A Reacfin White Paper on Artificial Intelligence applications to Finance:

Introduction to Machine Learning techniques used in the financial industry and a practical case study

By Arnaud Deltour and François Ducuroir

Reacfin
Know-How to Risk

TVA: BE 0862.986.729
BNP Paribas 001-4174957-56
RPM Nivelles

Tel: +32 (0)10 84 07 50
info@reacfin.com
www.reacfin.com

Reacfin s.a./n.v.
Place de l'Université 25
B-1348 Louvain-la-Neuve

ABSTRACT

Machine Learning ("ML") techniques, a sub-field of Artificial Intelligence, become increasingly popular within the financial industry to tackle issues involving large amounts of data.

In this paper we aim at providing the reader with a basic introduction to key ML concepts and techniques, explain how such approaches differ from the more traditional statistical analysis approach and illustrate this theoretical presentation with some simple yet very practical application within the financial industry.

We also illustrate our point with a case-study: a practical application of decision trees to build predictive LGD models in loan books management.

We wrap-up this paper with a high-level comparison between traditional statistical inference methods and ML techniques

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INTRODUCTION

Machine Learning ("ML") techniques become increasingly popular within the financial industry to tackle issues involving large amounts of data.

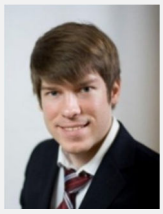
Machine Learning is a sub-field of Artificial Intelligence which derives from pattern recognition. Essentially, ML techniques are a set of mathematical methods which were developed to enable computers to autonomously:

- make predictions based on sets of various types of observations (some of which could prove irrelevant),
- progressively improve such predictions as they are faced with stable (stationary) conditions,
- adapt their results when faced with changing (transitory) conditions.

Such ML techniques share many similarities with classical statistical modeling techniques starting from the fact that they both deal with data. However, the key difference, between statistical techniques and ML techniques lies in the goal of these approaches. While statisticians start assuming a given model can best explain the behavior of the phenomenon considered and try to validate such assumption, ML techniques rather **aim at finding by themselves the method that best predicts the outcome of the studied phenomenon**.

In this paper we aim at providing the reader with a high level introduction to key ML concepts and techniques, explain how such approaches differ from the more traditional statistical analysis approach and illustrate this theoretical presentation with some simple yet **very practical application within the financial industry**.

Authors



Arnaud Deltour
Consultant

MSc in Applied Mathematics Engineering (Magna Cum Laude) and a MSc in Actuarial Sciences (Magna Cum Laude) from the Université of Louvain.
Member of Reacfin's Life, Health and Pensions Centre of Excellence.

François Ducuroir
Managing Partner

Master's degrees in Applied Mathematics and Applied Economics.
Over 20 years' experience in Financial Markets.
Teaching "Management of Banks and Financial institutions at the University of Louvain.

DIFFERENCES BETWEEN "MACHINE LEARNING" AND "STATISTICAL" TECHNIQUES

When applying inference techniques, statisticians will typically[1] start by assuming the explanatory model is known and key explaining variables are known. The objective of the statistical technique becomes then to confirm the model assumption and calibrate as accurately as possible the model parameters so that errors can be minimized.

Machine Learning ("ML") techniques on the contrary start from lesser assumption. The objective is that it is the ML algorithm itself that identifies the key explanatory variables and their impact on the response variable.

Basic concept illustration

Assume we observe a (possibly large) set of variables **x** (the vector of inputs) and an output "response" variable **y**.

Statistical inference techniques aim at calibrating the pre-assumed function $f(x_i)$ so that all that remains is an as limited as possible stochastic error (e.g. normally distributed).

The general form of statistical model can be written as:

$$y_i = f(x_i) + \varepsilon_i$$

where the residuals (ε_i) are "white noises", that is to say, where ε_i are iid[2] $\mathcal{N}(0, \sigma^2)$.

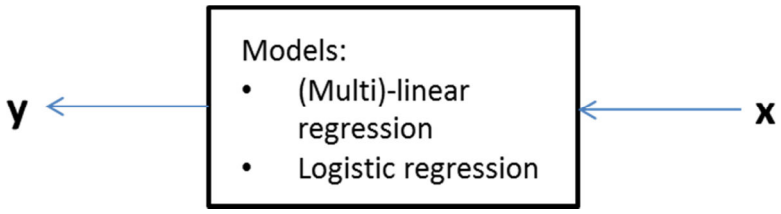


Figure 1: How statistical modelling works

[1] Although using some techniques which are bridges between Statistical inference and Machine Learning, identification of key variables may also be performed using statistical methods. For instance one could think of backward or forward regression approach which are also recursive algorithms..

[2] "iid" =independent and identically distributed

On the other side **Machine Learning techniques** rather consists of algorithms which operate on **x** to predict the best possible response **y**. It does not pre-assume a given model. Furthermore the algorithm (being typical a recursive technique) can grow in size if data complexity justifies it.

