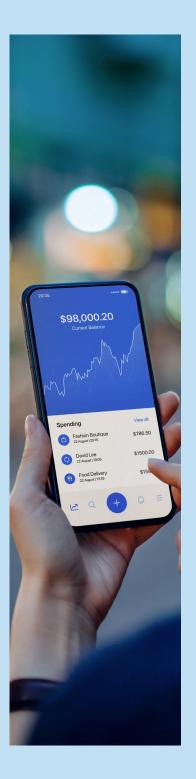
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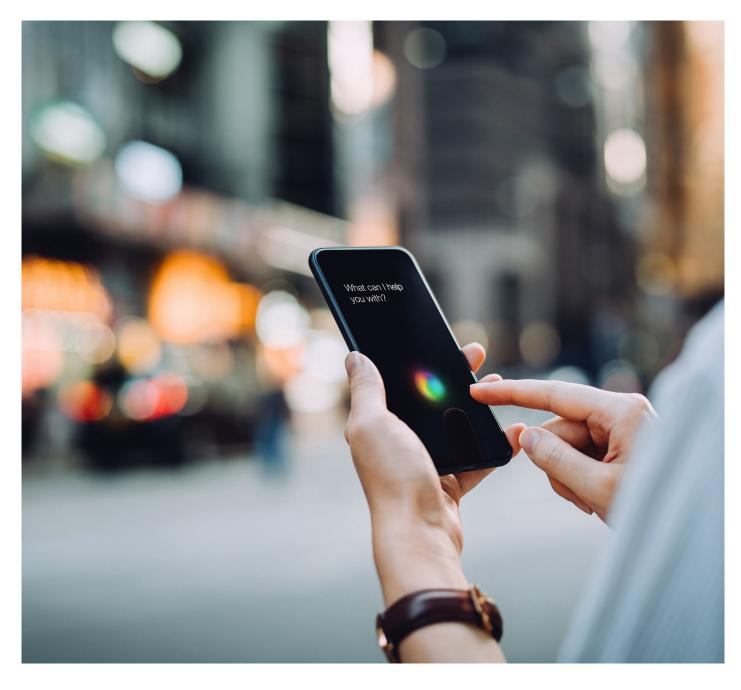


CULLING OUT CREDIT RISKS, Intelligently

Abstract

In a world of soaring household debt, it has never been more important for lenders to accurately assess and manage their credit risks. This paper presents how leveraging artificial intelligence and machine learning is key for financial institutions to manage their risk exposure more efficiently, through more efficient analysis of the wealth of information widely available today.





The role of AI in a world of increasing risk

For banking majors, credit risk has always been a challenging area, given the multiple factors that influence an individual's risk profile. However, with household debt in the US soaring to over \$15 trillion in the second quarter of 2021, it has become paramount for lenders to review credit risk more accurately than ever before to avoid costly borrower defaults.

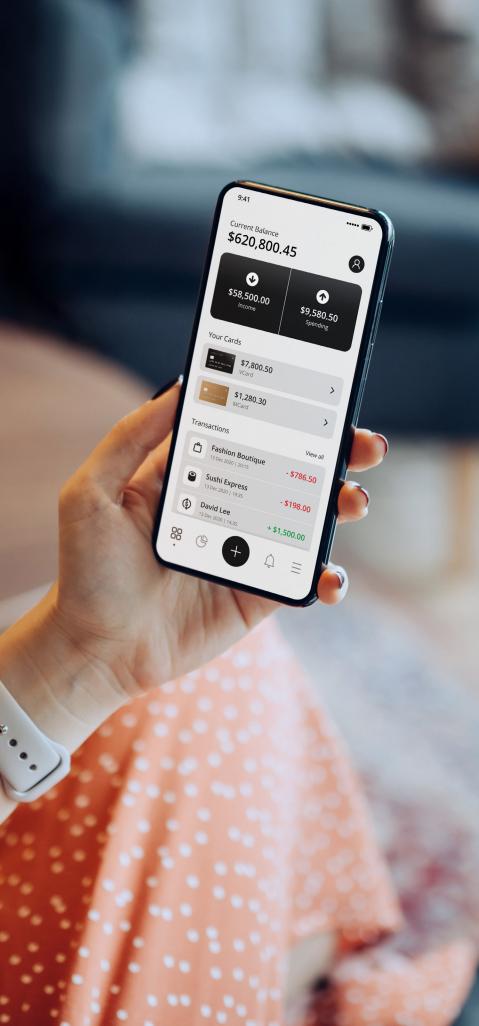
Towards this, it is necessary to better understand the various complex factors contributing to credit risk, looking beyond just the traditional portfolio analysis. It is now imperative for banks to adopt a comprehensive approach towards assessing their borrowers' financial health, which requires starting earlier in the customer lifecycle. Also, with seamless customer experience coming at a premium across the financial industry, lenders must work on identifying a solution that integrates smoothly with their existing offerings. It is in these two fronts that the potential of artificial intelligence (AI) can be leveraged to the hilt. Using AI to assess credit risk can turn massive amounts of real-time customer behavior and financial data into actionable insights. Also, with its ability to correctly predict outcomes like which customer should be offered a loan, AI can boost revenue and profitability while maintaining a first-rate customer experience.

