EUROPEAN CENTRAL BANK

BANKING SUPERVISION

A new approach to Early Warning Systems for smaller European banks

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DG Micro-prudential Supervision III
European Central Bank

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Agenda

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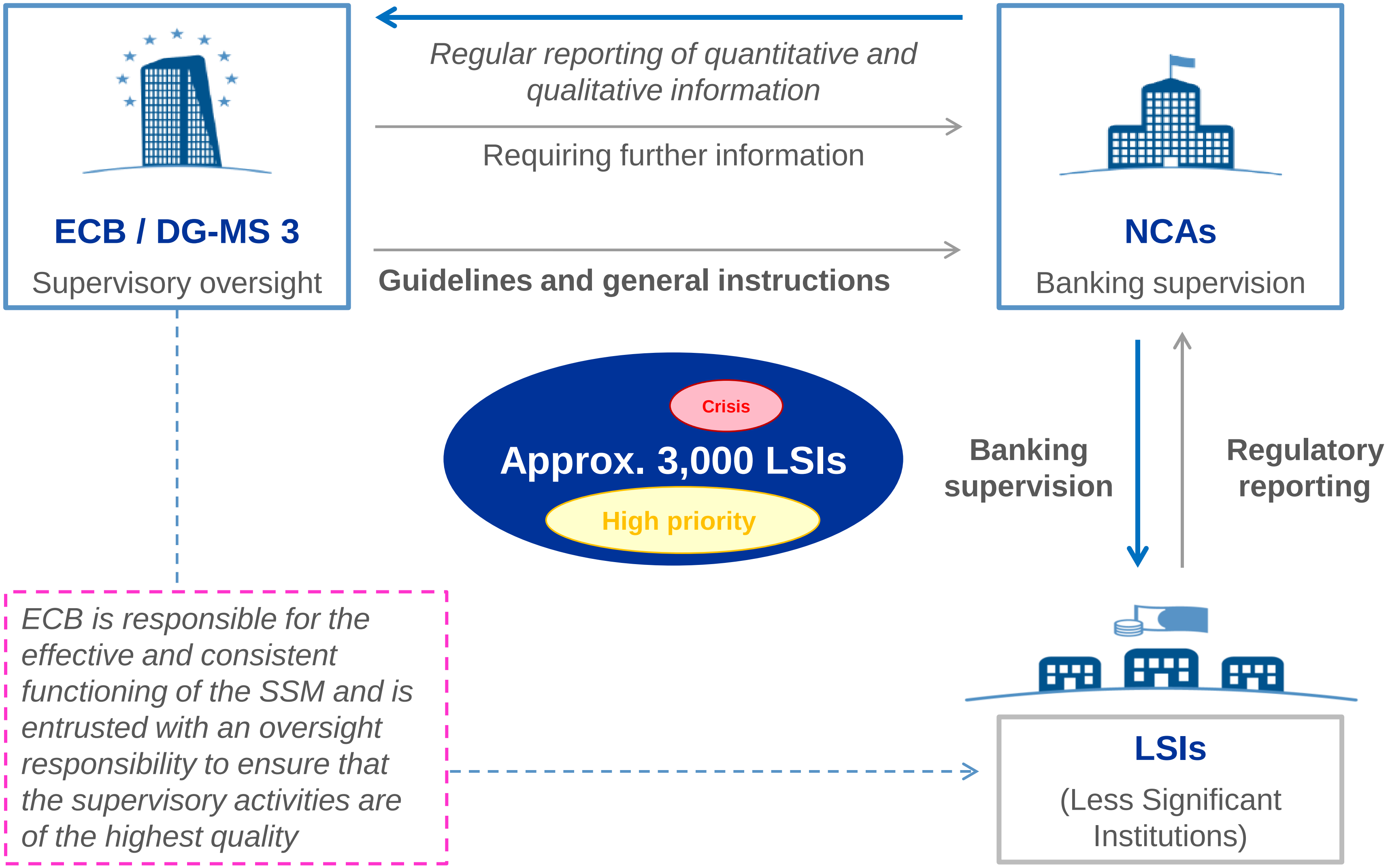
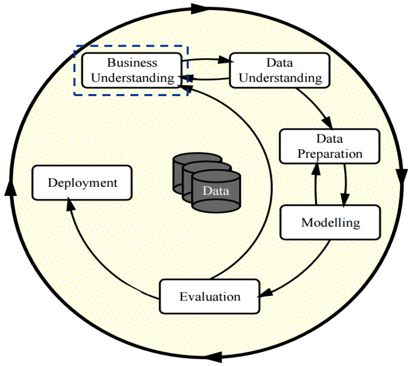
Background: General approach to indirect supervision



