Machine Learning for Official Statistics and SDGs

Supervised Classification

UNITED NATIONS
SIAP
Statistical Institute for Asia and the Pacific

[Classification]

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- The interest is on y that takes discrete values: 0/1, high school/prilmary school/no education; urban/rural
- There may be variables explaining why we observe that y belongs to a particular category
- A classifier is a tool that provides a classification for y

[Supervised *vs* unsupervised Classification]

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- We'll focus on **supervised** classification

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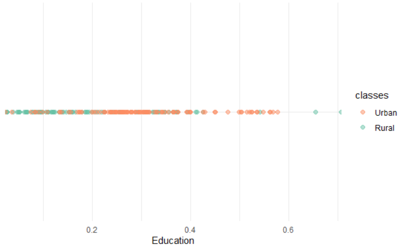

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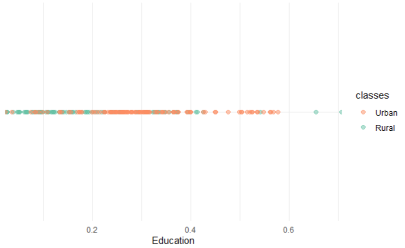

- A classifier determines the value of *Education* that separate "Rural" from "Urban", typically with a threshold rule : "if $x \geq x_t$ then y is categorized as Urban"

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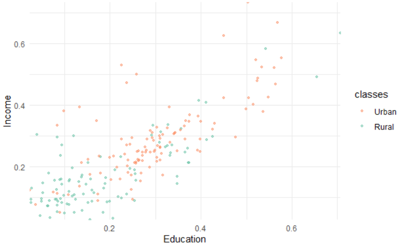

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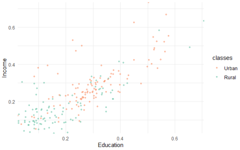

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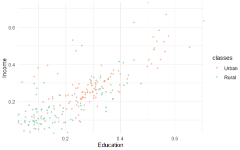

- A classifier will determine a **boundary** using both *Education* and *Income* to separate "Rural" from "Urban"

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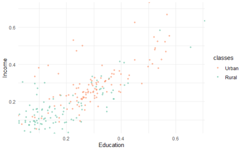

- A classifier will determine a **boundary** using both *Education* and *Income* to separate "Rural" from "Urban"
- The rule can be based on a linear relationship between *Education* and *Income* or can be non linear.

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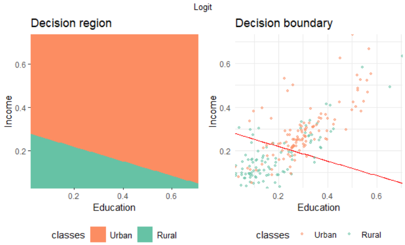

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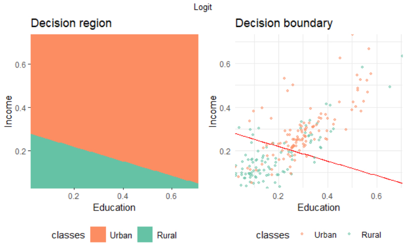

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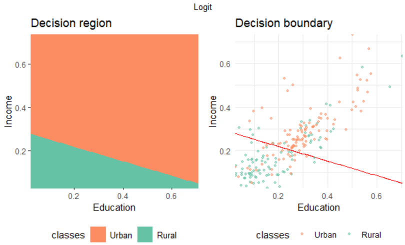

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  e.g. $\beta_1 Education + \beta_2 Income \geq T_0$

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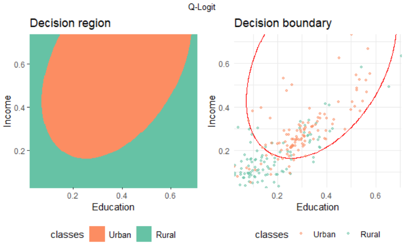

