E-Commerce Orders & Sales Analysis

In [1]:
```
pip install mysql-connector-python
```

```
Requirement already satisfied: mysql-connector-python in c:\users\faizal\anaconda3\lib\s
ite-packages (9.0.0)
Note: you may need to restart the kernel to use updated packages.
```

In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt
from matplotlib import style    ##for grid styling
%matplotlib inline
import seaborn as sns
```

```
C:\Users\Faizal\anaconda3\lib\site-packages\scipy\__init__.py:155: UserWarning: A NumPy
version >=1.18.5 and <1.25.0 is required for this version of SciPy (detected version 1.2
6.2
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

Importing libraries and connecting sql as well python and loading tables within sql and dataframes within python

In [3]:
```
import pandas as pd
import mysql.connector
import os

# List of CSV files and their corresponding table names
csv_files = [
    ('customers.csv', 'customers'),
    ('orders.csv', 'orders'),
    ('sellers.csv', 'sales'),
    ('products.csv', 'products'),
    ('online_retail_cleaned.csv', 'online_retail_cleaned'),
    ('payments.csv', 'payments'),
    ('order_items.csv', 'order_items'),
    ('geolocation.csv', 'geolocation') # Added payments.csv for specific handling
]

# Connect to the MySQL database
conn = mysql.connector.connect(
    host='localhost',
    user='root',
    password='12345677',
    database='ecommerce'
)
cursor = conn.cursor()

# Folder containing the CSV files
folder_path = "C:/Users/Faizal/Downloads/Target datasets"

def get_sql_type(dtype):
    if pd.api.types.is_integer_dtype(dtype):
        return 'INT'
    elif pd.api.types.is_float_dtype(dtype):
        return 'FLOAT'
    elif pd.api.types.is_bool_dtype(dtype):
```

```python
        return 'BOOLEAN'
    elif pd.api.types.is_datetime64_any_dtype(dtype):
        return 'DATETIME'
    else:
        return 'TEXT'

for csv_file, table_name in csv_files:
    file_path = os.path.join(folder_path, csv_file)

    # Read the CSV file into a pandas DataFrame
    df = pd.read_csv(file_path)

    # Replace NaN with None to handle SQL NULL
    df = df.where(pd.notnull(df), None)

    # Debugging: Check for NaN values
    print(f"Processing {csv_file}")
    print(f"NaN values before replacement:\n{df.isnull().sum()}\n")

    # Clean column names
    df.columns = [col.replace(' ', '_').replace('-', '_').replace('.', '_') for col in d

    # Generate the CREATE TABLE statement with appropriate data types
    columns = ', '.join([f'`{col}` {get_sql_type(df[col].dtype)}' for col in df.columns]
    create_table_query = f'CREATE TABLE IF NOT EXISTS `{table_name}` ({columns})'
    cursor.execute(create_table_query)

    # Insert DataFrame data into the MySQL table
    for _, row in df.iterrows():
        # Convert row to tuple and handle NaN/None explicitly
        values = tuple(None if pd.isna(x) else x for x in row)
        sql = f"INSERT INTO `{table_name}` ({', '.join(['`' + col + '`' for col in df.co
        cursor.execute(sql, values)

    # Commit the transaction for the current CSV file
    conn.commit()

# Close the connection
conn.close()
```

```
Processing customers.csv
NaN values before replacement:
customer_id                 0
customer_unique_id          0
customer_zip_code_prefix    0
customer_city               0
customer_state              0
dtype: int64

Processing orders.csv
NaN values before replacement:
order_id                            0
customer_id                         0
order_status                        0
order_purchase_timestamp            0
order_approved_at                 160
order_delivered_carrier_date     1783
order_delivered_customer_date    2965
order_estimated_delivery_date       0
dtype: int64

Processing sellers.csv
NaN values before replacement:
seller_id                 0
seller_zip_code_prefix    0
seller_city               0
```

```
seller_state                0
dtype: int64

Processing products.csv
NaN values before replacement:
product_id                      0
product category              610
product_name_length           610
product_description_length    610
product_photos_qty            610
product_weight_g                2
product_length_cm               2
product_height_cm               2
product_width_cm                2
dtype: int64

Processing online_retail_cleaned.csv
NaN values before replacement:
InvoiceNo           0
StockCode           0
Description         0
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     132424
Country             0
ItemTotal           0
dtype: int64

Processing payments.csv
NaN values before replacement:
order_id                0
payment_sequential      0
payment_type            0
payment_installments    0
payment_value           0
dtype: int64

Processing order_items.csv
NaN values before replacement:
order_id               0
order_item_id          0
product_id             0
seller_id              0
shipping_limit_date    0
price                  0
freight_value          0
dtype: int64

Processing geolocation.csv
NaN values before replacement:
geolocation_zip_code_prefix    0
geolocation_lat                0
geolocation_lng                0
geolocation_city               0
geolocation_state              0
dtype: int64
```

