

Deloitte.



Zen Risk

The future of machine learning in risk modelling



Introduction

The new regulatory and technology environment incentivises financial institutions (FIs) to transform the way they manage risk. One of the main objectives is to implement effective and efficient models, which accurately measure risk, in line with compliance requirements.

Through smart use of machine learning there is an opportunity to address current challenges whilst increasing the control and understanding of risk, and reducing model risk simultaneously.

Navigating internal challenges

Risk functions have an opportunity to improve the quantification of risk by using machine learning, without necessarily introducing black box solutions.

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.



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.

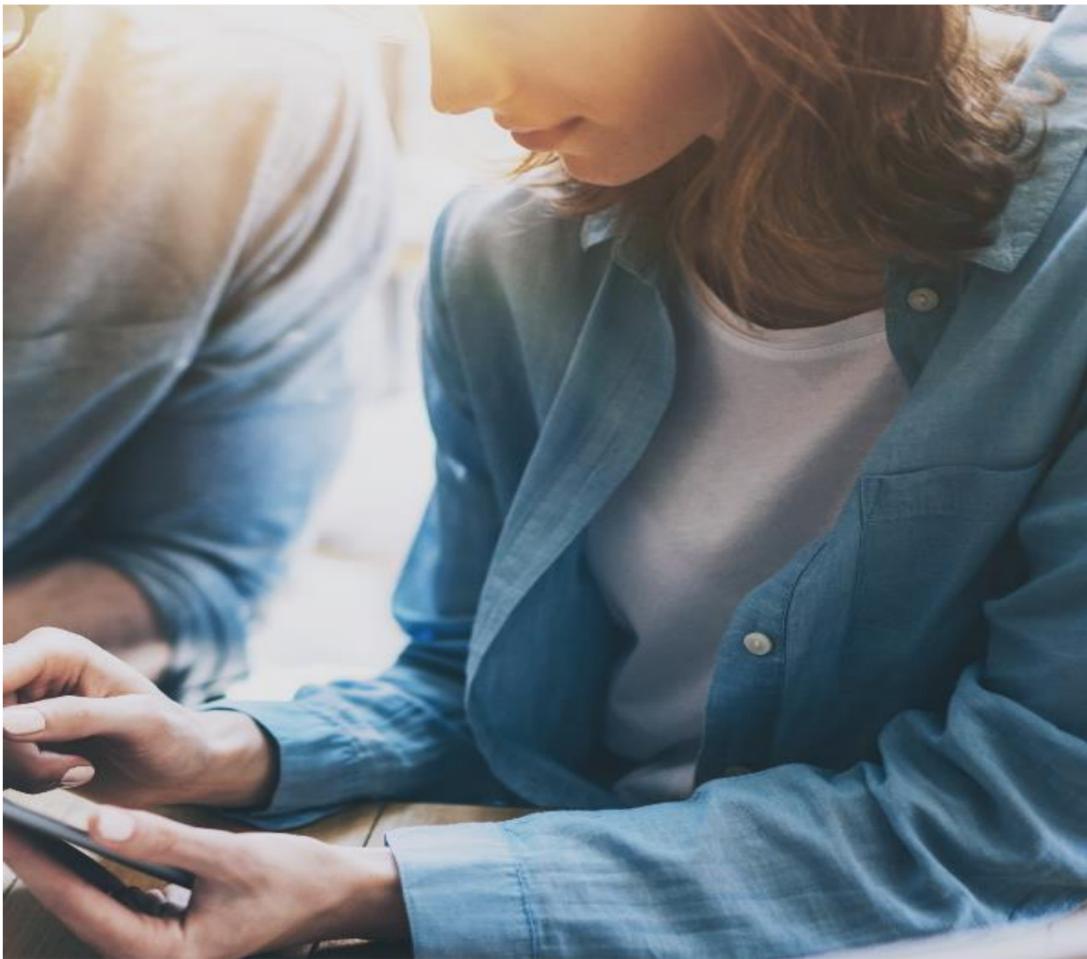
What are the **challenges** currently faced by Credit Risk Modelling teams?

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.

