Comprehensive Analysis of E-Commerce Data: Business Insights through Multi-level Querying

This project involves end-to-end data analysis on e-commerce data using Python and PostgreSQL. Starting from data extraction and loading, the project progresses through complex SQL querying within Python, and presents insights through visualizations. It showcases the integration of data engineering and analytical techniques to solve business problems and derive actionable insights.

PostgreSQL Configuration

In [10]:
```
import pandas as pd
import numpy as np
from sqlalchemy import create_engine
import urllib.parse
import os
from sqlalchemy.sql import text
import time
import matplotlib.pyplot as plt
import seaborn as sns

# PostgreSQL connection details
username = 'postgres'
password = urllib.parse.quote_plus('enterpassword')
host = 'localhost'
port = '5432'
database = 'retail_db'

# connection string
connection_string = f'postgresql://{username}:{password}@{host}:{port}/{database}'

# SQLAlchemy engine
engine = create_engine(connection_string)

try:
    engine.connect()
    print("Connection to PostgreSQL DB successful!")
except Exception as e:
    print(f"Error: {e}")
```

```
Connection to PostgreSQL DB successful!
```

In [ ]:

Customer and Sales Overview Insights:

- These queries focus on foundational insights into customer locations, order counts, and overall sales distribution.

1. List all unique cities where customers are located.

In [11]:
```
query_b1 = '''
    select
        distinct customer_city
    from customers;'''

df = pd.read_sql(query_b1, engine)
display(df)
```

	customer_city
0	bom jardim de minas
1	alto rio doce
2	alvorada do gurgueia
3	batatais
4	capao da porteira
...	...
4114	carbonita
4115	concordia do para
4116	independencia
4117	governador valadares
4118	balsa nova

4119 rows × 1 columns

2. Count the number of orders placed in 2017.

In [12]:
```
query_b2 = '''
    SELECT
        COUNT(order_id) FROM orders
    WHERE DATE_PART('year', order_purchase_timestamp::TIMESTAMP) = 2017;
'''
df = pd.read_sql(query_b2, engine)
display(df)
```

	count
0	45101

3. Find the total sales per category.

In [13]:
```
query_b3 = '''
```

```
        select
                upper(p.product_category) as product_category,
                '$'||ROUND(SUM(CAST(pa.payment_value AS NUMERIC)), 2) AS total_sales
        from products p
                join order_items o
                on o.product_id = p.product_id
        join payments pa
                on o.order_id = pa.order_id
        group by p.product_category
        order by p.product_category
'''

df = pd.read_sql(query_b3, engine)
display(df)
```

	product_category	total_sales
0	AGRO INDUSTRIA E COMERCIO	$118730.61
1	ART	$30992.93
2	ARTS AND CRAFTS	$2326.17
3	AUDIO	$60324.62
4	AUTOMOTIVE	$852294.33
...	...	...
69	TECHNICAL BOOKS	$24915.44
70	TELEPHONY	$486882.05
71	TOYS	$619037.69
72	WATCHES PRESENT	$1429216.68
73	None	$252801.71

74 rows × 2 columns

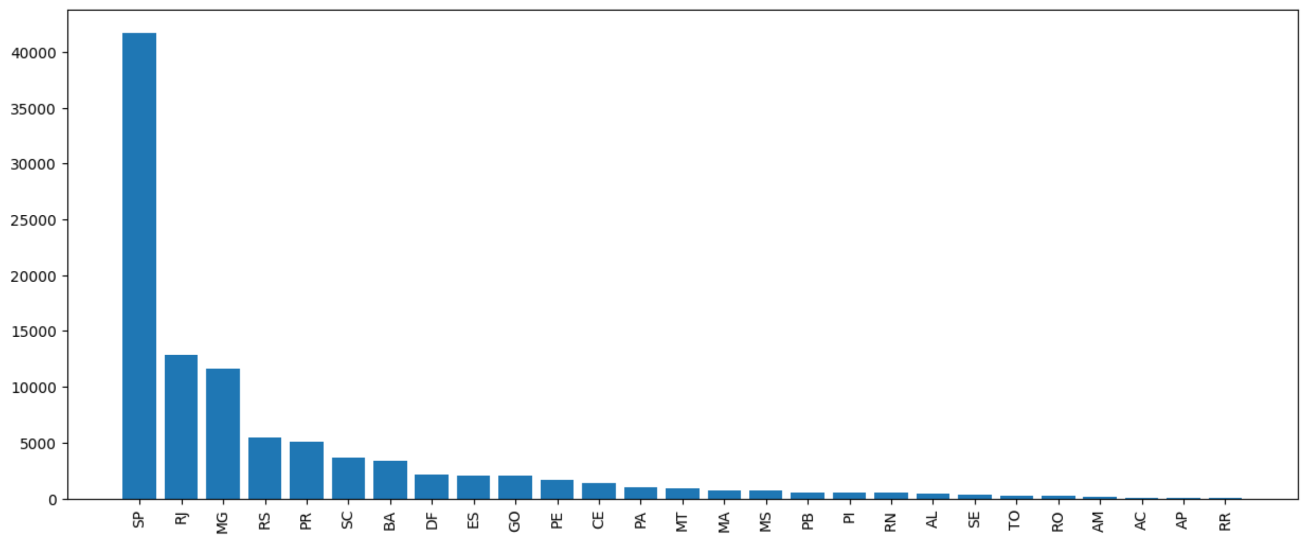
4. Calculate the percentage of orders that were paid in installments.

