Transaction Fraud Detection

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Introduction

Transaction Fraud

- Financial crime that involves using someone's financial information to make unauthorized transactions.
- Can involve credit card fraud, account takeovers, and more.

Why does it matter?

- Fraud affects millions globally both individuals and businesses.
- Detection is crucial for maintaining security and trust in digital transactions.

It is challenging to detect fraud

- Fraudsters constantly evolve tactics, making detection difficult.
- Fraud patterns often resemble legitimate transactions.

Data & Variables

A Credit Card Transactions Dataset provides detailed records of credit card transactions, including information about transaction times, amounts, and associated personal and merchant details. This dataset has over 1.85M rows.

Variables:

- Timestamp
- Credit card number
- Merchant information
- Transaction information
- Cardholder information
- Population of the city where the transaction occurred



Methods

- Logistic Regression
- Random Forest Classification
- k-NN Classification
- Gradient Boosting Classification



Reducing the Size & Optimizing Result

Dataset size after sampling: (100000, 24)

Target variable distribution after undersampling: is_fraud

- 0 579
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```
models = {
```

'Logistic Regression': LogisticRegression(max_iter=1000, solver='liblinear'),
'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42),
'k-NN': KNeighborsClassifier(n_neighbors=5),

'Gradient Boosting': GradientBoostingClassifier(n_estimators=100, random_state=42)



Logistic Regression

Training model: Logistic Regression													
Classification Report:													
	р	recision	recall	f1-score	support								
	0	0.79	0.97	0.87	87								
	1	0.96	0.75	0.84	87								
accurac	сy			0.86	174								
macro av	/g	0.87	0.86	0.85	174								
weighted av	/g	0.87	0.86	0.85	174								

ROC AUC: 0.8614

Random Forest

Training mode Classificatio	el: Random Fo on Report:	orest		
	precision	recall	f1-score	support
0	0.88	0.92	0.90	87
1	0.92	0.87	0.89	87
accuracy			0.90	174
macro avg	0.90	0.90	0.90	174
weighted avg	0.90	0.90	0.90	174

ROC AUC: 0.9719

		<-NN			
Training model Classification	: k-NN Report:				
	precision	recall	f1-score	support	
0	0.45	0.46	0.45	87	
1	0.45	0.44	0.44	87	
accuracy			0.45	174	
macro avg	0.45	0.45	0.45	174	
weighted avg	0.45	0.45	0.45	174	
ROC AUC: 0.457	0				

Gradient Boosting

Training model: Gradient Boosting Classification Report:

support	f1-score	recall	precision	
87 87	0.91 0.92	0.90 0.93	0.93 0.90	0 1
174 174 174	0.91 0.91 0.91	0.91 0.91	0.91 0.91	accuracy macro avg weighted avg

ROC AUC: 0.9804

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Which model is best?



Gradient Boosting is the most effective model for detecting fraud.

Logistic Regression

eature



Feature Importance Ranking for Model: Logistic Regression

Feature	Importance
amt	0.006362
merchant	0.000424
city	0.000420
last	0.000255
street	0.000233
job	0.000093
first	0.000093
ans_year	0.000041
age	0.000021
rans_hour	0.000019

Random Forest





k-NN Feature Importance (Permutation Importance)



rtance Ranking	for	k-NN
Importance		
0.205268		
0.030138		
0.00000		
0.00000		
0.00000		
0.00000		
0.00000		
0.00000		
0.00000		
0.00000		
	rtance Ranking Importance 0.205268 0.030138 0.000000 0.000000 0.000000 0.000000 0.000000	rtance Ranking for Importance 0.205268 0.030138 0.000000 0.000000 0.000000 0.000000 0.000000

Gradient Boosting

Gradient Boosting Feature Importance



What feature is the most important?

Top Features by Importance for Fraud Detection amt trans hour category · unix time Features last city · lat state first city_pop 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.0 0.8 Importance Score

The variable 'amt' (Transaction amount) has the greatest impact on transaction fraud, with an importance score of 0.7694. (Gradient Boosting)

Typical fraudulent transaction amounts?



Where are the transaction locations?



Where are the merchant locations?

16000





Merchant Location by Fraud Status

3D Plot of Merchant Locations by Fraud Status





Amount vs. Fraud



Fraud by Time and Day

Fraud Rate by Hour and Day of Week

Ч	0.012	0.011	0.011	0.014	0.001	0.001	0.001	0.002	0.001	0.000	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000	0.001	0.024	0.023	- 0.03
ay) 2	0.014		0.016		0.002	0.002	0.001	0.001	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.028	0.028	- 0.03
7 = Sund 3	0.018	0.018	0.016		0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.002	0.001	0.002	0.001	0.001	0.001	0.001	0.031	0.032	- 0.02
Monday, 4	0.020	0.021	0.016	0.013	0.002	0.002	0.000	0.002	0.001	0.001	0.001	0.002	0.001	0.001	0.003	0.001	0.002	0.001	0.001	0.001	0.001	0.002	0.036	0.032	- 0.02
/eek (1 = 5	0.018	0.017	0.019	0.016	0.002	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.002	0.002	0.001	0.001	0.002	0.002	0.002	0.002	0.034	0.036	- 0.01
Day of W 6	0.015	0.018	0.016	0.014	0.001	0.002	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.032	0.030	- 0.01
7	0.012	0.013	0.013	0.013	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.023	0.024	- 0.00
	o o	i	2	3	4	5	' 6	, 7	' 8	' 9	10	11 Hour	12 of Dav	13	' 14	15	16	17	18	19	20	21	22	23	

Fraud by Holiday and Non-Holiday



