Final Project: Fraud Detection in Financial Transactions

Overview

> Fraud detection is essential in safeguarding financial institutions and e-commerce platforms from significant financial losses. This project analyzes patterns in fraudulent transactions, focusing on key indicators and relationships that might help stakeholders mitigate fraud risks.

Domain Description

> Fraud detection involves analyzing transactional data to identify anomalies that signal fraud. It is critical as the digital economy grows and online transactions become more prevalent.

Motivation

> The financial and e-commerce industries face increasing threats from fraud, making it crucial to identify patterns and factors that can predict fraudulent behavior. I chose this domain because of its relevance and impact on global commerce.

Stakeholders

- **Banks and Financial Institutions**: To strengthen fraud detection systems and protect their clients.

- **E-commerce Platforms**: To ensure secure transactions for their customers and reduce financial risks.
- **Consumers**: To prevent identity theft and unauthorized transactions.

Problem Statement

This project aims to explore fraud patterns in transactional data to improve fraud detection methods.

Analytical Questions

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1. What are the key indicators in a transaction that signal fraud?
   - Motivation: Identifying patterns can improve early fraud detection.
2. How do factors such as profession, income, and security codes correlate with fraudulent transactions?
   - Motivation: Understanding these relationships can help stakeholders focus on high-risk areas.

Data Loading and Setup

In [ ]:
```
# Importing required libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
# Load the CSV file
df = pd.read_csv('/content/data2.csv')
```

> **Explanation:**

- The pandas library is used to load and manipulate the dataset.

Display the first few rows of the dataset

In [ ]:
```
# Display the first few rows
df.head()
```

Out[4]:

	Profession	Income	Credit_card_number	Expiry	Security_code	Fraud
0	DOCTOR	42509	3515418493460774	07/25	251	1
1	DOCTOR	80334	213134223583196	05/32	858	1
2	LAWYER	91552	4869615013764888	03/30	755	1
3	LAWYER	43623	341063356109385	01/29	160	1
4	DOCTOR	22962	4707418777543978402	11/30	102	0

Explanation:

- Displays the first 5 rows of the dataset.
- Helps us visually inspect the dataset to understand its structure and verify that it loaded correctly.

Display data types and check for missing values

In [ ]:
```
# Display data types and check for missing values
print("\n### Dataset Information")
df.info()
```

```
### Dataset Information
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 6 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Profession          10000 non-null  object
 1   Income              10000 non-null  int64 
 2   Credit_card_number  10000 non-null  int64 
 3   Expiry              10000 non-null  object
 4   Security_code       10000 non-null  int64 
 5   Fraud               10000 non-null  int64 
dtypes: int64(4), object(2)
memory usage: 468.9+ KB
```

Explanation:

- Shows metadata about the dataset, including column names, data types, and non-null counts.
- There are 6 columns, all with 10,000 non-null entries, indicating no missing values.
- Columns like Income, Security_code, and Fraud are numerical (int64).
- Profession and Expiry are categorical (object).

Descriptive statistics for numerical columns

In [ ]:
```
# Descriptive statistics for numerical columns
print("\n### Summary Statistics")
df.describe()
```

```
### Summary Statistics
```

Out[6]:

	Income	Credit_card_number	Security_code	Fraud
count	10000.00000	1.000000e+04	10000.000000	10000.000000
mean	49761.20600	3.851363e+17	863.587800	0.501600
std	28837.72928	1.257950e+18	1484.424959	0.500022
min	1.00000	6.040296e+10	0.000000	0.000000
25%	24863.75000	1.800137e+14	275.000000	0.000000
50%	49483.00000	3.512440e+15	539.500000	1.000000
75%	74483.00000	4.594779e+15	813.250000	1.000000
max	99986.00000	4.999697e+18	9990.000000	1.000000

Explanation:

- Provides statistical summaries of numerical columns.