In [14]:
```
query_b4 = '''
        select
                (SUM(CASE WHEN payment_installments > 1 THEN 1 ELSE 0 END) * 100.0) / COU
        from payments
'''

df = pd.read_sql(query_b4, engine)
display(df)
```

	test
0	49.417631

5. Count the number of customers from each state.

In [15]:
```
query_b5 = '''
    select
        customer_state,
        count(customer_id) as customer_count
    from customers
    group by 1
'''

df = pd.read_sql(query_b5, engine)
# display(df)
df = df.sort_values(by = "customer_count",ascending = False)
plt.figure(figsize=(15, 6))
plt.bar(df["customer_state"],df["customer_count"])
plt.xticks(rotation = 90)
plt.show()
```



Monthly Performance and Product Analysis:

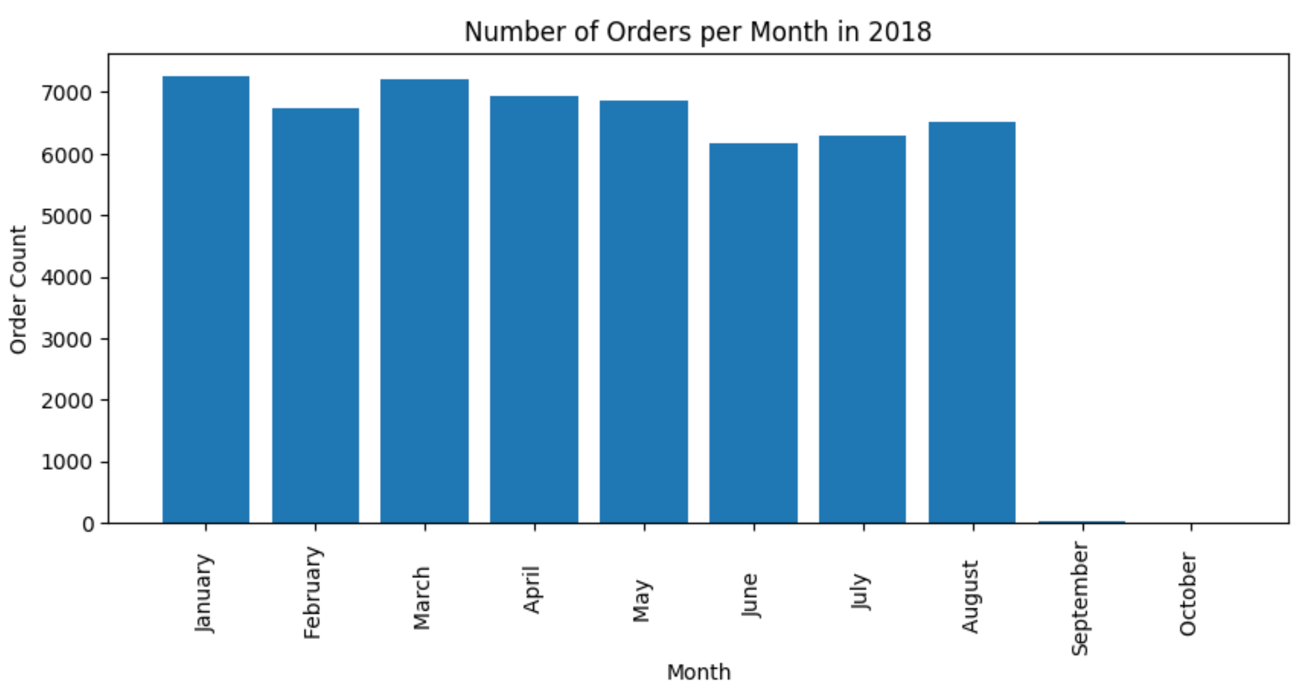
- These queries delve into monthly trends, product performance, and revenue breakdowns, providing more detailed operational insights.

