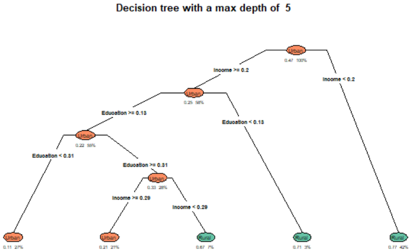

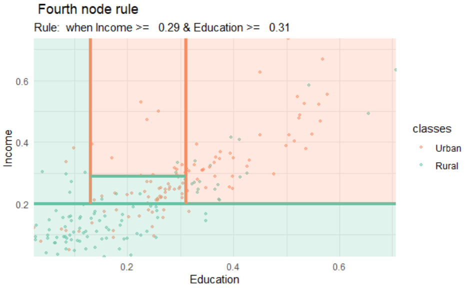

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[Problems with trees]

The decision trees suffer from *high variance*:

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- Take some data and build a tree

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$\hookrightarrow$ The two trees will likely be very different

[Example on a simple tree]

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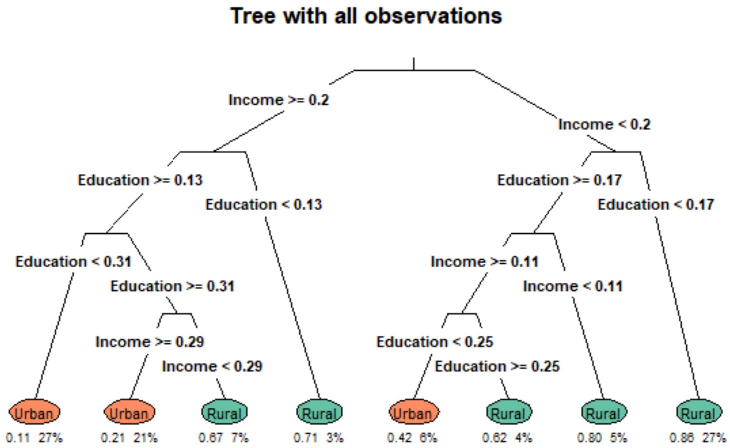
Which tree do you trust?



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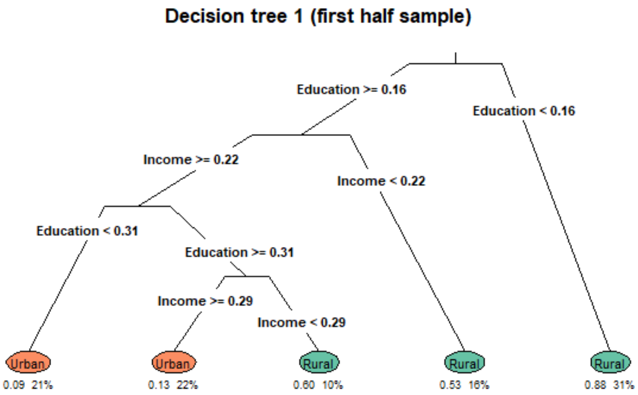

First tree with 50% of observations

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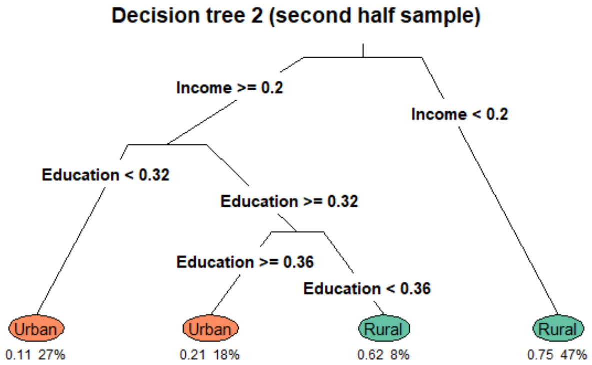
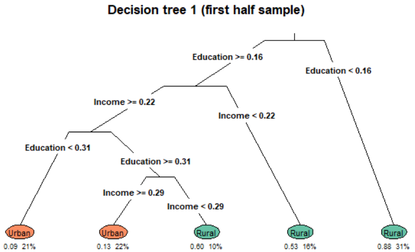


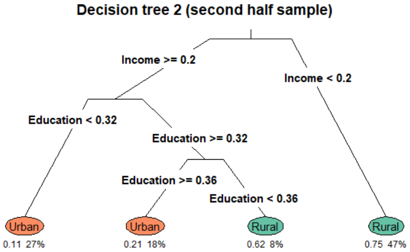
Second tree with 50% of observations

[Example on a simple tree]

Which tree do you trust?

