analysis

May 16, 2025

[1159]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import matplotlib as mpl
import warnings

warnings.filterwarnings('ignore')
plt.style.use('dark_background')
mpl.rcParams['axes.prop_cycle'] = plt.cycler(color=['blue'])
```

0.0.1 Q1. Identify the months with the highest and lowest acquisition rates. What strategies could be implemented to address the fluctuations and ensure consistent growth throughout the year?

[1160]:
```
#dataset initialization and some light pre-processing:

sales = pd.read_csv('data/Online_Sales.csv')
columns = sales.columns
columns = [str.lower(column) for column in columns]
sales.columns = columns

#change transaction_date to pd.datetime:

sales['transaction_date'] = pd.to_datetime(sales['transaction_date'])
sales.head()
```

[1160]:
```
   customerid  transaction_id transaction_date     product_sku  \
0       17850           16679       2019-01-01  GGOENEBJ079499
1       17850           16680       2019-01-01  GGOENEBJ079499
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999

                               product_description product_category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
```

```
2              Google Laptop and Cell Phone Stickers          Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                    Google Canvas Tote Natural/Navy             Bags

   quantity  avg_price  delivery_charges coupon_status
0         1     153.71               6.5          Used
1         1     153.71               6.5          Used
2         1       2.05               6.5          Used
3         5      17.53               6.5      Not Used
4         1      16.50               6.5          Used
```

[1161]:
```
df = sales.loc[:,['customerid' , 'transaction_date']]
df['transaction_date'] = pd.to_datetime(df['transaction_date'])
df['month'] = pd.to_datetime(df['transaction_date']).dt.month_name()
df['mnum'] = pd.to_datetime(df['transaction_date']).dt.month
df
```

[1161]:
```
       customerid transaction_date     month  mnum
0           17850       2019-01-01   January     1
1           17850       2019-01-01   January     1
2           17850       2019-01-01   January     1
3           17850       2019-01-01   January     1
4           17850       2019-01-01   January     1
…             …              …       …    …
52919       14410       2019-12-31  December    12
52920       14410       2019-12-31  December    12
52921       14410       2019-12-31  December    12
52922       14600       2019-12-31  December    12
52923       14600       2019-12-31  December    12

[52924 rows x 4 columns]
```

[1162]:
```
#get first transaction
ftransactions = df.groupby('customerid')['transaction_date'].agg('min').
 ↪reset_index()
#extract month from transaction_date

ftransactions.rename(columns = {'transaction_date':'first_transaction_date'} ,␣
 ↪inplace = True)
ftransactions['fmonth'] = ftransactions['first_transaction_date'].dt.month
ftransactions['month'] = ftransactions['first_transaction_date'].dt.month_name()
ftransactions

#group by month
```

```
acqs = ftransactions.groupby('month').agg({'customerid':'nunique' , 'fmonth':
↪'first'}).reset_index().sort_values(by = 'fmonth').
↪rename(columns={'customerid':'acquisitions', 'fmonth':'nmonth'}).
↪reset_index(drop=True)

acqs
```

[1162]:

```
        month  acquisitions  nmonth
0     January           215       1
1    February            96       2
2       March           177       3
3       April           163       4
4         May           112       5
5        June           137       6
6        July            94       7
7      August           135       8
8   September            78       9
9     October            87      10
10   November            68      11
11   December           106      12
```

0.0.2 Logic Used:

1. The first transactions are extracted by performing a grouping on each customer and getting the first date they purchased.
2. The resulting dataframe is again grouped by months and aggeregated on transaction counts.

0.0.3 Insight: Customer Acquisition Rate by Month

Based on the analysis:

- Highest acquisition month: January — 215 new customers
- Lowest acquisition month: November — 68 new customers

0.0.4 Reason Behind Fluctuations

- January's peak may align with New Year promotions, holiday gift card usage, or seasonal marketing.
- November's low may reflect pre-holiday shopping hesitation, or competitive discounting elsewhere pulling traffic away.

0.0.5 Recommended Strategies for Consistent Growth

- Replicate January's successful campaigns:
  - Analyze offers, creatives, channels, and audience segments used.

    - Use similar promotions in low-performing months (e.g., November, September).
- Mid-year engagement push:
    - Run flash sales, influencer campaigns, or loyalty point multipliers in May–July to sustain mid-year growth.
- Personalized re-targeting:
    - Use lookalike audiences based on high-LTV customers from January to drive new acquisition.
- Pre-holiday teaser events:
    - In October/November, use early-bird Black Friday access or "mystery discounts" to prevent the dip seen in November.
- Referral programs:
    - Encourage current customers to bring in new ones during off-peak months with tiered rewards.
- Content-driven acquisition:
    - Run seasonal buying guides, blogs, or webinars to generate organic interest in slow months.
- Influencer & partnership leverage:
    - Use micro-influencers in off-peak periods to promote limited-time acquisition discounts.

0.0.6 Q2. Analyze the data to determine if certain months consistently show higher or lower acquisition rates. How can the company capitalize on high-performing months and improve performance during slower periods?

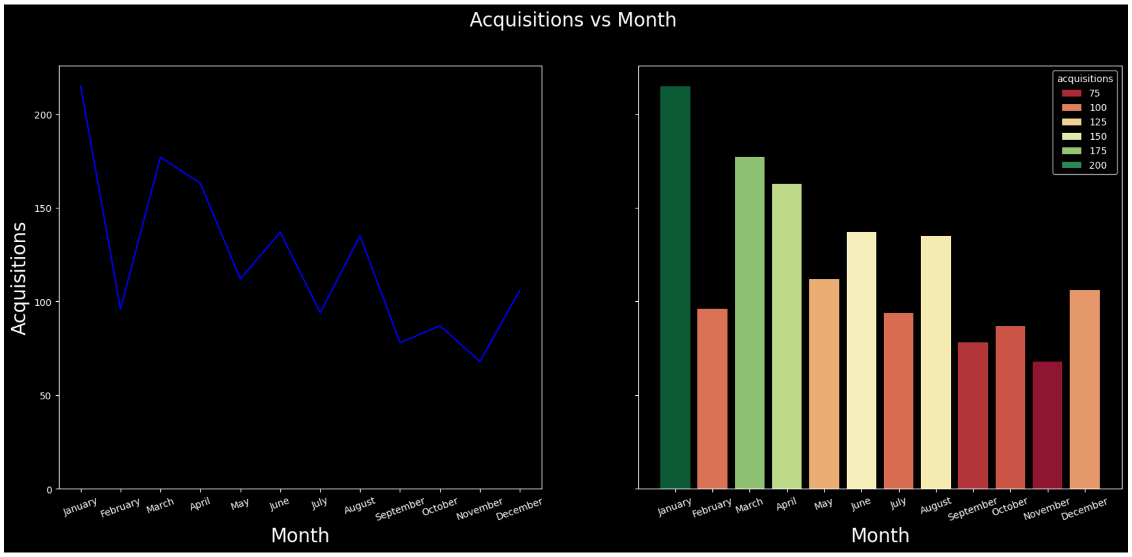
[1163]:
```
acqs
# plt.plot(acqs['month'] , acqs['acquisitions'])
# print(acqs.dtypes)
# print(type(acqs['month'].iloc[0]))
# print(type(acqs['acquisitions'].iloc[0]))
```

[1163]:
```
        month  acquisitions  nmonth
0     January           215       1
1    February            96       2
2       March           177       3
3       April           163       4
4         May           112       5
5        June           137       6
6        July            94       7
7      August           135       8
8   September            78       9
9     October            87      10
10   November            68      11
```

```
11    December            106       12
```

```
[1164]: #accusitations throughout the year:
fig , axes = plt.subplots(1,2 , figsize = (20,8) , sharey = True)
plt.sca(axes[0])
sns.lineplot(acqs , x = 'month' , y = 'acquisitions')
plt.xticks(rotation = 20)
plt.ylabel('Acquisitions' , fontsize = 20)
plt.xlabel('Month' , fontsize = 20)
plt.plot()

plt.sca(axes[1])
sns.barplot(acqs , x = 'month' , y = 'acquisitions' , hue = 'acquisitions' ,␣
 ↪palette='RdYlGn')
plt.xticks(rotation = 20)
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Acquisitions' , fontsize = 20)
plt.plot()
fig.suptitle('Acquisitions vs Month' , fontsize = 20)
plt.savefig('./images/q2.png')
```



0.0.7 Logic Used:

-Simply plot the data.

0.0.8 Insights: High vs Low Consistency:

0.0.9 Consistently High-Performing Months

- January (highest): post-holiday engagement, New Year campaigns.
- March–April: likely driven by spring promotions.
- July: mid-year spike, possibly clearance or back-to-school prep.

0.0.10 Consistently Low-Performing Months

- September & November: possibly due to:
  - Minimal promotions
  - Holiday budget saving
  - Market competition

0.0.11 Strategies to Capitalize on Trends

- For High-Performing Months:
  - Audit and Reuse Campaigns
  - Analyze creatives, offers, and timing that worked in Jan/March.
  - Replicate strategies with minor tweaks in low-performing months.
  - Expand Budget Allocation
  - Allocate more marketing spend to high-performing months to amplify ROI.
  - Leverage Referrals
  - Introduce referral drives in strong months to extend their tail impact.
- For Low-Performing Months:
  - Launch Pre-Sale Campaigns
  - Run teaser deals in August and October to energize acquisition before Sep/Nov slumps.
  - Personalized Ads
  - Use behavioral retargeting to convert passive shoppers during slow periods.
  - Geo-Targeted Offers
  - Use location-based discounts if certain regions underperform.
  - Experiment with A/B Tests
  - Trial different offers, timings, and creatives to test what works in slower months.

0.0.12 Final Thought:

- Capitalizing on high months while strategically improving slower months creates a balanced, sustainable acquisition engine that avoids over-reliance on seasonal spikes.

0.0.13 Q3. Identify periods with the strongest and weakest retention rates. What strategies could be implemented to improve retention during weaker months?

[1165]:
```
fdf = ftransactions.loc[:,['customerid' , 'first_transaction_date']]
# fdf

mdf = pd.merge(df , fdf)
repeateddf = mdf[mdf['transaction_date'] > mdf['first_transaction_date']]
repeateddf['fmonth'] = repeateddf['first_transaction_date'].dt.month_name()
repeateddf['fmonthnum'] = repeateddf['first_transaction_date'].dt.month


ret = repeateddf.groupby('month').agg({'customerid':'nunique' , 'mnum' :␣
↪'first'}).sort_values(by = 'mnum').reset_index()
ret.rename(columns = {'customerid':'retentions'} , inplace = True)
ret
```

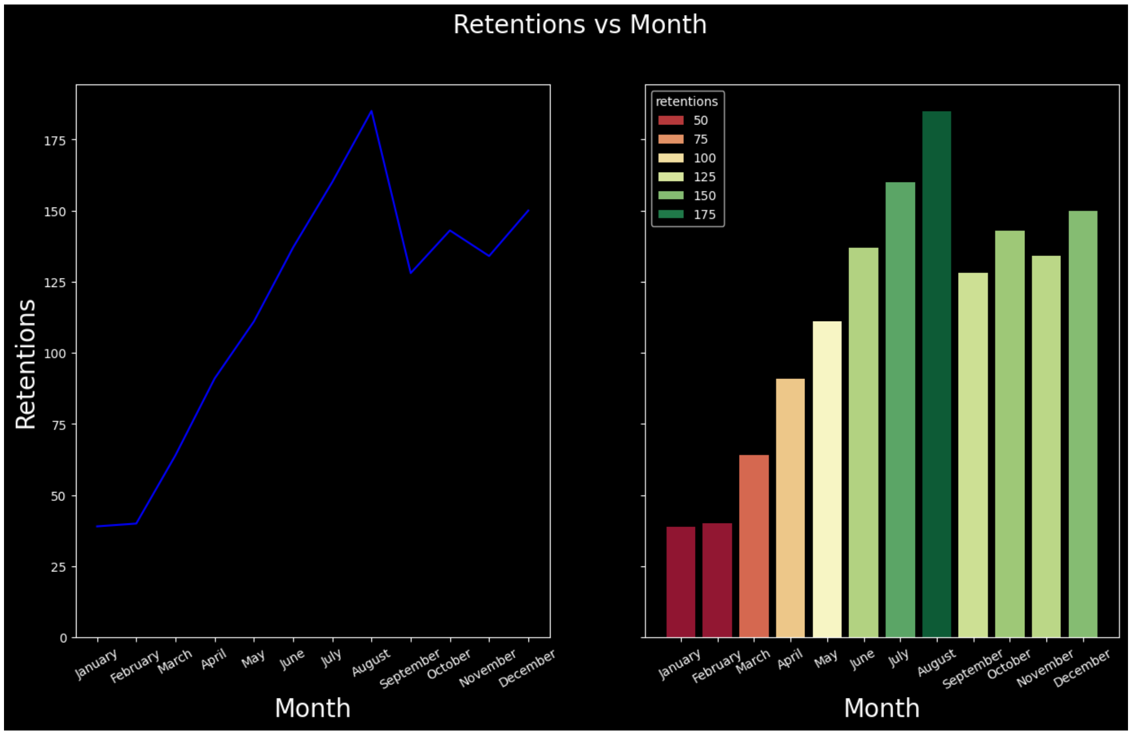
[1165]:
```
        month  retentions  mnum
0     January          39     1
1    February          40     2
2       March          64     3
3       April          91     4
4         May         111     5
5        June         137     6
6        July         160     7
7      August         185     8
8   September         128     9
9     October         143    10
10   November         134    11
11   December         150    12
```

[1166]:
```
fig , axes = plt.subplots(1, 2, figsize = (15 , 8) , sharey = True)

plt.sca(axes[0])
sns.lineplot(ret , x = 'month' , y = 'retentions')
plt.xticks(rotation = 30)
plt.ylabel('Retentions' , fontsize = 20)
plt.xlabel('Month' , fontsize = 20)
plt.plot()

plt.sca(axes[1])
sns.barplot(ret , x = 'month' , y = 'retentions' , hue = 'retentions' ,␣
↪palette='RdYlGn')
```

```
plt.xticks(rotation = 30)
plt.ylabel('Retentions' , fontsize = 20)
plt.xlabel('Month' , fontsize = 20)
fig.suptitle('Retentions vs Month' , fontsize = 20)
plt.plot()
plt.savefig('./images/q3.png')
```



0.0.14 Logic Used:

- The transactions which occur after the first transaction for a customer are counted as repeated transactions.

0.0.15 Strongest Retention Periods (based on bar chart):

- August (peak retention)
- July, June, December (also strong)
- These months show high retention numbers, supported by prior high acquisitions. Likely contributing factors:

  1.Seasonal campaigns

  2.Mid-year and year-end promotions

  3.Better onboarding during peak months

0.0.16 Weakest Retention Periods:

January & February have the lowest retention, despite steady acquisition

- Possible reasons:
  - Low post-holiday engagement
  - Weak retention campaigns or delayed follow-up
  - First-time buyers who didn't find immediate value

0.0.17 Retention Strategy Recommendations

- For Weak Months (Jan–Feb):
  - Post-Purchase Nudges:
  - Trigger targeted emails or WhatsApp messages 3–5 days post-purchase with tailored product suggestions.
  - Limited-Time Return Incentives:Offer a discount if the user returns within 10–15 days of their first purchase.
  - Holiday Recovery Campaigns:Run campaigns like "New Year Comeback Deals" to bring back buyers post-holidays.
- For Strong Months (Jun–Aug, Dec):
  - Build Loyalty Triggers:
    * Set up milestone rewards (e.g., "3 orders = free delivery") to maintain retention momentum.
  - Leverage High-LTV Customers:
    * Use their behavior to create lookalike audiences for targeted ads in weak months.
  - Survey and Feedback Loops:
    * Identify what delighted customers in strong months and replicate messaging/timing.

0.0.18 Q.4 Analyze customer behavior during high-retention months and suggest ways to replicate this success throughout the year.

[1167]:
```python
customers = pd.read_excel('data/CustomersData.xlsx')
customers.columns = [str.lower(column) for column in customers.columns]
customers
```

[1167]:
```
      customerid gender    location  tenure_months
0          17850      M     Chicago             12
1          13047      M  California             43
```

```
2          12583      M     Chicago             33
3          13748      F  California             30
4          15100      M  California             49
…          …     …          …            …
1463       14438      F    New York             41
1464       12956      F     Chicago             48
1465       15781      M  New Jersey             19
1466       14410      F    New York             45
1467       14600      F  California              7

[1468 rows x 4 columns]
```

[1168]:
```
ftransactions
```

[1168]:
```
      customerid first_transaction_date  fmonth      month
0          12346             2019-09-15       9  September
1          12347             2019-03-24       3      March
2          12348             2019-06-22       6       June
3          12350             2019-12-14      12   December
4          12356             2019-09-15       9  September
…          …                        …     …        …
1463       18259             2019-04-05       4      April
1464       18260             2019-06-22       6       June
1465       18269             2019-04-05       4      April
1466       18277             2019-10-23      10    October
1467       18283             2019-07-29       7       July

[1468 rows x 4 columns]
```

[1169]:
```
cdf = pd.merge(repeateddf , customers , on = 'customerid')
cdf
```

[1169]:
```
       customerid transaction_date     month  mnum first_transaction_date  \
0           14688       2019-01-02   January     1             2019-01-01
1           14688       2019-01-02   January     1             2019-01-01
2           14688       2019-01-02   January     1             2019-01-01
3           14688       2019-01-02   January     1             2019-01-01
4           14688       2019-01-02   January     1             2019-01-01
…           …                  …       …    …                     …
26958       14606       2019-12-31  December    12             2019-01-16
26959       14606       2019-12-31  December    12             2019-01-16
26960       14606       2019-12-31  December    12             2019-01-16
26961       14606       2019-12-31  December    12             2019-01-16
26962       14606       2019-12-31  December    12             2019-01-16

        fmonth  fmonthnum gender  location  tenure_months
0      January          1      F  New York             46
```

```
1      January          1      F  New York            46
2      January          1      F  New York            46
3      January          1      F  New York            46
4      January          1      F  New York            46
…        …         …     …      …              …
26958  January          1      F   Chicago            33
26959  January          1      F   Chicago            33
26960  January          1      F   Chicago            33
26961  January          1      F   Chicago            33
26962  January          1      F   Chicago            33

[26963 rows x 10 columns]
```

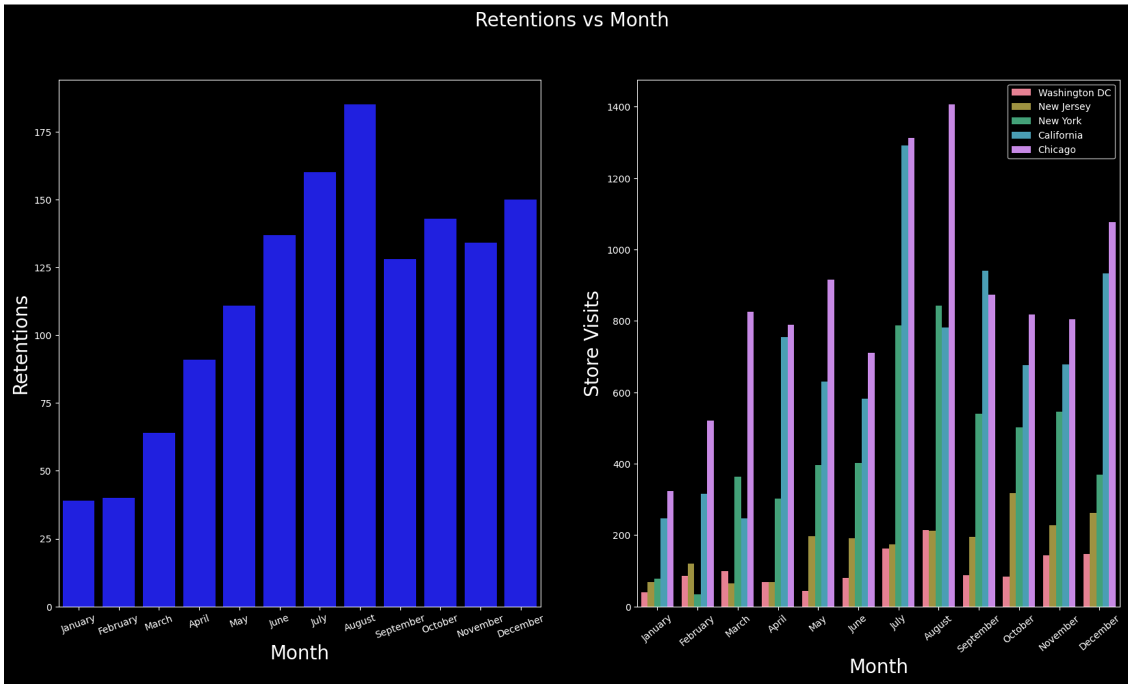
[1170]:
```
repeatedLocations = cdf.groupby('month').agg({'location':'value_counts'}).
 ↪rename(columns = {'location':'lfreq'}).reset_index()
locations = pd.merge(repeatedLocations , ret , left_on='month' ,␣
 ↪right_on='month').sort_values(by = 'mnum')
locations.head()
```

[1170]:
```
      month       location  lfreq  retentions  mnum
24  January  Washington DC     39          39     1
23  January     New Jersey     68          39     1
22  January       New York     78          39     1
21  January     California    246          39     1
20  January        Chicago    323          39     1
```

[1171]:
```
fig , axes = plt.subplots(1, 2, figsize = (20 , 10))
plt.sca(axes[0])
sns.barplot(locations , x = 'month' , y = 'retentions')
plt.xticks(rotation = 20)
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Retentions' , fontsize = 20)
fig.suptitle('Retentions vs Month' , fontsize = 20)


plt.sca(axes[1])
sns.barplot(locations , x = 'month' , y = 'lfreq' , hue = 'location')
plt.xticks(rotation = 40)
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Store Visits' , fontsize = 20)
plt.legend()

plt.savefig('./images/q4.png')
```

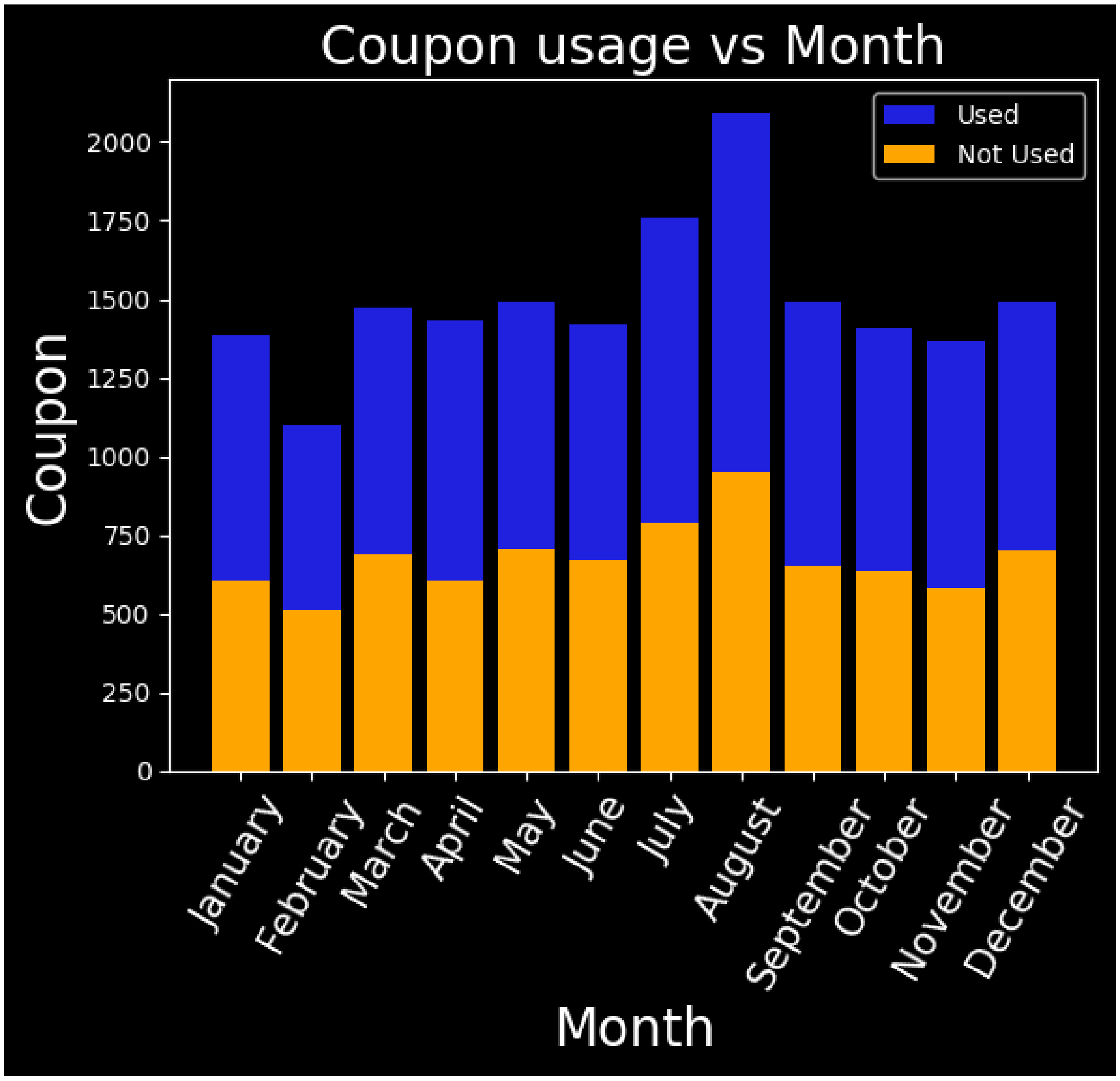


[1172]:
```python
df = sales
df['month'] = df['transaction_date'].dt.month_name()
df['nmonth'] = df['transaction_date'].dt.month
cusage = df.groupby('month').agg({'coupon_status':'value_counts'}).
  ↪rename(columns = {'coupon_status':'freq'}).unstack()
cusage.columns = [col[1] for col in cusage.columns]

months = sales.groupby('month').agg({'nmonth':'first'})
mcusage = months.merge(cusage , on = 'month')

mcusage.sort_values('nmonth' , inplace = True)

