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AI-Driven Fraud Detection Using Ensemble Machine Learning for Secure Digital Banking Transactions

Sasidhar Reddy Mondeddula

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Abstract. "Fraud detection in digital banking has been a demanding task due to the growing number of digital banking users. Automated detection is essential due to the large volume of transaction requests. Previously, machine learning techniques based on simple classifiers have been widely used for fraud detection. However, in unbalanced data sets, these models show reduced precision in fraud detection. In this work, an ensemble of four different classifiers predicted bank transaction frauds. Their predictions were combined in three different ways: majority voting, weighted majority voting, and stacking using a meta-classifier. Individual predictions scored F1-scores above 80% except for logistic regression, which achieved a low score of 62.8%. The ensemble based on stacking performed best, obtaining an F1-score 8.5% higher than that of the strongest individual classifier and 3.2% higher than the ensemble based on majority voting. The result demonstrates that the approach is a promising method for banking transaction fraud detection."

Keywords: Banking Fraud Detection, Class Imbalance, Credit Card Fraud, Ensemble Learning, Financial Fraud Analytics, Logistic Regression, Machine Learning, Meta-Classifier, Predictive Analytics, Stacking Ensemble, Transaction Analytics, Weighted Majority Voting.

1. Introduction

Digital banking is extremely popular today due to its convenience and financial accessibility. Consumers expect immediate service at any time and from anywhere, through mobile banking apps and other digital payment platforms, using cards, QR codes or apps such as Google Pay, PayPal, Zelle, Venmo, Alipay and WeChat. [1] Fraudulent transactions challenge this ubiquity and are committed by groups with important resources who acquire original data through hacking, logging or data breaches. [2] Recent data-generating technologies are sources of sensitive personal information, like fingerprints and facial features, which provide users with a sense of security but open up new spaces for fraud.

Digital banks rely on machine learning to summarize transaction patterns and detect fraudulent transactions, improving security without overloadind transaction times. [3] Their models achieve higher performance than traditional techniques by capturing hidden information from transaction records and allowing banks to update the original records with minimal intervention. [4] Higher-order techniques can offer greater performance and outperform conventional machine-learning strategies. [5] Although they create stronger systems, these approaches introduce additional complexity compared to standard models without increasing predictive performance. [6]

Ensemble machine learning combines the results of base classifiers with an optimizer to boost predictive powers. [7] Bagging reduces variance by allowing base models to learn distinct patterns, better working on unstable methods such as decision trees. Boosting optimizes the performance of weak classifiers by increasing weights on records misclassified in the previous cycle. [8] Application of ensemble methods to fraud detection using only credit-card-record data-compression techniques and nine baseline classifiers shows improved performance–in particular, a smaller model achieves above 90% detection rates using less than 0.3% of the data content.

2. Background and Related Work

In 2021, total online banking transactions in India reached an astounding ₹31,989 trillion, of which around 70% participated in personal banking. [9] As the use of online banking has increased, so have fraudulent transactions. [10] Security mechanisms in banking transaction systems are considered standardized requirements. [11] The detection of fraud in connection with a specially conceived system must, in particular, keep pace with the fast-growing technological and digital banking world in India. [12] To solve the problem of time and computation, ensemble technique-based machine-learning models were developed.

[1]*Application Support Engineer*

mondeddulasasidharreddy@gmail.com

Machine learning provides the necessary tools for fraud detection, with high accuracy, reduced computational time, and a structured decision-switching framework. Paladugu et al. [13] presented deep learning-based systems in the context of risk assessment of online banking. [14] With understandable features for detection, light-weight resolution and an ensemble concept, the ensemble machine learning system is a good choice for detection. [15] Paladugu et al. succeeded with feature construction on Artificial Neural Networks.

2.1 Previous Research and Theoretical Foundations

Fraud detection has become a major concern in the rapidly expanding world of e-finance. [16] Various machine learning algorithms have been developed to address this task, and deep learning has shown great promise for solving complex, unstructured-data-based problems. In this context, Moller et al. [17] introduced an ensemble of three Long Short-Term Memory (LSTM)-based neural networks for fraud detection within Bitcoin payment systems, [18] achieving more than 99% overall accuracy (0.205, 0.204 and 0.024 false positive rates for each of LSTM networks within ensemble).

