

Assignment 1 - EDA Report

Banking Transactions & Fraud Detection

Summary

From the dataset, we found a few main findings that call for next steps:

- Exploring the transactions with >1 LoginAttempts
- Exploring the accounts with > 9 transactions
- Exploring the accounts with > \$1500 across all age groups
- Exploring the Devices and IP Address with > 9 accounts
- Exploring the transactions with > 50% of Transaction Amount is Account Balance
- Explore the transactions tagged “Potential Frauds” from K-means Clustering

Data Overview

We analyzed a dataset of 2512 transaction records and 16 features, with no missing values.

From the initial descriptive statistics, we have a few findings:

- We see ~75% of TransactionAmounts <\$500, however we have a max of \$1919. This could be someone doing a large transaction, however an outlier to keep in mind.
- Similarly, ~75% of TransactionDuration <161, however we have a max of 300.
- Similarly, ~75% of transactions have 1 LoginAttempts, however we have a max of 5

Table below.

Missing Values:	Descriptive Statistics:
TransactionID	0
AccountID	0
TransactionAmount	0
TransactionDate	0
TransactionType	0
Location	0
DeviceID	0
IP Address	0
MerchantID	0
Channel	0
CustomerAge	0
CustomerOccupation	0
TransactionDuration	0
LoginAttempts	0
AccountBalance	0
PreviousTransactionDate	0
dtype: int64	
	TransactionAmount
	count 2512.000000
	mean 297.593778
	min 0.260000
	25% 81.885000
	50% 211.140000
	75% 414.527500
	max 1919.110000
	std 291.946243
	TransactionDuration
	count 2512.000000
	mean 119.643312
	min 10.000000
	25% 63.500000
	50% 112.500000
	75% 161.000000
	max 300.000000
	std 69.963757
	LoginAttempts
	count 2512
	mean 1.000000
	min 0.000000
	25% 1.000000
	50% 1.000000
	75% 5.000000
	max 14977.990000
	std 0.602662
	AccountBalance
	count 2512.000000
	mean 5114.302966
	min 101.250000
	25% 1504.370000
	50% 4735.510000
	75% 7678.820000
	max 3900.942499
	CustomerAge
	count 2512.000000
	mean 44.673965
	min 18.000000
	25% 27.000000
	50% 45.000000
	75% 59.000000
	max 80.000000
	std 17.792198
	CustomerOccupation
	count 2512.000000
	mean 2.000000
	min 1.000000
	25% 1.000000
	50% 1.000000
	75% 1.000000
	max 1.000000
	std 0.000000
	Location
	count 2512.000000
	mean 2.000000
	min 1.000000
	25% 2.000000
	50% 2.000000
	75% 2.000000
	max 2.000000
	std 0.000000
	DeviceID
	count 2512.000000
	mean 2.000000
	min 1.000000
	25% 2.000000
	50% 2.000000
	75% 2.000000
	max 2.000000
	std 0.000000
	IP Address
	count 2512.000000
	mean 1.000000
	min 0.000000
	25% 1.000000
	50% 1.000000
	75% 1.000000
	max 1.000000
	std 0.000000
	MerchantID
	count 2512.000000
	mean 1.000000
	min 0.000000
	25% 1.000000
	50% 1.000000
	75% 1.000000
	max 1.000000
	std 0.000000
	Channel
	count 2512.000000
	mean 1.000000
	min 0.000000
	25% 1.000000
	50% 1.000000
	75% 1.000000
	max 1.000000
	std 0.000000
	PreviousTransactionDate
	count 2512
	mean 2024-11-04 08:09:22,219745024
	min 2024-11-04 08:06:23
	25% 2024-11-04 08:07:53
	50% 2024-11-04 08:09:22
	75% 2024-11-04 08:10:53,249999872
	max 2024-11-04 08:12:23
	std NaN

TransactionID	2512
AccountID	495
TransactionAmount	2455
TransactionDate	2512
TransactionType	2
Location	43

