WHITE PAPER

Building Artificial Intelligence in Credit Risk: A Commercial Lending Perspective

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Commercial Lending and Credit Risk Assessment: A Slowly Changing Paradigm

Lenders of all shapes and sizes are on a path of digital transformation that will allow them to realize the benefits of process automation and capture new business opportunities. Before the outbreak of COVID-19, early adopters of innovative digital technologies were already gaining competitive advantage; today, for example, a financial technology company is now the largest mortgage originator (by volume) in the United States. Similarly, a Gartner survey of more than 3,000 CIOs revealed that the organizations that deployed artificial intelligence grew from 4% to 14% between 2018 and 2019.

Given these studies and trends, it's easy to see the impending disruption of the entire banking industry by AI – disruption that is accelerating, thanks to easier access to better and faster algorithms. According to the Financial Stability Board, use of AI, machine learning (ML) algorithms and automation is now commonplace across many lines of business within banks, including marketing, customer experience management, fraud detection and trading. It's expected that AI and ML could also be used to detect early warning signals of distress by analyzing cash flow forecasts, income and expenditure data, and more. In addition, these technologies could help generate more accurate forecasts using real-time data – specifically, short-term forecasts rather than longer term views.

However, adoption of AI and ML has been slow in other business areas. Credit risk quantification, for example, has evolved tremendously over the years. Yet there are still subsegments of the credit origination business – such as commercial credit lending – where these powerful technologies are rarely used.

Indeed, while we are now far past Altman's Z-score from 1968 (where a five-variable linear discriminant analysis model predicts commercial bankruptcy), the core of commercial credit lending has remained largely unaffected by advances in AI and ML. And it shows. According to a recent McKinsey study, the typical "time to decision" for commercial lending is between three and five weeks, while "time to cash," on average, fluctuates around three months. This is a far cry from the rapid, automation-centric decisioning enjoyed in consumer lending for decades, enabling near-instant approvals for customers. (And even in this market, there's still room for even greater adoption, as banks have been slow to adopt AI and ML automation and potentially more predictive classification models.)

COVID-19 is causing major disruption in credit risk management across multiple industries, resulting in uncertainty and supply chain disruption. Many firms were delaying adoption due to widely held concerns about the lack of transparency and interpretability of AI and ML models and incompatibilities with legacy systems. But the commercial business segment has other deeply engrained reasons for holding off. As also noted by the McKinsey study, commercial credit lending has been historically based on "years of root-cause analysis of defaults and assessment of soft factors." Operationally, this has translated into dependence on manual processes and cross-checks, which are still in use today. Why? Because of widely held trust and beliefs in a highly manual commercial underwriting process. These beliefs have hindered the adoption of all types of automation – including AI- and ML-powered techniques.

There are also major concerns about the quality of self-reported data. Loan officers know that organizations seeking a loan may use data from doctored books, unrealistic sales and growth projections, and more to strengthen their case. Banks currently rely on experienced loan officers to judge data accuracy – not AI and ML-driven analytics – who can seek out alternative data sources to gain clarity into an applicant's ability to repay a loan and scale the size of the loan appropriately.

What's needed to break through these long-held assumptions? What will it take for banks to trust AI and ML with judgments about data accuracy and commercial lending process automation? This will require:

1. Proving quantifiably that AI and ML are equally as effective as manual processes for commercial lending purposes.
2. Evolving the corporate culture and risk practices.
3. Developing an incremental approach to adopting AI and ML in commercial lending.

Drawing on recent academic evidence and business insights, this paper provides a contemporary look at what AI and ML adoption could mean for commercial lending and credit risk assessments. It also proposes different approaches to AI and ML adoption tailored to each step of the commercial lending process.

State of the Industry: Examining a Typical Credit Risk Origination Process

To better understand the real value of AI and ML for quantification and automation in commercial lending, let's explore the current state of the origination process within a typical bank. Figure 1 is an overview of common steps in the commercial lending process.

