Explainability

ML and AI in credit decisioning

experian

Introduction

Data and Advanced Analytics is integral to unlock improved business performance

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Why **ML models** will become the new normal

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Why **Explainability** is the key to unlocking the ML potential

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5 tips for implementing ML with Explainability

INTRO

DATA AND ADVANCED ANALYTICS IS INTEGRAL TO UNLOCK IMPROVED BUSINESS PERFORMANCE

Artificial Intelligence (AI) will have an impact on each of our lives. The technology continues to develop rapidly, with AI now applied to a vast array of use cases across a range of sectors. This has led to the expansion of AI in its deployment in business.

AI is now involved in important decisions that impact people's lives, from detection of disease to controlling autonomous vehicles. Within financial services, AI will also support important decisions around lending and access to credit. As we know, these lending decisions are of the upmost importance for the consumers and businesses involved. It is because of the impact of these decisions that we must fully understand how they are made, whether by a human or through AI.

In order to trust the use of AI systems, and to benefit from its potential, we must be able to explain the decisions made using AI. As a result, the term "Explainability", and the associated topic around it, has become important for businesses looking to take advantage of AI.

Within this report we'll use a combination of full spelling and acronyms for the two main terms. Artificial Intelligence will be written either as Artificial Intelligence or the acronym AI, and Machine Learning as either Machine Learning or using the acronym ML.

Explainability

The output of a statistical model is explainable when its internal behaviour can be directly understood by humans (interpretability) or when explanations (justifications) can be provided for the main factors that led to its output.

Source: EBA Report on big data and advanced analytics, January 2020.

Extracting value from data

The volume of data available to organisations continues to grow and this creates the potential to improve decision making capability. However, there is more pressure on analytics teams to use additional data sources to deliver operational performance improvements.

Advanced Analytics is therefore a big area of focus as businesses look to better understand and analyse high volumes of data from a wide variety of sources. It has led to increased focus and investment in Artificial Intelligence (AI), and specifically within credit decisioning, the use of Machine Learning (ML) to improve the effectiveness of models and decisions for creditworthiness, affordability, fraud, early warnings, and collections.

There are many areas that need to be explored further regarding the use of AI within financial services and other sectors where credit services are offered to consumers and businesses. These areas include ethics, fairness, bias, and privacy, with the regulatory bodies continuing to provide guidance as the technology develops.

Machine Learning and explainability

This report will focus on two things. First, we will look at the benefits of using Machine Learning to improve model performance and therefore credit decisions. Then we'll focus on the important role that explainability plays in maximising its use. Make no mistake, if you want to benefit from ML you must understand explainability. The report covers how explainability is achieved and why it is important for any ML based model to be supported by explainable results.

There are significant performance improvements that can be realised with the use of Machine Learning in decisioning. Let's cover how ML can enhance models and the impact on business performance.

Finding the edge

Machine Learning is a subset of AI technology. And it is Machine Learning that is being implemented currently in credit decisioning, and therefore the focus of this report. ML can unlock the ability to deliver models with enhanced predictive power for creditworthiness, affordability, and fraud assessments. Businesses that are not using or planning to use Machine Learning based models are leaving money on the table. Why? Because using Machine Learning improves the accuracy and effectiveness of models, leading to a more accurate assessment of 'good' and 'bad' customers. This translates to greater revenue and lower operational costs. But, as we'll come onto later, any business using ML based models must ensure they are fully explainable, otherwise they risk fines and possible reputational damage.

ML is capturing the attention of businesses

Businesses recognise the advantages that AI can bring, with 66% believing that Advanced Analytics, including Machine Learning and Artificial Intelligence, will radically change the way they do business. It is therefore no surprise that 66% of businesses state that adopting Advanced Analytics capabilities is a top business priority over the next 12 months. The challenge is to unlock the potential of ML whilst creating a structured methodology that allows full transparency of model creation and decision output.

Source: a commissioned study conducted by Forrester Consulting on behalf of Experian, August 2021.

Businesses see the AI potential

66%

of organisations state that adopting Advanced Analytics capabilities is a top business priorities over the next 12 months

53%

of businesses plan to engage with an external supplier for support with AI or Machine Learning in the next 12 or 24 months

52%

of businesses have increased their budget for Advanced Analytics for next 12 months

66%

of businesses believe Advanced Analytics, including AI and Machine Learning, are going to radically change the way they do business