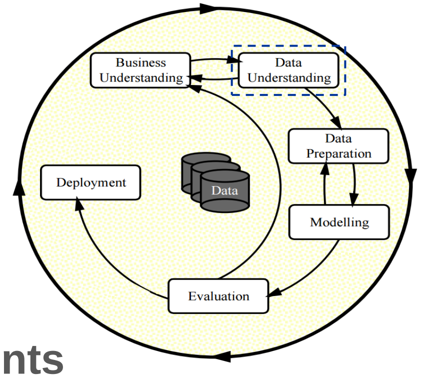
Motivation

- In order to fulfil its mandate DGMS3 has developed an early warning system tailored for indirect supervision in the context of less significant institutions = LSI-EWS
- Existing EWS are usually based on conventional modeling techniques, e.g. logit, calibrated using only a very small number of distress events
- In contrast, we propose a different approach:
  - Application of **machine learning** techniques to derive a decision tree based model
  - **Broadened definition of distress** based on triggering of Bank Recovery and Resolution Directive's (BRRD) early interventions measures in addition to conventional definition
    - Banks which breach or are close to breaching the minimum capital requirements
    - Complemented by qualitative indicators, e.g. notifications by National Competent Authorities
- Explanatory variables consider three different sets
  - **bank-specific**,
  - **banking-sector** variables and
  - country-level **macro-financial** indicators



We followed the CRISP-DM methodology when developing the LSI-EWS, to ensure a structured and robust approach.

Underlying data



- The quality of the resulting tool is determined by the underlying data → most important step in the project
- The study builds on a unique dataset comprising
  - more than **3,000 small banks** including approx. **350 distress events**
  - period from **2014Q4 – 2016Q1**
- Several challenges identified!

Data availability

Financial reporting data collection was only available once a year

Time gaps between reference date and submission of data

Data quality

Reporting is often not complete (missing values)

Reported data points might contain errors

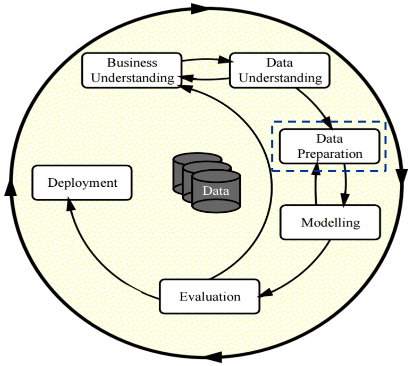
Data comparability

Majority of LSIs (approx. 75%) report financial figures according to national GAAP which are not in line with IFRS

Resulting comparability issues might distort prediction results

→ In-depth data preparation to mitigate issues and follow-up actions

Data pre-processing

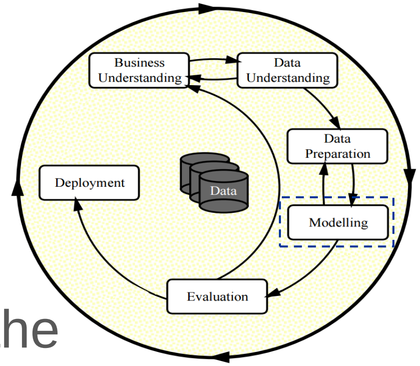


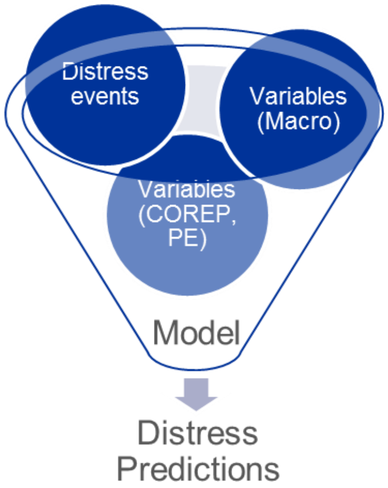
- Required to ensure that unreliable, noisy data and irrelevant/redundant information is eliminated, i.e.

  Data cleaning: Removal of certain banks and variables
  - Banks where the majority of relevant data is missing
  - Variables where the majority of values is missing or variance is nearly zero
  - Variables which are highly correlated with each other

  Data transformation: Create consistency and comparability across banks
  - Adjust data to consider nGAAP specifics, i.e. profitability adjusted for non IFRS compliant reserves
  - Normalization of variables through creation of ratios, e.g. RoA, RoE or NPL ratio
- Final set of indicators is selected based on their ability to predict distress: **Variables are ranked** according to their importance, captured by the AUC for each indicator; outcome presents the top 100 variables as input for the modelling

