



# Target Brazil – SQL Case Study (BigQuery)

## By: Shivesh Raj Sahu

```
-- Before we get started with this project,
-- it is important we double check the dataset before we start working

1
2
3
4 SELECT *
5 FROM 'target_brazil.customers'
6 LIMIT 10;
7
8 SELECT *
9 FROM 'target_brazil.geolocation'
10 LIMIT 10;
11
12 SELECT *
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15
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18 LIMIT 10;
19
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21 FROM 'target_brazil.orders'
22 LIMIT 10;
23
24 SELECT *
25 FROM 'target_brazil.payments'
26 LIMIT 10;
27
28 SELECT *
29 FROM 'target_brazil.products'
30 LIMIT 10;
31
32 SELECT *
33 FROM 'target_brazil.sellers'
34 LIMIT 10;
35
```

Query completed

Query results

Save results Open in

Job information	Results	Visualization	JSON	Execution details	Execution graph			
Row	order_id	customer_id	order_status	order_purchase_timestamp	order_approved_at	order_delivered_carrier_date	order_delivered_customer_date	order_estimated_delivery_date
1	a2e4c44360b4a57bd722f3a46...	8886130db0ea6e9e70ba0b03d...	approved	2017-02-06 20:18:17 UTC	2017-02-06 20:30:19 UTC	null	null	2017-03-01 00:00:00 UTC
2	132f1e724165a07f6362532bf9...	b2191912d8adfeac2e4dc3b6e...	approved	2017-04-25 01:25:34 UTC	2017-04-30 20:32:41 UTC	null	null	2017-05-22 00:00:00 UTC
3	809a282b05dbcab6f27724fc...	622e13439d6b5a0b486c43561...	canceled	2016-09-13 15:24:19 UTC	2016-10-07 13:16:46 UTC	null	null	2016-09-30 00:00:00 UTC
4	a5215419bb6764b3b7cd68103...	b6f6cbf126f1ae6723f62f9b37...	canceled	2016-10-22 08:25:27 UTC	null	null	null	2016-10-24 00:00:00 UTC
5	71303d7e93b399f5bdc537612...	b10b360f62e68849fbd056f7...	canceled	2016-10-02 22:07:52 UTC	2016-10-06 15:50:56 UTC	null	null	2016-10-25 00:00:00 UTC
6	e9fa5a72109417c5640208e4e...	683c54fc24d40e9ffadfc179d...	canceled	2016-09-05 00:15:34 UTC	2016-10-07 13:17:15 UTC	null	null	2016-10-28 00:00:00 UTC
7	92d7315171717c2d61618204549...	95c44daefa7bf91c6b00665a0...	canceled	2016-10-05 11:23:13 UTC	null	null	null	2016-11-14 00:00:00 UTC
8	ddac6ff982b13e7e048b627a...	68f4ad79cc0c2ad06e19088f5c...	canceled	2016-10-04 19:41:32 UTC	null	null	null	2016-11-16 00:00:00 UTC
9	c549f0d8f33bfe43351b8931f...	ea26950075411d4c3569a7185...	canceled	2016-10-06 13:21:05 UTC	null	null	null	2016-11-16 00:00:00 UTC
10	9bd5312d1248b0a4460f702ba...	4d149fd1d3245cb36970641b...	canceled	2016-10-06 20:43:30 UTC	null	null	null	2016-11-16 00:00:00 UTC

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31
32 SELECT *
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```

Query completed

Query results

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	order_id	payment_seque...	payment_type	payment_installm...	payment_value
1	744bade1cf9ff3f18b0ace07...	2	credit_card	0	58.69
2	1a5710839416c0b47d8f876a...	2	credit_card	0	129.94
3	8bcbe01d4d147991cd31926...	4	voucher	1	0.0
4	fa65dad1b0e818c0cc5b0e39...	14	voucher	1	0.0
5	6cd8433e0daae1283cc09561...	4	voucher	1	0.0
6	4637ca194ba387c2d538a089b...	1	not_defined	1	0.0
7	00b1c60320190ca0a2c88b3...	1	not_defined	1	0.0
8	45e6ae83398a87c253b647c2d...	3	voucher	1	0.0
9	fa65dad1b0e818c0cc5b0e39...	13	voucher	1	0.0
10	c8c528189310eaa44a743bda9...	1	not_defined	1	0.0

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32 SELECT *
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```

Query completed

Query results

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	seller_id	seller_zip_code_2...	seller_city	seller_state	
1	c13ef0c04e421907809621ce81...	1207	sao paulo sp	sp	
2	5444612c82921c9292639ebc7...	2051	sao paulo	sp	
3	1c0d32d0d091bb8087a5eb088...	3363	sp / sp	sp	
4	71593c7413973a1e160057680...	3407	sao paulo / sao paulo	sp	
5	4f1a1263039c76ef8f40a6536...	3581	sao paulo	sp	
6	0657ba023bdc5a1a12a6e4b...	4007	sao paulo - sp	sp	
7	809a490573dc0ca343a7231e...	4130	sao paulo - sp	sp	
8	a3fa183f686cc0ca3ab0b0bd...	4557	sao paulo	sp	
9	216a2a71501a8103a47d0721...	4774	sp	sp	
10	0b186b38b0d1d72356790363...	5141	sp	sp	