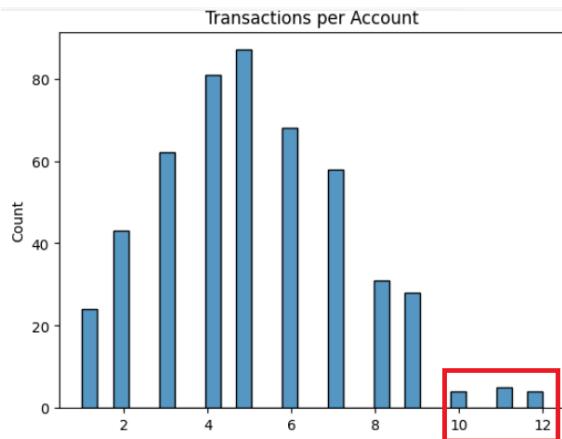
We also have expected uniqueness across Transaction IDs. We see 43 locations, and 100 Merchants. We have 681 Devices, while having 592 IP Addresses meaning we have some IPs with multiple devices. We also have 2510 AccountBalance, meaning 2 accounts have the same value. Interesting.

When looking at the distribution of Debit vs Credit, we see a strong preference for Debit (1944 vs 568). However, the spread between Channels (Branch, ATM, Online) is even.

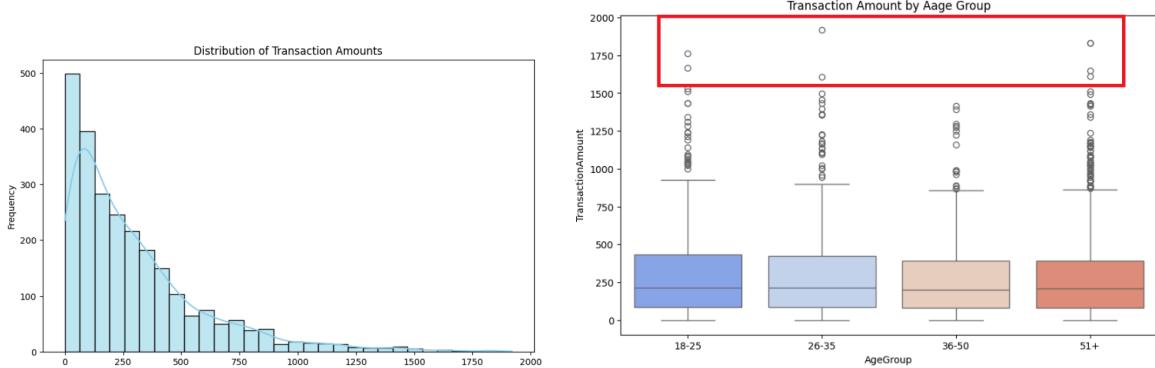
	count		count
TransactionType		Channel	
Debit	1944	Branch	868
Credit	568	ATM	833
		Online	811

Business Oriented

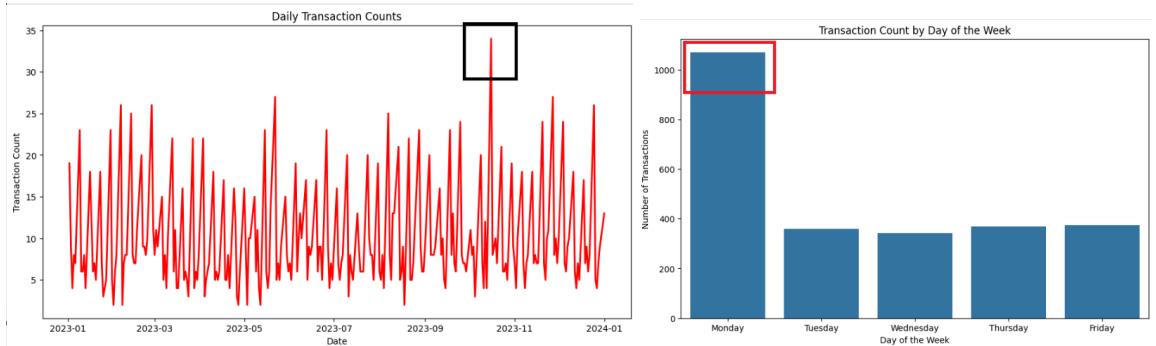
When we look at the Transactions per Account, we saw some outliers of a few accounts making > 9 transactions.