Figure 2 schematizes the views of machine learning techniques. Two particular methods that will be developed later on as case studies for this paper are cited for illustration purposes only.

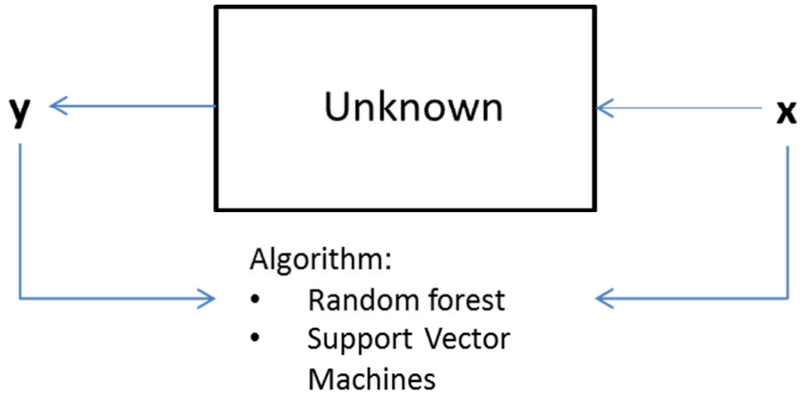


Figure 2: How machine learning works.

Two concepts must be well differentiated:

- ***Supervised Learning*** where a response variable **y exist.**
  - In such case a set of simultaneous observations of **y** and **x** (the "training sample") are used to define and calibrate the model that can best predict future realizations of **y** given the then prevailing outcomes of **x**.
- ***Unsupervised Learning*** that deals with issues for which no response variable **y** exist.
  - In this case the objective is to understand the relationships between the different variables or between the observations. "Clustering" (i.e. grouping observations) is a typical aim of Unsupervised Machine Learning techniques.

OVERVIEW OF SOME SIMPLE MACHINE LEARNING TECHNIQUES

In this paper we focus on three simple **supervised learning techniques:**

- Decision trees
- Random Forests
- Support Vector Machines

We typically distinguish two main types of problem to solve:

- *Classification:* the response variable **y** is qualitative (categorical)
- *Regression:* the response variable **y** is quantitative.

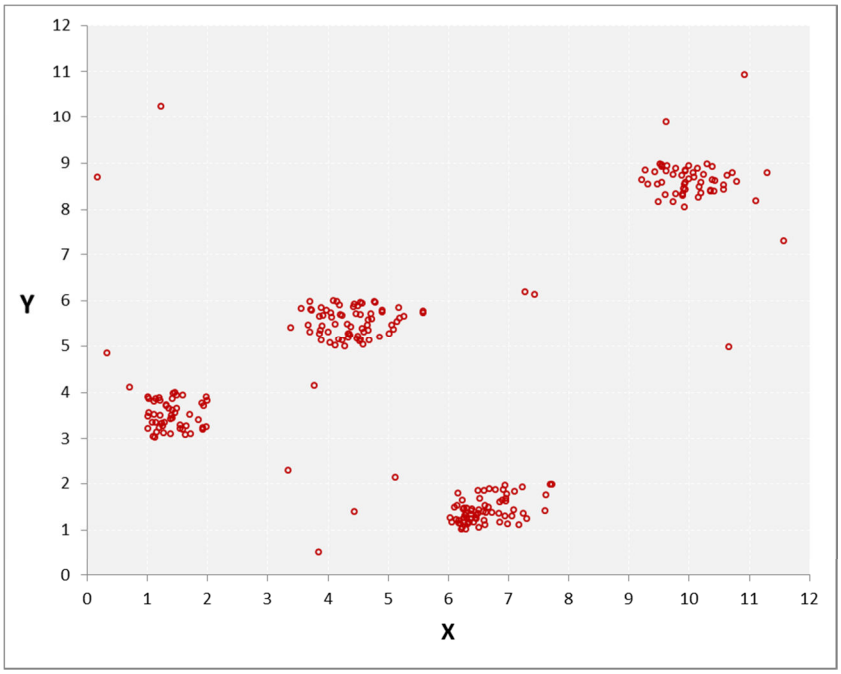
a) Decision trees

A decision tree-based method aims at segmenting the predictor space into regions with a single predicted value.

In other words, the objective here is to find ranges of values in the explanatory variables (x) which give typical value for the variable to be predicted (y).

