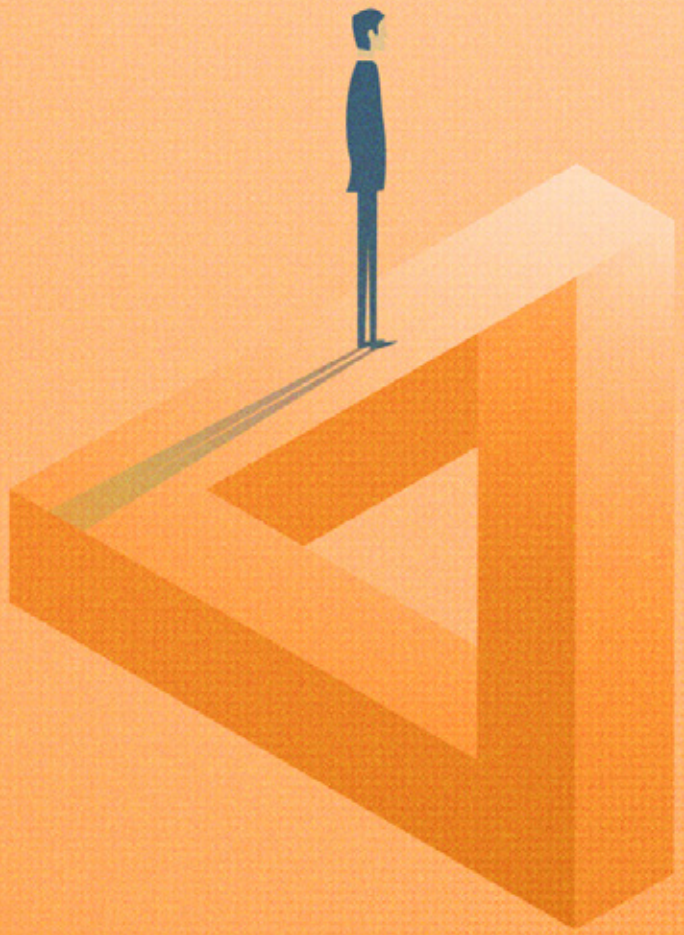
DataRobot

5 AI SOLUTIONS

EVERY CHIEF RISK OFFICER NEEDS





INTRODUCTION

"CONFUSION" MAY BE THE

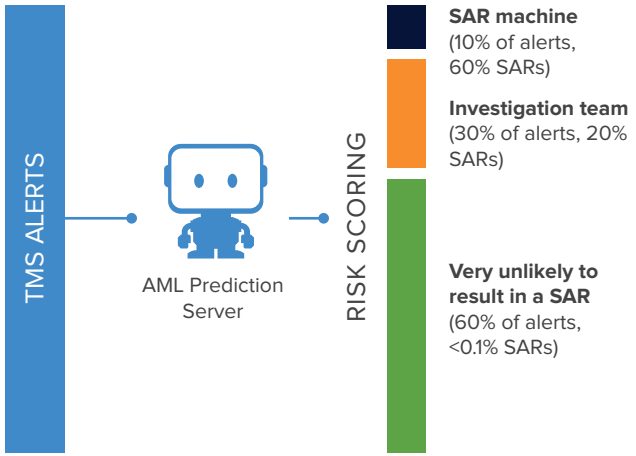
right term to describe the state of artificial intelligence (AI) in business today. Nobody really seems to agree on what AI is, let alone how it should be implemented in an enterprise like a bank. To some, AI is robotic process automation. To others, it's those little virtual assistants that show up in the corner of websites. In reality, though, AI is simply using a computer to perform some task that ordinarily requires human intelligence. It's a very broad definition, and it has very broad implications for any company that collects data.

For the risk manager, AI means greater efficiency, lower costs, and less risk. There are many potential applications of AI when it comes to managing risk in banking, but this report will focus on five key solutions with huge potential ROI that every chief risk officer (CRO) can begin building immediately. Representing foundational capabilities for risk management, these five solutions have the potential to substantially impact a bank's financial results, and an automated machine learning platform represents the most efficient and effective method of delivering on the promise of these AI use cases.



