FinalProjectPart3

August 5, 2024

1 BIA 678 - Final Project

Part 3

1. Who are our customers? Define the key segments of Instacart shoppers that emerge from clustering the customer data.

Consider behaviors, motivations, demographics, purchasing habits, lifestyle factors, and any other relevant attributes that distinguish customer groups. Identify 3-5 key segments.

2. What characterizes each segment?

For each key customer segment identified, dive deeper into analyzing:

- Common attributes of shoppers within the cluster (age, location, household profile, etc)
- Primary motivations and purchase drivers
- Frequency of orders, basket sizes, category preferences
- Brand affinity and loyalty patterns
- Channel and device preferences
- Price sensitivity and coupon usage

The goal is to paint a detailed, well-rounded profile of each segment.

3. How should we engage each segment?

For each key customer segment, provide concrete recommendations for marketing and engagement strategies based on their attributes, behaviors and motivations.

- What messages and channels will best resonate?

- What special offers or incentives would motivate purchases?
- How can the Instacart experience be tailored to their preferences?

Use both your data analysis and creative thinking to determine how to drive deeper connections with each segment.

4. What additional insights can Claude or Chatgpt unearth?

Leverage Claude's AI capabilities to uncover non-intuitive patterns, themes, behaviors or causal relationships related to the identified customer segments. What supplemental insights can Claude contribute beyond the student's analysis?

For each segment, they could ask ChatGPT or Claude follow-up questions like:

- What are some defining characteristics of this customer segment?

- What kind of purchasing patterns do they exhibit?
- What marketing strategies might resonate most with this segment?

ChatGPT and Claude can provide additional perspective by analyzing the data patterns for each cluster and offering insights into potential motivations, behaviors, and recommendations for engaging each segment.

Some sample prompts they could give ChatGPT or Claude include:

“Based on the purchasing data for customer segment X, what appears to motivate their purchases on Instacart? Provide 2-3 hypotheses.”

“For customer segment Y with [define key attributes of segment], what marketing strategies would you recommend to increase engagement?”

“Please analyze the purchasing patterns of customer segment Z and highlight any additional insights about how to cater offerings to appeal to this group.”

The goal is to enrich the analysis by leveraging ChatGPT and Claude to uncover deeper insights from the data that the students may have missed or not emphasized in their initial analysis. This allows them to better understand and engage key customer groups.

[1]:

```
# Import packages
import numpy as np
import pandas as pd

from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import plotly.express as px
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:

```
df_aisles = pd.read_csv('aisles.csv')
df_departments = pd.read_csv('departments.csv')
df_orders = pd.read_csv('orders.csv')
df_products = pd.read_csv('products.csv')
df_order_products = pd.read_csv('order_products__prior.csv')
```

[3]:

```
df_departments.head()
```

[3]:

```
   department_id department
0              1     frozen
1              2      other
2              3     bakery
3              4    produce
4              5    alcohol
```

[4]:

```
df_aisles.head()
```

[4]:

```
   aisle_id                       aisle
0         1       prepared soups salads
1         2           specialty cheeses
2         3         energy granola bars
3         4               instant foods
4         5  marinades meat preparation
```

[5]:

```
df_orders.head()
```

[5]:

```
   order_id  user_id eval_set  order_number  order_dow  order_hour_of_day  \
0   2539329        1    prior             1          2                  8
1   2398795        1    prior             2          3                  7
2    473747        1    prior             3          3                 12
3   2254736        1    prior             4          4                  7
4    431534        1    prior             5          4                 15

   days_since_prior_order
0                     NaN
1                    15.0
2                    21.0
3                    29.0
4                    28.0
```

[6]:

```
df_products.head()
```

[6]:

```
   product_id                                     product_name  aisle_id  \
0           1                       Chocolate Sandwich Cookies        61
1           2                                 All-Seasons Salt       104
2           3             Robust Golden Unsweetened Oolong Tea        94
3           4  Smart Ones Classic Favorites Mini Rigatoni Wit…        38
4           5                        Green Chile Anytime Sauce         5

   department_id
0             19
1             13
2              7
3              1
4             13
```

[7]:

```
df_order_products.head()
```

[7]:

```
   order_id  product_id  add_to_cart_order  reordered
0         2       33120                  1          1
1         2       28985                  2          1
2         2        9327                  3          0
3         2       45918                  4          1
4         2       30035                  5          0
```

[8]:
```python
temp = pd.merge(df_products, df_departments, on='department_id')
df_main = pd.merge(temp, df_aisles, on='aisle_id')
df_main.head()
```

[8]:
```
   product_id                                    product_name  aisle_id  \
0           1                      Chocolate Sandwich Cookies        61
1          78               Nutter Butter Cookie Bites Go-Pak        61
2         102                           Danish Butter Cookies        61
3         172  Gluten Free All Natural Chocolate Chip Cookies        61
4         285                    Mini Nilla Wafers Munch Pack        61

   department_id  department          aisle
0             19      snacks  cookies cakes
1             19      snacks  cookies cakes
2             19      snacks  cookies cakes
3             19      snacks  cookies cakes
4             19      snacks  cookies cakes
```

[11]:
```python
merged_order_products = pd.merge(df_order_products, df_main, on='product_id')
merged_order_products.head()
```

[11]:
```
   order_id  product_id  add_to_cart_order  reordered        product_name  \
0         2       33120                  1          1  Organic Egg Whites
1        26       33120                  5          0  Organic Egg Whites
2       120       33120                 13          0  Organic Egg Whites
3       327       33120                  5          1  Organic Egg Whites
4       390       33120                 28          1  Organic Egg Whites

   aisle_id  department_id  department aisle
0        86             16  dairy eggs  eggs
1        86             16  dairy eggs  eggs
2        86             16  dairy eggs  eggs
3        86             16  dairy eggs  eggs
4        86             16  dairy eggs  eggs
```

[12]:
```python
temp = df_orders.merge(df_order_products, on='order_id')
df_merged = temp.merge(df_main, on='product_id')
```

[13]:
```python
df_merged = df_merged[df_merged['eval_set'] == 'prior']
```

Recency

[14]:
```python
# Calculate recency as the number of days since the last order for each user
recency_df = df_merged.groupby('user_id')['days_since_prior_order'].mean().
 ↪reset_index()
recency_df.columns = ['user_id', 'recency']
recency_df.head()
```

[14]:

```
   user_id    recency
0        1  20.259259
1        2  15.967033
2        3  11.487179
3        4  15.357143
4        5  14.500000
```

Monetary

[15]:

```
quantity = df_merged.groupby('user_id').size().reset_index(name='no_products')
print(quantity.head())
```

```
   user_id  no_products
0        1           59
1        2          195
2        3           88
3        4           18
4        5           37
```

[16]:

```
full_orders = df_merged.merge(quantity, on='user_id', how='left')
print(full_orders.head())
```

