Machine Learning for Official Statistics and SDGs

Second 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

Second Live Lecture (Webinar):

Starts in **10** minutes

Christophe Bontemps, UN SIAP

UNITED NATIONS siap Statistical Institute for Asia and the Pacific

Machine Learning for Official Statistics and SDGs

Second Live Lecture (Webinar):

Starts in **5** minutes

Christophe Bontemps, UN SIAP

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Machine Learning for Official Statistics and SDGs

Classification

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[- Reminder -]

- Mute yourself always!

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- Ask questions in the chat

[- Agenda -]

- Introduction

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- Classification in a (*Machine learning Framework*)

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- Introduction
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- Next week

[Classification]

What is a classification problem?

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A **classifier** is a tool that provides a classification for y using (*or not*) additional information from other variables

[Supervised *vs* unsupervised Classification]

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

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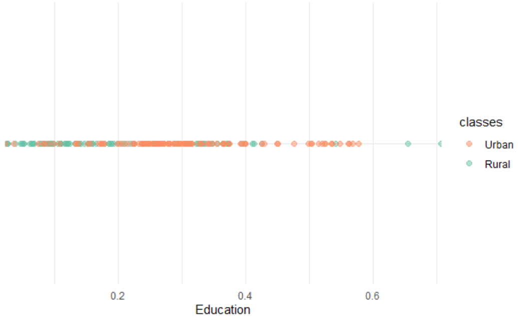

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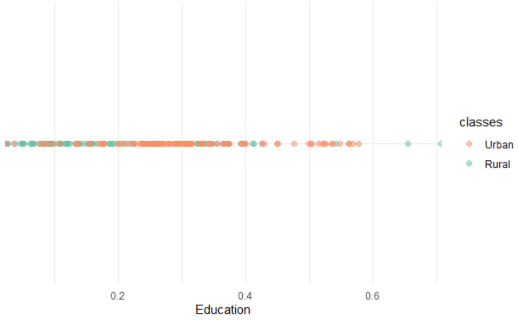

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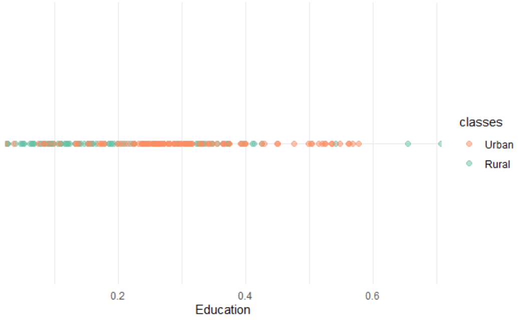

- A classifier "finds" the value of *Education* separating "*Rural*" from "*Urban*"
  Typically with a threshold rule: "if $x \geq T_0$ then category is *Urban*"

[Classification: A 2-D example]

[CLASSIFICATION: A 2-D EXAMPLE]

- You observe households in *Urban* or *Rural* areas and **two** variables (features): *Education* and *Income*

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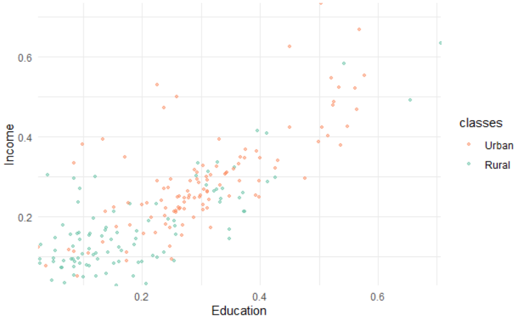

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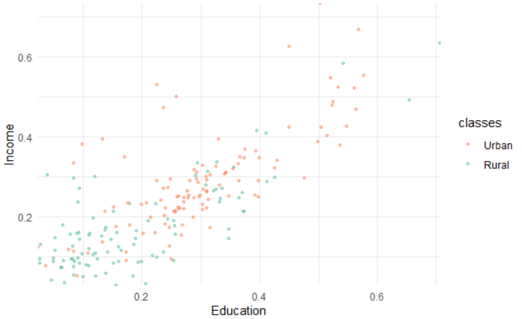

Where is the boundary? How to find it?

