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Real-Time Sanctions Screening for High-Volume Payments

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Abstract

Sanctions screening is critical for preventing terrorism financing, money laundering, and organized crime. Effectively enforcing compliance in a high-throughput environment, such as screening billions of financial transactions per year for a large bank, poses a unique challenge. Achieving a balance between matrix-like false-positive rates, detection times, and data freshness is central to the problem, which requires careful consideration of detection algorithms and their underlying data sources, together with the system's overall architecture.

A heuristic review identifies the main design considerations and explores each category in turn—screening architecture, detection algorithms, data quality and provenance, and overall scalability and performance. The results synthesize best current practice and highlight areas for further research.

Keywords: Sanctions Screening Systems, Financial Crime Prevention, Anti-Money Laundering (AML), Counter-Terrorist Financing, High-Throughput Transaction Monitoring, Compliance Detection Algorithms, False-Positive Rate Optimization, Real-Time Screening Architectures, Data Freshness Management, Financial Data Quality and Provenance, Scalable Compliance Platforms, Large-Scale Transaction Analytics, Risk-Based Screening Frameworks, Heuristic Compliance Design, Performance-Aware Detection Systems, Regulatory Technology (RegTech), Enterprise Compliance Architectures, Automated Watchlist Screening, Financial Systems Scalability, Trustworthy Compliance Operations.

1. Introduction

Formal compliance with government sanctions requires businesses and their partners to robustly track and monitor sanctioned individuals and entities. Successful transactions may be unwound or blocked after the fact, and regulatory authorities increasingly impose onerous fines for offenses. The importance of sanctions screening has led to a growing demand for financial transaction monitoring solutions that support high base rates and low false positive rates. Scalable, high-throughput sanctions screening systems for very large financial transaction volumes do exist, but the available designs are poorly documented, attention focused primarily on other aspects. To support future development of such systems, this section synthesizes knowledge accumulated from published papers, system implementations, discussions with industry practitioners, and recent literature on commercial and proprietary solutions. It identifies important architectural and algorithmic design considerations when building scalable sanctions screening systems for financial transaction monitoring solutions operating at the highest throughput levels. The first part outlines possible system architectures, discussing batch versus streaming processing paradigms, policies for managing and normalizing data structures, indexing techniques, and search strategies. The second part addresses algorithms and techniques employed for sanctions matching, including rule-based systems for checking transaction details against sanction lists and machine-learning-assisted page classification systems for identifying suspicious connections.

1.1. Overview of the Study

Sanctions screening constitutes a critical component of the AML/KYC compliance processes in the finance and banking industries. Characterized by extremely high throughputs that often exceed one thousand transactions per second, sanctions screening is challenging to implement in a robust way without affecting system performance. This

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paper provides a synthesis of the architecture of systems that perform sanctions screening for transactions having high rates of arrival. Fundamental scalability considerations inherent to the design of such systems are set out and explained. Several strategies for effectively responsive sanctions detection are elaborated, supported by research drawn from the fields of false positive reduction, provenance management, data quality, data governance, and machine-learning-assisted classification. These strategies apply during the latter stages of transaction processing where strict latency requirements are imposed by the external system operators.

The study contributes to a comprehensive overview of the domain of sanctions screening streaming systems that operate in high-throughput, low-latency, production environments. The potential to leverage recent developments in stream-based safe-ML classification extends above and beyond the basic use case, enabling the combination of data expansion techniques, like data-sampling, with safe-ML to trade false positive detection accuracy for classification efficiency. Such combinations could support operation in the financially normal-resource-poor topical domains.

Fig 1: Architecting High-Throughput Sanctions Screening: Scalability, Stream-Based Safe-ML, and Efficiency-Accuracy Trade-offs in Low-Latency Environments

2. Background and motivation

The growing adversarial threats posed by drug-trafficking networks, terrorist organizations, and other crime syndicates have led to an increase in the number of sanctions-eligible persons and entities in various jurisdictions worldwide. Paying particular attention to international regulations, sanctions monitoring and compliance screening have become essentials for financial institutions and organizations engaged in cross-border transactions. In contrast to common monitoring efforts that are geared toward alert generation, focused only on high-risk customers or transactions, sanctions screening is a high-throughput, extremely low-latency application that is designed to clear as many transactions as possible with multiple lists at a very low false-positive rate.

