XAPO BANK

SENIOR DATA ANALYST - BUSINESS CASE

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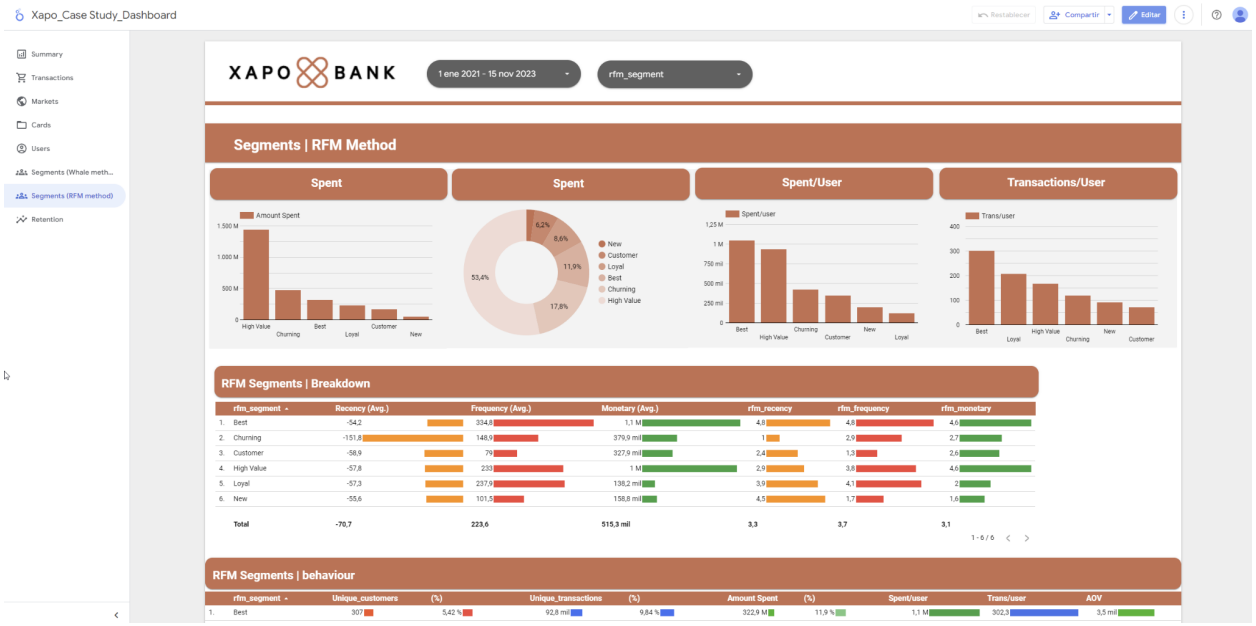
Case Study 1: Expanding a Crypto Bank Offering a Global Card

Approach, choices, thought process

1. First of all I started by **visualizing** the data from the different tables to get a picture of the data (**Data Studio** dashboard). Summarizing and categorizing data and analyzing trends and patterns over time.
2. Then I used **BigQuery** to explore the data, by joining the different tables and also including external info (geographical data, economics, banking, crypto, Merchants codes, internet penetration, etc.). Basically I tried to connect the dots and create tables to further analyze in my Dashboard. In this last step I created multiple custom dimensions and categorizations, while also creating calculated metrics.
3. I ended up with lots of **tables and charts** from which I derived lots of interesting insights about the bank's card performance, transaction behavior, user persona, segments, markets and user retention.

Dashboard

⇒ [Link to Data Studio dashboard.]



I built a Dashboard with **multiple pages** for each area of analysis:

- Transactions
- Users
- Cards
- Segments
- etc.

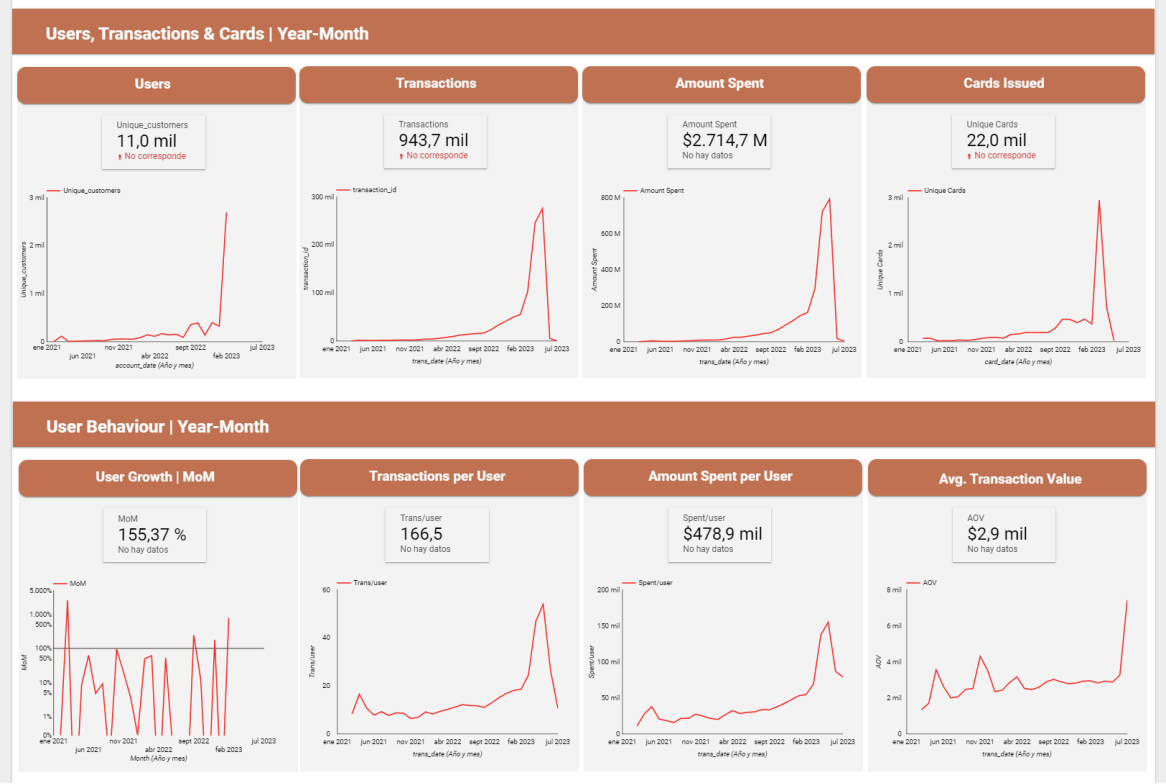
Exploratory data analysis, Interpretation of results and insights

⇒ Link to folder with all the queries.

General Insights

First I got some general insights that describe the overall performance of the card:

- Customers: 11k
- Transactions: 943K
- Spent: $2.714M
- Cards issued: 22k
- Trans/user: 166,5
- Spent/user: $478,9K
- AOV: $2,9K
- MoM user growth avg: 155%



⇒Link to file with queries for Calculated metrics

⇒Link to file with queries for MoM

Interpretation of results:

The bank has **grown** exponentially this year (users and spend). However we can clearly see in the charts above that the results are very **weird**. There were huge **spikes** in users, cards and transactions followed by nothing for several months.

- First, **4,9K users** (45% of total user base) created an account on **feb 28, 2023** and after that day nobody else created an account. Of these users, **75%** already had a card previous to account creation (card issuing date before account creation date).

  My assumptions from this behavior are that there might be an error in the dataset or maybe people could have a card before an account and one day the bank created an account for all of them.

Users

	Date_Dimension_account	Unique_customers	(%)
1.	28 feb 2023	4,9 mil	44,27 %
2.	30 sept 2022	45	0,41 %
3.	30 nov 2022	41	0,37 %
4.	31 dic 2022	39	0,35 %
5.	31 ago 2022	35	0,32 %
6.	11 dic 2022	34	0,31 %
7.	31 ene 2023	33	0,3 %
8.	23 dic 2022	33	0,3 %
	Total	**11 mil**	**100 %**

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```sql
, date_min as (
select customer_id, account_date, min (card_date) as min_card,
from users_feb
group by customer_id, account_date
)

, days_before_card as (
select customer_id,account_date, min_card, date_diff(min_card, account_date, day) as days_before
from date_min

)


