

# **Fleetcor Project - Account Management Impact and Visualization**

## **EXECUTIVE SUMMARY**

- 1) Write-off saving analysis: Summarize write-off in different views by line of business, portfolio, treatments, etc. Some of them are fuel customers, universal customers, and company card. Practically, we are looking at segmentation analysis to realize customer behavior. We are looking for cost reduction, revenue, retention-attribution.

Solution:

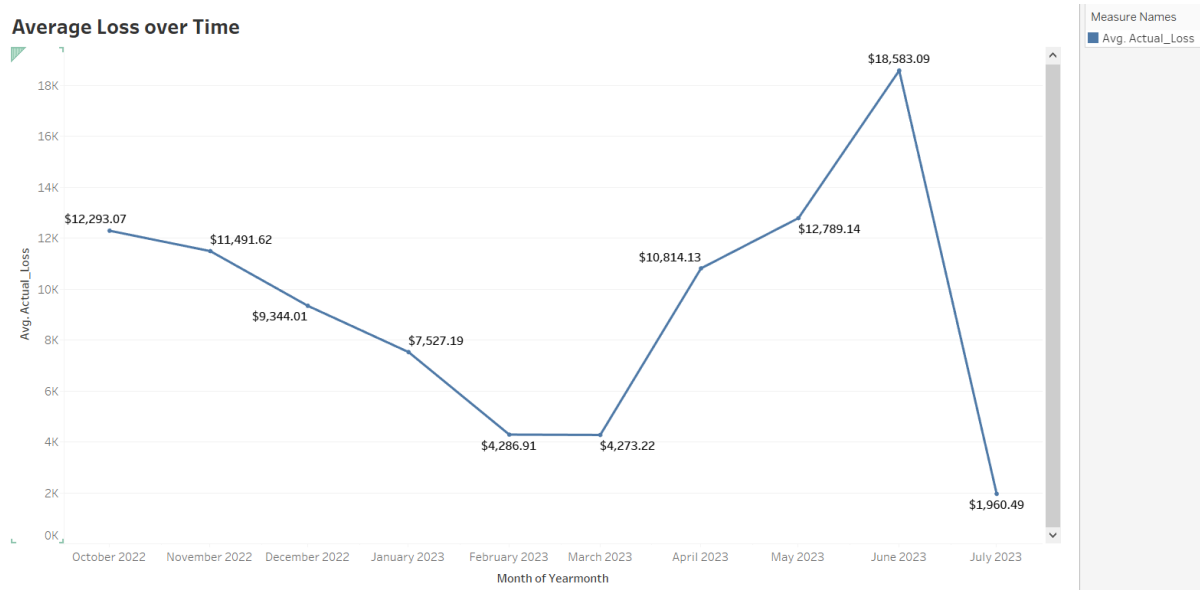
- a. The top factors for customer performance include WO\_AMOUNT, days\_past\_due, Segment\_Score, NSF\_AMT, CREDIT\_LIMIT
  - b. The best customers are those with days\_past\_due = 0 (lowest), NSF\_AMT = 5, WO\_AMOUNT = 60, CREDIT\_LIMIT > 5K.
  - c. We used the Multi-Variable Linear Regression model with R to arrive at the conclusions for this question.
- 2) Attrition analysis: Summarize change in spend, gallon pumped and revenue in different views by line of business, portfolio, treatments, etc.

