

Fraud Detection using SQL

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In the modern digital era, where technology has become an integral part of daily life, the volume of online transactions and data exchanges has grown exponentially. With this rise in digital interactions comes an increased risk of fraudulent activities, which have evolved in complexity and scale. Fraud not only results in substantial financial losses for businesses and consumers but also undermines trust in digital platforms, banking systems, and e-commerce services. As a result, fraud detection has become a critical area of focus for organizations aiming to safeguard their assets and maintain customer confidence. This project centers around the concept of fraud detection using Structured Query Language (SQL), a domain-specific language designed for managing and analyzing structured data in relational databases. SQL is widely adopted across industries and remains a foundational tool in data analytics, especially when working with large volumes of transactional data.

The primary goal of this project is to explore how SQL can be effectively used to detect potentially fraudulent activities through rule-based analysis and pattern recognition. SQL enables users to write queries that identify anomalies such as unusually large transactions, multiple transactions from the same user in a short time frame, geographic inconsistencies, or repeated failed login attempts. These indicators, when captured and analyzed correctly, can serve as early warning signs of fraud. Unlike advanced machine learning models, SQL does not require extensive computational resources or training data, making it an accessible and practical option for organizations that need fast, explainable, and easily deployable fraud detection systems. Moreover, SQL integrates seamlessly with most existing relational database systems, allowing fraud detection mechanisms to be built directly into current infrastructures without the need for additional platforms or tools.

This project not only implements a variety of fraud detection queries using SQL but also emphasizes the importance of designing efficient, scalable, and adaptable queries that can evolve alongside emerging fraud patterns. While SQL may not independently detect sophisticated, previously unseen fraud schemes, it is extremely effective as a first line of defense—filtering and flagging suspicious activities for further investigation. In addition, SQL serves as a powerful data preprocessing and feature engineering tool, playing a critical role when used in combination with machine learning or real-time monitoring systems. By the end of this project, the implementation will demonstrate how SQL-based fraud detection can significantly enhance data oversight, improve operational security, and contribute to a larger, more robust anti-fraud strategy. The project underscores that while technology continues to evolve, fundamental tools like SQL remain invaluable in the ongoing battle against digital fraud.

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Introduction



Fraud is everywhere these days—whether you are a small Fastfood shop or a large international business. While there are emerging technologies that employ machine learning and artificial intelligence to detect fraud, many instances of fraud detection still require strong data analytics to find abnormal charges.

Application of new SQL skills to analyze historical credit card transactions and consumption patterns in order to identify possible fraudulent transactions.

Accomplish three main tasks:

1. Data Modeling: Define a database model to store the credit card transactions data and create a new PostgreSQL database using your model.
2. Data Engineering: Create a database schema on PostgreSQL and populate your database from the CSV files provided.
3. Data Analysis: Analyze the data to identify possible fraudulent transactions

Literature survey

Existing System

Increasingly, machine learning is being used in fraud prevention and detection due to its ability to analyze large quantities of data, identify patterns, and adapt to new information. Some common applications of machine learning in fraud prevention include:

Anomaly

detection

Machine-learning algorithms can identify unusual patterns or deviations from normal behavior in transactional data. By "training" on historical data, the algorithms learn to recognize legitimate transactions and flag suspicious activities that may indicate fraud.

Risk

scoring

Machine-learning models can assign risk scores to transactions or user accounts based on various factors, such as transaction amount, location, frequency, and past behavior. Higher risk scores indicate a higher likelihood of fraud, enabling organizations to prioritize their resources and focus on specific transactions or accounts that warrant further investigation.

Network

analysis

Fraudulent actors often collaborate and form networks to carry out their activities. Machine-learning techniques, like graph analysis, can help uncover these networks by analyzing relationships between entities (such as users, accounts, or devices) and identifying unusual connections or clusters.

Text

analysis

Machine-learning algorithms can analyze unstructured text data, such as emails, social media posts, or customer reviews, to identify patterns or keywords that may indicate fraud or scams.

Identity

verification

Machine-learning models can analyze and verify user-provided information, such as images of identification documents or facial recognition data, to ensure that an individual is who they claim to be and prevent identity theft.

Adaptive

learning

One of the key strengths of machine learning is its ability to learn and adapt to new information. As fraudulent actors change their tactics, machine-learning models can be retrained on new data, allowing them to stay up to date and better equipped to detect emerging fraud patterns

Using machine learning in fraud prevention can be a powerful way for organizations to enhance their detection capabilities, reduce the risk of false positives, and improve overall security and customer experience.

Proposed System

I, Tarun in this independent SQL project idea, I have worked with multiple CSV files to create a database schema and database, then query your new database to identify potentially fraudulent transactions. Fraud is everywhere these days, and while there are emerging technologies that employ machine learning and artificial intelligence to detect fraud, many instances still require strong data analytics to find abnormal charges. You'll apply SQL skills to analyze historical credit card transactions and consumption patterns in order to identify possible fraudulent transactions.

System Requirement Specification

Hardware Requirements

Fraud Detection SQL

The hardware requirements for working with **SQL** and **Python** depend heavily on the **specific use case**—whether it's light development, data analysis, machine learning, or working with large-scale databases. Here's a breakdown by general usage level:

Python Hardware Requirements

Basic Scripting / Development

- **CPU:** Dual-core (Intel i3 or AMD equivalent)
- **RAM:** 4–8 GB
- **Storage:** SSD preferred, 10–20 GB free
- **GPU:** Not required

Data Analysis / Web Development

- **CPU:** Quad-core (Intel i5 or better)
- **RAM:** 8–16 GB
- **Storage:** SSD, 50+ GB free
- **GPU:** Optional (helpful for visualizations or specific tasks)

Machine Learning / AI

- **CPU:** 6-core or better (Intel i7/i9, AMD Ryzen 7/9)
- **RAM:** 16–64+ GB
- **Storage:** SSD, 100+ GB (datasets take space)
- **GPU:** NVIDIA GPU with CUDA support (e.g., RTX 3060 or better)

SQL Hardware Requirements

Local Development / Testing (e.g., SQLite, MySQL, PostgreSQL)

- **CPU:** Dual-core or quad-core
- **RAM:** 4–8 GB
- **Storage:** SSD, 20+ GB free
- **GPU:** Not required

Production Database Server (medium to large scale)

- **CPU:** Multi-core (8+ cores recommended)
- **RAM:** 32–128+ GB (RAM is crucial for caching and performance)
- **Storage:** Fast SSDs or NVMe (RAID for redundancy), sized based on DB size
- **GPU:** Not required unless using GPU-accelerated databases (rare)

Combo Setup (Python + SQL + Dev Workstation)

If you're doing data analysis, data science, or full-stack development:

- **CPU:** Quad-core or better
- **RAM:** 16 GB (32 GB for comfort with large datasets)
- **Storage:** 512 GB SSD
- **GPU:** Optional, but helpful for ML or data visualization

Software Requirements

- SQL
- PostgreSQL
- Entity Relationship Diagrams (ERDs)
- Python
- Pandas
- Plotly Express
- SQLAlchemy

Prerequisites

To successfully complete this project, you should be comfortable with the following:

- SQL fundamentals like querying, grouping data, joins, subqueries, and filtering data
- Creating database schemas and tables
- Importing data from CSV files into a database
- Basic Python programming for data analysis

Fraud Detection SQL

- Using Python libraries like Pandas for data manipulation and analysis

Step-by-Step Instructions

1. Define a database model to store the credit card transactions data and create a new PostgreSQL database using your model. Create an entity relationship diagram (ERD) by inspecting the provided CSV files.
2. Create a database schema on PostgreSQL and populate your database from the CSV files provided. Import the data from the corresponding CSV files after creating the schema.
3. Analyze the data to identify possible fraudulent transactions:
 - a. Find the top 100 highest transactions during early morning hours (7-9 AM)
 - b. Count transactions less than \$2.00 per cardholder to check for hacked cards
 - c. Identify the top 5 merchants prone to being hacked with small transactions
 - d. Create views for reusable queries
 - e. Create a report for fraudulent transactions of top customers using Python and data visualization libraries
 - f. Analyze outlier/anomalous transactions using techniques like standard deviation and interquartile range

Expected Outcomes

Upon completing this SQL project, you'll have gained valuable skills and experience, including:

- Designing a database schema to store financial transactions data
- Querying a database using complex SQL statements to uncover anomalous transactions
- Applying data analysis techniques to identify outliers and potentially fraudulent activity
- Communicating findings through visualizations and a report

CSV Files

id, name

- 1, Robert Johnson
- 2, Shane Shaffer
- 3, Elizabeth Sawyer
- 4, Danielle Green

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- 5, Sara Cooper
- 6, Beth Hernandez
- 7, Sean Taylor
- 8, Michael Floyd
- 9, Laurie Gibbs
- 10, Matthew Gutierrez
- 11, Brandon Pineda
- 12, Megan Price
- 13, John Martin
- 14, Gary Jacobs
- 15, Kyle Tucker
- 16, Crystal Clark
- 17, Michael Carroll
- 18, Malik Carlson
- 19, Peter Mckay
- 20, Kevin Spencer
- 21, Dana Washington
- 22, Austin Johnson
- 23, Mark Lewis
- 24, Stephanie Dalton
- 25, Nancy Contreras

Credit_card.csv

card,	id_card_holder
3.51711E+15,	1
4.76105E+18,	1
4.86676E+18,	2
6.75911E+11,	2

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3.00783E+13,	3
4.26369E+15,	4
5.84227E+11,	4
4.27647E+12,	5
4.26849E+15,	5
3.58135E+15,	6
4.15984E+18,	6
3.51695E+15,	7
4.53999E+15,	7
4.83448E+15,	8
3.00633E+13,	8
3.0182E+13,	9
4.96292E+18,	10
4.16531E+18,	10
2.13194E+14,	10
1.80099E+14,	11
4.64401E+18,	11
4.02791E+15,	11
5.0188E+11,	12
5.29719E+15,	12
3.76028E+14,	12
4.71177E+15,	13
5.13584E+15,	13
3.56195E+15,	13

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5.17595E+15,	14
4.72378E+18,	15
6.50024E+15,	15
5.03843E+11,	16
5.5706E+15,	16
5.50071E+15,	16
6.01199E+15,	17
4.498E+12,	18
3.4412E+14,	18
4.7432E+18,	19
5.36178E+15,	19
3.56107E+15,	19
3.53565E+15,	20
4.50641E+15,	20
4.58696E+18,	20
4.2791E+18,	21
5.01809E+11,	22
4.74104E+12,	23
4.18816E+15,	23
4.15072E+15,	23
4.6819E+12,	24
3.0143E+13,	24
3.5822E+15,	24
4.31965E+12,	25

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3.72415E+14, 25

Merchant.csv

	id	name	name	id_merchant_category
2	1	Murphy, Heath and Fields		1
3	2	Riggs-Adams		1
4	3	Sanders, Parks and Mcfarland		2
5	4	Mccarty-Thomas		3
6	5	Miller-Blevins		4
7	6	Wilson and Sons		1
8	7	Gomez-Kelly		4
9	8	Russell-Thomas		1
10	9	Curry, Scott and Richardson		3
11	10	Herrera Group		1
12	11	Stanton Group		4
13	12	Bell, Gonzalez and Lowe		4
14	13	Giles and Sons		4
15	14	Osborne-Page		2
16	15	Long, Harrell and Johnson		5
17	16	Bryant, Thomas and Collins		4
18	17	Bauer-Cole		3
19	18	Romero-Jordan		5
20	19	Santos-Fitzgerald		4
21	20	Kim-Lopez		2
22	21	Robertson-Smith		4
23	22	Dalton, Cameron and Jones		3
24	23	Wilson, Roberts and Davenport		5
25	24	Rodgers, Johnston and Macias		5
26	25	Vaughn, Wilson and Hall		1
27	26	Smith-Stephens		2
28	27	Horn Ltd		2
29	28	Hess-Fischer		5
30	29	Browning-Cantu		4
31	30	Atkinson Ltd		3

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32	31	Fisher, Salazar and Thomas	5
33	32	Norton, Burton and Smith	5
34	33	Vasquez-Parker	3
35	34	Combs-Jones	5
36	35	Jarvis-Turner	4
37	36	Hamilton-Mcfarland	1
38	37	Nguyen, Bautista and Williams	4
39	38	Brown LLC	3
40	39	Young-Navarro	5
41	40	Cox, Montgomery and Morgan	3
42	41	Ford, Williams and Dunn	4
43	42	Kennedy-Chen	3
44	43	Wallace and Sons	2
45	44	Little-Floyd	4
46	45	Velazquez Ltd	4
47	46	Miller, Chavez and Cobb	5
48	47	Martin Inc	1
49	48	Baker Inc	5
50	49	Davis, Lowe and Baxter	5
51	50	Johnson-Watts	1
52	51	Fisher-Bolton	1
53	52	Jensen-Stanley	5
54	53	Wallace PLC	4
55	54	Berry-Lopez	1
56	55	Johnson, Rivas and Anderson	1
57	56	Smith PLC	3
58	57	Thornton-Williams	4
59	58	Young, Hull and Williams	4
60	59	Williams Group	3
61	60	Smith-Richards	4
62	61	Richardson, Smith and Jordan	5
63	62	Cooper, Carpenter and Jackson	5
64	63	Reed Group	5
65	64	Cline, Myers and Strong	1
66	65	Allen, Ramos and Carroll	4
67	66	Robles Inc	3
68	67	Maxwell, Tapia and Villanueva	2
69	68	Ramirez-Carr	2

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70	69	Dominguez PLC	5
71	70	White-Hall	3
72	71	Greene LLC	1
73	72	Lopez-Kelly	1
74	73	Colon Ltd	3
75	74	Skinner-Williams	4
76	75	Martinez Group	1
77	76	Lowe PLC	1
78	77	Brown, Ballard and Glass	1
79	78	Ruiz-Anderson	4
80	79	Lee LLC	1
81	80	Kelly, Dyer and Schmitt	5
82	81	Fowler and Sons	5
83	82	Day-Murray	5
84	83	Solis Group	5
85	84	Marshall-Rojas	2
86	85	Patton-Rivera	3
87	86	Walker, Campbell and Sullivan	5
88	87	Griffin-Woodard	3
89	88	Armstrong PLC	5
90	89	Kelley-Roberts	5
91	90	Brown-Cunningham	4
92	91	Turner Ltd	4
93	92	Garcia-White	4
94	93	Rodriguez-Parker	5
95	94	Yoder-Zavala	5
96	95	Baxter-Smith	1
97	96	Johnson-Fuller	4
98	97	Ruiz-Chavez	3
99	98	Rivera PLC	4
100	99	Bond, Lewis and Rangel	1
101	100	Townsend-Anderson	1
102	101	Whitehead-Sexton	4
103	102	Walters-Ward	1
104	103	Jones, Clark and Hoover	2
105	104	Mcdaniel, Hines and Mcfarland	2
106	105	Garcia and Sons	4
107	106	Carter-Blackwell	4
108	107	Rowe-Abbott	4
109	108	Best Inc	1
110	109	Collins LLC	2

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111	110	Rodriguez, Dunlap and Nunez	2
112	111	Padilla-Clements	2
113	112	Greer Inc	3
114	113	Edwards-Aguirre	2
115	114	Greene-Wood	3
116	115	Williams Inc	4
117	116	Ferguson Ltd	2
118	117	Mitchell Group	2
119	118	Maldonado Group	2
120	119	Henderson and Sons	1
121	120	Vega, Jones and Castro	5
122	121	Fleming, Smith and Collins	3
123	122	Perry and Sons	3
124	123	Boone, Davis and Townsend	4
125	124	Mccarty PLC	1
126	125	Russell and Sons	4
127	126	Bartlett and Sons	4
128	127	Williams, Wright and Wagner	2
129	128	Pitts, Salinas and Garcia	2
130	129	Sweeney-Paul	2
131	130	Brown, Estrada and Powers	2
132	131	Harrison, Newton and Hansen	1
133	132	Pugh-Williams	3
134	133	Scott, Hess and Finley	3
135	134	Jenkins, Peterson and Beck	1
136	135	Jacobs, Torres and Walker	3
137	136	Martinez-Robinson	3
138	137	Garcia PLC	5
139	138	Mccullough-Murphy	5
140	139	Kidd-Lopez	5
141	140	Wheeler-Moreno	5
142	141	Wood-Ramirez	3
143	142	Thomas-Garcia	5
144	143	Guzman, Garcia and Church	3
145	144	Walker, Deleon and Wolf	1
146	145	Hood-Phillips	3
147	146	Pitts, Smith and Gonzalez	4
148	147	Marshall-Lopez	5

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149	148	Huerta, Keith and Walters	5
150	149	Clark and Sons	5
151	150	Johnson and Sons	2

merchant_category.csv

1	id	name
2	1	restaurant
3	2	coffee shop
4	3	bar
5	4	pub
6	5	food truck

transaction.csv

	id	date	amount	card	id_merchant	
37	1995	2018-01-05 01:10:27	5.09	501809222273	46	
38	1346	2018-01-05 03:11:18	12.2	4268491956169254	69	
39	2176	2018-01-05 05:47:28	4.64	5175947111814778	103	
40	1552	2018-01-05 06:26:45	10.74	372414832802279	86	
41	487	2018-01-05 06:27:06	4.6	4159836738768855913	48	
42	2077	2018-01-05 07:19:27	1.36	344119623920892	30	
43	314	2018-01-05 10:42:55	5.31	3561072557118696	8	
44	77	2018-01-05 16:58:08	4.57	5135837688671496	91	
45	1570	2018-01-06 01:43:44	10.04	5500708021555307	34	
46	2439	2018-01-06 02:16:41	1.33	4866761290278198714	127	
47	2258	2018-01-06 04:43:33	5.31	5297187379298983	42	
48	1867	2018-01-06 05:13:20	10.82	4866761290278198714	70	
49	846	2018-01-06 06:46:24	2.7	213193946980303	146	

Fraud Detection SQL

50	289 0	2018-01-06 07:00:32	18.35	3561954487988 605	76
51	329 1	2018-01-06 08:42:50	18.72	3535651398328 201	76
52	255 7	2018-01-06 08:49:34	16.28	4268491956169 254	101
53	325	2018-01-06 23:33:29	7.6	3760275493418 49	141
54	266 3	2018-01-07 00:30:25	17.84	4159836738768 855913	112
55	345 7	2018-01-07 01:10:54	175.0	3441196239208 92	12
56	447	2018-01-07 07:33:17	7.07	4834483169177 062	14
57	124 9	2018-01-07 10:31:33	10.9	5297187379298 983	135
58	210 8	2018-01-07 14:57:23	2.93	4319653513507	137
59	302 8	2018-01-07 15:10:27	17.29	4866761290278 198714	126
60	149	2018-01-07 16:50:22	5.83	4159836738768 855913	81
61	230 4	2018-01-07 20:35:00	2.5	6011987562414 062	104
62	138 4	2018-01-08 00:26:21	10.04	3581345943543 942	64
63	137 1	2018-01-08 01:12:52	10.4	5500708021555 307	121
64	129 1	2018-01-08 02:34:32	1029. 0	3581345943543 942	145
65	106 5	2018-01-08 04:15:30	11.49	4741042733274	130
66	134 0	2018-01-08 04:29:20	10.64	501809222273	116
67	154 4	2018-01-08 06:27:34	10.48	4027907156459 098	68
68	522	2018-01-08 10:48:26	11.06	4743204091443 101526	113
69	812	2018-01-08 11:15:36	333.0	3441196239208 92	95
70	164 0	2018-01-08 11:21:20	11.98	5500708021555 307	133
71	255 0	2018-01-08 11:35:55	15.84	4150721559116 778	15
72	209 5	2018-01-08 14:06:25	3.52	1800985390191 05	95

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73	313 0	2018-01-08 16:38:22	21.27	5297187379298 983	106
74	308 5	2018-01-08 19:31:23	17.43	584226564303	19
75	181 6	2018-01-08 20:10:59	11.55	3441196239208 92	102
76	348 0	2018-01-08 21:44:34	1.68	4681896441519	78
77	118 8	2018-01-08 21:44:58	10.64	5175947111814 778	84
78	379	2018-01-09 11:14:56	7.07	501809222273	136
79	687	2018-01-09 21:06:16	2.7	4506405265172 173	67
80	255 8	2018-01-09 21:43:47	16.37	4681896441519	64
81	754	2018-01-10 00:25:40	1.39	3724148328022 79	50
82	608	2018-01-10 03:17:20	0.87	503842928916	129
83	281 8	2018-01-10 03:24:29	16.64	3561954487988 605	65
84	865	2018-01-10 03:55:54	2.3	4150721559116 778	19
85	998	2018-01-10 10:07:20	10.91	6759111140852	78
86	143 6	2018-01-10 13:41:23	11.5	3517111172421 930	49
87	193 8	2018-01-10 14:50:30	5.64	5361779664174 555	44
88	602	2018-01-10 15:56:41	1.22	503842928916	27
89	328 9	2018-01-10 19:53:09	18.41	4159836738768 855913	23
90	136 1	2018-01-10 23:03:42	10.7	3535651398328 201	70
91	496	2018-01-11 00:39:12	3.23	503842928916	68
92	156	2018-01-11 09:27:30	5.55	6011987562414 062	107
93	315	2018-01-11 09:38:33	7.94	5135837688671 496	146
94	349 8	2018-01-11 09:58:11	1.62	5500708021555 307	149
95	333 1	2018-01-11 10:51:08	1.24	3006328138542 9	7

