# Machine Learning for Official Statistics & SDGs

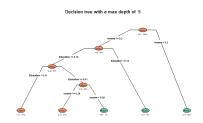
# **Decision Trees**



## [ DECISION TREES ]

*Trees* are method for classification or regression analysis.

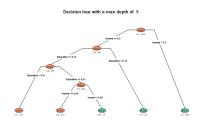
 $\hookrightarrow$  Focus on classification



## [ DECISION TREES ]

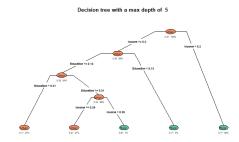
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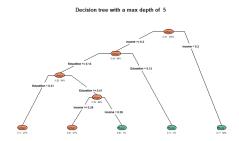


- ► Trees split the space into non-overlapping spaces
- ► Used to assign/predict a *class* following conditions
- ▶ Optimally, final classification is homogenous

Trees have a very simple structure and are easy to understand:



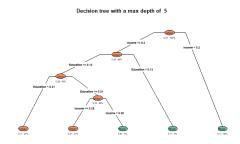
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#### Trees have:

► **Nodes** where splitting decisions are done

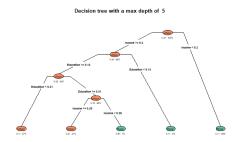
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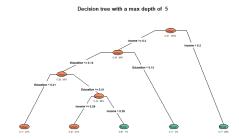
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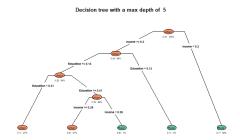
#### Trees have:

- ▶ **Nodes** where splitting decisions are done
- ► Branches following conditions
- ► Leaves are terminal nodes of the classification

#### How to build a tree?



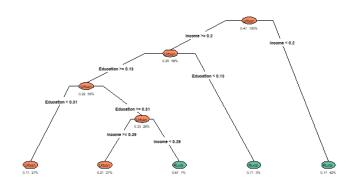
#### How to build a tree?



- ► Trees are based on recursive binary splits
- ► Each node uses a threshold on a variable
- ► Each node separates the observations in two sets

Let us see how this tree is constructed:

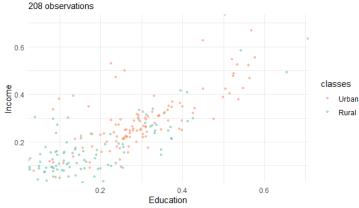
Decision tree with a max depth of 5



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

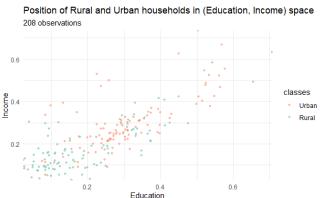
### The problem is a 2D space

Position of Rural and Urban households in (Education, Income) space

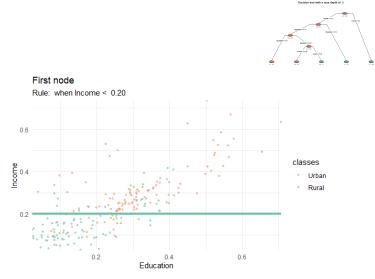




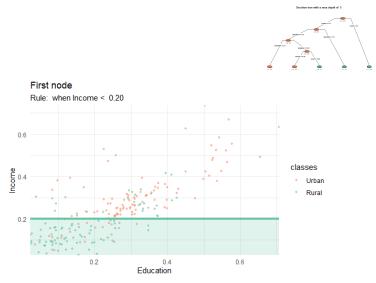




How to split the (Education, Income) space?

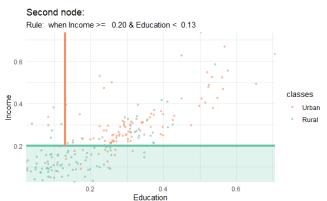


The first boundary decision line



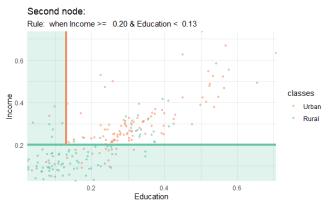
The space below the line is classified as rural





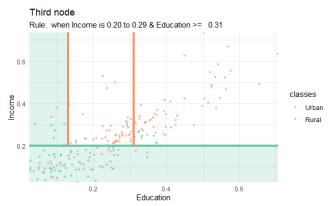
### Second boundary decision line





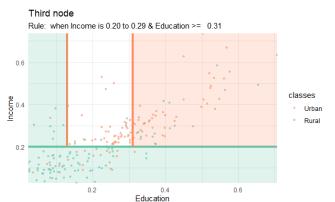
The space on the left of the line is classified as rural





Third boundary decision line





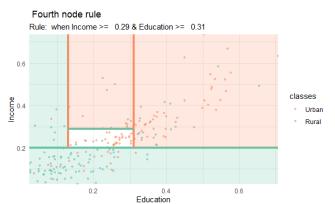
The space on the right of the line is classified as Urban





