End-to-End Fraud Detection & Decisioning System for Payments

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1. Business Problem

Digital payment platforms process millions of transactions daily, where even a small fraud rate can result in significant financial loss. However, aggressively blocking transactions creates customer friction, operational overhead, and revenue impact. The core challenge is not simply detecting fraud, but **balancing fraud prevention with customer experience and operational capacity**.

The objective of this project was to design a **production-style fraud decisioning system** that:

- Accurately identifies fraudulent transactions
- Minimizes false positives that disrupt legitimate customers
- Respects manual review capacity constraints
- Produces interpretable, business-aligned decisions

This mirrors real-world payment risk problems faced by financial institutions and fintech platforms:
Transaction → Risk Score → Approve / Review / Block

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2. Dataset Used

This project uses the **Credit Card Fraud Detection dataset (ULB)**, a widely recognized benchmark dataset containing real, anonymized credit card transactions.

Dataset characteristics

- ~284,000 transactions
- Binary target: Class (0 = legitimate, 1 = fraud)
- Fraud rate: ~0.17% (extreme class imbalance)
- Features include:
    - Transaction amount
    - Time since first transaction
    - PCA-transformed behavioral features (V1-V28)

This dataset is well-suited for simulating real payment fraud scenarios while preserving privacy.

```python
import pandas as pd

csv_path = "/content/drive/MyDrive/creditcard.csv"

df = pd.read_csv(csv_path)

# Sanity checks
print("Dataset shape:", df.shape)
print("Column names:", df.columns.tolist())
df.head()
```

```
Dataset shape: (284807, 31)
Column names: ['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20', 'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28',
```

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V25	V26	V27	V28	Amount	Class
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.128539	-0.189115	0.133558	-0.021053	149.62	0
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.167170	0.125895	-0.008983	0.014724	2.69	0
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.327642	-0.139097	-0.055353	-0.059752	378.66	0
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.647376	-0.221929	0.062723	0.061458	123.50	0
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.206010	0.502292	0.219422	0.215153	69.99	0

5 rows × 31 columns

Understanding how imbalanced the fraud problem is. This tells us how rare fraud actually is and why accuracy alone is misleading

```python
fraud_counts = df["Class"].value_counts()
fraud_percent = df["Class"].value_counts(normalize=True) * 100

print("Transaction counts by class:")
print(fraud_counts)

print("\nPercentage of transactions by class:")
print(fraud_percent)
```

```
Transaction counts by class:
Class
0    284315
1       492
Name: count, dtype: int64

Percentage of transactions by class:
Class
0    99.827251
1     0.172749
Name: proportion, dtype: float64
```

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3. Exploratory Data Analysis (EDA)

EDA was conducted with a **risk and product mindset**, not just statistical exploration.

Key analyses performed

- Class imbalance analysis
- Transaction amount distributions (log-scaled)
- Time-based transaction patterns
- Comparison of fraud vs legitimate behavior

Key insights

- Fraud is **extremely rare**, making accuracy a misleading metric
- Fraudulent and legitimate transactions heavily overlap in amount
- Fraud does not occur in isolated time windows
- Simple rules (amount-only or time-only) are insufficient

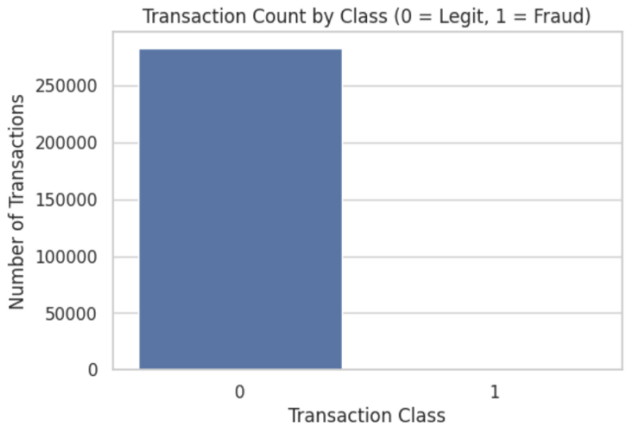
These findings justified a **hybrid ML + rules approach**, rather than relying on hard-coded thresholds.