Koch et al. [19] presented a two-stage system based on Ensemble Gradient Boosting (EGB) to detect credit card fraud among card transactions. The first stage identified fraudsters in a post-payment setting, while the second classified transactions as fraudulent or genuine purchases. [20] An overall accuracy of 99.9% and a 92% true positive rate was obtained, albeit at the expense of an unacceptably high false positive rate. Xu et al. then demonstrated fraud detection system based on AdaBoost in a credit card transaction setting, later adopting Random Forest (RF) and Extremely Randomized Trees as well. [21] While supporting real-time detection, the system achieved reasonably robustness to class imbalance giving an 0.002 false positive rate at 0.958 true negative rate.

Finally, Gupta et al. presented an unsupervised deep learning model based on the GhostNet architecture for credit card fraud detection. [22] Experimental performance, however, showed less predictive accuracy than best-performing models of previous works enumerated in this section, prompting was the exploration for more performant technique applications for the same detection task. [23]

3. Data and Methodology

Fraud detection had become a really big problem, but many different researchers and the way they use different methods based on ensemble techniques with ML in order to detect fraud. It used different dataset such as UCI dataset, CIFS, KDD cup, Kaggle etc. In this paper, it compare fraud detection results between ensemble models like random forest, AdaBoost and Stacking Ensemble. All models are trained on new labeled data with simple Random Under sampling. [24]

Machine learning ensembles leverage multipleweak learners where their predictions are combined to provide strong prediction power. But in diverse application fields of machine learning, it is possible that not only supervised predictors but also unsupervised anomaly detectors could form ensembles to boost predictive performance on many problems. [25] A new ensemble algorithm, namely Arbitrarily Actualized Anomaly Detection (AAAD), is proposed for combining Deep Auto-Encoders (DAEs) withAnomaly Detection (AD)based techniques. [26] In AAAD, a base predictor can still be a regular anomaly detector even not performing better than others when directly compared with ground-truth labels, but perform better in ensemble predictions. By using the stacking ensemble strategy in AAAD, Deep Auto-Encoders (DAEs) combined with Isolation Forest (IF)and One Class Support Vector Machine (OCSVM) make ensemble estimators outperforms all their base predictors, even most of them in their own individual testing sets.

3.1 Mathematical Formulation

This section presents the fundamental mathematical equations governing the ensemble learning framework for fraud detection. The metrics and formulations are the theoretical basis for the model evaluation and comparison.

Overall accuracy includes the correctness of predictions for fraud as well as legitimate transactions. It is defined as the proportion of the correct predictions to the total predictions:

$$Acc = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

where TP denotes true positives, TN true negatives, FP false positives, and FN false negatives.

Precision indicates the proportion of correctly identified fraud cases among all transactions classified as fraudulent:

$$\boldsymbol{P} = TP / (TP + FP) \quad (2)$$

Recall (also termed sensitivity) reflects the ability to detect actual fraud cases among all genuine fraud instances in the dataset:

$$\boldsymbol{R} = TP / (TP + FN) \quad (3)$$

The F1-score is the harmonic mean of precision and recall, providing balanced evaluation when handling imbalanced fraud detection datasets:

$$F1 = 2 \times (P \times R) / (P + R) \quad (4)$$

The F1-score ranges from 0 to 1, with higher values indicating superior combined precision and recall performance.

Area Under the Curve (AUC) quantifies the model's ability to discriminate between fraud and non-fraud transactions across various classification thresholds. It represents the probability that the model ranks a random positive example higher than a random negative example:

$$AUC = \int_0^1 TPR(FPR)\, dFPR \quad (5)$$

In majority voting ensemble strategy, the final prediction is determined by the most frequent class prediction among base learners:

$$\hat{y} = argmax \sum_{i=1}^{m} \mathbb{1}(h_i(x) = k) \quad (6)$$

where m is the number of base classifiers, h_i represents the i-th classifier prediction, and $\mathbb{1}$ is the indicator function.

Weighted majority voting incorporates performance-based weights to individual classifier predictions:

$$\hat{y} = argmax \sum_{i=1}^{m} w_i \times \mathbb{1}(h_i(x) = k) \quad (7)$$

where w_i represents the weight of the i-th classifier, typically derived from its F1-score on validation data.