1. Calculate the number of orders per month in 2018.

In [16]:
```
query_m1 = '''
        select
                TO_CHAR(order_purchase_timestamp::TIMESTAMP, 'Month') as month,
                count(order_id) as counts
        from orders
                where DATE_PART('year', order_purchase_timestamp::TIMESTAMP) = 2018
        group by
                TO_CHAR(order_purchase_timestamp::TIMESTAMP, 'Month'),
                DATE_PART('month', order_purchase_timestamp::TIMESTAMP)
        order by DATE_PART('month', order_purchase_timestamp::TIMESTAMP);
```

```
'''
df = pd.read_sql(query_m1, engine)
display(df)

plt.figure(figsize=(10, 4))
plt.xlabel('Month')
plt.ylabel('Order Count')
plt.title('Number of Orders per Month in 2018')
plt.bar(df["month"],df["counts"])
plt.xticks(rotation = 90)
plt.show()
```

	month	counts
0	January	7269
1	February	6728
2	March	7211
3	April	6939
4	May	6873
5	June	6167
6	July	6292
7	August	6512
8	September	16
9	October	4



2. Find the average number of products per order, grouped by customer city.

In [17]:
```
query_m2 = '''
    with order_counts as (
        select
            ord.order_id,
            ord.customer_id,
            count(oi.order_id) as count_orders
        from orders ord
            join order_items oi
            on ord.order_id = oi.order_id
        group by 1,2
    )

    select
        cus.customer_city, round(avg(oc.count_orders),2) as avg_orders
    from customers cus
        join order_counts oc
        on cus.customer_id = oc.customer_id
    group by 1 order by 1

'''
df = pd.read_sql(query_m2, engine)
display(df)
```

	customer_city	avg_orders
0	abadia dos dourados	1.00
1	abadiania	1.00
2	abaete	1.00
3	abaetetuba	1.27
4	abaiara	1.00
...	...	...
4105	xinguara	1.11
4106	xique-xique	1.00
4107	zacarias	1.00
4108	ze doca	1.00
4109	zortea	1.00

4110 rows × 2 columns

3. Calculate the percentage of total revenue contributed by each product category.

In [18]:
```
query_m3 = '''
    select
        p.product_category,
        ROUND((SUM(CAST(pa.payment_value AS NUMERIC)) * 100) /
            (SELECT SUM(CAST(payment_value AS NUMERIC)) FROM payments), 2) AS total_sales
    from products p
    join order_items o
        on o.product_id = p.product_id
    join payments pa
        on o.order_id = pa.order_id
    group by p.product_category
    order by p.product_category;
'''
df = pd.read_sql(query_m3, engine)
display(df)
```

	product_category	total_sales
0	Agro Industria e Comercio	0.74
1	Art	0.19
2	Arts and Crafts	0.01
3	audio	0.38
4	automotive	5.32
...	...	...
69	technical books	0.16
70	telephony	3.04
71	toys	3.87
72	Watches present	8.93
73	None	1.58

74 rows × 2 columns

4. Identify the correlation between product price and the number of times a product has been purchased.

In [19]:
```
query_m4 = '''
    select
        prd.product_category,
        count(oi.product_id) as product_counts,
        round(avg(cast(oi.price as integer)),2) as product_price
    from products as prd
        join order_items as oi
        on prd.product_id = oi.product_id
    group by 1
'''
```

```
df = pd.read_sql(query_m4, engine)
display(df)
```

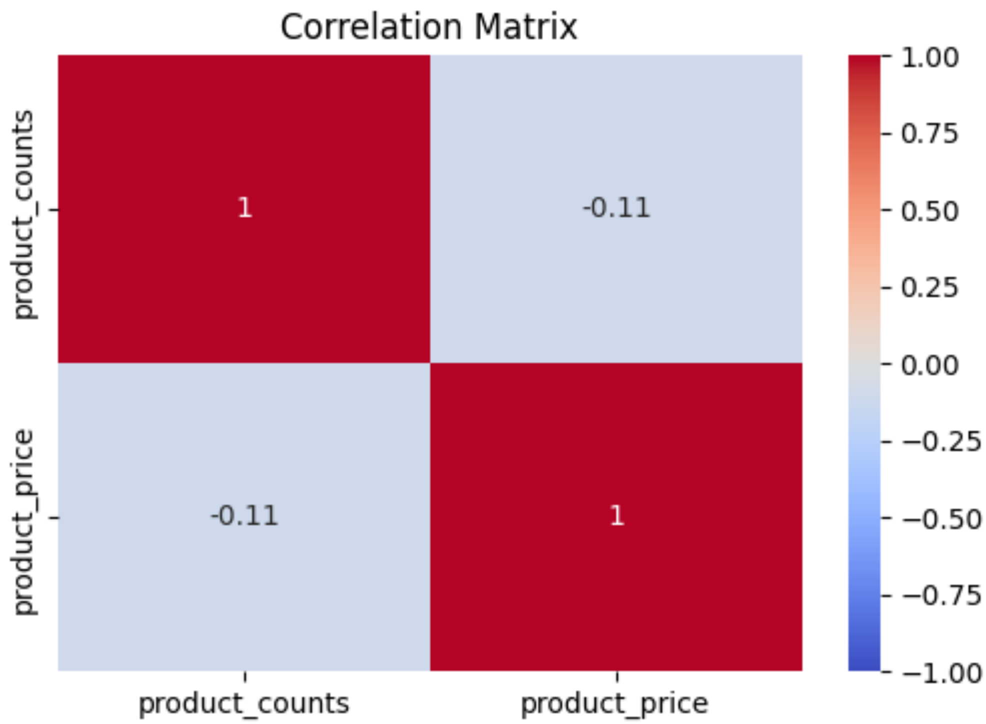
	product_category	product_counts	product_price
0	Agro Industria e Comercio	212	342.16
1	Art	209	115.85
2	Arts and Crafts	24	75.50
3	audio	364	139.31
4	automotive	4235	139.97
...	...	...	...
69	technical books	267	71.53
70	telephony	4545	71.24
71	toys	4117	117.60
72	Watches present	5991	201.17
73	None	1603	112.04

