Emirates NBD

KPMG

Anti-Money Laundering/Financing Terrorism Compliance Risk Rating:
A Data Science Approach

January 2022

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ABBREVIATIONS

USD	Unites States Dollars	**CXM**	Customer Experience
GDP	Gross Domestic Product	**RBA**	Rule Based Approach
AML	Anti-Money Laundering	**SAS EG**	SAS Enterprise Guide
ML	Money Laundering	**VARCLUS**	Variable Clustering
CBUAE	Central Bank of United Arab Emirates	**ML/FT**	Money Laundering/Financing Terrorism
FIs	Financial Institutions	**IV**	Information Value

Executive Summary

The Anti-Money Laundering ("AML") landscape is witnessing a period of considerable change as financial institutions ("FIs") face significant disruption to traditional risk management methodologies.

We are living in the era of the digitization—particularly among banks. The swift evolution of technology is leading to an explosion in the number and volume of transactions, growth in electronic payment methods, and cryptocurrency development. The introduction of new technologies implies increased sophistication in criminal methods of laundering money. To tackle this, most financial institutions are aggressively resorting to increased transaction monitoring in real time and enhanced due diligence of more customers.

This whitepaper focuses on how anti-money laundering processes at banks and other financial institutions can be made more efficient by leveraging the power of data analytics.

The ever-evolving regulatory landscape expects banks and FIs to be more vigilant than ever with customers and their funds. Banks spend millions of dollars every year on support functions – compliance, operations, etc. However, there has been little tangible progress in the battle against financial crime.

AML continues to be a key focus area for regulators across the world. An estimated USD 2 trillion is laundered annually through the global banking system, translating to roughly 2-5% of the global GDP.

Globally, regulatory actions have increased nearly fivefold in the last 10 years.   As per Finbold's recently published figures on fines issued in 2020 on account of AML breaches, the figure stands at USD 14.1 billion.

In early 2021, the Central Bank of the UAE (CBUAE) imposed financial sanctions on 11 banks in the UAE for failing to achieve appropriate levels of compliance relating to AML guidelines and framework.2

Managing ML risk is no insignificant task. However, this directly leads to increased manual intervention, resulting in an inefficient risk management landscape.

FIs are increasingly re-evaluating their traditional AML risk assessment methodologies through the deployment of sophisticated technologies, which utilize the power of robust advanced analytics techniques. The key benefits of deploying such methodologies include reducing 'noise' to focus on real high-risk customers and transactions, decreased operational costs due to the smaller number of customers for high-risk review, a better capture rate of bad customers, enhanced efficiency of AML processes, and ultimately, improved customer experience.

While advanced data analytics-based customer risk assessment frameworks are sophisticated and competent, it is only a first step towards leveraging advanced analytical models for AML risk management. As models are implemented, detailed processes must be designed to support the risk landscape, as shown by the models. Ongoing efforts must be made to enhance these models further, by integrating advanced techniques such as network analytics and link analysis to augment their predictive power and make processes more robust.

1. Challenges

Some of the key challenges banks face in battling financial crime include:

Complex AML Regulatory Requirements:

Compliance regulations across the globe are not consistently applied within banks and FIs, impacting the efficient implementation of policies and frameworks. However, this is key to the deployment of effective controls and protecting the financial services industry from the increasing threat of financial crime.

Wider Remit of AML Compliance:

Regulators across the globe are putting banks and FIs on the front line in the fight against financial crime, with increasingly rigorous compliance requirements for monitoring non-traditional customer profiles, which may posed increased risks for banks.

Innovative Financial Crime:

The financial crime landscape is constantly changing, with criminals finding new ways to commit crime via new technology, channels or products, i.e. mobile banking, digital currencies, etc.

Technology Limitations/Legacy Systems: Banks struggle to comply with these increased regulatory compliance expectations on account of manual processes and legacy technologies that no longer keep pace with the huge volumes of data being produced and the complexity of the global banking environment.

Operational Challenges Posed by the Pandemic:

With compliance teams still largely working remotely in many jurisdictions, updating systems and practices may be problematic. This may be particularly true in terms of knowledge transfer and onsite discussions, given the large volumes of sensitive data involved in AML compliance work.

Increasing Cost of Compliance:

Despite a variety of systems and technologies built in to investigate financial crime alerts, there is a constant backlog of pending reviews. An instant response by banks to a dynamic regulatory environment is to invest more in manpower and ramp up manual efforts to quickly tackle the current demands.

