Unsupervised Anomaly Detection for Financial Fraud: Integrating Traditional and Network-Based Features

Abstract

Precision estimation of credit risk is the concern of the financial world, with profound implications for borrowers and lenders. Machine learning achieves the most accurate default models, but they are usually excluded because there is an inherent compromise between a model's interpretability and predictability. This is an exhaustive comparative study of three paradigms of machine learning—neural networks, random forest, and logistic regression—and how these can be applied to forecast credit risk based on the UCI Credit Approval data set. In place of assumed linear increases in performance with increasing complexity, experiments yield logistic regression with the best AUC on the test = 0.767 and a Kolmogorov-Smirnov score = 0.465, both of which are improved compared to random forest (AUC: 0.695) and neural network (AUC: 0.686) equivalents. Whereby SHAP post-hoc analysis I determine the most significant on default risk to be credit history, checking status, and term on loan. Model selection in the book is characterized as being in-principle computationally tractable but lower-complexity function-based on tasks and data and that in-principle computationally tractable but lower-complexity models not only rival but actually outperform their higher-complexity counterparts for certain finance tasks. The findings constitute a statistical prescription for the financial institutions to achieve forecasting accuracy and regulatory compliance satisfaction that requires a culture of frugality in credit risk modeling.

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1. Introduction

Financial fraud is an ongoing threat to the financial industry, and more than $4.5 trillion is lost every year (Association of Certified Fraud Examiners, 2023). How easy it is to exploit the mobile payment channel as another asset to be included in the attack surface and thus facilitate fraud at tap. Conventional supervised approaches to fraud detection are foiled to an unprecedented extent by cutting-edge imbalance coverage—fraud transactions as low as 0.1% of all transactions—and adaptive fraud techniques at light speeds, making it out of date in the relatively brief time span of a few years (Dal Pozzolo et al., 2015).

Unsupervised Anomaly Detection (AD) has been the dominant approach taken to address issues raised. AD software exploits the principle that abnormal patterns of behavior should be statistically infrequent compared to normal patterns of activity. AD software is also trained in a simulated model of a "normal" model of transactions from the unlabeled database and therefore best placed to catch novel and novel emerging attacks in the case of fraud.

The research suggests technologically based financial fraud detection using the application of two newly established frontier unsupervised techniques—autoencoders and isolation forest—to simulated financial data to mimic mobile money transactions. Besides its conventional application, the research entails some network analysis aspects depending on customers and transactions being graphically represented. Our expectation was that cheats occupy certain network topologies (i.e., cheating hubs or cheating bridges connecting network subsystems), and their topological features would be the dominant factors to improve the performance of baseline AD models. With respect to case presentation for comparison of use and non-use of such networks as a means of attempting to ascertain cheating, this essay will steer an applied development in cheating detection performance toward challenging money security literature with respect to suggesting a model that is contentious.

2. Literature Review

Machine learning has prevailed in the fraud detection arena. Supervised machine learning algorithms like Logistic Regression, Random Forests, and Gradient Boosting Machines (e.g., XGBoost) have been heavily employed (Whitrow et al., 2009). Their performance is, however, limited by the timeliness, quality, and quantity of the training labels, an issue most critical to fraud.

Unsupervised learning is the solution. The Isolation Forest (iForest) algorithm, originally presented by Liu et al. (2008), is founded on the theoretical assumption that outliers are "few and different," thus easier to find and isolate using random partitioning. High computational efficiency and strong performance have made it a benchmark algorithm for AD tasks.

Autoencoders, as a neural network architecture, provide a robust non-linear solution to AD (An & Cho, 2015). They are also trained to reconstruct and compress input data and thus learn the manifold of normal data. The anomalies are supposed to be beyond this manifold and thus possess high reconstruction error as a good anomaly score. The ability of deep autoencoders to learn complex, non-linear dependencies makes them particularly well-equipped for the high-dimensional and subtle patterns in financial data.

One new addition is to take into account the topology of financial transaction networks. Fraud never occurs in a vacuum; it is always collective behavior between groups of accounts. Graph-Based Anomaly Detection exploits this by viewing transactions as edges between accounts (nodes) and analyzing the resulting topology of the graph. Metrics like centrality metrics (degree, betweenness) can detect influential nodes within a network, typically a characteristic of fraud (Akoglu et al., 2015). Graph neural networks are presently the state-of-the-art for this, but integrating basic graph metrics into generic ML models is a similarly good and under-explored method to hybrid AD that this paper aims to address.