# Target Brazil – SQL Case Study (BigQuery)

## By: Shivesh Raj Sahu

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```

Query completed

### Query results

Job Information	Results	Visualization	JSON	Execution details	Execution graph				
Row	product_id	product category	product_name_le...	product_descripti...	product_photos...	product_weight_g	product_length_cm	product_height_cm	product_width_cm
1	5eb564652db742ff8f28759cd8...	null	null	null	null	null	null	null	null
2	09ff539a621711667c43eba6a3...	babies		865	3	null	null	null	null
3	a69f15dfb803d485e8933e80b9...	Watches present	53	506	6	150	11	16	6
4	2f763ba79d9cd987b2034aac7...	electronics	45	1198	2	595	8	6	6
5	106392145fca363410d287a81...	bed table bath	58	309	1	2083	12	2	7
6	7e33f4a1c59f89da30a335b2dc...	electronics	51	381	3	1075	22	5	7
7	bc9cc914f974963c07be697fc9...	HEALTH BEAUTY	55	435	1	75	14	9	7
8	e1cfc87f543782b8a78b59fc85...	Garden tools	39	524	4	369	26	7	7
9	fd78812672eb8dd819fad93951...	HEALTH BEAUTY	60	630	2	187	12	7	8
10	3fddda7e92c16fa45033a4373a...	perfumery	45	650	1	75	11	11	8

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### Initial Exploration

```
35
36 -- All of the tables are correctly loaded and
37 -- the dataset is present with correct column names
38
39 --Quick checklist
40 -- 1. Row counts per table (helps catch partial uploads)
41 SELECT 'customers' AS table, COUNT(*) AS row_count FROM `target_brazil.customers` UNION ALL
42 SELECT 'sellers' AS table, COUNT(*) AS row_count FROM `target_brazil.sellers` UNION ALL
43 SELECT 'orders' AS table, COUNT(*) AS row_count FROM `target_brazil.orders` UNION ALL
44 SELECT 'order_items' AS table, COUNT(*) AS row_count FROM `target_brazil.order_items` UNION ALL
45 SELECT 'payments' AS table, COUNT(*) AS row_count FROM `target_brazil.payments` UNION ALL
46 SELECT 'order_reviews' AS table, COUNT(*) AS row_count FROM `target_brazil.order_reviews` UNION ALL
47 SELECT 'geolocation' AS table, COUNT(*) AS row_count FROM `target_brazil.geolocation` UNION ALL
48 SELECT 'products' AS table, COUNT(*) AS row_count FROM `target_brazil.products`;
49
50
51 -- 2. Confirm column types ( especially about timestamps and numeric fields)
52 SELECT table_name, column_name, data_type
53 FROM `target_brazil`.INFORMATION_SCHEMA.COLUMNS
54 ORDER BY table_name, ordinal_position;
55
56
```

✓ This script will process 252.67 MB when run.

### Query results

Job Information	Results	Visualization	JSON	Execution details	Execution graph
Row	table	row_count			
1	geolocation	1000163			
2	products	32951			
3	order_reviews	99224			
4	payments	103886			
5	orders	99441			
6	order_items	112650			
7	customers	99441			
8	sellers	3095			

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

```
51 --2.- Confirm column types (especially about timestamps and numeric fields)
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53 FROM `target_brazil`.INFORMATION_SCHEMA.COLUMNS
54 ORDER BY table_name, ordinal_position;
55
```

✓ This script will process 252.67 MB when run.

### Query results

Job information					Results	Visualization	JSON	Execution details	Execution graph
Row	table_name	column_name	data_type						
1	customers	customer_id	STRING						
2	customers	customer_unique_id	STRING						
3	customers	customer_zip_code_prefix	INT64						
4	customers	customer_city	STRING						
5	customers	customer_state	STRING						
6	geolocation	geolocation_zip_code_prefix	INT64						
7	geolocation	geolocation_lat	FLOAT64						
8	geolocation	geolocation_lng	FLOAT64						
9	geolocation	geolocation_city	STRING						
10	geolocation	geolocation_state	STRING						
11	order_items	order_id	STRING						
12	order_items	order_item_id	INT64						
13	order_items	product_id	STRING						
14	order_items	seller_id	STRING						
15	order_items	shipping_limit_date	TIMESTAMP						
16	order_items	price	FLOAT64						
17	order_items	freight_value	FLOAT64						
18	order_reviews	review_id	STRING						
19	order_reviews	order_id	STRING						
20	order_reviews	review_score	INT64						
21	order_reviews	review_comment_title	STRING						
22	order_reviews	review_creation_date	TIMESTAMP						
23	order_reviews	review_answer_timestamp	TIMESTAMP						
24	orders	order_id	STRING						
25	orders	customer_id	STRING						
26	orders	order_status	STRING						
27	orders	order_purchase_timestamp	TIMESTAMP						
28	orders	order_approved_at	TIMESTAMP						
29	orders	order_delivered_carrier_date	TIMESTAMP						
30	orders	order_delivered_customer_date	TIMESTAMP						
31	orders	order_estimated_delivery_date	TIMESTAMP						
32	payments	order_id	STRING						

# Target Brazil – SQL Case Study (BigQuery)

## By: Shivesh Raj Sahu

### 1.1 Data types of all columns in customers

Customers contains ID fields (STRING), location fields (STRING/INT64).

Types match the business meaning.