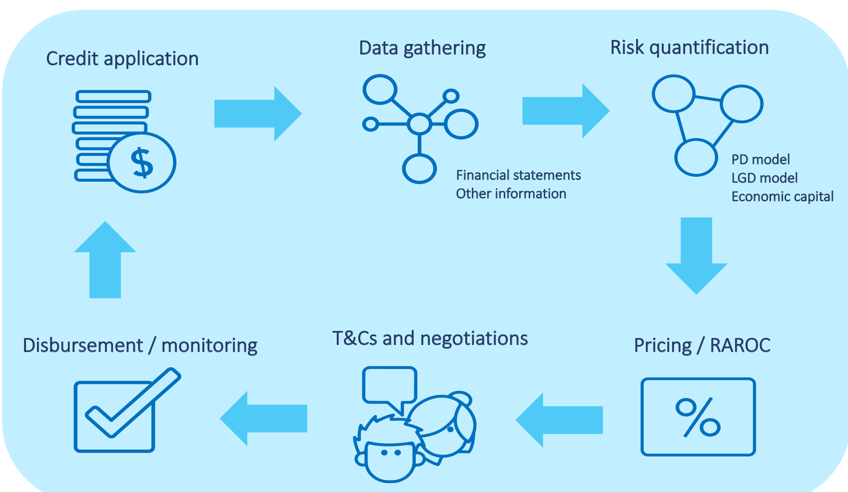

Figure 1. This presents the typical steps involved in commercial lending origination processes. These steps involve, at a high level, gathering the information, quantifying the risk (through probability of default – PD – and loss given default – LGD – assessment), determining risk adjusted return on capital (RAROC), pricing, assigning terms and conditions (T&Cs), and disbursing the loan.

Risk quantification is central to this process and encompasses the probability of default, loss given default and RAROC assessments. As common as these risk quantification tools may be today, obtaining reliable metrics can be extremely difficult.

For example, when building credit risk models for commercial lending purposes, data scientists face two key challenges: data scarcity and data quality. Data quality issues are a common challenge for all modeling projects, but data scarcity is particularly prevalent in commercial lending. Indeed, it's not uncommon for data scientists to launch modeling initiatives with only a handful of defaults, or to resort to using external data sets. This results in less-than-ideal representative data samples that lack, for example, all of the sought-after financial ratios within the pertinent economic sectors, industries and geographies.

Qualitative and Quantitative Considerations

When banks use imperfect data samples, they often need to include other judgmental qualitative metrics, such as an assessment of the management team's competencies and effectiveness, a measure of the firm's competitive position or an appreciation of the firm's physical location (prime vs. nonprime areas). The use of such qualitative metrics can be beneficial – for example, by supporting more nuanced risk assessments through the inclusion of hard-to-quantify information that could affect risk measurements. But collecting these types of data takes a great deal of time and money, as this work cannot be automated. Furthermore, although these qualitative metrics must ultimately go through a quantitative fitting phase – to derive weights, for example – they are often based largely on intuition and consensus.

In short, because of data quality issues, the highly quantitative process of commercial credit risk assessment must include qualitative considerations that are manually processed and approximately derived. Historically, such judgmental factors have helped in getting buy-in from credit analysts and other decision makers who may not have had full confidence in the self-reported quantitative factors, as revealed in data coming from the company requesting the loan. Incorporating expert human judgments also allows for oversight of the credit rating process.

As more advanced modeling techniques emerge and data volumes increase, one question remains: Can we use AI and ML to further improve the risk assessment?

An Academic Perspective: What the Research Shows

Credit risk remains the focus of many academic research studies, as finding better techniques to measure risk can have a huge impact on a bank's balance sheet and financial results. Many recent studies have focused on two questions pertinent to this paper:

- What is the impact of AI and ML algorithms on default predictions?
- What is the impact of using more extensive data sources for modeling?

Quantifying the Impact of AI and ML Algorithms

Most research studies highlight the performance and accuracy improvements made possible by AI and ML – but at the cost of increased model complexity and model opacity (for example, Louzada, et al., and Lessman, et al.). In addition, these studies show that while AI and ML algorithms generally perform better than traditional statistical estimation methods (such as logistic regression), there's broad industry consensus that small predictive performance gains in studies would most likely not translate into material gains in a business setting. In the real world, factors such as unclean data, deployment issues, stability, changing economic situations and changes in policy may quickly erode theoretical performance and accuracy gains.

An analysis of recent academic studies suggests that real gains in commercial lending can be achieved through the use of advanced AI and ML techniques. A synthesis of results from several studies is shown in Figure 2. Each point's coordinate on the graph represents the predictive performance measure obtained on studies where the baseline logistic regression's discriminatory performance acts as the X-value and the best AI/ML model's performance as the Y-value. As we can see, the AI or ML model outperformed logistic regressions in all five studies.