Fraud Detection SQL

96	212 8	2018-01-11 12:46:01	3.97	4834483169177 062	44
97	218 8	2018-01-11 13:20:31	229.0	5570600642865 857	115
98	171 6	2018-01-11 16:18:55	10.27	5361779664174 555	46
99	214 6	2018-01-11 19:36:21	1.72	4761049645711 555811	99
100	277 9	2018-01-11 22:55:51	19.5	4268491956169 254	8
101	104 8	2018-01-12 02:18:05	11.52	3582198969197 591	2
102	217 0	2018-01-12 02:48:29	1.84	3014296669918 7	2
103	202 5	2018-01-12 04:33:17	5.32	4188164051171 486	10
104	451	2018-01-12 06:34:53	6.19	3018196391334 0	40
105	444	2018-01-12 13:30:20	5.92	4506405265172 173	38
106	416	2018-01-12 13:59:09	4.45	501809222273	85
107	291	2018-01-12 16:29:03	4.69	4268491956169 254	144
108	337 3	2018-01-12 18:04:04	1.88	4681896441519	44
109	270	2018-01-12 22:14:25	6.4	4276466390111	112
110	193 7	2018-01-12 23:38:53	1.1	4506405265172 173	64
111	283 5	2018-01-13 02:02:40	17.12	3760275493418 49	2
112	317 5	2018-01-13 03:06:36	16.27	4268491956169 254	24
113	450	2018-01-13 03:20:50	4.89	2131939469803 03	58
114	222 2	2018-01-13 04:49:38	3.63	4506405265172 173	53
115	275 5	2018-01-13 06:07:45	19.24	4962915017023 706562	32
116	582	2018-01-13 14:36:43	1.35	4150721559116 778	102
117	154 6	2018-01-13 15:22:46	10.15	4711773125020 499	108
118	718	2018-01-13 18:34:36	2.22	4263694062533 017	9

Fraud Detection SQL

119	344 5	2018-01-13 22:18:00	2.11	3014296669918 7	3
120	238 6	2018-01-13 22:26:57	3.79	5500708021555 307	106
121	284 3	2018-01-14 03:20:21	14.69	584226564303	133
122	302 3	2018-01-14 05:02:22	17.84	3724148328022 79	52
123	287 9	2018-01-14 06:19:11	21.11	3535651398328 201	74
124	830	2018-01-14 07:06:57	3.15	584226564303	96
125	252 1	2018-01-14 07:33:54	15.21	4741042733274	21
126	148 2	2018-01-14 07:50:44	10.23	3760275493418 49	38
127	191 6	2018-01-14 10:04:25	12.33	4165305432349 489280	55
128	156 0	2018-01-14 13:30:29	10.94	3517111172421 930	19
129	315 9	2018-01-14 15:03:26	16.67	2131939469803 03	30
130	604	2018-01-14 15:31:50	1.42	3760275493418 49	97
131	970	2018-01-14 17:29:28	10.31	4506405265172 173	40
132	335 9	2018-01-15 03:37:27	1.47	4834483169177 062	139
133	278 7	2018-01-15 06:23:30	15.87	4539990688484 983	70
134	262 2	2018-01-15 10:27:56	15.51	4761049645711 555811	8
135	138 2	2018-01-15 11:52:41	11.67	4159836738768 855913	139
136	310 5	2018-01-15 11:55:38	17.16	3561954487988 605	101
137	258 1	2018-01-15 19:37:59	18.61	3561954487988 605	74
138	591	2018-01-15 20:53:52	2.95	4681896441519	98
139	271 4	2018-01-16 00:57:00	15.33	4506405265172 173	149
140	333 3	2018-01-16 02:26:16	1.65	3724148328022 79	31
141	306 8	2018-01-16 03:22:49	13.29	5297187379298 983	12

Fraud Detection SQL

142	306 5	2018-01-16 04:12:01	16.89	4711773125020 499	109
143	265 5	2018-01-16 06:29:35	17.64	675911140852	136
144	286 6	2018-01-16 08:02:04	17.36	3007829905351 2	116
145	680	2018-01-16 13:48:12	1.84	4268491956169 254	144
146	175 5	2018-01-16 13:51:42	13.52	4159836738768 855913	54
147	753	2018-01-16 18:45:54	1.48	4962915017023 706562	86
148	665	2018-01-16 19:19:48	2.55	3441196239208 92	99
149	327 8	2018-01-17 00:03:25	18.05	4279104135293 225293	133
150	651	2018-01-17 00:18:59	3.6	4159836738768 855913	44
151	246	2018-01-17 00:22:04	5.41	4743204091443 101526	105
152	297 1	2018-01-17 02:02:41	15.18	2131939469803 03	75
153	287 5	2018-01-17 04:56:56	16.46	3760275493418 49	42
154	758	2018-01-17 06:36:33	1.02	1800985390191 05	147
155	155 1	2018-01-17 06:59:43	10.0	4586962917519 654607	149
156	188 9	2018-01-17 07:31:03	12.67	4498002758300	89
157	159 3	2018-01-17 07:56:09	11.91	4681896441519	2
158	30	2018-01-17 09:09:33	3.82	4711773125020 499	111
159	733	2018-01-17 09:25:09	2.85	3561954487988 605	18
160	878	2018-01-17 11:09:35	12.27	3760275493418 49	146
161	334 0	2018-01-17 15:02:38	1.72	4498002758300	115
162	105	2018-01-17 16:57:27	1.25	4268491956169 254	65
163	840	2018-01-17 19:16:40	2.11	4268491956169 254	132
164	231 4	2018-01-17 20:06:45	2.69	3561072557118 696	29

Fraud Detection SQL

165	346 6	2018-01-18 03:12:14	3.44	3441196239208 92	5
166	263 3	2018-01-18 08:18:50	17.54	4165305432349 489280	104
167	283 8	2018-01-18 08:58:13	17.53	1800985390191 05	137
168	340 6	2018-01-18 11:17:37	1.24	3018196391334 0	116
169	266 2	2018-01-18 12:41:06	15.86	4319653513507	43
170	211 9	2018-01-18 14:13:09	2.61	3760275493418 49	26
171	309 5	2018-01-18 14:39:01	19.0	501879657465	15
172	130 3	2018-01-18 18:49:21	10.19	4159836738768 855913	116
173	288 2	2018-01-19 01:11:13	16.38	5500708021555 307	82
174	784	2018-01-19 01:34:25	2.59	4723783028106 084756	47
175	141 0	2018-01-19 03:01:33	10.39	4498002758300	132
176	295 6	2018-01-19 05:03:56	17.53	4962915017023 706562	82
177	338 1	2018-01-19 07:08:43	2.51	4681896441519	8
178	225 3	2018-01-19 10:15:55	3.93	4761049645711 555811	13
179	201 5	2018-01-19 11:41:42	3.27	2131939469803 03	124
180	118 3	2018-01-19 12:28:12	10.4	1800985390191 05	60
181	917	2018-01-19 13:15:49	10.16	3535651398328 201	81
182	679	2018-01-19 14:23:21	2.47	4150721559116 778	131
183	458	2018-01-19 17:44:59	5.96	6500236164848 279	138
184	124 5	2018-01-19 20:12:31	11.58	4866761290278 198714	132
185	223 8	2018-01-20 01:13:21	3.7	5361779664174 555	107
186	241 1	2018-01-20 02:23:13	2.17	4263694062533 017	109
187	195 4	2018-01-20 03:18:02	3.38	3006328138542 9	93

Fraud Detection SQL

188	279 1	2018-01-20 03:19:33	17.64	3007829905351 2	37
189	302	2018-01-20 04:32:42	4.51	501809222273	83
190	126 6	2018-01-20 07:47:30	10.58	3014296669918 7	34
191	145 6	2018-01-20 08:35:34	11.96	501879657465	121
192	256	2018-01-20 09:56:37	9.81	4159836738768 855913	69
193	244 5	2018-01-20 10:50:36	2.17	4711773125020 499	113
194	729	2018-01-20 13:44:37	1.83	501879657465	119
195	161 5	2018-01-20 16:31:01	10.51	584226564303	10
196	132 0	2018-01-20 17:30:16	13.84	4506405265172 173	109
197	193	2018-01-20 19:46:39	8.03	4263694062533 017	8
198	103 7	2018-01-20 20:11:29	10.12	3760275493418 49	37
199	277	2018-01-20 21:29:46	4.87	1800985390191 05	113
200	253 7	2018-01-20 22:58:27	16.44	6500236164848 279	18
201	141 7	2018-01-20 23:29:57	10.58	4723783028106 084756	110
202	870	2018-01-21 00:03:41	2.32	4711773125020 499	130
203	300 6	2018-01-21 01:30:19	20.29	5135837688671 496	136
204	132	2018-01-21 02:01:49	8.61	5175947111814 778	37
205	284 4	2018-01-21 05:38:08	16.29	3516952396080 247	106
206	494	2018-01-21 06:47:24	5.34	4498002758300	85
207	189 2	2018-01-21 13:18:10	10.38	4506405265172 173	15
208	227	2018-01-21 15:37:39	5.51	2131939469803 03	21
209	322	2018-01-21 16:05:43	2.88	5175947111814 778	75
210	149 2	2018-01-21 17:27:37	10.28	501809222273	148

Fraud Detection SQL

211	133 8	2018-01-21 20:28:17	10.24	4723783028106 084756	63
212	565	2018-01-21 23:04:02	2.22	3724148328022 79	149
213	170 4	2018-01-22 02:08:47	10.38	4681896441519	98
214	144 2	2018-01-22 08:07:03	1131. 0	5570600642865 857	144
215	204 4	2018-01-22 11:52:29	1.67	1800985390191 05	30
216	105 7	2018-01-22 14:56:43	10.75	5570600642865 857	117
217	193 5	2018-01-22 16:26:22	2.35	4723783028106 084756	96
218	136 4	2018-01-22 22:48:50	11.63	6011987562414 062	150
219	150 9	2018-01-23 01:51:00	11.3	4506405265172 173	134
220	349 9	2018-01-23 06:23:05	2.67	3516952396080 247	51
221	266 7	2018-01-23 06:29:37	1678. 0	501879657465	92
222	137 9	2018-01-23 08:07:03	10.47	4866761290278 198714	7
223	538	2018-01-23 08:18:10	1.48	5500708021555 307	35
224	207 0	2018-01-23 10:30:44	4.34	4027907156459 098	110
225	110	2018-01-23 12:06:35	6.38	5135837688671 496	94
226	231 9	2018-01-23 16:13:22	5.58	584226564303	33
227	392	2018-01-23 18:14:18	7.15	3006328138542 9	88
228	318	2018-01-24 01:31:16	3.54	3535651398328 201	81
229	221 2	2018-01-24 03:43:35	2.78	3581345943543 942	68
230	263	2018-01-24 07:14:27	5.56	5500708021555 307	36
231	146 3	2018-01-24 07:55:45	10.96	6500236164848 279	107
232	168	2018-01-24 08:28:08	5.0	4268491956169 254	141
233	319 6	2018-01-24 09:31:37	15.22	3760275493418 49	83

Fraud Detection SQL

2478	234	942	2018-01-24 10:54:25	10.69	3006328138542 9	2
	235	309 3	2018-01-24 12:41:48	17.21	4268491956169 254	133
	236	123 1	2018-01-24 13:06:03	13.39	3018196391334 0	91
	237	291 3	2018-01-24 13:17:19	1691. 0	4761049645711 555811	14
	238	314 4	2018-01-24 14:45:28	18.15	4681896441519	27
	239	297 3	2018-01-24 16:42:45	18.59	3561954487988 605	90
	240	226 5	2018-01-24 23:15:56	5.78	4539990688484 983	11
	241	148	2018-01-25 00:52:59	8.7	5175947111814 778	132
	242	273	2018-01-25 07:41:11	5.74	4711773125020 499	20
	243	150 2	2018-01-25 08:58:28	11.35	3760275493418 49	141
	244	178	2018-01-25 11:54:44	6.4	5500708021555 307	72
	245	184 1	2018-01-25 14:38:43	10.17	4165305432349 489280	24
	246	125 2	2018-01-25 16:52:06	10.1	3018196391334 0	80
	247	288 0	2018-01-26 05:10:21	16.54	584226564303	13
	248	175 8	2018-01-26 06:11:05	10.12	3561072557118 696	124
	249	938	2018-01-26 09:30:15	10.76	4498002758300	30
	250	969	2018-01-26 11:32:35	11.39	675911140852	67
	251	173 0	2018-01-26 13:10:00	11.95	2131939469803 03	11
		201 8- 01- 26 14:0 6:47	17.58	5361 7796 6417 4555	106	
	253	299	2018-01-26 20:32:12	7.0	4027907156459 098	78
	254	245 4	2018-01-26 21:32:03	17.08	4743204091443 101526	81

Fraud Detection SQL

255	103	2018-01-27 00:11:12	5.87	3441196239208 92	64
256	326 1	2018-01-27 00:56:55	16.14	4723783028106 084756	94
257	263 6	2018-01-27 04:07:35	18.58	4539990688484 983	49
258	345 2	2018-01-27 08:24:11	3.08	3582198969197 591	43
259	328 4	2018-01-27 08:36:58	15.15	6500236164848 279	71
260	639	2018-01-27 14:00:31	1.88	6500236164848 279	35
261	238 2	2018-01-27 18:02:40	1.83	4268491956169 254	85
262	149 5	2018-01-27 19:10:04	11.93	2131939469803 03	45
263	142	2018-01-27 23:35:44	6.12	4276466390111	135
264	137 4	2018-01-28 05:11:34	13.03	4268491956169 254	109
265	297 8	2018-01-28 14:38:33	19.93	3517111172421 930	71
266	911	2018-01-28 14:45:12	10.71	5135837688671 496	77
267	268 6	2018-01-28 17:01:39	17.62	5570600642865 857	82
268	328 0	2018-01-28 18:51:37	18.64	6500236164848 279	147
269	744	2018-01-28 19:30:38	0.72	6011987562414 062	36
270	231	2018-01-28 20:44:10	6.52	4279104135293 225293	44
271	266 0	2018-01-28 21:41:42	18.8	4027907156459 098	105
272	316 8	2018-01-29 02:00:47	18.65	4498002758300	90
273	285 2	2018-01-29 02:49:08	18.19	4723783028106 084756	40
274	549	2018-01-29 02:51:23	3.68	3561072557118 696	140
275	211 5	2018-01-29 05:15:42	3.54	4962915017023 706562	45
276	191 4	2018-01-29 06:32:49	10.24	3517111172421 930	49
277	536	2018-01-29 07:01:26	2.65	4150721559116 778	5

Fraud Detection SQL

278	681	2018-01-29 07:09:51	2.46	4723783028106 084756	138
279	179 8	2018-01-29 11:06:43	14.19	4165305432349 489280	59
280	356	2018-01-29 11:52:48	5.14	4761049645711 555811	131
281	201 4	2018-01-29 12:54:56	3.93	4743204091443 101526	142
282	202 9	2018-01-29 13:38:21	2.06	3561072557118 696	22
283	336 5	2018-01-29 14:09:08	2.37	5135837688671 496	92
284	247 3	2018-01-29 17:25:24	17.99	3561072557118 696	34
285	102 0	2018-01-29 19:47:14	10.25	5175947111814 778	91
286	207 6	2018-01-29 22:49:11	5.33	4506405265172 173	45
287	266 4	2018-01-29 23:55:06	16.73	584226564303	10
288	148 6	2018-01-30 02:32:22	10.15	3561072557118 696	87
289	217 7	2018-01-30 04:24:37	2.72	3018196391334 0	133
290	278 2	2018-01-30 04:52:53	17.05	5570600642865 857	147
291	264 6	2018-01-30 06:49:12	15.97	4279104135293 225293	82
292	102 7	2018-01-30 09:15:16	10.53	3561072557118 696	79
293	204 7	2018-01-30 14:21:12	2.86	3535651398328 201	32
294	213 2	2018-01-30 14:21:48	4.15	4188164051171 486	85
295	320 5	2018-01-30 16:34:45	16.91	3517111172421 930	112
296	26	2018-01-30 16:48:54	4.04	3760275493418 49	74
297	124 3	2018-01-30 17:53:56	10.85	4279104135293 225293	64
298	141 5	2018-01-30 18:31:00	1177. 0	4319653513507	64
299	218 6	2018-01-30 22:14:39	3.65	4159836738768 855913	102
300	312 6	2018-01-31 00:51:40	16.43	4188164051171 486	48

Fraud Detection SQL

301	331 0	2018-01-31 01:24:31	15.99	4159836738768 855913	105
302	108 0	2018-01-31 02:09:59	10.09	4586962917519 654607	118
303	647	2018-01-31 05:46:43	2.75	4319653513507	81
304	172 9	2018-01-31 06:01:51	10.28	4506405265172 173	26
305	154 5	2018-01-31 09:42:00	10.49	3517111172421 930	77
306	221 9	2018-01-31 10:34:42	4.17	584226564303	78
307	295 4	2018-01-31 11:06:22	18.78	4711773125020 499	48
308	777	2018-01-31 13:17:35	0.58	4741042733274	63
309	140 5	2018-01-31 18:25:03	11.25	4279104135293 225293	127
310	328 6	2018-01-31 23:44:43	16.02	4506405265172 173	44
311	165 7	2018-02-01 08:49:24	10.26	4723783028106 084756	115
312	45	2018-02-01 09:29:56	6.3	4539990688484 983	116
313	102 4	2018-02-01 11:05:57	10.49	4741042733274	138
314	899	2018-02-01 11:15:49	10.65	4279104135293 225293	65
315	127 9	2018-02-01 18:37:46	10.27	4150721559116 778	145
316	989	2018-02-01 20:33:09	11.62	3582198969197 591	4
317	151 6	2018-02-01 20:44:12	10.24	3517111172421 930	51
318	215 0	2018-02-01 21:52:43	1.54	4743204091443 101526	43
319	279 3	2018-02-02 03:11:47	15.95	4834483169177 062	27
320	277 6	2018-02-02 10:56:03	15.52	4644008655884 311378	95
321	136 0	2018-02-02 11:31:33	10.75	3724148328022 79	135
322	263 8	2018-02-02 16:57:12	15.27	4681896441519	53
323	349 1	2018-02-02 17:43:38	2.17	5500708021555 307	64

Fraud Detection SQL

324	175 2	2018-02-02 17:56:30	10.15	501809222273	127
325	245 6	2018-02-02 18:46:46	18.64	4741042733274	148
326	13	2018-02-02 21:41:12	4.29	6500236164848 279	148
327	248	2018-02-03 03:04:53	5.24	3582198969197 591	83
328	171 5	2018-02-03 06:57:16	12.39	5570600642865 857	69
329	224 5	2018-02-03 07:45:02	4.53	5570600642865 857	80
330	170 1	2018-02-03 12:53:24	10.23	4761049645711 555811	95
331	488	2018-02-03 14:33:11	7.05	3018196391334 0	3
332	638	2018-02-03 15:45:32	1.17	3516952396080 247	19
333	271 9	2018-02-03 16:27:12	15.98	4723783028106 084756	114
334	318 1	2018-02-03 16:34:30	18.53	3561072557118 696	86
335	339 5	2018-02-03 18:05:39	1.41	4866761290278 198714	65
336	143 5	2018-02-03 18:48:33	13.01	3018196391334 0	75
337	321 6	2018-02-03 19:32:30	17.94	3516952396080 247	104
338	238 9	2018-02-04 02:22:17	4.79	3006328138542 9	27
339	11	2018-02-04 04:00:18	6.9	6500236164848 279	125
340	201 1	2018-02-04 09:22:22	2.41	2131939469803 03	94
341	199 6	2018-02-04 16:13:14	2.92	5361779664174 555	4
342	198 1	2018-02-04 18:44:31	2.68	4741042733274	104
343	810	2018-02-04 19:02:09	0.51	3561954487988 605	75
344	328 1	2018-02-04 20:48:29	18.11	4539990688484 983	98
345	225 6	2018-02-04 22:25:14	5.94	4268491956169 254	43
346	150 5	2018-02-05 03:47:29	10.27	4268491956169 254	17

