Starbucks_Customer_Segmentation

November 29, 2022

1 Dataset

The data is contained in three files:

- portfolio.json - containing offer ids and meta data about each offer (duration, type, etc.)
- profile.json - demographic data for each customer
- transcript.json - records for transactions, offers received, offers viewed, and offers completed

Here is the schema and explanation of each variable in the files:

portfolio.json

- id (string) - offer id
- offer_type (string) - type of offer ie BOGO, discount, informational
- difficulty (int) - minimum required spend to complete an offer
- reward (int) - reward given for completing an offer
- duration (int) - time for offer to be open, in days
- channels (list of strings)

profile.json

- age (int) - age of the customer
- became_member_on (int) - date when customer created an app account
- gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or F)
- id (str) - customer id
- income (float) - customer's income

transcript.json

- event (str) - record description (ie transaction, offer received, offer viewed, etc.)
- person (str) - customer id
- time (int) - time in hours since start of test. The data begins at time t=0
- value - (dict of strings) - either an offer id or transaction amount depending on the record

[6]:
```
import pandas as pd
import numpy as np
import json

from sklearn.cluster import KMeans
from modules.binomial import BinomialExperiment
```

```python
import matplotlib.pyplot as plt
import matplotlib.ticker as tck
```

[2]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[7]:
```python
portfolio = pd.read_json('drive/MyDrive/Starbucks_Data/portfolio.json',␣
 ↪orient='records', lines=True)
profile = pd.read_json('drive/MyDrive/Starbucks_Data/profile.json',␣
 ↪orient='records', lines=True)
transcript = pd.read_json('drive/MyDrive/Starbucks_Data/transcript.json',␣
 ↪orient='records', lines=True)
```

2 Data Wrangling

2.1 Exploration & Cleaning

2.1.1 Profile

[8]:
```python
print(profile.shape)
profile.head()
```

```
(17000, 5)
```

[8]:

	gender	age	id	became_member_on	income
0	None	118	68be06ca386d4c31939f3a4f0e3dd783	20170212	NaN
1	F	55	0610b486422d4921ae7d2bf64640c50b	20170715	112000.0
2	None	118	38fe809add3b4fcf9315a9694bb96ff5	20180712	NaN
3	F	75	78afa995795e4d85b5d9ceeca43f5fef	20170509	100000.0
4	None	118	a03223e636434f42ac4c3df47e8bac43	20170804	NaN

[9]:
```python
# closer look at age = 118 shows this to be a "dummy" value with no gender info␣
 ↪and no income info.
profile.query('age == 118')
```

[9]:

	gender	age	id	became_member_on	income
0	None	118	68be06ca386d4c31939f3a4f0e3dd783	20170212	NaN
2	None	118	38fe809add3b4fcf9315a9694bb96ff5	20180712	NaN
4	None	118	a03223e636434f42ac4c3df47e8bac43	20170804	NaN
6	None	118	8ec6ce2a7e7949b1bf142def7d0e0586	20170925	NaN
7	None	118	68617ca6246f4fbc85e91a2a49552598	20171002	NaN

```
…       … …                                   …              …
16980   None  118  5c686d09ca4d475a8f750f2ba07e0440     20160901   NaN
16982   None  118  d9ca82f550ac4ee58b6299cf1e5c824a     20160415   NaN
16989   None  118  ca45ee1883624304bac1e4c8a114f045     20180305   NaN
16991   None  118  a9a20fa8b5504360beb4e7c8712f8306     20160116   NaN
16994   None  118  c02b10e8752c4d8e9b73f918558531f7     20151211   NaN

[2175 rows x 5 columns]
```