Solution:

- a. The top factors for customer performance include GALLONS, FUEL\_SPEND, NONFUEL\_SPEND, TOT\_SPEND
  - b. We are still working on this.
  - c. We are still working on this.
- 3) A tableau dashboard which contains the content above

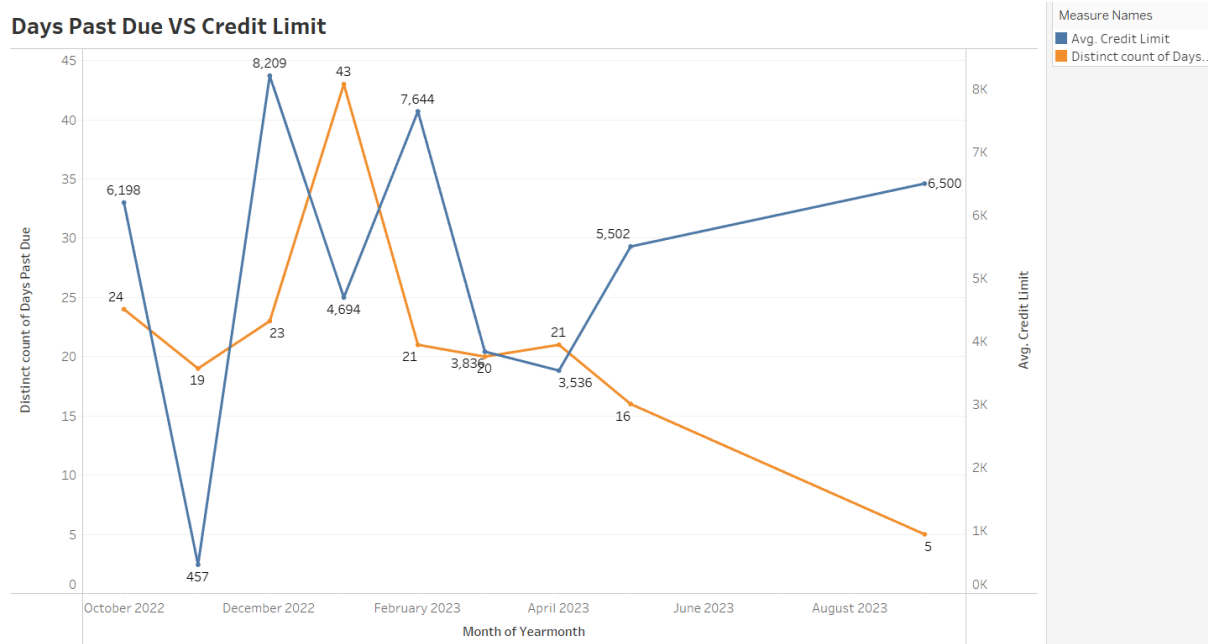
Solution:

- 1.



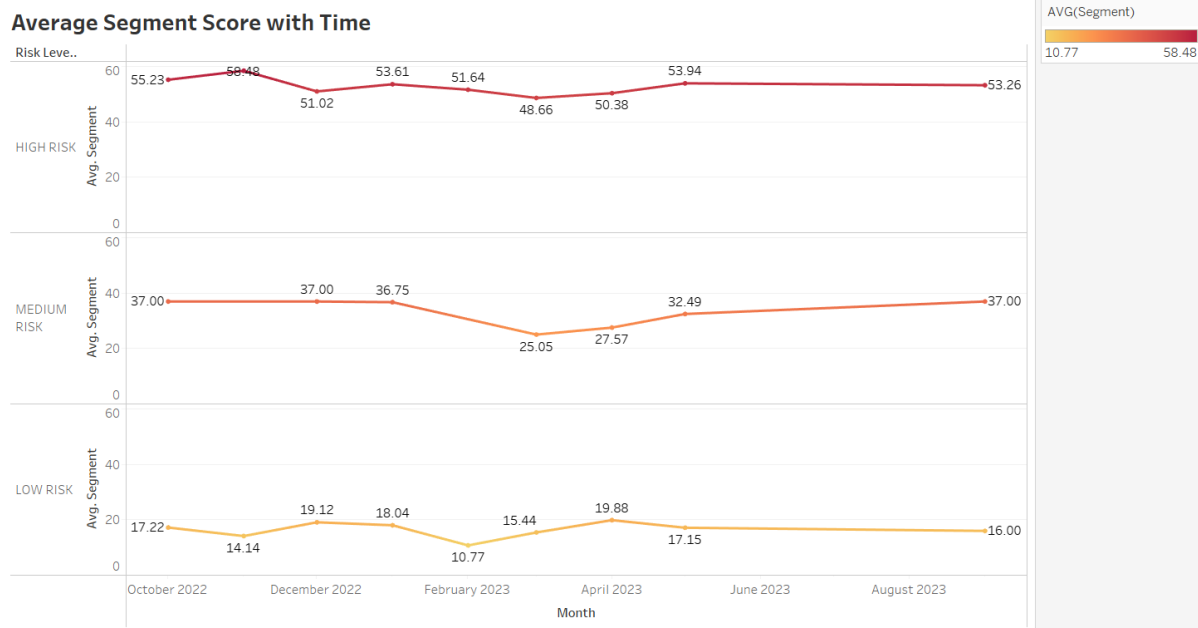
The line graph titled “Average Loss over Time” depicts the average write-off amounts plus average residual current balance from October 2022 to August 2023. Notably, the graph shows significant fluctuations in average loss during this period. In October 2022, the average write-off amount was at peak at approximately \$12,293.07, and gradually decreased to \$4286.91 by February 2022. It inflated after March 2023 upto \$18583.09 in June 2023. Which reflects their highest loss till date. After treatment, it dropped sharply to \$1960.49 by June 2023. This graph shows the effectiveness of the strategies used by Fleetcor to reduce their actual loss amount, while the company was performing really well till March 2023.