The growing volume of transactions processed by major financial institutions and organizations has long rendered traditional rules-based screening solutions untenable. Current research and development efforts directed at sanctions screening in operate a least-cost, least-risk, and least-time manner, applying commercial risk and compliance solutions, rule-based engines, and external services without concern for overall scalability, costs, processing performance, or success. Moving sanctions screening in high-throughput environments toward enhanced transparency, accountability, and governance is an enabler for true innovation.

2.1. Rationale and Significance of the Study

Sanctions play a crucial role in geopolitical relations and are among the primary regulatory obligations faced by the financial sector and, more broadly, by many organizations across multiple industries. Governments use these measures as instruments to exert diplomatic and economic pressure by blocking the target's assets and restricting their access to the international financial system. The intention is to deter terrorist activities, the proliferation of weapons of mass destruction, and human rights violations. Sanctions risk management in financial institutions is carried out by dedicated compliance teams, whose main objective is to verify whether incoming and outgoing financial transactions are in accordance with the lists of sanctioned countries, organizations, and individuals. When a match is detected, the financial institution has to freeze the transaction and notify the competent authority in the country.

When operating in a low-throughput environment, the compliance teams can manually review every match and determine whether it is a false positive or not. However, in international banks and financial institutions, the volumes of transactions can reach several millions per month, thus

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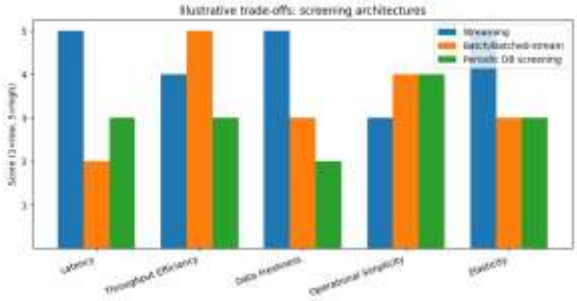
making these review processes impractical. Therefore, banks and financial institutions deploy screening systems to automatically check whether they match against any sanctions list. These systems have to work in a high-throughput environment, as the transactions have to be examined and cleared within a specific time-frame before they are committed. The performance of sanctions screening systems can be evaluated in terms of accuracy (percentage of false positives and false negatives) and execution time per transaction. Accuracy can be increased by using multiple commercial-off-the-shelf applications that combine classical lexical-based matching with machine-learning-assisted classification, while execution time can be optimized by adopting streaming data-processing architectures that fully consider transaction temporal semantics.



Equation 1) Core performance equations derived step-by-step

1.1 Throughput (capacity) of a screening pipeline

Step 1: Define per-stage service rate
Let the screening flow have stages $i = 1..k$ (e.g., ingest → normalize → search/index → scoring/ML → alert dispatch).
Let each stage sustain a maximum service rate μ_i (transactions/second).

Step 2: Bottleneck principle (serial pipeline)
If each transaction must pass through every stage sequentially, the **maximum sustainable pipeline throughput** is limited by the slowest stage:

$$T_{\max} = \min_i \mu_i$$

Why: if any stage can only do μ_b tx/s, then even if all others are faster, the system cannot output more than μ_b without backlogs forming before that stage.

Step 3: If you parallelize a stage
If a stage j is replicated with c_j identical workers and perfect load balancing, its effective capacity becomes:

$$\mu_j^{(\text{parallel})} = c_j \mu_j$$

Then:

$$T_{\max} = \min_i \mu_i^{(\text{effective})}$$

1.2 Latency (response time) and why it "blows up" near capacity

We can derive a minimal queueing relationship for *why* latency sharply rises when arrival rate approaches service rate.

Step 1: Arrival and service
Let:

- λ = arrival rate (tx/s)
- μ = service rate of the bottleneck stage (tx/s)
- utilization $\rho = \lambda/\mu$

For stability, you need:

$$\lambda < \mu \quad (\rho < 1)$$

Step 2: M/M/1 average time in system (classic baseline)
If arrivals are roughly Poisson and service times exponential (a simplifying baseline), average time in the system is:

$$W = \frac{1}{\mu - \lambda}$$

Step 3: Interpret

- If λ increases toward μ, denominator $(\mu - \lambda) \to 0$ so $W \to \infty$.