No type mismatches detected.

```
57 -- Now to start working on the Problem Statements
58
59
60 -- 1. Exploratory Analysis
61 -- 1.1 Data type of all columns in the "customers" table
62 -- Problem: Check the data types of all columns in the customers table.
63 SELECT
64   table_name,
65   column_name,
66   data_type
67 FROM `target_brazil.INFORMATION_SCHEMA.COLUMNS`
68 WHERE table_name = 'customers';
69
```

Query completed

Query results [Save results](#) [Open in](#)

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	table_name	column_name	data_type		
1	customers	customer_id	STRING		
2	customers	customer_unique_id	STRING		
3	customers	customer_zip_code_prefix	INT64		
4	customers	customer_city	STRING		
5	customers	customer_state	STRING		

### 1.2 Time range of orders

Orders span 2016-09-04 to 2018-10-17, covering two full years and partial years.

```
60 -- 1. Exploratory Analysis
61 -- 1.1 Data type of all columns in the "customers" table
62 -- Problem: Check the data types of all columns in the customers table.
63 SELECT
64   table_name,
65   column_name,
66   data_type
67 FROM `target_brazil.INFORMATION_SCHEMA.COLUMNS`
68 WHERE table_name = 'customers';
69
70 -- 1.2 Get the time range between which the orders were placed
71 -- Problem: Find the earliest and latest purchase dates in the orders table.
72 SELECT
73   MIN(order_purchase_timestamp) AS first_order_date,
74   MAX(order_purchase_timestamp) AS last_order_date
75 FROM `target_brazil.orders`;
76
```

Query completed

Query results [Save results](#) [Open in](#)

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	first_order_date	last_order_date			
1	2016-09-04 21:15:19 UTC	2018-10-17 17:30:18 UTC			

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 1.3 How many cities and states did customers come from?

Orders come from 4,119 cities across 27 states, looks like a wide geographic coverage.

```
76
77 -- 1.3 Count the Cities & States of customers who ordered
78 -- Problem: Find how many unique cities and states customers came from.
79 SELECT
80   COUNT(DISTINCT customer_city) AS unique_cities,
81   COUNT(DISTINCT customer_state) AS unique_states
82 FROM `target_brazil.customers`;
83
```

Query completed

Query results [Save results](#) [Open in](#)

Job information **Results** Visualization JSON Execution details Execution graph

Row	unique_cities	unique_states
1	4119	27

### 2.1 Year-over-year growth in orders

Orders grew sharply from 2017 to 2018, the numbers show ~ 20% increase.

```
84
85 -- 2. In-depth Exploration
86 -- 2.1 Growing trend in number of orders over years
87 -- Problem: Check if orders increased year by year.
88 SELECT
89   EXTRACT(YEAR FROM order_purchase_timestamp) AS year,
90   COUNT(*) AS total_orders
91 FROM `target_brazil.orders`
92 GROUP BY year
93 ORDER BY year;
```

Query completed

Query results

Job information **Results** Visualization JSON E

Row	year	total_orders
1	2016	329
2	2017	45101
3	2018	54011

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 2.2 Monthly seasonality (year x month)

Mid-year months peak

Year - end softens slightly (at least based on monthly counts that I can see)

```
94
95 -- 2.2 Monthly seasonality in orders
96 -- Problem: See if some months consistently get more orders.
97 SELECT
98   EXTRACT(YEAR FROM order_purchase_timestamp) AS year,
99   EXTRACT(MONTH FROM order_purchase_timestamp) AS month,
100   COUNT(*) AS total_orders
101 FROM `target_brazil.orders`
102 GROUP BY year, month
103 ORDER BY year, month;
104
```

Query completed

Query results

Job information	Results	Visualization	JSON	Execution
Row	year	month	total_orders	
1	2016	9	4	
2	2016	10	324	
3	2016	12	1	
4	2017	1	800	
5	2017	2	1780	
6	2017	3	2682	
7	2017	4	2404	
8	2017	5	3700	
9	2017	6	3245	
10	2017	7	4026	
11	2017	8	4331	
12	2017	9	4285	
13	2017	10	4631	
14	2017	11	7544	
15	2017	12	5673	
16	2018	1	7269	
17	2018	2	6728	
18	2018	3	7211	
19	2018	4	6939	
20	2018	5	6873	
21	2018	6	6167	



## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 2.3 Time of day when orders are placed

Most purchases occur in Afternoons and Night times, this will be useful for campaign timing.

```
104
105 -- 2.3 Time of day when orders are placed
106 -- Problem: Categorize orders into Dawn, Morning, Afternoon, Night.
107 SELECT
108   CASE
109     WHEN EXTRACT(HOUR FROM order_purchase_timestamp) BETWEEN 0 AND 6 THEN 'Dawn'
110     WHEN EXTRACT(HOUR FROM order_purchase_timestamp) BETWEEN 7 AND 12 THEN 'Morning'
111     WHEN EXTRACT(HOUR FROM order_purchase_timestamp) BETWEEN 13 AND 18 THEN 'Afternoon'
112     ELSE 'Night'
113   END AS time_of_day,
114   COUNT(*) AS total_orders
115 FROM `target_brazil.orders`
116 GROUP BY time_of_day
117 ORDER BY total_orders DESC;
118
```

✓ Query completed

Query results [Save results](#) [Open in](#)

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	time_of_day	total_orders			
1	Afternoon	38135			
2	Night	28331			
3	Morning	27733			
4	Dawn	5242			

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 3.1 Month-on-month orders by state

SP/RJ dominate volume each month

Smaller northern states are more volatile.

```
119
120 -- 3) Evolution of E-commerce orders in Brazil
121 -- 3.1 Month-on-month number of orders placed in each state
122 -- Problem: For every month, how many orders came from each customer state?
123 SELECT
124   EXTRACT(YEAR FROM o.order_purchase_timestamp) AS year,
125   EXTRACT(MONTH FROM o.order_purchase_timestamp) AS month,
126   c.customer_state AS state,
127   COUNT(*) AS orders
128 FROM `target_brazil.orders` AS o
129 JOIN `target_brazil.customers` AS c
130   ON o.customer_id = c.customer_id
131 GROUP BY year, month, state
132 ORDER BY year, month, state;
133
```

✓ This query will process 7.59 MB when run.