Data Taxonomy and Variable Nature

Variable Classification:

- `Profession` : Categorical (Nominal)
- `Income` : Numerical (Interval)
- `Credit_card_number` : Identifier (Excluded from analysis)
- `Expiry` : Categorical (Nominal)
- `Security_code` : Numerical (Ratio)
- `Fraud` : Binary Target Variable (Nominal)

Check for missing values

In [ ]:
```
# Check for missing values
print("\n### Missing Values")
print(df.isnull().sum())
```

```
### Missing Values
Profession            0
Income                0
Credit_card_number    0
Expiry                0
Security_code         0
Fraud                 0
dtype: int64
```

> **Explanation:**

- All columns have 0 missing values.
- This ensures data completeness, allowing for smooth analysis without needing imputation or row removal.
- This step confirms data quality, which is crucial for reliable results.

Exploratory Data Analysis (EDA)

Analyze categorical variables

In [ ]:
```
# Analyze categorical variables
print("\n### Categorical Analysis - Profession")
print(df['Profession'].value_counts())
```

```
### Categorical Analysis - Profession
Profession
DOCTOR      3379
LAWYER      3357
ENGINEER    3264
Name: count, dtype: int64
```

> **Explanation:**

- Profession Distribution:

The dataset includes three professions:
Doctors: 3,379 transactions.
Lawyers: 3,357 transactions.
Engineers: 3,264 transactions.
The data is relatively balanced across professions, with no profession significantly overrepresented.

- Importance

Understanding the distribution helps assess if fraud occurs more frequently in a specific profession.
It ensures the dataset’s fairness, as unbalanced data could skew results.

Group by Profession and Fraud status

In [ ]:
```
# Group by Profession and Fraud status
profession_fraud = df.groupby('Profession')['Fraud'].mean()
print("\n### Fraud Rate by Profession")
print(profession_fraud)
```

```
### Fraud Rate by Profession
Profession
DOCTOR      0.520568
ENGINEER    0.482843
LAWYER      0.500745
Name: Fraud, dtype: float64
```