select count(distinct customer_id) as users_had_card_before,round(count(distinct customer_id)/(select count(distinct customer_id) from days_before_card),2) as pct
from days_before_card
where days_before<0
```

Presiona Alt+F1 para ver las opciones de acc

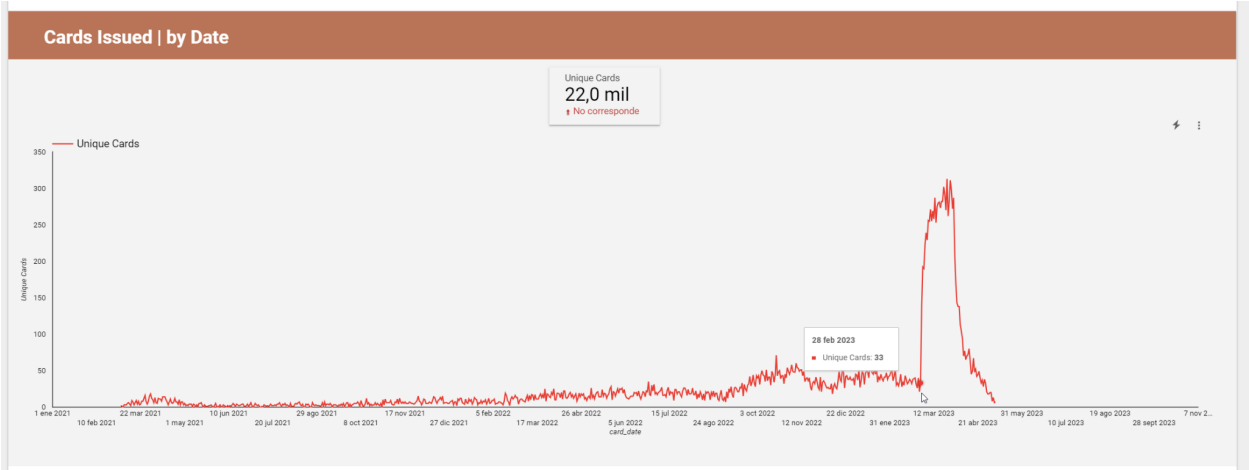
Resultados de la consulta

GUARDAR LOS RESULTADOS | EXPLORAR DATOS

INFORMACIÓN DEL TRABAJO | RESULTADOS | GRÁFICO VISTA PREVIA | JSON | DETALLES DE LA EJECUCIÓN | GRÁFICO DE EJECUCIÓN

Fila	users_had_card_before	pct
1	3166	0.75

- Second, there is a spike in **cards** in **March** (**36%** of all cards), driven by new users acquired in February.



Cards

	Date_Dimension_Cards	Unique_cards	(%)
1.	1 mar 2023	8,1 mil	36,79 %
2.	1 abr 2023	2 mil	9,29 %
3.	1 ene 2023	1,4 mil	6,14 %
4.	1 oct 2022	1,3 mil	6,05 %
5.	1 nov 2022	1,2 mil	5,63 %
6.	1 dic 2022	1,1 mil	4,88 %
7.	1 feb 2023	1 mil	4,62 %
8.	1 sept 2022	720	3,28 %
	Total	**22 mil**	**100 %**

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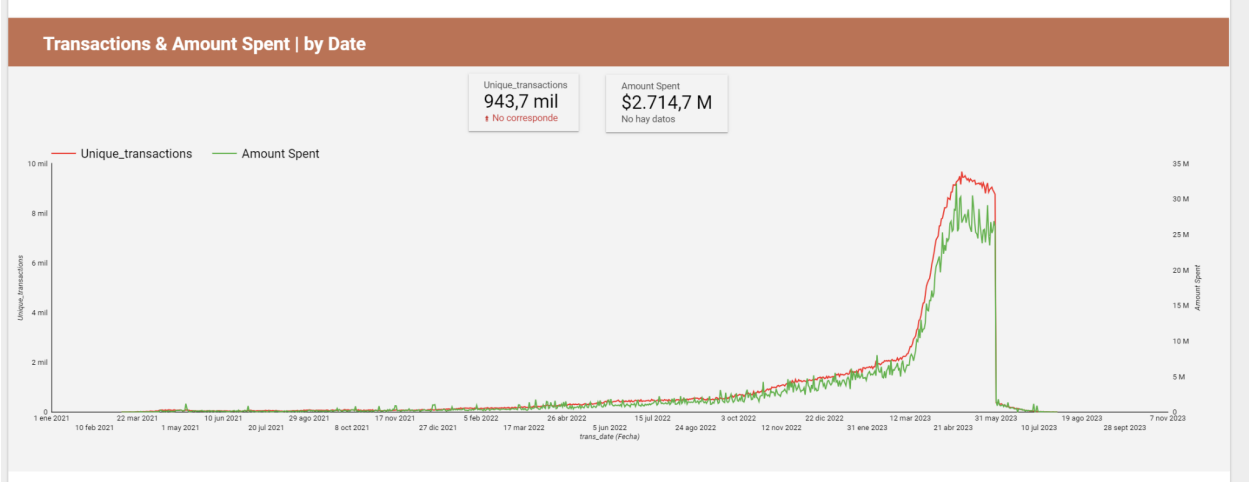
- Third, we have a spike in **transactions** and amount spent during **March-May 2023** (**67%** of all transactions). And also as well followed by very few transactions until July, where eventually there were no more transactions.



Date_Dimension: Year_Month

Transactions

	Date_Dimension_trans	Unique_transactions	(%)	Amount Spent	(%)	Trans/user	Spent/user	AOV
1.	1 may 2023	275,3 mil	29,18 %	$791,02 M	29,14 %	53,9	$154,83 mil	$2,87 mil
2.	1 abr 2023	245,9 mil	26,06 %	$721,17 M	26,57 %	46,8	$137,37 mil	$2,93 mil
3.	1 mar 2023	103,9 mil	11,01 %	$293,96 M	10,83 %	24,5	$69,4 mil	$2,83 mil
4.	1 feb 2023	55,3 mil	5,86 %	$162,99 M	6 %	18,6	$54,77 mil	$2,95 mil
5.	1 ene 2023	49,6 mil	5,25 %	$145,18 M	5,35 %	18,1	$53,06 mil	$2,93 mil
6.	1 dic 2022	41,4 mil	4,39 %	$116,84 M	4,3 %	16,9	$47,67 mil	$2,82 mil
7.	1 nov 2022	33,3 mil	3,53 %	$92,98 M	3,42 %	15,1	$42,13 mil	$2,79 mil
8.	1 oct 2022	23,6 mil	2,5 %	$68,46 M	2,52 %	13	$37,62 mil	$2,9 mil
	Total	**943,7 mil**	**100 %**	**$2.714,69 M**	**100 %**	**166,5**	**$478,87 mil**	**$2,88 mil**

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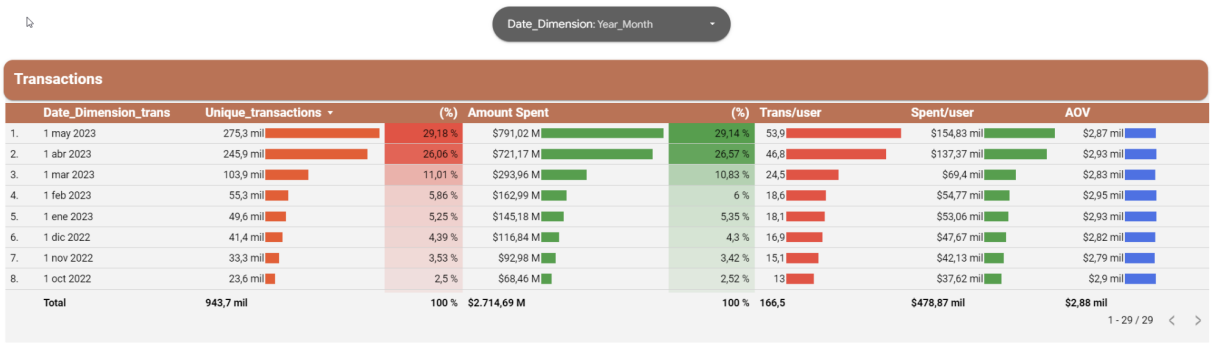
Transactions

Second, I went on to further analyze the **transactions** in greater detail to see if there was anything in particular during the spike period that would explain the behavior. While also trying to analyze changes in user **demography** or **card** type/currency during the spike vs. the average.

Interpretation of results:

- There were no changes in the transaction variables (payment method, status, type, etc.)
- There was no difference in user demography or card type/currency, etc.
- The only **changes** were:
    - 2x user base increase in February
    - 2X increase in transactions/User and amount spent/user during peak.
    - Spike in **Bitcoin** price **(mar-May)** that might have incentivized people to spend their BTC.

⇒ Link to file with queries for joining all tables



	Date_Dimension_trans	Unique_transactions	(%)	Amount Spent	(%)	Trans/user	Spent/user	AOV
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8.	1 oct 2022	23,6 mil	2,5 %	$68,46 M	2,52 %	13	$37,62 mil	$2,9 mil
	Total	943,7 mil	100 %	$2.714,69 M	100 %	166,5	$478,87 mil	$2,88 mil

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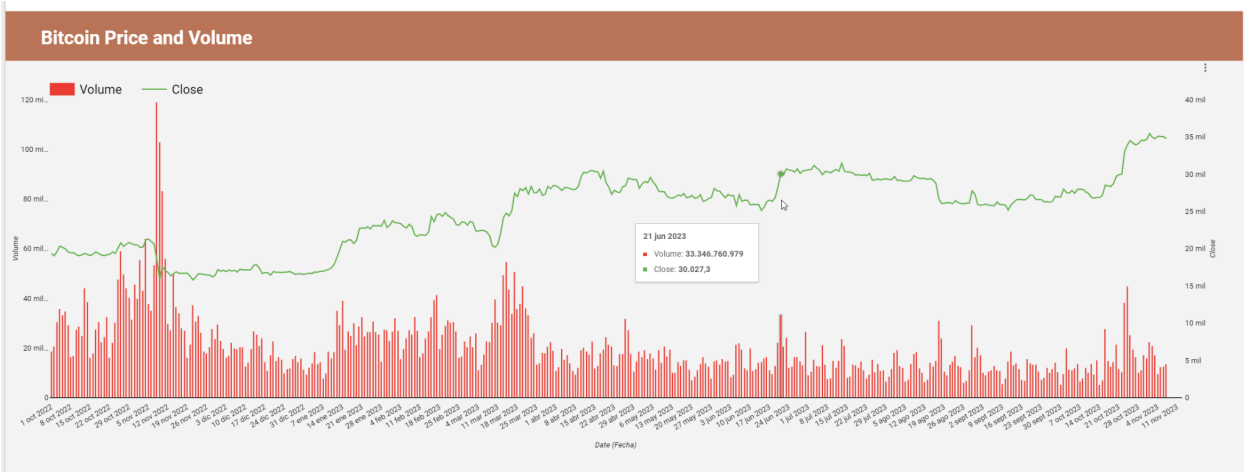
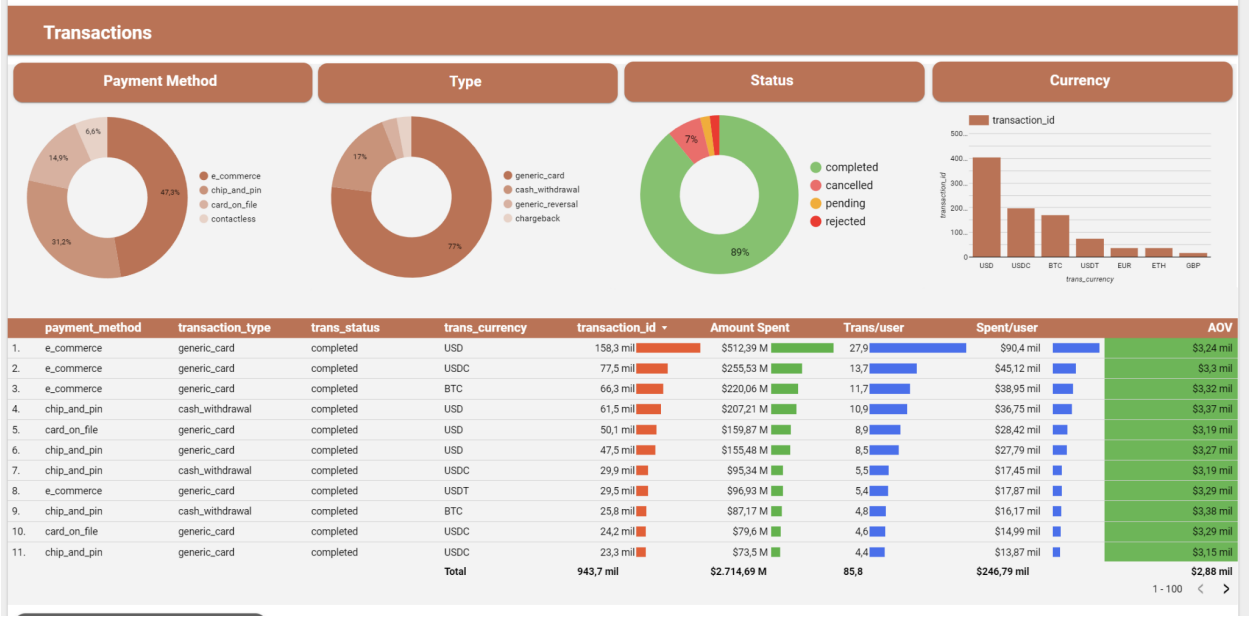


Third, I analyzed the different variables of **user**, **card** and **transaction** data:

a. **Transactions**

- Most of the transactions were in ecommerce (47%), using USD (43%)



	payment_method	transaction_type	trans_status	trans_currency	transaction_id	Amount Spent	Trans/user	Spent/user	AOV
1.	e_commerce	generic_card	completed	USD	158,3 mil	$512,39 M	27,9	$90,4 mil	$3,24 mil
2.	e_commerce	generic_card	completed	USDC	77,5 mil	$255,53 M	13,7	$45,12 mil	$3,3 mil
3.	e_commerce	generic_card	completed	BTC	66,3 mil	$220,06 M	11,7	$38,95 mil	$3,32 mil
4.	chip_and_pin	cash_withdrawal	completed	USD	61,5 mil	$207,21 M	10,9	$36,75 mil	$3,37 mil
5.	card_on_file	generic_card	completed	USD	50,1 mil	$159,87 M	8,9	$28,42 mil	$3,19 mil
6.	chip_and_pin	generic_card	completed	USD	47,5 mil	$155,48 M	8,5	$27,79 mil	$3,27 mil
7.	chip_and_pin	cash_withdrawal	completed	USDC	29,9 mil	$95,34 M	5,5	$17,45 mil	$3,19 mil
8.	e_commerce	generic_card	completed	USDT	29,5 mil	$96,93 M	5,4	$17,87 mil	$3,29 mil
9.	chip_and_pin	cash_withdrawal	completed	BTC	25,8 mil	$87,17 M	4,8	$16,17 mil	$3,38 mil
10.	card_on_file	generic_card	completed	USDC	24,2 mil	$79,6 M	4,6	$14,99 mil	$3,29 mil
11.	chip_and_pin	generic_card	completed	USDC	23,3 mil	$73,5 M	4,4	$13,87 mil	$3,15 mil
				Total	943,7 mil	$2.714,69 M	85,8	$246,79 mil	$2,88 mil

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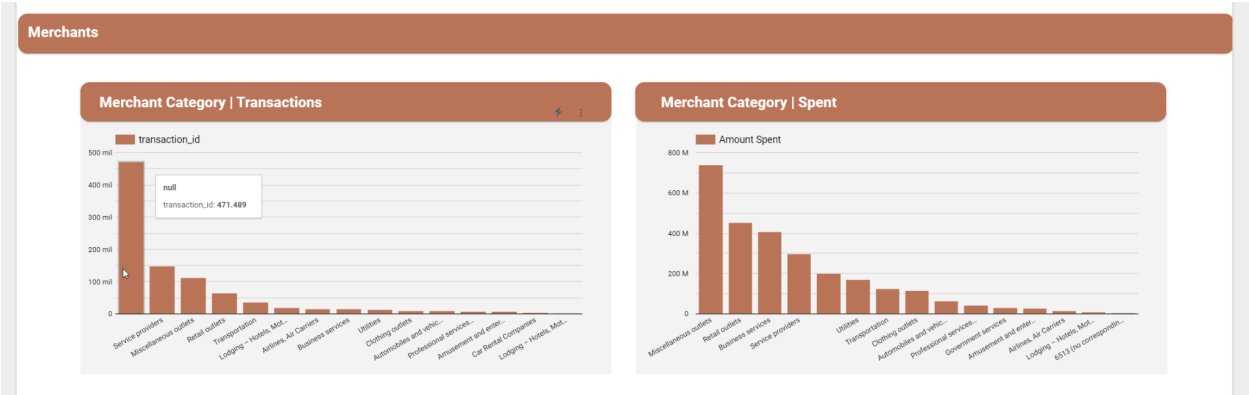
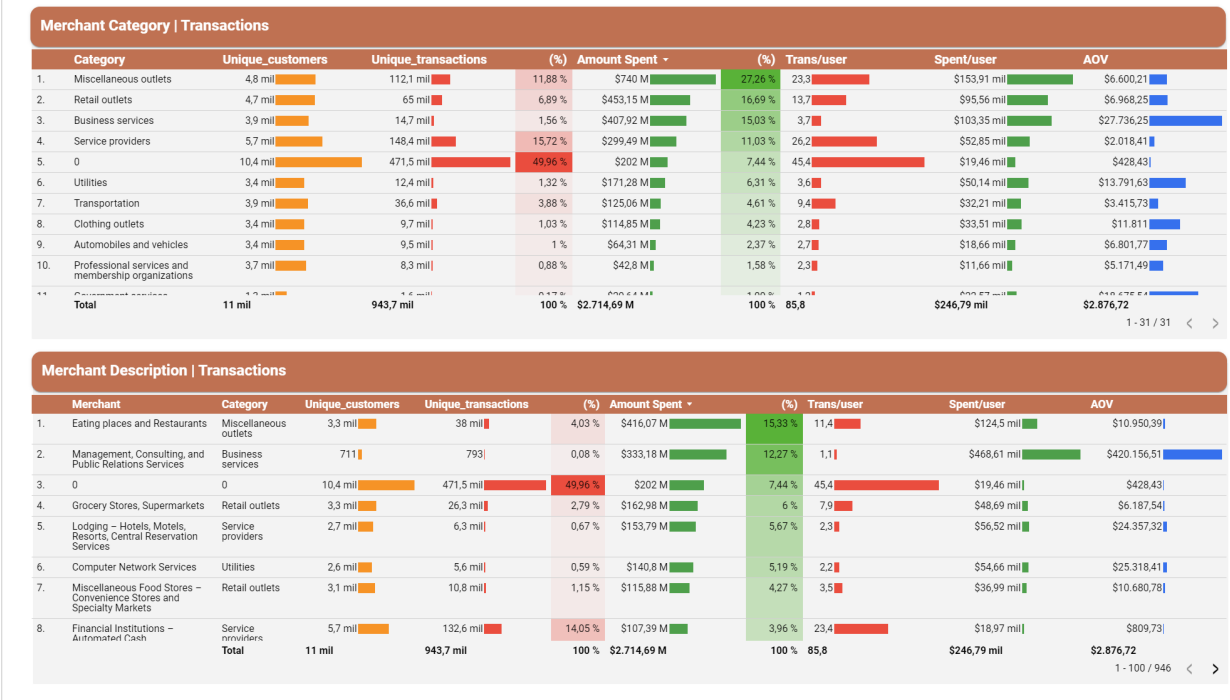
Transactions Mcc's

- Transactions with **MCCs with wrong values** (**50%** didn't match neither mcc_codes dataset nor external MCC datasets I downloaded)
- From the transactions with correct MCC values, the **top transactions** by total spending were:
    - ATMs (14%)
    - Restaurants, groceries and bars (12% - Miscellaneous outlets)





Merchant Category | Transactions

	Category	Unique_customers	Unique_transactions	(%)	Amount Spent	(%)	Trans/user	Spent/user	AOV
1.	Miscellaneous outlets	4,8 mil	112,1 mil	11,88 %	$740 M	27,26 %	23,3	$153,91 mil	$6.600,21
2.	Retail outlets	4,7 mil	65 mil	6,89 %	$453,15 M	16,69 %	13,7	$95,56 mil	$6.968,25
3.	Business services	3,9 mil	14,7 mil	1,56 %	$407,92 M	15,03 %	3,7	$103,35 mil	$27.736,25
4.	Service providers	5,7 mil	148,4 mil	15,72 %	$299,49 M	11,03 %	26,2	$52,85 mil	$2.018,41
5.	0	10,4 mil	471,5 mil	49,96 %	$202 M	7,44 %	45,4	$19,46 mil	$428,43
6.	Utilities	3,4 mil	12,4 mil	1,32 %	$171,28 M	6,31 %	3,6	$50,14 mil	$13.791,63
7.	Transportation	3,9 mil	36,6 mil	3,88 %	$125,06 M	4,61 %	9,4	$32,21 mil	$3.415,73
8.	Clothing outlets	3,4 mil	9,7 mil	1,03 %	$114,85 M	4,23 %	2,8	$33,51 mil	$11.811
9.	Automobiles and vehicles	3,4 mil	9,5 mil	1 %	$64,31 M	2,37 %	2,7	$18,66 mil	$6.801,77
10.	Professional services and membership organizations	3,7 mil	8,3 mil	0,88 %	$42,8 M	1,58 %	2,3	$11,66 mil	$5.171,49
	Total	**11 mil**	**943,7 mil**	**100 %**	**$2.714,69 M**	**100 %**	**85,8**	**$246,79 mil**	**$2.876,72**

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Merchant Description | Transactions

	Merchant	Category	Unique_customers	Unique_transactions	(%)	Amount Spent	(%)	Trans/user	Spent/user	AOV
1.	Eating places and Restaurants	Miscellaneous outlets	3,3 mil	38 mil	4,03 %	$416,07 M	15,33 %	11,4	$124,5 mil	$10.950,39
2.	Management, Consulting, and Public Relations Services	Business services	711	793	0,08 %	$333,18 M	12,27 %	1,1	$468,61 mil	$420.156,51
3.	0	0	10,4 mil	471,5 mil	49,96 %	$202 M	7,44 %	45,4	$19,46 mil	$428,43
4.	Grocery Stores, Supermarkets	Retail outlets	3,3 mil	26,3 mil	2,79 %	$162,98 M	6 %	7,9	$48,69 mil	$6.187,54
5.	Lodging – Hotels, Motels, Resorts, Central Reservation Services	Service providers	2,7 mil	6,3 mil	0,67 %	$153,79 M	5,67 %	2,3	$56,52 mil	$24.357,32
6.	Computer Network Services	Utilities	2,6 mil	5,6 mil	0,59 %	$140,8 M	5,19 %	2,2	$54,66 mil	$25.318,41