Fraud Detection SQL

347	268 8	2018-02-05 08:37:24	17.85	1800985390191 05	1
348	306 3	2018-02-05 09:39:22	15.73	503842928916	75
349	208 6	2018-02-05 15:54:02	1.52	3006328138542 9	145
350	174 0	2018-02-05 17:32:22	10.58	3018196391334 0	39
351	323 7	2018-02-05 17:36:46	17.7	3535651398328 201	50
352	607	2018-02-05 19:19:11	2.09	4539990688484 983	87
353	127 0	2018-02-05 19:35:31	10.08	501879657465	52
354	128 1	2018-02-05 20:08:01	10.92	4027907156459 098	34
355	329 7	2018-02-05 20:43:26	17.61	1800985390191 05	35
356	881	2018-02-05 21:59:07	10.81	3724148328022 79	65
357	181 9	2018-02-05 23:22:08	10.96	4159836738768 855913	67
358	107 9	2018-02-06 04:34:49	10.86	4586962917519 654607	132
359	349 4	2018-02-06 10:55:49	2.49	4761049645711 555811	100
360	372	2018-02-06 10:58:29	4.83	3760275493418 49	72
361	611	2018-02-06 18:29:49	2.53	3561072557118 696	102
362	199 8	2018-02-06 20:53:47	4.58	1800985390191 05	9
363	160 3	2018-02-06 22:44:18	10.32	3018196391334 0	45
364	241 8	2018-02-07 00:20:11	5.97	3724148328022 79	104
365	207 2	2018-02-07 01:36:19	5.64	4761049645711 555811	63
366	230	2018-02-07 02:48:38	7.68	4263694062533 017	63
367	111 5	2018-02-07 03:45:39	10.21	4741042733274	42
368	147 3	2018-02-07 15:53:22	10.33	3561072557118 696	49
369	859	2018-02-07 23:35:00	2.87	501809222273	70

Fraud Detection SQL

370	205	2018-02-08 04:15:41	7.02	3006328138542 9	96
371	287 8	2018-02-08 05:12:18	18.32	4866761290278 198714	57
372	208 5	2018-02-08 08:36:01	2.48	501809222273	85
373	748	2018-02-08 10:27:37	3.48	4962915017023 706562	139
374	347 3	2018-02-08 11:06:06	2.45	5361779664174 555	127
375	306 0	2018-02-08 12:15:41	15.39	675911140852	135
376	364	2018-02-08 16:35:44	7.15	4268491956169 254	97
377	310 2	2018-02-08 19:56:26	15.71	4741042733274	88
378	121	2018-02-08 21:10:00	5.52	584226564303	124
379	192 7	2018-02-09 00:54:12	1.72	4586962917519 654607	3
380	343 6	2018-02-09 07:38:19	1.16	503842928916	12
381	240 9	2018-02-09 11:38:37	445.0	3516952396080 247	112
382	657	2018-02-09 15:30:03	1.21	3582198969197 591	101
383	126 5	2018-02-09 19:25:44	11.11	501879657465	114
384	114 2	2018-02-10 02:01:54	11.43	5570600642865 857	68
385	313 3	2018-02-10 03:34:18	15.25	4150721559116 778	122
386	266 5	2018-02-10 05:36:19	15.92	3014296669918 7	126
387	262 9	2018-02-10 10:29:14	20.01	3581345943543 942	148
388	138 6	2018-02-10 10:55:31	10.14	4150721559116 778	35
389	331 3	2018-02-10 11:17:10	12.97	4743204091443 101526	135
390	155 6	2018-02-10 11:56:25	11.33	4506405265172 173	10
391	375	2018-02-10 12:04:36	7.39	4268491956169 254	105
392	341 8	2018-02-10 13:26:43	1.66	4276466390111	72

Fraud Detection SQL

393	301 3	2018-02-10 16:22:57	17.3	5570600642865 857	150
394	280 1	2018-02-10 16:43:22	15.67	3516952396080 247	25
395	148 7	2018-02-10 18:53:22	10.74	2131939469803 03	105
396	206	2018-02-11 00:03:19	7.51	501809222273	25
397	141 9	2018-02-11 02:48:31	12.98	3561954487988 605	115
398	144 6	2018-02-11 06:30:43	10.93	4962915017023 706562	65
399	738	2018-02-11 08:25:36	1.26	3582198969197 591	38
400	289 4	2018-02-11 14:38:30	15.76	4723783028106 084756	111
401	556	2018-02-11 16:04:02	2.74	4159836738768 855913	63
402	988	2018-02-11 17:50:29	11.46	4027907156459 098	131
403	144 9	2018-02-11 21:30:00	10.77	584226564303	142
404	229 0	2018-02-11 22:11:53	4.56	4761049645711 555811	127
405	255 4	2018-02-11 22:51:15	16.2	4539990688484 983	118
406	127	2018-02-12 03:44:20	3.69	4319653513507	116
407	212 6	2018-02-12 10:31:41	5.47	4188164051171 486	98
408	302 9	2018-02-12 15:16:31	19.8	5570600642865 857	39
409	430	2018-02-12 15:26:58	7.73	4761049645711 555811	150

3410

	201 8- 03- 20 08:5 8:40	2.06	4276 4663 9011 1	130	
797	236	2018-03-20 10:19:25	852.0	501879657465	35
798	916	2018-03-20 12:58:34	12.16	4723783028106 084756	109

Fraud Detection SQL

799	182	2018-03-20	1011.	3014296669918	
	1	13:05:54	0	7	141
800	300	2018-03-20	18.41	5361779664174	139
	3	15:18:33		555	
801	112	2018-03-20	11.54	4506405265172	53
	7	15:47:33		173	
802	340	2018-03-20	1.64	4866761290278	60
	7	17:15:15		198714	
803	205	2018-03-21	3.2	4711773125020	100
	6	01:10:18		499	
804	120	2018-03-21	10.54	3516952396080	107
	7	04:04:04		247	
805	552	2018-03-21	1.77	5570600642865	51
		08:07:16		857	
806	296	2018-03-21	18.18	501809222273	79
	6	10:17:56			
807	270	2018-03-21	16.19	1800985390191	12
	7	14:26:38		05	
808	190	2018-03-21	11.7	503842928916	12
	5	16:22:37			
809	79	2018-03-21	7.24	4681896441519	137
		17:16:06			
810	250	2018-03-21	16.71	4741042733274	90
	2	18:06:25			
811	298	2018-03-21	16.3	4644008655884	124
	5	20:15:49		311378	
812	291	2018-03-21	15.95	4268491956169	145
	6	21:49:48		254	
813	107	2018-03-22	5.39	4644008655884	138
		00:52:06		311378	
814	197	2018-03-22	4.98	4165305432349	49
	1	08:20:15		489280	
815	288	2018-03-22	6.82	4866761290278	112
		10:13:54		198714	
816	134	2018-03-22	10.45	3561954487988	33
	4	10:34:09		605	
817	285	2018-03-22	18.3	3517111172421	35
	3	11:56:50		930	
818	140	2018-03-22	11.2	4743204091443	76
	7	13:13:49		101526	
819	601	2018-03-22	2.3	4681896441519	55
		13:35:24			
820	318	2018-03-22	13.88	3006328138542	19
	8	14:16:15		9	
821	945	2018-03-22	11.36	6011987562414	59
		23:42:48		062	

Fraud Detection SQL

822	694	2018-03-23 07:13:23	1.46	3760275493418 49	121
823	541	2018-03-23 07:49:52	2.79	3760275493418 49	41
824	290 7	2018-03-23 09:31:49	14.26	503842928916	43
825	116 1	2018-03-23 12:13:43	11.46	4681896441519	99
826	188 6	2018-03-23 15:04:43	10.45	2131939469803 03	120
827	284 9	2018-03-23 17:23:57	18.88	5135837688671 496	136
828	229 2	2018-03-23 18:20:40	3.41	3007829905351 2	8
829	337 9	2018-03-24 00:51:57	3.08	4743204091443 101526	87
830	296 5	2018-03-24 01:13:41	15.83	5135837688671 496	133
831	950	2018-03-24 02:22:57	11.11	4761049645711 555811	137
832	147 4	2018-03-24 04:51:58	10.04	4681896441519	149
833	158 7	2018-03-24 09:19:46	12.34	5500708021555 307	42
834	180 4	2018-03-24 11:29:42	11.94	3561072557118 696	80
835	170 9	2018-03-24 12:10:08	10.14	4741042733274	114
836	310 4	2018-03-24 13:54:41	18.64	4723783028106 084756	14
837	137 5	2018-03-24 14:58:56	10.91	6500236164848 279	104
838	262 6	2018-03-24 17:21:08	18.1	5570600642865 857	64
839	348 5	2018-03-24 18:16:00	1.81	4027907156459 098	119
840	129 7	2018-03-24 22:30:49	10.15	6011987562414 062	83
841	178 4	2018-03-24 22:45:14	10.78	1800985390191 05	44
842	254 8	2018-03-25 00:54:15	15.48	5361779664174 555	107
843	27	2018-03-25 05:17:49	6.7	4586962917519 654607	95
844	46	2018-03-25 08:27:43	5.17	3007829905351 2	19

Fraud Detection SQL

845	111 6	2018-03-25 12:33:24	11.05	3760275493418 49	89
846	203 7	2018-03-25 13:07:44	2.62	4188164051171 486	65
847	264 8	2018-03-25 13:31:56	19.6	3441196239208 92	93
848	192 2	2018-03-25 15:00:40	12.27	4711773125020 499	108
849	111 8	2018-03-25 15:27:30	11.38	5361779664174 555	139
850	131 7	2018-03-25 17:32:11	11.37	4506405265172 173	36
851	199 3	2018-03-25 19:05:08	4.57	3561954487988 605	137
852	566	2018-03-26 02:44:07	3.11	4506405265172 173	60
853	238 5	2018-03-26 05:08:48	4.43	4263694062533 017	97
854	162 0	2018-03-26 07:41:59	1009. 0	3018196391334 0	111
855	289 5	2018-03-26 08:08:27	19.34	5500708021555 307	96
856	204	2018-03-26 08:14:09	6.2	501809222273	45
857	529	2018-03-26 12:28:38	2.16	3760275493418 49	53
858	144 7	2018-03-26 18:39:32	10.27	4834483169177 062	16
859	213 9	2018-03-26 22:58:10	2.85	4962915017023 706562	75
860	951	2018-03-27 02:40:54	13.77	4263694062533 017	48
861	766	2018-03-27 07:04:02	0.78	4268491956169 254	48
862	121 5	2018-03-27 12:20:26	11.01	3007829905351 2	95
863	286 5	2018-03-27 17:52:28	17.38	3014296669918 7	43
864	245 3	2018-03-27 18:10:00	15.79	5297187379298 983	30
865	583	2018-03-27 19:33:15	2.55	5500708021555 307	23
866	193 6	2018-03-27 21:24:13	4.39	4165305432349 489280	92
867	198 9	2018-03-28 04:11:22	3.05	5297187379298 983	70

Fraud Detection SQL

868	295 3	2018-03-28 05:30:09	19.55	3014296669918 7	23
869	257 0	2018-03-28 07:36:02	16.36	4165305432349 489280	67
870	340 5	2018-03-28 11:15:53	2.45	4159836738768 855913	24
871	171 1	2018-03-28 13:00:17	11.63	3561072557118 696	35
872	279 2	2018-03-28 14:44:02	18.68	3014296669918 7	149
873	315 1	2018-03-28 14:52:41	16.68	4539990688484 983	119
874	249 6	2018-03-28 19:25:33	14.22	4150721559116 778	46
875	181 0	2018-03-28 23:13:53	10.92	3517111172421 930	82
876	138 7	2018-03-28 23:56:44	10.46	4962915017023 706562	26
877	334 7	2018-03-29 00:33:24	1.41	584226564303	2
878	478	2018-03-29 06:38:59	5.39	5361779664174 555	3
879	154	2018-03-29 11:42:05	6.57	3581345943543 942	150
880	264 2	2018-03-29 13:21:16	16.07	4711773125020 499	74
881	576	2018-03-29 14:43:30	1.46	4276466390111	138
882	173 4	2018-03-29 17:18:07	10.59	4711773125020 499	83
883	336 4	2018-03-29 18:31:14	3.21	3760275493418 49	149
884	752	2018-03-29 18:33:39	2.53	3441196239208 92	21
885	249 5	2018-03-29 20:01:40	18.62	4866761290278 198714	11
886	197 4	2018-03-30 05:38:41	4.91	4159836738768 855913	18
887	400	2018-03-30 06:01:36	7.55	4027907156459 098	59
888	186 2	2018-03-30 08:12:28	12.96	4268491956169 254	103
889	153 7	2018-03-30 08:28:18	10.53	4188164051171 486	13
890	457	2018-03-30 12:57:30	6.27	4159836738768 855913	33

Fraud Detection SQL

891	310 6	2018-03-30 15:39:04	19.87	501809222273	33
892	817	2018-03-30 16:04:04	1.52	4743204091443 101526	104
893	115 3	2018-03-30 17:01:55	10.58	4761049645711 555811	3
894	222 0	2018-03-30 17:36:58	1.26	3517111172421 930	61
895	274 3	2018-03-30 18:46:40	17.2	503842928916	138
896	507	2018-03-30 21:04:57	3.08	4498002758300	80
897	274	2018-03-30 22:54:28	6.43	4268491956169 254	126
898	114 5	2018-03-30 23:00:32	10.79	4723783028106 084756	135
899	107 2	2018-03-31 00:50:30	11.53	3517111172421 930	139
900	127 1	2018-03-31 03:26:27	10.46	4711773125020 499	53
901	304 2	2018-03-31 04:35:13	16.53	5570600642865 857	90
902	294 1	2018-03-31 06:08:07	14.21	4276466390111	87
903	243 5	2018-03-31 08:48:53	3.65	5361779664174 555	129
904	289 7	2018-03-31 09:18:18	13.98	5175947111814 778	75
905	265 3	2018-03-31 12:54:47	18.59	4743204091443 101526	109
906	909	2018-03-31 16:18:26	11.41	4743204091443 101526	30
907	333 5	2018-03-31 17:56:51	2.35	3018196391334 0	111
908	323 5	2018-03-31 20:12:10	21.04	3724148328022 79	103
909	390	2018-03-31 21:50:44	4.22	4962915017023 706562	24
910	179	2018-03-31 22:41:23	6.82	3014296669918 7	92
911	193 4	2018-03-31 23:13:53	1.56	3441196239208 92	142
912	739	2018-04-01 01:48:11	1.71	3007829905351 2	19
913	774	2018-04-01 07:17:21	100.0	4319653513507	111

Fraud Detection SQL

914	233 2	2018-04-01 11:54:51	1.08	675911140852	140
915	117 7	2018-04-01 13:53:19	14.36	2131939469803 03	40
916	266 9	2018-04-01 15:55:53	18.67	5570600642865 857	82
917	140 2	2018-04-01 17:19:09	10.81	4644008655884 311378	123
918	241 9	2018-04-01 19:06:02	1.29	3582198969197 591	54
919	256 4	2018-04-01 19:59:57	17.75	4711773125020 499	83
920	193 0	2018-04-01 20:08:33	4.18	4681896441519	136
921	212 4	2018-04-01 21:08:23	2.62	4319653513507	82
922	294	2018-04-02 01:50:15	7.08	3724148328022 79	138
923	902	2018-04-02 14:52:44	11.24	4539990688484 983	42
924	261 6	2018-04-02 18:34:50	17.15	3724148328022 79	80
925	180 6	2018-04-02 22:19:53	11.15	4644008655884 311378	26
926	386	2018-04-03 01:38:27	5.08	4150721559116 778	8
927	135 9	2018-04-03 03:23:37	1077. 0	3441196239208 92	100
928	131 4	2018-04-04 00:47:59	10.28	3561954487988 605	38
929	955	2018-04-04 01:34:45	10.29	5361779664174 555	145
930	518	2018-04-04 06:41:06	6.07	3007829905351 2	122
931	110 7	2018-04-04 10:11:32	10.56	4150721559116 778	102
932	246 6	2018-04-04 12:57:15	16.61	4723783028106 084756	53
933	247 1	2018-04-05 01:29:17	16.22	4743204091443 101526	124
934	592	2018-04-05 02:07:01	2.04	3582198969197 591	4
935	252 9	2018-04-05 04:38:57	13.83	6011987562414 062	57
936	319 5	2018-04-05 06:19:44	17.54	3760275493418 49	134

Fraud Detection SQL

937	460	2018-04-05 12:46:25	5.53	4268491956169 254	128
938	262 4	2018-04-05 19:52:03	14.39	3018196391334 0	93
939	160 4	2018-04-05 22:50:44	11.37	1800985390191 05	92
940	322 8	2018-04-06 00:53:35	15.8	4268491956169 254	26
941	222 5	2018-04-06 02:30:41	1.44	4263694062533 017	72
942	268 9	2018-04-06 02:42:53	13.57	5135837688671 496	60
943	629	2018-04-06 13:03:31	1.43	3561954487988 605	118
944	204 2	2018-04-06 13:45:51	1.59	584226564303	141
945	349 5	2018-04-06 14:08:53	2.94	4743204091443 101526	80
946	861	2018-04-06 16:57:28	1.02	1800985390191 05	50
947	280 9	2018-04-06 17:25:52	15.32	4586962917519 654607	135
948	236 6	2018-04-06 17:48:38	1.78	4188164051171 486	56
949	213 7	2018-04-06 19:58:27	4.44	3760275493418 49	34
950	277 1	2018-04-07 04:37:00	15.11	5361779664174 555	142
951	305 3	2018-04-07 07:18:20	14.8	5297187379298 983	23
952	341 2	2018-04-07 08:18:17	2.58	503842928916	120
953	338	2018-04-07 09:06:38	3.22	4681896441519	124
954	138 9	2018-04-07 09:36:01	10.38	4027907156459 098	99
955	196 4	2018-04-07 14:02:37	5.55	3006328138542 9	59
956	164 2	2018-04-07 15:15:19	10.8	5135837688671 496	24
957	296 4	2018-04-07 15:21:18	17.64	4279104135293 225293	65
958	396	2018-04-07 16:40:23	6.5	675911140852	122
959	175 0	2018-04-07 20:28:00	10.92	3760275493418 49	20

Fraud Detection SQL

960	224 3	2018-04-08 04:28:30	3.79	5500708021555 307	71
961	398	2018-04-08 05:03:56	7.18	4279104135293 225293	50
962	134 1	2018-04-08 06:03:50	1063. 0	4319653513507	16
963	125 1	2018-04-08 07:06:20	11.73	3561954487988 605	83
964	327	2018-04-08 09:08:35	4.34	4279104135293 225293	71
965	166 2	2018-04-08 09:46:08	10.53	5175947111814 778	65
966	150 8	2018-04-08 11:31:27	11.26	675911140852	108
967	212 9	2018-04-08 14:37:51	4.58	5297187379298 983	105
968	194 4	2018-04-08 16:34:54	1.49	3535651398328 201	109
969	111 3	2018-04-08 18:03:55	10.15	3724148328022 79	84
970	113 0	2018-04-08 18:14:22	10.06	4319653513507	96
971	220	2018-04-08 18:49:37	8.07	5361779664174 555	74
972	346 0	2018-04-08 20:15:13	1.21	3561072557118 696	37
973	287 3	2018-04-08 21:13:01	16.24	4711773125020 499	124
974	131 2	2018-04-08 21:40:55	10.14	3006328138542 9	26
975	318 4	2018-04-09 02:20:29	17.81	4165305432349 489280	78
976	142 7	2018-04-09 04:09:54	10.01	3535651398328 201	54
977	319 0	2018-04-09 04:21:58	16.43	4723783028106 084756	107
978	267 5	2018-04-09 06:41:33	21.02	5175947111814 778	50
979	302 0	2018-04-09 07:08:11	17.73	4150721559116 778	61
980	232 0	2018-04-09 08:30:25	1.99	4539990688484 983	124
981	342 3	2018-04-09 10:24:32	283.0	4761049645711 555811	50
982	600	2018-04-09 10:33:41	1.91	3006328138542 9	76

Fraud Detection SQL

983	227 8	2018-04-09 10:45:20	3.65	5361779664174 555	113
984	329	2018-04-09 18:28:25	269.0	4319653513507	36
985	290 4	2018-04-09 18:40:01	17.76	4279104135293 225293	116
986	489	2018-04-09 18:59:37	8.31	4743204091443 101526	14
987	220 1	2018-04-09 19:04:52	1.77	5361779664174 555	9
988	332 9	2018-04-09 20:12:09	3.41	1800985390191 05	98
989	940	2018-04-09 21:08:59	10.47	3006328138542 9	103
990	109 2	2018-04-09 21:26:54	11.24	4644008655884 311378	77
991	287	2018-04-09 23:29:21	5.54	584226564303	11
992	151 5	2018-04-10 02:51:58	10.71	3517111172421 930	91
993	408	2018-04-10 06:08:01	543.0	3516952396080 247	63
994	892	2018-04-10 09:14:37	10.32	5297187379298 983	14
995	318 5	2018-04-10 12:54:34	15.81	584226564303	115
996	149 3	2018-04-10 13:16:51	10.3	4761049645711 555811	134
997	503	2018-04-10 17:14:29	7.33	4268491956169 254	86
998	894	2018-04-10 17:25:44	10.13	4027907156459 098	67
999	231 7	2018-04-10 17:32:28	3.86	3006328138542 9	45
1000	205 2	2018-04-10 17:43:42	1.5	6500236164848 279	40
1001	116 3	2018-04-10 23:03:20	10.24	4319653513507	101
1002	140 0	2018-04-11 00:35:22	10.48	4962915017023 706562	21
1003	764	2018-04-11 02:50:37	325.0	3018196391334 0	45
1004	118 6	2018-04-11 04:05:46	12.35	5135837688671 496	119
1005	324 7	2018-04-11 04:29:45	20.13	4268491956169 254	126

Fraud Detection SQL

1006	288	2018-04-11	19.28	4159836738768	145
	9	05:08:59		855913	
1007	281	2018-04-11	16.07	5135837688671	34
	6	08:26:52		496	
1008	313	2018-04-11	4.28	3006328138542	10
		16:45:26		9	
1009	333	2018-04-11	2.12	4150721559116	88
	0	18:29:01		778	
1010	188	2018-04-12	10.34	3535651398328	14
	0	01:35:50		201	

SQL/schema.sql

-- Exported from QuickDBD: <https://www.quickdatabasediagrams.com/>

-- Link to schema: <https://app.quickdatabasediagrams.com/#/d/s8Wnqm>

-- NOTE! If you have used non-SQL datatypes in your design, you will have to change these here.