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- This operational reality: near-capacity systems experience queue buildup and latency spikes.

1.3 Little's Law (linking backlog, throughput, latency)

A second key relationship often used in streaming system sizing is **Little's Law**:

Step 1: Define

- L = average number of transactions "in the system" (in-flight + queued)
- λ = average arrival/throughput rate (tx/s)
- W = average time in system (s)

Step 2: Relationship

$$L = \lambda W$$

Step 3: Use
If you have an SLA latency bound $W \leq W_{\text{SLA}}$, then backlog must satisfy:

$$L \leq \lambda W_{\text{SLA}}$$

1.4 Elasticity (scaling for bursty volumes)

Let load vary over time: $\lambda(t)$. If you can provision $c(t)$ workers, each with per-worker capacity μ_0, then:

$$\mu(t) = c(t)\mu_0$$

To keep stable and avoid latency blow-ups:

$$\lambda(t) < \mu(t) = c(t)\mu_0 \Rightarrow c(t) > \frac{\lambda(t)}{\mu_0}$$

3. Architectures for high-throughput screening

Architectures for high-throughput screening: streaming versus batch processing; data models and normalization; indexing and search strategies
When dealing with fast-paced transaction streams, sanctions screening must be designed accordingly. Processing transactions with no visible delay is generally expected by customers, preventing the effective integration of checking tasks into banking operations. Consequently, solutions must offer appropriate throughput rates with short response times. Several performance and scalability-related aspects should be particularly addressed.
Sanctions detection is normally formulated as a pattern-matching problem against a set of rules or signatures. A typical security application is therefore based on elements widely available in the information retrieval community and on techniques tailored to specific requirements. The screening challenge shares important characteristics with several strategic IR areas, such as processing very large document collections, high-throughput/low-latency applications, and data synthesis from diverse, semi-structured sources. Although sanctions-screening databases can grow to billions of entries and may contain picture or audio data, their overall scale remains much smaller than the Web. Streaming processing can also be applied to specialized domains such as news providing energy-efficient and cost-effective alternatives by enabling smaller and less-scalable distribution networks.

3.1. Streaming versus batch processing
Depending on expected throughput and the evaluation of latency, different screening processing paradigms offer alternative advantages. A natural approach involves screening transactions as they are generated, allowing for immediate settlement and minimizing latency and cost. Modern transaction systems regularly generate multiple thousands of transactions on a daily basis or, for particularly busy institutions, perhaps even several thousands in a single day. Processing these transactions in a single batch, often referred to as the "batched stream" model, is both time- and space-efficient, as the batch is normally kept in volatile memory during screening.
In business scenarios where the interaction with the customer is done– or at least semi-automatically done– via pages on the internet, a different model can often be applied: transactions can be logged in a database table and screened periodically (for example every 1 or 2 minutes). As they are filtered, they can be either approved, either automatically or through a semi-automated process, or

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placed into an exception database for further consideration. When there is a low-volume stream of transactions that simply cannot be batched because of the subtler requirements for timely screening, it is often possible to screen such opportunities using a sound approach of collaborative screening.

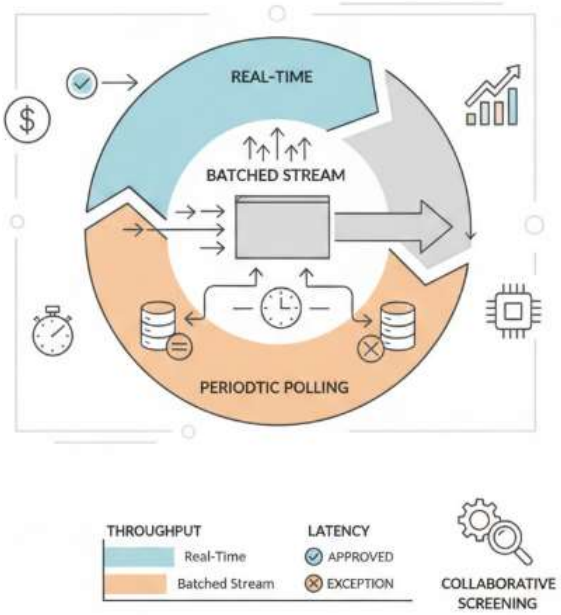

Fig 2: Optimizing Transaction Screening: A Multi-Paradigm Framework for Throughput-Latency Trade-offs in Real-Time Financial Systems

3.2. Data models and normalization

Data models and normalization considerations relate to matching algorithms, targeted searches, and the definitions of containment. In practical implementations, sanctions screening databases are frequently nondisclosed by screening provider companies that specialize in both on-premise and cloud solutions. These service providers are also the main data sources, integrating world-wide lists, geopolitical entities, institutions, people, companies, and their aliases, also as geographical data for matching purposes. In that context, active users of these systems have access to all data assets of these companies, comprising normalized datasets and also public feeds indicating changes per country per day.

