

BUSINESS CASE STUDY

TARGET SQL



SHILPA S SCALER DSML OCT'22 BEGINNER BATCH MAY 21, 2023

1.Exploratory analysis

SELECT *

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.sellers`

LIMIT 15

Row	seller_id //	seller_zip_code_	seller_city //	seller_state /
1	4be2e7f96b4fd749d52dff41f8	69900	rio branco	AC
2	327b89b872c14d1c0be7235ef	69005	manaus	AM
3	4221a7df464f1fe2955934e30f	48602	bahia	BA
4	651530bf5c607240ccdd89a30	44600	ipira	BA
5	2b402d5dc42554061f8ea98d1	44900	irece	BA
6	d03698c2efd04a549382afa66	45658	ilheus	BA
7	c72de06d72748d1a0dfb2125b	46430	guanambi	BA
8	fc59392d66ef99377e50356ee	40243	salvador	BA
9	b00af24704019bd2e1b335e70	40130	salvador	BA

Results per page: $50 \checkmark 1 - 15 \text{ of } 15$

SELECT *

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.products`

Row	product_id //	product_category //	product_name_l	product_descrip	product_photos_	product_weight_	product_length_	product_height_	product_width_c
1	5eb564652d	null	null	null	null	null	null	null	null
2	09ff539a621	babies	60	865	3	null	null	null	null
3	2f763ba79d	electronics	45	1198	2	595	8	6	6
4	a69f15dfb80	Watches present	53	506	6	150	11	16	6
5	e1cfc87f543	Garden tools	39	524	4	369	26	7	7
6	106392145fc	bed table bath	58	309	1	2083	12	2	7
7	7e33f4a1c59	electronics	51	381	3	1075	22	5	7
8	bc9cc914f97	HEALTH BEAUTY	55	435	1	75	14	9	7
9	5ae533eac9	computer acces	58	1340	1	83	12	8	8

Results per page: 50 ▼ 1 − 15 of 15 | ⟨ ⟨ ⟩

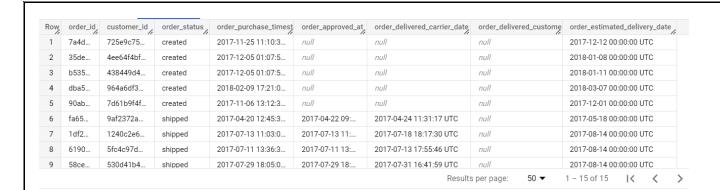
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.payments`

LIMIT 15

Row	order_id	payment_sequential	payment_type //	payment_installments	payment_value	
1	1a57108394169c0b47d8f876a	2	credit_card	0	129.94	
2	744bade1fcf9ff3f31d860ace07	2	credit_card	0	58.69	
3	8bcbe01d44d147f901cd31926	4	voucher	1	0.0	
4	fa65dad1b0e818e3ccc5cb0e3	14	voucher	1	0.0	
5	6ccb433e00daae1283ccc9561	4	voucher	1	0.0	
6	4637ca194b6387e2d538dc89b	1	not_defined	1	0.0	
7	00b1cb0320190ca0daa2c88b3	1	not_defined	1	0.0	
8	45ed6e85398a87c253db47c2d	3	voucher	1	0.0	
9	fa65dad1b0e818e3ccc5cb0e3	13	voucher	1	0.0	
				Result	s per page: 50	0 ▼ 1 – 15 of 1

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.orders`

LIMIT 15



SELECT *

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.order_reviews`` LIMIT 15

Row	review_id /	order_id //	review_score	review_comment_title	review_creation_date	review_answer_timestamp
1	be7e29	777c6	1	null	0001-04-17 00:00:00 UTC	0001-04-17 07:40:00 UTC
2	e12151	4338a	1	null	0001-04-17 00:00:00 UTC	0001-04-17 09:04:00 UTC
3	41d614	b8aae	1	null	0001-04-17 00:00:00 UTC	0002-04-17 03:48:00 UTC
4	c95032	b159d	1	null	0001-04-17 00:00:00 UTC	0001-04-17 10:24:00 UTC
5	76823a	2a300	1	null	0001-04-17 00:00:00 UTC	0002-04-17 13:58:00 UTC
6	fe270df	a39d3	1	null	0001-04-17 00:00:00 UTC	0003-04-17 12:49:00 UTC
7	1b71e0	0e530f	1	null	0001-04-17 00:00:00 UTC	0010-04-17 12:45:00 UTC
8	efe402	264c0	1	null	0001-04-17 00:00:00 UTC	0002-04-17 01:16:00 UTC

Results per page: $50 ext{ } ext{ } ext{ } 1 - 15 ext{ of } 15$

SELECT *

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.order_items`

LIMIT 15

Row	order_id	order_item_id	product_id //	seller_id	shipping_limit_date	price	freight_value
1	f09e36e2	1	44d53f1240	b64d51f0435e884e8de603b1655155ae	2018-07-09 13:31:36 UTC	3.0	12.79
2	f9ccaff72	1	44d53f1240	b64d51f0435e884e8de603b1655155ae	2018-08-14 14:04:44 UTC	3.0	15.23
3	c79bdf06	1	5304ff3fa35	cf6f6bc4df3999b9c6440f124fb2f687	2017-05-12 19:05:20 UTC	3.5	8.72
4	37193e64	1	98224bfc1e	ce616e1913288884e7742faac9d981db	2018-06-28 01:30:49 UTC	3.5	7.39
5	95d6357f	1	98224bfc1e	ce616e19132888884e7742faac9d981db	2018-06-12 19:15:14 UTC	3.5	18.23
6	95d6357f	2	98224bfc1e	ce616e19132888884e7742faac9d981db	2018-06-12 19:15:14 UTC	3.5	18.23
7	95d6357f	3	98224hfc1e	ce616e19132888884e7742faac9d981dh	2018-06-12 19:15:14 HTC	3.5	18 23