2. The Need of the hour

Adapting new technologies, particularly in areas of automation, can help banks fulfil their obligations. At a time, where most regulators are emphasizing a risk-based approach rather than a rule based one, such technologies become even more crucial.

FIs hold vast amounts of data that can aid in curbing financial crime. However, traditionally, this data is held in fragmented areas and systems, and FIs have not been able to utilize the power of this information. Advanced data analytics allow FIs to be smarter about how their information can be utilized to drive better outcomes.

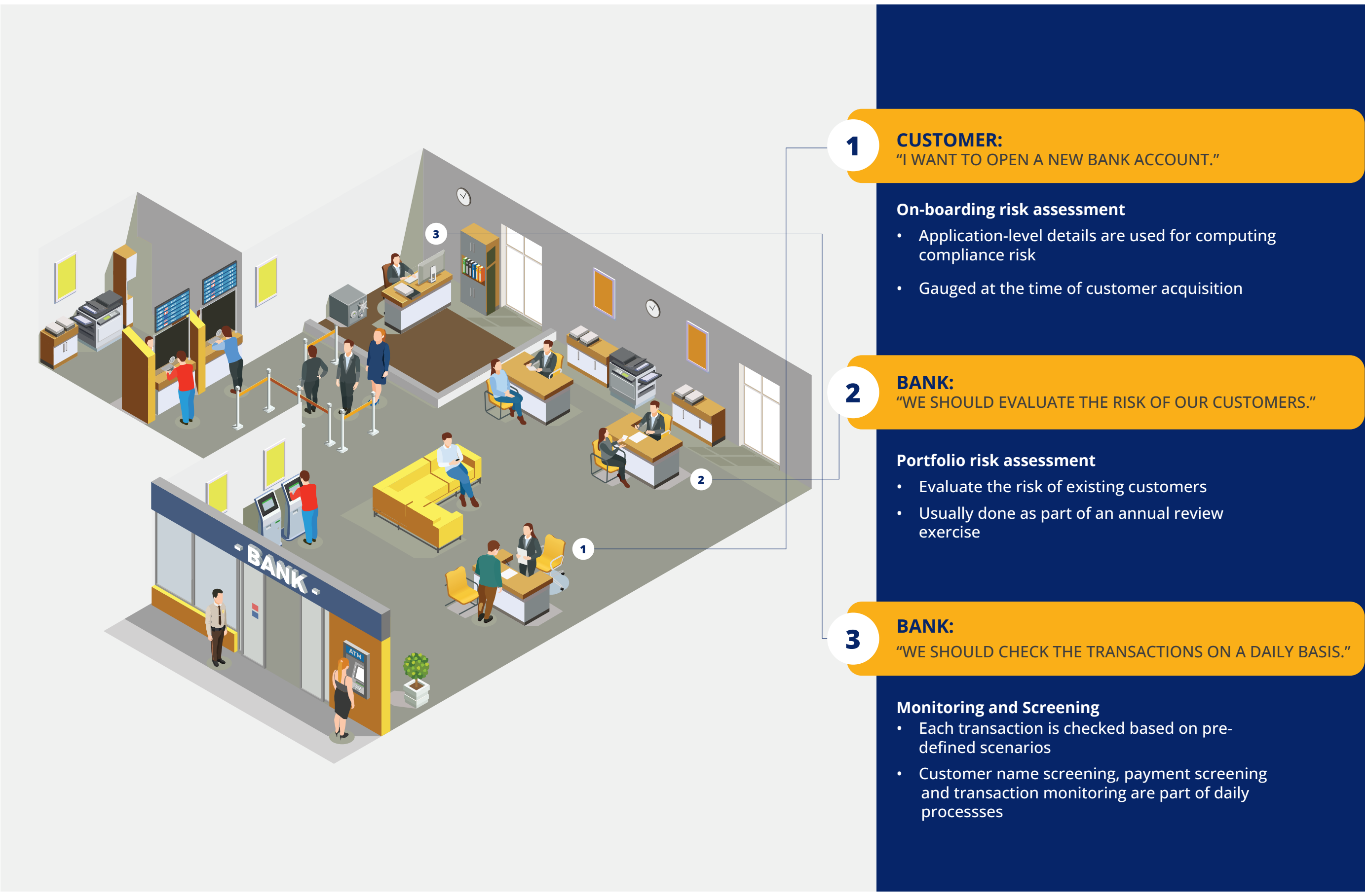
This allows an enhanced customer experience across relationship lifecycles. For example, long review processes which are often a result of a higher number of false positives generated by traditional monitoring processes leads to low customer satisfaction levels. Therefore, data and analytics intelligence must be synergized to improve the efficiency of AML processes. Robust analytical methods help in reducing cost, mitigating ML risk, and improving customer experience.