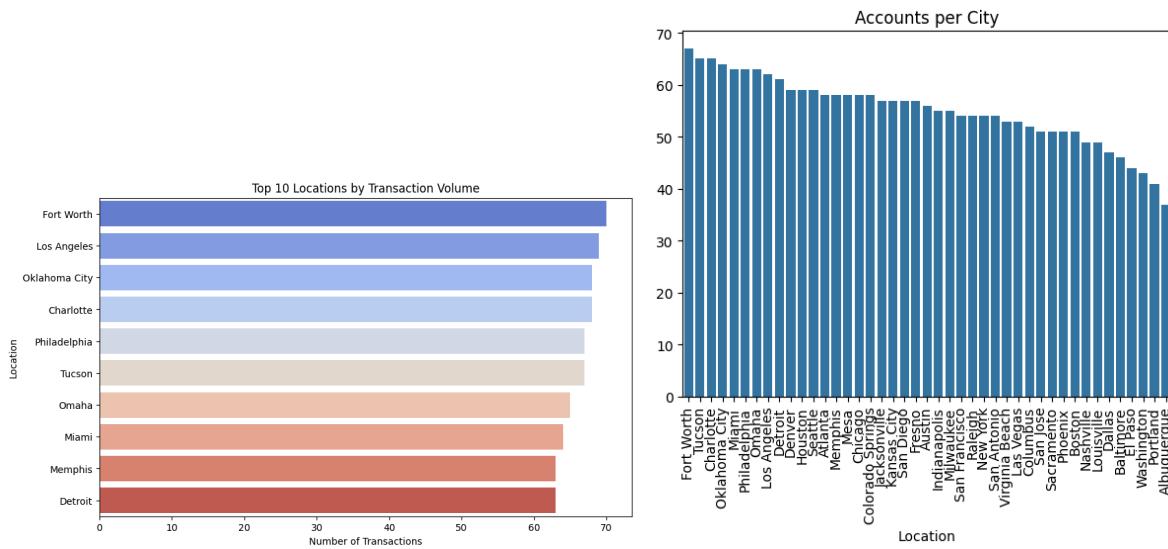
When looking at the distribution of amounts and ages, we see very few accounts with > \$1500. Especially in the lower age groups.



