Final Project

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from datetime import date
from datetime import timedelta
import statsmodels.api as sm
from sklearn.cluster import KMeans
from sklearn.linear_model import LinearRegression
import statsmodels.formula.api as smf
from sklearn.metrics import r2_score
from statsmodels.tsa.api import ExponentialSmoothing,SimpleExpSmoothing,Holt
from sklearn.metrics import mean_squared_error
from math import sqrt
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.model_selection import GridSearchCV
from sklearn import preprocessing
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import precision_recall_curve
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
```

Summary Stats

In [2]:

```
am=pd.read_csv(r"angels_market.csv")
```

In [3]:

```
am.head()
```

Out[3]:

	vendorID	theme	homeState	carnivals	complaints	est_energy	est_hourly_vol	LL_passh
0	1	Hot Chocolate/Warm Treats	Maine	3	9	57.291961	118	
1	2	Local Artists	Vermont	1	2	39.404898	105	
2	3	Fortune Teller	New Hampshire	5	4	47.175958	94	
3	4	Fried Dough and Pizza	Maine	8	0	58.192568	118	
4	5	craft beer	New Hampshire	7	6	56.657908	102	

In [4]:

```
am.isnull().sum()
```

Out[4]:
```
vendorID             0
theme                0
homeState            0
carnivals            0
complaints           0
est_energy           0
est_hourly_vol       0
LL_passholder        0
est_hourly_gross     0
dtype: int64
```

In [5]:
```
am.describe()
```

Out[5]:

	vendorID	carnivals	complaints	est_energy	est_hourly_vol	LL_passholder	est_hourly_gros
count	700.000000	700.000000	700.000000	700.000000	700.000000	700.000000	700.00000
mean	345.375714	5.135714	5.237143	47.501858	110.152857	0.204286	216.54335
std	204.173508	2.202258	4.914525	14.172002	15.903799	0.403467	41.56156
min	1.000000	0.000000	0.000000	3.069903	1.000000	0.000000	4.00000
25%	167.750000	4.000000	0.000000	39.596198	103.000000	0.000000	193.81000
50%	346.500000	5.000000	4.500000	47.955097	110.500000	0.000000	217.49000
75%	521.250000	7.000000	9.000000	57.336190	119.000000	0.000000	242.50250
max	700.000000	13.000000	20.000000	91.567936	147.000000	1.000000	322.57000

In [6]:
```
am.groupby('theme')['est_hourly_gross'].describe()
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
theme								
3	1.0	6.000000	NaN	6.00	6.0000	6.000	6.0000	6.00
4	1.0	8.000000	NaN	8.00	8.0000	8.000	8.0000	8.00
5	2.0	6.500000	2.121320	5.00	5.7500	6.500	7.2500	8.00
7	2.0	7.500000	0.707107	7.00	7.2500	7.500	7.7500	8.00
8	1.0	7.000000	NaN	7.00	7.0000	7.000	7.0000	7.00
9	1.0	4.000000	NaN	4.00	4.0000	4.000	4.0000	4.00
Canadian Snacks	74.0	221.436892	32.846742	124.75	201.3850	219.380	241.6525	281.79
DIY Ice Sculpture	19.0	222.981053	30.426289	146.03	203.4200	235.810	245.6150	263.95
Fortune Teller	9.0	207.072222	24.840857	175.46	196.1000	200.680	211.0900	263.86
Fried Dough and Pizza	75.0	219.167333	33.469934	144.95	196.2050	217.500	240.0800	291.67
Games Of Chance	85.0	222.085176	32.229983	144.69	203.1500	219.060	242.2700	304.66
Homemade Holiday Gifts	104.0	215.885385	35.286296	81.29	199.5650	217.720	238.9900	286.68
Hot Chocolate/Warm Treats	113.0	214.720354	34.439647	147.03	186.1400	208.810	240.6000	289.43

	count	mean	std	min	25%	50%	75%	max
theme								
Local Artists	74.0	224.376216	33.268683	168.56	199.9550	223.995	243.4200	322.57
Local Politician	10.0	222.541000	53.044376	144.15	179.8125	225.930	261.2800	294.42
Maine Tourism Promotion	15.0	215.484000	39.236643	134.64	196.3300	215.290	227.9650	298.84
Specialty Ice Cream	30.0	217.727333	46.960541	137.75	181.8300	212.875	251.2225	305.13
Steaming Hot Cocktails	42.0	218.952381	37.998176	146.69	186.3550	217.465	250.4350	296.16
Video Game/eSports	23.0	217.996522	36.144350	138.03	204.8950	225.590	235.5000	273.78
craft beer	19.0	221.432105	41.563303	146.69	191.8300	228.270	246.9250	285.85

first observation was that the dataset contains 6 themes, that are not labelled correctly. This can be due to a data entry error, or vendors with extremely unique themes that did not show up due to scheduling conflicts or insufficient resources to set up their stalls. The latter is more liekly the case, becuase the hourly gross and energy consumption associated with these themes are almost negligible in comparision to the rest of the themes. Furthermore, we see that Local Artists generate the highest average hourly income among all other vendor themes.

In [7]:

```
am['complaints'].value_counts()
```

Out[7]:

```
complaints
0     192
5      46
3      46
9      43
6      43
7      41
8      39
1      39
4      38
2      35
11     26
10     23
12     22
13     18
14     15
17     12
15      9
16      6
20      3
19      2
18      2
Name: count, dtype: int64
```

192/700=27.42% of the time, customers have had no complaints filed against the vendors in previous carnivals. These would be the safest options for Lobsterland to select for their angels market. However, a glaring limitation with this dataset is the severity of the complaints. If regular complaints can be different from severe complaints, it would be easier for Lobsterland management to select vendors with no serious complaints filed in their past visits.

In [8]:

```
am.columns
```

Out[8]:

```
Index(['vendorID', 'theme', 'homeState', 'carnivals', 'complaints',
       'est_energy', 'est_hourly_vol', 'LL_passholder', 'est_hourly_gross'],
      dtype='object')
```

In [9]:

```
am[['carnivals', 'complaints','est_energy', 'est_hourly_vol', 'LL_passholder', 'est_hc
```

Out[9]:

	complaints	est_energy	est_hourly_vol	LL_passholder	est_hourly_gross
carnivals					
0	0.000000	53.063056	121.666667	0.333333	262.243333
1	6.103448	49.618059	111.137931	0.206897	211.392759
2	4.977273	49.382926	112.636364	0.250000	219.491364
3	5.451220	48.877076	110.426829	0.134146	223.403293
4	5.065574	46.268356	111.581967	0.213115	218.328033
5	5.210526	46.254998	108.248120	0.225564	214.606541
6	5.859813	48.024971	109.392523	0.196262	213.119720
7	5.180723	45.633131	110.373494	0.180723	213.287831
8	4.381818	47.858361	110.054545	0.236364	220.763273
9	4.360000	51.035565	111.360000	0.200000	223.352000
10	4.333333	53.554833	111.333333	0.333333	203.035000
11	10.200000	50.731888	106.800000	0.200000	197.976000
12	4.000000	54.071423	109.500000	0.000000	175.115000
13	5.000000	39.578069	93.500000	0.250000	179.262500

By looking at the different number of carnivals the vendors have appeared in, we can see that the average estimated hourly volume of customers is the highest for a vendor with 0 past carnival apperances, amounting to 121 per hour. Visitors at Lobsterland seem to enjoy exploring new vendors they have not seen at other parks before. The repetitiveness seems to bore customers, as we see how the hourly volume decreases with number of carnival visits.