3. Identifying Opportunities in Customer Risk Assessment Processes

Customer screening is a vital step to determine the risk of money laundering/terrorism financing associated with each customer. Thus, it is important that the risk assessment framework is robust and in line with the bank's risk appetite and simultaneously adheres to the regulatory classification, type of products and services, etc. collected during customer onboarding. Often, a popular rule-based approach is defined based on experience for risk classification. This traditional approach isn't failsafe. As the intricacies of AML guidelines increase, it leads to an increased number of cases for manual review.

There are two ways in which such scenarios can be handled using data analytics.

Figure 1: The compliance lifecycle of a customer



Risk Identification:

Regulators encourage FIs to use a variety of risk factors when assessing customers' ML risk. While the existing (traditional) rule-based methodology covers the essence of regulation requirements, it lacks the following:

- **For new-to-bank customers:** Traditionally utilized risk factors can be augmented with statistically derived attributes created by a more meaningful combination of features/variables.

- **For existing customers:** The traditional approach of risk assessment can be made more dynamic by incorporating account activity and transaction behavior of customers. It can further be improved by including alerts and triggering data from other transaction monitoring systems.

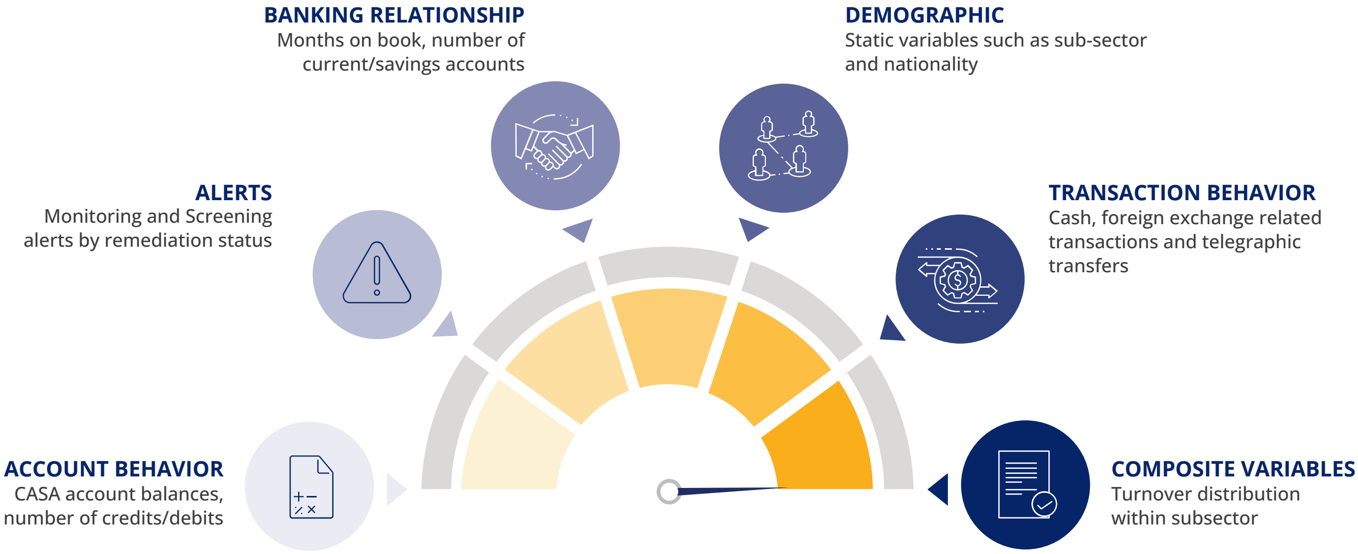
- By creating a scoring framework, a detailed web of risk factors was derived for new customers based on data collected at the time of sourcing. On the other hand, all possible types of data related to customer behavior that dynamized the risk identification process were included.