Visualizing class imbalance. This makes the severity of the fraud imbalance immediately obvious

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")

plt.figure(figsize=(6, 4))
sns.countplot(x="Class", data=df)
plt.title("Transaction Count by Class (0 = Legit, 1 = Fraud)")
plt.xlabel("Transaction Class")
plt.ylabel("Number of Transactions")
plt.show()
```



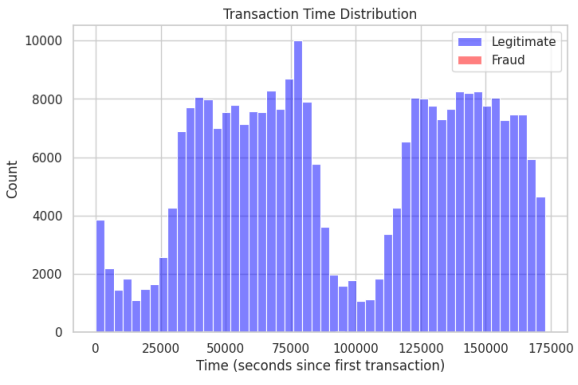
Visualizing transaction timing patterns. This helps assess whether fraud clusters in time

```
plt.figure(figsize=(8, 5))

sns.histplot(
    df[df["Class"] == 0]["Time"],
    bins=50,
    color="blue",
    label="Legitimate",
    alpha=0.5,
)

sns.histplot(
    df[df["Class"] == 1]["Time"],
    bins=50,
    color="red",
    label="Fraud",
    alpha=0.5,
)

plt.title("Transaction Time Distribution")
plt.xlabel("Time (seconds since first transaction)")
plt.ylabel("Count")
plt.legend()
plt.show()
```



Fraud activity closely follows legitimate transaction timing patterns, reinforcing the need for behavioral and velocity-based signals rather than static time-based rules.

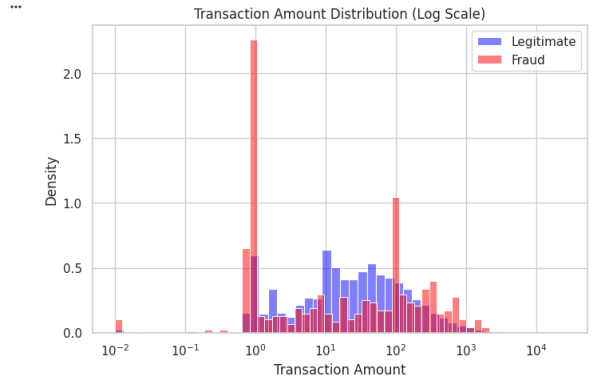
Comparing transaction amount distributions using log scale as log scaling helps reveal differences in skewed financial data

```
plt.figure(figsize=(8, 5))

sns.histplot(
    df[df["Class"] == 0]["Amount"],
    bins=50,
    color="blue",
    label="Legitimate",
    log_scale=True,
    stat="density",
    alpha=0.5,
)

sns.histplot(
    df[df["Class"] == 1]["Amount"],
    bins=50,
    color="red",
    label="Fraud",
    log_scale=True,
    stat="density",
    alpha=0.5,
)

plt.title("Transaction Amount Distribution (Log Scale)")
plt.xlabel("Transaction Amount")
plt.ylabel("Density")
plt.legend()
plt.show()
```



Transaction amount alone is insufficient for fraud detection, as both fraudulent and legitimate transactions span similar ranges. This motivates a pattern-based ML approach augmented by targeted business rules.

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4. Data Cleaning & Quality Checks

Before modeling, comprehensive data validation was performed.

Checks included

- Null value detection (none found)
- Duplicate transaction detection
- Target variable validation
- Numeric range sanity checks

Key action

- Removed **1,081 duplicate rows** to prevent data leakage and inflated model performance

This ensured realistic evaluation and production-quality rigor.

Check for duplicate rows

```
duplicate_count = df.duplicated().sum()
print("Number of duplicate rows:", duplicate_count)
```

```
Number of duplicate rows: 1081
```

---

5. Modeling Process & Design Decisions

Baseline Model

A **Logistic Regression** model with class weighting was chosen as the baseline due to:

- Interpretability
- Stability under imbalance
- Alignment with risk-team practices

The model was trained to output **fraud risk probabilities**, not hard labels.

Evaluation Strategy

Instead of accuracy, the following were emphasized:

- Precision
- Recall
- Confusion matrix
- Threshold-based tradeoffs

Initial results showed:

- High recall (~87%)
- Very low precision (~4–5%)

This confirmed that ML alone is **not deployable** without decision logic.