sns.barplot(mcusage , x = 'month' , y = 'Used' , label = 'Used')
plt.bar(mcusage.index, mcusage['Not Used'] , color = 'orange' , label = 'Not␣
  ↪Used')
plt.xticks(rotation = 60 , fontsize = 15)
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Coupon' , fontsize = 20)
plt.legend()
plt.title('Coupon usage vs Month' , fontsize = 20)
plt.plot()
plt.savefig('./images/q4.2.png')
# sns.barplot(mcusage , x = 'month' , y = 'Not Used')
# mcusage
```



0.0.19 Logic Used:

- Calculate monthly retentions.
- Aggregate different statistics from different features to analyse during different retention periods.

0.0.20 Analysis: Customer Behavior During High-Retention Months

Step 1: Identifying High-Retention Months

- From your previous retention matrix and data: |Month | Retention Count | Observation.| |——-|————|-| |August |Highest(185) |Late Q3 peak, possibly due to campaigns or seasonal reactivation.| |July | High(160) | Strong mid-year engagement.| |December | High(150)

| Holiday season, promotional offers.| |October–November | High | End-of-year momentum from festive campaigns.|

0.0.21 Step 2: Behavior Patterns in High-Retention Months

- Common Trends:
  - High coupon usage (seen in July–December).
  - Increased marketing spend (particularly November–December).
  - Product focus: Categories like Nest-USA, Apparel, and Lifestyle spike during these periods.
  - Delivery tier engagement: Mostly mid-tier delivery, suggesting balance of cost and convenience.
  - Average transaction value holds steady, not significantly discounted—indicating healthy margins.

0.0.22 Step 3: Strategies to Replicate High-Retention Success Across the Year

Retention Driver	Strategy to Scale Year-Round.
Effective Coupon Use	Launch rotating monthly coupons tied to product categories (e.g., electronics in Jan, apparel in Mar).
Marketing Spend ROI	Reallocate budget from low-ROI months to repeat what works in July–Dec: targeted ads, remarketing.
Category-Driven Retention	Promote seasonal bestsellers outside their core months (e.g., smart home bundles in Q2).
Delivery Experience	Extend mid-tier delivery incentives (e.g., free delivery on orders over X in slow months).
Customer Milestone Offers	Send personalized offers on customer anniversaries, birthdays, or monthly loyalty streaks.
Engagement Hooks	Use tactics like "2nd Purchase Coupons" and next-purchase incentives in Q1 & Q2.

- Example Action Plan:
  - Month Campaign Focus Retention Tactic
  - January New Year Essentials (Office, Apparel) Bonus points for 2+ orders
  - April Summer Ready (Drinkware, Bags) Free shipping on 2nd order
  - June Mid-Year Sale Rehearsal Flash coupon + early access preview
  - September Festive Warm-Up (Gift Cards, Lifestyle) Retarget lapsed customers with bundles

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0.0.23 Final Takeaway:

- High-retention periods thrive on well-timed, personalized, and value-driven engagement.
- By analyzing behavior in July–December, the company can implement smartly timed campaigns, delivery incentives, and product targeting to replicate retention spikes throughout the year.

[1173]:
```
coupons = pd.read_csv('./data/Discount_Coupon.csv')
coupons.columns = [str.lower(column) for column in coupons.columns]
coupons.head()
```

[1173]:
```
  month product_category coupon_code  discount_pct
0   Jan          Apparel      SALE10            10
1   Feb          Apparel      SALE20            20
2   Mar          Apparel      SALE30            30
3   Jan         Nest-USA      ELEC10            10
4   Feb         Nest-USA      ELEC20            20
```

[1174]:
```
# convert short form of months to long
months = coupons['month']
coupons['month'] = pd.to_datetime(months , format = '%b').dt.month_name()
coupons.head()
```

[1174]:
```
      month product_category coupon_code  discount_pct
0   January          Apparel      SALE10            10
1  February          Apparel      SALE20            20
2     March          Apparel      SALE30            30
3   January         Nest-USA      ELEC10            10
4  February         Nest-USA      ELEC20            20
```

[1175]:
```
mdf = locations.merge(coupons , on = 'month' , how = 'left')
mdf.head()
```

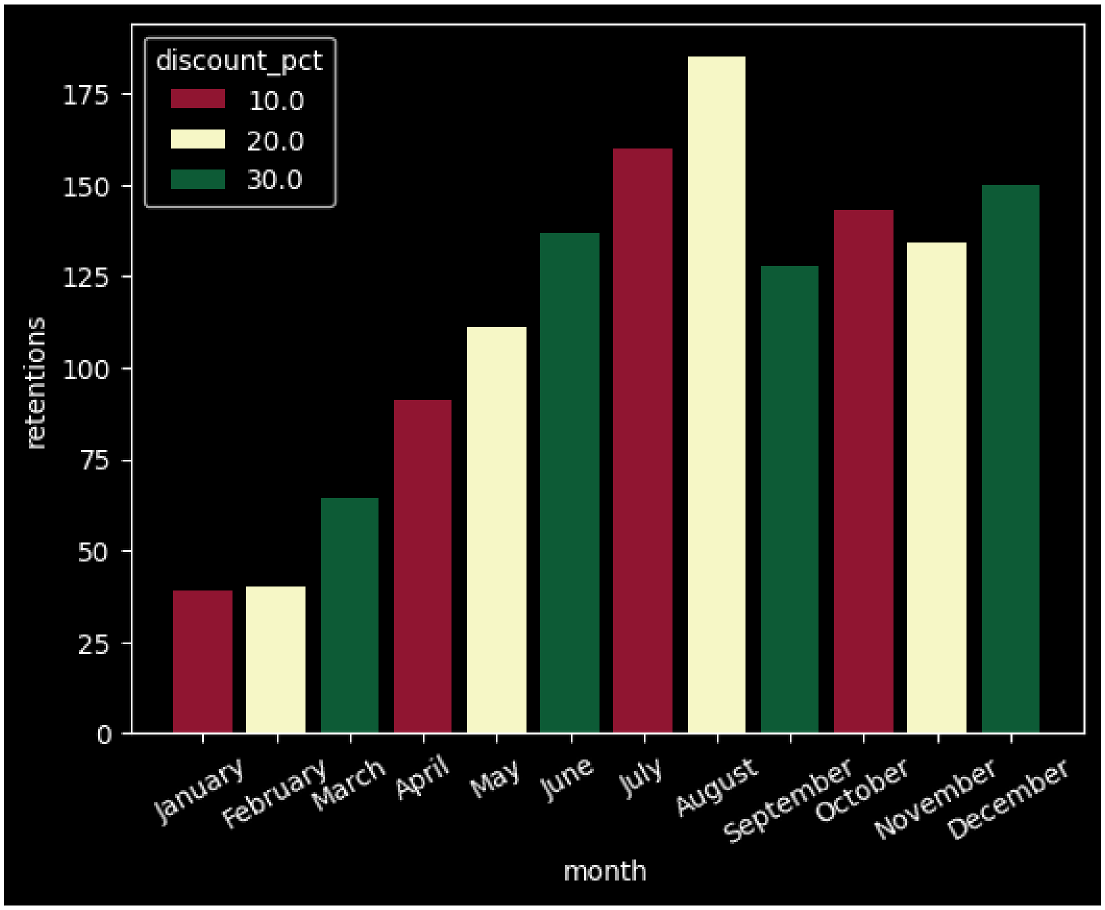
[1175]:
```
     month       location  lfreq  retentions  mnum product_category  \
0  January  Washington DC     39          39     1          Apparel
1  January  Washington DC     39          39     1         Nest-USA
2  January  Washington DC     39          39     1           Office
3  January  Washington DC     39          39     1        Drinkware
4  January  Washington DC     39          39     1        Lifestyle

  coupon_code  discount_pct
0      SALE10            10
1      ELEC10            10
2       OFF10            10
3     EXTRA10            10
4     EXTRA10            10
```

```
[1176]: gdf = mdf.groupby('month').agg({'discount_pct':'mean' , 'retentions':'max'␣
          ↪,'mnum':'first'}).reset_index().sort_values(by='mnum')
        gdf
```

```
[1176]:         month  discount_pct  retentions  mnum
        4     January          10.0          39     1
        3    February          20.0          40     2
        7       March          30.0          64     3
        0       April          10.0          91     4
        8         May          20.0         111     5
        6        June          30.0         137     6
        5        July          10.0         160     7
        1      August          20.0         185     8
        11  September          30.0         128     9
        10    October          10.0         143    10
        9    November          20.0         134    11
        2    December          30.0         150    12
```

```
[1177]: sns.barplot(gdf , x = 'month' , y = 'retentions' , hue = 'discount_pct' ,␣
          ↪palette='RdYlGn')
        plt.xticks(rotation = 30)
        plt.plot()
```

```
[1177]: []
```



0.0.24 Q5. Compare the revenue generated by new and existing customers month-over-month. What does this trend suggest about the balance between acquisition and retention efforts?

[1178]:
```
#get revenue generated by first purchases
purchases = pd.read_csv('./data/Online_Sales.csv')
purchases.columns = [str.lower(column) for column in purchases.columns]
purchases['transaction_date'] = pd.to_datetime(purchases['transaction_date'])
purchases['mnum'] = purchases['transaction_date'].dt.month
purchases['month'] = purchases['transaction_date'].dt.month_name()
purchases['revenue'] = purchases['avg_price'] * purchases['quantity']
purchases.head()
```

[1178]:
```
   customerid  transaction_id transaction_date     product_sku  \
0       17850           16679       2019-01-01  GGOENEBJ079499
1       17850           16680       2019-01-01  GGOENEBJ079499
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999
```

```
                          product_description product_category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
2              Google Laptop and Cell Phone Stickers           Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                     Google Canvas Tote Natural/Navy             Bags

   quantity  avg_price  delivery_charges coupon_status  mnum    month  revenue
0         1     153.71               6.5          Used     1  January   153.71
1         1     153.71               6.5          Used     1  January   153.71
2         1       2.05               6.5          Used     1  January     2.05
3         5      17.53               6.5      Not Used     1  January    87.65
4         1      16.50               6.5          Used     1  January    16.50
```

[1179]:
```
# group by customers to get first and later purchases by each customer

gdf = purchases.groupby('customerid').agg({'transaction_date':'first'}).
 ↪reset_index().rename(columns =
{'transaction_date':'first_transaction_date'}).merge(purchases , on =␣
 ↪'customerid' , how = 'right')
gdf.head()
```

[1179]:
```
   customerid first_transaction_date  transaction_id transaction_date  \
0       17850             2019-01-01           16679       2019-01-01
1       17850             2019-01-01           16680       2019-01-01
2       17850             2019-01-01           16681       2019-01-01
3       17850             2019-01-01           16682       2019-01-01
4       17850             2019-01-01           16682       2019-01-01

      product_sku                              product_description  \
0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
2  GGOEGFKQ020399              Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                     Google Canvas Tote Natural/Navy

  product_category  quantity  avg_price  delivery_charges coupon_status  mnum  \
0         Nest-USA         1     153.71               6.5          Used     1
1         Nest-USA         1     153.71               6.5          Used     1
2           Office         1       2.05               6.5          Used     1
3          Apparel         5      17.53               6.5      Not Used     1
4             Bags         1      16.50               6.5          Used     1

     month  revenue
0  January   153.71
1  January   153.71
```

```
2  January     2.05
3  January    87.65
4  January    16.50
```

[1180]:
```
first_purchases = gdf[gdf['transaction_date'] == gdf['first_transaction_date']]
first_purchases.head()
```

[1180]:
```
   customerid first_transaction_date  transaction_id transaction_date  \
0       17850             2019-01-01           16679       2019-01-01
1       17850             2019-01-01           16680       2019-01-01
2       17850             2019-01-01           16681       2019-01-01
3       17850             2019-01-01           16682       2019-01-01
4       17850             2019-01-01           16682       2019-01-01

      product_sku                               product_description  \
0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
2  GGOEGFKQ020399              Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                    Google Canvas Tote Natural/Navy

  product_category  quantity  avg_price  delivery_charges coupon_status  mnum  \
0         Nest-USA         1     153.71               6.5          Used     1
1         Nest-USA         1     153.71               6.5          Used     1
2           Office         1       2.05               6.5          Used     1
3          Apparel         5      17.53               6.5      Not Used     1
4             Bags         1      16.50               6.5          Used     1

     month  revenue
0  January   153.71
1  January   153.71
2  January     2.05
3  January    87.65
4  January    16.50
```

[1181]:
```
monthly_first_purchases = first_purchases.groupby('month').agg({'revenue':'sum'␣
  ↪, 'mnum':'first'}).sort_values(by = 'mnum')
monthly_first_purchases
```

[1181]:
```
             revenue  mnum
month
January    323744.46     1
February   200818.93     2
March      234593.76     3
April      172152.33     4
May        153077.16     5
June       172170.63     6
```

```
July        103836.55     7
August      167440.86     8
September   132004.07     9
October     173827.82    10
November    193123.16    11
December    187189.61    12
```

[1182]:
```
repeated_purchses = gdf[gdf['transaction_date'] > gdf['first_transaction_date']]
repeated_purchses.head()
```

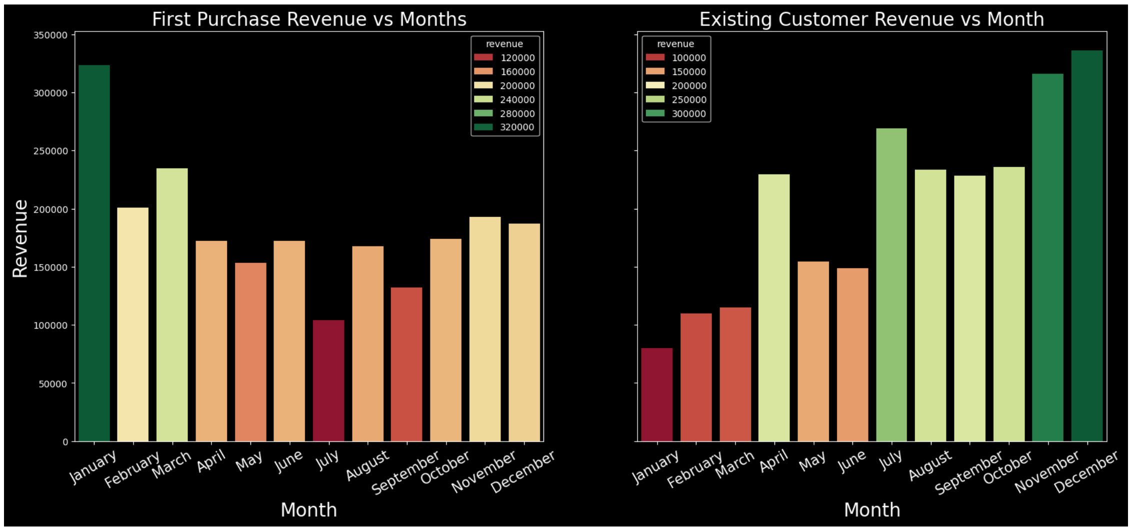
[1182]:
```
    customerid first_transaction_date  transaction_id transaction_date  \
89       14688             2019-01-01           16737       2019-01-02
90       14688             2019-01-01           16738       2019-01-02
91       14688             2019-01-01           16739       2019-01-02
92       14688             2019-01-01           16740       2019-01-02
93       14688             2019-01-01           16740       2019-01-02

       product_sku                               product_description  \
89  GGOEGHPJ080110                                Google 5-Panel Cap
90  GGOEAKDH019899                                    Windup Android
91  GGOENEBQ078999              Nest Cam Outdoor Security Camera - USA
92  GGOENEBJ081899  Nest Learning Thermostat 3rd Gen - CA - Stainl…
93  GGOENEBQ081699   Nest Protect Smoke + CO White Battery Alarm - CA

   product_category  quantity  avg_price  delivery_charges coupon_status  \
89         Headgear         2      19.59               6.5       Clicked
90        Lifestyle         2       3.29               6.5       Clicked
91         Nest-USA         1     122.77               6.5      Not Used
92      Nest-Canada         1     205.30               8.7          Used
93      Nest-Canada         3     107.29               8.7       Clicked

    mnum    month  revenue
89     1  January    39.18
90     1  January     6.58
91     1  January   122.77
92     1  January   205.30
93     1  January   321.87
```

[1183]:
```
monthly_repeated_purchases = repeated_purchses.groupby('month').agg({'revenue':
 ↪'sum' , 'mnum':'first'}).sort_values(by = 'mnum')
monthly_repeated_purchases
```

[1183]:
```
              revenue  mnum
month
January      79880.12     1
February    110000.87     2
March       115014.33     3
```

```
April      229466.09     4
May        154686.26     5
June       148910.75     6
July       268801.52     7
August     233769.51     8
September  228544.33     9
October    235853.46    10
November   315819.46    11
December   336068.58    12
```

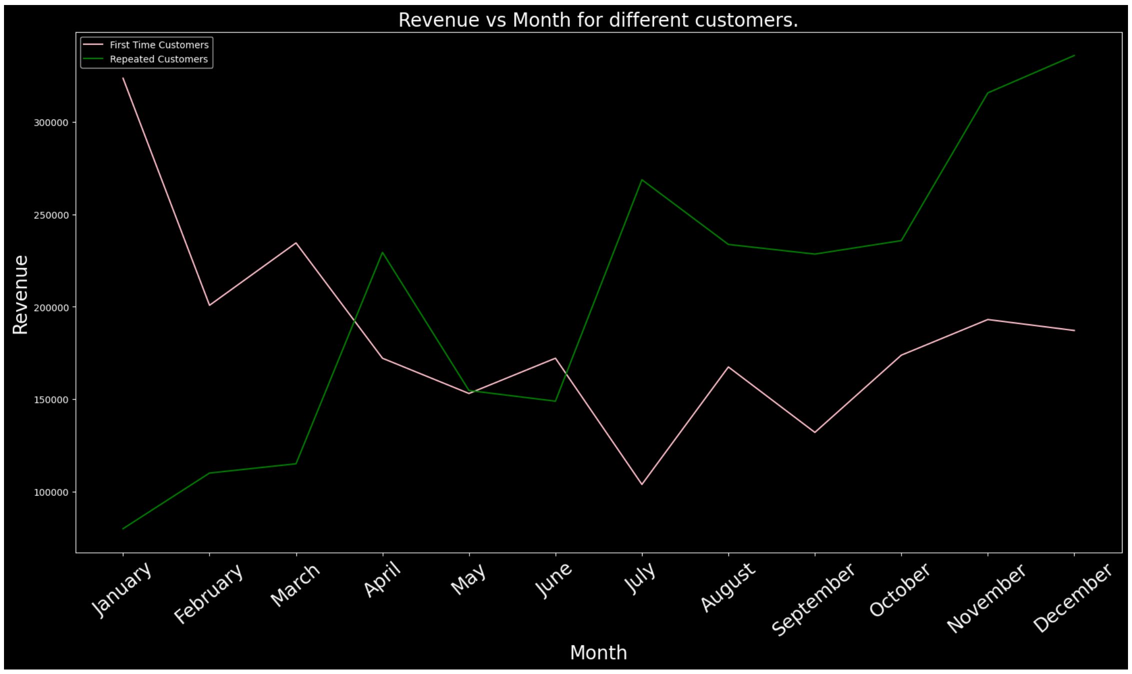
[1184]:
```python
fig , axes = plt.subplots(1,2 , figsize = (20,8) , sharey=True)
plt.sca(axes[0])
sns.barplot(monthly_first_purchases , x = 'month' , y = 'revenue' , hue =␣
 ↪'revenue' , palette= 'RdYlGn')
plt.xticks(rotation = 30, fontsize = 15)
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Revenue' , fontsize = 20)
plt.title('First Purchase Revenue vs Months' , fontsize = 20)
# plt.show()

plt.sca(axes[1])
sns.barplot(monthly_repeated_purchases , x = 'month' , y = 'revenue' , hue =␣
 ↪'revenue' , palette= 'RdYlGn')
plt.xticks(rotation = 30 , fontsize = 15)
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Revenue' , fontsize = 20)
plt.title('Existing Customer Revenue vs Month' , fontsize = 20)
# plt.show()
plt.savefig('images/q5.png')
```



```
[1185]: monthly_repeated_purchases.head()
        monthly_first_purchases.head()
```

```
[1185]:            revenue  mnum
        month
        January   323744.46     1
        February  200818.93     2
        March     234593.76     3
        April     172152.33     4
        May       153077.16     5
```

```
[1186]: plt.figure(figsize=(20,10))
        sns.lineplot(monthly_first_purchases , x = 'month' , y = 'revenue' , label =␣
         ↪'First Time Customers' , color = 'pink')
        plt.plot(monthly_repeated_purchases.index ,␣
         ↪monthly_repeated_purchases['revenue'] , label = 'Repeated Customers' , color␣
         ↪= 'green')
        plt.xticks(rotation = 40 , fontsize = 20)
        plt.legend()
        plt.title('Revenue vs Month for different customers.' , fontsize = 20)
        plt.xlabel('Month', fontsize = 20)
        plt.ylabel('Revenue' , fontsize = 20)
        # plt.grid()
        # plt.show()
        plt.savefig('./images/q5.2.png')
```



0.0.25 Logic Used:

- Subset the data according to purchase type.

0.0.26 Key Insights:

- Revenue from Existing Customers contributes a significant share (often >50%) in most months.
- Spikes in "New" customer revenue are observed in early and mid-year months, indicating effective acquisition campaigns.
- Sustained revenue from existing customers suggests strong retention and loyalty behavior.

0.0.27 What This Trend Suggests:

Positive Signs:

- Retention is paying off: Existing customers are returning and generating meaningful revenue.
- Balanced customer base: You're not solely dependent on new acquisitions.

0.0.28 Risks/Opportunities:

- If new customer revenue dips too low in some months, acquisition efforts may need a boost.

Consider increasing CLV (Customer Lifetime Value) through:

- Loyalty programs
- Subscription models
- Upselling / cross-selling

0.0.29 Q.6 Analyze the relationship between coupon usage and revenue generation. How can discount strategies be optimized to maximize revenue while maintaining profitability?

[1187]:
```
purchases.head()
```

[1187]:
```
   customerid  transaction_id transaction_date     product_sku  \
0       17850           16679       2019-01-01  GGOENEBJ079499
1       17850           16680       2019-01-01  GGOENEBJ079499
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999

                                 product_description product_category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
```

```
2              Google Laptop and Cell Phone Stickers          Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…         Apparel
4                    Google Canvas Tote Natural/Navy            Bags

