Preface

Topic: Lobster Land Winter Carnival Proposal

Group:Caribou

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Summary Stats

Data Processing

In [115…

```
%cd E:\22FALL\AD654\Final\data
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df = pd.read_csv('angels_market.csv')
# df.head()
```

```
E:\22FALL\AD654\Final\data
```

In [2]:

```
# description of variables
# df.describe()
```

In [3]:

```
# Information of dataset
# df.info()
```

In [4]:

```
# count NA values
# df.isna().sum()
```

In [5]:

```
# get unique variable in homeState
df['homeState'].unique()
```

Out[5]:

```
array(['Maine', 'Vermont', 'New Hampshire', 'Quebec', 'Connecticut',
       'Massachusetts', 'Ontario', '6', '5', '2', '7', '4'], dtype=object)
```

In [6]:

```
# get unique variable in theme
df['theme'].unique()
```

Out[6]:

```
array(['Hot Chocolate/Warm Treats', 'Local Artists', 'Fortune Teller',
       'Fried Dough and Pizza', 'craft beer', 'Homemade Holiday Gifts',
       'Video Game/eSports', 'Games Of Chance', 'Steaming Hot Cocktails',
       'Canadian Snacks', 'Maine Tourism Promotion', 'DIY Ice Sculpture',
       'Local Politician', 'Specialty Ice Cream', '8', '3', '4', '7', '5',
       '9'], dtype=object)
```

In [7]:

```
# data processing
df_new = df.copy()
state = ['Maine', 'Vermont', 'New Hampshire', 'Quebec', 'Connecticut',
       'Massachusetts', 'Ontario']
```

```
df_new['homeState'] = np.where(df_new['homeState'].isin(state),
                               df['homeState'], np.NaN)
df_new['theme'] = np.where(df_new['theme'].isin(['8', '3', '4', '7', '5','9'])
                           np.NaN, df['theme'])
```

In [8]:
```
df_new.isna().sum()
```

Out[8]:
```
vendorID           0
theme              8
homeState          8
carnivals          0
complaints         0
est_energy         0
est_hourly_vol     0
LL_passholder      0
est_hourly_gross   0
dtype: int64
```

In [9]:
```
# drop NA variable
df_new_c = df_new.dropna()
df_new_c = df_new_c.drop('vendorID', axis=1)
```

In [10]:
```
# mean value of estimate value
df_new_c.groupby('homeState')['est_energy','est_hourly_vol','est_hourly_gross']
```

```
C:\Users\ranfe\AppData\Local\Temp/ipykernel_1128/689612109.py:2: FutureWarnin
g: Indexing with multiple keys (implicitly converted to a tuple of keys) will
be deprecated, use a list instead.
  df_new_c.groupby('homeState')['est_energy','est_hourly_vol','est_hourly_gros
s'].mean()
```

Out[10]:

	est_energy	est_hourly_vol	est_hourly_gross
homeState			
Connecticut	49.491742	113.125000	222.371250
Maine	47.495915	110.956835	219.283405
Massachusetts	44.172066	115.481481	224.830000
New Hampshire	47.629391	112.228571	218.738857
Ontario	48.428355	115.187500	223.366875
Quebec	48.727077	110.351852	212.406296
Vermont	51.418017	109.783333	216.440167

In [11]:
```
# correlation of each variables
df_new_c.corr()
```

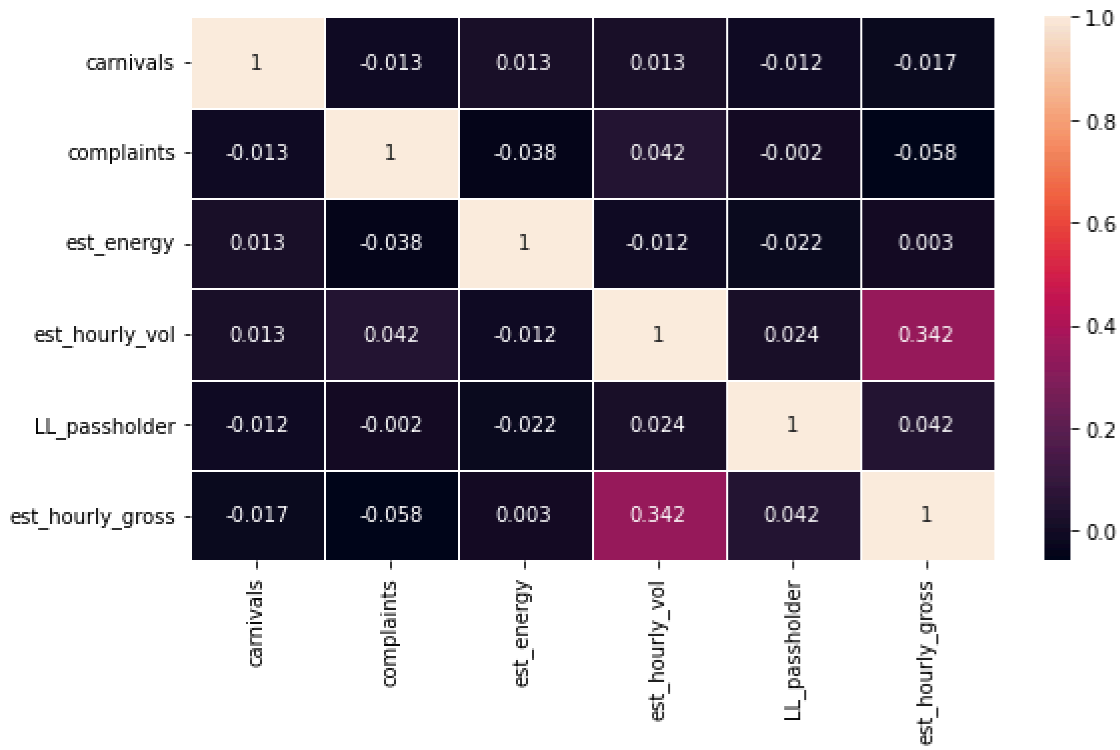
Out[11]:

	carnivals	complaints	est_energy	est_hourly_vol	LL_passholder	est_hourly
carnivals	1.000000	-0.013400	0.012801	0.012601	-0.012359	-0.
complaints	-0.013400	1.000000	-0.037507	0.042317	-0.002088	-0.0
est_energy	0.012801	-0.037507	1.000000	-0.011543	-0.021859	0.0
est_hourly_vol	0.012601	0.042317	-0.011543	1.000000	0.023960	0.
LL_passholder	-0.012359	-0.002088	-0.021859	0.023960	1.000000	0.0
est_hourly_gross	-0.017352	-0.058495	0.003329	0.342181	0.042162	1.0

Data Visualizations

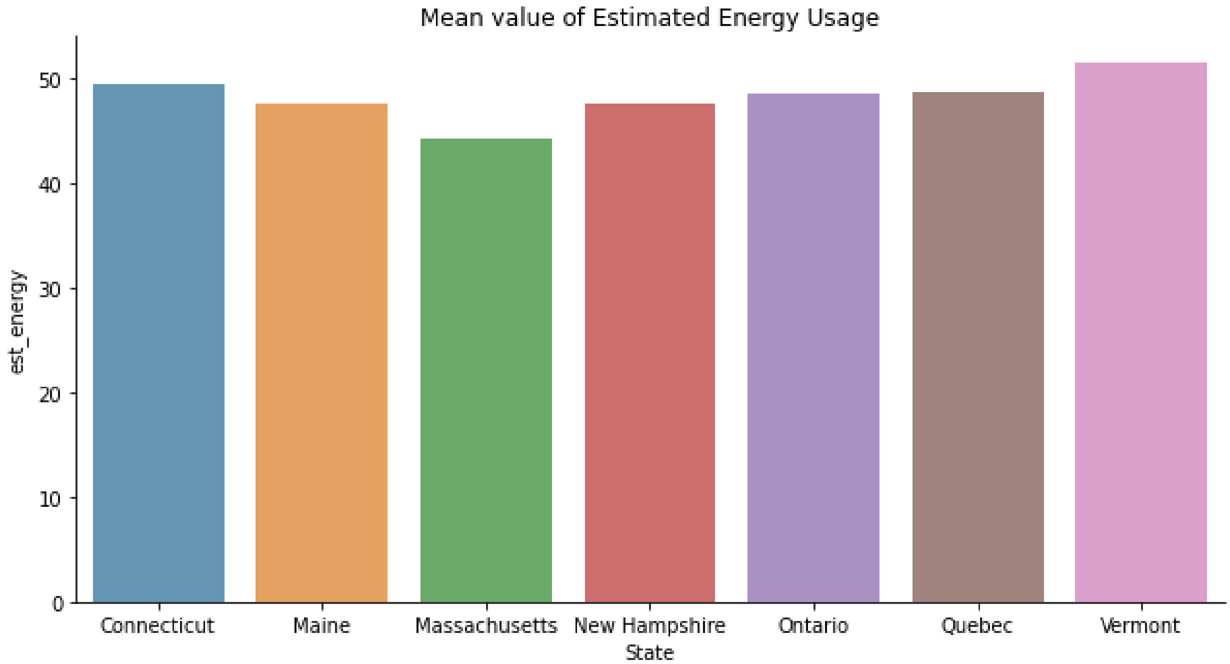
In [125…

```
# correlation plot
fig, ax = plt.subplots(1, 1, figsize=(9,5))
sns.heatmap(df_new_c.corr().round(3),
            annot=True, fmt='g', linewidth=0.5, ax=ax)

plt.show()
```



