Cohort Analysis

In this assignment our job is to perform a cohort analysis on the customers of the company. We will group the customers into cohorts that are groups sharing common charecteristics.

In [22]:
```
#loading the required packages

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
```

In [23]:
```
# Load the datasets
online_sales = pd.read_csv('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Online_
discount_coupons = pd.read_csv('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Di
tax_amount = pd.read_excel('C:\\Users\\sujoydutta\\Desktop\\Data analysis\\Projects\\Marketing insights\\Tax_am
```

In [24]:
```
# Merging datasets using 'CustomerID' as the common key
merged_data = pd.merge(online_sales, discount_coupons, on='Product_Category', how='left')
merged_data = pd.merge(merged_data, tax_amount, on='Product_Category', how='left')

merged_data.head()
```

Out[24]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_name	Product_Category	Quantity	Avg_Price	Delivery_Charges	Co
0	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
3	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
4	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	

In [25]:
```
#examining the merged dataset
merged_data.head()
```

Out[25]:

	CustomerID	Transaction_ID	Transaction_Date	Product_SKU	Product_name	Product_Category	Quantity	Avg_Price	Delivery_Charges	Co
0	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
1	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
2	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
3	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	
4	17850	16679	20190101	GGOENEBJ079499	Nest Learning Thermostat 3rd Gen-USA - Stainle...	Nest-USA	1	153.71	6.5	

In [26]:
```
#getting information of the dataset
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 630688 entries, 0 to 630687
Data columns (total 14 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   CustomerID        630688 non-null  int64  
 1   Transaction_ID    630688 non-null  int64  
 2   Transaction_Date  630688 non-null  int64  
 3   Product_SKU       630688 non-null  object 
 4   Product_name      630688 non-null  object 
 5   Product_Category  630688 non-null  object 
 6   Quantity          630688 non-null  int64  
 7   Avg_Price         630688 non-null  float64
 8   Delivery_Charges  630688 non-null  float64
 9   Coupon_Status     630688 non-null  object 
 10  Month             630288 non-null  object 
 11  Coupon_Code       630288 non-null  object 
 12  Discount_pct      630288 non-null  float64
 13  GST               630688 non-null  float64
dtypes: float64(4), int64(4), object(6)
memory usage: 72.2+ MB
```

In [27]:
```
# Calculating Invoice Value for each transaction in the merged dataset
merged_data['Invoice_Value'] = (
    (merged_data['Quantity'] * merged_data['Avg_Price']) *
    (1 - merged_data['Discount_pct']) *
    (1 + merged_data['GST']) +
    merged_data['Delivery_Charges']
).abs()
```

In [31]:
```
# Extracting relevant columns
cohort_data = merged_data[['CustomerID', 'Transaction_Date', 'Invoice_Value']]
cohort_data.head()
```

Out[31]:

	CustomerID	Transaction_Date	Invoice_Value
0	17850	20190101	1515.229
1	17850	20190101	3206.039
2	17850	20190101	4896.849
3	17850	20190101	1515.229
4	17850	20190101	3206.039

In [32]:
```
# Convert 'Transaction_Date' in DataFrame to datetime data type
cohort_data['Transaction_Date'] = pd.to_datetime(merged_data['Transaction_Date'], format='%Y%m%d')
cohort_data['Transaction_Date']
```

```
C:\Users\sujoydutta\AppData\Local\Temp\ipykernel_6844\4112860847.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  cohort_data['Transaction_Date'] = pd.to_datetime(merged_data['Transaction_Date'], format='%Y%m%d')
```

Out[32]:
```
0        2019-01-01
1        2019-01-01
2        2019-01-01
3        2019-01-01
4        2019-01-01
            ...    
630683   2019-12-31
630684   2019-12-31
630685   2019-12-31
630686   2019-12-31
630687   2019-12-31
Name: Transaction_Date, Length: 630688, dtype: datetime64[ns]
```

In [33]:
```
# Calculating the first purchase month for each customer
cohort_data['FirstPurchaseMonth'] = cohort_data.groupby('CustomerID')['Transaction_Date'].transform('min').dt.t
cohort_data['FirstPurchaseMonth']
```

```
C:\Users\sujoydutta\AppData\Local\Temp\ipykernel_6844\1830222443.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  cohort_data['FirstPurchaseMonth'] = cohort_data.groupby('CustomerID')['Transaction_Date'].transform('min').d
t.to_period('M')
```