Screening companies use additional data cleansing processes on these data before inject into their matching engines. These processes include address de-duplication in the same way that email address de-duplication before cleans start with rules on Brazil, BR, BRASIL etc and Canada, CA, CANADA. In a production environment, it is important to permit endpoint freedom in the construction of the rules, for example: “the endpoint mapping from BR to BRAZIL needs to evaluate the following addresses; BRAZIL, BRASIL, BR, BRA…, if not, indicate to the public the rule modification…” At the same time, screening companies have legal teams that define which synonym rules can be published and who is responsible to approve the rule-update proposition.

Dimension	Streaming (score 1-5)	Batch/Batched-stream (score 1-5)	Periodic DB screening (score 1-5)
Latency	5	2	3
Throughput Efficiency	4	5	3
Data Freshness	5	3	2
Operational Simplicity	3	4	4
Elasticity	5	3	3

3.3. Indexing and search strategies

The single most common indexing strategy for sanctions screening systems is dictionary indexing. Subsequently, the list of sanctions names, aliases, and related terms from appropriate authorities is instantiated as a dictionary during initial system setup. Many systems go even further, creating an inverted index mapping dictionary elements—most often last names—to a main data structure, either a set or list, that maintains corresponding source records. Unfortunately, dictionary indexing approaches do not scale well to high-throughput settings. They are trivially sufficient for screening systems with low base rates but

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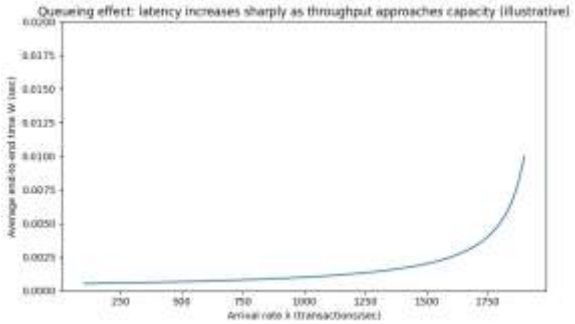
become increasingly inefficient as screening volumes grow. The fault lies with the linear-time membership test involved in the single-key lookup operation, an essential step in any dictionary indexing strategy. More sophisticated screening solutions rely on more general indexing and search strategies to achieve sub-word-indexing performance with far larger lists.

An alternative transformation of the sanctions matching task into the nearest-neighbor search problem leads to fundamentally different screening architectures. Many records in financial systems appear to be compound names and are reliably encoded as sequences of words. Consequently, many compound names can be viewed as more than simple dictionaries but instead as point sets embedding a wealth of proximity information. Growing the sanctions name list with phonetic variants of the original names generates point sets that can be rapidly searched for the most similar entry via a number of highly scalable indexing methods. Subsequently, the best matching name or name-phrase and its distance to the input phrase can be generated efficiently. Such index structures—most of which rely on space-partitioning trees—allow searching the index in sub-linear time, achieving order-of-magnitude performance improvements over a simple dictionary membership test.

4. Algorithms for sanctions detection

Existing sanctions detection mechanisms can be classified into rule-based (or signature-based) methods, which apply matching rules against a reference data set for detection, and machine-learning-assisted classification models, which predict whether a financial transaction is sanctioned based on past cases. Rule-based methods have the advantage that the detection function is easy to implement and test; these algorithms attain near-zero error rates on the training set. Incorrect decisions only occur when candidate matches are flagged for review or further analysis. However, completing that task with limited resources at scale is the overriding problem.