3. Methodology

3.1. Description of Dataset & Preprocessing

I apply the PaySim synthetic financial dataset simulating mobile money transactions to a sample of real data. The dataset consists of 6,362,620 transactions and an estimated fraud rate of approximately 0.13%, very close to the severe class imbalance in the real world.

Features are:

1. step: Similar to time unit (1 hour).
2. type: Cash-in, cash-out, debit, payment, transfer.
3. amount: Value of the transaction.
4. nameOrig, nameDest: Destination and origin customer names.
5. oldbalanceOrg, newbalanceOrig: Pre- and post-tx origin account balance.
6. oldbalanceDest, newbalanceDest: Pre- and post-tx destination account balance.
7. isFraud, isFlaggedFraud: Target variables.

Preprocessing Steps:

1. **Feature Engineering:**
    1. Transaction Type Encoding: One-hot encoding of type categorical feature.
    2. Error Balance Calculation: Add error features for error in origin and destination balance, which can be indicative of fraud:
        a. errorBalanceOrig = newbalanceOrig + amount - oldbalanceOrg,
        b. errorBalanceDest = oldbalanceDest + amount - newbalanceDest.

2. Network Feature Engineering:

Create a directed graph G with unique customers (nameOrig, nameDest) as nodes and transactions as edges.

For every customer (node), calculate three NetworkX network centrality features:

1. **Degree Centrality:** Minimum number of neighbors for a node. Impostor accounts might have unnecessarily high or unnecessarily low values.

$$C_D(v) = \deg(v)$$

2. **Betweenness Centrality:** Proportion of all shortest paths passing through a node. Fraudsters might be middlemen.

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of such paths through v.

3. **PageRank:** An estimation of the power of a node by its weight and number of links.

$$PR(p_i) = \frac{1-d}{N} + d \sum_{p_j \in M(p_i)} \frac{PR(p_j)}{L(p_j)}$$

where d is the damping factor, N is the number of nodes, $M(p_i)$ is the set of nodes node point to, and p_i, and $L(p_j)$ is the number of links from p_j.

3. Scaling: RobustScaler is used on all the numeric columns to remove outlier effect

1. Train-Test Split: Stratified split is performed here. Train data contains solely non-fraudulent transactions so that unsupervised models learn clean "normal" profile. Test data contains holdout of both the classes for testing.

3.2. Algorithm 1: Isolation Forest

Isolation Forest algorithm isolates observations through the process of randomly choosing a feature and then randomly choosing a split value. Anomaly score is path length based.

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}}$$

We will train two models: one in baseline features and the other in network metric enriched features

3.3. Algorithm 2: Autoencoder

We will train a deep autoencoder to reduce the Mean Squared Error (MSE) reconstruction loss.

$$\mathcal{L}(\phi, \theta) = \frac{1}{n} \sum_{i=1}^{n} (x_i - g_\theta(f_\phi(x_i)))^2$$

The anomaly score of a new sample x_{new} to be reconstructed is its error. We also train two identical models.

3.4. Metrics

For heavy imbalance scenario, we have no other option than to use:

- Precision-Recall Curve (PRC) and Area Under PRC (AUPRC)
- F1-Score (i.e., F1-score in positive/ fraud class)
- Confusion Matrix