```
   order_id  user_id eval_set  order_number  order_dow  order_hour_of_day  \
0   2539329        1    prior             1          2                  8
1   2398795        1    prior             2          3                  7
2    473747        1    prior             3          3                 12
3   2254736        1    prior             4          4                  7
4    431534        1    prior             5          4                 15

   days_since_prior_order  product_id  add_to_cart_order  reordered  \
0                     NaN         196                  1          0
1                    15.0         196                  1          1
2                    21.0         196                  1          1
3                    29.0         196                  1          1
4                    28.0         196                  1          1

  product_name  aisle_id  department_id department        aisle  no_products
0         Soda        77              7  beverages  soft drinks           59
1         Soda        77              7  beverages  soft drinks           59
2         Soda        77              7  beverages  soft drinks           59
3         Soda        77              7  beverages  soft drinks           59
4         Soda        77              7  beverages  soft drinks           59
```

[17]:

```
quantity_items = full_orders.groupby('user_id')['no_products'].sum().
  ↪reset_index(name='monetary')
print(quantity_items.describe())
```

```
             user_id      monetary
count  206209.000000  2.062090e+05
mean   103105.000000  6.644075e+04
```

```
std     59527.555167  2.265653e+05
min         1.000000  9.000000e+00
25%     51553.000000  1.521000e+03
50%    103105.000000  6.889000e+03
75%    154657.000000  3.534400e+04
max    206209.000000  1.387562e+07
```

Frequency

[18]:

```
frequency = df_merged.groupby('user_id')['order_id'].count()
frequency = frequency.reset_index()
frequency.columns = ['user_id', 'frequency']
frequency.head()
```

[18]:

```
   user_id  frequency
0        1         59
1        2        195
2        3         88
3        4         18
4        5         37
```

[19]:

```
# Merge RFM metrics into a single DataFrame
rfm = recency_df.merge(frequency, on='user_id').merge(quantity_items,␣
 ↪on='user_id')

# Assign RFM quartiles
rfm['R_quartile'] = pd.qcut(rfm['recency'], 4, ['4','3','2','1'])
rfm['F_quartile'] = pd.qcut(rfm['frequency'].rank(method='first'), 4,␣
 ↪['1','2','3','4'])
rfm['M_quartile'] = pd.qcut(rfm['monetary'], 4, ['1','2','3','4'])

# Calculate RFM score
rfm['RFM_Score'] = rfm.R_quartile.astype(str) + rfm.F_quartile.astype(str) +␣
 ↪rfm.M_quartile.astype(str)

rfm.head()
```

[19]:

```
   user_id    recency  frequency  monetary R_quartile F_quartile M_quartile  \
0        1  20.259259         59      3481          2          2          2
1        2  15.967033        195     38025          2          4          4
2        3  11.487179         88      7744          3          3          3
3        4  15.357143         18       324          2          1          1
4        5  14.500000         37      1369          3          1          1

  RFM_Score
0       222
1       244
2       333
```

```
3        211
4        311
```

[20]:

```
# Calculate percentiles
recency_threshold = rfm['recency'].quantile(0.90)
frequency_threshold = rfm['frequency'].quantile(0.90)
monetary_threshold = rfm['monetary'].quantile(0.90)

print(f"Recency Threshold: {recency_threshold}")
print(f"Frequency Threshold: {frequency_threshold}")
print(f"Monetary Threshold: {monetary_threshold}")

bad_customers = rfm[
    (rfm['recency'] >= recency_threshold) &
    (rfm['frequency'] <= frequency_threshold) &
    (rfm['monetary'] <= monetary_threshold)
]

print(bad_customers)
```

```
Recency Threshold: 26.097560975609756
Frequency Threshold: 386.0
Monetary Threshold: 148996.0
        user_id    recency  frequency  monetary R_quartile F_quartile  \
7             8  30.000000         49      2401          1          2
11           12  26.169014         74      5476          1          2
24           25  30.000000         21       441          1          1
32           33  28.700000         53      2809          1          2
40           41  26.314815         65      4225          1          2
…           …         …          …         …          …          …
206169   206170  26.113208         67      4489          1          2
206171   206172  28.100000         28       784          1          1
206172   206173  30.000000         18       324          1          1
206187   206188  27.307692         63      3969          1          2
206202   206203  29.103093        119     14161          1          3

       M_quartile RFM_Score
7               2       122
11              2       122
24              1       111
32              2       122
40              2       122
…             …         …
206169          2       122
206171          1       111
206172          1       111
206187          2       122
206202          3       133
```

```
[20620 rows x 8 columns]
```

Normalize the RFM

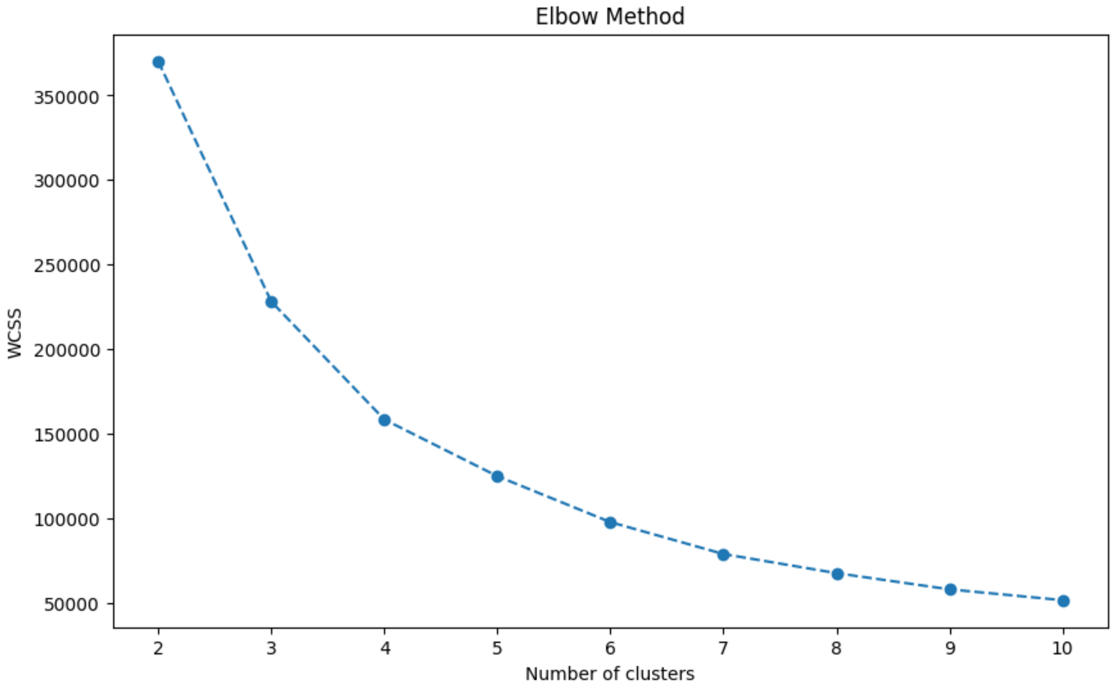
[21]:
```
scaler = StandardScaler()
```

[22]:
```
rfm_normalized = rfm[['recency', 'frequency', 'monetary']]
rfm_normalized = scaler.fit_transform(rfm_normalized)
rfm_normalized = pd.DataFrame(rfm_normalized)
rfm_normalized.head()
```

[22]:
```
          0         1         2
0  0.664536 -0.481321 -0.277889
1  0.069007  0.184668 -0.125420
2 -0.552554 -0.339308 -0.259073
3 -0.015613 -0.682097 -0.291823
4 -0.134538 -0.589054 -0.287210
```

[23]:
```
ssd = []
for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=100, n_init=10,␣
 ↪random_state=42)
    kmeans.fit(rfm_normalized)
    ssd.append(kmeans.inertia_)

