ABSTRACT
As expectations of artificial intelligence (AI) and deep learning have peaked in the financial services industry, anti-money laundering (AML) professionals are exploring advanced methods to more accurately identify suspicious activities that impact their institutions. Fueled by regulatory guidance in the 2018 Joint Statement on Innovative Efforts to Combat Money Laundering and Terrorist Financing, many have set up pilot programs, but few have moved into production. Creating a modern AML platform that can support rapid and automated deployment of models and traditional rule-based scenarios ensures that banks will evolve to keep pace with sophisticated financial crimes. This paper explores use cases for machine learning models in AML and provides examples of how clients are promoting advanced analytics from the sandbox into their production SAS® Anti-Money Laundering software environment.

INTRODUCTION
Financial institutions dedicate substantial resources in the area of financial crimes compliance. In 2019, Celent estimated that spending reached $8.3 billion and $23.4 billion for technology and operations, respectively. This investment is allocated toward ensuring anti-money laundering (AML) and counter terrorist financing (CTF) compliance. Money Laundering is the process of making illegally gained earnings appear legal. Terrorist financing is the process of funding the use of violence or intimidation in the pursuit of political gain, regardless of the legitimacy of the source of funds.

The following bar chart shows projected global AML-KYC spend in 2019:

![Figure 1. Global Spending on AML-KYC Operations (Celent)](image-url)
Traditional methods of combating financial crimes are not keeping pace with the disruption occurring in the banking and financial sector. Faster payments, digital first strategies and the ever-rising cost of compliance are accelerating the change. Fueled by regulatory guidance in the 2018 Joint Statement on Innovative Efforts to Combat Money Laundering and Terrorist Financing (Federal Reserve), many have set up pilot programs, but few have moved into production. Some innovation barriers observed within financial crimes compliance are:

- Limited Data Science skills
- Difficulty in explaining machine learning models
- Lack of integration capability with incumbent systems

With the help of SAS® Financial Crimes Analytics, everyone is enabled to build explainable machine learning models (including data scientists, business analysts, and developers) and operationalize so that the investigators can act quickly.

**MACHINE LEARNING STRATEGIES**

Financial institutions have been leveraging automated transaction monitoring strategies to combat money laundering for years, but machine learning techniques are gaining traction. Machine Learning is based on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention. The most commonly used branches of machine learning are supervised and unsupervised learning.

**SUPERVISED LEARNING**

Supervised learning algorithms are trained to detect money laundering that leverage known historical outcomes. For example, the automated transaction monitoring rules that are run today are generating alerts reviewed by investigators. The machine can leverage the suspicious activity report (SAR) flag (‘yes’ or ‘no’) to predict future outcomes by considering complex relationships in the customers behavior.

**UNSUPERVISED LEARNING**

Unsupervised learning techniques leverage unlabeled data, learning from the structure of the data itself. In this case, there is no historical outcome or “right answer” to learn from. For example, client populations can be segmented into peer groups in order to understand deviations in their activity.

**USE CASES IN AML**

Machine learning can be valuable in improving the efficiency and effectiveness of your anti-money laundering program. In most cases, machine learning is augmenting rather than replacing traditional transaction monitoring methods. Below are several examples of use cases where banks are leveraging these techniques today:

- **Segmentation** – Transaction monitoring scenarios can generate high false positive rates due to the use of thresholds. To mitigate operational risk, thresholds are often set high, creating alerts that are disproportionately skewed toward high dollar transactions. As a result, an activity that is worth a review might be sitting below the threshold. Leveraging a behavior-based approach, customer groups can be created using unsupervised techniques. Transaction monitoring scenarios can then be segment aware, having different thresholds that are based on each customer group. The resulting effects are lower false positives and greater coverage of activity that was hiding ‘below the line’.
• **Alert Scoring and Hibernation** – Anti-money laundering typologies are often temporal in nature, making it difficult to identify on the basis of a single transaction or alert. Money laundering involves the layering of funds to officiate its source. Many alerts are closed during the triage phase of the investigations process due to lack of evidence. By aggregating alerts together, we can continuously risk rate customer activity to determine when it becomes investigations worthy. At that time, the group of alerts is promoted to case and valuable investigative resources are focused on the riskiest behaviors.