74 rows × 3 columns

In [20]:
```
arr1 = df["product_counts"]
arr2 = df["product_price"]
np.corrcoef(arr1,arr2)
```

Out[20]:
```
array([[ 1.        , -0.10629728],
       [-0.10629728,  1.        ]])
```

In [21]:
```
corr_matrix = df[["product_counts", "product_price"]].corr()
plt.figure(figsize=(6, 4))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)

plt.title('Correlation Matrix')
plt.show()
```



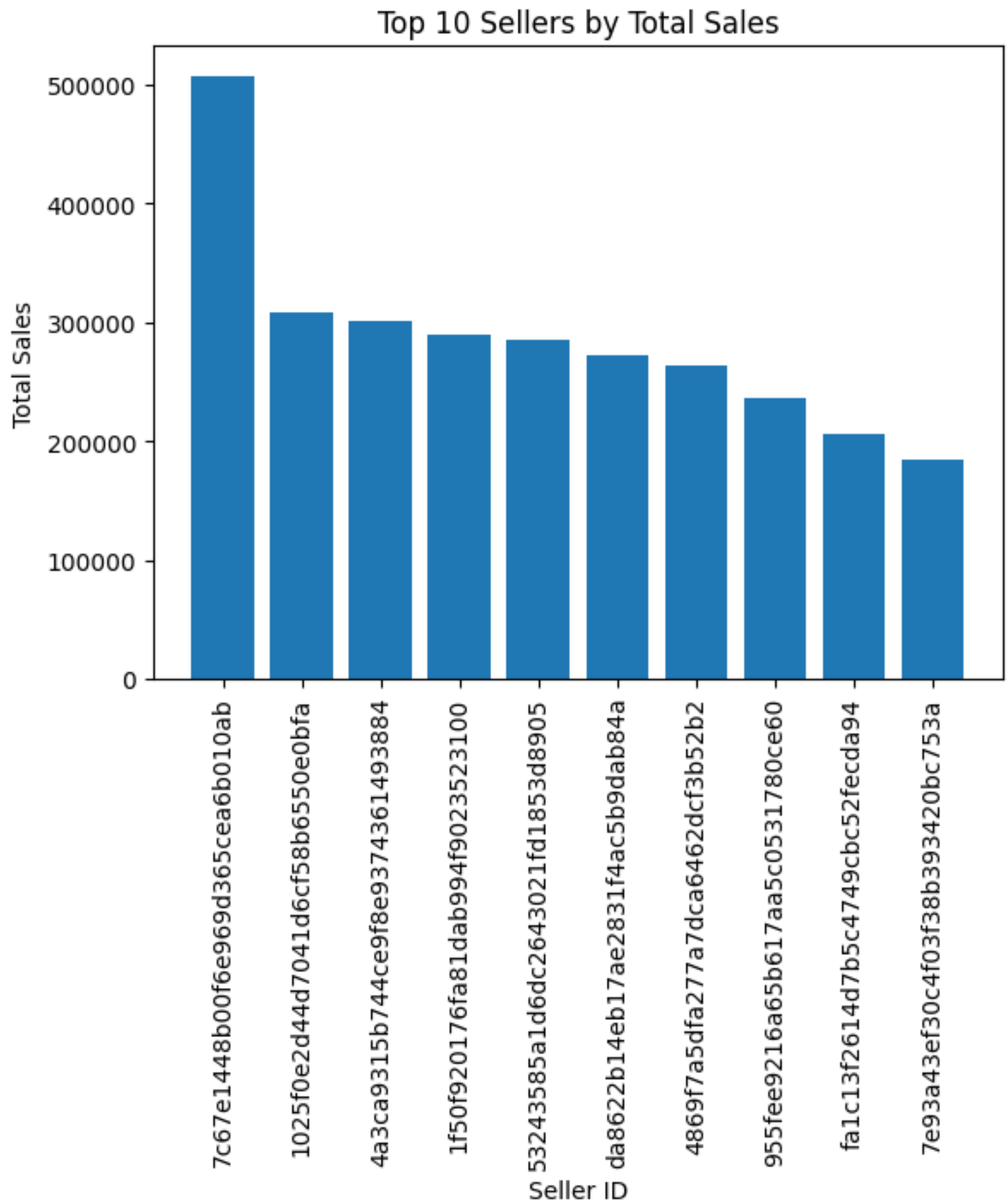
5. Calculate the total revenue generated by each seller, and rank them by revenue.