In [4]:

```
db = mysql.connector.connect(host = "localhost",
                            username = "root",
                            password = "12345677",
                            database = "ecommerce")

cur = db.cursor()
```

List all unique cities where customers are located.

Objective: To identify the diverse geographical locations of customers, which can help in targeted marketing and regional sales strategies.

SQL Query: Used a SELECT DISTINCT statement to fetch unique city names from the customers table. Tools Used: SQL for querying, Python and Pandas for fetching and displaying the results.

In [5]:
```
query = """ select distinct customer_city from customers """

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data)
df.head()
```

Out[5]:

	0
0	franca
1	sao bernardo do campo
2	sao paulo
3	mogi das cruzes
4	campinas

Count the number of orders placed in 2017.

Objective: To determine the sales volume for the year 2017, helping in year-over-year growth analysis.

SQL Query: Used COUNT and YEAR functions to filter and count orders by the year 2017. Tools Used: SQL for querying, Python for executing the query and presenting the data.

In [6]:
```
query = """ select count(order_id) from orders where year(order_purchase_timestamp) = 20

cur.execute(query)

data = cur.fetchall()

"total orders placed in 2017 are", data[0][0]
```

Out[6]:
```
('total orders placed in 2017 are', 315707)
```

Find the total sales per category.

Objective: To analyze which product categories are generating the most revenue.

SQL Query: Joined products, order_items, and payments tables to sum payment values grouped by product categories.

Tools Used: SQL for complex joins and aggregation, Pandas for further manipulation, and visualization.

In [7]:
```
query = """ select upper(products.product_category) category,
round(sum(payments.payment_value),2) sales
from products join order_items
on products.product_id = order_items.product_id
join payments
on payments.order_id = order_items.order_id
group by category
"""

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ["Category", "Sales"])
df
```

Out[7]:

	Category	Sales
0	PERFUMERY	3.243127e+07
1	FURNITURE DECORATION	9.153129e+07
2	TELEPHONY	3.116045e+07
3	FASHION BAGS AND ACCESSORIES	1.396213e+07
4	BED TABLE BATH	1.096034e+08
...	...	...
69	CDS MUSIC DVDS	7.676352e+04
70	LA CUISINE	1.864659e+05
71	FASHION CHILDREN'S CLOTHING	5.028288e+04
72	PC GAMER	1.391635e+05
73	INSURANCE AND SERVICES	2.076864e+04

74 rows × 2 columns

Calculate the percentage of orders that were paid in installments.

Objective: To understand customer payment preferences and the impact of installment payments on revenue.

SQL Query: Used conditional aggregation (CASE statements) to calculate the percentage of installment payments.

Tools Used: SQL for querying, Python for calculating and displaying the percentage.

In [8]:
```
query = """ select ((sum(case when payment_installments >= 1 then 1
else 0 end))/count(*))*100 from payments
"""

cur.execute(query)

data = cur.fetchall()
```

```
"the percentage of orders that were paid in installments is", data[0][0]
```

Out[8]:
```
('the percentage of orders that were paid in installments is',
 Decimal('99.9981'))
```

Count the number of customers from each state.

Objective: To identify customer distribution across different states, aiding in region-specific marketing efforts.

SQL Query: Used GROUP BY and COUNT to aggregate customer counts by state.

