WHITE PAPER

6 Keys to Credit Risk Modeling for the Digital Age

The emerging role of machine learning and alternative data in credit decision making

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The importance of effective credit risk models

To which customers or prospects should we make our most attractive offers?

What is the probability that certain customers – or those who look just like them – will default?

What is the appropriate credit limit and interest rate for a given customer or purchase?

For past-due accounts, which customers are most likely to be worth the effort of collections?

Which customers should be allowed to use their credit cards even when they have missed their payment?

Do our lending portfolios and customer pool represent an acceptable overall level of risk?

Answering such questions with speed, precision and confidence can dramatically change business results. This is true for any entity that extends credit, from traditional banks to alternative lenders, car dealers, mortgage companies, communications providers, government agencies, health care systems, insurance companies, credit management services and retailers that offer lines of credit. Speed, precision and confidence are key to a great customer experience at lower operating cost.

Speed

In this digital age, we have been conditioned to expect immediate response. The organization that takes longer to return a credit decision will lose out to more agile competitors. A lag of even 10 minutes can make a difference.

Precision

Many banks still use highly manual processes for loan underwriting, subject to human bias and inconsistency that lead to poor decisions and underperforming loans. Firms that make more accurate credit decisions will maximize revenue and minimize defaults.

For real precision, it's not enough to rely on scores from credit bureaus alone. Savvy organizations will use a wealth of alternative data for deeper insight. For example, in the UK – where there is no universal credit score or rating – lenders assess potential borrowers on their own unique criteria, using algorithms that are essentially trade secrets (and competitive differentiators). Better banks build highly segmented models for unique types of customers – far more accurate than generic models.

Confidence

Financial institutions that bring on the most creditworthy customers and make the right offers will mitigate risks related to exposures and maintain regulatory compliance while reducing the cost of doing business. Those that have transparency and rigor in their credit scoring methodology can confidently defend the fairness and validity of their credit decisions.

The goal is to strike the right balance between risk aversion and business development. High credit exposure can lead to high default rates and charge-offs; too little risk appetite can mean lost revenue and damaged customer relationships.

Calculating credit scores/ratings for new credit applications and existing accounts helps manage this balancing act. However, traditional credit scoring approaches and processes often have serious limitations.

Limitations of legacy credit risk modeling approaches

Long model development times

Organizations that develop their own credit risk models see long lead times to get them built and deployed. Business users determine a need for a new model, which triggers weeks or months of data collection and model development effort – as much as a year. By the time the new model is deployed, market conditions and customer needs have changed, so the process starts over.

Cumbersome process

Heavy resources are required for manual activities throughout the model life cycle, such as getting business buy-in, accessing data, cleansing it, securing approvals, developing IT specifications, validating models, coding and recoding models, documenting them, producing audit reports and other operational activities. Fettered by handoffs and manual interventions, the entire analytics and modeling process can be slow and inefficient.

High outsourcing costs

Consulting companies can manage custom model development, if you don't mind high annual costs, minimal control over the underlying credit risk algorithms and long turnaround for model updates. Segmentation is limited because it adds further costs.

You could purchase external cloud or on-premises decision management tools, but those are generally "black boxes" that require continued third-party support. As a result, hundreds of organizations that have used this approach in the past have successfully brought these capabilities in-house on open enterprise platforms.

Incomplete view of risk

Legacy credit risk tools generally cannot access the novel, alternative data that would generate a more accurate risk score – or get the data fast enough to react to market changes. Tools based on disparate products that don't integrate well can increase regulatory risk. Generating customer-level versus account-level credit scores is practically impossible and could triple the data volume.

Data management issues

It's common to find different data definitions among business, IT and risk units. Users don't always follow data set naming conventions, so it's hard to find the right data set, understand its purpose or be sure which is the most recent one. Data updates may be sporadic, and data quality is suspect.

Loss of corporate knowledge

Developers vary in their coding styles, and some use difficult-to-manage approaches. When they leave the organization, they take critical knowledge with them. Their replacements (if you can even find the right coding and modeling talent) typically

> Lack of model precision can lead to erroneous client ratings that cause firms to take on risky or unprofitable loans – or worse, to reject worthy clients that would have been good business.