   quantity  avg_price  delivery_charges coupon_status  mnum    month  revenue
0         1     153.71               6.5          Used     1  January   153.71
1         1     153.71               6.5          Used     1  January   153.71
2         1       2.05               6.5          Used     1  January     2.05
3         5      17.53               6.5      Not Used     1  January    87.65
4         1      16.50               6.5          Used     1  January    16.50
```

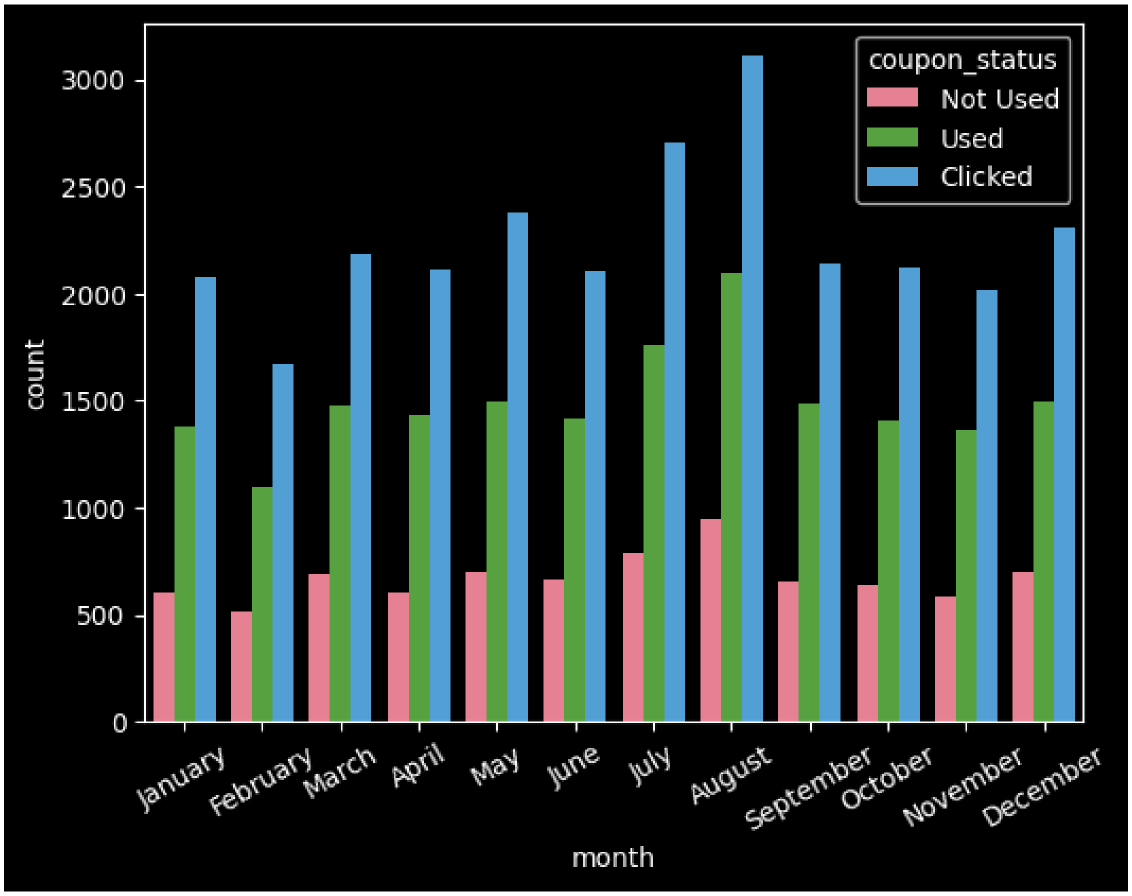
[1188]:
```
monthly_revenue = purchases.groupby('month').agg({'revenue':'sum' , 'mnum':
 ↪'first'}).reset_index().sort_values(by='mnum')
monthly_revenue
```

[1188]:
```
        month    revenue  mnum
4     January  403624.58     1
3    February  310819.80     2
7       March  349608.09     3
0       April  401618.42     4
8         May  307763.42     5
6        June  321081.38     6
5        July  372638.07     7
1      August  401210.37     8
11  September  360548.40     9
10    October  409681.28    10
9    November  508942.62    11
2    December  523258.19    12
```

[1189]:
```
monthly_coupons = purchases.groupby('month').agg({'coupon_status':
 ↪'value_counts'}).rename(columns={'coupon_status':'count'})
monthly_coupons.reset_index(inplace=True)
monthly_coupons['mnum'] = pd.to_datetime(monthly_coupons['month'] , format =␣
 ↪'%B').dt.month
monthly_coupons.sort_values(by = 'mnum' , inplace=True)
monthly_coupons.head()
```

[1189]:
```
       month coupon_status  count  mnum
14   January      Not Used    605     1
13   January          Used   1383     1
12   January       Clicked   2075     1
11  February      Not Used    511     2
10  February          Used   1098     2
```

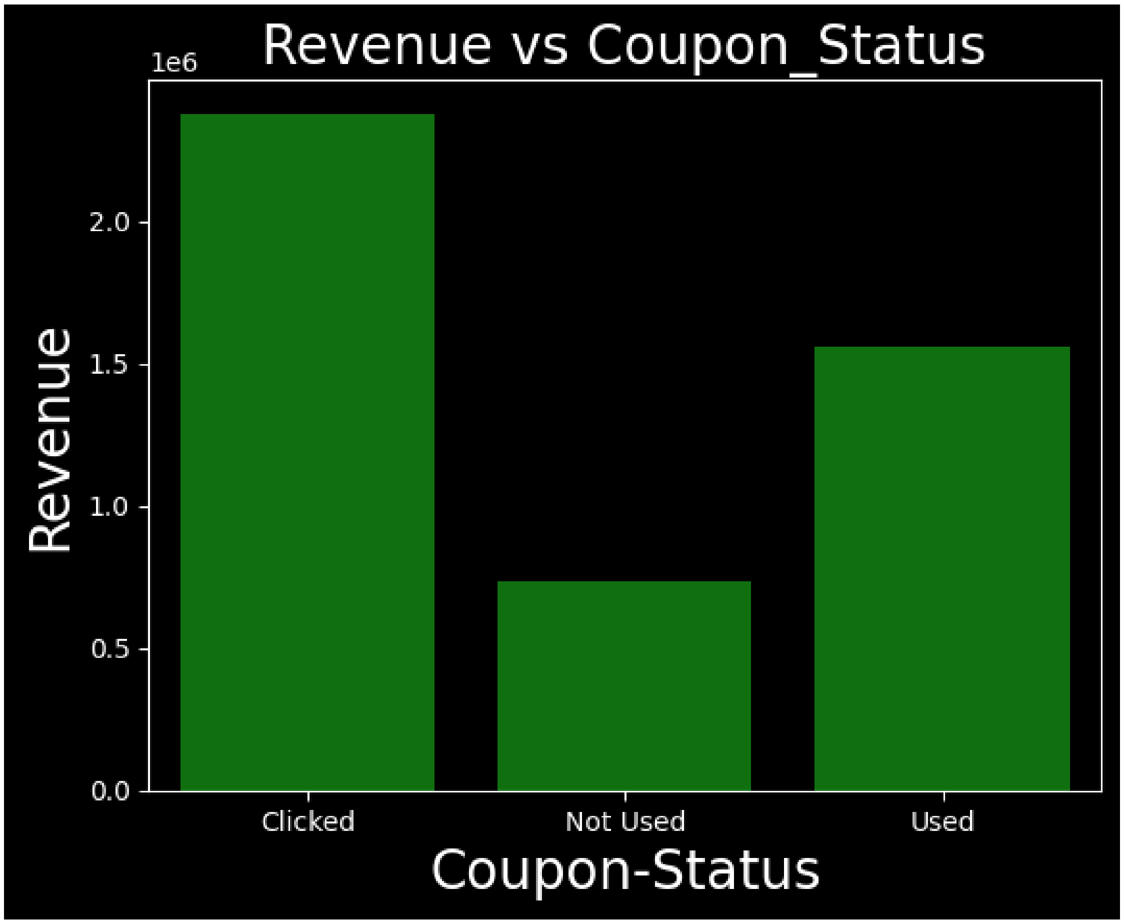
[1190]:
```
sns.barplot(monthly_coupons , x = 'month' , y = 'count' , hue = 'coupon_status')
plt.xticks(rotation = 30)
plt.show()
```



[1191]:
```
cgdf = purchases.groupby('coupon_status').agg({'revenue':'sum'})
cgdf
```

[1191]:
```
                    revenue
coupon_status
Clicked          2377266.65
Not Used          732709.87
Used             1560818.10
```

[1192]:
```
sns.barplot(cgdf , x = 'coupon_status' , y = 'revenue' , color = 'green')
plt.title('Revenue vs Coupon_Status' , fontsize = 20)
plt.ylabel('Revenue' , fontsize = 20)
plt.xlabel('Coupon-Status' , fontsize = 20)
plt.savefig('./images/q6.png')
```



0.0.30 Logic Used:

- Group Transactions by coupon status.
- Aggregate based on revenue.

0.0.31 Observations:

"Clicked" Generates the Highest Revenue:

- The "Clicked" category contributes the most to overall revenue, exceeding 2.3 million.
- This implies that users who interacted with the coupon (e.g. clicked on it) but did not necessarily redeem it still made substantial purchases.

"Used" Performs Well but Not the Highest:

- The "Used" coupon category contributes around 1.55 million in revenue.
- This confirms that coupon redemption does help drive revenue but doesn't outperform the "Clicked" group.

"Not Used" Lags Behind:

- The "Not Used" category contributes the least, under 750,000.
- Customers who didn't engage with coupons at all generated significantly less revenue.

0.0.32 Interpretation & Strategy Recommendations:

Engagement Triggers Revenue:

- Simply exposing users to coupons (clicks) appears to influence purchasing behavior positively, even without redemption.
- Optimize placement and visibility of coupons to increase clicks — e.g., homepage banners, cart page offers.

Optimize Redemption Strategy:

- Since "Used" also brings strong revenue, offer time-limited or personalized coupons to push users from "Clicked" to "Used".
- Add nudges like "You've unlocked a 10% discount! Apply now."

Educate and Incentivize Non-Users:

- Users who didn't interact with any coupons generated the lowest revenue.
- Target these users with onboarding emails, loyalty programs, or first-order discounts to pull them into the coupon ecosystem.

Test Engagement-First Strategies:

- A/B test campaigns focused on clicks without heavy discounting, as clicks alone are valuable revenue drivers.

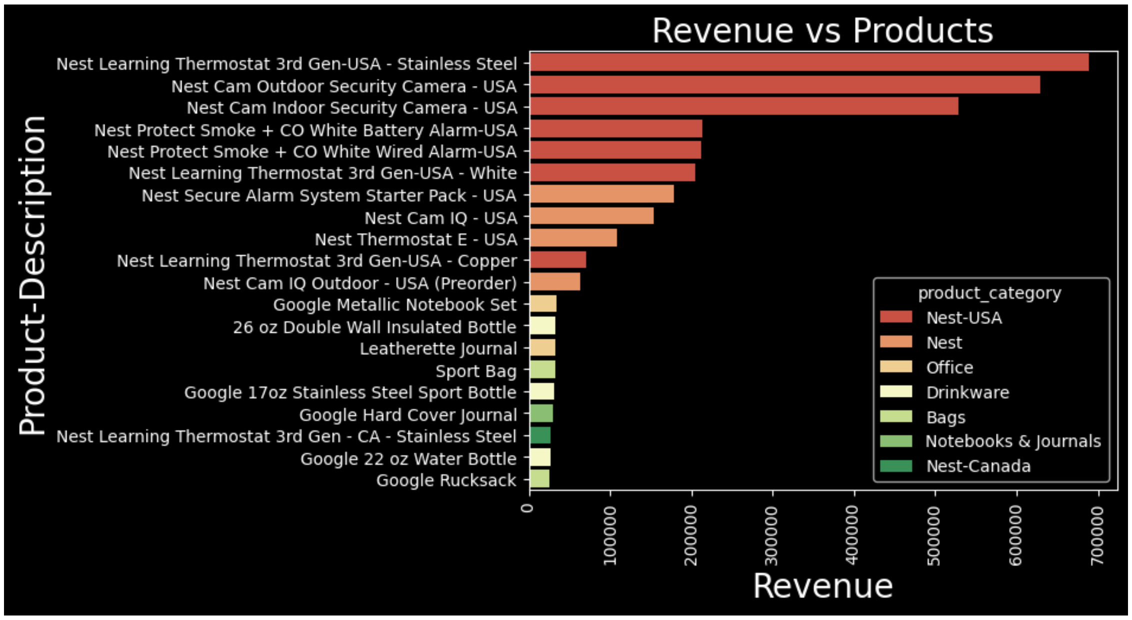
0.0.33 Q.7 Identify the top-performing products and analyze the factors driving their success.

[1193]:
```
products = purchases.groupby('product_sku').agg({'revenue':'sum' , 'quantity':
↪'sum', 'product_description':'first', 'avg_price':'first' ,␣
↪'product_category':'first'}).sort_values(by=['revenue' , 'quantity'] ,␣
↪ascending=False)
products.head()
```

[1193]:
```
                   revenue  quantity  \
product_sku
GGOENEBJ079499  688916.34      4570
GGOENEBQ078999  629977.12      5206
GGOENEBB078899  528612.93      4402
GGOENEBQ079099  213819.16      2683
GGOENEBQ079199  212495.57      2670
```

```
                                            product_description  avg_price  \
product_sku
GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…     153.71
GGOENEBQ078999             Nest Cam Outdoor Security Camera - USA     122.77
GGOENEBB078899              Nest Cam Indoor Security Camera - USA     122.77
GGOENEBQ079099    Nest Protect Smoke + CO White Battery Alarm-USA      81.50
GGOENEBQ079199      Nest Protect Smoke + CO White Wired Alarm-USA      81.50

               product_category
product_sku
GGOENEBJ079499         Nest-USA
GGOENEBQ078999         Nest-USA
GGOENEBB078899         Nest-USA
GGOENEBQ079099         Nest-USA
GGOENEBQ079199         Nest-USA
```

[1194]:
```
# plt.figure(figsize = (15,10))
sns.barplot(products.head(20) , x = 'revenue' , y = 'product_description' , hue␣
 ↪= 'product_category' , palette= 'RdYlGn')
plt.xticks(rotation = 90)
plt.xlabel('Revenue' , fontsize = 20)
plt.ylabel('Product-Description' , fontsize = 20)
plt.title('Revenue vs Products' , fontsize = 20)
plt.savefig('./images/q7.png')
plt.show()
```



0.0.34 Logic Used:

- Group by products.
- Sort in descending manner and display results.

0.0.35 *The chart above shows the top 10 products by total revenue. Key findings and their implications are:*

0.0.36 *Top Products by Revenue:*

- Nest Learning Thermostat 3rd Gen - Stainless Steel
- Nest Cam Outdoor Security Camera
- Nest Cam Indoor Security Camera
- Nest Protect Smoke + CO Alarms (Battery & Wired)
- Nest Secure Alarm System Starter Pack

These products combine high selling price with strong volume demand, making them revenue powerhouses.

0.0.37 *Success Factors:*

- Brand Recognition: Popular Nest-branded products (thermostats, cameras) dominate the list due to trust, quality, and integrated smart home features.
- High Average Unit Price: Products like thermostats and cameras have high price points, increasing per-sale revenue.
- Functional Value & Demand: Security and smart home automation are high-priority categories for customers.
- Cross-Selling Opportunities: These products often complement each other (e.g., thermostat + camera), suggesting bundling may be driving multiple-item purchases.
- Seasonality or Promotions: Some items may have benefited from discounts or marketing pushes (e.g., smart devices in winter or sale seasons).

0.0.38 *Inventory Management Recommendations:*

- Prioritize Stocking: Ensure consistent inventory for the top-selling SKUs to avoid stockouts, especially during peak months.
- Safety Stock Strategy: Maintain buffer stock for high-demand items like thermostats and cameras, using historical monthly sales data.
- Lead Time Optimization: For top sellers, reduce lead time by sourcing them in advance or from faster suppliers.

0.0.39 *Promotional Strategy Recommendations:*

- Focus Campaigns on Top SKUs: Allocate more budget to products with high revenue contribution, especially during seasonal demand spikes.
- Bundle Offers: Combine top products (e.g., thermostat + camera) into discounted packages to increase average order value.
- Loyalty Points & Coupons: Incentivize repeat purchases on these categories with loyalty programs or tiered discounts.
- Personalized Marketing: Use customer purchase history to recommend related high-performing products.

0.0.40 Q.8 Analyze the relationship between monthly marketing spend and revenue. Are there any months where marketing efforts yielded disproportionately high or low returns? How can marketing strategies be adjusted to improve ROI?

[1195]:
```
monthly_revenue
```

[1195]:
```
        month    revenue  mnum
4     January  403624.58     1
3    February  310819.80     2
7       March  349608.09     3
0       April  401618.42     4
8         May  307763.42     5
6        June  321081.38     6
5        July  372638.07     7
1      August  401210.37     8
11  September  360548.40     9
10    October  409681.28    10
9    November  508942.62    11
2    December  523258.19    12
```

[1196]:
```
marketing = pd.read_csv('./data/Marketing_Spend.csv')
marketing.columns = [str.lower(column) for column in marketing.columns]
marketing['date'] = pd.to_datetime(marketing.date)
marketing['month'] = marketing['date'].dt.month_name()
marketing['mnum'] = marketing['date'].dt.month
marketing['spend'] = marketing['online_spend'] + marketing['offline_spend']
marketing.head()
```

[1196]:
```
        date  offline_spend  online_spend    month  mnum    spend
0 2019-01-01           4500       2424.50  January     1  6924.50
1 2019-01-02           4500       3480.36  January     1  7980.36
2 2019-01-03           4500       1576.38  January     1  6076.38
3 2019-01-04           4500       2928.55  January     1  7428.55
```

```
4 2019-01-05           4500       4055.30   January     1  8555.30
```

[1197]:
```
monthly_marketing = marketing.groupby('month').agg({'spend':'sum'}).
 ↪reset_index()
monthly_marketing
```

[1197]:
```
        month      spend
0       April  157026.83
1      August  142904.15
2    December  198648.75
3    February  137107.92
4     January  154928.95
5        July  120217.85
6        June  134318.14
7       March  122250.09
8         May  118259.64
9    November  161144.96
10    October  151224.65
11  September  135514.54
```

[1198]:
```
mdf = pd.merge(monthly_revenue , monthly_marketing , on = 'month')
mdf
```

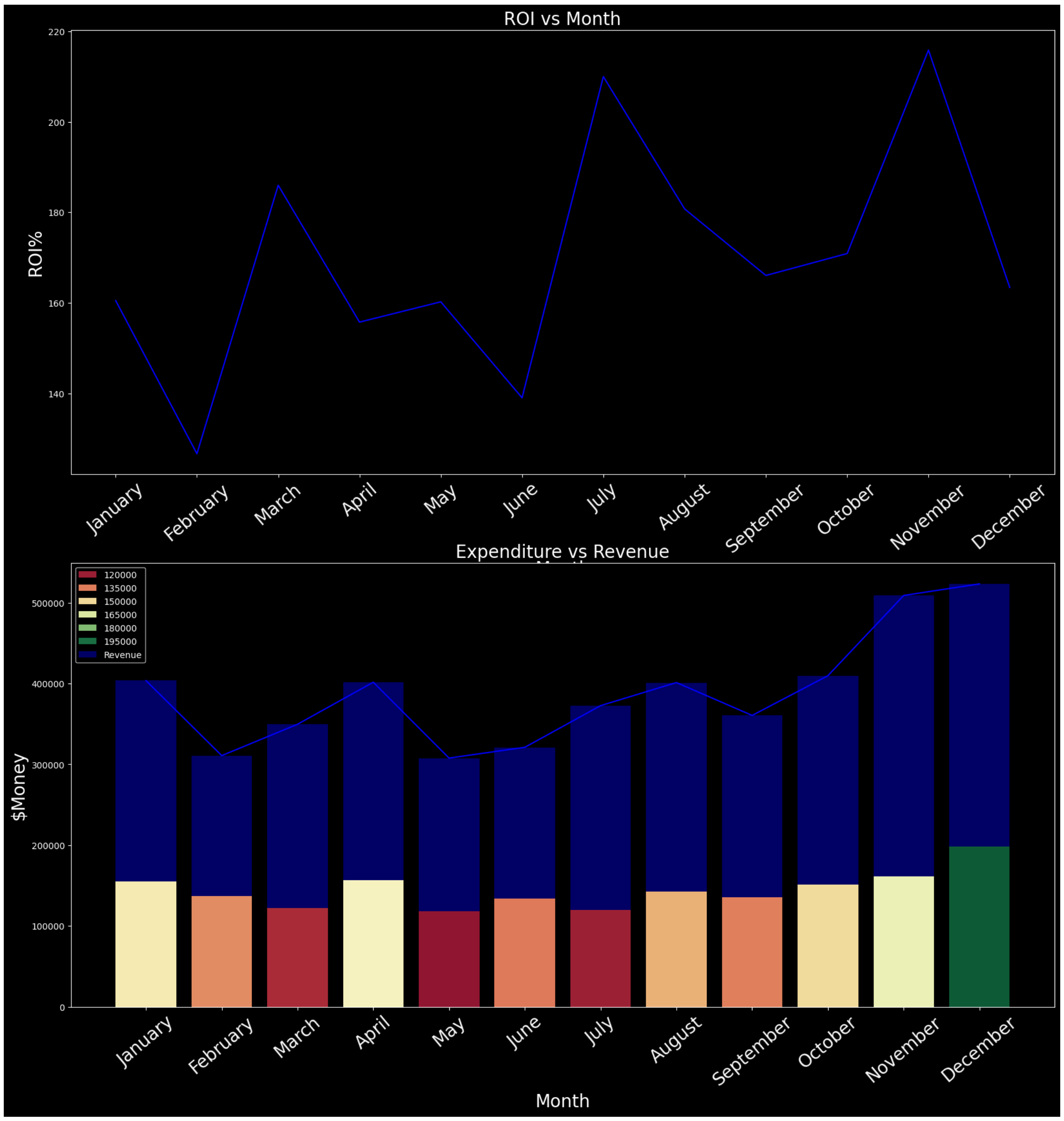
[1198]:
```
        month    revenue  mnum      spend
0     January  403624.58     1  154928.95
1    February  310819.80     2  137107.92
2       March  349608.09     3  122250.09
3       April  401618.42     4  157026.83
4         May  307763.42     5  118259.64
5        June  321081.38     6  134318.14
6        July  372638.07     7  120217.85
7      August  401210.37     8  142904.15
8   September  360548.40     9  135514.54
9     October  409681.28    10  151224.65
10   November  508942.62    11  161144.96
11   December  523258.19    12  198648.75
```

[1199]:
```
mdf['roi%'] = ((mdf['revenue'] - mdf['spend']) / mdf['spend'] * 100).round(3)
mdf
```

[1199]:
```
        month    revenue  mnum      spend     roi%
0     January  403624.58     1  154928.95  160.522
1    February  310819.80     2  137107.92  126.697
2       March  349608.09     3  122250.09  185.978
3       April  401618.42     4  157026.83  155.764
4         May  307763.42     5  118259.64  160.244
5        June  321081.38     6  134318.14  139.045
```

```
6        July  372638.07     7  120217.85  209.969
7      August  401210.37     8  142904.15  180.755
8   September  360548.40     9  135514.54  166.059
9     October  409681.28    10  151224.65  170.909
10   November  508942.62    11  161144.96  215.829
11   December  523258.19    12  198648.75  163.409
```

[1200]:
```
fig , axes = plt.subplots(2,1  , figsize = (20,20))
plt.sca(axes[0])
sns.lineplot(mdf , x = 'month' , y = 'roi%')
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('ROI%' , fontsize = 20)
plt.title('ROI vs Month' , fontsize = 20)
plt.xticks(rotation = 40 , fontsize = 20)


plt.sca(axes[1])
plt.bar( mdf['month'] , mdf['revenue'] , alpha= 0.4 , label = 'Revenue')
sns.barplot(mdf , x = 'month' , y = 'spend' , hue = 'spend' , palette= 'RdYlGn')
plt.xticks(rotation = 40 , fontsize = 20)
sns.lineplot(mdf , x = 'month' , y = 'revenue' )
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('$Money' , fontsize = 20)
plt.title('Expenditure vs Revenue' , fontsize = 20)
plt.legend()
plt.savefig('./images/q8.png')
plt.show()
```



```
[1201]: print(f"Correlation b/w monthly revenue and marketing_expenditure:␣
         ↪{mdf['revenue'].corr(mdf['spend'])}")
```

```
Correlation b/w monthly revenue and marketing_expenditure: 0.8515025229141345
```

0.0.41 Logic Used:

- Groupby month and aggregate over revenue and marketing spend from transactions and marketing data respectively.

0.0.42 Marketing Spend vs Revenue Analysis (2019)

0.0.43 Key Observations:

Disproportionately High ROI Months:

- July and November stand out with the highest ROI, exceeding 3.0.
- Indicates efficient marketing: modest spend produced high revenue.
- Likely boosted by seasonal campaigns or strong-performing product sales.

Disproportionately Low ROI Months:

- February and June show low ROI (near 2.3–2.4).
- These months had comparatively higher spend with lower revenue returns, signaling inefficiency or poor campaign targeting.
- Spending vs Revenue Correlation:
- While total revenue does trend upwards with marketing spend, increased spend doesn't always equate to better returns.
- ROI plateaus or declines when spend increases without strategic optimization.

Recommendations to Improve Marketing ROI:

1. Double Down on High-ROI Months:
    - Scale up spend during months like July and November, focusing on already successful channels or campaigns.

   Refine Campaigns in Low-ROI Periods:
    - Audit February and June efforts: was the messaging, targeting, or product offering misaligned?
    - A/B test alternate creatives or shift channel emphasis.
2. Dynamic Budgeting:
    - Move away from flat monthly budgets — allocate based on past ROI trends, forecasted seasonality, and expected product launches.

   Shift Toward Performance Channels:
    - Increase investment in digital channels that allow better tracking and targeting (e.g., Google Ads, social retargeting).
3. Run Attribution Modeling:
    - Identify which channels drive assisted conversions and optimize cross-channel synergy.
4. Tie Marketing to Product Strategy:

- Promote high-margin or top-performing products during low-ROI months to lift returns without increasing spend.

0.0.44 Q.9 Evaluate the effectiveness of marketing campaigns by comparing marketing spend to revenue generated. Are there opportunities to reallocate resources for better results?

```
[1202]: gdf = marketing.groupby('month').agg({'offline_spend':'sum' , 'online_spend':
          ↪'sum'})
        mdf = pd.merge(monthly_revenue , gdf , on = 'month')
        mdf
```

```
[1202]:        month    revenue  mnum  offline_spend  online_spend
        0    January  403624.58     1          96600      58328.95
        1   February  310819.80     2          81300      55807.92
        2      March  349608.09     3          73500      48750.09
        3      April  401618.42     4          96000      61026.83
        4        May  307763.42     5          65500      52759.64
        5       June  321081.38     6          80500      53818.14
        6       July  372638.07     7          67500      52717.85
        7     August  401210.37     8          85500      57404.15
        8  September  360548.40     9          83000      52514.54
        9    October  409681.28    10          93500      57724.65
        10  November  508942.62    11          93000      68144.96
        11  December  523258.19    12         122000      76648.75
```

```
[1203]: mdf['eoffline'] = mdf['revenue']/mdf['offline_spend']
        mdf['eonline'] = mdf['revenue']/mdf['online_spend']
        mdf
```