--Card Holder

```
CREATE TABLE "card_holder" (  
    "id" SERIAL NOT NULL,  
    "name" VARCHAR(50) NOT NULL,  
    CONSTRAINT "pk_card_holder" PRIMARY KEY (
```

Fraud Detection SQL

```
        "id"
    )
);

-- Credit Card

CREATE TABLE "credit_card" (
    "card" VARCHAR(20) NOT NULL,
    "id_card_holder" INT NOT NULL,
    CONSTRAINT "pk_credit_card" PRIMARY KEY (
        "card"
    )
);
```

-- Merchant

```
CREATE TABLE "merchant" (
    "id" SERIAL NOT NULL,
    "name" VARCHAR(255) NOT NULL,
    "id_merchant_category" INT NOT NULL,
    CONSTRAINT "pk_merchant" PRIMARY KEY (
        "id"
    )
);
```

-- Merchant Category

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Fraud Detection SQL

```
CREATE TABLE "merchant_category"
```

```
( "id" SERIAL NOT NULL,
```

```
"name" VARCHAR(50) NOT NULL,
```

```
CONSTRAINT "pk_merchant_category" PRIMARY KEY (
```

```
"id"
```

```
)
```

```
);
```

```
-- Transaction
```

```
CREATE TABLE "transaction" (
```

```
"id" INT NOT NULL,
```

```
"date" TIMESTAMP NOT NULL,
```

```
"amount" FLOAT NOT NULL,
```

```
"card" VARCHAR(20) NOT NULL,
```

```
"id_merchant" INT NOT NULL,
```

```
CONSTRAINT "pk_transaction" PRIMARY KEY (
```

```
"id"
```

```
)
```

```
);
```

```
ALTER TABLE "credit_card" ADD CONSTRAINT "fk_credit_card_id_card_holder" FOREIGN  
KEY("id_card_holder")
```

```
REFERENCES "card_holder" ("id");
```

```
ALTER TABLE "credit_card" ADD CONSTRAINT "check_credit_card_length" CHECK (char_length("card")  
<= 20);
```

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Fraud Detection SQL

```
--ALTER TABLE "credit_card" DROP CONSTRAINT check_credit_card_length
```

```
ALTER TABLE "merchant" ADD CONSTRAINT "fk_merchant_id_merchant_category" FOREIGN  
KEY("id_merchant_category")
```

```
REFERENCES "merchant_category" ("id");
```

```
ALTER TABLE "transaction" ADD CONSTRAINT "fk_transaction_card" FOREIGN KEY("card")  
REFERENCES "credit_card" ("card");
```

```
ALTER TABLE "transaction" ADD CONSTRAINT "fk_transaction_id_merchant" FOREIGN  
KEY("id_merchant")
```

```
REFERENCES "merchant" ("id");
```

Seed.sql

```
INSERT INTO card_holder VALUES
```

```
(1, 'Robert Johnson'),
```

```
(2, 'Shane Shaffer'),
```

```
(3, 'Elizabeth Sawyer'),
```

```
(4, 'Danielle Green'),
```

```
(5, 'Sara Cooper'),
```

```
(6, 'Beth Hernandez'),
```

```
(7, 'Sean Taylor'),
```

```
(8, 'Michael Floyd'),
```

```
(9, 'Laurie Gibbs'),
```

```
(10, 'Matthew Gutierrez'),
```

```
(11, 'Brandon Pineda'),
```

```
(12, 'Megan Price'),
```

```
(13, 'John Martin'),
```

```
(14, 'Gary Jacobs'),
```

Fraud Detection SQL

(15, 'Kyle Tucker'),
(16, 'Crystal Clark'),
(17, 'Michael Carroll'),
(18, 'Malik Carlson'),
(19, 'Peter Mckay'),
(20, 'Kevin Spencer'),
(21, 'Dana Washington'),
(22, 'Austin Johnson'),
(23, 'Mark Lewis'),
(24, 'Stephanie Dalton'),
(25, 'Nancy Contreras');

INSERT INTO credit_card VALUES

(3517111172421930, 1),
(4761049645711555811, 1),
(4866761290278198714, 2),
(675911140852, 2),
(30078299053512, 3),
(4263694062533017, 4),
(584226564303, 4),
(4276466390111, 5),
(4268491956169254, 5),
(3581345943543942, 6),
(4159836738768855913, 6),

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(3516952396080247, 7),
(4539990688484983, 7),
(4834483169177062, 8),
(30063281385429, 8),
(30181963913340, 9),
(4962915017023706562, 10),
(4165305432349489280, 10),
(213193946980303, 10),
(180098539019105, 11),
(4644008655884311378, 11),
(4027907156459098, 11),
(501879657465, 12),
(5297187379298983, 12),
(376027549341849, 12),
(4711773125020499, 13),
(5135837688671496, 13),
(3561954487988605, 13),
(5175947111814778, 14),
(4723783028106084756, 15),
(6500236164848279, 15),
(503842928916, 16),
(5570600642865857, 16),
(5500708021555307, 16),
(6011987562414062, 17),

Fraud Detection SQL

```
(4498002758300, 18),  
(344119623920892, 18),  
(4743204091443101526, 19),  
(5361779664174555, 19),  
(3561072557118696, 19),  
(3535651398328201, 20),  
(4506405265172173, 20),  
(4586962917519654607, 20),  
(4279104135293225293, 21),  
(501809222273, 22),  
(4741042733274, 23),  
(4188164051171486, 23),  
(4150721559116778, 23),  
(4681896441519, 24),  
(30142966699187, 24),  
(3582198969197591, 24),  
(4319653513507, 25),  
(372414832802279, 25);
```

```
INSERT INTO merchant_category VALUES
```

```
(1, 'restaurant'),  
(2, 'coffee shop'),  
(3, 'bar'),  
(4, 'pub'),
```


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(5, 'food truck');

INSERT INTO merchant VALUES

(1, 'Murphy, Heath and Fields', 1),

(2, 'Riggs-Adams', 1),

(3, 'Sanders, Parks and Mcfarland', 2),

(4, 'Mccarty-Thomas', 3),

(5, 'Miller-Blevins', 4),

(6, 'Wilson and Sons', 1),

(7, 'Gomez-Kelly', 4),

(8, 'Russell-Thomas', 1),

(9, 'Curry, Scott and Richardson', 3),

(10, 'Herrera Group', 1),

(11, 'Stanton Group', 4),

(12, 'Bell, Gonzalez and Lowe', 4),

(13, 'Giles and Sons', 4),

(14, 'Osborne-Page', 2),

(15, 'Long, Harrell and Johnson', 5),

(16, 'Bryant, Thomas and Collins', 4),

(17, 'Bauer-Cole', 3),

(18, 'Romero-Jordan', 5),

(19, 'Santos-Fitzgerald', 4),

(20, 'Kim-Lopez', 2),

(21, 'Robertson-Smith', 4),

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(22, 'Dalton, Cameron and Jones', 3),
(23, 'Wilson, Roberts and Davenport', 5),
(24, 'Rodgers, Johnston and Macias', 5),
(25, 'Vaughn, Wilson and Hall', 1),
(26, 'Smith-Stephens', 2),
(27, 'Horn Ltd', 2),
(28, 'Hess-Fischer', 5),
(29, 'Browning-Cantu', 4),
(30, 'Atkinson Ltd', 3),
(31, 'Fisher, Salazar and Thomas', 5),
(32, 'Norton, Burton and Smith', 5),
(33, 'Vasquez-Parker', 3),
(34, 'Combs-Jones', 5),
(35, 'Jarvis-Turner', 4),
(36, 'Hamilton-Mcfarland', 1),
(37, 'Nguyen, Bautista and Williams', 4),
(38, 'Brown LLC', 3),
(39, 'Young-Navarro', 5),
(40, 'Cox, Montgomery and Morgan', 3),
(41, 'Ford, Williams and Dunn', 4),
(42, 'Kennedy-Chen', 3),
(43, 'Wallace and Sons', 2),
(44, 'Little-Floyd', 4),
(45, 'Velazquez Ltd', 4),

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(46, 'Miller, Chavez and Cobb', 5),
(47, 'Martin Inc', 1),
(48, 'Baker Inc', 5),
(49, 'Davis, Lowe and Baxter', 5),
(50, 'Johnson-Watts', 1),
(51, 'Fisher-Bolton', 1),
(52, 'Jensen-Stanley', 5),
(53, 'Wallace PLC', 4),
(54, 'Berry-Lopez', 1),
(55, 'Johnson, Rivas and Anderson', 1),
(56, 'Smith PLC', 3),
(57, 'Thornton-Williams', 4),
(58, 'Young, Hull and Williams', 4),
(59, 'Williams Group', 3),
(60, 'Smith-Richards', 4),
(61, 'Richardson, Smith and Jordan', 5),
(62, 'Cooper, Carpenter and Jackson', 5),
(63, 'Reed Group', 5),
(64, 'Cline, Myers and Strong', 1),
(65, 'Allen, Ramos and Carroll', 4),
(66, 'Robles Inc', 3),
(67, 'Maxwell, Tapia and Villanueva', 2),
(68, 'Ramirez-Carr', 2),
(69, 'Dominguez PLC', 5),

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(70, 'White-Hall', 3),
(71, 'Greene LLC', 1),
(72, 'Lopez-Kelly', 1),
(73, 'Colon Ltd', 3),
(74, 'Skinner-Williams', 4),
(75, 'Martinez Group', 1),
(76, 'Lowe PLC', 1),
(77, 'Brown, Ballard and Glass', 1),
(78, 'Ruiz-Anderson', 4),
(79, 'Lee LLC', 1),
(80, 'Kelly, Dyer and Schmitt', 5),
(81, 'Fowler and Sons', 5),
(82, 'Day-Murray', 5),
(83, 'Solis Group', 5),
(84, 'Marshall-Rojas', 2),
(85, 'Patton-Rivera', 3),
(86, 'Walker, Campbell and Sullivan', 5),
(87, 'Griffin-Woodard', 3),
(88, 'Armstrong PLC', 5),
(89, 'Kelley-Roberts', 5),
(90, 'Brown-Cunningham', 4),
(91, 'Turner Ltd', 4),
(92, 'Garcia-White', 4),
(93, 'Rodriguez-Parker', 5),

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(94, 'Yoder-Zavala', 5),
(95, 'Baxter-Smith', 1),
(96, 'Johnson-Fuller', 4),
(97, 'Ruiz-Chavez', 3),
(98, 'Rivera PLC', 4),
(99, 'Bond, Lewis and Rangel', 1),
(100, 'Townsend-Anderson', 1),
(101, 'Whitehead-Sexton', 4),
(102, 'Walters-Ward', 1),
(103, 'Jones, Clark and Hoover', 2),
(104, 'Mcdaniel, Hines and Mcfarland', 2),
(105, 'Garcia and Sons', 4),
(106, 'Carter-Blackwell', 4),
(107, 'Rowe-Abbott', 4),
(108, 'Best Inc', 1),
(109, 'Collins LLC', 2),
(110, 'Rodriguez, Dunlap and Nunez', 2),
(111, 'Padilla-Clements', 2),
(112, 'Greer Inc', 3),
(113, 'Edwards-Aguirre', 2),
(114, 'Greene-Wood', 3),
(115, 'Williams Inc', 4),
(116, 'Ferguson Ltd', 2),
(117, 'Mitchell Group', 2),

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(118, 'Maldonado Group', 2),
(119, 'Henderson and Sons', 1),
(120, 'Vega, Jones and Castro', 5),
(121, 'Fleming, Smith and Collins', 3),
(122, 'Perry and Sons', 3),
(123, 'Boone, Davis and Townsend', 4),
(124, 'McCarty PLC', 1),
(125, 'Russell and Sons', 4),
(126, 'Bartlett and Sons', 4),
(127, 'Williams, Wright and Wagner', 2),
(128, 'Pitts, Salinas and Garcia', 2),
(129, 'Sweeney-Paul', 2),
(130, 'Brown, Estrada and Powers', 2),
(131, 'Harrison, Newton and Hansen', 1),
(132, 'Pugh-Williams', 3),
(133, 'Scott, Hess and Finley', 3),
(134, 'Jenkins, Peterson and Beck', 1),
(135, 'Jacobs, Torres and Walker', 3),
(136, 'Martinez-Robinson', 3),
(137, 'Garcia PLC', 5),
(138, 'McCullough-Murphy', 5),
(139, 'Kidd-Lopez', 5),
(140, 'Wheeler-Moreno', 5),
(141, 'Wood-Ramirez', 3),

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(142, 'Thomas-Garcia', 5),
(143, 'Guzman, Garcia and Church', 3),
(144, 'Walker, Deleon and Wolf', 1),
(145, 'Hood-Phillips', 3),
(146, 'Pitts, Smith and Gonzalez', 4),
(147, 'Marshall-Lopez', 5),
(148, 'Huerta, Keith and Walters', 5),
(149, 'Clark and Sons', 5),
(150, 'Johnson and Sons', 2);

INSERT INTO transaction VALUES

(222, '2018-01-01 21:35:10', 6.22, 3561954487988605, 69),
(2045, '2018-01-01 21:43:12', 3.83, 5135837688671496, 85),
(395, '2018-01-01 22:41:21', 9.61, 213193946980303, 82),
(3309, '2018-01-01 23:13:30', 19.03, 4263694062533017, 5),
(567, '2018-01-01 23:15:10', 2.95, 4498002758300, 64),
(1683, '2018-01-02 01:13:21', 11.24, 4263694062533017, 127),
(2083, '2018-01-02 02:06:21', 1.46, 4319653513507, 93),
(3488, '2018-01-02 04:36:45', 3.36, 4506405265172173, 136),
(2635, '2018-01-02 05:45:43', 16.69, 5297187379298983, 120),
(432, '2018-01-02 10:13:09', 8.55, 5175947111814778, 70),
(2918, '2018-01-02 11:28:35', 15.85, 180098539019105, 16),
(2020, '2018-01-02 13:17:15', 2.64, 501879657465, 84),
(1084, '2018-01-02 15:10:33', 10.52, 6500236164848279, 39),

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(3490, '2018-01-02 16:14:55', 3.12, 3517111172421930, 21),
(1179, '2018-01-02 19:40:46', 10.44, 4741042733274, 55),
(99, '2018-01-02 23:27:46', 1031.0, 501879657465, 95),
(191, '2018-01-03 05:13:19', 2.76, 3535651398328201, 149),
(2387, '2018-01-03 08:44:46', 3.89, 4027907156459098, 74),
(2512, '2018-01-03 10:18:20', 14.57, 4268491956169254, 106),
(793, '2018-01-03 10:34:16', 2.63, 30181963913340, 35),
(533, '2018-01-03 15:23:58', 1.39, 4962915017023706562, 100),
(1077, '2018-01-03 18:16:55', 10.27, 501809222273, 84),
(2120, '2018-01-03 21:04:28', 1.91, 3561072557118696, 108),
(1302, '2018-01-04 00:29:04', 12.45, 3561954487988605, 39),
(2022, '2018-01-04 01:28:18', 2.81, 4644008655884311378, 89),
(2806, '2018-01-04 01:35:21', 20.33, 3516952396080247, 112),
(2922, '2018-01-04 03:00:19', 17.59, 501809222273, 100),
(2650, '2018-01-04 03:05:18', 1685.00000000000002, 3516952396080247, 80),
(1510, '2018-01-04 06:34:37', 10.22, 4188164051171486, 80),
(139, '2018-01-04 11:15:55', 5.72, 3535651398328201, 99),
(1331, '2018-01-04 13:41:56', 12.7, 5135837688671496, 122),
(530, '2018-01-04 14:38:12', 2.84, 3535651398328201, 73),
(2859, '2018-01-04 17:19:14', 15.48, 5175947111814778, 72),
(2694, '2018-01-04 19:24:31', 14.31, 4586962917519654607, 134),
(2127, '2018-01-05 00:49:22', 2.32, 4188164051171486, 136),
(1995, '2018-01-05 01:10:27', 5.09, 501809222273, 46),
(1346, '2018-01-05 03:11:18', 12.2, 4268491956169254, 69),

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(2176, '2018-01-05 05:47:28', 4.64, 5175947111814778, 103),
(1552, '2018-01-05 06:26:45', 10.74, 372414832802279, 86),
(487, '2018-01-05 06:27:06', 4.6, 4159836738768855913, 48),
(2077, '2018-01-05 07:19:27', 1.36, 344119623920892, 30),
(314, '2018-01-05 10:42:55', 5.31, 3561072557118696, 8),
(77, '2018-01-05 16:58:08', 4.57, 5135837688671496, 91),
(1570, '2018-01-06 01:43:44', 10.04, 5500708021555307, 34),
(2439, '2018-01-06 02:16:41', 1.33, 4866761290278198714, 127),
(2258, '2018-01-06 04:43:33', 5.31, 5297187379298983, 42),
(1867, '2018-01-06 05:13:20', 10.82, 4866761290278198714, 70),
(846, '2018-01-06 06:46:24', 2.7, 213193946980303, 146),
(2890, '2018-01-06 07:00:32', 18.35, 3561954487988605, 76),
(3291, '2018-01-06 08:42:50', 18.72, 3535651398328201, 76),
(2557, '2018-01-06 08:49:34', 16.28, 4268491956169254, 101),
(325, '2018-01-06 23:33:29', 7.6, 376027549341849, 141),
(2663, '2018-01-07 00:30:25', 17.84, 4159836738768855913, 112),
(3457, '2018-01-07 01:10:54', 175.0, 344119623920892, 12),
(447, '2018-01-07 07:33:17', 7.07, 4834483169177062, 14),
(1249, '2018-01-07 10:31:33', 10.9, 5297187379298983, 135),
(2108, '2018-01-07 14:57:23', 2.93, 4319653513507, 137),
(3028, '2018-01-07 15:10:27', 17.29, 4866761290278198714, 126),
(149, '2018-01-07 16:50:22', 5.83, 4159836738768855913, 81),
(2304, '2018-01-07 20:35:00', 2.5, 6011987562414062, 104),
(1384, '2018-01-08 00:26:21', 10.04, 3581345943543942, 64),

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(1371, '2018-01-08 01:12:52', 10.4, 5500708021555307, 121),
(1291, '2018-01-08 02:34:32', 1029.0, 3581345943543942, 145),
(1065, '2018-01-08 04:15:30', 11.49, 4741042733274, 130),
(1340, '2018-01-08 04:29:20', 10.64, 501809222273, 116),
(1544, '2018-01-08 06:27:34', 10.48, 4027907156459098, 68),
(522, '2018-01-08 10:48:26', 11.06, 4743204091443101526, 113),
(812, '2018-01-08 11:15:36', 333.0, 344119623920892, 95),
(1640, '2018-01-08 11:21:20', 11.98, 5500708021555307, 133),
(2550, '2018-01-08 11:35:55', 15.84, 4150721559116778, 15),
(2095, '2018-01-08 14:06:25', 3.52, 180098539019105, 95),
(3130, '2018-01-08 16:38:22', 21.27, 5297187379298983, 106),
(3085, '2018-01-08 19:31:23', 17.43, 584226564303, 19),
(1816, '2018-01-08 20:10:59', 11.55, 344119623920892, 102),
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(1188, '2018-01-08 21:44:58', 10.64, 5175947111814778, 84),
(379, '2018-01-09 11:14:56', 7.07, 501809222273, 136),
(687, '2018-01-09 21:06:16', 2.7, 4506405265172173, 67),
(2558, '2018-01-09 21:43:47', 16.37, 4681896441519, 64),
(754, '2018-01-10 00:25:40', 1.39, 372414832802279, 50),
(608, '2018-01-10 03:17:20', 0.87, 503842928916, 129),
(2818, '2018-01-10 03:24:29', 16.64, 3561954487988605, 65),
(865, '2018-01-10 03:55:54', 2.3, 4150721559116778, 19),
(998, '2018-01-10 10:07:20', 10.91, 675911140852, 78),
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(1938, '2018-01-10 14:50:30', 5.64, 5361779664174555, 44),
(602, '2018-01-10 15:56:41', 1.22, 503842928916, 27),
(3289, '2018-01-10 19:53:09', 18.41, 4159836738768855913, 23),
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(496, '2018-01-11 00:39:12', 3.23, 503842928916, 68),
(156, '2018-01-11 09:27:30', 5.55, 6011987562414062, 107),
(315, '2018-01-11 09:38:33', 7.94, 5135837688671496, 146),
(3498, '2018-01-11 09:58:11', 1.62, 5500708021555307, 149),
(3331, '2018-01-11 10:51:08', 1.24, 30063281385429, 7),
(2128, '2018-01-11 12:46:01', 3.97, 4834483169177062, 44),
(2188, '2018-01-11 13:20:31', 229.0, 5570600642865857, 115),
(1716, '2018-01-11 16:18:55', 10.27, 5361779664174555, 46),
(2146, '2018-01-11 19:36:21', 1.72, 4761049645711555811, 99),
(2779, '2018-01-11 22:55:51', 19.5, 4268491956169254, 8),
(1048, '2018-01-12 02:18:05', 11.52, 3582198969197591, 2),
(2170, '2018-01-12 02:48:29', 1.84, 30142966699187, 2),
(2025, '2018-01-12 04:33:17', 5.32, 4188164051171486, 10),
(451, '2018-01-12 06:34:53', 6.19, 30181963913340, 40),
(444, '2018-01-12 13:30:20', 5.92, 4506405265172173, 38),
(416, '2018-01-12 13:59:09', 4.45, 501809222273, 85),
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(3373, '2018-01-12 18:04:04', 1.88, 4681896441519, 44),
(270, '2018-01-12 22:14:25', 6.4, 4276466390111, 112),
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(718, '2018-01-13 18:34:36', 2.22, 4263694062533017, 9),
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(2843, '2018-01-14 03:20:21', 14.69, 584226564303, 133),
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(830, '2018-01-14 07:06:57', 3.15, 584226564303, 96),
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(3159, '2018-01-14 15:03:26', 16.67, 213193946980303, 30),
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(2787, '2018-01-15 06:23:30', 15.87, 4539990688484983, 70),
(2622, '2018-01-15 10:27:56', 15.51, 4761049645711555811, 8),