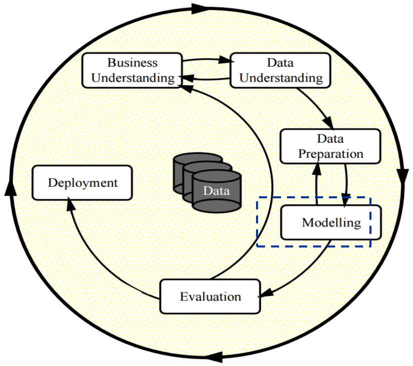
Modelling –
Why to apply ML for distress prediction



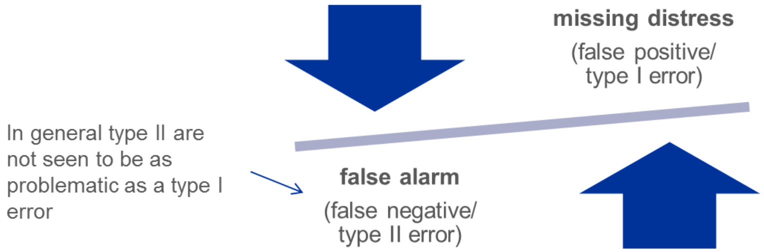


- LSI-EWS as a complement to the LSI Risk Assessment System within the SREP and other projects which are mainly based on expert knowledge
  - In respective cases "ground truth" considered to be known
  - Follow a different approach and learn from data/past observations a model
  - In addition, recent literature suggests the application of Machine Learning (ML) approaches for default prediction
- Supervised learning setting using a decision tree classifier considering
  - Predictive performance, transparency and usability of the model
  - Robustness of the model and results
  - Capability to handle missing values
- Quinlan's C5.0 classifier to build the classification tree model comprising boosting, which constructs an ensemble of classifiers

Modelling

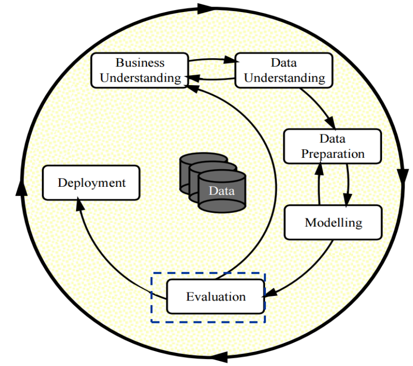


- Prediction horizon is 3-months

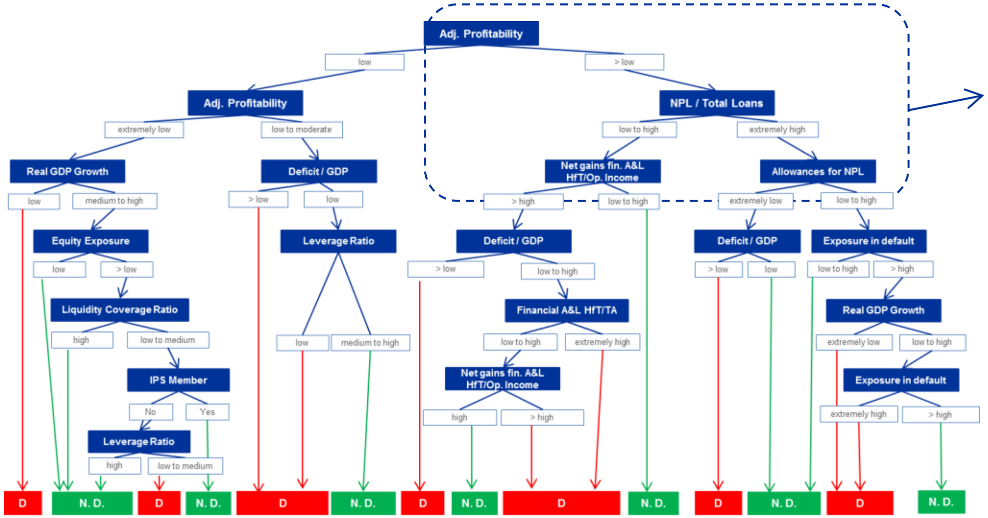


- **Conservative approach** to avoid missing distresses:
  We assume during modelling that the cost of misclassifying a distress event is twice as large as the cost of misclassifying a non-distress event
- To increase the robustness of the variables to be included in the final model we follow a similar approach to Alessi and Detken (2014):
  - Instead of using a single tree, n separate decision trees (trials) are grown and combined to make - more accurate - predictions. **= Boosting**
  - Then, rank variables by occurrence within the trials and select the top 20 variables to go into the final model complemented by expert judgement
  - Ensures robustness of the model