Interpretability

Business lines expect intuitiveness to use models for business decisioning and reporting.

Robust model validation

Validation functions need innovative tools to provide sufficient independent challenge to ensure models return accurate and stable estimates.

Regular monitoring

Model developers need to create predictive and stable models over time.

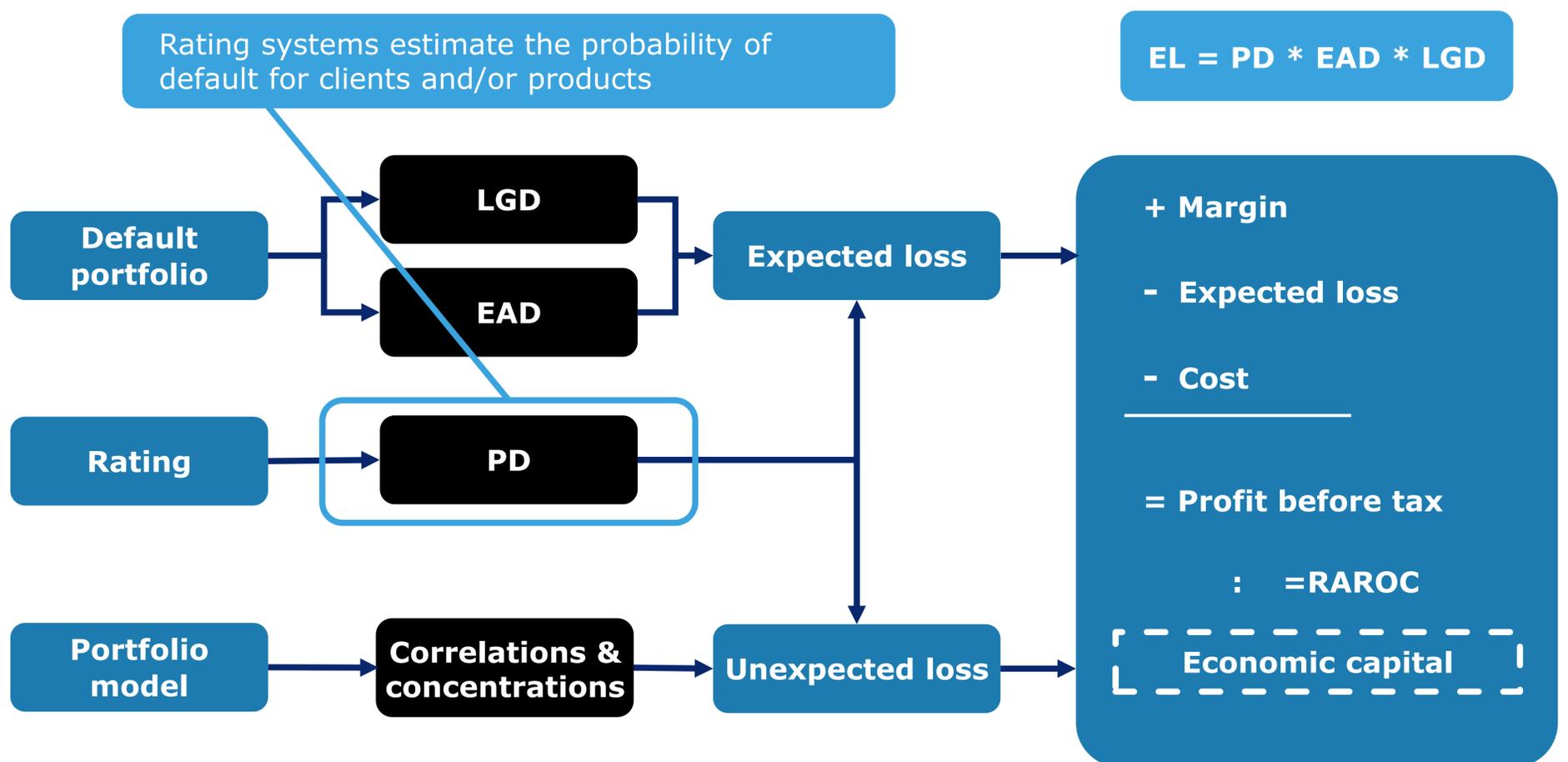


Current situation in Credit Risk

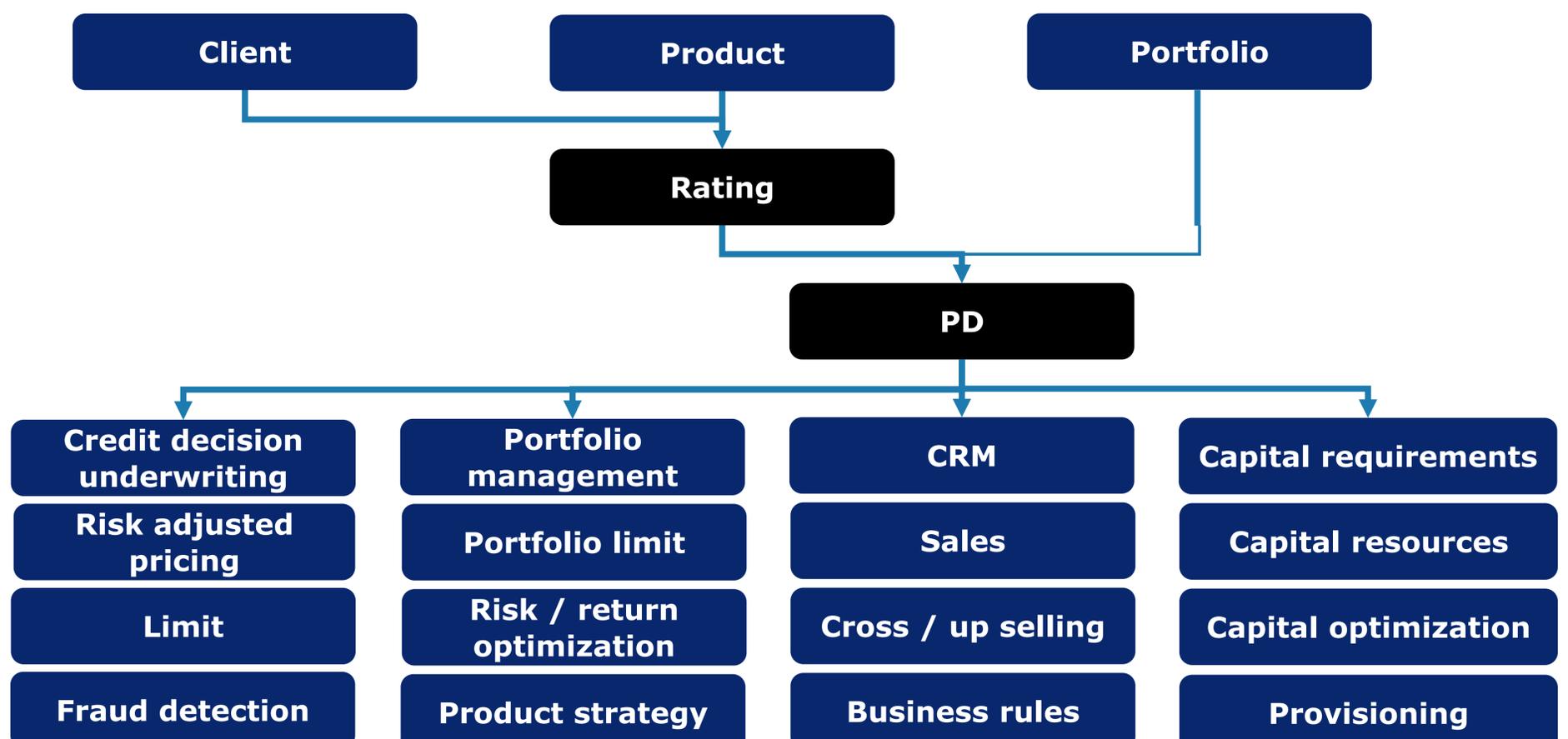
The **rating system** is the heart of the risk controlling in the bank

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 performance is beneficial to the bottom line. If lending requests can be assessed more accurately, it means acceptance rates can be increased as there is less risk of misleadingly rejecting solvent customers. Therefore, an improvement in the model accuracy by a few percentage points can save future losses in the millions for large portfolios.