Risk Assessment:

Most banks currently use a Rule-Based Approach (RBA) to compute ML risk. These traditional methods are logically sound; however, they are infamously known for incorrectly classifying too many customers as high-risk, leading to customer resentment and eventually closing the relationship. A deep dive into this approach reveals two main areas of improvement:

- **Static risk factors:** The approach frequently uses static attributes to monitor risk. Factors used to analyze an existing customer's risk should focus more on the customer's transaction behavior with the bank, than demographic attributes (industry, estimated turnover, etc.) collected at the time of onboarding.

Figure 2: The Assortment of Variable Categories for Model Development



- **Weightage for risk factors:** There is weightage assigned to each factor used in the RBA, that indicates the importance of its corresponding factor. This is a primary cause for misclassification and a high number of false positives, which eventually has a negative impact on customer experience.

Based on these findings, an advanced risk rating methodology and scorecard framework was designed to fill in the gaps in risk identification and assessment methods of the RBA. Key areas around which this scorecard framework was designed include:

- Leveraging dynamic risk factors wherever possible.
- Using a more scientific approach—deploying statistical analysis to choose most predictive risk factors, assigning weights to each attribute, and computing a regression analysis driven final ML risk score.
- Continuously updating risk scores based on the most up-to-date information available in the systems.

4. Emirates NBD's Approach to Developing a Scoring Mechanism

To come to grips with advancing technologies, FIs need to develop data driven and agile solutions.

A vast amount of data from various systems was combined and analyzed to design a statistical scoring framework that addresses the risk assessment requirements at different stages of a compliance lifecycle. The scorecards, developed in addition to the techniques and tools used, are described in subsequent sections in detail.

4.1. Application Scorecard

As the name suggests, an application scorecard assigns a score to the customer at the time of acquisition. Like a typical credit risk scorecard, it utilizes information captured in the application form and other documents collected from the customer at the time of onboarding, to assign a weighted score that reflects the ML risk associated with the customer at the time of onboarding.

Analysing information captured by Emirates NBD in its operations, around 150 such customer features were identified in the application form for non-individual and individual customers. This information was used to create composite features, which are powerful predictors of customer behavior. For instance, the initial deposit was combined with industry risk to compare the deposit amount of a customer with their peers in the same industry. If the deposit was not in line with the industry peers, the customers were penalized when assigning a score. A combination of raw and composite attributes was then used to design a multi-variate scoring framework. Once each customer application was entered into the system, a framework assigned a final score based on multiple scoring attributes. The score was categorized into three risk groups—high, medium, and low—based on pre-decided score cutoffs. A separate level of due diligence was performed based on the assigned ML risk category. This type of framework resulted in a targeted approach, focusing the reviews/actions based on the right risk categorization, reducing time taken and manual effort.

4.2. Behavior Scorecard

A behavior scorecard is used to assess existing customers' performance. ML risk among current customers can be better calculated by assessing their behavior with the bank post onboarding. For this reason, multiple factors related to account/transaction behavior were analyzed along with the static attributes.

Attributes such as amount of cash deposits, annual turnover, amount/frequency of transactions in high-risk countries, and adversely closed alerts from other transaction monitoring systems were added to the model.

Apart from direct variables, many composite attributes were also defined. For instance, customers' total amount of transactions were compared with their industry peers to identify outlying patterns. A variable that combines the number of alerts and transactions in high risk countries was also incorporated into the modeling base.