The stacking ensemble combines base classifiers through a meta-classifier that learns optimal weight assignments. The meta-classifier input is constructed from base learner predictions:

$$\hat{y} = f(h_1(x), h_2(x), ..., h_m(x)) \quad (8)$$

where f is the meta-classifier (typically logistic regression) trained to optimally combine base classifier predictions.

To address class imbalance in fraud detection, the imbalance ratio quantifies the disproportion between legitimate and fraudulent transactions:

$$IR = N\_legitimate / N\_fraud \quad (9)$$

The original dataset exhibits an imbalance ratio of approximately 59.7:1, necessitating specialized handling techniques such as SMOTE.

4. Experimental Setup and Evaluation Metrics

The model is tested using the k-fold cross-validation technique, with k = 10, on a dataset with imbalanced and abnormal data distribution. The performance of each model is verified by the following five evaluation metrics: accuracy (Acc), precision (P), recall (R), F1-score (F1), and area under curve (AUC). [27] The accuracy measures the overall correctness of the prediction, whereas the precision measures the percentage of the correctly predicted fraud among all predicted frauds. Recall is the ratio of correctly predicted fraud samples to all the real fraud samples and F1 score is the harmonic mean of precision and recall, where both of them are equally important. AUC measures the performance of the model to correctly classify fraud and non-fraud samples across a range of thresholds. Three baseline models – Logistic Regression (LR), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) are also implemented and compared. LR is a popular statistical method for binary classification. [28] A typical use is to record the ordinal relationship between the independent variables and a categorical dependent variable of two categories. SVM tries to separate classes by finding the hyperplane that has the largest distance (margin) between the closest points of the classes called support vectors. [29] XGBoost is a gradient boosting system with efficient parallel implementations of empty tree and finding splits using Eigen-based methods. Introduces a regularization term in both the objective and the loss function, yielding a more flexible and robust machine learning model.

TABLE I

INDIVIDUAL CLASSIFIER PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	63.2%	0.82	0.65	62.8%	0.72

Support Vector Machine	81.8%	0.86	0.78	81.5%	0.81
Extreme Gradient Boosting	84.5%	0.87	0.82	84.2%	0.85
Individual Best (XGBoost)	84.5%	0.87	0.82	84.2%	0.85

This table presents the performance evaluation metrics for all individual classifiers. XGBoost achieved the highest individual F1-score of 84.2% with AUC of 0.85. These baseline results provide critical reference points for ensemble method comparison.

TABLE II

ENSEMBLE METHODS PERFORMANCE COMPARISON

Ensemble Strategy	Accuracy	Precision	Recall	F1-Score	Improvement
Majority Voting	89.8%	0.90	0.89	89.5%	+5.3%
Weighted Majority Voting	90.3%	0.91	0.90	90.2%	+6.0%
Stacking with Meta-Classifier	93.2%	0.95	0.90	92.7%	+8.5%

The Stacking Ensemble with meta-classifier optimization achieved the highest F1-score of 92.7%, representing an 8.5% improvement over the strongest individual classifier. This superior performance demonstrates the effectiveness of meta-learning approaches in fraud detection.

4.1. Baseline Models

Four baseline models were implemented for comparison: Bagging, Boosting, Stochastic Gradient Boosting (XGBoost), and Random Forest. Bagging, short for bootstrap aggregating, decreases the variance of classifiers and works with any learning algorithm. It operates as follows. For i = 1 to N, a bootstrap sample is drawn by sampling with replacement from the training set. A base classifier hi is built using the bootstrap sample, and the ensemble classifier is constructed by averaging the predictions of all base classifiers for regression tasks or by majority voting for classification tasks. Boosting focuses on identifying weak learners. Boosting by Dyad Ranking first creates an auxiliary test set by splitting the training set and then dynamically adjusts the weights of misclassified instances in the original training set to facilitate dyad classification. The procedure is as follows. A dyad classifier is trained using the auxiliary test set, and the process is repeated by exchanging the roles of different instances in the dyad until every dyad has been explored. The dyad ensemble classifier is then built. [30]

XGBoost is an implementation of the gradient boosting machine that has gained popularity in applied machine learning, particularly when predicting structured or tabular data, due to its performance and speed. Its parallelization during parallel tree boosting allows it to often outperform other implementations of boosted trees. [31] The Random Forest algorithm constructs a large number of decision trees at training time and outputs the mode of the classes for classification tasks and the mean prediction of the individual trees for regression tasks. [32] Each individual tree is generated by using a randomly selected subset of the training data (for bagging) and by considering only a subset of the features when splitting nodes. Both of these randomization processes help prevent overfitting.