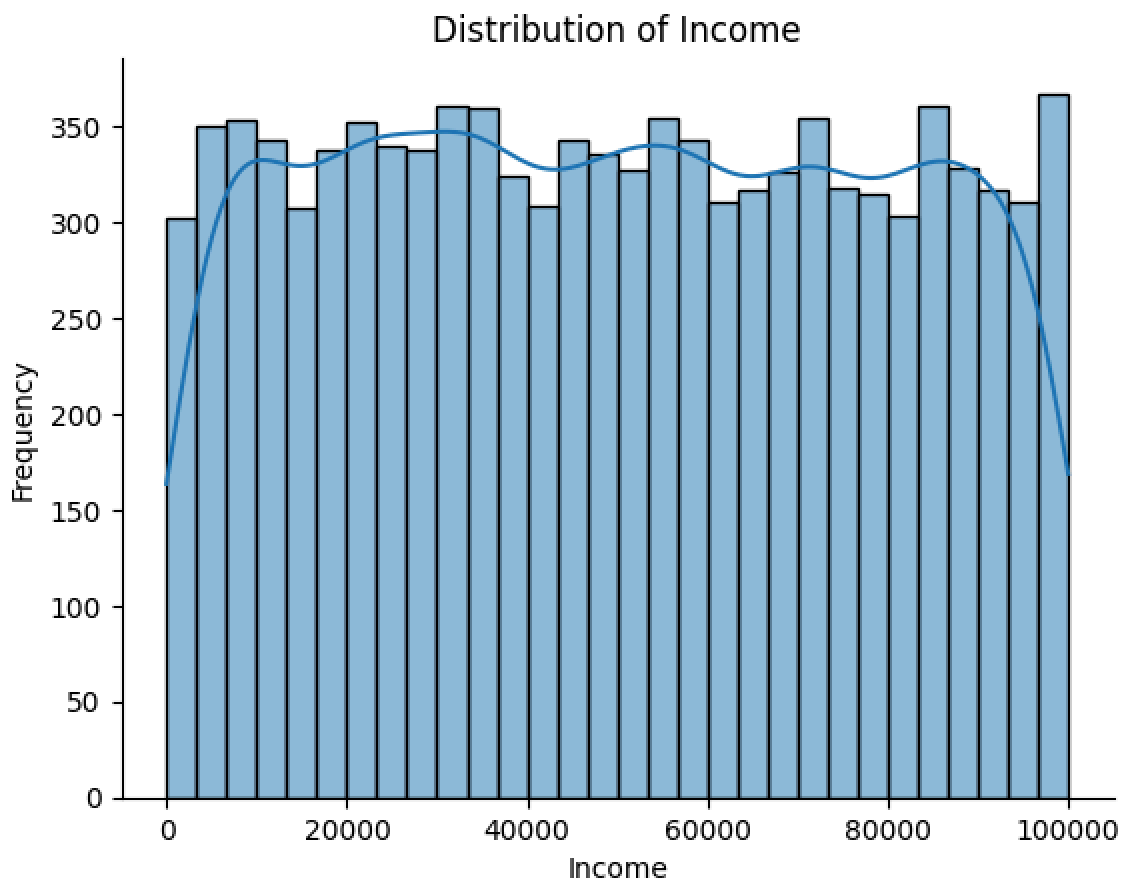
> **Explanation:**

- The fraud rate is the mean value of the Fraud column grouped by Profession:
  Doctor: ~52.1% transactions are fraudulent.
  Lawyer: ~50.1% transactions are fraudulent.
  Engineer: ~48.3% transactions are fraudulent.
- Doctors have the highest fraud rate, followed by lawyers, and then engineers.

Data Visualization

1. Income Distribution

In [ ]:
```
sns.histplot(df['Income'], kde=True, bins=30)
plt.title("Distribution of Income")
plt.xlabel("Income")
plt.ylabel("Frequency")