print(ssd)
plt.figure(figsize=(10, 6))
plt.plot(range(2, 11), ssd, marker='o', linestyle='--')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```

```
[370322.70615242654, 228145.91356135975, 158385.00706322378, 124850.9966116589,
97677.36165405795, 78799.28059761126, 67497.22382892345, 57903.54291209088,
51506.45996736195]
```



[24]:
```
rfm_normalized.columns = ['recency', 'frequency', 'monetary']
```

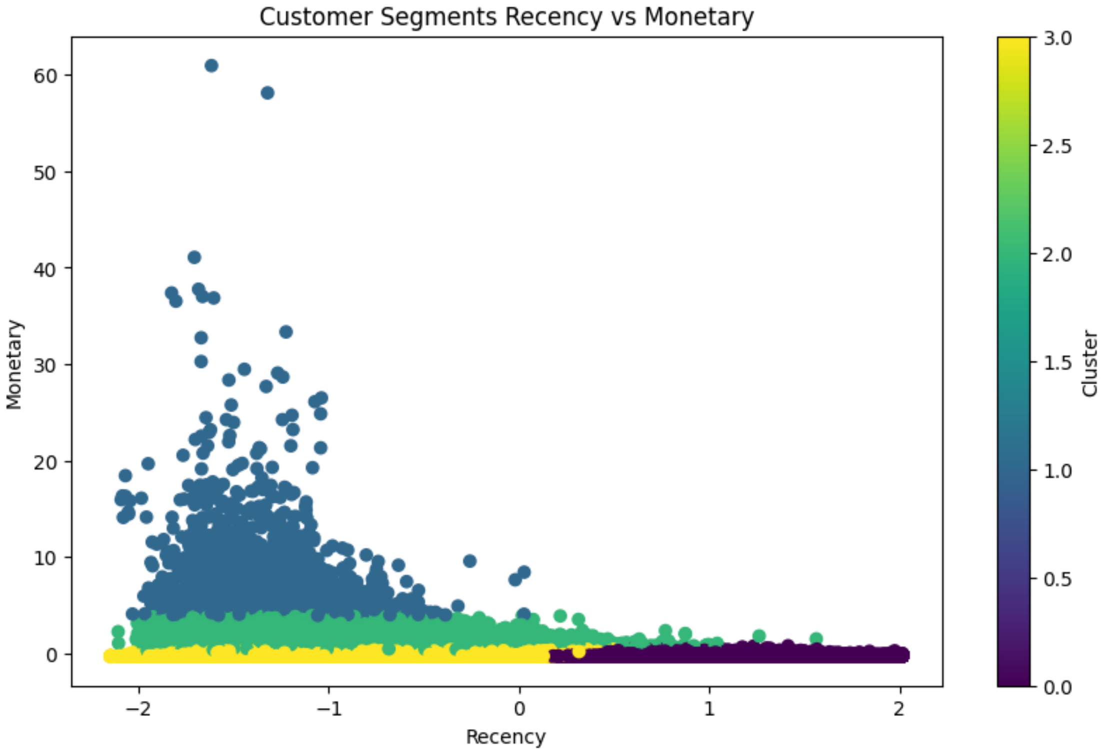
[25]:
```
kmeans = KMeans(n_clusters=4, max_iter=300, n_init=10, random_state=42)
kmeans.fit(rfm_normalized)
rfm_normalized.loc[:,'user_id'] = rfm['user_id']
rfm_normalized.head()
```

[25]:
```
    recency  frequency  monetary  user_id
0  0.664536  -0.481321 -0.277889        1
1  0.069007   0.184668 -0.125420        2
2 -0.552554  -0.339308 -0.259073        3
3 -0.015613  -0.682097 -0.291823        4
4 -0.134538  -0.589054 -0.287210        5
```

[26]:
```
rfm_normalized['cluster'] = kmeans.labels_
```

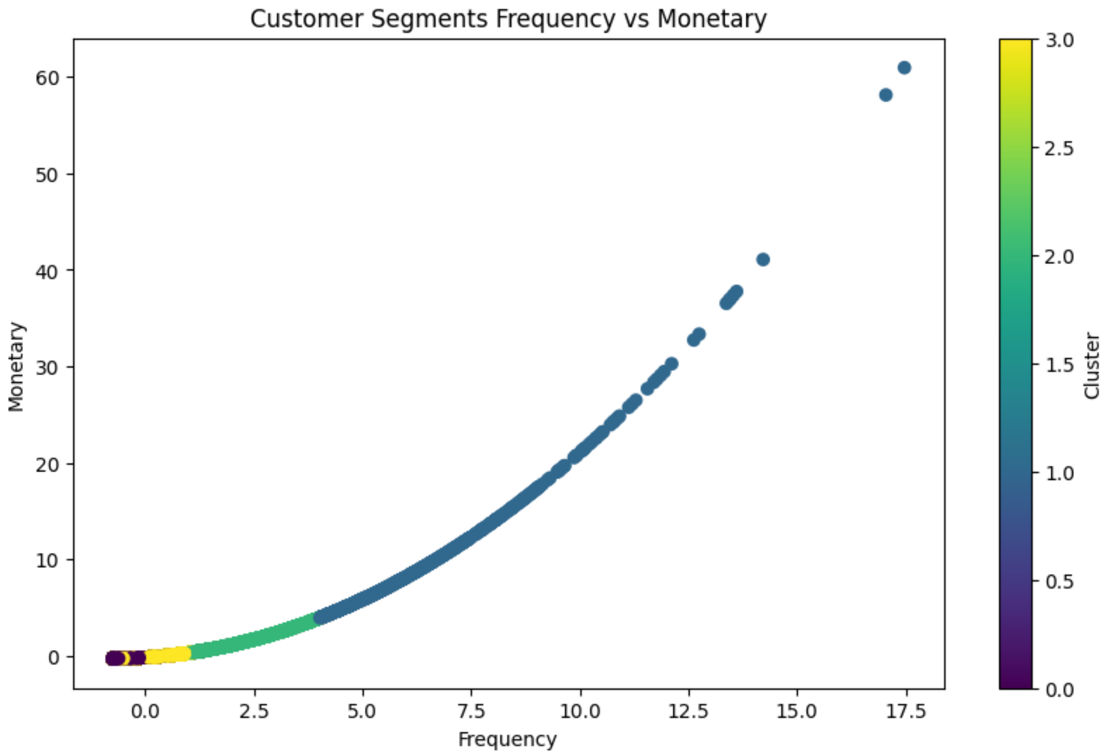
Monetary vs recency Cluster

[27]:
```
plt.figure(figsize=(10, 6))
plt.scatter(rfm_normalized['recency'], rfm_normalized['monetary'],␣
  ↪c=rfm_normalized['cluster'], cmap='viridis')
plt.xlabel('Recency')
plt.ylabel('Monetary')
plt.title('Customer Segments Recency vs Monetary')
plt.colorbar(label='Cluster')
plt.show()
```