This can be best illustrated with a graphical example in which one wants to predict **y** given **x**:

Figure 3 - Example of segmentation approach – graph 1



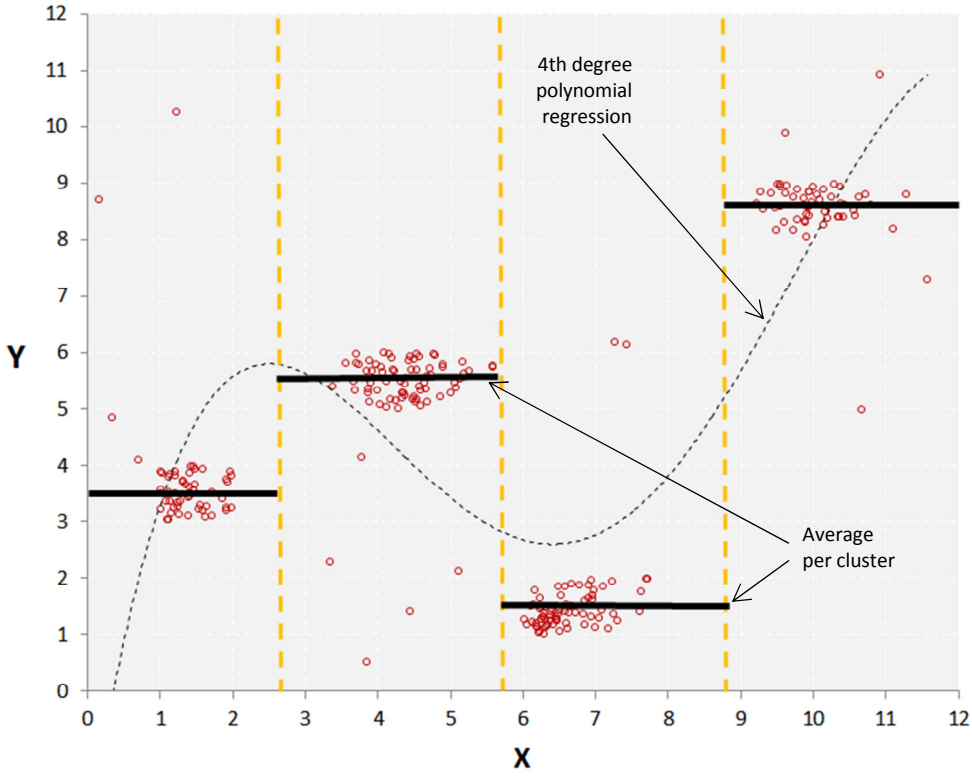
Obviously, realizations of x and y's come frequently "per groups" (segments):

- If the value of x lies between 1 and 2, y will typically lies between 3 and 4
- When x lies between 3.5 and 5.5, y will typically lie between 5 and 6
- When x ranges between 6 and 8, y will rather be small, between 1 and 2
- If x ranges between 9 and 11, y seems to range between 8 and 9

One could then consider that the prediction for each segment is its average value of y.

Such simple segmentation-based average will obviously prove a much better predictor than more classical regression technique (even if using complex non-linear techniques, as graphically illustrated in figure 4).

Figure 4 - Example of segmentation approach – graph 2



Using a tree-based method, each observation is thus allocated into a single region. In order to make a prediction for a specific observation, the decision-tree methods will typically either use a mean (for regression trees) or a "vote" (for classification trees) among the observations in the region to which it belongs.

Decision trees have the advantage to produce models which are easily implementable, relatively transparent and interpretable (if not too large).

However, if not carefully built, overfitting[3] may rapidly arise. Cross-validation[4] and the concept of "pruning"[5] can help to avoid that problem.

Tree-based methods are among the simplest methods and most popular among ML Techniques. However, they provide less accurate (and in some cases less reliable) predictions than more advanced supervised learning approaches which elaborate on in the next sections. Moreover decision trees may prove quite

[3] Overfitting relates to excessively complex models for which the large number of explanatory variables and parameters, is unreasonably important compared to the number of observations.

[4] "Cross-Validation" are recursive validation methods based on multiple statistical sampling (e.g. A first iteration would consist in partitioning the full data set in k sub-sets, (k-1) of which will be considered as "learning samples" on which the calibration is performed and one used as "test sample" on which the results quality is assessed. Following iterations would then consist in redoing the some analysis choosing a different test sample.)

[5] "Pruning" are techniques which consist in reducing the size of decision trees to reduce their complexity and reduce risks of overfitting.

inefficient when the objective is to give predictions beyond the range of observable data.

Decision trees should nevertheless not be overlooked for applications in finance as their results prove to be among the easier to interpret (which is key in finance where expert-based validation and corrections may prove critical success factors). Such methods will also enable robust validation using statistical inference methods which may prove a must-have in a set of application within the financial industry.

To summarize it, the key advantages and disadvantages of Decision Trees are:

Pros:

- Easily interpretable
- Non-linear decision boundary possible (see exhibit above)

Cons:

- Overfitting if not carefully built (pruning and cross-validation needed)
- Does not predict beyond the range observable in the data
- Although non-linear decision boundary can be modelled, it only restricts to "rectangular" classification boxes.

Specifically, decision tree methods will prove particularly adequate in **credit risk assessment problems** thanks to the type of results they provide. These consist in a set of classification clusters based on a set of (possibly limited) ex-ante observed variables. As such the results prove relatively comprehensive for credit analysts, origination staff and their controllers or managers so that it can be implemented in banking organization while limiting the related operational risks which could be induced by more complex methods. For instance, they prove to be quite **efficient alternatives to logistic regressions** for banking applications such as:

- the determination of basic internal rating models (i.e. ex-ante categorizations of debtors for their expected probability of default)
- The ex-ante assessment of expected Loss-Given-Default (both through-the-cycle or in down-turn conditions) for advanced LGD models.