Fraud Detection SQL

(1382, '2018-01-15 11:52:41', 11.67, 4159836738768855913, 139),
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(3065, '2018-01-16 04:12:01', 16.89, 4711773125020499, 109),
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Fraud Detection SQL

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Fraud Detection SQL

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Fraud Detection SQL

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Fraud Detection SQL

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Fraud Detection SQL

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Implementation (Coding)

Identifying Outliers using Standard Deviation

```
# initial imports
import pandas as pd
import numpy as np
import random
from sqlalchemy import create_engine
from numpy import mean
from numpy import std
from numpy import percentile
import plotly.express as px
```

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Fraud Detection SQL

```
# create a connection to the database
engine = create_engine("postgresql://postgres:Istay@10314@localhost:5432/fraud_detection")

# Loading data from the database

def execute_query(query):

    transaction_df = pd.read_sql(sql=query, con=engine, index_col='date', parse_dates='date')

    return transaction_df

# Loading data of daily transactions from jan to jun 2018 for card holder 25
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \
        FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d, \
        public.merchant_category e \
        WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND \
        d.id_merchant_category=e.id'

transaction_df = execute_query(query)
transaction_df.head()
```

2018-01-01 21:35:10	13	John Martin	3561954487988605	6.22	food truck
2018-01-01 21:43:12	13	John Martin	5135837688671496	3.83	bar
2018-01-01 22:41:21	10	Matthew Gutierrez	213193946980303	9.61	food truck
2018-01-01 23:13:30	4	Danielle Green	4263694062533017	19.03	pub
2018-01-01 23:15:10	18	Malik Carlson	4498002758300	2.95	restaurant

```
# code a function to identify outliers based on standard deviation
# calculate summary statistics
data_mean, data_std = mean(transaction_df['amount']), std(transaction_df['amount'])

# identify outliers
```

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Fraud Detection SQL

```
cut_off = data_std * 3

lower, upper = data_mean - cut_off, data_mean + cut_off

# identify outliers
outliers = [x for x in transaction_df['amount'] if x < lower or x > upper]

print('Identified outliers: %d' % len(outliers))

# remove outliers
outliers_removed = [x for x in transaction_df['amount'] if x >= lower and x <= upper]

print('Non-outlier observations: %d' % len(outliers_removed))

transaction_df['outlier'] = (transaction_df['amount'] > upper) | (transaction_df['amount'] < lower)

outlier = transaction_df[transaction_df['outlier']==True]
outlier
```

```
Identified outliers: 77
Non-outlier observations: 3423
```

2018-01-02 23:27:46	12	Megan Price	501879657465	1031.0	restaurant	True
2018-01-04 03:05:18	7	Sean Taylor	3516952396080247	1685.0	food truck	True
2018-01-08 02:34:32	6	Beth Hernandez	3581345943543942	1029.0	bar	True
2018-01-22 08:07:03	16	Crystal Clark	5570600642865857	1131.0	restaurant	True
2018-01-23 06:29:37	12	Megan Price	501879657465	1678.0	pub	True
2018-01-24 13:17:19	1	Robert Johnson	4761049645711555811	1691.0	coffee shop	True
2018-01-30 18:31:00	25	Nancy Contreras	4319653513507	1177.0	restaurant	True
2018-02-17 01:27:19	16	Crystal Clark	5570600642865857	1430.0	restaurant	True

Fraud Detection SQL

2018-02-19 16:00:43	7	Sean Taylor	3516952396080247	1072.0	food truck	True
2018-02-19 22:48:25	18	Malik Carlson	344119623920892	1839.0	restaurant	True
2018-02-27 15:27:32	6	Beth Hernandez	3581345943543942	1145.0	bar	True
2018-03-01 21:29:05	3	Elizabeth Sawyer	30078299053512	1119.0	pub	True
2018-03-04 15:50:53	9	Laurie Gibbs	30181963913340	1534.0	coffee shop	True
2018-03-05 08:26:08	16	Crystal Clark	5570600642865857	1617.0	bar	True
2018-03-06 07:18:09	25	Nancy Contreras	4319653513507	1334.0	bar	True
2018-03-12 00:44:01	12	Megan Price	501879657465	1530.0	coffee shop	True
2018-03-20 10:19:25	12	Megan Price	501879657465	852.0	pub	True
2018-03-20 13:05:54	24	Stephanie Dalton	30142966699187	1011.0	bar	True
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	1009.0	coffee shop	True
2018-04-03 03:23:37	18	Malik Carlson	344119623920892	1077.0	restaurant	True
2018-04-08 06:03:50	25	Nancy Contreras	4319653513507	1063.0	pub	True
2018-04-18 23:23:29	7	Sean Taylor	3516952396080247	1086.0	coffee shop	True
2018-04-21 19:41:51	6	Beth Hernandez	3581345943543942	2108.0	coffee shop	True
2018-05-08 13:21:01	24	Stephanie Dalton	30142966699187	1901.0	restaurant	True
2018-05-13 06:31:20	25	Nancy Contreras	4319653513507	1046.0	food truck	True
2018-05-29 02:55:08	16	Crystal Clark	5570600642865857	1203.0	food truck	True
2018-06-03 20:02:28	18	Malik Carlson	344119623920892	1814.0	pub	True
2018-06-04 03:46:15	25	Nancy Contreras	4319653513507	1162.0	pub	True
2018-06-06 21:50:17	25	Nancy Contreras	4319653513507	749.0	restaurant	True
2018-06-10 04:54:27	9	Laurie Gibbs	30181963913340	1795.0	pub	True
2018-09-04 01:35:39	1	Robert Johnson	4761049645711555811	1790.0	coffee shop	True

Fraud Detection SQL

2018-09-06 08:28:55	1	Robert Johnson	4761049645711555811	1017.0	bar	True
2018-09-06 21:55:02	1	Robert Johnson	4761049645711555811	1056.0	restaurant	True
2018-09-10 22:49:41	18	Malik Carlson	344119623920892	1176.0	restaurant	True
2018-09-11 15:16:47	6	Beth Hernandez	3581345943543942	1856.0	food truck	True
2018-09-23 19:20:23	12	Megan Price	501879657465	1075.0	pub	True
2018-09-25 23:23:21	9	Laurie Gibbs	30181963913340	1095.0	food truck	True
2018-09-26 08:48:40	1	Robert Johnson	4761049645711555811	1060.0	restaurant	True
2018-10-07 14:40:34	3	Elizabeth Sawyer	30078299053512	757.0	bar	True
2018-10-07 18:29:20	9	Laurie Gibbs	30181963913340	1179.0	pub	True
2018-10-19 01:07:37	3	Elizabeth Sawyer	30078299053512	1053.0	restaurant	True
2018-11-13 17:07:25	16	Crystal Clark	5570600642865857	1911.0	restaurant	True
2018-11-17 05:30:43	18	Malik Carlson	344119623920892	1769.0	food truck	True
2018-11-20 05:24:28	3	Elizabeth Sawyer	30078299053512	1054.0	bar	True
2018-11-25 20:44:07	12	Megan Price	501879657465	1123.0	bar	True
2018-11-27 15:36:05	12	Megan Price	501879657465	1802.0	bar	True
2018-11-27 17:20:29	6	Beth Hernandez	3581345943543942	1279.0	restaurant	True
2018-11-27 17:27:34	1	Robert Johnson	4761049645711555811	1660.0	pub	True
2018-12-03 02:38:52	16	Crystal Clark	5570600642865857	1014.0	restaurant	True
2018-12-07 07:22:03	1	Robert Johnson	4761049645711555811	1894.0	bar	True
2018-12-13 12:09:58	18	Malik Carlson	344119623920892	1154.0	restaurant	True
2018-12-13 15:51:59	7	Sean Taylor	3516952396080247	2249.0	food truck	True
2018-12-14 08:51:41	12	Megan Price	501879657465	748.0	pub	True
2018-12-18 13:33:37	25	Nancy Contreras	4319653513507	1074.0	coffee shop	True
2018-12-18 17:20:33	7	Sean Taylor	3516952396080247	1296.0	bar	True
2018-12-19 16:10:03	9	Laurie Gibbs	30181963913340	1724.0	pub	True

Fraud Detection SQL

2018-12-21 09:56:32	24	Stephanie Dalton	30142966699187	1301.0	pub	True
2018-12-24 15:55:06	16	Crystal Clark	5570600642865857	1634.0	pub	True
2018-12-25 19:10:42	24	Stephanie Dalton	30142966699187	1035.0	pub	True
2018-12-30 23:23:09	1	Robert Johnson	4761049645711555811	1033.0	pub	True

77 rows × 6 columns

```
# find anomalous transactions for 3 random card holders
```

```
import datetime
```

```
start_time = datetime.time(7,0,0)
```

```
end_time = datetime.time(9,0,0)
```

```
anomalous_transactions = outlier.between_time(start_time, end_time).sort_values('amount',  
ascending=False)
```

```
px.scatter(anomalous_transactions, x='name', y='amount', color='category')
```

Identifying Outliers Using Interquartile Range

```
# code a function to identify outliers based on interquartile range
```

```
# calculate interquartile range
```

```
q25, q75 = percentile(transaction_df['amount'], 25), percentile(transaction_df['amount'], 75)
```

```
iqr = q75 - q25
```

```
print('Percentiles: 25th=%.3f, 75th=%.3f, IQR=%.3f' % (q25, q75, iqr))
```

```
# calculate the outlier cutoff
```

```
cut_off = iqr * 1.5
```

```
lower, upper = q25 - cut_off, q75 + cut_off
```

```
# identify outliers
```

```
outliers_2 = [x for x in transaction_df['amount'] if x < lower or x > upper]
```

```
print('Identified outliers: %d' % len(outliers_2))
```

```
# remove outliers
```

```
outliers_removed_2 = [x for x in transaction_df['amount'] if x >= lower and x <= upper]
```

```
print('Non-outlier observations: %d' % len(outliers_removed_2))
```

```
transaction_df['outlier'] = (transaction_df['amount'] > upper) | (transaction_df['amount'] < lower)
```

```
outlier_2 = transaction_df[transaction_df['outlier']==True]
```

```
outlier_2
```

```
Percentiles: 25th=3.735, 75th=14.648, IQR=10.913
```

```
Identified outliers: 110
```

```
Non-outlier observations: 3390
```

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Fraud Detection SQL

2018-01-02 23:27:46	12	Megan Price	501879657465	1031.0	restaurant	True
2018-01-04 03:05:18	7	Sean Taylor	3516952396080247	1685.0	food truck	True
2018-01-07 01:10:54	18	Malik Carlson	344119623920892	175.0	pub	True
2018-01-08 02:34:32	6	Beth Hernandez	3581345943543942	1029.0	bar	True
2018-01-08 11:15:36	18	Malik Carlson	344119623920892	333.0	restaurant	True
2018-01-11 13:20:31	16	Crystal Clark	5570600642865857	229.0	pub	True
2018-01-22 08:07:03	16	Crystal Clark	5570600642865857	1131.0	restaurant	True
2018-01-23 06:29:37	12	Megan Price	501879657465	1678.0	pub	True
2018-01-24 13:17:19	1	Robert Johnson	4761049645711555 811	1691.0	coffee shop	True
2018-01-30 18:31:00	25	Nancy Contreras	4319653513507	1177.0	restaurant	True
2018-02-09 11:38:37	7	Sean Taylor	3516952396080247	445.0	bar	True
2018-02-17 01:27:19	16	Crystal Clark	5570600642865857	1430.0	restaurant	True
2018-02-19 16:00:43	7	Sean Taylor	3516952396080247	1072.0	food truck	True
2018-02-19 22:48:25	18	Malik Carlson	344119623920892	1839.0	restaurant	True
2018-02-27 15:27:32	6	Beth Hernandez	3581345943543942	1145.0	bar	True
2018-03-01 21:29:05	3	Elizabeth Sawyer	30078299053512	1119.0	pub	True
2018-03-04 15:50:53	9	Laurie Gibbs	30181963913340	1534.0	coffee shop	True
2018-03-05 08:26:08	16	Crystal Clark	5570600642865857	1617.0	bar	True
2018-03-06 07:18:09	25	Nancy Contreras	4319653513507	1334.0	bar	True
2018-03-09 04:51:38	6	Beth Hernandez	3581345943543942	389.0	restaurant	True
2018-03-12 00:44:01	12	Megan Price	501879657465	1530.0	coffee shop	True
2018-03-20 10:19:25	12	Megan Price	501879657465	852.0	pub	True
2018-03-20 13:05:54	24	Stephanie Dalton	30142966699187	1011.0	bar	True
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	1009.0	coffee shop	True
2018-04-01 07:17:21	25	Nancy Contreras	4319653513507	100.0	coffee shop	True
2018-04-03 03:23:37	18	Malik Carlson	344119623920892	1077.0	restaurant	True
2018-04-08 06:03:50	25	Nancy Contreras	4319653513507	1063.0	pub	True
2018-04-09 10:24:32	1	Robert Johnson	4761049645711555 811	283.0	restaurant	True
2018-04-09 18:28:25	25	Nancy Contreras	4319653513507	269.0	restaurant	True
2018-04-10 06:08:01	7	Sean Taylor	3516952396080247	543.0	food truck	True
2018-10-11 23:29:33	3	Elizabeth Sawyer	30078299053512	206.0	restaurant	True
2018-10-16 13:27:33	1	Robert Johnson	4761049645711555 811	484.0	food truck	True
2018-10-19 01:07:37	3	Elizabeth Sawyer	30078299053512	1053.0	restaurant	True
2018-10-19 12:32:37	16	Crystal Clark	5570600642865857	178.0	food truck	True
2018-10-23 22:47:13	16	Crystal Clark	5570600642865857	393.0	food truck	True
2018-10-28 02:12:58	25	Nancy Contreras	4319653513507	137.0	pub	True
2018-11-13 05:58:47	24	Stephanie Dalton	30142966699187	466.0	bar	True
2018-11-13 17:07:25	16	Crystal Clark	5570600642865857	1911.0	restaurant	True
2018-11-17 05:30:43	18	Malik Carlson	344119623920892	1769.0	food truck	True
2018-11-20 05:24:28	3	Elizabeth Sawyer	30078299053512	1054.0	bar	True

Fraud Detection SQL

2018-11-23 09:08:05	12	Megan Price	501879657465	233.0	restaurant	True
2018-11-25 20:44:07	12	Megan Price	501879657465	1123.0	bar	True
2018-11-26 20:54:39	1	Robert Johnson	4761049645711555811	267.0	food truck	True
2018-11-27 15:36:05	12	Megan Price	501879657465	1802.0	bar	True
2018-11-27 17:20:29	6	Beth Hernandez	3581345943543942	1279.0	restaurant	True
2018-11-27 17:27:34	1	Robert Johnson	4761049645711555811	1660.0	pub	True
2018-12-03 02:38:52	16	Crystal Clark	5570600642865857	1014.0	restaurant	True
2018-12-05 19:24:27	9	Laurie Gibbs	30181963913340	57.0	bar	True
2018-12-07 07:22:03	1	Robert Johnson	4761049645711555811	1894.0	bar	True
2018-12-13 12:09:58	18	Malik Carlson	344119623920892	1154.0	restaurant	True
2018-12-13 15:51:59	7	Sean Taylor	3516952396080247	2249.0	food truck	True
2018-12-14 08:51:41	12	Megan Price	501879657465	748.0	pub	True
2018-12-18 13:33:37	25	Nancy Contreras	4319653513507	1074.0	coffee shop	True
2018-12-18 17:20:33	7	Sean Taylor	3516952396080247	1296.0	bar	True
2018-12-19 16:10:03	9	Laurie Gibbs	30181963913340	1724.0	pub	True
2018-12-21 09:56:32	24	Stephanie Dalton	30142966699187	1301.0	pub	True
2018-12-24 15:55:06	16	Crystal Clark	5570600642865857	1634.0	pub	True
2018-12-25 19:10:42	24	Stephanie Dalton	30142966699187	1035.0	pub	True
2018-12-28 16:20:31	3	Elizabeth Sawyer	30078299053512	313.0	pub	True
2018-12-30 23:23:09	1	Robert Johnson	4761049645711555811	1033.0	pub	True

110 rows × 6 columns

find anomalous transactions for 3 random card holders

```
anomalous_transactions2 = outlier_2.between_time(start_time, end_time).sort_values('amount',
ascending=False)
anomalous_transactions2
```

2018-12-07 07:22:03	1	Robert Johnson	4761049645711555 811	189 4.0	bar	T ru e
------------------------	---	-------------------	-------------------------	------------	-----	--------------

Fraud Detection SQL

2018-03-05 08:26:08	1 6	Crystal Clark	5570600642865857	161 7.0	bar	T ru e
2018-03-06 07:18:09	2 5	Nancy Contreras	4319653513507	133 4.0	bar	T ru e
2018-01-22 08:07:03	1 6	Crystal Clark	5570600642865857	113 1.0	restaur ant	T ru e
2018-09-26 08:48:40	1	Robert Johnson	4761049645711555 811	106 0.0	restaur ant	T ru e
2018-09-06 08:28:55	1	Robert Johnson	4761049645711555 811	101 7.0	bar	T ru e
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	100 9.0	coffee shop	T ru e
2018-12-14 08:51:41	1 2	Megan Price	501879657465	748. 0	pub	T ru e
2018-04-01 07:17:21	2 5	Nancy Contreras	4319653513507	100. 0	coffee shop	T ru e

```
px.scatter(anomalous_transactions2, x='name', y='amount', color='category')
```

For Outlier calculation using standard deviation, results in 77 records whereas using Interquartile range results in 110 records. There seems to be fraudulent transactions in Bar category wherein amount spent between 7-9 AM in the Bar

Visual Data Analysis of Fraudulent Transactions

```
# initial imports
import pandas as pd
import calendar
import plotly.express as px
import hvplot.pandas
from sqlalchemy import create_engine
import datetime
```

In [51]:

Fraud Detection SQL

```
# create a connection to the database
engine = create_engine("postgresql://postgres:Istay@10314@localhost:5432/fraud_detection")
```

In [52]:

```
# Loading data from the database
```

```
def execute_query(query):

    transaction_df = pd.read_sql(sql=query, con=engine, index_col='date', parse_dates='date')

    return transaction_df

def fraud_transactions(df):
    start_time = datetime.time(7,0,0)
    end_time = datetime.time(9,0,0)
    return df.between_time(start_time, end_time).sort_values('amount', ascending=False)
```

In [58]:

```
# Loading data for card holder 2 and 18 from the database
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \
        FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d,
        public.merchant_category e \
        WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND
        d.id_merchant_category=e.id AND b.card=c.card'

transaction_df = execute_query(query)

suspect_df = fraud_transactions(transaction_df).head(100)
suspect_df
```

2018-12-07 07:22:03	1	Robert Johnson	4761049645711555811	1894.00	bar
2018-03-05 08:26:08	16	Crystal Clark	5570600642865857	1617.00	bar
2018-03-06 07:18:09	25	Nancy Contreras	4319653513507	1334.00	bar
2018-01-22 08:07:03	16	Crystal Clark	5570600642865857	1131.00	restaurant
2018-09-26 08:48:40	1	Robert Johnson	4761049645711555811	1060.00	restaurant
2018-09-06 08:28:55	1	Robert Johnson	4761049645711555811	1017.00	bar
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	1009.00	coffee shop
2018-12-14 08:51:41	12	Megan Price	501879657465	748.00	pub
2018-04-01 07:17:21	25	Nancy Contreras	4319653513507	100.00	coffee shop
2018-08-26 07:15:18	20	Kevin Spencer	4506405265172173	23.13	food truck
2018-08-28 07:17:14	10	Matthew Gutierrez	4165305432349489280	20.71	coffee shop
2018-10-07 08:16:54	20	Kevin Spencer	4586962917519654607	20.44	food truck