In [22]:
```
query_m5 = '''
    select
        sel.seller_id,
        SUM(CAST(pa.payment_value AS NUMERIC)) as total_sales,
        rank() over(order by SUM(CAST(pa.payment_value AS NUMERIC)) desc) as seller_rankin
    from sellers sel
        join order_items oi
            on oi.seller_id = sel.seller_id
        join payments pa
            on pa.order_id = oi.order_id
    group by 1
'''
df = pd.read_sql(query_m5, engine)
display(df)
```

	seller_id	total_sales	seller_rankings
0	7c67e1448b00f6e969d365cea6b010ab	507166.91	1
1	1025f0e2d44d7041d6cf58b6550e0bfa	308222.04	2
2	4a3ca9315b744ce9f8e9374361493884	301245.27	3
3	1f50f920176fa81dab994f9023523100	290253.42	4
4	53243585a1d6dc2643021fd1853d8905	284903.08	5
...	...	...	...
3090	ad14615bdd492b01b0d97922e87cb87f	19.21	3091
3091	702835e4b785b67a084280efca355756	18.56	3092
3092	4965a7002cca77301c82d3f91b82e1a9	16.36	3093
3093	77128dec4bec4878c37ab7d6169d6f26	15.22	3094
3094	cf6f6bc4df3999b9c6440f124fb2f687	12.22	3095

3095 rows × 3 columns

In [23]:
```
# Top 10 sellers:
top_10_sellers = df.nlargest(10, 'total_sales')
plt.bar(top_10_sellers['seller_id'], top_10_sellers['total_sales'])
plt.xlabel('Seller ID')
plt.ylabel('Total Sales')
plt.title('Top 10 Sellers by Total Sales')
plt.xticks(rotation=90)
plt.show()
```



Strategic Growth and Customer Retention Analytics

1. Calculate the moving average of order values for each customer over their order history.

- These queries focus on advanced metrics like growth rates, retention, and top customer behavior, offering insights for strategic decision-making.

In [24]:
```
query_a1 = '''
    WITH cte AS (
```

```
        SELECT
            orders.customer_id,
            orders.order_purchase_timestamp,
            payments.payment_value
        FROM orders
        INNER JOIN payments
        USING (order_id)
    )
    SELECT
        customer_id,
        order_purchase_timestamp,
        payment_value,
        AVG(payment_value) OVER (
            PARTITION BY customer_id
            ORDER BY order_purchase_timestamp
            ROWS BETWEEN 2 PRECEDING AND CURRENT ROW
        ) AS moving_avg
    FROM cte
    ORDER BY customer_id desc;

'''

df = pd.read_sql(query_a1, engine)
display(df)
```

	customer_id	order_purchase_timestamp	payment_value	moving_avg
0	ffffe8b65bbe3087b653a978c870db99	2017-09-29 14:07:03	18.37	18.37
1	ffffa3172527f765de70084a7e53aae8	2017-09-02 11:53:32	45.50	45.50
2	ffff42319e9b2d713724ae527742af25	2018-06-13 16:57:05	214.13	214.13
3	fffeda5b6d849fbd39689bb92087f431	2018-05-22 13:36:02	63.13	63.13
4	fffecc9f79fd8c764f843e9951b11341	2018-03-29 16:59:26	0.64	0.64
...	...	...	...	...
103881	000379cdec625522490c315e70c7a9fb	2018-04-02 13:42:17	107.01	107.01
103882	0002414f95344307404f0ace7a26f1d5	2017-08-16 13:09:20	179.35	179.35
103883	0001fd6190edaaf884bcaf3d49edf079	2017-02-28 11:06:43	195.42	195.42
103884	000161a058600d5901f007fab4c27140	2017-07-16 09:40:32	67.41	67.41
103885	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.74