7.	Miscellaneous Food Stores – Convenience Stores and Specialty Markets	Retail outlets	3,1 mil	10,8 mil	1,15 %	$115,88 M	4,27 %	3,5	$36,99 mil	$10.680,78
8.	Financial Institutions – Automated Cash	Service providers	5,7 mil	132,6 mil	14,05 %	$107,39 M	3,96 %	23,4	$18,97 mil	$809,73
		Total	**11 mil**	**943,7 mil**	**100 %**	**$2.714,69 M**	**100 %**	**85,8**	**$246,79 mil**	**$2.876,72**

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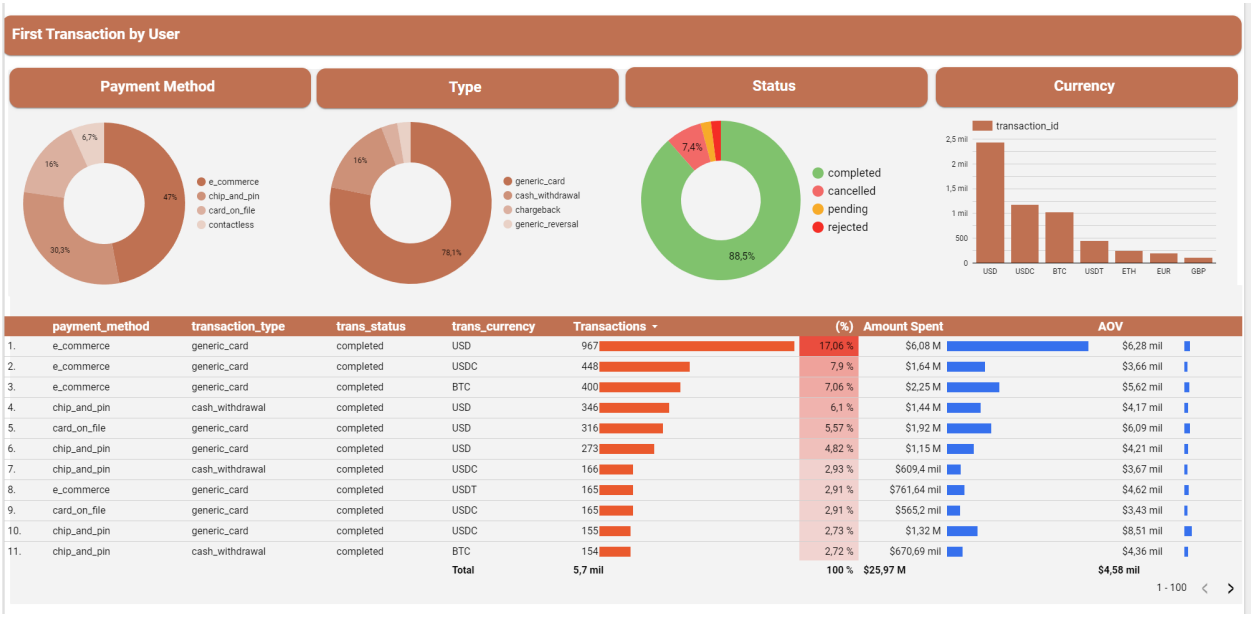
Top 1% Transactions

The biggest transactions by spending (**top1%**) accumulated **$700M** (**25%**) of total spent, were $900k avg and were done solely on **Business services** (Management, Consulting, and Public Relations Services).

First transactions

- The most common **first transactions** made by users were:
  - 17% ecommerce, using USD
  - 17% Restaurants, groceries and bars (Miscellaneous outlets)
  - 15% ATM



	payment_method	transaction_type	trans_status	trans_currency	Transactions	(%)	Amount Spent	AOV
1.	e_commerce	generic_card	completed	USD	967	17,06 %	$6,08 M	$6,28 mil
2.	e_commerce	generic_card	completed	USDC	448	7,9 %	$1,64 M	$3,66 mil
3.	e_commerce	generic_card	completed	BTC	400	7,06 %	$2,25 M	$5,62 mil
4.	chip_and_pin	cash_withdrawal	completed	USD	346	6,1 %	$1,44 M	$4,17 mil
5.	card_on_file	generic_card	completed	USD	316	5,57 %	$1,92 M	$6,09 mil
6.	chip_and_pin	generic_card	completed	USD	273	4,82 %	$1,15 M	$4,21 mil
7.	chip_and_pin	cash_withdrawal	completed	USDC	166	2,93 %	$609,4 mil	$3,67 mil
8.	e_commerce	generic_card	completed	USDT	165	2,91 %	$761,64 mil	$4,62 mil
9.	card_on_file	generic_card	completed	USDC	165	2,91 %	$565,2 mil	$3,43 mil
10.	chip_and_pin	generic_card	completed	USDC	155	2,73 %	$1,32 M	$8,51 mil
11.	chip_and_pin	cash_withdrawal	completed	BTC	154	2,72 %	$670,69 mil	$4,36 mil
				Total	5,7 mil	100 %	$25,97 M	$4,58 mil

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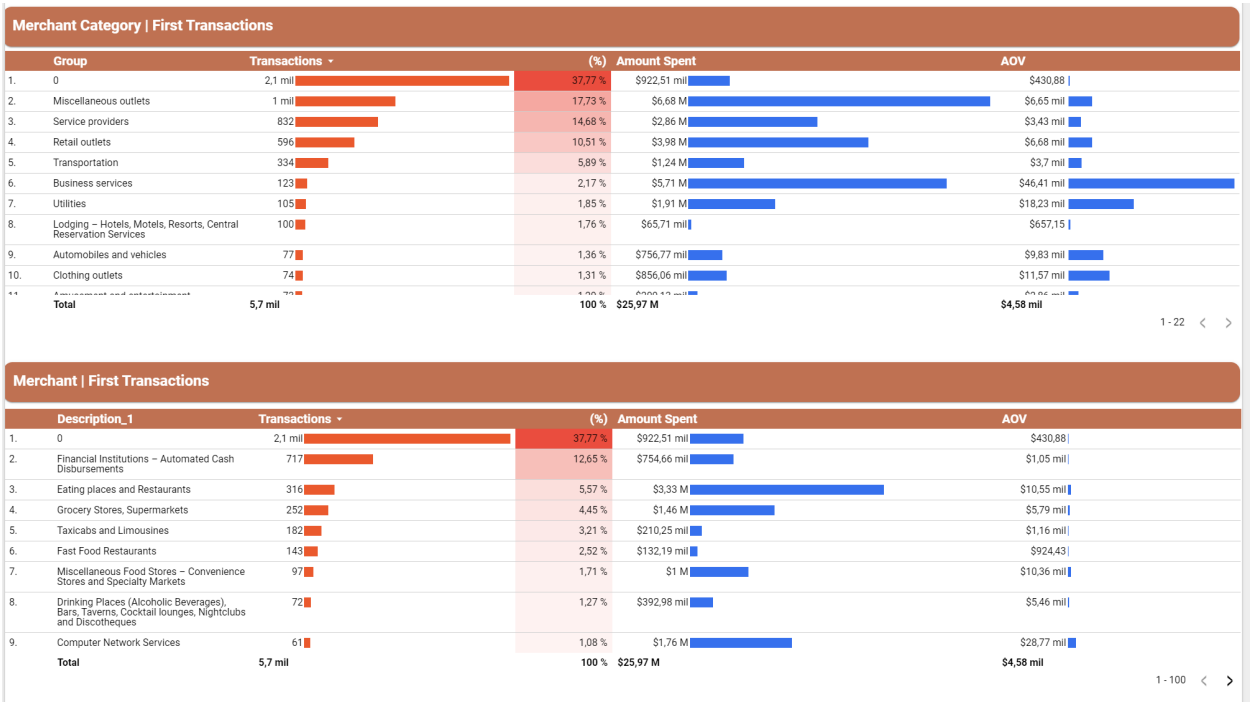

	Group	Transactions	(%)	Amount Spent	AOV
1.	0	2,1 mil	37,77 %	$922,51 mil	$430,88
2.	Miscellaneous outlets	1 mil	17,73 %	$6,68 M	$6,65 mil
3.	Service providers	832	14,68 %	$2,86 M	$3,43 mil
4.	Retail outlets	596	10,51 %	$3,98 M	$6,68 mil
5.	Transportation	334	5,89 %	$1,24 M	$3,7 mil
6.	Business services	123	2,17 %	$5,71 M	$46,41 mil
7.	Utilities	105	1,85 %	$1,91 M	$18,23 mil
8.	Lodging – Hotels, Motels, Resorts, Central Reservation Services	100	1,76 %	$65,71 mil	$657,15
9.	Automobiles and vehicles	77	1,36 %	$756,77 mil	$9,83 mil
10.	Clothing outlets	74	1,31 %	$856,06 mil	$11,57 mil
	Total	5,7 mil	100 %	$25,97 M	$4,58 mil

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	Description_1	Transactions	(%)	Amount Spent	AOV
1.	0	2,1 mil	37,77 %	$922,51 mil	$430,88
2.	Financial Institutions – Automated Cash Disbursements	717	12,65 %	$754,66 mil	$1,05 mil
3.	Eating places and Restaurants	316	5,57 %	$3,33 M	$10,55 mil
4.	Grocery Stores, Supermarkets	252	4,45 %	$1,46 M	$5,79 mil
5.	Taxicabs and Limousines	182	3,21 %	$210,25 mil	$1,16 mil
6.	Fast Food Restaurants	143	2,52 %	$132,19 mil	$924,43
7.	Miscellaneous Food Stores – Convenience Stores and Specialty Markets	97	1,71 %	$1 M	$10,36 mil
8.	Drinking Places (Alcoholic Beverages), Bars, Taverns, Cocktail lounges, Nightclubs and Discotheques	72	1,27 %	$392,98 mil	$5,46 mil
9.	Computer Network Services	61	1,08 %	$1,76 M	$28,77 mil
	Total	5,7 mil	100 %	$25,97 M	$4,58 mil

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⇒ Link to file with queries for first transactions

Cohort Analysis

Report measuring monthly user retention.

Results: 84% avg. yearly user retention.

Retention Cohorts

cohort_index / user_count

cohort_month (...	0	1	2	3	4	5	6	7	8	9	10	11	12
feb 2022	82	81	77	76	73	74	74	73	74	75	75	75	75
mar 2022	109	108	101	88	87	87	88	88	90	91	90	92	93
abr 2022	161	155	144	132	129	130	130	132	133	132	135	136	140
may 2022	150	150	139	119	109	111	113	114	114	116	121	131	131
jun 2022	182	178	160	148	144	146	149	150	148	154	158	158	-
jul 2022	168	167	153	141	138	140	141	142	148	149	147	3	-
ago 2022	180	176	164	152	146	148	150	156	157	156	2	1	-
sept 2022	184	180	170	155	154	154	158	162	161	1	-	-	-
oct 2022	349	346	324	296	290	299	304	300	5	1	-	-	-
nov 2022	407	401	378	347	341	353	353	9	-	-	-	-	-
dic 2022	285	279	266	247	249	247	10	2	-	-	-	-	-
ene 2023	339	334	318	298	297	4	2	-	-	-	-	-	-
feb 2023	279	273	262	247	5	1	-	-	-	-	-	-	-
mar 2023	1.260	1.245	1.176	58	2	-	-	-	-	-	-	-	-
abr 2023	1.003	942	87	26	-	-	-	-	-	-	-	-	-
may 2023	16	4	1	-	-	-	-	-	-	-	-	-	-

Cohort analysis

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	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	cohort_month	0	1	2	3	4	5	6	7	8	9	10	11	12
2	2021-03	100%	100,0%	88,9%	77,8%	72,2%	66,7%	72,2%	72,2%	66,7%	72,2%	72,2%	72,2%	72,2%
3	2021-04	100%	94,5%	86,8%	84,6%	81,3%	81,3%	81,3%	78,0%	81,3%	82,4%	83,5%	80,2%	81,3%
4	2021-05	100%	93,8%	91,7%	91,7%	93,8%	89,6%	89,6%	89,6%	93,8%	87,5%	85,4%	87,5%	89,6%
5	2021-06	100%	95,2%	95,2%	95,2%	81,0%	81,0%	76,2%	81,0%	76,2%	81,0%	76,2%	85,7%	85,7%
6	2021-07	100%	92,0%	88,0%	84,0%	80,0%	80,0%	84,0%	76,0%	80,0%	80,0%	80,0%	84,0%	84,0%
7	2021-08	100%	97,2%	94,4%	86,1%	75,0%	72,2%	72,2%	72,2%	77,8%	77,8%	77,8%	83,3%	83,3%
8	2021-09	100%	96,2%	80,8%	80,8%	73,1%	73,1%	73,1%	73,1%	73,1%	73,1%	73,1%	73,1%	73,1%
9	2021-10	100%	97,6%	92,9%	90,5%	92,9%	92,9%	92,9%	90,5%	90,5%	90,5%	92,9%	92,9%	92,9%
10	2021-11	100%	96,2%	96,2%	84,6%	82,7%	82,7%	82,7%	84,6%	84,6%	84,6%	84,6%	86,5%	86,5%
11	2021-12	100%	100,0%	94,6%	85,1%	82,4%	83,8%	85,1%	85,1%	83,8%	82,4%	86,5%	87,8%	86,5%
12	2022-01	100%	93,9%	92,7%	85,4%	79,3%	80,5%	81,7%	80,5%	81,7%	81,7%	85,4%	84,1%	85,4%
13	2022-02	100%	98,8%	93,9%	92,7%	89,0%	90,2%	90,2%	89,0%	90,2%	91,5%	91,5%	91,5%	91,5%
14	2022-03	100%	99,1%	92,7%	80,7%	79,8%	79,8%	80,7%	80,7%	82,6%	83,5%	82,6%	84,4%	85,3%
15	2022-04	100%	96,3%	89,4%	82,0%	80,1%	80,7%	80,7%	82,0%	82,6%	82,0%	83,9%	84,5%	87,0%
16	2022-05	100%	100,0%	92,7%	79,3%	72,7%	74,0%	75,3%	76,0%	76,0%	77,3%	80,7%	87,3%	87,3%
17	2022-06	100%	97,8%	87,9%	81,3%	79,1%	80,2%	81,9%	82,4%	81,3%	84,6%	86,8%	86,8%	0,0%
18	2022-07	100%	99,4%	91,1%	83,9%	82,1%	83,3%	83,9%	84,5%	88,1%	88,7%	87,5%	1,8%	0,0%
19	2022-08	100%	97,8%	91,1%	84,4%	81,1%	82,2%	83,3%	86,7%	87,2%	86,7%	1,1%	0,6%	0,0%
20	2022-09	100%	97,8%	92,4%	84,2%	83,7%	83,7%	85,9%	88,0%	87,5%	0,5%	0,0%	0,0%	0,0%
21	2022-10	100%	99,1%	92,8%	84,8%	83,1%	85,7%	87,1%	86,0%	1,4%	0,3%	0,0%	0,0%	0,0%
22	2022-11	100%	98,5%	92,9%	85,3%	83,8%	86,7%	86,7%	2,2%	0,0%	0,0%	0,0%	0,0%	0,0%
23	2022-12	100%	97,9%	93,3%	86,7%	87,4%	86,7%	3,5%	0,7%	0,0%	0,0%	0,0%	0,0%	0,0%
24	2023-01	100%	98,5%	93,8%	87,9%	87,6%	1,2%	0,6%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
25	2023-02	100%	97,8%	93,9%	88,5%	1,8%	0,4%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
26	2023-03	100%	98,8%	93,3%	4,6%	0,2%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
27	2023-04	100%	93,9%	8,7%	2,6%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
28	2023-05	100%	25,0%	6,3%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
29	AVG.	100%	94,6%	85,5%	76,1%	81,9%	81,7%	78,7%	81,9%	82,4%	82,6%	83,0%	84,5%	84,8%
30														

⇒ Link to file with queries for Cohorts

b. **Users**