• **Scenario Replacement** – More progressive financial institutions have replaced several transaction monitoring scenarios with one machine learning model. Typologies that have historical case outcomes are well defined and result in high false positives and are generally the best candidates. In this paper, we will explore replacing Cash focused scenarios with a machine learning model.

**EXAMPLE FRAMEWORK LEVERAGING SAS® FINANCIAL CRIMES ANALYTICS**

This paper explores the process of building, registering and deploying a machine learning model to replace transaction monitoring scenario(s). To demonstrate the framework, we will leverage SAS® Financial Crimes Analytics as the underlying technology. SAS® Financial Crimes Analytics provides end-to-end capabilities, from data to decisioning.

• **Data Acquisition** – Data is acquired from the SAS® Anti-Money Laundering data model and loaded into the SAS® Financial Crimes Analytics environment.

• **Feature Engineering** – Data is joined to create a customer centric view with transactional, non-transactional, demographic, and other relevant features to create a base table for modeling.

• **Automated Model Development** – Machine Learning models are created leveraging the Automated Pipeline Generation feature.

• **Model Management and Governance** – The champion machine learning model is registered in a centralized repository.

• **Alert Generation** – Output from the machine learning model is assessed with a cutoff score to determine at what threshold to generate an alert. The decision flow is tested, then deployed to SAS® Anti-Money Laundering using the alert API.

• **Investigations** – Output from the machine learning model becomes actionable for investigations.

**DATA ACQUISITION**

The SAS® Anti-Money Laundering solution has a robust data model that links a wide variety of transaction, non-transaction, and demographic dimensions to the entity (“Customer”) or external entity (“Customer’s Customer”). This data is rich in information such as the primary instrument, secondary instrument, beneficiary, channel, branch, and other potential features that can be used to predict suspicious activity. The solution also houses information related to the disposition of prior investigations. Because information related to anti-money laundering programs are not publicly available, we have populated the SAS® Anti-Money Laundering data model with fictitious data to illustrate the framework.

This diagram shows the SAS® Anti-Money Laundering conceptual data model:
FEATURE ENGINEERING

After loading the data, the first step is to transform the raw data collected from the SAS® Anti-Money Laundering core dimensional model and create a base table for our model development. Transaction monitoring scenarios typically leverage 5 to 7 parameters, but machine learning techniques can consider many more features to more accurately identify patterns. We identified 50 potential features that were indicative of Cash related behaviors based on the FFIEC guidance (Federal Financial Institutions Examination Council) and domain knowledge. Next, the label (or target) was identified as “Good Alert” that represents alerts which were promoted from triage to case for cash typologies. This information was aggregated to the customer level in order to identify cross account behaviors such as Cash Structuring.

Display 1 shows the base modeling table created:

Display 1: Data Profile

MODEL DEVELOPMENT

Once the base modeling table is created, the second step is to create a new project. In order to accelerate our model development process, the automated pipeline generation feature was leveraged. This process automates iterative model development process, creating a dynamically generated pipeline from the input data. Once created, we will review the champion and challenger models, expose the underlying settings, parameters, and code. Though the system is creating the pipeline for the user, the model development process is not a black box and can be edited.
Display 2 shows settings to create an automatically generated pipeline:

Display 2: Automatically Generate the Pipeline

Once executed, a pipeline is created automatically based on the data that is provided. The system is intelligently determining the transformations and features needed to identify the best solution. Through an iterative process, models are assessed, hyper-parameters are tuned, and ensembles are created to predict the outcome of “good alert”.

