

Artificial Intelligence and Fraud Detection in Digital Financial Services: A Hybrid Analytical Framework

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ABSTRACT

Fraud in digital financial services is rare, adaptive and costly, and no single detection approach handles all three properties: supervised models learn known fraud patterns but miss new ones, anomaly detection flags unusual transactions regardless of whether they are fraudulent, and expert rules encode domain knowledge but are brittle. This paper proposes a hybrid analytical framework that combines the three through rank-based fusion and examines it in a simulation of 40,000 transactions with a 1.6% fraud rate, of which 19% follow a pattern absent from the training data. Under a 1% alert budget, the supervised model attains precision of 14% and recall of 9% but catches none of the novel fraud; the anomaly detector attains 19% precision and 13% recall and catches 15% of novel fraud; rules attain 11% and 7%; and the hybrid attains the highest precision (22%) and recall (14%) while retaining 9% recall of novel fraud. The paper explains why fusion improves on its components, how the component weights should be set from the organisation's fraud mix and alert capacity, and how the framework supports the feedback loop in which analyst decisions retrain the supervised component and anomaly findings become new rules. Implications for alert management, model governance and the evolution of fraud detection as attackers adapt are discussed.

Keywords: fraud detection; digital financial services; hybrid models; anomaly detection; supervised learning; alert budget

1. Introduction

Digital financial services, including payments, lending, wallets and trading platforms, process transactions at a scale and speed that only automated fraud detection can police. Fraud has three properties that make detection hard. It is rare, so that detectors must find a few hundred cases among millions and every alert consumes scarce analyst time. It is adaptive: fraudsters change tactics when detected, so that patterns learned from history decay. And it is costly, both in direct losses and in the customer friction that false alerts create [1], [2].

Three analytical approaches address these properties differently. Supervised machine learning, trained on labelled historical fraud, achieves high precision on patterns it has seen and decays on patterns it has not [3]. Anomaly detection, which scores transactions by their deviation

from normal behaviour, needs no labels and can surface novel patterns but flags much benign unusual activity [4]. Expert rules encode knowledge of fraud typologies in explicit conditions that are transparent and fast but brittle and easily evaded. Operational fraud systems combine them informally, usually by running rules first and models second.

This paper proposes a principled hybrid in which the three components are fused by rank, examines it in a simulation that includes novel fraud absent from training data, and derives guidance on weighting, alert management and the feedback loop that keeps the system current.

2. Background

2.1 Fraud detection methods

Surveys of fraud analytics [1], [2] document the shift from rules to supervised models and the persistent problems of class imbalance, concept drift and label latency. Supervised methods including gradient boosting [3] dominate benchmark performance on historical data. Anomaly methods such as isolation forests [4] are used for unsupervised screening. Ensembles that combine scores have been shown to improve robustness.

2.2 Evaluation under alert budgets

Because analysts can review only a fixed number of alerts, detection should be evaluated at the operating point the budget implies: precision and recall among the top-ranked transactions, rather than area under the ROC curve alone [5]. Recall of novel fraud, measured on patterns excluded from training, indicates robustness to adaptation.

2.3 Hybrid architectures

Combining heterogeneous detectors raises the question of how to fuse scores on different scales. Rank-based fusion, which converts each score to a percentile and takes a weighted average, is scale-free and robust, and it allows components to be weighted by their expected contribution [6].

2.4 Adaptation and concept drift

Fraud differs from most classification problems in that the positive class is produced by adversaries who respond to the classifier. A pattern that is detected stops being used, and a new one replaces it; the supervised model's training distribution therefore drifts away from the operational distribution at a rate set by fraudsters' agility. Two consequences follow for detection design. The system needs a component that does not depend on past labels, so that it can register patterns that have never been seen; and it needs a mechanism for converting newly discovered patterns into labelled examples quickly, so that the supervised component catches up. The hybrid framework supplies the first through anomaly detection and the second through the feedback loop.

3. The Hybrid Framework

The framework has three detection components and a fusion layer. The supervised component is a gradient-boosting classifier trained on labelled transactions. The anomaly component is an isolation

forest trained on legitimate transactions. The rules component encodes typologies as conditions. Each produces a score; the fusion layer converts scores to percentile ranks and combines them:

$$S_{\text{hybrid}} = w_{\text{sup}} \text{rank}(s_{\text{sup}}) + w_{\text{anom}} \text{rank}(s_{\text{anom}}) + w_{\text{rule}} \text{rank}(s_{\text{rule}}), \quad (1)$$

with weights summing to one. Alerts are the top q fraction by hybrid score, where q is the alert budget. A feedback loop returns analyst decisions as labels to the supervised component and promotes confirmed anomaly findings to rules.