> It is not unusual for months to pass from the moment you decide to build a new credit scoring model until the model is deployed in the production environment. All the while the old model is delivering less precision as the world continues to change.

rewrite code to match their own programming style. How do you validate and manage your corporate knowledge in such a patchwork process – or defend it to regulators?

Slow credit decisions

Getting from a credit score to a customer-facing decision can be sluggish. Even with online loan sites that appear to front a sophisticated decision environment, there is often a lot of manual processing behind the scenes. Once a credit score has been generated and business rules have been run – either from a third-party or in-house system – the result might be bogged in a slow information delivery environment. Operational staff or systems don't get vital information quickly enough, especially for decisions based on a complex flow of actions with multiple models and business rules.

When two people seek an answer to the same question or repeat the same exercise, they should get the same answer. This isn't happening when they're using different tools and programming approaches.

It's time for change

There is new urgency to resolving these deficiencies in the credit scoring and decision process. Competitive pressures, for one. Banks are rapidly losing ground to non-bank lenders such as digital lenders and even telecom providers and other entities that are moving into financial services.

By 2016 fintechs had already captured 30 percent of personal loan volume in the US and had matched or surpassed banks in attracting consumers to their credit cards, auto loans and student loans.[1]

Furthermore, they're handling those loans more efficiently, according to McKinsey and Co. "Aggressive fintechs, some prominent non-bank lenders, and early-adopting incumbents have enhanced their customer offerings, largely automated their processes, and made their risk models more precise. As a result, they can undercut traditional banks on price (our research has shown that digital attackers' cost/income ratio is 33 percent, compared with 55 percent at incumbent banks)."[2]

Margins are further squeezed by low interest rates and high compliance costs, McKinsey notes: "Thirty percent of the respondents in our survey say regulatory cost for risk increased by more than 50 percent over the last five years. Moreover, 46 percent predict costs will continue to increase somewhat over the next five years."

Amid these realities, it's time to reevaluate the cost efficiency and sustainability of credit risk scoring models and processes. Banks and non-bank lenders alike are starting to rethink how they assess credit risk and make decisions, from approving a credit card applicant to identifying at-risk accounts to balancing portfolios and mitigating enterprisewide risk.

It's time to transform inconsistent approaches, with manual handoffs, into more efficient and automated systems.

1 *Fact or Fiction: Are FinTechs Different from Other Lenders?* TransUnion, 2017 transunion.com/fintech

2 McKinsey and Co., *The Future of Risk Management in the Digital Era*, October 2017

Six pillars of modern credit risk modeling and decision making

As organizations see the benefits of modernizing the credit scoring environment, there is growing interest in establishing analytics and modeling disciplines in-house. But to get the expected value, they must have a comprehensive plan and long-term vision. This is especially true for banks, where modeling activities are heavily regulated and audited.

Technology advances such as high-performance, in-memory processing and machine learning have redefined the possibilities. Look beyond traditional modeling approaches and stepping-stone processes. Here are the six pillars of an effective and proactive credit risk modeling and decision system.

1. A comprehensive, integrated platform

When bringing credit modeling in-house, first create a vision for your comprehensive activities. This vision will help to establish an end-to-end integrated framework – one platform for data acquisition, data quality, modeling data set creation, exploration, in-house model development, model validation, model monitoring and documentation, back-testing and portfolio reporting.

Most vendors of credit risk systems focus on a specific area or customer segment or are struggling to integrate technologies they have acquired to create a seamless and consistent end-to-end experience.

Smooth, systemic integration of these steps is essential. It reduces governance and implementation risk. It ensures that the output of each phase, including parameters and conditions for data sets and models, is seamlessly incorporated into the next phase. Reduces maintenance costs and key personal risk. And it brings unity and consistency to managing various types of risk, such as debt collection, stress testing and IFRS 9 and CECL compliance.

2. Robust data management with traditional and alternative data sources

Credit risk scoring is only as good as the data that feeds the process. So it's essential to have strong capabilities to access, transform, standardize and cleanse all requisite data – including third-party bureau, transactional, application, billing payment and collections data.

If you want to keep pace with new market entrants who are innovating their credit decision practices, look beyond traditional data sources. For business lending, for example, credit decisions can incorporate creative new data points such as online reviews from sites such as Google, Amazon, Yelp and TripAdvisor; numbers of FedEx packages shipped or apps downloaded; eatery menus or smartphone activity, just for starters. Thinking beyond account balances and credit bureau scores leads to new ways to become more customer-centric.