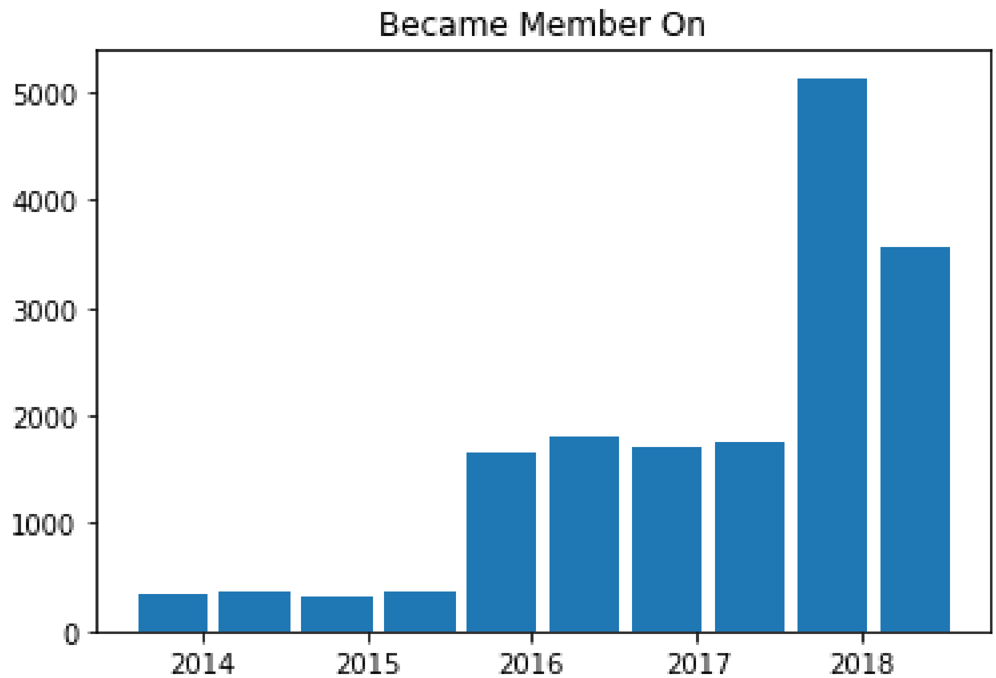
[10]:
```
print("Age = 118 count: " + str(len(profile[profile.age == 118])))
print("Gender = None count: " + str(sum(profile['gender'].isna())))
print("Income = NA count: " + str(sum(profile['income'].isna())))
```

```
Age = 118 count: 2175
Gender = None count: 2175
Income = NA count: 2175
```

[11]:
```
# convert dates to Datetime
profile['became_member_on'] = pd.to_datetime(profile['became_member_on'],␣
 ↪format='%Y%m%d')

# fill gender NA's with unknown
profile['gender'] = profile['gender'].fillna('Unknown')

# replace income na's with 0 -- will create buckets of income from 0-30k that␣
 ↪will satisfy "unknowns"
profile['income'].fillna(0, inplace = True)
profile['income_bucket'] = pd.cut(profile['income'], bins = [0, 30000, 50000,␣
 ↪80000, 200000], labels = ["unknown", "under 50k", "50k-80k", "over 80k"],␣
 ↪include_lowest=True)

profile['age_bucket'] = pd.cut(profile['age'], bins = [0,24,40,60,80,117,200],␣
 ↪labels = ['24 and Under','25-40','41-60','61-80','81 and Over','Unknown'],␣
 ↪include_lowest = False)
```

[12]:
```
plt.hist(x=profile.became_member_on, rwidth=0.85)
plt.title('Became Member On')
```

[12]: Text(0.5, 1.0, 'Became Member On')



became member is heavily scewed toward new users and does not contain enough variablity for segmentation.

[13]:
```
# drop income, age, became member on
profile = profile.drop(columns = ['income', 'age', 'became_member_on'])
```

[14]:
```
profile.head()
```

[14]:

	gender	id	income_bucket	age_bucket
0	Unknown	68be06ca386d4c31939f3a4f0e3dd783	unknown	Unknown
1	F	0610b486422d4921ae7d2bf64640c50b	over 80k	41-60
2	Unknown	38fe809add3b4fcf9315a9694bb96ff5	unknown	Unknown
3	F	78afa995795e4d85b5d9ceeca43f5fef	over 80k	61-80
4	Unknown	a03223e636434f42ac4c3df47e8bac43	unknown	Unknown

[15]:
```
# Dummy encode the users frame to create our input array for clustering.
# Using dummy (not one-hot) to avoid correlation among dummy variables and␣
↪improve clustering.
profile_dummies = pd.get_dummies(profile, columns =␣
↪['gender','income_bucket','age_bucket'], drop_first = False)
```