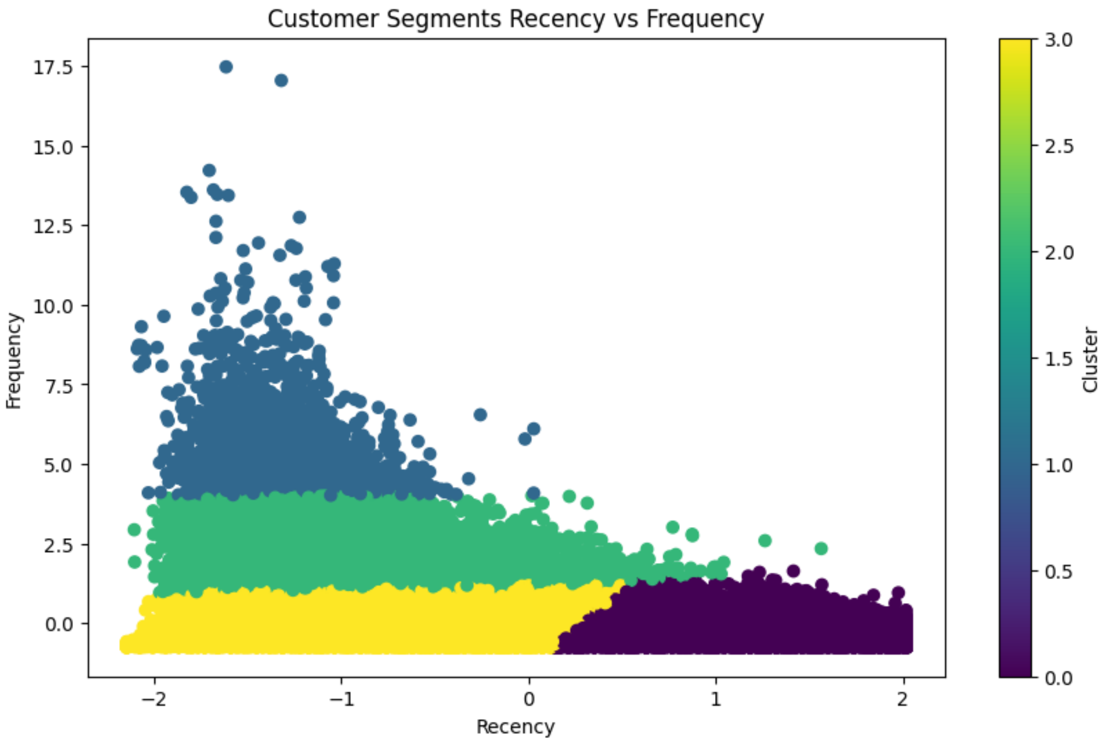
[28]:

```
plt.figure(figsize=(10, 6))
plt.scatter(rfm_normalized['frequency'], rfm_normalized['monetary'],␣
 ↪c=rfm_normalized['cluster'], cmap='viridis')
plt.xlabel('Frequency')
plt.ylabel('Monetary')
plt.title('Customer Segments Frequency vs Monetary')
plt.colorbar(label='Cluster')
plt.show()
```



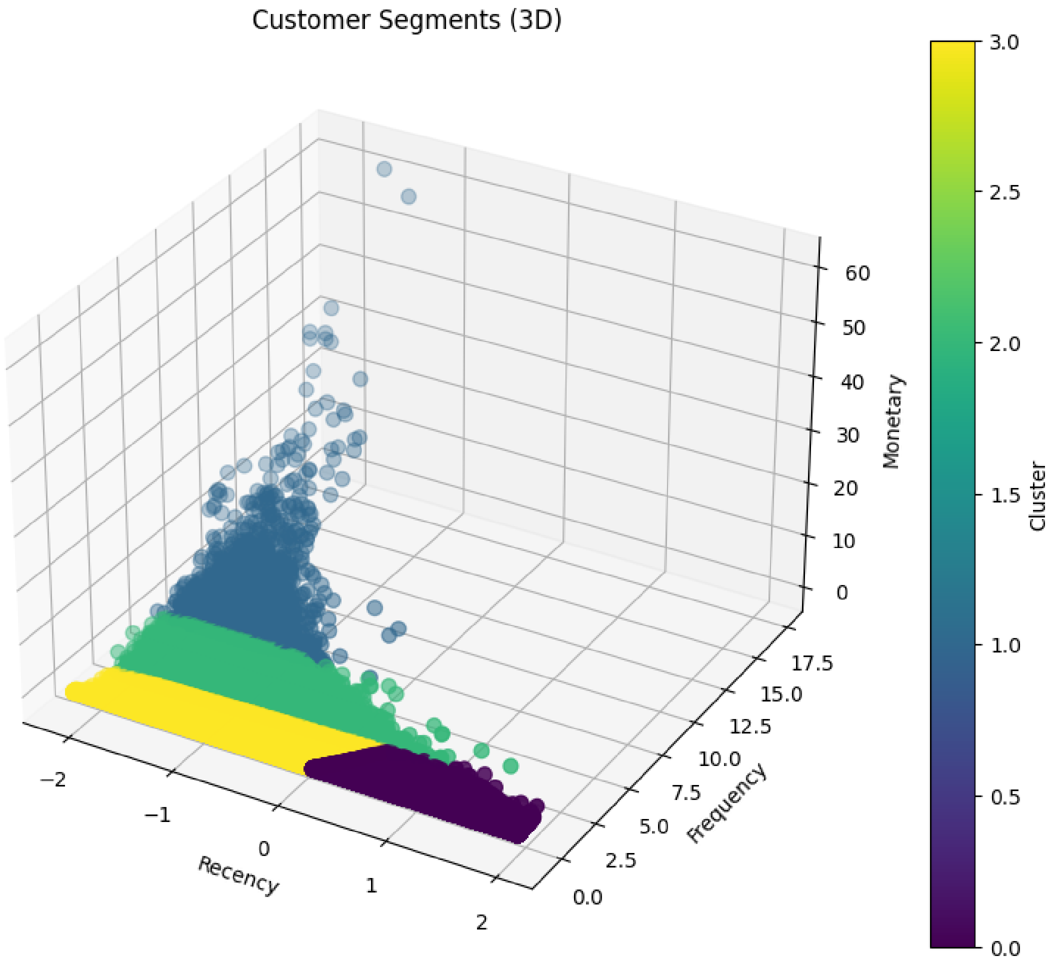
[29]:

```
plt.figure(figsize=(10, 6))
plt.scatter(rfm_normalized['recency'], rfm_normalized['frequency'],␣
  ↪c=rfm_normalized['cluster'], cmap='viridis')
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.title('Customer Segments Recency vs Frequency')
plt.colorbar(label='Cluster')
plt.show()
```