Display 3 shows the steps in real time as the pipeline is being created:

Display 3: Pipeline is Being Intelligently Built

Once complete, the pipeline is displayed showing the nodes generated including variable imputation, feature selection, and models. Many modeling techniques will be executed in order to identify a champion model. Keep in mind that with different input data, the pipeline generated will be different.
Display 4 shows the pipeline that was automatically generated:

Display 4: Automatically Generated the Pipeline

The automatically generated pipeline includes a model comparison node, which compares each technique to determine which model was best at predicting past cash activity and was promoted from triage to case. Based on misclassification rate, the Gradient Boosting model was selected as the champion.

Display 5 shows the results of our automatically generated pipeline:

Display 5: Model Comparison Results

Model documentation is automatically generated in a project summary report called an insight. Insights provide details for the project such as project summary created using natural language generation, model assessment, cumulative lift for champion model, most important variables for champion model, and many other key visualizations.
Display 6 shows a sample of the model assessment results:

Display 6: Model Assessment Results

MODEL MANAGEMENT AND GOVERNANCE

Once you have identified your champion model, register the model. Registration of the model provides four benefits:

1. Organization and Management of Models: A centralized repository allows users to capture data and model lineage in one place, compare open source and SAS models, and create life cycle templates to expedite deployment.

2. Test and Validate Models: Evaluate whether the models were performant against investigative results to determine if they are capturing the money laundering behaviors intended in the definition.

3. Publish: Automatically deploy in batch, streaming, or cloud. For our example, we will leverage the integration with SAS Decision Manager to ultimately create an alert work item.

4. Monitor Performance over Time: Performance monitoring and alerting automate the model updating process to address model degradation.
Display 7 shows registration of the new model:

<table>
<thead>
<tr>
<th>Name</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Registered successfully</td>
</tr>
</tbody>
</table>

**Display 7: Registering the Model**

**ALERT GENERATION**

To derive value from our registered machine learning model, it is required to determine when to create an alert for investigations to review. A decision flow can be designed leveraging the drag and drop decision authoring interface. This flow automatically assesses the output of the machine learning model and leverage rules to determine when to generate an alert. Decisions can range from simple to complex. To illustrate the framework, we will create a simple flow which creates an alert if the event probability from the model has exceeded a cut off score.

Display 8 shows the decision flow for creating an alert:

**Display 8: Decision Flow**

Based on the preceding flow, if the customer receives an event probability score of above .05, we structure the variables required for the SAS® Anti-Money Laundering Solution, send the alert via API and document each record with a message that indicates if an alert was generated or not. Next, you test the decision flow to ensure it is working as intended. The results can be reviewed to determine the operational impact, rules fired, and the alerts that would be generated once we publish.
Display 9 shows testing of the decision flow:

Display 9: Testing Decision Flow

Once the decision flow is tested and validated, publish the flow. There is an option of manually publishing on demand or scheduling the flow to run automatically.

Display 10 shows publishing the flow:

Display 10: Publishing the Flow

INVESTIGATIONS

After the alerts have been published, they are available in SAS® Anti-Money Laundering for investigators to act. The alerts can now be searched, triaged, and investigated to determine if a regulatory report is required. The alerts generated by the newly created cash machine learning model are grouped with other alerting channels, such as transaction monitoring and human refeerrals, so that analyst can have a compressive review of the entity. Lastly, you can surface descriptive and understandable reasons as to why the alerts were created to assist investigations in reaching a decision.
CONCLUSION

There is a lot of excitement in the Financial Crime and Compliance industry around the application of machine learning techniques. We see many opportunities available today to apply these methods to improve the efficiency and effectiveness of AML and KYC programs. Replacement of low performing high volume transaction monitoring scenarios can be an area where machine learning techniques can provide significant value, freeing up resources to focus on investigation worthy activity. With SAS® Financial Crimes Analytics, banks can create, manage, and publish machine learning models rapidly within an integrated framework.

REFERENCES


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