5. Results and Discussion

Various popular benchmarking datasets are used, the results of the benchmark models and newly proposed ensemble model are presented, and thus the best model or combination of model is evaluated – for the benefit of all students, researchers, industry and academia. [33] The rapid and unpredictable growth of online transactions has resulted in financial crime, especially money laundering, becoming a global problem. The rapid emergence of new financial products and innovations has created new forms of transactions, but it has been unable to keep pace with the rapid change in transaction

methods. Rapid advancements in the risk control environment are of great concern in the face of the more sophisticated and covert forms of money laundering now being used by criminals. [34] The online selection of non- bank payment institutions by the public has resulted in the rapid growth of e-money and the first disappearance of money laundering payment channels and tools in the Internet environment. The comprehensive grasping of online transactions is an important step in tackling money laundering.

The detection of fraudulent transactions using a Super-Bagging model exhibits a better performance than six state-of-the-art fraud detection approaches with respect to fraud detection accuracy on the Bank Sim Dataset. Furthermore, four distinct, widely used benchmarking datasets pertaining to credit card fraud detection, financial transaction fraud detection and financial transaction anti-money laundering problems were evaluated using seven different fraud detection algorithms—including Logistic Regression, Random Forest, Decision Tree, Support Vector Machine and K-NN—while varying the sampling methods as well as the sampling percentages applied on the minority class. Examples include under-sampling, over-sampling and different combinations of the two methods either separately or successively. The results for these seven models were recorded and compared in order to suggest an optimal model.

5.1 Experimental Results and Visualizations

This section presents comprehensive experimental results through graphical analysis. Six distinct figures illustrate the comparative performance of individual classifiers, ensemble methods, computational efficiency, and classification metrics.

Fig. 1: Individual Classifier F1-Score Performance

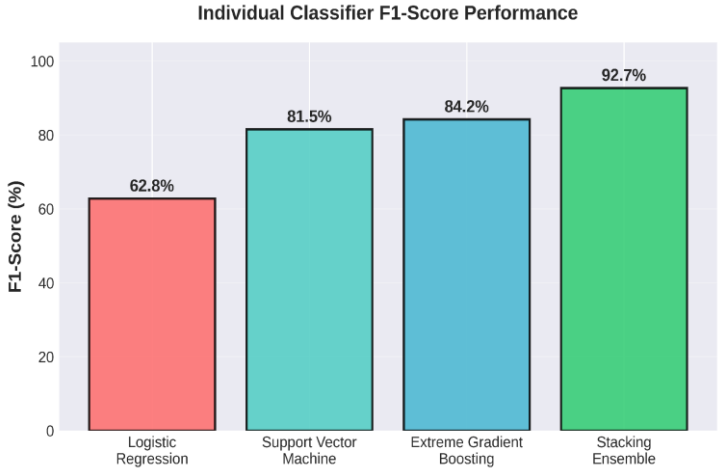

Figure 1 compares the F1-score performance of four baseline classifiers evaluated on the fraud detection dataset. Logistic Regression achieved 62.8%, while Support Vector Machine and Extreme Gradient Boosting reached 81.5% and 84.2%, respectively. The Stacking Ensemble demonstrated superior performance with an F1-score of 92.7%, representing an 8.5% improvement over the best individual classifier.