103886 rows × 4 columns

2. Calculate the cumulative sales per month for each year.

In [25]:

```
query_a2 = '''
    WITH cte AS (
        SELECT
```

```
            DATE_PART('YEAR', orders.order_purchase_timestamp::TIMESTAMP) as YEAR,
            DATE_PART('month', orders.order_purchase_timestamp::TIMESTAMP) as MONTH,
            ROUND(SUM(CAST(payment_value AS NUMERIC)),2) as total_sales
        FROM orders
        INNER JOIN payments
        USING (order_id)
        GROUP BY YEAR ,MONTH
    )
    SELECT
        YEAR::varchar,
        MONTH,
        total_Sales,
        SUM(total_sales) OVER (
            PARTITION BY YEAR
            ORDER BY YEAR, MONTH
        ) AS cumulative_sales
    FROM cte
    ORDER BY YEAR ,MONTH ;

'''

df = pd.read_sql(query_a2, engine)
display(df)
print(df.columns)
```

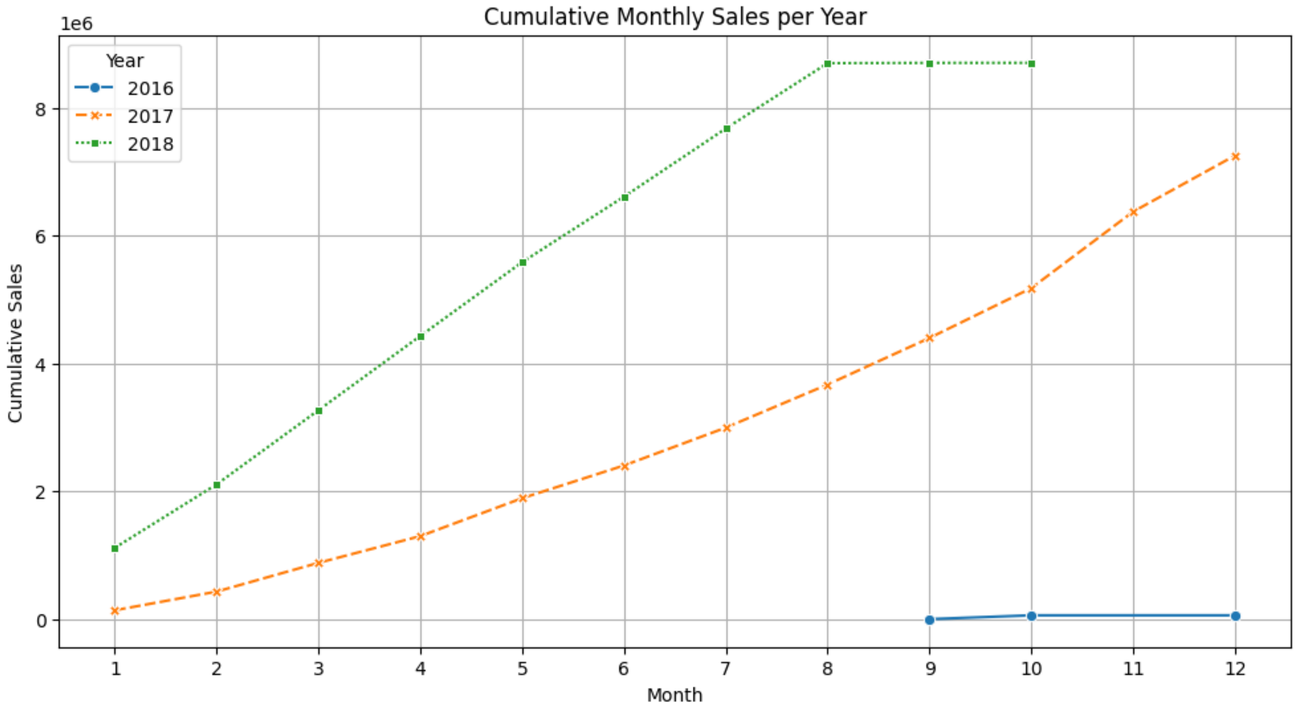
	year	month	total_sales	cumulative_sales
0	2016	9.0	252.24	252.24
1	2016	10.0	59090.48	59342.72
2	2016	12.0	19.62	59362.34
3	2017	1.0	138488.04	138488.04
4	2017	2.0	291908.01	430396.05
5	2017	3.0	449863.60	880259.65
6	2017	4.0	417788.03	1298047.68
7	2017	5.0	592918.82	1890966.50
8	2017	6.0	511276.38	2402242.88
9	2017	7.0	592382.92	2994625.80
10	2017	8.0	674396.32	3669022.12
11	2017	9.0	727762.45	4396784.57
12	2017	10.0	779677.88	5176462.45
13	2017	11.0	1194882.80	6371345.25
14	2017	12.0	878401.48	7249746.73
15	2018	1.0	1115004.18	1115004.18
16	2018	2.0	992463.34	2107467.52
17	2018	3.0	1159652.12	3267119.64
18	2018	4.0	1160785.48	4427905.12
19	2018	5.0	1153982.15	5581887.27
20	2018	6.0	1023880.50	6605767.77
21	2018	7.0	1066540.75	7672308.52
22	2018	8.0	1022425.32	8694733.84
23	2018	9.0	4439.54	8699173.38
24	2018	10.0	589.67	8699763.05

```
Index(['year', 'month', 'total_sales', 'cumulative_sales'], dtype='object')
```