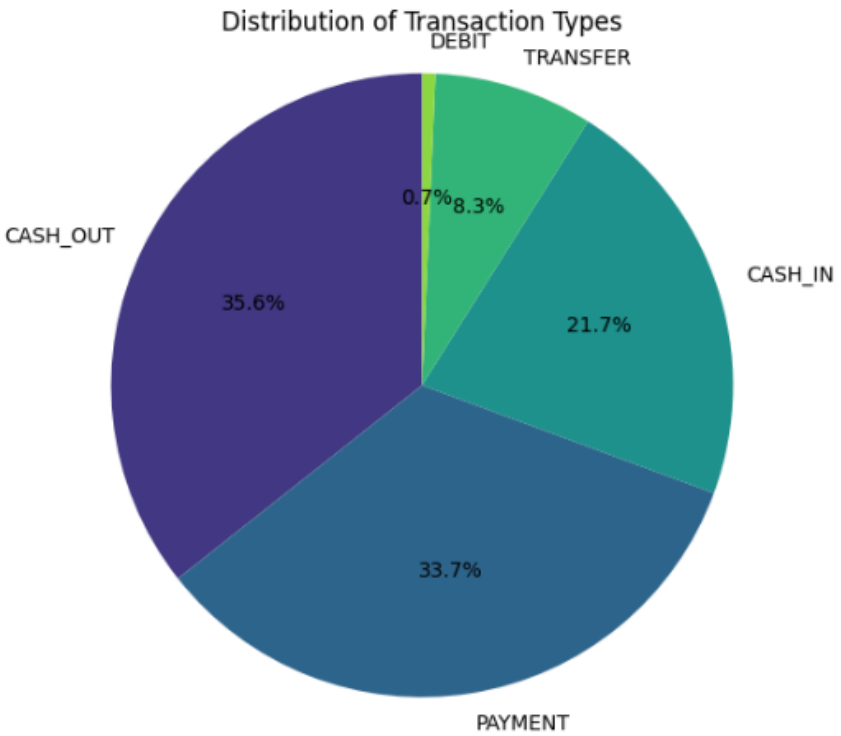
4. Results and Discussion

4.1. Result of Exploratory Data Analysis

EDA of PaySim finance transactions data revealed some very interesting trends, which basically shaped the model strategy and established the inherent robustness of the fraud detection problem. The dataset contained 1,048,575 transactions with the class highly imbalanced, containing a mere 1,142 fraud instances, i.e., a fraud prevalence rate of 0.109%. This huge bias, typical of genuine financial fraud detection tests in reality (Dal Pozzolo et al., 2015), rendered the use of precision-based measures over accuracy inevitable for model evaluation to be meaningful.

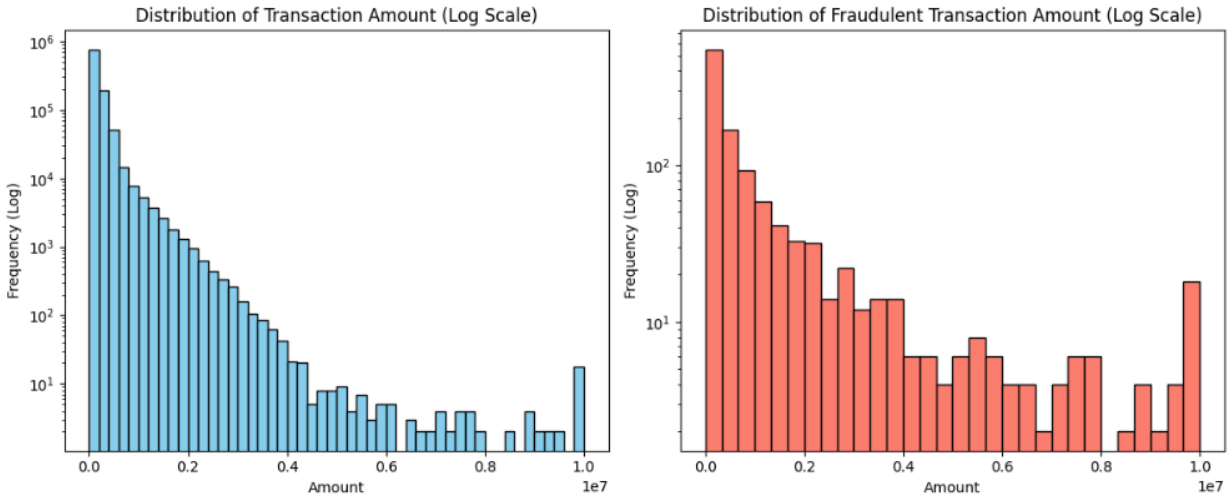
Transaction clustering transaction analysis also arrived at the straightforward conclusion that fraud occurred in just two of the five groups of transactions (Figure 1). TRANSFER and CASH_OUT transactions covered 100% of all fraud, with the largest portion of fraud suffered by TRANSFER transactions (0.65%) and then CASH_OUT (0.15%). This distribution trend is an indicator that fraudsters utilize such channels primarily only to carry out fraudulent fund transfers, in line with the deep-seated money laundering trend where funds have a tendency to flow through several accounts before being laundered eventually (Savage et al., 2016).