[52]:

```
fig = plt.figure(figsize=(12, 8))
ax = fig.add_subplot(111, projection='3d')

sc = ax.scatter(rfm_normalized['recency'], rfm_normalized['frequency'],␣
 ↪rfm_normalized['monetary'],
                c=rfm_normalized['cluster'], cmap='viridis', s=50)

ax.set_xlabel('Recency')
ax.set_ylabel('Frequency')
ax.set_title('Customer Segments (3D)')
ax.set_zlabel('Monetary')
plt.colorbar(sc, ax=ax, label='Cluster')
plt.show()
```



This scatter plot represents the recency vs monetary. The following observations are:

Cluster 0 (Blue)

- Consists of customers with lower recency while having higher monetary and frequency values. These customers indicate that these customers have occasional shopping events but typically spend a more than a usual customer.
- These customers are High-value, low recent customers. Instacart can reach out to them via email/messages as they aren't typically using the service often. Reaching out directly to their personal channels is a great way to entice them
- Instacart can provide heavy discounts to entice these customers to not only visit more often but also provide a good experience for the customers who like to spend a lot at Instacart.
- Additional Insights from ChatGPT
  - Messages and Channels:
    - Channels: Email, in-app notifications, personalized landing pages.

    - Messages: Messages such as “We miss you! Come back for your favorite premium items” or “Exclusive offer for our top customers – we value your loyalty!” Emphasize appreciation for their past high-value purchases and encourage them to return.
  - Special Offers or Incentives:
    - VIP Programs: Introduce a VIP loyalty program with tiered rewards to entice them to return and maintain their high-value shopping habits. Offer exclusive benefits like early access to sales, special discounts, and personalized promotions.
    - Personal Shopper: Offer a personal shopper service to provide a more tailored and convenient shopping experience. Include exclusive access to premium products, ensuring they can easily find and purchase high-quality items.
  - Tailored Instacart Experience:
    - Premium Experience: Ensure a seamless and premium shopping experience with priority support, making them feel valued and special. Implement a dedicated customer support line or chat for VIP customers.
    - Tailored Content: Provide personalized content and product recommendations based on their previous high-value purchases. Use their shopping history to suggest new or similar premium products they might enjoy. Send personalized shopping lists, recipes, and exclusive content that align with their preferences and shopping behavior.

Cluster 1 (Yellow)

- Mostly spread across a range of Recency values but remains at low Monetary values. This segment may include customers with varied recency who consistently spend very little.
- Similar to customers from the blue clusters, we can provide a series of channels and messages via email, messages, in-app notifications to give customers updates on coupons and discounts.
- Regard, special offers and incentive, Instacart can cater their bundle discounts, bulk discounts, or even packaged deals (ie. 2 for 1, 2 for 50% off) to increase the users’ usage rate as well as increasing the size of their carts/basket.

- To tailore the experience for these customers, Instacart can reach out to the customers and provide them savings opportunity and design the user experience to help guide and persuade the users to buy on Instacart more.
- Additional Insights from ChatGPT
  - Messages and Channels:
    - Channels: Email, in-app notifications, and direct mail.
    - Messages: Emphasize value and savings, such as “Save on your favorites!” or “Exclusive deals for you.”
  - Special Offers or Incentives:
    - Bundle Deals: Offer discounts on bundle purchases to increase order size.

        - Referral Bonuses: Provide incentives for referring friends (e.g., 10 off for both parties).
    - Tailored Instacart Experience:
        - Budget-Friendly Options: Highlight cost-effective alternatives and bulk purchase options.
        - Savings Alerts: Notify them of sales and discounts on items they frequently purchase.

- Cluster 2 (Green)
    - These customers are located mostly at moderate to higher Recency values with slightly higher Monetary values than Cluster 1 (Yellow). These customers haven't purchased recently but have a higher spending history than cluster 1, indicating potential value if correct actions are taken to market towards these customers. Similar actions can be taken with the previous clusters such as the discounts for bulk items like cluster 1 or bigger discounts for single items like Cluster 0 to entice customers to return to using Instacart.
    - Additional Insights from ChatGPT
        - Messages and Channels:
            - Channels: Email, push notifications, and social media.
            - Messages: Highlight product variety and quality, such as "Discover new products!" or "Curated picks for you."
        - Special Offers or Incentives:
            - Exclusive Access: Provide early access to sales and new product launches.
            - Membership Benefits: Promote a premium membership that offers additional discounts and perks.
        - Tailored Instacart Experience:
            - Personalized Offers: Use their purchase history to offer personalized discounts on items they like.
            - Subscription Services: Encourage subscribing to regular deliveries for frequently bought items.

Cluster 4 (Purple)

- Cluster 4 customers are concentrated at higher Recency values (close to or above zero) and very low Monetary values. These customers have make more recent purchases than the other customers but have low spending. These customers, while spending little amounts everytime they use Instacart, can still be great for Instacart since they are using the service more often than the other clusters of customers.
- To engage with these customers, Instacart can send messages/emails to these customers to thank them for their loyalty and continued usage. Furthermore, these can be sent through the app's notifications to since the users are most likely using the app often to make their purchases.

- Instacart can provide special Offers or incentives can include loyalty programs with exclusive benefit, early access to new products or sales and personalized discounts or offers. Since these customers aren't here to shop often, Instacart can give them a bigger discount for the high amount of items and monetary spend.

- Instacart can tailor the customer experience by providing personalized shopping experiences with specific recommendations, give customers a priority in the delivery queue, or invitations to provide feedback for customer support and future marketing materials.
- Additional Insights from ChatGPT
  - Messages and Channels:
    - Channels: Email, in-app notifications, personalized landing pages.
    - Messages: Focus on appreciation and exclusivity, such as "Thank you for being a loyal customer!" or "Exclusive offer for our top customers."
  - Special Offers or Incentives:
    - VIP Programs: Introduce a VIP loyalty program with tiered rewards.
    - Personal Shopper: Offer a personal shopper service or exclusive access to premium products.
  - Tailored Instacart Experience:
    - Premium Experience: Ensure a seamless and premium shopping experience with priority support.
    - Tailored Content: Provide personalized content and product recommendations based on their high-value purchases.