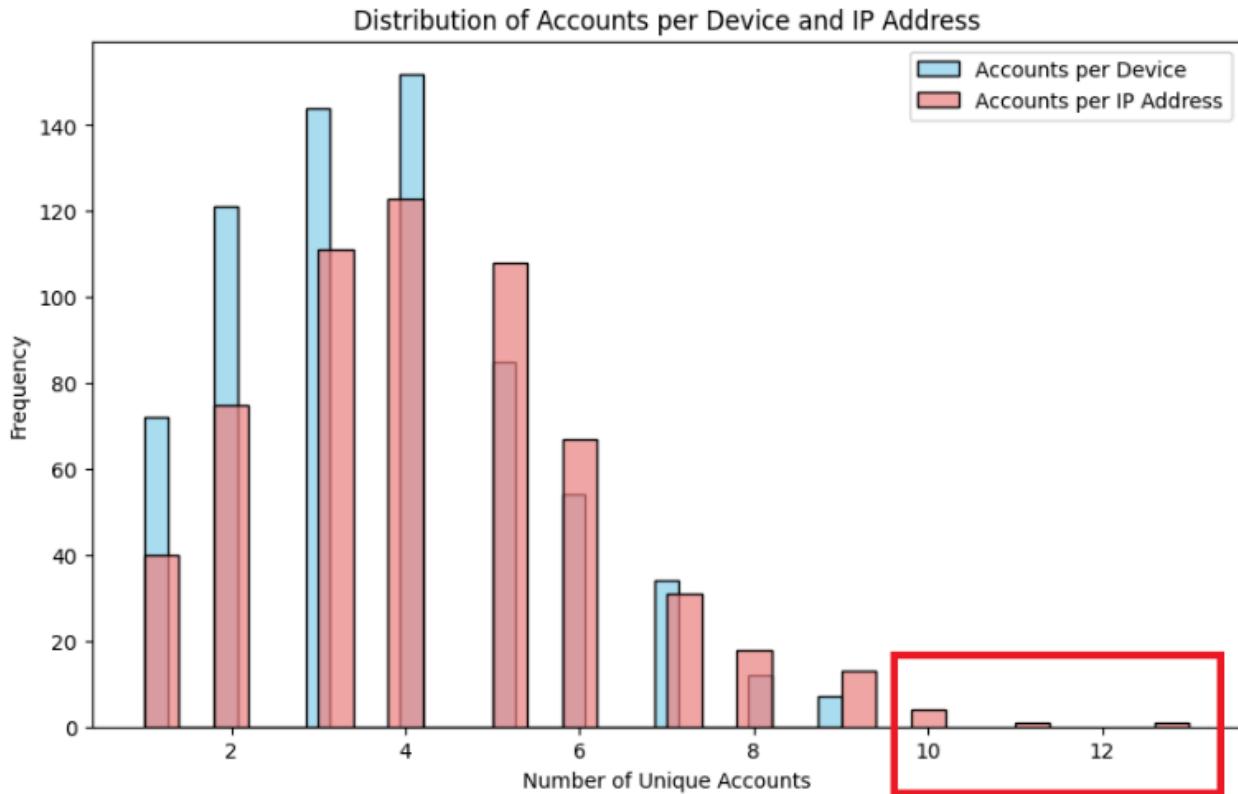
Looking at the data across time (days/yearly), we see a spike of transactions usually on Mondays. We should confirm if these are not outliers. Also there is a day in Late October with a very high and unusual amount of transactions. We should confirm this is not due to holiday traffic and expected.



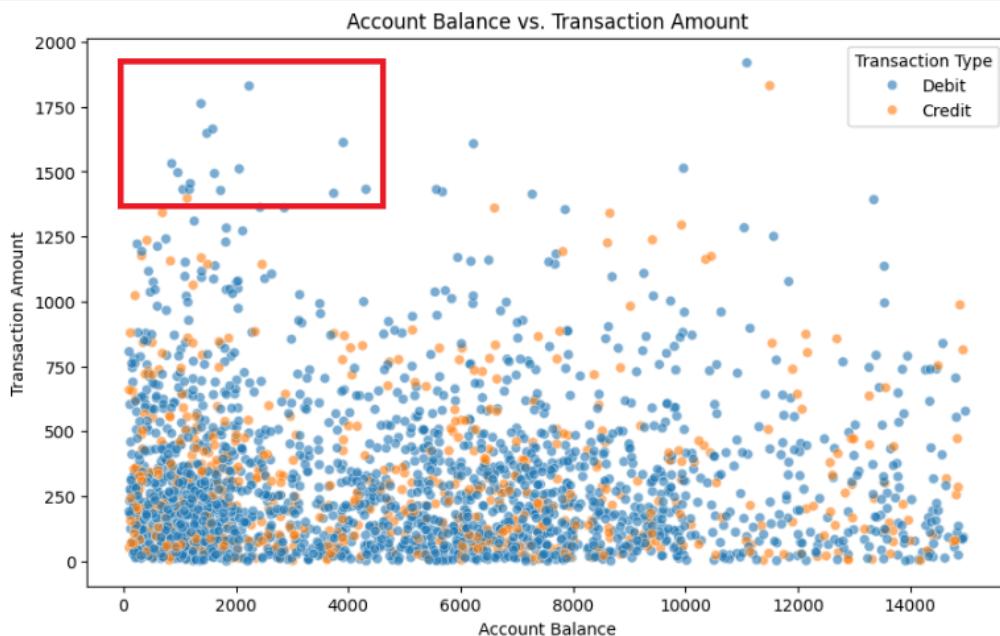
When looking at the top cities and locations, we see the same cities when looking at transaction volumes and # of accounts. There is some spread but overall Fort Worth, LA, Charlotte, OKC are in the top 10 for both.