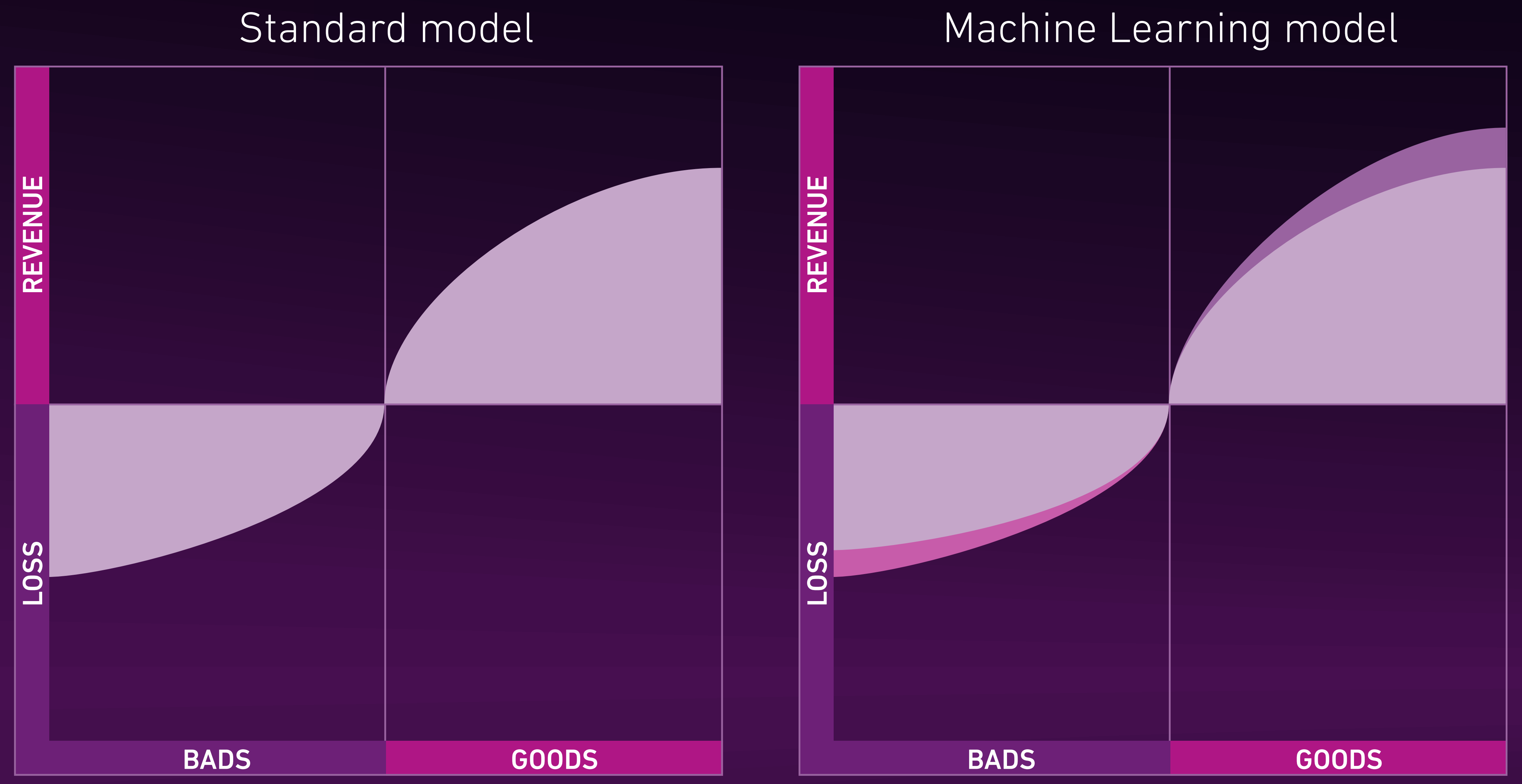
Base: 598 senior decision-makers in financial services and telecommunications firms globally.
Source: a commissioned study conducted by Forrester Consulting on behalf of Experian, August 2021.

Increased model predictiveness

One of the biggest benefits of Machine Learning is the ability to improve the predictiveness of models. The adoption of Machine Learning can increase the GINI coefficient, which is used to assess the effectiveness of credit risk models, to an average level of 20% relative to existing non-ML models. The more predictive or accurate the models, the more profit is delivered through better assessment of credit risk.

The availability of new data sources, combined with the power of cloud computing, is making the use of Machine Learning even more attractive for organisations. The performance of ML models tends to improve when more data is available to train the model. From a credit risk perspective, the use of Advanced Analytics to consume and analyse vast amounts of data has meant that businesses can incorporate more data sources and variables into their decisioning logic. A good example of this is the use of transactional data from Open Banking, which provides much more depth of information for credit risk modelling. Machine Learning is used to categorise the transactional data into different categories of income and expenditure so it can be easily ingested into the modelling phase where ML can be used again to develop a custom score. As a result, ML can use alternative data to identify customers that previously may have been considered “thin-file” - opening the door to more customers whilst supporting greater financial inclusion.