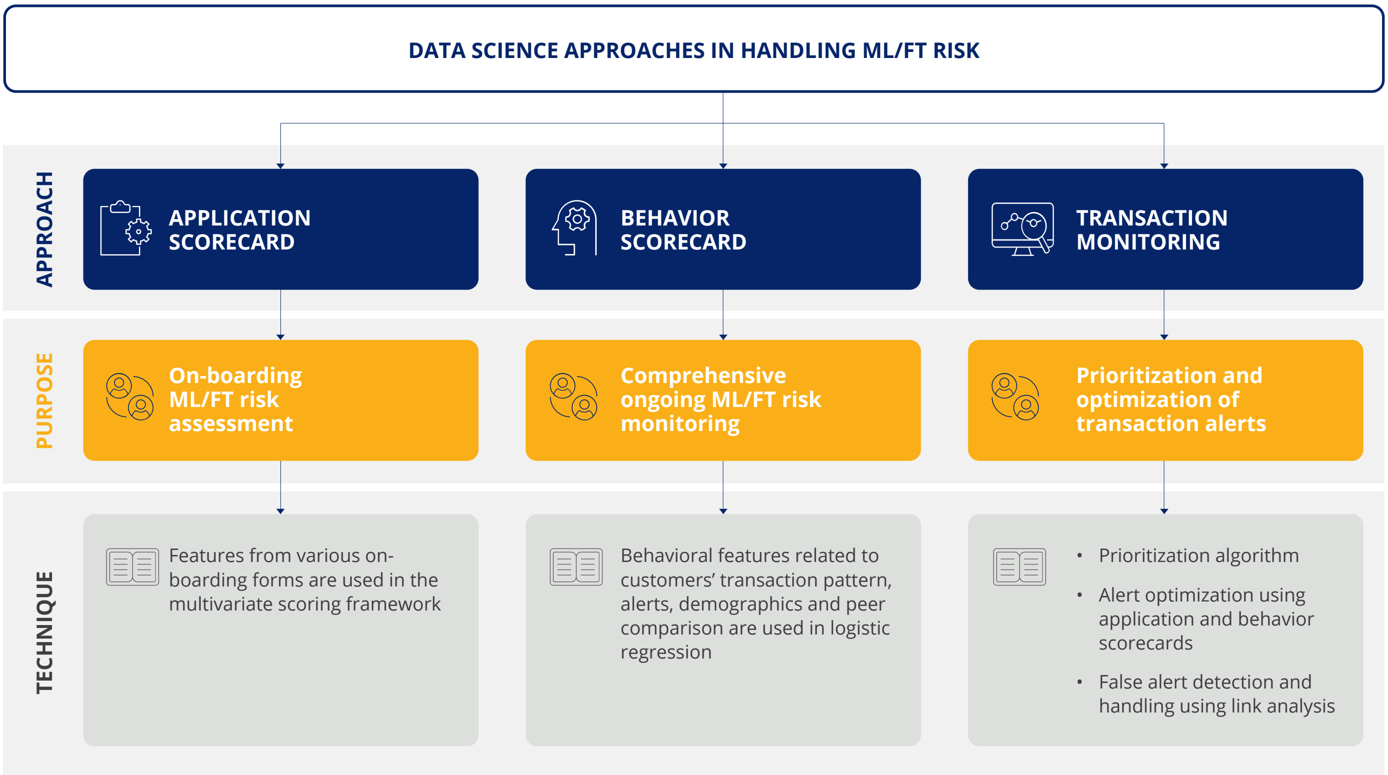
More than five hundred raw attributes and ratios were added to the modeling base. Logistic regression was run to formulate a final modeling equation that assigned a behavior score at the customer level, based on final model attributes. A low score implies higher chances of a customer performing a suspicious transaction in the coming months.

A behavior score derived in such a way is comprehensive as it looks at a variety of demographic and behavioral factors before assessing customers' ML risk.

4.3. Transaction Monitoring

Every bank customer goes through daily transaction monitoring systems, where in-built scenarios trigger alerts on certain transactions which are deemed high-risk, based on empirical observations. Depending on the size of the bank, millions of transactions go through this process every day, making it tedious. Often, the number of scenarios defined increases with regulatory requirements. This ultimately leads to the generation of a high number of alerts for manual review. Also, the magnitude of the task is such that scenarios cannot realistically capture all suspicious transactions, leading to a high number of false positives.

Figure 3: Data Science Approaches in Handling ML/FT Risk



To improve this process, an alert rationalization exercise was pursued wherein all historical alerts were analyzed for predictive strength. An attempt was made to improve the predictive strength of alerts where false positives were significantly high. The behavior score of existing customers and the application score of new to bank customers were leveraged in conjunction with each scenario to improve predictability.

Apart from improving the quality of alerts, transaction monitoring process improvement was recommended by suggesting the prioritization of multiple alerts based on the severity and predictive capability of each alert.