[Classification: A 2-D example]

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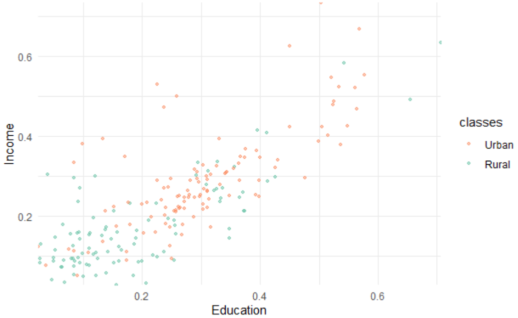

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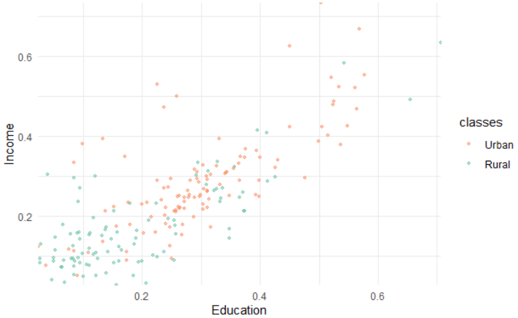

- The rule can be based on a linear relationship between *Education* and *Income* or can be non linear.

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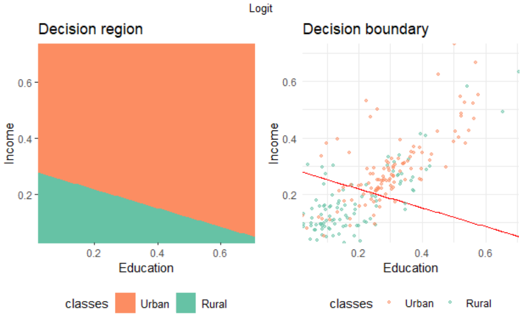

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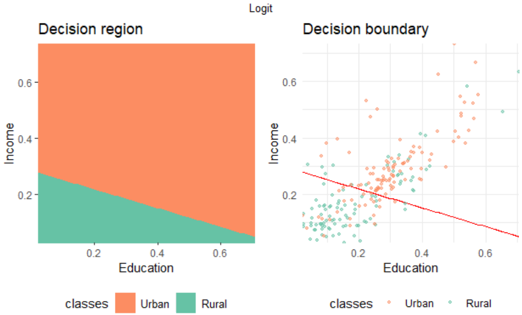

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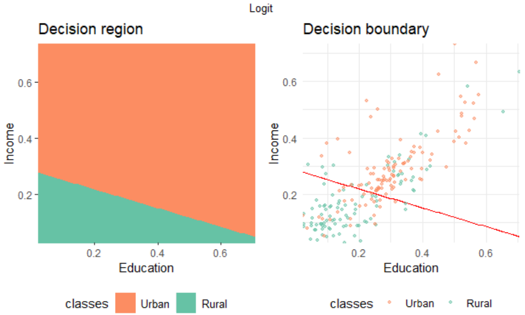

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  e.g.: $\beta_0 + \beta_1 Education + \beta_2 Income \geq T_0 \Leftrightarrow Urban$

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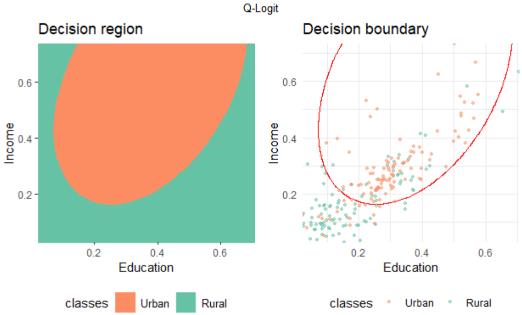

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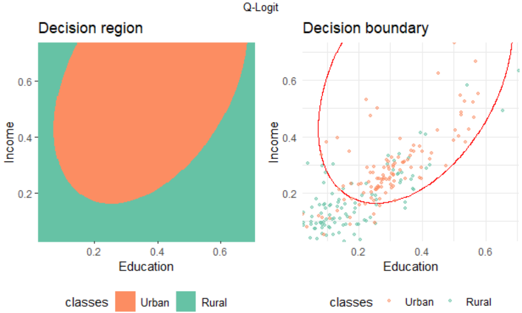

- The rule that separated the two classes is non linear in the variables *Education* and *Income*

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[How to select the right model?]