Lenders that capitalize on modern technology to re-engineer their credit risk scoring and decision systems can improve the quality of leads and make better recommendations, while reducing manual activities, maintenance costs and losses.

Where permitted by law and culture, consider using data from telco and utility payments, mobile phone use, e-money transfers, social media, online activities such as purchases and browsing, and psychometrics. Use these data sources with care, because causality can be hard to establish, and there's a fine line between being personalized and being intrusive.

To expedite data management tasks and reduce training costs, look for powerful and user-friendly interfaces for managing data, creating modeling data sets, mining data and reporting. To accelerate decisions with very large data sets, take advantage of powerful in-database processing capabilities.

3. Predictive analytics for deeper and more proactive insights

Rules, thresholds and if-then decision logic based on business assumptions are no longer enough. For deeper insights, embed multiple forms of analytics into the scoring process. Combine analytics with decision logic to automatically deliver highly relevant, interactive offers in real time, even in high-volume environments.

When you layer multiple analytics methods, you can more accurately assess creditworthiness of an individual account or at the portfolio level. For example, anomaly detection and predictive analytics can uncover new forms of risk by examining what's happening right now, not just comparing it to the past. Online behavior analytics can establish links that represent potential pluses or red flags. And self-learning techniques take fraud detection to the next level.

When selecting a model development tool, look for the abilities to:

- Perform application and behavior scoring for all lending products and customer segments, such as wholesale and retail.
- Support fast closing with high-performance, in-memory, parallel calculations at a granular level.
- Trace all calculation steps and store the results for future audit purposes.
- Streamline implementation with rich out-of-the-box capabilities that can be customized with imported code.
- Use GUI interfaces to reduce programming errors and reduce training time for new hires.

Consider whether the solution offers compatible products within related risk and finance areas, such as capital calculation and IFRS 9, to minimize integration work and maintain higher consistency among models and rules used across those areas.

Create challenger models using novel methods and data, and backtest/parallel-run them to compare with existing champions as a low-risk way to experiment.

Machine learning takes credit scoring to the next level

Machine learning makes discoveries and adapts to what it sees in the data through automated model building. With every iteration, the algorithms get smarter and deliver more accurate results. It's easy to see the value of machine learning to keep pace with the emerging risks of new digital channels – and the imperative to manage all credit risk more carefully and profitably.

Deep learning takes machine-learning further by applying it to multilayer artificial neural networks. Deep neural networks move vast amounts of data through many layers of hardware and software, each layer generating its own representation of the data and passing what it "learned" to the next layer. One credit bureau that worked with SAS used the neural net approach to improve predictive ability by as much as 15 percent.

Trouble is, the process can be so complex that even its programmers do not know how the learning machine reached its results. Yet regulators require that results be interpretable.

Now it is possible to map inputs into the hidden layers of neural networks to be able to interpret the attributes coming into the final network. This groundbreaking work enables credit decisions to be based on hundreds of thousands of tested attributes. These fine-tuned algorithms determine what is most predictive of credit risk, far beyond conventional, static attributes such as account balance and transaction history.

4. Cohesive model risk management platform

Credit models must reach production while they are still accurate and reflect what's happening today. Lending policies, economic conditions, products, pricing, competitive pressures and seasonality can all affect model performance. This calls for establishing a cohesive model risk management process – an automated environment to quickly develop, deploy, track and assess models.

Look for a formalized model development platform that:

- Enables modelers to quickly develop new credit risk models, incorporate existing models and their own custom code, with no re-programming required.
- Promotes collaboration and standardization through sharing and reuse of analytic assets such as data sources, data extraction logic, filters, segmentation logic, models, parameters and derived variables.
- Automatically self-documents the model life cycle, with all related information stored in one easily accessible place for audits.

A comprehensive model risk management platform with user-friendly graphical interfaces makes it possible to create and deploy models in days instead of months.

> The credit decisions you make are highly dependent on the models you use to make them. The challenge is to develop accurate credit risk models that get into production quickly and can be readily updated to support accurate lending decisions. Shorter time to value yields significant ROI.

