# 01 — Exploratory Data Analysis (EDA)

**Dataset:** Kaggle Credit Card Fraud Detection (`creditcard.csv`)
**Goal:** Understand structure, class imbalance, and basic patterns that differentiate *fraud* vs *legit* transactions.

Key checks:

1. Schema overview (rows, columns, dtypes, missingness)
2. Class imbalance (0=legit, 1=fraud)
3. Descriptives by class
4. Distributions: `Amount`, `Time`, selected `V*` components
5. Simple correlations with `Class`
6. Quick anomalies sanity checks (duplicates, extreme values)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

pd.set_option("display.precision", 3)
pd.set_option("display.max_columns", 50)

sns.set(context="notebook", style="whitegrid")
```

## Load dataset

The dataset contains 284,807 transactions and 31 columns:
`Time`, `Amount`, `Class`, and 28 anonymised PCA-like features `V1..V28`.
`Class=1` denotes *fraud*.

```
PATH = "../data/creditcard.csv"
df = pd.read_csv(PATH)
df.shape, df.columns.tolist()[:10]
```

```
((284807, 31), ['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7',
'V8', 'V9'])
```

## Schema & missingness

We inspect dtypes and nulls. The Kaggle version typically has **no missing values**, but we verify.

```
df.info()
df.isna().sum().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64  
dtypes: float64(30), int64(1)
memory usage: 67.4 MB

0
```

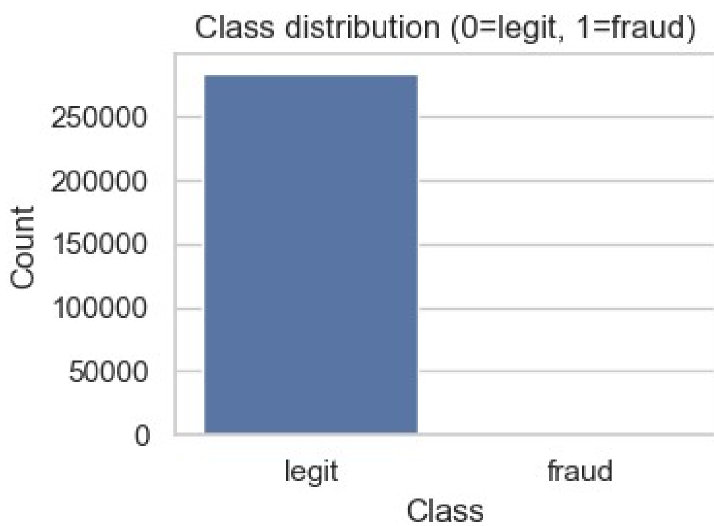
## Class balance

The dataset is **highly imbalanced**. We compute counts and proportions.

```
counts = df['Class'].value_counts().rename({0:"legit", 1:"fraud"})
props  = (counts / counts.sum()).round(4)
display(pd.DataFrame({"count": counts, "prop": props}))
```

```
plt.figure(figsize=(4,3))
sns.barplot(x=counts.index, y=counts.values)
plt.title("Class distribution (0=legit, 1=fraud)")
plt.ylabel("Count"); plt.xlabel("Class")
plt.tight_layout(); plt.show()
```

| | count | prop |
|---|---|---|
| Class | | |
| legit | 284315 | 0.998 |
| fraud | 492 | 0.002 |




## Descriptive statistics (overall & by class)

We look at summary stats overall and then compare *fraud vs legit* for `Amount` and `Time`.

```
display(df.describe().T[['mean','std','min','max']].head(12))

byc = df.groupby('Class')
[['Amount','Time']].agg(['count','mean','median','std','min','max'])
byc
```

| | mean | std | min | max |
|---|---|---|---|---|
| Time | 9.481e+04 | 47488.146 | 0.000 | 172792.000 |
| V1 | 1.168e-15 | 1.959 | -56.408 | 2.455 |
| V2 | 3.417e-16 | 1.651 | -72.716 | 22.058 |
| V3 | -1.380e-15 | 1.516 | -48.326 | 9.383 |
| V4 | 2.074e-15 | 1.416 | -5.683 | 16.875 |
| V5 | 9.604e-16 | 1.380 | -113.743 | 34.802 |
| V6 | 1.487e-15 | 1.332 | -26.161 | 73.302 |
| V7 | -5.556e-16 | 1.237 | -43.557 | 120.589 |
| V8 | 1.213e-16 | 1.194 | -73.217 | 20.007 |
| V9 | -2.406e-15 | 1.099 | -13.434 | 15.595 |

```
V10   2.239e-15      1.089  -24.588      23.745
V11   1.673e-15      1.021   -4.797      12.019

       Amount                                                Time
\
        count      mean  median      std   min        max    count
mean
Class