To avoid the human-limited review of flagged records, machine-learning METHODS have been proposed to automatically filter, classify, or score transactions for sanctions similarity. Models are trained on past cases, with a pre-screening mechanism to control the amount of reviewed records. However, for low-frequency events such as sanctions matches, model performance is often constrained by insufficient data. Supervised re-sampling strategies have been proposed to alleviate such issues, and data augmentation techniques can also offer a viable alternative. These supervised models thus provide additional presentation and prioritization for downstream human reviewers. With growing interest in such data-driven approaches, especially by the leading financial crimes monitoring network, further advancements are expected at all stages of the data pipeline from collection to presentation.



Equation 2) Detection-quality equations (false positives, false negatives, and trade-offs)

2.1 Confusion matrix definitions

Let:

- TP = true positives (real sanctions hits flagged)
- FP = false positives (clean transactions flagged)
- TN = true negatives (clean transactions cleared)
- FN = false negatives (sanctioned transactions missed)

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2.2 Metrics derived step-by-step

False Positive Rate (FPR)
Out of all truly clean transactions $(FP + TN)$, the fraction incorrectly flagged is:

$$\text{FPR} = \frac{FP}{FP + TN}$$

False Negative Rate (FNR)
Out of all truly sanctioned $(FN + TP)$, the fraction missed is:

$$\text{FNR} = \frac{FN}{FN + TP}$$

Precision (PPV) (how many flagged are actually sanctioned):

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (TPR) (how many sanctioned you catch):

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1 score (harmonic mean of precision and recall):

$$F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

2.3 Thresholding and ROC (why tuning matters)

For ML scoring, you often flag if score $s \geq \tau$ (threshold τ). As τ decreases:

- more transactions flagged ⇒ Recall increases but FPR also increases.

4.1. Rule-based approaches
Rule-based sanctions screening methods match at least one input data tuple against all supporting tuples using equality or similarity predicates on relevant attributes. The relevant rule-supported data can be modeled as a database table, where rule conditions and the matching transaction records are on separate sides. Grouped rule learning divides the predicate list into multiple smaller subsets, serving as inputs to separate rule classifiers. Less frequently occurring or emerging rule predicates can thus be automatically classified, improving rule learning effectiveness. Two key components are required to efficiently detect sanctions violations against large lists, usually maintained by government authorities. First, a scalable indexing and search engine provides high-speed support for detecting relations specified by the rules. Second, the rules are dynamically detected by monitoring the transaction history. These components can significantly decrease the storage and processing costs of a sanctions system while maintaining real-time performance.
Rule-based screening methods entail searching for a match between a set of candidate pairs extracted from the data and an additional set of relations, which are usually stored in a different location. Rule conditions and momentary entries on the matching side may be stored separately. A scalable indexing and search engine enables timely detection of relations specified by the rules. Additionally, a periodic, off-line mining process identifies important relations of the same kind from the historical transaction records, and this mined data serves as the matching condition of the other side. By combining these components, the overall storage and processing costs of a sanctions system can be substantially reduced while retaining real-time performance.

4.2. Machine learning-assisted classification
An alternative for sanctions detection is provided by machine learning models for text classification. Supervised models assume the availability of labeled training data, which can be generated by integrating source data with historical transaction records. Existing transaction logs can also be used to create negative instances by sampling for data entries that do not match any sanctions list. If no past transaction records exist, a simpler model can be developed from two or more years of historical transactions, where from one year matches for any sanctions list are extracted, and the remainder are treated as negatives. Such training data must carefully consider data provenance. Closed but unmodeled entities can be identified as problematic

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patterns. Semantic anomaly scores can be added as features to detect never-before-seen problematic entity pairs. Semi-supervised learning approaches require far fewer labeled training data but capitalize on their small quantity of positive samples and large amount of negative samples. Weakly supervised models treat the querying of sanctions lists as distant supervision for transfer learning. Unsupervised approaches can leverage noise-contrastive estimation and contrasting target classification strategies in combination with a pre-trained Word2Vec embedding model to improve generalization performance. Further, feasibility considerations can concentrate resources by focusing on rather than ruling out suspicious transactions. A ranking paradigm is thus employed where the detection task is re-cast as a ranking task for the purpose of ranking-the-top-n detection.