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$\hookrightarrow$ Need for a criterion to determine what is a good classifier

- Measures of fit in classification are different and specific

[Measures of fit in classification]

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Each criterion answers to a different question

[Accuracy and Confusion Matrix]

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↪ 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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	FN (False Negative)	TN (True Negative)

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- Accuracy is then the ratio:

$$Acuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$= \frac{TruePositives + TrueNegatives}{N}$$

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- It is the proportion of accurate predictions

[Confusion Matrix & Accuracy]

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.

[Problem 1: Accuracy is one number]

Accuracy is not the *panacea* and may be misleading

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- Compute *Sensitivity* & *Specificity* from the confusion matrix
- They may go in different directions

[Sensitivity or *True Positive Rate*]

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- *Sensitivity*: focuses on predicted positives (here *Urban*) *vs* 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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[SPECIFICITY OR *True Negative Rate*]

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- *Sensitivity* focuses on predicted negatives (*Rural*) *vs* observed negatives

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

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

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

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

[Problem 2: Imbalanced outcomes]

Imagine you observe much more Urban than Rural

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95	5

[PROBLEM 2: IMBALANCED OUTCOMES]

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Accuracy = (TP + TN)/ 100 = 95 %

Sensitivity = TP/(TP + FN) = 95/95 = **100 %**

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

[Logit as You know it]

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

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Where t_0 is a **threshold** probability
- If $t_0 = 1/2$ (default), then the rule is equivalent to:

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- If $t_0 \neq 1/2$, then there exist a threshold T_0 such that :

$$x_i'\widehat{\beta} > T_0 \Leftrightarrow \widehat{y}_i = 1$$

[Logit as a classifier]

- Once estimated, $\widehat{\pi}_i$ provide a simple rule for classification

$$\widehat{\pi}_i > t_0 \Leftrightarrow \widehat{y}_i = 1$$

Where t_0 is a **threshold** probability

- If $t_0 = 1/2$ (default), then the rule is equivalent to:

$$x_i'\widehat{\beta} > 0 \Leftrightarrow \widehat{y}_i = 1$$

- If $t_0 \neq 1/2$, then there exist a threshold T_0 such that :

$$x_i'\widehat{\beta} > T_0 \Leftrightarrow \widehat{y}_i = 1$$

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

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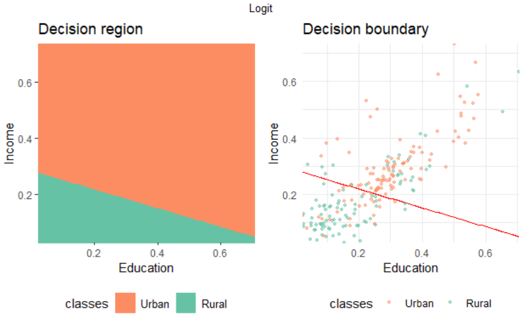

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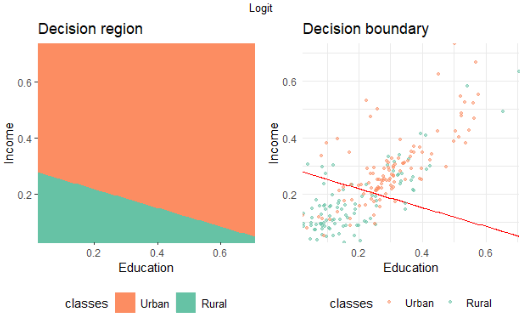
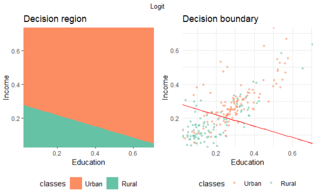


- This partition is sensitive to the choice of the threshold T_0 (and hence t_0)

[Importance of the threshold]



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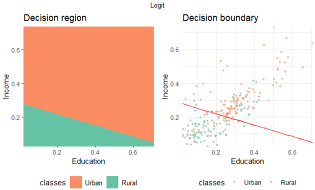

- Changing t_0 will change the predictions & the classification
  A **higher** t_0 will allocate **less** observations to the $y = 1$ category (Urban)
  A **lower** t_0 will allocate **more** observations to the $y = 1$ category
- The choice of t_o should be done according to the data and observed classes repartition
- *Specificity* and *Sensitivity* are affected by t_0

