

# Analyzing eCommerce Business Performance with SQL



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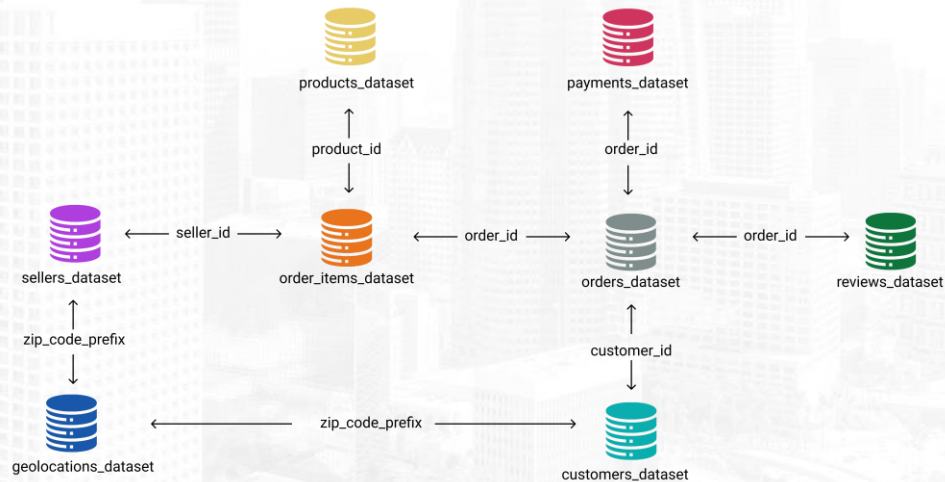
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“Bachelor of Physics from Padjadjaran University> Someone who enjoys learning new things, has good analytical and planning skill. Enjoy to solve problem related to data analysis using Excel, SQL, Python and Looker Studio. Have a high interest in a career in the data field.”

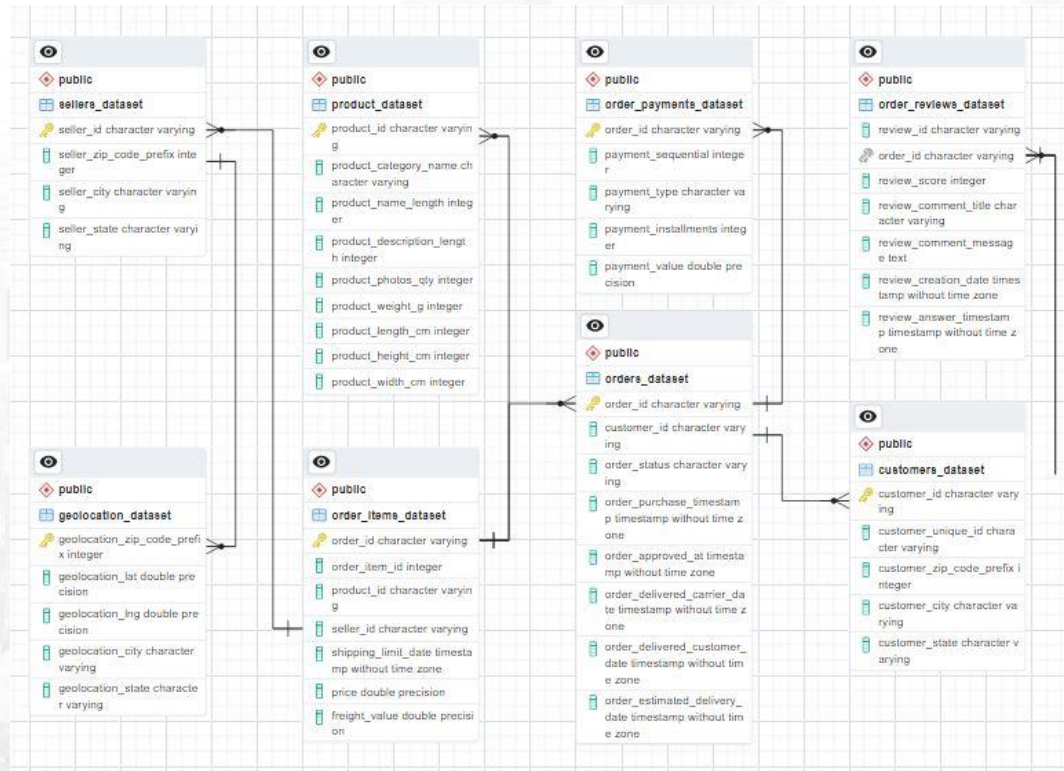
“In a company measuring business performance is very important tracking, monitoring, and assessing success or failure of various business processes. Therefore, in this paper will analyze the business performance for an eCommerce company, taking into account some business metrics such as customers growth, product quality and payment type.”