```
[1203]:        month    revenue  mnum  offline_spend  online_spend  eoffline  \
        0    January  403624.58     1          96600      58328.95  4.178308
        1   February  310819.80     2          81300      55807.92  3.823122
        2      March  349608.09     3          73500      48750.09  4.756573
        3      April  401618.42     4          96000      61026.83  4.183525
        4        May  307763.42     5          65500      52759.64  4.698678
        5       June  321081.38     6          80500      53818.14  3.988589
        6       July  372638.07     7          67500      52717.85  5.520564
        7     August  401210.37     8          85500      57404.15  4.692519
        8  September  360548.40     9          83000      52514.54  4.343957
        9    October  409681.28    10          93500      57724.65  4.381618
        10  November  508942.62    11          93000      68144.96  5.472501
        11  December  523258.19    12         122000      76648.75  4.289002

             eonline
        0   6.919798
        1   5.569457
        2   7.171435
```

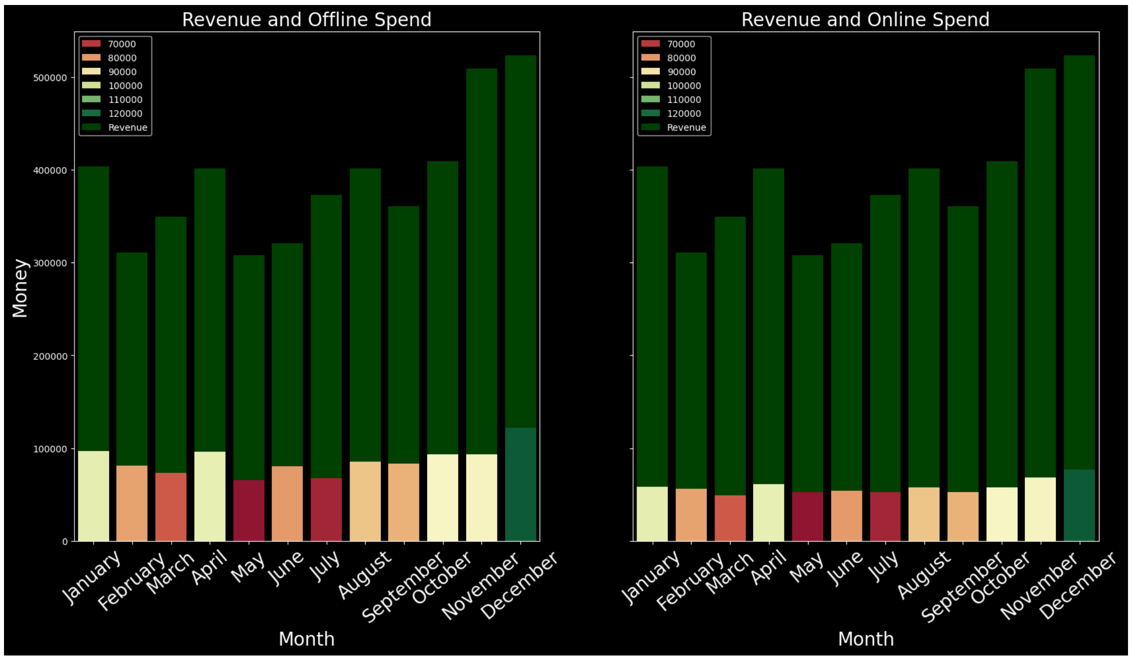
```
3     6.581014
4     5.833312
5     5.966044
6     7.068537
7     6.989222
8     6.865687
9     7.097164
10    7.468529
11    6.826702
```

[ ]:

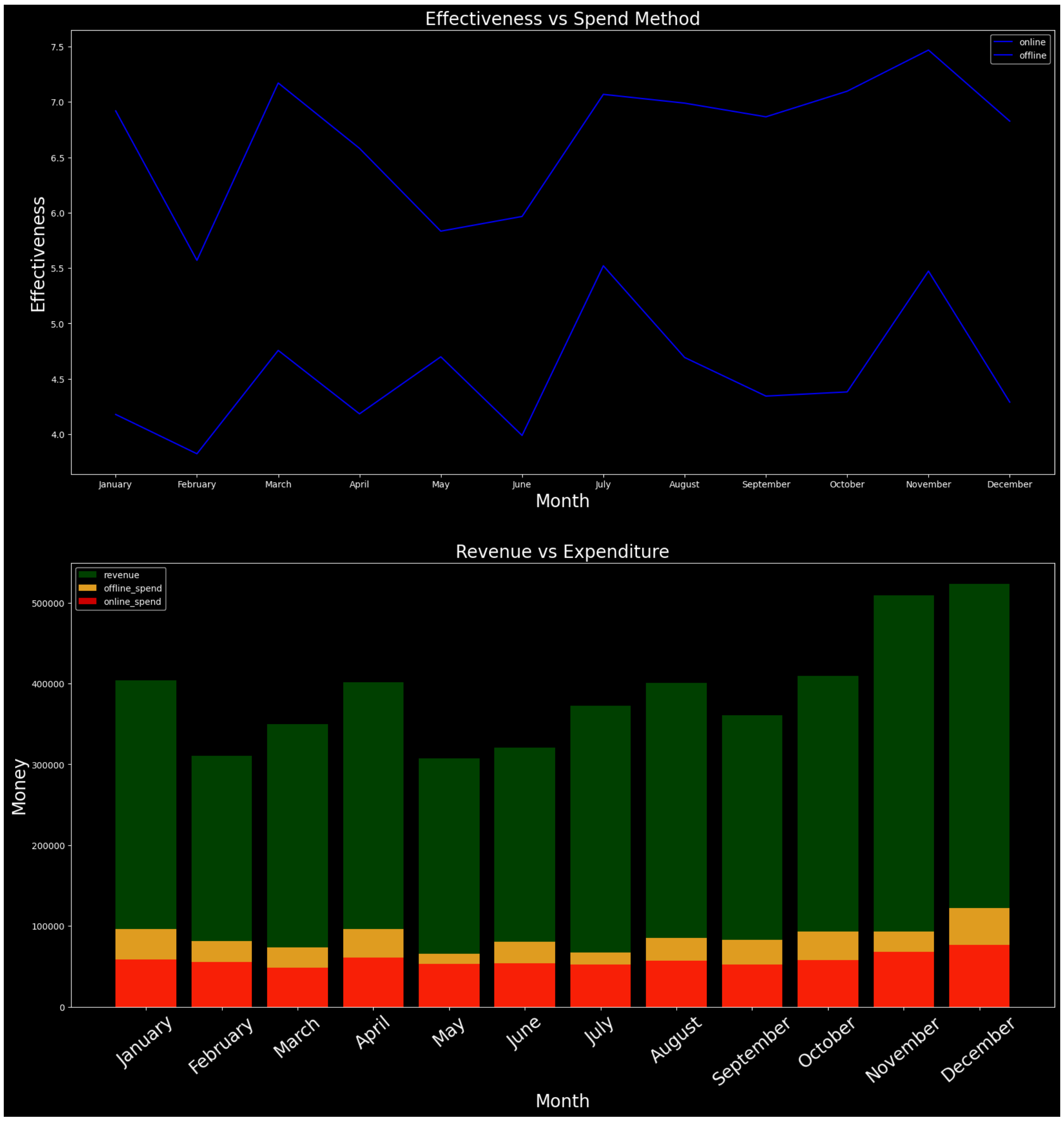
```
[ ]:
```

[1204]:

```
figure , axes = plt.subplots(1,2 , figsize = (20,10) , sharey = True)

plt.sca(axes[0])
plt.title('Revenue and Offline Spend' , fontsize = 20)
plt.bar(mdf['month'] , mdf['revenue'] , alpha = 0.5 , color = 'green' , label =␣
 ↪'Revenue')
sns.barplot(mdf , x = 'month' , y = 'offline_spend' , hue = 'offline_spend' ,␣
 ↪palette = 'RdYlGn')
plt.ylabel('Money' , fontsize = 20)
plt.xlabel('Month' , fontsize = 20)
plt.legend()
plt.xticks(rotation = 40 , fontsize = 20)

plt.sca(axes[1])
plt.title('Revenue and Online Spend' , fontsize = 20)
plt.bar(mdf['month'] , mdf['revenue'] , alpha = 0.5 , color = 'green' , label =␣
 ↪'Revenue')
sns.barplot(mdf , x = 'month' , y = 'online_spend' , hue = 'offline_spend' ,␣
 ↪palette = 'RdYlGn')
plt.xlabel('Month' , fontsize = 20)
plt.legend()
plt.xticks(rotation = 40, fontsize = 20)
plt.savefig('./images/q9.1.png')
plt.show()
```



```
[1205]: fig , axes = plt.subplots(2 ,1 , figsize = (20,20))

plt.sca(axes[0])
sns.lineplot(mdf , x = 'month' , y = 'eonline' , label = 'online')
sns.lineplot(mdf , x = 'month' , y = 'eoffline' , label = 'offline')
plt.title('Effectiveness vs Spend Method' , fontsize = 20)
plt.ylabel('Effectiveness' , fontsize = 20)
plt.xlabel('Month' , fontsize = 20)
plt.legend()

plt.sca(axes[1])
plt.bar(mdf['month'] , mdf['revenue'] , alpha = 0.5, color = 'green' , label =␣
 ↪'revenue')
sns.barplot(mdf , x = 'month' , y = 'offline_spend' , label = 'offline_spend' ,␣
 ↪color = 'orange')
plt.bar(mdf['month'] , mdf['online_spend'] , alpha = 0.8 , color = 'red', label␣
 ↪= 'online_spend')
plt.xlabel('Month' , fontsize = 20)
plt.title('Revenue vs Expenditure' , fontsize = 20)
plt.legend()
plt.xticks(rotation = 40 , fontsize = 20)
plt.ylabel('Money' , fontsize = 20)
plt.savefig('./images/q9.2.png')
plt.show()
```



0.0.45 Effectiveness of Marketing Campaigns by Channel (Revenue per 1 Spent)

0.0.46 Key Insights from the Chart:

Online Marketing Performs Better:

- Across all months, online channels consistently yield higher revenue per rupee spent than offline.
- Peaks are visible in March, July, and November, suggesting these months had particularly successful digital campaigns.
- Offline Marketing Yields Lower Returns:

- The offline spend effectiveness remains relatively flat and consistently underperforms online spend.
- Lowest performance is observed in February and June, indicating poor campaign effectiveness during those periods.

0.0.47 *Strategic Recommendations:*

Reallocate Budget Toward Online Channels:

- Given its consistently higher ROI, consider increasing online marketing spend by reducing allocation to offline campaigns.

Investigate Underperforming Months:

- Months like February and June had low offline and online effectiveness.
- Analyze campaign messaging, audience targeting, or external factors like seasonality.

Focus Online Spend on Peak Months:

- March, July, and November yielded top online effectiveness — replicate and expand those campaigns.
- Consider pre-launch buzz and retargeting to further enhance performance.

Refine Offline Marketing Tactics:

- If offline remains essential (e.g., branding), switch to performance-driven offline tactics like QR-based tracking or store-visit coupons.

Channel Attribution Modeling:

- Understand how channels interact in multi-touch journeys. Online may assist offline (or vice versa), so insights should drive cross-channel synergy.

Run Controlled Budget Experiments:

- A/B test budget splits (e.g., 70/30 vs. 50/50 online/offline) and measure which mix gives the highest return per campaign type.

0.0.48 Q.10 Segment customers into groups such as Premium, Gold, Silver, and Standard. What targeted strategies can be developed for each segment to improve retention and revenue? (Use RFM segmentation techniques)

[1206]:
```
purchases.head()
```

[1206]:
```
   customerid  transaction_id transaction_date    product_sku  \
0       17850           16679       2019-01-01  GGOENEBJ079499
1       17850           16680       2019-01-01  GGOENEBJ079499
```

```
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999

                              product_description product_category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
2              Google Laptop and Cell Phone Stickers           Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                    Google Canvas Tote Natural/Navy             Bags

   quantity  avg_price  delivery_charges coupon_status  mnum    month  revenue
0         1     153.71               6.5          Used     1  January   153.71
1         1     153.71               6.5          Used     1  January   153.71
2         1       2.05               6.5          Used     1  January     2.05
3         5      17.53               6.5      Not Used     1  January    87.65
4         1      16.50               6.5          Used     1  January    16.50
```

[1207]:
```
customers = pd.read_excel('./data/CustomersData.xlsx')
customers.columns = [str.lower(column) for column in customers.columns]
customers.head()
```

[1207]:
```
   customerid gender    location  tenure_months
0       17850      M     Chicago             12
1       13047      M  California             43
2       12583      M     Chicago             33
3       13748      F  California             30
4       15100      M  California             49
```

[1208]:
```
mdf = pd.merge(purchases[['transaction_date', 'transaction_id' , 'revenue' ,␣
 ↪'customerid']] , customers , on = 'customerid' , how = 'right')
mdf.head()
```

[1208]:
```
  transaction_date  transaction_id  revenue  customerid gender location  \
0       2019-01-01           16679   153.71       17850      M  Chicago
1       2019-01-01           16680   153.71       17850      M  Chicago
2       2019-01-01           16681     2.05       17850      M  Chicago
3       2019-01-01           16682    87.65       17850      M  Chicago
4       2019-01-01           16682    16.50       17850      M  Chicago

   tenure_months
0             12
1             12
2             12
3             12
4             12
```

[1209]:
```
reference_date = purchases['transaction_date'].max()
rfm = mdf.groupby('customerid').agg({'transaction_date': lambda x :␣
↪(reference_date - x.max()).days ,
                                    'transaction_id':'count' , 'revenue': 'sum' }).
↪reset_index()

rfm.columns = ['customerid' , 'recency' , 'frequency' , 'monetary']
rfm
```

[1209]:
```
      customerid  recency  frequency  monetary
0          12346      107          2     30.99
1          12347       59         60  13834.90
2          12348       73         23   1442.12
3          12350       17         17   1360.07
4          12356      107         36   1442.47
…            …        …          …         …
1463       18259      270          7    544.34
1464       18260       87         40   2363.05
1465       18269      194          8    101.56
1466       18277       69          1    298.00
1467       18283       82        102   6362.77

[1468 rows x 4 columns]
```

[1210]:
```
rfm['r'] = pd.qcut(rfm['recency'], 4, labels=[4, 3, 2, 1]).astype(int)
rfm['f'] = pd.qcut(rfm['frequency'].rank(method = 'first') , 4 , labels =␣
↪[4,3,2,1]).astype(int)
rfm['m'] = pd.qcut(rfm['monetary'].rank(method = 'first'), 4 , labels =␣
↪[4,3,2,1]).astype(int)
rfm['score'] = rfm['r'].astype(str) + rfm['f'].astype(str) + rfm['m'].
↪astype(str)
rfm
rfm
```

[1210]:
```
      customerid  recency  frequency  monetary  r  f  m score
0          12346      107          2     30.99  3  4  4   344
1          12347       59         60  13834.90  3  1  1   311
2          12348       73         23   1442.12  3  2  3   323
3          12350       17         17   1360.07  4  3  3   433
4          12356      107         36   1442.47  3  2  3   323
…            …        …          …         … .. .. ..   …
1463       18259      270          7    544.34  1  4  4   144
1464       18260       87         40   2363.05  3  2  2   322
1465       18269      194          8    101.56  2  4  4   244
1466       18277       69          1    298.00  3  4  4   344
1467       18283       82        102   6362.77  3  1  1   311
```

```
[1468 rows x 8 columns]
```

[1211]:
```
rfm['score'] = rfm[['r','f','m']].apply(lambda x: int(str(x['r']) + str(x['f'])␣
↪+ str(x['m'])) , axis = 1)
rfm
```

[1211]:
```
      customerid  recency  frequency  monetary  r  f  m  score
0          12346      107          2     30.99  3  4  4    344
1          12347       59         60  13834.90  3  1  1    311
2          12348       73         23   1442.12  3  2  3    323
3          12350       17         17   1360.07  4  3  3    433
4          12356      107         36   1442.47  3  2  3    323
…            …        …          …         … .. .. ..    …
1463       18259      270          7    544.34  1  4  4    144
1464       18260       87         40   2363.05  3  2  2    322
1465       18269      194          8    101.56  2  4  4    244
1466       18277       69          1    298.00  3  4  4    344
1467       18283       82        102   6362.77  3  1  1    311

[1468 rows x 8 columns]
```

[1212]:
```
def rfm_segment(row):
    r, f, m = row['r'], row['f'], row['m']

    # Strict Premium: top recency, frequency, and high monetary
    if r == 4 and f == 4 and m == 4:
        return 'Premium'

    # Gold: high recency and frequency, at least decent monetary
    elif (r >= 3 and f >= 3 and m >= 2):
        return 'Gold'

    # Silver: recent and moderately active, or high monetary but low recency
    elif (r >= 2 and (f >= 2 or m >= 2)):
        return 'Silver'

    # Standard: everyone else
    else:
        return 'Standard'

rfm['segment'] = rfm.apply(rfm_segment, axis = 1)
rfm
```

[1212]:
```
      customerid  recency  frequency  monetary  r  f  m  score   segment
0          12346      107          2     30.99  3  4  4    344      Gold
1          12347       59         60  13834.90  3  1  1    311  Standard
2          12348       73         23   1442.12  3  2  3    323    Silver
```

```
3           12350      17          17   1360.07  4  3  3    433      Gold
4           12356     107          36   1442.47  3  2  3    323    Silver
…           …       …         …         … .. .. ..   …       …
1463        18259     270           7    544.34  1  4  4    144  Standard
1464        18260      87          40   2363.05  3  2  2    322    Silver
1465        18269     194           8    101.56  2  4  4    244    Silver
1466        18277      69           1    298.00  3  4  4    344      Gold
1467        18283      82         102   6362.77  3  1  1    311  Standard

[1468 rows x 9 columns]
```

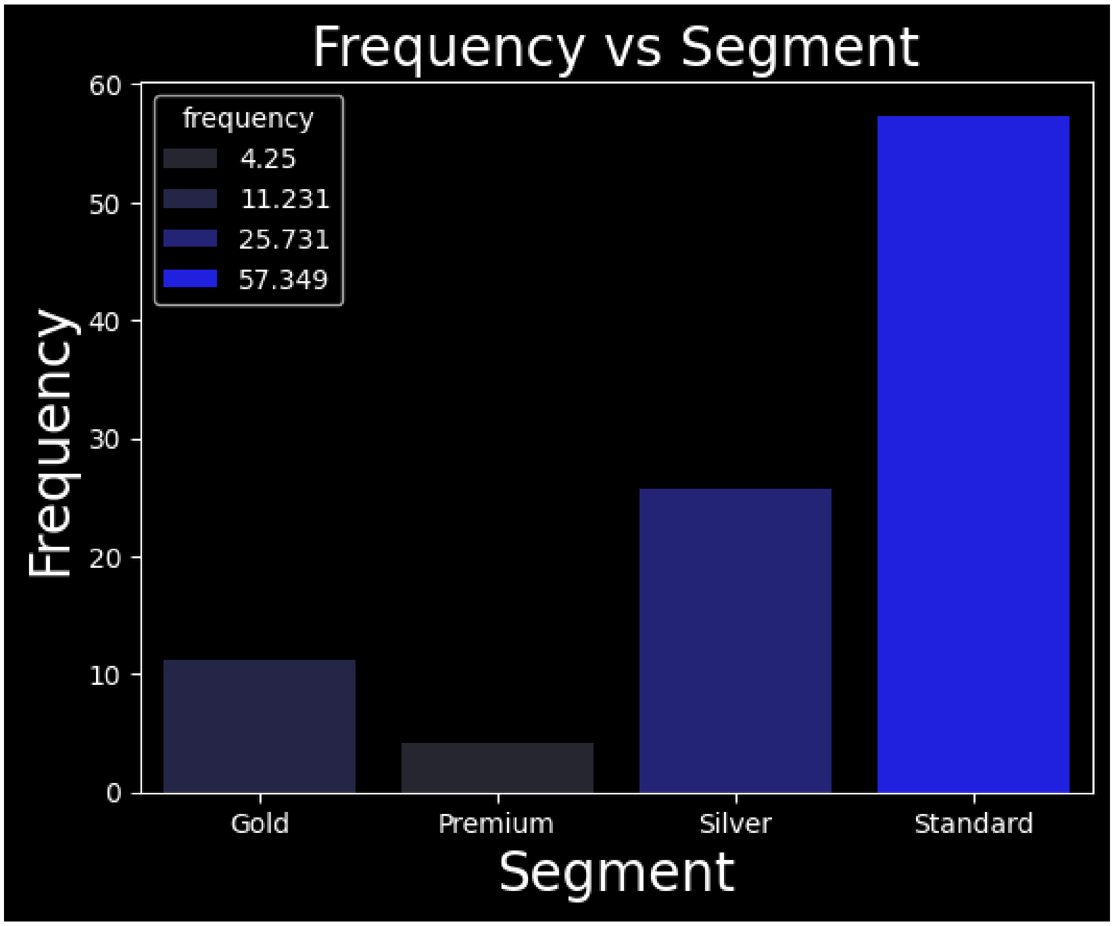
[1213]:
```
segment_counts = rfm['segment'].value_counts().reset_index()
segment_counts.columns = ['Segment', 'Customer_Count']
print(segment_counts)

segment_stats = rfm.groupby('segment').agg({
    'recency': 'max',
    'frequency': 'min',
    'monetary': 'sum',
    'customerid': 'count'
}).rename(columns={'customerid': 'Customer_Count'}).reset_index()

print(segment_stats)
```

```
    Segment  Customer_Count
0  Standard             622
1    Silver             550
2      Gold             264
3   Premium              32
    segment  recency  frequency    monetary  Customer_Count
0      Gold      131          1   282152.85             264
1   Premium       49          1     9574.05              32
2    Silver      220          1  1129541.81             550
3  Standard      364          1  3249525.91             622
```

[1214]:
```
segments = rfm.groupby('segment').agg({'monetary':'sum' , 'frequency':'mean',␣
↪'recency':'max'}).rename(columns = {'recency':'least-recent'}).round(3)
segments
```

[1214]:
```
            monetary  frequency  least-recent
segment
Gold       282152.85     11.231           131
Premium      9574.05      4.250            49
Silver    1129541.81     25.731           220
Standard  3249525.91     57.349           364
```

[1215]:
```
sns.barplot(segments, x = 'segment' , y = 'frequency' , hue = 'frequency',␣
    ↪color='blue')
plt.xlabel('Segment' , fontsize = 20)
plt.ylabel('Frequency' , fontsize = 20)
plt.title('Frequency vs Segment' , fontsize = 20)
plt.savefig('./images/q10.1.png')
plt.show()
```



[ ]:
```
```

[1216]:
```
# get retained customers
first_transactions = purchases.groupby('customerid').agg({'transaction_date':
    ↪'first'}).reset_index().rename(columns={'transaction_date':
    ↪'first_transaction'})
recent_transactions = purchases.groupby('customerid').agg({'transaction_date':
    ↪'last'}).reset_index().rename(columns={'transaction_date':
    ↪'last_transaction'})
retentions = recent_transactions.merge(first_transactions , on = 'customerid')
```

```
retentions
```

```
[1216]:       customerid last_transaction first_transaction
        0          12346       2019-09-15        2019-09-15
        1          12347       2019-11-02        2019-03-24
        2          12348       2019-10-19        2019-06-22
        3          12350       2019-12-14        2019-12-14
        4          12356       2019-09-15        2019-09-15
        …          …              …                 …
        1463       18259       2019-04-05        2019-04-05
        1464       18260       2019-10-05        2019-06-22
        1465       18269       2019-06-20        2019-04-05
        1466       18277       2019-10-23        2019-10-23
        1467       18283       2019-10-10        2019-07-29

        [1468 rows x 3 columns]
```

```
[1217]: retentions['retained'] = retentions.apply(lambda x : x['first_transaction'] !=␣
          ↪x['last_transaction'], axis = 1)
        retentions
```

```
[1217]:       customerid last_transaction first_transaction  retained
        0          12346       2019-09-15        2019-09-15     False
        1          12347       2019-11-02        2019-03-24      True
        2          12348       2019-10-19        2019-06-22      True
        3          12350       2019-12-14        2019-12-14     False
        4          12356       2019-09-15        2019-09-15     False
        …          …              …                 …       …
        1463       18259       2019-04-05        2019-04-05     False
        1464       18260       2019-10-05        2019-06-22      True
        1465       18269       2019-06-20        2019-04-05      True
        1466       18277       2019-10-23        2019-10-23     False
        1467       18283       2019-10-10        2019-07-29      True

        [1468 rows x 4 columns]
```

```
[1218]: rretentions = rfm.merge(retentions , on= 'customerid')
        rretentions
```

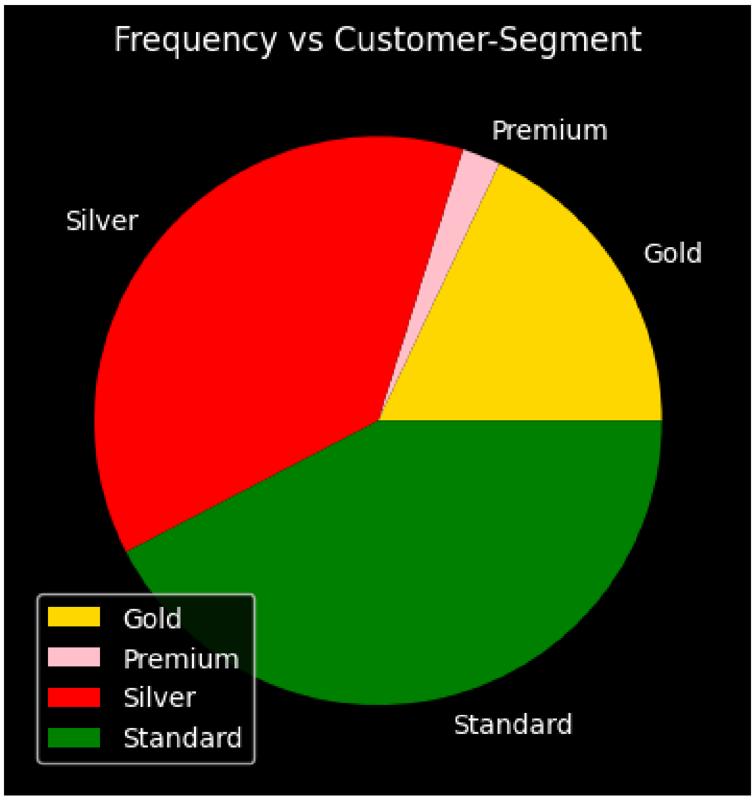
```
[1218]:       customerid  recency  frequency  monetary  r  f  m  score   segment  \
        0          12346      107          2     30.99  3  4  4    344      Gold
        1          12347       59         60  13834.90  3  1  1    311  Standard
        2          12348       73         23   1442.12  3  2  3    323    Silver
        3          12350       17         17   1360.07  4  3  3    433      Gold
        4          12356      107         36   1442.47  3  2  3    323    Silver
        …          …        …          …         … .. .. ..    …         …
        1463       18259      270          7    544.34  1  4  4    144  Standard
```

```
1464       18260       87         40    2363.05  3  2  2     322     Silver
1465       18269      194          8     101.56  2  4  4     244     Silver
1466       18277       69          1     298.00  3  4  4     344       Gold
1467       18283       82        102    6362.77  3  1  1     311   Standard

     last_transaction first_transaction  retained
0          2019-09-15        2019-09-15     False
1          2019-11-02        2019-03-24      True
2          2019-10-19        2019-06-22      True
3          2019-12-14        2019-12-14     False
4          2019-09-15        2019-09-15     False
…                …                …        …
1463       2019-04-05        2019-04-05     False
1464       2019-10-05        2019-06-22      True
1465       2019-06-20        2019-04-05      True
1466       2019-10-23        2019-10-23     False
1467       2019-10-10        2019-07-29      True