In these applications, the fact that decision trees result in simple tables of categories which often remain quite interpretable make them easy to deploy in the context of credit origination process.

b) Ensemble methods and Random forests

Random forests belong to "ensemble methods" which combine the predictions of several based estimators built with a specific learning algorithm in order to improve predictive power and/or robustness with respect to a single estimator.

Bagging, boosting and random forests are the most common ensemble methods.

Random forests, as its name indicates, is based on the decision tree methods we discussed above. Such algorithm randomly produces multiple trees which are then combined to give a single prediction (the average through all trees for regression or a vote for classification problems).

Combining a large number of trees improves the prediction accuracy but often make the interpretation of results more challenging.

While the relevance of each explanatory variable can be assessed[6], statistical inference validation is far less efficient for random forests than with single decision tree methods.

To sum-it up, main advantages and disadvantages of Random Forest methods can broadly be summarized as follows:

Pros:

- Higher predictive power than the single underlying estimator (i.e. than single decision trees).
- Within the random forest algorithm an inner cross-validation process exists, without any additional computing burden (*"out-of-bag error" computation*)[7]
- High capacity to handle large datasets (with lots of input variables and/or lots of observations)

Cons:

- Black-box method: lack of transparency of results. Expert judgement is thus difficult to incorporate in practice.
- When based on regression trees, random forest may prove inefficient for predictions beyond the range observable in the data.

In finance, while Random Forest may help beef-up credit assessment methods (for instance in the context of debtors "Scoring" applications), we have rather observed that their usual applications rather concentrates in fields such as **algorithmic trading** or **modeling of retail customers behaviors and preferences**. Among others we could observe pretty efficient results in the modeling of **Residential Mortgages prepayments** or that of **lapses in Life Insurance**. They also give good results **in the insurance industry** when used to build complex pricing frameworks aimed at better **predicting future claims risks** of particular policies.

c) Support Vector Machines (SVM):

SVM methods are used for classification problems. The basic algorithms are dedicated to binary classification[8] (i.e. when the response variable has two classes).

[6] E.g. through "variable-importance plots"

[7] For more details see for instance "The Elements of Statistical Learning: Data Mining, Inference, and Prediction" by Trevor Hastie, Robert Tibshirani & Jerome Friedman, section "15.3 Details of Random Forests", pp 592 & 593, Second Edition, Springer, 2008.

[8] However, method extensions exist which will enable to handle cases with more than two response classes. These go beyond the scope of the very high-level introduction paper.

The basic method[9] is to find an optimal hyperplane to linearly separate the two classes. Support vector machines extend that idea to pattern that are not linearly separable with the help of the Kernel function (i.e. a similarity function which may be non-linear and used to separate the classes).

A particularity of SVM comes from the fact that only the "difficult points" (close to the hyperplane) influence the optimum (as opposed to other techniques such as neural networks and linear regression where every point influence the solution).

Like for the random trees methods a main drawback of SVM is that results interpretation may prove difficult.

Originally built to solve classification problems, some generalized versions exist to solve regression problems (e.g. SVR: support vector regression).

The main advantages and disadvantages of SVM methods can be summarized as follows:

Pros:

- Unique solution (global optimum)
- Flexibility: can deal with lots of data patterns through the Kernel functions
- Extensions exist for categorical response variable with more than two classes

Cons:

- Black-box method: lack of transparency of results (only graphical visualizations). Expert judgement is thus difficult to incorporate in practice.

With regard to practical application in the finance industry, our experience shows that the SVM prove particularly effective in:

- Predictive operational risks models
- Claims predictions in Health and P&C insurance (e.g. car insurance, fire insurance)
- Predictive anti-money laundering models
- Like for decision trees and ensemble methods, they are also often used to refine predictive credit performance models (e.g. scorecards). However, their less intuitive interpretation may make them harder to implement in the context for pre-established banking processes and organizations.

[9] called "Support Vector Classifier"

PRACTICAL CASE STUDY: LOSS GIVEN DEFAULT MODELING

In this section, we present a simple real-world application of decision tree and random forest algorithm recently deployed by Reacfin to assess and predict Loss-Given-Default parameters of credit models used by a European commercial bank.

a) Context

Under Basel III (i.e. CRR & CRD IV), banks may calculate their credit risk capital requirements using an internal ratings based approach (IRB).
For corporate credit, the directives distinguish between two possible alternatives:

- Foundation IRB approach which broadly consist in estimating ratings scales only based on probabilities of default and adequately allocating each of the corporate loans to a specific rating class
- Advanced IRB where the ratings scale is established considering not only the PD's by also all other credit parameters including Loss-Given-Default (LGD), Maturity adjustments, Exposure-at-Default Conversion factors, etc.)

Figure 6 recalls the fundamental relation in Credit Risk.

