## Models in the bank

A model can be understood as a quantitative process that consumes inputs and produces estimates or classifications as an output. This is uncertain in nature.

- There is a variety of the models used in a bank. Examples are:
  - Stress models (scenario-based stress losses)
  - Financial crime detection,
  - Pricing models,
  - Marketing models,
  - **> Credit risk (PD, LGD, EAD)**



## What is a default?



## What is a credit loss?



## Credit loss - example

**Assume that a borrower XYZ takes out a $400,000 loan for a condo. After making installment payments on the loan for a few years, the borrower faces financial difficulties and defaults when the loan has an outstanding balance, or exposure at default, of $300,000. The bank forecloses on the condo and is able to sell it for $240,000. What is the PD, LGD, EL and net loss to the bank?**

- EAD =
- Net loss =
- PD =
- LGD =
- EL =

Now, let's assume that we project out a **potential** but **not certain** loss. The expected loss would be different. Using the same figures from the scenario above, but assuming 50% probability of default in one year horizon, the expected loss is:

- EL = PD · EAD · LGD =



## How to combine variables into credit rating?

We are interested in which of the variables' combination would imply the best risk assessment.

<u>General Linear Models (GLM):</u> each outcome $Y$ of the dependent variables is assumed to be generated from a particular distribution in an exponential family, a large class of probability distributions. The mean $\mu$ of the distribution depends on the independent variables $X$ through:

$$E(Y|X) = \mu = g^{-1}(X\beta)$$

Where $E(Y|X)$ is the expected value of $Y$ conditional on $X$, $X\beta$ is a linear predictor, a linear combination of unknown parameters $\beta$, $g$ is a link function.

We assume that:

- $Y = 1$, if an event occurred (e.g., default),
- $Y = 0$, if an event did not occur.

**Examples of the link functions ($g$) – often used in practice:**

| Logistic function (logit) | CDF of the normal distribution (probit) |
|---|---|
| $g(p) = \ln\left(\frac{p}{1-p}\right)$ | $g(p) = \Phi^{-1}(p)$ |



## Measuring discriminatory power of the model (I/III)

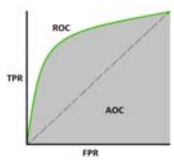
Receiver operating characteristic (ROC) is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied

- The ROC curve says *how much the model is capable of distinguishing* between classes. Higher the AUC (**area under the curve = integral**), better the model is at predicting 0s as 0s and 1s as 1s.

  By example: higher the AUC, better the model is at distinguishing between clients who would default from those who will not.

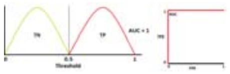
- The ROC curve is plotted with TPR against the FPR where TPR is on y-axis and FPR is on the x-axis.
  - **TPR (True Positive Rate, sensitivity)** = TP / (TP + FN)
  - **Specificity** = TN / (TN + FP)
  - **FPR** = 1 – Specificity = FP / (TN + FP)
  - Example – confusion matrix:

| N = 1000 | Predicted: No default | Predicted: Default | |
|---|---|---|---|
| Actual: No default | TN = 500 | FP = 10 | 510 |
| Actual: Default | FN = 20 | TP = 470 | 490 |
| | 520 | 480 | 1000 |

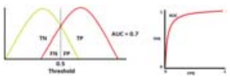


# Measuring discriminatory power of the model (II/III)

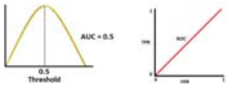
The higher Area Under the Curve (AUC), the better



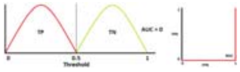
An ideal situation. When two curves do not overlap at all means model has an ideal measure of separability. It perfectly distinguishes between 1s and 0s.



When two distributions overlap, we introduce type 1 and type 2 error. Depending upon the threshold, we can minimize or maximize them. AUC = 0.7 means there is a 70% chance that model will be able to distinguish between 1s and 0s.



This is the worst situation. When AUC is approximately 0.5, model has no discrimination capacity to distinguish between 1s and 0s.

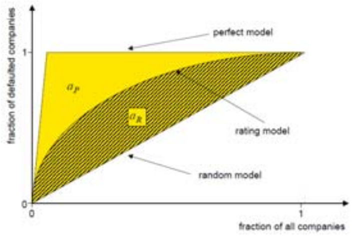


What does AUC = 0 mean?



# Measuring discriminatory power of the model (III/III)

Cumulative Accuracy Profile




We sort the observations (e.g., clients) from the least to the most reliable according to the credit rating predicted by the model.

$a_R$ – area between the model's curve and the random model's curve,
$a_P$ – area between the random model's curve and the perfect model's curve,
AR (accuracy ratio) = $a_R$ / $a_P$