[16]:
```
profile_dummies.head()
```

[16]:
```
                                 id  gender_F  gender_M  gender_O  \
0  68be06ca386d4c31939f3a4f0e3dd783         0         0         0
1  0610b486422d4921ae7d2bf64640c50b         1         0         0
2  38fe809add3b4fcf9315a9694bb96ff5         0         0         0
3  78afa995795e4d85b5d9ceeca43f5fef         1         0         0
4  a03223e636434f42ac4c3df47e8bac43         0         0         0

   gender_Unknown  income_bucket_unknown  income_bucket_under 50k  \
0               1                      1                        0
1               0                      0                        0
2               1                      1                        0
3               0                      0                        0
4               1                      1                        0

   income_bucket_50k-80k  income_bucket_over 80k  age_bucket_24 and Under  \
0                      0                       0                        0
1                      0                       1                        0
2                      0                       0                        0
3                      0                       1                        0
4                      0                       0                        0

   age_bucket_25-40  age_bucket_41-60  age_bucket_61-80  \
0                 0                 0                 0
1                 0                 1                 0
2                 0                 0                 0
3                 0                 0                 1
4                 0                 0                 0

   age_bucket_81 and Over  age_bucket_Unknown
0                       0                   1
1                       0                   0
2                       0                   1
3                       0                   0
4                       0                   1
```

2.1.2 Portfolio & Transcript

[17]:
```
portfolio
```

[17]:
```
   reward                      channels  difficulty  duration     offer_type  \
0      10        [email, mobile, social]          10         7           bogo
1      10   [web, email, mobile, social]          10         5           bogo
2       0          [web, email, mobile]           0         4  informational
3       5          [web, email, mobile]           5         7           bogo
4       5                  [web, email]          20        10       discount
5       3   [web, email, mobile, social]           7         7       discount
```

```
6       2  [web, email, mobile, social]          10          10        discount
7       0       [email, mobile, social]           0           3   informational
8       5  [web, email, mobile, social]           5           5            bogo
9       2            [web, email, mobile]        10           7        discount

                                 id
0  ae264e3637204a6fb9bb56bc8210ddfd
1  4d5c57ea9a6940dd891ad53e9dbe8da0
2  3f207df678b143eea3cee63160fa8bed
3  9b98b8c7a33c4b65b9aebfe6a799e6d9
4  0b1e1539f2cc45b7b9fa7c272da2e1d7
5  2298d6c36e964ae4a3e7e9706d1fb8c2
6  fafdcd668e3743c1bb461111dcafc2a4
7  5a8bc65990b245e5a138643cd4eb9837
8  f19421c1d4aa40978ebb69ca19b0e20d
9  2906b810c7d4411798c6938adc9daaa5
```

[18]:
```python
(portfolio.isnull()).sum()
```

[18]:
```
reward        0
channels      0
difficulty    0
duration      0
offer_type    0
id            0
dtype: int64
```

[19]:
```python
print(transcript.shape)
transcript.head()
```

```
(306534, 4)
```

[19]:
```
                             person           event  \
0  78afa995795e4d85b5d9ceeca43f5fef  offer received
1  a03223e636434f42ac4c3df47e8bac43  offer received
2  e2127556f4f64592b11af22de27a7932  offer received
3  8ec6ce2a7e7949b1bf142def7d0e0586  offer received
4  68617ca6246f4fbc85e91a2a49552598  offer received

                                              value  time
0  {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}     0
1  {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}     0
2  {'offer id': '2906b810c7d4411798c6938adc9daaa5'}     0
3  {'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}     0
4  {'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}     0
```

[20]:
```python
(transcript.isnull()).sum()
```

[20]:
```
person    0
event     0
value     0
time      0
dtype: int64
```

[21]:
```
#closer look at 'value' for each event type
for e in transcript.event.unique():
    print(transcript.loc[transcript.event == e, ['event','value']].head(1).
↪values)
```

```
[['offer received' {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}]]
[['offer viewed' {'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}]]
[['transaction' {'amount': 0.8300000000000001}]]
[['offer completed'
  {'offer_id': '2906b810c7d4411798c6938adc9daaa5', 'reward': 2}]]
```