Data pre-processing stages:

- Prepare raw dataset to be processed
- Create a new database according to the many tables that have been prepared
- Make sure there are no errors in the input data type of each column
- Importing data in csv format into database using PostgreSQL
- Creating an Entity Relationship Diagram (ERD) in accordance with the provision in the figure beside.
- Export the ERD in the form of an image and make sure the naming of the columns between the tables are related and the data types are correct





## The Entity Relationship Diagram (ERD) of Analizing eCommerce\_Business\_Performance





# Annual Customer Activity Growth Analysis



Average monthly active user (MAU) per year

	year double precision 	average_mau numeric 
1	2016	108.67
2	2017	3694.83
3	2018	5338.20



Total customers doing repeat order per year

	year double precision 	repeating_customer bigint 
1	2016	3
2	2017	1256
3	2018	1167

Total new customers per Year

	year double precision 	new_customers bigint 
1	2016	326
2	2017	43708
3	2018	52062

Average order frequency for every year

	year double precision 	average_order numeric 
1	2016	1.01
2	2017	1.03
3	2018	1.02



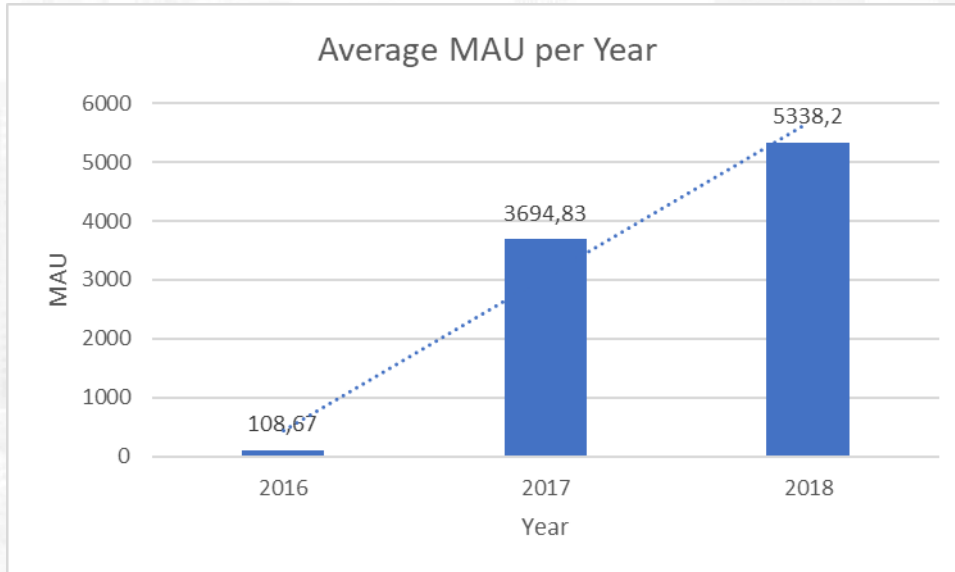
# Annual Customer Activity Growth Analysis

Combine the five data tables

	<b>year</b> double precision 🔒	<b>average_mau</b> numeric 🔒	<b>new_customer</b> bigint 🔒	<b>repeating_customer</b> bigint 🔒	<b>average_order</b> numeric 🔒
1	2016	108.67	326	3	1.01
2	2017	3694.83	43708	1256	1.03
3	2018	5338.20	52062	1167	1.02