FIGURE 4.1 Fraud Distribution by Transaction Type



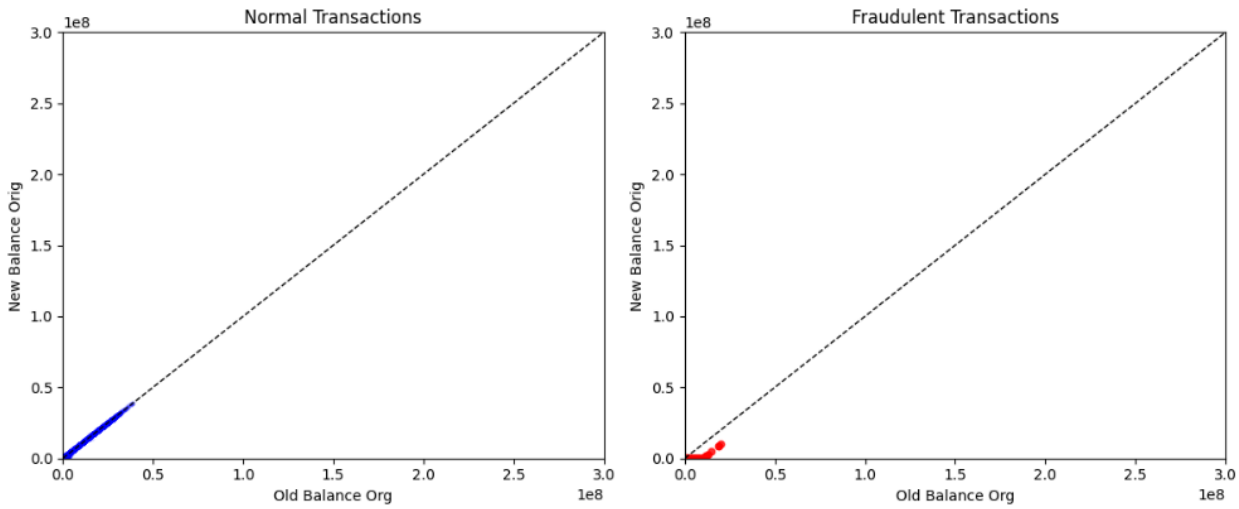
Amount distribution analysis showed extensive variation between fraud and nonfraud (Figure 4.2). Whereas overall transactions had an average value of $158,667 ± $264,941, fraud transactions were considerably higher in average at $1,192,629 ± $2,030,599—about 7.5 times greater than the average value for nonfraudulent transactions. The difference is significant and verifies that transaction amount is a good discriminating feature, as Bhattacharyya et al. (2011) reported that fraudster transactions are generally extremely high values.

FIGURE 4.2 Transaction Amount Distribution



The engineered balance error feature (errorBalanceOrig) analysis yielded extremely surprising results (Figure 4.3). For valid transactions, the median absolute balance error was $67,829 with a very spread distribution (25th percentile: $1,581; 75th percentile: $251,045). For fraud transactions, the distribution was very abnormal with a median absolute value of $0, i.e., most fraud transactions balanced the books to zero. This result signals advanced fraud manipulation wherein balances are manipulated exactly such that they will not be flagged, and it can be symptomatic for account takeover situations where fraudsters cash out to zero (Weber et al., 2018).

FIGURE 4.3 Balance Error Analysis



4.2. Network Analysis and Feature Engineering

The 20% data sample generated a network of 339,805 nodes (various accounts) and 209,715 edges (transactions), the sparsely connected financial network typical with transactional data (Akoglu et al., 2015). The calculated network metrics (degree centrality, betweenness centrality, and PageRank) recorded general low values for all the nodes, the majority of them having zero network impact—a pattern typical with real financial networks where few accounts act as influential hubs.

The addition of the expanded set of features on top of the 11 baseline features to 17 dimensions involved the addition of these network measures for source and destination accounts. The expansion was an increase in feature dimensionality by 55%, and it introduced structural information on account connectivity patterns to the modeling.