2.



The line graph titled “Days Past Due VS Credit Limit” depicts the relationship between the average credit limit and the distinct count of days past due. Notably, the orange line represents the distinct count of days past due, which exhibits fluctuations over time. In October 2022, there was a significant increase in days past due (around 24 days), and January 2023 also had a high count of days past due (approximately 43 days). Conversely, the blue line represents the average credit limit, which started around 6,198 in October 2022, peaked at approximately 8,209 in December 2022, and experienced fluctuations throughout the period. It can be said that the relationship between DAYS\_PAST\_DUE and CREDIT\_LIMIT is inversely proportional. The customers with a smaller number of DAYS\_PAST\_DUE are likely to have a high credit limit and are really good customers, as for the customers with a larger number of DAYS\_PAST\_DUE they will have a relatively lower credit limit and are more risky customers (many of them may have to be written-off in the future).

3.



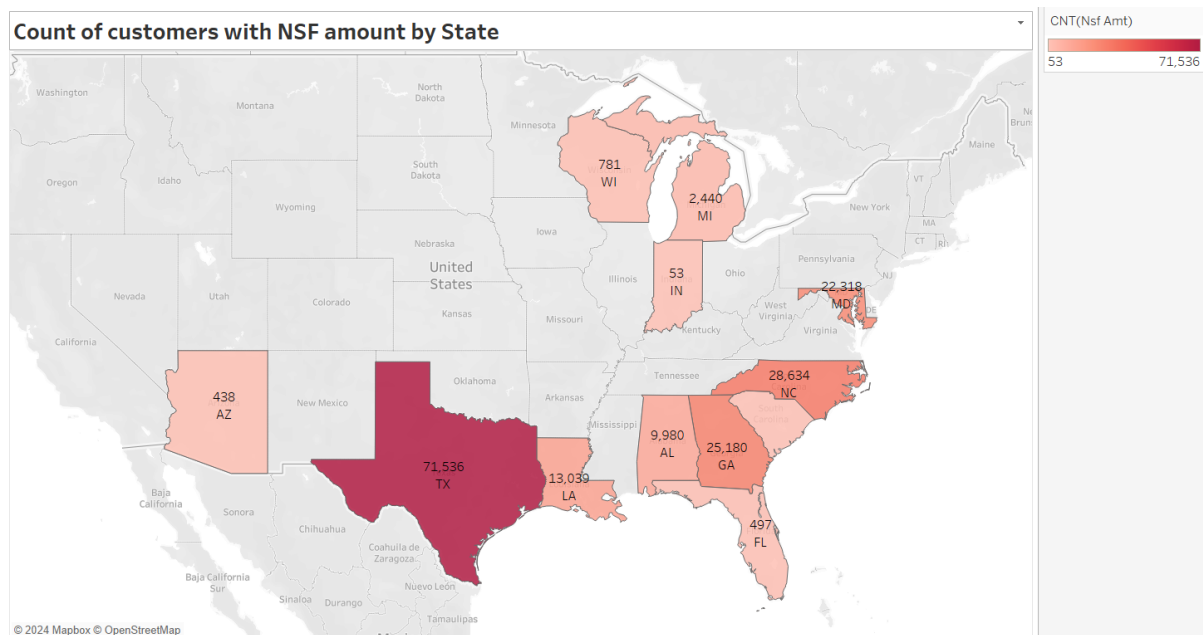
Examining "Average Segment Score with Time" reveals risk-based customer distribution from October 2022 to August 2023. High Risk Stability: The high-risk segment remains relatively stable around a score of 50, with slight fluctuations.