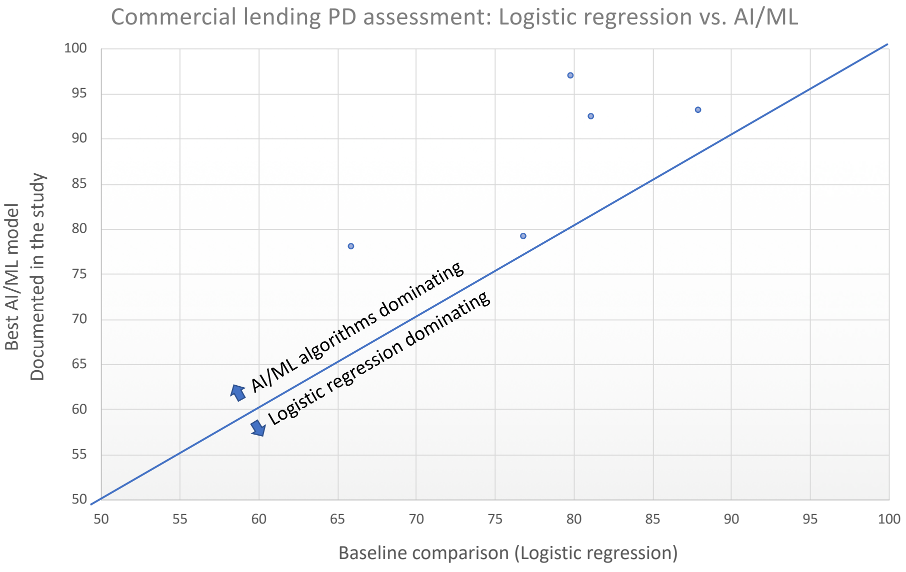

Figure 2: Analysis of gains from AI and ML in commercial lending contexts. Each point is an independent study (see references in the appendix). The coordinates presents the predictive performances of a logistic regression (on the X-axis) vs. AI/ML (on the Y-axis). A point lying on the diagonal would imply that an equal performance was obtained on logistic regression and on an AI/ML algorithm.

The gains in predictive power vary from 2% to 3%, on average, and as high as over 15% in one case (measured in AUC – area under the curve – or accuracy metrics; see references for details). In yet another study specific to commercial credit risk (from 2017), the authors found a performance lift of 3% to 4% in the accuracy ratio by using more advanced algorithms alone (such as random forest and gradient boosting).

It's important to note that these numbers are based on a small subset of studies – and there are other studies in which ML models offered no lift above traditional methods. But it's clear that a sufficient number clearly suggest that significant lift is possible with ML.

Exploring the Impact of More Diversified Data Sources

We've seen that AI and ML algorithms can add value to the credit decisioning process. But what happens if – instead of looking simply at the predictive prowess of algorithms alone – we allow for greater or wider data feeds?

The answer is simple: much greater predictive power! For example, in the commercial credit risk study mentioned above, we see that the addition of behavioral information to a financial-based model generates a 12% nominal accuracy improvement relative to the current model. In comparison, the use of advanced algorithms alone had generated a much lesser, yet interesting, gain of 3% to 4%, in line with what was seen above.

Similarly, a fintech company successfully analyzed historical click patterns on its website to improve the predictive performance of its risk scores. Its performance improvements go beyond anything that can be achieved with more traditional approaches used for publicly traded companies, which rely heavily on rating agencies' valuations and stock volatility-implied risk measures.

Should Banks Jump on the AI Bandwagon for Commercial Lending?

As we have seen, advanced algorithms are increasingly powerful and promising in the context of credit risk quantification. And as noted previously, there are also a growing number of companies – such as financial technology providers – that are embracing AI and ML and generating real results. These providers are now progressing on the management of the more complex and opaque model types.

What does that mean for banks? If they want to stay current and competitive, they should consider better approaches and advanced algorithms that can deliver better predictions. Better, more accurate credit risk predictions translate into tangible benefits, such as:

- Reduced losses.
- Better or more favorable capital requirements.
- Potential reductions in operational costs for banks.

The Benefits Outweigh the Challenges of Using AI and ML Algorithms and New Data Types

Operationalizing advanced models and changing how banks perform commercial credit underwriting is a huge effort facing significant challenges. To succeed, banks will need a well-structured, step-by-step plan, a dedicated team of data scientists and data engineers, and clear business targets. This plan should encompass all areas where AI-driven automation is sought and outline specific benefits. The right plan should focus on clearly defined goals – for example, improving automation by 10%, reducing losses by 10 million or lowering "time to cash" by 10 days.