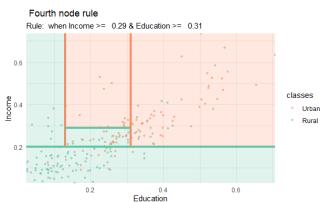
Fourth boundary decision line





The space above the line is classified as Urban





Finally, the remaining space is classified as rural





We need several tools to build a tree:

► A method to choose the decision variable (one per node)



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- ► A criterion to define best threshold



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- ► A criterion to define best threshold
- ► A criterion to measure the quality of each split
- ► A way to decide when to stop (the terminal node becomes a leaf)

## [ TOOLS TO BUILD A TREE ]

At each node, one can measure the *purity* of each split

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Introduction

## [ TOOLS TO BUILD A TREE ]

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- ► Misclassification error rate
- ▶ The Gini coefficient measures the purity in each node  $\kappa$

$$D_{\kappa} = \sum_{m=1}^{M} \widehat{p}_{m\kappa} (1 - \widehat{p}_{m\kappa})$$

where  $\hat{p}_{m\kappa}$  is the proportion of class m in node  $\kappa$ .

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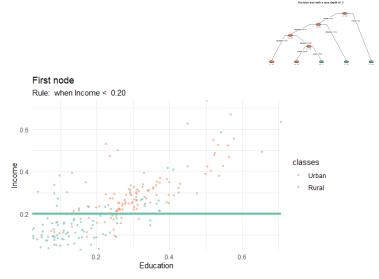
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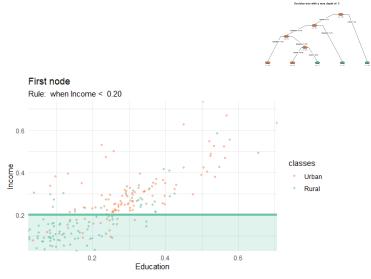
We expect that there is an Information gain from the splitting

 $Information \ Gain = Entropy_{Before} - Entropy_{After}$ 

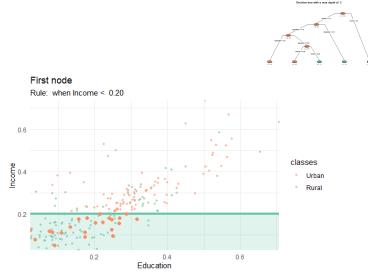




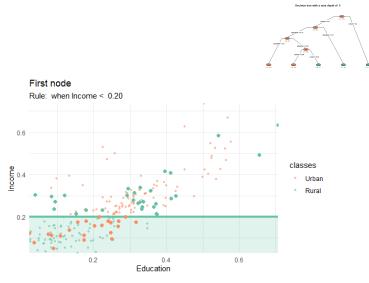
First the boundary decision line



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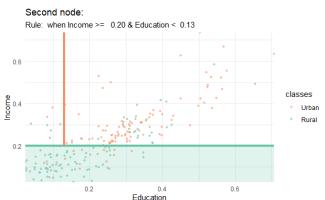


Some "Urban" are classified as rural  $\hookrightarrow$  Impurity



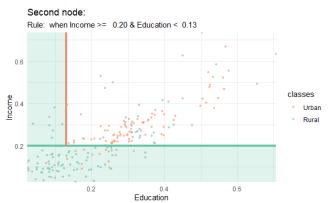
Some "Rural" are classified as Urban  $\hookrightarrow$  Impurity





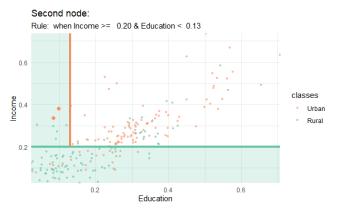
#### Second boundary decision line





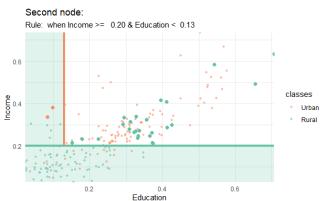
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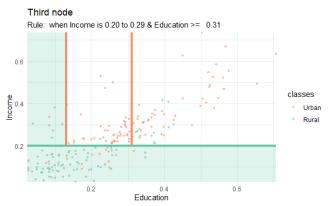
Some "Urban" are classified as Rural





Some "Rural" are classified as Urban





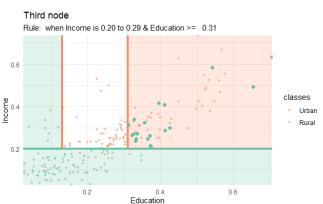
Third boundary decision line





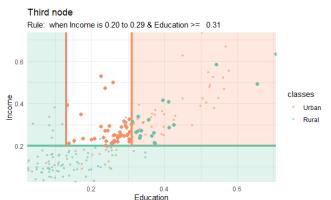
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Some "Rural" are classified as Urban





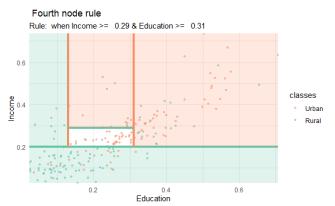
"Urban" seem well classified in the remaining space