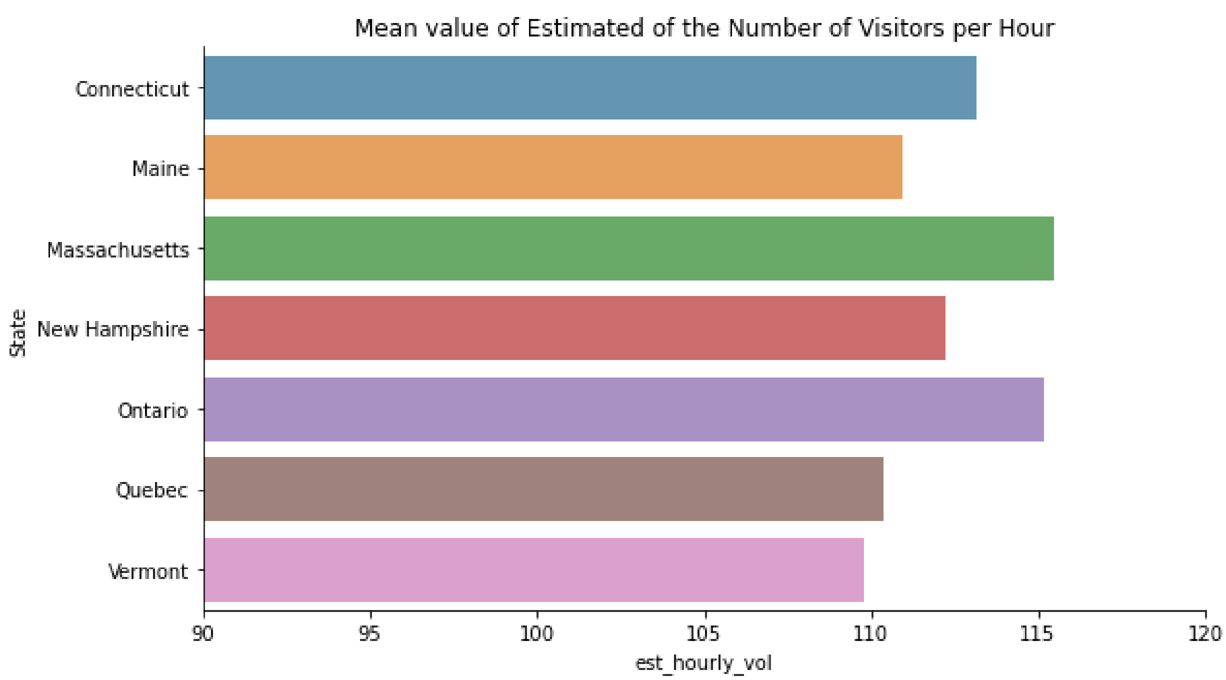
In [124…

```
# Estimate Energe usage
est_eng_mean = df_new_c.groupby('homeState')['est_energy'].mean()
fig, ax = plt.subplots(1, 1, figsize=(9,5))
sns.barplot(x=est_eng_mean.index, y=est_eng_mean, alpha=0.75,ax=ax)
plt.title('Mean value of Estimated Energy Usage')
ax.set_xlabel('State')
ax.spines[['top','right']].set_visible(False)
plt.tight_layout()
plt.show()
```



In [126…

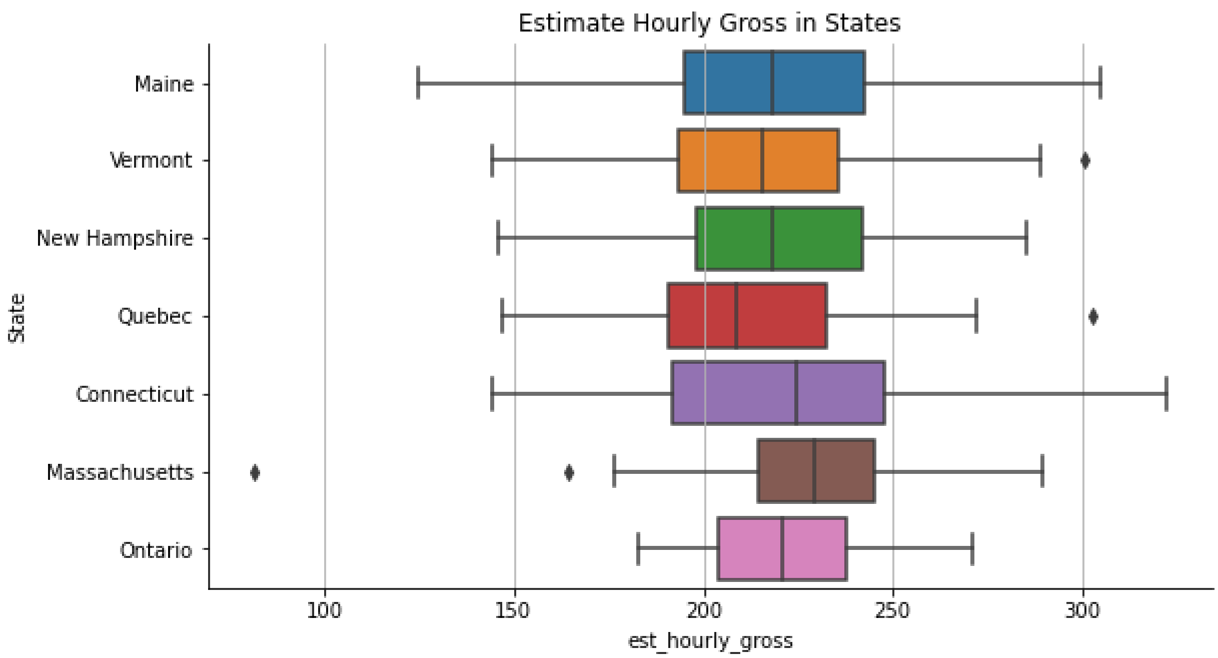
```
# Estimate hourly volumn
est_hr_mean = df_new_c.groupby('homeState')['est_hourly_vol'].mean()
fig, ax = plt.subplots(1, 1, figsize=(9,5))
sns.barplot(y=est_hr_mean.index, x=est_hr_mean, alpha=0.75,ax=ax)
plt.title('Mean value of Estimated of the Number of Visitors per Hour')
ax.set_ylabel('State')
ax.spines[['top','right']].set_visible(False)
ax.set_xlim([90, 120])
plt.tight_layout()
plt.show()
```