5. Data quality, provenance, and governance

In commercial settings, data quality for sanctions screening is crucial to align with reasonable-efforts requirements for transaction monitoring underlegislation. A sanctions screening business case demonstrates how data and decision qualities can be managed. Missing or stale records for watchlist and reference data accelerate false positives. Incomplete integration of source data limits detection of hidden connections with screened entities. Poor provenance contributes to regulatory risk. An approach using source timestamps to manage data freshness and granularity improves results.

Integrating and enriching source data from address and name screening, customer due diligence, and anti-money-laundering risk systems validate and extend watchlist matches. Staging tables are populated incrementally; background data retains the finest detail. Manual operations notwithstanding, freshness-management challenges persist. Senior management auditing trading systems, a classification oversight, and escalating response times establish overdue fixes as operations-resilience obligations. Provenance and auditability are realized with immutable append-only state tables that allow changes to be detected and tracked. Source timestamps accompany records, enabling change monitoring and facilitating sensitivity analyses. Auditability reconciles high-data-provenance demands in a timely and cost-effective manner, adding benefit to governance ratings. Activity visibility is extended to both actions such as payments and prevented actions such as trading restrictions.

5.1. Source integration and data freshness

As a source of transaction data, foreign financial institutions are subject to the rules and regulations put in place by the authorities in charge of the correspondent account. These rules and regulations are reflected in the internal procedures of financial institutions located in a country subject to such rules and regulations. Sanction compliance is checked by processing the incoming payment message (MT103). During this process, the financial institution checks whether any sanctions imposed are being breached. A check on any sanction lists that may contain the beneficiary bank is executed in real time. If a sanction list check fails, a separate internal procedure to investigate whether the sanction is, in fact, valid is triggered.

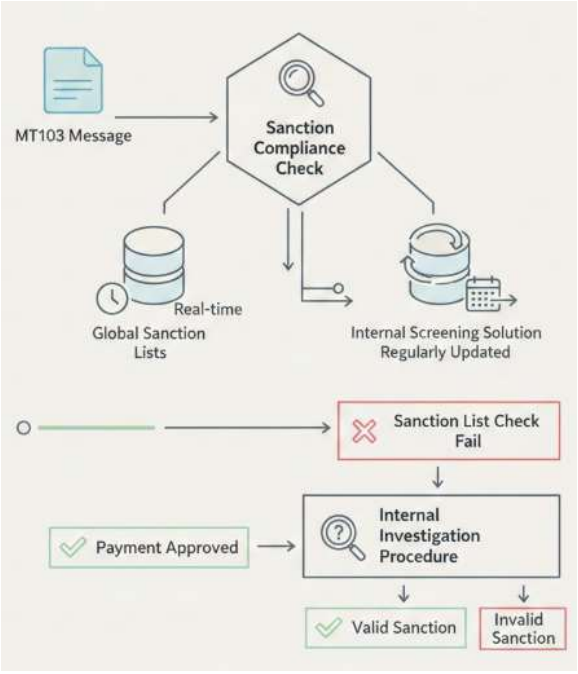

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Fig 3: Architecting Compliance: Real-Time Sanction Screening Integration and Automated Investigative Protocols in Correspondent Banking

One way to check the sanctions is through an internal sanctions screening list that is regularly updated using one of the internal screening solutions. The internal list is a separate and additional list that contains the names of banks that should not be present in the payment flows. It must be fed with the most recent names and, as such, must be refreshed regularly. The embarkation of names on the list follows a set of internal procedures of the financial institution which have been defined in accordance with all relevant norms.

5.2. Provenance tracking and auditability

For both regulatory and operational reasons, screening data must be regularly reviewed and updated to maintain a minimal false-noise ratio, an increasingly critical feature as sanctions regimes become more dynamic. Data freshness is further recognized as a key requirement by some machine-assisted ruleset management frameworks, which rely on regularly refreshed sources to spot changes in entity characteristics or the addition of new records.

Changes are also difficult to detect. The types of changes that commonly introduce risk to financial institutions are jumps in risk score, a probable change of financial element, or family relations or cooperations with other entities that are watched. Continuous provenance and change indexing, however, can facilitate auditing of data freshness and completeness; indeed, successful integration schemata include active monitoring indexed in a provenance layer, allowing traffic lights for freshness indicators, trend detection of variables and cross-reference for probable change notification.