Scoping out the opportunity

With the growing popularity of virtual assistants, autonomous vehicles, and automated management systems, AI in combination with machine learning (ML) is being successfully deployed across an increasing number of business domains. This brings us to the question of whether a similar opportunity exists in the financial services industry for AI/ML.

A survey conducted by Lendlt and Brighterion in Q3 2020 found that over half the financial institutions surveyed were already using Al for credit risk, with another 25% planning to leverage it in the future. Additionally, nearly 90% of those surveyed planned to invest even more in Al over the next 2-5 years. Thus, it seems to be a foregone conclusion that those who aren't investing in Al will lose out, especially those responsible for credit risk management.

This is borne out by credit scoring finding its place among the top 6 Al use cases, in a survey by the Global Association of Risk Professionals (GARP) and analytic leader SAS in 2018. At 45%, Al is clearly used heavily in credit scoring. This is followed by a 37% use of Al in risk grading - a financial function that oversees credit scoring. This clearly shows there is huge scope for Al being applied in credit risk management.

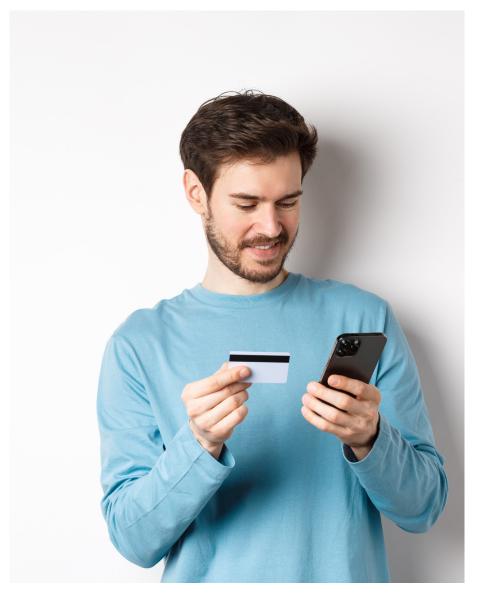


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Insights, impact, and experience

Today, the widespread prevalence of unstructured data — whether text, image, voice, or sensor-generated — and the vast improvements in computing power make machine learning (ML), which is a subset of artificial intelligence, a viable tool for building credit risk models. What makes machine learning systems even more impactful is their capability to implement rules that learn and adapt to changes in the environment. Instead of looking through a narrow lens of internally collected historical data, banks can now benefit from a continuous and comprehensive flow of insights based on both traditional and alternative sources of data.

Banks have traditionally relied on rulebased systems which are cumbersome and require substantial manual effort to clean and analyze data from a variety of sources. Yet, these systems create only a partial picture of a customer's credit history, without placing it against the context of other market actions. On the other hand, with ML algorithms that use alternative data, banks can discover risk elements early, rather than traversing the environment after the risk becomes a reality.



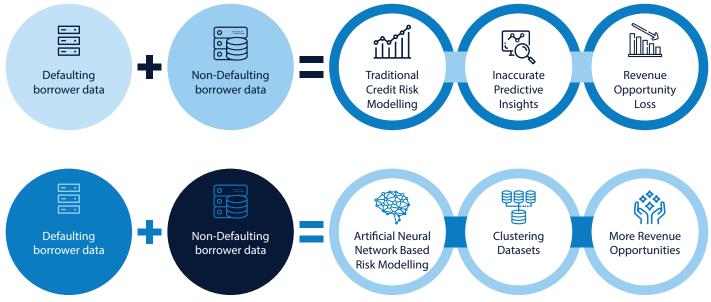


Fig 1: How machine learning models lead to better revenue opportunities

Also, today banks and financial institutions spend a substantial amount of money on verifying the authenticity of loan applicants' information. However, leveraging Al and alternative data sources to verify the authenticity of the information provided by the applicants eliminates the need for conducting physical investigations, leading to significant reduction in processing costs for loan disbursals.