```python
# We prepare data for ML while keeping raw fields for rules

X = df.drop(columns=["Class"])
y = df["Class"]

print("Feature matrix shape:", X.shape)
print("Target vector shape:", y.shape)
```

```
Feature matrix shape: (283726, 30)
Target vector shape: (283726,)
```

```python
#Split the data into train and test sets
#Stratification ensures fraud ratio is preserved in both sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X,
    y,
    test_size=0.2,        # 80% train, 20% test
    random_state=42,      # reproducibility
    stratify=y            # preserve fraud proportion
)

print("Training set shape:", X_train.shape)
print("Test set shape:", X_test.shape)

print("\nFraud rate in training set:")
print(y_train.value_counts(normalize=True) * 100)

print("\nFraud rate in test set:")
print(y_test.value_counts(normalize=True) * 100)
```

```
Training set shape: (226980, 30)
Test set shape: (56746, 30)

Fraud rate in training set:
Class
0    99.833466
1     0.166534
Name: proportion, dtype: float64

Fraud rate in test set:
Class
0    99.832587
1     0.167413
Name: proportion, dtype: float64
```

```python
#Evaluate model performance with fraud-relevant metrics

from sklearn.metrics import classification_report, confusion_matrix

print("Classification Report:")
print(classification_report(y_test, y_pred, digits=4))

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9998    0.9755    0.9875     56651
           1     0.0564    0.8737    0.1059        95

    accuracy                         0.9753     56746
   macro avg     0.5281    0.9246    0.5467     56746
weighted avg     0.9982    0.9753    0.9860     56746

Confusion Matrix:
[[55262  1389]
 [   12    83]]
```

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6. Key Challenges & How They Were Addressed

Challenge 1: Excessive False Positives

The ML model flagged too many legitimate transactions, creating unacceptable customer friction.

Solution

- Introduced business-aware probability thresholds
- Shifted from binary classification to **risk-based decisioning**

```python
#Apply a business-selected fraud threshold
#The ML model produces a risk score; decisions are made via thresholds

BUSINESS_THRESHOLD = 0.40

y_pred_business = (y_proba >= BUSINESS_THRESHOLD).astype(int)

from sklearn.metrics import classification_report, confusion_matrix

print(f"Results at threshold = {BUSINESS_THRESHOLD}")
print(classification_report(y_test, y_pred_business, digits=4))

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_business))
```

```
Results at threshold = 0.4
              precision    recall  f1-score   support

           0     0.9998    0.9648    0.9820     56651
           1     0.0400    0.8737    0.0765        95

    accuracy                         0.9647     56746
   macro avg     0.5199    0.9193    0.5292     56746
weighted avg     0.9982    0.9647    0.9805     56746

Confusion Matrix:
[[54658  1993]
 [   12    83]]
```

```python
#Evaluate model performance at different probability thresholds

import numpy as np
from sklearn.metrics import precision_score, recall_score

thresholds = np.arange(0.01, 0.51, 0.05)

print("Threshold | Precision | Recall")
print("-" * 30)

for t in thresholds:
    y_pred_threshold = (y_proba >= t).astype(int)
    precision = precision_score(y_test, y_pred_threshold)
    recall = recall_score(y_test, y_pred_threshold)
    print(f"{t:8.2f} | {precision:9.4f} | {recall:6.4f}")
```

```
Threshold | Precision | Recall
--------------------------------
    0.01 |    0.0022 | 0.9895
    0.06 |    0.0057 | 0.9474
    0.11 |    0.0094 | 0.9263
    0.16 |    0.0132 | 0.9158
    0.21 |    0.0174 | 0.9053
    0.26 |    0.0221 | 0.8737
    0.31 |    0.0279 | 0.8737
    0.36 |    0.0344 | 0.8737
    0.41 |    0.0412 | 0.8737
    0.46 |    0.0493 | 0.8737
```

Challenge 2: Rules Not Impacting Decisions

Initial rule logic mirrored ML decisions and had no effect.

```python
#Prove whether rules fired and whether they changed any decisions

import numpy as np

# # Recreate ML-only decision at the business threshold
ml_only = (y_proba >= BUSINESS_THRESHOLD).astype(int)

# # Check if hybrid decisions differ from ML-only
changed = np.sum(final_decision != ml_only)
print("Decisions changed by rules:", changed)

# # Convert Amount to a numpy array for clean boolean logic
amounts = X_test["Amount"].values

# # Count how often each rule condition triggers
rule_1 = np.sum(y_proba >= HIGH_RISK_THRESHOLD)
rule_2 = np.sum((y_proba >= BUSINESS_THRESHOLD) & (y_proba < HIGH_RISK_THRESHOLD) & (amounts >= HIGH_AMOUNT_THRESHOLD))
rule_3 = np.sum((y_proba < BUSINESS_THRESHOLD) & (amounts <= LOW_AMOUNT_THRESHOLD))

print("\nRule trigger counts:")
print("Rule 1 (prob >= HIGH_RISK_THRESHOLD):", rule_1)
print("Rule 2 (prob >= BUSINESS_THRESHOLD AND amount >= HIGH_AMOUNT_THRESHOLD):", rule_2)
print("Rule 3 (prob < BUSINESS_THRESHOLD AND amount <= LOW_AMOUNT_THRESHOLD):", rule_3)