Segmenting by departments

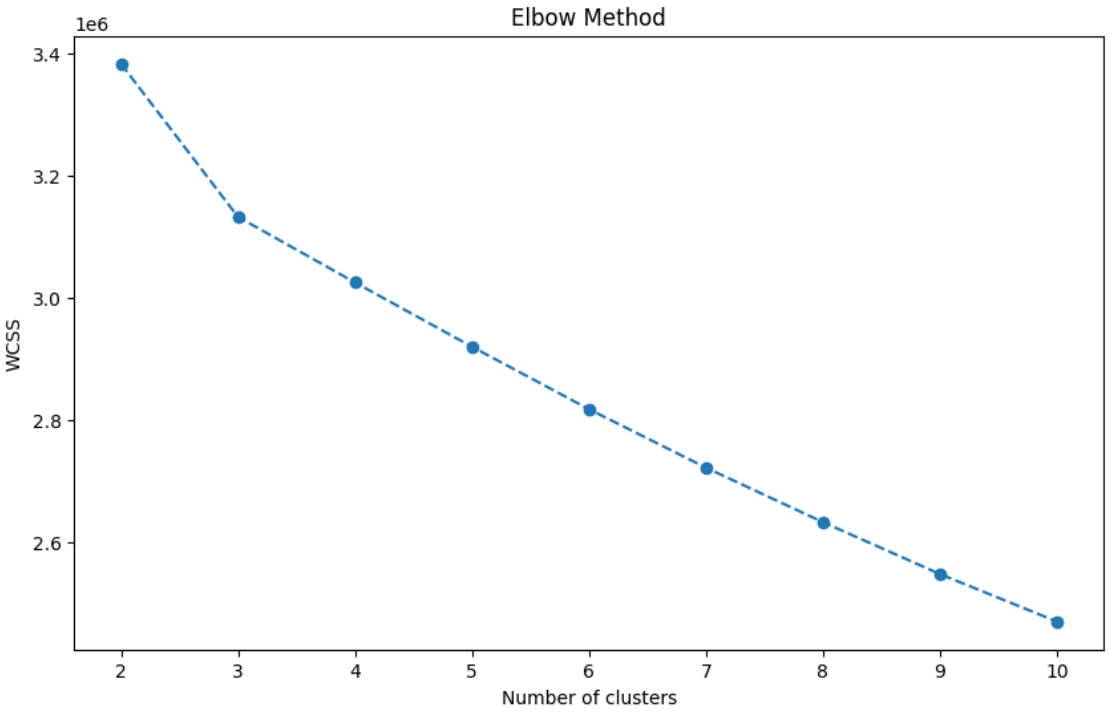
[31]:
```
user_by_department_df = pd.crosstab(df_merged['user_id'],␣
 ↪df_merged['department'])
user_by_department_df.head()
```

[31]:
```
department  alcohol  babies  bakery  beverages  breakfast  bulk  canned goods  \
user_id
1                 0       0       0         13          3     0             0
2                 0       0       2          9          3     0             1
3                 0       0       0          3          0     0             0
4                 2       0       2          3          0     0             1
5                 0       0       0          0          0     0             1

department  dairy eggs  deli  dry goods pasta  …  household  international  \
user_id                                        …
1                   13     0                0  …          2              0
2                   48    21                0  …          0              3
3                   21     2                4  …          1              0
4                    0     2                0  …          2              0
5                    8     1                1  …          0              2
```

```
department  meat seafood  missing  other  pantry  personal care  pets  \
user_id
1                      0        0      0       1              0     0
2                      1        0      0      11              1     0
3                      0        0      0       4              0     0
4                      0        0      0       0              0     0
5                      0        0      0       2              0     0

department  produce  snacks
user_id
1                 5      22
2                36      42
3                38       9
4                 2       1
5                19       1

[5 rows x 21 columns]
```

[32]:

```
scaler = StandardScaler()
scaled_df = scaler.fit_transform(user_by_department_df)
scaled_df = pd.DataFrame(scaled_df)



# Determine the optimal number of clusters using the Elbow method
sse = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, max_iter=300, random_state=42, n_init=10)
    kmeans.fit(scaled_df)
    sse.append(kmeans.inertia_)

# Plot the SSE to find the elbow point
plt.figure(figsize=(10, 6))
plt.plot(range(2, 11), sse, marker='o', linestyle='--')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



[38]:

```
kmeans = KMeans(n_clusters=5, max_iter=300, random_state=42, n_init=10)
kmeans.fit_predict(ps)
```

[38]:

```
array([3, 0, 3, …, 0, 2, 3], dtype=int32)
```

[39]:

```
user_by_department_df['cluster'] = kmeans.labels_
user_by_department_df.head(20)
```

[39]:

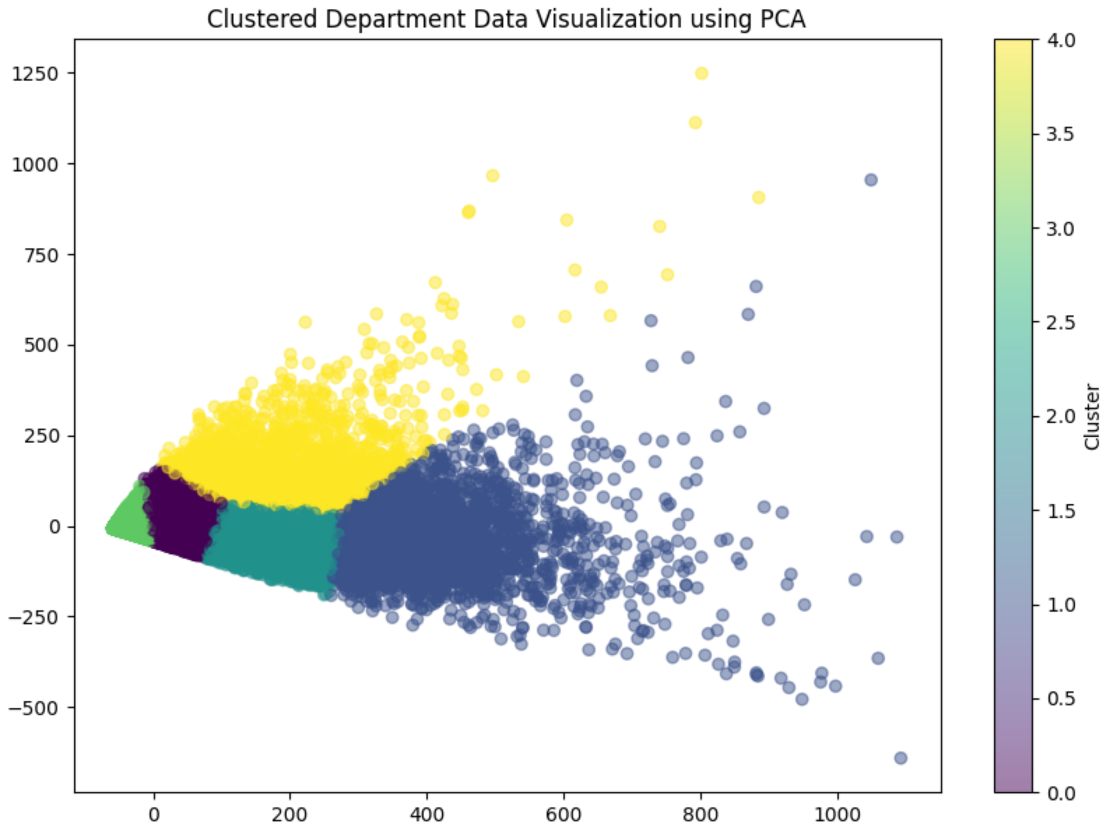
```
department  alcohol  babies  bakery  beverages  breakfast  bulk  canned goods  \
user_id
1                 0       0       0         13          3     0             0
2                 0       0       2          9          3     0             1
3                 0       0       0          3          0     0             0
4                 2       0       2          3          0     0             1
5                 0       0       0          0          0     0             1
6                 0       0       0          0          0     0             3
7                 0       0       5         51          0     0             6
8                 0       0       0          0          0     0             5
9                 0       6       4          8          3     0             1
10                0       0       0          0          0     0             2
11                0       0       4         19          0     0             5
12                0       0       2          3          1     0             2
13                0       0      14          2          2     0             5
14               13       0      14          2          2     0            11
```