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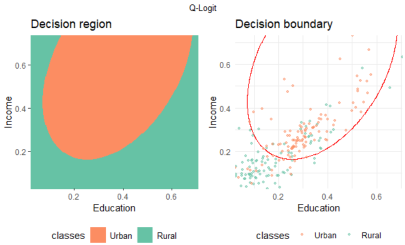

- The rule that separated the two classes is non linear in the variables *Education* and *Income*

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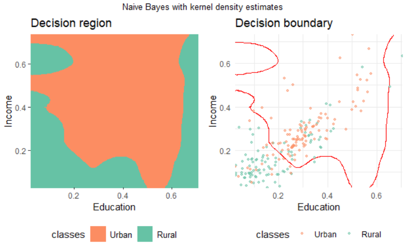

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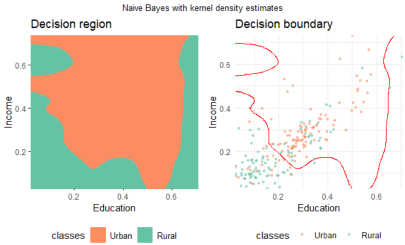

- It is hard to understand how the two classes are built using *Education* and *Income*

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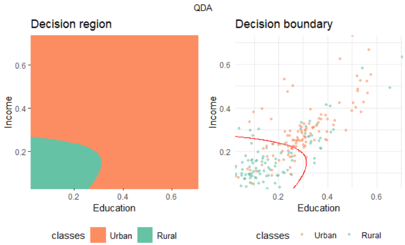

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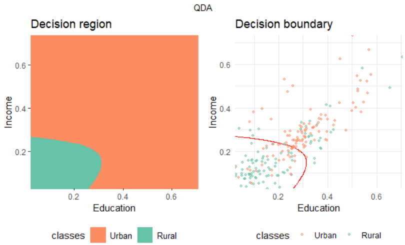

- The boundary is very complex but uses *Education* and *Income* features.

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- Measures of fit in classification are different and specific

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  All answer to different questions and solve different problems

[Accuracy and Confusion Matrix]

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$\hookrightarrow$ We want the maximum possible accuracy.

- Equivalently, we may want to minimize the *error rate* or *misclassification rate*

$$\Pr\left[y_0 \neq \widehat{f}(x_0)\right]$$

[Confusion Matrix & Accuracy]

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	Observed (True)	
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$$= \frac{TruePositives + TrueNegatives}{N}$$

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- It is the proportion of accurate predictions

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In practice, with a classifier we have:

		Observed (True)	
		Urban	Rural
Predicted	Urban	87 (TP)	28 (FP)
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$$= \frac{156}{208} = 0.75$$

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- We have an accurate prediction in 75% of the cases.

[Confusion Matrix & Accuracy]

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- One may need other measures, such as *Specificity* or *Sensitivity*

[Sensitivity or *True Positive Rate*]

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[SENSITIVITY OR *True Positive Rate*]

		Observed (True) Urban	Observed (True) Rural
Predicted	Urban	87 (TP)	28 (FP)
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Table: Confusion Matrix

- *Sensitivity* focuses on "positives" (here *Urban*), *i.e.* on predicted positives *vs* the observed positives

$$Sensitivity = \frac{TP}{TP + FN}$$

$$= \frac{87}{87 + 24} = 0.78$$

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- On *Urban*, we correctly predict in 78% of the cases

[Specificity or *True Negative Rate*]

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- *Sensitivity* focuses on negatives (*Rural*), *i.e.* on predicted positives *vs* the observed positives

$$Specificity = \frac{TN}{TN + FP}$$

$$= \frac{69}{69 + 28} = 0.71$$

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- On *Rural*, we predict correctly in **only** 71% of the cases

[Confusion Matrix & Kappa (κ)]

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- The larger κ is, the better the model for a given distribution of classes in a data set