The resulting model



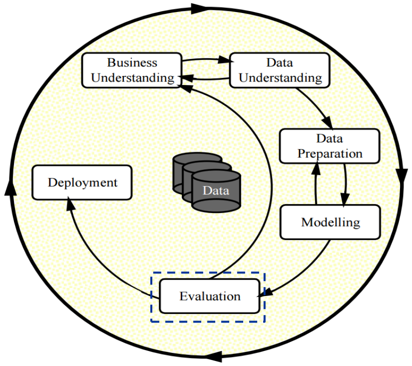
- The identified tree consists of 19 nodes and covers 12 distinct explanatory variables (see also annex)
- The indicator in the parent node is profitability, adjusted for different accounting standards across SSM jurisdictions.
- The tree nicely illustrates interactions between different variables, e.g.:



For profitable banks, one can notice that if the non-performing loans ratio is high, the coverage ratio is considered.
→ Coverage ratio can compensate if sufficient allowances on non-performing loans are created…

D	Bank identified as likely to get into distress
N. D.	No indication for distress

Validation



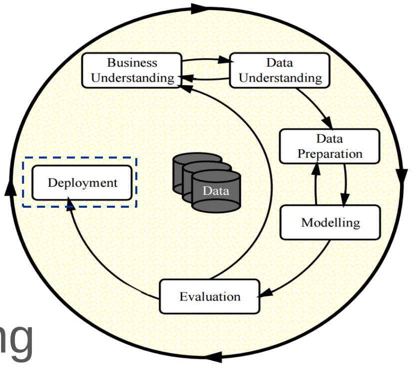
- The in-sample predictive performance of the LSI-EWS is very high which is confirmed by an out-of-sample validation (based on a 75% vs. 25% split of initial data)
- Results assessed in terms of
  - **A**rea **U**nder the receiver operating characteristic **C**urve and
  - **Cohen's kappa** statistic

  Both are standard measures of accuracy in the early warning system literature and are robust to imbalances in the class distribution

	In-sample (Training)	Out-of-Sample (Test)
AUC	0.95	0.92
Cohen's Kappa	0.886	0.803
Type I error rate	0.010	0.033
Type II error rate	0.109	0.099

- Application of a logit model also showed very good results, but the logit model missed more distress events than the decision tree

Conclusion



- The LSI-EWS provides a new approach for identifying bank distress in the European banking system:
  - Distress is based on a broadened definition, e.g. considering the BRRD, to overcome the problem of limited actual distress events and to ensure a forward looking approach
  - The tool follows a machine learning approach based on a decision tree model to provide more transparency and good performance
    → confirmed by promising first results and additional backtesting
- Several items identified to further improve the current approach:
  - Enrichment of the data (FINREP and additional variables) and extension of the prediction horizon to up to six months
  - Differentiate between severeness of distress events
- Finally, deploy the LSI-EWS in the supervisory process

Questions?

STRENGTHENING THE EU BANKING SECTOR

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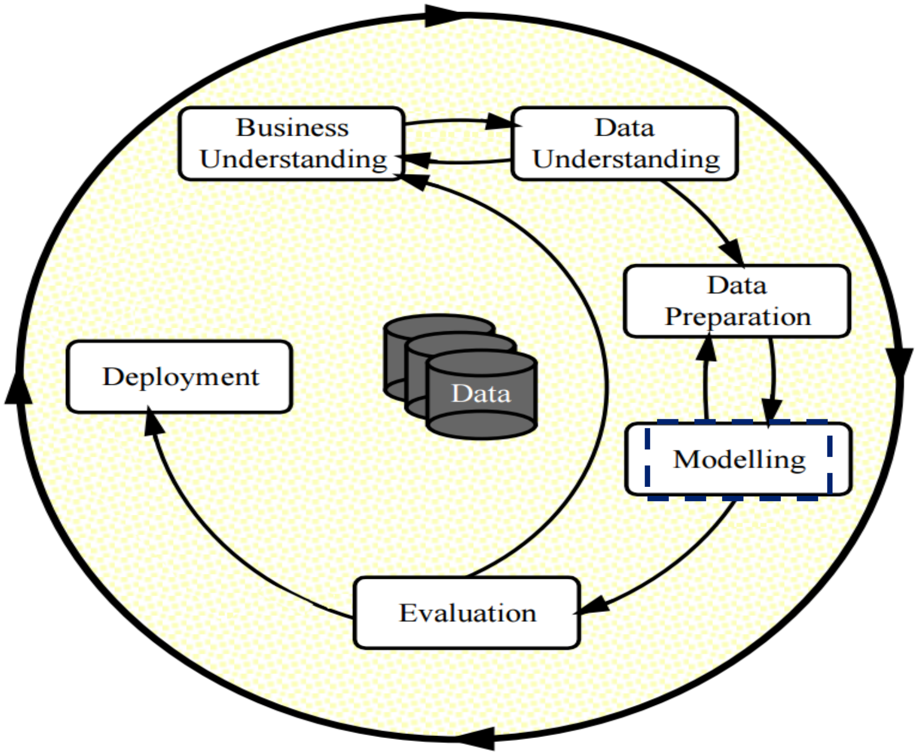
General model development process (CRISP-DM)