[22]:
```
# Cleaning portfolio & transcript & combining with profile
# Filter df for important events, only (events with event ID attached, all we␣
↪care about is response or non-response)
sig_events = ['offer received', 'offer viewed', 'offer completed']
filtered_df = transcript.loc[transcript['event'].isin(sig_events)].
↪reset_index(drop = True).copy()

# Create offer_id variable from value NOTE: value is a series of dict. Offer ID␣
↪key when event is viewed is "offer id." It's "offer_id" when event is␣
↪completed.
filtered_df['offer_id'] = filtered_df['value'].apply(
  lambda x: x['offer_id'] if 'offer_id' in x.keys() else x['offer id']
  )
filtered_df.drop(columns = ['value'],
                     inplace = True)

# Dedup the dataframe for person, event and offer_id. Take min(time) for each.
deduped_df = filtered_df.groupby(['person','event','offer_id'], as_index =␣
↪False)['time'].agg(np.min)

# Pivot out event with time as the values to see when each person received and␣
↪completed each offer
pivoted_df = deduped_df.pivot(index = ['person','offer_id'], columns =␣
↪['event'], values = 'time').reset_index(drop = False)

# Filter pivoted_df so that we're only working with valid test cases for␣
↪response rates
    # Must be a viewed time.
    # Completed time can't be less than viewed time (greater than and NaN both␣
↪okay)
```

```python
    # Days between view and receipt must <= the offer term in days
filtered_pivot = pivoted_df.loc[
  (~pivoted_df['offer viewed'].isnull()) &
  (~(pivoted_df['offer completed'] < pivoted_df['offer viewed']))
  ]
filtered_pivot = filtered_pivot.merge(
  portfolio[['id','duration','offer_type']],
  how = 'left',
  left_on = 'offer_id',
  right_on = 'id'
  ).drop(columns = 'id')
# Convert offer viewed and offer completed (hours) to days
filtered_pivot[['offer received','offer viewed','offer completed']] =␣
↪filtered_pivot[['offer received','offer viewed', 'offer completed']] / 24

# Add a column for response, 1 if completion happened in offer window. Else 0.
filtered_pivot['offer_response'] = filtered_pivot.apply(
  lambda x: 1 if x['offer completed'] - x['offer received'] <= x['duration']␣
↪else 0, axis = 1
)

# filter the final product for only person that appears in users_clean
filtered_pivot = filtered_pivot.loc[filtered_pivot['person'].isin(profile['id'].
↪unique())].reset_index(drop = True).copy()
filtered_pivot =␣
↪filtered_pivot[['person','offer_id','offer_type','offer_response']]
```

[23]:
```python
filtered_pivot.head()
```

[23]:
```
                             person                          offer_id  \
0  0009655768c64bdeb2e877511632db8f  3f207df678b143eea3cee63160fa8bed
1  0009655768c64bdeb2e877511632db8f  5a8bc65990b245e5a138643cd4eb9837
2  00116118485d4dfda04fdbaba9a87b5c  f19421c1d4aa40978ebb69ca19b0e20d
3  0011e0d4e6b944f998e987f904e8c1e5  0b1e1539f2cc45b7b9fa7c272da2e1d7
4  0011e0d4e6b944f998e987f904e8c1e5  2298d6c36e964ae4a3e7e9706d1fb8c2

      offer_type  offer_response
0  informational               0
1  informational               0
2           bogo               0
3       discount               1
4       discount               1
```