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- This can be transformed into:

$$\pi = \frac{exp(-x'\beta)}{1 + exp(-x'\beta)}$$

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$\hookrightarrow$ *"The logit models log of odd ratios as linear in x"*

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$\hookrightarrow$ The logit classifier depends on the linear combination of the x's

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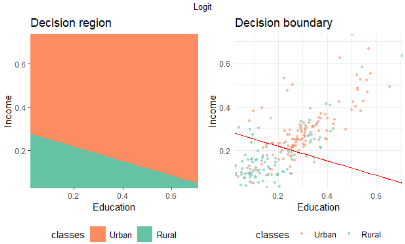

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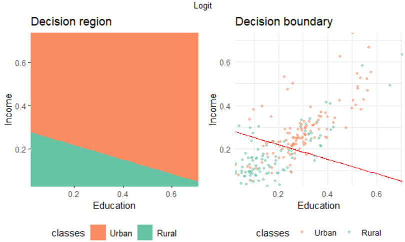

- This partition is sensitive to the choice of the threshold T_0 (and the t_0)

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- *Specificity* and *Sensitivity* are affected by t_0

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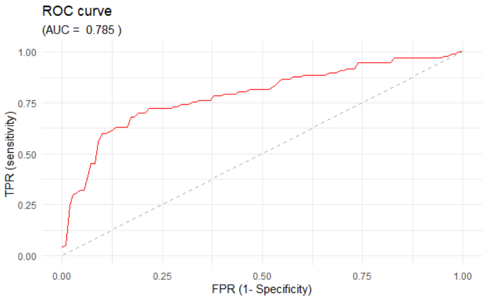

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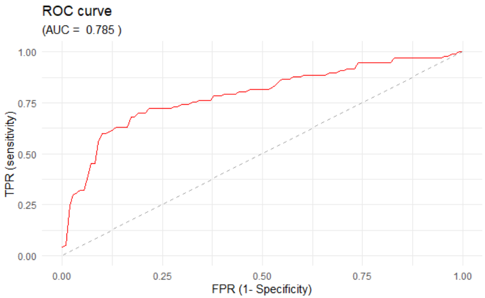

- *(sometimes x is sensitivity with inverted x-axis)*

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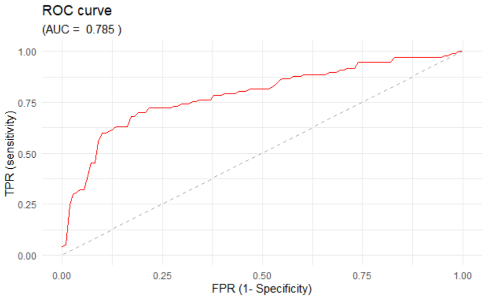

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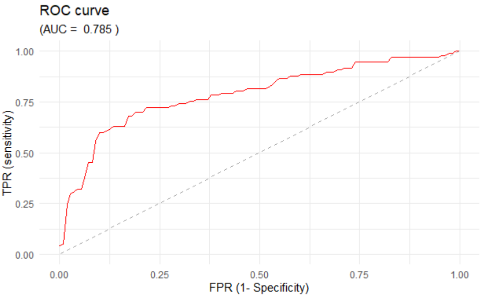

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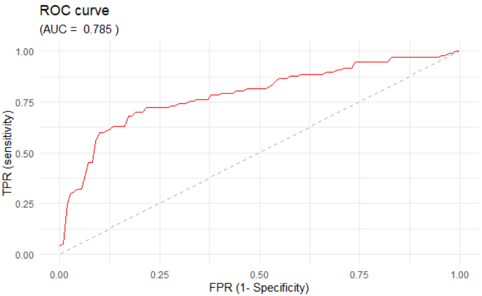

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- If $t_0 \nearrow$, specificity $\nearrow$ and sensitivity $\searrow$

[AUC as a measure of fit]

[Train & Validation set]

[CV on measures of fit]

[Model comparison]

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  One may use the **ROC** to change the threshold parameter

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