# 🛡️ Fraud Detection Assignment - A Riskified Analysis

## Submitted by Pooja Chouhan

# 📝 Assignment Description

This assignment involves analyzing historical e-commerce transactions to estimate fraud risk and optimize model thresholding, with the goal of minimizing chargebacks and maximizing approval revenue.

**Objective**:

- Use model classification scores to determine an appropriate threshold for approving transactions.
- Understand the trade-offs between approvals, chargebacks, and revenue.
- Identify risk trends by product type and customer behavior to improve fraud prevention.

**Data Overview**:

- Contains ~40,000 historical orders with features like product type, account age, billing zip, classification scores, etc.
- Orders are labeled as either `approved` or `chargeback`.

**Tools & Technologies Used**:

- Python 3 (Jupyter Notebook)
- pandas, numpy (for manipulation)
- matplotlib, seaborn (for visualization)
- scikit-learn (for modeling)

**Steps covered in this Notebook**:

1. Data Loading & Cleaning
2. Exploratory Data Analysis
3. Feature Engineering
4. Fraud Detection Modeling
5. Evaluation & Insights
6. Business Recommendations

**Business Context**:
Riskified guarantees approved orders for merchants — if an approved order turns into a

chargeback, Riskified reimburses the merchant. Hence, balancing approvals with fraud risk is crucial for profitability.