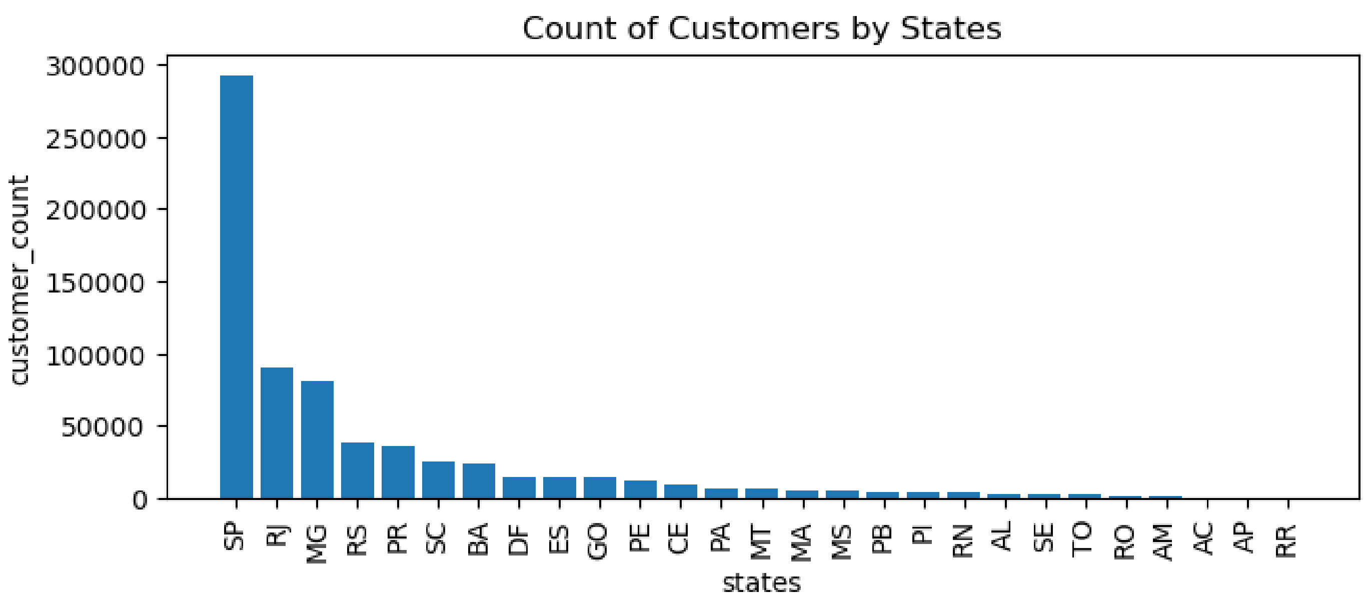
Tools Used: SQL for querying, Python, Pandas, Matplotlib for visualization.

In [9]:
```
query = """ select customer_state ,count(customer_id)
from customers group by customer_state
"""

cur.execute(query)

data = cur.fetchall()
df = pd.DataFrame(data, columns = ["state", "customer_count" ])
df = df.sort_values(by = "customer_count", ascending= False)

plt.figure(figsize = (8,3))
plt.bar(df["state"], df["customer_count"])
plt.xticks(rotation = 90)
plt.xlabel("states")
plt.ylabel("customer_count")
plt.title("Count of Customers by States")
plt.show()
```



Calculate the number of orders per month in 2018.

Objective: To analyze monthly sales trends within 2018, identifying peak and low sales periods.

SQL Query: Used MONTHNAME and YEAR functions to group and count orders by month in 2018.

Tools Used: SQL for querying, Python, Pandas, Seaborn for visualization.