Iterative process

*The **C**ross **I**ndustry **S**tandard **P**rocess for **D**ata **M**ining (CRISP-DM) is a process model that describes commonly used approaches that data mining experts use to tackle problems*

Target Variable

A bank is considered in distress when:

- It is facing a conventional bank distress event (following prior literature), e.g. bankruptcy or liquidation
- It meets the condition for early intervention (art.27 BRRD), e.g. breach of thresholds for capital adequacy indicators
- It is placed under special administration (art.29 BRRD) triggered by notification;
- It is deemed to be failing or likely to fail (art.32 BRRD) e.g. rely on emergency liquidity assistance ;
- There is a rapid and significant deterioration of its financial situation (art.96 Framework Regulation) triggered by notification.

Data Sources - Overview

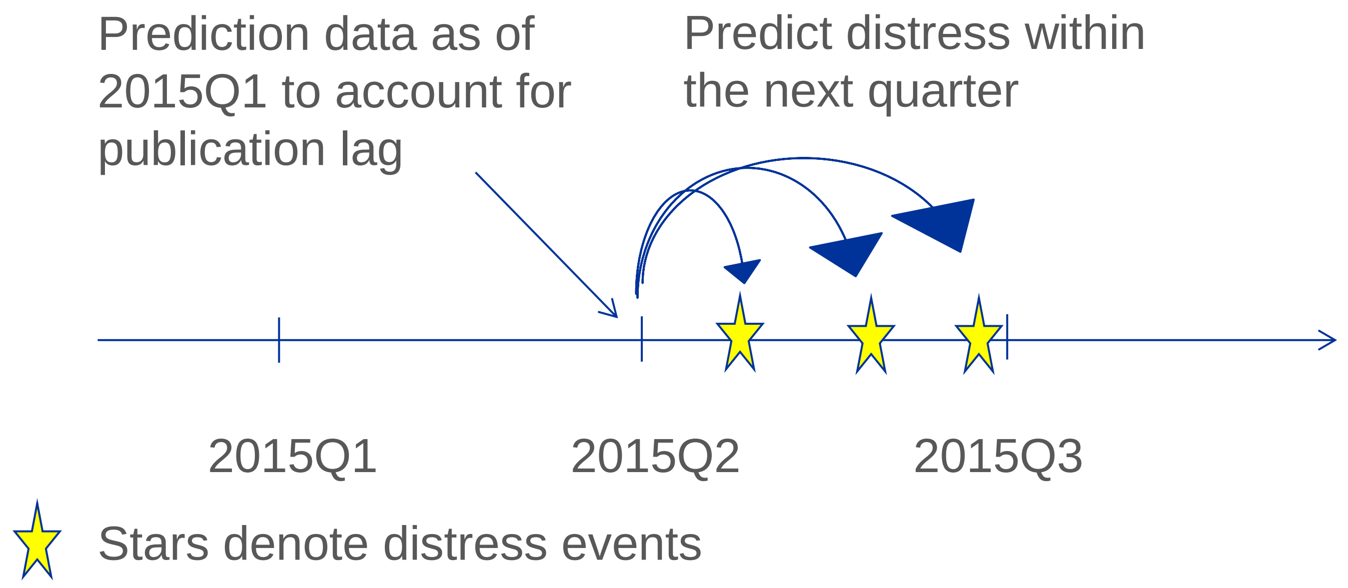
Bank Specific Variables

- Financial Reporting Data
- Capital Requirements
- Euro-system Liquidity and Collateral
- Qualitative Information

Macro-Economic and Banking Structure Variables

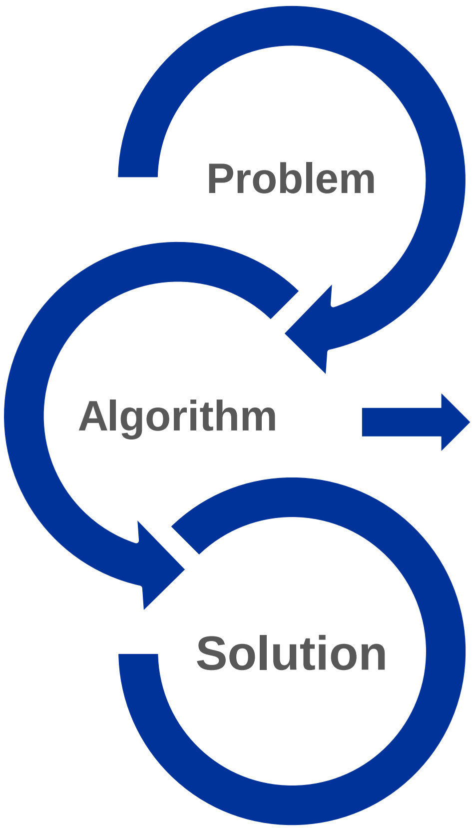
- Macro-Economic Information
- Banking Sector Structure