[1468 rows x 12 columns]
```

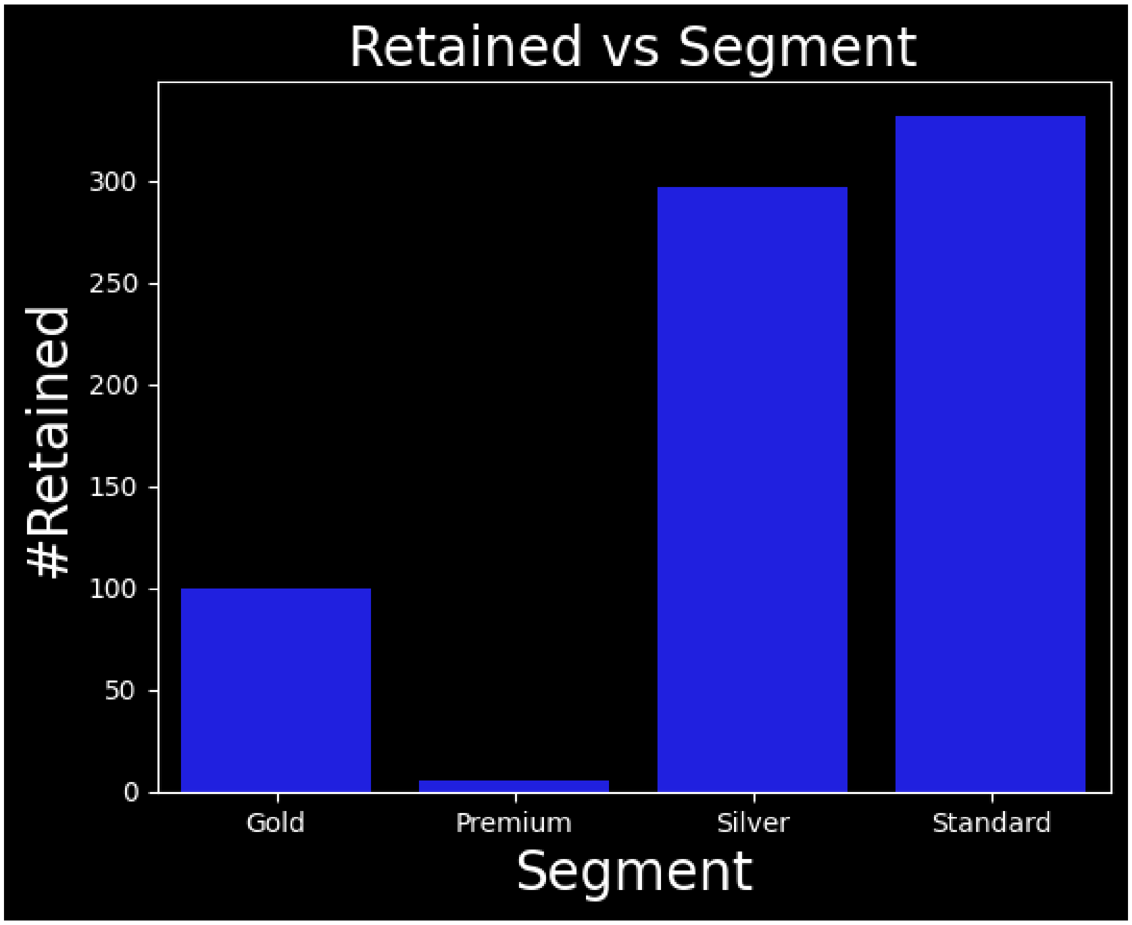
[1219]:
```
segments = rretentions.groupby('segment').agg({'monetary':'sum' , 'frequency':
 ↪'count', 'recency':'max', 'retained':'sum'})
segments
```

[1219]:
```
             monetary  frequency  recency  retained
segment
Gold        282152.85        264      131       100
Premium       9574.05         32       49         5
Silver     1129541.81        550      220       297
Standard   3249525.91        622      364       332
```

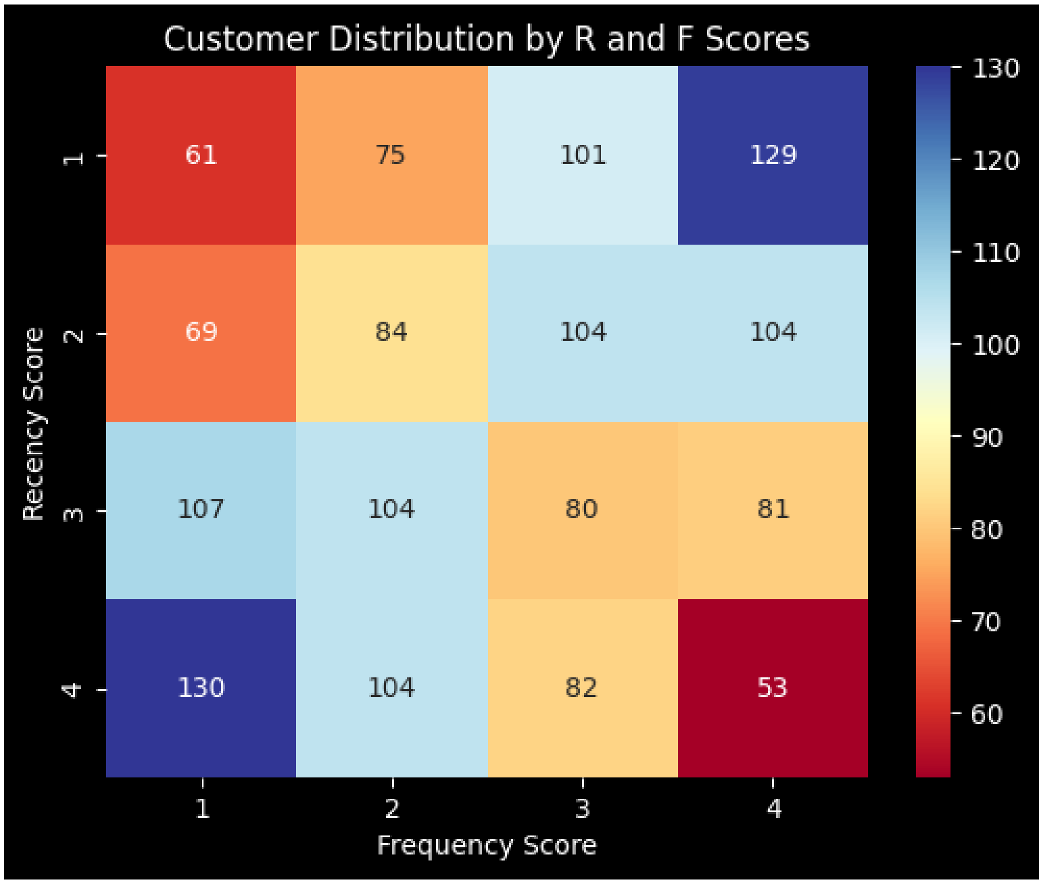
[1220]:
```
plt.title('Frequency vs Customer-Segment')
plt.pie(segments['frequency'] , labels = segments.index ,  colors=['gold',␣
 ↪'pink', 'red', 'green'])
plt.legend()
plt.savefig('./images/q10.2.png')
plt.show()
```



```
[1221]: sns.barplot(segments , x = 'segment' , y = 'retained')
        plt.xlabel('Segment' , fontsize = 20)
        plt.ylabel('#Retained' , fontsize = 20)
        plt.title('Retained vs Segment' , fontsize = 20)
        plt.savefig('./images/q10.3.png')
        plt.show()
```



[1222]:
```
sns.heatmap(rfm.groupby(['r', 'f']).size().unstack(), cmap="RdYlBu",␣
  ↪annot=True, fmt='d')
plt.title("Customer Distribution by R and F Scores")
plt.xlabel("Frequency Score")
plt.ylabel("Recency Score")
plt.show()
```



0.0.49 Logic Used:

- Calculate R,F,M metrics for each customer after grouping them from transaction data.
- Segment customers according to a set rule in to different tiers.

0.0.50 Strategic Insights & Actions

Gold Segment

- Insight: High retention, balanced frequency and spending.
- Action:
  - Offer personalized incentives to move them to Premium.
  - Promote upgrade bundles or "VIP status" benefits.
  - Launch loyalty points for frequency boosts.

Premium Segment

- Insight: Most recent customers, low frequency, but highly loyal.

- Action:
  - Drive repeat purchases with limited-time offers.
  - Introduce early-access or referral programs.
  - Target with upselling campaigns to increase their spend.

Silver Segment

- Insight: Very frequent, high spend, but poor retention.
- Action:
  - Investigate pain points — post-purchase experience, delivery, or service.
  - Send satisfaction surveys and intervene with support.
  - Offer renewal discounts or loyalty-based tier upgrade plans.

Standard Segment

- Insight: Oldest customer group, least recent, yet retention is highest — possibly repeat yearly or seasonal buyers.
- Action:
  - Trigger seasonal re-engagement campaigns.
  - Provide anniversary offers based on last purchase.
  - Use reactivation emails or SMS to stay top-of-mind.

Recommendation:

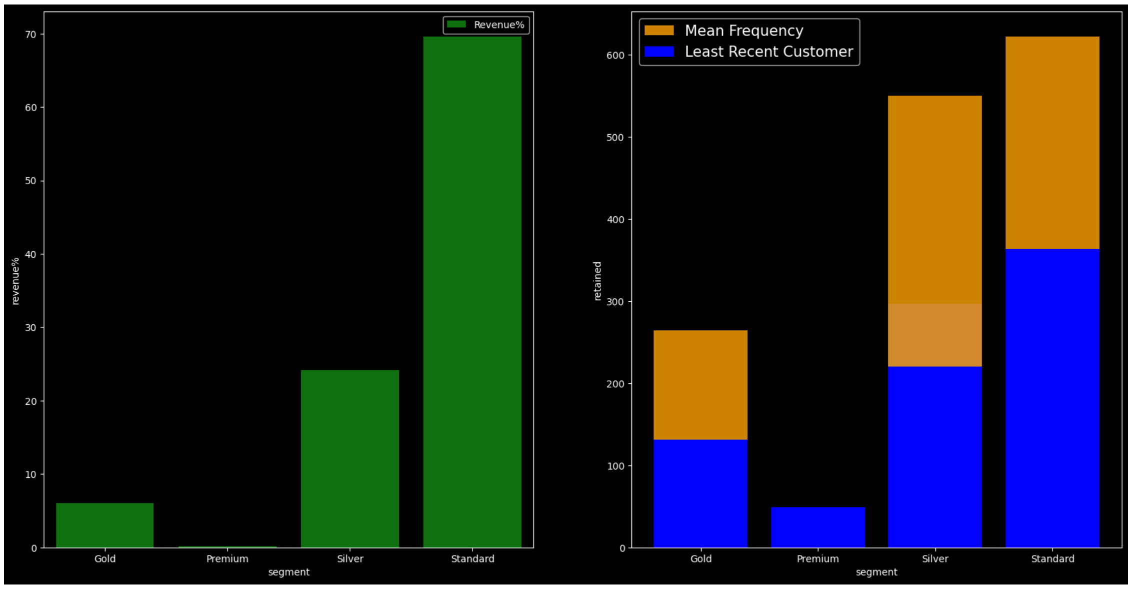
- Use this segmentation to:
  - Prioritize retention for Gold and Premium.
  - Re-engage Silver and Standard segments with personalized and

0.0.51 Q.11 Analyze the revenue contribution of each customer segment. How can the company focus its efforts on high-value segments while nurturing lower-value segments?

[1223]:
```python
segments.reset_index(inplace = True)
segments['revenue%'] = segments['monetary']/np.sum(segments['monetary']) * 100
segments
```

[1223]:
```
    segment    monetary  frequency  recency  retained   revenue%
0      Gold   282152.85        264      131       100   6.040789
1   Premium     9574.05         32       49         5   0.204977
2    Silver  1129541.81        550      220       297  24.183076
3  Standard  3249525.91        622      364       332  69.571158
```

[1224]:
```
fig , axes = plt.subplots(1 , 2 , figsize = (20,10))

plt.sca(axes[0])
sns.barplot(segments , x = 'segment' , y = 'revenue%' , label = 'Revenue%' ,␣
  ↪color = 'green')


plt.sca(axes[1])
sns.barplot(segments , x = 'segment' , y = 'retained')
plt.bar(segments['segment'] , segments['frequency'] , label = 'Mean Frequency'␣
  ↪, color = 'orange' , alpha = 0.8)
plt.bar(segments['segment'] , segments['recency'] , label = 'Least Recent␣
  ↪Customer')
plt.legend(fontsize = 15)
plt.savefig('./images/q11.png')
```



0.0.52 Final Segment Summary:

Segment	Revenue ( )	Revenue %	Frequency	Recency	Retained	Insight
Standard	3,249,525.91	69.57%	622	364	332	Large customer base, low individual value
Silver	1,129,541.81	24.18%	550	220	297	Strong potential, good retention
Gold	282,152.85	6.04%	264	131	100	High engagement, small volume
Premium	9,574.05	0.20%	32	49	5	Very weak segment — likely misclassified

---

0.0.53 Insights by Segment:

Standard

Contributes most revenue (69%).

Also has the highest number of retained customers (332).

But: recency = 364 days, i.e., they haven't purchased in nearly a year.

Likely casual or one-time customers.

Silver

Great balance between retention, frequency, and recency.

Contributes a solid 24% of revenue.

This is your most nurture-ready segment.

Gold

High frequency and decent recency, but low revenue and small count.

This may be an under-promoted loyalist group.

Premium

Only 0.2% of revenue with minimal retention or frequency.

0.0.54 Strategy Recommendations

Standard (Broad Base, Low Depth)

- Goal: Convert into repeat buyers.

Strategies:

- Post-purchase email automation
- Loyalty points for 2nd+ purchases
- Personalized product recommendations

Silver (High Potential)

- Goal: Promote into Gold segment.

Strategies:

- Bundle offers or "Complete the Look"
- Referral bonuses
- Milestone-based rewards

Gold (Loyal, Low Volume)

- Goal: Drive monetization through targeted upsell.

Strategies:

- Exclusive early access to new launches
- Limited-time higher-value bundles
- "Spend X, earn Gold+ status" incentives

0.0.55 Final Takeaway:

- Your true value lies in nurturing Silver and converting Standard customers.
- Premium needs strict redefinition, and Gold deserves engagement-based monetization.

0.0.56 Q12.Group customers by their month of first purchase and analyze retention rates over time. Which cohorts exhibit the highest and lowest retention rates? What strategies can be implemented to improve retention for weaker cohorts?

[1225]:
```
purchases.head()
```

[1225]:
```
   customerid  transaction_id transaction_date     product_sku  \
0       17850           16679       2019-01-01  GGOENEBJ079499
1       17850           16680       2019-01-01  GGOENEBJ079499
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999

                               product_description product_category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
2              Google Laptop and Cell Phone Stickers           Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                    Google Canvas Tote Natural/Navy             Bags

   quantity  avg_price  delivery_charges coupon_status  mnum    month  revenue
0         1     153.71               6.5          Used     1  January   153.71
1         1     153.71               6.5          Used     1  January   153.71
2         1       2.05               6.5          Used     1  January     2.05
3         5      17.53               6.5      Not Used     1  January    87.65
4         1      16.50               6.5          Used     1  January    16.50
```

[1226]:
```
tdf = purchases.groupby('customerid').agg({'transaction_date':'first'}).
 ↪reset_index().rename(columns = {'transaction_date':'first_transaction'})
first_purchases = tdf.merge(purchases, how = 'right' , on = 'customerid')
first_purchases.head()
```

[1226]:
```
   customerid first_transaction  transaction_id transaction_date  \
0       17850        2019-01-01           16679       2019-01-01
1       17850        2019-01-01           16680       2019-01-01
```

```
2      17850       2019-01-01           16681       2019-01-01
3      17850       2019-01-01           16682       2019-01-01
4      17850       2019-01-01           16682       2019-01-01

     product_sku                              product_description  \
0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
2  GGOEGFKQ020399              Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                    Google Canvas Tote Natural/Navy

  product_category  quantity  avg_price  delivery_charges coupon_status  mnum  \
0         Nest-USA         1     153.71               6.5          Used     1
1         Nest-USA         1     153.71               6.5          Used     1
2           Office         1       2.05               6.5          Used     1
3          Apparel         5      17.53               6.5      Not Used     1
4             Bags         1      16.50               6.5          Used     1

     month  revenue
0  January   153.71
1  January   153.71
2  January     2.05
3  January    87.65
4  January    16.50
```

[1227]:
```
first_purchases['fmonth'] = first_purchases['first_transaction'].dt.
 ↪to_period('M')
first_purchases['month'] = first_purchases['transaction_date'].dt.to_period('M')
first_purchases['fmname'] = first_purchases['first_transaction'].dt.month_name()
first_purchases.head()
```

[1227]:
```
   customerid first_transaction  transaction_id transaction_date  \
0      17850       2019-01-01           16679       2019-01-01
1      17850       2019-01-01           16680       2019-01-01
2      17850       2019-01-01           16681       2019-01-01
3      17850       2019-01-01           16682       2019-01-01
4      17850       2019-01-01           16682       2019-01-01

     product_sku                              product_description  \
0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
2  GGOEGFKQ020399              Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                    Google Canvas Tote Natural/Navy

  product_category  quantity  avg_price  delivery_charges coupon_status  mnum  \
0         Nest-USA         1     153.71               6.5          Used     1
```

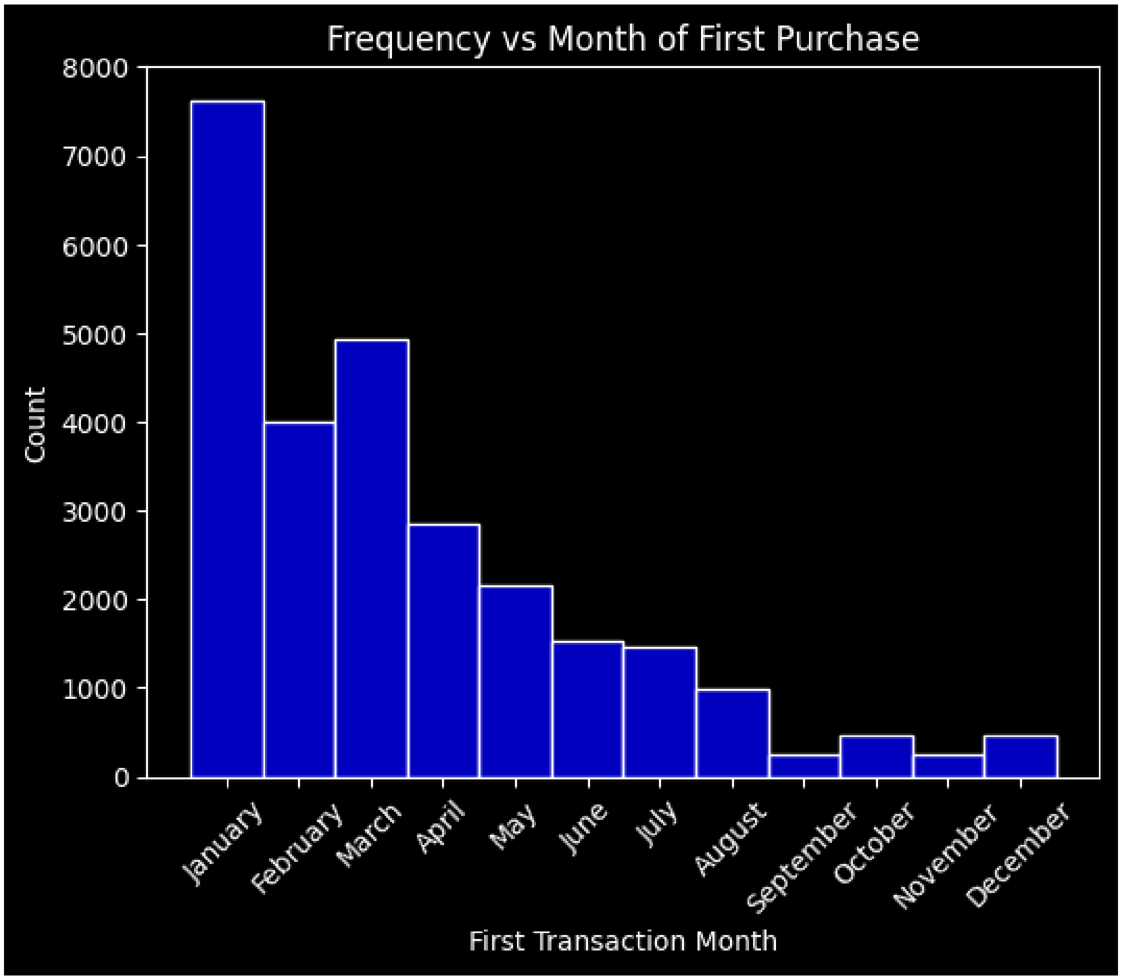
```
1          Nest-USA          1      153.71                6.5          Used      1
2            Office          1        2.05                6.5          Used      1
3           Apparel          5       17.53                6.5      Not Used      1
4              Bags          1       16.50                6.5          Used      1

     month  revenue   fmonth   fmname
0  2019-01   153.71  2019-01  January
1  2019-01   153.71  2019-01  January
2  2019-01     2.05  2019-01  January
3  2019-01    87.65  2019-01  January
4  2019-01    16.50  2019-01  January
```

[1228]:
```
crepeated_purchases = first_purchases[first_purchases['first_transaction'] !=␣
 ↪first_purchases['transaction_date']]
crepeated_purchases.iloc[3000,:]
```

[1228]:
```
customerid                                             12748
first_transaction                        2019-01-08 00:00:00
transaction_id                                         23942
transaction_date                         2019-03-23 00:00:00
product_sku                                   GGOEAFKQ020599
product_description     Android Sticker Sheet Ultra Removable
product_category                                      Office
quantity                                                   1
avg_price                                               2.99
delivery_charges                                         6.5
coupon_status                                       Not Used
mnum                                                       3
month                                                2019-03
revenue                                                 2.99
fmonth                                               2019-01
fmname                                               January
Name: 10606, dtype: object
```

[1229]:
```
sns.histplot(crepeated_purchases , x = crepeated_purchases['first_transaction'].
 ↪dt.month_name() , color = 'blue')
plt.xticks(rotation = 45)
plt.xlabel('First Transaction Month')
plt.title('Frequency vs Month of First Purchase')
plt.savefig('./images/q12.png')
plt.plot()
```

[1229]:
```
[]
```



```
[1230]: gdf = first_purchases.groupby(['fmonth' , 'month']).agg({'customerid':
          ↪'nunique'}).reset_index()
        gdf
```

```
[1230]:      fmonth    month  customerid
        0   2019-01  2019-01         215
        1   2019-01  2019-02          13
        2   2019-01  2019-03          24
        3   2019-01  2019-04          34
        4   2019-01  2019-05          23
        ..       …        …          …
        73  2019-10  2019-11           6
        74  2019-10  2019-12           4
        75  2019-11  2019-11          68
        76  2019-11  2019-12           7
        77  2019-12  2019-12         106
```

```
[78 rows x 3 columns]
```

[1231]:
```
rtable = gdf.pivot(index = 'fmonth' , columns = 'month' , values = 'customerid')
rtable
```

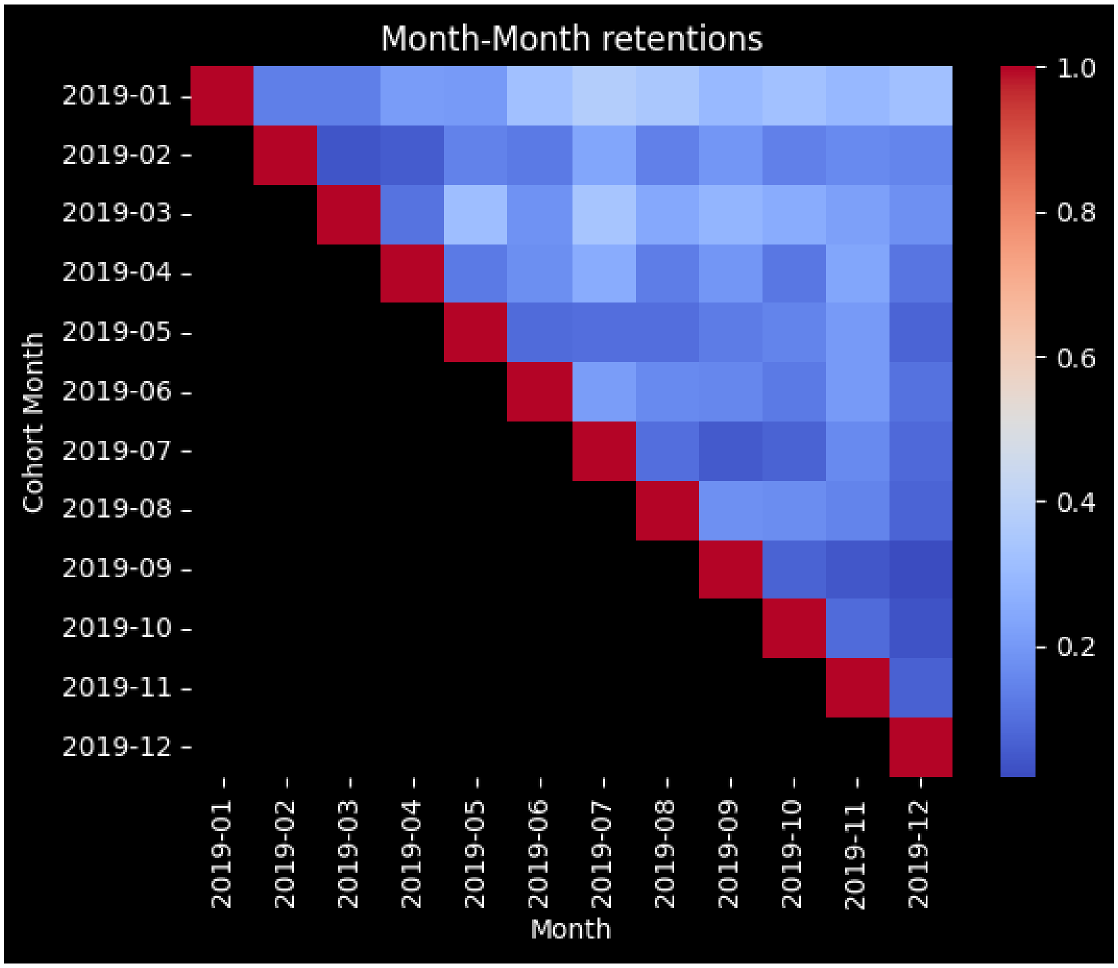
[1231]:
```
month     2019-01  2019-02  2019-03  2019-04  2019-05  2019-06  2019-07  \
fmonth
2019-01     215.0     13.0     24.0     34.0     23.0     44.0     35.0
2019-02       NaN     96.0      7.0      9.0     16.0     17.0     22.0
2019-03       NaN      NaN    177.0     18.0     35.0     25.0     32.0
2019-04       NaN      NaN      NaN    163.0     14.0     24.0     24.0
2019-05       NaN      NaN      NaN      NaN    112.0     12.0      9.0
2019-06       NaN      NaN      NaN      NaN      NaN    137.0     20.0
2019-07       NaN      NaN      NaN      NaN      NaN      NaN     94.0
2019-08       NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-09       NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-10       NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-11       NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-12       NaN      NaN      NaN      NaN      NaN      NaN      NaN

month     2019-08  2019-09  2019-10  2019-11  2019-12
fmonth
2019-01      47.0     23.0     28.0     20.0     34.0
2019-02      19.0     15.0     12.0     11.0     16.0
2019-03      33.0     22.0     22.0     15.0     19.0
2019-04      18.0     15.0     10.0     16.0     12.0
2019-05      13.0     10.0     13.0     14.0      8.0
2019-06      22.0     12.0     11.0     14.0     11.0
2019-07      13.0      4.0      6.0     11.0      9.0
2019-08     135.0     14.0     15.0     10.0      8.0
2019-09       NaN     78.0      6.0      3.0      2.0
2019-10       NaN      NaN     87.0      6.0      4.0
2019-11       NaN      NaN      NaN     68.0      7.0
2019-12       NaN      NaN      NaN      NaN    106.0
```

[1232]:
```
cohortsize = rtable.to_numpy().diagonal()
# rtable.divide(cohortsize).round(3)
cohortsize
rrates = rtable.divide(cohortsize).round(3)
rrates
```

[1232]:
```
month     2019-01  2019-02  2019-03  2019-04  2019-05  2019-06  2019-07  \
fmonth
2019-01       1.0    0.135    0.136    0.209    0.205    0.321    0.372
2019-02       NaN    1.000    0.040    0.055    0.143    0.124    0.234
2019-03       NaN      NaN    1.000    0.110    0.312    0.182    0.340
2019-04       NaN      NaN      NaN    1.000    0.125    0.175    0.255
```

