Zen Risk

The future of machine learning in risk modelling

Introduction

The new regulatory and technology environment provides incentives for financial institutions (FIs) to transform the way they manage risk. The main objective is to implement a compliant and effective process to deploy models, which accurately measure and control risk.

Through smart use of machine learning there is an opportunity to address current challenges, by increasing the control and understanding of risk through new techniques which reduce model risk. Machine learning also drives benefits, by reducing time spent on data remediation and introducing processes, which increase the accuracy of credit risk models.

Navigating internal challenges

Enabled by technology, risk functions have an opportunity to improve the quantification of risk, however, use of **black box** solutions remains a constraint.

The use of ML has the potential to generate analytical insights, support new products and services, and reduce market frictions and inefficiencies. For the past several years institutions have been experimenting with ML building challenger credit risk models and observing significant increases in model performance. It is now the time to move ML from the lab to live production.

What are the **challenges** currently faced by Credit Risk Modelling teams?

Regulatory and Business Expectations

- Regulatory constraints are becoming complex and there is a greater emphasis on owning model risk.
- Risk functions are confronted by increased time and cost pressures.
- Businesses demand more accurate and responsive models.

Modelling Framework Constraints

- Data management at the build stage typically takes an exorbitant amount of time and effort.
- Teams are constrained by existing modelling frameworks that don't allow for innovation.
- Classical models and the decisions made on the back of them can't be further improved.

In order to realise the potential of ML, we need to satisfy the high standards set by the credit risk industry with regards to:

- **Regulatory requirements** for models to be compliant,
- **Business requirements** for models to be explainable, and
- **Analytical requirements** for models to have high and stable performance.

ML models can offer higher predictive power, deeper analytical insight, increased operational efficiency and comply with regulations. However, the current ML modelling process needs enhancement to accommodate components considered integral to credit risk management:

Auditing and benchmarking

Regulators expect modelling approaches that are transparent and easy to audit.

Robust model validation

To ensure models return stable estimates to ensure prudent and conservative risk measures.

Interpretability

For business lines to comfortably understand models and use models for risk monitoring and reporting.

Regular monitoring

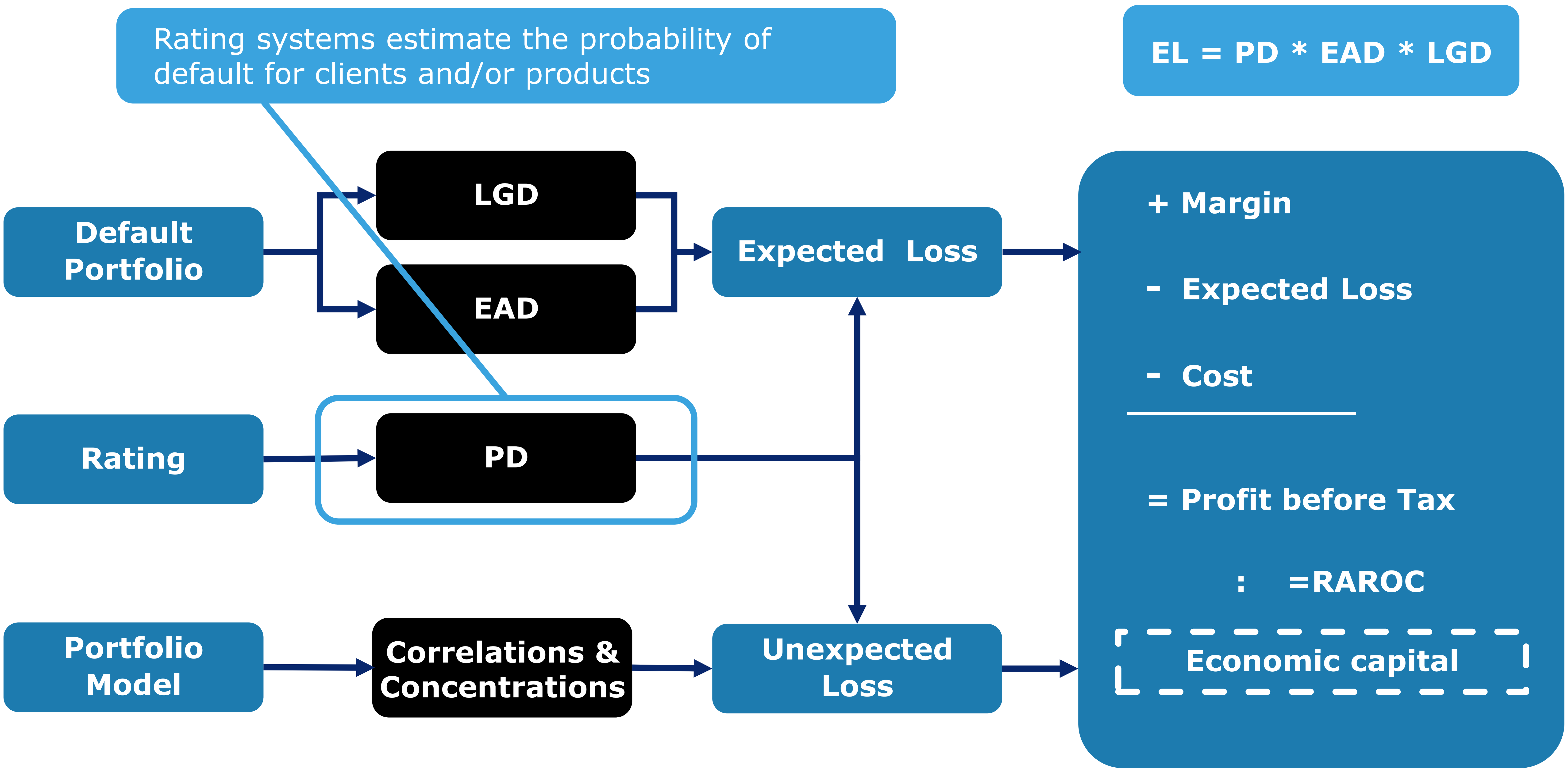
Coupled with assessments of predictive power to ensure stable performance over time.