[The ROC Curve]

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↪ *Be careful of the axes*

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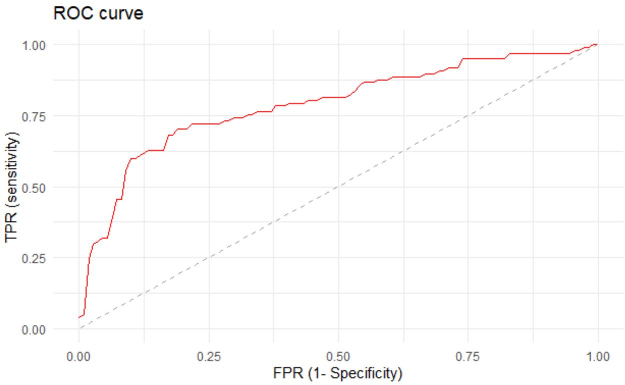

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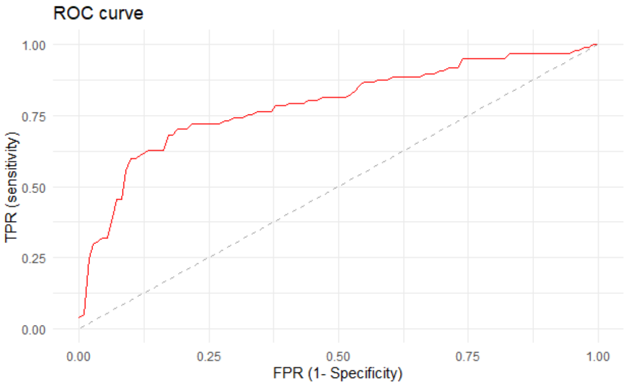

↪ *sometimes on a ROC curve, x is sensitivity with inverted x-axis*

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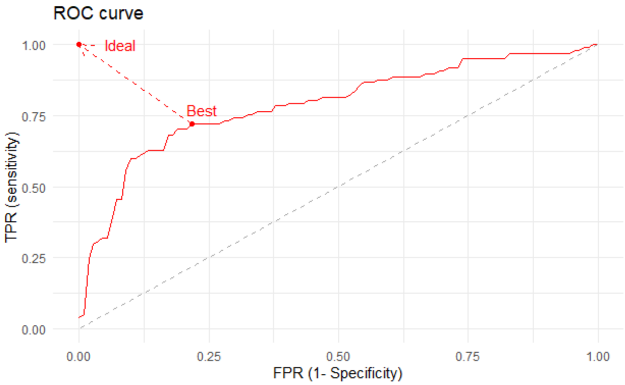

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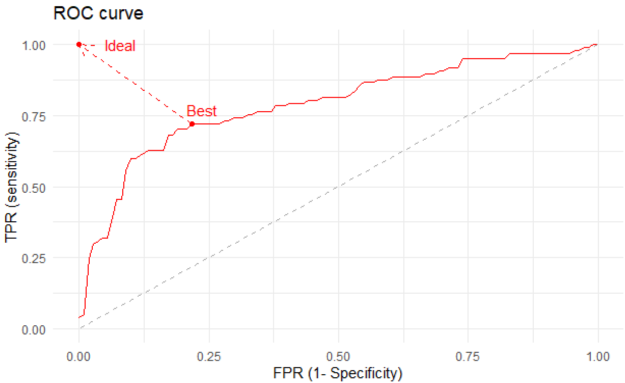

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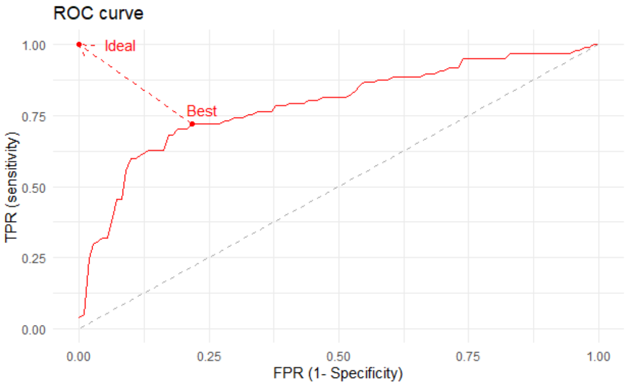