When looking at the distribution of Devices and IP Addresses, we see outliers with a few accounts 10 or greater.

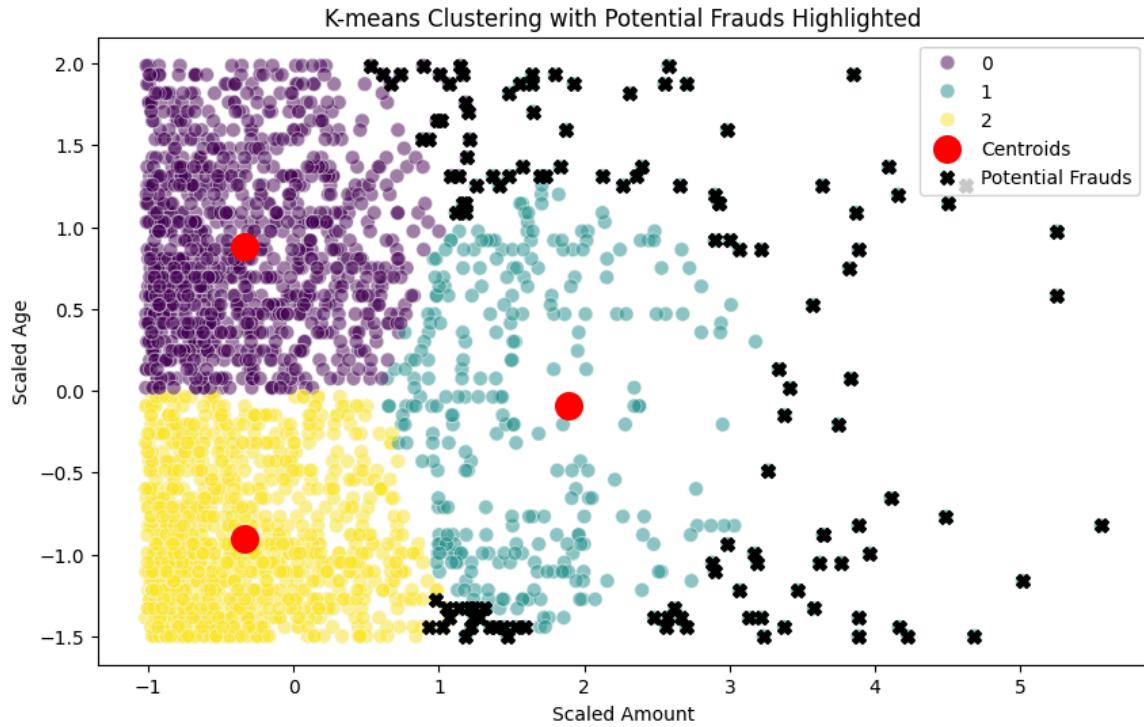


If we compare the Account Balance vs Transaction Amount, we see a few transactions with > 50% of the Account Balance is transacted away. These could be cases to explore unless they are moving banking accounts or companies.