ANTI-MONEY LAUNDERING AND KNOW YOUR CUSTOMER

Every year banks spend millions of dollars on detecting, investigating, and reporting potential money laundering – and for good reason. It's not uncommon for regulators to levy fines for inadequate or lax anti-money laundering (AML) monitoring that exceed one billion dollars. Consequently, banks have created systems that are designed to generate huge numbers of alerts, all of which must be manually investigated and most of which do not result in Suspicious Activity Reports (SARs).



Transaction monitoring systems (TMS) are (mostly) rule-based systems that are designed to identify transactions that might be indicative of money laundering. These systems, which are designed to avoid missing potential money laundering (false negatives) at any cost, generate reams of alerts, forcing banks to spin up large investigative teams to handle all of them.

Machine learning models can be used to score alerts according to how likely they are to actually result in a SAR filing. The bank has complete control over how conservatively this system performs so that the number of false negatives can be reduced to near zero.

In addition, machine learning has the capability to explain how these predictions are made. Investigators can be told that not only does a transaction merit further investigation, but the models can also indicate the top drivers of that prediction, reducing time spent on investigations.

Machine learning also positively impacts a bank's Know Your Customer (KYC) process. Banking regulators provide little guidance in terms of what type of information banks should collect as a part of their due diligence. Machine learning can help banks determine which questions actually correlate with potential money laundering. This not only improves the process and increases a bank's ability to target the right accounts for heightened scrutiny, but it also gives them a quantitative justification for their processes that can be communicated to regulators.



FRAUD DETECTION/ PREVENTION



Losses due to fraud increase every year, with some estimates claiming worldwide losses to fraud as high as $200B in 2017. Despite the cost, many banks are either fighting fraud with antiquated, rules-based systems or with expensive, black-box vendor models.

Running a successful fraud solution means not only minimizing losses due to fraud, but also minimizing irritation and impact to existing customers. Blocking a legitimate transaction or placing excessive holds on a deposit may not result in a direct loss to the bank, but they still have a tangible, substantial impact in terms of customer satisfaction, retention, and churn.

Machine learning is the ideal solution for fighting fraud. By the very nature of the business, banks record mountains of relevant information about all types of transactions and their counterparties, and whether or not these transactions are fraudulent. This historical data is the foundation of the machine learning approach.

Machine learning models can predict which checks are likely to be bad, which ATM deposit envelopes are likely to be empty, which loan applications are likely to be based on identity fraud, and which point-of-sale transactions are likely to be fraudulent. Implementing these models can prevent millions of dollars in losses to fraudsters.

Be aware that implementing and monitoring fraud prevention models will require modification of core systems within a bank. Making changes to these systems may give even the most veteran CTO heartburn. In addition models must be monitored for accuracy over time, as new types of fraud emerge and the models age. In spite of these complexities, however, the increased accuracy that machine learning provides far outweighs the cost of implementing these new solutions.



STREAMLINING MODEL RISK MANAGEMENT



of respondents identified documentation that is incomplete is the largest barrier for validation timelines.

The Federal Reserve requires banks with assets greater than $50 billion to independently validate the models they build, causing these large banks to create elaborate model risk management teams to review and approve every model built within a bank.

Part of the reason that model validation is so difficult is that most models today are custom-built by hand. Data science teams—and validation teams—don't have the well-established testing and quality control measures in place that software development teams have built over the past several decades.

Another reason for the challenge is documentation. A recent survey conducted by McKinsey & Company found that of the leading financial institutions, 76 percent of respondents identified documentation that is incomplete or of poor quality as the largest barrier for their validation timelines.

Following a systematic and unbiased approach to model building is key to a sustainable model risk management practice. Model developers must be disciplined in the way models are developed and must utilize tools to make the process more reliable and consistent. These same tools should also make the documentation tasks easier, providing interpretability and insights that speed documentation for regulators. These new technologies make safely developing highly-accurate models quicker and easier. Both model developers and model validators must be open to utilizing these new tools.



CREDIT RISK & LOSS FORECASTING

New financial accounting standards are based on an “expected loss” method. Unlike the incurred loss method that is based on backward-looking loss rates, the expected loss method applies when the loss has not yet occurred, but its occurrence is probable. In other words, the loss of future-flow is expected with some probability and must be estimated. Machine learning provides the most robust framework for producing highly accurate and transparent expected loss predictions.





