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

[65]:
```
import pandas as pd
import numpy as np
import json

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

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

[2]:
```
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).
```

[35]:
```
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

[36]:
```
print(profile.shape)
profile.head()
```

```
(17000, 5)
```

[36]:

	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

[37]:
```
# closer look at age = 118 shows this to be a "dummy" value with no gender info␣
↪and no income info.
profile.query('age == 118')
```

[37]:

	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]
```

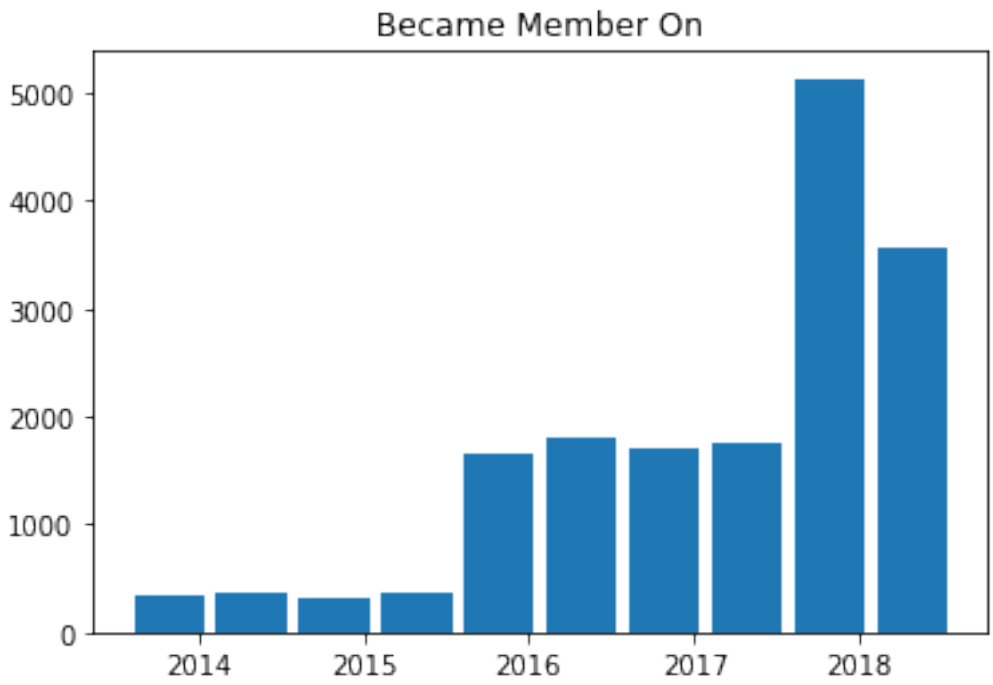
[38]:
```
print("Age = 118 count: " + str(len(profile[profile.age == 118])))
print("Gender = None count: " + str(sum(profile['gender'].isna())))
print("Income = NA count: " + str(sum(profile['income'].isna())))
```

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

[39]:
```
# 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)
```

[40]:
```
plt.hist(x=profile.became_member_on, rwidth=0.85)
plt.title('Became Member On')
```

[40]:
```
Text(0.5, 1.0, 'Became Member On')
```



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

[41]:
```
# drop income, age, became member on
profile = profile.drop(columns = ['income', 'age', 'became_member_on'])
```

[42]:
```
profile.head()
```

[42]:

	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

[49]:
```
# 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)
```

[50]:
```
profile_dummies.head()
```

[50]:

	id	gender_F	gender_M	gender_O	gender_Unknown	income_bucket_unknown	income_bucket_under 50k	income_bucket_50k-80k	income_bucket_over 80k	age_bucket_24 and Under	age_bucket_25-40	age_bucket_41-60	age_bucket_61-80	age_bucket_81 and Over	age_bucket_Unknown
0	68be06ca386d4c31939f3a4f0e3dd783	0	0	0	1	1	0	0	0	0	0	0	0	0	1
1	0610b486422d4921ae7d2bf64640c50b	1	0	0	0	0	0	0	1	0	0	1	0	0	0
2	38fe809add3b4fcf9315a9694bb96ff5	0	0	0	1	1	0	0	0	0	0	0	0	0	1
3	78afa995795e4d85b5d9ceeca43f5fef	1	0	0	0	0	0	0	1	0	0	0	1	0	0
4	a03223e636434f42ac4c3df47e8bac43	0	0	0	1	1	0	0	0	0	0	0	0	0	1

2.1.2 Portfolio & Transcript

[32]:
```
portfolio
```

[32]:

	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
```