# Annual Customer Activity Growth Analysis

## Average Monthly Active User



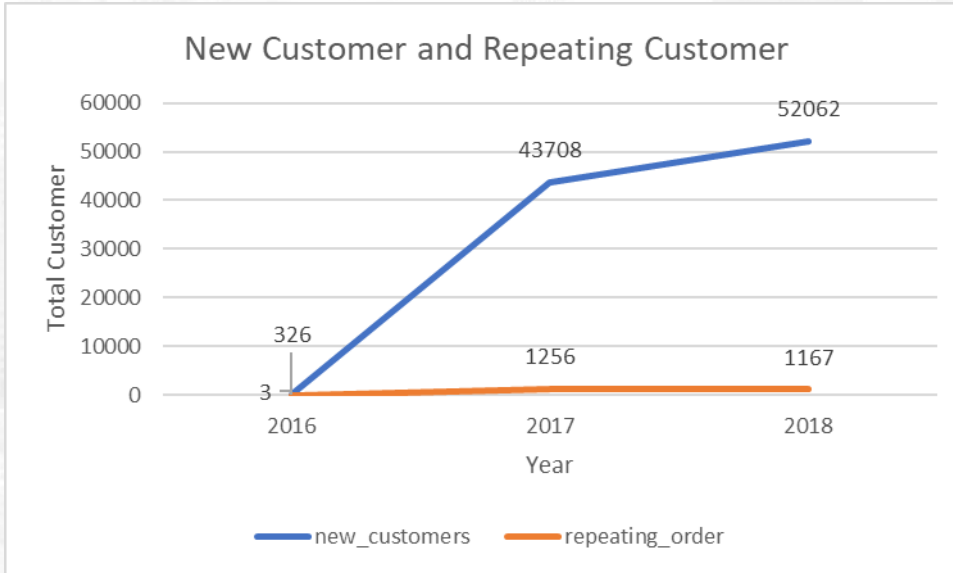
### Interpretation

MAU measures the number of users who have made transactions with the company product every single month.

MAU has increased every year, especially in 2017 and 2018 there was rapidly increased. The lowest activity occurred in 2016 because transaction data was only available from September.

# Annual Customer Activity Growth Analysis

## New Customer and Customer doing Repeat Order



### Interpretation



New customer are customers who have made transactions for the first time, while repeating customer are customers who have made transactions more than once.

Total new customers has increased every year. However, total customers who make repeat transactions has decreased in 2018. From the average order data, it is known that most customers only place orders once a year.





# Annual Product Category Quality Analysis


Revenue per year

	<b>year</b> double precision 	<b>revenue</b> numeric 
1	2016	46653.74
2	2017	6921535.24
3	2018	8451584.77

Total canceled orders per year

	<b>year</b> double precision 	<b>total_cancel</b> bigint 
1	2016	26
2	2017	265
3	2018	334

Top categories that generate the most revenue per year

	<b>year</b> double precision 	<b>product_category_name</b> character varying 	<b>revenue</b> numeric 
1	2016	furniture_decor	6899.35
2	2017	bed_bath_table	580949.20
3	2018	health_beauty	866810.34

Categories that experienced the most canceled orders per year

	<b>year</b> double precision 	<b>product_category_name</b> character varying 	<b>total_cancel</b> bigint 
1	2016	toys	3
2	2017	sports_leisure	25
3	2018	health_beauty	27

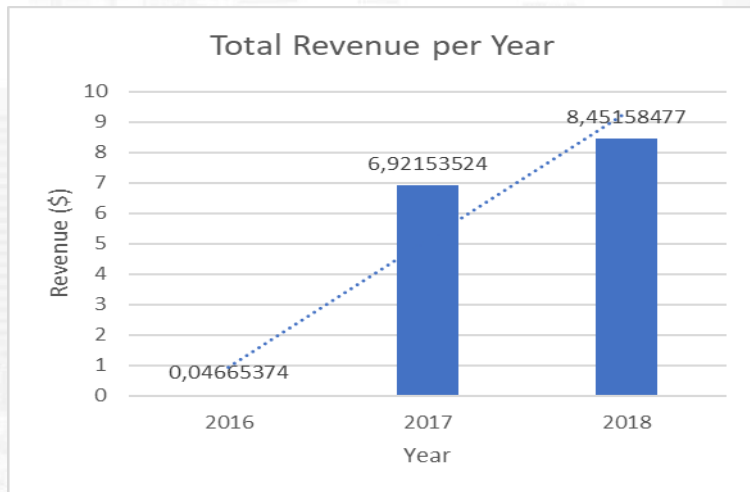
# Annual Product Category Quality Analysis