5. Techniques and Tools Used

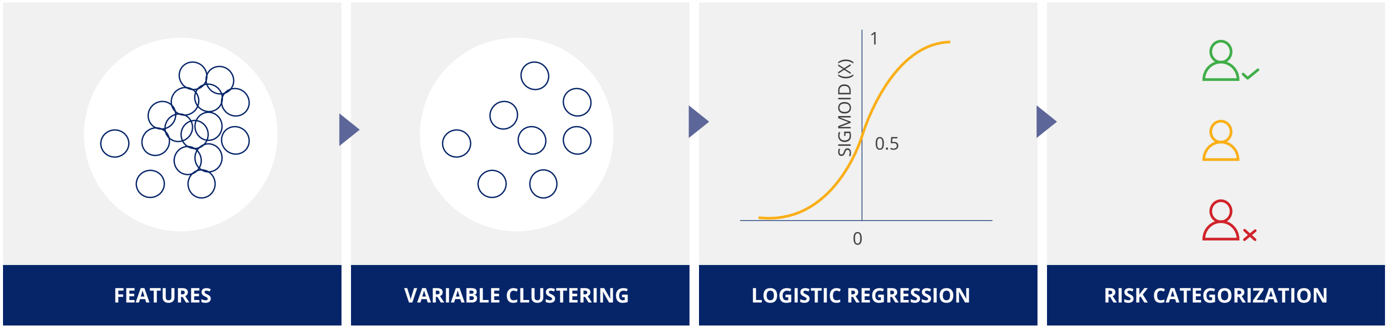
A variety of techniques were used for variable shortlisting, building scorecards, and transaction monitoring. All models were developed in SAS E-Miner or SAS EG.

Scorecard variable shortlisting (based on missing percentage and IV) and grouping were carried out in SAS E-Miner using the Interactive Grouping node. After the first level of variable reduction, all remaining attributes were further shortlisted using the Variable Clustering node in E-Miner. The most predictive attribute from each cluster was shortlisted and used in a logistic regression equation with a stepwise regression method.

For alert rationalization, sensitivity analysis was performed in SAS EG to revise the thresholds for various trigger scenarios.

A brief description of all the techniques used in the scorecard development and alert rationalization process is provided below.

Figure 4: Techniques in Categorizing ML/FT Risk



Cluster Analysis.

Multiple variable categories were defined for each scorecard. Around 500+ attributes were created at a customer level using business logic.

Variables were shortlisted based on their predictive strength before running a regression. Subsequently, a clustering process was used to identify homogeneous groups of attributes amongst which the best attribute was used for regression model development.

The VARCLUS procedure in SAS E-Miner was leveraged for variable reduction. This procedure divides a set of variables into disjoint hierarchical clusters. A linear combination of variables is associated with each cluster. However, for modeling purposes, the 'BEST VARIABLE' option was used to shortlist the final set of attributes. Alternatively, IV of each attribute can also be mapped to the cluster output and the most predictive variable from each cluster can be selected for model development

Logistic Regression.

This is a typical parametric classification technique. Logistic regression technique was used for model building since the prediction problem is binary in nature – customers will or will not perform an ML/FT-related activity.

The dependent variable is either 0 or 1. The binary logistic regression was run to predict the probability of a customer doing an ML/FT-related transaction. To do this, the regression equation first calculates the odds of that event happening across all independent attributes. The logarithm of odds is then computed to transform the dependent variable into a continuous probability.

$$l = \log \frac{\mathrm{p}}{(1-\mathrm{p})} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

Where β_i are model parameters and l is the log odds.

Each customer is rank-ordered from high to low probability of carrying out money laundering or a suspicious transaction. The threshold for different risk levels is then decided by grouping the riskiest customers in a way that the maximum number of bad customers are captured above a certain level of probability.

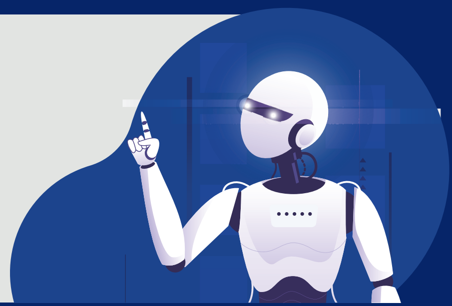
Sensitivity Analysis.

To optimize the quality of alerts, each alert was complemented with customer-level scores, based on the stage of the customer lifecycle. To further improve the predictability of some alerts, the thresholds were revisited for the lowest-performing alerts. Each threshold was then marginally increased and reduced by a few percentage notches to assess improvements in the percentages of bad customers captured. By doing so, alerts were prioritized based on the associated risk level, optimizing the utilization of resources in handling the alerts.

Regulatory Guidance.