- Most of the users are women (61%)
- Aged between 26-36 years (71%)
- With incomes:
    - 50% between $50-100
    - 40% $200-250k
- Most common occupations are Crypto trader and blockchain developers (15%)

	occupation	income group	gender	age_group	Unique_customers	(%)	Transactions	(%)	Amount Spent	(%)	AOV	Spent/user	Trans/user
1.	Blockchain Developer	2) 51-100k	Female	3) 26 - 30	90	0,82 %	8,3 mil	0,88 %	$22,19 M	0,82 %	$2,68 mil	$246,56 mil	92
2.	Blockchain Developer	4) 201-250k	Female	4) 31 - 36	81	0,74 %	8,1 mil	0,86 %	$19,77 M	0,73 %	$2,45 mil	$244,02 mil	99,8
3.	Data Analyst	2) 51-100k	Female	3) 26 - 30	71	0,65 %	8 mil	0,85 %	$24,6 M	0,91 %	$3,07 mil	$346,5 mil	112,9
4.	Financial Advisor	2) 51-100k	Female	4) 31 - 36	73	0,66 %	7,6 mil	0,81 %	$20,04 M	0,74 %	$2,63 mil	$274,59 mil	104,6
5.	Crypto Trader	2) 51-100k	Female	3) 26 - 30	82	0,75 %	7,6 mil	0,81 %	$19,66 M	0,72 %	$2,58 mil	$239,74 mil	92,7
6.	Crypto Trader	4) 201-250k	Female	4) 31 - 36	70	0,64 %	7,3 mil	0,77 %	$15,94 M	0,59 %	$2,18 mil	$227,66 mil	104,3
7.	Crypto Trader	2) 51-100k	Female	4) 31 - 36	87	0,79 %	6,8 mil	0,72 %	$19,58 M	0,72 %	$2,87 mil	$225,11 mil	78,3
8.	Crypto Trader	4) 201-250k	Female	3) 26 - 30	73	0,66 %	6,7 mil	0,71 %	$14,77 M	0,54 %	$2,2 mil	$202,29 mil	91,9
				Total	11 mil	100 %	943,7 mil	100 %	$2.714,69 M	100 %	$2,88 mil	$246,79 mil	85,8

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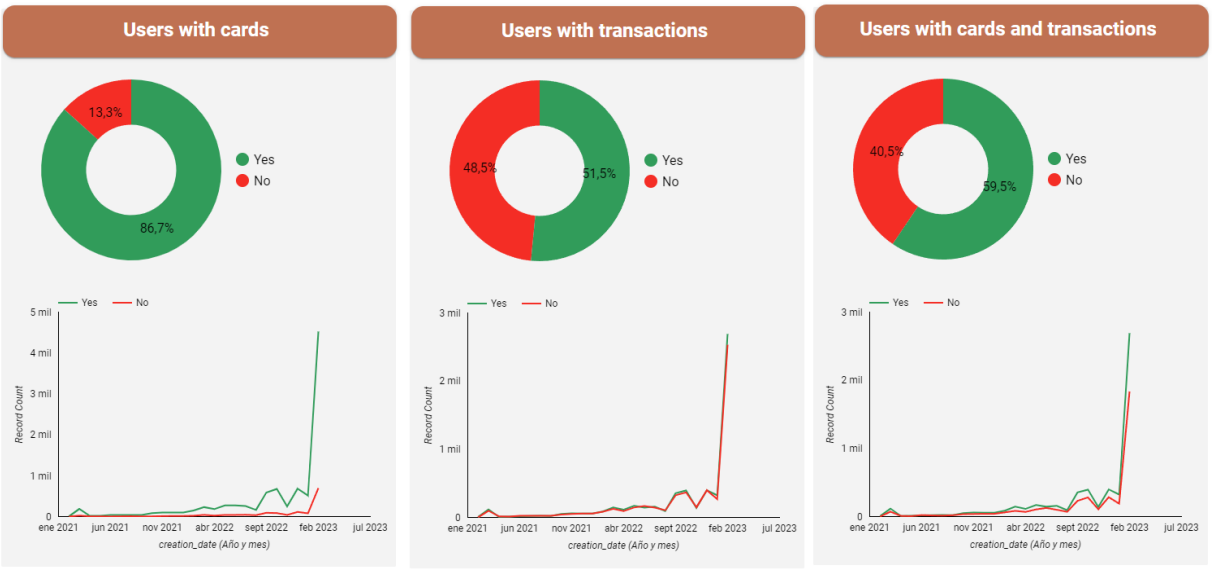
c. **Cards**

- 87% of users have a card (of whom 60% made transactions)
- **53%** of total users made transactions
- 74% of issued cards are active



⇒ [Link to file with queries for cards]

- **90%** of cards are **debit** cards
- Most common subtypes are Metal cards (43%), followed closely by virtual (41%).
- Most common currency is BTC (36%), despite USD being by far the most common transaction currency.
- The most common card is debit, BTC, metal (15%)
- The most common first card by user is BTC, debit, metal (6,32%)

Card Type | User Behaviour

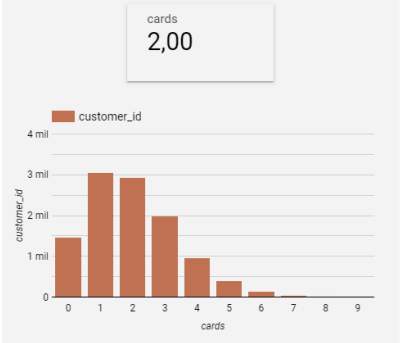
	card_currency	card_type	subtype	Cards	(%)	Transactions	(%)	Amount Spent	(%)	AOV	Spent/user	Trans/user
1.	BTC	debit	metal	3,2 mil	14,52 %	139,6 mil	14,8 %	$409,48 M	15,08 %	$2,93 mil	$149,17 mil	50,9
2.	BTC	debit	virtual	2,9 mil	13,36 %	125,5 mil	13,3 %	$335,8 M	12,37 %	$2,68 mil	$129,55 mil	48,4
3.	USDT	debit	metal	2,4 mil	11,03 %	102,6 mil	10,88 %	$280,79 M	10,34 %	$2,74 mil	$129,04 mil	47,2
4.	USDT	debit	virtual	2,3 mil	10,5 %	98,9 mil	10,48 %	$295,7 M	10,89 %	$2,99 mil	$142,64 mil	47,7
5.	USDC	debit	virtual	1,8 mil	8,13 %	78,5 mil	8,32 %	$247,64 M	9,12 %	$3,16 mil	$150,54 mil	47,7
6.	USDC	debit	metal	1,8 mil	8,2 %	73,7 mil	7,81 %	$213,02 M	7,85 %	$2,89 mil	$127,71 mil	44,2
7.	ETH	debit	metal	1,2 mil	5,54 %	56,3 mil	5,96 %	$159,11 M	5,86 %	$2,83 mil	$137,76 mil	48,7
8.	ETH	debit	virtual	1,1 mil	5,23 %	49,5 mil	5,24 %	$140,4 M	5,17 %	$2,84 mil	$129,05 mil	45,5
9.	BTC	debit	plastic	1,1 mil	4,82 %	45,7 mil	4,85 %	$149,67 M	5,51 %	$3,27 mil	$148,04 mil	45,2
			Total	22 mil	100 %	943,7 mil	100 %	$2.714,69 M	100 %	$2,88 mil	$284,74 mil	99

Card Type | What Type users get first?

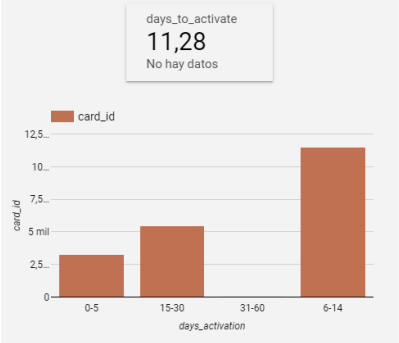
	card_rank	currency	type	subtype	Cards	(%)
1.	1	BTC	debit	metal	1,4 mil	6,32 %
2.	1	BTC	debit	virtual	1,3 mil	5,74 %
3.	1	USDT	debit	metal	1 mil	4,72 %
4.	1	USDT	debit	virtual	984	4,48 %
5.	2	BTC	debit	metal	939	4,27 %
				Total	22 mil	100 %

- On avg. **each user:**
  - has 2 cards
  - Takes 11 days to activate it
  - Takes 12 days to make a transaction with it

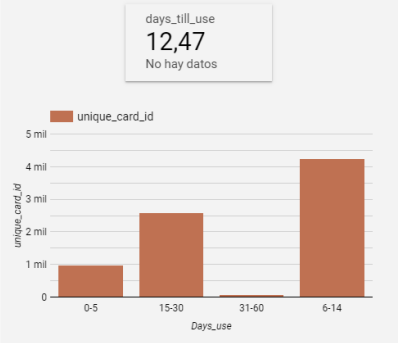
Cards by User



Time to Activate



Time to Use



Segments

I analyzed possible user segments in **2 ways:**

1) "**RFM**" Method: recency, frequency and monetary value (quartiles)
2) **Spending** Segments ("Whales" Method)

By using these types of segmentations we can understand the different **kinds** of users we have (good, bad, etc.). Analyze their behavior, characteristics and plan our actions towards them accordingly.

1) RFM

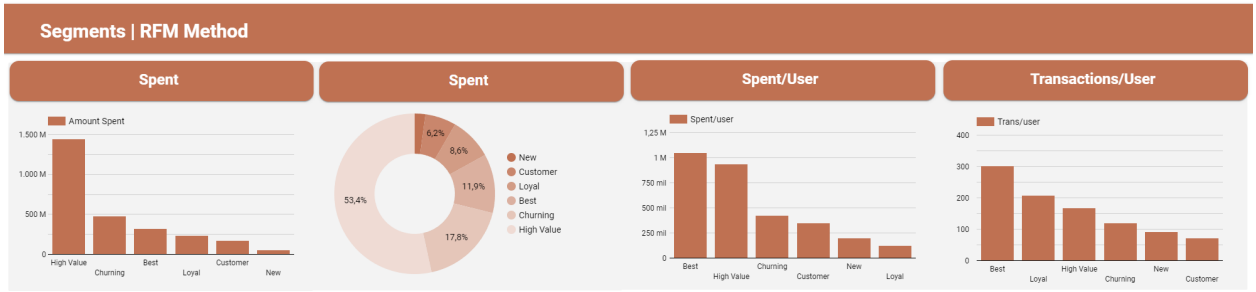
By "**RFM**" Segments, analyzing **recency, frequency and monetary value** (**quartiles**)

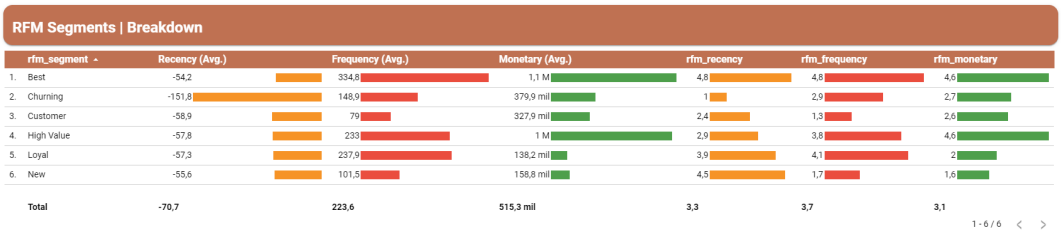
- Best: top quartile on each metric
- High Value: Customers in the top quartile for monetary value and frequency and any quartile for Recency.
- Loyal: Customers in the top quartile for frequency and any quartile for monetary value and Recency.
- Churning: Customers in the bottom quartile for Recency and any quartile for frequency and monetary value.
- New: Customers in the top quartile for Recency and any quartile for frequency and monetary value.

By analyzing by **RFM**, we can **know**:

- who are our **new** clients
- who are **churning** and try to reactivate them (emails, sms, push notifications, discounts, coupons, etc.)
- The behavior of our **loyal and high value** clients and how to retain them even longer, and increase their frequency and value.
- Who are our **best** customers and give them a special treatment while also understanding them to get more like them.

Results:

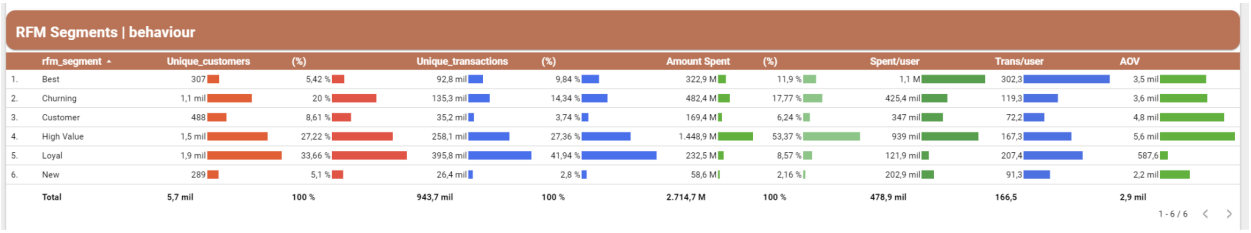




RFM Segments | Breakdown

	rfm_segment	Recency (Avg.)	Frequency (Avg.)	Monetary (Avg.)	rfm_recency	rfm_frequency	rfm_monetary
1.	Best	-54,2	334,8	1,1 M	4,8	4,8	4,6
2.	Churning	-151,8	148,9	379,9 mil	1	2,9	2,7
3.	Customer	-58,9	79	327,9 mil	2,4	1,3	2,6
4.	High Value	-57,8	233	1 M	2,9	3,8	4,6
5.	Loyal	-57,3	237,9	138,2 mil	3,9	4,1	2
6.	New	-55,6	101,5	158,8 mil	4,5	1,7	1,6
	Total	-70,7	223,6	515,3 mil	3,3	3,7	3,1

1 - 6 / 6



RFM Segments | behaviour

	rfm_segment	Unique_customers	(%)	Unique_transactions	(%)	Amount Spent	(%)	Spent/user	Trans/user	AOV
1.	Best	307	5,42 %	92,8 mil	9,84 %	322,9 M	11,9 %	1,1 M	302,3	3,5 mil
2.	Churning	1,1 mil	20 %	135,3 mil	14,34 %	482,4 M	17,77 %	425,4 mil	119,3	3,6 mil
3.	Customer	488	8,61 %	35,2 mil	3,74 %	169,4 M	6,24 %	347 mil	72,2	4,8 mil
4.	High Value	1,5 mil	27,22 %	258,1 mil	27,36 %	1.448,9 M	53,37 %	939 mil	167,3	5,6 mil
5.	Loyal	1,9 mil	33,66 %	395,8 mil	41,94 %	232,5 M	8,57 %	121,9 mil	207,4	587,6
6.	New	289	5,1 %	26,4 mil	2,8 %	58,6 M	2,16 %	202,9 mil	91,3	2,2 mil
	Total	5,7 mil	100 %	943,7 mil	100 %	2.714,7 M	100 %	478,9 mil	166,5	2,9 mil

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Best customer Segment:

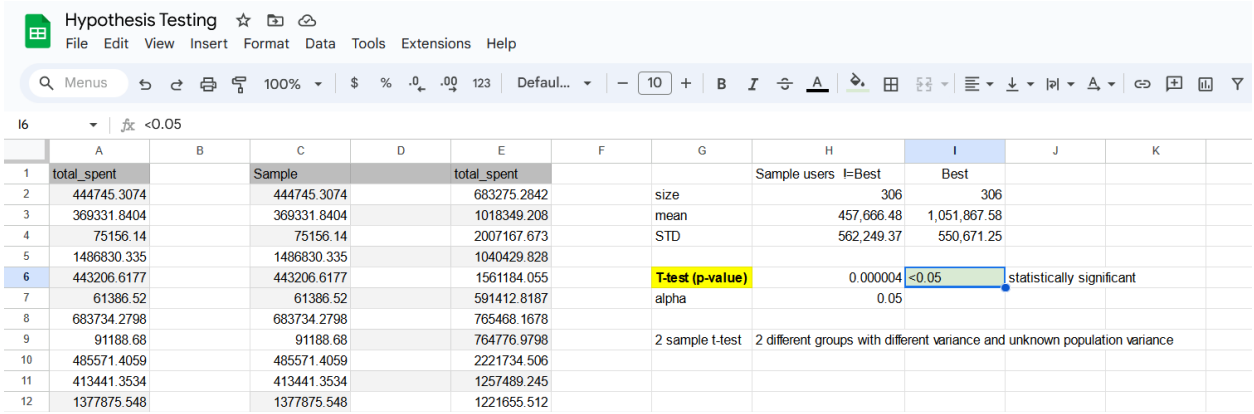
- Demographic indicators similar to avg
- 95% more credit cards than avg.
- Spending categories
    - 15% restaurants
    - 13% en Business services, Management, Consulting, and Public Relations Services

⇒ Link to file with queries for RFM segments

Hypothesis testing

I tested the “Best” RFM segment. I got all the users from this segment that made purchases and their accumulated value by user and compared it with a random sample (same size) of all the users, to test if there was a difference on the mean spending by user.

Results: Best segment difference in spending was **Statistically significant.**



	A	B	C	D	E	F	G	H	I	J	K
1	total_spent		Sample		total_spent			Sample users I=Best	Best		
2	444745.3074		444745.3074		683275.2842		size	306	306		
3	369331.8404		369331.8404		1018349.208		mean	457,666.48	1,051,867.58		