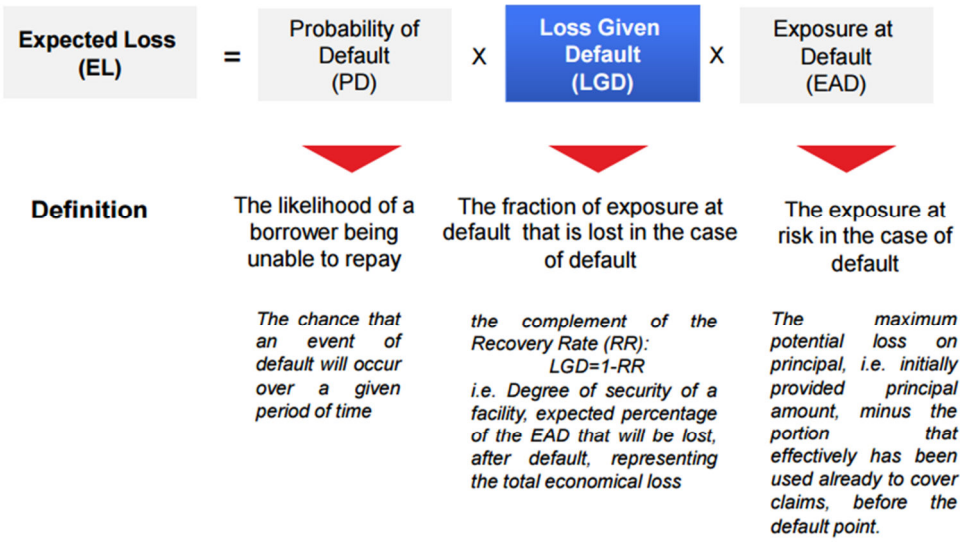


Figure 6: fundamental relation of Credit Risk

Given this decomposition of the expected loss and knowing that using advanced IRB approaches, reductions in LGD estimates by 10% or more[10] are relatively standard, one will easily understand the relevance for banks of using best predictive techniques to assess such parameter.

For instance, per € 1Bn EAD, a 10% reduction in LGD induces (at same pricing level) a positive P&L impact:

- For BB rated debtors (i.e. 1Y-PD~2-3%) of about + €2-3Mn/Year
- For B rated debtors (i.e. 1Y-PD~3-5%) of about + €3-5Mn/Year

[10] Compared to assumptions taken under the Foundation IRB approach

b) Method and example

The LGD values being a continuous value between 0 and 1, regression trees techniques can be used (given the loan's & the debtor's characteristics, market parameters, etc.).

A possible resulting regression tree is presented in figure 7 below[11].

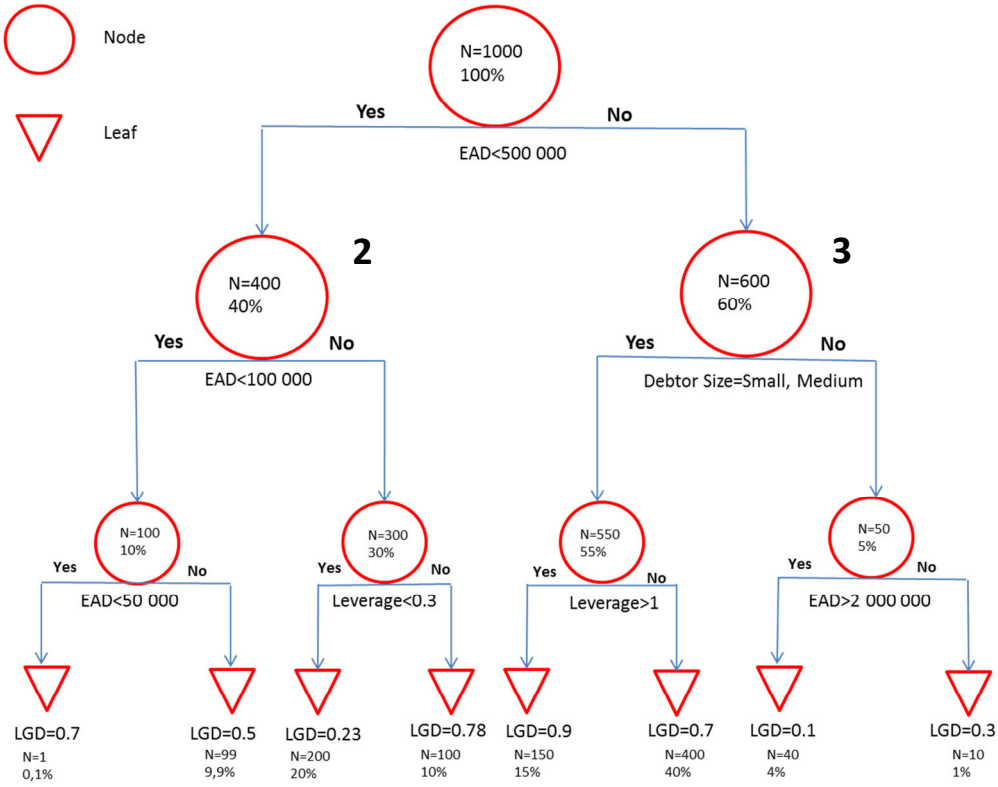


Figure 7: regression tree.