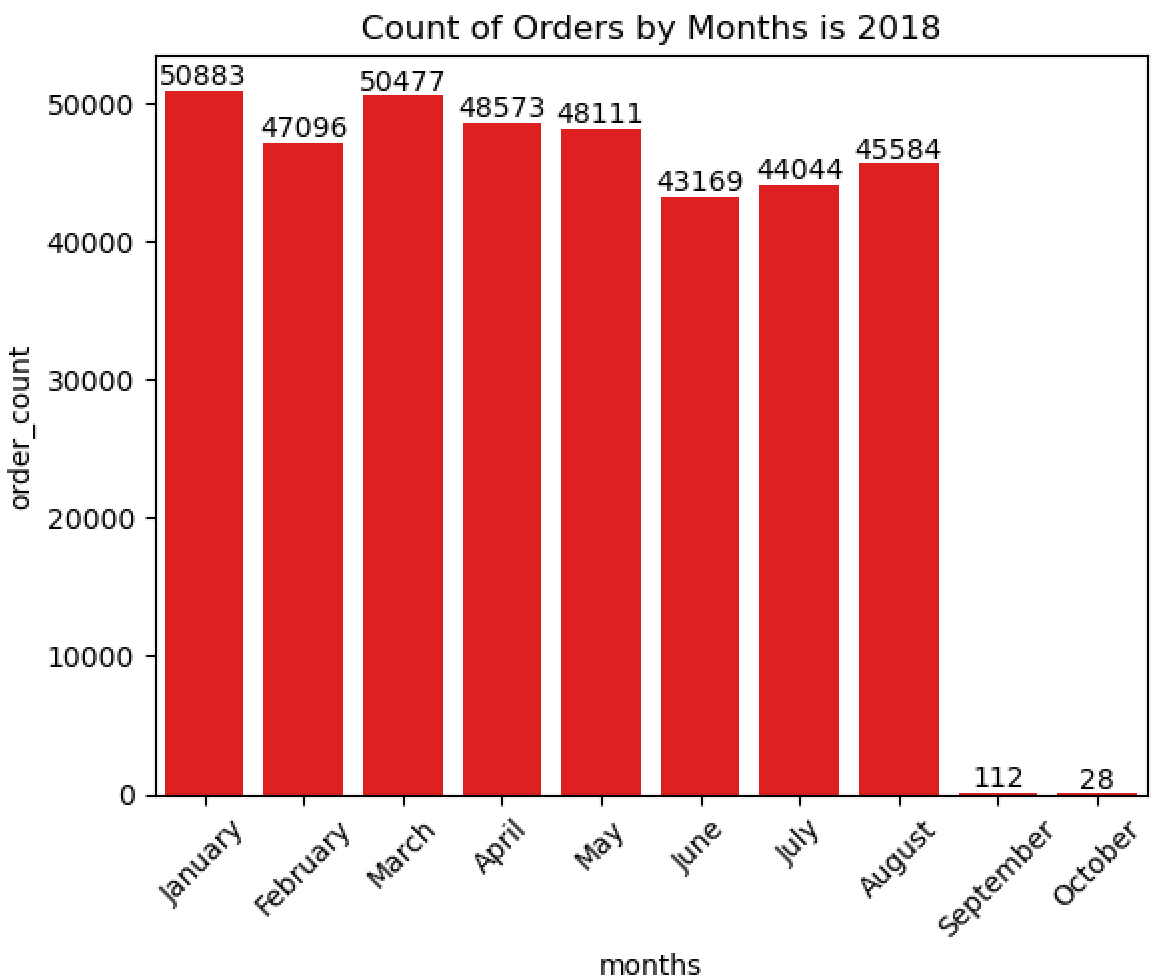
In [10]:
```
query = """ select monthname(order_purchase_timestamp) months, count(order_id) order_cou
from orders where year(order_purchase_timestamp) = 2018
group by months
"""

cur.execute(query)

data = cur.fetchall()
df = pd.DataFrame(data, columns = ["months", "order_count"])
o = ["January", "February","March","April","May","June","July","August","September","Oct

ax = sns.barplot(x = df["months"],y =  df["order_count"], data = df, order = o, color =
plt.xticks(rotation = 45)
ax.bar_label(ax.containers[0])
plt.title("Count of Orders by Months is 2018")

plt.show()
```



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

Objective: To determine purchasing behavior in different cities by analyzing the average number of products per order.

SQL Query: Used subqueries and joins to count products per order and calculate the average grouped by city.

Tools Used: SQL for querying, Python, Pandas for data handling and presentation.

In [11]:
```
query = """with count_per_order as
(select orders.order_id, orders.customer_id, count(order_items.order_id) as oc
from orders join order_items
on orders.order_id = order_items.order_id
group by orders.order_id, orders.customer_id)

select customers.customer_city, round(avg(count_per_order.oc),2) average_orders
from customers join count_per_order
on customers.customer_id = count_per_order.customer_id
group by customers.customer_city order by average_orders desc
"""

cur.execute(query)

data = cur.fetchall()
df = pd.DataFrame(data,columns = ["customer city", "average products/order"])
df.head(10)
```

Out[11]:

	customer city	average products/order
0	padre carvalho	196.00
1	celso ramos	182.00
2	datas	168.00
3	candido godoi	168.00
4	matias olimpio	140.00
5	cidelandia	112.00
6	curralinho	112.00
7	picarra	112.00
8	morro de sao paulo	112.00
9	teixeira soares	112.00

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

Objective: To understand the revenue distribution across product categories and identify top revenue generators.