4	75156.14		75156.14		2007167.673		STD	562,249.37	550,671.25		
5	1486830.335		1486830.335		1040429.828						
6	443206.6177		443206.6177		1561184.055		T-test (p-value)	0.000004	<0.05	statistically significant	
7	61386.52		61386.52		591412.8187		alpha	0.05			
8	683734.2798		683734.2798		765468.1678						
9	91188.68		91188.68		764776.9798		2 sample t-test	2 different groups with different variance and unknown population variance			
10	485571.4059		485571.4059		2221734.506						
11	413441.3534		413441.3534		1257489.245						
12	1377875.548		1377875.548		1221655.512						

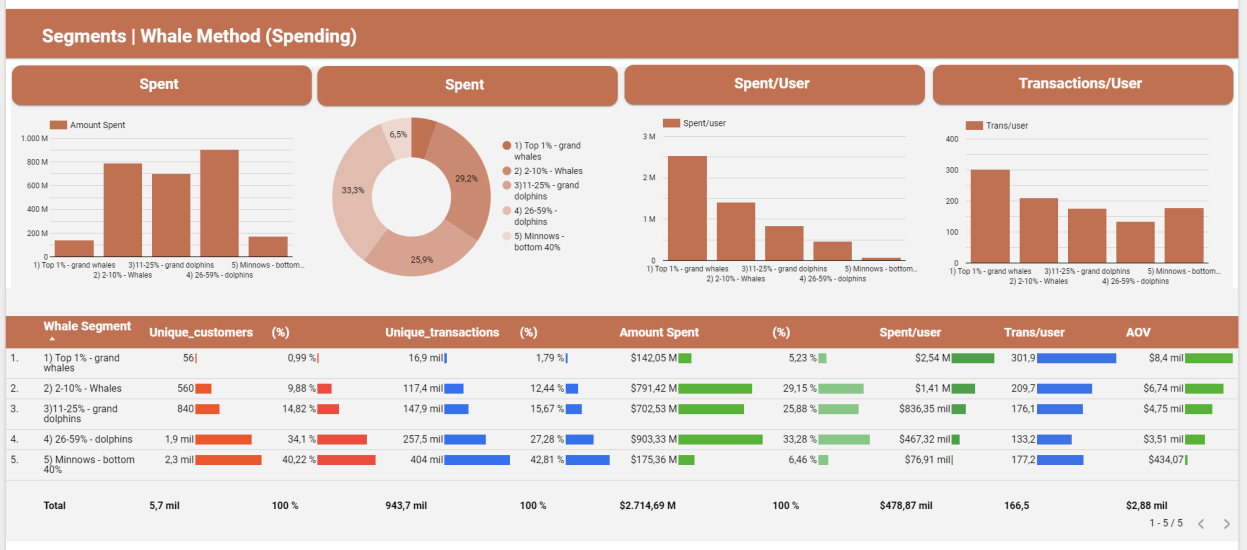
⇒ Link to file with Hypothesis Testing

2) Spending Segments ("Whales" Method):

- top 1%: grand whales
- 2 - 10%: whales
- 11 - 25%: grand dolphins
- 26 - 60%: dolphins
- less than 60%: minnows.

By analyzing the value users are providing to our business, we can get to know who are the most profitable ones. And by analyzing them, we can understand them better in order to find more customers like them, retain them longer and make them spend even more.

Results:



Top 10% (all whales) of spenders:

- represented 35% of all amount spent
- Spent 3-4 times more than avg.
- 2,5x AOV
- Demographic indicators similar to avg
- 70% more credit cards than avg.
- Spending categories
    - 30% of spending in Business services, Management, Consulting, and Public Relations Services
    - 13% restaurants

⇒ Link to file with queries for spending segment

Markets

Fifth, I analyzed the Markets and potential for expansion in **2 ways:**

1) **Entering** new markets (we don't have users there)
2) **Expanding** current markets where we have good users

1) **Entering new markets** (we don't have users there):

I gathered all relevant countries where we don't have users and analyzed them according to certain **indicators (economic, crypto, banking, internet penetration)**.

- Crypto ownership (%)
- GDP/capita
- Inflation (higher incentive to use USD or crypto than local currency)
- Internet penetration (%)
- Bancarization (people with bank accounts (%))
- Population
- Tax rate (crypto and USD offshore account)

	Country1	CPI_Change	GDP_capita	internet_pct	Crypto Ownership	Percent_people_with_bank_accounts	Population	Total_tax_rate
1.	Iran (Islamic Republic of)	39,9 %	5,4 mil	88,8 %	13,46 %	89,6	82,9 M	44,7 %
2.	Morocco	0,2 %	3,2 mil	59,5 %	4,9 %	42,2	36,9 M	45,8 %
3.	Nepal	5,6 %	1,1 mil	53,9 %	4,43 %	52,8	28,6 M	41,8 %
4.	Ethiopia	15,8 %	857,5	16,2 %	4,01 %	34,8	112,1 M	37,7 %
5.	Cambodia	2,5 %	1,6 mil	32,8 %	3,34 %	32,6	16,5 M	23,1 %
6.	Belarus	5,6 %	6,7 mil	73,6 %	2,92 %	81,2	9,5 M	53,3 %
7.	Tanzania	3,5 %	1,1 mil	52 %	2,34 %	23,3	58,0 M	43,8 %
8.	Georgia	4,9 %	4,8 mil	91,7 %	2,32 %	70,5	3,7 M	9,9 %
9.	Algeria	2 %	3,9 mil	59,6 %	2,18 %	44,1	43,1 M	66,1 %
10.	Ghana	7,2 %	2,2 mil	45,9 %	2,16 %	39,2	30,8 M	55,4 %
11.	Moldova	4,8 %	4,5 mil	100,7 %	2,05 %	64,3	2,7 M	38,7 %
12.	Tunisia	6,7 %	3,3 mil	52,2 %	2,01 %	35,7	11,7 M	60,7 %
13.	Somalia	0	305,7	1,7 %	1,89 %	0	15,4 M	0
	Total	**631,8 %**	**443,2 mil**	**1.302,7 %**	**80,31 %**	**1,4 mil**	**1.376,6 M**	**3.794 %**

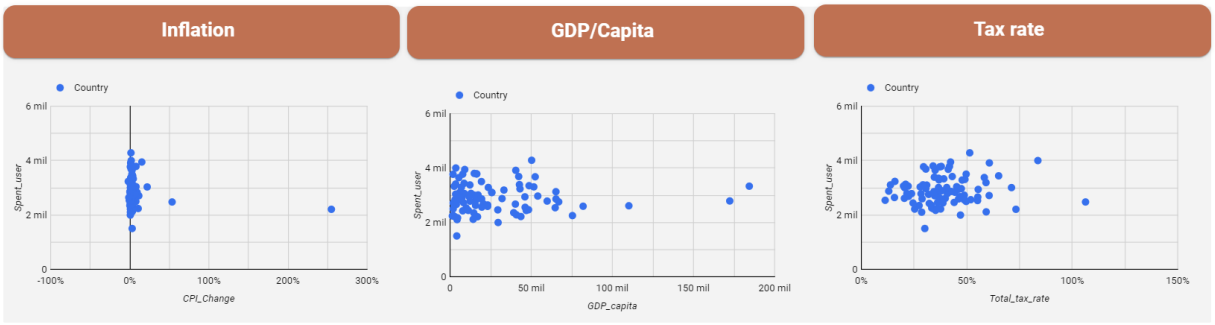
1 - 95 / 95

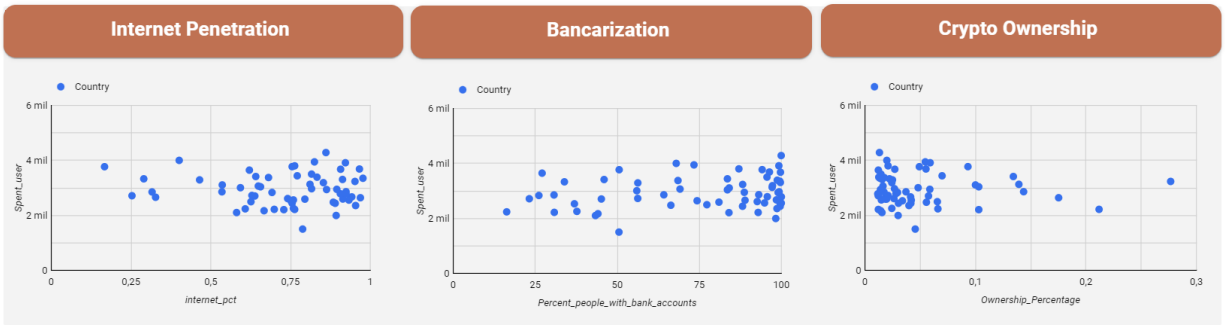
- The best markets according to this analysis were:
  - Iran
  - Morocco
  - Belarus
  - Georgia
  - Moldova
  - Kazakhstan
  - Myanmar
  - Tunisia
  - Ghana

⇒ Link to file with queries for missing countries

Some of these countries might have **problems** regarding: politics, sanctions, regulations, etc. (i.e: Iran).

Furthermore, I analyzed the **relationship** between card **performance (spent/user)** and the countries **indicators** mentioned above and I found no relationship whatsoever. My assumption is that the sample data is too small and also because it might be dummy data it might not reflect real life behavior.





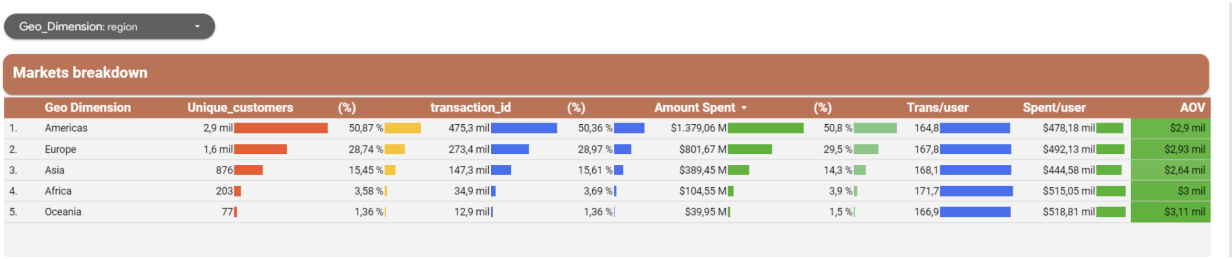
2) **Expanding current markets** where we have good users:

The **user** count is distributed around the **world**:

- 50% of users are from Americas, 35% from USA and 15% from LATAM
- 28% from Europe
- 15% Asia
- The remaining are from Oceania and Africa.

The absolut main market right now is the USA (3,8k users, 35%) and the rest of the countries have max between 100-200 users.

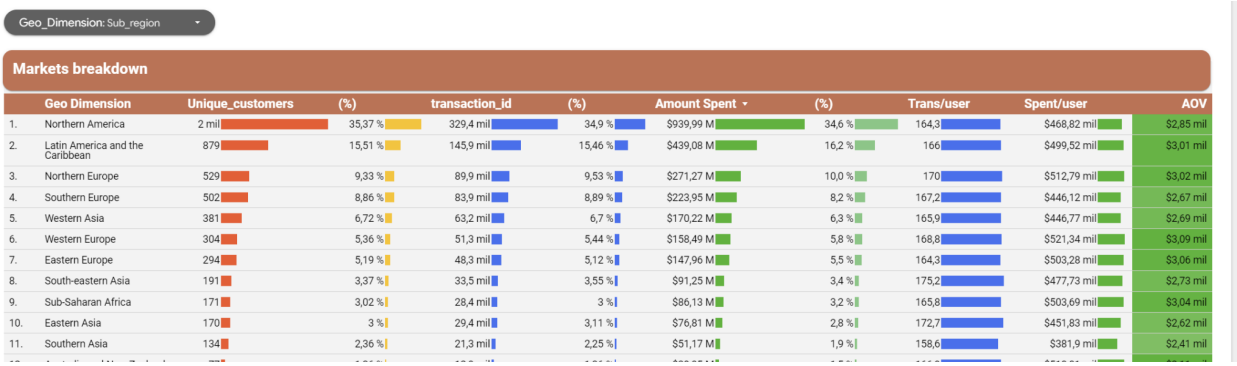
Transaction behavior by **Region**


Geo_Dimension: region

Markets breakdown

	Geo Dimension	Unique_customers	(%)	transaction_id	(%)	Amount Spent	(%)	Trans/user	Spent/user	AOV
1.	Americas	2,9 mil	50,87 %	475,3 mil	50,36 %	$1.379,06 M	50,8 %	164,8	$478,18 mil	$2,9 mil
2.	Europe	1,6 mil	28,74 %	273,4 mil	28,97 %	$801,67 M	29,5 %	167,8	$492,13 mil	$2,93 mil
3.	Asia	876	15,45 %	147,3 mil	15,61 %	$389,45 M	14,3 %	168,1	$444,58 mil	$2,64 mil
4.	Africa	203	3,58 %	34,9 mil	3,69 %	$104,55 M	3,9 %	171,7	$515,05 mil	$3 mil
5.	Oceania	77	1,36 %	12,9 mil	1,36 %	$39,95 M	1,5 %	166,9	$518,81 mil	$3,11 mil

Transaction behavior by **sub-region**


Geo_Dimension: Sub_region

Markets breakdown

	Geo Dimension	Unique_customers	(%)	transaction_id	(%)	Amount Spent	(%)	Trans/user	Spent/user	AOV
1.	Northern America	2 mil	35,37 %	329,4 mil	34,9 %	$939,99 M	34,6 %	164,3	$468,82 mil	$2,85 mil
2.	Latin America and the Caribbean	879	15,51 %	145,9 mil	15,46 %	$439,08 M	16,2 %	166	$499,52 mil	$3,01 mil
3.	Northern Europe	529	9,33 %	89,9 mil	9,53 %	$271,27 M	10,0 %	170	$512,79 mil	$3,02 mil
4.	Southern Europe	502	8,86 %	83,9 mil	8,89 %	$223,95 M	8,2 %	167,2	$446,12 mil	$2,67 mil
5.	Western Asia	381	6,72 %	63,2 mil	6,7 %	$170,22 M	6,3 %	165,9	$446,77 mil	$2,69 mil
6.	Western Europe	304	5,36 %	51,3 mil	5,44 %	$158,49 M	5,8 %	168,8	$521,34 mil	$3,09 mil
7.	Eastern Europe	294	5,19 %	48,3 mil	5,12 %	$147,96 M	5,5 %	164,3	$503,28 mil	$3,06 mil
8.	South-eastern Asia	191	3,37 %	33,5 mil	3,55 %	$91,25 M	3,4 %	175,2	$477,73 mil	$2,73 mil
9.	Sub-Saharan Africa	171	3,02 %	28,4 mil	3 %	$86,13 M	3,2 %	165,8	$503,69 mil	$3,04 mil
10.	Eastern Asia	170	3 %	29,4 mil	3,11 %	$76,81 M	2,8 %	172,7	$451,83 mil	$2,62 mil
11.	Southern Asia	134	2,36 %	21,3 mil	2,25 %	$51,17 M	1,9 %	158,6	$381,9 mil	$2,41 mil

Transaction behavior by **Country**


Geo_Dimension: Country

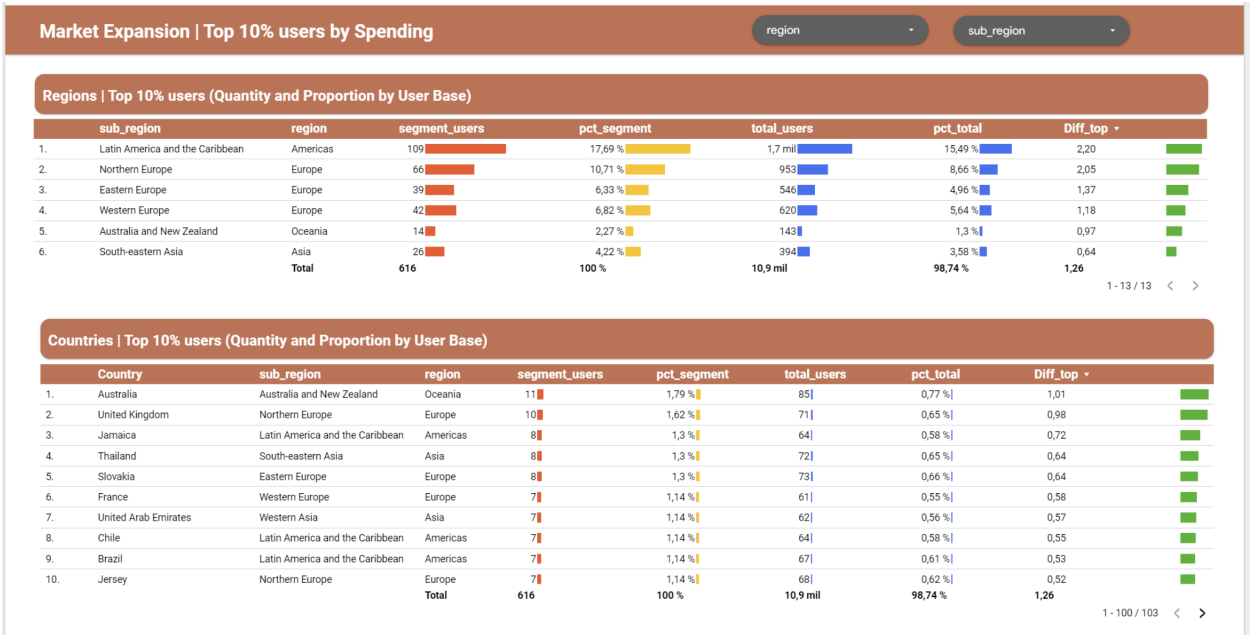
Markets breakdown

	Geo Dimension	Unique_customers	(%)	transaction_id	(%)	Amount Spent	(%)	Trans/user	Spent/user	AOV
1.	United States of America	2 mil	34,87 %	324,6 mil	34,4 %	$928,47 M	34,2 %	164,2	$469,64 mil	$2,86 mil
2.	United Kingdom of Great Britain and Northern Ireland	43	0,76 %	8,6 mil	0,91 %	$31,67 M	1,2 %	199,8	$736,57 mil	$3,69 mil
3.	Martinique	57	1,01 %	9,4 mil	0,99 %	$28,5 M	1,0 %	164,1	$500 mil	$3,05 mil
4.	Australia	47	0,83 %	8,6 mil	0,91 %	$25,4 M	0,9 %	182,1	$540,44 mil	$2,97 mil
5.	Serbia	46	0,81 %	8,3 mil	0,88 %	$24,38 M	0,9 %	181,5	$530,03 mil	$2,92 mil
6.	Isle of Man	47	0,83 %	6,8 mil	0,72 %	$24,28 M	0,9 %	144,9	$516,5 mil	$3,57 mil
7.	Slovakia	39	0,69 %	6,9 mil	0,73 %	$24,1 M	0,9 %	176,5	$618,04 mil	$3,5 mil
8.	Jersey	38	0,67 %	7,3 mil	0,77 %	$23,83 M	0,9 %	192,2	$627,14 mil	$3,26 mil
9.	Brazil	41	0,72 %	6,8 mil	0,72 %	$23,37 M	0,9 %	165,8	$570 mil	$3,44 mil
10.	Netherlands	37	0,65 %	6,1 mil	0,64 %	$22,29 M	0,8 %	163,8	$602,37 mil	$3,68 mil
11.	Thailand	39	0,69 %	5,9 mil	0,62 %	$22,19 M	0,8 %	150,8	$568,99 mil	$3,77 mil