ML can drive more predictive decisions by analysing large volumes of data - both structured and unstructured – as well as non-linear relationships in the data, in a very short period of time. And, because of the improved model performance, some organisations are entrusting ML models to deliver increased automation within their decisioning. This drives down operational costs but also enables faster time to decision for customers because ML helps reduce the volume of back-office checks.



ML models allows you to more accurately assess “goods” and “bads” whilst lowering operational costs.

Reduced bad debt

Improved acceptance

> The more predictive and accurate the model the more profit realised

ML can deliver significant model performance improvement which translates to improved acceptance and reduced bad debt.

CASE STUDY

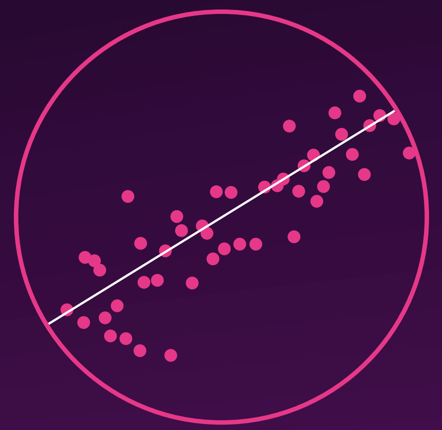
Development of a custom credit risk score for a bank using Machine Learning.

Here's a real life example of how one business has moved from a regression-based model to an ML-based model in an effort to increase acceptance and grow customer acquisition.

The innovative score, based on Machine Learning, proved more predictive than the incumbent logistic regression-based score.

PREVIOUS APPROACH

The bank used a traditional logistic regression–based risk model for new account decisioning to predict probability of default in the 18 months following loan approval.



Incumbent

Regression-based risk model

OBJECTIVE

Regional bank wanted to aggressively grow its indirect loan portfolio

BENCHMARK

Benchmark of Machine Learning model against the incumbent model

TESTING

Tests to ensure performance increase on the bank's incumbent model.

RESULT

5% GINI uplift
for ML model vs incumbent logistic regression model.

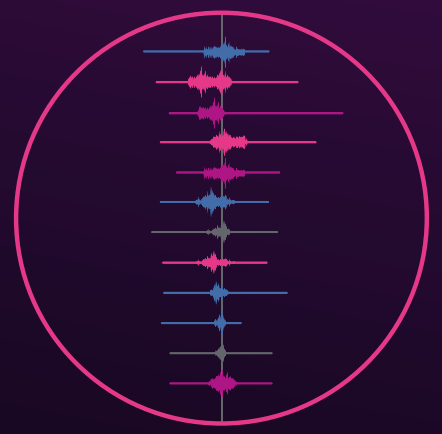
Full transparency with ability to derive adverse action codes for reject decisions

Improved predictive performance led to the replacement with the ML model.

Bank achieved their goal of increasing application approval rates and reducing risk within their indirect loan portfolio.

PROPOSAL

Decision made to test the use of Machine Learning (ML) model with greater predictive power to generate higher loan approval rates and reduced risk.