Out[33]:
```
0         2019-01
1         2019-01
2         2019-01
3         2019-01
4         2019-01
           ...   
630683    2019-12
630684    2019-12
630685    2019-12
630686    2019-12
630687    2019-12
Name: FirstPurchaseMonth, Length: 630688, dtype: period[M]
```

In [34]:
```
# Getting the cohort index based on the number of months since the first purchase
cohort_data['CohortIndex'] = (
    (cohort_data['Transaction_Date'].dt.to_period('M') - cohort_data['FirstPurchaseMonth']).apply(lambda x: x.n
)
cohort_data['CohortIndex']
```

```
C:\Users\sujoydutta\AppData\Local\Temp\ipykernel_6844\747533931.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  cohort_data['CohortIndex'] = (
```

Out[34]:
```
0         1
1         1
2         1
3         1
4         1
         ..
630683    1
630684    1
630685    1
630686    1
630687    1
Name: CohortIndex, Length: 630688, dtype: int64
```

In [35]:
```
# Group the data by the first purchase month and cohort index
cohort_data = cohort_data.groupby(['FirstPurchaseMonth', 'CohortIndex']).agg(
    TotalCustomers=('CustomerID', 'nunique'),
    TotalRevenue=('Invoice_Value', 'sum')
).reset_index()
cohort_data.round()
```

Out[35]:

	FirstPurchaseMonth	CohortIndex	TotalCustomers	TotalRevenue
0	2019-01	1	215	101071550.0
1	2019-01	2	13	9882640.0
2	2019-01	3	24	11300315.0
3	2019-01	4	34	28921521.0
4	2019-01	5	23	7263371.0
...	...	...	...	...
73	2019-10	2	6	2390306.0
74	2019-10	3	4	682336.0
75	2019-11	1	68	53840226.0
76	2019-11	2	7	1102275.0
77	2019-12	1	106	61584100.0

78 rows × 4 columns

In [36]:
```
# Creating a pivot table to represent the cohort analysis
cohorts = cohort_data.pivot_table(
    index=['FirstPurchaseMonth'],
    columns='CohortIndex',
    values='TotalCustomers'
)
cohorts
```

Out[36]:

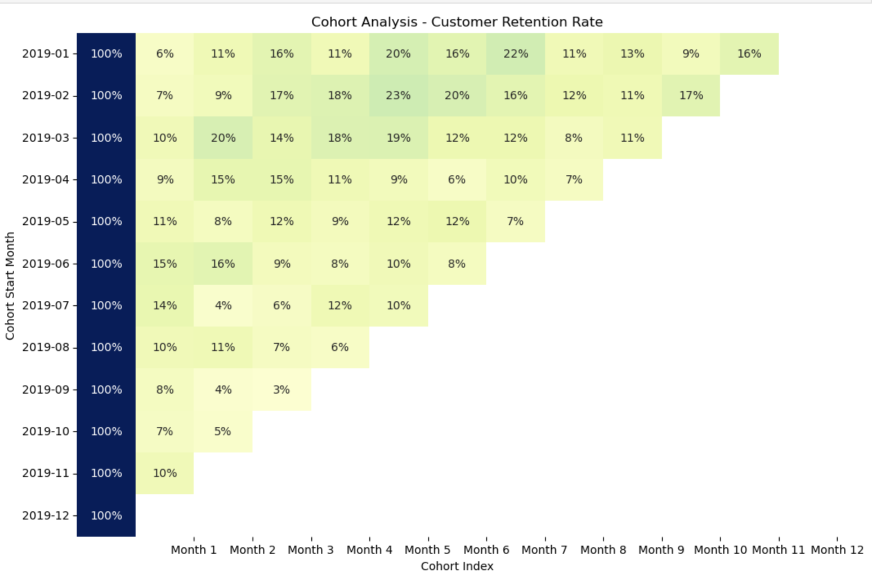
CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12
FirstPurchaseMonth												
2019-01	215.0	13.0	24.0	34.0	23.0	44.0	35.0	47.0	23.0	28.0	20.0	34.0
2019-02	96.0	7.0	9.0	16.0	17.0	22.0	19.0	15.0	12.0	11.0	16.0	NaN
2019-03	177.0	18.0	35.0	25.0	32.0	33.0	22.0	22.0	15.0	19.0	NaN	NaN
2019-04	163.0	14.0	24.0	24.0	18.0	15.0	10.0	16.0	12.0	NaN	NaN	NaN
2019-05	112.0	12.0	9.0	13.0	10.0	13.0	14.0	8.0	NaN	NaN	NaN	NaN
2019-06	137.0	20.0	22.0	12.0	11.0	14.0	11.0	NaN	NaN	NaN	NaN	NaN
2019-07	94.0	13.0	4.0	6.0	11.0	9.0	NaN	NaN	NaN	NaN	NaN	NaN
2019-08	135.0	14.0	15.0	10.0	8.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-09	78.0	6.0	3.0	2.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-10	87.0	6.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-11	68.0	7.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-12	106.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [37]:
```
# Calculating the retention rates for each cohort over time
cohort_size = cohorts.iloc[:, 0]
retention = cohorts.divide(cohort_size, axis=0)
retention
```