Medium Risk Fluctuation: The medium-risk segment shows a decrease and then an increase, returning to approximately the starting point by August.

Low Risk Decline: The low-risk segment consistently decreases over time, indicating a reduction in the number of low-risk customers or a shift in their risk level.

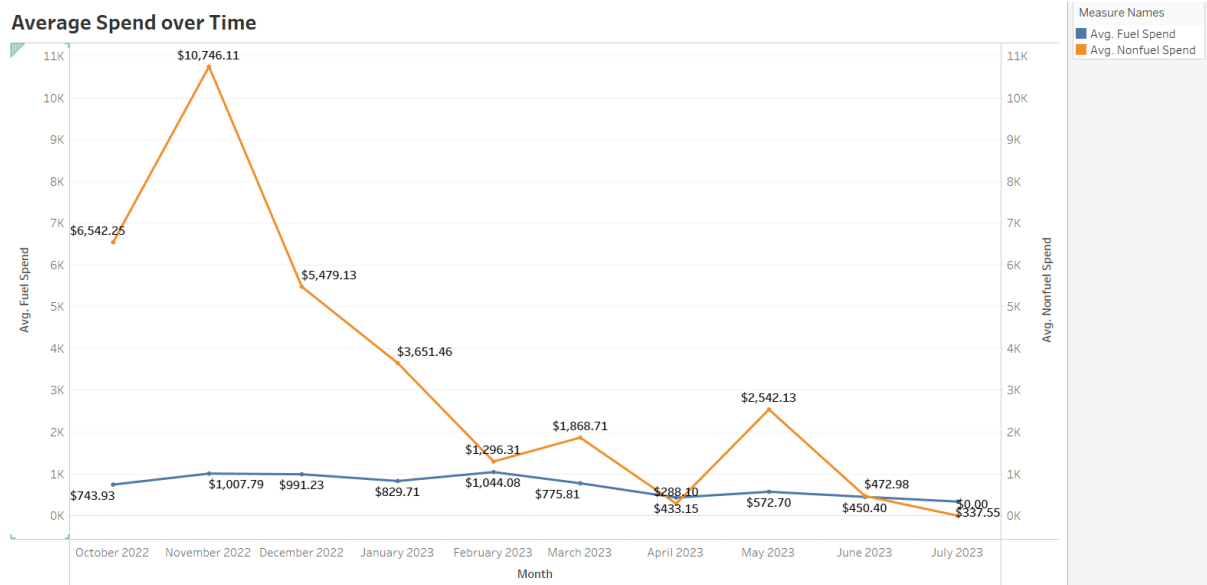
These trends suggest that while high-risk customers maintain their risk level, there is a notable change in the medium and low-risk segments, which could be indicative of shifting customer profiles or the effectiveness of risk management strategies. This indicates that the customers with MEDIUM RISK are more likely to improve their risk assessment with proper risk management strategies(perhaps the company can provide such customers with some perks if they pay their credit card bill on time like rewards points which can be redeemed later), and as for the customers with HIGH RISK they should be written-off as they are unlikely to improve their risk assessment(the company will only incur more losses while trying to preserve these group of customers). The customers with LOW RISK are the best customers as they have a great credit score due to them being timely with their credit card bill payments.