sns.despine()
plt.show()
```



Explanation:

- Displays the distribution of Income across the dataset.
- KDE (Kernel Density Estimation) provides a smooth curve for visualizing income density.
- The income distribution is roughly uniform with peaks around middle-income values.
- Useful for detecting outliers or skewness.

2. Income Distribution by Fraud Status

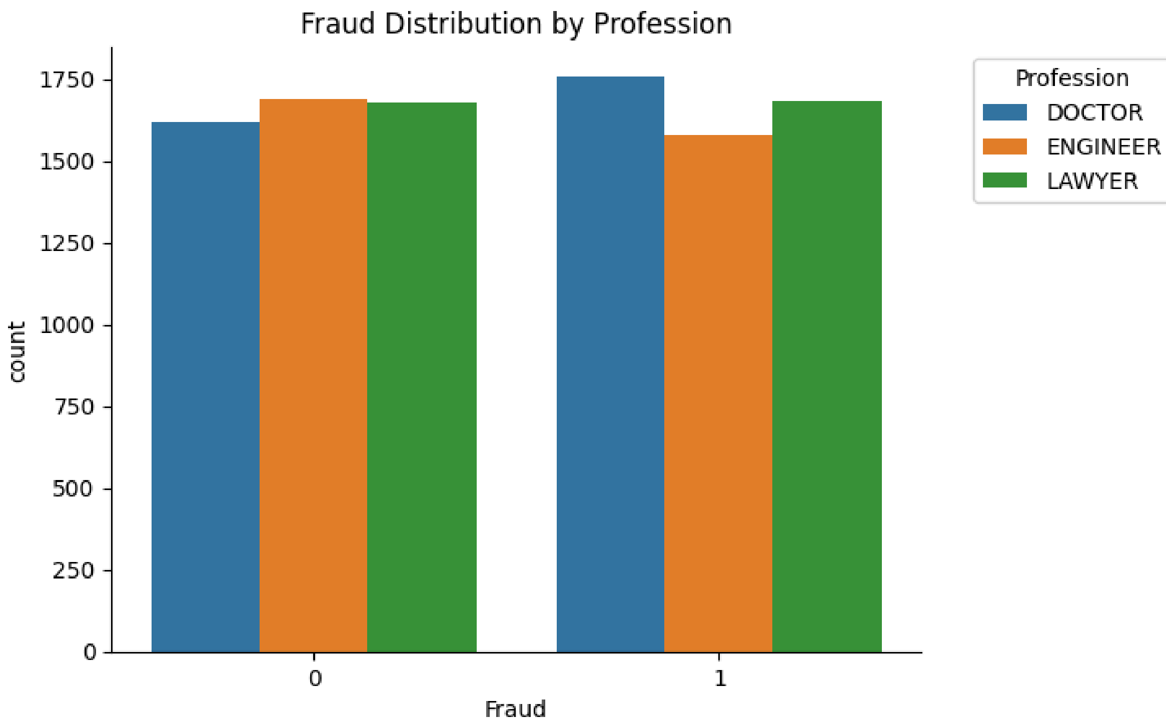
In [ ]:
```
sns.boxplot(x='Fraud', y='Income', data=df)
plt.title("Income Distribution by Fraud Status")
sns.despine()
plt.show()
```