Banks will also need to bolster their IT maintenance and monitoring, including tighter governance processes. More advanced models are more complex, require modern technology platforms, demand greater and faster computing power (for training and scoring), and need built-in data lineage and flexibility.

Given these challenges, it's important that before banks begin exploring and using AI and ML analytic models, they must:

- Perform tests to identify exactly where they can improve the commercial loan process using advanced AI and ML models.
- Be equipped with the right set of tools and resources.
- Start small and learn before aiming for bigger AI and ML projects with bigger potential impacts.

Use Cases: Exploring the Real-World Value of AI, ML and Automation in Commercial Credit Underwriting

So where can banks get started with AI and ML automation in their commercial loan processes? Let's take a look at a few use cases.

Credit Application Phase

As defined in the simplified origination process shown in Figure 1, during the loan application phase, AI and ML can be used to anticipate credit needs by analyzing credit line usage and understanding historical data patterns. For instance, an agricultural business is likely to have seasonal credit needs; these needs can be modeled to understand typical versus atypical patterns. By understanding how a client company's recent financial behavior deviates from past behavior, banks can detect or create opportunities for expanding their business relationship with the customer – or get early insights into potential causes of concern. In both cases, having early insights enables financial providers to take action with a relevant response – i.e., extending credit proactively or declining a loan.

Banks will also need to evolve their lending criteria as the impact of COVID-19 changes over time. For instance, they will need to more frequently review their lending process, risk decisioning process, and the availability and quality of data used to assess creditworthiness in a post-COVID world. With the right information sets and models, AI and ML could help banks rapidly identify which companies are more or less affected.

Data Gathering

Traditional modeling techniques typically rely on two sets of information: financial statement information (often in the form of ratios for liquidity and coverage) and qualitative information. These are extremely valuable data points, but banks now have access to much more information to supplement them. For example, they could:

- Add banking transactional data information to existing quantification tools (PD, LGD, RAROC, etc.), either as extra inputs in the decision flow or for use in a new model development process. (Examples of transactional data can include a history of late payments, line of credit usage, cash flow movements, patterns of deposits and withdrawals, and more, which supplement existing data sources.)
- Apply natural language processing (NLP) to financial statements to gain deeper insights.
- Use NLP on social media feeds (such as Twitter, Yelp or others) to capture the changing sentiment on companies. This may reveal lowered reviews for a hotel or sanitation issues for a restaurant chain that could affect credit risk.

These are just a few ways in which banks can start incorporating diversified data sources and help those involved in commercial lending leverage the predictive power of AI and ML algorithms – and reap significant business benefits.

Credit Risk Quantification

Testing more advanced techniques for loss given default (LGD) models may be an easy place to start, given the historically low predictive performance of these models. For example, in the context of real estate lending, property value estimation is becoming increasingly accessible, as nearly all information is now available online (for example, the prices and taxes of similar properties, location information and velocity of markets). Organizations can potentially use this data to build better LGD models. Testing advanced algorithms for PD models should also be a priority, given findings shared in the model comparison discussed previously.

It is also interesting to note that building AI and ML models, even if they aren't in production (for example, due to regulatory concerns or other internal considerations, such as user acceptance) can still have positive impacts on organizations. Indeed, building and tracking other advanced benchmarks can help banks determine (and quantify) inefficiencies due to substandard predictions from outdated algorithms. The insights banks gain can build a better business case for further investment and use.

In addition, one way to benefit from the enhanced ability of complex algorithms to find nonlinear patterns in data is to use them for variable creation. Such variables can then be used in simpler modeling algorithms, thus incorporating some complexity while maintaining the interpretability and openness of simpler techniques.

Building models using advanced algorithms will also help organizations gradually build up internal expertise in this area, as well as optimize their management and implementation.

Pricing and RAROC

There are many opportunities to incorporate AI and ML algorithms into pricing and risk-adjusted return on capital (RAROC). For example, by using deep learning methods such as artificial neural networks (which have proven very effective in complex modeling settings), banks can approximate with great success the economic capital consumption of their loans. This also avoids a full re-run of economic capital models at origination, which are lengthy analytic modeling processes to run, and enables efficient measurement of capital requirements; this, in turn, translates into better pricing decisions. Additionally, pricing models can be much more precise if they include more dimensions than purely risk-related ones (for example, modeling the extent of the relationship, the growth potential, the long-term prospect of an industry, the maturity curve, etc.).