In [26]:

```
df.columns = [col.strip().upper() for col in df.columns]


# pivot table for plotting.
pivot_df = df.pivot(index='MONTH', columns='YEAR', values='CUMULATIVE_SALES')

# line plot.
```

```python
plt.figure(figsize=(12, 6))
sns.lineplot(data=pivot_df, markers=True)


plt.title('Cumulative Monthly Sales per Year')
plt.xlabel('Month')
plt.ylabel('Cumulative Sales')
plt.xticks(ticks=range(1, 13))
plt.legend(title='Year')
plt.grid(True)

plt.show()
```



3. Calculate the year-over-year growth rate of total sales.

In [27]:
```python
query_a3 = '''
    WITH cte AS (
        SELECT
            DATE_PART('YEAR', orders.order_purchase_timestamp::TIMESTAMP) as YEAR,
            ROUND(SUM(CAST(payment_value AS NUMERIC)),2) as total_sales
        FROM orders
        INNER JOIN payments
        USING (order_id)
        GROUP BY YEAR
    )
    select
        year::varchar,
        total_sales,
        ROUND((((total_sales - LAG(total_sales,1) over (order by year ))/LAG(total_sales,1
    from cte;
'''
df = pd.read_sql(query_a3, engine)
display(df)
```

	year	total_sales	y_o_y_growthreate
0	2016	59362.34	NaN
1	2017	7249746.73	12112.7
2	2018	8699763.05	20.0

4. Calculate the retention rate of customers, defined as the percentage of customers who make another purchase within 6 months of their first purchase.

In [28]:

```
query_a4 = '''
    WITH customer_purchases AS (
        SELECT
            customer_id,
            MIN(order_purchase_timestamp::date) AS first_purchase_date,
            MAX(order_purchase_timestamp::date) AS last_purchase_date
        FROM orders
        GROUP BY customer_id
    ),
    retained_customers AS (
        SELECT
            customer_id
        FROM customer_purchases
        WHERE last_purchase_date <= (first_purchase_date + INTERVAL '6 months')
        AND first_purchase_date < last_purchase_date
    )
    SELECT
        COUNT(*) AS retained_customer_count,
        ROUND((COUNT(*) * 100.0 / (SELECT COUNT(DISTINCT customer_id) FROM orders)),2) AS
    FROM retained_customers;
'''
df = pd.read_sql(query_a4, engine)
display(df)
```

	retained_customer_count	retention_rate_percentage
0	0	0.0

5. Identify the top 3 customers who spent the most money in each year.

In [29]:

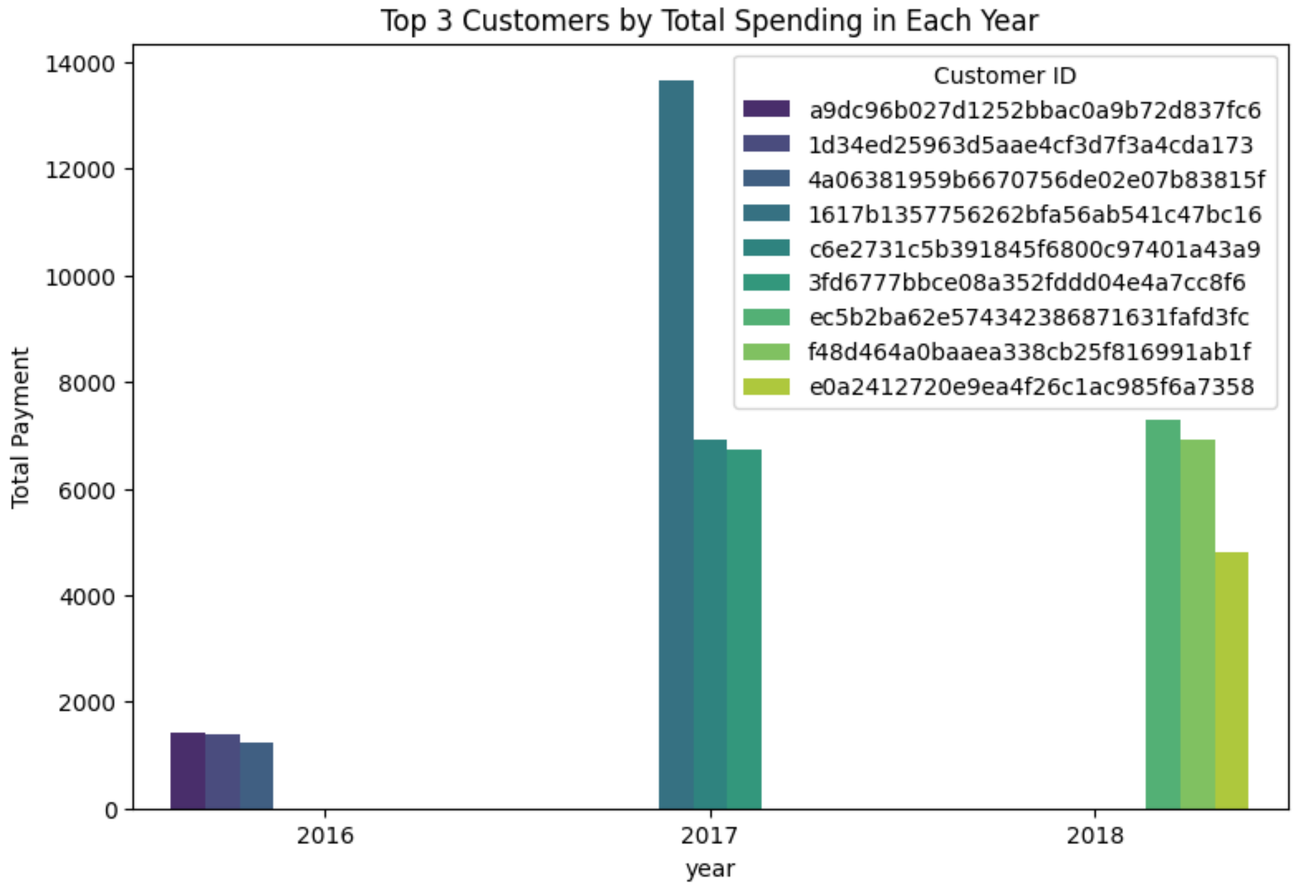
```
query_a5 = '''
    WITH yearly_customer_spending AS (
        SELECT
            DATE_PART('YEAR', orders.order_purchase_timestamp::TIMESTAMP) AS year,
            orders.customer_id,
            SUM(CAST(payments.payment_value AS NUMERIC)) AS total_payment
        FROM orders
        INNER JOIN payments
        USING (order_id)
```

```
        GROUP BY DATE_PART('YEAR', orders.order_purchase_timestamp::TIMESTAMP), orders.cus
    ),

    ranked_payments as (
        SELECT
            year,
            customer_id,
            total_payment,
            DENSE_RANK() OVER (PARTITION BY year ORDER BY total_payment DESC) AS rank
        FROM yearly_customer_spending
    )

    select
        year::varchar,
        customer_id,
        total_payment

    from ranked_payments
    WHERE rank <= 3
    ORDER BY year, rank;
'''
df = pd.read_sql(query_a5, engine)
display(df)
```

	year	customer_id	total_payment
0	2016	a9dc96b027d1252bbac0a9b72d837fc6	1423.55
1	2016	1d34ed25963d5aae4cf3d7f3a4cda173	1400.74
2	2016	4a06381959b6670756de02e07b83815f	1227.78
3	2017	1617b1357756262bfa56ab541c47bc16	13664.08
4	2017	c6e2731c5b391845f6800c97401a43a9	6929.31
5	2017	3fd6777bbce08a352fddd04e4a7cc8f6	6726.66
6	2018	ec5b2ba62e574342386871631fafd3fc	7274.88
7	2018	f48d464a0baaea338cb25f816991ab1f	6922.21
8	2018	e0a2412720e9ea4f26c1ac985f6a7358	4809.44

In [30]:

```
plt.figure(figsize=(9, 6))
sns.barplot(data=df, x='year', y='total_payment', hue='customer_id', palette='viridis')

plt.title('Top 3 Customers by Total Spending in Each Year')
plt.xlabel('year')
plt.ylabel('Total Payment')
plt.legend(title='Customer ID')
# plt.xticks([])

plt.show()
```


Top 3 Customers by Total Spending in Each Year
Customer ID
a9dc96b027d1252bbac0a9b72d837fc6
1d34ed25963d5aae4cf3d7f3a4cda173
4a06381959b6670756de02e07b83815f
1617b1357756262bfa56ab541c47bc16
c6e2731c5b391845f6800c97401a43a9
3fd6777bbce08a352fddd04e4a7cc8f6
ec5b2ba62e574342386871631fafd3fc
f48d464a0baaea338cb25f816991ab1f
e0a2412720e9ea4f26c1ac985f6a7358
Total Payment
0
2000
4000
6000
8000
10000
12000
14000
2016
2017
2018
year