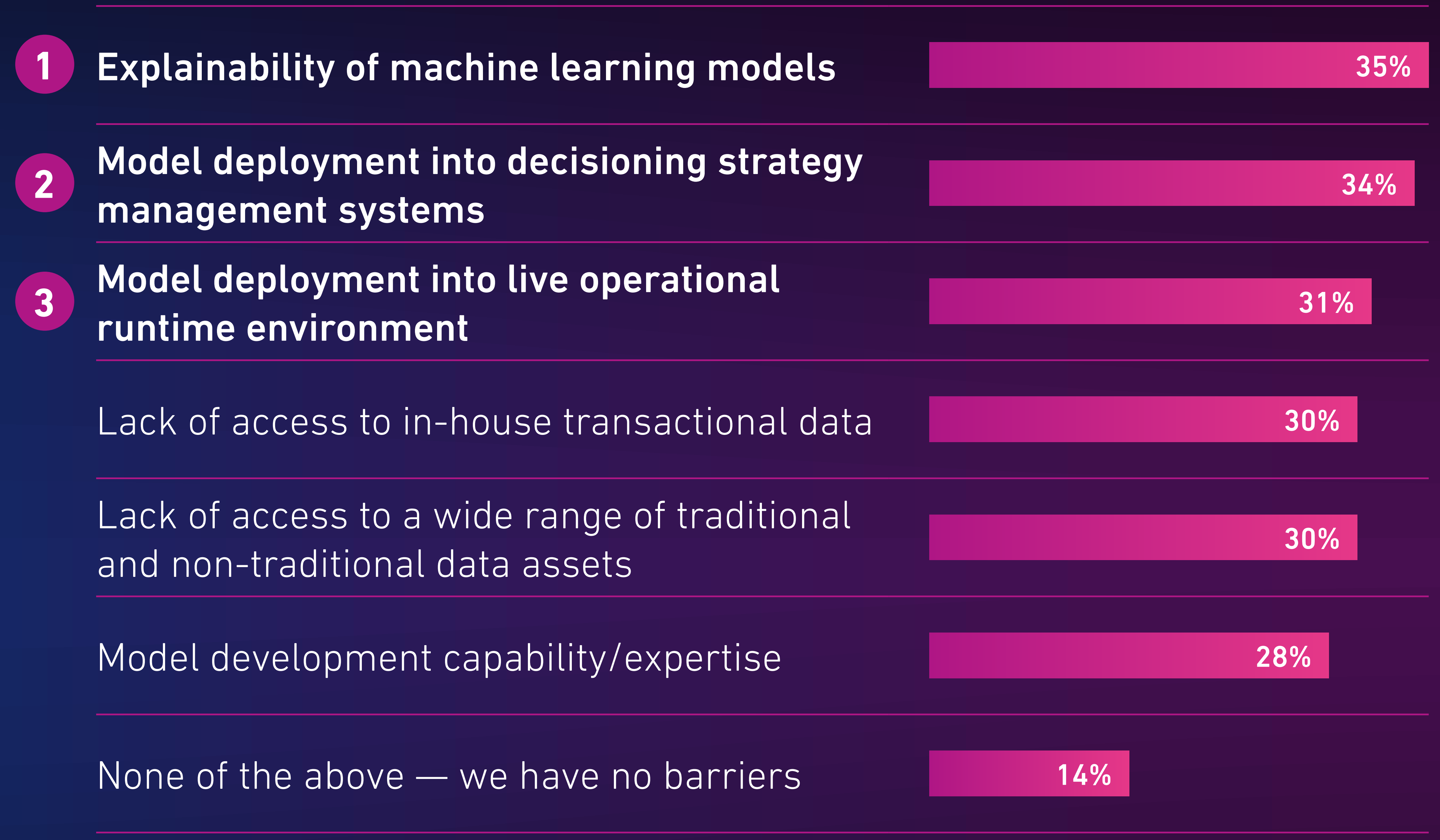


Proposed

ML-based risk model

Gradient boosting machines (GBMs) algorithm selected for custom score development. This type of algorithm is highly predictive and offers more transparency than some other machine learning frameworks such as neural network models.

What are the main barriers to adopting Machine Learning in your organization?



Base: 396 senior decision-makers in financial services firms globally.

Source: A commissioned study conducted by Forrester Consulting on behalf of Experian, August 2021.

(*) Gartner Identifies the Top Strategic Technology Trends for 2021, October 2020.

Explainability is the biggest barrier to ML adoption

Despite the value Machine Learning models can deliver to performance, many businesses are yet to deploy these models within their business. In Experian's recent research conducted with Forrester Consulting, lack of explainability was the biggest barrier to Machine Learning adoption. Given the use of Machine Learning is still in its early stages for credit decisioning, there is trepidation around implementation of ML based models. In addition to concerns around providing the necessary explainability, businesses are also concerned about the lack of internal knowledge and expertise in this area.

Again, our Forrester research identified that, aside from the COVID-19 pandemic, **lack of expertise and technology infrastructure to incorporate machine learning and big data (32%)** was one of the biggest overall challenges prohibiting businesses from achieving their top initiatives.

This lack of expertise has meant that only around half of projects involving AI end up put into production, as highlighted by Gartner research*. However, tools are now available that allow businesses to ingest, map and deploy ML models without the need to invest heavily in data scientists and developers.

Why Explainability?

To Justify

Why was this loan rejected?

To Control

Why was this loan accepted?

To Improve/Discover

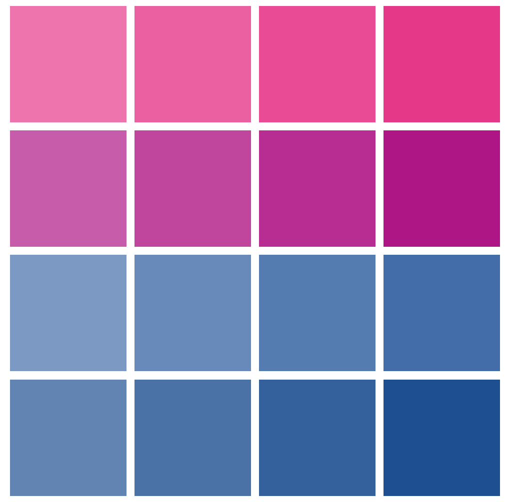
How can these variables be adjusted to improve approvals or rejections?