3 Cluster profile

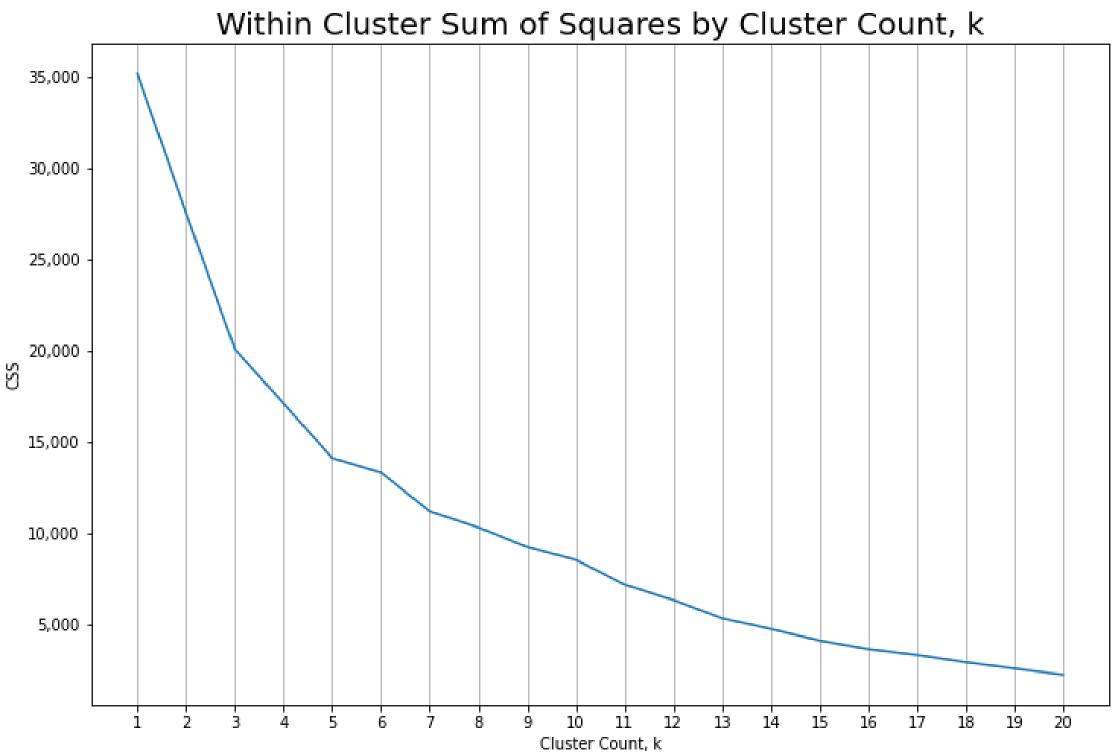
[24]:
```
profile_dummies.head()
```

[24]:
```
                                 id  gender_F  gender_M  gender_O  \
0  68be06ca386d4c31939f3a4f0e3dd783         0         0         0
1  0610b486422d4921ae7d2bf64640c50b         1         0         0
2  38fe809add3b4fcf9315a9694bb96ff5         0         0         0
3  78afa995795e4d85b5d9ceeca43f5fef         1         0         0
4  a03223e636434f42ac4c3df47e8bac43         0         0         0

   gender_Unknown  income_bucket_unknown  income_bucket_under 50k  \
0               1                      1                        0
1               0                      0                        0
2               1                      1                        0
3               0                      0                        0
4               1                      1                        0

   income_bucket_50k-80k  income_bucket_over 80k  age_bucket_24 and Under  \
0                      0                       0                        0
1                      0                       1                        0
2                      0                       0                        0
3                      0                       1                        0
4                      0                       0                        0

   age_bucket_25-40  age_bucket_41-60  age_bucket_61-80  \
0                 0                 0                 0
1                 0                 1                 0
2                 0                 0                 0
3                 0                 0                 1
4                 0                 0                 0

   age_bucket_81 and Over  age_bucket_Unknown
0                       0                   1
1                       0                   0
2                       0                   1
3                       0                   0
4                       0                   1
```

[25]:
```
profile_x = np.array(profile_dummies.drop(columns = 'id'))
```

[26]:
```
# determine optimal centroids using within cluster sum of squares
css = []
for i in range(20):
    kmeans = KMeans(i+1)
    kmeans.fit(profile_x)
    css.append(kmeans.inertia_)
```

[27]:
```
%matplotlib inline
# Plot wcss for each centroid count
fig, ax = plt.subplots(1,1,figsize = (12,8));
ax.plot([i+1 for i in range(20)], css);
ax.set_xticks([i+1 for i in range(20)]);
ax.grid(b = True, axis = 'x');
ax.yaxis.set_major_formatter(tck.StrMethodFormatter('{x:,.0f}'));
ax.set_ylabel('CSS', fontsize = 10);
ax.set_xlabel('Cluster Count, k', fontsize = 10);
ax.set_title('Within Cluster Sum of Squares by Cluster Count, k', fontsize =␣
↪20);
```



optimal clusters looks to be between 4 and 6. Let's split the difference and use 5