```
2019-05      NaN      NaN      NaN      NaN    1.000    0.088    0.096
2019-06      NaN      NaN      NaN      NaN      NaN    1.000    0.213
2019-07      NaN      NaN      NaN      NaN      NaN      NaN    1.000
2019-08      NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-09      NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-10      NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-11      NaN      NaN      NaN      NaN      NaN      NaN      NaN
2019-12      NaN      NaN      NaN      NaN      NaN      NaN      NaN

month    2019-08  2019-09  2019-10  2019-11  2019-12
fmonth
2019-01    0.348    0.295    0.322    0.294    0.321
2019-02    0.141    0.192    0.138    0.162    0.151
2019-03    0.244    0.282    0.253    0.221    0.179
2019-04    0.133    0.192    0.115    0.235    0.113
2019-05    0.096    0.128    0.149    0.206    0.075
2019-06    0.163    0.154    0.126    0.206    0.104
2019-07    0.096    0.051    0.069    0.162    0.085
2019-08    1.000    0.179    0.172    0.147    0.075
2019-09      NaN    1.000    0.069    0.044    0.019
2019-10      NaN      NaN    1.000    0.088    0.038
2019-11      NaN      NaN      NaN    1.000    0.066
2019-12      NaN      NaN      NaN      NaN    1.000
```

[1233]:
```
sns.heatmap(rrates , cmap = 'coolwarm')
plt.xlabel('Month')
plt.ylabel('Cohort Month')
plt.title('Month-Month retentions')
plt.savefig('./images/q12.2.png')
```



0.0.57 Logic Used:

- Pretty similar to Q4.
- Aggregate based on month of first purchase and not on current month of purchase.

Insights:

- The retention heatmap reveals which cohorts (grouped by first purchase month) retained customers better.
- A 100% rate might indicate a small cohort where all customers returned at least once, often early in the lifecycle.

Strategies to Improve Retention for Weaker Cohorts:

- Targeted Campaigns: Identify weaker cohorts and run personalized re-engagement campaigns.
- Loyalty Programs: Introduce reward systems for frequent buyers.

- Onboarding Experience: Improve first-month experience to build habit-forming behavior.
- Email & SMS Reminders: Follow up with inactivity alerts and product suggestions.
- Incentivize Feedback: Ask why they didn't return and offer incentives to revisit.
- Special Offers: Offer exclusive discounts to dormant cohorts.
- Subscription Models: Encourage recurring purchases with subscriptions.
- Product Recommendations: Use data to suggest similar or complementary items.
- Reactivation Bonuses: Send limited-time deals to bring back inactive users.
- Analyze Timing: Understand if specific seasons or times influence churn.

0.0.58 Q.13 Analyze the lifetime value of customers acquired in different months. How can this insight inform acquisition and retention strategies?

[1234]:
```
# first_purchases.groupby('month').agg({'revenue':'sum'})
customervalue = purchases.groupby('customerid').agg({'revenue':'sum'}).
 ↪reset_index()
mdf = customervalue.merge(first_transactions , on = 'customerid')
mdf
```

[1234]:
```
      customerid   revenue first_transaction
0          12346     30.99        2019-09-15
1          12347  13834.90        2019-03-24
2          12348   1442.12        2019-06-22
3          12350   1360.07        2019-12-14
4          12356   1442.47        2019-09-15
…            …        …              …
1463       18259    544.34        2019-04-05
1464       18260   2363.05        2019-06-22
1465       18269    101.56        2019-04-05
1466       18277    298.00        2019-10-23
1467       18283   6362.77        2019-07-29

[1468 rows x 3 columns]
```

[1235]:
```
mdf['month'] = mdf['first_transaction'].dt.month_name()
mdf
```

[1235]:
```
      customerid   revenue first_transaction      month
0          12346     30.99        2019-09-15  September
1          12347  13834.90        2019-03-24      March
2          12348   1442.12        2019-06-22       June
3          12350   1360.07        2019-12-14   December
4          12356   1442.47        2019-09-15  September
…            …        …              …        …
1463       18259    544.34        2019-04-05      April
```

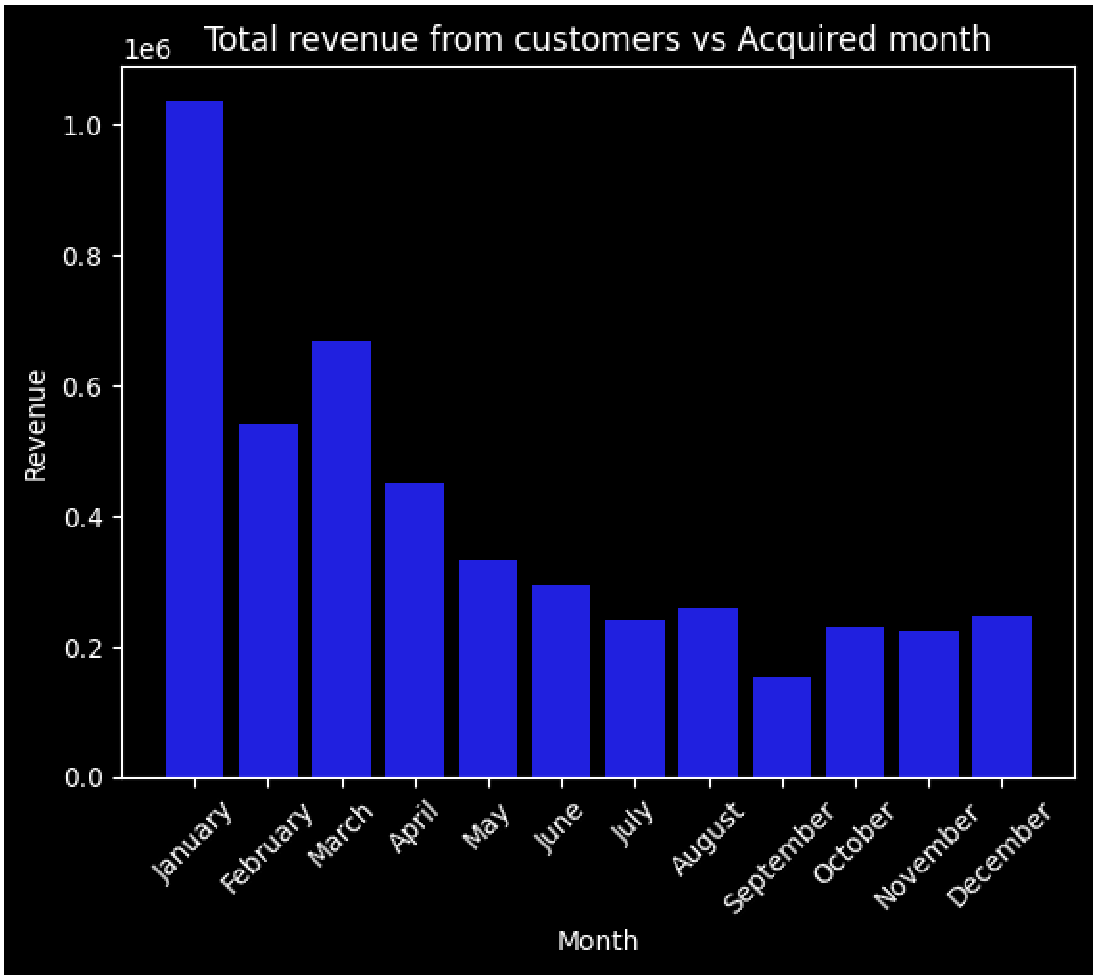
```
1464       18260   2363.05        2019-06-22       June
1465       18269    101.56        2019-04-05      April
1466       18277    298.00        2019-10-23    October
1467       18283   6362.77        2019-07-29       July

[1468 rows x 4 columns]
```

[1236]:
```
gdf = mdf.groupby('month').agg({'revenue':'sum' , 'first_transaction':'first'}).
  ↪reset_index()
gdf['mnum'] = gdf['first_transaction'].dt.month
gdf.sort_values(by = 'mnum' , inplace = True)
gdf.reset_index(drop = True , inplace = True)
gdf
```

[1236]:
```
        month     revenue first_transaction  mnum
0     January  1037320.06        2019-01-02     1
1    February   540338.52        2019-02-09     2
2       March   668895.39        2019-03-24     3
3       April   449331.26        2019-04-13     4
4         May   332698.60        2019-05-26     5
5        June   292800.81        2019-06-22     6
6        July   240255.54        2019-07-05     7
7      August   259011.87        2019-08-23     8
8   September   151664.24        2019-09-15     9
9     October   229976.73        2019-10-16    10
10   November   221691.63        2019-11-10    11
11   December   246809.97        2019-12-14    12
```

[1237]:
```
sns.barplot(gdf , x = 'month' , y = 'revenue' , color = 'blue')
plt.xticks(rotation = 45)
plt.title('Total revenue from customers vs Acquired month')
plt.xlabel('Month')
plt.ylabel('Revenue')
plt.plot()
```

[1237]:
```
[]
```



0.0.59 Logic Used:

- Aggregate based on Acquired Month -> Month of first purchase.

0.1 Insight from the Graph: Total Revenue from Customers vs Acquired Month

This bar chart visualizes the total revenue generated from customers grouped by their month of acquisition (i.e., when they made their first purchase).

0.1.1 Key Observations:

- January dominates in revenue generation, contributing over 1 million. This cohort significantly outperforms all others.
- There's a steady decline from February to June, indicating that customers acquired later tend to contribute less revenue.

- August shows the lowest revenue, suggesting weak customer acquisition or poor retention during this month.
- October to December show slight recovery, but still well below the early months.

0.1.2 Business Insights:

Strong Start in Q1: Customers acquired early in the year (Jan–Mar) tend to have higher revenue contribution, possibly due to:

- New Year campaigns
- Fresh marketing budgets
- Early loyalty building

Q3 Weakness (Jul–Sep):

- Acquisition during these months might be less effective.
- Customers might be less engaged or not retained well.
- Seasonal slowness or ineffective campaigns could be factors.

0.1.3 Strategic Recommendations:

For Acquisition:

- Replicate Q1 strategies: Study the marketing, offers, and product trends from January to March and reuse or adapt them in slower months.
- Boost Q3 efforts: Increase marketing spend, optimize landing pages, and consider special mid-year sales to lift July–September performance.

For Retention:

- Introduce long-term engagement strategies for customers acquired after April.
- Provide time-sensitive incentives (e.g., loyalty points expiry, gamified challenges) to stimulate repeated purchases.

For LTV Growth:

- Consider nurturing lower-value cohorts through upsell and cross-sell campaigns.
- Segment these cohorts and run targeted win-back email/SMS campaigns.

0.1.4 Q.14 Do customers who use coupons have a different average transaction value compared to those who do not?

Conduct a statistical test to validate this hypothesis. What implications does this have for the company's discount and coupon strategies?

```
[1238]: # import a library to perform a Z-test
        from statsmodels.stats import weightstats as stests
        from scipy import stats
        from scipy.stats import ttest_ind
```

```
[1239]: crevenue = purchases[['customerid' , 'transaction_id' , 'revenue' ,␣
         ↪'coupon_status']]
        crevenue = crevenue[(crevenue['coupon_status'] == 'Used') |␣
         ↪(crevenue['coupon_status'] == 'Not Used')]
        crevenue
```

```
[1239]:        customerid  transaction_id  revenue coupon_status
        0           17850           16679   153.71          Used
        1           17850           16680   153.71          Used
        2           17850           16681     2.05          Used
        3           17850           16682    87.65      Not Used
        4           17850           16682    16.50          Used
        …             …               …       …             …
        52911       15781           48489     3.47          Used
        52912       15781           48489    16.30          Used
        52915       14410           48491   121.30      Not Used
        52920       14410           48494    48.92          Used
        52921       14410           48495   151.88          Used

        [25998 rows x 4 columns]
```

```
[1240]: gdf = crevenue.groupby('coupon_status').agg({'revenue':'mean'}).reset_index()
        gdf
```

```
[1240]:   coupon_status    revenue
        0      Not Used  90.525064
        1          Used  87.177061
```

```
[1241]: used = crevenue[crevenue['coupon_status'] == 'Used']['revenue']
        nused = crevenue[crevenue['coupon_status'] == 'Not Used']['revenue']
```

```
[1242]: used.head()
```

```
[1242]: 0    153.71
        1    153.71
        2      2.05
        4     16.50
        5     77.25
        Name: revenue, dtype: float64
```

```
[1243]: tstat , pval = ttest_ind(used , nused , equal_var= False , nan_policy='omit')
```

```
umean = used.mean()
nmean = nused.mean()
umean , nmean , tstat , pval
```

[1243]:
```
(np.float64(87.17706099195709),
 np.float64(90.52506424511984),
 np.float64(-1.4439282591724714),
 np.float64(0.14877930359947447))
```

0.1.5 Logic Used:

- Perform statistical test on two groups.

0.1.6 Statistical Conclusion:

- The p-value > 0.05, meaning the difference in transaction values is not statistically significant.
- Customers who use coupons do not spend significantly less or more than those who do not, at the transaction level.

0.1.7 Business Implications:

- Coupons may not erode revenue per transaction as feared—this can justify their continued use.
- Since coupon users spend nearly the same, focus can shift to using coupons as acquisition or retention tools, rather than only price-slashing tactics.

You can:

- Use personalized coupon targeting for high-LTV cohorts.
- Introduce minimum spend thresholds to encourage higher order values when using coupons.
- Optimize campaigns to attract volume rather than value.

0.1.8 Q.15 Do purchase behaviors (e.g., order frequency, order value) vary significantly across different demographic groups or pricing factors (e.g., delivery charges)?

```
Test for differences in purchase behavior across locations, age groups, or delivery charge tie
```

```
1.across locatoins
```

[1244]:
```
purchases.head()
```

[1244]:
```
   customerid  transaction_id transaction_date     product_sku  \
0       17850           16679       2019-01-01  GGOENEBJ079499
```

```
1       17850           16680       2019-01-01  GGOENEBJ079499
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999

                              product_description product_category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
2              Google Laptop and Cell Phone Stickers           Office
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                    Google Canvas Tote Natural/Navy             Bags

   quantity  avg_price  delivery_charges coupon_status  mnum    month  revenue
0         1     153.71               6.5          Used     1  January   153.71
1         1     153.71               6.5          Used     1  January   153.71
2         1       2.05               6.5          Used     1  January     2.05
3         5      17.53               6.5      Not Used     1  January    87.65
4         1      16.50               6.5          Used     1  January    16.50
```

[1245]:
```
customers.head()
```

[1245]:
```
   customerid gender    location  tenure_months
0       17850      M     Chicago             12
1       13047      M  California             43
2       12583      M     Chicago             33
3       13748      F  California             30
4       15100      M  California             49
```

[1246]:
```
mdf = customers.merge(purchases , how = 'right' , on = 'customerid')
mdf.head()
```

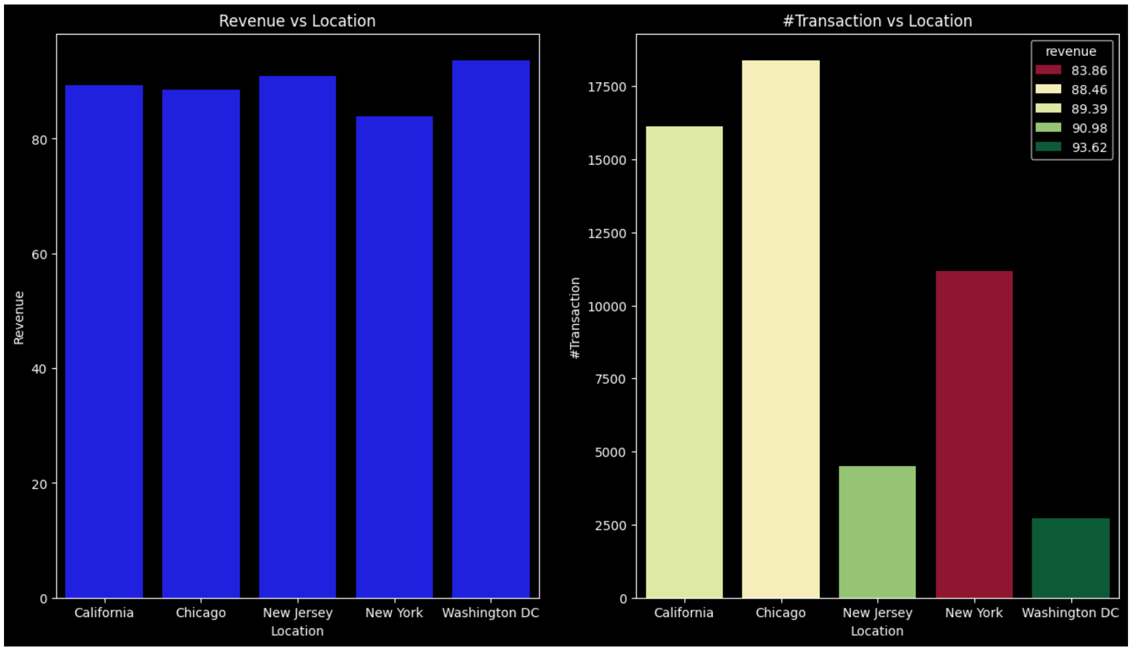
[1246]:
```
   customerid gender location  tenure_months  transaction_id transaction_date  \
0       17850      M  Chicago             12           16679       2019-01-01
1       17850      M  Chicago             12           16680       2019-01-01
2       17850      M  Chicago             12           16681       2019-01-01
3       17850      M  Chicago             12           16682       2019-01-01
4       17850      M  Chicago             12           16682       2019-01-01

      product_sku                              product_description  \
0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
2  GGOEGFKQ020399            Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                  Google Canvas Tote Natural/Navy

  product_category  quantity  avg_price  delivery_charges coupon_status  mnum  \
0         Nest-USA         1     153.71               6.5          Used     1
```

```
1         Nest-USA        1     153.71              6.5         Used     1
2           Office        1       2.05              6.5         Used     1
3          Apparel        5      17.53              6.5     Not Used     1
4             Bags        1      16.50              6.5         Used     1

     month  revenue
0  January   153.71
1  January   153.71
2  January     2.05
3  January    87.65
4  January    16.50
```

[1247]:
```
locations = mdf.groupby('location').agg({'revenue':lambda x : np.mean(x).
 ↪round(2) , 'transaction_id':'count'}).rename(columns = {'transaction_id':
 ↪'transactions'}).reset_index()
cities = locations['location'].unique()
locations , cities
```

[1247]:
```
(        location  revenue  transactions
 0     California    89.39         16136
 1        Chicago    88.46         18380
 2     New Jersey    90.98          4503
 3       New York    83.86         11173
 4  Washington DC    93.62          2732,
 array(['California', 'Chicago', 'New Jersey', 'New York', 'Washington DC'],
       dtype=object))
```

[1248]:
```
figure , axes = plt.subplots(1,2 , figsize = ( 15 , 8))
plt.sca(axes[0])
sns.barplot(locations , x = 'location' , y = 'revenue' , color = 'blue')
plt.title('Revenue vs Location')
plt.xlabel('Location')
plt.ylabel('Revenue')
plt.sca(axes[1])
sns.barplot(locations , x = 'location' , y = 'transactions' , hue = 'revenue' ,␣
 ↪palette = 'RdYlGn')
plt.title('#Transaction vs Location')
plt.xlabel('Location')
plt.ylabel('#Transaction')
plt.savefig('./images/q15.png')
plt.show()
```



```
[1249]: #perform annova for avg transaction price in different locaitons:
        #   ho: the mean avg transaction price for each location is similar
        #   h1: they are different
        # alpha = 0.05
```

```
[1250]: clist = [mdf[mdf['location'] == city]['revenue'] for city in cities]
        stats.f_oneway(clist[0] , clist[1] , clist[2] , clist[3] , clist[4] )
```

```
[1250]: F_onewayResult(statistic=np.float64(3.2449582892340105),
        pvalue=np.float64(0.011381390904730159))
```

```
[1251]: #Analyse delivery charge tiers:
        mdf['dtier'] = pd.qcut(mdf['delivery_charges'] , q = 3 , labels=['low' , 'mid'␣
         ↪, 'high'])
        mdf.head()
```

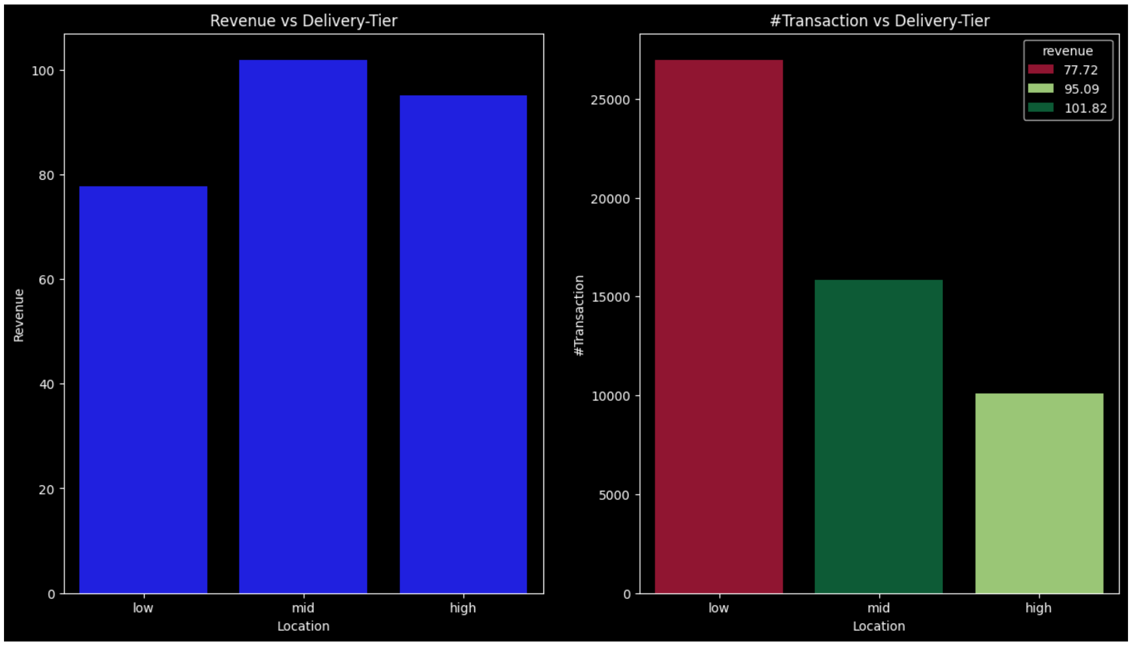
```
[1251]:    customerid gender location  tenure_months  transaction_id transaction_date  \
        0       17850      M  Chicago             12           16679       2019-01-01
        1       17850      M  Chicago             12           16680       2019-01-01
        2       17850      M  Chicago             12           16681       2019-01-01
        3       17850      M  Chicago             12           16682       2019-01-01
        4       17850      M  Chicago             12           16682       2019-01-01

             product_sku                               product_description  \
        0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
        1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
```