Seeing the unseen

Why is explainability so important? Well, fundamentally it is the key to unlocking the potential of Machine Learning within decisioning systems. Delivering an improved model is only part of the equation, the other is the ability to explain the logic behind the calculation. Without it, there are regulatory implications as credit risk models are classified as high-risk type models. In fact, regulation dictates that every decision within credit risk should be fully explainable. This means that many businesses have avoided the use of Machine Learning for fear of not being able to explain the reason behind the decisions made by a ML-based model. The models must be easily interpretable by humans evaluating the output and be delivered in a clear and transparent manner with a reason code.

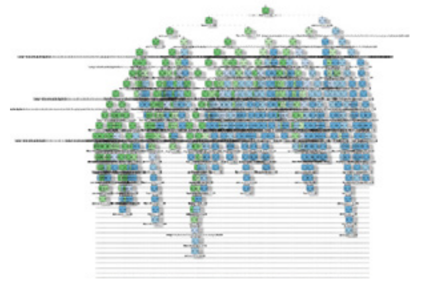
Machine Learning is no longer mysterious and opaque

THEN



NEW LEARNING PROCESS

LEARNED FUNCTION



OUTPUT

Loan rejected (P = .83)

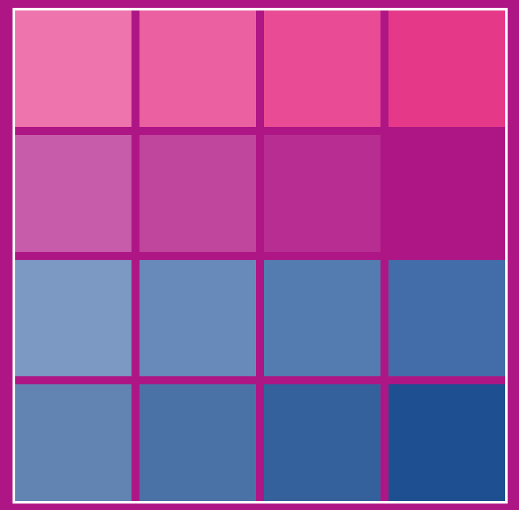
USER WITH A TASK

Why did you do that?

Why not something else?

How do I correct an error?