Current situation in Credit Risk

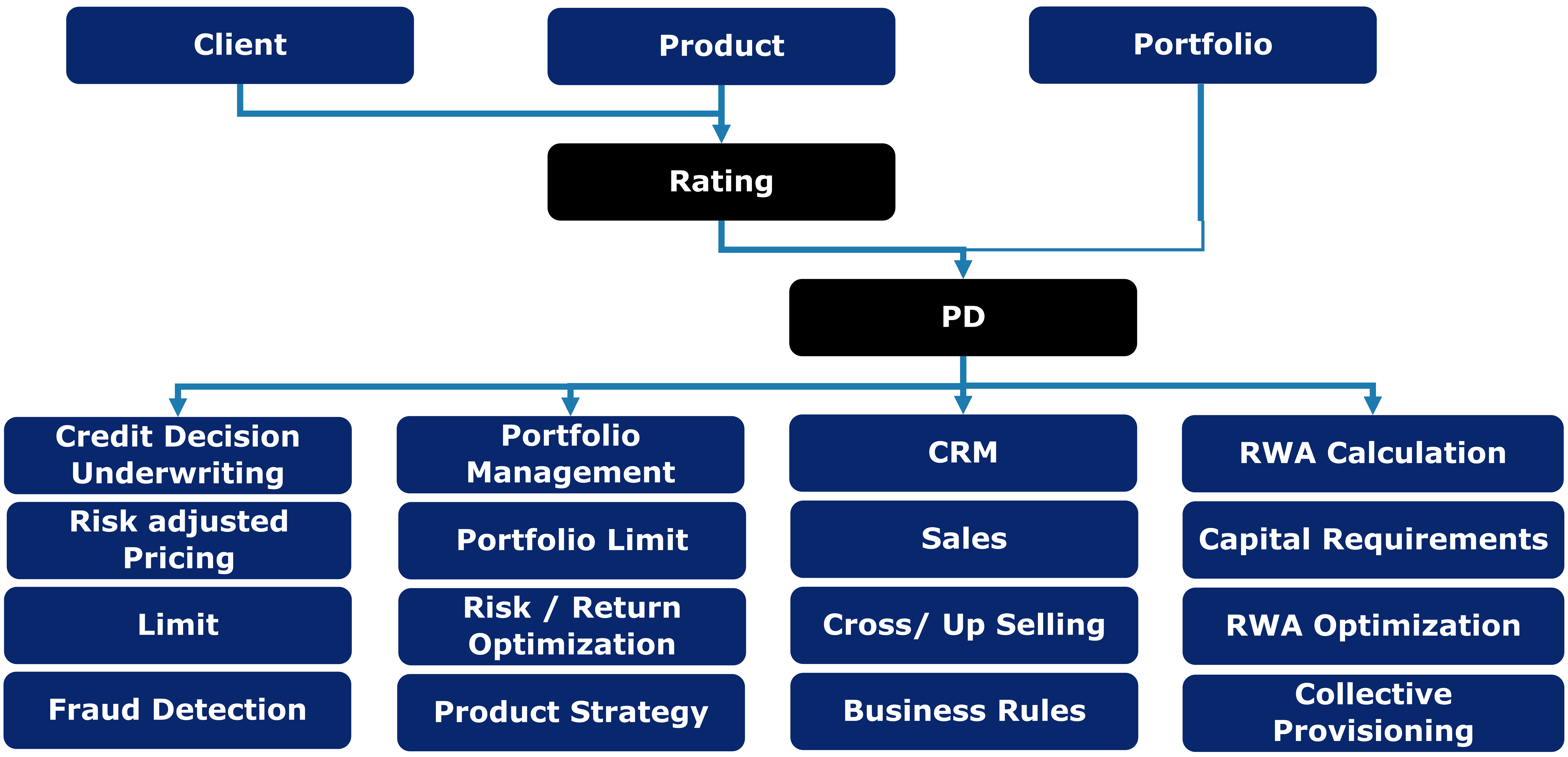
The **rating system** is the heart of the risk controlling in the bank