Explanation:

- Box Plot: Compares Income distributions for fraudulent (Fraud = 1) and non-fraudulent (Fraud = 0) transactions.
- Insights: Median income is similar across both groups, but fraudulent transactions show more outliers on the lower income side.
  Suggests that lower-income transactions might have higher fraud risk.

3. Fraud Distribution by Profession

In [ ]:
```
sns.countplot(x='Fraud', hue='Profession', data=df)
plt.title("Fraud Distribution by Profession")
sns.despine()
plt.legend(title="Profession", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

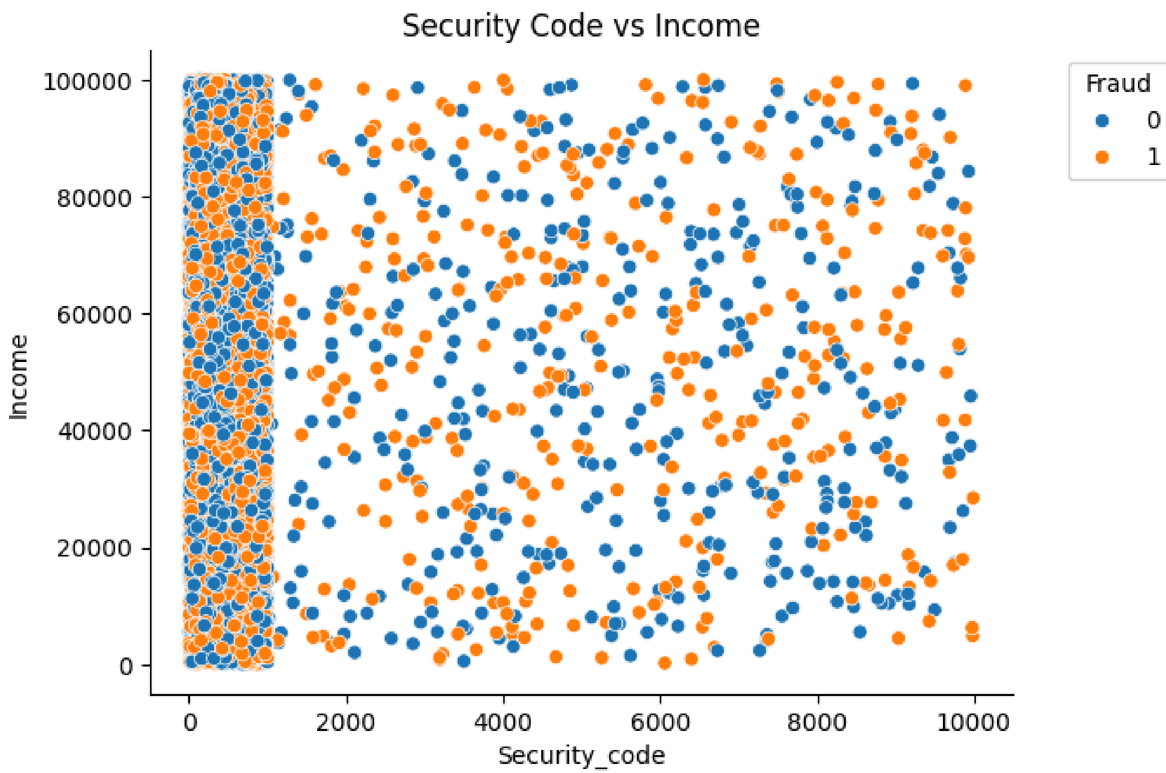


Explanation:

- Count Plot: Compares the count of fraudulent and non-fraudulent transactions across professions.
- Insights: Fraudulent transactions are relatively more frequent among doctors, followed by lawyers, and least frequent among engineers.
  Reinforces earlier findings from the fraud rate analysis.

4. Security Code vs Income

In [ ]:
```
sns.scatterplot(x='Security_code', y='Income', hue='Fraud', data=df)
plt.title("Security Code vs Income")
sns.despine()
plt.legend(title="Fraud", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