SELECT *

 ${\bf FROM\ `dsml\text{-}scaler\text{-}sql1.Business_Case_Target_SQL.geolocation`}$

LIMIT 15

11	geolocation_zip_code_pre	geolocation_lat	geolocation_lng	geolocation_city	geolocation_state
1	49010	-10.9105145187545	-37.052400776992329	aracaju	SE
2	49047	-10.9268145	-37.071063000000009	aracaju	SE
3	49030	-10.9701647943045	-37.061643830745815	aracaju	SE
4	49048	-10.9401835317389	-37.070850242714528	aracaju	SE
5	49050	-10.9271573528005	-37.063078689600516	aracaju	SE
6	49015	-10.9233705001607	-37.045169150380509	aracaju	SE
7	49045	-10.9304065823184	-37.067178493623359	aracaju	SE
8	49052	-10.9229735178891	-37.057752502914184	aracaju	SE
9	49044	-10.99208099999999	-37.103470999999956	aracaju	SE

Results per page: $50 \checkmark 1 - 15 \text{ of } 15$

SELECT*

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers`

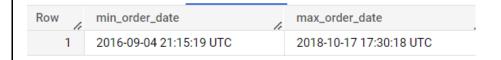
LIMIT 15

Row	customer_id	customer_unique_id	customer_zip_code_prefix	customer_city	customer_state
1	0735e7e4298a2ebbb46649346570476a	fcb003b1bdc0df64b4d065d9bb94f8c4	59650	acu	RN
2	903b3d86e3990db01619a4ebe3edef4e	46824822b15da44e983b021d0e945379	59650	acu	RN
3	38c97666e962d4fea7fd6a83e69f20cd	b6108acc674ae5c99e29adc1047d1049	59650	acu	RN
4	77c2f46cf580f4874c9a5751c2d88474	402cce5c0509000eed9e77fece8056e2	63430	ico	CE
5	4d3ef4cfffb8ad4767c199c36a4cfee6	6ba00666ab7eada5ceec279b259e44b5	63430	ico	CE
6	3000841b86e1fbe9493b523245d5c68d	796a0b1a21f597704057184a16ab4d71	63430	ico	CE
7	3c325415ccc7e622c66dec4bc9120030	05d1d2d9f0161c5f397ce7fc770910d4	63430	ico	CE
8	04f3a7b250e3be964f01bf22bccdc602	c34585a0276ecc5e4fb03de755e8f7d0	63430	ico	CE
9	894202b8ef01f4719a4691e79dd24c17	01a4fe5fc00bbdb0b0a4af5a5345cca5	63430	ico	CE

Initial exploration of dataset like checking the characteristics of data:

- 1. Data type of columns in the above tables include integer, string, float, timestamp.
- 2. Time period for which the data is given is 2016 to 2018.

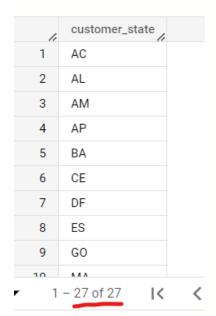
SELECT min(order_purchase_timestamp) as min_order_date, max(order_purchase_timestamp) as max_order_date
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.orders`



3. Cities and States of customers ordered during the given period.

SELECT customer_state
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers`
GROUP BY customer_state
ORDER BY customer_state asc

SELECT customer_city
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers`
GROUP BY customer_city
ORDER BY customer_city asc



11	customer_city
1	abadia dos dourados
2	abadiania
3	abaete
4	abaetetuba
5	abaiara
6	abaira
7	abare
8	abatia
9	abdon batista
	1 – 50 of 4119 <

Customers are spread across 27 states and 4119 cities as per the info. from the orders table.

SELECT geolocation_state

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.geolocation`

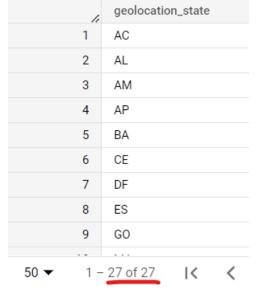
GROUP BY geolocation_state

ORDER BY geolocation_state asc

SELECT geolocation_city

 ${\bf FROM\ `dsml\text{-}scaler\text{-}sql1.Business_Case_Target_SQL.geolocation`}$

GROUP BY geolocation_city



11	geolocation_city
1	* cidade
2	arraial do cabo
3	4o. centenario
4	4º centenario
5	abadia de goias
6	abadia dos dourados
7	abadiania
8	abadiânia
9	abaete
10	abaetetuba
50 ▼	1 - 50 of <u>8011</u> <

Customers are spread across 27 states and 8011 cities as per the info. from the geolocations table.

2.In-depth Exploration

1. Is there a growing trend on e-commerce in Brazil? How can we describe a complete scenario? Can we see some seasonality with peaks at specific months?