Fraud Detection SQL

2018-10-18 07:16:04	16	Crystal Clark	5500708021555307	19.86	pub
2018-03-03 08:42:02	24	Stephanie Dalton	4681896441519	19.50	food truck
2018-06-04 08:30:28	4	Danielle Green	584226564303	19.49	food truck
2018-03-26 08:08:27	16	Crystal Clark	5500708021555307	19.34	pub
2018-06-01 08:56:59	11	Brandon Pineda	180098539019105	19.33	restaurant
2018-12-23 07:39:47	10	Matthew Gutierrez	4962915017023706562	19.27	pub
2018-09-23 07:30:56	15	Kyle Tucker	4723783028106084756	19.02	restaurant
2018-02-21 08:21:10	5	Sara Cooper	4268491956169254	18.98	food truck
2018-07-04 08:51:29	10	Matthew Gutierrez	213193946980303	18.93	coffee shop
2018-08-02 07:44:24	19	Peter Mckay	5361779664174555	18.93	food truck
2018-06-09 07:29:28	23	Mark Lewis	4188164051171486	18.82	pub
2018-06-02 07:45:48	23	Mark Lewis	4150721559116778	18.76	food truck
2018-01-06 08:42:50	20	Kevin Spencer	3535651398328201	18.72	restaurant
2018-06-24 07:28:48	14	Gary Jacobs	5175947111814778	18.60	pub
2018-06-23 07:12:06	8	Michael Floyd	4834483169177062	18.56	restaurant
2018-08-14 08:38:49	18	Malik Carlson	4498002758300	18.54	restaurant
2018-10-07 07:08:08	24	Stephanie Dalton	3582198969197591	18.53	food truck
2018-02-27 08:27:00	2	Shane Shaffer	675911140852	18.52	restaurant
2018-12-11 07:42:50	1	Robert Johnson	3517111172421930	14.92	restaurant
2018-04-07 07:18:20	12	Megan Price	5297187379298983	14.80	food truck
2018-08-02 07:13:49	7	Sean Taylor	3516952396080247	14.42	coffee shop
2018-12-15 08:34:15	25	Nancy Contreras	372414832802279	14.36	food truck
2018-04-24 07:41:49	15	Kyle Tucker	6500236164848279	14.30	food truck
2018-10-22 07:41:56	13	John Martin	4711773125020499	13.83	coffee shop
2018-09-03 07:27:55	12	Megan Price	376027549341849	13.59	pub
2018-03-10 08:52:09	2	Shane Shaffer	675911140852	13.53	coffee shop
2018-04-27 08:08:38	19	Peter Mckay	3561072557118696	13.52	food truck
2018-02-26 07:31:20	20	Kevin Spencer	4586962917519654607	13.46	pub
2018-10-27 08:04:44	23	Mark Lewis	4150721559116778	12.98	coffee shop
2018-05-01 07:40:00	15	Kyle Tucker	6500236164848279	12.98	bar
2018-03-30 08:12:28	5	Sara Cooper	4268491956169254	12.96	coffee shop
2018-01-17 07:31:03	18	Malik Carlson	4498002758300	12.67	food truck
2018-08-08 08:36:23	11	Brandon Pineda	180098539019105	12.52	coffee shop
2018-07-30 08:49:16	5	Sara Cooper	4276466390111	12.50	food truck
2018-11-30 08:52:20	7	Sean Taylor	4539990688484983	12.32	coffee shop
2018-12-29 08:11:55	18	Malik Carlson	4498002758300	12.25	restaurant

Fraud Detection SQL

2018-02-19 08:50:36	1	Robert Johnson	4761049645711555811	12.17	food truck
2018-01-20 08:35:34	12	Megan Price	501879657465	11.96	bar
2018-07-31 07:44:59	24	Stephanie Dalton	4681896441519	11.93	bar
2018-01-17 07:56:09	24	Stephanie Dalton	4681896441519	11.91	restaurant
2018-06-08 07:25:30	25	Nancy Contreras	372414832802279	11.88	coffee shop
2018-12-31 08:22:17	23	Mark Lewis	4188164051171486	11.87	restaurant
2018-08-30 08:46:49	4	Danielle Green	584226564303	11.86	bar
2018-04-08 07:06:20	13	John Martin	3561954487988605	11.73	food truck
2018-09-15 08:33:49	16	Crystal Clark	5500708021555307	11.72	coffee shop
2018-12-18 07:45:28	21	Dana Washington	4279104135293225293	11.70	food truck
2018-02-25 07:37:03	13	John Martin	5135837688671496	11.68	pub
2018-05-04 08:21:59	11	Brandon Pineda	4027907156459098	11.65	pub

100 rows × 5 columns

```
px.scatter(suspect_df, x=suspect_df.index, y='amount', color='category', size='amount',
hover_data=['name', 'category'], labels = {'x' : 'Date', 'y' : 'Amount'}, title='Early Hour
Transactions')
```

Data Analysis Questions 1

Use hvPlot to create a line plot showing a time series from the transactions along all the year for **card holders 2 and 18**. In order to contrast the patterns of both card holders, create a line plot containing both lines. What difference do you observe between the consumption patterns? Does the difference could be a fraudulent transaction? Explain your rationale.

```
# Loading data for card holder 2 and 18 from the database
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \
FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d,
public.merchant_category e \
WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND
d.id_merchant_category=e.id AND a.id IN (2, 18) AND b.card=c.card'

transaction_df = execute_query(query)
transaction_df.head()

data_by_id = transaction_df.groupby('id')
data_by_id
```

Tarun S Gowda

Fraud Detection SQL

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x0000021B074868C8>
```

In [61]:

```
# plot for cardholder 2

cardholder_2 = data_by_id.get_group(2)['amount'].hvplot(ylabel='Amount', xlabel='Date',
title="Transactions by Id Holder 2")
cardholder_2

WARNING:param.CurvePlot03139: title_format is deprecated. Please use title instead
WARNING:param.CurvePlot03139: title_format is deprecated. Please use title instead

# plot for cardholder 18

cardholder_18 = data_by_id.get_group(18)['amount'].hvplot(ylabel='Amount', xlabel='Date',
title="Transactions by Id Holder 18")
cardholder_18

WARNING:param.CurvePlot03302: title_format is deprecated. Please use title instead
WARNING:param.CurvePlot03302: title_format is deprecated. Please use title instead

# combined plot for card holders 2 and 18
cardholder_2 * cardholder_18

WARNING:param.OverlayPlot04094: title_format is deprecated. Please use title instead
WARNING:param.OverlayPlot04094: title_format is deprecated. Please use title instead
```

Conclusions for Question 1

The consumption pattern for both the id holder is very different. Id Holder 2 makes too many small transactions. Id Holder 18 has transactions ranging till \$1839. Id Holder 2 is more susceptible to fraudulent transactions

Data Analysis Question 2

Use Plotly Express to create a series of six box plots, one for each month, in order to identify how many outliers could be per month for **card holder id 25**. By observing the consumption patterns, do you see any anomalies? Write your own conclusions about your insights.

```
# Loading data of daily transactions from jan to jun 2018 for card holder 25
card_holder_id = 25
start_date = '2018-01-01'
end_date = '2018-07-01'
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \
FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d,
public.merchant_category e \
```

Tarun S Gowda

Fraud Detection SQL

```
WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND
d.id_merchant_category=e.id AND a.id={card_holder_id} \
AND date BETWEEN \'{start_date} 00:00:00\':::timestamp AND \'{end_date} 00:00:00\':::timestamp'
transaction_df = execute_query(query)
transaction_df.head()
```

2018-01-02 02:06:21	25	Nancy Contreras	4319653513507	1.46	food truck
2018-01-05 06:26:45	25	Nancy Contreras	372414832802279	10.74	food truck
2018-01-07 14:57:23	25	Nancy Contreras	4319653513507	2.93	food truck
2018-01-10 00:25:40	25	Nancy Contreras	372414832802279	1.39	restaurant
2018-01-14 05:02:22	25	Nancy Contreras	372414832802279	17.84	food truck

```
# change the numeric month to month names
transaction_df['Month'] = transaction_df.index.month_name()
transaction_df.head()
```

2018-01-02	2	Nancy	431965351350	1.4	food	Janua
02:06:21	5	Contreras	7	6	truck	ry
2018-01-05	2	Nancy	372414832802	10.	food	Janua
06:26:45	5	Contreras	279	74	truck	ry
2018-01-07	2	Nancy	431965351350	2.9	food	Janua
14:57:23	5	Contreras	7	3	truck	ry
2018-01-10	2	Nancy	372414832802	1.3	restaura	Janua
00:25:40	5	Contreras	279	9	nt	ry
2018-01-14	2	Nancy	372414832802	17.	food	Janua
05:02:22	5	Contreras	279	84	truck	ry

```
# creating the six box plots using plotly express
px.box(transaction_df, y='amount', hover_data=['category','card'],x='Month', color='category',
title='Transactions by Id Holder 25')
```

Conclusions for Question 2

There seems to be fraudulent transactions pertaining to Restaurant & Food Truck category where Food Truck is ranging from 1.46 to 1046

Identifying Outliers using Standard Deviation

```
# initial imports
import pandas as pd
```

Fraud Detection SQL

```
import numpy as np
import random
from sqlalchemy import create_engine
from numpy import mean
from numpy import std
from numpy import percentile
import plotly.express as px
```

In [92]:

```
# create a connection to the database
engine = create_engine("postgresql://postgres:Istay@10314@localhost:5432/fraud_detection")

# Loading data from the database

def execute_query(query):

    transaction_df = pd.read_sql(sql=query, con=engine, index_col='date', parse_dates='date')

    return transaction_df
```

In [93]:

```
# Loading data of daily transactions from jan to jun 2018 for card holder 25
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \
        FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d,
        public.merchant_category e \
        WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND
        d.id_merchant_category=e.id'
```

```
transaction_df = execute_query(query)
transaction_df.head()
```

2018-01-01 21:35:10	13	John Martin	3561954487988605	6.22	food truck
2018-01-01 21:43:12	13	John Martin	5135837688671496	3.83	bar
2018-01-01 22:41:21	10	Matthew Gutierrez	213193946980303	9.61	food truck
2018-01-01 23:13:30	4	Danielle Green	4263694062533017	19.03	pub
2018-01-01 23:15:10	18	Malik Carlson	4498002758300	2.95	restaurant

```
# code a function to identify outliers based on standard deviation
# calculate summary statistics
data_mean, data_std = mean(transaction_df['amount']), std(transaction_df['amount'])
```

```
# identify outliers
cut_off = data_std * 3
```

```
lower, upper = data_mean - cut_off, data_mean + cut_off
```

```
# identify outliers
outliers = [x for x in transaction_df['amount'] if x < lower or x > upper]
```

```
print('Identified outliers: %d' % len(outliers))
```

Fraud Detection SQL

```
# remove outliers
outliers_removed = [x for x in transaction_df['amount'] if x >= lower and x <= upper]

print('Non-outlier observations: %d' % len(outliers_removed))

transaction_df['outlier'] = (transaction_df['amount'] > upper) | (transaction_df['amount'] < lower)

outlier = transaction_df[transaction_df['outlier']==True]
outlier
```

Identified outliers: 77
Non-outlier observations: 3423

2018-01-02	1			103	restaurant	T
23:27:46	2	Megan Price	501879657465	1.0		ru
						e
2018-01-04	7	Sean Taylor	3516952396080247	168	food	T
03:05:18				5.0	truck	ru
						e
2018-01-08	6	Beth Hernandez	3581345943543942	102	bar	T
02:34:32				9.0		ru
						e
2018-01-22	1	Crystal Clark	5570600642865857	113	restaurant	T
08:07:03	6			1.0		ru
						e
2018-01-23	1	Megan Price	501879657465	167	pub	T
06:29:37	2			8.0		ru
						e
2018-01-24	1	Robert Johnson	4761049645711555	169	coffee	T
13:17:19			811	1.0	shop	ru
						e
2018-01-30	2	Nancy Contreras	4319653513507	117	restaurant	T
18:31:00	5			7.0		ru
						e
2018-02-17	1	Crystal Clark	5570600642865857	143	restaurant	T
01:27:19	6			0.0		ru
						e
2018-02-19	7	Sean Taylor	3516952396080247	107	food	T
16:00:43				2.0	truck	ru
						e
2018-02-19	1	Malik Carlson	344119623920892	183	restaurant	T
22:48:25	8			9.0		ru
						e

Fraud Detection SQL

2018-02-27 15:27:32	6	Beth Hernandez	3581345943543942	114 5.0	bar	T ru e
2018-03-01 21:29:05	3	Elizabeth Sawyer	30078299053512	111 9.0	pub	T ru e
2018-03-04 15:50:53	9	Laurie Gibbs	30181963913340	153 4.0	coffee shop	T ru e
2018-03-05 08:26:08	1 6	Crystal Clark	5570600642865857	161 7.0	bar	T ru e
2018-03-06 07:18:09	2 5	Nancy Contreras	4319653513507	133 4.0	bar	T ru e
2018-03-12 00:44:01	1 2	Megan Price	501879657465	153 0.0	coffee shop	T ru e
2018-03-20 10:19:25	1 2	Megan Price	501879657465	852. 0	pub	T ru e
2018-03-20 13:05:54	2 4	Stephanie Dalton	30142966699187	101 1.0	bar	T ru e
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	100 9.0	coffee shop	T ru e
2018-04-03 03:23:37	1 8	Malik Carlson	344119623920892	107 7.0	restauran t	T ru e
2018-04-08 06:03:50	2 5	Nancy Contreras	4319653513507	106 3.0	pub	T ru e
2018-04-18 23:23:29	7	Sean Taylor	3516952396080247	108 6.0	coffee shop	T ru e
2018-04-21 19:41:51	6	Beth Hernandez	3581345943543942	210 8.0	coffee shop	T ru e
2018-05-08 13:21:01	2 4	Stephanie Dalton	30142966699187	190 1.0	restauran t	T ru e
2018-05-13 06:31:20	2 5	Nancy Contreras	4319653513507	104 6.0	food truck	T ru e

Fraud Detection SQL

2018-05-29 02:55:08	1 6	Crystal Clark	5570600642865857	120 3.0	food truck	T ru e
2018-06-03 20:02:28	1 8	Malik Carlson	344119623920892	181 4.0	pub	T ru e
2018-06-04 03:46:15	2 5	Nancy Contreras	4319653513507	116 2.0	pub	T ru e
2018-06-06 21:50:17	2 5	Nancy Contreras	4319653513507	749. 0	restauran t	T ru e
2018-06-10 04:54:27	9	Laurie Gibbs	30181963913340	179 5.0	pub	T ru e
2018-09-04 01:35:39	1	Robert Johnson	4761049645711555 811	179 0.0	coffee shop	T ru e
2018-09-06 08:28:55	1	Robert Johnson	4761049645711555 811	101 7.0	bar	T ru e
2018-09-06 21:55:02	1	Robert Johnson	4761049645711555 811	105 6.0	restauran t	T ru e
2018-09-10 22:49:41	1 8	Malik Carlson	344119623920892	117 6.0	restauran t	T ru e
2018-09-11 15:16:47	6	Beth Hernandez	3581345943543942	185 6.0	food truck	T ru e
2018-09-23 19:20:23	1 2	Megan Price	501879657465	107 5.0	pub	T ru e
2018-09-25 23:23:21	9	Laurie Gibbs	30181963913340	109 5.0	food truck	T ru e
2018-09-26 08:48:40	1	Robert Johnson	4761049645711555 811	106 0.0	restauran t	T ru e
2018-10-07 14:40:34	3	Elizabeth Sawyer	30078299053512	757. 0	bar	T ru e
2018-10-07 18:29:20	9	Laurie Gibbs	30181963913340	117 9.0	pub	T ru e

Fraud Detection SQL

2018-10-19 01:07:37	3	Elizabeth Sawyer	30078299053512	105 3.0	restaurant	T ru e
2018-11-13 17:07:25	1 6	Crystal Clark	5570600642865857	191 1.0	restaurant	T ru e
2018-11-17 05:30:43	1 8	Malik Carlson	344119623920892	176 9.0	food truck	T ru e
2018-11-20 05:24:28	3	Elizabeth Sawyer	30078299053512	105 4.0	bar	T ru e
2018-11-25 20:44:07	1 2	Megan Price	501879657465	112 3.0	bar	T ru e
2018-11-27 15:36:05	1 2	Megan Price	501879657465	180 2.0	bar	T ru e
2018-11-27 17:20:29	6	Beth Hernandez	3581345943543942	127 9.0	restaurant	T ru e
2018-11-27 17:27:34	1	Robert Johnson	4761049645711555 811	166 0.0	pub	T ru e
2018-12-03 02:38:52	1 6	Crystal Clark	5570600642865857	101 4.0	restaurant	T ru e
2018-12-07 07:22:03	1	Robert Johnson	4761049645711555 811	189 4.0	bar	T ru e
2018-12-13 12:09:58	1 8	Malik Carlson	344119623920892	115 4.0	restaurant	T ru e
2018-12-13 15:51:59	7	Sean Taylor	3516952396080247	224 9.0	food truck	T ru e
2018-12-14 08:51:41	1 2	Megan Price	501879657465	748. 0	pub	T ru e
2018-12-18 13:33:37	2 5	Nancy Contreras	4319653513507	107 4.0	coffee shop	T ru e
2018-12-18 17:20:33	7	Sean Taylor	3516952396080247	129 6.0	bar	T ru e

Fraud Detection SQL

2018-12-19 16:10:03	9	Laurie Gibbs	30181963913340	172 4.0	pub	T ru e
2018-12-21 09:56:32	2 4	Stephanie Dalton	30142966699187	130 1.0	pub	T ru e
2018-12-24 15:55:06	1 6	Crystal Clark	5570600642865857	163 4.0	pub	T ru e
2018-12-25 19:10:42	2 4	Stephanie Dalton	30142966699187	103 5.0	pub	T ru e
2018-12-30 23:23:09	1	Robert Johnson	4761049645711555 811	103 3.0	pub	T ru e

77 rows × 6 columns

```
# find anomalous transactions for 3 random card holders
```

```
import datetime
start_time = datetime.time(7,0,0)
end_time = datetime.time(9,0,0)
```

```
anomalous_transactions = outlier.between_time(start_time, end_time).sort_values('amount',
ascending=False)
```

```
px.scatter(anomalous_transactions, x='name', y='amount', color='category', title='Anomalous
Transactions')
```

Identifying Outliers Using Interquartile Range

```
# code a function to identify outliers based on interquartile range
```

```
# calculate interquartile range
```

```
q25, q75 = percentile(transaction_df['amount'], 25), percentile(transaction_df['amount'], 75)
```

```
iqr = q75 - q25
```

```
print('Percentiles: 25th=%.3f, 75th=%.3f, IQR=%.3f' % (q25, q75, iqr))
```

```
# calculate the outlier cutoff
```

```
cut_off = iqr * 1.5
```

```
lower, upper = q25 - cut_off, q75 + cut_off
```

```
# identify outliers
```

```
outliers_2 = [x for x in transaction_df['amount'] if x < lower or x > upper]
```

```
print('Identified outliers: %d' % len(outliers_2))
```

```
# remove outliers
```

```
outliers_removed_2 = [x for x in transaction_df['amount'] if x >= lower and x <= upper]
```

```
print('Non-outlier observations: %d' % len(outliers_removed_2))
```

```
transaction_df['outlier'] = (transaction_df['amount'] > upper) | (transaction_df['amount'] < lower)
```