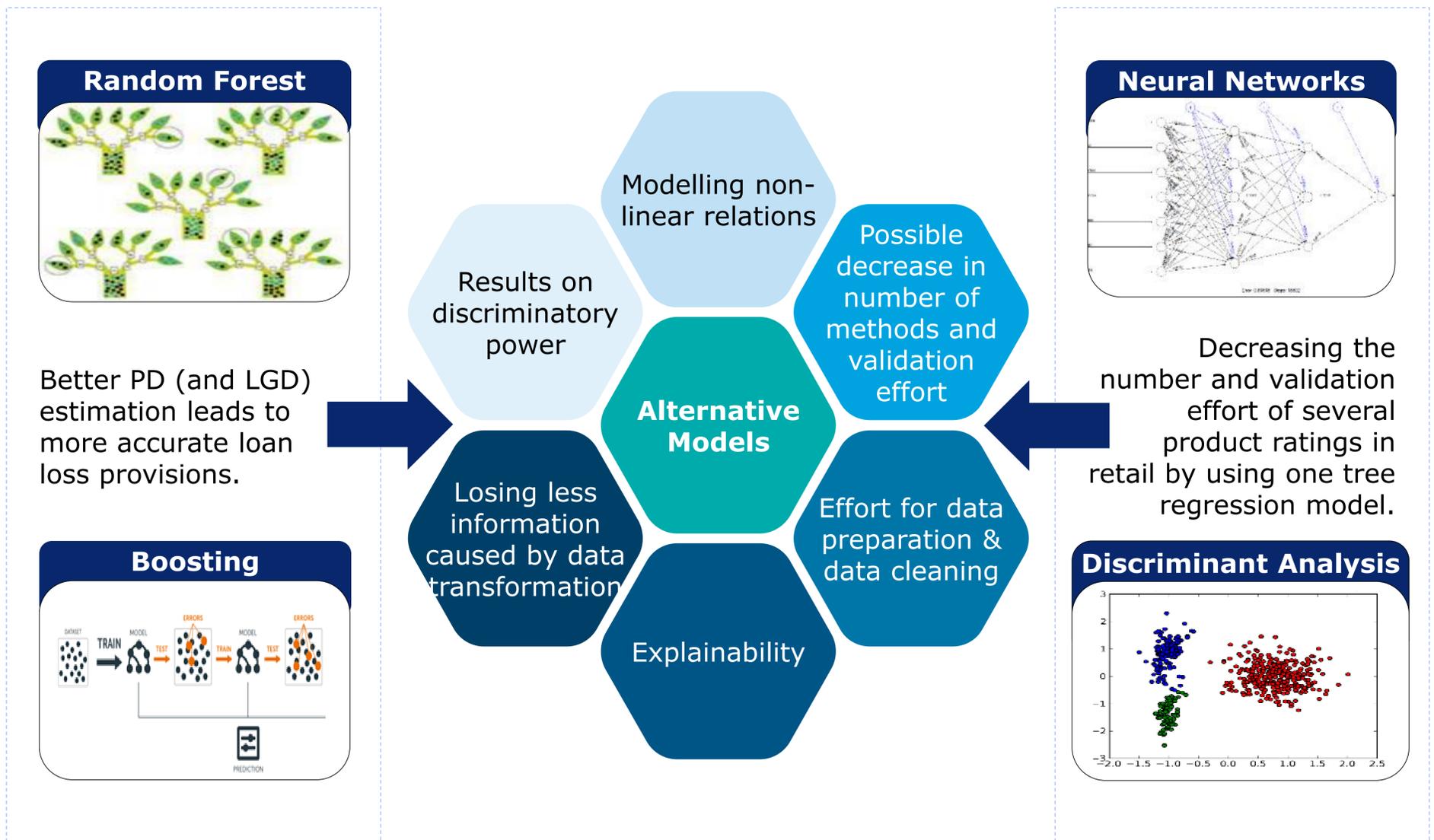
Impact of the Rating System on the RAROC



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.