SELECT EXTRACT(YEAR from order_purchase_timestamp) as year_of_purchase,

COUNT(customer_id) as no_of_unique_customers

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.orders`

GROUP BY year_of_purchase

ORDER BY year_of_purchase

Row	year_of_purchase	no_of_unique_customers
1	2016	329
2	2017	45101
3	2018	54011

SELECT FORMAT_DATETIME('%b-%Y',order_purchase_timestamp) as month_yr_purchase,

COUNT(customer_id) as no_of_unique_customers

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.orders`

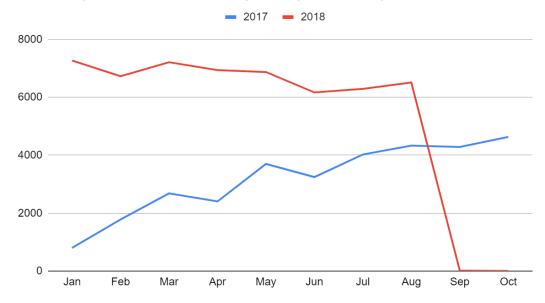
GROUP BY month_yr_purchase

ORDER BY month_yr_purchase asc

1.	month_yr_purchas	se no_of_unique_customers
1	Apr-2017	2404
2	Apr-2018	6939
3	Aug-2017	4331
4	Aug-2018	6512
5	Dec-2016	1
6	Dec-2017	5673
7	Feb-2017	1780
8	Feb-2018	6728
9	Jan-2017	800
10	Jan-2018	7269
11	Jul-2017	4026
12	Jul-2018	6292
age:	50 ▼ 1 − 2	25 of 25 < < >

7600	
2017	2018
800	7269
1780	6728
2682	7211
2404	6939
3700	6873
3245	6167
4026	6292
4331	6512
4285	16
4631	4
	1780 2682 2404 3700 3245 4026 4331 4285





A clear hike in the online purchase in June, July and Aug can be traced across 2017 and 2018.

What time do Brazilian customers tend to buy (Dawn, Morning, Afternoon or Night)?

select time_of_purchase, sum(no_of_unique_customers) as no_of_unique_customers (SELECT EXTRACT(HOUR from order_purchase_timestamp) as hr_of_purchase, CASE WHEN EXTRACT(HOUR from order_purchase_timestamp) BETWEEN 0 and 6 WHEN EXTRACT(HOUR from order_purchase_timestamp)BETWEEN 6 and 12 then 'Morning' WHEN EXTRACT(HOUR from order_purchase_timestamp) BETWEEN 12 and 18 then 'Afternoon' else 'Night' end as time_of_purchase, COUNT(customer_id) as no_of_unique_customers, FROM `dsml-scaler-sql1.Business_Case_Target_SQL.orders` **GROUP BY 1,2** ORDER BY 1) as subquery group by time_of_purchase order by no_of_unique_customers desc

11	time_of_purchase	no_of_unique_customers
1	Afternoon	38135
2	Night	28331
3	Morning	27733
4	Dawn	5242

Brazilian customers tend to buy the most in the afternoon with 38,000+ unique purchases in a year, followed by 28,000+ purchase during the night, followed by morning in the 3rd position with 27000+ unique purchases in a year and lastly during dawn with 5000+ purchases.

3. Evolution of E-commerce orders in the Brazil region

1. Get month on month orders by states.

SELECT FORMAT_DATETIME('%b-%Y',order_purchase_timestamp) as month_yr_purchase, customer_state,

COUNT(o.order_id) as no_of_orders

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o

ON c.customer_id = o.customer_id

GROUP BY month_yr_purchase,customer_state

ORDER BY month_yr_purchase,customer_state asc

11	month_yr_purchase	customer_state	no_of_orders
1	Apr-2017	AC	5
2	Apr-2017	AL	23
3	Apr-2017	AM	13
4	Apr-2017	BA	93
5	Apr-2017	CE	43
6	Apr-2017	DF	35
7	Apr-2017	ES	46
8	Apr-2017	GO	41
9	Apr-2017	MA	27
10	Apr-2017	MG	275
11	Apr-2017	MS	15
12	Apr-2017	MT	27

Results per page: $50 \checkmark 1 - 50 \text{ of } 565$

COUNT(o.customer_id) as no_of_unique_customers

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o

ON c.customer_id = o.customer_id

GROUP BY month_yr_purchase,customer_state

ORDER BY month_yr_purchase,customer_state asc

7

11	month_yr_purchase	customer_state	no_of_unique_customers
1	Apr-2017	AC	5
2	Apr-2017	AL	23
3	Apr-2017	AM	13
4	Apr-2017	BA	93
5	Apr-2017	CE	43
6	Apr-2017	DF	35
7	Apr-2017	ES	46
8	Apr-2017	GO	41
9	Apr-2017	MA	27
10	Apr-2017	MG	275
11	Apr-2017	MS	15
12	Apr-2017	MT	27

Results per page: 50 ▼ 1 – 50 of 565 **| < <**

2. Distribution of customers across the states in Brazil

SELECT customer_state,
COUNT(o.customer_id) as no_of_unique_customers
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c
INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o
ON c.customer_id = o.customer_id
GROUP BY customer_state
ORDER BY no_of_unique_customers desc

1.	customer_state	no_of_unique_customers
1	SP	41746
2	RJ	12852
3	MG	11635
4	RS	5466
5	PR	5045
6	SC	3637
7	BA	3380
8	DF	2140
9	ES	2033
10	GO	2020
11	PE	1652
12	CE	1336

Results per page: $50 \checkmark 1 - 27 \text{ of } 27$

❖ The state with the largest number of customers is Sao Paulo with 41,000+ unique customers, Rio De Janeiro stands second with 12,500+ customers and Minas Gerais in the 3rd position with 11,500+ customers.

4. Impact on Economy:

Analyse the money movement by e-commerce by looking at order prices, freight, and others.