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- If $t_0 \nearrow$, specificity $\nearrow$ and sensitivity $\searrow$

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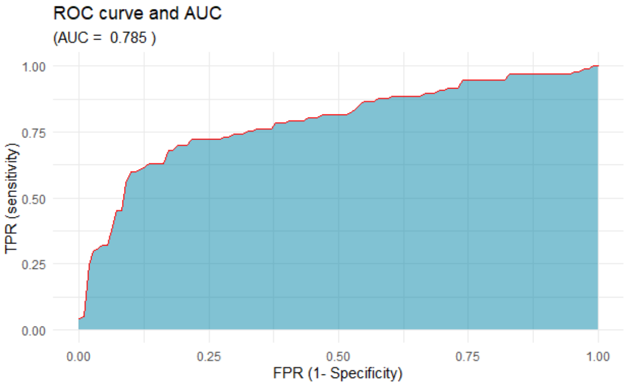

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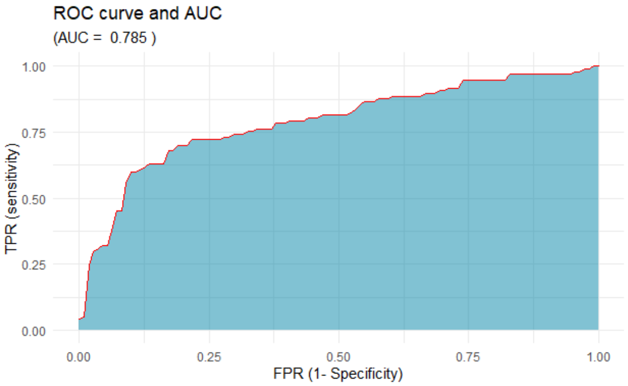

- The greater the area, the better the model

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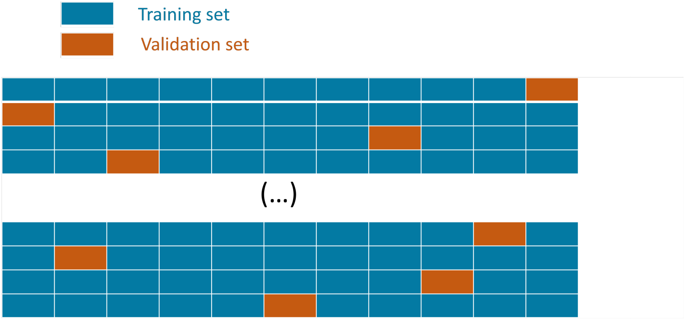

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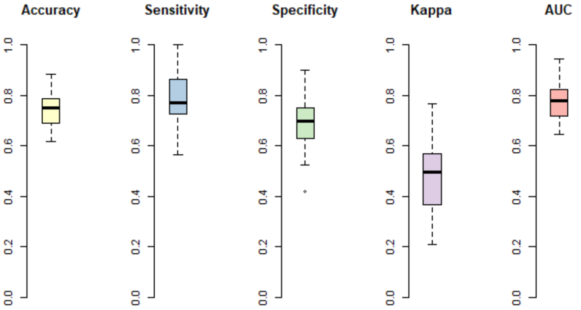

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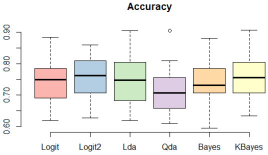
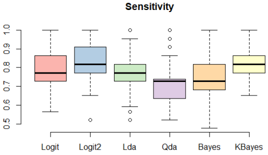
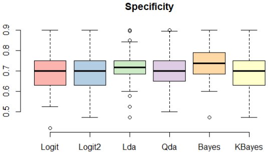


Accuracy of all CV validation sets,on all models



Sensitivity of all CV validation sest, on all models



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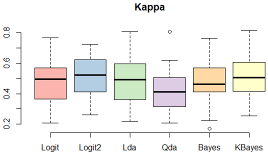
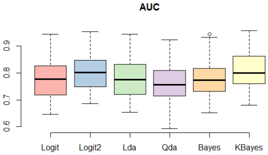


Kappa of all CV validation sets, on all models



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

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- Time is the limit...

[Q&A]

Write your questions in the chat

[Next week]

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Have a nice week!