In [10]:

```
am.pivot_table('est_energy', index='carnivals', columns='homeState', margins=True)
```

Out[10]:

homeState	2	4	5	6	7	Connecticut	Maine	Massachusetts	New Hampshire	C
carnivals										
0	NaN	NaN	NaN	NaN	NaN	NaN	67.347419	NaN	NaN	24.
1	NaN	NaN	NaN	NaN	NaN	70.402830	51.466190	15.123110	51.413808	
2	NaN	NaN	NaN	NaN	NaN	39.321509	49.078409	43.918733	55.899673	38.
3	NaN	NaN	NaN	NaN	NaN	49.074666	50.051878	49.420920	43.738546	56.
4	NaN	NaN	NaN	NaN	NaN	45.274890	45.303136	52.379832	48.519645	54.
5	8.0	9.0	NaN	NaN	5.0	48.751408	47.293545	45.295418	45.015961	
6	NaN	NaN	8.000000	NaN	NaN	53.089609	47.941747	37.817052	46.709815	50.
7	NaN	NaN	NaN	NaN	NaN	46.444979	44.287974	39.836256	47.052452	56.

homeState	2	4	5	6	7	Connecticut	Maine	Massachusetts	New Hampshire	(
carnivals										
8	NaN	NaN	4.000000	NaN	5.0	60.632120	48.504658	44.061156	44.141029	19.
9	NaN	NaN	NaN	NaN	NaN	NaN	46.064036	NaN	56.671373	74.
10	NaN	NaN	NaN	NaN	NaN	NaN	51.681988	NaN	NaN	
11	NaN	NaN	NaN	NaN	NaN	NaN	54.290327	48.709060	57.043688	
12	NaN	NaN	NaN	NaN	NaN	NaN	50.549629	NaN	57.593216	
13	NaN	NaN	NaN	5.0	NaN	NaN	51.104092	NaN	NaN	
All	8.0	9.0	6.666667	5.0	5.0	49.491742	47.495915	44.172066	47.629391	48.

After creating a pivot table to show the energy consumptions among different homestates, we see that vendors from Vermont have the highest average energy consumption, 51.41% compared to other homestates, whereas vendors from Massachusetts consume the least energy for operating their stalls, at 44.17%. Lobsterland should consider hiring more vendors from MA to save up on utility costs.

Segmentation and Targeting

In [11]:

```
mf = pd.read_csv(r'maine_families.csv')
```

In [12]:

```
mf.head()
```

Out[12]:

	householdID	total_ppl	own_rent	square_foot	household_income	number_pets	region
0	1	1.0	own	3309	82050.03	1	Aroostook
1	2	1.0	own	3814	83077.81	2	Midcoast
2	3	2.0	rent	2592	91401.41	2	Downeast_Acadia
3	4	1.0	own	2628	73048.55	1	Greater Portland
4	5	1.0	rent	2442	89145.36	2	Kennebec Valley

Segmentation

Dealing with NANs with mean values.

In [13]:

```
mf.isna().sum()
```

Out[13]:

```
householdID          0
total_ppl           75
own_rent             0
square_foot          0
household_income     0
number_pets          0
```

```
region                      0
entertainment_spend_est     0
travel_spend_est            0
LL_passholder               0
dtype: int64
```

In [14]:
```
mean_value=mf['total_ppl'].mean()
mf['total_ppl'].fillna(value=mean_value, inplace=True)
```

In [15]:
```
mf.isna().sum()
```

Out[15]:
```
householdID                0
total_ppl                  0
own_rent                   0
square_foot                0
household_income           0
number_pets                0
region                     0
entertainment_spend_est    0
travel_spend_est           0
LL_passholder              0
dtype: int64
```

Keep numeric variables only.

In [16]:
```
numeric = mf
```

In [17]:
```
numeric = numeric.drop('householdID', axis=1)
numeric = numeric.drop('own_rent', axis=1)
numeric = numeric.drop('region', axis=1)
numeric = numeric.drop('LL_passholder', axis=1)
```

In [18]:
```
numeric.head()
```

Out[18]:

	total_ppl	square_foot	household_income	number_pets	entertainment_spend_est	travel_spend_est
0	1.0	3309	82050.03	1	3189.11	2028.559211
1	1.0	3814	83077.81	2	4175.35	4713.28000C
2	2.0	2592	91401.41	2	1814.98	3479.07000C
3	1.0	2628	73048.55	1	1945.14	3842.42000C
4	1.0	2442	89145.36	2	4410.86	1913.28000C

Data scaling

In [19]:
```
scaling = numeric
```

In [20]:
```
scaling['total_ppl'] = stats.zscore(scaling.total_ppl)
scaling['square_foot'] = stats.zscore(scaling.square_foot)
scaling['household_income'] = stats.zscore(scaling.household_income)
scaling['number_pets'] = stats.zscore(scaling.number_pets)
```

```
scaling['entertainment_spend_est'] = stats.zscore(scaling.entertainment_spend_est)
scaling['travel_spend_est'] = stats.zscore(scaling.travel_spend_est)
```

In [21]:

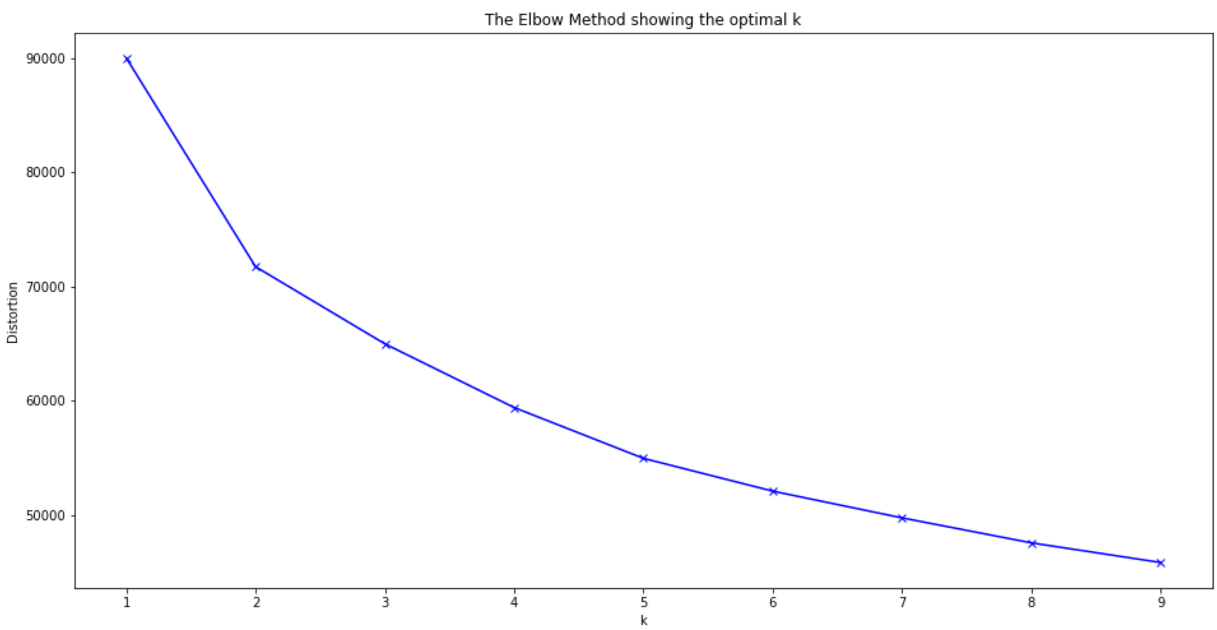
```
scaling.head()
```

Out[21]:

	total_ppl	square_foot	household_income	number_pets	entertainment_spend_est	travel_spend_es
0	-0.714042	0.232960	-0.101357	-0.644446	-0.213953	-1.82079
1	-0.714042	0.851909	-0.061449	0.621159	0.588903	1.13456
2	0.515857	-0.645826	0.261750	0.621159	-1.332575	-0.22406
3	-0.714042	-0.601703	-0.450877	-0.644446	-1.226617	0.17591
4	-0.714042	-0.829672	0.174149	0.621159	0.780622	-1.94769