4.1Get % increase in cost of orders from 2017 to 2018 (include months between Jan to Aug only) - You can use "payment_value" column in payments table.

```
ROUND(((payment_value_2018 - payment_value_2017)/payment_value_2017)*100,2) as percentage_increase
FROM
(select
SUM(CASE WHEN
EXTRACT(YEAR from order_purchase_timestamp)= 2017
THEN p.payment_value
ELSE 0
END) as payment_value_2017,
SUM(CASE WHEN
EXTRACT(YEAR from order_purchase_timestamp)= 2018
THEN p.payment_value
ELSE 0
END) as payment_value_2018
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o
INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.payments` p
ON o.order_id = p.order_id
WHERE EXTRACT(YEAR from o.order_purchase_timestamp) in (2017,2018) and
EXTRACT(MONTH from o.order_purchase_timestamp) between 1 and 8)
      percentage_increase
1
                 136.98
```

- The total payment value of orders showed a zen percentage plus increase in 2018 when compared to 2017. It shows a 137% hike in 2018.E-commerce has influenced the money movements in the country positively.
 - 4.1 Mean & Sum of price and freight value by customer state

```
SELECT
```

```
SUM(price) as total_order_value,
SUM(freight_value) as total_freight_value,
AVG(price) as mean_order_value,
AVG(freight_value) as mean_freight_value
```

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o

ON c.customer_id = o.customer_id

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.order_items` oi

ON oi.order_id = o.order_id

```
      Row
      total_order_value
      total_freight_value
      mean_order_value
      mean_freight_value

      1
      13591643.70001...
      2251909.540000...
      120.6537390146...
      19.99031992898...
```

❖ The mean order value and mean freight value amounts to 121 and 20 Brazilian real respectively.

```
SELECT customer_state,
SUM(price) as total_order_value,
SUM(freight_value) as total_freight_value,
AVG(price) as mean_order_value,
```

```
AVG(freight_value) as mean_freight_value
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c
INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o
ON c.customer_id = o.customer_id
INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.order_items` oi
ON oi.order_id = o.order_id
GROUP BY customer_state
ORDER BY mean_order_value desc,mean_freight_value desc
```

1.	customer_state	total_order_value	total_freight_value	mean_order_value	mean_freight_value
1	PB	115268.0800000	25719.729999999	191.4752159468	42.72380398671
2	AL	80314.81000000	15914.589999999	180.8892117117	35.84367117117
3	AC	15982.94999999	3686.749999999	173.7277173913	40.07336956521
4	RO	46140.64000000	11417.38	165.9735251798	41.06971223021
5	PA	178947.80999999	38699.30000000	165.6924166666	35.83268518518
6	AP	13474.29999999	2788.500000000	164.3207317073	34.00609756097
7	PI	86914.079999999	21218.20000000	160.3580811808	39.14797047970
8	ТО	49621.74000000	11732.67999999	157.52933333333	37.24660317460
9	RN	83034.979999999	18860.099999999	156.9659357277	35.65236294896
10	CE	227254.70999999	48351.589999999	153.7582611637	32.71420162381
11	SE	58920.85000000	14111.46999999	153.0411688311	36.65316883116
12	RR	7829.429999999	2235.190000000	150.5659615384	42.98442307692

When it comes to the statistics of each state in Brazil, 191 and 43 Brazilian real stands as the highest mean order value and mean freight value respectively.

5. Analysis on sales, freight, and delivery time

5.1 Calculate days between purchasing, delivering and estimated delivery

```
#checking for null values if any before applying formula.
select order_purchase_timestamp, order_delivered_carrier_date,order_estimated_delivery_date
from `dsml-scaler-sql1.Business_Case_Target_SQL.orders`o
WHERE order_purchase_timestamp is null or order_delivered_carrier_date is null or order_estimated_delivery_date is null
#Found some 1783 null values are present in order_delivered_carrier_date
#No null values in order_purchase_timestamp and order_estimated_delivery_date
```

#diff_btwn_delivering_v/s_purchasing =order_delivered_customer_date - order_purchase_timestamp #diff_btwn_estimated_delivery_v/s_purchase= order_estimated_delivery_date - order_purchase_timestamp #diff_btwn_estimated_delivery_v/s_delivery = order_estimated_delivery_date - order_delivered_customer_date

#diff_btwn_delivering_vs_purchasing =order_delivered_customer_date - order_purchase_timestamp select order_delivered_customer_date,order_purchase_timestamp, DATE_DIFF(order_delivered_customer_date,order_purchase_timestamp,DAY) as diff_btwn_delivering_vs_purchasing from `dsml-scaler-sql1.Business_Case_Target_SQL.orders`o ORDER BY diff_btwn_delivering_vs_purchasing desc

11	order_delivered_customer_date_	order_purchase_timestamp	diff_btwn_delivering_vs_purchasing
1	2017-09-19 14:36:39 UTC	2017-02-21 23:31:27 UTC	209
2	2018-09-19 23:24:07 UTC	2018-02-23 14:57:35 UTC	208
3	2017-09-19 15:12:50 UTC	2017-03-07 23:59:51 UTC	195
4	2017-09-19 14:38:21 UTC	2017-03-09 13:26:57 UTC	194
5	2017-09-19 14:00:04 UTC	2017-03-08 22:47:40 UTC	194
6	2017-09-19 14:33:17 UTC	2017-03-08 18:09:02 UTC	194
7	2018-07-13 20:51:31 UTC	2018-01-03 09:44:01 UTC	191
8	2017-09-19 17:00:07 UTC	2017-03-13 20:17:10 UTC	189
9	2017-09-19 14:38:18 UTC	2017-03-15 11:24:27 UTC	188
10	2017-09-19 16:28:58 UTC	2017-03-16 11:36:00 UTC	187
11	2017-09-19 17:14:25 UTC	2017-03-15 23:23:17 UTC	187
12	2017-09-19 18:13:19 UTC	2017-03-17 12:32:22 UTC	186
		Results per page: 50	0 ▼ 1 - 50 of 99441 <