[47]:
```
(portfolio.isnull()).sum()
```

[47]:
```
reward        0
channels      0
difficulty    0
duration      0
offer_type    0
id            0
dtype: int64
```

[43]:
```
print(transcript.shape)
transcript.head()
```

```
(306534, 4)
```

[43]:
```
                             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
```

[44]:
```
(transcript.isnull()).sum()
```

[44]:
```
person    0
event     0
value     0
time      0
dtype: int64
```

[45]:
```
#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}]]
```

[51]:
```
# 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)
```

```
    # 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']]
```

[52]:
```
filtered_pivot.head()
```

[52]:

	person	offer_id	offer_type	offer_response
0	0009655768c64bdeb2e877511632db8f	3f207df678b143eea3cee63160fa8bed	informational	0
1	0009655768c64bdeb2e877511632db8f	5a8bc65990b245e5a138643cd4eb9837	informational	0
2	00116118485d4dfda04fdbaba9a87b5c	f19421c1d4aa40978ebb69ca19b0e20d	bogo	0
3	0011e0d4e6b944f998e987f904e8c1e5	0b1e1539f2cc45b7b9fa7c272da2e1d7	discount	1
4	0011e0d4e6b944f998e987f904e8c1e5	2298d6c36e964ae4a3e7e9706d1fb8c2	discount	1

3 Cluster profile

[53]:
```
profile_dummies.head()
```

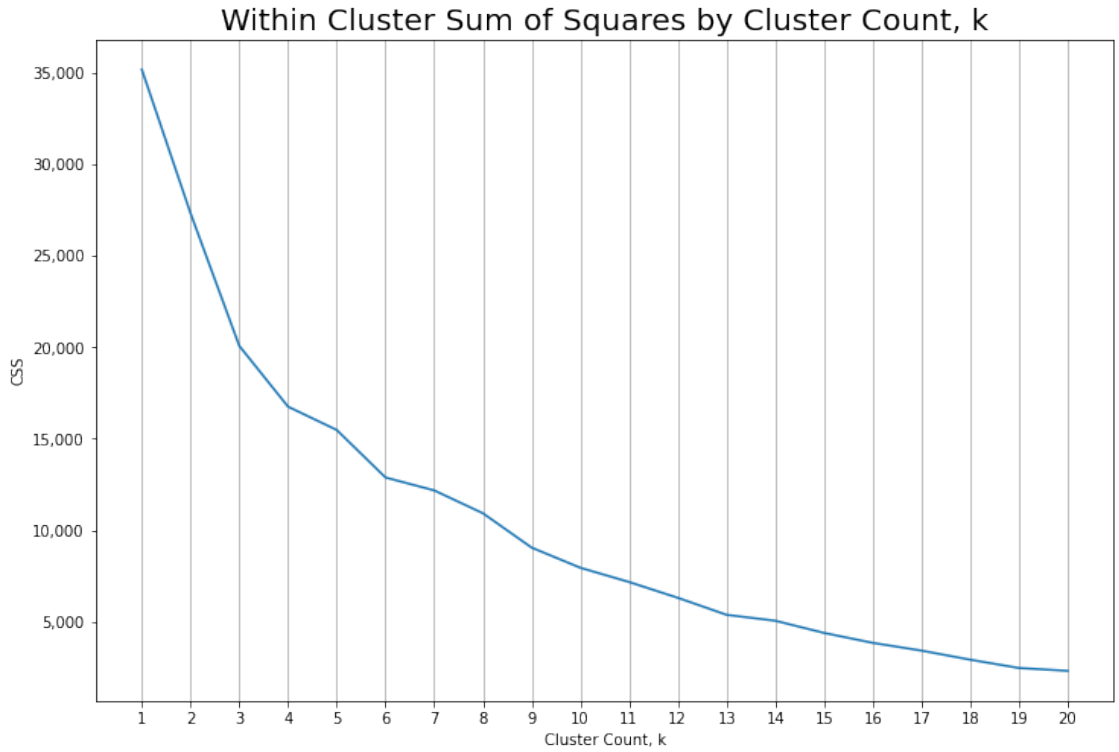
[53]:

	id	gender_F	gender_M	gender_O	gender_Unknown	income_bucket_unknown	income_bucket_under 50k	income_bucket_50k-80k	income_bucket_over 80k	age_bucket_24 and Under	age_bucket_25-40	age_bucket_41-60	age_bucket_61-80	age_bucket_81 and Over	age_bucket_Unknown
0	68be06ca386d4c31939f3a4f0e3dd783	0	0	0	1	1	0	0	0	0	0	0	0	0	1
1	0610b486422d4921ae7d2bf64640c50b	1	0	0	0	0	0	0	1	0	0	1	0	0	0
2	38fe809add3b4fcf9315a9694bb96ff5	0	0	0	1	1	0	0	0	0	0	0	0	0	1
3	78afa995795e4d85b5d9ceeca43f5fef	1	0	0	0	0	0	0	1	0	0	0	1	0	0
4	a03223e636434f42ac4c3df47e8bac43	0	0	0	1	1	0	0	0	0	0	0	0	0	1

[54]:
```
profile_x = np.array(profile_dummies.drop(columns = 'id'))
```

[55]:
```
# 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_)
```

[56]:
```
%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

[57]:
```
profile_kmeans = KMeans(5, random_state = 1)
label = profile_kmeans.fit_predict(profile_x)
```

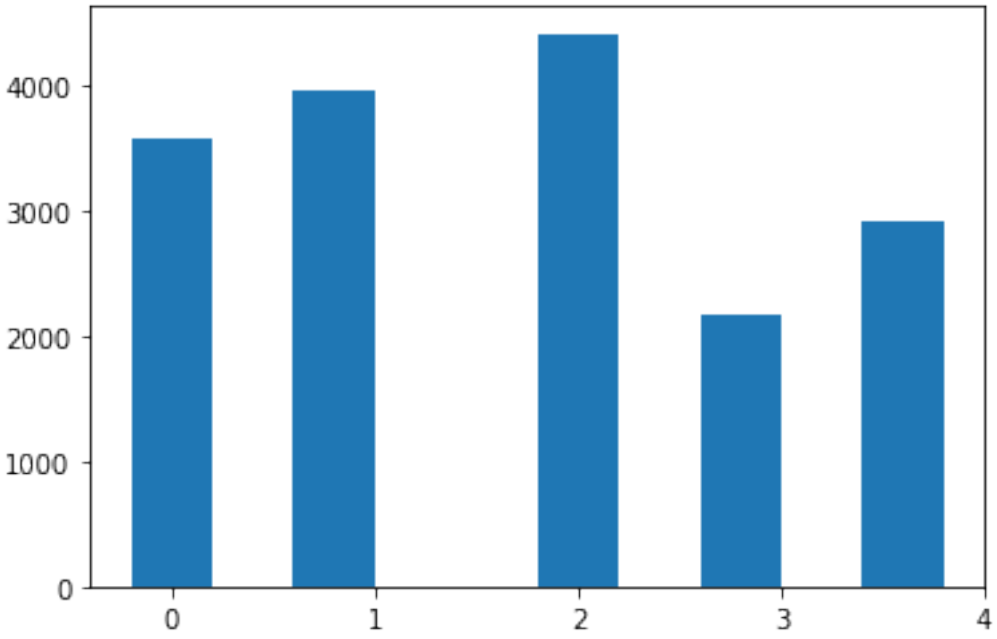
[58]:
```
# add cluster to profile
profile['cluster'] = label
```

[59]:
```
profile.head()
```

[59]:

	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

[60]:
```
# 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()))));
```

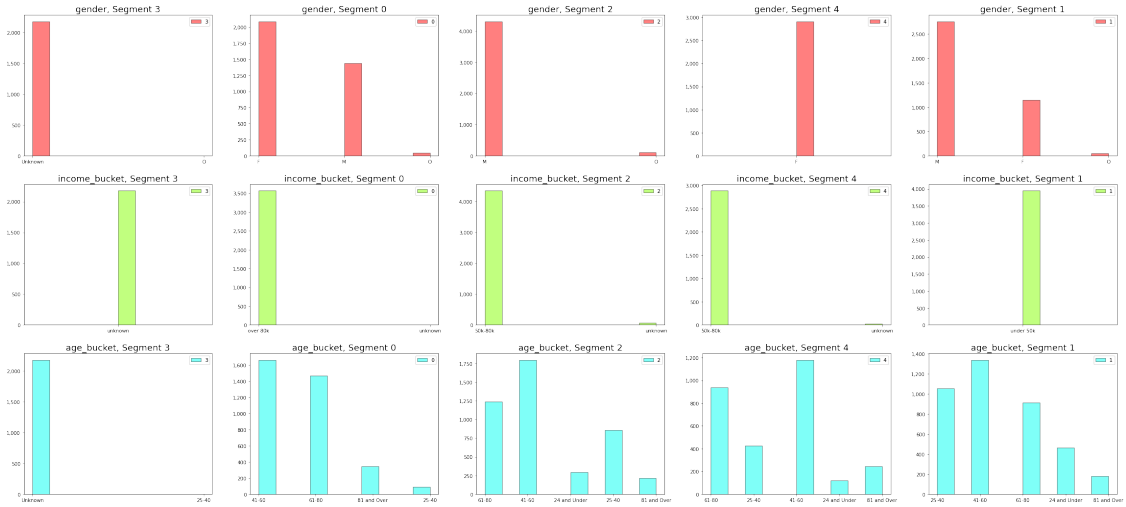


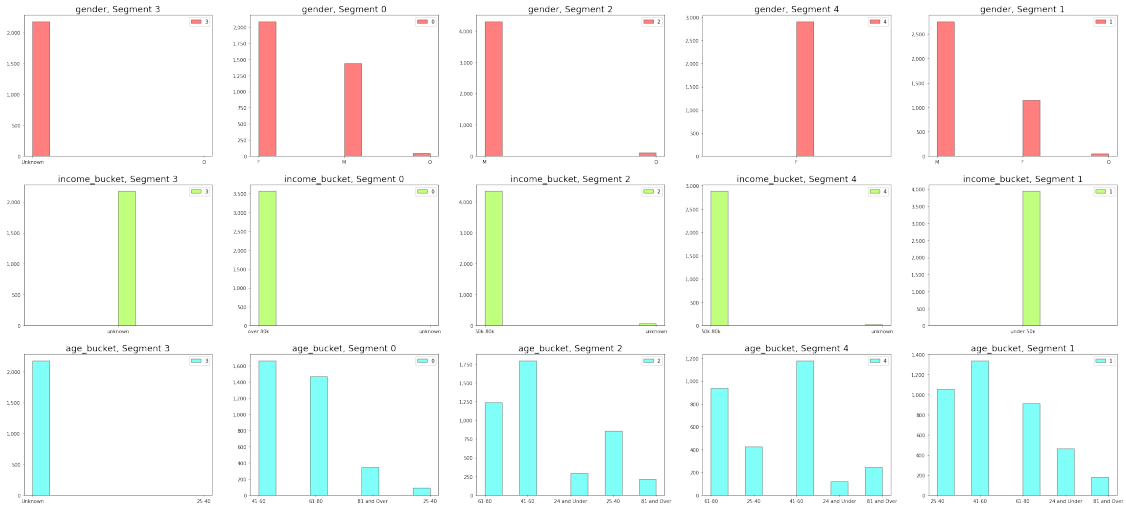
[73]:
```
def contrast_var_distributions(df, test_vars, segment_var = None):
    """
    Plots a series of histograms to contrast distributions of variables of␣
↪interest.