In [128…

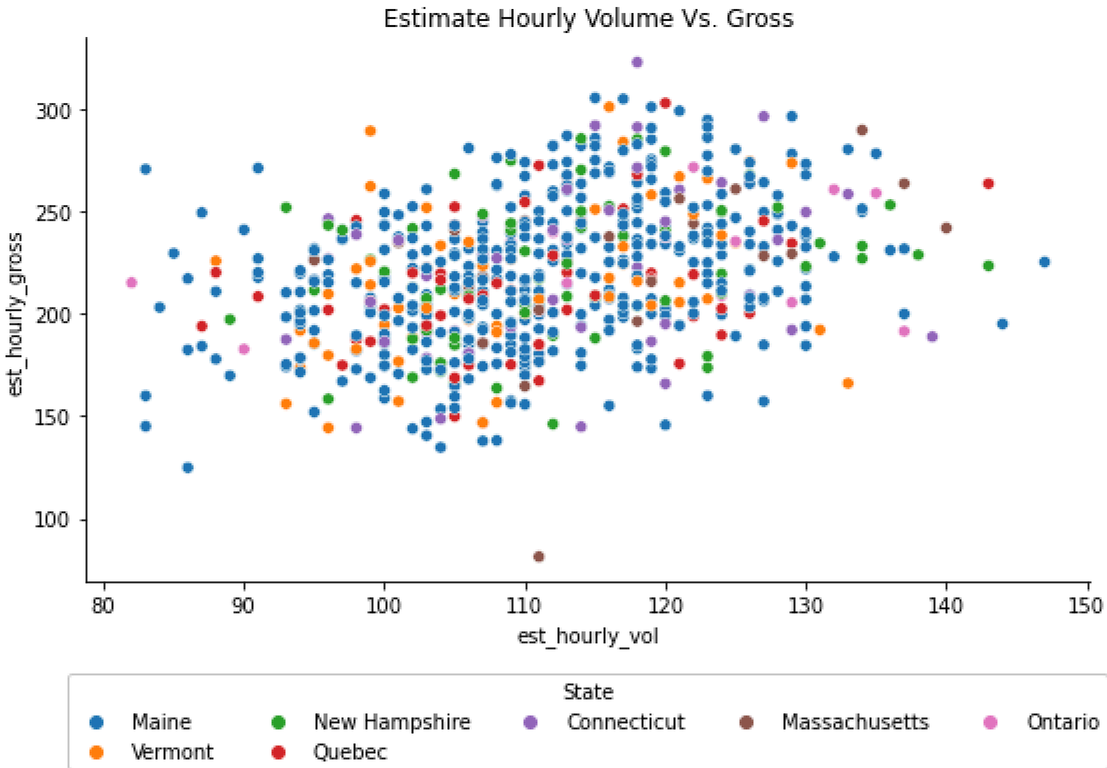
```
# Estimate hourly gross
fig, ax = plt.subplots(1, 1, figsize=(9,5))
sns.boxplot(data=df_new_c, x='est_hourly_gross', y='homeState', ax=ax)
ax.grid(axis='x')
ax.set_title('Estimate Hourly Gross in States')
```

```
ax.set_ylabel('State')
ax.spines[['top','right']].set_visible(False)
plt.show()
```



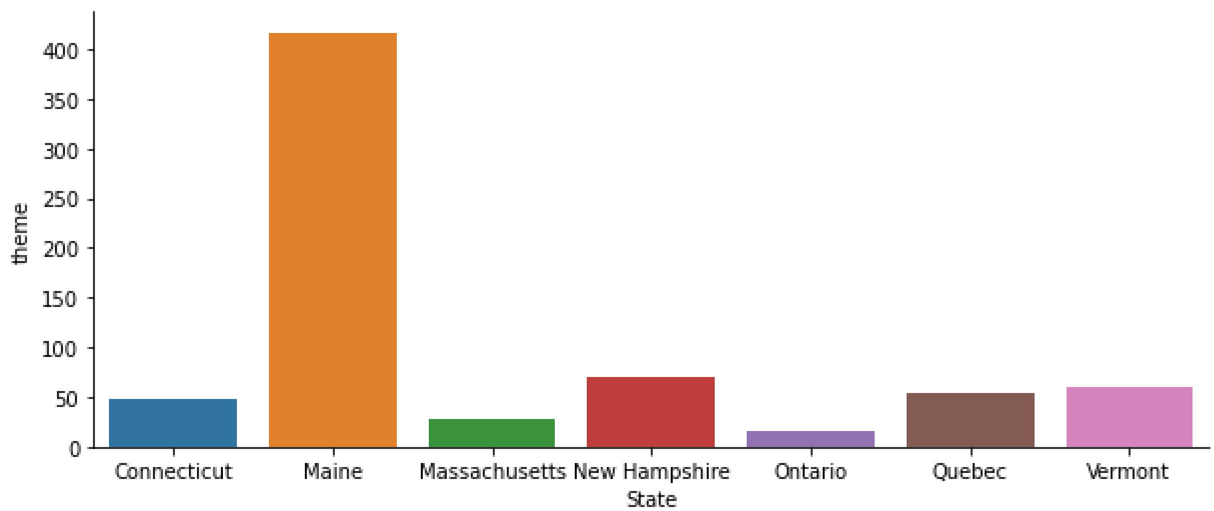
In [133…

```
# estimate horly volume vs. estimated horly gross
fig, ax = plt.subplots(1, 1,figsize=(9,5))
sns.scatterplot(x=df_new_c.est_hourly_vol, y=df_new_c.est_hourly_gross,
                hue=df_new_c.homeState, ax=ax)
ax.legend(loc='upper center', bbox_to_anchor=(0.5, -0.15),
          fancybox=True, shadow=True, ncol=5)
ax.set_title('Estimate Hourly Volume Vs. Gross')
ax.get_legend().set_title('State')
ax.spines[['top','right']].set_visible(False)
plt.show()
```



In [132…

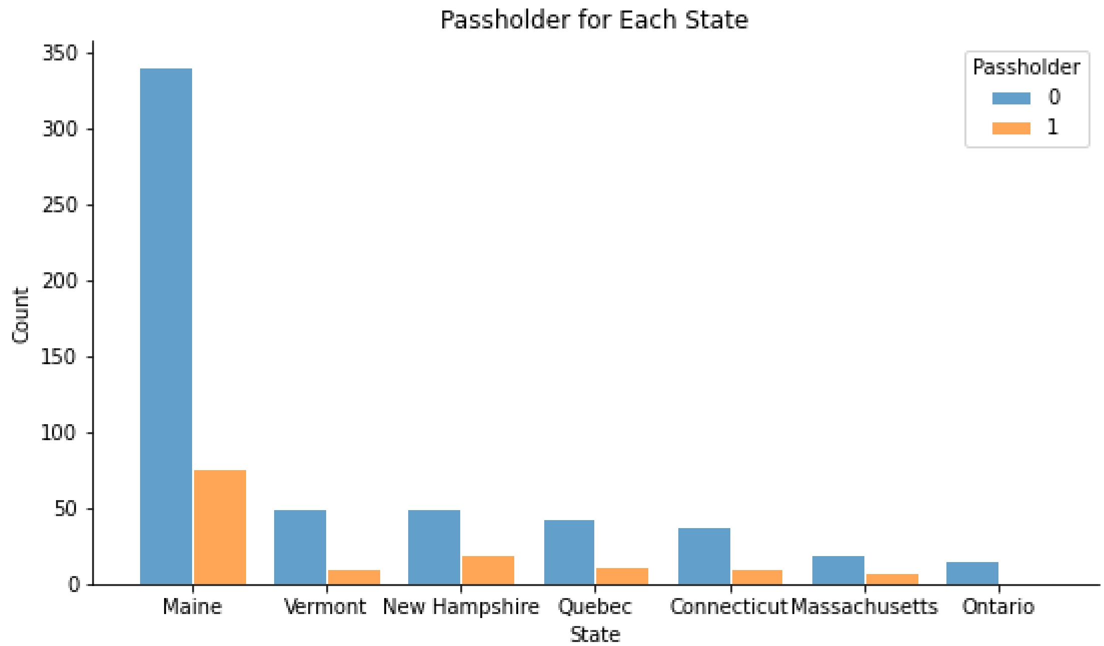
```
# theme count for each states
theme = df_new_c.groupby('homeState')['theme'].count()
fig, ax = plt.subplots(1, 1, figsize=(10,4))
sns.barplot(x=theme.index, y=theme, ax=ax)
ax.set_xlabel('State')
ax.spines[['top','right']].set_visible(False)
plt.show()
```