NOW



NEW LEARNING PROCESS

EXPLAINABLE MODEL

EXPLAINABLE INTERFACE

Loan rejected

Low income factor

Address flag

USER WITH A TASK

I understand why

I understand why not

I know when to trust you

Reason Code Analysis

Easily explain to customers

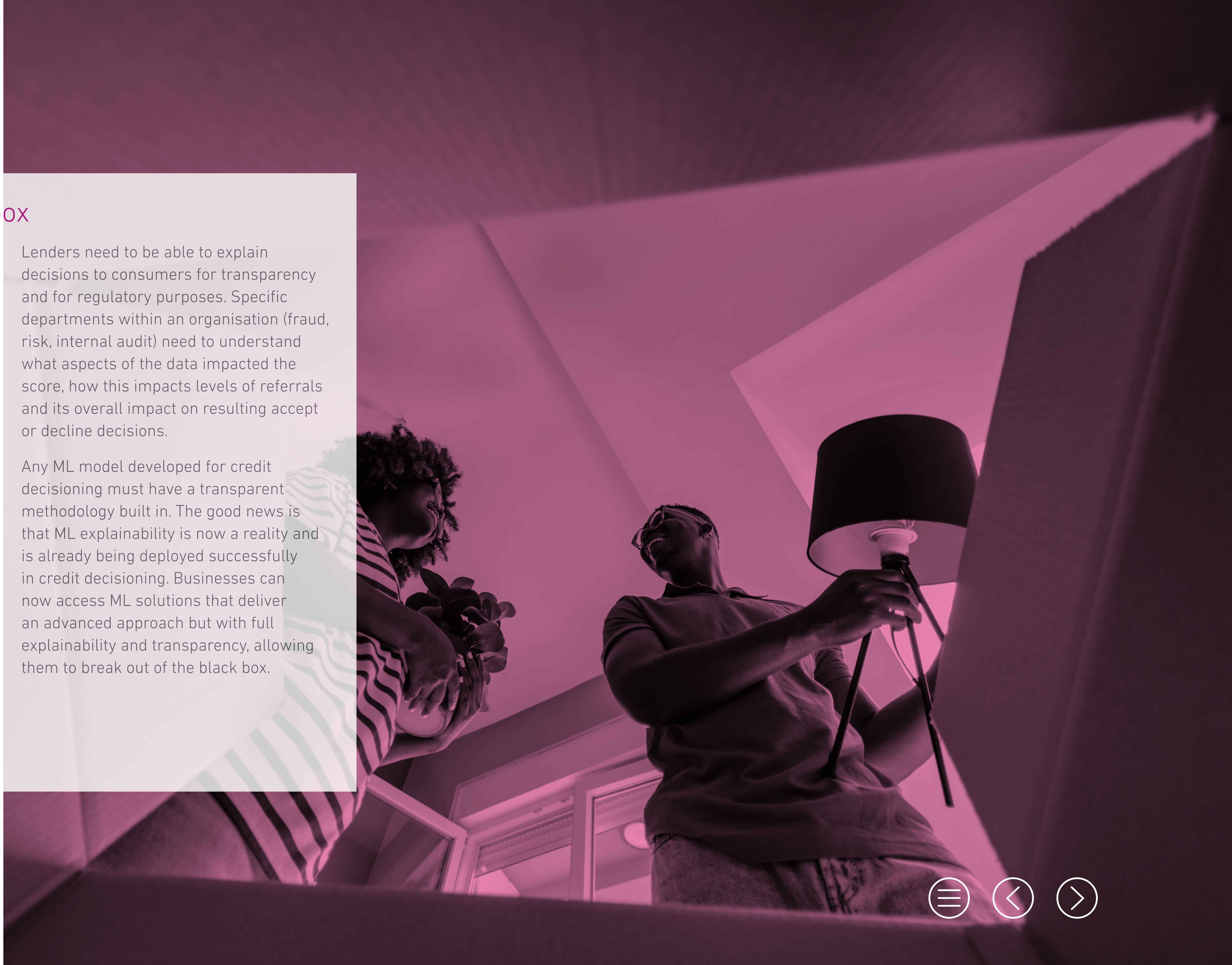
Breaking out of the black box

One of the major concerns limiting implementation is the so-called black box of Machine Learning, related to some methods developed using this process. As analytics has progressed from statistical models to Machine Learning based models, it has created more sophisticated algorithms that have ended up becoming hard to explain.

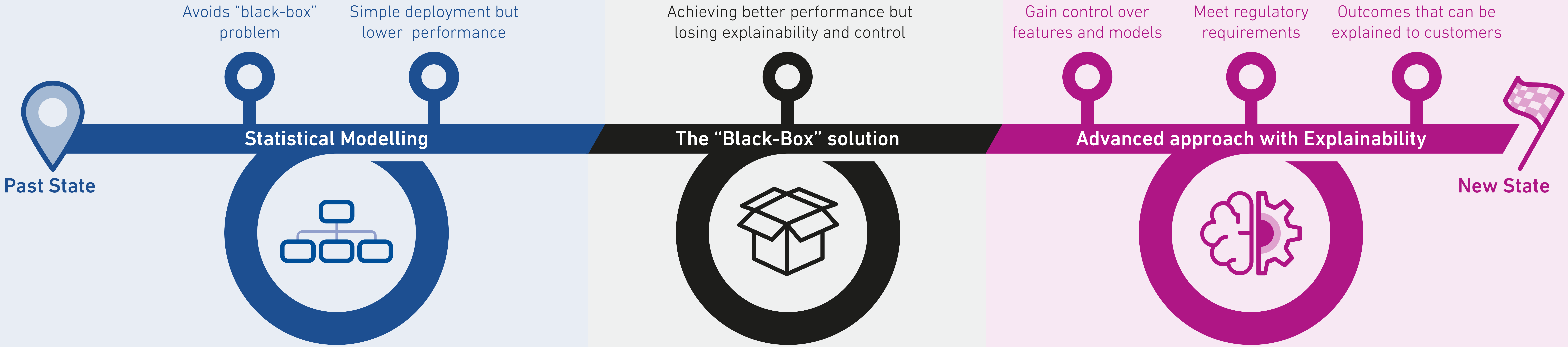
These algorithms can deliver significant improvement in model performance, but many have not been able to provide the required transparency in terms of how the decision came to be made. In the context of credit risk, this means that an ML model may be able to deliver improvements in the ability to identify defaults for new customer applications but without the ability to explain how the result was generated. This opens many potential concerns around trust in the model and fairness or ethics of the decisions.

Lenders need to be able to explain decisions to consumers for transparency and for regulatory purposes. Specific departments within an organisation (fraud, risk, internal audit) need to understand what aspects of the data impacted the score, how this impacts levels of referrals and its overall impact on resulting accept or decline decisions.

Any ML model developed for credit decisioning must have a transparent methodology built in. The good news is that ML explainability is now a reality and is already being deployed successfully in credit decisioning. Businesses can now access ML solutions that deliver an advanced approach but with full explainability and transparency, allowing them to break out of the black box.