```
outlier_2 = transaction_df[transaction_df['outlier']==True]
```

Fraud Detection SQL

outlier_2

Percentiles: 25th=3.735, 75th=14.648, IQR=10.913

Identified outliers: 110

Non-outlier observations: 3390

2018-01-02 23:27:46	12	Megan Price	501879657465	1031.0	restaurant	True
2018-01-04 03:05:18	7	Sean Taylor	3516952396080247	1685.0	food truck	True
2018-01-07 01:10:54	18	Malik Carlson	344119623920892	175.0	pub	True
2018-01-08 02:34:32	6	Beth Hernandez	3581345943543942	1029.0	bar	True
2018-01-08 11:15:36	18	Malik Carlson	344119623920892	333.0	restaurant	True
2018-01-11 13:20:31	16	Crystal Clark	5570600642865857	229.0	pub	True
2018-01-22 08:07:03	16	Crystal Clark	5570600642865857	1131.0	restaurant	True
2018-01-23 06:29:37	12	Megan Price	501879657465	1678.0	pub	True
2018-01-24 13:17:19	1	Robert Johnson	4761049645711555 811	1691.0	coffee shop	True
2018-01-30 18:31:00	25	Nancy Contreras	4319653513507	1177.0	restaurant	True
2018-02-09 11:38:37	7	Sean Taylor	3516952396080247	445.0	bar	True
2018-02-17 01:27:19	16	Crystal Clark	5570600642865857	1430.0	restaurant	True
2018-02-19 16:00:43	7	Sean Taylor	3516952396080247	1072.0	food truck	True
2018-02-19 22:48:25	18	Malik Carlson	344119623920892	1839.0	restaurant	True
2018-02-27 15:27:32	6	Beth Hernandez	3581345943543942	1145.0	bar	True
2018-03-01 21:29:05	3	Elizabeth Sawyer	30078299053512	1119.0	pub	True
2018-03-04 15:50:53	9	Laurie Gibbs	30181963913340	1534.0	coffee shop	True
2018-03-05 08:26:08	16	Crystal Clark	5570600642865857	1617.0	bar	True
2018-03-06 07:18:09	25	Nancy Contreras	4319653513507	1334.0	bar	True
2018-03-09 04:51:38	6	Beth Hernandez	3581345943543942	389.0	restaurant	True
2018-03-12 00:44:01	12	Megan Price	501879657465	1530.0	coffee shop	True
2018-03-20 10:19:25	12	Megan Price	501879657465	852.0	pub	True
2018-03-20 13:05:54	24	Stephanie Dalton	30142966699187	1011.0	bar	True
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	1009.0	coffee shop	True
2018-04-01 07:17:21	25	Nancy Contreras	4319653513507	100.0	coffee shop	True
2018-04-03 03:23:37	18	Malik Carlson	344119623920892	1077.0	restaurant	True
2018-04-08 06:03:50	25	Nancy Contreras	4319653513507	1063.0	pub	True
2018-04-09 10:24:32	1	Robert Johnson	4761049645711555 811	283.0	restaurant	True
2018-04-09 18:28:25	25	Nancy Contreras	4319653513507	269.0	restaurant	True
2018-04-10 06:08:01	7	Sean Taylor	3516952396080247	543.0	food truck	True
2018-10-11 23:29:33	3	Elizabeth Sawyer	30078299053512	206.0	restaurant	True
2018-10-16 13:27:33	1	Robert Johnson	4761049645711555 811	484.0	food truck	True
2018-10-19 01:07:37	3	Elizabeth Sawyer	30078299053512	1053.0	restaurant	True
2018-10-19 12:32:37	16	Crystal Clark	5570600642865857	178.0	food truck	True

Fraud Detection SQL

2018-10-23 22:47:13	16	Crystal Clark	5570600642865857	393.0	food truck	True
2018-10-28 02:12:58	25	Nancy Contreras	4319653513507	137.0	pub	True
2018-11-13 05:58:47	24	Stephanie Dalton	30142966699187	466.0	bar	True
2018-11-13 17:07:25	16	Crystal Clark	5570600642865857	1911.0	restaurant	True
2018-11-17 05:30:43	18	Malik Carlson	344119623920892	1769.0	food truck	True
2018-11-20 05:24:28	3	Elizabeth Sawyer	30078299053512	1054.0	bar	True
2018-11-23 09:08:05	12	Megan Price	501879657465	233.0	restaurant	True
2018-11-25 20:44:07	12	Megan Price	501879657465	1123.0	bar	True
2018-11-26 20:54:39	1	Robert Johnson	4761049645711555 811	267.0	food truck	True
2018-11-27 15:36:05	12	Megan Price	501879657465	1802.0	bar	True
2018-11-27 17:20:29	6	Beth Hernandez	3581345943543942	1279.0	restaurant	True
2018-11-27 17:27:34	1	Robert Johnson	4761049645711555 811	1660.0	pub	True
2018-12-03 02:38:52	16	Crystal Clark	5570600642865857	1014.0	restaurant	True
2018-12-05 19:24:27	9	Laurie Gibbs	30181963913340	57.0	bar	True
2018-12-07 07:22:03	1	Robert Johnson	4761049645711555 811	1894.0	bar	True
2018-12-13 12:09:58	18	Malik Carlson	344119623920892	1154.0	restaurant	True
2018-12-13 15:51:59	7	Sean Taylor	3516952396080247	2249.0	food truck	True
2018-12-14 08:51:41	12	Megan Price	501879657465	748.0	pub	True
2018-12-18 13:33:37	25	Nancy Contreras	4319653513507	1074.0	coffee shop	True
2018-12-18 17:20:33	7	Sean Taylor	3516952396080247	1296.0	bar	True
2018-12-19 16:10:03	9	Laurie Gibbs	30181963913340	1724.0	pub	True
2018-12-21 09:56:32	24	Stephanie Dalton	30142966699187	1301.0	pub	True
2018-12-24 15:55:06	16	Crystal Clark	5570600642865857	1634.0	pub	True
2018-12-25 19:10:42	24	Stephanie Dalton	30142966699187	1035.0	pub	True
2018-12-28 16:20:31	3	Elizabeth Sawyer	30078299053512	313.0	pub	True
2018-12-30 23:23:09	1	Robert Johnson	4761049645711555 811	1033.0	pub	True

110 rows × 6 columns

find anomalous transactions for 3 random card holders

```
anomalous_transactions2 = outlier_2.between_time(start_time, end_time).sort_values('amount',
ascending=False)
anomalous_transactions2
```

2018-12-07 07:22:03	1	Robert Johnson	4761049645711555 811	189 4.0	bar	T ru e
------------------------	---	-------------------	-------------------------	------------	-----	--------------

Fraud Detection SQL

2018-03-05 08:26:08	1 6	Crystal Clark	5570600642865857	161 7.0	bar	T ru e
2018-03-06 07:18:09	2 5	Nancy Contreras	4319653513507	133 4.0	bar	T ru e
2018-01-22 08:07:03	1 6	Crystal Clark	5570600642865857	113 1.0	restaur ant	T ru e
2018-09-26 08:48:40	1	Robert Johnson	4761049645711555 811	106 0.0	restaur ant	T ru e
2018-09-06 08:28:55	1	Robert Johnson	4761049645711555 811	101 7.0	bar	T ru e
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	100 9.0	coffee shop	T ru e
2018-12-14 08:51:41	1 2	Megan Price	501879657465	748. 0	pub	T ru e
2018-04-01 07:17:21	2 5	Nancy Contreras	4319653513507	100. 0	coffee shop	T ru e

```
px.scatter(anomalous_transactions2, x='name', y='amount', color='category', title="Early Hour Transactions")
```

For Outlier calculation using standard deviation, results in 77 records whereas using Interquartile range results in 110 records. There seems to be fraudulent transactions in Bar category wherein amount spent between 7-9 AM in the Bar

Visual Data Analysis of Fraudulent Transactions

```
# initial imports
import pandas as pd
import calendar
import plotly.express as px
import hvplot.pandas
from sqlalchemy import create_engine
import datetime

# create a connection to the database
engine = create_engine("postgresql://postgres:Istay@10314@localhost:5432/fraud_detection")

# Loading data from the database

def execute_query(query):

    transaction_df = pd.read_sql(sql=query, con=engine, index_col='date', parse_dates='date')

    return transaction_df

def fraud_transactions(df):
    start_time = datetime.time(7,0,0)
    end_time = datetime.time(9,0,0)
    return df.between_time(start_time, end_time).sort_values('amount', ascending=False)

# Loading data for card holder 2 and 18 from the database
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \
        FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d, \
        public.merchant_category e \
        WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND \
        d.id_merchant_category=e.id AND b.card=c.card'

transaction_df = execute_query(query)

suspect_df = fraud_transactions(transaction_df).head(100)
suspect_df
```

2018-12-07 07:22:03	1	Robert Johnson	4761049645711555811	1894.00	bar
2018-03-05 08:26:08	16	Crystal Clark	5570600642865857	1617.00	bar
2018-03-06 07:18:09	25	Nancy Contreras	4319653513507	1334.00	bar
2018-01-22 08:07:03	16	Crystal Clark	5570600642865857	1131.00	restaurant

Fraud Detection SQL

2018-09-26 08:48:40	1	Robert Johnson	4761049645711555811	1060.00	restaurant
2018-09-06 08:28:55	1	Robert Johnson	4761049645711555811	1017.00	bar
2018-03-26 07:41:59	9	Laurie Gibbs	30181963913340	1009.00	coffee shop
2018-12-14 08:51:41	12	Megan Price	501879657465	748.00	pub
2018-04-01 07:17:21	25	Nancy Contreras	4319653513507	100.00	coffee shop
2018-08-26 07:15:18	20	Kevin Spencer	4506405265172173	23.13	food truck
2018-08-28 07:17:14	10	Matthew Gutierrez	4165305432349489280	20.71	coffee shop
2018-10-07 08:16:54	20	Kevin Spencer	4586962917519654607	20.44	food truck
2018-10-18 07:16:04	16	Crystal Clark	5500708021555307	19.86	pub
2018-03-03 08:42:02	24	Stephanie Dalton	4681896441519	19.50	food truck
2018-06-04 08:30:28	4	Danielle Green	584226564303	19.49	food truck
2018-03-26 08:08:27	16	Crystal Clark	5500708021555307	19.34	pub
2018-06-01 08:56:59	11	Brandon Pineda	180098539019105	19.33	restaurant
2018-12-23 07:39:47	10	Matthew Gutierrez	4962915017023706562	19.27	pub
2018-09-23 07:30:56	15	Kyle Tucker	4723783028106084756	19.02	restaurant
2018-02-21 08:21:10	5	Sara Cooper	4268491956169254	18.98	food truck
2018-07-04 08:51:29	10	Matthew Gutierrez	213193946980303	18.93	coffee shop
2018-08-02 07:44:24	19	Peter Mckay	5361779664174555	18.93	food truck
2018-06-09 07:29:28	23	Mark Lewis	4188164051171486	18.82	pub
2018-06-02 07:45:48	23	Mark Lewis	4150721559116778	18.76	food truck
2018-01-06 08:42:50	20	Kevin Spencer	3535651398328201	18.72	restaurant
2018-06-24 07:28:48	14	Gary Jacobs	5175947111814778	18.60	pub
2018-06-23 07:12:06	8	Michael Floyd	4834483169177062	18.56	restaurant
2018-08-14 08:38:49	18	Malik Carlson	4498002758300	18.54	restaurant
2018-10-07 07:08:08	24	Stephanie Dalton	3582198969197591	18.53	food truck
2018-02-27 08:27:00	2	Shane Shaffer	675911140852	18.52	restaurant
2018-12-11 07:42:50	1	Robert Johnson	3517111172421930	14.92	restaurant
2018-04-07 07:18:20	12	Megan Price	5297187379298983	14.80	food truck
2018-08-02 07:13:49	7	Sean Taylor	3516952396080247	14.42	coffee shop
2018-12-15 08:34:15	25	Nancy Contreras	372414832802279	14.36	food truck
2018-04-24 07:41:49	15	Kyle Tucker	6500236164848279	14.30	food truck
2018-10-22 07:41:56	13	John Martin	4711773125020499	13.83	coffee shop
2018-09-03 07:27:55	12	Megan Price	376027549341849	13.59	pub
2018-03-10 08:52:09	2	Shane Shaffer	675911140852	13.53	coffee shop
2018-04-27 08:08:38	19	Peter Mckay	3561072557118696	13.52	food truck
2018-02-26 07:31:20	20	Kevin Spencer	4586962917519654607	13.46	pub
2018-10-27 08:04:44	23	Mark Lewis	4150721559116778	12.98	coffee shop
2018-05-01 07:40:00	15	Kyle Tucker	6500236164848279	12.98	bar
2018-03-30 08:12:28	5	Sara Cooper	4268491956169254	12.96	coffee shop
2018-01-17 07:31:03	18	Malik Carlson	4498002758300	12.67	food truck
2018-08-08 08:36:23	11	Brandon Pineda	180098539019105	12.52	coffee shop

Fraud Detection SQL

2018-07-30 08:49:16	5	Sara Cooper	4276466390111	12.50	food truck
2018-11-30 08:52:20	7	Sean Taylor	4539990688484983	12.32	coffee shop
2018-12-29 08:11:55	18	Malik Carlson	4498002758300	12.25	restaurant
2018-02-19 08:50:36	1	Robert Johnson	4761049645711555811	12.17	food truck
2018-01-20 08:35:34	12	Megan Price	501879657465	11.96	bar
2018-07-31 07:44:59	24	Stephanie Dalton	4681896441519	11.93	bar
2018-01-17 07:56:09	24	Stephanie Dalton	4681896441519	11.91	restaurant
2018-06-08 07:25:30	25	Nancy Contreras	372414832802279	11.88	coffee shop
2018-12-31 08:22:17	23	Mark Lewis	4188164051171486	11.87	restaurant
2018-08-30 08:46:49	4	Danielle Green	584226564303	11.86	bar
2018-04-08 07:06:20	13	John Martin	3561954487988605	11.73	food truck
2018-09-15 08:33:49	16	Crystal Clark	5500708021555307	11.72	coffee shop
2018-12-18 07:45:28	21	Dana Washington	4279104135293225293	11.70	food truck
2018-02-25 07:37:03	13	John Martin	5135837688671496	11.68	pub
2018-05-04 08:21:59	11	Brandon Pineda	4027907156459098	11.65	pub

100 rows × 5 columns

```
px.scatter(suspect_df, x=suspect_df.index, y='amount', color='category', size='amount',
hover_data=['name', 'category'], labels = {'x' : 'Date', 'y' : 'Amount'}, title='Early Hour
Transactions')
```

Data Analysis Questions 1

Use hvPlot to create a line plot showing a time series from the transactions along all the year for **card holders 2 and 18**. In order to contrast the patterns of both card holders, create a line plot containing both lines. What difference do you observe between the consumption patterns? Does the difference could be a fraudulent transaction? Explain your rationale.

```
# Loading data for card holder 2 and 18 from the database
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \
FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d,
public.merchant_category e \
WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND
d.id_merchant_category=e.id AND a.id IN (2, 18) AND b.card=c.card'
```

```
transaction_df = execute_query(query)
transaction_df.head()
```

```
data_by_id = transaction_df.groupby('id')
data_by_id
```

<pandas.core.groupby.generic.DataFrameGroupBy object at 0x0000021B074868C8>

Fraud Detection SQL

```
# plot for cardholder 2
```

```
cardholder_2 = data_by_id.get_group(2)['amount'].hvplot(ylabel='Amount', xlabel='Date',  
title="Transactions by Id Holder 2")  
cardholder_2
```

WARNING:param.CurvePlot03139: title_format is deprecated. Please use title instead

WARNING:param.CurvePlot03139: title_format is deprecated. Please use title instead

```
# plot for cardholder 18
```

```
cardholder_18 = data_by_id.get_group(18)['amount'].hvplot(ylabel='Amount', xlabel='Date',  
title="Transactions by Id Holder 18")  
cardholder_18
```

WARNING:param.CurvePlot03302: title_format is deprecated. Please use title instead

WARNING:param.CurvePlot03302: title_format is deprecated. Please use title instead

```
# combined plot for card holders 2 and 18  
cardholder_2 * cardholder_18
```

WARNING:param.OverlayPlot04764: title_format is deprecated. Please use title instead

WARNING:param.OverlayPlot04764: title_format is deprecated. Please use title instead

Conclusions for Question 1

The consumption pattern for both the id holder is very different. Id Holder 2 makes too many small transactions. Id Holder 18 has transactions ranging till \$1839. Id Holder 2 is more susceptible to fraudulent transactions

Data Analysis Question 2

Use Plotly Express to create a series of six box plots, one for each month, in order to identify how many outliers could be per month for **card holder id 25**. By observing the consumption patterns, do you see any anomalies? Write your own conclusions about your insights.

```
# Loading data of daily transactions from jan to jun 2018 for card holder 25  
card_holder_id = 25  
start_date = '2018-01-01'  
end_date = '2018-07-01'  
query = f'SELECT a.id, a.name, b.card, c.date, c.amount, e.name as "category" \  
FROM public.card_holder a, public.credit_card b, public.transaction c, public.merchant d,  
public.merchant_category e \  
WHERE a.id = b.id_card_holder AND b.card=c.card AND c.id_merchant=d.id AND  
d.id_merchant_category=e.id AND a.id={card_holder_id} \  
AND date BETWEEN \'{start_date} 00:00:00\':timestamp AND \'{end_date} 00:00:00\':timestamp'  
transaction_df = execute_query(query)  
transaction_df.head()
```

Fraud Detection SQL

2018-01-02 02:06:21	25	Nancy Contreras	4319653513507	1.46	food truck
2018-01-05 06:26:45	25	Nancy Contreras	3724148328022 79	10.7 4	food truck
2018-01-07 14:57:23	25	Nancy Contreras	4319653513507	2.93	food truck
2018-01-10 00:25:40	25	Nancy Contreras	3724148328022 79	1.39	restaurant
2018-01-14 05:02:22	25	Nancy Contreras	3724148328022 79	17.8 4	food truck

change the numeric month to month names

```
transaction_df['Month'] = transaction_df.index.month_name()
transaction_df.head()
```

2018-01-02 02:06:21	2 5	Nancy Contreras	431965351350 7	1.4 6	food truck	Janua ry
2018-01-05 06:26:45	2 5	Nancy Contreras	372414832802 279	10. 74	food truck	Janua ry
2018-01-07 14:57:23	2 5	Nancy Contreras	431965351350 7	2.9 3	food truck	Janua ry
2018-01-10 00:25:40	2 5	Nancy Contreras	372414832802 279	1.3 9	restaurationt	Janua ry
2018-01-14 05:02:22	2 5	Nancy Contreras	372414832802 279	17. 84	food truck	Janua ry

creating the six box plots using plotly express