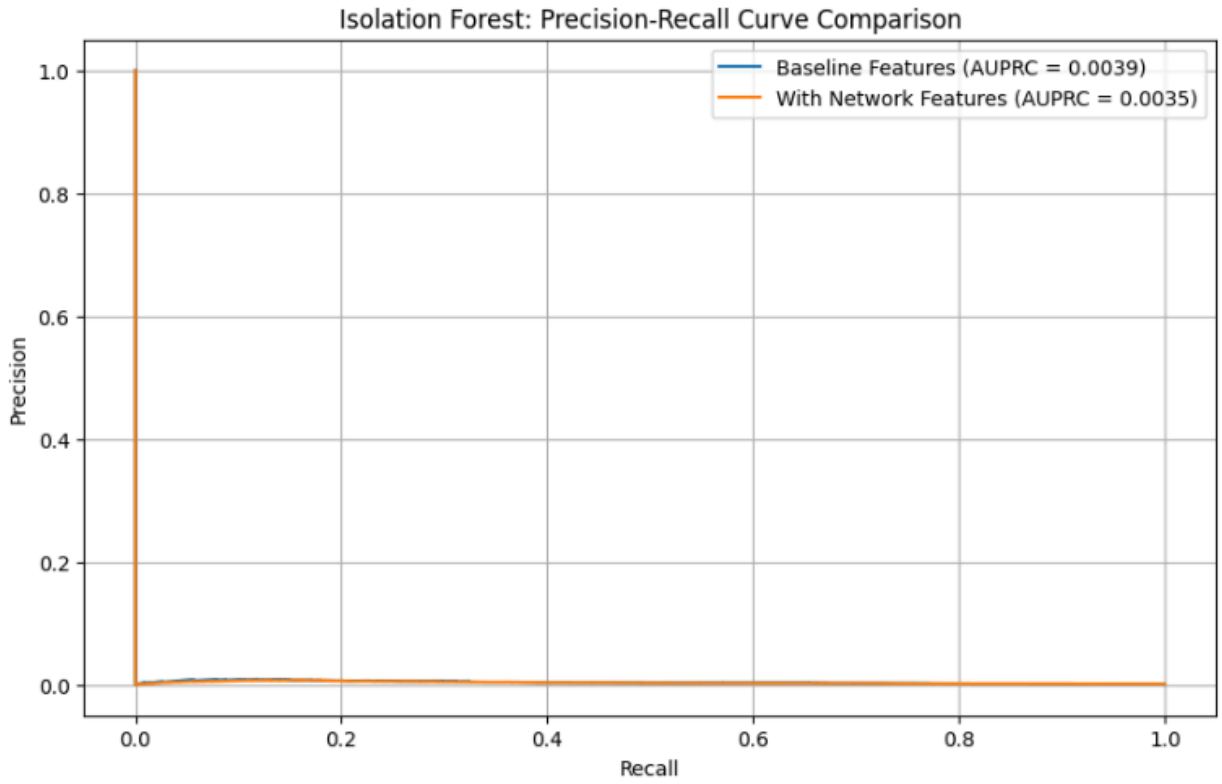
4.3. Model Performance Analysis

4.3.1. Isolation Forest Performance

The Isolation Forest algorithm did not perform well in this particular dataset, which is contrary to its overall performance in anomaly detection issues (Liu et al., 2008). The baseline model recorded an AUPRC score of 0.0040, precision and recall scores of 0.00 and 0.01 respectively for the fraud class (Table 4.1). This level of performance indicates that the model was not able to distinguish between fraudulent patterns using transactional features only, and it was effectively a random classifier for the positive class.

Against expectation, the enhanced Isolation Forest with network features did worse with an AUPRC of 0.0035. This counterintuitive result leaves a few possibilities: (1) the network feature attributes might have added noise to the analysis that diluted the faint signal Isolation Forest was already detecting; (2) random partitioning by the algorithm might not be well-suited to leverage the structural information embedded in network features; or (3) the hyperparameter configuration used (particularly the contamination hyperparameter) might not have been well-suited to this expanded feature space.