12.	Trinidad and Tobago	45	0,79 %	7,4 mil	0,78 %	$22,12 M	0,8 %	163,4	$491,59 mil	$3,01 mil

High spending segment (Countries with most of this users)

By **Spending Segments** (**Whale** Method):

- **Top 10%** spending users (35% of total spending) and the proportion each **country** has of them compared to their participation in the user base.
- The **best markets** according to this analysis were:
    - Australia
    - UK
    - Jamaica
    - Thailand
    - United Arab Emirates



Market Expansion | Top 10% users by Spending

region | sub_region

Regions | Top 10% users (Quantity and Proportion by User Base)

	sub_region	region	segment_users	pct_segment	total_users	pct_total	Diff_top
1.	Latin America and the Caribbean	Americas	109	17,69 %	1,7 mil	15,49 %	2,20
2.	Northern Europe	Europe	66	10,71 %	953	8,66 %	2,05
3.	Eastern Europe	Europe	39	6,33 %	546	4,96 %	1,37
4.	Western Europe	Europe	42	6,82 %	620	5,64 %	1,18
5.	Australia and New Zealand	Oceania	14	2,27 %	143	1,3 %	0,97
6.	South-eastern Asia	Asia	26	4,22 %	394	3,58 %	0,64
		Total	**616**	**100 %**	**10,9 mil**	**98,74 %**	**1,26**

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Countries | Top 10% users (Quantity and Proportion by User Base)

	Country	sub_region	region	segment_users	pct_segment	total_users	pct_total	Diff_top
1.	Australia	Australia and New Zealand	Oceania	11	1,79 %	85	0,77 %	1,01
2.	United Kingdom	Northern Europe	Europe	10	1,62 %	71	0,65 %	0,98
3.	Jamaica	Latin America and the Caribbean	Americas	8	1,3 %	64	0,58 %	0,72
4.	Thailand	South-eastern Asia	Asia	8	1,3 %	72	0,65 %	0,64
5.	Slovakia	Eastern Europe	Europe	8	1,3 %	73	0,66 %	0,64
6.	France	Western Europe	Europe	7	1,14 %	61	0,55 %	0,58
7.	United Arab Emirates	Western Asia	Asia	7	1,14 %	62	0,56 %	0,57
8.	Chile	Latin America and the Caribbean	Americas	7	1,14 %	64	0,58 %	0,55
9.	Brazil	Latin America and the Caribbean	Americas	7	1,14 %	67	0,61 %	0,53
10.	Jersey	Northern Europe	Europe	7	1,14 %	68	0,62 %	0,52
			Total	**616**	**100 %**	**10,9 mil**	**98,74 %**	**1,26**

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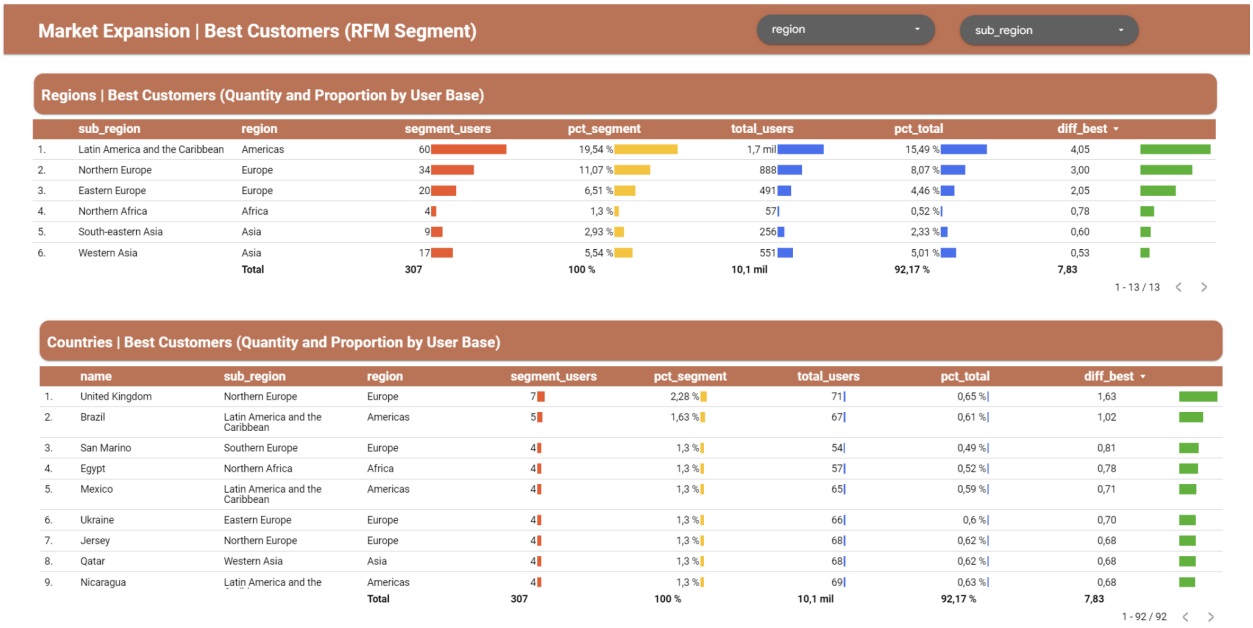
⇒ Link to file with queries for top 10% spenders and country data

RFM

By **Best customer Segment** (**RFM** Method), those with high recency, frequency and monetary value (top quartile on each metric)

- Analyzing the proportion each **country** has of them compared to their participation in the user base.
- The **best markets** according to this analysis were:
    - UK
    - Brazil
    - Egypt
    - Mexico
    - San Marino
    - Ukraine



Market Expansion | Best Customers (RFM Segment)

region | sub_region

Regions | Best Customers (Quantity and Proportion by User Base)

	sub_region	region	segment_users	pct_segment	total_users	pct_total	diff_best
1.	Latin America and the Caribbean	Americas	60	19,54 %	1,7 mil	15,49 %	4,05
2.	Northern Europe	Europe	34	11,07 %	888	8,07 %	3,00
3.	Eastern Europe	Europe	20	6,51 %	491	4,46 %	2,05
4.	Northern Africa	Africa	4	1,3 %	57	0,52 %	0,78
5.	South-eastern Asia	Asia	9	2,93 %	256	2,33 %	0,60
6.	Western Asia	Asia	17	5,54 %	551	5,01 %	0,53
		Total	**307**	**100 %**	**10,1 mil**	**92,17 %**	**7,83**

1 - 13 / 13

Countries | Best Customers (Quantity and Proportion by User Base)

	name	sub_region	region	segment_users	pct_segment	total_users	pct_total	diff_best
1.	United Kingdom	Northern Europe	Europe	7	2,28 %	71	0,65 %	1,63
2.	Brazil	Latin America and the Caribbean	Americas	5	1,63 %	67	0,61 %	1,02
3.	San Marino	Southern Europe	Europe	4	1,3 %	54	0,49 %	0,81
4.	Egypt	Northern Africa	Africa	4	1,3 %	57	0,52 %	0,78
5.	Mexico	Latin America and the Caribbean	Americas	4	1,3 %	65	0,59 %	0,71
6.	Ukraine	Eastern Europe	Europe	4	1,3 %	66	0,6 %	0,70
7.	Jersey	Northern Europe	Europe	4	1,3 %	68	0,62 %	0,68
8.	Qatar	Western Asia	Asia	4	1,3 %	68	0,62 %	0,68
9.	Nicaragua	Latin America and the	Americas	4	1,3 %	69	0,63 %	0,68
			Total	**307**	**100 %**	**10,1 mil**	**92,17 %**	**7,83**

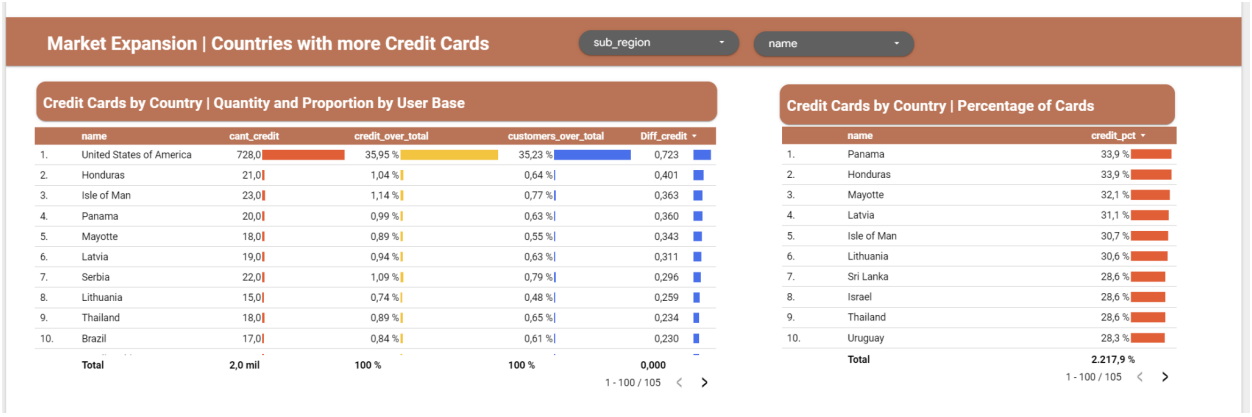
1 - 92 / 92

⇒ Link to file with queries to analyze the proportions by market

Credit cards

Countries with the most **credit cards** (volume and percentage of users).

- Because credit cards normally are **more profitable** than debit cards (interests and higher fees)
- The best markets according to this analysis were:
    - USA
    - Honduras
    - Panama
    - Mayotte
    - Latvia
    - Lithuania



Market Expansion | Countries with more Credit Cards

sub_region | name

Credit Cards by Country | Quantity and Proportion by User Base

	name	cant_credit	credit_over_total	customers_over_total	Diff_credit
1.	United States of America	728,0	35,95 %	35,23 %	0,723
2.	Honduras	21,0	1,04 %	0,64 %	0,401
3.	Isle of Man	23,0	1,14 %	0,77 %	0,363
4.	Panama	20,0	0,99 %	0,63 %	0,360
5.	Mayotte	18,0	0,89 %	0,55 %	0,343
6.	Latvia	19,0	0,94 %	0,63 %	0,311
7.	Serbia	22,0	1,09 %	0,79 %	0,296
8.	Lithuania	15,0	0,74 %	0,48 %	0,259
9.	Thailand	18,0	0,89 %	0,65 %	0,234
10.	Brazil	17,0	0,84 %	0,61 %	0,230
	Total	**2,0 mil**	**100 %**	**100 %**	**0,000**

1 - 100 / 105

Credit Cards by Country | Percentage of Cards

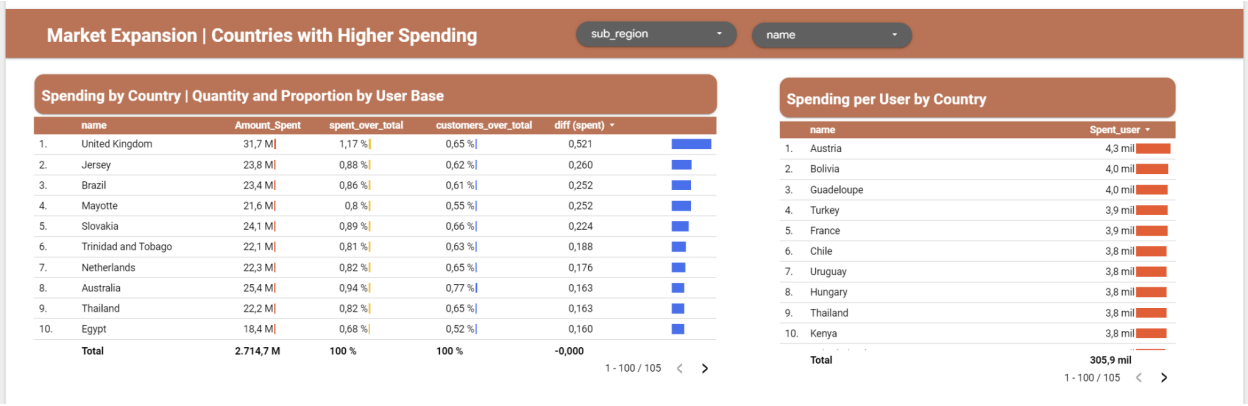
	name	credit_pct
1.	Panama	33,9 %
2.	Honduras	33,9 %
3.	Mayotte	32,1 %
4.	Latvia	31,1 %
5.	Isle of Man	30,7 %
6.	Lithuania	30,6 %
7.	Sri Lanka	28,6 %
8.	Israel	28,6 %
9.	Thailand	28,6 %
10.	Uruguay	28,3 %
	Total	**2.217,9 %**

1 - 100 / 105

⇒ Link to file with queries for top Countries with the most credit cards

Biggest spending

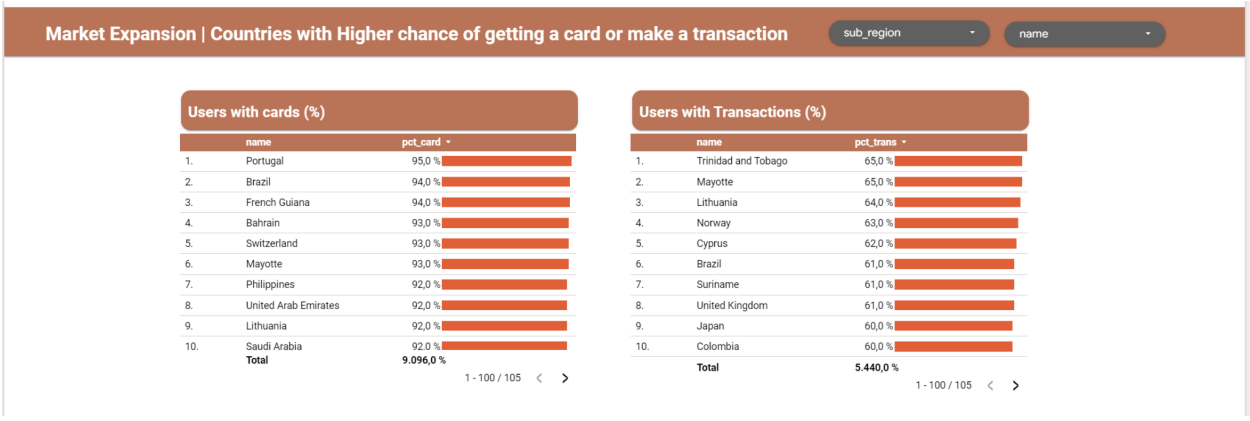
- Countries with **biggest spending** in proportion to users
    - The best markets according to this analysis were:
        - UK
        - Brazil
        - Mayotte
        - Slovakia



Highest ratios of users with cards and transactions (%):

Countries with **highest ratios** of users with **cards and transactions** (%):

- The best markets according to this analysis were:
    - UK
    - Brazil
    - Mayotte
    - Lithuania



⇒ Link to file with queries for Countries with highest ratios of users with cards and transactions (%):

Hypothesis testing

I tested the **United Kingdom** and **Brazil**, which were countries that appeared a lot in my market analysis as potential good markets with good users.

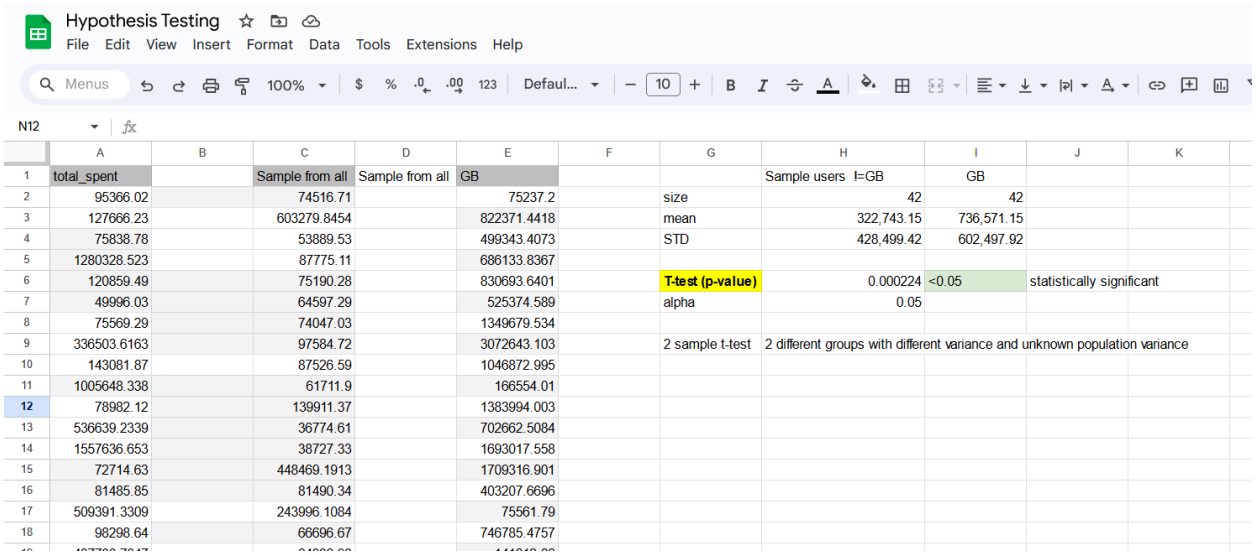
Also I tested **Spain**, one of the **worst** in terms of spending. Just in case to test if my the method I applied to the Hypothesis testing was correct.

In my method I got all the users from UK/GB that made purchases and compared it with a random sample (same size) of all the users worldwide (except UK) to test if there was a difference on the mean spending by user.

I used a **t-test**, with 1 tail (increase) and 2 samples with different variances.

Results: UK and Brazil differences in spending were Statistically significant and Spain not.

UK:

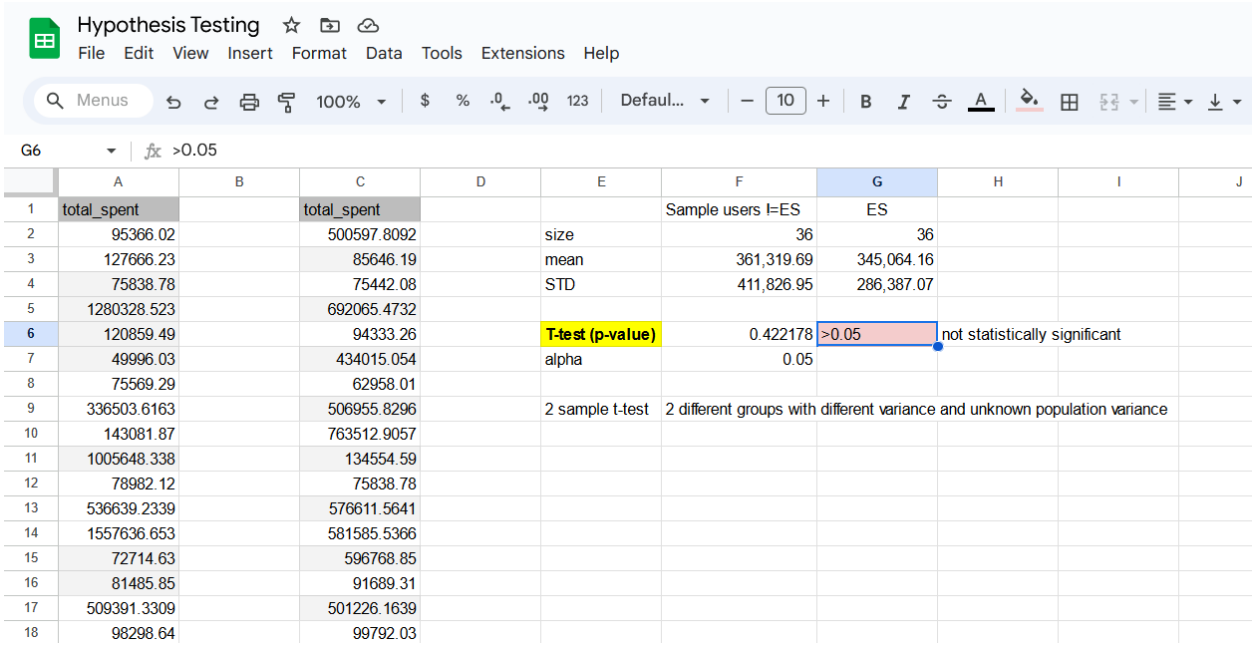


	A	B	C	D	E	F	G	H	I	J	K
1	total_spent		Sample from all	Sample from all	GB			Sample users !=GB	GB		
2	95366.02		74516.71		75237.2		size	42	42		
3	127666.23		603279.8454		822371.4418		mean	322,743.15	736,571.15		
4	75838.78		53889.53		499343.4073		STD	428,499.42	602,497.92		