Query results [Save results](#) [Open in](#)

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	year	month	state	orders	
1	2016	9	RR	1	
2	2016	9	RS	1	
3	2016	9	SP	2	
4	2016	10	AL	2	
5	2016	10	BA	4	
6	2016	10	CE	8	
7	2016	10	DF	6	
8	2016	10	ES	4	
9	2016	10	GO	9	
10	2016	10	MA	4	
11	2016	10	MG	40	
12	2016	10	MT	3	
13	2016	10	PA	4	
14	2016	10	PB	1	
15	2016	10	PE	7	
16	2016	10	PI	1	
17	2016	10	PR	19	
18	2016	10	RJ	56	
19	2016	10	RN	4	
20	2016	10	RR	1	
21	2016	10	RS	24	

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 3.2 Customer distribution across states

Top states by unique customers: SP, RJ, MG ... quiet a long tail beyond that

SP alone contributes ~ 40k unique customers vs less than 1k in smaller states

```
134 -- 3.2 Customer distribution across states
135 -- Problem: How many distinct customers are in each state?
136 SELECT
137   customer_state AS state,
138   COUNT(DISTINCT customer_unique_id) AS unique_customers
139 FROM `target_brazil.customers`
140 GROUP BY state
141 ORDER BY unique_customers DESC;
```

Query completed

Query results

Job information	Results	Visualization	JSON	Execution time
Row	state	unique_customers		
1	SP	40302		
2	RJ	12384		
3	MG	11259		
4	RS	5277		
5	PR	4882		
6	SC	3534		
7	BA	3277		
8	DF	2075		
9	ES	1964		
10	GO	1952		
11	PE	1609		
12	CE	1313		
13	PA	949		
14	MT	876		
15	MA	726		
16	MS	694		
17	PB	519		
18	PI	482		
19	RN	474		
20	AL	401		
21	SE	342		
22	TO	273		

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 4.1 Percentage increase in total payments from 2017 -> 2018 (Jan-Aug)

Total payments rose about 136.98% from January to August 2017 to 2018, indicating strong growth

```
144 -- 4) Impact on the Economy
145 -- 4.1 % increase in order cost from 2017 -> 2018 (Jan-Aug only)
146 -- Problem: Compare total cost of orders (use payments.payment_value) across 2017 vs 2018, restricting to
147 months 1-8.
148 WITH monthly AS (
149 --SELECT
150 --  EXTRACT(YEAR FROM o.order_purchase_timestamp) AS yr,
151 --  EXTRACT(MONTH FROM o.order_purchase_timestamp) AS mo,
152 --  SUM(p.payment_value) AS total_paid
153 --FROM `target_brazil.orders` o
154 --JOIN `target_brazil.payments` p USING (order_id)
155 --WHERE EXTRACT(MONTH FROM o.order_purchase_timestamp) BETWEEN 1 AND 8
156 --GROUP BY yr, mo
157 ),
158 by_year AS (
159 --SELECT yr AS year, SUM(total_paid) AS total_paid
160 --FROM monthly
161 --GROUP BY yr
162 )
163 SELECT
164 --SUM(CASE WHEN year = 2017 THEN total_paid END) AS total_2017_JanAug,
165 --SUM(CASE WHEN year = 2018 THEN total_paid END) AS total_2018_JanAug,
166 --SAFE_DIVIDE(
167 --  SUM(CASE WHEN year = 2018 THEN total_paid END) -
168 --  SUM(CASE WHEN year = 2017 THEN total_paid END),
169 --  SUM(CASE WHEN year = 2017 THEN total_paid END)
170 --) * 100 AS pct_increase_JanAug_2018_vs_2017
171 FROM by_year;
```

Query completed

Query results

Save results Open in

Job Information	Results	Visualization	JSON	Execution details	Execution graph
Row	total_2017_JanAug	total_2018_JanAug	pct_increase_JanAug_2018_vs_2017		
1	3669022.11999992	8694733.84000018	136.97687164667107		

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 4.2 Total & Average order price by state

Highest total order value in SP and RJ, average order value varies by state.

```
172 -- 4.2 Total & Average order price by state
173 -- Problem: For each state, compute total and average order price.
174 -- Order price here = sum of order_items.price for an order.
175 WITH order_price AS (
176   SELECT
177     oi.order_id,
178     SUM(oi.price) AS order_price
179   FROM `target_brazil.order_items` oi
180   GROUP BY oi.order_id
181 )
182 SELECT
183   c.customer_state AS state,
184   SUM(op.order_price) AS total_order_price,
185   AVG(op.order_price) AS avg_order_price,
186   COUNT(DISTINCT op.order_id) AS orders_count
187 FROM order_price op
188 JOIN `target_brazil.orders` o USING (order_id)
189 JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
190 GROUP BY state
191 ORDER BY total_order_price DESC;
192
```

✓ This script will process 252.67 MB when run.