In addition to selecting the best parameters through statistical analysis, it is important that all local and international regulatory guidance is considered on a regular basis to ensure that models are compliant with these guidelines. The guidelines give a broad level of indication on the type of compliance risk parameters that can be considered by banks and FIs, based on local and international benchmarking and research. It is essential to consider these factors when assessing the most significant parameters for a bank based on its internal data.

KEY DIFFERENCES BETWEEN TRADITIONAL AND STATISTICAL RISK ASSESSMENT



TRADITIONAL METHOD

TRANSACTION RISK

Each transaction goes through monitoring systems

Pre-defined scenarios trigger alerts for certain transactions

A case for investigation is created for alerts

PORTFOLIO RISK

Static information is collected at the time of on-boarding

The information runs through a manually calibrated model

High risk customers are pushed for annual review

ON-BOARDING

Application-level data runs through a rule-based model and is used for the risk segmentation of each customer

STATISTICAL METHOD

TRANSACTION RISK

The case for investigation is created for alerts

Alerts are prioritized based on efficacy and empirical ratios

Pre-defined scenarios are enhanced using A/B score

After 12 months are completed on the books, the risk ratings of customers are updated based on their behavior score

Due diligence is enhanced for high-risk customers

Behavior score is used to risk rate and group customers

Customers' demographic information is combined

PORTFOLIO RISK

A score-based risk rating is stored in the system for future reference until customers complete 12 months on the books

More documents are collected to proceed through standard process

Upfront rejection and high risk customers are pushed for due diligence

ON-BOARDING

Application-level data is used to compute a score and risk rate customers

6. Benefits

Introducing analytically driven and advanced practices can lead to numerous quantifiable and immeasurable benefits. Some of these are specified below.

Insightful Data.

With improved data quality and well-defined data sets, decision-makers can view large amounts of customer data through an interactive and intuitive interface, making it easier to identify visual patterns and inconsistencies.

Operational Efficiency.

With an analytically strong customer risk assessment program, banks can alleviate the risk of getting high volumes of alerts by narrowing the parameters. This can bring consistency to alert reviews for the vast majority based on pre-fed rules in the analytics program, and better utilize experienced professionals to review outliers.

Comprehensive Risk Assessment.

Using a multi-variate approach allows for a comprehensive risk assessment for each customer as it combines varied and most predictive risk factors into one score. A holistic approach like this can also be easily scaled up to accommodate any changes in the regulatory requirement with ease. For example, within traditional high-risk customer profiles, contingent rules on customer account activity, such as those dealing in high risk sectors, can be utilized to extract financial crime risk exposure across customers.

Better Risk Mitigation.

By introducing statistical logic, all redundant and correlated risk factors can be dropped from a manual risk rating model. Mathematical models also help in assigning an optimal weight for each risk factor. This improves the predictability of statistical models, making them more robust, consistent, and reliable.

Management Oversight and Governance.

With the right set of tools, banks can implement appropriate governance, oversight, and accountability frameworks. This allows the board of directors and senior management to have better oversight and control in addressing the compliance risk associated with customers through analytics-driven decisions, rather than relying on judgment and discretion.

Reduction in AML Cost.

While maintaining the required standards, controls and effectiveness, AML processes have always been manually driven. These manual efforts cannot be negated completely from certain sensitive tasks, e.g. reviewing potentially risky customers. By providing a smaller but more selective set of customers for risk review, an FI can benefit from reduced AML cost and higher efficiency. These models help in identifying the right set of customers for annual review—reducing the population under review by 30% and capturing an additional 57% bad customers.

Minimize Reputational Risk:

Failure to comply with regulatory guidelines and/or preventing money laundering activities financially damages the reputation of large FIs. Having stringent, robust and flexible AML processes, which are powered analytically, can ultimately mitigate reputational risk.

Enhanced Customer Experience:

Investing in advanced analytics for improving AML procedures leads not only to a review of fewer customers, but also the right set of customers. This means that onboarding time will improve significantly for less risky customers and that periodic and trigger reviews will be more precise. Ultimately, this should translate into a better customer experience.

7. The Way Forward

With data at the heart of AML and compliance functions within banks, data analytics-driven tools can be used to prevent other financial crimes, notably:

Transaction monitoring: Traditional rule-based monitoring, leading to 95% of false positives, can be eliminated with big data analysis. By integrating data from multiple sources (customer profile, risk assessment, legacy information, other available financial transaction data, including clients' financial records, if available—into a single big data platform) the accuracy of analytics and its predictive power can be increased.

