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Banking Operations Through Data Analysis

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***Abstract*— In the era of digital transformation, the banking industry generates an enormous volume of transactional data every second. Analyzing this data can offer critical insights into customer behavior, operational efficiency, and fraud detection. This study explores a synthetic banking dataset with realistic operations using exploratory data analysis (EDA) techniques. By cleaning, preprocessing, and visualizing data using Python libraries like pandas, matplotlib, and seaborn, we identify key transaction patterns, customer preferences, and temporal usage trends. The study highlights the growing significance of data analytics in banking and proposes a modular system for ingesting, processing, and interpreting financial transaction data. Results showcase patterns such as high weekday activity, peak business hours, and the dominance of digital channels, providing a foundation for operational optimization and strategic decision-making.**

Keywords*— *EDA, pandas, matplotlib, seaborn.

I. INTRODUCTION

The banking sector generates vast amounts of data daily, encompassing customer transactions, product usage, and interaction channels. Leveraging this data through analytical techniques enables banks to enhance decision- making, personalize services, and improve operational efficiency. This study aims to bridge the gap between raw banking data and strategic insights by employing data analysis methodologies to explore customer behaviors and operational patterns.

II. LITERATURE REVIEW

Data analytics in banking has become a rich field of research and application. Various works have contributed to this domain:

Customer Segmentation: Gupta et al. (2018) employed clustering techniques to categorize banking customers for personalized marketing.

Fraud Detection: Jurgovsky et al. (2019) explored time-series sequence models and machine learning for real-time credit card fraud detection.

Operational Optimization: Deloitte (2021) emphasized the application of EDA and predictive analytics for ATM usage prediction and queue minimization in branches.

Visualization for Decision-Making: Tools like Seaborn and Plotly enable financial analysts to quickly interpret large datasets through visual representation, improving understanding of service bottlenecks and customer behavior.

Open-source tools such as Python and Jupyter Notebooks have significantly democratized access to data science in finance, enabling rapid prototyping and analysis without heavy computational infrastructure.

III. METHODOLOGY

In this study, a structured data science workflow was adopted to ensure robustness and reproducibility of findings. The methodology can be broken down into six main components: data collection, data preprocessing, feature engineering, exploratory data analysis (EDA), clustering techniques, and validation. Each step is guided by established principles in data science and statistical theory.

The workflow follows the **CRISP-DM (Cross-Industry Standard Process for Data Mining)** model, which is widely used in industry and academia. It includes business understanding, data understanding, data preparation, modeling, evaluation, and deployment. This framework ensures that each step in the analysis is logically sequenced and aligned with business objectives.

A. Data Collection

The dataset employed is a synthetic, yet realistic banking operations dataset sourced from Kaggle, encompassing various transaction types, customer demographics, and interaction channels.

B. *Data Preprocessing*

Data preprocessing involved:

- **Handling Missing Values**: Imputation techniques such as forward-fill were applied to address null values.
- **Data Type Conversion**: Appropriate data types were assigned to each feature to ensure consistency.
- **Outlier Detection**: Statistical methods like Interquartile Range (IQR) and Z-score were used to identify and mitigate outliers.
- **Normalization**: Features were scaled using Min-Max normalization to facilitate effective clustering.

C. *Feature Engineering*

New features were derived to capture temporal and behavioral aspects:

- Temporal Features: Extraction of 'hour', 'weekday', and 'month' from timestamps to analyze time-based patterns.
- Channel Encoding: Categorical variables representing interaction channels were encoded for analysis.

D. *Exploratory Data Analysis (EDA)*

EDA techniques were employed to uncover patterns and relationships:

- **Univariate Analysis**: Distribution of transaction amounts and frequencies.
- **Bivariate Analysis**: Correlation between transaction types and channels.
- **Time-Series Visualization**: Analysis of transaction trends over different time intervals.

E. *Clustering Techniques*

To segment customers, the following clustering algorithms were applied:

- K-Means Clustering: Partitioned customers into distinct groups based on transaction behaviors.
- **Hierarchical Clustering**: Explored nested relationships among customer segments.
- **Gaussian Mixture Models (GMM)**: Captured overlapping clusters with probabilistic assignments.