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In [1]:
```
# Imported required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [5]:
```
# Display settings
pd.set_option('display.float_format', lambda x: '%.4f' % x)
sns.set(style='whitegrid')
```

In [7]:
```
# Load the dataset
df = pd.read_csv("D:/Riskified_Sample_Dataset.csv")
df.head()
```

Out[7]:

| | order_id | order_date | order_status | price | digital_product | customer_account_age | o |
|---|---|---|---|---|---|---|---|
| **0** | 945827823 | 2019-06-28 | approved | 16.4400 | False | 759 | |
| **1** | 932303597 | 2019-06-18 | approved | 150.0000 | True | 894 | |
| **2** | 916501223 | 2019-06-07 | approved | 105.9400 | False | 5160 | |
| **3** | 916516038 | 2019-06-07 | approved | 100.0000 | True | 1267 | |
| **4** | 925554558 | 2019-06-13 | approved | 225.0000 | True | 889 | |

# 1 Set Threshold to Approve 90% of Orders

In [9]:
```
#.quantile(0.10) is the 10th percentile of score to find the threshold
threshold_90 = df['classification_score'].quantile(0.10)
df['model_decision'] = df['classification_score'].apply(lambda x: 'approve' if x >=
print(f"Threshold for 90% approval: {threshold_90:.6f}\n")
```

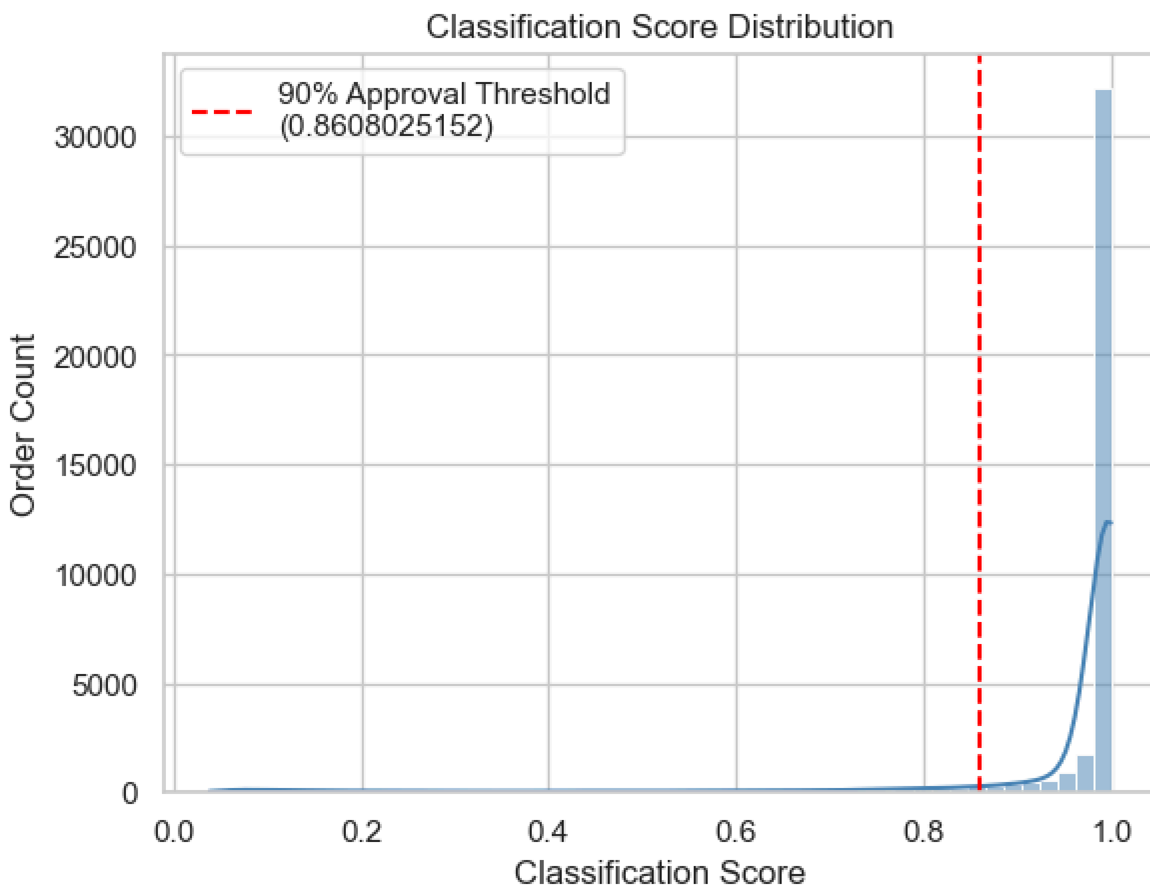
```
Threshold for 90% approval: 0.860803
```

💬 Commentary: To automate order approval based on model scores, we must identify a threshold score such that the top 90% of orders are approved.

This means we approve any order with a classification score above the 10th percentile.

## 2 Classification Score Distribution

In [11]:
```
sns.histplot(df['classification_score'], bins=50, kde=True, color='steelblue')
plt.axvline(threshold_90, color='red', linestyle='--', label=f'90% Approval Thresho
plt.title('Classification Score Distribution')
plt.xlabel('Classification Score')
plt.ylabel('Order Count')
plt.legend()
plt.show()
```




💬 Commentary: The distribution is skewed towards higher scores (near 1), suggesting that most transactions appear trustworthy. The 10th percentile threshold (~0.1) helps us approve 90% of the orders.

## 3 Fee Calculation for 50% Chargeback/Revenue Ratio

In [13]:
```
# Model-based decision
df['model_decision'] = np.where(df['classification_score'] >= threshold_90, 'approv

# Approved only
```

```
approved_orders = df[df['model_decision'] == 'approve']
chargeback_sum = approved_orders[approved_orders['order_status'] == 'chargeback']['
total_approved_sum = approved_orders['price'].sum()

# Fee % such that chargeback / revenue = 0.5
fee_required = chargeback_sum / (0.5 * total_approved_sum)
print(f"Required fee percentage to keep CHB/Revenue = 50%:: {fee_required:.4f} (or
```

```
Required fee percentage to keep CHB/Revenue = 50%:: 0.0020 (or 0.20%)
```

💬 Commentary: Riskified earns a percentage fee on approved orders and guarantees reimbursement for chargebacks.
We calculate the minimum fee percentage that ensures that total chargebacks are only 50% of the revenue collected.

# 4️⃣ Risk Comparison: Digital vs Tangible Products

In [15]:
```
product_risk = df.groupby('digital_product').apply(
    lambda x: pd.Series({
        'Total Orders': len(x),
        'Chargebacks': (x['order_status'] == 'chargeback').sum(),
        'Chargeback Rate (%)': 100 * (x['order_status'] == 'chargeback').mean()
    })
).reset_index()