#diff_btwn_estimated_delivery_vs_purchase= order_estimated_delivery_date - order_purchase_timestamp select order_estimated_delivery_date,order_purchase_timestamp,

DATE_DIFF(order_estimated_delivery_date,order_purchase_timestamp,DAY) as diff_btwn_estimated_delivery_vs_purchase from `dsml-scaler-sql1.Business_Case_Target_SQL.orders`o

ORDER BY diff_btwn_estimated_delivery_vs_purchase desc

1.	order_estimated_delivery_date_	order_purchase_timestamp	diff_btwn_estimated_delivery_vs_purchase
1	2018-07-12 00:00:00 UTC	2018-02-06 20:44:56 UTC	155
2	2018-08-03 00:00:00 UTC	2018-03-06 09:47:07 UTC	149
3	2017-07-04 00:00:00 UTC	2017-02-07 18:01:15 UTC	146
4	2017-08-08 00:00:00 UTC	2017-03-16 02:30:51 UTC	144
5	2017-08-22 00:00:00 UTC	2017-03-30 15:23:23 UTC	144
6	2017-08-04 00:00:00 UTC	2017-03-14 19:23:22 UTC	142
7	2017-10-11 00:00:00 UTC	2017-05-23 22:28:36 UTC	140
8	2018-01-30 00:00:00 UTC	2017-10-05 21:39:05 UTC	116
9	2017-10-19 00:00:00 UTC	2017-07-01 15:47:06 UTC	109
10	2018-06-13 00:00:00 UTC	2018-02-26 00:11:02 UTC	106
11	2010 04 04 06 00-00-00 UTO	2017 12 25 22-45-25 UTO	101
	F	Results per page: 50 ▼	1 - 50 of 99441 <

#diff_estimated_delivery_vs_delivery = order_estimated_delivery_date - order_delivered_customer_date

select order_estimated_delivery_date,order_delivered_customer_date,

DATE_DIFF(order_estimated_delivery_date,order_delivered_customer_date,DAY) as diff_btwn_estimated_delivery_vs_delivery from `dsml-scaler-sql1.Business_Case_Target_SQL.orders`o

ORDER BY diff_btwn_estimated_delivery_vs_delivery desc

11	order_estimated_delivery_date	order_delivered_customer_date_	diff_btwn_estimated_delivery_vs_delivery
1	2018-08-03 00:00:00 UTC	2018-03-09 23:36:47 UTC	146
2	2017-07-04 00:00:00 UTC	2017-02-14 14:27:45 UTC	139
3	2018-07-12 00:00:00 UTC	2018-02-27 16:35:43 UTC	134
4	2017-10-11 00:00:00 UTC	2017-06-09 13:35:54 UTC	123
5	2018-01-30 00:00:00 UTC	2017-10-13 13:49:07 UTC	108
6	2018-03-22 00:00:00 UTC	2017-12-28 22:18:23 UTC	83
7	2018-04-25 00:00:00 UTC	2018-02-01 01:52:34 UTC	82
8	2018-04-27 00:00:00 UTC	2018-02-08 19:21:39 UTC	77
9	2018-01-11 00:00:00 UTC	2017-10-25 20:22:10 UTC	77
10	2018-02-16 00:00:00 UTC	2017-11-30 16:12:50 UTC	77
11	2018-04-09 00:00:00 UTC	2018-01-22 22:58:10 UTC	76
12	2017-01-11 00:00:00 UTC	2016-10-27 10:58:35 UTC	75
		Deculto per pega. FO -	1 F0 of 00441 14

Results per page: 50 ▼ 1 - 50 of 99441 **| < <**

❖ As per the analysis the highest difference between purchase and estimated delivery stands at nearly 210 days, difference between estimated delivery and purchase at 155 days and difference between estimated delivery and delivery at positive 146 days meaning an early product delivery of 146 days.

**Instead of order_delivered_carrier_date have used order_delivered_customer_date in all the above 3 formulas because order_delivered_customer_date is the delivery date from customers perspective. Also order_delivered_carrier_date contains many null values. It needs to be filtered out if order_delivered_carrier_date needs to be considered.

- 5.2 Find time_to_delivery & diff_estimated_delivery. Formula for the same given below:
 - time_to_delivery = order_delivered_customer_date-order_purchase_timestamp

select order_delivered_customer_date,order_purchase_timestamp,
DATE_DIFF(order_delivered_customer_date,order_purchase_timestamp,DAY) as time_to_delivery
from `dsml-scaler-sql1.Business_Case_Target_SQL.orders`o
ORDER BY time_to_delivery desc

1.	order_delivered_customer_date	order_purchase_timestamp ▼	time_to_delivery 🔻
1	2017-09-19 14:36:39 UTC	2017-02-21 23:31:27 UTC	209
2	2018-09-19 23:24:07 UTC	2018-02-23 14:57:35 UTC	208
3	2017-09-19 15:12:50 UTC	2017-03-07 23:59:51 UTC	195
4	2017-09-19 14:38:21 UTC	2017-03-09 13:26:57 UTC	194
5	2017-09-19 14:00:04 UTC	2017-03-08 22:47:40 UTC	194
6	2017-09-19 14:33:17 UTC	2017-03-08 18:09:02 UTC	194
7	2018-07-13 20:51:31 UTC	2018-01-03 09:44:01 UTC	191
8	2017-09-19 17:00:07 UTC	2017-03-13 20:17:10 UTC	189
9	2017-09-19 14:38:18 UTC	2017-03-15 11:24:27 UTC	188
10	2017-09-19 16:28:58 UTC	2017-03-16 11:36:00 UTC	187
11	2017-09-19 17:14:25 UTC	2017-03-15 23:23:17 UTC	187
10	2017 00 10 10 10 12 10 UTC	2017 02 17 12:22:22 LITO	104
	Results per page:	50 ▼ 1 − 50 of 99441	I< < >

 diff_estimated_delivery = order_estimated_delivery_date order_delivered_customer_date