0      284315   88.291  22.00   250.105   0.0  25691.16   284315
94838.202
1         492  122.211   9.25   256.683   0.0   2125.87      492
80746.807


        median        std    min        max
Class
0      84711.0  47484.016    0.0  172792.0
1      75568.5  47835.365  406.0  170348.0
```

## Basic hygiene checks

- Duplicates (row-level)
- Constant/near-zero-variance columns
- Obvious invalid values (negative amounts)

```
dup_rows = df.duplicated().sum()
neg_amount = (df['Amount'] < 0).sum()
nzv = df.drop(columns=['Class']).nunique().sort_values().head(5)

print(f"Duplicate rows: {dup_rows}")
print(f"Negative Amount values: {neg_amount}")
nzv
```

## Distributions: `Amount` & `Time`

`Time` is seconds from the first transaction; `Amount` is the transaction value.
We compare distributions for fraud vs legit using random subsamples for readability.

```
from scipy import stats

sample = df.sample(50000, random_state=425)

fig, axes = plt.subplots(1, 2, figsize=(10, 4))

# Separate the data
legit_amount = sample[sample['Class'] == 0]['Amount']
fraud_amount = sample[sample['Class'] == 1]['Amount']
legit_time = sample[sample['Class'] == 0]['Time']
```

```
fraud_time = sample[sample['Class'] == 1]['Time']

# Plot Amount KDE
x_range_amount = np.linspace(min(sample['Amount']),
max(sample['Amount']), 100)
kde_legit_amount = stats.gaussian_kde(legit_amount)
kde_fraud_amount = stats.gaussian_kde(fraud_amount)

axes[0].plot(x_range_amount, kde_legit_amount(x_range_amount),
label='Legit', alpha=0.7)
axes[0].plot(x_range_amount, kde_fraud_amount(x_range_amount),
label='Fraud', alpha=0.7)
axes[0].fill_between(x_range_amount, kde_legit_amount(x_range_amount),
alpha=0.3)
axes[0].fill_between(x_range_amount, kde_fraud_amount(x_range_amount),
alpha=0.3)
axes[0].set_title("Amount density by Class")
axes[0].legend()

# Plot Time KDE
x_range_time = np.linspace(min(sample['Time']), max(sample['Time']),
100)
kde_legit_time = stats.gaussian_kde(legit_time)
kde_fraud_time = stats.gaussian_kde(fraud_time)

axes[1].plot(x_range_time, kde_legit_time(x_range_time),
label='Legit', alpha=0.7)
axes[1].plot(x_range_time, kde_fraud_time(x_range_time),
label='Fraud', alpha=0.7)
axes[1].fill_between(x_range_time, kde_legit_time(x_range_time),
alpha=0.3)
axes[1].fill_between(x_range_time, kde_fraud_time(x_range_time),
alpha=0.3)
axes[1].set_title("Time density by Class")
axes[1].legend()

plt.tight_layout()
plt.show()
```

## Boxplots: Amount and Time by Class

Boxplots highlight differences in central tendency and spread between classes.

```
fig, axes = plt.subplots(1,2, figsize=(10,4))
sns.boxplot(data=sample, x="Class", y="Amount", ax=axes[0])
axes[0].set_title("Amount by Class")
sns.boxplot(data=sample, x="Class", y="Time", ax=axes[1])
axes[1].set_title("Time by Class")
plt.tight_layout(); plt.show()
```

## Distributions of selected `V*` components

The `V1..V28` columns are anonymised components (PCA-like).
We plot a few that often show separation (your results may vary): `V3`, `V4`, `V10`, `V14`.

```
cols = ["V3", "V4", "V10", "V14"]
fig, axes = plt.subplots(2, 2, figsize=(10, 7))
for col, ax in zip(cols, axes.ravel()):
    # Plot density for each class separately
    sample[sample['Class'] == 0][col].plot.density(ax=ax,
label='Legit', alpha=0.7)
    sample[sample['Class'] == 1][col].plot.density(ax=ax,
label='Fraud', alpha=0.7)
    ax.fill_between(ax.lines[0].get_xdata(), ax.lines[0].get_ydata(),
alpha=0.3)
    ax.fill_between(ax.lines[1].get_xdata(), ax.lines[1].get_ydata(),
alpha=0.3)
    ax.set_title(f"{col} density by Class")
    ax.legend()
plt.tight_layout(); plt.show()
```

## Correlation with `Class`

Because `Class` is binary, Pearson correlation is equivalent to point-biserial correlation.
We compute correlations between each feature and `Class` and show the top signals.

```
corr = df.corr(numeric_only=True)
['Class'].drop('Class').sort_values(key=np.abs, ascending=False)
corr.head(12).to_frame("corr_with_Class")
```

## Fraud vs Legit: side-by-side summary table

Simple per-class summaries to identify directional differences.

```
summary_cols = ["Amount","Time","V3","V4","V10","V14"]
summary = (df.groupby("Class")[summary_cols]
             .agg(['mean','median','std','min','max'])
             .round(3))
summary
```