A path through ML explainability



Statistical solutions or simplified Machine Learning models (e.g. decision trees)

Playing safe

Avoid embracing new ML methodologies but limiting business model

The risk of developing improved models but without knowing how they work

Regulatory pressure

With new regulations paying special attention to non-transparent solutions, the "black-box" approach is ending

Models with improved performance now able to provide explainable results

Revised approach

Explainable models and decisions with reduced IT effort and cost

Building trust in the process

Explainability is important because it builds trust into the process. Within each organisation, teams will rely on explainability to either fulfil specific tasks or to understand and discover improvements in the model performance. Regulators and auditors require businesses to ensure that they can provide evidence of the rationale behind lending and credit decisions. Consumers also have the right to receive information regarding what contributed most to a given score or decision. Reason code logic allows businesses to be able to explain why a score was given.

Advanced ML models developed and deployed with full explainability means businesses can now optimise performance. Comprehensive documentation is available to meet the regulatory requirements, giving businesses the confidence to deploy these models and take advantage of the performance potential.

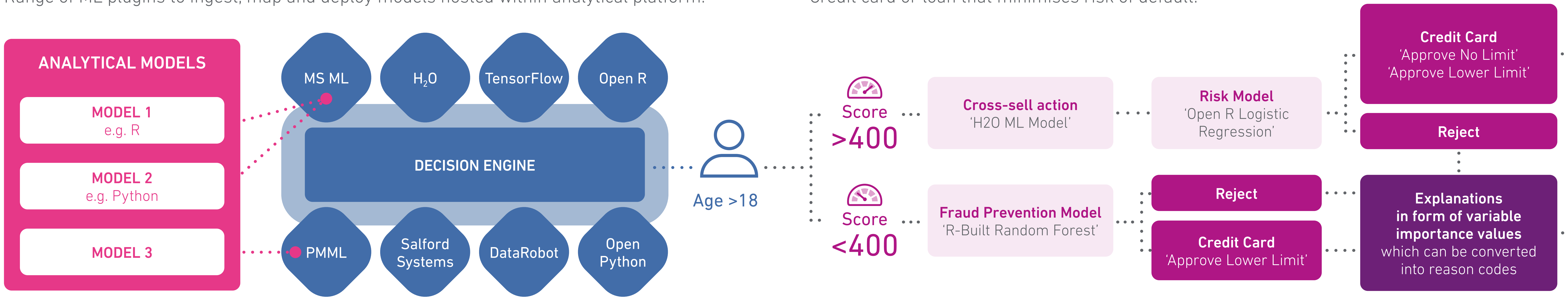
Businesses can now access a range of ML methodologies that provide full explainability and transparency

Machine Learning models built and tested

Range of ML plugins to ingest, map and deploy models hosted within analytical platform.

Decision process carried out with explainability

Credit card or loan that minimises risk of default.



Upgrading your models

ML can provide the same transparency for credit risk modelling as traditional models, but it is important to understand that not all ML models provide the same level of transparency. Upgrading from traditional logistic regression models to Machine Learning models increases predictiveness but the ML methodology must provide explainability to ensure the performance uplift comes with the confidence of transparency for auditing and regulatory purposes.

Gradient boosting machines (GBMs) for example, is a type of ML algorithm that is highly predictive and offers greater transparency than some other popular Machine Learning frameworks such as neural network models. GBMs are built from neural network models. GBMs are built from a combination of decision tree sub models which means that you can understand how these are built to trace the inputs into the decision. Neural network algorithms on the other hand are more complex and harder to understand.

SHAP (SHapley Additive exPlanations) Values

One such approach to improve the interpretability of ML models is the use of SHAP-values*. This involves the ability to provide contrastive explanations, to understand which model features contributed most and least to the result. It is best explained using the concept of a game and players. By using SHAP-values we can understand the relative contribution of each player to the outcome of the game. In the same way we can understand what features of a Machine Learning model led to the outcome. For example, Experian has developed its own approach based on SHAP for Machine Learning projects and has integrated it into its core business to help businesses with explainable credit risk, affordability, and fraud decisions. This allows businesses to understand, for example, the reasons behind a credit decision. Businesses will then have evidence of how the decision was made for auditing and regulatory purposes, and also for internal teams to assess model performance for potential improvements.

(*) A Unified Approach to Interpreting Model Predictions, Scott M. Lundberg & Su-In Lee, 2017.