In [22]:

```
distortions = []
K = range(1,10)
for k in K:
 kmeanModel = KMeans(n_clusters=k)
 kmeanModel.fit(scaling)
 distortions.append(kmeanModel.inertia_)
plt.figure(figsize=(16,8))
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```



although the elbow chart shows that 2 might be the best k value for clustering, but after I tried, 4 will be better.

In [23]:

```
kmeanModel = KMeans(n_clusters = 4, random_state = 123)
kmeanModel.fit(scaling)
scaling['Cluster']=kmeanModel.predict(numeric)
```

In [24]:

```
mf['Cluster'] = scaling['Cluster']
```

In [25]:

```
numeric['Cluster'].value_counts()
```

Out[25]:

```
Cluster
0    4107
2    4001
3    3715
1    3177
Name: count, dtype: int64
```

In [26]:

```
mf.groupby('Cluster')[['total_ppl',
                       'square_foot',
                      'household_income',
                      'number_pets',
                      'entertainment_spend_est',
                      'travel_spend_est']].mean()
```

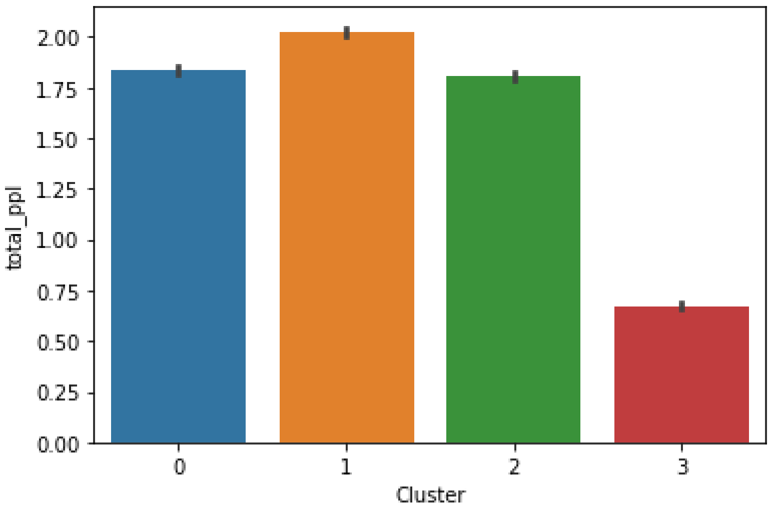
Out[26]:

	total_ppl	square_foot	household_income	number_pets	entertainment_spend_est	travel_spe
Cluster						
0	1.836754	3044.093255	70318.073190	2.230338	2818.574716	3175.2
1	2.026723	3304.224111	108964.347913	1.480327	4726.343009	4398.6
2	1.807080	3019.701325	69843.729708	0.794801	2823.141722	3188.3
3	0.671862	3150.065410	95688.971254	1.506057	3739.469335	4163.4

In [27]:

```
sns.barplot(x = 'Cluster', y = 'total_ppl', data = mf)
```

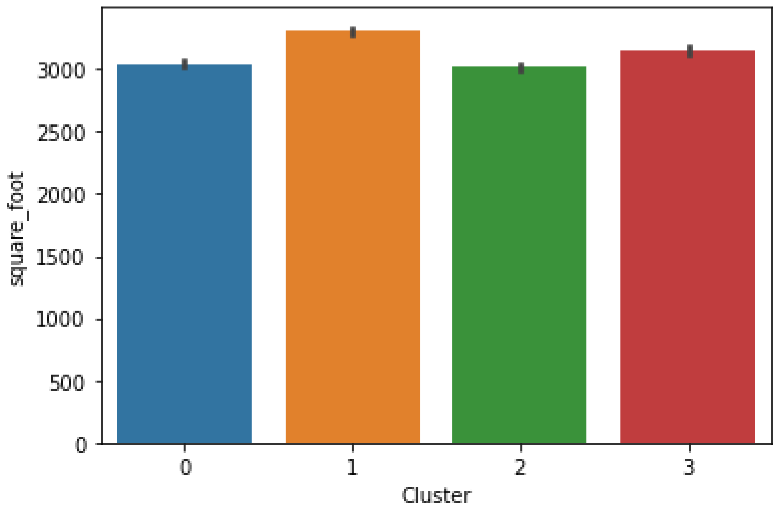
Out[27]: <AxesSubplot:xlabel='Cluster', ylabel='total_ppl'>



In [28]:

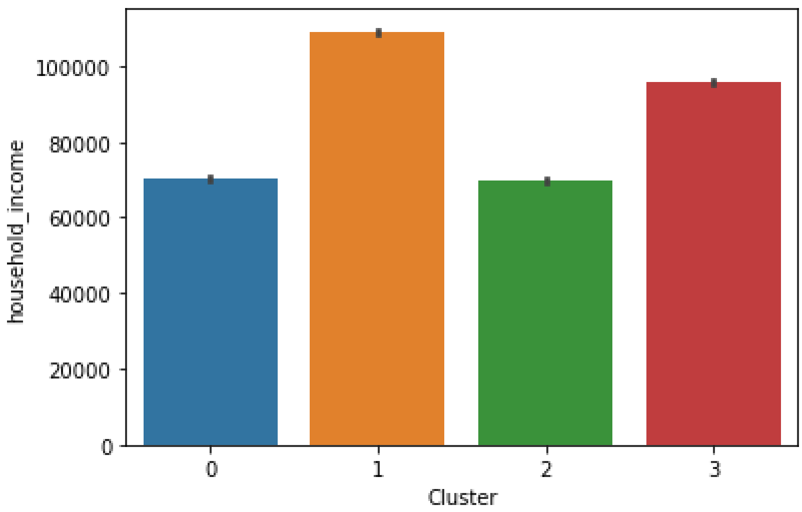
```
sns.barplot(x = 'Cluster', y = 'square_foot', data = mf)
```

Out[28]: <AxesSubplot:xlabel='Cluster', ylabel='square_foot'>



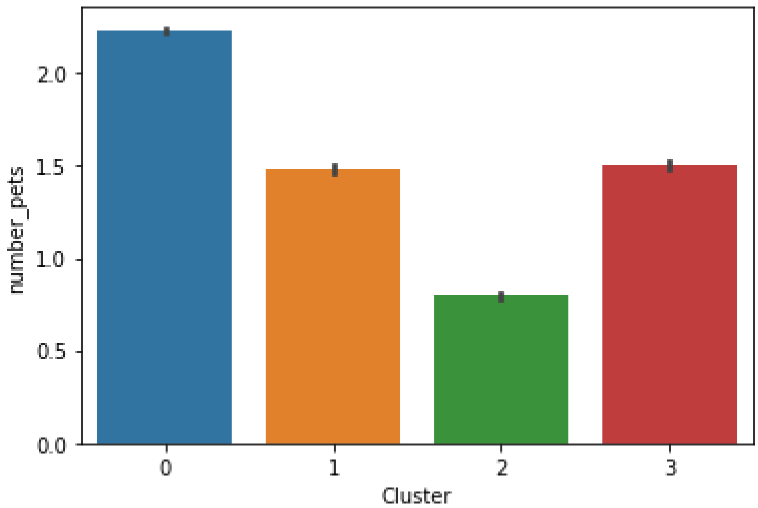
In [29]:
```
sns.barplot(x = 'Cluster', y = 'household_income', data = mf)
```

Out[29]: <AxesSubplot:xlabel='Cluster', ylabel='household_income'>



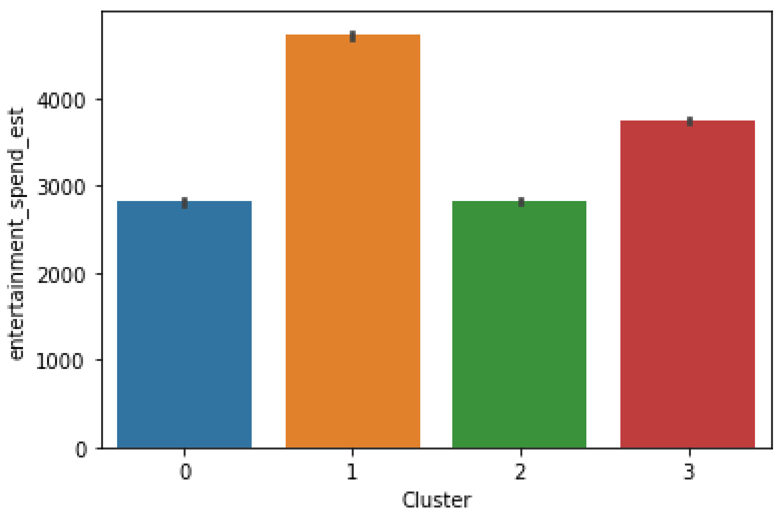
In [30]:
```
sns.barplot(x = 'Cluster', y = 'number_pets', data = mf)
```

Out[30]: <AxesSubplot:xlabel='Cluster', ylabel='number_pets'>



In [31]:
```
sns.barplot(x = 'Cluster', y = 'entertainment_spend_est', data = mf)
```

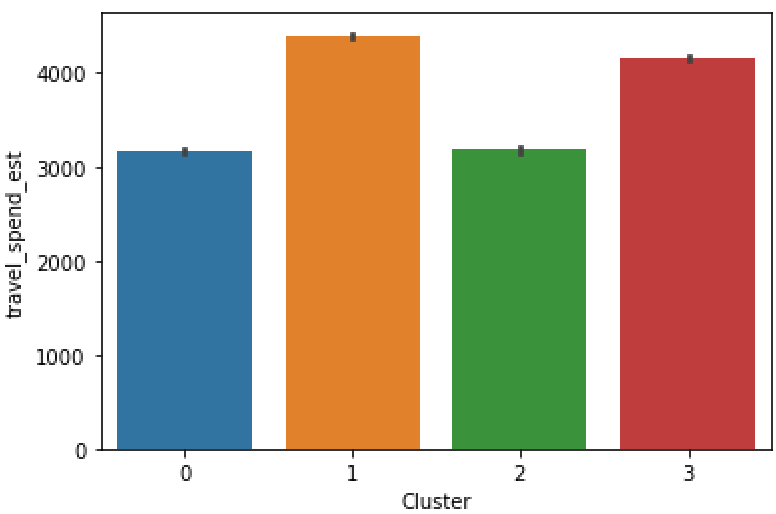
Out[31]: <AxesSubplot:xlabel='Cluster', ylabel='entertainment_spend_est'>



In [32]:

```
sns.barplot(x = 'Cluster', y = 'travel_spend_est', data = mf)
```

Out[32]: <AxesSubplot:xlabel='Cluster', ylabel='travel_spend_est'>



Clustering

Cluster 0: Pet Lover

Cluster 0 is known to me as Pet Lover because they have the largest number of family pets of the four clusters. And they are very willing to invest in their pets, willing to buy bigger homes and spend more on travel for their pets. Sometimes they even sacrifice their entertainment time for their pets.

Cluster 1: Big Family

I refer to Cluster 1 as a Big Family because they have the highest total household size, total household income and total spending in all areas, which means they are willing to spend, and although they may not have the highest per capita spending, they are undoubtedly the largest customer when it comes to the household as a unit.

Cluster 2: Low Class

Cluster 2 is what I would call Low Class. The household income and family home size show that this Cluster is the least financially capable of the four clusters. They basically have no pet ties and will keep their spending as low as possible when they go out.

Cluster 3: Single Elite

I call Cluster 3 Single Elite because they are busy working, some don't even live at home. The size of the home shows their financial strength is strong, and they have the highest per capita income, per capita entertainment spending and per capita travel spending of the four Clusters.

Targeting

Cluster 0: Pet Lover

For Cluster 0, since their bond with pets is very deep, I would suggest Lobster Land to introduce some projects where people and pets can play together, or some Pet Special projects such as pet restaurants, pet grooming, etc.

Cluster 1: Big Family

For Cluster 1, there may be more family members, so Lobster Land can offer them services with a family concept, such as parent-child tickets, or hold entertainment programs that require parents and children to participate together to attract them.

Cluster 2: Low Class

Even though Cluster 2's spending power is not high, they still have considerable willingness to spend. So for this cluster, what Lobster Land can do is to issue various coupons to them to stimulate them to come and spend.

Cluster 3: Single Elite

For Cluster 3, their spending power and willingness to spend are very strong. For this cluster, Lobster Land can send them the newly launched high quality entertainment programs to attract them to spend money.

Conjoint Analysis & Memo Section

In [33]:
```
bbq = pd.read_csv("bbq_lake.csv")
```

In [34]:
```
bbq.describe()
```

Out[34]:

	bundleID	avg_rating
count	384.000000	384.000000
mean	192.500000	7.052063
std	110.995495	1.699184
min	1.000000	1.690000
25%	96.750000	5.879500

	bundleID	avg_rating
50%	192.500000	7.121000
75%	288.250000	8.510000
max	384.000000	9.970000

In [35]:

```
bbq.isnull().sum()
```

Out[35]:

```
bundleID      0
starter       0
maindishI     0
maindishII    0
side          0
dessert       0
avg_rating    0
dtype: int64
```

In [36]:

```
bbq.info
```

Out[36]:

```
<bound method DataFrame.info of      bundleID               starter                     mai
ndishI     maindishII  \
0           1  Fried Chicken Tenders             BBQ Brisket         Sausage
1           2  Fried Chicken Tenders             BBQ Brisket         Sausage
2           3  Fried Chicken Tenders             BBQ Brisket         Sausage
3           4  Fried Chicken Tenders             BBQ Brisket         Sausage
4           5  Fried Chicken Tenders             BBQ Brisket         Sausage
..        ...                    ...                     ...             ...
379       380   Jumbo Shrimp Cocktail  Pork and Brisket Combo  Steak Sampler
380       381   Jumbo Shrimp Cocktail  Pork and Brisket Combo  Steak Sampler
381       382   Jumbo Shrimp Cocktail  Pork and Brisket Combo  Steak Sampler
382       383   Jumbo Shrimp Cocktail  Pork and Brisket Combo  Steak Sampler
383       384   Jumbo Shrimp Cocktail  Pork and Brisket Combo  Steak Sampler

                   side            dessert  avg_rating
0        Mac and Cheese      Peach Cobbler        5.81
1        Mac and Cheese  Apple Pie a la Mode        8.93
2         Mashed Potato      Peach Cobbler        6.20
3         Mashed Potato  Apple Pie a la Mode        8.71
4    French Fry Platter      Peach Cobbler        8.24
..                  ...                ...         ...
379      Mac and Cheese  Apple Pie a la Mode        5.91
380       Mashed Potato      Peach Cobbler        6.30
381       Mashed Potato  Apple Pie a la Mode        7.65
382  French Fry Platter      Peach Cobbler        8.67
383  French Fry Platter  Apple Pie a la Mode        8.83

[384 rows x 7 columns]>
```

In [37]:

```
del bbq['bundleID']
```

In [38]:

```
bbq.head()
```

Out[38]:

	starter	maindishI	maindishII	side	dessert	avg_rating
0	Fried Chicken Tenders	BBQ Brisket	Sausage	Mac and Cheese	Peach Cobbler	5.81
1	Fried Chicken Tenders	BBQ Brisket	Sausage	Mac and Cheese	Apple Pie a la Mode	8.93

	starter	maindishI	maindishII	side	dessert	avg_rating
2	Fried Chicken Tenders	BBQ Brisket	Sausage	Mashed Potato	Peach Cobbler	6.20
3	Fried Chicken Tenders	BBQ Brisket	Sausage	Mashed Potato	Apple Pie a la Mode	8.71
4	Fried Chicken Tenders	BBQ Brisket	Sausage	French Fry Platter	Peach Cobbler	8.24

In [39]:
```
bbq.columns
```

Out[39]:
```
Index(['starter', 'maindishI', 'maindishII', 'side', 'dessert', 'avg_rating'], dtype
='object')
```

In [40]:
```
bbq1 = pd.get_dummies(bbq, drop_first=True, columns=['starter','maindishI','maindishI
```

In [41]:
```
bbq1.columns
```

Out[41]:
```
Index(['avg_rating', 'starter_Fried Chicken Tenders',
       'starter_Jumbo Shrimp Cocktail', 'starter_Sticky Chicken Tenders',
       'maindishI_BBQ Chicken', 'maindishI_Pork and Brisket Combo',
       'maindishI_Pulled Pork', 'maindishII_Fajita', 'maindishII_Sausage',
       'maindishII_Steak Sampler', 'side_Mac and Cheese', 'side_Mashed Potato',
       'dessert_Peach Cobbler'],
      dtype='object')
```

In [42]:
```
X = bbq1[['starter_Fried Chicken Tenders','starter_Jumbo Shrimp Cocktail','starter_Sti
 'maindishI_Pork and Brisket Combo','maindishI_Pulled Pork','maindishII_Fajita','mainc
          'side_Mac and Cheese', 'side_Mashed Potato','dessert_Peach Cobbler']]
y = bbq1['avg_rating']
```

In [43]:
```
regressor = LinearRegression()
regressor.fit(X, y)
```

Out[43]:
```
LinearRegression()
```

In [44]:
```
regressor.intercept_
```

Out[44]:
```
6.968645833333335
```

In [45]:
```
bbq1.columns
```

Out[45]:
```
Index(['avg_rating', 'starter_Fried Chicken Tenders',
       'starter_Jumbo Shrimp Cocktail', 'starter_Sticky Chicken Tenders',
       'maindishI_BBQ Chicken', 'maindishI_Pork and Brisket Combo',
       'maindishI_Pulled Pork', 'maindishII_Fajita', 'maindishII_Sausage',
       'maindishII_Steak Sampler', 'side_Mac and Cheese', 'side_Mashed Potato',
       'dessert_Peach Cobbler'],
      dtype='object')
```

In [46]:
```
coef_df = pd.DataFrame(regressor.coef_, X.columns, columns=['Coefficient'])
coef_df
```

Out[46]:

	Coefficient
starter_Fried Chicken Tenders	0.103854

	Coefficient
starter_Jumbo Shrimp Cocktail	-0.451771
starter_Sticky Chicken Tenders	0.093333
maindishI_BBQ Chicken	-0.207917
maindishI_Pork and Brisket Combo	1.063646
maindishI_Pulled Pork	0.577188
maindishII_Fajita	-0.498313
maindishII_Sausage	0.342917
maindishII_Steak Sampler	0.232813
side_Mac and Cheese	0.419687
side_Mashed Potato	-0.002500
dessert_Peach Cobbler	-0.739167

After analyzing the coefficients of the linear regression model, built after dummifying the input variables, we can see that the reference levels are as follows:

Starter: Crabcakes and Shrimp

Maindish 1: BBQ Brisket

Maindish 2: Beef Short Rib

Side: French Fry Platter

Dessert: Apple Pie a la Mode

By deep-diving into the stength of the coefficients, we see that for starters, Fried Chicken tenders are the most popular among customers. However, Fried Chicken Tenders cost 3.5 dollars, whereas Sticky chicken tenders costs 2.9 dollars. It is more logical for lobsterland to offer the Sticky chicken tenders as a starter since the vendor cost for sticky chicken is 0.6 dollars lower compared to Fried Chicken tenders, and the difference in coefficients is 11.27 %. (0.103854-0.093333)/0.093333.

In terms of maindish_1, the 'Pork and Brisket Combo' is the most popular among customers. Another contender for maindish_1 is 'Pulled Pork', the cost difference between them is only 6.1-6=0.1 dollars. This small difference between their costs is not significant enough to sway our opinion from the obvious coefficient difference of (1.063646-0.577188)/0.577188 or 84.28%. So the best choice for maindish_1 would be 'Pork and Brisket Combo' for 6.1 dollars.

Talking about maindish_II, 'Sausage' seems to be the most popular choice. 'Steak Sampler' is also a crowd favorite. The cost difference between them is 5.3- 4.7=0.6 dollars. The difference in coefficients is (0.342917-0.232813)/0.232813 or 47.29% . The cost increase is only (5.3-4.7)/4.7=12.77% . Taking these factors into account, it is more resonable for Lobsterland to offer 'Sausage' as a second maindish despite its higher cost, due to the relative difference in coefficient strength.

For the side, 'Mac and Cheese' is relatively the most popular dish among customers. The french fry platter costs 0.25-0.15= 0.1 dollars less compared to mac and cheese, however, based on the relative popularity of mac and cheese, 0.0 compared to 0.419687. Mac and cheese is the best choice here, despite the increased costs. Lobsterland management should select mac and cheese for their preffered side order.

Finally, for desserts, 'The Peach Cobbler' is relatively poor as a dessert choice for customers, compared to 'Apple Pie a la Mode'. The unit cost for this dessert is 0.9-0.6=0.3 dollars higher than Peach Cobbler, however, given the huge negative coefficient associated with Peach Cobbler, Lobsterland should consider having Apple Pie a la Mode as the dessert to make sure its customers are satisfied with the food.

My final recommendation for the menu to Lobsterland would be as follows:

Starter: Sticky Chicken Tenders

Maindish_1: Pork and Brisket Combo

Maindish_2: Sausage

Side: Mac and Cheese

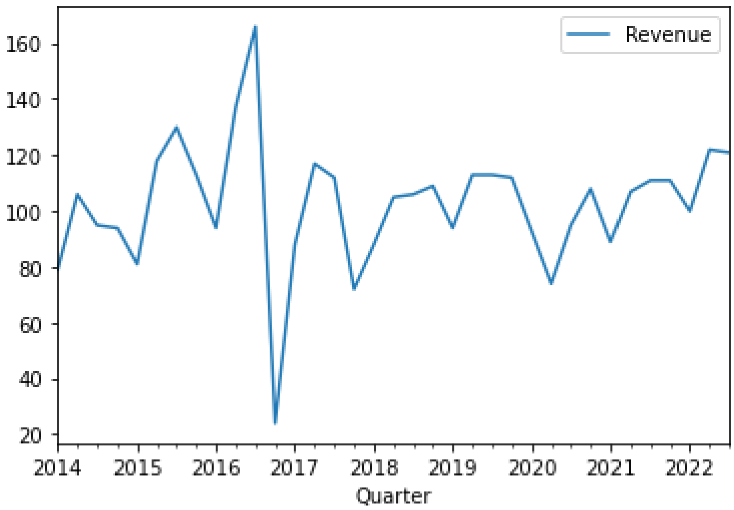
Dessert: Apple Pie a la Mode

Forecasting Total Revenue

In [47]:
```
df = pd.read_excel('TSQ.xlsx',index_col='Quarter',date_format = True)
```

In [48]:
```
df.plot()
```

Out[48]: <AxesSubplot:xlabel='Quarter'>

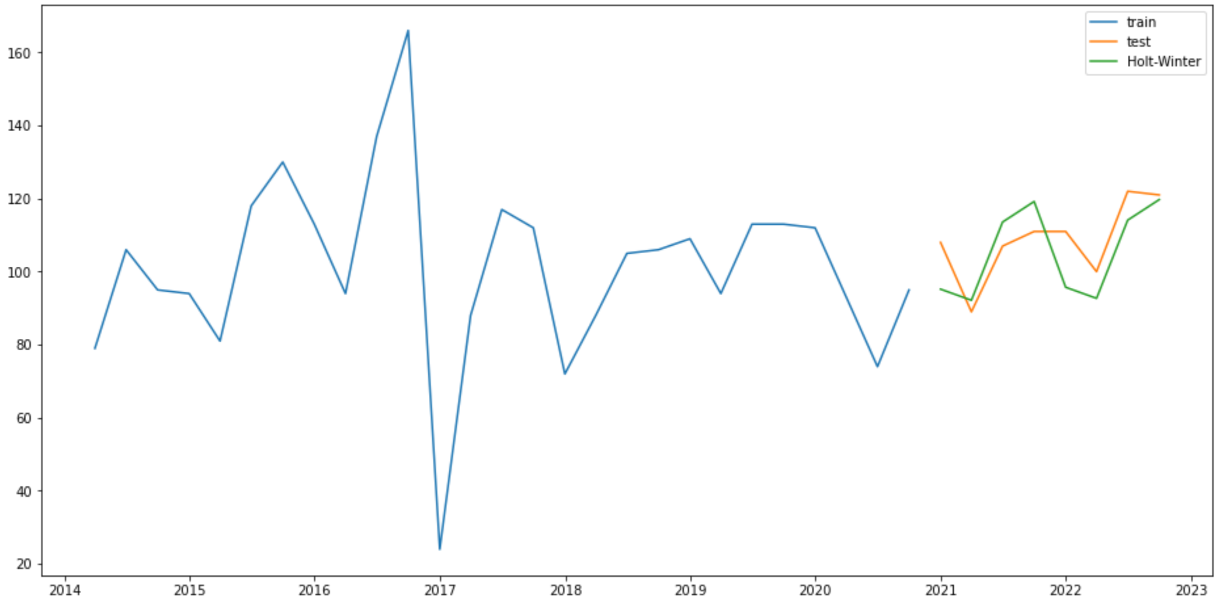


In [49]:
```
train = df[0:27]
test = df[27:]
```

In [50]:

```
y_hat_avg = test.copy()
fit = ExponentialSmoothing(np.asarray(df['Revenue']),seasonal_periods=4,trend='add',s
y_hat_avg['Holt-Winter'] = fit.forecast(len(test))
Q4_2022 = fit.forecast(1)
plt.figure(figsize=(16,8))
plt.plot(train['Revenue'],label='train')
plt.plot(test['Revenue'],label='test')
plt.plot(y_hat_avg['Holt-Winter'],label='Holt-Winter')
plt.legend(loc='best')
rms = sqrt(mean_squared_error(test['Revenue'],y_hat_avg['Holt-Winter']))
print(rms)
```

```
8.9095562096062
```



In [51]:

```
pred_2022 = round(int(y_hat_avg['Holt-Winter'][-3]+ \
                 y_hat_avg['Holt-Winter'][-2]+y_hat_avg['Holt-Winter'][-1]+Q4_2022),0)
```

In [52]:

```
print(f"Total Revenue of TSQ in 2022 is around: {pred_2022} million")
```

```
Total Revenue of TSQ in 2022 is around: 421 million
```

In this forecasting case, I tried to use data from Yahoo Finance ar first, however, there is only open price, close price and volume. I don't think the revenue can be clarified by those inidcator. Therefore, I directly use annual revenue data of TSQ throguh: https://www.macrotrends.net/stocks/charts/TSQ/townsquare-media/revenue (https://www.macrotrends.net/stocks/charts/TSQ/townsquare-media/revenue). Based on this data, I also tried Simple Exponential Smoothing and ARIMA, but those methods don't fit well. Compared to annual revenues, quarter revenues have clear pattern and enough data to seperate into train and test sets.

Classification

In [53]:

```
cv1 = pd.read_csv(r'carnival_visitors.csv')
cv1.head()
```

Out[53]:

	householdID	est_inc_USD	est_netw_USD	hhold_field	hhold_oldest	hhold_pax	hhold_youngest
0	23	59245	381931	Govt	48	2	8
1	27	116628	457159	Tech	51	5	21
2	36	65835	394803	Services	50	4	13
3	41	132483	429296	Tech	54	2	11
4	44	83444	488210	Education	51	7	12

Identify the categorical and numerical variables

In [54]:

```
cv1.dtypes
```

Out[54]:

```
householdID        int64
est_inc_USD        int64
est_netw_USD       int64
hhold_field       object
hhold_oldest       int64
hhold_pax          int64
hhold_youngest     int64
homeState         object
hhold_car         object
stream_subs        int64
primary            int64
dtype: object
```

In [55]:

```
cv1['primary'].value_counts()
```

Out[55]:

```
primary
1    8124
0    6876
Name: count, dtype: int64
```

Dealing with missing values

In [56]:

```
cv1 = cv1.dropna()
```

In [57]:

```
cv1.isnull().sum()
```

Out[57]:

```
householdID       0
est_inc_USD       0
est_netw_USD      0
hhold_field       0
hhold_oldest      0
hhold_pax         0
hhold_youngest    0
homeState         0
hhold_car         0
stream_subs       0
primary           0
dtype: int64
```

Dummifying

In [58]:

```
cv1.columns
```

Out[58]:

```
Index(['householdID', 'est_inc_USD', 'est_netw_USD', 'hhold_field',
       'hhold_oldest', 'hhold_pax', 'hhold_youngest', 'homeState', 'hhold_car',
       'stream_subs', 'primary'],
      dtype='object')
```

In [59]:

```
cv1 = pd.get_dummies(cv1, drop_first=True, columns=['hhold_field','homeState','hhold_
```

In [60]:

```
cv1.columns
```

Out[60]:

```
Index(['householdID', 'est_inc_USD', 'est_netw_USD', 'hhold_oldest',
       'hhold_pax', 'hhold_youngest', 'stream_subs', 'primary',
       'hhold_field_Finance', 'hhold_field_Govt', 'hhold_field_Manufacturing',
       'hhold_field_Other', 'hhold_field_Services', 'hhold_field_Tech',
       'homeState_Connecticut', 'homeState_Maine', 'homeState_Massachusetts',
       'homeState_New Hampshire', 'homeState_New York', 'homeState_Ontario',
       'homeState_Quebec', 'homeState_Rhode Island', 'homeState_US_Other',
       'homeState_Vermont', 'hhold_car_LuxurySedan', 'hhold_car_Pickup',
       'hhold_car_SUV', 'hhold_car_Sedan'],
      dtype='object')
```

In [61]:

```
X=cv1[['est_inc_USD', 'est_netw_USD', 'hhold_oldest',
 'hhold_pax', 'hhold_youngest', 'stream_subs',
 'hhold_field_Finance', 'hhold_field_Govt', 'hhold_field_Manufacturing',
 'hhold_field_Other', 'hhold_field_Services', 'hhold_field_Tech',
 'homeState_Ontario',
 'homeState_Quebec', 'homeState_US_Other',
 'homeState_Vermont', 'hhold_car_LuxurySedan', 'hhold_car_Pickup',
 'hhold_car_SUV', 'hhold_car_Sedan']]
y=cv1['primary']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=
```

In [62]:

```
log_reg = sm.Logit(y_train, sm.add_constant(X_train)).fit()
log_reg = sm.Logit(y_test, sm.add_constant(X_test)).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.612681
         Iterations 5
Optimization terminated successfully.
         Current function value: 0.609360
         Iterations 5
```

In [63]:

```
log_reg.summary()
```

Out[63]:

Logit Regression Results

Dep. Variable:	primary	**No. Observations:**	5780
Model:	Logit	**Df Residuals:**	5759
Method:	MLE	**Df Model:**	20
Date:	Thu, 24 Aug 2023	**Pseudo R-squ.:**	0.1154
Time:	11:13:56	**Log-Likelihood:**	-3522.1
converged:	True	**LL-Null:**	-3981.5

Covariance Type:	nonrobust	**LLR p-value:**	7.820e-182

	coef	std err	z	P>|z|	[0.025	0.975]
const	4.4785	0.387	11.585	0.000	3.721	5.236
est_inc_USD	-9.601e-06	1.69e-06	-5.665	0.000	-1.29e-05	-6.28e-06
est_netw_USD	2.236e-06	5.56e-07	4.020	0.000	1.15e-06	3.33e-06
hhold_oldest	-0.1094	0.006	-17.784	0.000	-0.121	-0.097
hhold_pax	0.0489	0.018	2.712	0.007	0.014	0.084
hhold_youngest	-0.0072	0.004	-1.851	0.064	-0.015	0.000
stream_subs	0.2429	0.017	14.252	0.000	0.209	0.276
hhold_field_Finance	-0.8389	0.114	-7.380	0.000	-1.062	-0.616
hhold_field_Govt	-1.0127	0.099	-10.231	0.000	-1.207	-0.819
hhold_field_Manufacturing	-0.2369	0.191	-1.240	0.215	-0.611	0.137
hhold_field_Other	-0.4296	0.188	-2.283	0.022	-0.798	-0.061
hhold_field_Services	0.2013	0.114	1.771	0.077	-0.021	0.424
hhold_field_Tech	-0.5273	0.115	-4.575	0.000	-0.753	-0.301
homeState_Ontario	-0.1264	0.129	-0.977	0.329	-0.380	0.127
homeState_Quebec	0.0086	0.122	0.071	0.944	-0.230	0.247
homeState_US_Other	-0.1840	0.147	-1.249	0.212	-0.473	0.105
homeState_Vermont	0.0418	0.098	0.425	0.671	-0.151	0.235
hhold_car_LuxurySedan	0.2381	0.115	2.074	0.038	0.013	0.463
hhold_car_Pickup	-0.1644	0.132	-1.244	0.214	-0.424	0.095
hhold_car_SUV	-0.0389	0.108	-0.359	0.720	-0.251	0.174
hhold_car_Sedan	0.1104	0.117	0.941	0.347	-0.120	0.340

After building the model the above summary indicates some high p-value of some the variable in which the homestate_quebec have maximum p-value which can brings lots of reson behind this but the most impactable is the different country as it's hard to travel all the way from canada or the time, fuel, resorces would be extra as compared to people live nearby and finally it does not give much statistical significance to the model.

Predicting the model

In [64]:

```
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
```

Out[64]:

```
KNeighborsClassifier()
```

In [65]:

```
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
predictions = knn.predict(X_test)
print(accuracy_score(y_test, predictions))
```

```
print(confusion_matrix(y_test, predictions))
print(classification_report(y_test, predictions))
```

```
0.5271626297577855
[[1177 1445]
 [1288 1870]]
              precision    recall  f1-score   support

           0       0.48      0.45      0.46      2622
           1       0.56      0.59      0.58      3158

    accuracy                           0.53      5780
   macro avg       0.52      0.52      0.52      5780
weighted avg       0.52      0.53      0.53      5780
```

In this model we can identify that the accuracy score is 53% and sensitivity rate is 59% with the specificity rate is 45% through which we can conclude that the balanced accuracy of the model is sensitivity+specificity/2 which would be 52%.

Predicting the model through decision tree classification

In [66]:

```
dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
predictions = dtc.predict(X_test)
print(accuracy_score(y_test, predictions))
print(confusion_matrix(y_test, predictions))
print(classification_report(y_test, predictions))
```

```
0.6252595155709343
[[1575 1047]
 [1119 2039]]
              precision    recall  f1-score   support

           0       0.58      0.60      0.59      2622
           1       0.66      0.65      0.65      3158

    accuracy                           0.63      5780
   macro avg       0.62      0.62      0.62      5780
weighted avg       0.63      0.63      0.63      5780
```

We have predicted the model again with decision tree classifier as it works for both continuous as well as categorical output variables and also this suggest our team to determine the potential and primary purpose of the visitors to visit in winter carnival for either consume or entertain purpose and in this model we can identify that the accuracy score is 62% and sensitivity rate is 64% with the specificity rate is 59% through which we can conclude that the balanced accuracy of the model is sensitivity+specificity/2 which would be 62%.

Accuracy of train and test set

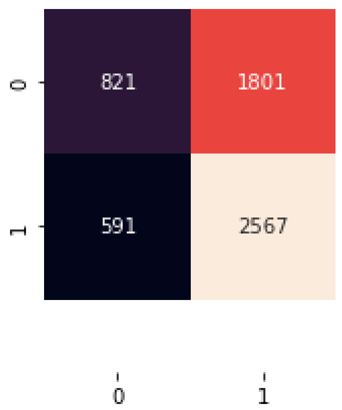
In [67]:

```
y_predict = classifier.predict(X_test)
logmodel = LogisticRegression(max_iter=500)
logmodel.fit(X_train, y_train)
```

Out[67]:

```
LogisticRegression(max_iter=500)
```

In [68]:
```
predictions = logmodel.predict(X_test)
accuracy_score(y_test, predictions)
```
Out[68]:
```
0.586159169550173
```
In [69]:
```
predictions = logmodel.predict(X_train)
print(metrics.accuracy_score(y_train,predictions))
```
```
0.573537893644019
```
In this section we can observe that the accuracy score of testing set is 0.5862 and on other hand the accracy score of training set is 0.5735.

In [70]:
```
%matplotlib inline
predictions = logmodel.predict(X_test)
mat = confusion_matrix(y_test, predictions)
sns.heatmap(mat, fmt='g', square=True, annot=True, cbar=False)
a, b = plt.ylim()
a += 0.5
b -= 0.5
plt.ylim(a, b)
plt.show()
```


The number 821 corresponds to the number of visitors who were correctly predicted by the model who visit the winter carnival with mood of consuming the food and drinks and enjoy the evening , meaning they will contribute more towards carnival merchandise and snack stores that can generate stronger revenue model

The number 2567 corresponds to the number of visitors that the model correctly predicted to visit the winter carnival with entertain purpose and experience the amazing live performance, comedy shows and competitions that will create thrill and excitement among the visitors and probably they'll refer and recommend theirs friends and neighbours to visit the winter carnival that will also simultaneously increase the visitors traffic and profit margin of the park.

The analysis of the confusion matrix model and the p-values for all variables suggests that visitors are more inclined to attend the winter carnival for entertainment purposes. They value the experience of witnessing thrilling competitions and live performances, cherishing memorable moments. Additionally, there's room for improvement in the food section.

Introducing attractive discount offers and bundle deals could enhance the overall visitor experience and encourage them to spend more at the park.

While these are key findings, there could be other factors influencing visits. Some individuals might be nearby residents seeking a break from screens, while others might be lured by one-day pass promotions. In essence, the winter carnival caters to various customer segments. The main focus is to boost the park's popularity and revenue model, acknowledging different visitor priorities and preferences.

A/B Testing

In [71]:

```
sp = pd.read_csv(r'snowmobile_pics.csv')
sp.head()
```

Out[71]:

	recipient	pic_seen	site_duration	spend	register
0	1	Racers in Action	18.20	16.60	0
1	2	Starting Line	28.61	15.30	0
2	3	Sharp Turn	10.90	16.32	1
3	4	Sharp Turn	11.30	22.62	0
4	5	Racers in Action	19.70	17.30	0

In [72]:

```
sp.groupby('pic_seen').mean()
```

Out[72]:

	recipient	site_duration	spend	register
pic_seen				
Racers in Action	1693.945946	22.949189	16.781892	0.440541
Sharp Turn	1734.473730	10.975394	18.606778	0.348511
Starting Line	1673.040941	24.294059	14.016289	0.341463

Set alpha threshhold to be .05 for all comparisons.

Situation I

lobster Land prioritizing the kpi "register"

i. Pic: Racers in Action vs. Pic: Sharp Turn

The null hypothesis H0 is that Pic: Racers in Action and Pic: Sharp Turn are equally effective at "register".

In [73]:

```
group_a = sp.loc[sp['pic_seen'] == 'Racers in Action', 'register'].values
group_b = sp.loc[sp['pic_seen'] == 'Sharp Turn', 'register'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to 4.48659813805182, p-value is equal to 7.6013670601284866e-06
```

Since the p-value for our t-test is less than .05, we reject the null hypothesis that Pic: Racers in Action and Pic: Sharp Turn are equally effective at "register". Furthermore, 44.05% recipients who received "Racers in Action" registered but only 34.85% recipents who received "Sharp Turn" registered. Therefore, we can conclude that "Racers in Action" is more effective than "Sharp Turn" at the kpi "register".

ii. Pic: Racers in Action vs. Pic: Starting Line

The null hypothesis H0 is that Pic: Racers in Action and Pic: Starting Line are equally effective at "register".

In [74]:

```
group_a = sp.loc[sp['pic_seen'] == 'Racers in Action', 'register'].values
group_b = sp.loc[sp['pic_seen'] == 'Starting Line', 'register'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to 4.8480946527362345, p-value is equal to 1.331438616096751e-06
```

Since the p-value for our t-test is less than .05, we reject the null hypothesis that Pic: Racers in Action and Pic: Starting are equally effective at "register". Furthermore, 44.05% recipients who received "Racers in Action" registered but only 34.15% recipents who received "Starting Line" registered. Therefore, we can conclude that "Racers in Action" is more effective than "Starting Line" at the kpi "register".

iii. Pic: Sharp Turn vs. Pic: Starting Line

The null hypothesis H0 is that Pic: Sharp Turn and Pic: Starting Line are equally effective at "register".

In [75]:

```
group_a = sp.loc[sp['pic_seen'] == 'Sharp Turn', 'register'].values
group_b = sp.loc[sp['pic_seen'] == 'Starting Line', 'register'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to 0.35460817550947715, p-value is equal to 0.7229158305143963
```

Since the p-value for our t-test is more than .05, we fail to reject the null hypothesis that Pic: Sharp Turn and Pic: Starting are equally effective at "register". Furthermore, 34.85% recipients who received "Sharp Turn" registered and 34.15% recipents who received "Starting Line" registered. These two percentages are indeed pretty close. Therefore, we can conclude that Pic: Sharp Turn and Pic: Starting Line are equally effective at the kpi "register". In summary, for the kpi "register", "Racers in Action" > "Sharp Turn" = "Starting Line"

Situation II

Lobster Land prioritizing the kpi site_duration

i. Pic: Racers in Action vs. Pic: Sharp Turn

The null hypothesis H0 is that Pic: Racers in Action and Pic: Sharp Turn are equally effective at "site_duration".

In [76]:
```
group_a = sp.loc[sp['pic_seen'] == 'Racers in Action', 'site_duration'].values
group_b = sp.loc[sp['pic_seen'] == 'Sharp Turn', 'site_duration'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to 180.71977956194002, p-value is equal to 0.0
```

Since the p-value for our t-test is less than .05, we reject the null hypothesis that Pic: Racers in Action and Pic: Sharp Turn are equally effective at "site_duration". Also, since the mean of site_duration for Racers in Action is 22.95 and the mean of site_duration for Sharp Turn is 10.98, we can conclude that Racers in Action is more effective than Sharp Turn at site_duration.

ii. Pic: Racers in Action vs. Pic: Starting Line

The null hypothesis H0 is that Pic: Racers in Action and Pic: Starting Line are equally effective at "site_duration".

In [77]:
```
group_a = sp.loc[sp['pic_seen'] == 'Racers in Action', 'site_duration'].values
group_b = sp.loc[sp['pic_seen'] == 'Starting Line', 'site_duration'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to -9.911415184705456, p-value is equal to 1.0724418388111107e-22
```

Since the p-value for our t-test is less than .05, we reject the null hypothesis that Pic: Racers in Action and Pic: Starting Line are equally effective at "site_duration". Also, since the mean of site_duration for Racers in Action is 22.95 and the mean of site_duration for Starting Line is 24.29, we can conclude that Racers in Action is less effective than Starting Line at site_duration.

iii. Pic: Sharp Turn vs. Pic: Starting Line

The null hypothesis H0 is that Pic: Sharp Turn and Pic: Starting Line are equally effective at "site_duration"

In [78]:
```
group_a = sp.loc[sp['pic_seen'] == 'Sharp Turn', 'site_duration'].values
group_b = sp.loc[sp['pic_seen'] == 'Starting Line', 'site_duration'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to -112.12607762440105, p-value is equal to 0.0
```

Since the p-value for our t-test is less than .05, we reject the null hypothesis that Pic: Sharp Turn and Pic: Starting Line are equally effective at "site_duration". Also, since the mean of site_duration for Sharp Turn is 10.98 and the mean of site_duration for Starting Line is 24.29, we can conclude that Sharp Turn is less effective than Starting Line at site_duration.

In summary, for the kpi site_duration, Starting Line > Racers in Action > Sharp Turn

Situation III

Lobster Land prioritizing the kpi "spend"

i. Pic: Racers in Action vs. Pic: Sharp Turn

The null hypothesis H0 is that Pic: Racers in Action and Pic: Sharp Turn are equally effective at "spend"

In [79]:
```
group_a = sp.loc[sp['pic_seen'] == 'Racers in Action', 'spend'].values
group_b = sp.loc[sp['pic_seen'] == 'Sharp Turn', 'spend'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to -23.596074151014385, p-value is equal to 3.5328205740249146e-110
```

Since the p-value for our t-test is less than .05, we reject the null hypothesis that Pic: Racers in Action and Pic: Sharp Turn are equally effective at "spend". Also, since the mean of spend for Racers in Action is 16.78 and the mean of spend for Sharp Turn is 18.61, we can conclude that Racers in Action is less effective than Sharp Turn at spend.

ii. Pic: Racers in Action vs. Pic: Starting Line

The null hypothesis H0 is that Pic: Racers in Action and Pic: Starting Line are equally effective at "spend".

In [80]:
```
group_a = sp.loc[sp['pic_seen'] == 'Racers in Action', 'spend'].values
group_b = sp.loc[sp['pic_seen'] == 'Starting Line', 'spend'].values

t_statistic, p_value = stats.ttest_ind(group_a, group_b)
print(f't-value is equal to {t_statistic}, p-value is equal to {p_value}')
```

```
t-value is equal to 40.53370629078891, p-value is equal to 2.4333914152341534e-270
```

Since the p-value for our t-test is less than .05, we reject the null hypothesis that Pic: Racers in Action and Pic: Starting Line are equally effective at "spend". Also, since the mean of spend for Racers in Action is 16.78 and the mean of spend for Starting Line is 14.02, we can conclude that Racers in Action is more effective than Starting Line at spend.

In summary, for the kpi "spend", we have Sharp Turn > Racers in Action > Starting Line

Putting every kpi comparison together, we have:

For the kpi register: Racers in Action > Sharp Turn = Starting Line

For the kpi site_duration: Starting Line > Racers in Action > Sharp Turn

For the kpi spend: we have Sharp Turn > Racers in Action > Starting Line

Recommendation to Lobster Land

If Lobster Land can prioritize a specific kpi, it be be easier for it to choose what picture to use based on above summary.However, if Lobster Land has to choose a pic to use without targetting a specific kpi, I'd recommendation it to choose "Racers in Action" as "Racers in Action" performs the best in general.

In [ ]:
```

```