    If a segment_var is provided, segments will be plotted in each figure to␣
↪see how segments differ.
    """
    test_vars = test_vars
    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]:
```
# Open this grid of histograms in an interactive window. Too small to␣
↪understand, when inline.
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

[61]:
```
# 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()
```

[61]:

	person	offer_id	offer_type	offer_response	cluster
0	0009655768c64bdeb2e877511632db8f	3f207df678b143eea3cee63160fa8bed	informational	0	2
1	0009655768c64bdeb2e877511632db8f	5a8bc65990b245e5a138643cd4eb9837	informational	0	2
2	00116118485d4dfda04fdbaba9a87b5c	f19421c1d4aa40978ebb69ca19b0e20d	bogo	0	3
3	0011e0d4e6b944f998e987f904e8c1e5	0b1e1539f2cc45b7b9fa7c272da2e1d7	discount	1	2
4	0011e0d4e6b944f998e987f904e8c1e5	2298d6c36e964ae4a3e7e9706d1fb8c2	discount	1	2

[62]:
```
# 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
```

[62]:

cluster	bogo	discount	informational
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

[63]:
```
# no responses for informational, so drop it
response_tests = response_rates[['bogo','discount']]
response_tests
```

[63]:

cluster	bogo	discount
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
```

[67]:
```
# 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()
```

[68]:
```
figs[0]
```

[69]:
```
figs[1]
```

[70]:
```
figs[2]
```

[71]:
```
figs[3]
```

[72]:
```
figs[4]
```