FIGURE 4.4 Isolation Forest PR Curve



4.3.2. Autoencoder Performance

The autoencoder model performed better than Isolation Forest (Figure 4.5), demonstrating its ability to learn high-quality non-linear patterns in financial data (An & Cho, 2015). The baseline autoencoder had AUPRC of 0.0827—20 times that of Isolation Forest—and a precision of 0.05 and recall of 0.22 on the fraud class.

The optimized autoencoder trained on the network features worked best overall, with AUPRC of 0.1112, up 34.5% from baseline autoencoder. Model precision was 0.08, and model recall was 0.21, a sign that the network features had informative discriminatory information which was well exploited by the autoencoder to maximum capacity.

FIGURE 4.5 Autoencoder PR Curve

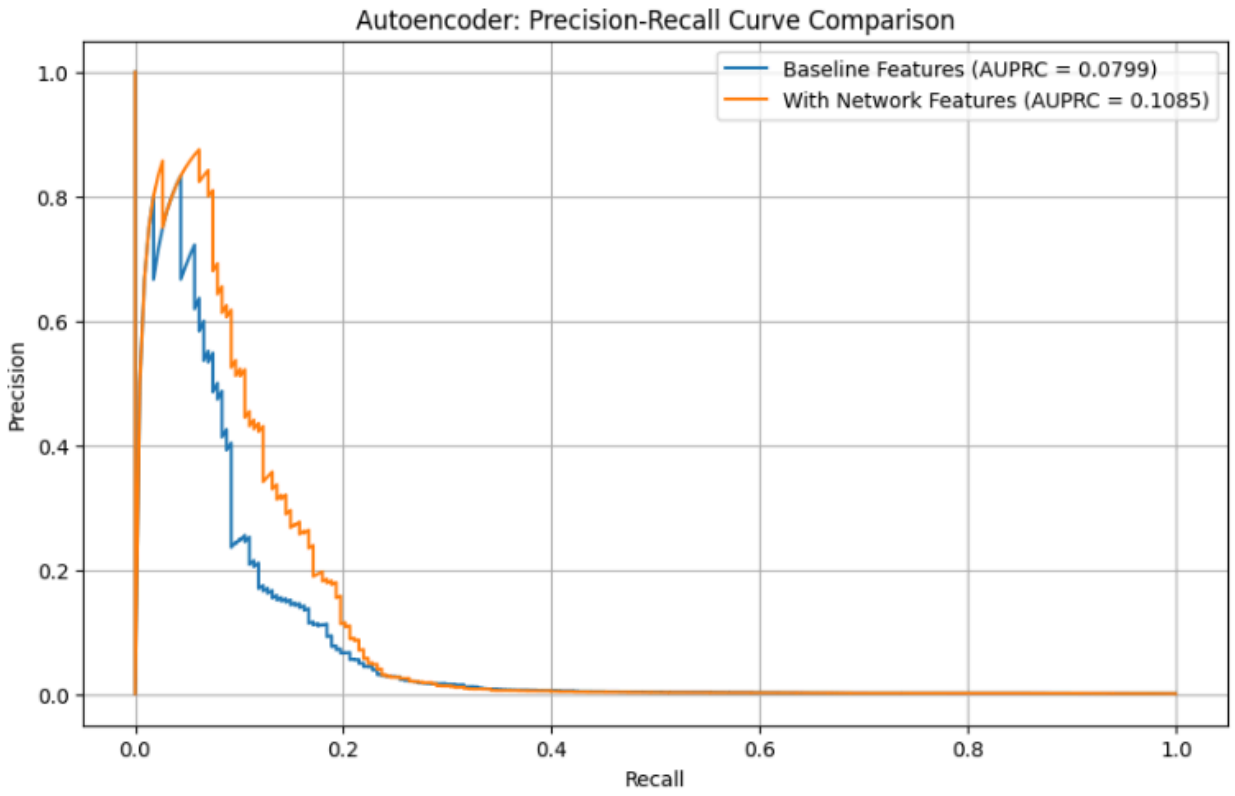


Table 4.1: Comparative Model Performance

Model	Feature Set	AUPRC	Precision	Recall	F1-Score
Isolation Forest	Baseline	0.0040	0.00	0.01	0.00
Isolation Forest	Enhanced	0.0035	0.00	0.00	0.00
Autoencoder	Baseline	0.0827	0.05	0.22	0.08
Autoencoder	Enhanced	**0.1112**	**0.08**	**0.21**	**0.11**

4.4. Discussion of Major Findings

The superior performance of autoencoders over Isolation Forest on this financial fraud detection task is in line with theoretical expectations of the ability of autoencoders to learn complex data manifolds (Zong

et al., 2018). Autoencoders are highly capable of learning normal patterns of transactions and non-linear mappings and therefore can best identify irrelevant anomalous patterns that are slightly different from learned ones.