Let’s take the rating system as an example, this is the engine of any model driven risk function. This set of scoring models has a direct impact on the profit of the bank as misclassified clients who default produce economic loss for the bank. Higher rating system predictability is beneficial to the bottom line because requests can be assessed more accurately, which means acceptance rates can be increased and at less risk as misleadingly rejected but solvent customers are included in the portfolio through new models. Therefore, an improvement in the model accuracy by a few percentage points can save future losses in the millions for large portfolios.

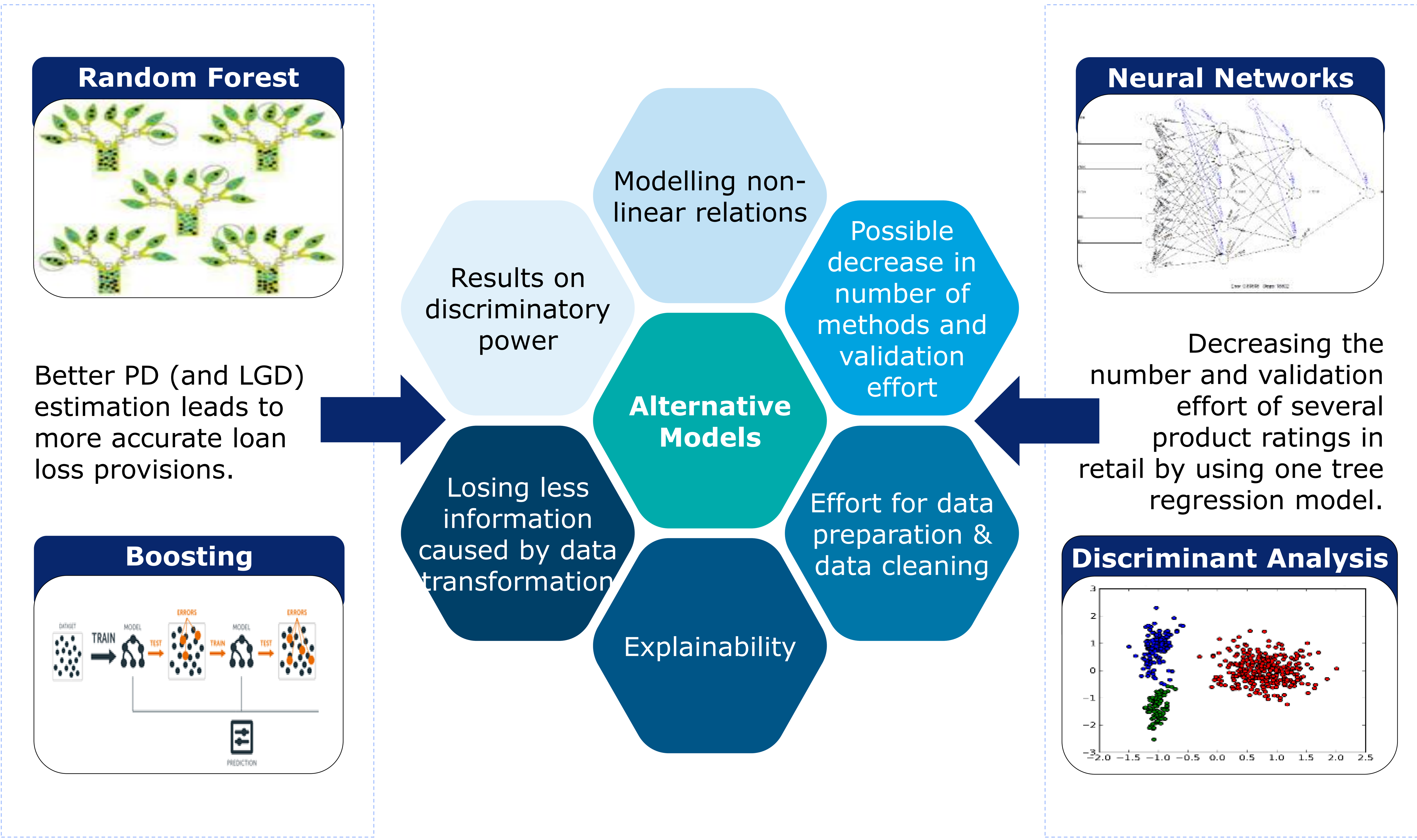
Impact of the Rating System on the RAROC



Rating Systems are used in several applications



Alternatives to logistic regression models increase complexity of the modelling but may have some interesting advantages for banks. These alternative approaches outperform the common logistic regression in developing credit risk rating models.



However, the challenge is to identify alternative models, which improve on the logistic regression models commonly used whilst avoiding overfitting, ensuring temporal stability and that caters for low default portfolios.

Our Zen Risk Platform

Addressing the challenges and delivering tangible benefits

With the increase in computational power and data availability, Financial Institutions can implement Machine Learning techniques to improve the decision making processes and to better quantify risks associated with market activities.

How does it work ?

Our Hybrid Approach

We developed a transparent, regulatory compliant solution which allows you to make smarter decisions with Machine Learning. The outcomes of our hybrid approach are interpretable and auditable by the business experts and regulators.