CREDIT RISK & LOSS FORECASTING

The new expected loss standards require that banks use information about past events (i.e., historical data) and "reasonable and supportable" forecasts when estimating expected credit losses. Although this is a huge change to the current incurred loss standards, it also provides a unique opportunity because the new standards do not prescribe how lenders choose to make the estimate, but only that the forecasts must be "reasonable and supportable." This gives banks the flexibility to implement the best models and methodologies to forecast expected loss for their portfolio, as long as the forecasts can be proven to be reasonable and supportable.

Accurate and transparent models for predicting expected losses should be at the core of successful compliance programs. Machine learning models detect the patterns in a bank's historical data in order to accurately estimate credit losses, and these models are no longer black boxes. Modern tools allow stakeholders to understand how these models work in a detailed way, including why individual predictions were made. Not only is this useful from a compliance perspective, but also from an underwriting and portfolio management perspective.

Granular credit loss models are also the foundation of good risk adjusted pricing. Pricing inefficiencies —overpricing or underpricing risk—can easily be spotted by predicting the expected loss at a given price. Overpricing may indicate potential for volume growth, and underpricing may indicate the need for adjustment in policy or risk selection. Superior pricing analytics may also identify market pricing inefficiencies, including opportunities to acquire portfolios where risk is overpriced or opportunities to originate and sell portfolios where risk is underpriced.

1913	**Federal Reserve Act**	Federal Reserve Bank created
1921	**Revenue Act**	Standards for reserving for bad debts
1934	**Securities Exchange Act**	SEC established
1965	**Loan Loss Estimation**	Process established
1973	**FASB**	Financial reporting standards established
1976	**ALLL**	Banks with assets >$25M required to report loss allowances
1993	**GAAP**	Interagency Policy Statement on the Allowance for Loan and Lease Losses
2000	**OCC 2000-16**	Guidance on managing risks arising from models
2011	**SR 11-7**	Guidance on Model Risk Management
2016	**CECL**	Restructuring of ALLL to account for lifetime loan losses
2017	**TRIM**	Guidance on the reduction of unwarranted variability in model risk management
2018	**IFRS-9**	International standards for credit impairment and loss forecasting



TARGETED RISK REVIEW

Risk review functions have moved beyond their traditional "loan review" scope and are now looking at risk holistically – credit risk, operational risk, compliance risk, etc. As a result, risk review teams now focus less on transactional risk and more on process and controls.

Very few risk review teams, though, are leveraging machine learning to improve the quality and efficiency of their work, but they should. Machine learning can guide field work based on business mix, risk metrics, and past reviews of similar areas.

Control weaknesses may be identified by the number and type of operational errors or client complaints, and process problems may be identified by deterioration in risk metrics.