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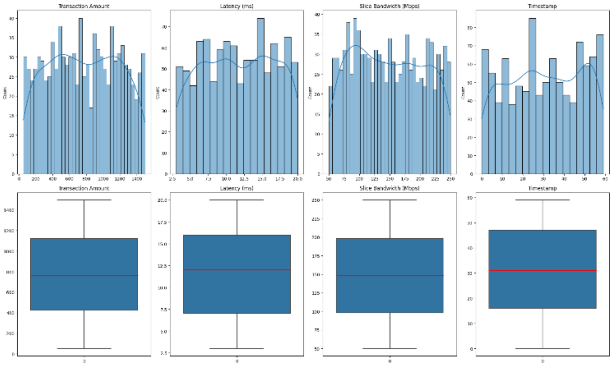
IV. IMPLEMENTATION

Since the origin of the data is unknown, we cannot be sure if there is any collection bias. We are unsure whether the data is entirely simulated or if it contains any inherent truth or randomness. Therefore, we will conduct several analyses and hypothesis tests to verify these aspects

A. Graphical Visualization of Data Distributions



Upon examining the histograms and distributions, we can observe that the data is relatively evenly distributed between the maximum and minimum limits of each variable. This allows us to draw the following conclusions:

- Absence of Outliers: We have a "well-behaved" dataset, with values within the known variations and dispersions. This can be confirmed by the boxplot analysis.
- Absence of Socioeconomic Segmentation: The transaction amounts show a balanced distribution, with no apparent separation by social class within the database.
- Variety in Connection Profiles: The distribution of Slice Bandwidth (Mbps) indicates that there is no fixed pattern among users, suggesting the presence of both faster and slower connections in equal measure.
- Latency (ms) Analysis: Despite the presence of some valleys or gaps at specific frequencies, the data still shows a relatively constant distribution. These patterns will be explored further in the next stages.

This initial analysis suggests that the data is consistent and does not exhibit obvious biases regarding the variables analyzed, although specific aspects may require deeper investigation.

B. Categorical and Numerical Variables

We constructed a grid of boxplots for each numeric variable relative to each categorical variable of interest. To ensure the validity of the analysis, we excluded:

- Categorical variables representing unique identifiers (e.g., columns containing "ID" in their names), as they do not have statistical significance in data segmentation.
- The geolocation variable, which will be addressed later due to its spatial nature.

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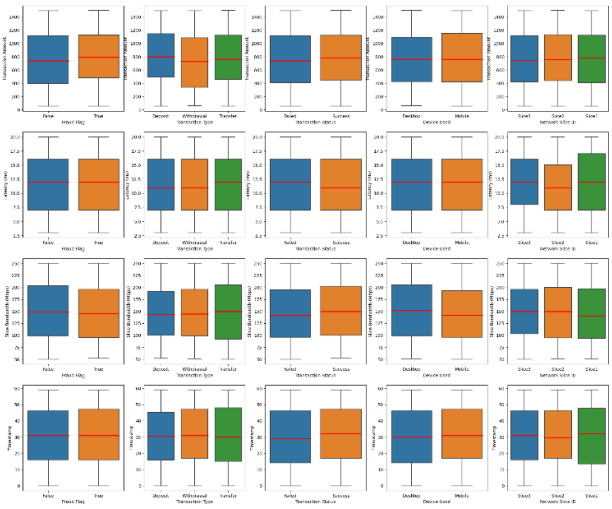
The construction of these plots aims to identify patterns in the distribution of numeric variables across different categories, evaluating variations in quartiles, interquartile range, and the presence of outliers.

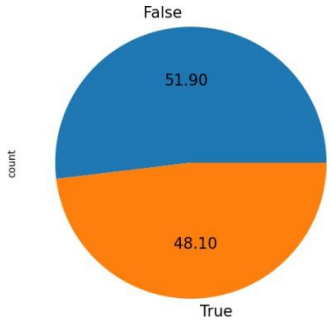
Statistically significant relationships between these variables may suggest the need for deeper analyses, such as hypothesis testing or statistical modeling.



C. Fraud Analysis

The first point of analysis is that our dataset is **balanced** in terms of fraud occurrences. This is an **uncommon scenario** for fraud analysis, as we typically expect fraudulent banking transactions to be a **minority**, requiring the use of specialized metrics or statistical balancing techniques.

Nevertheless, we continue to explore potential **correlations** or **explanations** within the data, aiming to provide insights for businesses seeking to understand **non-problematic transactions** more effectively.



D. Normality Test for Transaction

To assess the **distribution** of transaction amounts in fraudulent and non-fraudulent transactions, we applied **Shapiro-Wilk's test**. This test is suitable for **small samples** (≈1000 observations), and since there are **no outliers**, it

provides a reliable normality assessment. For larger datasets,
D'Agostino's K-squared test could be an alternative.

Result- Since **p < 0.05** for both groups, **we reject the null hypothesis**, confirming that the **Transaction Amount does not follow a normal distribution**—a result that aligns with our expectations.