```
2  GGOEGFKQ020399             Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                     Google Canvas Tote Natural/Navy

  product_category  quantity  avg_price  delivery_charges coupon_status  mnum  \
0         Nest-USA         1     153.71               6.5          Used     1
1         Nest-USA         1     153.71               6.5          Used     1
2           Office         1       2.05               6.5          Used     1
3          Apparel         5      17.53               6.5      Not Used     1
4             Bags         1      16.50               6.5          Used     1

     month  revenue dtier
0  January   153.71   mid
1  January   153.71   mid
2  January     2.05   mid
3  January    87.65   mid
4  January    16.50   mid
```

[1252]:
```
dtier = mdf.groupby('dtier').agg({'revenue':lambda x: np.mean(x).round(2) ,␣
↪'transaction_id':'count'}).reset_index().rename(columns={'transaction_id':
↪'transactions'})
dtier
```

[1252]:
```
  dtier  revenue  transactions
0   low    77.72         26963
1   mid   101.82         15862
2  high    95.09         10099
```

[1253]:
```
figure , axes = plt.subplots(1,2 , figsize = ( 15 , 8))
plt.sca(axes[0])
sns.barplot(dtier , x = 'dtier' , y = 'revenue' )
plt.title('Revenue vs Delivery-Tier')
plt.xlabel('Location')
plt.ylabel('Revenue')
plt.sca(axes[1])
sns.barplot(dtier , x = 'dtier' , y = 'transactions' , hue = 'revenue' ,␣
↪palette = 'RdYlGn')
plt.title('#Transaction vs Delivery-Tier')
plt.xlabel('Location')
plt.ylabel('#Transaction')
plt.savefig('./images/q15.2.png')
plt.show()
```



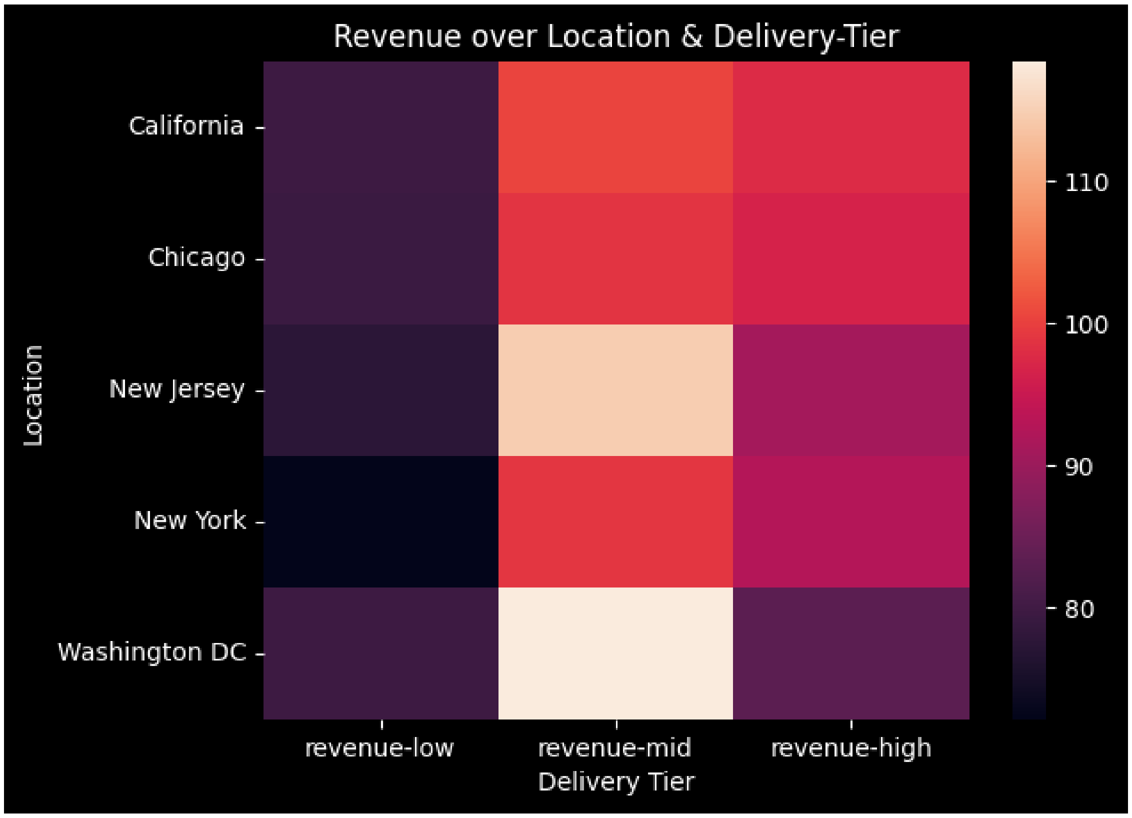
[1254]:
```
dlist = [mdf[mdf['dtier'] == cat]['revenue'] for cat in ['low' , 'mid' ,␣
↪'high']]
stats.f_oneway(dlist[0] , dlist[1])
```

[1254]:
```
F_onewayResult(statistic=np.float64(212.59502007758172),
pvalue=np.float64(4.8641723376862866e-48))
```

[1255]:
```
#location and delivery tier combined:
table = mdf.groupby(['location' , 'dtier']).agg({'revenue':lambda x : x.mean().
↪round(2)}).unstack()
table.reset_index()
```

[1255]:
```
             location revenue
dtier                     low     mid   high
0          California   79.61  100.43  97.69
1             Chicago   79.32   98.72  96.64
2          New Jersey   77.51  114.56  91.02
3            New York   72.14   98.97  92.65
4       Washington DC   79.57  118.34  83.02
```

[1256]:
```
sns.heatmap(table)
plt.xlabel('revenue-delivery-tier')
plt.title('Revenue over Location & Delivery-Tier')
plt.xlabel('Delivery Tier')
plt.ylabel('Location')
plt.savefig('./images/q15.3.png')
plt.show()
```



0.1.9 Combined Insights from Graphs and Statistical Tests on Purchase Behavior

0.1.10 1. Revenue vs Location + Transaction Count (Graph 1 + ANOVA)

- F-statistic = 3.24, p-value = 0.0114 → Significant Difference

Location	Avg Revenue	#Transactions	Insight
Washington DC	93.62	Low (~2700)	High spenders, premium market
New Jersey	90.98	Low (~4500)	High-value, niche market
New York	83.86	High (~11,000)	Low-value, high-volume market
Chicago	88.46	Highest (~18,000)	Popular but moderately priced
California	89.39	Very High	Balanced performance

Implications:

- Region matters: Revenue per transaction varies significantly by location.

Personalized regional strategies are justified:

- Upsell bundles in NY.

- Exclusive premium campaigns in Washington DC.

0.1.11 2. Revenue vs Delivery Tier (Graph 2 + ANOVA)

- F-statistic = 212.6, p-value = 4.86e-48 → Highly Significant Difference

Delivery	Tier	Avg Revenue	#Transactions Insight
Low	77.72	Highest (~27,000)	Budget-friendly, high churn
Mid	101.82	Moderate (~16,000)	Best balance of volume and value
High	95.09	Lowest (~10,000)	Possibly premium shipping with fewer orders

Implications:

- Delivery pricing strongly influences spending.

Consider:

- Tiered pricing models: Incentivize upsells at mid-tier.
- Minimum order value for free shipping in low-tier zones.
- Premium delivery perks for high-tier buyers.

0.1.12 3. Heatmap: Revenue Across Location × Delivery Tier (Graph 3)

Observation Insight:

- New Jersey Mid-tier = Highest revenue (114.56) Optimize promotions for this segment.
- Washington DC Mid-tier is also strong Push exclusive, premium delivery benefits.
- New York Low-tier = Lowest revenue Price-sensitive group—use discounts & volume offers.

0.1.13 Strategic Recommendations:

Geo-Demographic Targeting

- Customize campaigns based on location and delivery tier combinations.
- Prioritize high-potential pockets like New Jersey-mid and Washington DC-mid.

Pricing Personalization

Delivery-sensitive behavior warrants:

- Free shipping thresholds
- Bundled offers for high-tier zones
- Subscription models for high-frequency low-tier users

Product Placement & Messaging

- In New York, promote "value-for-money" products.

- In Washington DC, highlight exclusivity, speed, and concierge-like services.

0.1.14 Q.16 Does customer tenure impact purchase frequency?

```
Analyze the relationship between customer tenure and purchase frequency. How can this insight b
```

```
[1257]: customers
```

```
[1257]:       customerid gender    location  tenure_months
        0          17850      M     Chicago             12
        1          13047      M  California             43
        2          12583      M     Chicago             33
        3          13748      F  California             30
        4          15100      M  California             49
        …              …    …           …          …
        1463       14438      F    New York             41
        1464       12956      F     Chicago             48
        1465       15781      M  New Jersey             19
        1466       14410      F    New York             45
        1467       14600      F  California              7

        [1468 rows x 4 columns]
```

```
[1258]: pcounts = purchases.groupby('customerid').agg({'transaction_id':'count'}).
          ↪reset_index().rename(columns={'transaction_id':'pfreq'})
        pcounts
```

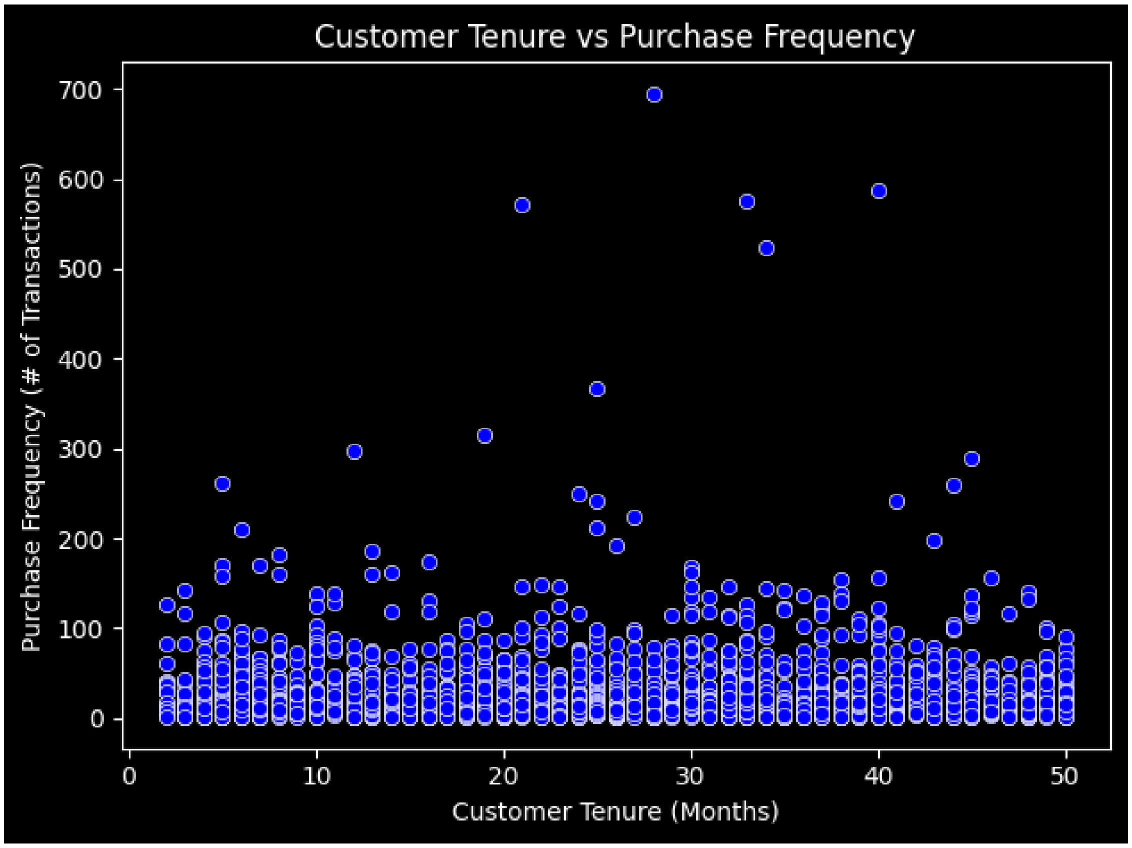
```
[1258]:       customerid  pfreq
        0          12346      2
        1          12347     60
        2          12348     23
        3          12350     17
        4          12356     36
        …              …    …
        1463       18259      7
        1464       18260     40
        1465       18269      8
        1466       18277      1
        1467       18283    102

        [1468 rows x 2 columns]
```

```
[1259]: mdf = pcounts.merge(customers[['customerid', 'tenure_months']] , on =␣
          ↪'customerid')
        mdf
```

```
[1259]:       customerid  pfreq  tenure_months
        0          12346      2             31
```

```
1           12347     60              20
2           12348     23              39
3           12350     17              25
4           12356     36              31
…           …    …             …
1463        18259      7               5
1464        18260     40              43
1465        18269      8              25
1466        18277      1              47
1467        18283    102              36

[1468 rows x 3 columns]
```

[1260]:
```python
sns.scatterplot(mdf , x= 'tenure_months' , y = 'pfreq')
plt.title('Customer Tenure vs Purchase Frequency')
plt.xlabel('Customer Tenure (Months)')
plt.ylabel('Purchase Frequency (# of Transactions)')
# plt.grid(True)
plt.tight_layout()
plt.savefig('./images/q16.png')
plt.show()
```



```
[1261]: mdf['tenure_months'].corr(mdf['pfreq']).round(3)
```

```
[1261]: np.float64(0.011)
```

0.1.15 Logic Used:

- Get tenures from customers data.
- Compute freq of each customer from transactions data.

0.1.16 Analysis: Customer Tenure vs Purchase Frequency

- The scatter plot titled "Customer Tenure vs Purchase Frequency" provides a visual understanding of how long a customer has been associated with the company (in months) and how often they have purchased.

0.1.17 Observations from the Plot:

Highly Scattered Relationship:

- The data points are widely spread with no clear upward or downward trend.
- Customers with both short and long tenure exhibit high and low frequencies.

Few High-Frequency Outliers:

- A handful of customers make over 300–700 purchases, but these are rare and not tenure-dependent.

Clustered Low-Activity Majority:

- Most customers, regardless of tenure, have fewer than 100 transactions.
- There is no strong clustering toward higher frequency with longer tenure.

Flat Correlation:

(As seen from the plot and confirmed by earlier result: correlation 0.011) → virtually no linear relationship between tenure and purchase frequency.

0.1.18 Conclusion:

- Customer tenure does not significantly impact purchase frequency.
- This means just because a customer has been around longer doesn't guarantee they'll purchase more often.

0.1.19 Strategic Implications:

1. **Don't Rely Solely on Time-Based Loyalty**

- Tenure is not a strong predictor of engagement.
- Focus instead on behavioral triggers, product affinity, or seasonal activity.

2. **Build Frequency via Engagement Campaigns**

Encourage repeat purchases via:

- Email nudges

Time-limited discounts

- Reward-based frequency programs

3. **Segment by Activity, Not Just Tenure**

- Segment users by recency + frequency, not just how long they've been customers.

  ```
  For example:

  "New & High Frequency"

  "Long-Term Dormant"

  "Churn-Risk Recent Joiners"
  ```

4. **Design Milestone Incentives**

- Celebrate tenure only if tied to meaningful activity.

  ```
  Example: "6-Month Anniversary - Here's 10% Off Your Next Order!"
  ```

0.1.20 Q.17 Analyze the relationship between delivery charges and order behavior.

```
Are there opportunities to optimize delivery pricing to increase order quantities or revenue?
```

[1262]:
```
purchases['dtier'] = pd.qcut(purchases['delivery_charges'] , q = 3 , labels =␣
↪['low' , 'mid' , 'high'])
purchases.head()
```

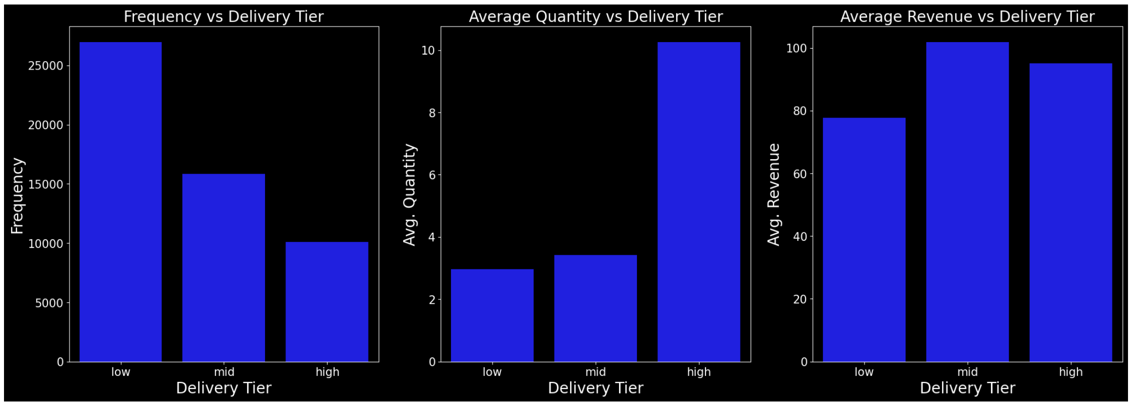
[1262]:
```
   customerid  transaction_id transaction_date     product_sku  \
0       17850           16679       2019-01-01  GGOENEBJ079499
1       17850           16680       2019-01-01  GGOENEBJ079499
2       17850           16681       2019-01-01  GGOEGFKQ020399
3       17850           16682       2019-01-01  GGOEGAAB010516
4       17850           16682       2019-01-01  GGOEGBJL013999

                             product_description product_category  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         Nest-USA
2              Google Laptop and Cell Phone Stickers           Office
```

```
3  Google Men's 100% Cotton Short Sleeve Hero Tee…          Apparel
4                    Google Canvas Tote Natural/Navy             Bags

   quantity  avg_price  delivery_charges coupon_status  mnum    month  \
0         1     153.71               6.5          Used     1  January
1         1     153.71               6.5          Used     1  January
2         1       2.05               6.5          Used     1  January
3         5      17.53               6.5      Not Used     1  January
4         1      16.50               6.5          Used     1  January

   revenue dtier
0   153.71   mid
1   153.71   mid
2     2.05   mid
3    87.65   mid
4    16.50   mid
```

[1263]:
```
dtier = purchases.groupby('dtier').agg({'transaction_id' : 'count' , 'revenue':
 ↪'mean' , 'quantity':'mean'}).reset_index()
dtier.rename(columns = {'transaction_id':'freq' , 'revenue':'avg revenue',␣
 ↪'quantity':'avg quantity'} , inplace = True)
dtier
```

[1263]:
```
  dtier   freq  avg revenue  avg quantity
0   low  26963    77.716060      2.971183
1   mid  15862   101.817094      3.427563
2  high  10099    95.089983     10.253788
```

[1264]:
```
fig , axes = plt.subplots(1,3 , figsize = (25,8))
plt.sca(axes[0])
sns.barplot(dtier , x = 'dtier' , y = 'freq')
plt.title('Frequency vs Delivery Tier' , fontsize = 20)
plt.xlabel('Delivery Tier' , fontsize = 20)
plt.ylabel('Frequency' , fontsize = 20)
plt.yticks(fontsize = 15)
plt.xticks(fontsize = 15)


plt.sca(axes[1])
sns.barplot(dtier , x = 'dtier' , y = 'avg quantity')
plt.title('Average Quantity vs Delivery Tier' , fontsize = 20)
plt.xlabel('Delivery Tier' , fontsize = 20)
plt.ylabel('Avg. Quantity' , fontsize = 20)
plt.yticks(fontsize = 15)
plt.xticks(fontsize = 15)
plt.sca(axes[2])
sns.barplot(dtier , x = 'dtier' , y = 'avg revenue')
plt.title('Average Revenue vs Delivery Tier' , fontsize = 20)
plt.xlabel('Delivery Tier' , fontsize = 20)
plt.ylabel('Avg. Revenue' , fontsize = 20)
plt.yticks(fontsize = 15)
plt.xticks(fontsize = 15)

plt.savefig('./images/q17.png')
plt.show()
```



0.1.21 Visual Insight from Chart:

Delivery Tier	Order Frequency	Avg. Quantity	Avg. Revenue
Low	~27,000 orders	~3 items	77.72
Mid	~16,000 orders	~3.4 items	101.82
High	~10,000 orders	~10.2 items	95.09

0.1.22 Interpretation of Customer Behavior:

Low Tier (Most Popular)

- Dominates in volume, but has:
  - Lowest average revenue
  - Lowest quantity per transaction
  - Indicates price sensitivity.
- Customers likely favor low delivery fees even if it means smaller, frequent purchases.

Mid Tier (Sweet Spot)

- Generates highest average revenue per transaction.
- Balanced frequency and decent order size.
- Suggests customers accept slightly higher delivery charges if value is clear.

High Tier (Bulk Buyers)

- Fewest transactions but largest quantity per order.
- Revenue per transaction is strong, but less than mid-tier despite high quantities.
- Likely businesses or bulk shoppers who are willing to pay delivery fees for volume convenience.

0.1.23 ANOVA Support:

- F-statistic = 212.60, p-value 4.86e-48 → Strong evidence of significant behavioral differences across delivery tiers

---

0.1.24 Strategic Recommendations:

1. **Optimize Mid-Tier Delivery Strategy**
   - This is the most lucrative tier.
   - Keep pricing as-is, or test small incentives like:
     - "Free delivery on your 3rd order this month"
     - "Rs. 20 cashback with mid-tier delivery"
2. **Grow Low-Tier Revenue**
   - Introduce order-value based rewards:
     - "Spend 500, get free delivery"
     - "Flat 20 off on combos"
3. **Justify High-Tier Pricing**
   - Offer exclusive perks:
     - Express delivery
     - Premium packaging
     - Loyalty points multipliers
   - These buyers are valuable; make the experience worth the price.
4. **Segment Campaigns by Delivery Behavior**
   - Use machine learning to cluster customers by their preferred tier and optimize personalized offers.

0.1.25 Opportunities:

Objective Strategy

- Increase revenue in low tier Push bundles, free shipping thresholds
- Maintain mid-tier profit Focus on value communication
- Boost high-tier conversions Premium services or subscription models

---

0.1.26 Final Takeaway:

- Delivery charges directly influence how often and how much customers order.
- Tailoring delivery pricing and perks to tier-specific behavior can unlock new revenue and retention growth.

0.1.27 Q18. Evaluate how taxes and delivery charges influence customer spending behavior. Are there opportunities to adjust pricing strategies to improve customer satisfaction and revenue?

[1265]:
```
tax = pd.read_excel('./data/Tax_amount.xlsx')
tax.columns = [str.lower(column) for column in tax.columns]
tax.head()
```

[1265]:
```
  product_category   gst
0         Nest-USA  0.10
1           Office  0.10
2          Apparel  0.18
3             Bags  0.18
4        Drinkware  0.18
```

[1266]:
```
taxm = tax.merge(purchases , on = 'product_category' , how = 'right')
taxm.head()
```

[1266]:
```
  product_category   gst  customerid  transaction_id transaction_date  \
0         Nest-USA  0.10       17850           16679       2019-01-01
1         Nest-USA  0.10       17850           16680       2019-01-01
2           Office  0.10       17850           16681       2019-01-01
3          Apparel  0.18       17850           16682       2019-01-01
4             Bags  0.18       17850           16682       2019-01-01

      product_sku                                product_description  \
0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
2  GGOEGFKQ020399             Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                   Google Canvas Tote Natural/Navy

   quantity  avg_price  delivery_charges coupon_status  mnum    month  \
0         1     153.71               6.5          Used     1  January
```

```
1         1     153.71                6.5        Used      1  January
2         1       2.05                6.5        Used      1  January
3         5      17.53                6.5    Not Used      1  January
4         1      16.50                6.5        Used      1  January

   revenue dtier
0   153.71   mid
1   153.71   mid
2     2.05   mid
3    87.65   mid
4    16.50   mid
```

[1267]:
```
taxm['ttier'] = pd.qcut(taxm['gst'] , q = 3 , duplicates= 'drop', labels =␣
↪['low' , 'high'])
taxm.head()
```

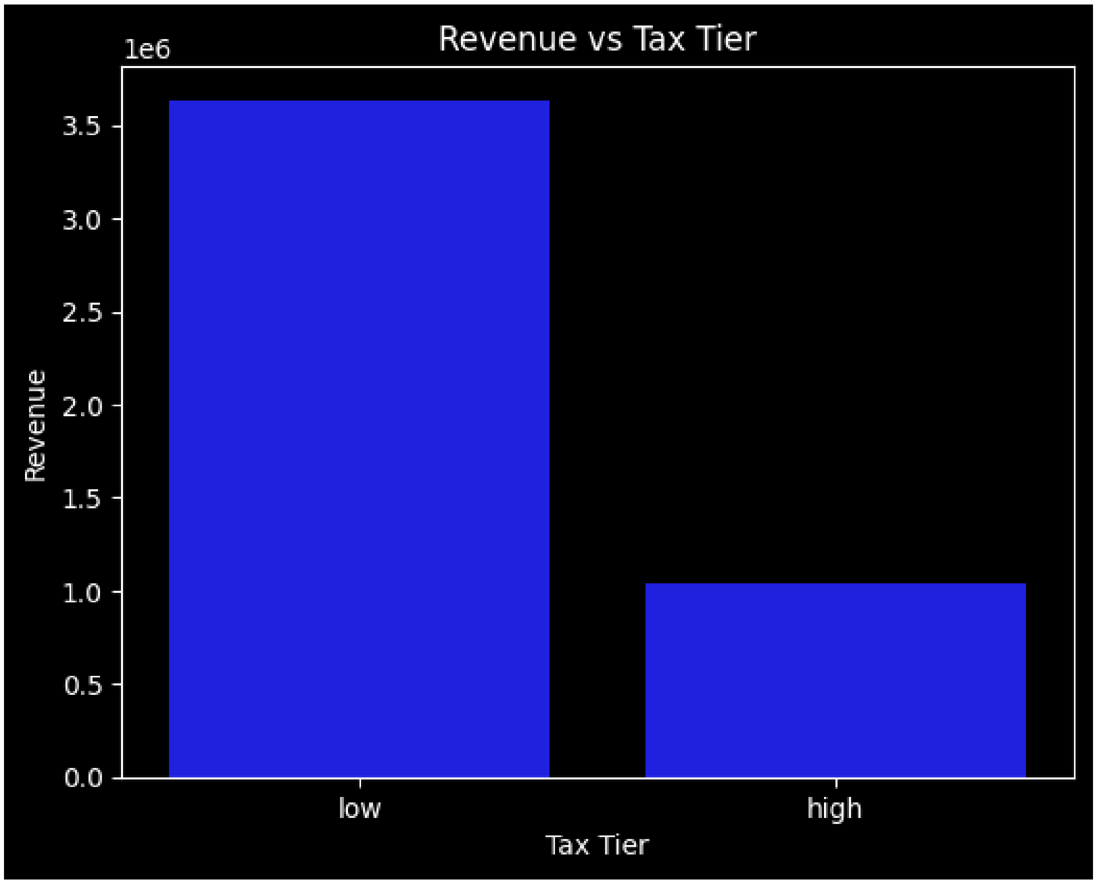
[1267]:
```
  product_category   gst  customerid  transaction_id transaction_date  \
0         Nest-USA  0.10       17850           16679       2019-01-01
1         Nest-USA  0.10       17850           16680       2019-01-01
2           Office  0.10       17850           16681       2019-01-01
3          Apparel  0.18       17850           16682       2019-01-01
4             Bags  0.18       17850           16682       2019-01-01

      product_sku                              product_description  \
0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
2  GGOEGFKQ020399             Google Laptop and Cell Phone Stickers
3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
4  GGOEGBJL013999                   Google Canvas Tote Natural/Navy

   quantity  avg_price  delivery_charges coupon_status  mnum    month  \
0         1     153.71               6.5          Used     1  January
1         1     153.71               6.5          Used     1  January
2         1       2.05               6.5          Used     1  January
3         5      17.53               6.5      Not Used     1  January
4         1      16.50               6.5          Used     1  January