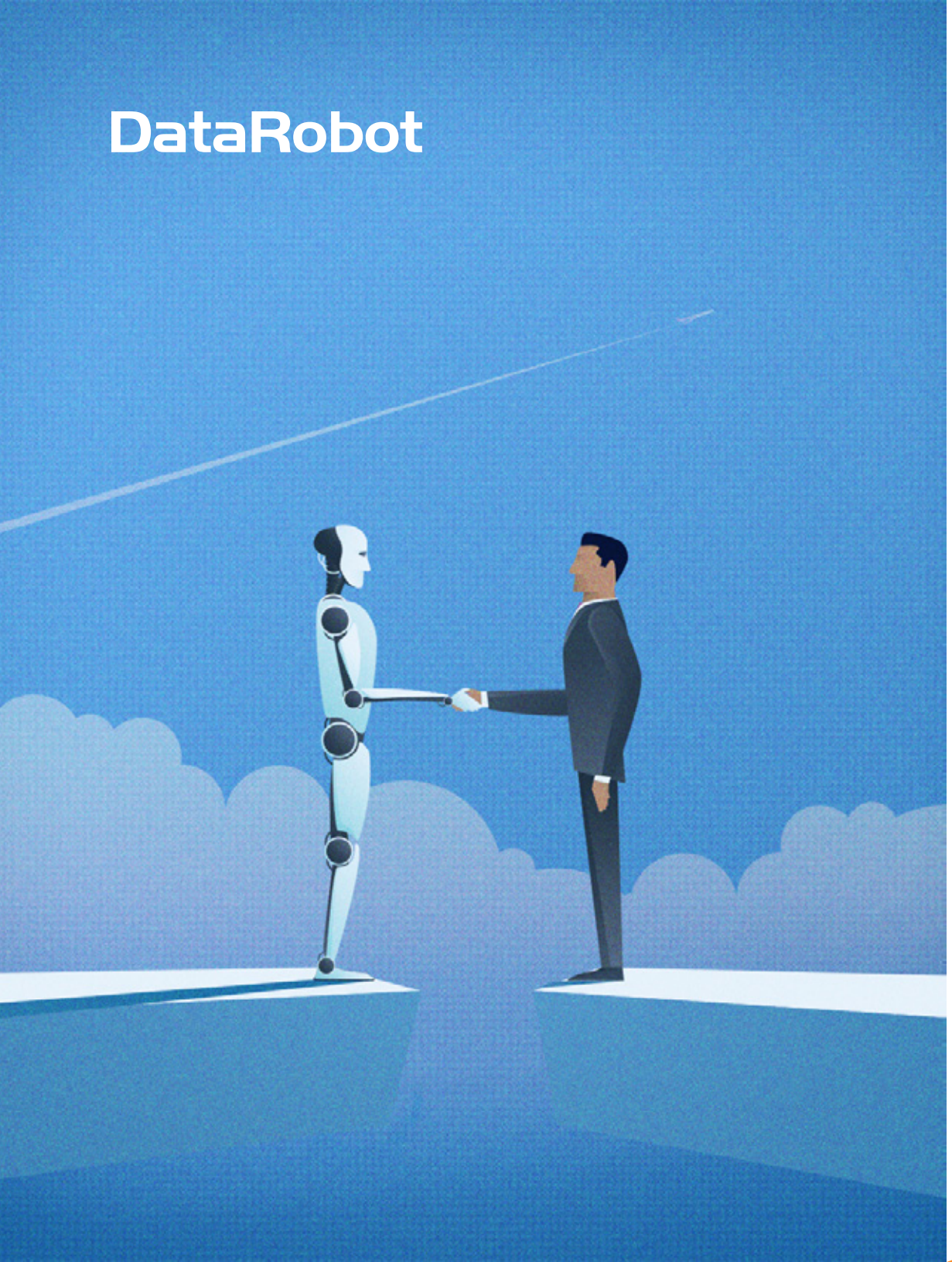
OPERATIONAL RISK: Identify potential control weaknesses using error rates, historical operational data, and client complaints as well as new business volumes, employee turnover, client attrition rates, and operational risk metrics

COMPLIANCE RISK: Predict policy exception levels based on historical trends, product mix, control self assessments, audit findings

CREDIT RISK: Predict risk levels across a lending unit and identify pockets of higher or rising risk using delinquency, risk rating, collections data, and external risk indicators

Risk review management uses the historical findings of their teams, along with risk metrics of all kinds, to identify significant or escalating risks, plan their reviews, and allocate their resources optimally.

Risk review teams constitute a key part of the third line of defense – assuring bank management and bank boards that no significant risks go unnoticed, unmitigated, and unmanaged. By utilizing machine learning, these functions can be made smarter, faster, more effective, and more efficient.



CONCLUSION

THESE FIVE AI SOLUTIONS

represent some of the key use cases that any risk organization must pay careful attention to, but they are far from an exhaustive list. In fact, most organizations find that work in any of these areas results in both a strong ROI and also in an explosion of other potential opportunities.

DataRobot has helped many regional and global financial institutions build their capability and capacity to build AI solutions. DataRobot's automated machine learning allows organizations to increase their capacity and speed-to-market without having to scale or build expensive data science teams. By combining modern machine learning technology with automation, transparency, documentation, and flexibility, DataRobot enables banks to increase revenue, drive down waste, and reduce risk.

SIGN UP FOR A FREE TRIAL TODAY TO FIND OUT HOW DATAROBOT CAN HELP YOUR ORGANIZATION.

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