1 Traditional Model

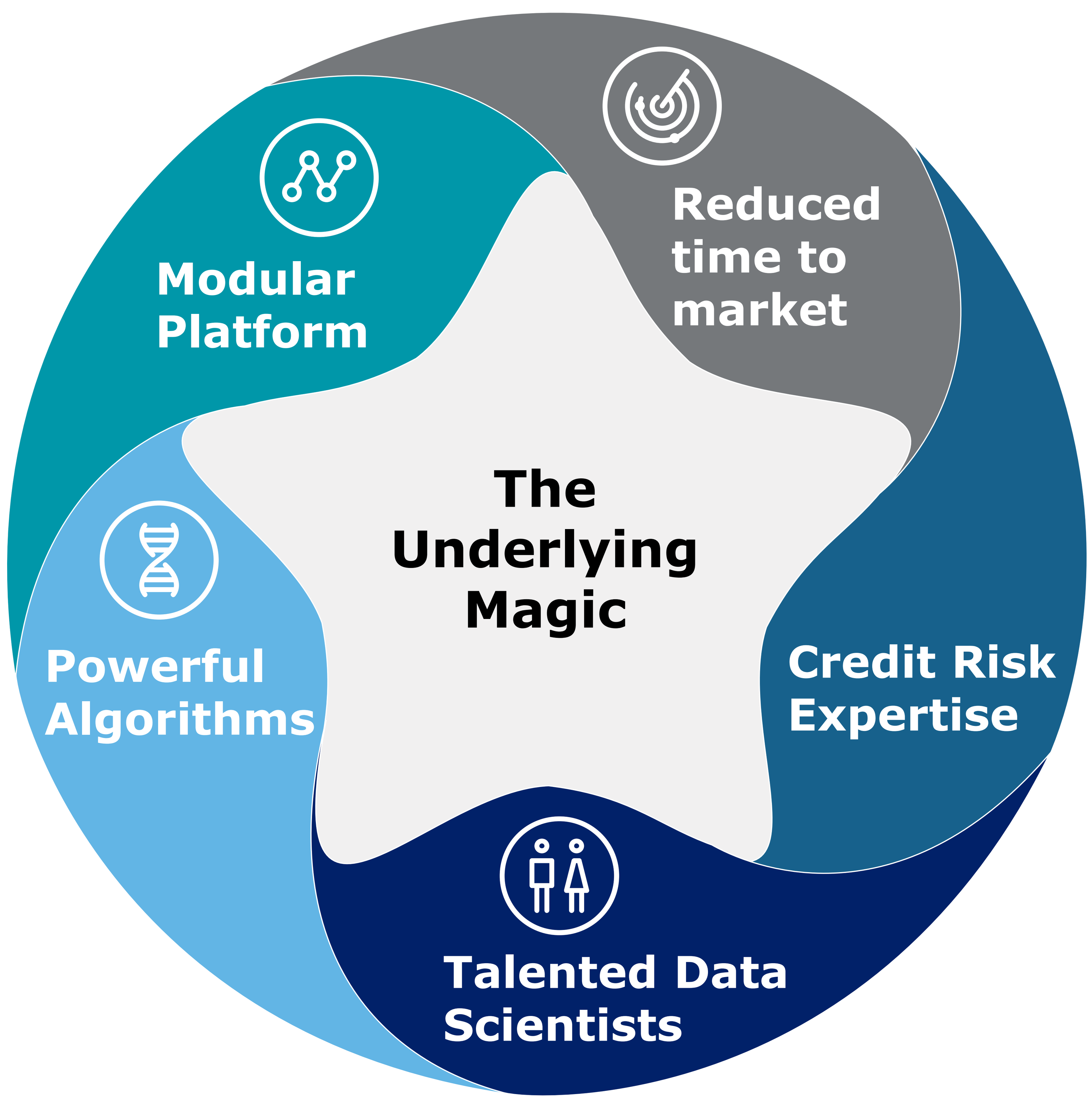
Build a traditional logistic regression model to forecast the default probability. The model is **less accurate**, however, it is **auditable**. Furthermore, the model is developed using business inputs.

2 Machine Learning

Build alternative models based on machine learning algorithms. These models are **highly accurate**, but can be viewed as **black-boxes**.

What is the value proposition?

- **Reduction of losses:** An improvement in the model quality by a few percentage points of the accuracy power saves future losses in millions.
- **Increase in profitability:** Erroneously rejected but solvent customers are included in the portfolio by using new models - banking the underbanked.
- **Savings on economic and regulatory capital:** Expected losses are estimated more precisely and Financial Institutions have a more fair valuation of their capital/equity requirements.
- **Reduction of costs with model development and maintenance:** The annual maintenance efforts for model development, monitoring and maintenance are reduced through automated procedures.
- **Opening the black-box**: Deloitte's approach is transparent, auditable, regulatory compliant and it allows Financial Institutions to explain black-box Machine Learning algorithms.



As they operate in regulated environments, to ensure compliance, organizations have to make sure that the algorithms are stable, transparent, auditable and that outcomes are interpretable for business users, regulators as well as any stakeholders involved in the approval processes.

Design a set of complementary rules derived from ML to enhance the traditional model's predictions. These business rules are created for the misclassified sub-populations identified by the ML model.

In our case studies we have found that 20% of the misclassified population accounts for 80% of the difference in forecasts between the two models and that the business rules can drastically reduce model errors.

Mixed Model

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Complementary Rules

Combine the complementary rules with the traditional model. The classic model is overruled with justified business rules resulting in a mixed model. The resulting model is accurate, and more importantly auditable.

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