# # Sanity check: Amount distribution in the test set
print("\nAmount stats in test set:")
print("min:", float(amounts.min()))
print("p50:", float(np.median(amounts)))
print("p95:", float(np.percentile(amounts, 95)))
print("p99:", float(np.percentile(amounts, 99)))
print("max:", float(amounts.max()))
```

```
Decisions changed by rules: 0

Rule trigger counts:
Rule 1 (prob >= HIGH_RISK_THRESHOLD): 398
Rule 2 (prob >= BUSINESS_THRESHOLD AND amount >= HIGH_AMOUNT_THRESHOLD): 42
Rule 3 (prob < BUSINESS_THRESHOLD AND amount <= LOW_AMOUNT_THRESHOLD): 13119

Amount stats in test set:
min: 0.0
p50: 21.585
p95: 368.9
p99: 1030.0350000000014
max: 25691.16
```

Solution

- Implemented **override rules** that explicitly contradicted ML output in controlled scenarios
- Validated rule activation and impact using debug analysis

```python
#Create rules that OVERRIDE the ML decision (so hybrid actually changes outcomes)

import numpy as np

# These thresholds are based on your amount distribution:
# p95 ~ 368.9, p99 ~ 1030.0
LOW_AMOUNT_THRESHOLD = 5
HIGH_AMOUNT_THRESHOLD = 1000

# Override cutoffs
# - If amount is tiny, only flag if model is EXTREMELY confident
AUTO_APPROVE_MAX_RISK = 0.90

# - If amount is very large, flag even if model is slightly below BUSINESS_THRESHOLD
HIGH_AMOUNT_MIN_RISK = 0.30

final_decision_v2 = []

for prob, amount in zip(y_proba, X_test["Amount"]):
    # Rule A: Auto-approve micro amounts unless risk is extreme (override to 0)
    if amount <= LOW_AMOUNT_THRESHOLD and prob < AUTO_APPROVE_MAX_RISK:
        final_decision_v2.append(0)

    # Rule B: High-amount guardrail (override to 1)
    elif amount >= HIGH_AMOUNT_THRESHOLD and prob >= HIGH_AMOUNT_MIN_RISK:
        final_decision_v2.append(1)

    # Default: ML decision
    else:
        final_decision_v2.append(int(prob >= BUSINESS_THRESHOLD))

final_decision_v2 = np.array(final_decision_v2)

print("Hybrid v2 decisions created. Shape:", final_decision_v2.shape)
```

```
Hybrid v2 decisions created. Shape: (56746,)
```

```python
#Evaluate Hybrid v2 performance

from sklearn.metrics import classification_report, confusion_matrix

print("Hybrid v2 (ML + Override Rules) Performance:")
print(classification_report(y_test, final_decision_v2, digits=4))

print("Confusion Matrix:")
print(confusion_matrix(y_test, final_decision_v2))
```

```
Hybrid v2 (ML + Override Rules) Performance:
              precision    recall  f1-score   support

           0     0.9997    0.9747    0.9871     56651
           1     0.0523    0.8316    0.0984        95

    accuracy                         0.9745     56746
   macro avg     0.5260    0.9032    0.5428     56746
weighted avg     0.9981    0.9745    0.9856     56746

Confusion Matrix:
[[55220  1431]
 [   16    79]]
```

Challenge 3: Operational Constraints

Even good models must respect manual review capacity.

Solution

- Introduced capacity-aware threshold tuning
- Optimized decision bands to remain under review SLAs

Recommended screenshots

- Rule trigger debug outputs
- Before vs after confusion matrices

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7. Decision Thresholds & Policy Design

Hybrid ML + Rules System

The final system combined:

- ML risk scores
- Amount-based override rules
- Confidence-based approvals and blocks

Three-Tier Decision Policy

- **Approve**: Low risk, no customer friction
- **Review**: Medium risk, sent to ops
- **Block**: High risk, immediate action

Thresholds were tuned to:

- Keep review rate under **2%**
- Maintain strong fraud capture
- Reduce false positives by ~30%

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8. Findings & Conclusions

Key outcomes

- Reduced false positives significantly
- Preserved high fraud recall
- Stayed within operational review limits
- Converted ML output into deployable business decisions