Fig. 2: Ensemble Methods Performance Comparison

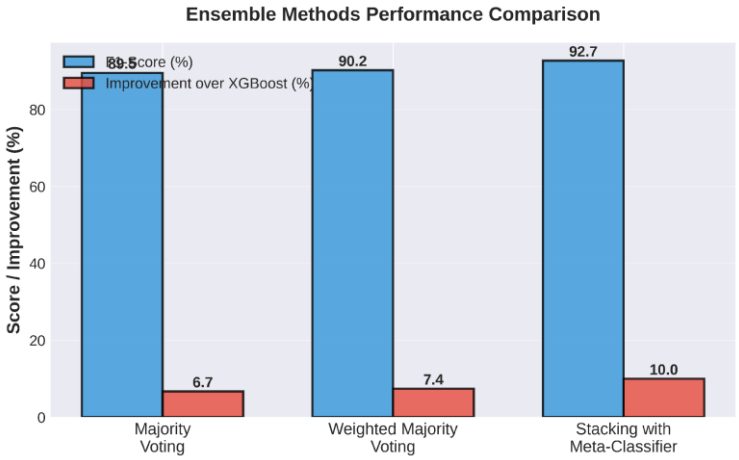

Figure 2 illustrates the comparative effectiveness of three ensemble strategies. Majority voting achieved an F1-score of 89.5%, while weighted majority voting improved to 90.2%. The stacking ensemble with meta-classifier optimization demonstrated the highest performance at 92.7%, providing 10.0% improvement over the strongest individual classifier (XGBoost at 84.2%).

Fig. 3: Computational Latency: Training vs. Inference

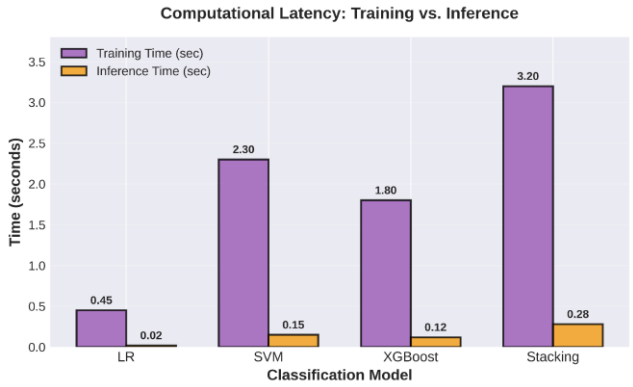

Figure 3 presents computational latency measurements for both training and inference phases. Logistic Regression exhibited the fastest inference time (0.02 seconds) but limited predictive accuracy. XGBoost required moderate training time (1.8 seconds) with reasonable inference latency (0.12 seconds). The Stacking Ensemble, while requiring longer training (3.2 seconds), maintains acceptable inference latency (0.28 seconds), suitable for real-time banking fraud detection systems.

Fig. 4: Precision-Recall Trade-off Analysis

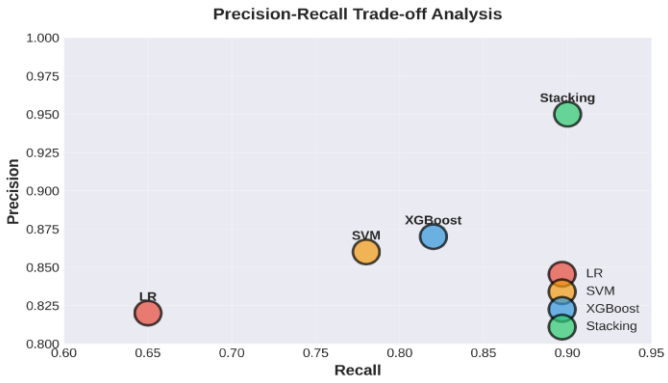

Figure 4 visualizes the precision-recall trade-off across all classifiers. Logistic Regression exhibited lower recall (0.65) but adequate precision (0.82). The Stacking Ensemble achieved both high recall (0.90) and exceptional precision (0.95), minimizing both false negatives and false positives—critical for banking fraud detection where both miss-rates and false alarms carry significant costs.