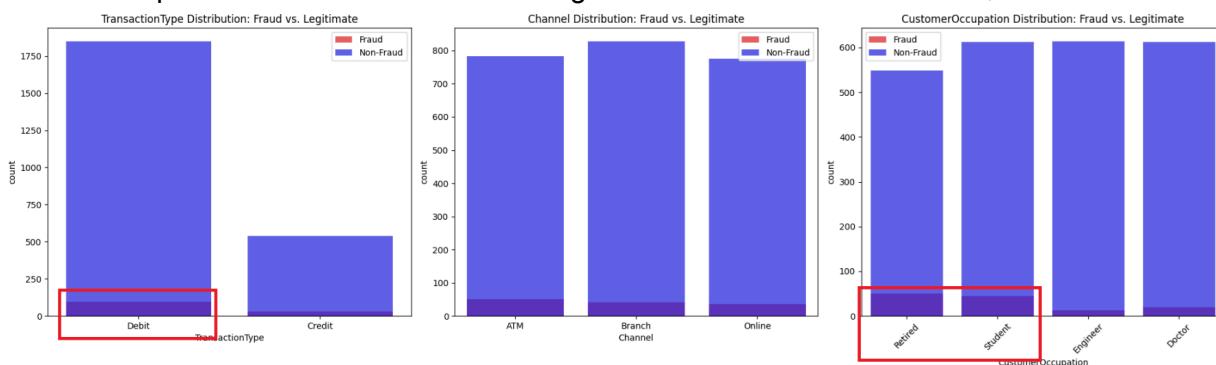
K-means Clustering

Finally, I leverage a k-means clustering from Kaggle to group transactions by similarity and identify transactions with unique attributes. From this we identified 126 potential fraudulent cases.

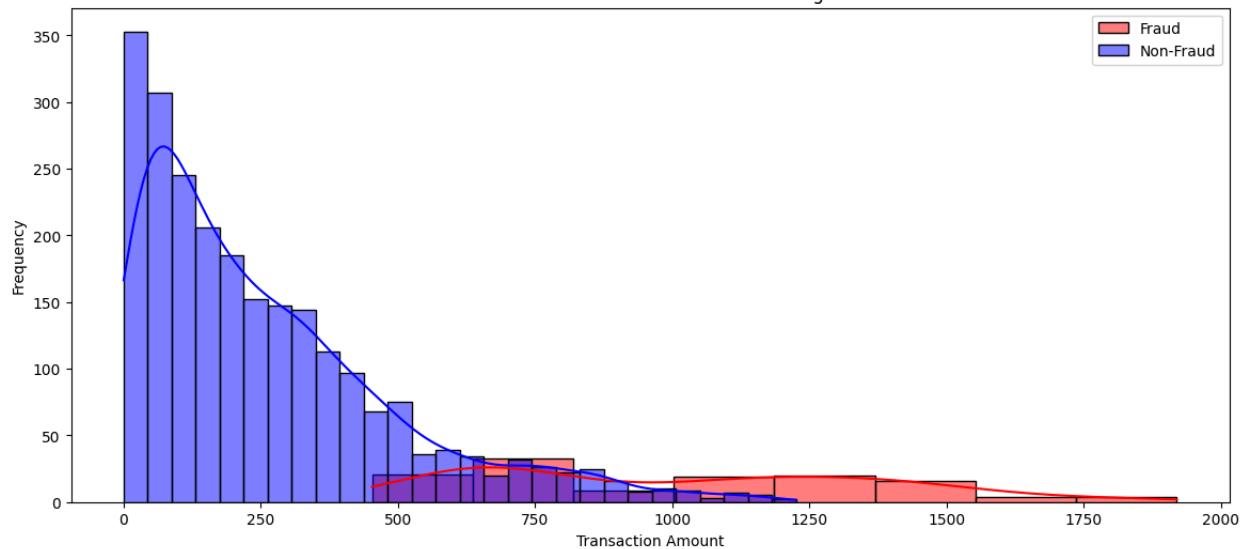


When comparing the statistics of the “potential fraud” vs “not fraud” tagged cases. We found:

- The potential fraud cases were seen more often in Debit cases
- Retired and Student people were more impacted. The customer age also supported this for most cases around 20s and 60+ (this intuitively makes sense as well)
- The potential fraud cases were on higher transactional amounts of >\$500



TransactionAmount Distribution: Fraud vs. Legitimate



CustomerAge Distribution: Fraud vs. Legitimate