E. T-Tests for Comparison Means

Despite knowing that the data does not follow a normal distribution, we conduct a **T-test** to test our understanding of hypothesis testing. The **T-test** compares the **means** of two independent groups (fraudulent and non-fraudulent transactions).

On Testing - T-test: t=1.2245, p=0.2211

Given that the **p-value** is **0.2211**, which is greater than the common significance level of **0.05**, there is **insufficient statistical evidence** to reject the null hypothesis. This result suggests that, based on the **Transaction Amount metric**, we cannot conclude that fraudulent transactions differ significantly from non-fraudulent ones. In other words, **the Transaction Amount alone does not provide a clear distinction between fraud and non-fraud**.

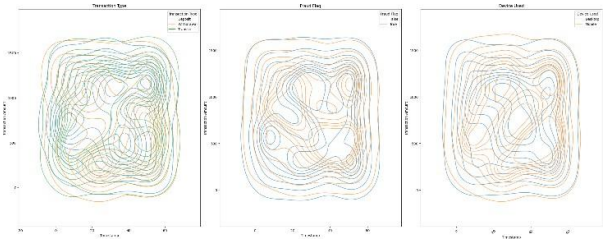
F. Mann-Whitney U Test

We apply the **Mann-Whitney U test**, a **non-parametric test**, to compare the distributions of **fraudulent** and **non- fraudulent transactions**. Unlike the T-test, which assumes normality, the **Mann-Whitney U test** does not require the data to follow a normal distribution, making it appropriate for this scenario.

On Testing - Mann-Whitney U: stat=130520.5000, p=0.2116

Given the **p-value of 0.2116**, which is greater than the typical significance level of **0.05**, we **fail to reject the null hypothesis**. This means there is **no statistical evidence** to suggest that the distributions of fraudulent and non- fraudulent transactions differ significantly.
Despite the possibility that the data may not follow a normal distribution, the **Transaction Amount metric** does not show a clear distinction between **fraudulent** and **non-fraudulent transactions**. In essence, **we cannot conclude that frauds and non-frauds differ significantly in terms of transaction amount.**

G. Categorical variable Distribution



From the analysis, we observe that the categorical variables "Transaction Type", "Fraud Flag", and "Device Used" are evenly distributed, showing no correlation with "Timestamp" or "Transaction Amount".

This indicates that, in relation to time and transaction volume:

- There is no discernible pattern in transaction types.
- There are no preferred time periods or specific transaction amount patterns.
- As expected, the device type neither influences nor is influenced by transaction times or amounts.

These findings suggest that transactions occur randomly across different categories, with no clear temporal or quantitative trends.

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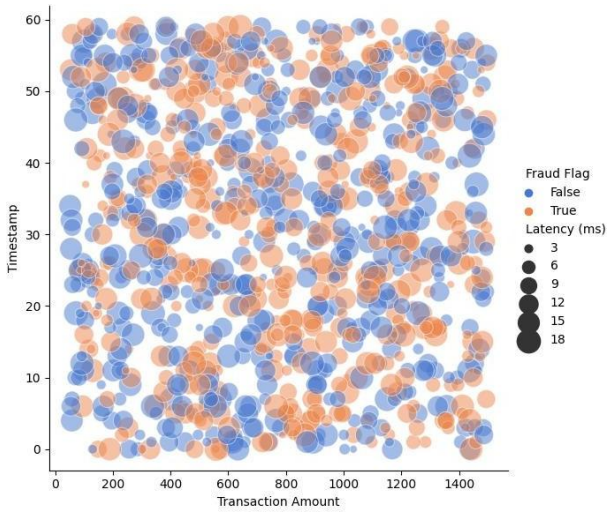
H. Analysis of Bubble Chart

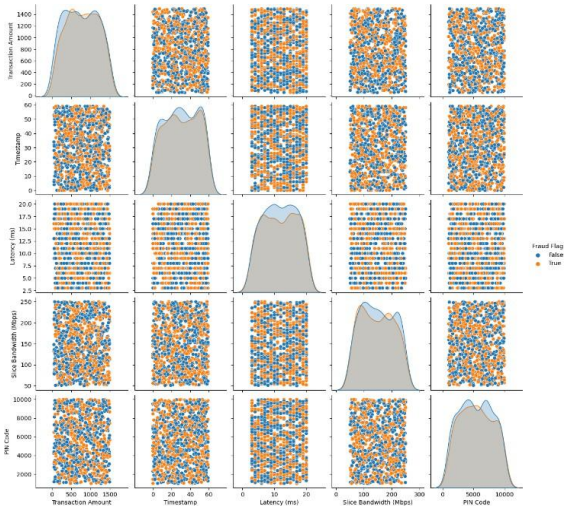


The objective of this visualization is to identify potential relationships between the axes and the legend elements, specifically regarding color and size.