5. Automated delivery of credit decisions

Once rules and models have assessed credit risk, you need to get that information immediately to the point of decision – to operational systems that support loan origination, customer relationship management, debt collection, online banking, mobile banking apps, call centers, points of sale, ATMs and so on.

For example, based on model results, a banking customer may automatically get a loan pre-approval message immediately after completing an application form on the bank's website. A credit card customer may get an invitation to a one-time credit limit increase or receive "convenience checks" in the mail to draw funds from that card at no interest rate for the next billing cycle.

The firm that can automate this process will rapidly deliver data-driven credit decisions in alignment with the company's risk appetite and customer contact policies. To achieve that, look for a real-time decision management platform that:

- Combines analytics with business logic and credit strategies to automatically deliver intelligent, real-time recommendations to interactive channels.
- Supports complex decision diagrams and processes that can interact with multiple data sources and apply advanced analytic techniques and business logic.
- Taps into diverse data sources to make the right decision or take the best action – either historical data (previous interactions, payment information, preferences, etc.) or data received during the interaction (such as online behavior).
- Provides an intuitive graphical user interface so business users can easily define risk policy rules and construct automated decision processes without IT assistance – no complicated coding required.
- Streamlines the process of setting up decision processes by offering reusable, out-of-the-box tasks that can be augmented with custom tasks created by coding.
- Supports streaming analytics that enhance the customer experience by predicting their needs in real time and acting on analytical insights even before the customer realizes action is needed.

Automate and enhance the decision-making process for high-volume, customer-facing systems and carry out focused, consistent strategies across channels.

6. Transparency and governance

Given the low level of regulatory tolerance for "black box" analytic models and processes, everything from data creation to analytics, deployment and reporting should be transparent. Not only is this information valuable corporate intellectual property, it will be needed if regulators question your credit decision methodology. Anyone who needs to see details on any phase of the development process should be able to easily do so.

For example, how data is transformed to create aggregated and derived variables, the parameters chosen for model fitting, how variables entered the model, validation details and other artifacts should be stored in one place and accessible through a graphical user interface for review.

Model developers should have automated tools that easily explain the causality of all the major statistical relationships.

Credit risk modeling and decision management in action

A modern credit risk and decision management platform enables the board, executives and owners of individual lending products to:

- Understand the impact of economic changes and business decisions on capital reserve and P&L.
- Plan capital investment and lending products based on reliable expected loss calculations.
- Support marketing in planning customer acquisition, cross-sell or up-sell campaigns.

Here are some prime possibilities for putting better credit risk management practices to work.

Use transaction history in customers' savings and checking accounts to gauge cash flows, and use that to adjust risk-based credit limits.

Adapt credit limits to boost customer loyalty

With deeper, analytics-driven credit insights, you can be more confident of setting appropriate base credit limits for new customers, and then adjusting that limit over time based on usage and repayment patterns to optimize the amount of unused capacity on the credit card.

Or think more creatively. Suppose you have a customer who has opted into location-based awareness and typically uses 90 percent of his credit card limit. You see that he is going to a business where he normally makes purchases of $150 to $300, but he only has $120 credit remaining on his card. Since he has a good payment history and good cash flow in his other accounts, the system automatically sends him an SMS with a limited-time offer to increase his credit limit by $500 for one month. The bank may have just earned (or reaffirmed) the customer's loyalty.

Use risk-based pricing to win the business

Where should you set the interest rate for a given loan, such as a car loan, for a given customer? You could do market research, see what others are doing in the market, and set it there.

Or think more creatively. If the average interest rate is, say, 14 percent, offer good customers 2 percentage points below that, with the additional enticement of a reduction of another percentage point for exemplary repayment. For customers who represent a slightly higher risk, offer to approve the loan at 15 percent. The rate is a little higher, but the customer gets approved. When your credit scoring approach is very refined and efficient, you can make these decisions in ways that add real value to the business.

More effectively up-sell/cross-sell credit risk products

You could use standard tactics for expanding your share of a customer's wallet, such as promoting a credit card when selling a mortgage or car loan.

Or think more creatively. Use analytics to understand which credit cards to sell to specific customers based on their unique characteristics and what that might tell you about their rewards preferences. The frequent traveler may be more receptive to a card with air miles, the shopper more inclined to choose a card that offers discounts with partner retailers, the saving and investing types might prefer cash-back rewards. Analytic insights can support making the best offer.