Outcomes are different from one tree to another





$\hookrightarrow$ Instability of the outcome (= high variance)

[How to use trees?]

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In classification, we do not average but take the *majority vote* rule

[*Bagging*]

Bagging scheme:

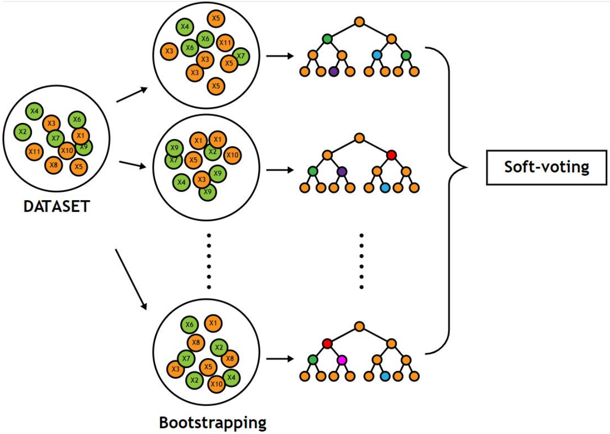

Image from igem.org

[Some simple mathematics...]

Aggregating the results of trees can help decrease the variance

[SOME SIMPLE MATHEMATICS...]

Aggregating the results of trees can help decrease the variance

- Intuitively, if $U_i, \ldots U_B$ are iid with variance σ^2, then the average of these variables has a lower variance

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$$\begin{aligned} Var\left(\frac{1}{B}\sum_{i=1}^{B} U_i\right) &= \frac{\sigma^2}{B} \\ &< \sigma^2 \end{aligned}$$

[Some simple mathematics...]

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\end{aligned}
$$

- This is a simple principle that is used here

[*Bagging*]

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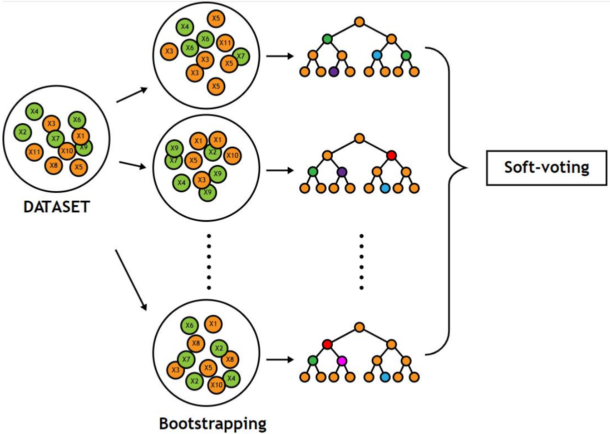

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[The problem with *Bagging*]

Bootstrapped (*Bagging*) trees use **the same set of variables**

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$$Var\left(\frac{1}{B}\sum_{i=1}^{B} U_i\right) \quad = \quad \rho \cdot \sigma^2 + \frac{\sigma^2}{B}$$

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$\hookrightarrow$ *Random forest* use a *decorrelation* algorithm by adding ***randomness*** in the set of variables used

[Random Forest]

Random forest use two mechanisms:

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- Bootstrap aggregating (*bagging*) of trees → **Forest**

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$\hookrightarrow$ Construct B trees, on B bootstrapped samples

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$\hookrightarrow$ At each node, randomly select only **m** variables

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$$Var_{Random\ forest} = \rho \cdot \sigma^2 + \frac{\sigma^2}{B}$$

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Common practice (p = *nb of variables*):

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- $m \approx \sqrt{p}$ in classification

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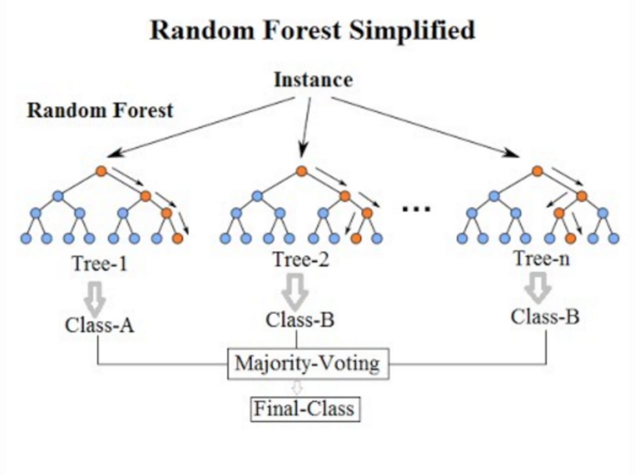
Common practice (p = *nb of variables*):