```
px.box(transaction_df, y='amount', hover_data=['category', 'card'], x='Month', color='category',
title='Transactions by Id Holder 25')
```

Conclusions for Question 2

There seems to be fraudulent transactions pertaining to Restaurant & Food Truck category where Food Truck is ranging from 1.46 to 1046

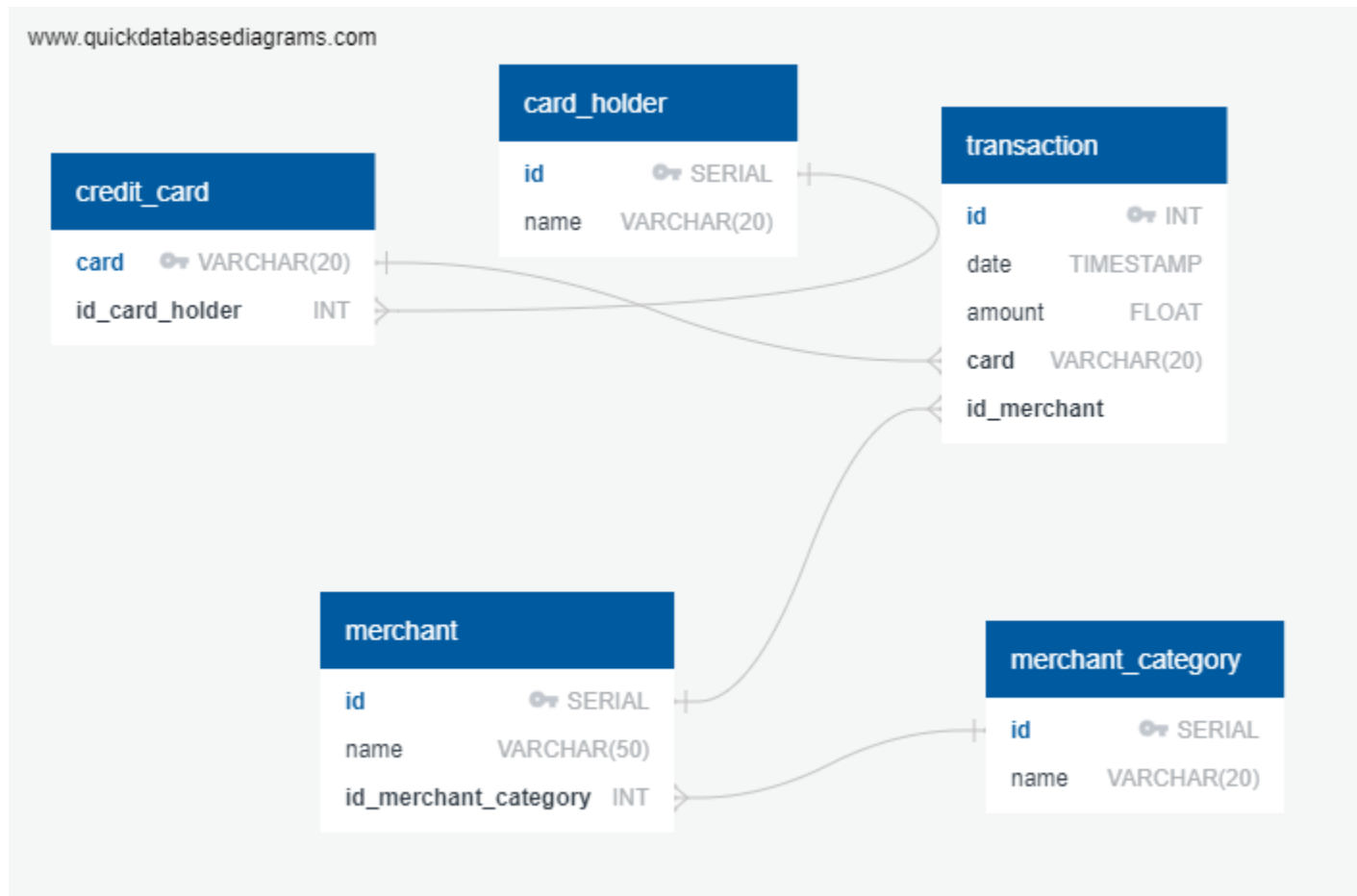
Data Modeling

Create an entity relationship diagram (ERD) by inspecting the provided CSV files.

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Note: For the credit_card table, the card column should be a VARCHAR(20) datatype rather than an INT. Tool used to develop ERD [Quick Database Diagrams](http://www.quickdatabasediagrams.com) to create your model.



Data Engineering

Using your database model as a blueprint, create a database schema for each of your tables and relationships. Specify data types, primary keys, foreign keys, and any other constraints you defined. After creating the database schema, import the data from the corresponding CSV files.

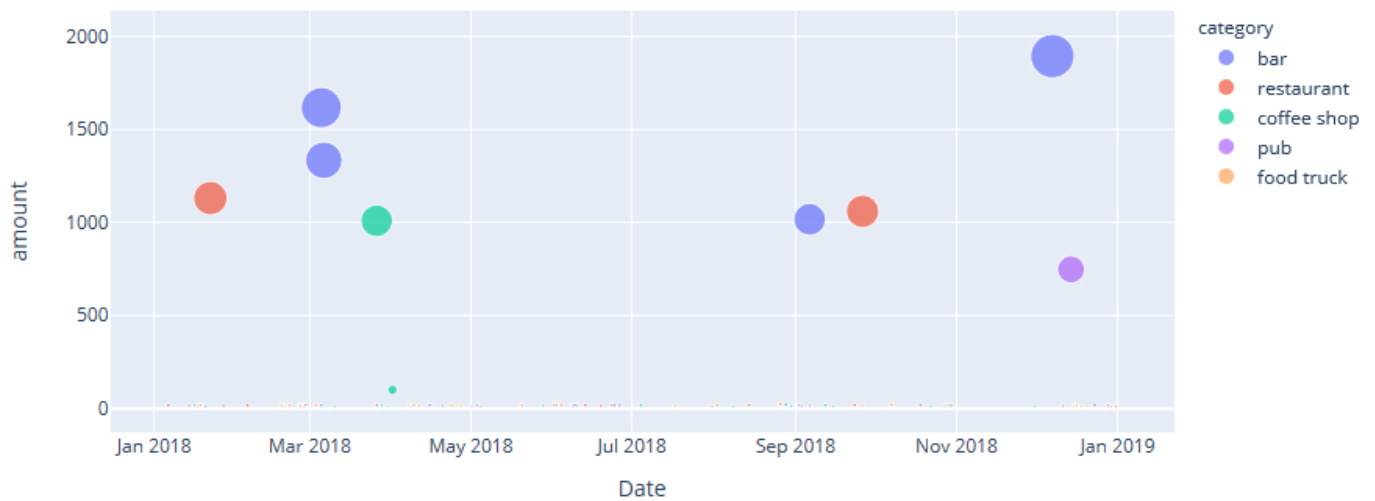
Data Analysis

Now that your data is prepared within the database, it's finally time to identify fraudulent transactions using SQL and Pandas DataFrames.

Top 100 highest transactions during early hours i.e. 7:00 to 9:00 AM

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Early Hour Transactions



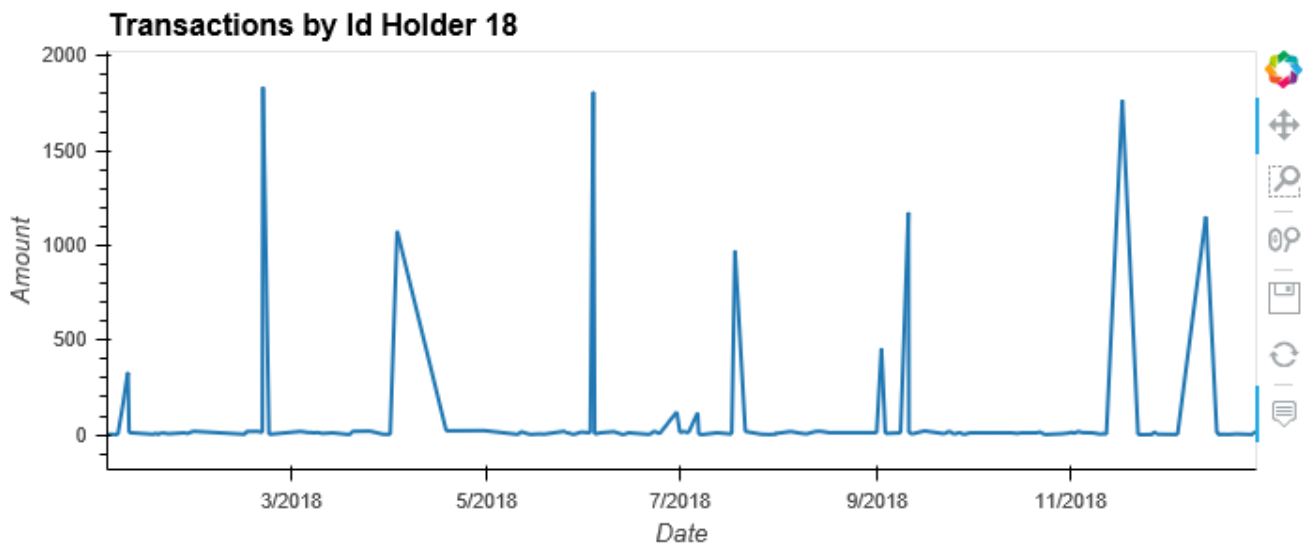
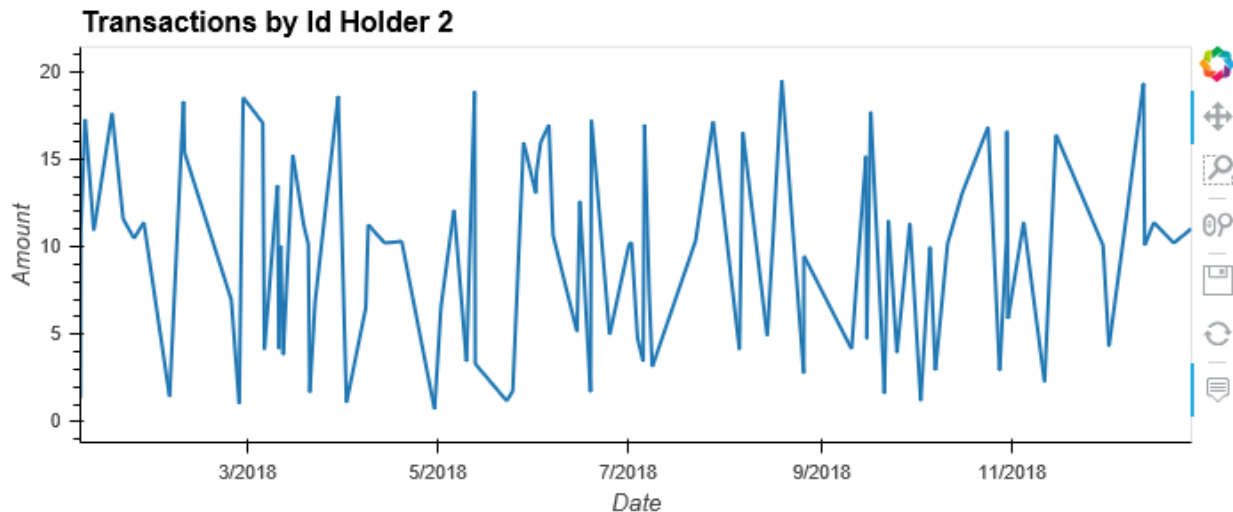
- Some fraudsters hack a credit card by making several small payments (generally less than \$2.00), which are typically ignored by cardholders. Count the transactions that are less than \$2.00 per cardholder. Is there any evidence to suggest that a credit card has been hacked? Explain your rationale.
- What are the top five merchants prone to being hacked using small transactions?
- Once you have a query that can be reused, create a view for each of the previous queries.

Created a report for fraudulent transactions of some top customers of the firm using Pandas, Plotly Express, hvPlot, and SQLAlchemy to create the visualizations.

- Fraudulent transactions in the history of two of the most important customers of the firm on the basis of their cardholders' IDs are 18 and 2.

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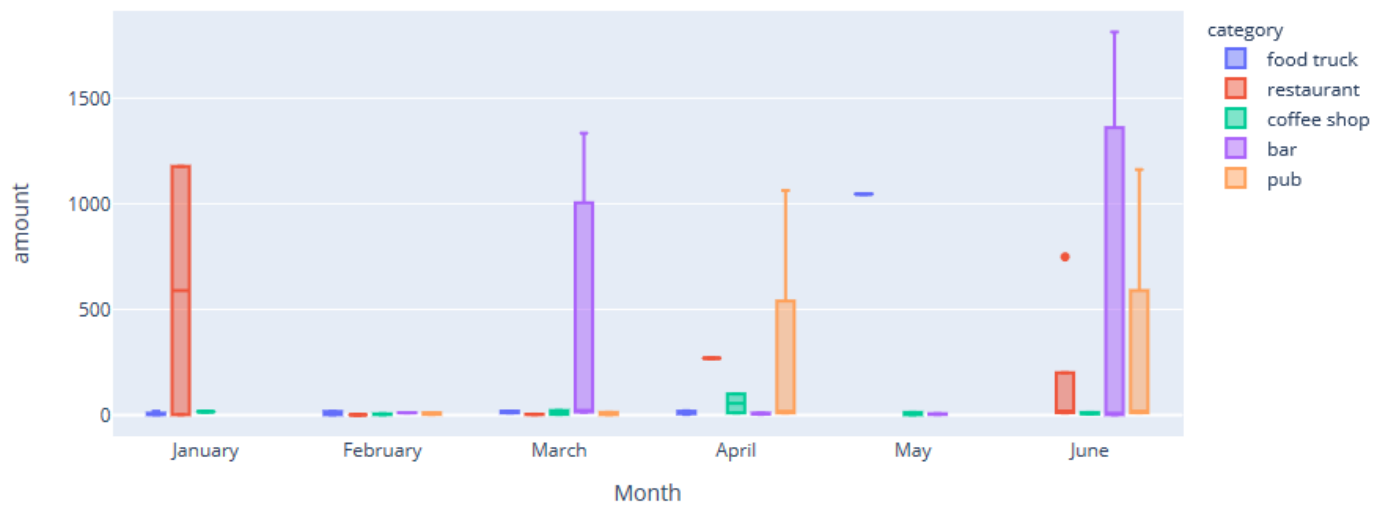
Warning: pandas.Series.plot() is deprecated. Please use plot_series instead.



- Observation : The consumption pattern for both the id holder is very different. Id Holder 2 makes too many small transactions. Id Holder 18 has transactions ranging till \$1839. Id Holder 2 is more susceptible to fraudulent transactions
- The CEO of the firm's biggest customer suspects that someone has used her corporate credit card without authorization in the first quarter of 2018 to pay for several expensive restaurant bills. You are asked to find any anomalous transactions during that period.
 - Using Plotly Express, created a series of six box plots, one for each month, in order to identify how many outliers there are per month for cardholder ID 25.

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Transactions by Id Holder 25



- - Observations : There seems to be fraudulent transactions pertaining to Restaurant & Food Truck category where Food Truck is ranging from \$1.46 to \$1046

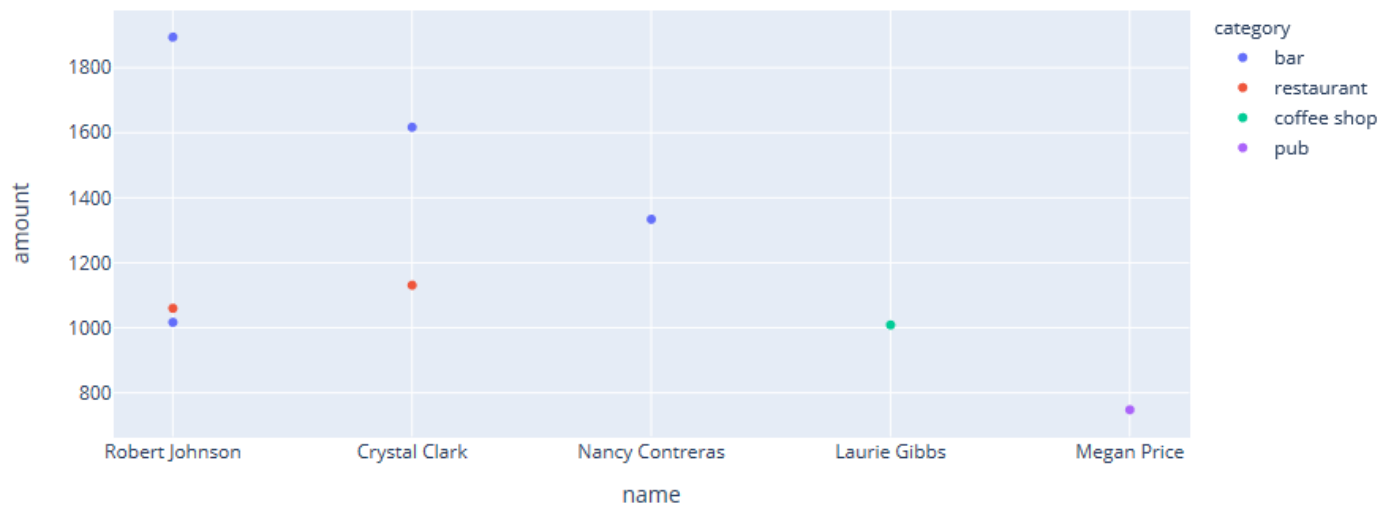
Challenge

Another approach to identify fraudulent transactions is to look for outliers in the data. Standard deviation or quartiles are often used to detect outliers.

Identifying Outliers based on Standard Deviation

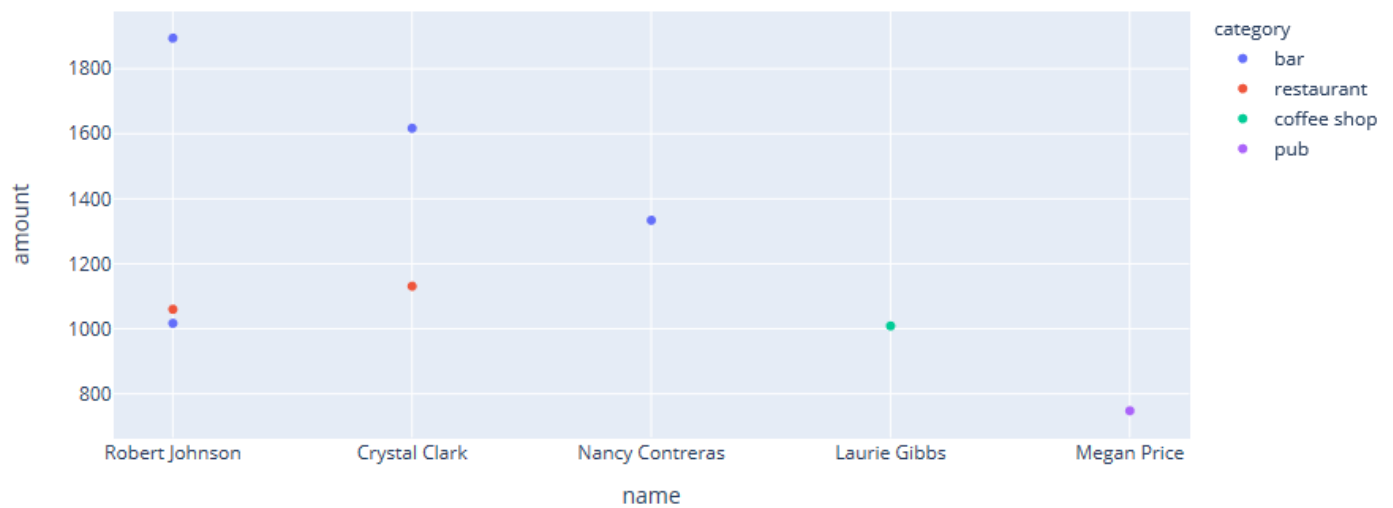
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Anomalous Transactions



Identifying Outliers based on Interquartile Range

Anomalous Transactions



Advantages of Fraud Detection Using SQL

- 1. Direct Access to Data**
 - a. SQL allows direct querying of transactional databases, which is useful for analyzing large volumes of financial or user behavior data in real-time.
- 2. Simplicity and Readability**
 - a. SQL is relatively easy to understand and write, especially for pattern-matching queries (e.g., finding duplicates, anomalies, or suspicious trends).
- 3. Custom Rule Creation**
 - a. You can define custom business rules using SQL, such as flagging transactions above a certain amount or multiple transactions from different locations in a short time.
- 4. Integration with Existing Systems**
 - a. Most organizations already use relational databases. SQL-based solutions integrate well with existing infrastructure without the need for additional tools.
- 5. Low Cost**
 - a. No need for additional software if you're using your existing RDBMS. It's a cost-effective way to start simple fraud detection.
- 6. Automation Capabilities**
 - a. SQL queries can be scheduled to run periodically using cron jobs or database jobs to detect fraud continuously.

Disadvantages of Fraud Detection Using SQL

- 1. Limited to Known Patterns**
 - a. SQL works best with rules-based detection. It struggles to detect unknown or evolving fraud patterns (unlike machine learning approaches).
- 2. Lacks Advanced Analytics**
 - a. No built-in support for statistical modeling, anomaly detection, or machine learning unless paired with external tools.
- 3. Scalability Issues**
 - a. Complex queries on large datasets can become slow and resource-intensive, especially without proper indexing or optimization.
- 4. Hard to Maintain Complex Rules**
 - a. As fraud detection rules grow in complexity, SQL queries become harder to read, maintain, and debug.
- 5. No Real-Time Alerts by Default**
 - a. SQL is not inherently event-driven. Without additional tools, it doesn't provide real-time fraud alerts or streaming data analysis.
- 6. Security Risks**

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- a. Poorly written queries or over-permissioned accounts can expose sensitive data or create performance bottlenecks.

When to Use SQL for Fraud Detection

- Ideal for small to medium-sized datasets.
- Good for initial screening or prototyping rule-based fraud detection.
- Useful when fraud patterns are known and consistent.

Future Scope of Fraud Detection Using SQL

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Continued Use as a Foundational Layer

- **Data Preprocessing & Feature Engineering:** SQL will remain essential for cleaning, transforming, and aggregating transactional data before feeding it into more advanced systems (like machine learning models).
- **Rule-Based Triggers:** Many industries will still rely on SQL to define hard-coded rules for detecting known fraud patterns, such as:
 - Sudden large withdrawals
 - Multiple failed login attempts
 - Rapid succession of transactions

2. Integration with Modern Technologies

- **SQL + AI/ML Integration:**
 - SQL will be used to extract features from databases, while Python or R can run machine learning models.
 - Tools like BigQuery ML, Snowflake, and Azure Synapse allow running ML models *using SQL itself*, bridging the gap.
- **Use in Real-Time Pipelines:**
 - With platforms like Apache Kafka and Flink, SQL is evolving into **streaming SQL** for real-time fraud detection (e.g., KSQL in Kafka).

3. Expansion with Cloud Data Warehouses

- Platforms like **Snowflake, BigQuery, and Amazon Redshift** are enabling advanced analytics directly through SQL.
- These cloud data warehouses provide scalability, allowing more complex fraud detection logic to be handled using SQL at larger scales.

4. Visualization and Reporting

- SQL will continue to be used to build dashboards and alerts in tools like **Tableau, Power BI, and Looker** for fraud monitoring.
- Analysts and fraud teams rely heavily on SQL to generate insights, KPIs, and reports from transactional data.

5. Low-Code / No-Code Enhancements

- Future tools may offer visual interfaces that generate SQL queries in the background, allowing non-technical users to set up fraud detection workflows using SQL-like logic.

Conclusion

Fraud detection using SQL continues to be a valuable and practical approach, especially in environments where transactional data is stored in relational databases and where known patterns of fraudulent behavior can be identified through clearly defined rules. SQL offers a straightforward, cost-effective method to implement fraud

Fraud Detection SQL

detection logic, enabling organizations to flag suspicious transactions, detect anomalies, and generate alerts based on business-specific criteria. Its accessibility and integration with existing database systems make it an ideal choice for initial screening processes and for building real-time dashboards and reports. While SQL excels at rule-based detection, it does face limitations when dealing with large-scale, dynamic, and evolving fraud patterns that require predictive capabilities or advanced anomaly detection. In such cases, SQL is best used in combination with more sophisticated tools such as machine learning algorithms or real-time data processing platforms. Nevertheless, the future of fraud detection still sees a prominent role for SQL, not as a standalone solution, but as a critical component of a multi-layered fraud detection system. Whether through data preprocessing, feature engineering, or integration into cloud data platforms, SQL continues to support the foundation of more complex analytical pipelines. As the threat of fraud becomes more advanced, SQL will remain a reliable tool for extracting meaningful patterns from structured data and enhancing the effectiveness of broader fraud detection strategies.

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