Prediction horizon

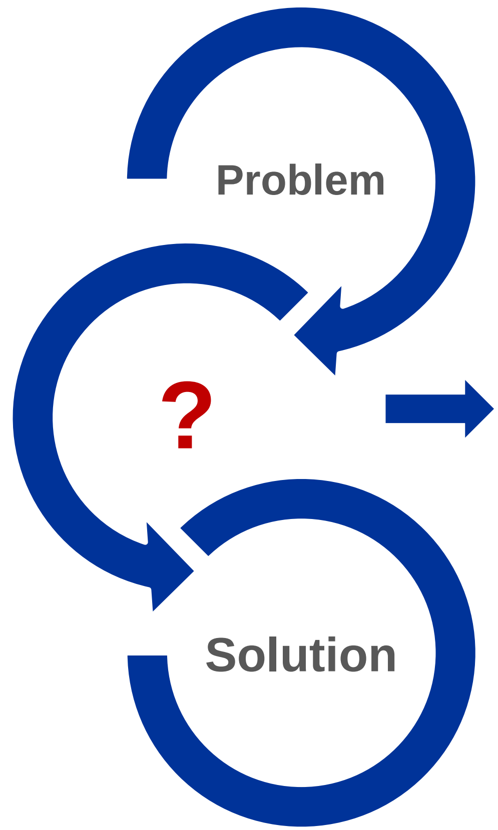


- Short prediction horizon counterbalanced by the definition of distress, which is based on early signs of financial difficulties, allowing supervisors to react

What is Machine Learning (ML)?



Transform input to output



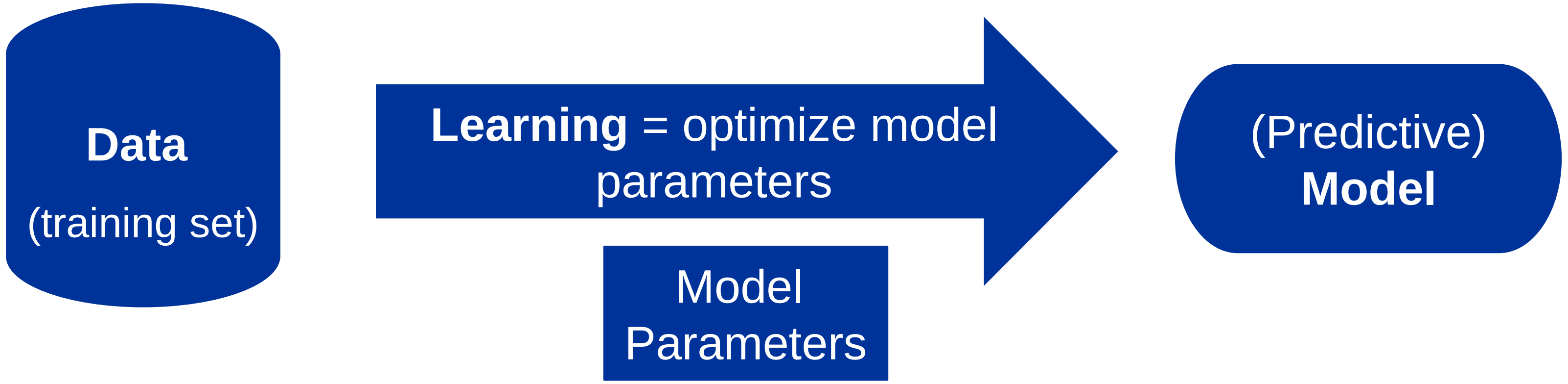
Unclear how to transform input to output

<u>But</u>: What we lack in knowledge, we make up for in data!