- $m \approx \sqrt{p}$ in classification
- $m \approx p/3$ in regression

[RANDOM FOREST]

Random forest scheme:



[Optimizing Random Forest]

Random forest are sensitive to several *hyperparameters*

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  - ...

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[Random Forest on an Example]

The impact of the number of trees:

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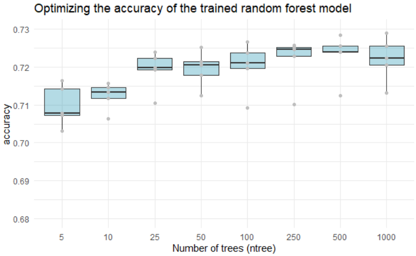

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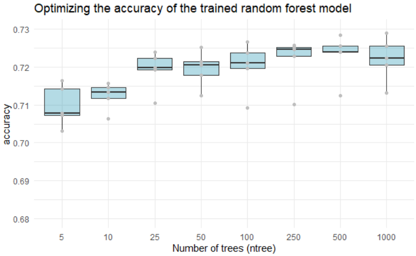

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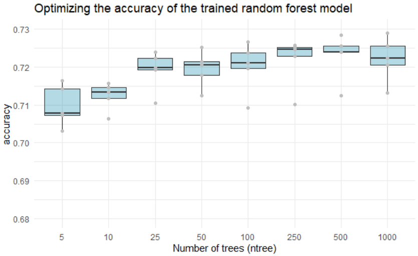

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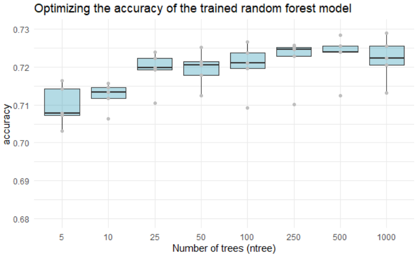

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↪ More tree reduces variance (up-to a certain point)

[Improvements]

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↪ "*Boosting*"

[Boosting]

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- *"Mistakes"* at stage t are overweighed for stage $t + 1$

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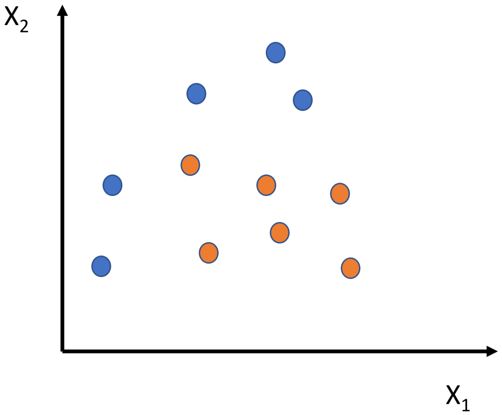

Two classes of observations: Orange and blue

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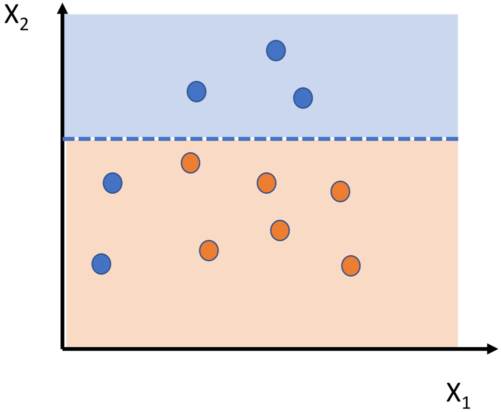

First weak learner

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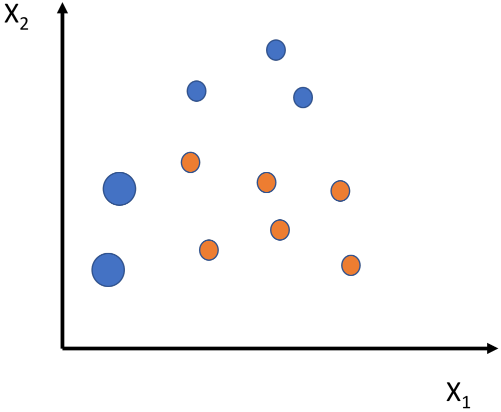