product_risk['Product Type'] = product_risk['digital_product'].map({True: 'Digital'
product_risk.drop('digital_product', axis=1, inplace=True)
product_risk
```

Out[15]:

| | Total Orders | Chargebacks | Chargeback Rate (%) | Product Type |
|---|---|---|---|---|
| **0** | 13538.0000 | 40.0000 | 0.2955 | Tangible |
| **1** | 27287.0000 | 320.0000 | 1.1727 | Digital |

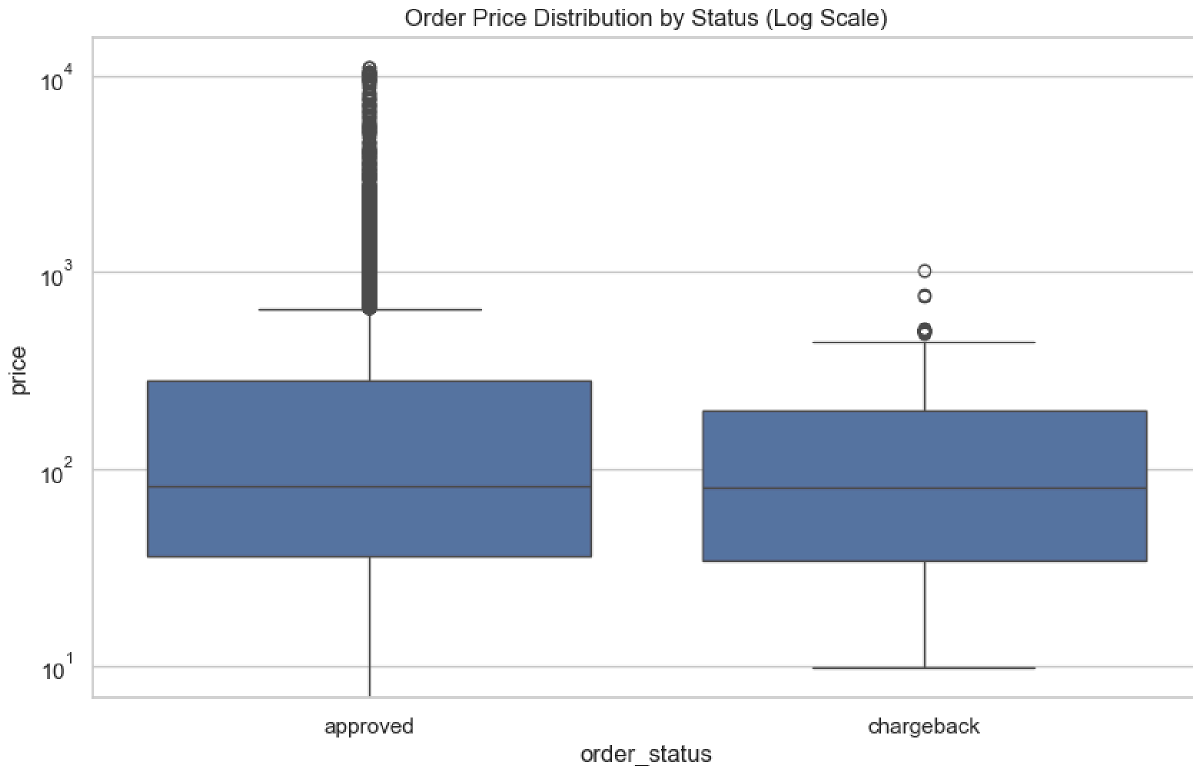
💬 Commentary: We compare chargeback rates between digital and non-digital (tangible) products.
Digital products are often more susceptible to fraud due to their instant, anonymous delivery.

# 5️⃣ Exploratory Analysis

## 📌 Insight 1: Are High-Value Orders Riskier?

In [17]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='order_status', y='price')
plt.yscale('log')
```