Metric	Formula	Value (illustrative)
Accuracy	(TP+TN)/(TP+FP+TN+FN)	0.988
Precision (PPV)	TP/(TP+FP)	0.8
Recall (TPR)	TP/(TP+FN)	0.4444444444444444
False Positive Rate (FPR)	FP/(FP+TN)	0.002036659877800407
False Negative Rate (FNR)	FN/(FN+TP)	0.5555555555555556

6. System scalability and performance considerations

Scalable, high-throughput systems for the screening of sanctions-related activity need to cope with many conflicting performance objectives: supporting high transaction volumes (throughput), response times of seconds rather than minutes (latency), scaling up and down depending on workload (elasticity), tolerating system or component failures (fault tolerance), and covering system or service interruptions (resilience). Performance optimization requires consideration of all aspects of the system architecture, algorithm design, and the available technology stack.

Integrating performance concerns directly into the design of a sanctions screening system requires examining the key components of the overall system together with the broader context in which screening takes place. High-throughput sanctions screening systems are part of a larger end-to-end business process that starts when a transaction is created and ends with its final disposition by the relevant control functions. Performance can be improved not just by optimizing the sanctions screening step alone but also by eliminating or offloading non-essential functionality outside the screening engine or service.

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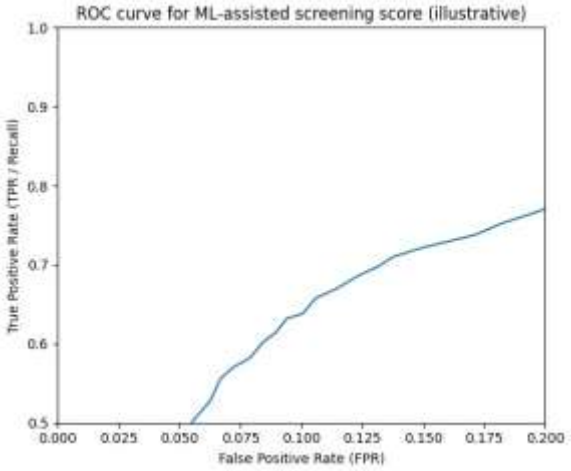

Equation 3) Indexing/search "equations": why dictionary lookups stop scaling

3.1 Dictionary membership cost

Let N = number of candidate entries to check (e.g., names/aliases).
If membership test is linear in N (as described), then:

$$T_{\text{lookup}}(N) = O(N)$$

At throughput λ, compute per second scales as:

$$\text{work/sec} \propto \lambda \cdot O(N)$$

So doubling list size doubles compute at fixed throughput.

3.2 Sub-linear index structures (nearest neighbor / trees)

With a space-partitioning tree or ANN index, average query cost can be:

$$T_{\text{search}}(N)$$
$$\approx O(\log N) \quad \text{(idealized; depends on dimension/structure)}$$

Then:

$$\text{work/sec} \propto \lambda \cdot O(\log N)$$

6.1. Throughput, latency, and elasticity

Throughput represents the volume of transactions that a sanctions screening system can process in a defined time unit (e.g., transactions per second). For high-throughput financial services such as payments or trade finance, throughput constitutes a major consideration. Provided that processing conforms to established Service Level Agreements for sanctions screening, delays may be acceptable provided that they do not introduce artificial constraints for transaction processing. In batch-oriented screening approaches, throughput is determined by the slowest component of the screening function chain, such as integration of data from upstream systems (e.g., SWIFT), search of the sanctions database or of an associated ML model, and delivery of alerts to downstream components.
Latency denotes the delay between request and delivery of results. In a sanctions screening system, low latency is desirable because it allows for nimble and proactive response to detection of potential sanctions violations—for instance, allocation of additional resources to investigate a potential match—and minimizes the financial exposure time associated with alerts during risky time intervals (e.g., for ongoing armed conflict). Latency may be further reduced by progressively assigning an alert risk level, enabling preallocation of detection resources to high-risk alerts.
In contrast to throughput and latency, elasticity indicates the system capability to respond to fluctuating volume and velocity of transactional data by scaling to automatically match the required level of performance. The business case for ML-assisted risk classification partly depends on elasticity, because Financial Transmit and Services institutions rarely conduct sustained screening of messages at the velocity represented by SWIFT in abnormal scenarios (e.g., outbreak of armed conflict, economic sanctions taking effect). Here, performance requirements may be met at appropriate cost through an ML model infrastructure that scales to match sudden peaks.