Additionally, the unstructured data that banks and financial institutions collect through their day-to-day business activities can also be used for more effective decision-making. The notes taken during personal conversations with customers at the time of application are, for example, a very useful source of information when assessing the risk of the customer. Similarly, the conversations of call center personnel can be gleaned for customer insights that can then be used to assess cross-sell potentialities and improve the effectiveness of other marketing strategies.

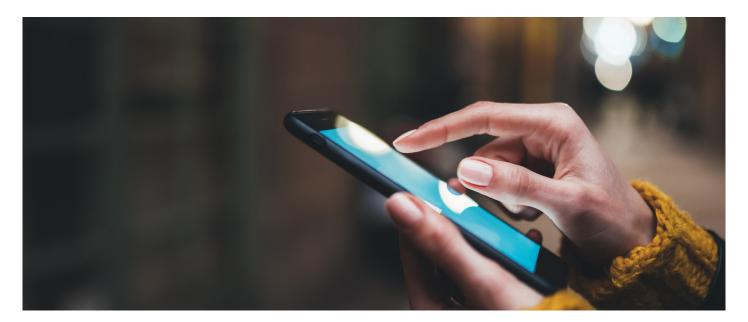
How machines are learning

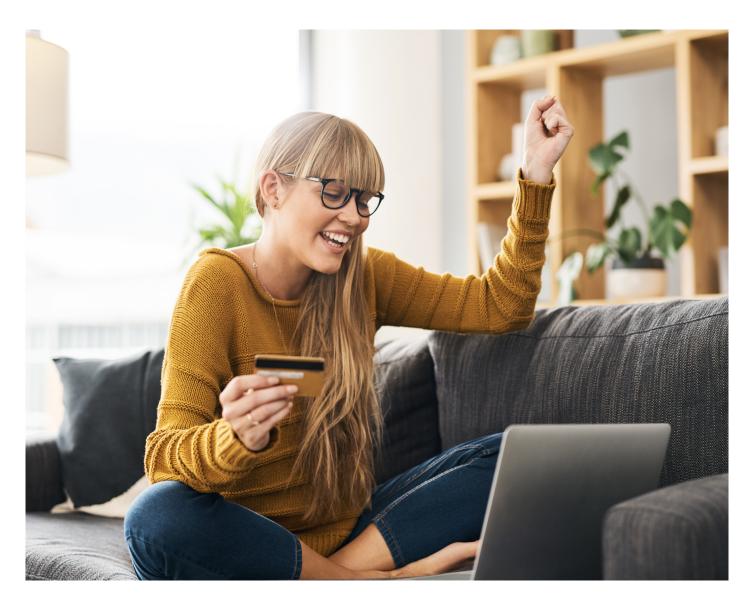
As ML becomes increasingly represented and influential in finance its growing use in credit risk management can be illustrated through the below two rapidly developing and interesting applications:

 Credit risk modelling: Logistic regression is the cornerstone of traditional probability of default (PD) models. Traditionally, logistic regression models have been simple to understand and interpret; and have been the market standard for decades. Despite this, traditional models fail to capture complex relationships present in the data. In other words, the data contains more predictive power than traditional methods can extract. According to a case study by Deloitte France on PD modeling , models developed using ML techniques such as neural networks, gradient boosting, random forest, and stacking methods all outperform traditional logistic regression models across multiple performance measures.

 Early warning signals: The use of early warning indicators for managing credit risk has become common from the point of view of identifying entities that are at a higher risk of default, well before occurrence of the actual default. Typically, early warning systems heavily rely on expert judgement while using a combination of parameters to arrive at possible scenarios.

This is where artificial intelligence shines, as it excels at discovering patterns in large, unstructured, highvelocity data. These patterns can be used to detect credit defaults with a properly designed AI algorithm accurately generating early warning signals by using a variety of indicators. Institutions can also analyze textual information using natural language processing (NLP). This technology is omnipresent in our daily lives - for example, translation apps, virtual assistants on smartphones and intelligent customer service from retailers. With NLP, AI can capture and analyze social media posts of customers and financial news, akin to credit analysis that is traditionally done by humans.