Query results [Save results](#)

Job information	Results	Visualization	JSON	Execution details	Execution
Row	state	total_order_price	avg_order_price	orders_count	
1	SP	5202955.049999...	125.7511794561...	41375	
2	RJ	1824092.669999...	142.9315679360...	12762	
3	MG	1585308.030000...	137.3274454261...	11544	
4	RS	750304.020000...	138.1266605301...	5432	
5	PR	683083.760000...	136.6714205682...	4998	
6	SC	520553.339999...	144.1177574750...	3612	
7	BA	511349.989999...	152.2781387730...	3358	
8	DF	302603.939999...	142.4018541176...	2125	
9	GO	294591.949999...	146.7822371699...	2007	
10	ES	275037.309999...	135.8208938271...	2025	
11	PE	262788.029999...	159.4587560679...	1648	
12	CE	227254.709999...	171.2544913338...	1327	
13	PA	178947.810000...	184.4822783505...	970	
14	MT	156453.529999...	173.2597231450...	903	
15	MA	119648.220000...	161.6867837837...	740	
16	MS	116812.640000...	164.7568970380...	709	
17	PB	115268.080000...	216.6693233082...	532	
18	PI	86914.080000...	176.2963083164...	493	
19	RN	83034.980000...	172.2717427385...	482	
20	AL	80314.810000...	195.4131630170...	411	

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 4.3 Total & Average freight by state

Total freight is highest where volume is highest, avg freight highlights logistics cost differences

```
192
193 -- 4.3 Total & Average freight by state
194 -- Problem: For each state, compute total and average freight cost.
195 WITH order_freight AS (
196   SELECT
197     oi.order_id,
198     SUM(oi.freight_value) AS order_freight
199   FROM `target_brazil.order_items` oi
200   GROUP BY oi.order_id
201 )
202 SELECT
203   c.customer_state AS state,
204   SUM(ofr.order_freight) AS total_freight,
205   AVG(ofr.order_freight) AS avg_freight,
206   COUNT(DISTINCT ofr.order_id) AS orders_count
207 FROM order_freight ofr
208 JOIN `target_brazil.orders` o USING (order_id)
209 JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
210 GROUP BY state
211 ORDER BY total_freight DESC;
212
213
```

✓ Query completed

Query results [Save results](#)

Job Information	Results	Visualization	JSON	Execution details	Execution
Row	state	total_freight	avg_freight	orders_count	
1	SP	718723.0700000...	17.37095033232...	41375	
2	RJ	305589.3100000...	23.94525231154...	12762	
3	MG	270853.4600000...	23.46270443520...	11544	
4	RS	135522.7400000...	24.94895802650...	5432	
5	PR	117851.6799999...	23.57976790716...	4998	
6	BA	100156.6800000...	29.82628945801...	3358	
7	SC	89660.2599999...	24.82288482834...	3612	
8	PE	59449.6599999...	36.07382281553...	1648	
9	GO	53114.9800000...	26.46486297957...	2007	
10	DF	50625.5000000...	23.82376470588...	2125	
11	ES	49764.5999999...	24.57511111111...	2025	
12	CE	48351.5900000...	36.43676714393...	1327	
13	PA	38699.3000000...	39.89618556701...	970	
14	MA	31523.7699999...	42.59968918918...	740	
15	MT	29715.4299999...	32.90745293466...	903	
16	PB	25719.7299999...	48.34535714285...	532	
17	PI	21218.2	43.03894523326...	493	
18	MS	19144.0300000...	27.00145275035...	709	
19	RN	18860.0999999...	39.12883817427...	482	
20	AL	15914.5900000...	38.72163017031...	411	

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 5.1 Per-order delivery time & difference vs estimate (single query)

Most deliveries cluster around certain days

diff\_estimate\_days < 0 means earlier than promised

```
213
214 -- 5) Sales, Freight & Delivery Time
215 -- 5.1 Delivery time & difference vs estimated - per order (single query)
216 -- Problem: For each delivered order, compute:
217 -- ..... time_to_deliver := delivered_date - purchase_date (days)
218 -- ..... diff_estimated_delivery := delivered_date - estimated_date (days)
219 SELECT
220   o.order_id,
221   c.customer_state AS state,
222   DATE(o.order_purchase_timestamp) AS purchase_date,
223   DATE(o.order_delivered_customer_date) AS delivered_date,
224   DATE(o.order_estimated_delivery_date) AS estimated_date,
225   DATE_DIFF(DATE(o.order_delivered_customer_date),
226             DATE(o.order_purchase_timestamp), DAY) AS time_to_deliver_days,
227   DATE_DIFF(DATE(o.order_delivered_customer_date),
228             DATE(o.order_estimated_delivery_date), DAY) AS diff_estimated_delivery_days
229 FROM `target_brazil.orders` o
230 JOIN `target_brazil.customers` c
231   ON o.customer_id = c.customer_id
232 WHERE o.order_delivered_customer_date IS NOT NULL;
233
```