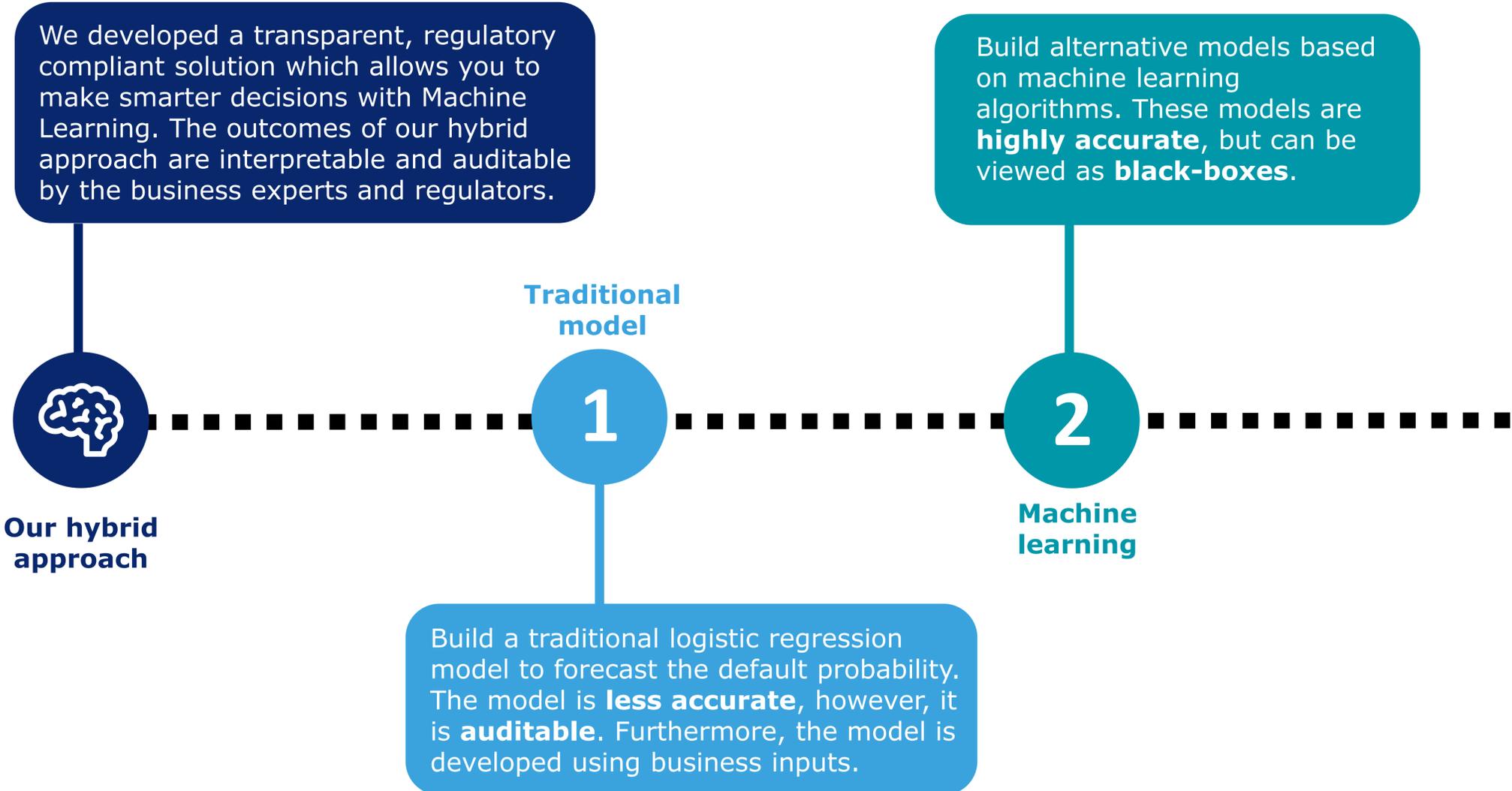


Our Zen Risk Platform

Addressing the challenges and delivering tangible benefits

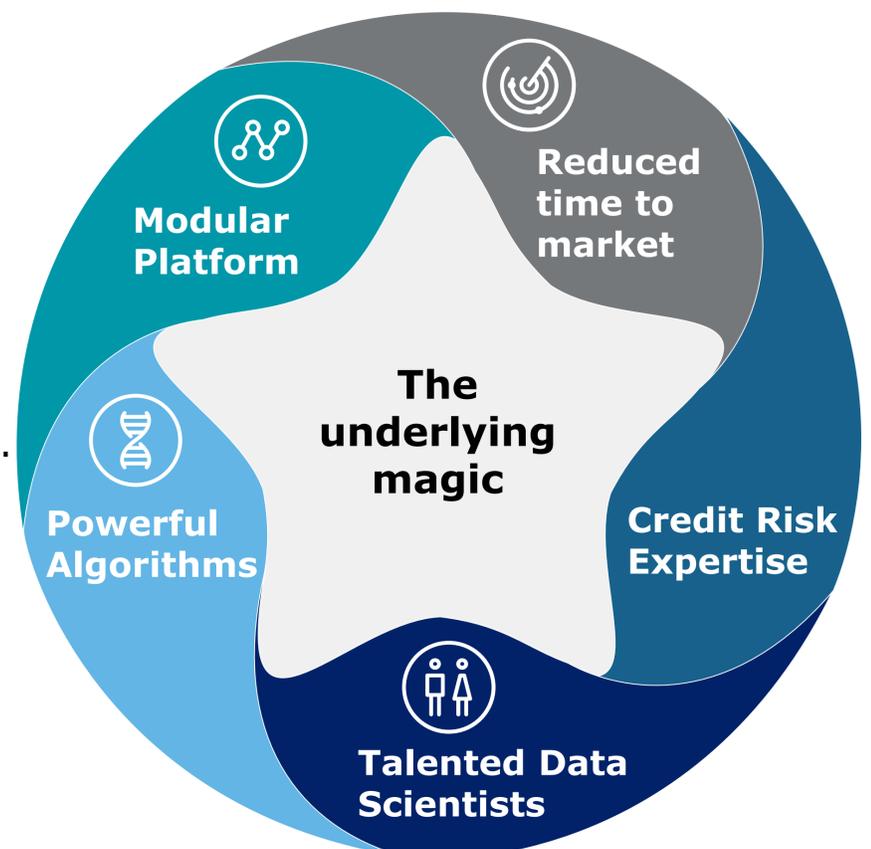
With the increase in computational power and data availability, Financial Institutions can implement Machine Learning techniques to improve the decision making processes and to better quantify risks associated with market activities.

How does it work ?



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.



Organizations need 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

3

Complementary rules

4

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.



Get in touch



Hervé Phaure

Partner

Risk Advisory

hphaure@deloitte.fr



Franck Affali

Senior manager

Risk Advisory

aaffali@deloitte.fr



Lorraine Thiery

Senior consultante

Risk Advisory

lthiery@deloitte.fr



Erwan Robin

Senior consultant

Risk Advisory

erobin@deloitte.fr



Kevin Vuong

Consultant

Risk Advisory

kvuong@deloitte.fr





This publication has been written in general terms and we recommend that you obtain professional advice before acting or refrain from action on any of the contents of this publication. Deloitte LLP accepts no liability for any loss occasioned to any person acting or refraining from action as a result of any material in this publication.

Deloitte LLP is a limited liability partnership registered in England and Wales with registered number OC303675 and its registered office at 1 New Street Square, London, EC4A 3HQ, United Kingdom.

Deloitte LLP is the United Kingdom affiliate of Deloitte NSE LLP, a member firm of Deloitte Touche Tohmatsu Limited, a UK private company limited by guarantee ("DTTL"). DTTL and each of its member firms are legally separate and independent entities. DTTL and Deloitte NSE LLP do not provide services to clients. Please see www.deloitte.com/about to learn more about our global network of member firms.

© 2020 Deloitte LLP. All rights reserved.