Combine the five data tabels

	<b>year</b> double precision 🔒	<b>top_product</b> character varying 🔒	<b>top_revenue_product</b> numeric 🔒	<b>total_revenue</b> numeric 🔒	<b>top_cancel_product</b> character varying 🔒	<b>total_cancel_product</b> bigint 🔒	<b>total_cancel_order</b> bigint 🔒
1	2016	furniture_decor	6899.35	46653.74	toys	3	26
2	2017	bed_bath_table	580949.20	6921535.24	sports_leisure	25	265
3	2018	health_beauty	866810.34	8451584.77	health_beauty	27	334

# Annual Product Category Quality Analysis

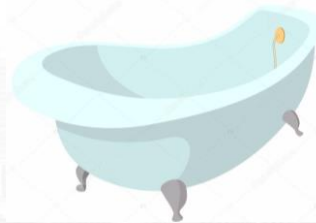
## Total Revenue



## Top Product



**2016**  
Furniture and  
decoration



**2017**  
Bathtub



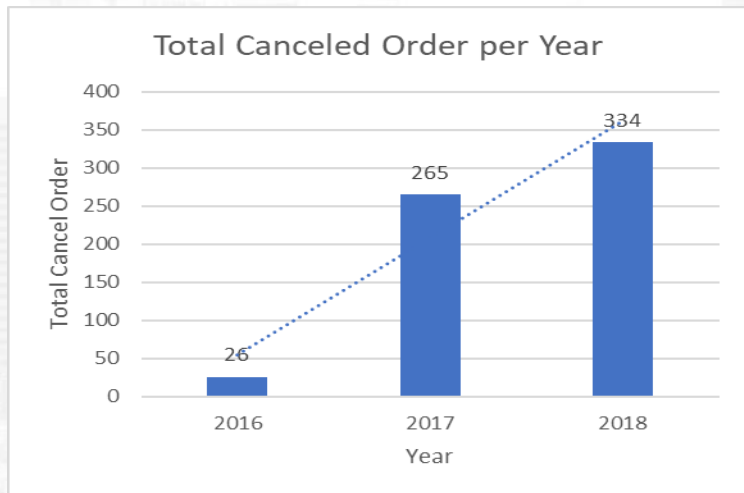
**2018**  
Health and  
Beauty

### Interpretation:

Total revenue has increased every year, showing that the company has good growth. There are several best-selling product categories that differ each year. In 2016 the products were dominated by furniture decoration. In 2017 the products were dominated by bed tables, and in 2018 the products were dominated by health and beauty.

# Annual Product Category Quality Analysis

## Total Cancel Order



## Top Cancelled Product



**2016**  
Toys



**2017**  
Bathtub



**2018**  
Health and  
Beauty

### Interpretation:

Total canceled orders are increasing every year, further research is needed to determine the factors of order cancellation. The products with the most cancellations are different each year. In 2016 the canceled products were dominated by toys, in 2017 the canceled products were dominated by sports leisure and in 2018 the canceled products were dominated by health and beauty.

# Analysis of Annual Payment Type Usage

Total uses of each payment type in order of highest usage

	payment_type character varying 🔒	num_of_usage bigint 🔒
1	credit_card	76795
2	boleto	19784
3	voucher	5775
4	debit_card	1529
5	not_defined	3

Total uses of each payment type for each year

	year double precision 🔒	payment_type character varying 🔒	num_of_usage bigint 🔒
1	2016	credit_card	258
2	2016	boleto	63
3	2016	voucher	23
4	2016	debit_card	2
5	2017	credit_card	34568

# Analysis of Annual Payment Type Usage

Combined table of total users using payment types for each year

	<b>payment_type</b> character varying 🔒	<b>year_2016</b> numeric 🔒	<b>year_2017</b> numeric 🔒	<b>year_2018</b> numeric 🔒
1	credit_card	258	34568	41969
2	boleto	63	9508	10213
3	voucher	23	3027	2725
4	debit_card	2	422	1105
5	not_defined	0	0	3



## Payment Type Usage

### Interpretation:

Analyzing the performance of each payment type will provide insights for building partnerships with payment method providers. The most widely used payment methods over the past 3 years are credit cards, boleto, vouchers, and debit cards. The highest increase in debit card usage occurred from 2017 to 2018, while voucher usage actually decreased from 2017 to 2018.

Credit card payment methods usually offer many benefits such as rewards and discounts so customers are more interested in making payments with this method.

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