In [131…

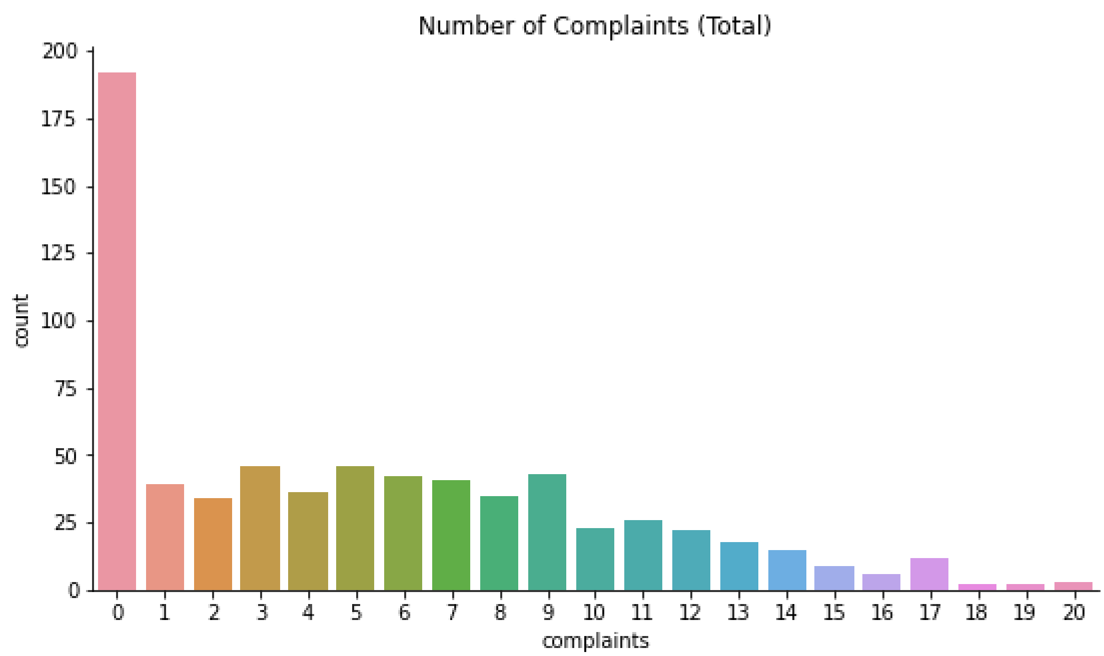
```
# passholder for each state
passholder = df_new_c[['homeState', 'LL_passholder']]
fig, ax = plt.subplots(1, 1, figsize=(9,5))
sns.histplot(passholder,x='homeState', hue='LL_passholder',
             multiple="dodge", shrink=.8, alpha=0.7, edgecolor='white', ax=ax)
ax.set_title('Passholder for Each State')
ax.get_legend().set_title('Passholder')
ax.set_xlabel('State')
```

```
ax.spines[['top','right']].set_visible(False)
plt.show()
```



In [134…

```
fig, ax = plt.subplots(1, 1, figsize=(9,5))
sns.countplot(x=df_new_c.complaints, ax=ax)
ax.set_title('Number of Complaints (Total)')
ax.spines[['top','right']].set_visible(False)
plt.show()
```



Summary of Angel's Market Data

According to the correlation of each variable in the dataset, there is no significant correlation between the variables except for `est_hourly_vol` and `est_horly_gross`, in other words the variables are relatively independent. In addition, we plot the mean value for three different estimate variables. The mean value of estimate energy usage for every state is not varied a lot, Massachusetts has the lowest estimate energy usage of all states. However, there is a big different in the mean value of estimate of hourly gross. We also try to examine the relationship between the `est_hourly_vol` and `est_hourly_gross`, and it turns out that there is no relationship between these variables.

The state of Maine has the most themes compared to other states. The good thing is there are not too many complaints about carnival activities, most of the majority of vendors can still accept these activities. Overall, the entire dataset has much more vendor about Maine than other regions. Because of the geographic location, there are more opportunities for local people to attend this event. This is why most of the variables are related to Maine.

Based on the number of complaints and carnival events, we would suggest the management continues to hold similar events and can bring in vendors from different states for development. In addition, encourage vendor to apply their pass. The management can offer some discount for the vendor if they have a valid pass.

The limitation of this dataset is we did not have an estimate of sales per hour based on estimate number of visitors. We might use this variable to find the correlation between theme and hourly gross, and determine which theme generates the most sales for the Angel's market.

Segmentation and Targeting

In [20]:
```
family = pd.read_csv('maine_families.csv')
family.head()
```

Out[20]:

	householdID	total_ppl	own_rent	square_foot	household_income	number_pets	r
0	1	1.0	own	3309	82050.03	1	Aroc
1	2	1.0	own	3814	83077.81	2	Mic
2	3	2.0	rent	2592	91401.41	2	Downeast_/
3	4	1.0	own	2628	73048.55	1	Greater Po
4	5	1.0	rent	2442	89145.36	2	Kennebec

In [21]:
```
family.isnull().sum()
```

Out[21]:
```
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 [22]:
```
family = family.dropna()
```

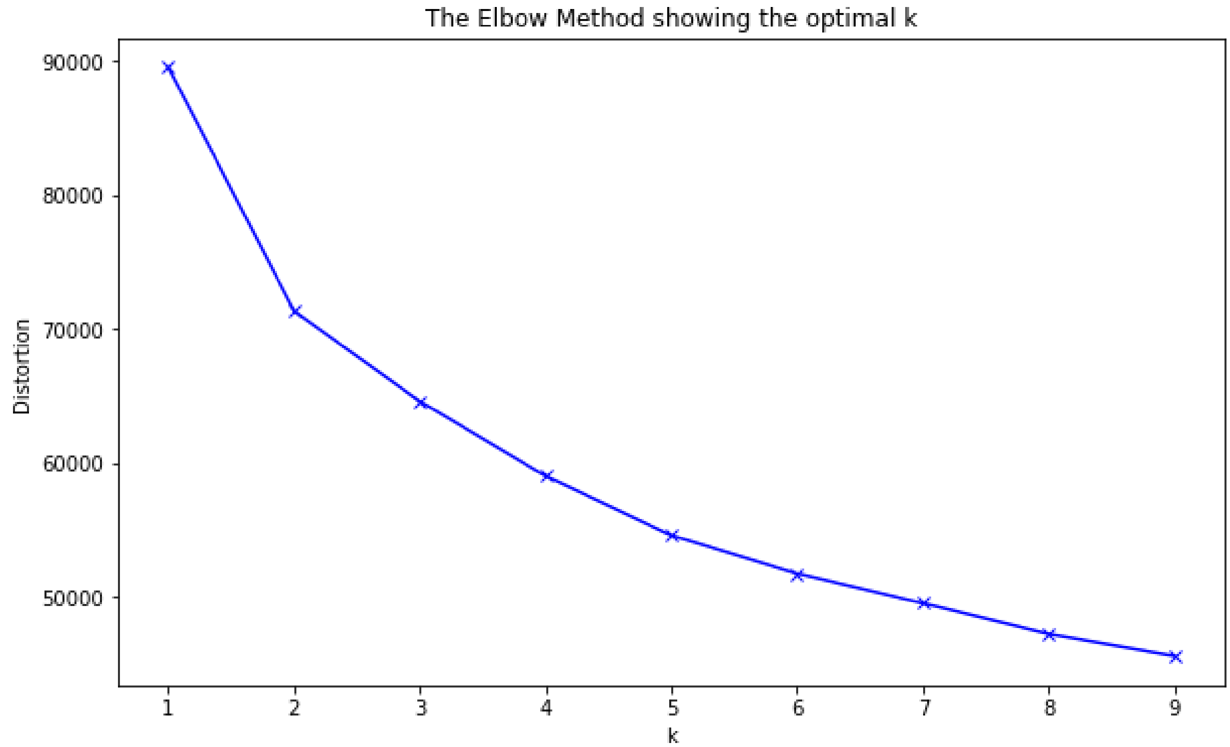
K-means Clustering

In [23]:
```
from sklearn.preprocessing import StandardScaler

df = family.drop(columns = ["householdID", "own_rent", "region", "LL_passholde
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)
scaled_family = pd.DataFrame(scaled_data, columns=df.columns)
scaled_family.head()
```

Out[23]:

	total_ppl	square_foot	household_income	number_pets	entertainment_spend_est	travel_sp
0	-0.712254	0.231940	-0.099660	-0.643910	-0.211759	-
1	-0.712254	0.850669	-0.059785	0.621277	0.590405	
2	0.514566	-0.646533	0.263151	0.621277	-1.329415	-
3	-0.712254	-0.602426	-0.448896	-0.643910	-1.223549	
4	-0.712254	-0.830314	0.175622	0.621277	0.781958	-

In [24]:
```
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