Back-End Considerations

Terms and conditions (T&Cs) management is one of many back-end processes that banks could improve using AI and ML. For instance, a typical covenant used by banks is one where businesses need to disclose and report their current state of accounts, inventories or other assets at a certain frequency (for example, weekly or monthly). This is done to track as closely as possible the financial health of the company and limit further indebtedness when some thresholds aren't met. This process is typically very labor intensive and requires human involvement. Banks can use AI and ML tools in conjunction with robotic process automation to make this process more efficient while including far more data sources than is possible through manual human efforts.

Disbursement and Monitoring

Finally, the disbursement and monitoring phases of commercial lending create excellent AI and ML opportunities. Examples include continuous account monitoring, patterns and transactions identification and categorization, IFRS 9 loan-loss provisioning, and fraud and capital requirements modeling.

Realizing the Benefits

While COVID-19 has introduced major disruption in credit risk management, as we have seen, the underwriting process of commercial loans offers ample opportunities where banks can begin introducing AI, ML and automation into their organizations and realize significant benefits. Banks will also benefit from accelerating digitalization efforts and strengthening their model governance, development, and deployment processes. Although these benefits – and the degree to which they are realized – will vary depending on where a given bank starts, and relevance of the use cases they choose to focus on, there is little doubt that as adoption increases, so will the business value. Banks will gain better quantification tools (including those that automate decision flows), which will translate into lowered losses, better profit margins, greater pricing strategies, and even potentially reduce capital requirements and loan-loss provisions.

Operationally, the adoption of AI and ML automation can also have a direct impact on customer satisfaction. Increased automation typically:

- Reduces documentation burdens for customers and back-office employees.
- Speeds time to decision.
- Directly affects the amount of analysis required for credit origination decisions, which will translate into faster originations, fewer delays and higher customer satisfaction rates.
- Allows account managers to concentrate on what should be their primary focus: business development and customer satisfaction.

Learn More

Are you ready to reap the benefits of an end-to-end integrated risk modeling process that includes traditional modeling techniques, AI and ML, and automated decisioning while providing choice, governance, scalability and control? For more information, go to sas.com/ai.

References

General

ALTMAN, E., *Financial ratios, discriminant analysis and the prediction of corporate bankruptcy*, The Journal of Finance, vol XXIII, 1968

BASHAM, D. Zhao, J. Dr., *Machine learning: Challenges, Lessons, and Opportunities in Credit Risk Modeling*, Moody's Analytics Risk Perspectives, volume IX, July 2017

Financial Stability Board (FSB), *Artificial intelligence and machine learning in financial services: Market developments and stability implications*, 1 November 2017

GHAILAN, O. et al., *Improving Credit Scorecard Modeling Through Applying Text Analytics*, International of Advanced Computer Science and Applications, Vol 7, no 4, 2016

HURLEY, M., ABEDAYO, J., *Credit scoring in the era of big data*, Yale Journal of Law and Technology, Vol. 18, issue 1, article 5, 2017

LAURENT, P. et al., *Intelligent automation entering the business world*, Deloitte, White Paper

LESSMAN et al., "Benchmarking state-of-the art classification algorithms for credit scoring: An update of research," *European Journal of Operational Research* 247(1): 124-136. (2015)

LOUZADA, F. et al., *Classification methods applied to credit scoring: A systematic review and overall comparison*, 8 February 2016 (preprint submitted to Elsevier)

OSKARDOTTIR, M. et al., *The value of big data for credit scoring: Enhancing financial inclusion using mobile phone data and social network analysis*, Applied Soft Computing Journal 74, 2019

Figure 2 References

Chakraborty, C., et al., *Machine Learning at Central Banks*, Bank of England, Working Paper 674, 2017

Chow, Jacky C. K., *Analysis of Financial Credit Risk Using Machine Learning*, Cornell University, 2017

Guégan, D., et al., *Regulatory Learnings: How to Supervise Machine Learning Models? An application to Credit Scoring*, ScienceDirect.com, 2018

Liu, L., et al., *A Comparison of Machine Learning Algorithms for Prediction of Past Due Service in Commercial Credit*, Kennesaw State University, 2018

Petropoulos, A., et al., *A Robust Machine Learning Approach for Credit Risk Analysis of Large Loan Level Datasets Using Deep Learning and Extreme Gradient Boosting*, Bank of Greece, 2018

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