5	1280328.523		87775.11		686133.8367						
6	120859.49		75190.28		830693.6401		T-test (p-value)	0.000224	<0.05	statistically significant	
7	49996.03		64597.29		525374.589		alpha	0.05			
8	75569.29		74047.03		1349679.534						
9	336503.6163		97584.72		3072643.103		2 sample t-test	2 different groups with different variance and unknown population variance			
10	143081.87		87526.59		1046872.995						
11	1005648.338		61711.9		166554.01						
12	78982.12		139911.37		1383994.003						
13	536639.2339		36774.61		702662.5084						
14	1557636.653		38727.33		1693017.558						
15	72714.63		448469.1913		1709316.901						
16	81485.85		81490.34		403207.6696						
17	509391.3309		243996.1084		75561.79						
18	98298.64		66696.67		746785.4757						

BR:

	A	B	C	D	E	F	G	H	I
1	Random Sample		BR			Sample users !=BR	BR		
2	67985.96		415568.7767		size	40	40		
3	68637.9		1200412.299		mean	303,674.78	570,000.29		
4	737603.2451		1837554.877		STD	296,549.91	487,693.43		
5	60647.9		1203329.817						
6	64120.04		579932.2902		**T-test (p-value)**	0.001972	<0.05	statistically significant	
7	484118.1578		585857.4764		alpha	0.05			
8	71818.6		545012.6388						
9	73986.82		128915.11		2 sample t-test	2 different groups with different variance and unknown population variance			
10	68975.99		335801.0872						

ES:



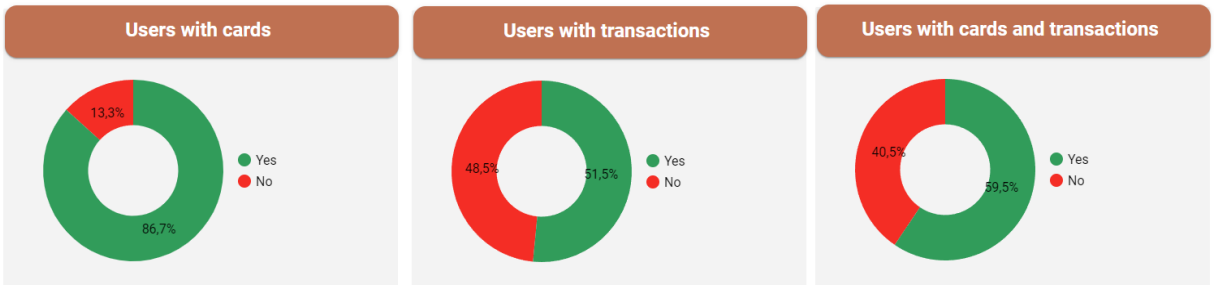
	A	B	C	D	E	F	G	H	I	J
1	total_spent		total_spent			Sample users !=ES	ES			
2	95366.02		500597.8092		size	36	36			
3	127666.23		85646.19		mean	361,319.69	345,064.16			
4	75838.78		75442.08		STD	411,826.95	286,387.07			
5	1280328.523		692065.4732							
6	120859.49		94333.26		**T-test (p-value)**	0.422178	>0.05	not statistically significant		
7	49996.03		434015.054		alpha	0.05				
8	75569.29		62958.01							
9	336503.6163		506955.8296		2 sample t-test	2 different groups with different variance and unknown population variance				
10	143081.87		763512.9057							
11	1005648.338		134554.59							
12	78982.12		75838.78							
13	536639.2339		576611.5641							
14	1557636.653		581585.5366							
15	72714.63		596768.85							
16	81485.85		91689.31							
17	509391.3309		501226.1639							
18	98298.64		99792.03							

⇒ Link to file for Hypothesis testing

Recommendations and design of A/B test(s) to validate their impact

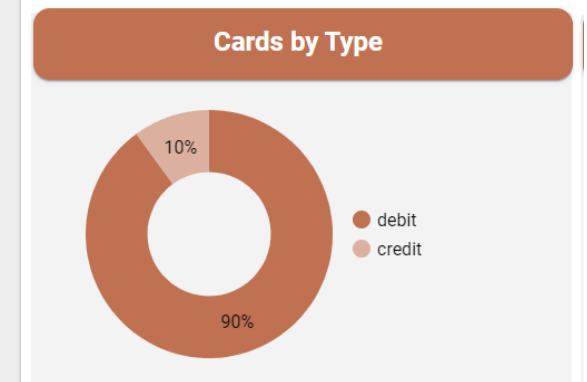
1) Increase the amount of **users** that make **transactions**.

- As we saw on my analysis:
  - Only 53% of total users made transactions
  - Only 60% of users with cards made transactions



- We should be **targeting** those that **didn't transact** with discounts, coupons or any incentive for the most common MCCs for first transactions (17% Restaurants, groceries and bars (Miscellaneous outlets))
- **A/B test:**
  - Significance level (**alpha**): 0.05
  - Grab all the users that didn't transact and created an account recently (year=2023)
  - Take **2 samples** (size: we don't know the population variance nor delta, so we cannot set an exact size. but I would take the 2.8k users from this year that didn't transact and take 2 random samples of **1.000** users)
    - **Control** sample: we wont send them anything
    - **Test** sample: send emails, sms, push notifications, ads, etc
  - Run the experiment for **1 month** and analyze the results by measuring either:
    - The difference in mean amount of transactions between the 2 samples. (T-test)
    - The difference in mean transaction rate (%) (transact/all). (Bernoulli Z-test)
  - If the results are **statistically significant** (**p-value** < 0.05 (alpha)), we can reject the null hypothesis (that both samples performed the same) and assume that our campaign worked and users that were **targeted transacted more** than those who weren't.

2) Increase the amount of **credit cards**:
   - Credit cards normally are **more profitable** than debit cards (interests and higher fees)
   - As we saw on my analysis:
     - **90%** of cards are **debit** cards



   - We should be **targeting** those that **don't have credit cards** to incentivise them to order one. We could send emails, sms, push notifications and advertising that make our credit cards attractive (i.e: **perks and benefits** like one-time signing bonus, cash backs, rewards points, flier miles, etc.)
   - **A/B test:**
     - Significance level (**alpha**): 0.05
     - Grab all the users that don't have a credit card and created an account recently (year=2023)
     - Take **2 samples** (size: we don't know the population variance nor delta, so we cannot set an exact size. but I would take the 7k users from this year that don't have a credit card and take 2 samples of **2-3k** users.
       - **Control** sample: we wont send them anything
       - **Test** sample: send emails, sms, push notifications, ads, etc
     - Run the experiment for **1 month** and analyze the results by measuring either:
       - The difference in mean amount of credit cards ordered between the 2 samples. (T-test)
       - The difference in mean credit cards rate (%) (transact/all). (Bernoulli Z-test)
     - If the results are **statistically significant** (**p-value** < 0.05 (alpha)), we can reject the null hypothesis (that both samples performed the same) and assume that our campaign worked and users that were **targeted ordered more credit cards** than those who weren't.

3) **Reactivate churning** users:
   - The cost of **acquiring** new customers is **5x higher** than the cost of **retaining** existing

customers. It's crucial to retain our customers over time, and maximize their lifecycle and **LTV**.

- As we saw on my analysis:
    - **20%** of customers are **churning**, representing 17% of all value.

- We should be **targeting** those users that **didn't transact** in a **while** (**lower quartile** in **recency**) with discounts, coupons or any incentive to try to reactivate them.
- **A/B test:**
    - Significance level (**alpha**): 0.05
    - Grab all the users that didn't transact in a while (lower quartile in recency) and created an account recently (year=2023)
    - Take **2 samples** (size: we don't know the population variance nor delta, so we cannot set an exact size. but I would take the 600 users from this year that are churning and take 2 samples of **300** users.
        - **Control** sample: we wont send them anything
        - **Test** sample: send emails, sms, push notifications, ads, etc
    - Run the experiment for **1 month** and analyze the results by measuring either:
        - The difference in mean amount of transactions between the 2 samples. (T-test)
        - The difference in mean reactivation rate (%) (transact/all). (Bernoulli

Z-test)

- If the results are **statistically significant** (**p-value** < 0.05 (alpha)), we can reject the null hypothesis (that both samples performed the same) and assume that our campaign worked and users that were **targeted transacted more** than those who weren't.

Case Study 2: ETH Wallets

Question 1:

Which are the **top 10% addresses** in terms of transaction volume in the past 6 months? What can you tell about their transactional behavior? Classify them in spenders and accumulators.

Results:

Google Drive Folder with the results in **CSV's.**

Queries:

```sql
with

-- table with all the addresses that sent ETH and their total sent value in the last 6
months

sender_addresses AS (
SELECT from_address, sum(value) as Sending_Volume
FROM `bigquery-public-data.crypto_ethereum.transactions`
where date_trunc(date(block_timestamp), MONTH) >= date_trunc(date_add(CURRENT_DATE,
INTERVAL -6 MONTH), MONTH) -- after current month - 6 months (not date - 6 months)
group by (from_address)
)

-- table with all the addresses that received ETH and their total received value in
the last 6 months

,receiver_addresses AS (
SELECT to_address, sum(value) as Receiving_Volume
FROM `bigquery-public-data.crypto_ethereum.transactions`
where date_trunc(date(block_timestamp), MONTH) >= date_trunc(date_add(CURRENT_DATE,
INTERVAL -6 MONTH), MONTH)
group by (to_address)
)

-- table merging 2 previous tables with balances table, showing how much each address
sent and received and calculating new columns: total volume (sent or received) and net
volume (received - sent)

,all_addresses AS (
SELECT address, Sending_Volume,Receiving_Volume,
       Sending_Volume + Receiving_Volume as total_volume,
       Receiving_Volume - Sending_Volume as net_volume
FROM `bigquery-public-data.crypto_ethereum.balances` as a join sender_addresses as s
      ON a.address = s.from_address
        join receiver_addresses as r ON a.address = r.to_address
)
```

```
-- top 10% addresses in terms of transaction volume in the past 6 months. Query
separating table into 10 groups according to their total volume and getting only the
10th decile (biggest group, top 10%)

,top_volume AS (
select *
from (select *, NTILE(10) over(order by total_volume) AS v_decile
      from all_addresses)
where v_decile = 10
order by total_volume DESC
)


-- top 10% of addresses that received more ETH than what they sent (from the top 10%
addresses in transaction volume)

,top_accumulators AS (
select *
from (select *, NTILE(10) over(order by net_volume) AS a_decile
      from top_volume)
where a_decile = 10
order by net_volume DESC
)

-- top 10% of addresses that sent more ETH than what they received (smallest group,
bottom 10%), (from the top 10% addresses in transaction volume)

,top_spenders AS (
select *
from (select *, NTILE(10) over(order by net_volume) AS s_decile
      from top_volume)
where s_decile = 1
order by net_volume ASC
)



/*

-- query to get top 10% addresses in terms of transaction volume in the past 6 months
SELECT *
```

```
from top_volume

-- query to get top 10% spending addresses
SELECT *
from top_spenders

-- query to get top 10% accumulating addresses
SELECT *
from top_accumulators

*/
```

Question 2:

Which are the **top 5% wallets** by balance? For each of them determine:

- first transaction date
- last transaction date
- monthly transacted volume in ETH
- transaction frequency
- total number of transactions
- total transacted volume in ETH

Results:

Google Drive Folder with the results in CSV's.

I limited the amount of data in the queries and tables because it was too large and took too long to load (i.e: limit 200 wallets and limit 1000 transactions).

Queries:

```
with

-- table with the top 5% wallets by balance (Getting the biggest from 20 groups).

top_5pcnt AS (
select *
from (select *, NTILE(20) over(order by eth_balance) AS percentile
      from `bigquery-public-data.crypto_ethereum.balances`)
where percentile = 20
order by eth_balance DESC
)

-- table with the transactions made by the top 5% wallets

,transactions AS (SELECT address, from_address, to_address, block_timestamp, value
                  FROM top_5pcnt as a join
bigquery-public-data.crypto_ethereum.transactions as b
                        ON a.address = b.from_address
                        OR a.address = b.to_address
)


/*

-- first and last transaction dates by address (both sending or receiving)

select address, min(block_timestamp) as first_transaction_date, max(block_timestamp)
as last_transaction_date
from transactions
group by address

-- monthly transacted volume in ETH  by address and month, (both sending or
receiving), 1 ETH = 10^18 Wei

select address, date_trunc(date(block_timestamp), MONTH) AS month, sum
(value)/1000000000000000000 as monthly_transacted_volume_ETH
from transactions
group by address, month
```

```
order by address, month

-- monthly transaction frequency per address

select address, date_trunc(date(block_timestamp), MONTH) AS month, count (address) as
freq_transactions_per_month
from transactions
group by address, month
order by address, month

-- total number of transactions by address

select address, count (address) as total_transactions
from transactions
group by address
order by total_transactions desc

-- total transacted volume in ETH by address, 1 ETH = 10^18 Wei

select address, sum (value)/1000000000000000000 as total_transacted_volume_ETH
from transactions
group by address
order by total_transacted_volume_ETH desc


*/
```