distortions = []
K = range(1,10)
for k in K:
    kmeanModel = KMeans(n_clusters=k)
    kmeanModel.fit(scaled_family)
    distortions.append(kmeanModel.inertia_)

plt.figure(figsize=(10,6))
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
```



We think k=4 could be used in the model. As shown in the elbow plot, a sharp bend occurs when k = 5. As k increases after k = 5, the distance has not dropped as much as before.

In [25]:
```
kmeans = KMeans(n_clusters=5, random_state = 100)
kmeans.fit(scaled_family)
```

Out[25]:
```
KMeans(n_clusters=5, random_state=100)
```

In [26]:
```
cluster_labels = kmeans.labels_
cluster_family = scaled_family.assign(Cluster = cluster_labels)
cluster_family.head()
```

Out[26]:

	total_ppl	square_foot	household_income	number_pets	entertainment_spend_est	travel_s
0	-0.712254	0.231940	-0.099660	-0.643910	-0.211759	-
1	-0.712254	0.850669	-0.059785	0.621277	0.590405	
2	0.514566	-0.646533	0.263151	0.621277	-1.329415	-
3	-0.712254	-0.602426	-0.448896	-0.643910	-1.223549	
4	-0.712254	-0.830314	0.175622	0.621277	0.781958	-

In [27]:
```
family_new = pd.get_dummies(family, drop_first=True,
                            columns=["own_rent", "LL_passholder"])
family_new = pd.get_dummies(family_new, drop_first=False,
                            columns=["region"])
family_new.head()
```

Out[27]:

	householdID	total_ppl	square_foot	household_income	number_pets	entertainment_spend_
0	1	1.0	3309	82050.03	1	318
1	2	1.0	3814	83077.81	2	4175
2	3	2.0	2592	91401.41	2	1814
3	4	1.0	2628	73048.55	1	1945
4	5	1.0	2442	89145.36	2	4410

In [28]:
```
family_new.columns
```

Out[28]:
```
Index(['householdID', 'total_ppl', 'square_foot', 'household_income',
       'number_pets', 'entertainment_spend_est', 'travel_spend_est',
       'own_rent_rent', 'LL_passholder_Yes', 'region_Aroostook',
       'region_Downeast_Acadia', 'region_Greater Portland',
       'region_Kennebec Valley', 'region_Midcoast'],
      dtype='object')
```

In [29]:
```
#include the categorical variables
add = family_new[['own_rent_rent', 'LL_passholder_Yes', 'region_Aroostook',
       'region_Downeast_Acadia', 'region_Greater Portland',
       'region_Kennebec Valley', 'region_Midcoast']]
result = pd.concat([cluster_family, add], axis=1, join="inner")
result.head()
```

Out[29]:

	total_ppl	square_foot	household_income	number_pets	entertainment_spend_est	travel_s
0	-0.712254	0.231940	-0.099660	-0.643910	-0.211759	-
1	-0.712254	0.850669	-0.059785	0.621277	0.590405	
2	0.514566	-0.646533	0.263151	0.621277	-1.329415	-
3	-0.712254	-0.602426	-0.448896	-0.643910	-1.223549	
4	-0.712254	-0.830314	0.175622	0.621277	0.781958	-

In [30]:
```
result.columns
```

Out[30]:
```
Index(['total_ppl', 'square_foot', 'household_income', 'number_pets',
       'entertainment_spend_est', 'travel_spend_est', 'Cluster',
       'own_rent_rent', 'LL_passholder_Yes', 'region_Aroostook',
       'region_Downeast_Acadia', 'region_Greater Portland',
       'region_Kennebec Valley', 'region_Midcoast'],
      dtype='object')
```

In [31]:
```
#summary statistics about each of your clusters.
result.groupby(['Cluster']).agg({
    'total_ppl': 'mean',
    'square_foot': 'mean',
    'household_income': 'mean',
    'number_pets': 'mean',
    'entertainment_spend_est': 'mean',
    'travel_spend_est': 'mean',
    'Cluster': 'mean',
    'own_rent_rent': 'mean',
```

```
    'LL_passholder_Yes': 'mean',
    'region_Aroostook': 'mean',
    'region_Downeast_Acadia': 'mean',
    'region_Greater Portland': 'mean',
    'region_Kennebec Valley': 'mean',
    'region_Midcoast': 'mean'
}).round(2)
```

Out[31]:

	total_ppl	square_foot	household_income	number_pets	entertainment_spend_est	tra
Cluster						
0	0.25	1.18	-0.48	0.00	-0.55	
1	0.23	-0.57	-0.54	-0.94	-0.44	
2	0.54	0.16	1.04	-0.02	1.16	
3	-1.16	-0.13	0.52	-0.03	0.32	
4	0.27	-0.53	-0.50	0.95	-0.43	

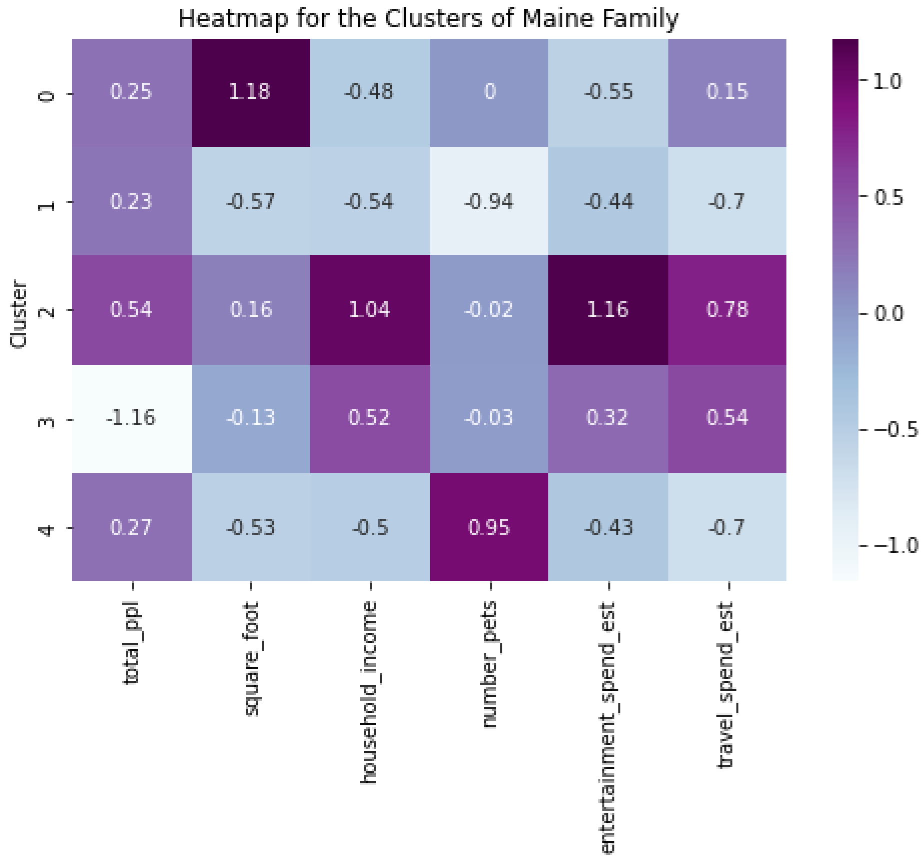
Cluster Visualizations

In [135…

```
import seaborn as sns

summary = result.groupby(['Cluster']).agg({
    'total_ppl': 'mean',
    'square_foot': 'mean',
    'household_income': 'mean',
    'number_pets': 'mean',
    'entertainment_spend_est': 'mean',
    'travel_spend_est': 'mean'
}).round(2)

plt.figure(figsize = (8,5))
sns.heatmap(summary, annot = True, cmap='BuPu', fmt='g').set_title('Heatmap fo
```

Out[135]:

```
Text(0.5, 1.0, 'Heatmap for the Clusters of Maine Family')
```



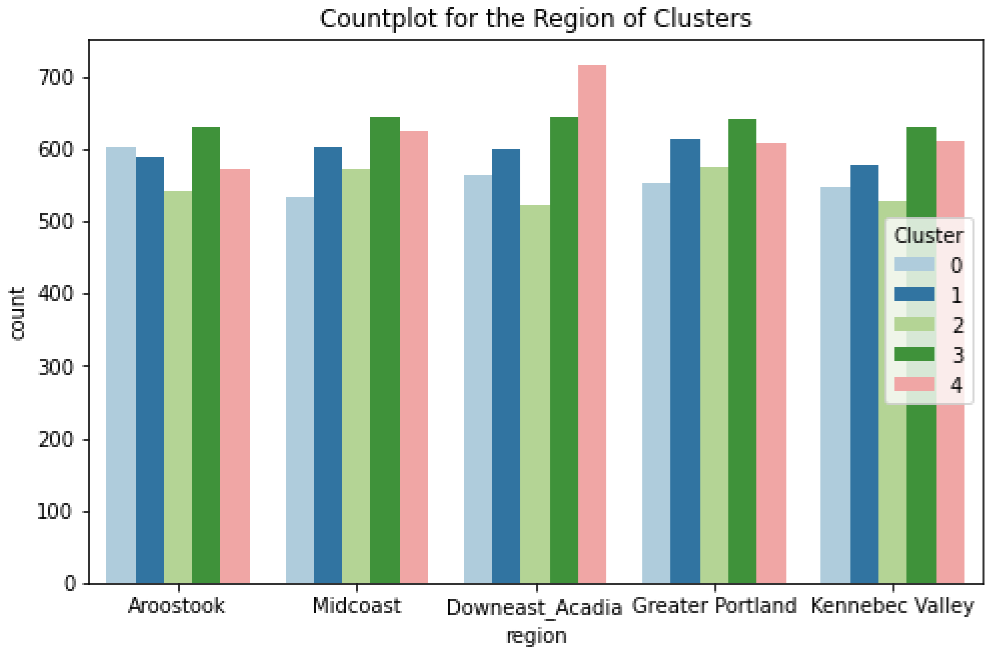
The heatmap shows that the families in cluster 2 have the highest number of individuals living in the home, the highest total annual income for the household, and the highest household's annual spending on travel and entertainment. The families in cluster 4 have the highest total number of pets owned by members of the household. And the families in cluster 0 have the highest number of square feet in the residence. While the families in cluster 1 have the lowest total number of pets owned by members of the household. The families in cluster 3 have the lowest number of individuals living in the home.

In [136…

```
family['Cluster'] = result['Cluster'].astype('category')
plt.figure(figsize=(8,5))
sns.countplot(x='region', hue='Cluster', data = family, palette='Paired').set_
plt.legend(loc='center right', title = 'Cluster')
```

Out[136]:

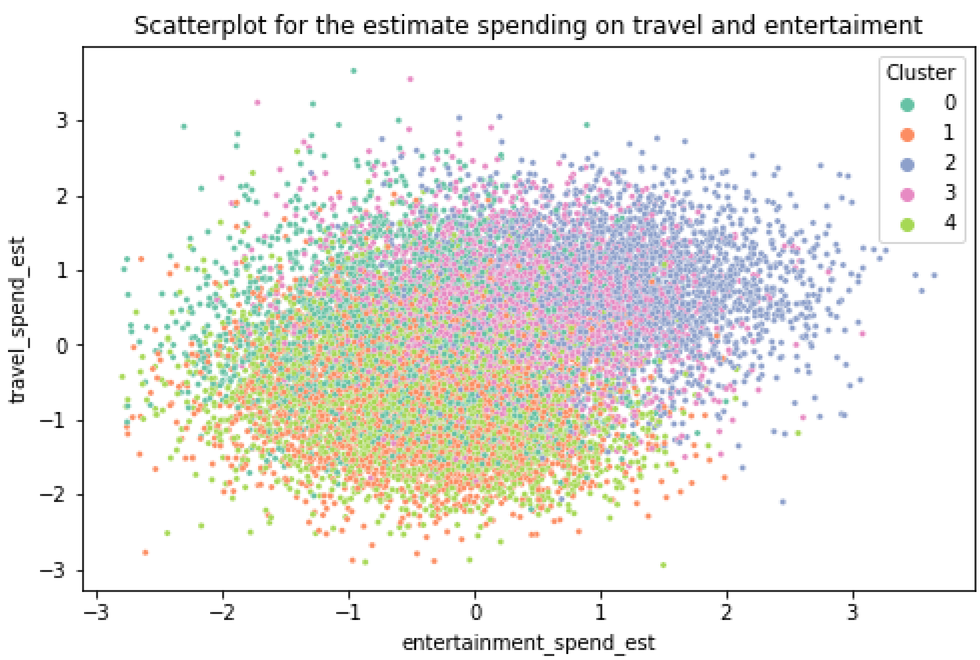
```
<matplotlib.legend.Legend at 0x13f0a340cd0>
```



The count plot shows the distribution of families' regions in five clusters. The families in the different clusters are almost distributed evenly in five regions. However, one thing worth noting is that the number of families in cluster 4 is higher in the Downeast Acadia region.

In [137…

