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A Temenos white paper

The Explainable AI Approach to Sanctions Screening

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Introduction

Sanctions are an integral and important lever used by governments and global institutions like the United Nations, the Office of Foreign Assets Control and the European Union to fight financial crime. Based on the global social, security, economic and political climate, these organizations can issue sanctions and restrictions directed at states, individuals, high-risk groups, or legal entities suspected of being involved in illicit activities.

Developments in sanctions screening, especially in recent years, are driving banks' urgency to accelerate the modernization of their sanctions screening approaches, and increasingly banks are looking to Artificial Intelligence (AI) as the game-changing and innovative way forward to cope with these changes and uncertainties.

This whitepaper focuses on the driving forces behind banks' sanction screening modernization efforts, and the approaches and reasons behind successful applications of AI in these modernization initiatives, as well as the understanding of the ensuing financial and qualitative business benefits.

1

Increasing importance of sanctions screening in the fight against financial crimes

In line with the global effort to fight crimes and as required by their central banks and governments (it is a criminal offence not to comply in most jurisdictions), banks' principal objective of using sanctions screening is to prevent transactions to and from entities/individuals/countries on sanctions lists. Sanctions screening is done as part of Financial Crime Compliance (FCC) program to help identify sanctioned persons and organizations, as well as unlawful conduct. It aids in the identification of areas that may be subject to fines and the formulation of compliance risk policies.

We have seen in the news recently that banks have faced hefty fines, such as to the tune of USD 1.5B and USD 1.2B by a German and a British bank respectively, based on the severity and impact of their screening lapses. Driven by the significance of these financial and reputational costs as well as repercussions, most banks have geared up on their sanctions screening improvements and nominated them to be among their top initiatives.

Another aspect which has been witnessed in the Russian-Ukrainian war that resulted in additions of large number of entities and individuals to the sanctions lists is the explosion of sanctions screening to unmanageable levels in most banks all over the world.

2

Growing sanctions list, complexities, and cost of sanctions screening in banks

Banking has seen unprecedented growth in digitalization that was further accelerated by the recent lock downs due to the pandemic. This has led to increased banking activities and transactions across all regions, business segments, and, unfortunately, innumerable new channels for illicit exploitations. Proactively, regulators are getting stricter and applying heavier fines on banks for compliance lapses, while, at the other end, insidiously, criminals are becoming more sophisticated in their tactics that attack and damage banks' reputation. Added to all these with current political climates, the pace of sanctions list increase has been accelerated, with the recent Russian Sanction being an example.

On the cost of sanctions compliance, recently, a major global bank has estimated that a full-time employee, trained in financial crime management and who can execute on the remit of sanction screening activities, could cost between USD 135K and USD 270K annually. However, this cost has been steadily increasing in the last few years and exacerbated by inflation and general shortage of skillsets. Coupled with the estimates that a compliance team typically comprises between 80 to 100 staff, the annual cost could be as high as between USD 12M and USD 29M. The broader implication for larger banks is these would lead to cost optimization and trade-off challenges, while for smaller banks, without the economy of scale, these could lead to business viability challenges.

As all payment transactions are subject to sanctions screenings, which has been traditionally a manual process utilizing static rule-based approaches, with limited abilities in assisting compliance officers to process the rising false positives, as well as being burdened by resource intensive internal controls, such as “4-Eye”, banks are urgently looking for solutions to ensure that they are not ill-prepared when, in the near term, operating costs of compliance more than doubles.

Lastly, it is very important that any AI system used in AML sanction screening is explainable so that it can be easily analyzed, understood, and augmented by regulators and business stakeholders. Another important aspect relates to customer satisfaction and the speed of payment deliveries from customers to beneficiaries which can be hindered by a manual sanction screening checking.

These developments in sanctions screening are the key driving forces behind banks’ urgency to modernize sanctions screening using game-changing and innovative methods.

3

Trends in banks moving from archaic and static-rule-based filtering algorithm to AI

Increasingly banks are adopting “smart screening” solutions that leverage the combination of traditional static rules-based approaches with advanced machine learning and AI scorings. This generic approach is a natural progress adopted by most banks stepping into an AI approach. While it can address the issues highlighted previously of helping to score and rank out true matches from false ones across names and transactions thus allowing for the segregation into buckets for differentiated screening work flows down-streams, it falls short of keeping pace with the sanctions growth trends described in the previous section.