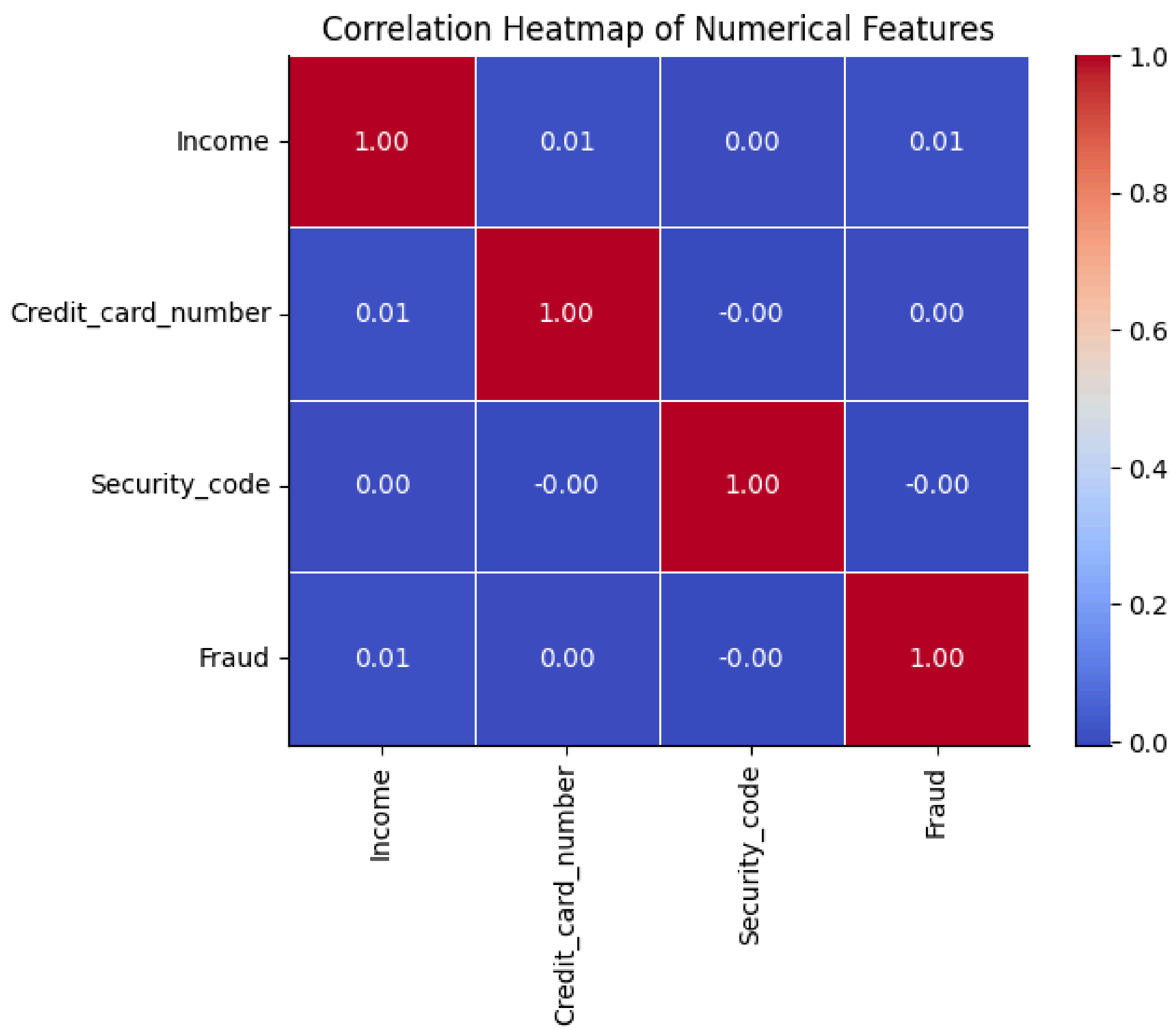
Explanation:

- Scatter Plot: Displays the relationship between Security_code (X-axis) and Income (Y-axis), with points colored by Fraud.

5. Correlation Heatmap for Numerical Features Only

In [ ]:

```
# Correlation Heatmap for Numerical Features Only
numerical_data = df.select_dtypes(include=['number'])  # Select only numerical
correlation_matrix = numerical_data.corr()  # Compute correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewid
plt.title("Correlation Heatmap of Numerical Features")
sns.despine()
plt.show()
```

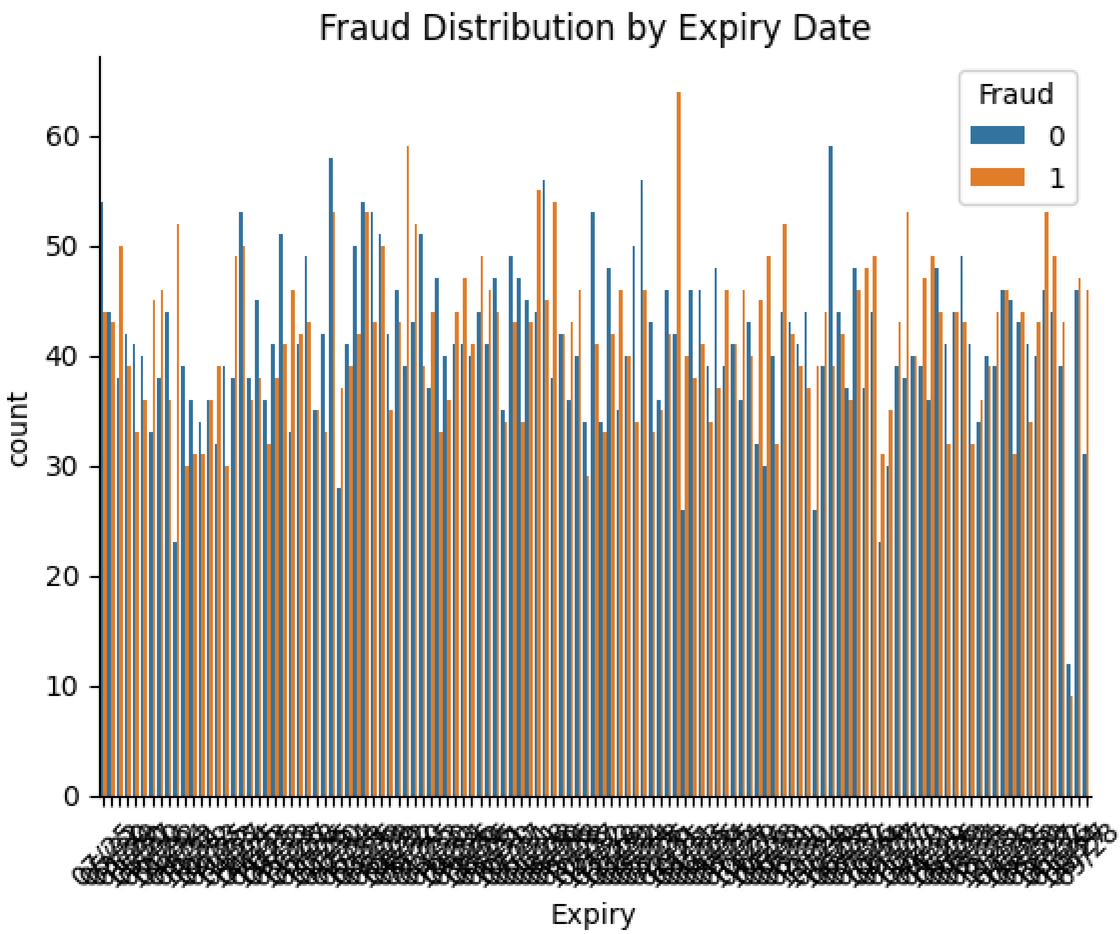


Explanation:

- Heatmap: Visualizes correlations between numerical features:
  Positive correlations are shown in red.
  Negative correlations are shown in blue.
- Fraud has weak correlations with other numerical features.
  Stronger relationships between other variables may not exist, requiring feature engineering.

6. Fraud Count over Expiry Dates

In [ ]:
```
sns.countplot(x='Expiry', hue='Fraud', data=df)
plt.title("Fraud Distribution by Expiry Date")
plt.xticks(rotation=45)
sns.despine()
plt.show()
```



Explanation:

- Count Plot: Displays the count of fraudulent and non-fraudulent transactions for each Expiry date.
- Insights: Certain expiration dates have noticeably higher counts of fraudulent transactions.