6.2. Fault tolerance and resilience

A system's ability to operate without errors in the face of failures is termed fault tolerance. Scenarios where users

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expect continued availability during updates and maintenance require a more nuanced notion of fault tolerance known as resilience. To construct a fault-tolerant system, failure modes and rates must be identified and eliminated, often by introducing redundancy; the more critical the task, the more redundancy is needed. Because redundancy increases cost, its use must be economically justified.

Systems designed for very high throughput typically consist of multiple, independent components executing processes in parallel. If the system contains sufficient spare capacity, the redundancy enabled by the parallel architecture also confers resilience. Furthermore, if partitions of highly modular data or algorithm functionality can be isolated and independently taken offline for repair, update, or maintenance, both throughput and latency respond well even when a partition is temporarily removed from service. Careful architectural design can therefore yield a naturally resilient structure for such systems. Failure detection, sequence data validation, output monitoring, and other application-independent techniques can be deployed at low cost. When these measures are not sufficient, redundancy can be added at various levels of the architecture—servers, applications, processes, or functional elements—to enable continued operation at degraded service levels.

7. Conclusion

Highly scalable and performant sanctions screening systems are essential for high-throughput transaction processing, yet only rudimentary approaches to batch and streaming systems have been described. The proposed architectures emphasize trade-offs between performance, throughput, and flexibility, while supporting both canonical batch and streaming patterns. Several screening algorithms are considered, including rule-based systems and techniques that leverage machine learning for detection. Data quality and provenance concerns are addressed in the context of sanctions-sourcing, along with issues of operational performance and elasticity.

The presented architectures should provide a foundation for high-throughput sanctions screening and offer a toolkit of scalable, customizable methods appropriate for high-speed transaction environments. Extracting and unifying information from sanctioned entities within a continuously evolving dataset is a fundamental challenge in rule-matching systems for these environments. Tracking the temporal provenance of entities and their attributes addresses data freshness concerns in any matching system and disciplinary provenance support is essential for both source integration and rule evaluation. Further work will explore the completeness and accuracy of detection and matching methods, especially for sanctions entities with non-standard names and aliases.

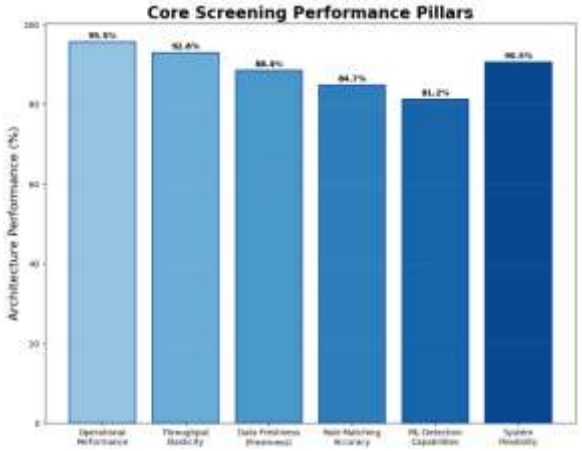

Fig 4: Core Screening Performance Pillars

7.1. Final Thoughts and Future Directions

Scalable sanctions screening systems for high-throughput financial transaction processing: use an objective, evidence-based, formal structure; present clear, testable claims and data-supported arguments.

A sanctions screening solution addressing the above issues can lay the groundwork for future research in this domain, enabling flexible exploration and a deeper understanding of the factors that determine technology efficiency and suitability. Upstream and downstream applications of sanctions detection also benefit from an accurate, up-to-date, and exhaustive database of multiple sanctions source lists, with capabilities for sensitive-name identification, data provenance recording and tracking, provide detailed

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alerts, and ensuring ease of integration with existing workflows.

Support for bottom-up efforts is equally valuable, especially when aiming to meet specific organization needs in an efficient, cost-friendly manner. System throughput and latency naturally stand out as primary design considerations, underlying all strategic decisions within the broader development plan. In addition to optimizing resource utilization, such considerations pave the way toward low-latency, near-real-time solutions for destinations handling tens of thousands of transactions per hour. Expandability, versatility, and fault tolerance also support increasingly high throughput requirements across application levels, without compromising the demand for precision—indeed, by increasing it in selected operational contexts.

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