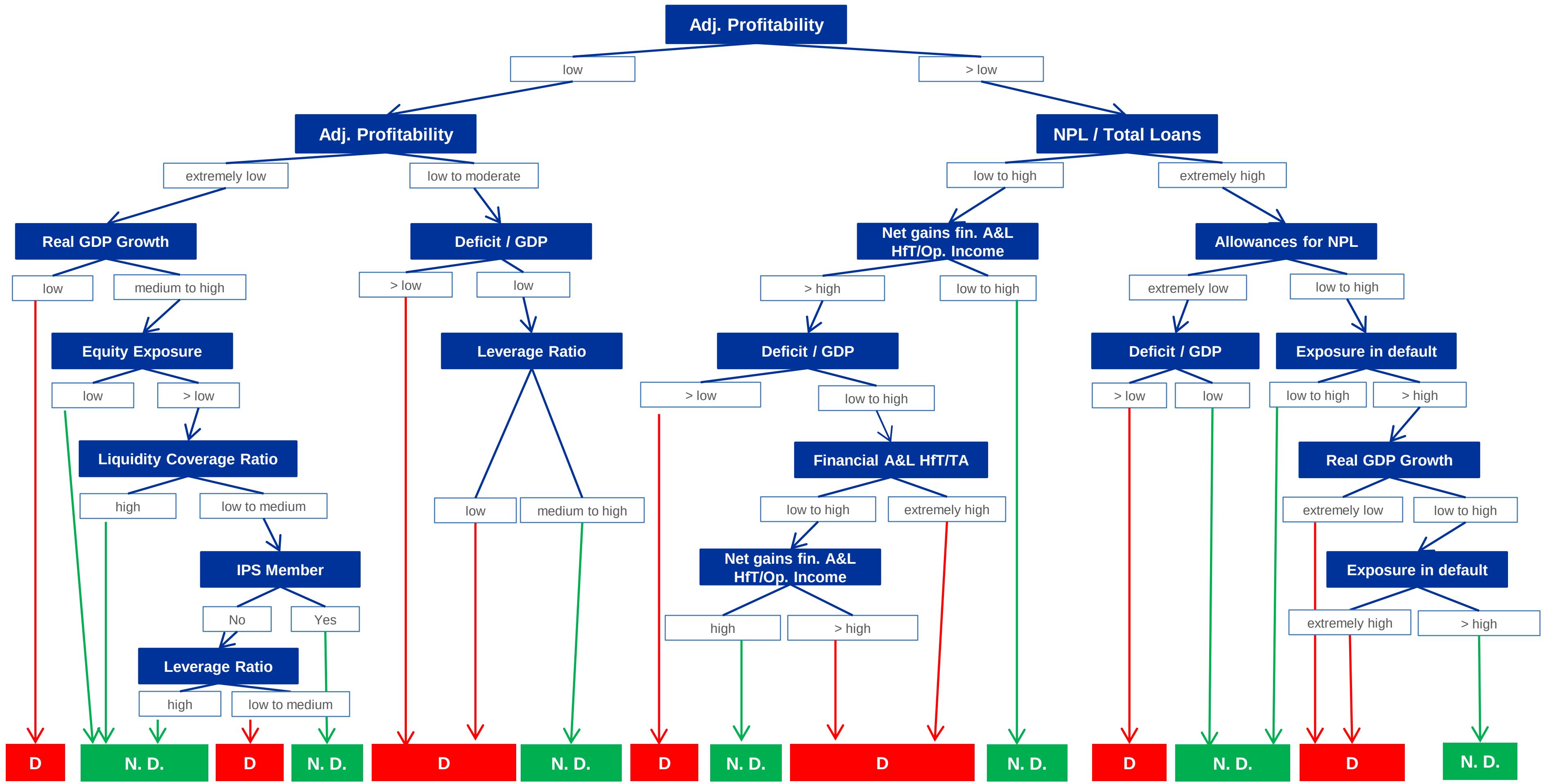
What is Machine Learning?

- Assumption that there is a **process** that explains the data we observe
  - Details of the process regarding underlying data generation unknown
  - But: Process not completely random, there are **certain patterns**!

  → construct a good and **useful approximation of the process**
- "Machine learning is programming computers to **optimize** a performance criterion using example data or **past experience**." (Ethem Alpaydın)



The model


Adj. Profitability
low
> low
Adj. Profitability
NPL / Total Loans
extremely low
low to moderate
low to high
extremely high
Real GDP Growth
Deficit / GDP
Net gains fin. A&L HfT/Op. Income
Allowances for NPL
low
medium to high
> low
low
> high
low to high
extremely low
low to high
Equity Exposure
Leverage Ratio
Deficit / GDP
Deficit / GDP
Exposure in default
low
> low
> low
low to high
> low
low
low to high
> high
Liquidity Coverage Ratio
Financial A&L HfT/TA
Real GDP Growth
high
low to medium
low
medium to high
low to high
extremely high
extremely low
low to high
IPS Member
Net gains fin. A&L HfT/Op. Income
Exposure in default
No
Yes
high
> high
extremely high
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Leverage Ratio
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Annex – Validation terminology

Outcome of the diagnostic test	Condition (e.g. Disease) As determined by the Standard of Truth		
	Positive	**Negative**	**Row Total**
Positive	TP	FP	TP+FP (Total number of subjects with positive test)
Negative	FN	TN	FN + TN (Total number of subjects with negative test)
Column total	TP+FN (Total number of subjects with given condition)	FP+TN (Total number of subjects without given condition)	N = TP+TN+FP+FN (Total number of subjects in study)

Table 1. Terms used to define sensitivity, specificity and accuracy

Sensitivity, specificity and accuracy are described in terms of TP, TN, FN and FP.