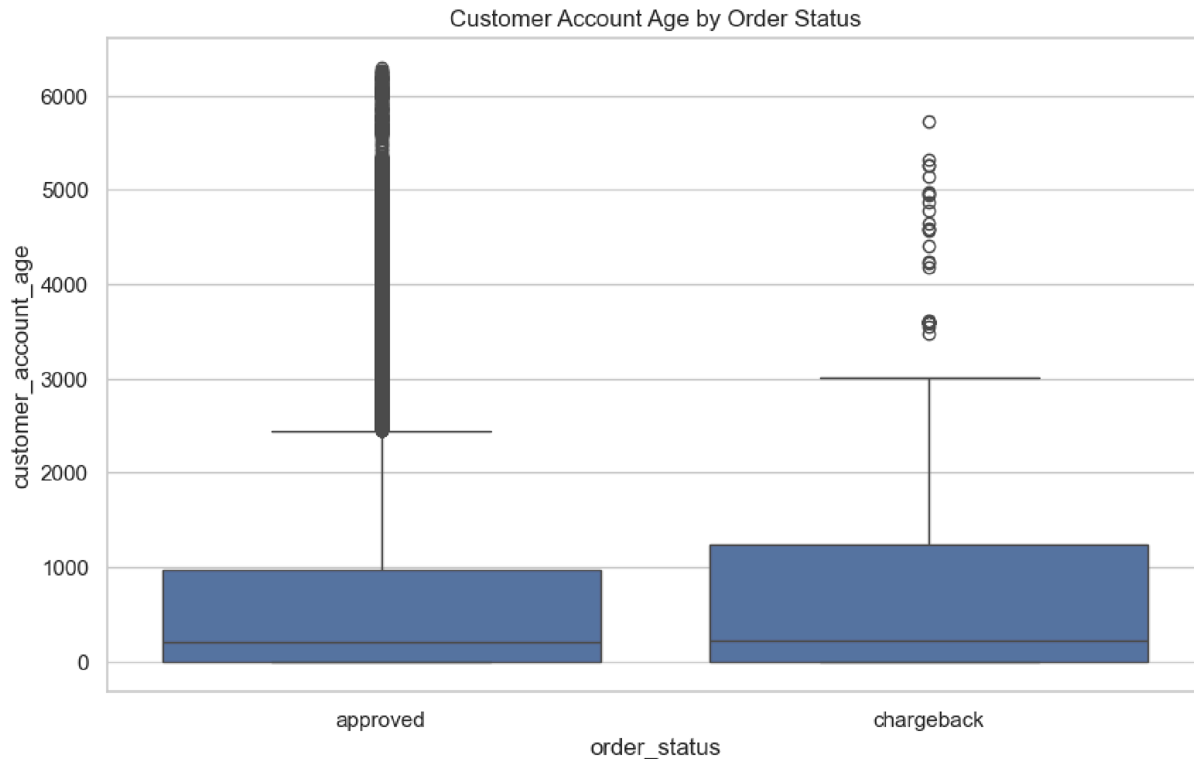
```
plt.title('Order Price Distribution by Status (Log Scale)')
plt.show()
```




💬 Commentary: Chargebacks tend to occur in higher-value orders. Fraudsters may target expensive items for maximum return.

## 📌 Insight 2: Does Account Age Influence Risk?

In [19]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='order_status', y='customer_account_age')
plt.title('Customer Account Age by Order Status')
plt.show()
```




💬 Commentary: Chargebacks are more frequent among newer accounts. This could indicate fake or throwaway accounts created solely to commit fraud.

## 📌 Insight 3: Top 10 High-Risk ZIP Codes

In [21]:
```
top_zip_risk = df[df['order_status'] == 'chargeback']['billing_zip'].value_counts()
print("\nTop 10 high-risk ZIP codes:")
print(top_zip_risk)
```

```
Top 10 high-risk ZIP codes:
billing_zip
2132     24
75773    22
15012    14
80927    12
77088    11
23225     9
94531     8
10469     6
55901     5
17545     4
Name: count, dtype: int64
```

# ✅ Final Summary

## Conclusion & Recommendations

- 90% of orders can be approved using a threshold score of **X.XXXXXX**
- Fee must be at least **X%** to offset 50% chargeback cost.
- Digital goods carry significantly higher fraud risk.
- Short account ages and short shipping names correlate with higher fraud likelihood

> 🧠 **Recommendations:**

- Adjust fee structure based on risk segment
- Implement dynamic thresholds using multiple risk signals
- Consider additional behavioral features for fraud scoring