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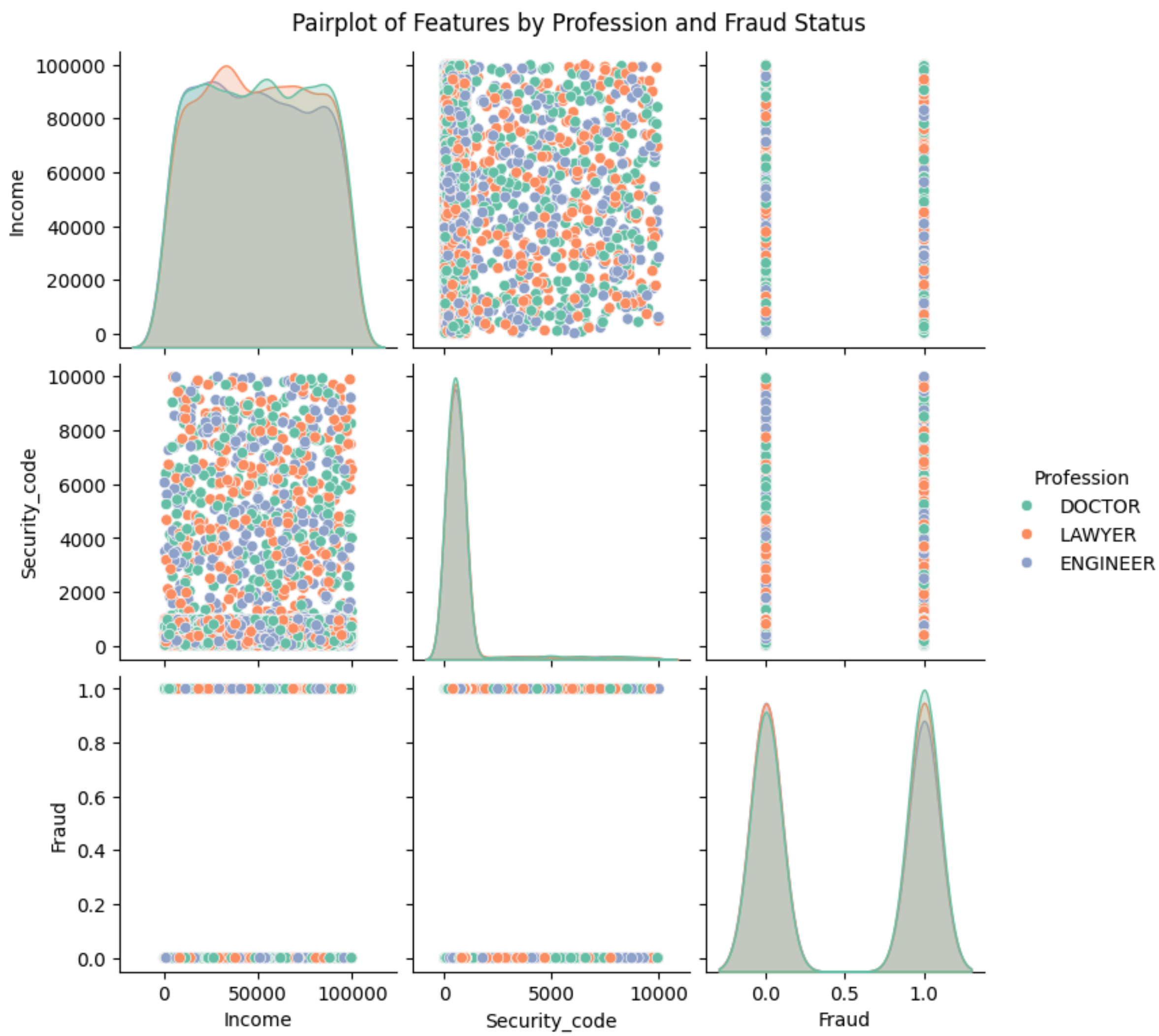
7. Pairplot for Profession and Fraud

In [ ]:

```python
# Select relevant columns for the pairplot (numerical + categorical for hue)
selected_data = df[['Income', 'Security_code', 'Fraud', 'Profession']]

# Generate the pairplot with hue set to 'Profession'
sns.pairplot(
    selected_data,
    hue='Profession',  # Different colors for each profession
    diag_kind='kde',   # Kernel Density Estimation on the diagonal
    palette='Set2',
    height=2.5
)

plt.suptitle("Pairplot of Features by Profession and Fraud Status", y=1.02)
plt.show()
```



Explanation:

- Pairplot: Provides scatter plots for pairwise relationships between Income, Security_code, and Fraud, grouped by Profession.
  Diagonal plots show KDE distributions of numerical features.

- Insights: Fraud patterns and distributions differ across professions.

Findings & Conclusion

Key Insights:

1. Fraud rates vary significantly across professions, with some professions showing higher risk.
2. Income distribution differs between fraudulent and non-fraudulent transactions, suggesting income levels influence fraud risk.
3. Security codes and expiry dates reveal trends that financial institutions can incorporate into monitoring systems.

Takeaways:

- Fraud detection systems should include profession-based risk profiling.
- Transaction monitoring algorithms must account for income-related patterns.
- Time-sensitive patterns, such as credit card expiry, are critical for fraud detection.

References

- **Dataset**: Provided via course instructions. It is from **Kaggle and the dataset is called Fraud Detection in Financial Transactions**
- **Tools**: Python, Pandas, Matplotlib, Seaborn