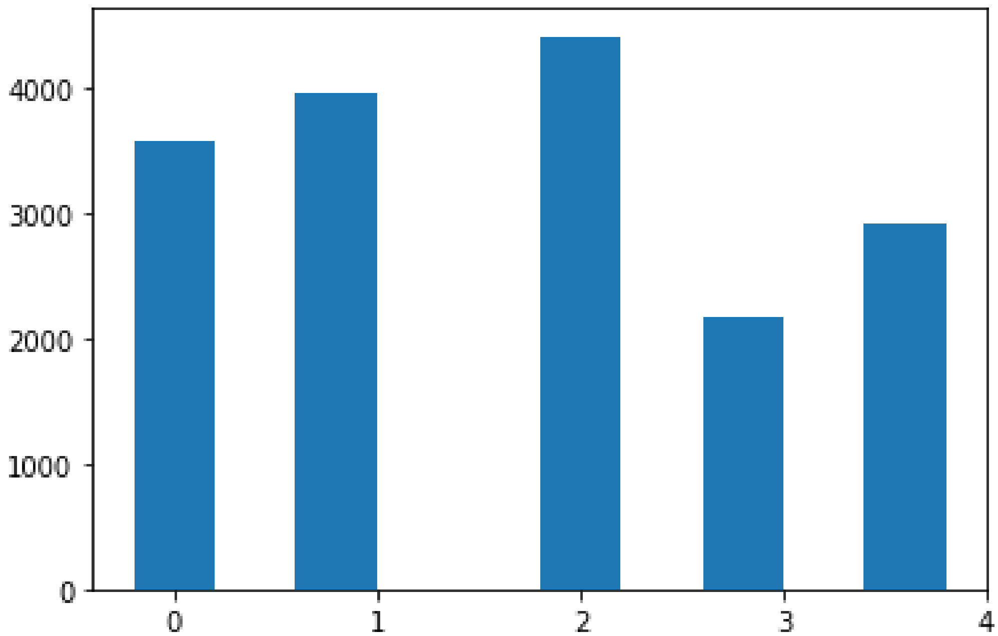
[28]:
```
profile_kmeans = KMeans(5, random_state = 1)
label = profile_kmeans.fit_predict(profile_x)
```

[29]:
```
# add cluster to profile
profile['cluster'] = label
```

[30]:
```
profile.head()
```

[30]:
```
    gender                                id income_bucket age_bucket  cluster
0  Unknown  68be06ca386d4c31939f3a4f0e3dd783       unknown    Unknown        3
1        F  0610b486422d4921ae7d2bf64640c50b      over 80k      41-60        0
2  Unknown  38fe809add3b4fcf9315a9694bb96ff5       unknown    Unknown        3
3        F  78afa995795e4d85b5d9ceeca43f5fef      over 80k      61-80        0
4  Unknown  a03223e636434f42ac4c3df47e8bac43       unknown    Unknown        3
```

[31]:
```
# Check to see if any segments are too small to be useful
fig_cluster, ax_cluster = plt.subplots(1,1)
ax_cluster.hist(profile.cluster, align = 'left');
ax_cluster.set_xticks(list(range(len(profile.cluster.unique()))));
```