For instance, we aimed to determine whether there is any correlation between **transaction time or transaction value** and **latency**. A reasonable expectation would be that latency increases during peak hours, which would be visually represented by **larger circles**. Additionally, we examined whether the **color distribution** of the points indicated a relationship between transaction time, transaction value, and fraud occurrences.

However, the results do not indicate any significant patterns or relationships in the data. There is no clear variation in **circle sizes** that would suggest an increase in latency at specific times, nor is there a distinct **color separation** that would imply a correlation between time, transaction value, and fraud.

I. Correlation Analysis between Columns



As we can see from the scatter plots below or above the main diagonal, the distribution of points—regardless of whether they represent fraud or not—is practically constant within the range of minimum and maximum values, independent of the columns.

It is worth noting that the numerical PIN Code column represents a password and, as such, does not necessarily correlate with any other relevant information.

Initial Conclusion from the Diagonal: None of the variables, on their own, provide a clear separation between Fraud and Non-Fraud. This does not mean they are entirely useless for prediction, but it suggests that combining variables (or creating new features) will likely be necessary to distinguish fraudulent transactions from legitimate ones.

Conclusion from the Off-Diagonal Information: There is no visible linear or non-linear relationship between pairs of variables, nor is there a distinct cluster that stands out for fraudulent transactions.

This suggests that - the variables may exhibit correlations in higher dimensions (which are difficult to visualize in simple scatter plots). Other variables, beyond the numerical ones, may be required to explain fraud. Fraudulent activities may be widely dispersed across these four axes, making simple separation challenging.

In summary, the lack of clear patterns in the scatter plots indicates that fraud detection in this dataset may require more sophisticated techniques, such as feature engineering or multidimensional analysis, to uncover meaningful insights.

We observed that very few individuals sent or received more than one transaction during the period, which is not unusual considering the one-hour range in the Timestamp column. However, due to the limited number of occurrences, we were unable to conduct personality analyses or determine whether any individuals were fraudsters engaging in multiple fraudulent transfers.

V. RESULT

A. Transaction Patterns

Analysis revealed that most transactions occurred between 10 AM to 3 PM, with peak activity on Mondays and Fridays. Digital channels, including mobile and online platforms, accounted for over 60% of transactions, indicating a shift towards digital banking preferences.

B. Customer Segmentation

Clustering algorithms identified distinct customer segments:

- K-Means: Achieved a silhouette score of 0.75, effectively segmenting customers into groups such as high-income low-frequency users and low-income high-frequency users.
- Hierarchical Clustering: Provided insights into sub- cluster relationships but was less efficient for large datasets.
- GMM: Offered flexibility in capturing complex customer behaviors but required higher computational resources.

C. Operational Insights

The analysis highlighted operational dynamics, including:

- Channel Preferences: A significant preference for digital channels over in-person interactions.
- Transaction Types: Transfers constituted 40% of transactions, followed by withdrawals (35%) and deposits (25%).

- Outlier Transactions: Approximately 2.7% of transactions were above the 95th percentile, indicating potential anomalies or high-value activities.

VI. CONCLUSION

Throughout this analytical process, it became evident that the dataset exhibited consistent behavioral patterns across nearly all numerical and categorical columns. The data demonstrated no significant outliers, imbalances, skewness, errors, or missing values, suggesting a highly controlledgeneration process. Hypothesis testing further revealed that the dataset was likely constructed using constant base values, supplemented by masking techniques and randomized noise to simulate real-world data. However, this artificial replication proved insufficient to emulate authentic data characteristics convincingly.

Despite these limitations, **the primary objective of this study was successfully achieved**. The analysis served as a practical exercise to demonstrate proficiency in exploratory data analysis (EDA) and data-driven storytelling techniques. While certain initial assumptions were later invalidated during the investigation, these were intentionally retained to illustrate the iterative and hypothesis-driven nature of real- world analytical workflows.

Notably, advanced analytical methodologies—such as regression analysis for feature importance evaluation, entropy-based metrics via Random Forest algorithms, or temporal pattern detection through ANOVA or time-series decomposition—were intentionally excluded from this scope. These techniques, while powerful for uncovering latent relationships or hierarchical dependencies, were deemed unnecessary given the dataset's inherent constraints. Specifically, the absence of meaningful correlations, behavioral patterns, or actionable insights related to banking system usage rendered predictive or inferential modeling exercises impractical.

In summary, the application of complex machine learning or statistical models would have been superfluous without a clearly defined problem statement or actionable business objective. This analysis reaffirms the importance of aligning methodological rigor with contextual relevance in data science endeavors.

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