```
result['Cluster'] = result['Cluster'].astype('category')
plt.figure(figsize=(8,5))
sns.despine()
p1 = sns.scatterplot(x = 'entertainment_spend_est', y = 'travel_spend_est', s=
                     palette='Set2', data = result).set_title('Scatterplot for
```



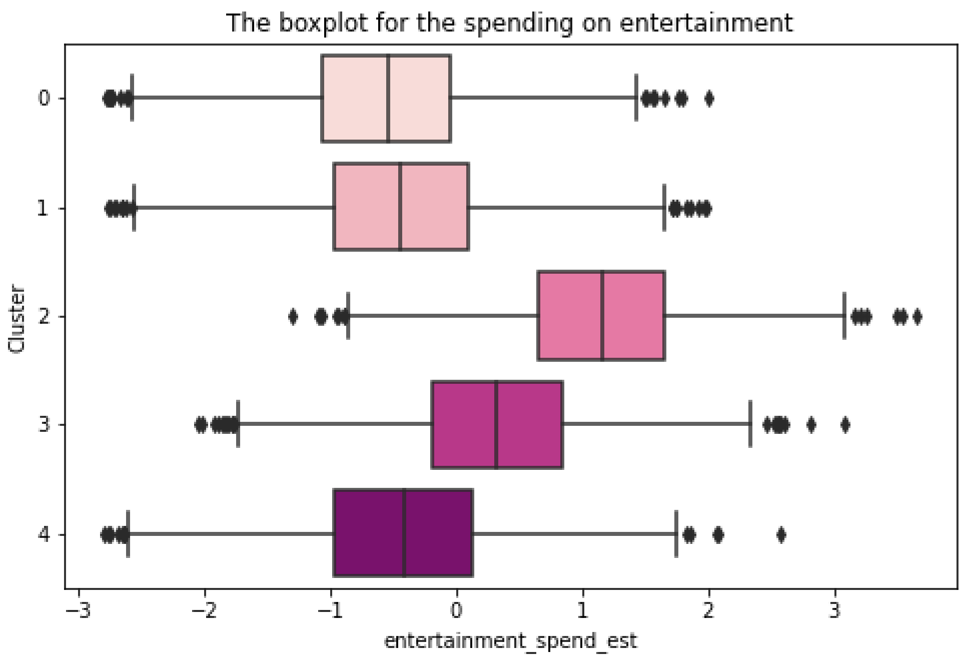
The scatterplot shows the distribution for the estimate spending on travel and entertaiment. It shows that the families in the cluster 2 would spend most money on the entertaiment. And families in the cluster 3 would also spend lots of money on the entertaiment. Compared with the families in the cluster 2 and 3, the budget on the entertainment for the families in cluster

0 and 4 is lower. All the families in cluster 0, 2 and 3 would spend much money on travel. While the families in the cluster 4 would not spend much money on travel.

For more details about the spending on travel and entertaiment, please see the two figures below.

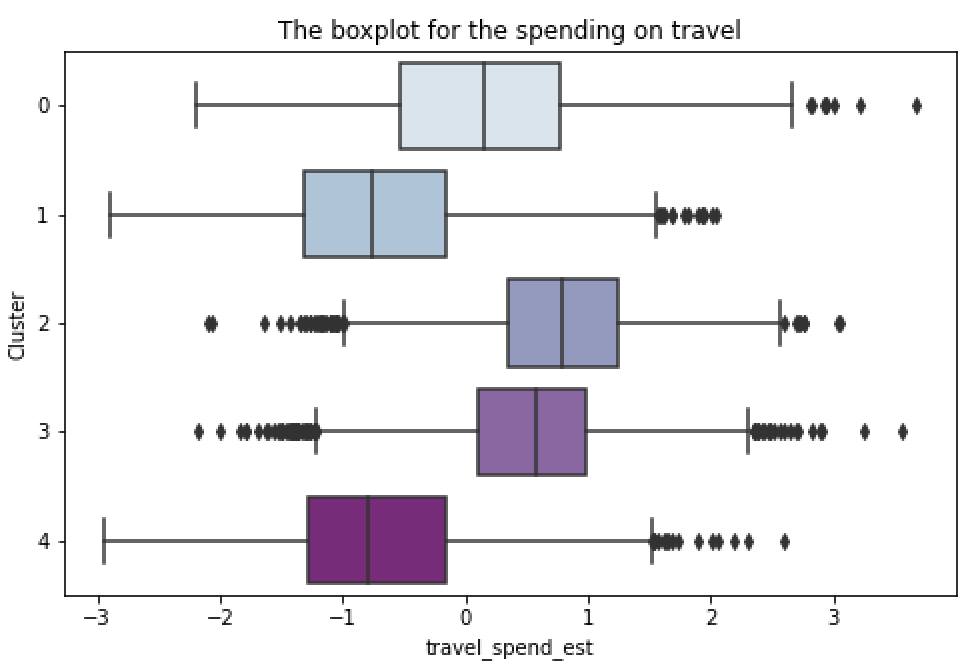
In [138…
```
plt.figure(figsize = (8,5))
sns.boxplot(y = 'Cluster', x='entertainment_spend_est', data = result, palette=
```

Out[138]:
```
Text(0.5, 1.0, 'The boxplot for the spending on entertainment')
```



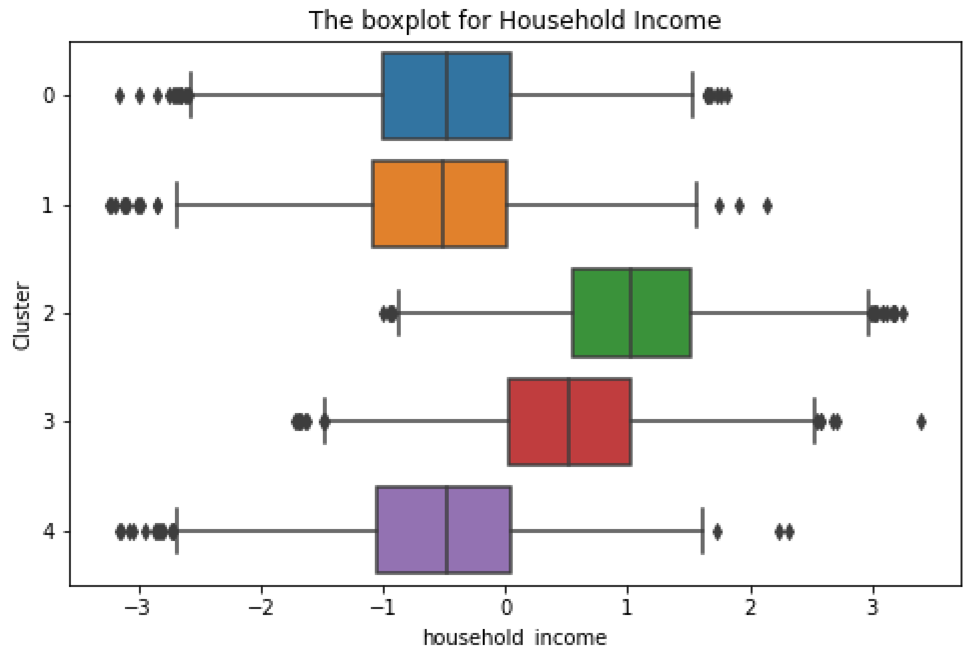
In [139…
```
plt.figure(figsize = (8,5))
sns.boxplot(y = 'Cluster', x='travel_spend_est', data = result, palette='BuPu'
```

Out[139]:
```
Text(0.5, 1.0, 'The boxplot for the spending on travel')
```



In [140…
```
plt.figure(figsize = (8,5))
sns.boxplot(y = 'Cluster', x='household_income', data = result).set_title('The
```

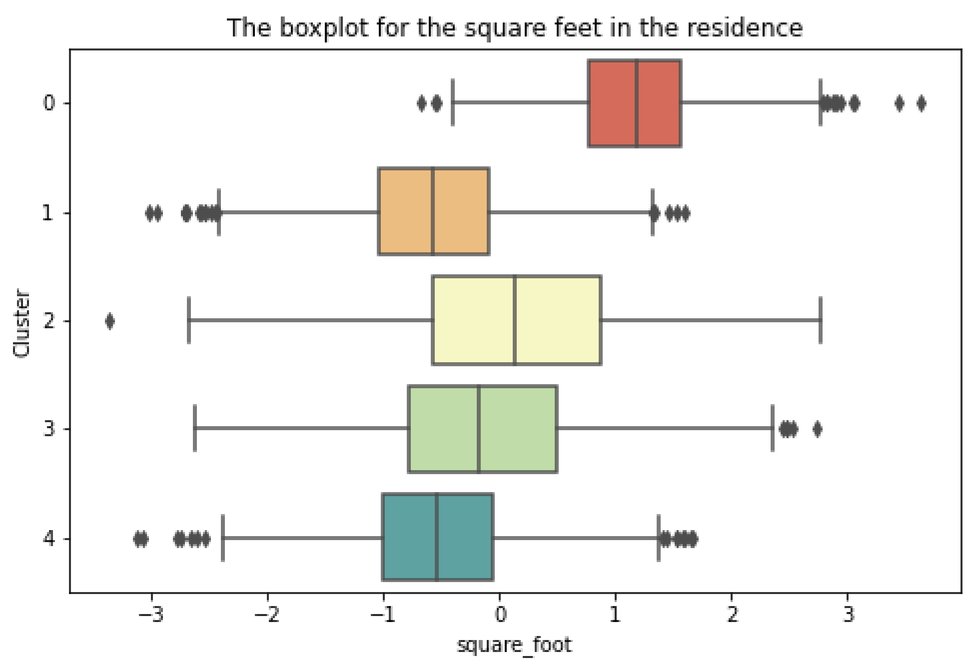
Out[140]:
```
Text(0.5, 1.0, 'The boxplot for Household Income')
```



This barplot shows that the families in the Cluster 2 have the highest income, while the household's annual income for families in Cluster 0, 1, and 4 is low.

In [141…
```
plt.figure(figsize = (8,5))
sns.boxplot(y = 'Cluster', x='square_foot', data = result, palette='Spectral')
```

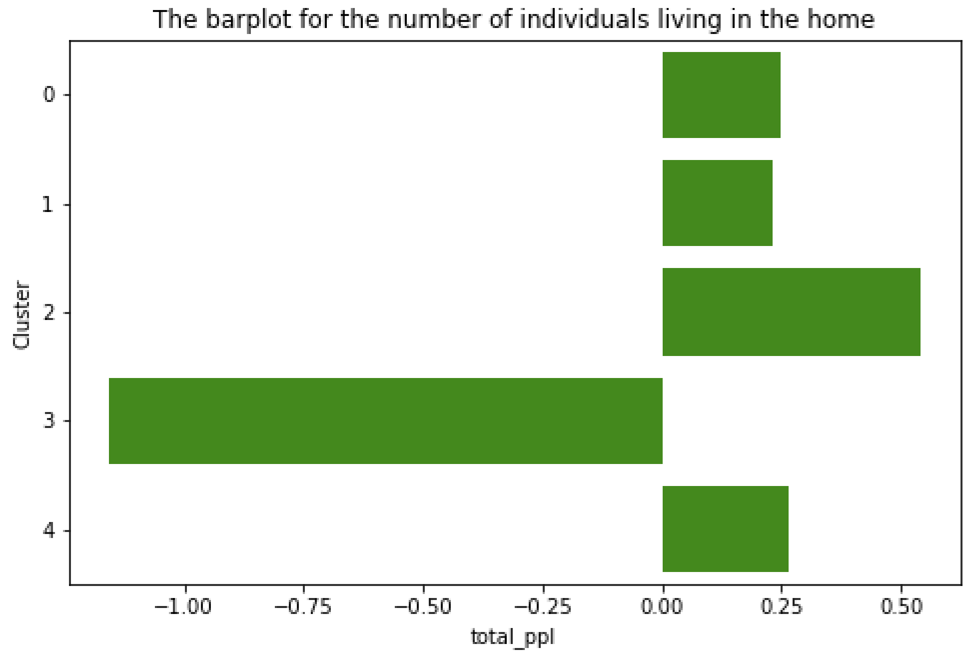
Out[141]:
```
Text(0.5, 1.0, 'The boxplot for the square feet in the residence')
```



The box plot shows that the families in cluster have the largest residence which is much bigger than other clusters. While the families in cluster 1 and 4 have the smallest residence.

In [142…
```
plt.figure(figsize =  (8,5))
sns.barplot(y = 'Cluster', x = 'total_ppl', ci = None, color='xkcd:grass green
```

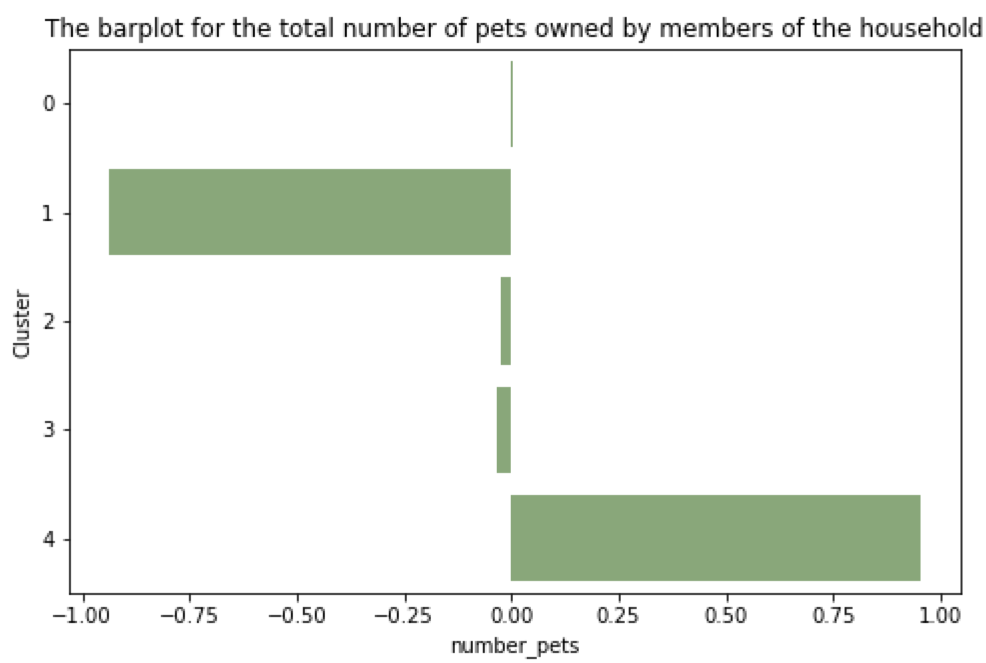
Out[142]:
```
Text(0.5, 1.0, 'The barplot for the number of individuals living in the hom
e')
```



The bar plot indicates that the families in Cluster 3 has the lowest families members living together and it is much lower than other four clusters. While the families in cluster 2 is largest.

In [143…
```
plt.figure(figsize =  (8,5))
sns.barplot(y = 'Cluster', x = 'number_pets', ci = None, color='xkcd:sage', da
```

Out[143]:
```
Text(0.5, 1.0, 'The barplot for the total number of pets owned by members of
the household')
```



This plot indicates that there is no much difference in cluster 0, 2 and 3 on owning pets. However, families in cluster 4 owns many pets which shows their love to pets. While the families in cluster 1 don't pet a lot, comparing with other clusters.

Targeting

We name the cluster 0 as 'Family with biggest residence and lowest budget on entertainment' since the group spend the lowest money on the entertainment and have the biggest square feet of their residence. Though this cluster spend lowest money on the entertainment, the families are still willing to have a reasonable budget on travel. And they live in a bigest apartment or house but it doesn't mean much, since the household's annual income is not high. Our group would send the marketing emails to the families in this cluster with more details and images more on travel part and less on the entertainment part. Since they don't have a high budget and their income is not high, we recommend the park could send them some deals and conpons.

We name the cluster 1 as 'Family with Lowest total budget on travel and entertainment' since their budget on the entertainment and travel is lowest among the five clusters and other variables don't show their protential interest in the Lobster Land. The variables are low in also lowest on number of square feet in the residence, total annual income for the household and total number of pets owned by members of the household. We recommend the park send some good deals and conpons that really attract them and could let them save lots of money.