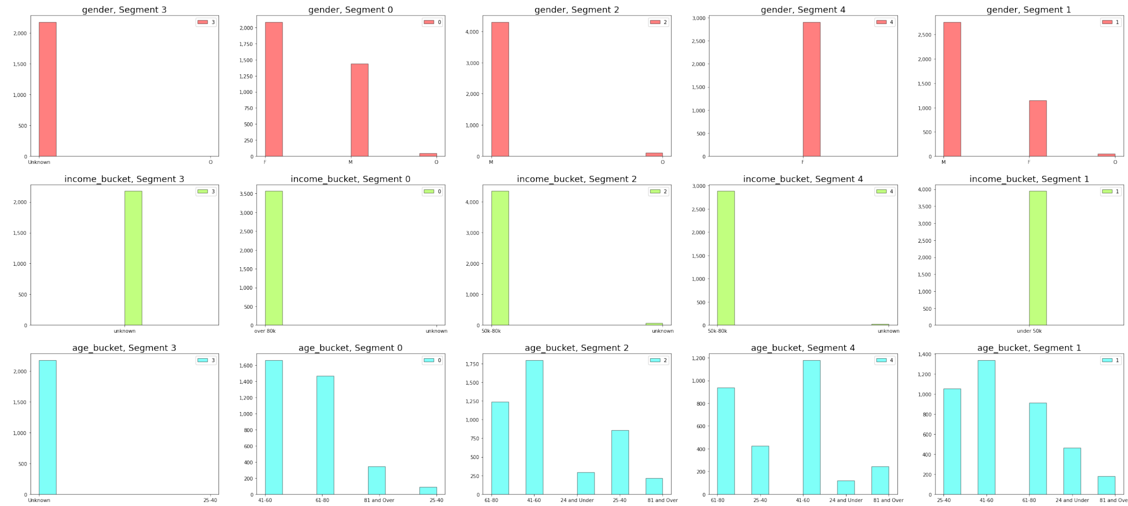


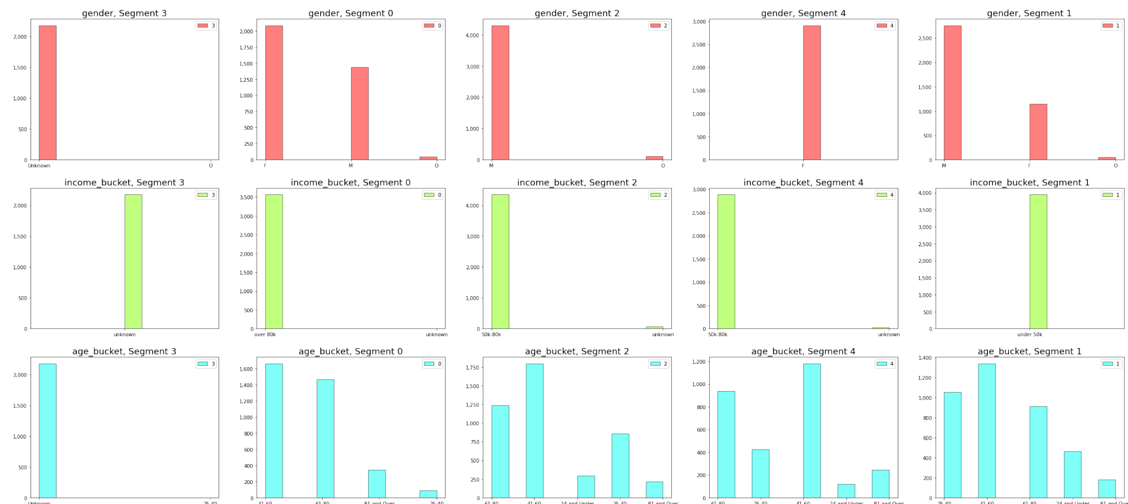
[32]:
```
def contrast_var_distributions(df, test_vars, segment_var = None):
    """
    Plots a series of histograms to contrast distributions of variables of␣
↪interest.
    If a segment_var is provided, segments will be plotted in each figure to␣
↪see how segments differ.
    """
    test_vars = test_vars
    n_test = len(test_vars)
    n_seg = len(df[segment_var].unique()) if segment_var else 1

    fig, ax = plt.subplots(n_test,n_seg,figsize = (8*n_seg,6*n_test))
    for i, col in enumerate(test_vars):
```

```
        if segment_var:
            # Get a color mapper object to allow me to color segments␣
↪differently
            # Will also scale with added/removed segments
            # Color mapper object will have n_seg colors, each of which I can␣
↪call by index with cmap(), later
            cmap = plt.cm.get_cmap('hsv', n_seg)
            for k, seg in enumerate(df[segment_var].unique()):
                ax[i,k].hist(
                    df[col][df[segment_var] == seg],
                    alpha = 0.5,
                    label = seg,
                    color = cmap(i),
                    edgecolor = 'black'
                )
                ax[i,k].set_title(col + ', Segment ' + str(seg), fontsize = 18)
                ax[i,k].legend()
                # Comma-format y axis ticks. Found here:
                # https://stackoverflow.com/questions/25973581/
↪how-do-i-format-axis-number-format-to-thousands-with-a-comma-in-matplotlib
                ax[i,k].yaxis.set_major_formatter(tck.StrMethodFormatter('{x:,.
↪0f}'))
        else:
            # Add 2 to cmap to avoid multiple charts of same color
            cmap = plt.cm.get_cmap('hsv', n_test + 2)
            ax[i].hist(
                df[col],
                color = cmap(i),
                edgecolor = 'black'
            )
            ax[i].set_title(col, fontsize = 18, pad = 20)
            ax[i].yaxis.set_major_formatter(tck.StrMethodFormatter('{x:,.0f}'))

            fig.tight_layout()

    return fig
```

[76]:
```
# Grid of histograms
contrast_var_distributions(profile, ['gender','income_bucket','age_bucket'],␣
↪'cluster')
```

[76]:





Clusters:

In general: * Income was a prominent difference (1 unknown, 1 high, 1 low, 2 middle segments) * Gender was the secondary difference * Segments are mostly income/gender-based

Cluster-specific: * Cluster 0: High-Earners (more than 80k income). All ages. * Cluster 1: Low-Earners (under 50k income). All ages. * Cluster 2: Middle-Earners Male. * Cluster 3: The unknowns. Users who do not provide demo data. * Cluster 4: Middle-Earners Female.