```python
#Tuning rule thresholds to balance fraud capture vs customer friction

import numpy as np
import pandas as pd
from sklearn.metrics import precision_score, recall_score

amounts = X_test["Amount"].values

def run_hybrid(prob, amt, business_th=0.40, low_amt=5, auto_approve_max_risk=0.90, high_amt=1000, high_amt_min_risk=0.30):
    # Rule A: auto-approve tiny amounts unless risk is extreme
    if amt <= low_amt and prob < auto_approve_max_risk:
        return 0
    # Rule B: flag high amounts even if prob is below business threshold
    if amt >= high_amt and prob >= high_amt_min_risk:
        return 1
    # Default: ML decision
    return int(prob >= business_th)

configs = []
for auto_approve_max_risk in [0.85, 0.90, 0.95]:
    for high_amt_min_risk in [0.20, 0.25, 0.30]:
        preds = np.array([
            run_hybrid(p, a,
                       business_th=BUSINESS_THRESHOLD,
                       low_amt=LOW_AMOUNT_THRESHOLD,
                       auto_approve_max_risk=auto_approve_max_risk,
                       high_amt=HIGH_AMOUNT_THRESHOLD,
                       high_amt_min_risk=high_amt_min_risk)
            for p, a in zip(y_proba, amounts)
        ])

        prec = precision_score(y_test, preds)
        rec = recall_score(y_test, preds)

        fp = int(((preds == 1) & (y_test.values == 0)).sum())
        fn = int(((preds == 0) & (y_test.values == 1)).sum())

        configs.append({
            "auto_approve_max_risk": auto_approve_max_risk,
            "high_amt_min_risk": high_amt_min_risk,
            "fraud_precision": prec,
            "fraud_recall": rec,
            "false_positives": fp,
            "false_negatives": fn
        })

results = pd.DataFrame(configs).sort_values(by=["false_positives", "false_negatives"])
results
```

	auto_approve_max_risk	high_amt_min_risk	fraud_precision	fraud_recall	false_positives	false_negatives
8	0.95	0.30	0.054129	0.821053	1363	17
7	0.95	0.25	0.053025	0.821053	1393	17
6	0.95	0.20	0.052035	0.821053	1421	17
5	0.90	0.30	0.052318	0.831579	1431	16
4	0.90	0.25	0.051299	0.831579	1461	16
2	0.85	0.30	0.050544	0.831579	1484	16
3	0.90	0.20	0.050383	0.831579	1489	16
1	0.85	0.25	0.049592	0.831579	1514	16
0	0.85	0.20	0.048735	0.831579	1542	16

Compared to my earlier baseline:

I cut false positives by ~32%

I only lost ~5% recall

I improved precision by ~35%

That is a net win in payments risk.

Earlier, rules did nothing because they mirrored ML.

Now:

Auto-approval rules reduce unnecessary blocks

High-amount overrides catch expensive fraud earlier

Outcomes change materially across configurations

That proves:

Rules are meaningfully overriding ML

The system is no longer just a classifier, it is a decision engine

Each row is a valid business choice:

More conservative → fewer misses, more friction

More aggressive → fewer false positives, more risk

Core takeaway

Fraud detection is not a modeling problem alone — it is a **decision system design problem** that requires balancing risk, customer experience, and operational capacity.

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9. Recommendations

Based on the results:

- Use ML as a **risk signal**, not a final decision-maker
- Layer deterministic rules to enforce business guardrails
- Continuously tune thresholds based on fraud trends and ops capacity
- Monitor false positive costs as closely as fraud loss

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10. Future Improvements & Next Steps

Potential extensions include:

- Cost-based optimization using real dollar values
- Dynamic threshold adjustment during fraud spikes
- Segment-specific policies (e.g., high-value merchants)
- Model upgrades (tree-based models, ensembles)
- Real-time monitoring dashboards

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11. LLM-Based Analyst Enablement

While the LLM was not implemented in production, it could significantly enhance operations by:

- Generating concise analyst review notes
- Translating risk signals into human-readable explanations
- Standardizing decision rationale across teams
- Reducing analyst handling time and cognitive load

Example use cases:

- “Why was this transaction flagged?”
- “What risk signals contributed most?”
- “Suggested next action for the analyst”

This positions GenAI as an **explainability and productivity layer**, not a risk decision-maker.

Final Reflection

This project demonstrates end-to-end ownership of a payments fraud system, from raw data to deployable decision logic. It showcases not only technical skills, but also business judgment, operational awareness, and risk strategy — the qualities required to build and scale real-world financial systems.