 ${\tt select}\ order_estimated_delivery_date, order_delivered_customer_date,$

 ${\color{blue} {\sf DATE_DIFF}} (order_estimated_delivery_date, order_delivered_customer_date, DAY) \ as \ diff_estimated_delivery \ and \ an article of the control of the contr$

from `dsml-scaler-sql1.Business_Case_Target_SQL.orders`o

ORDER BY diff_estimated_delivery desc

1.	order_estimated_delivery_date	order_delivered_customer_date	diff_estimated_delivery
1	2018-08-03 00:00:00 UTC	2018-03-09 23:36:47 UTC	146
2	2017-07-04 00:00:00 UTC	2017-02-14 14:27:45 UTC	139
3	2018-07-12 00:00:00 UTC	2018-02-27 16:35:43 UTC	134
4	2017-10-11 00:00:00 UTC	2017-06-09 13:35:54 UTC	123
5	2018-01-30 00:00:00 UTC	2017-10-13 13:49:07 UTC	108
6	2018-03-22 00:00:00 UTC	2017-12-28 22:18:23 UTC	83
7	2018-04-25 00:00:00 UTC	2018-02-01 01:52:34 UTC	82
8	2018-04-27 00:00:00 UTC	2018-02-08 19:21:39 UTC	77
9	2018-01-11 00:00:00 UTC	2017-10-25 20:22:10 UTC	77
10	2018-02-16 00:00:00 UTC	2017-11-30 16:12:50 UTC	77
11	2018-04-09 00:00:00 UTC	2018-01-22 22:58:10 UTC	76
12	2017-01-11 00:00:00 UTC	2016-10-27 10:58:35 UTC	75

❖ The highest expected time for product delivery is 209 days and the highest difference in estimated delivery comes to a positive 146 days meaning an early product delivery of 146 days.

1 - 50 of 99441

5.3 Group data by state, take mean of freight_value, time_to_delivery, diff_estimated_delivery

50 ▼

SELECT subq.customer_state,

AVG(freight_value) as mean_freight_value,

AVG(time_to_delivery) as mean_time_to_delivery,

AVG(diff_estimated_delivery) as mean_diff_estimated_delivery

from

(select customer_state,freight_value,order_delivered_customer_date,order_purchase_timestamp, DATE_DIFF(order_delivered_customer_date,order_purchase_timestamp,DAY) as time_to_delivery,

DATE_DIFF(order_estimated_delivery_date,order_delivered_customer_date,DAY) as diff_estimated_delivery

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o

ON c.customer_id = o.customer_id

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.order_items` oi

Results per page:

ON oi.order_id = o.order_id

ORDER BY time_to_delivery desc) as subq

GROUP BY customer_state

11	customer_state	mean_freight_value	mean_time_to_delivery	mean_diff_estimated_delivery
1	MT	28.1662843601	17.508196721311	13.639344262295094
2	MA	38.2570024271	21.203750000000	9.109999999999923
3	AL	35.8436711711	23.992974238875	7.9765807962529349
4	SP	15.1472753904	8.25960855241909	10.26559438451439
5	MG	20.6301668063	11.515522180072	12.397151041263502
6	PE	32.9178626799	17.792096219931	12.552119129438733
7	RJ	20.9609239316	14.689382157500	11.14449314293797
8	DF	21.0413549459	12.501486199575	11.274734607218704
9	RS	21.7358043303	14.708299364095	13.203000163052323
10	SE	36.6531688311	20.978666666666	9.1653333333333276
11	PR	20.5316515679	11.480793060718	12.533899805275263
12	PA	35.8326851851	23.301707779886	13.37476280834913

Results per page:

50 ▼ 1 - 27 of 27 | **〈 〉**



5.4 Sort the data to get the following:

5.5 Top 5 states with highest/lowest average freight value - sort in desc/asc limit 5

#cte version

with cte as

(SELECT subq.customer_state,

ROUND(AVG(freight_value),0) as mean_freight_value,

ROUND(AVG(time_to_delivery),0) as mean_time_to_delivery,

ROUND(AVG(diff_estimated_delivery),0) as mean_diff_estimated_delivery

from

(select customer_state,freight_value,order_delivered_customer_date,order_purchase_timestamp,

DATE_DIFF(order_delivered_customer_date,order_purchase_timestamp,DAY) as time_to_delivery,

DATE_DIFF(order_estimated_delivery_date,order_delivered_customer_date,DAY) as diff_estimated_delivery

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o

ON c.customer_id = o.customer_id

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.order_items` oi

ON oi.order_id = o.order_id

ORDER BY time_to_delivery desc) as subq

GROUP BY customer_state)

select * from cte

ORDER BY mean_freight_value desc

LIMIT 5

Row	customer_state	mean_freight_value	mean_time_to_delivery	mean_diff_estimated_delivery
1	PB	43.0	20.0	12.0
2	RR	43.0	28.0	17.0
3	RO	41.0	19.0	19.0
4	AC	40.0	20.0	20.0
5	PI	39.0	19.0	11.0