Query completed

#### Query results

Job information		Results	Visualization	JSON	Execution details		Execution graph			
Row	order_id		state		purchase_date	delivered_date	estimated_date	time_to_deliver_d...	diff_estimated_d...	
1	770d331c84e5b214bd9dc70a1...		RJ		2016-10-07	2016-10-14	2016-11-29	7	-46	
2	dabf2b0e35b423f94618bf965f...		SP		2016-10-09	2016-10-16	2016-11-30	7	-45	
3	8beb59392e21af5eb9547ae1a...		RJ		2016-10-08	2016-10-19	2016-11-30	11	-42	
4	1950d777989f6a877539f53795...		MG		2018-02-19	2018-03-21	2018-03-09	30	12	
5	bfb0f9bdef84302105ad712db...		SP		2016-09-15	2016-11-09	2016-10-04	55	36	
6	cd3b8574c82b42fc8129f6d502...		SP		2016-10-03	2016-10-14	2016-11-23	11	-40	
7	31b0dd6152d2e471443deb03...		RJ		2016-10-05	2016-10-13	2016-11-23	8	-41	
8	a8c3f65a43b2e956cbfca10db4...		SP		2016-10-04	2016-10-20	2016-11-24	16	-35	
9	a041155864e51411164582913...		SP		2016-10-04	2016-10-13	2016-11-24	9	-42	
10	50013835d7b14aefb45282586...		SP		2016-10-04	2016-10-21	2016-11-24	17	-34	
11	1ff217aa612f6cd7c4255c9bfe9...		SP		2016-10-04	2016-10-24	2016-11-24	20	-31	
12	6eb51c1c9c69f78ea9fd4665fb...		SP		2016-10-04	2016-10-13	2016-11-24	9	-42	
13	d2d67121a09535b3a7b6a00e...		SP		2016-10-04	2016-10-13	2016-11-24	9	-42	
14	5cc475c7c03290048eb2e742c...		SP		2016-10-04	2016-12-12	2016-11-24	69	18	
15	0a0837a5eee9e7a9ce2b1fa831...		SP		2016-10-04	2016-10-22	2016-11-24	18	-33	
16	85841af0d94e5d0cd3a9c0e42e...		SP		2016-10-05	2016-10-13	2016-11-25	8	-43	
17	f716dffba1232aaf7c899fb8c1...		RJ		2016-10-07	2016-10-14	2016-11-25	7	-42	
18	719628a909505f12f342015fd5...		SP		2016-10-05	2016-10-18	2016-11-25	13	-38	
19	5c973d2b4652e1dec15353b59...		RJ		2016-10-07	2016-10-14	2016-11-25	7	-42	
20	ca3b8093576a51bea61c9782c...		SP		2016-10-05	2016-10-24	2016-11-25	19	-32	
21	92b44b87f1f7670b8911c5f0e6...		SP		2016-10-05	2016-10-13	2016-11-25	8	-43	

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 5.2 Top 5 states, highest & lowest average freight

Highest avg freight in RR, RO, ...

lowest in SP, MG, ... suggesting a denser networks

```
234 -- 5.2 Top 5 states - highest & lowest average freight
235 -- Problem: Rank states by average freight per order.
236 -- Query for the highest 5
237 WITH order_freight AS (
238   SELECT order_id, SUM(freight_value) AS order_freight
239   FROM `target_brazil.order_items`
240   GROUP BY order_id
241 )
242 SELECT
243   c.customer_state AS state,
244   AVG(ofr.order_freight) AS avg_freight
245 FROM order_freight ofr
246 JOIN `target_brazil.orders` o USING (order_id)
247 JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
248 GROUP BY state
249 ORDER BY avg_freight DESC
250 LIMIT 5;
251
252 -- Query for the lowest 5
253 -- same CTE as above
254 WITH order_freight AS (
255   SELECT order_id, SUM(freight_value) AS order_freight
256   FROM `target_brazil.order_items`
257   GROUP BY order_id
258 )
259 SELECT
260   c.customer_state AS state,
261   AVG(ofr.order_freight) AS avg_freight
262 FROM order_freight ofr
263 JOIN `target_brazil.orders` o USING (order_id)
264 JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
265 GROUP BY state
266 ORDER BY avg_freight ASC
267 LIMIT 5;
268
```

✓ Query completed

#### Query results

Job information		Results	Visualiization	JSON	Execution details	Execution graph
Row	state	avg_freight				
1	RR	48.59108695652...				
2	PB	48.34535714285...				
3	RO	46.22421052631...				
4	AC	45.51543209876...				
5	PI	43.03894523326...				



## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

```
234 -- 5.2 Top 5 states – highest & lowest average freight
235 -- Problem: Rank states by average freight per order.
236 -- Query for the highest 5
237 WITH order_freight AS (
238   SELECT order_id, SUM(freight_value) AS order_freight
239   FROM `target_brazil.order_items`
240   GROUP BY order_id
241 )
242 SELECT
243   c.customer_state AS state,
244   AVG(ofr.order_freight) AS avg_freight
245 FROM order_freight ofr
246 JOIN `target_brazil.orders` o USING (order_id)
247 JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
248 GROUP BY state
249 ORDER BY avg_freight DESC
250 LIMIT 5;
251
252 -- Query for the lowest 5
253 -- same CTE as above
254 WITH order_freight AS (
255   SELECT order_id, SUM(freight_value) AS order_freight
256   FROM `target_brazil.order_items`
257   GROUP BY order_id
258 )
259 SELECT
260   c.customer_state AS state,
261   AVG(ofr.order_freight) AS avg_freight
262 FROM order_freight ofr
263 JOIN `target_brazil.orders` o USING (order_id)
264 JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
265 GROUP BY state
266 ORDER BY avg_freight ASC
267 LIMIT 5;
```

✓ Query completed

### Query results

Job Information		Results	Visualization	JSON	Execution details	Execution graph
Row	state	avg_freight				
1	SP	17.37095033232...				
2	MG	23.46270443520...				
3	PR	23.57976790716...				
4	DF	23.82376470588...				
5	RJ	23.94525231154...				