4.



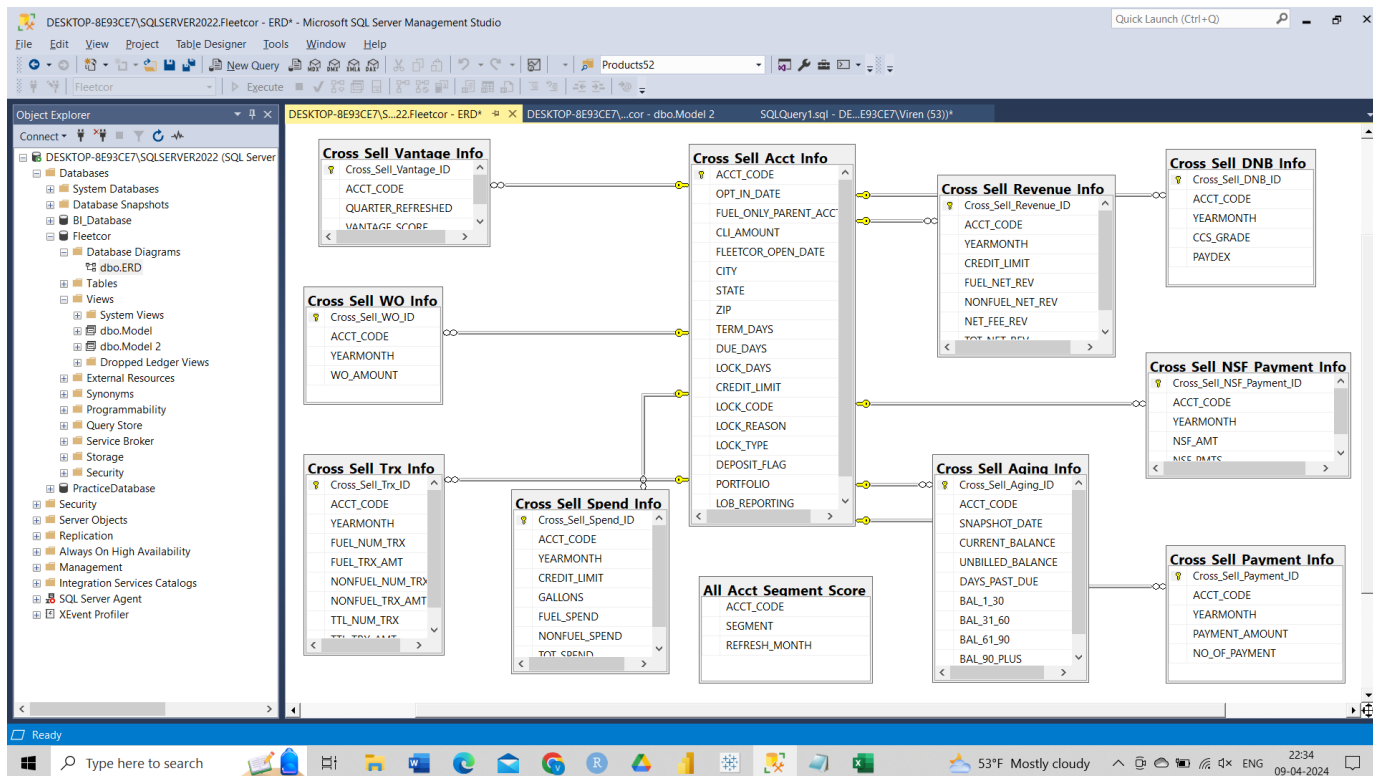
The map displays the count of customers with Non-Sufficient Funds (NSF) amounts by state in the United States. This color-coded map represents the number of customers with NSF amounts in each state. Texas (TX) has the highest count at 71,536, shown in dark red. Other states like Georgia (GA), North Carolina (NC), and Maryland (MD) also have significant counts. Many states have lower or no data available and are coloured in light grey. This indicates that customers from the above regions have a high possibility of being written-off and the company needs to rethink their strategies for tackling such areas.