- ❖ Paraiba (PB) and Roraima (RR) emerges as the states with highest mean freight value of 43 Brazilian real.
- 5.6 Top 5 states with highest/lowest average time to delivery

```
with cte as
(SELECT subq.customer_state,
ROUND(AVG(freight_value)) as mean_freight_value,
ROUND(AVG(time_to_delivery)) as mean_time_to_delivery,
ROUND(AVG(diff_estimated_delivery)) as mean_diff_estimated_delivery
(select customer_state,freight_value,order_delivered_customer_date,order_purchase_timestamp,
DATE_DIFF(order_delivered_customer_date,order_purchase_timestamp,DAY) as time_to_delivery,
DATE_DIFF(order_estimated_delivery_date,order_delivered_customer_date,DAY) as diff_estimated_delivery
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c
INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o
ON c.customer_id = o.customer_id
INNER JOIN 'dsml-scaler-sql1.Business_Case_Target_SQL.order_items' oi
ON oi.order_id = o.order_id
ORDER BY time_to_delivery desc) as subq
GROUP BY customer_state)
select * from cte
ORDER BY mean_time_to_delivery desc
LIMIT 5
```

Row	customer_state	mean_freight_value	mean_time_to_delivery	mean_diff_estimated_delivery
1	AP	34.0	28.0	17.0
2	RR	43.0	28.0	17.0
3	AM	33.0	26.0	19.0
4	AL	36.0	24.0	8.0
5	PA	36.0	23.0	13.0

- Amapa (AP) and Roraima (RR) emerges as the states with highest mean time to delivery i.e., 28 days.
- 5.7Top 5 states where delivery is really fast/ not so fast compared to estimated date

#cte version with cte as (SELECT subq.customer_state, ROUND(AVG(freight_value)) as mean_freight_value, ROUND(AVG(time_to_delivery)) as mean_time_to_delivery, ROUND(AVG(diff_estimated_delivery)) as mean_diff_estimated_delivery from (select customer_state, freight_value, order_delivered_customer_date, order_purchase_timestamp, DATE_DIFF(order_delivered_customer_date,order_purchase_timestamp,DAY) as time_to_delivery, DATE_DIFF(order_estimated_delivery_date,order_delivered_customer_date,DAY) as diff_estimated_delivery FROM `dsml-scaler-sql1.Business_Case_Target_SQL.customers` c INNER JOIN 'dsml-scaler-sql1.Business_Case_Target_SQL.orders' o ON c.customer_id = o.customer_id INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.order_items` oi ON oi.order_id = o.order_id ORDER BY time_to_delivery desc) as subq GROUP BY customer_state) select * from cte ORDER BY mean_diff_estimated_delivery desc LIMIT 5

Row	customer_state	mean_freight_value	mean_time_to_delivery	mean_diff_estimated_delivery
1	AC	40.0	20.0	20.0
2	RO	41.0	19.0	19.0
3	AM	33.0	26.0	19.0
4	RR	43.0	28.0	17.0
5	AP	34.0	28.0	17.0

Acre (AC) and Rondonia (RO) are the top 2 states with highest difference in estimated delivery of a positive 20 and 19 days meaning an early delivery of 20 and 19 days.

6. Payment type analysis:

6.1 Month over Month count of orders for different payment types

```
from

(SELECT FORMAT_DATETIME('%b-%Y',order_purchase_timestamp) as month_yr_purchase,
payment_type,
COUNT(payment_value) as count_payment_value
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.payments` p
INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o
ON p.order_id = o.order_id
GROUP BY FORMAT_DATETIME('%b-%Y',order_purchase_timestamp),payment_type) as subq
ORDER BY month_yr_purchase desc
```

11	month_yr_purchase	payment_type	count_payment_value
1	Sep-2018	not_defined	1
2	Sep-2018	voucher	15
3	Sep-2017	credit_card	3283
4	Sep-2017	voucher	287
5	Sep-2017	UPI	903
6	Sep-2017	debit_card	43
7	Sep-2016	credit_card	3
8	Oct-2018	voucher	4
9	Oct-2017	voucher	291
10	Oct-2017	credit_card	3524
11	Oct-2017	UPI	993

```
#Year wise count of orders grouped by payment type select *
from
(SELECT EXTRACT(YEAR from order_purchase_timestamp) as year_of_purchase,
payment_type,
COUNT(payment_value) as count_payment_value
FROM `dsml-scaler-sql1.Business_Case_Target_SQL.payments` p
INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o
ON p.order_id = o.order_id
GROUP BY EXTRACT(YEAR from order_purchase_timestamp),payment_type) as subq
ORDER BY year_of_purchase desc
```

11	year_of_purchase	payment_type	count_payment_value
1	2018	credit_card	41969
2	2018	voucher	2725
3	2018	not_defined	3
4	2018	debit_card	1105
5	2018	UPI	10213
6	2017	voucher	3027
7	2017	credit_card	34568
8	2017	UPI	9508
9	2017	debit_card	422
10	2016	credit_card	258
11	2016	voucher	23
12	2016	debit_card	2

- ❖ Credit card showed the highest hike in the number of transactions from nearly 250 in 2016 to 34,500+ in 2017 and reaching nearly 42000 in 2018. UPI holds the second highest number of transactions with 10000+ transactions in 2018, nearly 9500 transactions in 2017 f rom just 63 transactions in 2016.
- 6.2 Count of orders based on the no. of payment instalments.