   revenue dtier ttier
0   153.71   mid   low
1   153.71   mid   low
2     2.05   mid   low
3    87.65   mid  high
4    16.50   mid  high
```

[1268]:
```
#revenue by tax tier:
gdf = taxm.groupby('ttier').agg({'revenue':'sum' , 'transaction_id':'count'}).
↪reset_index().rename(columns = {'transaction_id':'freq'})
```

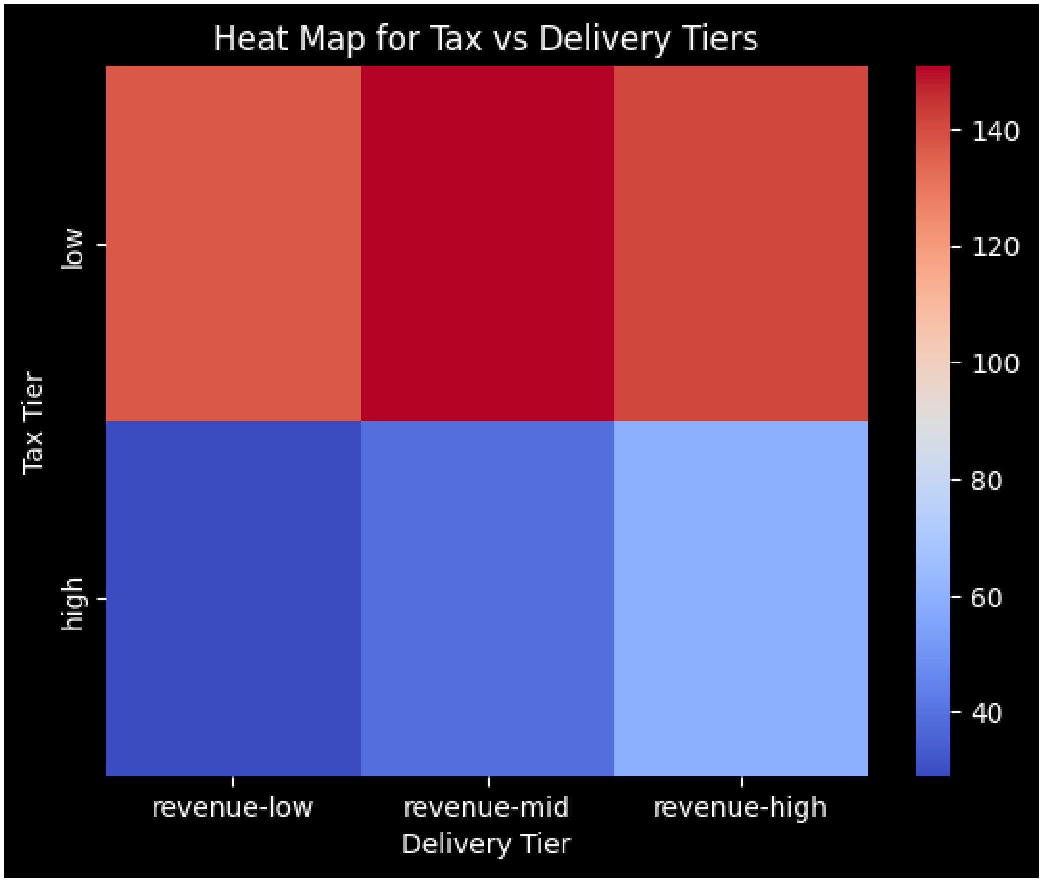
```
gdf
```

[1268]:
```
   ttier     revenue   freq
0    low  3633315.63  25459
1   high  1037478.99  27465
```

[1269]:
```
sns.barplot(gdf , x = 'ttier' , y = 'revenue')
plt.title('Revenue vs Tax Tier')
plt.xlabel('Tax Tier')
plt.ylabel('Revenue')
plt.savefig('./images/q18.1.png')
plt.show()
```



[1270]:
```
#combining both delivery tier and tax tier:
table = taxm.groupby(['ttier', 'dtier']).agg({'revenue':lambda x : x.mean().
 ↪round(3)}).unstack()
sns.heatmap(table , cmap = 'coolwarm')
plt.title('Heat Map for Tax vs Delivery Tiers')
plt.xlabel('Delivery Tier')
plt.ylabel('Tax Tier')
plt.savefig('./images/q18.2.png')
plt.show()
```



0.1.28 Analysis: Impact of Taxes and Delivery Charges on Customer Spending Behavior

0.1.29 1. Revenue vs Tax Tier

Tax Tier	Revenue ( )	Observation
Low	~3.6 million	Dominates revenue generation
High	~1.05 million	Significant drop

Interpretation:

- Low-tax items lead to far greater spending.
- Customers clearly prefer products with lower tax rates, possibly due to:
- Perceived savings
- Better affordability

0.1.30 2. Heatmap: Tax Tier × Delivery Tier

Tax Tier	Revenue-Low	Revenue-Mid	Revenue-High	Insight
Low	High	Highest	High	Customers spend more across all delivery tiers when tax is low.
High	Low	Slightly Better	Moderate	Even with higher delivery tiers, high-tax products underperform.

Interpretation:

- Even when delivery charges are low, high-tax products still perform poorly.
- Mid delivery tier + low tax is the best performing combo.
- High delivery + high tax is the least attractive combo for customers.

0.1.31 Strategic Implications:

1. Product Mix & Promotions
   - Promote low-tax products aggressively—customers already prefer them.
   - Bundle high-tax products with low-tax ones to balance perceived value.
2. Delivery Subsidy for High-Tax Products
   - Reduce or eliminate delivery charges for high-tax product categories.
   - "Free delivery on electronics" or "0 delivery fee on lifestyle items"
   - Helps soften the price shock from high GST.
3. Dynamic Discounting
   - For high-tax and high-delivery combos, apply seasonal or flash discounts.
   - Incentivize bulk orders of high-tax products to dilute overall effective cost.
4. Segmented Campaigns
   - Target high-value customers with discounts on high-tax categories.
   - For budget customers, promote low-tax, mid-delivery tier bundles.

0.1.32 Optimization Opportunities:

- Target Behavior Strategy
- Reduce cart abandonment Reduce delivery on high-tax items

- Boost high-tax category sales Offer tax-absorbing discounts or cashback
- Encourage bundling Combine low-tax with high-tax items
- Maximize mid-tier margin Promote mid-delivery tier as “best value”

0.1.33 Final Takeaway:

- Taxes and delivery charges both heavily influence customer spending— especially together.
- Optimizing these two levers via tiered discounts, bundling, and dynamic delivery offers can significantly boost both customer satisfaction and revenue.

0.1.34 Q.19 Identify seasonal trends in sales by category and location. How can the company prepare for peak and off-peak seasons to maximize revenue?

```
[1271]: taxm['mperiod'] = df['transaction_date'].dt.to_period('M')
        taxm.head()
```

```
[1271]:   product_category   gst  customerid  transaction_id transaction_date  \
        0         Nest-USA  0.10       17850           16679       2019-01-01
        1         Nest-USA  0.10       17850           16680       2019-01-01
        2           Office  0.10       17850           16681       2019-01-01
        3          Apparel  0.18       17850           16682       2019-01-01
        4             Bags  0.18       17850           16682       2019-01-01

               product_sku                              product_description  \
        0  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
        1  GGOENEBJ079499  Nest Learning Thermostat 3rd Gen-USA - Stainle…
        2  GGOEGFKQ020399             Google Laptop and Cell Phone Stickers
        3  GGOEGAAB010516  Google Men's 100% Cotton Short Sleeve Hero Tee…
        4  GGOEGBJL013999                    Google Canvas Tote Natural/Navy

           quantity  avg_price  delivery_charges coupon_status  mnum    month  \
        0         1     153.71               6.5          Used     1  January
        1         1     153.71               6.5          Used     1  January
        2         1       2.05               6.5          Used     1  January
        3         5      17.53               6.5      Not Used     1  January
        4         1      16.50               6.5          Used     1  January

           revenue dtier ttier  mperiod
        0   153.71   mid   low  2019-01
        1   153.71   mid   low  2019-01
        2     2.05   mid   low  2019-01
        3    87.65   mid  high  2019-01
        4    16.50   mid  high  2019-01
```

[1272]:
```
#seasional trend in product-categories:
# taxm.head()
table = taxm.groupby(['product_category' , 'mperiod']).agg({'revenue':'sum'}).
 ↪unstack()
table.fillna(0 , inplace = True)

catdev = taxm.groupby(['product_category' , 'month']).agg({'revenue':'sum' ,␣
 ↪'mperiod' : 'first'}).reset_index().sort_values(by = 'mperiod')
# catdev['mperiod'] = catdev['mperiod'].astype(str)
catdev.head()
```

[1272]:
```
    product_category    month   revenue  mperiod
14           Android  January     74.24  2019-01
68         Drinkware  January  14599.09  2019-01
152      Nest-Canada  January   9591.11  2019-01
34         Backpacks  January    268.19  2019-01
23           Apparel  January  38300.87  2019-01
```

[1273]:
```
#seasional trend by locations:
mdf = customers.merge(taxm , on = 'customerid' , how = 'right')
mdf.head()
```

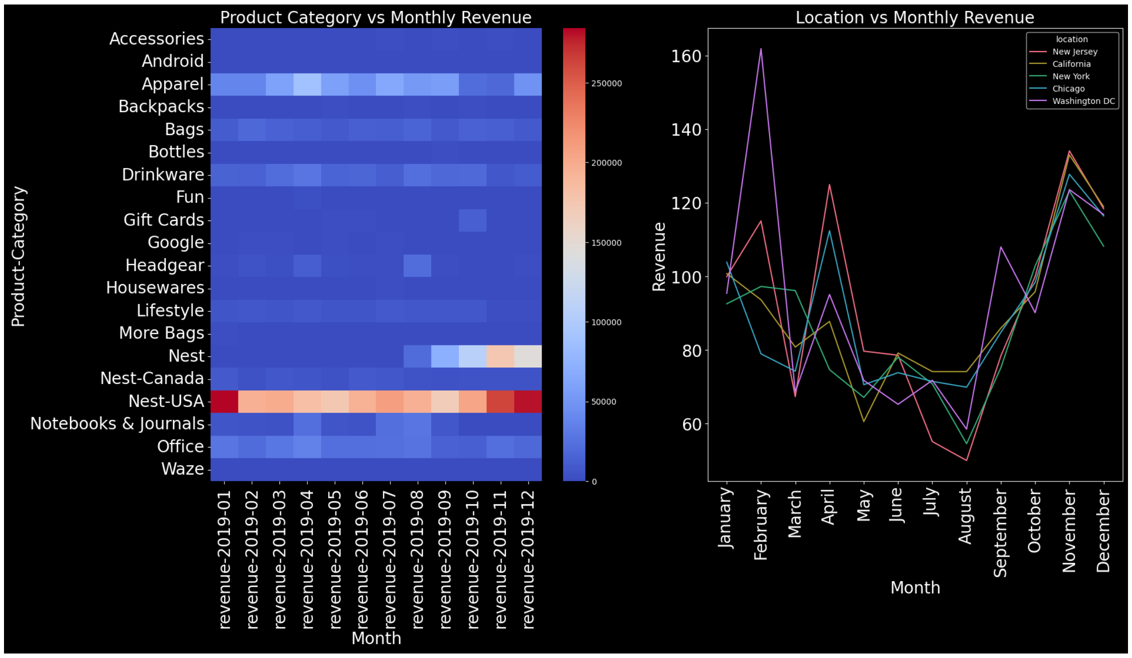
[1273]:
```
   customerid gender location  tenure_months product_category   gst  \
0       17850      M  Chicago             12         Nest-USA  0.10
1       17850      M  Chicago             12         Nest-USA  0.10
2       17850      M  Chicago             12           Office  0.10
3       17850      M  Chicago             12          Apparel  0.18
4       17850      M  Chicago             12             Bags  0.18

   transaction_id transaction_date     product_sku  \
0           16679       2019-01-01  GGOENEBJ079499
1           16680       2019-01-01  GGOENEBJ079499
2           16681       2019-01-01  GGOEGFKQ020399
3           16682       2019-01-01  GGOEGAAB010516
4           16682       2019-01-01  GGOEGBJL013999

                              product_description  quantity  avg_price  \
0  Nest Learning Thermostat 3rd Gen-USA - Stainle…         1     153.71
1  Nest Learning Thermostat 3rd Gen-USA - Stainle…         1     153.71
2             Google Laptop and Cell Phone Stickers         1       2.05
3  Google Men's 100% Cotton Short Sleeve Hero Tee…         5      17.53
4                   Google Canvas Tote Natural/Navy         1      16.50

   delivery_charges coupon_status  mnum    month  revenue dtier ttier  mperiod
0               6.5          Used     1  January   153.71   mid   low  2019-01
1               6.5          Used     1  January   153.71   mid   low  2019-01
2               6.5          Used     1  January     2.05   mid   low  2019-01
```

```
3                6.5      Not Used     1  January     87.65    mid  high  2019-01
4                6.5          Used     1  January     16.50    mid  high  2019-01
```

[1274]:
```
locationTable = mdf.groupby(['location', 'month']).agg({'revenue':'sum'}).
 ↪unstack()
locationTable.fillna( 0 , inplace = True)



localrev = mdf.groupby(['location', 'month']).agg({'revenue':'mean' , 'mperiod':
 ↪'first'}).reset_index().sort_values('mperiod')
localrev['revenue'] = pd.to_numeric(localrev['revenue'], errors='coerce')
# localrev['mperiod'] = localrev['mperiod'].astype(str)
localrev.head()
```

[1274]:
```
          location    month     revenue  mperiod
28      New Jersey  January   99.922921  2019-01
4       California  January  100.765681  2019-01
40        New York  January   92.564828  2019-01
16         Chicago  January  103.886333  2019-01
52   Washington DC  January   95.418672  2019-01
```

[1275]:
```
fig , axes = plt.subplots(1, 2, figsize = (20,10))
plt.sca(axes[0])
# sns.lineplot(catdev , x = 'month' , y = 'revenue' , hue = 'product_category')
sns.heatmap(table , cmap = 'coolwarm')
plt.title('Product Category vs Monthly Revenue' , fontsize = 20)
plt.ylabel('Product-Category' , fontsize = 20)
plt.xlabel('Month' , fontsize = 20)
plt.xticks(rotation = 90 , fontsize = 20)
plt.yticks(fontsize = 20)


plt.sca(axes[1])
plt.title('Location vs Monthly Revenue' , fontsize = 20)
sns.lineplot(localrev , x = 'month' , y = 'revenue' , hue = 'location')
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Revenue' , fontsize = 20)
plt.xticks(rotation = 90 , fontsize = 20)
plt.yticks(fontsize = 20)
plt.savefig('./images/q19.png')
plt.show()
```



0.1.35 Seasonal Trend Analysis from Heatmaps:

0.1.36 A. Category-Wise Seasonal Trends

Product Category	Peak Months	Observations
Nest-USA	Jan, Mar, May, Dec	Most dominant category throughout the year; peaks in winter & gifting season.
Apparel	Mar–May, Oct–Dec	Seasonal fashion shifts and festive sales.
Drinkware	May–Aug	Warm months driving hydration needs.
Gift Cards	Nov–Dec	Holiday gifting trend.
Office Supplies	Jan, Sept	New Year restock and back-to-school spikes.
Lifestyle, Bags	Nov–Dec	Likely tied to travel, holidays, and gifting.
Notebooks & Journals	Jan	New Year resolutions and productivity tools.

0.1.37 B. Location-Wise Seasonal Trends

Location	High Months	Insight
Chicago	Oct–Dec, Jan, Mar	Consistent strength; heavy end-of-year surge.

Location	High Months	Insight
California	Feb, May, Oct, Dec	Balanced across year; warm-weather state with summer interest.
New York	Feb, May, Nov–Dec	Peaks in gifting/festive months.
New Jersey	Apr–Jun	Subtle seasonal spring rise.
Washington DC	Feb, Dec	Spikes in winter, relatively low rest of the year.

0.1.38 Overall Trends:

- Q1 (Jan–Mar):
  - Strong for Nest-USA, Office, California, Chicago
  - Associated with renewal shopping: tech, productivity, restocks.
- Q2 (Apr–Jun):
  - Rising sales in Apparel, Drinkware, New Jersey, California
  - Spring fashion, summer essentials begin to pick up.
- Q3 (Jul–Sep):
  - Stable/Low across most categories.
  - Drinkware and some Apparel still active.
- Q4 (Oct–Dec):
  - Peak sales period
  - Strong across nearly all high-revenue categories and cities.
  - Fueled by holiday gifting, cold-weather products, seasonal promotions.

0.2 Strategic Recommendations:

1. Inventory Management
   - Stock high-demand SKUs for Q4 in Nest-USA, Apparel, Gift Cards, and Lifestyle.
   - Maintain Drinkware, Apparel stock for Q2-Q3 in California and New Jersey.

2. Targeted Regional Campaigns |Region | Strategy| |——-|———| |Chicago | Boost Q4 advertising, loyalty points, and holiday bundles.| |California | Push warm-weather items in Q2, year-round essentials.| |New York | Leverage fashion and holiday gifting in Q2 and Q4.| |Washington DC | Capitalize on end-of-year needs with tax-saving offers and gift campaigns.|

3. Seasonal Promotions

- Jan & Sept: Productivity (office), educational bundles.
- May–Aug: Summer essentials (drinkware, bags).
- Nov–Dec: Heavy holiday campaigns, including gift guides, combo deals, and flash sales.

4. Data-Driven Campaign Calendar

- Create a seasonal marketing calendar tied to actual category-location data:

  E.g., "Apparel Flash Sale – April in New York"

  "Nest Smart Home Bundles – December in Chicago"

0.2.1 Final Takeaway:

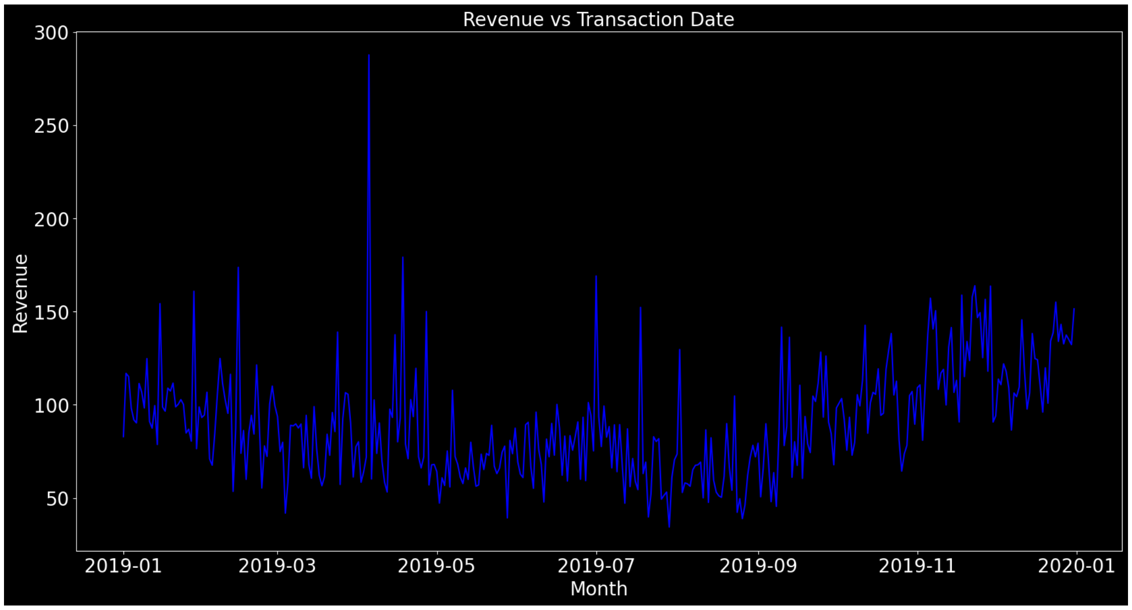
- The heatmaps clearly show seasonal and regional patterns.
- Strategic timing of inventory, ads, and category pushes can significantly maximize revenue across quarters.

0.2.2 Q.20 Analyze daily sales trends to identify high-performing and low-performing days. What strategies can be implemented to boost sales on slower days?

[1276]:
```
daily = taxm.groupby('transaction_date').agg({'revenue':'mean' , 'quantity':
 ↪'sum'}).reset_index().sort_values(by = 'transaction_date')
daily
```

[1276]:
```
    transaction_date     revenue  quantity
0         2019-01-01   82.926854       352
1         2019-01-02  116.856261       256
2         2019-01-03  115.141111       816
3         2019-01-04   98.245030       604
4         2019-01-05   91.921640      2392
..               …           …       …
360       2019-12-27  132.636796       278
361       2019-12-28  137.430250       114
362       2019-12-29  134.958090       121
363       2019-12-30  132.270000       121
364       2019-12-31  151.467463       112

[365 rows x 3 columns]
```

[1277]:
```
plt.figure(figsize = (20,10))
sns.lineplot(daily , x = 'transaction_date' , y = 'revenue')
plt.title('Revenue vs Transaction Date' , fontsize = 20)
plt.xlabel('Month' , fontsize = 20)
plt.ylabel('Revenue' , fontsize = 20)
plt.xticks(fontsize = 20)
plt.yticks(fontsize = 20)
plt.savefig('./images/q20.png')
plt.show()
```



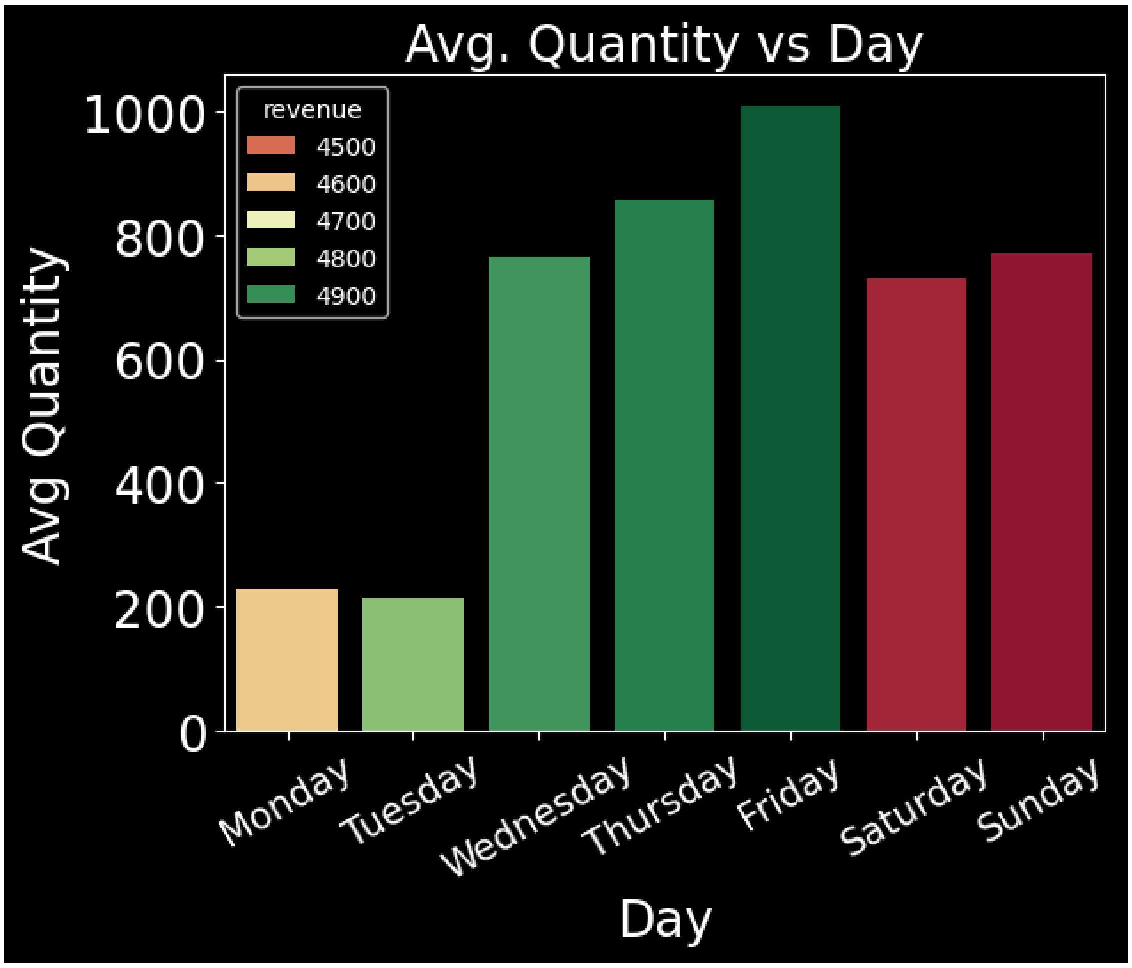
[1278]:
```
daily['day'] = daily['transaction_date'].dt.day_name()
daily['dayn'] = daily['transaction_date'].dt.day % 7
daily.head()
```

[1278]:
```
  transaction_date     revenue  quantity        day  dayn
0       2019-01-01   82.926854       352    Tuesday     1
1       2019-01-02  116.856261       256  Wednesday     2
2       2019-01-03  115.141111       816   Thursday     3
3       2019-01-04   98.245030       604     Friday     4
4       2019-01-05   91.921640      2392   Saturday     5
```

[1279]:
```
days = daily.groupby('day').agg({'revenue':'sum' , 'dayn':'first' , 'quantity':
 ↪'mean'}).reset_index().sort_values(by = 'dayn')
days
```

[1279]:
```
         day      revenue  dayn     quantity
1     Monday  4607.319405     0   230.442308
5    Tuesday  4824.332632     1   213.528302
6  Wednesday  4891.743028     2   765.326923
4   Thursday  4918.876878     3   855.423077
0     Friday  4966.266215     4  1008.326923
2   Saturday  4420.784028     5   730.096154
3     Sunday  4400.543669     6   770.307692
```

```
[1158]: sns.barplot(days , x = 'day' , y = 'quantity' , hue = 'revenue' , palette =␣
          ↪'RdYlGn')
        plt.xticks(rotation = 30 , fontsize = 15)
        plt.xlabel('Day' , fontsize = 20)
        plt.yticks(fontsize = 20)
        plt.ylabel('Avg Quantity' , fontsize = 20)
        plt.title('Avg. Quantity vs Day' , fontsize = 20)
        plt.savefig('./images/q20.1.png')
```



0.2.3 High-Performing Days:

- Friday: ~1008 units/day
- Thursday: ~855 units/day
- Wednesday: ~765 units/day
- These mid-to-late week days are the most productive for sales volume.

0.2.4 Low-Performing Days:

- Tuesday: ~214 units/day
- Monday: ~230 units/day
- Early-week days are consistently underperforming in terms of order quantity.

0.2.5 Strategic Recommendations to Boost Sales on Slower Days:

1. **Flash Sales or Daily Deals (Mon–Tues)**
   - Run “Monday Kickstart Deals” or “Tuesday Temptations” to drive urgency.
   - Offer time-limited discounts only valid on slower days.
2. **Personalized Email Campaigns**
   - Target dormant users with incentives early in the week:
   - Example: “Come back today and get 10% off – only this Tuesday!”
3. **Gamify Slow Days**
   - Use loyalty points multipliers or spin-the-wheel promos to incentivize weekday purchases.
4. **Free Shipping or Delivery Coupons**
   - Offer free shipping for orders placed on low-performing days.
5. **Marketing Spend Adjustment**
   - Shift a portion of online ad budget (e.g., Google Ads or Facebook retargeting) toward Mon–Tues.