SQL Query: Joined products, order_items, and payments tables, then calculated revenue percentages for each category.

Tools Used: SQL for complex joins and percentage calculations, Python, Pandas for analysis.

In [12]:
```
query = """select upper(products.product_category) category,
round((sum(payments.payment_value)/(select sum(payment_value) from payments))*100,2) sal
from products join order_items
on products.product_id = order_items.product_id
join payments
on payments.order_id = order_items.order_id
group by category order by sales_percentage desc"""
```

```
cur.execute(query)
data = cur.fetchall()
df = pd.DataFrame(data,columns = ["Category", "percentage distribution"])
df.head()
```

Out[12]:

	Category	percentage distribution
0	BED TABLE BATH	171.16
1	HEALTH BEAUTY	165.65
2	COMPUTER ACCESSORIES	158.45
3	FURNITURE DECORATION	142.94
4	WATCHES PRESENT	142.84

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

Objective: To explore the relationship between product pricing and purchase frequency.

SQL Query: Joined products and order_items tables to calculate average price and count of purchases per product.

Tools Used: SQL for querying, Python, Pandas, NumPy for correlation analysis.

In [13]:

```
cur = db.cursor()
query = """select products.product_category,
count(order_items.product_id),
round(avg(order_items.price),2)
from products join order_items
on products.product_id = order_items.product_id
group by products.product_category"""

cur.execute(query)
data = cur.fetchall()
df = pd.DataFrame(data,columns = ["Category", "order_count","price"])

arr1 = df["order_count"]
arr2 = df["price"]

a = np.corrcoef([arr1,arr2])
print("the correlation is", a[0][-1])
```

```
the correlation is -0.10631514167157562
```

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

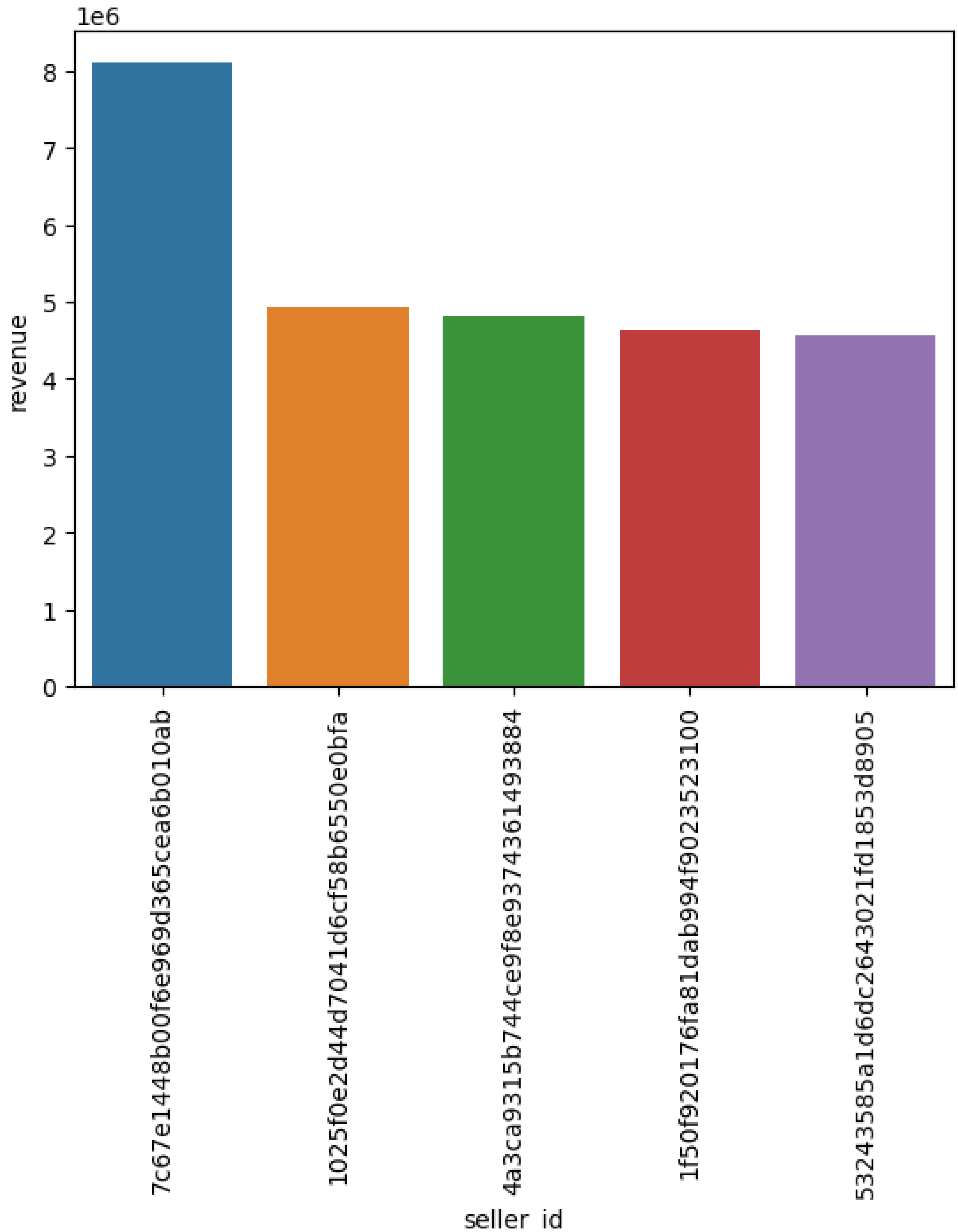
Objective: To identify top-performing sellers based on the total revenue generated.