Out[37]:

CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12
FirstPurchaseMonth												
2019-01	1.0	0.060465	0.111628	0.158140	0.106977	0.204651	0.162791	0.218605	0.106977	0.130233	0.093023	0.15814
2019-02	1.0	0.072917	0.093750	0.166667	0.177083	0.229167	0.197917	0.156250	0.125000	0.114583	0.166667	NaN
2019-03	1.0	0.101695	0.197740	0.141243	0.180791	0.186441	0.124294	0.124294	0.084746	0.107345	NaN	NaN
2019-04	1.0	0.085890	0.147239	0.147239	0.110429	0.092025	0.061350	0.098160	0.073620	NaN	NaN	NaN
2019-05	1.0	0.107143	0.080357	0.116071	0.089286	0.116071	0.125000	0.071429	NaN	NaN	NaN	NaN
2019-06	1.0	0.145985	0.160584	0.087591	0.080292	0.102190	0.080292	NaN	NaN	NaN	NaN	NaN
2019-07	1.0	0.138298	0.042553	0.063830	0.117021	0.095745	NaN	NaN	NaN	NaN	NaN	NaN
2019-08	1.0	0.103704	0.111111	0.074074	0.059259	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-09	1.0	0.076923	0.038462	0.025641	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-10	1.0	0.068966	0.045977	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-11	1.0	0.102941	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2019-12	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [38]:
```
# Creating a heatmap to visualize cohort retention rates
plt.figure(figsize=(12, 8))
plt.title('Cohort Analysis - Customer Retention Rate')
sb.heatmap(retention, annot=True, fmt='.0%', cmap='YlGnBu', vmin=0, vmax=1, cbar=False)
plt.xticks(1 + retention.columns.values, [f'Month {i}' for i in range(1, len(retention.columns) + 1)])
plt.xlabel('Cohort Index')
plt.ylabel('Cohort Start Month')
plt.show()
```



In [39]:
```
# Remove rows with NaN values from the cohort table
cohort_data = cohort_data.dropna()

# Reset the index of the DataFrame
cohort_data.reset_index(drop=True, inplace=True)
```

In [40]:
```
#viewing the cleaned cohort data
cohort_data.round()
```

Out[40]:

	FirstPurchaseMonth	CohortIndex	TotalCustomers	TotalRevenue
0	2019-01	1	215	101071550.0
1	2019-01	2	13	9882640.0
2	2019-01	3	24	11300315.0
3	2019-01	4	34	28921521.0
4	2019-01	5	23	7263371.0
...	...	...	...	...
73	2019-10	2	6	2390306.0
74	2019-10	3	4	682336.0
75	2019-11	1	68	53840226.0
76	2019-11	2	7	1102275.0
77	2019-12	1	106	61584100.0

