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# AI and Machine Learning for Credit Rating Models – Part II

## The foundations of machine learning

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# AI and Machine Learning for Credit Rating Models

## The foundations of machine learning

**In this second part in our series on AI and Machine Learning (ML) for Credit Rating Models, we begin by taking a look at the foundations of ML algorithms followed by understanding how to define and differentiate between ML algorithms and rule based methods. We then conclude by focusing on the steps required to building a successful ML based model.**

### The three paradigms of machine learning

Research in the field of ML has been growing rapidly with many algorithms available to overcome some of the challenges we find in risk management especially for regulatory Pillar I modelling.

ML is primarily split into **three key learning paradigms** or approaches designed to train ML models depending on the goal of the models, problem environment and the type of data required.

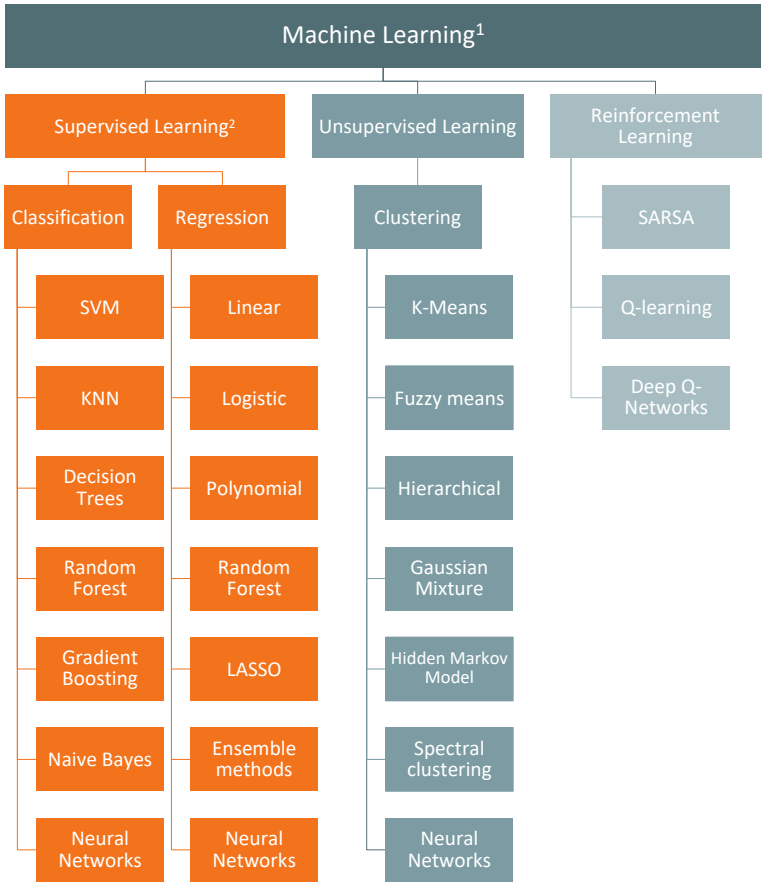
1. **Supervised Learning**
   Learning from labelled data with the aim to learn a general rule that maps the inputs to the outputs.

2. **Unsupervised Learning**
   Learning from unlabeled data with the aim to understand the structure of the data and find patterns.

3. **Reinforcement Learning**
   Learning by trial and error based on rewarding desired behaviours and punishing undesired ones. The goal is to achieve the maximum reward and optimal solution.

In an internal-ratings based (IRB) setting, supervised learning algorithms are preferred where labelled datasets (e.g., dataset composed of obligors' default statuses) are used to find the relationship between the inputs and outputs.

Moreover, combinations of different ML approaches may be used for example, it is not unusual to use unsupervised learning clustering techniques to segment portfolios into common groups before adopting a classification type method to build an IRB model.