SQL Query: Joined order_items and payments tables, calculated total revenue per seller, and used DENSE_RANK for ranking.

Tools Used: SQL for querying and ranking, Python, Pandas for visualization.

In [14]:
```
query = """ select *, dense_rank() over(order by revenue desc) as rn from
(select order_items.seller_id, sum(payments.payment_value)
revenue from order_items join payments
on order_items.order_id = payments.order_id
group by order_items.seller_id) as a """

cur.execute(query)
data = cur.fetchall()
df = pd.DataFrame(data, columns = ["seller_id", "revenue", "rank"])
df = df.head()
sns.barplot(x = "seller_id", y = "revenue", data = df)
plt.xticks(rotation = 90)
plt.show()
```



Calculate the moving average of order values for

each customer over their order history.

Objective: To smooth out fluctuations in order values and identify spending patterns over time.

SQL Query: Used window functions to calculate the moving average of order values.

Tools Used: SQL for querying, Python, Pandas for handling and presenting the data.

In [15]:
```
query = """select customer_id, order_purchase_timestamp, payment,
avg(payment) over(partition by customer_id order by order_purchase_timestamp
rows between 2 preceding and current row) as mov_avg
from
(select orders.customer_id, orders.order_purchase_timestamp,
payments.payment_value as payment
from payments join orders
on payments.order_id = orders.order_id) as a"""
cur.execute(query)
data = cur.fetchall()
df = pd.DataFrame(data)
df
```

Out[15]:

	0	1	2	3
0	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
1	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
2	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
3	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
4	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
...	...	...	...	...
2908803	ffffe8b65bbe3087b653a978c870db99	2017-09-29 14:07:03	18.37	18.370001
2908804	ffffe8b65bbe3087b653a978c870db99	2017-09-29 14:07:03	18.37	18.370001
2908805	ffffe8b65bbe3087b653a978c870db99	2017-09-29 14:07:03	18.37	18.370001
2908806	ffffe8b65bbe3087b653a978c870db99	2017-09-29 14:07:03	18.37	18.370001
2908807	ffffe8b65bbe3087b653a978c870db99	2017-09-29 14:07:03	18.37	18.370001

2908808 rows × 4 columns

Calculate the cumulative sales per month for each year.

Objective: To track the progressive accumulation of sales over each month in different years.

SQL Query: Used window functions to calculate cumulative sales.

Tools Used: SQL for querying, Python, Pandas for analysis.