Decision trees are generally presented upside down, with the **root node** at the top and the **leaves nodes** at the bottom.
The root node contains all observations of the original data set. In the example illustrated in figure 7, we consider a sample of 1000 observations (equal to 100% of the dataset). A **parent node** can be split in two **branches** which results in two **children nodes**. This "splitting process" continues until we reach a leaf, which is a node that is not further split.

Associated with each non-leaf node will be a test or question that splits the data in different subgroups. In our example, the first splitting criterion is based on the Exposure-at-default (EAD). The first rule is: "is the EAD of the loan inferior to EUR 500 000?"). Thus, if, for a given loan, the EAD is smaller than EUR 500 000, this loan belongs to node 2 (40% belongs to this node). If it is bigger, that loan belongs to node 3 (60% belongs to this node). Node 2 and 3 are classical nodes and the splitting process is thus repeated again and again until the leaf nodes are reached.

[11] Every amount or value is given for illustration purpose only.

Note that a particular variable can be used several times as splitting variable (i.e. it can appear in several splitting rules through the tree). At each node, several questions arise:

- On which variable should the split be based? And what is the best splitting point for this variable?
- How do we define this notion of "best" splitting variable/point?
- How is it decided to stop the splitting process (i.e. when is a node considered as a leaf or not)?

The process to get the **deepest tree** possible, which might be large and (overly) complex, is described below[12]. In order to decide which variable should be used to determine the splitting criteria and the optimal splitting point, the notion of "**impurity of a node**" is introduced.

Suppose a continuous variable X_j and splitting point s are chosen in order to split the dataset so that the dataset is divided into $R_1(j,s)$ and $R_2(j,s)$:

$$\begin{cases} R_1(j,s) = \{x | x_j \leq s\} \\ R_2(j,s) = \{x | x_j > s\} \end{cases}$$

Then typically residual sum of square is used as the "node impurity" measure for continuous response variables.

We have the following facts:

- Each observation i belongs to one specific group.
- Each observation having its own value for the LGD response variable (LGD_i), we can compute the mean $\overline{LGD_1}$ and $\overline{LGD_2}$ for each group $R_1(j,s)$ and $R_2(j,s)$.

Then, the residual sum of square of a node R can be computed as:

$$SS_R = \sum_{i \in Node\ R} (LGD_i - \overline{LGD_R})^2$$

Where $\overline{LGD_R}$ is the mean of the response variable LGD observed in node R. Let's denote a parent node T and its two children nodes R_1 and R_2. The optimal splitting variable and point are then obtained through the maximisation of:

$$\Delta I = SS_T - (SS_{R_1} + SS_{R_2})$$

The desired split thus corresponds to the split that results in the largest impurity reduction going from (1) the impurity of the parent node and (2) the sum of the two children nodes impurities. Each variable X_j and all possible splitting points s are examined and the split with the biggest ΔI is chosen. Intuitively, that corresponds to group observations in regions with homogenous LGD values.

[12] As already mentioned, this tree will likely cause overfitting. Cross-validation and pruning, which can help to solve that problem, are not tackled in that text.

In a next step, the child node becomes a parent node and the above process is repeated. In this way, the deepest regression tree can be built until each leaf node corresponds to the lowest impurity or when some minimum node size[13] is reached.

Regression trees give thus an easy rule to predict the LGD of a specific observation. Each loan can thus be classified easily by following the subsequent rules.

It's also possible to know in which segment most of the data are situated. In figure 7, 55% of the data have an exposure-at-default higher than 500 000 euros and with a debtor working in the agriculture sector.

For example, take a loan with the following characteristics:

- Exposure-at-default = EUR 650 000
- Debtor_Size = Medium
- Leverage = 55%

The regression tree gives a LGD prediction of 0.7. That means that, on average, a loan with the above characteristics will lose 70% of its Exposure-at-default in case of default. In our specific case, that represents a loss of EAD*LGD = 0.7*650 000= EUR 455 000.

A fast exploration of the tree gives some insight on the riskiness of some classes. For example, let's take a loan with the following characteristics:

- EAD = EUR 700 000
- Debtor_Size = Small
- Leverage = 125%

The regression tree gives a LGD prediction of 0.9. That means that, on average, a loan with the above characteristics will lose 90% of its Exposure-at-default in case of default. In our specific case, that represents a loss equal to EAD*LGD = 0.9 *700 000=630 000. On the opposite, the safest class has a predicted LGD of 10%.

[13] The node size is measured by the number of observations contained in that node.

CONCLUSIONS - COMPARING ML AND STATISTICAL MODELING

Having explained the fundamental difference between both ML & statistical modeling approaches and having illustrate those with examples of methods and practical application, we wrap-up this paper by providing the reader with an overall comparison between the approaches highlighting their main pros and cons.