Sensitivity = TP/(TP + FN) = (Number of true positive assessment)/(Number of all positive assessment)

Specificity = TN/(TN + FP) = (Number of true negative assessment)/(Number of all negative assessment)

Accuracy = (TN + TP)/(TN+TP+FN+FP) = (Number of correct assessments)/Number of all assessments)

Annex – Validation terminology

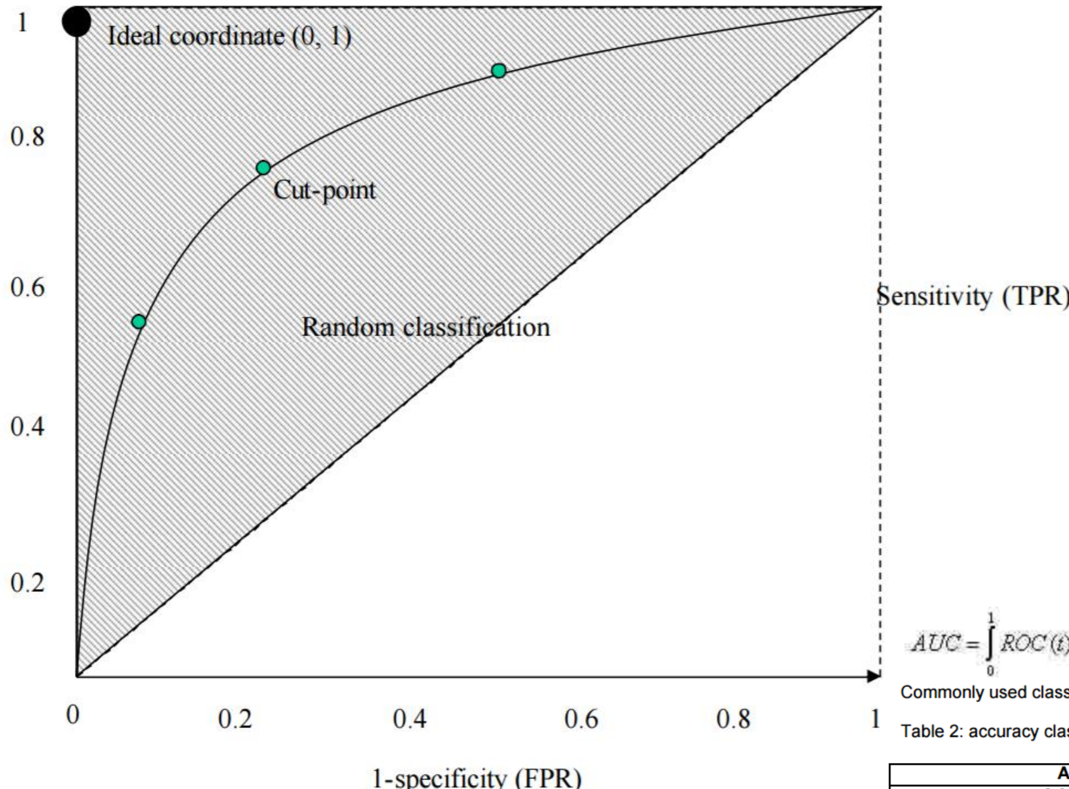

Figure 1: ROC Space: shadow area represents better diagnostic classification

TPR= TP/(TP+FN)

And

FPR = FP/(FP+TN)

$$AUC = \int_0^1 ROC(t)\,dt$$

Commonly used classification using AUC for a diagnostic test is summarized in table 2:

Table 2: accuracy classification by AUC for a diagnostic test

AUC Range	Classification
0.9 < AUC < 1.0	Excellent
0.8 < AUC < 0.9	Good
0.7 < AUC < 0.8	Worthless
0.6 < AUC < 0.7	Not good

As we can see from the above equations, TPR is equivalent to sensitivity and FPR is equivalent to (1 – specificity). All possible combinations of TPR and FPR compose a ROC space. One TPR and one FPR together determine a single point in the ROC space, and the position of a point in the ROC space shows the tradeoff between sensitivity and specificity, i.e. the increase in sensitivity is accompanied by a decrease in specificity. Thus the location of the point in