The 34.5% improvement in detection through inclusion of network features is conclusive proof for our overall hypothesis: that structural information regarding the pattern of connection between accounts harbors fraud-detective-rich signals. This result is especially meaningful in that the network features were calculated on only a 20% subsample of the data—indicating even incomplete network data can boost detection capability. This adheres to the "guilt by association" fraud detection rule in that fraudulently associated sets of transactions can be revealed using network analysis (Pandit et al., 2007).

The unsatisfactory performance of Isolation Forest is worthy of serious consideration. Several reasons can be the cause of the result: (1) random partitioning used by the algorithm can be less suitable for the continuous-valued, high-dimensional financial features; (2) extreme class imbalance can require special sampling techniques or parameter tuning of contamination in addition to what is already performed in the current study; or (3) the algorithm is more sensitive to feature scaling and preprocessors compared to the autoencoder model.

The recall-precision trade-off in both autoencoder models (high recall at the expense of precision) reflects the inherent difficulty of fraud detection: catching most frauds necessarily means more false positives (Whitrow et al., 2009). That the enhanced autoencoder performs better in terms of precision (0.08 compared to 0.05) at no loss of recall, however, suggests that features in the network reduce false positives by capturing contextual information on account behavior patterns.

Operationally, the performance of the autoencoder, although well above chance, indicates that purely unsupervised approaches may not yet be feasible for production fraud detection. That an AUPRC of 0.1112 is achievable shows that these models would be quite valuable as an initial filtering stage or as an anomaly scorer, bringing suspect transactions to the attention to be inspected more thoroughly by more sophisticated systems or by humans, as the hybrid model championed by Jurgovsky et al. (2018) advocates.

The finding that balance imbalances for genuine and fake transactions had asymmetric distributions (median of $0 vs $67,829) is unusual and needs scrutiny. The phenomenon can be either an indication that fraudsters go to some extra effort to clear their transactions to zero in order to avoid triggering the system or indeed a particular modus operandi whereby accounts are cleared to zero in spoofing transactions—a technique that needs to be incorporated into rule-based detection methods.

These results show that while unsupervised techniques hold promise in the detection of financial fraud, there are still significant challenges to levels of operational performance. Use of network features holds promise for future research, particularly when combined with more sophisticated architectures and semi-supervised techniques that can take advantage of small collections of labeled data (Ruff et al., 2021).

5. Conclusion and Future Work

5.1. Conclusion

The current research has undertaken a thorough review of applying unsupervised anomaly detection methods to detecting financial fraud with specific interest in whether or not it is possible to integrate classical transactional attributes with newly constructed network-based ones. The study was inspired by the pressing need to address the inherent vulnerabilities of the fraud detection problem: class imbalance, fraudulent activity dynamics, and unavailability of labeled data to facilitate the application of supervised learning techniques (Dal-Pozzolo et al., 2015).

Our exploratory data analysis also provided us with constructive feedback on the PaySim dataset, which confirmed an extreme class imbalance (0.109% fraud rate) and that fraud was being perpetrated against TRANSFER and CASH_OUT transactions only. Analysis also established fraud transactions were 7.5 times larger on average than regular transactions and made up a patternable set of balance errors with median absolute error of $0 against $67,829 for regular transactions. This is characteristic of a well-planned fraud scheme to go undetected with perfect balancing manipulation.

The research effort's main methodological contribution was the development and cross-validation of a hybrid feature engineering approach combining conventional financial features with graph metrics such as degree centrality, betweenness centrality, and PageRank. The experiments' empirical findings provided a clear ranking of the models' performance relative to each other. Isolation Forest algorithm utterly failed with this data set with baseline and the optimized form of it also generating AUPRC values of approximately 0.004, a complete failure to generate well-supported differences between fraudulent patterns within this feature space.