	Machine learning	Statistical modeling
Possibility to limit the number of assumptions	+	-
Inference: Assessing the reliability of modeling assumptions	-	+
Prediction: ability to extrapolate future or unobserved realizations of a variable given other explanatory observations	+	-
"Big Data": ability to handle large sets of data both in terms of number of observations ("rows") or variables ("columns")	+	-
Human interactions: ability/need of incorporating material users ex-ante opinions (e.g. Expert Judgment)	-	+

Table 8: comparison of both worlds

Usually, statistical modelling gives better insight for **inference** but the framework of statistical modelling typically needs many assumptions.

- First, one needs to take a main assumption over a particular model for the "nature" dynamic (linear regression, logistic regression, etc.).
- Secondly, one will have, for each model, an associated set of derived assumptions (which may often be overlooked):
    - For example, in linear regression, the error term must be of zero mean, normally distributed, independent of **x** and of constant variance.

While all of these assumptions could obviously be criticized in practice statistical techniques such as linear regression nevertheless became common market practice.

On the other side machine learning techniques do not rely on as many assumptions. All is about the data and what they could tell the algorithm: one searches the best algorithm to predict the response variable **y** with the best accuracy. As a result properly used ML techniques may prove to produce the best predicting models.

Results however will need careful attentions as they derive from automated procedures and could induce conclusions which do not match business logic.

Machine learning techniques are usually seen as "black boxes" to be opposed to "white-boxes" models of usual statistical modeling culture. In-depth practical experience remains thus a must-have to adequately implement ML algorithms.

REACFIN'S SUPPORT

Reacfin is a consulting firm specialized in Risk Management, Actuarial Science, Portfolio Modeling and Quantitative Finance. We regularly support financial institutions in the development, the implementation and the validation of their new models.

With this White Paper we aim at illustrating the themes of some of our recent missions and research work.

We deeply believe that risk taking & innovation are inherent to the business models of financial institutions yet only scrupulous & systematic approaches can ensure the adequacy and robust implementation of new models.

To that extend we offer unrivalled modeling and validation support which combine the academic excellence of our consultants with high-end benchmarking services. As we illustrate it in this white paper, we indeed have an efficient access to a large network of professionals and practitioners of the financial industry which enable us to clearly define standard- and best practices. Access to such comparable otherwise proves quite challenging to most banks, asset managers and insurance companies.

We look forward having the opportunity to also serve your company soon.

In the following exhibits, we illustrate our focus and provide a few additional examples of our recent assignments.

Introduction to machine learning techniques used in the financial industry and a practical case study
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Reacfin

Reacfin s.a. is a Belgian-based **actuary, risk & portfolio management consulting firm**.

We develop **innovative solutions and robust tools** for Risk and Portfolio management.

The company started its activities in 2004 as a spin-off of the University of Louvain, focused on actuarial consultancy to Belgian insurers, pension funds and mutual organizations. Rapidly, Reacfin expanded its business internationally and broadened its scope to various aspects of quantitative & qualitative risk management, financial modeling and strategic advice to financial institutions.

Spread over its 3 offices in Louvain-La-Neuve, Antwerp and Luxembourg, Reacfin employs a team of high-end consultants most of which hold PhD's or highly specialized university degrees.

What we do

- Modeling
- Risk implementation advisory
- Validation & model reviews
- Specialized strategic risk consulting

We put great emphasis at strictly articulating our work around **5 fundamental driving values:**

Excellence: our outstanding feature

To deliver more than is expected from us, we attract the best people and develop their skills to the most cutting-hedging techniques supported by a robust and rigorous knowledge management framework.

Innovation: our founding ambition

Leveraging on our profound academic roots, we are dedicated on creating inventive solutions by combining our extensive professional experience with the latest scientific research.

Integrity: our commitment

We put work ethics, client's best interest and confidentiality as the foundation of our work. We are fully independent and dedicated at telling the truth.

Solution-driven: our focus

We produce for our clients' tangible long-term sustainable value. We help our clients not only to reach the top, we help them reaching the stable top.

Reliability: our characteristic

We never compromise on the quality of our work, the respect of deadlines & budgets and our other commitments. We don't produce reports, we deliver results!