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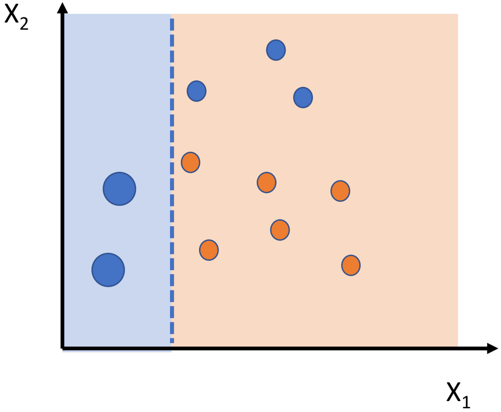

Second weak learner with misclassification overweighed

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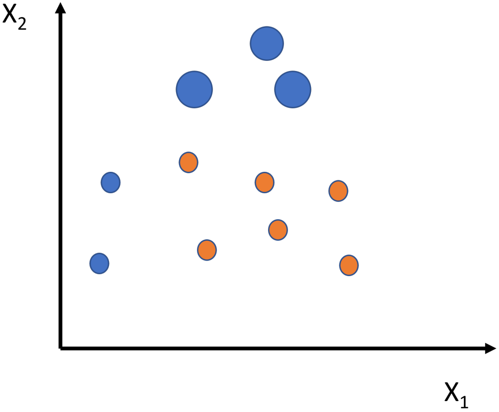

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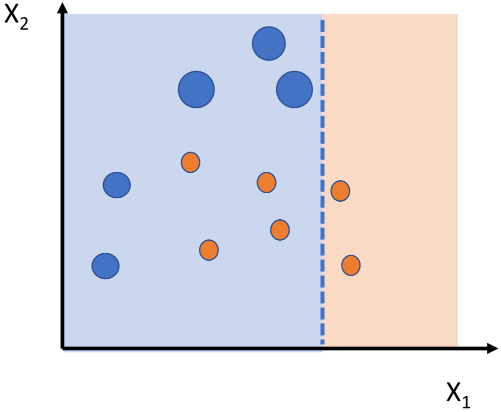

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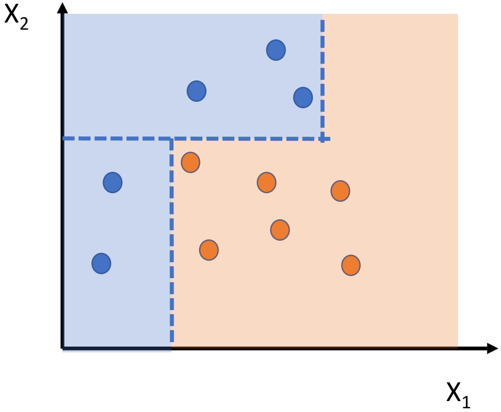

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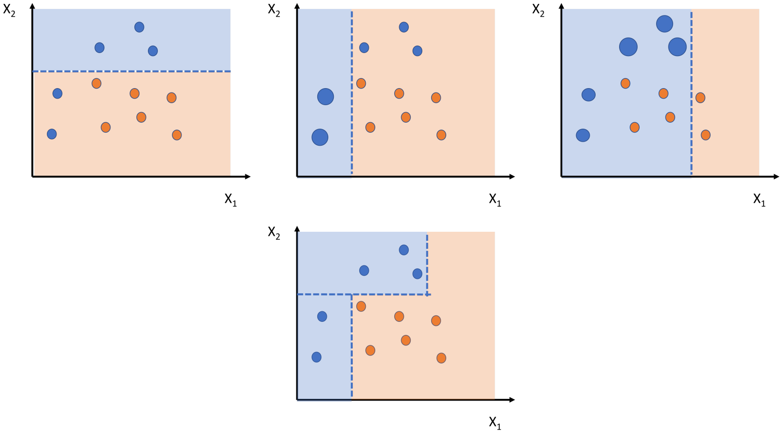

Combining *weak learners* creates an efficient tree

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[Q&A]

Write your questions in the chat

[Agenda]

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Have a nice week and a happy learning!