5.



By looking at the above visual, avg fuel spend rarely crosses the threshold of \$1000 while, avg non fuel spend reaches upto \$10,000 and then sharply drops off indicating a significant amount of people whose account have been locked mainly due to non payment of their credit card balance. The company needs to focus on their group of customers who cannot keep up with their payments even with high credit limits.

## MAIN SECTION



## Steps:

1. Clean and modify the data.
2. Add in SQL Server database.
3. Create ERD.

❖ MODEL VIEW OF DATA:

❖ CONSOLIDATED DATA:



SQLQuery1.sql - DESKTOP-8E93CE7\SQLSERVER2022\Fleetcor (DESKTOP-8E93CE7\Viren (53)) - Microsoft SQL Server Management Studio

File Edit View Query Project Tools Window Help

Connect to Fleetcor

Object Explorer

- DESKTOP-8E93CE7\SQLSERVER2022 (SQL Ser
  - Databases
    - System Databases
    - Database Snapshots
    - BI\_Database
    - Fleetcor
      - Database Diagrams
      - Tables
        - System Tables
        - FileTables
        - External Tables
        - Graph Tables
        - dbo.All\_Acct\_Segment\_Score
        - dbo.All\_Acct\_Segment\_Score\_1
        - dbo.All\_Acct\_Segment\_Score\_2
        - dbo.Consolidated\_Data
        - dbo.Cross\_Sell\_Acct\_Info
        - dbo.Cross\_Sell\_NSF\_Payment\_Info
        - dbo.Cross\_Sell\_DNB\_Info
        - dbo.Cross\_Sell\_Revenue\_Info
        - dbo.Cross\_Sell\_Spend\_Info
        - dbo.Cross\_Sell\_Trx\_Info
        - dbo.Cross\_Sell\_Vantage\_Info
        - dbo.Cross\_Sell\_WO\_Info
        - Dropped Ledger Tables
      - Views
      - External Resources
      - Synonyms
      - Programmability
      - Query Store
      - Service Broker
      - Storage
      - Security

SQLQuery1.sql - DE...E93CE7\Viren (53))