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 5.3 Top 5 states, highest & lowest average delivery time

```
268
269 -- 5.3 Top 5 states – highest & lowest average delivery time
270 -- Problem: Rank states by average delivery days.
271 -- Query for the highest 5
272 WITH per_order AS (
273   SELECT
274     o.order_id, c.customer_state AS state,
275     DATE_DIFF(DATE(o.order_delivered_customer_date),
276       DATE(o.order_purchase_timestamp), DAY) AS time_to_deliver_days
277   FROM `target_brazil.orders` o
278   JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
279   WHERE o.order_delivered_customer_date IS NOT NULL
280 )
281 SELECT
282   state,
283   AVG(time_to_deliver_days) AS avg_delivery_days
284 FROM per_order
285 GROUP BY state
286 ORDER BY avg_delivery_days DESC
287 LIMIT 5;
288
289 -- Query for the lowest 5
290 -- same CTE as above
291 WITH per_order AS (
292   SELECT
293     o.order_id, c.customer_state AS state,
294     DATE_DIFF(DATE(o.order_delivered_customer_date),
295       DATE(o.order_purchase_timestamp), DAY) AS time_to_deliver_days
296   FROM `target_brazil.orders` o
297   JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
298   WHERE o.order_delivered_customer_date IS NOT NULL
299 )
300 SELECT
301   state,
302   AVG(time_to_deliver_days) AS avg_delivery_days
303 FROM per_order
304 GROUP BY state
305 ORDER BY avg_delivery_days ASC
306 LIMIT 5;
307
```

✓ Query completed

#### Query results

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	state	avg_delivery_days			
1	RR	29.34146341463...			
2	AP	27.17910447761...			
3	AM	26.35862068965...			
4	AL	24.50125944584...			
5	PA	23.72515856236...			

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

```
268
269 -- 5.3 Top 5 states - highest & lowest average delivery time
270 -- Problem: Rank states by average delivery days.
271 -- Query for the highest 5
272 WITH per_order AS (
273     SELECT
274         o.order_id, c.customer_state AS state,
275         DATE_DIFF(DATE(o.order_delivered_customer_date),
276             DATE(o.order_purchase_timestamp), DAY) AS time_to_deliver_days
277     FROM `target_brazil.orders` o
278     JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
279     WHERE o.order_delivered_customer_date IS NOT NULL
280 )
281 SELECT
282     state,
283     AVG(time_to_deliver_days) AS avg_delivery_days
284 FROM per_order
285 GROUP BY state
286 ORDER BY avg_delivery_days DESC
287 LIMIT 5;
288
289 -- Query for the lowest 5
290 -- same CTE as above
291 WITH per_order AS (
292     SELECT
293         o.order_id, c.customer_state AS state,
294         DATE_DIFF(DATE(o.order_delivered_customer_date),
295             DATE(o.order_purchase_timestamp), DAY) AS time_to_deliver_days
296     FROM `target_brazil.orders` o
297     JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
298     WHERE o.order_delivered_customer_date IS NOT NULL
299 )
300 SELECT
301     state,
302     AVG(time_to_deliver_days) AS avg_delivery_days
303 FROM per_order
304 GROUP BY state
305 ORDER BY avg_delivery_days ASC
306 LIMIT 5;
```

✔ Query completed

### Query results

Job information		Results	Visualization	JSON	Execution details	Execution graph
Row	state	avg_delivery_days				
1	SP	8.700530929744...				
2	PR	11.93804590696...				
3	MG	11.94654337296...				
4	DF	12.89903846153...				
5	SC	14.90752748801...				

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 5.4 Top 5 states, earliest vs. estimate (negative = earlier)

AC/AP/... deliver earlier than promised on average, AC delivers ~ -2.3 days earlier than estimated

AL/MA/... tend to be late

```
307
308 -- 5.4 Top 5 states - fastest vs estimate
309 -- Problem: Where is delivery earliest relative to estimate?
310 -- Use average delivered - estimated; more negative = faster than estimate.
311 -- Query for the fastest relative to estimate
312 WITH per_order AS (
313   SELECT
314     c.customer_state AS state,
315     DATE_DIFF(DATE(o.order_delivered_customer_date),
316       DATE(o.order_estimated_delivery_date), DAY) AS diff_vs_estimate_days
317   FROM `target_brazil.orders` o
318   JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
319   WHERE o.order_delivered_customer_date IS NOT NULL
320   AND o.order_estimated_delivery_date IS NOT NULL
321 )
322 SELECT
323   state,
324   AVG(diff_vs_estimate_days) AS avg_diff_vs_estimate_days
325 FROM per_order
326 GROUP BY state
327 ORDER BY avg_diff_vs_estimate_days ASC -- most negative first (earliest vs est.)
328 LIMIT 5;
329
330 -- Query for the worst relative to estimate, i.e., latest
331 -- same CTE as above
332 WITH per_order AS (
333   SELECT
334     c.customer_state AS state,
335     DATE_DIFF(DATE(o.order_delivered_customer_date),
336       DATE(o.order_estimated_delivery_date), DAY) AS diff_vs_estimate_days
337   FROM `target_brazil.orders` o
338   JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
339   WHERE o.order_delivered_customer_date IS NOT NULL
340   AND o.order_estimated_delivery_date IS NOT NULL
341 )
342 SELECT
343   state,
344   AVG(diff_vs_estimate_days) AS avg_diff_vs_estimate_days
345 FROM per_order
346 GROUP BY state
347 ORDER BY avg_diff_vs_estimate_days DESC -- most positive (latest vs est.)
348 LIMIT 5;
349
```

Query completed

#### Query results

Job information		Results	Visualization	JSON	Execution details	Execution graph
Row	state	avg_diff_vs_esti...				
1	AC	-20.72499999999...				
2	RO	-20.10288065843...				
3	AP	-19.68656716417...				
4	AM	-19.56551724137...				
5	RR	-17.29268292682...				

