# Automated Threshold Tuning

**Getting Ahead of the Curve**

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A successful anti-money laundering program is more than just a detection platform. A tremendous amount of data, analyst reviews, and reporting influence investigation efficiency and investigator productivity. Even though rule-based systems are plagued by high levels of false positives, it is still the preferred method because rules are readily explainable. However, it is imperative to build a system that enforces and tunes those rules.

## CURRENT STATE OF AUTOMATED THRESHOLD TUNING

In 2011, Model Risk Management regulation SR-11/7 scrutinized whole model governance programs. Under this regulation, financial institutions need to clearly identify all financial crime and compliance models and provide ongoing validation. Statistical tuning is performed by applying above-the-line (ATL) and below-the-line (BTL) testing to validate and tune thresholds and parameters. This process, known as threshold tuning, is done to verify the performance of models.

For surveillance modeling, a majority of cases are rule-based as compared to machine learning-based. Therefore, tuning is focused on rule-based models, which is a highly labor intensive process. It requires independent validation, which happens every few years when a line is defined.

- **Productive vs. Non-Productive Alerts:** The typical process starts by identifying productive vs. non-productive alerts. The definition of productivity can vary by organization.
- **Thresholds for False Negatives:** Define how much a threshold should be decreased to understand the percentage of a false negative rate. Industry standard is 10% matrix as a starting point, which is expected to be documented in a validation report.
- **Sampling:** Sample with a reduced threshold to validate with confidence the threshold level.
- **Risk Appetite/Tolerance Level:** Once all the outcomes are available, analytics is used to determine the appropriate tolerance level based on the organization's risk appetite.

Keeping an AML perspective is key to a successful threshold tuning process. Engage the Financial Investigating Unit (FIU) and replicate their thought processes. Merge both MRM and FIU to agree on common grounds.

**"The automated threshold tuning process is not extremely automated in the true sense of the word."**

*Senior Compliance Manager, Compliance Analytics at a leading global Tier 1 financial institution*

## HOW DO REGULATORS INFLUENCE AUTOMATED THRESHOLD TUNING?

Regulators expect financial institutions to explain models from a business perspective. However, they are not expected to detect all suspicious activities – zero tolerance is unrealistic.

**Explain-ability:** In threshold tuning, all decisions, outcomes, and processes must be explained to regulators. Details should include what behaviors/scenarios are being used and if there is complete coverage to mitigate residual risk. In addition, clear details of ATL/BTL thresholds must be included. The goal is to explain the model tuning process as a lifecycle.

**Documentation:** Complete documentation is expected for:

– Purpose: Exact purpose and intended use of the model, such as segmentation of the model.

– Data: Upfront documentation of a data matrix.

– Execution: The delivery process and team is expected to be consistent and documented.

– Outcome: The outcome of results, such as sampling, analytics, and final threshold, should be documented with supporting evidence.

– Model Lifecycle: Sustainability of the program is based on the quality of documentation. Traceability between risk assessment and scenario coverage will provide added evidence of an effective threshold tuning program. Risk assessment gap analysis from the governance team and threshold tuning from model analysis should be included. Details of exact scenarios and what risks to monitor should be included to support complete model lifecycle.

From a regulator's perspective, the quality of a threshold tuning program is assessed based on the quality of the documentation produced.

**How to Define Effectiveness**

- **Productivity Ratio:** Fluctuation in productivity ratio (good vs. bad alerts) can be an indication for model tuning.
- **Data:** Understand the data Key Risk Indicators (KRIs).
- **Coverage:** Provide complete coverage based on risk profile.

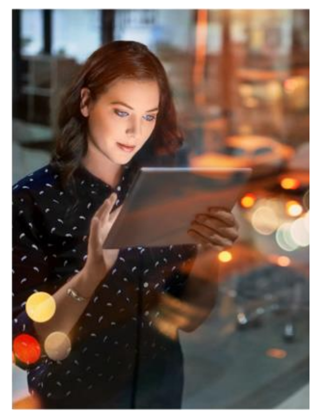
### Challenges and Areas of Automation

- **Fragmented Feedback Loop:** The outcome of historical alerts is a key input for the threshold tuning process, which is completely fragmented now. Typically, historical data is manually replicated for the model risk management process, which is a separate platform to understand historical outcome. This approach is very time consuming because it takes few days to get the data from the transaction monitoring system. By the time data is available for tuning, it is not current.

- **Manual Sampling Process:** The steps to change a threshold and perform sampling is a manual process. Thresholds that change in a transaction monitoring system generate alerts for investigation. Once the investigation is complete, the outcome is populated in the tuning system for further analysis. This manual process makes the tuning process lengthy and expensive.

- **Silo Workflow Process:** There are various steps in a tuning process, including data preparation, sampling, analytics and productization of new thresholds. Currently, the entire process is done in various stages and in different systems. Cost is certainly the main factor here; however, due to its siloed nature, it is very hard to keep track of effectiveness.

In summary, a more standardized process can provide consistency in the program, eventually helping automation. More tools and automated workflows will reduce the overall process.



**"Will automated tuning ever by fully automated so that it is self-maintaining? No. The real question is to what extent can you use automation?"**

*Senior Compliance Manager, Compliance Analytics at a leading global Tier 1 financial institution*

## WHERE DO WE GO FROM HERE?

Both in-house and vendor models are leveraged by financial institutions for anti-money laundering. In-house models are typically more organization-specific, but lack of a control environment due to their operational nature. Vendor packages are more controlled and can be leveraged for more elegant in-house machine learning models. This means machine learning and artificial intelligence vendor platforms with controls should be used for organizational specific monitoring. This approach is key to support the dynamic nature of money laundering patterns.

As previously discussed, manual sampling and siloed processes make threshold tuning extremely expensive and inefficient. There is a tremendous scope and merit to automated threshold tuning. An automated tuning platform should include:

- A fully integrated data provision mechanism from a transaction monitoring production system(s) to expedite data preparation. The data provision program should include not just the resulting events information, but also the investigators.

- The ability to leverage essential data sets needed for model execution. Keep in mind – more information available for machine learning models results in better performance of the models.

- Agile model authoring and updating ability in preferred statistical language(s) with required data set filters.
- The ability to review model execution results with fully integrated visual analytics.
- Automation to push update models in production (once tested).
- Flexible governance, audit, and documentation capabilities to meet product/service specific requirements.

## KEY ADVANTAGES TO AUTOMATING THRESHOLD TUNING

- **Faster and Cost-Efficient:** Traditional tuning takes 6-8 months. Automation results in faster feedback and productization of updated models, which will make the tuning process much quicker and allow for more frequent reviews.
- **Data Accuracy and Standardization:** Automation eliminates manual data movement and can help reduce data quality issues, providing the opportunity to tackle data standardization.
- **Better Machine Learning by Factoring More Information:** Automation allows an institution to factor more information as part of the 'investigation feedback loop system,' which means the machine has more information to learn from. This will eventually help create more efficient machine learning models.

There is tremendous merit to the automated threshold tuning approach. Although traditional rule-based monitoring is not going away, a hybrid approach of both rule-based and machine learning models is most effective.

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