4. Simulation Design

The harness generates 40,000 transactions with amount, hour, new-device indicator, velocity, geographic-mismatch indicator and merchant risk. Known fraud follows a logistic process in these features; a novel pattern, high-velocity small-amount transactions, affects 0.3% of transactions and is excluded from training labels. The realised fraud rate is 1.6%, of which 19% is the novel pattern. Components are trained on 70% of transactions and evaluated on the rest at a 1% alert budget by precision, recall and recall of novel fraud; AUC and average precision are also reported. Fusion weights are 0.6, 0.3 and 0.1. Parameters are design values; the harness examines how the components and the hybrid behave on known and novel fraud.

5. Results

5.1 Component and hybrid performance

Table 1 and Figure 1 report results. The supervised model has the highest precision among single components on known fraud but catches no novel fraud, because the novel pattern is absent from its labels. The anomaly detector has the best single-component AUC (0.79) and catches 15% of novel fraud, since the pattern is anomalous, but its precision is limited by benign anomalies. Rules are weakest on every metric. The hybrid attains the highest precision (22%) and recall (14%) at the 1% budget and retains 9% recall of novel fraud, inheriting the anomaly component's robustness while improving precision through the supervised component.

5.2 Why fusion helps

The components err differently. The supervised model's false positives are legitimate transactions that resemble known fraud; the anomaly detector's are unusual but legitimate transactions; the rules' are transactions that satisfy a condition for benign reasons. A transaction that ranks high on all three is far more likely to be fraud than one that ranks high on one, and rank fusion rewards such agreement. The hybrid's precision exceeds every component's because agreement is informative, and its novel-fraud recall is non-zero because the anomaly component can lift a novel case into the alert set even when the supervised component scores it low.

5.3 The weight trade-off

The hybrid's novel-fraud recall (9%) is below the anomaly detector's (15%) because the fusion weights favour the supervised component. Raising the anomaly weight would raise novel recall and lower precision on known fraud. The weights therefore encode a choice between exploiting known

patterns and exploring for new ones, which the organisation should set from its fraud mix: where novel fraud is a growing share, the anomaly weight should rise.

Table 1: Detection performance at a 1% alert budget (12,000 held-out transactions; fraud rate 1.6%; 19% of fraud novel)

Component	AUC	Average precision	Precision at 1%	Recall at 1%	Recall of novel fraud at 1%
Supervised (gradient boosting)	0.749	0.064	14.2%	9.3%	0.0%
Anomaly (isolation forest)	0.787	0.114	19.2%	12.6%	15.2%
Rules	0.606	0.042	10.8%	7.1%	0.0%
Hybrid (rank fusion)	0.780	0.090	21.7%	14.2%	9.1%

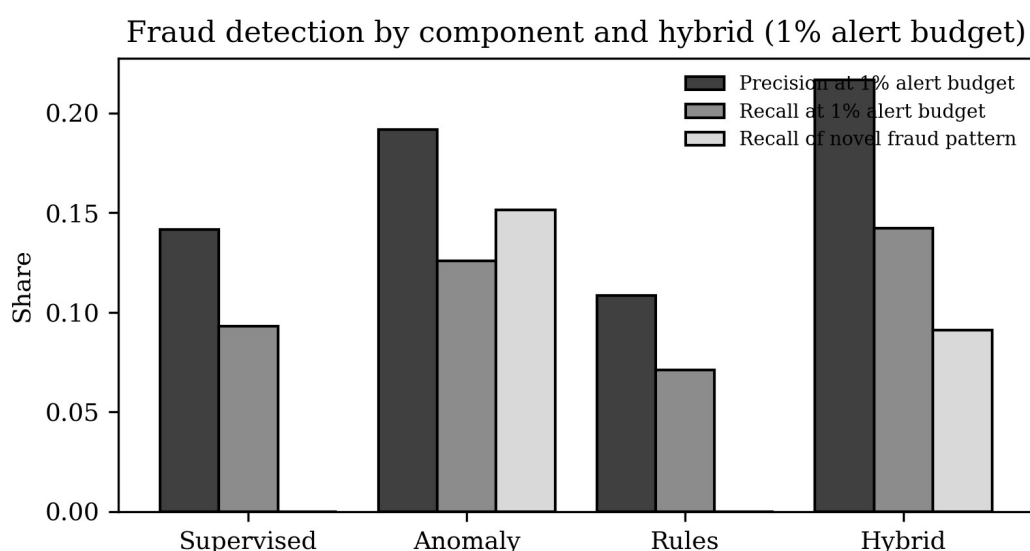


Figure 1: Precision, recall and novel-fraud recall at a 1% alert budget by component and for the hybrid