78 rows × 4 columns

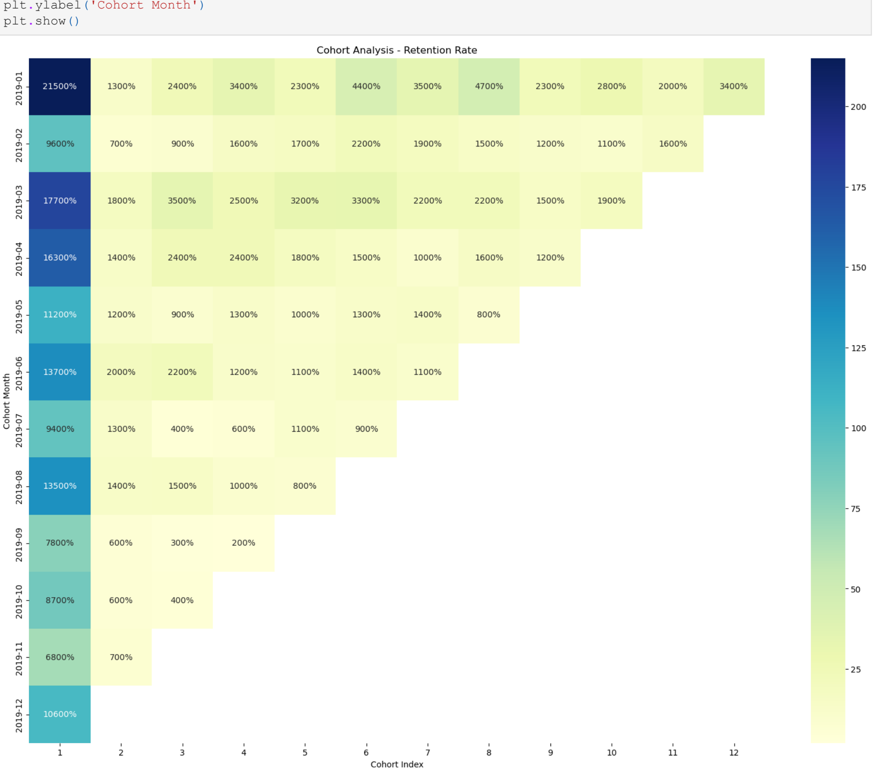
In [41]:
```
# Cohort metrics table
cohort_metrics = cohort_data.pivot_table(index=[ 'FirstPurchaseMonth'], columns='CohortIndex', values=['TotalCu


cohort_metrics
```

Out[41]:

	TotalCustomers										...				
CohortIndex	1	2	3	4	5	6	7	8	9	10	...	3	4	5	6
FirstPurchaseMonth															
2019-01	215.0	13.0	24.0	34.0	23.0	44.0	35.0	47.0	23.0	28.0	...	1.130031e+07	2.892152e+07	7.263371e+06	1.303335e+07
2019-02	96.0	7.0	9.0	16.0	17.0	22.0	19.0	15.0	12.0	11.0	...	3.185927e+06	5.464640e+06	5.901013e+06	1.044326e+07
2019-03	177.0	18.0	35.0	25.0	32.0	33.0	22.0	22.0	15.0	19.0	...	9.076607e+06	7.720443e+06	1.149867e+07	1.752918e+07
2019-04	163.0	14.0	24.0	24.0	18.0	15.0	10.0	16.0	12.0	NaN	...	4.195253e+06	7.428573e+06	6.280578e+06	7.573408e+06
2019-05	112.0	12.0	9.0	13.0	10.0	13.0	14.0	8.0	NaN	NaN	...	2.982523e+06	3.534678e+06	4.296835e+06	8.957424e+06
2019-06	137.0	20.0	22.0	12.0	11.0	14.0	11.0	NaN	NaN	NaN	...	3.194789e+06	3.781086e+06	2.510709e+06	9.131961e+06
2019-07	94.0	13.0	4.0	6.0	11.0	9.0	NaN	NaN	NaN	NaN	...	1.810631e+06	3.654439e+06	5.981508e+06	7.220105e+06
2019-08	135.0	14.0	15.0	10.0	8.0	NaN	NaN	NaN	NaN	NaN	...	2.741047e+06	7.144423e+06	4.141043e+06	NaN
2019-09	78.0	6.0	3.0	2.0	NaN	NaN	NaN	NaN	NaN	NaN	...	6.298675e+05	1.611835e+05	NaN	NaN
2019-10	87.0	6.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	6.823357e+05	NaN	NaN	NaN
2019-11	68.0	7.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN
2019-12	106.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN

12 rows × 24 columns

In [42]:
```
# Making a heatmap for retention rate
plt.figure(figsize=(20,15))
sb.heatmap(cohort_metrics['TotalCustomers'], annot=True, fmt='.0%', cmap='YlGnBu')
plt.title('Cohort Analysis - Retention Rate')
plt.xlabel('Cohort Index')
plt.ylabel('Cohort Month')
plt.show()
```



In [43]:
```
# Creating a heatmap for average revenue
plt.figure(figsize=(20, 10))
sb.heatmap(cohort_metrics['TotalRevenue'], annot=True, fmt='.0f', cmap='YlGnBu')
plt.title('Cohort Analysis - Average Revenue')
plt.xlabel('Cohort Index')
plt.ylabel('Cohort Month')
plt.show()
```

Remark: The first cohort is by far the best performing cohort in terms of retention rate and revenue.