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

```
307
308 -- 5.4 Top 5 states - fastest vs estimate
309 -- Problem: Where is delivery earliest relative to estimate?
310 -- Use average delivered - estimated; more negative = faster than estimate.
311 -- Query for the fastest relative to estimate
312 WITH per_order AS (
313     SELECT
314         c.customer_state AS state,
315         DATE_DIFF(DATE(o.order_delivered_customer_date),
316             DATE(o.order_estimated_delivery_date), DAY) AS diff_vs_estimate_days
317     FROM `target_brazil.orders` o
318     JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
319     WHERE o.order_delivered_customer_date IS NOT NULL
320     AND o.order_estimated_delivery_date IS NOT NULL
321 )
322 SELECT
323     state,
324     AVG(diff_vs_estimate_days) AS avg_diff_vs_estimate_days
325 FROM per_order
326 GROUP BY state
327 ORDER BY avg_diff_vs_estimate_days ASC -- most negative first (earliest vs est.)
328 LIMIT 5;
329
330 -- Query for the worst relative to estimate, i.e., latest
331 -- same CTE as above
332 WITH per_order AS (
333     SELECT
334         c.customer_state AS state,
335         DATE_DIFF(DATE(o.order_delivered_customer_date),
336             DATE(o.order_estimated_delivery_date), DAY) AS diff_vs_estimate_days
337     FROM `target_brazil.orders` o
338     JOIN `target_brazil.customers` c ON o.customer_id = c.customer_id
339     WHERE o.order_delivered_customer_date IS NOT NULL
340     AND o.order_estimated_delivery_date IS NOT NULL
341 )
342 SELECT
343     state,
344     AVG(diff_vs_estimate_days) AS avg_diff_vs_estimate_days
345 FROM per_order
346 GROUP BY state
347 ORDER BY avg_diff_vs_estimate_days DESC -- most positive (latest vs est.)
348 LIMIT 5;
349
```

✓ Query completed

### Query results

Job information		Results	Visualization	JSON	Execution details	Execution graph
Row	state	avg_diff_vs_esti...				
1	AL	-8.707808564231...				
2	MA	-9.571827057182...				
3	SE	-10.02089552238...				
4	ES	-10.49624060150...				
5	BA	-10.79453316953...				

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 6.1 Month-on-month number of orders by payment type

Payment mix is dominated by credit\_card

Other types (boleto, voucher) are smaller but steady

```
350
351 -- 6) Payments Analysis
352 -- 6.1 Month-on-month number of orders by payment type
353 -- Problem: For every month, how many orders used each payment_type?
354 -- Count distinct orders per type to be safe.
355 SELECT
356   EXTRACT(YEAR FROM o.order_purchase_timestamp) AS year,
357   EXTRACT(MONTH FROM o.order_purchase_timestamp) AS month,
358   p.payment_type,
359   COUNT(DISTINCT p.order_id) AS orders
360 FROM `target_brazil.payments` p
361 JOIN `target_brazil.orders` o USING (order_id)
362 GROUP BY year, month, payment_type
363 ORDER BY year, month, payment_type;
```

✓ Query completed

#### Query results

Job information	Results	Visualization	JSON	Execution details	Execution graph
Row	year	month	payment_type	orders	
1	2016	9	credit_card	3	
2	2016	10	UPI	63	
3	2016	10	credit_card	253	
4	2016	10	debit_card	2	
5	2016	10	voucher	11	
6	2016	12	credit_card	1	
7	2017	1	UPI	197	
8	2017	1	credit_card	582	
9	2017	1	debit_card	9	
10	2017	1	voucher	33	
11	2017	2	UPI	398	
12	2017	2	credit_card	1347	
13	2017	2	debit_card	13	
14	2017	2	voucher	69	
15	2017	3	UPI	590	

## Target Brazil – SQL Case Study (BigQuery)

By: Shivesh Raj Sahu

### 6.2 Orders by payment installments

Most Brazilian e-commerce orders in this dataset are paid in full (1 installment) or split across 2 to 4 installments

```
365 -- 6.2 Orders by number of payment installments
366 -- Problem: How many orders used 1, 2, 3... installments?
367 SELECT
368   p.payment_installments,
369   COUNT(DISTINCT p.order_id) AS orders
370 FROM `target_brazil.payments` p
371 GROUP BY p.payment_installments
372 ORDER BY p.payment_installments;
```

Query completed

#### Query results

Job information	Results	Visualization	JSON	Execution details
Row	payment_installm...	orders		
1	0	2		
2	1	49060		
3	2	12389		
4	3	10443		
5	4	7088		
6	5	5234		
7	6	3916		
8	7	1623		
9	8	4253		
10	9	644		
11	10	5315		
12	11	23		
13	12	133		
14	13	16		
15	14	15		

## **Target Brazil – SQL Case Study (BigQuery)**

**By: Shivesh Raj Sahu**

### **Final section**

#### **Actionable insights & recommendations**

- Staff campaigns later in the day: Afternoon and Night contribute most orders, therefore prioritize push/email and support staffing in those windows.
- Regional logistics: States with highest avg freight and longest delivery times are prime targets for 3PL renegotiation or micro-fulfillment pilots.
- Promise accuracy: Where delivered is earlier than estimate (negative average), tighten ETA windows to improve conversion while keeping promise-keep high.
- Installments product: If many orders use more than 3 installments, surface installment messaging earlier in the funnel, negotiate card rates.
- State-specific growth: SP/RJ drive volume, smaller northern states show volatility, therefore test regional promos and inventory placement to smooth demand.