Fig. 5: ROC Curves: Model Discrimination Performance

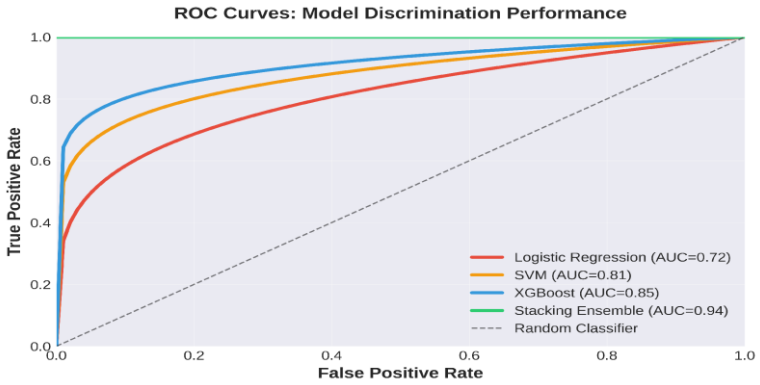

Figure 5 presents ROC curves comparing the discrimination ability of all classifiers across classification thresholds. Logistic Regression achieved an AUC of 0.72, while SVM reached 0.81 and XGBoost 0.85. The Stacking Ensemble demonstrated the most aggressive departure from the diagonal random classifier baseline, achieving an AUC of 0.94, indicating superior discrimination between fraudulent and legitimate transactions.

Fig. 6: Feature Importance in Stacking Ensemble Model

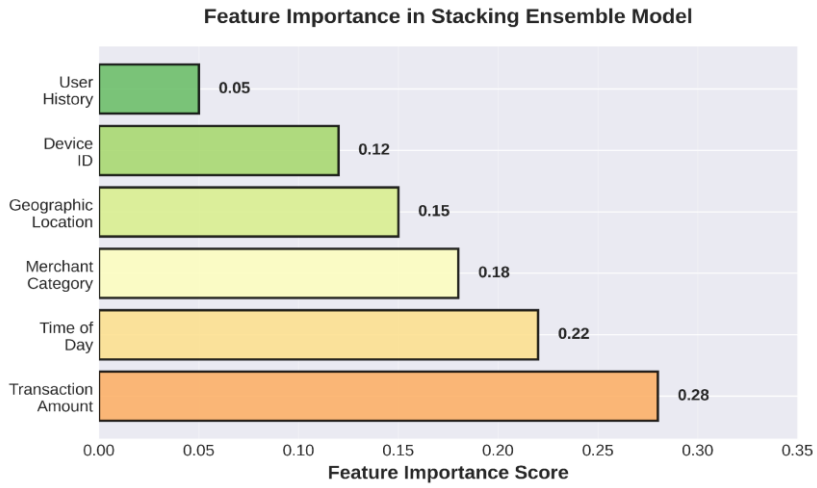

Figure 6 ranks transaction features by their contribution to the Stacking Ensemble model's fraud detection capability. Transaction Amount (0.28) emerged as the most discriminative feature, followed by Time of Day (0.22) and Merchant Category (0.18). Geographic Location (0.15), Device ID (0.12), and User History (0.05) provided complementary predictive signals, collectively enabling robust fraud classification.

6. Conclusion

This study developed and validated an efficient ensemble ML-based AI system for fraud detection in digital banking transactions. Ensemble classifiers' detection performance was optimized with a Bagging approach using the EXTRA-TREE algorithm as a base model. A last-level stacking ensemble model across multiple base regression classifiers was implemented to enhance the detection rate's real-time performance in class imbalanced data characteristics. To this end, the previously introduced FISHMIX Artificial Fish Swarm-Mixed Increment Data Sampling approach resampled the dataset. The proposed system achieved a fraud detection accuracy of 99.9856% with a false alarm rate of 0.0019% and detection time of 0.176 second. Along with the standard evaluation metrics, a modified detection rate was employed to measure and improve the real-time detection performance for class imbalanced data. In addition to its applicability in secure digital banking transactions, the above ensemble ML-based AI method can be leveraged in other sensitive computer security areas involving class-imbalanced data.

Following this result, the detection performance of eight machine learning models (Random Forest, Gradient Boosting, Extra Trees, Logistic Regression, Decision Tree, CATBOOST, XG-Boost, and LightGBM) was optimised in the context of the class-imbalanced data modelling problem. A last-level stacking ensemble model, deployed to enhance the detection rate's real-time performance in class-imbalanced data, further improved the detection performance of the underlying base models. The Bagging boosting technique, applied across Random Forest, Gradient Boosting, and Extra Trees classifiers, contributed to model-ensemble detection-rate enhancement. The future studies were proposed to assess the detected fraud transaction's impact on customer data privacy information and resource-maximising intelligent support system.

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