In [16]:
```
query = """select years, months , payment, sum(payment)
over(order by years, months) cumulative_sales from
(select year(orders.order_purchase_timestamp) as years,
month(orders.order_purchase_timestamp) as months,
```

```
round(sum(payments.payment_value),2) as payment from orders join payments
on orders.order_id = payments.order_id
group by years, months order by years, months) as a
"""
cur.execute(query)
data = cur.fetchall()
df = pd.DataFrame(data)
df
```

Out[16]:

	0	1	2	3
0	2016	9	7062.72	7.062720e+03
1	2016	10	1654533.44	1.661596e+06
2	2016	12	549.36	1.662146e+06
3	2017	1	3877665.12	5.539811e+06
4	2017	2	8173424.27	1.371323e+07
5	2017	3	12596180.79	2.630942e+07
6	2017	4	11698064.83	3.800748e+07
7	2017	5	16601726.96	5.460921e+07
8	2017	6	14315738.65	6.892495e+07
9	2017	7	16586721.75	8.551167e+07
10	2017	8	18883096.96	1.043948e+08
11	2017	9	20377348.61	1.247721e+08
12	2017	10	21830980.63	1.466031e+08
13	2017	11	33456718.39	1.800598e+08
14	2017	12	24595241.44	2.046551e+08
15	2018	1	31220117.02	2.358752e+08
16	2018	2	27788973.52	2.636641e+08
17	2018	3	32470259.35	2.961344e+08
18	2018	4	32501993.46	3.286364e+08
19	2018	5	32311500.23	3.609479e+08
20	2018	6	28668654.02	3.896166e+08
21	2018	7	29863140.97	4.194797e+08
22	2018	8	28627909.00	4.481076e+08
23	2018	9	124307.12	4.482319e+08
24	2018	10	16510.76	4.482484e+08

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

Objective: To measure annual sales growth and assess overall business performance.

SQL Query: Used subqueries and window functions to calculate YoY growth rates.

Tools Used: SQL for querying, Python, Pandas for presentation.

In [17]:
```
query = """with a as(select year(orders.order_purchase_timestamp) as years,
round(sum(payments.payment_value),2) as payment from orders join payments
on orders.order_id = payments.order_id
group by years order by years)

select years, ((payment - lag(payment, 1) over(order by years))/
lag(payment, 1) over(order by years)) * 100 from a"""

cur.execute(query)
data = cur.fetchall()
df = pd.DataFrame(data, columns = ["years", "yoy % growth"])
df
```

Out[17]:

	years	yoy % growth
0	2016	NaN
1	2017	12112.703758
2	2018	20.000924

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

Objective: To evaluate customer loyalty and the effectiveness of retention strategies.

SQL Query: Used subqueries and joins to identify repeat purchases within 6 months.

Tools Used: SQL for querying, Python, Pandas for analysis.

In [18]:
```
query = """with a as (select customers.customer_id,
min(orders.order_purchase_timestamp) first_order
from customers join orders
on customers.customer_id = orders.customer_id
group by customers.customer_id),

b as (select a.customer_id, count(distinct orders.order_purchase_timestamp) next_order
from a join orders
on orders.customer_id = a.customer_id
and orders.order_purchase_timestamp > first_order
and orders.order_purchase_timestamp <
date_add(first_order, interval 6 month)
group by a.customer_id)

select 100 * (count( distinct a.customer_id)/ count(distinct b.customer_id))
from a left join b
on a.customer_id = b.customer_id ;"""

cur.execute(query)
data = cur.fetchall()

data
```