SELECT \* FROM Consolidated\_Data

Results Messages

	LOOK_DAYS	LOOK_REASON	NSF_AMT	NSF_PMTS	CCS_GRADE	PAYDEX	VANTAGE_SCORE	DAYS_PAST_DUE	BAL_1_30	BAL_31_60	BAL_61_90	BAL_90_PLUS	SEGMENT	ACCT_CODE	STATE	ZIP	CREDIT_LIMIT	FUE
1	7	BAD AGENCY	700	1	D	75	592	0	0	0	0	0	45	114536	TX	75093	5700	0.12
2	3	BAD AGENCY	600.06	1	D	46	647	110	0	0	6.6	1115.74	28	118709	MD	21239	3500	10.4
3	7	BAD AGENCY	2400.91	1	B	80	614	112	0	1939.18	4539.9	1988.29	11	112535	LA	70068	6500	0
4	3	COLLECT	4415.72	1	C2	80	643	71	20	20	9711.69	0	6	181724	TX	78052	11000	439
5	10	BAD AGENCY	472	1	F	48	569	0	0	0	0	0	25	115875	TX	77433	3500	11.1
6	7	BAD AGENCY	5	1	F	48	562	55	0	3188.86	0	0	26	143383	GA	31206	500	-9.3
7	5	BAD AGENCY	277	1	D	61	564	0	0	0	0	0	44	130093	NC	28216	300	6.7
8	10	BAD AGENCY	5645.34	2	D	57	741	0	0	0	0	0	60	112476	GA	30062	4000	22.1
9	10	BAD AGENCY	472	1	D	52	584	246	0	0	50	1516.9	30	115875	TX	77433	3500	11.1
10	5	BAD AGENCY	277	1	C1	67	513	148	0	0	43.14	395.91	4	130093	NC	28216	300	1.3
11	7	BAD AGENCY	700	1	C1	78	617	4	10152.56	0	0	0	39	114536	TX	75093	5700	0.12
12	10	BAD AGENCY	5645.34	2	D	57	741	95	0	61	663.35	3904.01	22	112476	GA	30062	4000	1.4
13	10	BAD AGENCY	5645.34	2	C1	79	741	65	61	663.35	3904.01	0	55	112476	GA	30062	4000	42.2
14	7	BAD AGENCY	3531.32	1	C1	75	539	0	918.25	0	0	0	61	122848	NC	27606	2100	19.1
15	10	BAD AGENCY	472	1	C1	68	569	125	522	0	0	944.9	63	115875	TX	77433	3500	11.1
16	7	COLLECT	2309.52	1	C1	75	633	96	0	783.52	3910.09	2146.66	47	184416	TX	78247	11760	163
17	7	BAD AGENCY	3531.32	1	D	72	539	0	0	0	0	0	63	122848	NC	27606	2100	19.1
18	7	BAD AGENCY	1073.42	2	B	80	622	52	0	7663.19	0	0	23	112535	LA	70068	6500	36.1
19	10	BAD AGENCY	5645.34	2	D	63	663	6	3904.01	0	0	0	30	112476	GA	30062	4000	32
20	10	BAD AGENCY	472	1	D	52	584	216	0	50	522	994.9	50	115875	TX	77433	3500	0
21	7	BAD AGENCY	5	1	D	61	570	116	0	0	364.17	2793.22	62	143383	GA	31206	500	37.1
22	7	BAD AGENCY	700	1	C1	64	592	34	1494.09	10152.56	0	0	10	114536	TX	75093	5700	152
23	7	BAD AGENCY	5	1	C2	64	562	25	0	2793.22	0	0	62	143383	GA	31206	500	4.6
24	7	BAD AGENCY	5	1	F	63	570	25	0	2793.22	0	0	50	143383	GA	31206	500	37.1
25	5	BAD AGENCY	45900	8	B	80	518	0	0	0	0	0	22	133826	AL	35406	6500	211
26	7	Other	356.3	1	B	75	647	15	10	50	0	0	4	295250	GA	30105	700	8.9
27	18	BAD AGENCY	100	1	F	51	652	0	0	0	0	0	16	119137	GA	30238	3500	-0.2
28	5	BAD AGENCY	277	1	D	60	493	148	0	0	43.14	395.91	4	130093	NC	28216	300	6.7
29	10	BAD AGENCY	5645.34	2	D	57	663	65	61	663.35	3904.01	0	31	112476	GA	30062	4000	22.1
30	3	BAD AGENCY	489.54	2	D	46	647	50	10	1112.34	0	0	18	118709	MD	21239	3500	0

Query executed successfully.

DESKTOP-8E93CE7\SQLSERVER20... DESKTOP-8E93CE7\Viren ... Fleetcor 00:00:07 3,69,205 rows

Ready

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## Steps:

1. Select random data (because in this project, data is huge to execute)
2. Remove null records by executing the query
3. Save the data in CSV format.

## Group 2 Members:

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2. Pratik Chavan
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5. Namitha Mundada
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