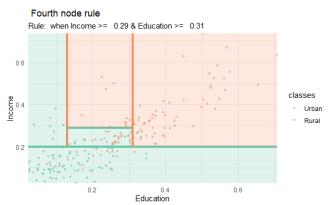
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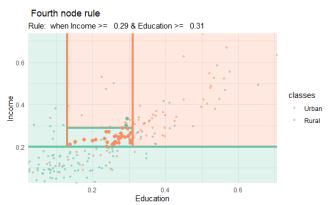
Finally, the remaining space is classified as rural





Few "Rural" are classified as Urban





Many "Urban" are classified as Rural

The construction is based on recursive binary splits

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  - ► The maximum *depth* of the tree

Wrap-up

#### [ HOW TO BUILD A TREE? ]

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Wrap-up

# [ HOW TO BUILD A TREE? ]

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Introduction

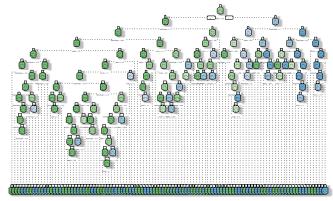
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  - ➤ ...

#### [ TREES CAN BE COMPLEX ]

Introduction

Trees can decompose the space in very specific zones.

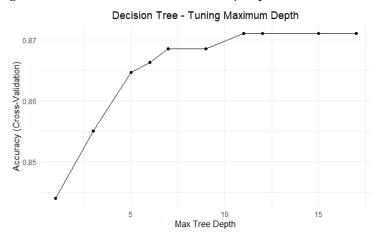
 $\hookrightarrow$  Example with the full set of variables



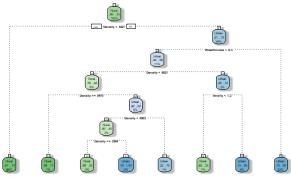
Decision tree with no constrains

Using CV, we can select the maximum depth parameter

#### Using CV, we can select the maximum depth parameter



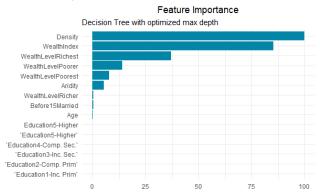
#### The resulting tree



Tree Selected (max depth = 11)

Tree with optimal depth

#### The resulting tree



Feature importance (also confusion matrix, kappa, etc..)

#### SELECTING THE **COMPLEXITY** OF A TREE 1

The complexity of a tree is a parameter  $C_p$  governing the trade-off between tree size |T| and its overall accuracy D(T):

$$D_{C_p}(T) = D(T) + C_p \cdot |T|$$

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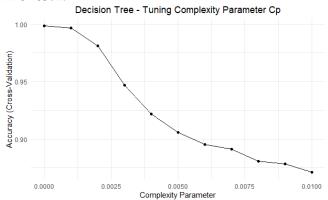
- ▶  $D(T) = \sum_{\kappa=1}^{K} D_{\kappa}$ : the total *impurity* of the tree
- ightharpoonup | T| is the number of terminal nodes of the tree
- $\hookrightarrow$  A model with  $C_p = 0$  will impose no constrains
- $\hookrightarrow$  A value of  $C_p = 1$  only **one** terminal (and initial) node.

#### [ SELECTING THE **COMPLEXITY** OF A TREE ]

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#### The result:

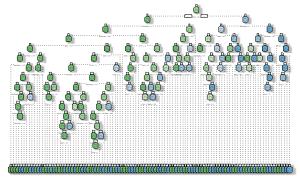
Introduction



Grid search

## [ SELECTING THE **COMPLEXITY** OF A TREE ]

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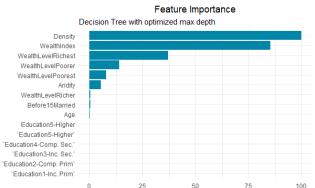


Tree with optimized Cp

Final tree with optimal complexity parameter

#### [ SELECTING THE **COMPLEXITY** OF A TREE ]

#### The result:



Feature importance (also confusion matrix, kappa, etc..)

One can also prune a tree

1. Final trees may be too large and too complex

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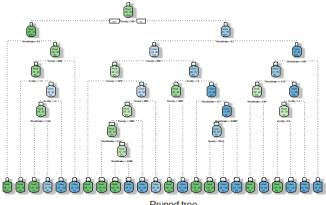
- 1. Final trees may be too large and too complex
- $\hookrightarrow$  Risk of overfitting
  - 2. Pruning techniques use the same criteria on each leave
- $\hookrightarrow$  Remove least important nodes

## [ PRUNED TREE ]

After "pruning":

#### [ PRUNED TREE ]

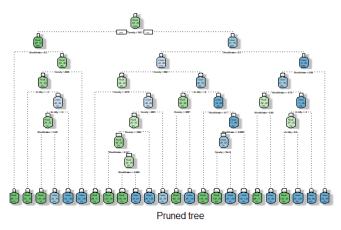
#### After "pruning":



Pruned tree

#### [ Pruned tree ]

#### After "pruning":



 $\hookrightarrow$  Easier to interpret & no loss of accuracy

# [QUIZ TIME]

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- $\hookrightarrow$  There are powerful methods using many trees...