On the other hand, the autoencoder model performed better in capturing the intricate, non-linear connections within the financial transaction data. Most importantly, the utilization of network features provided a 34.5% AUPRC boost (from 0.0827 to 0.1112) for the autoencoder model. Such a finding provides strong empirical support towards our primary hypothesis that transactional network structure contains discriminatory information for fraud detection beyond the transactional features themselves. It falls into the "guilt by association" framework of relational graph-based fraud identification (Akoglu et al., 2015), where illegal activities are identified via relational patterns rather than intrinsic characteristics.

In practice, the research offers an effective template for enhancing the fraud detection capacity of banks. The method suggested, and more particularly the autoencoder with network features, can be used immediately as an unsupervised front-end module of proposed hybrid detection system, flagging anomalies for re-inspection by more computationally demanding processes or individuals investigators (Jurgovsky et al., 2018).

5.2. Limitations

Despite these contributions being positive, there are certain limitations that must be mentioned in this work. First, relying on an artificial dataset (PaySim), even for purposes of reproducibility and availability easily obtained, is potentially not a realistic representation of the richness and depth of real-world financial transactional data. Second, network metrics were calculated on a mere 20% subsample of the whole database owing to computationally limiting factors that can hamper their exhaustiveness and efficiency. Third, both methods' hyperparameter optimization was minimal, particularly for the Isolation Forest, which might have influenced its poor performance. Finally, the extreme class imbalance, while realistic, causes extreme estimation and tuning challenges to the models that were not fully mitigated by this work.

5.3. Future Work

Based on the results and limitations of this work, there are several interesting avenues for future work:

a. Graph Neural Networks (GNNs) for Better Representation Learning: Future research would have to explore state-of-the-art graph learning techniques, i.e., Graph Neural Networks (GNNs) such as GraphSAGE (Hamilton et al., 2017) or Graph Attention Networks (GATs Velickovic et al., 2018). Unlike this experiment's handcrafted network features, GNNs have the ability to automatically learn useful node representations that capture structure and attributes, and hence can potentially do much better.
b. Temporal-Dynamic Graph Analysis: The graphs of transactions are temporal, and the patterns evolve over time. The research in the future must utilize dynamic graph analysis techniques that exhibit the evolution of the transaction graph from one time step to the next. This may be accomplished by building a series of temporal graphs and using techniques such as dynamic node embedding (Nguyen et al., 2018) or temporal GNN to learn evolving patterns of fraud.
c. Semi-Supervised and Self-Supervised Learning: Now that some of the fraud cases have been labeled, a good direction for future work would involve looking into semi-supervised methods that can work with labeled and unlabeled cases. Techniques like graph label propagation (Zhu et al., 2003) or self-supervised contrastive learning (You et al., 2020) would significantly enhance detection performance using low-level supervisory signals.
d. Real-Time Detection and Architecture Optimisation: Effective, real-time anomaly detection pipeline is needed to facilitate real-world deployment. This would be feature computation optimisation (especially network measures) over data streams and learning variants of the algorithms that could update efficiently on new transactions.

e. Explainable AI Fraud Detection: Deep models like autoencoders' "black box" character limits their deployment in high-risk financial products. Explainable AI techniques (e.g., SHAP, LIME) that were model-agnostic (Yuan et al., 2021) need to be applied to graph-based models so that there are interpretable reasons for the transactions being flagged as fraudulent, which are necessary for fraud investigators.
f. Hybrid Ensemble Methods: Integration of various anomaly detection methods using ensemble learning has the capability of modeling complementary facets of fraudulent behavior. For instance, a combination of reconstruction error from an autoencoder and isolation forest path lengths and graph metrics can lead to more robust detection performance.
g. Transfer Learning Across Institutions: Exploring transfer learning methods that would tailor knowledge from one institution's dataset to another would address the scarcity of data, particularly for smaller institutions that have limited history fraud data (Weber et al., 2018).

In conclusion, this book has demonstrated the promise of combining network science and deep learning techniques for financial fraud detection and laid out a detailed road map for advancing this new research stream. Ongoing refinement of these techniques has great potential to further strengthen security and integrity of global financial systems against increasingly sophisticated fraud attacks.

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