Out[18]:
```
[(None,)]
```

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

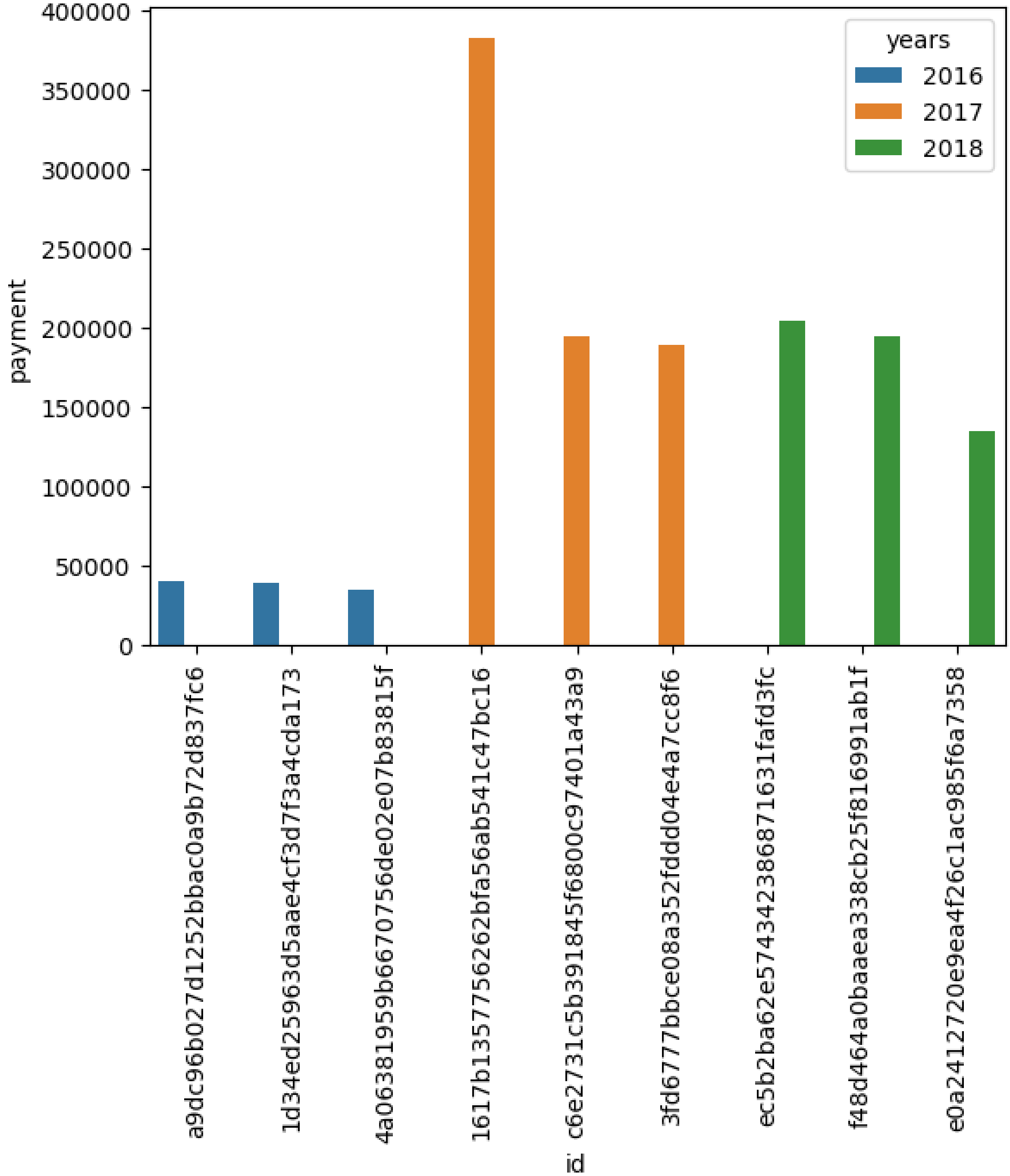
Objective: To recognize high-value customers and tailor strategies to retain them.

SQL Query: Used subqueries and DENSE_RANK to rank customers by annual spending.

Tools Used: SQL for querying, Python, Pandas, Seaborn for visualization.

In [19]:
```
query = """select years, customer_id, payment, d_rank
from
(select year(orders.order_purchase_timestamp) years,
orders.customer_id,
sum(payments.payment_value) payment,
dense_rank() over(partition by year(orders.order_purchase_timestamp)
order by sum(payments.payment_value) desc) d_rank
from orders join payments
on payments.order_id = orders.order_id
group by year(orders.order_purchase_timestamp),
orders.customer_id) as a
where d_rank <= 3 ;"""

cur.execute(query)
data = cur.fetchall()
df = pd.DataFrame(data, columns = ["years","id","payment","rank"])
sns.barplot(x = "id", y = "payment", data = df, hue = "years")
plt.xticks(rotation = 90)
plt.show()
```


400000
350000
300000
250000
200000
150000
100000
50000
0
payment
years
2016
2017
2018
a9dc96b027d1252bbac0a9b72d837fc6
1d34ed25963d5aae4cf3d7f3a4cda173
4a06381959b6670756de02e07b83815f
1617b1357756262bfa56ab541c47bc16
c6e2731c5b391845f6800c97401a43a9
3fd6777bbce08a352fddd04e4a7cc8f6
ec5b2ba62e574342386871631fafd3fc
f48d464a0baaea338cb25f816991ab1f
e0a2412720e9ea4f26c1ac985f6a7358
id