SHAP values explained

Imagine two things

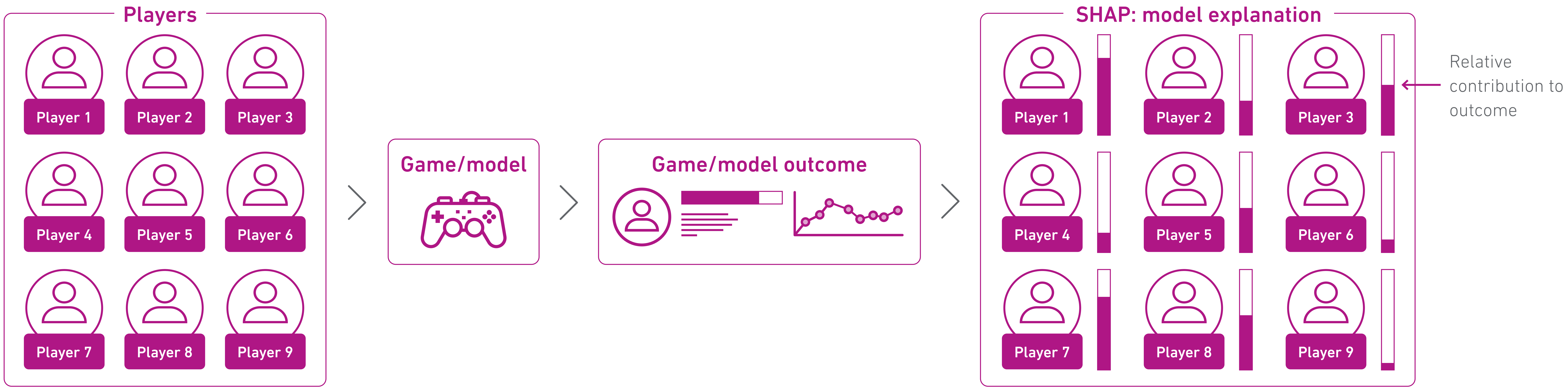
1 A game

The "game" is reproducing the outcome of the model.

2 Some players

The "players" are the features included in the model.

Imagine now that we have a predictive model



What Shapley does is quantify the contribution that each player brings to the game.

How does this apply to machine learning explainability? SHAP does the same thing for the model by quantifying the contribution that each feature brings to the prediction made by the model.

This allows us to understand the features that contributed most and least to the result. From that we take a confidence level and understand the importance of the individual features that enables the decisions to be **explained** and **interpreted**.

.03 5 TIPS FOR IMPLEMENTING ML WITH EXPLAINABILITY

Analytical models are becoming more accurate and efficient. This translates into several benefits that businesses can unlock to help deliver competitive advantage. In this regard, ML models can:

1. **Improve outcomes for borrowers:** ML allows for individualised credit scores that better assess borrowers' creditworthiness and can assist in providing access to credit to people who may otherwise be denied when using a traditional mathematical technique.
2. **Reduce the cost of lending:** By increasing efficiency in risk management, ML models can lower the costs of lending and provide opportunities to inspect and continually optimise lending decisions.
3. **Better decision-making:** ML helps provide objective, consistent, data-driven decisions through analysis of borrowers' relevant credit data.
4. **Support financial inclusion:** ML supports financial inclusion, supporting access to credit for certain consumer groups (e.g., students, startup businesses, migrants who have recently moved to a new country) that may otherwise have limited access to credit if their credit data file is too thin to assess using traditional techniques.
5. **Enhance accuracy:** ML is more sensitive to real-time indicators of the potential borrower's creditworthiness, such as the current level of income, employment opportunities, and forecasted earnings.

Experian has developed a standardised framework for developing and deploying ML models with the required level of explainability

1. Business Understanding
2. Data Understanding
3. Data Preparation

50% faster

Experian has improved methodologies to bring 50% faster time to value on the traditional modelling steps.

Enriched process

The process has been further enriched with a standardised and innovative framework for the required level of explainability.

Machine Learning Explainability

1	**Relative Feature Importance**	By calculating scores for each feature, you can determine which features attribute the most to the predictive power of your model.
2	**Partial Dependencies**	A partial dependence plot can show whether the relationship between the target and a feature is linear, monotonic or more complex.
3	**SHAP Values**	SHAP Values shows the average expected marginal contribution of one attribute after all possible combinations have been considered.

4. Modelling
5. Evaluation
6. Deployment and Production

Power and accuracy together with transparency and explainability

At Experian we continue to innovate with AI to support credit risk models. With our Analytical Component Extension (ACE) framework, we provide businesses with access to a comprehensive range of Machine Learning plugins to ingest, map and deploy models simply and effectively using drag and drop functionality. All without the need to invest heavily in data scientists and developers.

Our next generation Explainability plugin uses our patent-pending Machine Learning Explanation (MLE) method to automatically provide 'feature importance' for each model input.

This means businesses can see which variables, for a specific observation, were important in producing that specific result. This is using the SHAPs framework covered earlier in the report, allowing us to understand decision transparency and interpretability. For example, we can understand why an applicant was rejected for credit, and the key driver behind their low credit score, such as low-income ranking. This can be translated into reason codes and used for regulatory and auditing purposes. The business benefit is improved operational performance whilst satisfying all regulatory requirements.

Working with Experian

Ingest, map and deploy ML models without the need to invest heavily in data scientists and developers

Find out more

Contact your local Experian consultant or visit **experianacademy.com** to be kept up to date with our latest insights.

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