```
15                0       0       0         20          0     0             0
16                0       0       0          0          1     0             0
17               35       0      10         59          5     0            12
18                0       0       0          6          0     0             0
19                0       0      11         26          3     0            12
20                0       0       0          0          0     0             0

department  dairy eggs  deli  dry goods pasta  …  international  \
user_id                                        …
1                   13     0                0  …              0
2                   48    21                0  …              3
3                   21     2                4  …              0
4                    0     2                0  …              0
5                    8     1                1  …              2
6                    2     0                0  …              0
7                   32    13                0  …              0
8                   12     0                1  …              1
9                   24     3                0  …              0
10                  16    15                0  …              1
11                  23     8                0  …              1
12                   8     2                2  …              0
13                  27     0                3  …              1
14                  12     5                9  …              3
15                   0     0                0  …              0
16                   6     0                2  …              0
17                  44     7                5  …              0
18                   5     2                1  …              0
19                  28     5                8  …              1
20                   0     0                0  …              0

department  meat seafood  missing  other  pantry  personal care  pets  \
user_id
1                      0        0      0       1              0     0
2                      1        0      0      11              1     0
3                      0        0      0       4              0     0
4                      0        0      0       0              0     0
5                      0        0      0       2              0     0
6                      2        0      0       1              0     0
7                      8        0      0       9              0     1
8                      0        0      0       3              0     0
9                      1        0      0       4              0     0
10                    13        0      0      22              0     0
11                     0        1      1      11              0     0
12                     1        0      0       8              2    12
13                     0        5      0       2              0     0
14                     2        1      6      51              0     0
15                     0        0      0       0              0     0
```

```
16                     1        0      0       1              0     0
17                     0        0      0      30              0     0
18                     1        0      0       4              3     0
19                     6        0      0      24             17     0
20                     0        0      0       0              0     0

department  produce  snacks  cluster
user_id
1                 5      22        3
2                36      42        0
3                38       9        3
4                 2       1        3
5                19       1        3
6                 6       0        3
7                57      19        0
8                27       0        3
9                 7      13        3
10               72       1        0
11               11       0        3
12               24       5        3
13               17       3        3
14               32       3        3
15                0      51        3
16               44       7        3
17               14       6        0
18               16       1        3
19                4       9        3
20               11      11        3

[20 rows x 22 columns]
```

[44]:

```
# Apply PCA to reduce dimensions to 2D for visualization
pca = PCA(n_components=2)
pca_samples = pca.fit_transform(user_by_department_df)
ps = pd.DataFrame(pca_samples)
ps.head()

# Plot the clusters
plt.figure(figsize=(10, 7))
scatter = plt.scatter(pca_samples[:, 0], pca_samples[:, 1],␣
  ↪c=user_by_department_df['cluster'], cmap='viridis', alpha=0.5)
plt.title('Clustered Department Data Visualization using PCA')
plt.colorbar(scatter, label='Cluster')
plt.show()
```



```
[45]: c0 = user_by_department_df[user_by_department_df['cluster']==0].
       ↪drop('cluster',axis=1).mean()
      c1 = user_by_department_df[user_by_department_df['cluster']==1].
       ↪drop('cluster',axis=1).mean()
      c2 = user_by_department_df[user_by_department_df['cluster']==2].
       ↪drop('cluster',axis=1).mean()
      c3 = user_by_department_df[user_by_department_df['cluster']==3].
       ↪drop('cluster',axis=1).mean()
      c4 = user_by_department_df[user_by_department_df['cluster']==4].
       ↪drop('cluster',axis=1).mean()
```

```
[46]: c0.sort_values(ascending=False)[0:10]
```

```
[46]: department
      produce          69.420062
      dairy eggs       40.304421
      snacks           20.938774
      beverages        19.572870
      frozen           17.313947
      pantry           14.097011
```

```
bakery                8.787184
canned goods          8.201348
deli                  7.948510
dry goods pasta       6.605519
dtype: float64
```

```
[47]: c1.sort_values(ascending=False)[0:10]
```

```
[47]: department
      produce            392.687300
      dairy eggs         170.382337
      snacks              72.721718
      frozen              52.944237
      pantry              52.151281
      beverages           50.613127
      bakery              34.561900
      canned goods        31.604055
      deli                31.449573
      dry goods pasta     25.975720
      dtype: float64
```

```
[48]: c2.sort_values(ascending=False)[0:10]
```

```
[48]: department
      produce            186.209473
      dairy eggs          77.879742
      snacks              32.415498
      frozen              27.593623
      beverages           26.678700
      pantry              26.591554
      canned goods        16.520656
      bakery              15.853913
      deli                15.629723
      dry goods pasta     12.679696
      dtype: float64
```

```
[49]: c3.sort_values(ascending=False)[0:10]
```

```
[49]: department
      produce         14.908235
      dairy eggs       9.731931
      beverages        6.570938
      snacks           6.068310
      frozen           5.133971
      pantry           4.068359
      bakery           2.372013
      canned goods     2.192443
```