Reacfin's 4 **core fields of expertise:**

Risk & Portfolio Management

ALM, Portfolio Management & Quantitative Finance

- Implementation and calibration of stochastic models for valuation, trading and risk Management purposes
- Times series analysis & modelling
- Pricing of financial instruments & development of ALM models
- Design/review/implementation of systematic trading & hedging strategies
- Business intelligence in ALM or Portfolio Management
- Tools development (Valuation, Pricing, hedging, portfolio replication, etc.)
- Design of Capital Management solutions

Qualitative Risk Management, Restructuring & Operations

- Organization & Governance
- Businesses restructuring & change management
- Implementation and industrialization of processes
- Internal & regulatory reporting (KRI's & KPI's dashboards)
- Model Review frameworks
- Model Documentation

Insurance specialties

Life, Health and Pension

- DFA* Models
- Capital Requirement assessment
- Business valuation support
- Product development (pricing, profitability, ...) & Reserving
- Model validation

Non-Life

- Reserving: triangle methods, individual claims modelling
- Pricing: frequency and severity modelling, large claims analysis, credibility methods, commercial constraints
- DFA models: cash-flows projection, calibration of models
- Reinsurance: modelling covers, optimal reinsurance programs

(*) DFA = Dynamic Financial Analysis

What we deliver

State of the art technical skills

- Expertise in most advanced quantitative modelling & academic excellence of a spin-off
- All our consultants hold multiple masters or Phd.
- Best-in-class qualitative risk management leveraging on highly experienced senior consultants

Balanced and pragmatic approach

- Client-centric solutions focussed on deliverables
- Respecting the principle of proportionality
- Cost efficient within tight pre-agreed budgets

No black box Solutions

- We deliver results, not reports!
- Open source solutions
- Close cooperation with our clients

Clearly structured processes

- Lean & efficient tailored project management
- Regular progress reviews
- Close cooperation with our clients

Document-ation, coaching & training

- Clear & comprehensive documentation compliant existing or upcoming regulation
- Adapted trainings at all levels of the organisation
- Coaching support for implementation and operationnalisation of processes

Example of a recent mission

Client Situation

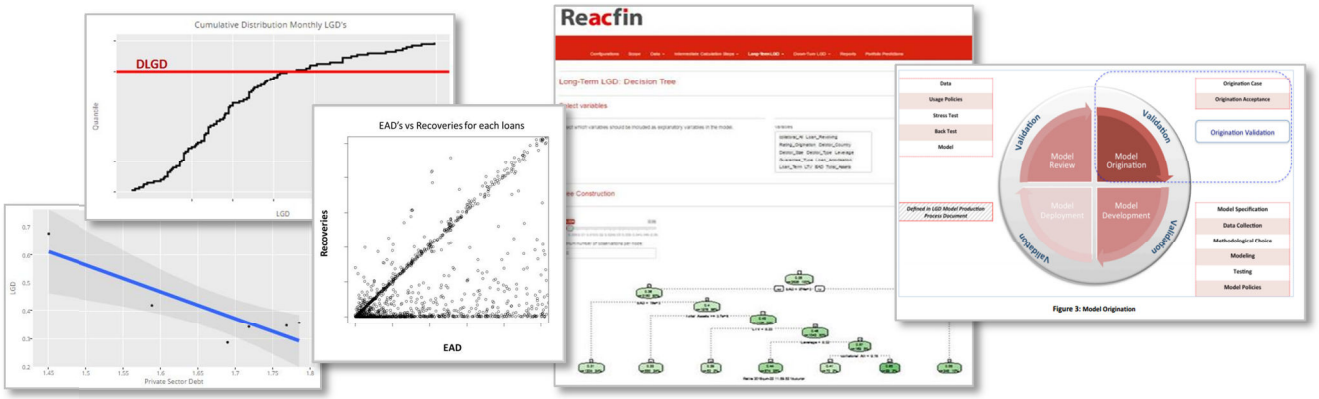
- Client: European Bank in a new EU country with a large portfolio of SME loans
- Under review by ECB (Systemic Bank)
- Experienced recent distressed credit environment
- Using a simple 'One-Fits-All' average LGD for all loans
- Ambition to switch to Advanced-IRB approaches for regulatory purposes

Issues

- Too simple LGD model generates adverse selection in loans origination
- Challenging remarks from local regulator and ECB on LGD modeling (to compliant with CRR/CRD IV requirements)
- Issues with data quality
- Limited model development culture (material gaps in model lifecycle processes, uneven documentation of recovery process, etc.)

Reacfin's Contribution

- Context review: loan portfolio mix, Recovery processes, PD/Internal Rating Models, etc.
- Benchmarking vs. European peers standard & best practices
- Segmentation of the loan book and clustering of the recovery process using Machine learning algorithms (incl. Regression Trees and Random Forest algorithms)
- Modeling of distribution based Work-Out & Implied Market LGD approaches
- Development & deployment of user-friendly automated tools to compute the LGD under the new proposed method (incl. data collection tools, testing & design of processes)
- Development of a Model Management & model Governance Framework policy.
- Documentation and support with presentation to local regulator



Results & Benefits

- More accurate pricing of new loans (materially reducing adverse selection of debtors) and better risk quantification and segmentation;
- Advancement towards A-IRB approach (and significant reductions in capital requirements
- Increased management awareness regarding organizational and data management issues.

CONTACT DETAILS

François Ducuroir
Managing Partner

T +32 472 72 32 05
M francois.ducuroir@reacfin.com

Reacfin s.a./n.v.
Place de l'Université 25
B-1348 Louvain-la-Neuve

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www.reacfin.com
info@reacfin.com
+ 32 (0)10 84 07 50

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