Sanctions screening: As global sanctions regimes across the globe gain complexity, compliance with such sanctions does not get easier. With increasing global attention on sanctions compliance, process efficiency may be obtained by building robust technical infrastructure that can generate accurate results.

Third-party risk assessment: A cost-effective solution to eliminating third-party risk can be arrived at by gathering credible data and analyzing information, via multiple disconnected software systems, using a tool that can collate data from multiple sources and give accurate insights.

- **Regulatory reporting** – Banks will be able to obtain and analyze comprehensive, quality data about their customers, and screen them against sanctions lists provided by authorities for each country in which the bank operates.
- **Global compliance** – Where a bank has operations across jurisdictions, a lack of consistent AML regulations in different locations may lead to compliance gaps. With data analytics, the bank can comply with regulatory requirements and synergize the data gathering process better

Periodic Monitoring of the Models:

With time, the performance of any scorecard may deteriorate, owing to factors such as changes in portfolio composition, transaction patterns, economic situation, or policies that can impact onboarding drastically. Hence, it is imperative that all scorecards are regularly monitored for deteriorating performance. If such a change in predictive capability is observed, then the scorecard must be redeveloped to improve performance. Regulatory requirements can also prompt the redevelopment of the scorecard. Constant monitoring and reporting of scorecard performance are therefore necessary.

Using Data Science.

Network science tools are more powerful than any statistical model. They help expose links in transactions that cannot be revealed by analytical models, such as regression. Cases where multiple customers are transacting to a single vendor or customer to avoid detection by traditional, rule-based methods on transaction thresholds, may be unmasked using link analysis.

However, measures can be taken to use machine learning techniques, such as link analysis and network science, and integrate them with the existing scorecard framework. This has the potential to increase the predictability of transaction monitoring and other trigger review procedures.

8. Looking Ahead

Amid the increasing sophistication of money laundering schemes, transforming AML processes is an ever-evolving process. Coping with regulatory requirements and fighting financial crime by deploying sophisticated techniques should be a top priority for FIs. These can lead to an increased capture rate of bad customers, reduced compliance costs, and an improved customer experience. Managing money laundering risk is a journey. It is imperative organizations exert every effort to use more advanced analytics and stay ahead of crime.

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ABOUT EMIRATES NBD'S CUSTOMER INTELLIGENCE & ENGAGEMENT UNIT

The Customer Intelligence & Engagement (CIE) unit at Emirates NBD Dubai is an Analytics, Business Intelligence and Digital Marketing function that supports various business units and segments to lead initiatives in the areas of portfolio growth, customer experience enhancement, revenue maximization, cost optimization, marketing campaigns and digitization of banking.

We would like to extend our appreciation to the members of the KPMG team for their guidance and contribution to the whitepaper.

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ABOUT KPMG

KPMG's Risk Consulting practice helps organizations apply a risk lens to corporate strategy. Our solutions include Anti-Money Laundering, Sanctions and other Compliance risk models' development and validation. KPMG's team combines subject matter knowledge with expertise in statistical model development and validation. We support clients across the financial community to achieve robust risk management frameworks that satisfy compliance demands and regulatory requirements, contributing to better decision making and enhancing performance.

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ACKNOWLEDGEMENTS

The Compliance Scorecard framework was developed by the Analytics, Compliance and Governance teams at Emirates NBD. In addition, we are grateful to Suvo Sarkar (Head of Retail Banking and Wealth Management), Victor Matafonov (Group Chief Compliance Officer), Vikram Krishna (Head of Group Marketing & Customer Experience), Michael Sai Chung Wong (Head of Financial Crime Compliance), Ashish Rathi (Head of Business Support and Governance Wholesale Banking), Shekhar Krishnamurthy (Head of Retail Banking Strategy), Essa Ali Obaid (RBWM Governance), Reny John (Head of CDD and Deputy MLTFRO), and Venkat Rao for their valuable feedback and support. We would also like to thank, Akshay Sandhu for designing the paper. Joe Cyriack, Ashwin Georgy and Joby Jacob and the members of the CIE Data & Analytics team for orchestrating the development and implementation of the compliance scorecard framework at Emirates NBD.

We would like to extend our appreciation to the members of the KPMG team for their guidance and contribution to the whitepaper.