5.4 Sensitivity

The hybrid's margin over the best single component depends on how differently the components err; where the anomaly detector's false positives coincide with the supervised model's, fusion adds little. The novel-fraud results depend on the novel pattern being anomalous in the available features, which is true of the simulated pattern and of many but not all real ones. Precision levels are low in absolute terms because fraud is rare and the features are few; richer features raise all components. The qualitative conclusions, that fusion improves precision through agreement and that an unsupervised component is necessary for novel fraud, hold across these variations.

6. Operating the Framework

6.1 Setting weights and budget

Weights should be set by back-testing on recent data with a held-out period that includes patterns absent from training, as in the simulation, and revisited quarterly. The alert budget should be set where the marginal alert's expected prevented loss equals analyst cost; the precision curve from the hybrid score supplies the marginal precision.

6.2 The feedback loop

Analyst decisions on alerts are the labels that retrain the supervised component; without them, it decays as fraud adapts. Confirmed anomaly findings that recur should be promoted to rules, which are fast and transparent, and rules whose precision falls should be retired. The framework thus migrates knowledge from exploration (anomaly) through exploitation (supervised) to codification (rules).

6.3 Alert management

Alerts should be routed by hybrid score and by component agreement: transactions flagged by all components to automated action, those flagged by one to analyst review, with reasons drawn from the contributing component. Presenting the component scores alongside the hybrid score helps analysts calibrate and provides the explanation that regulators and customers increasingly require.

6.4 Governance

Each component is a model with its own validation needs; the fusion layer adds a configuration, the weights, that changes system behaviour and should be under change control. Monitoring should track precision by component over time, since a falling supervised precision signals drift and a rising anomaly precision signals a new pattern.

6.5 Customer friction

False alerts impose friction on legitimate customers, including declined transactions, verification calls and account holds, and friction drives attrition. The alert budget should therefore be set with customer cost included alongside analyst cost, and the routing in Section 6.3 should reserve automated declines for high-agreement cases and use lighter-touch interventions, such as step-up authentication, for single-component alerts. The hybrid's higher precision at a given budget reduces friction directly, which is a customer-experience benefit as well as an operational one.

6.6 Regulatory and explanation requirements

Financial regulators increasingly require that automated decisions affecting customers be explainable and that fraud systems be validated. The component structure of the hybrid supports both: each alert carries the contribution of each component, rules are inherently explainable, and the supervised and anomaly components can be documented and validated separately. Fusion weights and their rationale should be part of the model documentation.

6.7 Extending the components

The framework accommodates additional components without changing its structure. Graph-based detectors that score transactions by the network of accounts and devices they connect to, sequence models that score the recent history of an account, and consortium signals shared across providers each produce a score that rank fusion can absorb. The practical constraint is that each component adds validation and monitoring burden, so components should be added when back-testing shows they err differently from those already present.

6.8 Measuring success

Fraud programmes are often judged by losses, which rise and fall with attack volume regardless of detection quality. Better measures are precision and recall at the operating budget, tracked over time; the share of confirmed fraud first identified by each component, which shows where discovery is happening; and the lag between a new pattern's first appearance and its incorporation into rules or labels, which measures the feedback loop's speed. These measures are available from the framework's own logs and should be reported alongside losses.

7. Limitations

The transaction process and the novel pattern are stylised; real fraud is more varied and novel patterns may not be anomalous in the features available. The rules component is minimal. Fusion weights were set rather than optimised, and label latency and analyst behaviour are not modelled. All reported values are simulation outputs and are not estimates of detection performance for any provider.

8. Conclusion

Fraud in digital financial services is rare, adaptive and costly, and a hybrid framework that fuses supervised, anomaly and rule-based detection by rank addresses all three better than any component alone. In simulation it achieved the highest precision and recall at a fixed alert budget while retaining substantial recall of fraud absent from training data. Its operation depends on weights set from the fraud mix, a budget set from analyst economics, and a feedback loop that converts analyst findings into labels and rules, so that the system adapts as fraud does. The framework's lasting contribution is less any particular component than the discipline of evaluating detection at the operating budget, on known and novel fraud alike, and of treating the detection system as a learning process rather than a fixed model.

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