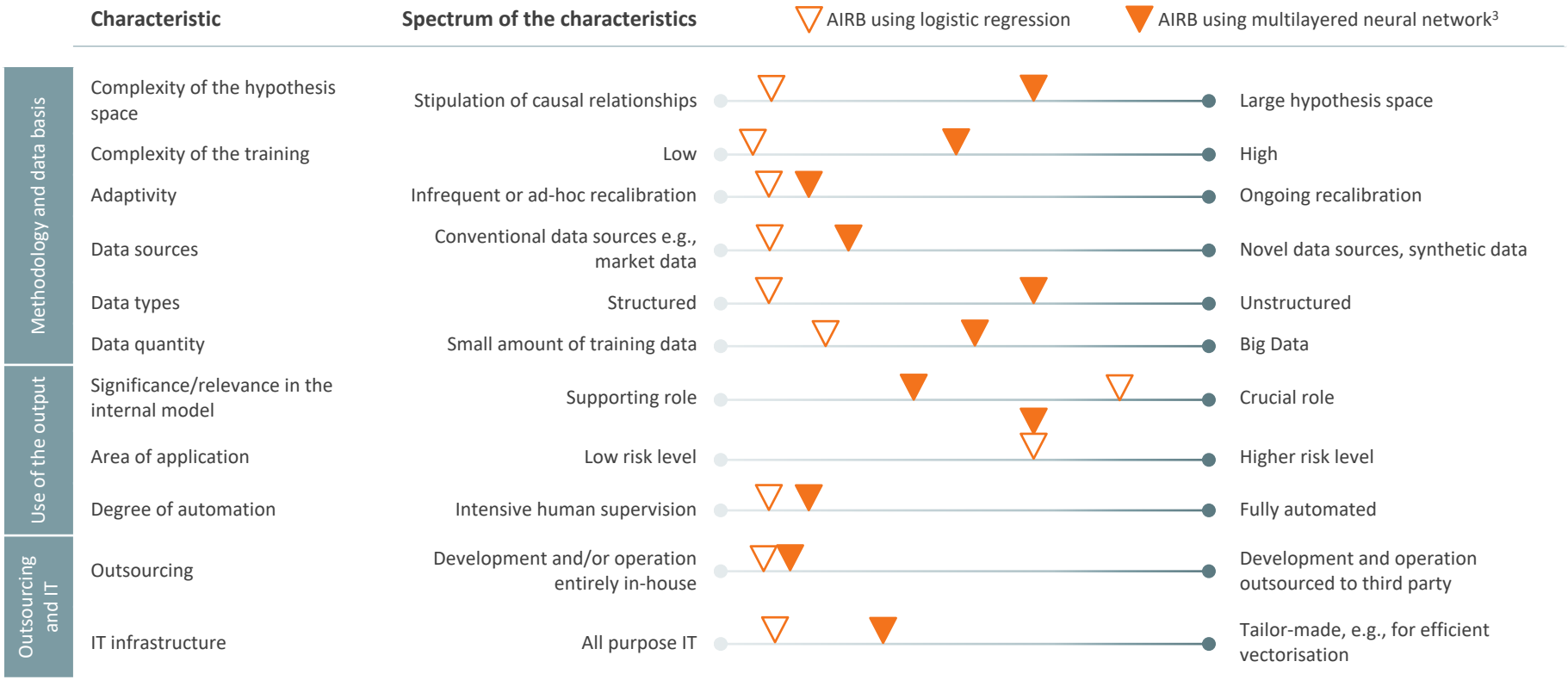



[1] These algorithms represent some of the most popular methods within machine learning. This list is not fully exhaustive.
[2] Some algorithms can appear under multiple different categories e.g.; neural networks may be used for both classification and regression type problems.

# AI and Machine Learning for Credit Rating Models

## Machine learning algorithms have distinct characteristics

**There is no standard definition of machine learning due to the large number of unique available algorithms[1]. However, ML algorithms have certain characteristics which differentiate them from traditional methods[2], including variation in the hypothesis space, model training complexity, easiness to deal with different data types and volume, and relevance in the AIRB model.**




Source: BaFin and Deutsche Bundesbank, 2021

**Did you know?**

A hypothesis is a function which describes a relationship between the model inputs and outcomes. Thus, the hypothesis space is the set of all possible hypotheses and the aim of the learning algorithm is to select the hypothesis which best describes the relationship. The hypothesis space is significantly affected by the quality and representativeness of the data input.

[1] BaFin and Deutsche Bundesbank, 2021, "Machine learning in risk models – Characteristics and supervisory priorities consultation paper"
[2] In the table above, two advanced IRB (AIRB) rating systems used to estimate borrowers' probability of default (PD) are compared against each other, with one based on a logistic regression approach and the other based on a multi-layered neural network.
[3] The characteristics of a neural network are typically more pronounced. Other ML methods have their own profiles.

# AI and Machine Learning for Credit Rating Models

## The 6 key steps to building a ML algorithm for credit rating models

**During the ML model development phase, stronger considerations for the potential pitfalls must be made for example tackling model bias at the data preparation stage and understanding the model behaviour during the initial model validation stage. European regulators[1] are increasingly focused on building trustworthy AI in particular for high risk applications such as credit scoring[2].**

### 1 Define objectives

- Define aim and requirements
- Understand operational constraints
- Establish prudent governance framework
- Consider the risks of model application

**Consideration - Ethics**

What are the ethical considerations?

### 2 Collect and prepare data

- Data acquisition
- Data cleaning
- Exploratory data analysis (EDA)
- Normalise or standardise data
- Data splitting (training, validation and testing sets)
- K-fold cross validation

**Consideration – Model bias**

Identify any dataset imbalances to mitigate potential biases.

### 3 Model assembly

- Select most optimal learning algorithm using different visualization methods. Popular algorithms include:
  - Random forest
  - Gradient Boosting
  - Neural Networks
  - SVM
- Configure and tune hyperparameters
- Focus on feature selection, engineering and extraction to reduce chances of model overfitting and improve model interpretability

### 4 Run training and evaluation

- Evaluate model using validation dataset
- For classification type problems, measure the accuracy, sensitivity, specificity and MCC
- For regression type problems measure the $R^2$, MSE and RMSE
- Further tune hyperparameters

**Consideration - Fairness**

Ensure model is treating all groups fairly and set prediction thresholds accordingly.

### 5 Initial model validation

- Perform data validation
- Perform model validation
- Benchmark model performance
- Assess importance of explanatory variables

**Consideration - Interpretability**

Understand model behaviour on real data and interpret model outputs. Ensure economic intuition holds.

### 6 Deploy, document and maintain

- Implement model
- Provide clear documentation
- Re-train model when required
- Consider frequency of updates
- Identify solutions to 'model drift' and 'data drift'
- Periodic model validation

[1] European Commission (EC) and European Banking Authority (EBA)

[2] The Artificial Intelligence Act (AI Act) by the EC proposes AI used for the assessment of borrowers' credit worthiness should be classified as high risk and therefore subject to further scrutiny by financial supervisors. The AI Act is the first legislative package of its kind, and we expect this act to form precedence for further law reforms across the globe.

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