The benefits of managing credit risk with AI

In this era of digital transformation, as banks adopt new frameworks for credit risk management to enable the efficient processing of large amounts of readily available data, AI can make a massive difference. Here are several benefits for banks to consider:

 Quicker credit decisions: Making credit decisions can take a long time, from manually retrieving customer information to reviewing a profile.
With artificial intelligence, financial institutions can automatically extract information from annual financial statements and other publicly available information. As a result, loan processing time will be significantly reduced. Al also enables complex calculations to be performed without human supervision, eliminating the need for manual calculations.

- Credit loss reduction: The purpose of credit risk management tools is to predict delinquencies and reduce losses well before they occur. While AI can predict delinquencies up to a year in advance, the only requirement is to have the appropriate data.
- Real-time creditworthiness scores: A credit risk management system that uses artificial intelligence continuously monitors the data of the customers so

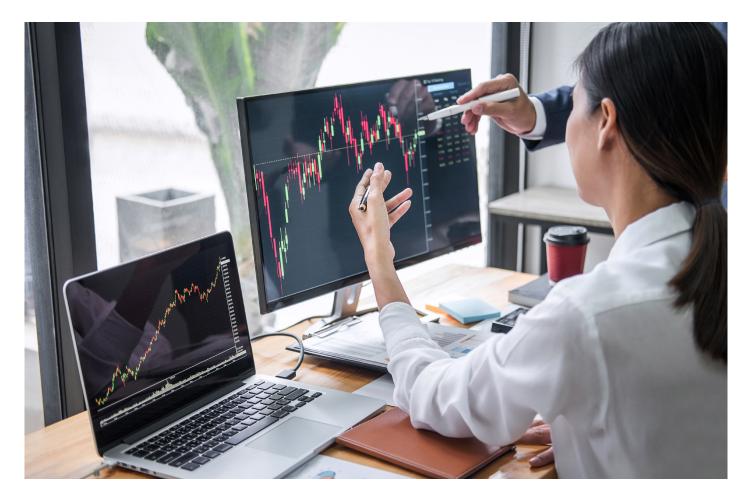
that it can provide clear insights into a customer's creditworthiness at any given time.

- Improved customer experience: To improve the accuracy of the credit system and improve the overall customer experience, AI analyzes customer data to provide customers with the customizations they need.
- Better regulatory compliance: For any bank to comply with all regulatory requirements, it is necessary to provide accurate and transparent data. The use of AI in a credit scoring system delivers accurate, real-time, and transparent data.

The challenge of opacity

The adoption of AI is greatly hindered by the lack of transparency in ML's "black box" models. Because there is typically no intuitive way to explain the relationships between a model's inputs and its outputs, multiple stakeholders including credit professionals and regulators are very often opposed to fully utilizing ML.

While ML's complex models can lead to outstanding and even superhuman performance, it is the inability to explain how they work that is the cause for concern. This concern is even more relevant given the increasing potential for adverse outcomes as AI adoption increases. Additionally, overfitting can occur since ML models are more sensitive to outliers than traditional analytics.



What the future holds

By 2025, artificial intelligence and machine learning systems will drastically alter the credit risk management landscape. Al will use even more alternate data sources, making processes even more efficient and robust, thereby continuing to enhance and enrich credit risk management processes. Further, its effectiveness in creating enhanced customer experiences will provide it a continuing key role.

Overall, while credit scoring models will continue to be based on traditional

methods their outcomes will be strengthened by applying ML-enabled methodologies. With the help of such process automation, credit risk management will only become more and more efficient over time.

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Authors



Abhishek Prasad

Practice Lead, Digital Transformation Services, Infosys BPM

Abhishek looks after Analytics in Financial Services and his responsibilities include driving growth strategy, transformation, go-to-market and customer success. An FRM certified analytics professional with over 15 years of experience, he is adept at conceiving, designing, and delivering advanced analytics solutions across the retail banking and retirement services space globally.

Prior to Infosys BPM, Abhishek has been with Citi and Tata Consultancy Services across diverse roles involving model development/validations, risk and fraud reporting, and campaign management for leading US and Australian banks.



Sourav Ghosh

Senior Industry Principal, Infosys BPM

Sourav is a Senior Industry Principal with Infosys BPM's Digital Transformation Services, and is responsible for Financial Services & Insurance – Digital solution design and service delivery. An IBM-certified design thinking practitioner, he advises organizations on their operations strategy, assists them in improving profitability and efficiency of business processes, and helps in executing business transformation through calibration of operating model and technology. Prior to Infosys BPM, Sourav had been with IBM, Satyam, Tata Consultancy Services and Standard Chartered Bank in diverse roles across India, US, and UK.



For more information, contact infosysbpm@infosys.com

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