Proactively manage the portfolio of business loans

Assessing a portfolio of business loans typically involves assessing customers based on their annual financial statements, and then re-rating that customer based on interim financial reports.

Or think more creatively. You could integrate data from news feeds and social media, then apply text analytics to understand what's happening in the market, news about that customer and the tone of sentiment surrounding that customer. Are its mining activities creating real environmental damage? Did its CEO just make inflammatory comments or shoot a beloved lion? Did it just experience a big chemical spill or factory calamity? Are its online reviews and ratings favorable, indicating good business health and potential?

This breaking news can go into the rating model as supplemental attributes to re-rate the customer in real time or daily.

Exploit machine learning in novel ways

Machine learning can uncover correlations among different attributes that traditional linear models would miss. Banks and nontraditional financial entities are turning to machine learning to make more precise decisions about debt collection, loan approval and such. Machine learning is proving especially valuable when using alternative data, where attributes may be indirectly correlated.

Or think even more creatively. Use machine learning to identify which variables have good predictive quality (it might not be what you'd think), and then pour that insight into traditional models. Or build a primary model with traditional modeling techniques or rules, and a parallel model with machine learning. Where the machine learning model can be difficult to interpret, the companion traditional model can explain the result.

Better models, more manageable and repeatable model processes, ongoing model performance modeling… It's easy to see how modernizing the model development process will reduce losses and operational risk.

Successes around the globe

Not surprisingly, banks have been the early adopters, but similar successes are emerging in all types of organizations around the world. By investing in an end-to-end, automated platform, organizations see productivity gains, faster model turnaround, deeper corporate knowledge, and faster and more accurate credit decisions. For example:

- An Irish retail bank with 70 percent of its loan bank in mortgages faced a spike in risk during a recession that slashed housing values by nearly 50 percent and led to a 16 percent impairment in its mortgage books. The bank used analytics-driven credit scoring with its marketing automation and campaign management system to make smarter debt management decisions. The bank forecast a 1 percent performance improvement – an estimated $3.1 million – from more targeted collections efforts.
- A South American bank in a country of economic and political crises wanted to differentiate itself by improving its credit risk and market risk evaluations. The credit department streamlined the process for developing and implementing credit models. The solution gets better models into production about a year earlier and is expected to reduce annual credit losses by 5 percent, or US$250 million per year.
- An Eastern European bank upgraded its collection processes based on deeper credit risk insights and increased claims recovery by 70 percent. A major debt purchaser in the UK found that it could sustain profitability even during lean times by more accurately assessing batches of debt and individual debtors.
- A US bank with assets of $1 billion was averaging credit losses of $25 million a year. Using credit scoring tools that improved model performance and reduced the modeling cycle from four months to two months, the bank was able to reduce those losses by 5 percent.

Closing thoughts

Bringing analytics, automation and governance rigor to credit scoring model development and decision delivery delivers bottom-line benefits:

- **Improve performance**. Develop more predictive models, and get credit insights to decision systems while the opportunity is at hand.
- **Automatically make the right decisions**. Combine analytics with decision logic to meet customer needs with the right credit proposition at the right time.
- **Optimize the consumption of valuable IT resources**. Empower business users to construct and modify the automated decision process without IT assistance.

Whether your organization relies on outsourcing – or uses internally developed systems built from traditional coding or a combination of niche products – consider moving up. Gain the advantages of an end-to-end approach with full integration and governance as a part of your digital transformation and risk management evolution.

SAS and credit risk management

Risk management is a core strength and top focus area for SAS. SAS® risk management solutions are deployed in more than 1,500 organizations in more than 60 countries. Ranked in 2018 as a top-five vendor in this category for the ninth consecutive year, SAS has also earned the distinction of being named by Gartner as a category leader for predictive analytics and machine learning (2018), real-time interaction management (2017) and data science platforms (2017), and by Chartis as a leader in model risk management (2017), enterprise stress testing (2017) and credit risk for banking (2018).

SAS solutions for credit risk modeling and decision making are delivered through SAS Credit Scoring, SAS Real-Time Decision Manager, SAS Decision Manager, SAS Event Stream Processing, and SAS Visual Data Mining and Machine Learning. These offerings support a seamless experience for the end-to-end processes of developing and deploying credit models, rendering decisions, monitoring and reporting.

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