```
household        2.180075
deli             2.044169
dtype: float64
```

```
[50]: c4.sort_values(ascending=False)[0:10]
```

```
[50]: department
      dairy eggs    162.728482
      produce       121.575408
      snacks        108.269260
      beverages      94.950565
      frozen         51.588959
      pantry         37.713425
      bakery         31.734504
      deli           24.625345
      breakfast      23.130991
      household      18.287578
      dtype: float64
```

1.0.1 Cluster 0

Persona Description Based on Cluster of Shoppers Sorted by Departments

Persona: Health-Conscious Convenience Seeker Demographics:

- Age: 25-45
- Gender: Mixed, with a slight skew towards females
- Income Level: Middle to upper-middle class
- Location: Urban and suburban areas
- Household Composition: Families with children, single professionals, and health-conscious couples

Shopping Behavior:

- Primary Focus: Fresh produce, dairy, and healthy snacks
- Shopping Frequency: Regular, with weekly or bi-weekly shopping trips
- Basket Size: Medium to large, with a diverse range of items
- Preferred Shopping Time: Weekends and evenings

Motivations and Values:

- Health and Wellness: Prioritizes fresh, natural, and organic products
- Convenience: Balances health-conscious choices with convenience items for a busy lifestyle
- Quality: Willing to pay a premium for high-quality and specialty items
- Sustainability: Cares about eco-friendly packaging and sustainable sourcing

Marketing and Engagement Strategies: Messages and Channels:

- Channels: Email newsletters, mobile app notifications, social media (especially Instagram and Pinterest), and influencer partnerships

- Messages: Focus on health benefits, convenience, and quality. Use phrases like “Fresh and healthy choices delivered to your door,” “Discover the best organic produce,” and “Quick and nutritious meals for your busy life.”

Special Offers or Incentives:

- Discounts on Fresh Produce: Offer discounts or bundles on fresh fruits and vegetables.
- Loyalty Programs: Introduce a rewards program for frequent shoppers, offering points for every purchase that can be redeemed for discounts or exclusive products.
- Personalized Recommendations: Provide personalized product recommendations based on their purchase history, emphasizing new and seasonal items.

Tailored Instacart Experience: * Customized Shopping Lists: Create pre-made shopping lists focusing on healthy meal plans or quick and easy meals. * Subscription Services: Offer subscription boxes for fresh produce, dairy, and snacks, allowing them to receive regular deliveries of their favorite items. * Content and Recipes: Share healthy recipes and meal prep ideas through the app and email newsletters, using ingredients they frequently purchase.

1.0.2 Cluster 3

Persona Description Based on Cluster of Shoppers Sorted by Departments

Persona: Budget-Conscious Family Shopper Demographics:

- Age: 30-50
- Gender: Mixed, with a slight skew towards females
- Income Level: Lower-middle to middle class
- Location: Suburban and rural areas
- Household Composition: Families with children, possibly multi-generational households

Shopping Behavior:

- Primary Focus: Essential groceries and household items
- Shopping Frequency: Weekly or bi-weekly shopping trips
- Basket Size: Large, with a focus on bulk purchases and essentials
- Preferred Shopping Time: Weekends and late afternoons

Motivations and Values:

```
Budget-Conscious: Prioritizes affordable and value-for-money products.
Convenience: Seeks convenient options that save time, such as pre-packaged and ready-to-eat ite
Family-Oriented: Focuses on products that meet the needs of the entire family, including child
Quantity: Buys in bulk to maximize savings and minimize shopping trips.
```

Marketing and Engagement Strategies: Messages and Channels:

- Channels: Email newsletters, mobile app notifications, social media (especially Facebook), and direct mail.
- Messages: Emphasize savings, value, and family-friendliness. Use phrases like “Save more on family essentials,” “Affordable groceries for your home,” and “Stock up and save.”

Special Offers or Incentives:

- Bulk Discounts: Offer discounts on bulk purchases and family-sized packs.

- Loyalty Programs: Introduce a rewards program where they can earn points for every purchase and redeem them for discounts on future orders.
- Family Packs: Provide special offers on family packs of popular items like snacks, beverages, and frozen meals.

Tailored Instacart Experience:

- Budget-Friendly Options: Highlight budget-friendly and value-for-money products in the app.
- Shopping Lists: Create pre-made shopping lists focused on family essentials and budget-friendly meal plans.
- Savings Alerts: Notify them of sales and discounts on frequently purchased items and bulk deals.

4. Additional Insights from AI (Claude or ChatGPT)

Claude or ChatGPT can further uncover:

```
Defining Characteristics:
    Cluster Characteristics: Primarily families looking for affordability and value, likely to
    Household Composition: Large households with multiple members, requiring diverse grocery ne

Purchasing Patterns:
    Cluster Patterns: Regular, large basket sizes with a focus on essential and bulk items.
    Seasonal Trends: Likely to see increased purchasing around back-to-school periods and holid

Marketing Strategies:
    Cluster Strategies: Highlight savings, bulk deals, and family-friendly products.
    Engagement Tactics: Use personalized discounts, loyalty rewards, and convenient delivery op
```

Follow-up Questions to Ask AI:

```
Cluster Characteristics:
    What are the common triggers for purchases in this segment?
    How do they respond to different types of promotions (e.g., percentage discounts vs. buy-on

Purchasing Patterns:
    What are the most commonly purchased items within each department for this segment?
    Are there any notable changes in purchasing behavior during certain times of the year?

Marketing Strategies:
    What specific messaging resonates most with this segment?
    How can we optimize the shopping experience to meet their needs for convenience and afforda
```

By leveraging AI to delve deeper into these segments, Instacart can uncover non-intuitive patterns and behaviors, allowing for more effective and personalized engagement strategies.

1.0.3 Cluster 4

Persona: Frequent Premium Shopper Demographics:

```
Age: 25-45
Gender: Mixed, with no significant skew
```

```
Income Level: Upper-middle to high
Location: Urban areas
Household Composition: Likely to be smaller households, singles, or couples without children
```

Shopping Behavior:

```
Primary Focus: High-quality and diverse grocery items
Shopping Frequency: Very frequent, possibly several times a week
Basket Size: Large, driven by the variety and premium quality of purchases
Preferred Shopping Time: Regularly shops throughout the week, favoring convenience and freshnes
```

Motivations and Values:

```
Quality Over Quantity: Prefers high-quality items and is willing to pay a premium.
Health and Wellness: Values health-conscious options and products that fit a healthy lifestyle
Food Experience: Enjoys the process of cooking and trying new foods and flavors.
```

Marketing and Engagement Strategies:

Messages and Channels:

```
Channels: Social media platforms, email campaigns, and app notifications geared toward a tech-s
Messages: Highlight the quality, exclusivity, and unique offerings available. Use phrases like
```

Special Offers or Incentives:

```
Exclusive Access: Provide early access to new products or special editions.
Loyalty Rewards: Enhance rewards for frequent purchases, especially in high-spend categories.
```

Tailored Instacart Experience:

```
Premium Recommendations: Offer personalized suggestions based on past purchases and preferences
Customized Delivery Options: Provide flexible delivery windows to accommodate their busy lifest
```