3.1 Response Rates by Cluster

[33]:
```
# Merge cluster labels with filtered_pivot
responses = filtered_pivot.merge(profile[['id','cluster']], how = 'left',␣
 ↪left_on = 'person', right_on = 'id').drop(columns = 'id')
responses.head()
```

[33]:
```
                            person                          offer_id  \
0  0009655768c64bdeb2e877511632db8f  3f207df678b143eea3cee63160fa8bed
1  0009655768c64bdeb2e877511632db8f  5a8bc65990b245e5a138643cd4eb9837
2  00116118485d4dfda04fdbaba9a87b5c  f19421c1d4aa40978ebb69ca19b0e20d
3  0011e0d4e6b944f998e987f904e8c1e5  0b1e1539f2cc45b7b9fa7c272da2e1d7
4  0011e0d4e6b944f998e987f904e8c1e5  2298d6c36e964ae4a3e7e9706d1fb8c2

      offer_type  offer_response  cluster
0  informational               0        2
1  informational               0        2
2           bogo               0        3
3       discount               1        2
4       discount               1        2
```

[34]:
```
# Check response rates for each discount type
response_rates = responses.groupby(
    ['cluster','offer_type'],
    as_index = False
)['offer_response'].agg({'offer_response':'mean'}).round(2).pivot(
    index = 'cluster',
    columns = 'offer_type',
    values = 'offer_response')

response_rates
```

[34]:
```
offer_type  bogo  discount  informational
cluster
0           0.71      0.79            0.0
1           0.35      0.63            0.0
2           0.48      0.68            0.0
3           0.09      0.22            0.0
4           0.66      0.76            0.0
```

[35]:
```
# no responses for informational, so drop it
response_tests = response_rates[['bogo','discount']]
response_tests
```

[35]:
```
offer_type  bogo  discount
cluster
0           0.71      0.79
```

```
1           0.35      0.63
2           0.48      0.68
3           0.09      0.22
4           0.66      0.76
```

[36]:
```python
# Check each cluster's set of response rates for statistical significance
figs = dict()
for idx in response_tests.index:
    p_control = response_tests.loc[idx, 'bogo']
    p_treatment = response_tests.loc[idx, 'discount']

    n_control = len(responses[(responses.offer_type == 'bogo') & (responses.
 ↪cluster == idx)])
    n_treatment = len(responses[(responses.offer_type == 'discount') &␣
 ↪(responses.cluster == idx)])

    figs[idx] = BinomialExperiment(p_control = p_control, p_treatment =␣
 ↪p_treatment, n_control = n_control, n_treatment = n_treatment).
 ↪plot_confidence()
```

[37]:
```python
figs[0]
```

[38]:
```python
figs[1]
```

[39]:
```python
figs[2]
```

[40]:
```python
figs[3]
```

[41]:
```python
figs[4]
```

3.2 Conclusion

Cluster 0, the High-Earners - This app user group responded over 70% to both bogos (71%) and discounts (79%). It is by far the most successful group regarding bogos. With this group, I would recommend changing very little, they tend to respond well to both bogos and discounts.

Cluster 1, the Low-Earners - This app group responded to 35% of the bogo offers, but 63% of the discount offers. The inference here would suggest that low earners could also likely be single and bogo offers are generally less relevant as they don't often travel in pairs. My suggestion for this group would be to focus nearly entirely on discount offers rather than bogos.

Cluster 2, The Male Middle-Earners - The male middle earners responded to 48% of the bogo offers and 68% to the discount offers. I would suggest focusing on more discount offers to entice more visits, but I would not stop bogo offers, they are still effective, but could be released to this user group at a slower pace than the discount offers. I would also see if overall instore data was available to look at the types of orders men make, so that the discounts can be tailored to them.

Cluster 3, the Unknowns - This group was by far the least successful in responding as they responded to bogos at a 9% rate and discounts at a 22% rate. The response rate along with the fact they did not provide their demographics data suggests these users have very little involvement with Starbucks. My suggestion would be to entice them with a special discount to provide their demographics data first and foremost. Specialized campaigns to build more engagement with the app could also bring these fringe customers into the Starbucks fold.

Cluster 4, the Female Middle-Earners - This group is the 2nd most successful group responding to 66% of the bogos and 76% of the discounts. I would not change much with this group; although knowing it is female, you could tailor the offers to orders more females make, if that data is available.