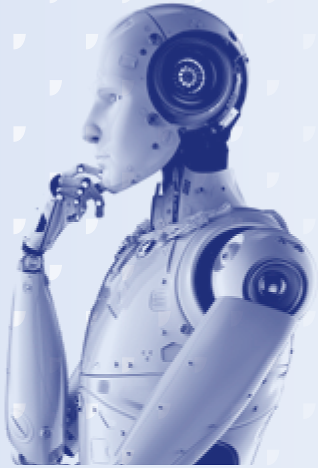
Banks are only just beginning to realize that, unlike credit scoring, the AI models involved for sanctions screening may require perfect true positive accuracy as only this can this translate to a viable business case. This release from the manual workflow empowers banks the flexibility to redeploy full-time skilled professionals to other areas of financial crime that aligns with market and political developments. Additionally, human errors in the screening process, driven by fatigue caused by high-volume manual processing, are significantly reduced. Furthermore, it allows banks to have a solution that easily scales up to the increasing level of sanctions screening. Additionally, this will increase the customer satisfaction as legitimate payments are rapidly processed.

Another aspect that banks are coming to realize is the need for the AI model to be contextually explainable to a level that is accepted by their regulators, at the very least. Globally, there are many episodes of opaque AI models being rejected by regulators for deployment and this fundamentally stems from the regulator’s concerns with the prevalence of AI being utilized in financial institutions as well as in non-financial institutions that indirectly affect the financial system. Regulators insist, that there is 100% explainability on how the data is mapped to scores and decisions and that the underlying AI models can be easily understood, analyzed and augmented by the regulating authorities and business stakeholders.

4

How will explainable AI successfully overcome the challenges faced by incumbent AI solutions while not compromising on accuracy and PII

Primarily the decision problem for the AI solution is the examination of sanctions screening alerts raised on payments and the classification of both name match and entity match to “True” or “False” on their scores. The match scores from both match pipelines are then assessed by the bank to decide to release or review a payment. Essentially, a name match, as the term implies, is how close the payee’s and payer’s name matches with the name on the sanction lists, example John Smith versus Jon Smyth, while entity match assesses other information of the payee or payer, such as their addresses and companies.



High payment volume means deploying an ever-increasing number of personnel to separate true and false positives on the alerts raised by pattern matching algorithms. The sheer volume of false positives is the major barrier to a successful and sustainable AI driven screening business case. Therefore, any new AI solutions must take on a more novel approach in dealing with sanction alerts.

In AI solutions that successfully overcome the challenge, they involved breaking down the sanctions screening problem into two classification problems, “Name Match” and “Entity Match”. The former computes the probability of the alert entity as having the same name as the sanctioned entity, whereas the latter computes the probability of the alert entity as having the same entity type (individual, organization etc.) as the sanctioned entity. With advanced explainable AI algorithms and used in combination, these two classification scores prove very effective in isolating false positives alerts raised from the pattern matching algorithms. Another reason for these AI solutions’ success was that they were designed and calibrated to maintain 100% true positive accuracy, a non-negotiable in sanction screening, at the outset.

Another reason for their success is an innovation that involves how to protect Personally Identifiable Information (PII) throughout the workstream, which in many past endeavors because of inadequate designs, has prevented AI solutions from being implemented. These successful AI solutions were designed to essentially not require any PII to work by first developing, on the banks’ premises, a features calculator engine that converts personal unstructured data to anonymous data that was then streamed to the AI models that compute the scores.

Having AI models fully explainable is also very important for success as their implementations is dependent on the financial regulator’s understanding of how the models work and endorsing them for use. Not only are these successful AI models inherently explainable, they are able to generate explainable outputs at all three levels, at full population (model rule base), sub-population groups exhibiting similar behavior (rules applicable to individual risk buckets) and single transactions (interpretable rules/drivers-based output for each transaction), that provided additionally clear and actionable drivers that further enhanced their compliance with regulation as well as value with the business users.

Finally, the solutions were designed for easy deployment that aligns to the banks’ urgency to modernize sanction screening as well as with capabilities for real time model performance monitoring consistent with the requirement for fast respond speed in fulfilling payments requests.

5

Benefits and ROI of incorporating explainable AI to sanction screen work streams

As with most AI driven initiatives, Return on Investment (ROI) expectations and estimations can be complex and far from straightforward. We can broadly attribute them to uncertainties in estimating quantitative business values, including productivity gained, cost savings and revenue gained, as well as the qualitative ones, including skills retention, improved skills agility, and better workflow experience.

A structured approach is to first focus on the item that has the biggest impact and then fine tune from there. In the case of sanctions screening, the business case is mainly driven by the need to prepare and streamline human intensive activities in the current workstream for the future. This helps paves the way for ROI estimation to be based on how many full-time compliance officers can the AI solution help to release for redeployment to other critical areas of the financial crime remit.

The need to comply with the bank's non-negotiable KPIs imposed on the AI models, such as the 100% true positives requirement, helped to put structures around the calibration of the AI models that made the estimation of false positives release, a measure of how many alerts that can be reduced for manual review, more precise and explainable.

With these estimation challenges out of the way, the rest of the process is straightforward and involves allocating facts and figures such as staff cost, customer size, alerts per day and number of alerts handled per staff per day to estimate the range of savings due to the XAI models. The rest of the quantitative business values, as well as the qualitative ones can then be considered, if still necessary, for the bank to make its decision on the AI investment.

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About Temenos

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