50 **▼** 1 – 13 of 13 **| ⟨**

select *
from(

SELECT EXTRACT(YEAR from order_purchase_timestamp) as year_of_purchase, payment_installments,

payment_installments

COUNT(payment_installments) as count_payment_installments

FROM `dsml-scaler-sql1.Business_Case_Target_SQL.payments` p

INNER JOIN `dsml-scaler-sql1.Business_Case_Target_SQL.orders` o

ON p.order_id = o.order_id

 ${\tt GROUP~BY~EXTRACT} ({\tt YEAR~from~order_purchase_timestamp}), payment_installments)$

order by year_of_purchase desc

Results per page:

N .	year_of_purchase	payment_installment	count_payment_installments_
1	2018	0	2
2	2018	1	29138
3	2018	2	7020
4	2018	3	5507
5	2018	4	3697
6	2018	5	2654
7	2018	6	2020
8	2018	7	765
9	2018	8	2545
10	2018	9	262
11	2018	10	2248
12	2018	11	9

2018		2017		2016	
payment_ installments	count_payment _installments	payment_ installments	count_payment _installments	payment_ installments	count_payment _installments
0	2				
1	29138	1	23262	1	146
2	7020	2	5362	2	31
3	5507	3	4910	3	44
4	3697	4	3375	4	26
5	2654	5	2565	5	20
6	2020	6	1882	6	18
7	765	7	848	7	13
8	2545	8	1720	8	3
9	262	9	379	9	3
10	2248	10	3038	10	42
11	9	11	14		
12	58	12	75		
13	9	13	7		
14	6	14	9		
15	48	15	26		
16	3	16	2		
17	5	17	3		
18	11	18	16		
20	5	20	12		
23	1	21	3		
24	2	22	1		
		24	16		

- ❖ The jump of count of customers who opted payment instalments from 146 in 2016 to 23,000+ in 2017 to 29,000+ in 2018 shows their movement from reluctance towards opting payment instalments to acceptance of the same.
- ❖ The enhanced number of customers opting for 10 payment instalments over 2017 and 2018 shows their readiness to opt till 10 payment instalments. The declining count beyond 10 payment instalments shows their reluctance towards higher count of payment instalments.

7. Actionable Insights

- a) A clear hike in the online purchase in the months of June, July and Aug can be traced across 2017 and 2018.
 - a) Customers of Target in Brazil are widespread across 27 states and 4119 cities as per the info. from the orders table.
 - b) A clear growing trend on e-commerce in Brazil can be seen from the data from the enhancement in the number of customers from 329 in 2016 to 45,000+ in 2017 to 54,000 in 2018.
 - c) Brazilian customers tend to buy the most in the afternoon with 38,000+ unique purchases in a year, followed by 28,000+ purchase during the night, followed by morning in the 3rd position with 27000+ unique purchases in a year and lastly during dawn with 5000+ purchases.
 - d) The state with the largest number of customers is Sao Paulo (SP) with 41,000+ unique customers, Rio De Janeiro (RJ) stands second with 12,500+ customers and Minas Gerais (MG) in the 3rd position with 11,500+ customers.
 - e) The total payment value of orders showed a zen percentage plus increase in 2018 when compared to 2017. It shows a 137% hike in 2018.E-commerce has influenced the money movements in the country positively.
 - f) The mean order value and mean freight value amounts to 121 and 20 Brazilian real respectively.
 - g) When it comes to the statistics of each state in Brazil, 191 and 43 Brazilian real stands as the highest mean order value and mean freight value respectively.

- h) As per the analysis the highest difference between purchase and estimated delivery stands at nearly 210 days, difference between estimated delivery and purchase at 155 days and difference between estimated delivery and delivery at positive 146 days meaning an early product delivery of 146 days.
- i) The highest expected time for product delivery is 209 days and the highest difference in estimated delivery comes to a positive 146 days meaning an early product delivery of 146 days which is a huge achievement.
- j) Paraiba (PB) and Roraima (RR) emerged as the states with highest mean freight value of 43 Brazilian real.
- k) Amapa (AP) and Roraima (RR) emerged as the states with highest mean time to delivery i.e., 28 days.
- I) Acre (AC) and Rondonia (RO) are the top 2 states with highest difference in estimated delivery of a positive 20 and 19 days meaning an early delivery of 20 and 19 days.
- m) Credit card showed the highest hike in the number of transactions from nearly 250 in 2016 to 34,500+ in 2017 and reaching nearly 42000 in 2018. UPI holds the second highest number of transactions with 10000+ transactions in 2018, nearly 9500 transactions in 2017 from just 63 transactions in 2016.
- n) The jump of count of customers who opted payment instalments from 146 in 2016 to 23,000+ in 2017 to 29,000+ in 2018 shows their movement from reluctance towards opting payment instalments to acceptance of the same.
- o) The enhanced number of customers opting for 10 payment instalments over 2017 and 2018 shows their readiness to opt till 10 payment instalments. The declining count beyond 10 payment instalments shows their reluctance towards higher count of payment instalments.

8. Recommendations

- a) Any roll out of offers for customers is recommended to be planned in the months of June, July, August as there is a hike in purchase during these months over the last 2 years -2017 and 2018.
- b) Since customers of Target are already widespread across the states, now priority should be on maintaining the customers along with business expansion.
- c) Any roll out of offers for customers is recommended to be given during afternoon followed by night-time looking at the increased number of customers making purchase during those timings of the day.
- d) The enhancing number of E-commerce transactions can be positively used to influence the money movements in the country.
- e) The highest difference in estimated delivery comes to a positive 146 days meaning an early product delivery of 146 days which is a huge achievement which is a good criterion to maintain. In fact, the estimation of the same should be calculated much more accurately.
- f) But when it comes to the statistics of each state, Acre (AC) and Rondonia (RO) are the top 2 states with highest difference in estimated delivery of a positive 20 and 19 days meaning an early delivery of 20 and 19 days which is still a good number.
- g) Chances are there that credit card transactions will see a hike with any further customerfriendly credit-card related purchase offers.
- h) Customers must be subjected for a study to learn about their thought process with respect to opting higher number of payment instalments.