We name the cluster 2 as 'Large Family with highest income and highest budget' since the their budget on the entertainment and travel is highest among the five clusters and they are richest with highest household income and largest number of individuals living in the home. Since they would spend most money on the entertainment and travel and they earn lots of money, the families are the top potential visitors for Lobster Land and they would like to come with a big family. We recommend the park send more marketing emails and advertisement to these families. And let them know Lobster Land have lots of fun on entertainment and it is a ideal place to travel for whole family. We also recommend park target this cluster with some expensive activities.

We name the cluster 3 as 'Small Family with good income and budget', since this cluster also have a high budget on the entertainment and travel and the income of the household is high. The only thing should be noticed is that the number of individuals living in the home is lowest. Since the families in this cluster have a good budget and income, we would recommend the park send more marketing emails and advertisement to these families and emphasize that the Lobster Land is also good for a small group of family.

We name the cluster 4 as 'Pets lover', since the total number of pets owned by members of the household in this group is highest. Though the spending on entertainment and travel and the annual household's income is really low in this group, the members in this cluster really like pets. We recommend the park hold some games for people and dog which could increase human-dog interaction. And when the park send the marketing email, they should emphasize Lobster Land is super pet-friendly and have lots of games for them. As for their low budget, park should send them more good deals and conpons.

Conclusion for Cluster and Targeting

Our team finally create 5 clusters for maine families and named 'Family with biggest residence and lowest budget on entertainment', 'Family with Lowest total budget on travel and entertainment', 'Large Family with highest income and highest budget', 'Small Family with good income and budget' and 'Pets lover'. For 'Family with biggest residence and lowest budget on entertainment', we recommend park send the marketing emails with more details and images more on travel part and less on the entertainment part, and also some deals and conpons. For 'Family with Lowest total budget on travel and entertainment', we recommend the park send some good deals and conpons that really attract them and could let them save lots of money. For 'Large Family with highest income and highest budget', these group is the main target for park management and we recommend the park send more marketing emails and advertisement to big families. For 'Small Family with good income and budget', we would recommend the park send more marketing emails and advertisement to these families and emphasize that the Lobster Land is also good for a small group of family. For 'Pets lover', we recommend the park hold some games for people and dog which could increase human-dog interaction.

Conjoint Analysis & Memo Section

In [39]:
```
import numpy as np
import pandas as pd
import os
from sklearn.linear_model import LinearRegression
from sklearn import metrics
import seaborn as sns
import matplotlib.pyplot as plt
```

In [40]:
```
lake_df = pd.read_csv('bbq_lake.csv',index_col=0)
vendor_df = pd.read_csv('vendor_costs.csv')
```

In [41]:
```
lake_df.columns[:-1]
```

Out[41]:
```
Index(['starter', 'maindishI', 'maindishII', 'side', 'dessert'], dtype='objec
t')
```

Conjoint Analysis

In [42]:
```
lake_df_dummy = pd.get_dummies(lake_df, drop_first=True, columns=lake_df.colum
X=lake_df_dummy.drop(columns=['avg_rating'])
y=lake_df_dummy['avg_rating']
```

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

In [44]:
```
coef_df = pd.DataFrame(regressor.coef_, X.columns, columns=['Coefficient'])
coef_df.loc['starter_Crabcakes and Shrimp']= 0
coef_df.loc['maindishI_BBQ Brisket']= 0
coef_df.loc['maindishII_Beef Short Rib']= 0
coef_df.loc['dessert_Apple Pie a la Mode']=0
coef_df.loc['side_French Fry Platter']=0
```

In [45]:
```
temp_info = coef_df.index.str.split('_')
coef_df = coef_df.assign(food_type = [i[0] for i in temp_info],
                           Item = [i[1] for i in temp_info])

#(lambda x:x.split('_'))
```

In [46]:
```
coef_plot_df= coef_df.groupby('food_type').apply(lambda x: x.sort_values(by=['(
coef_plot_df
```

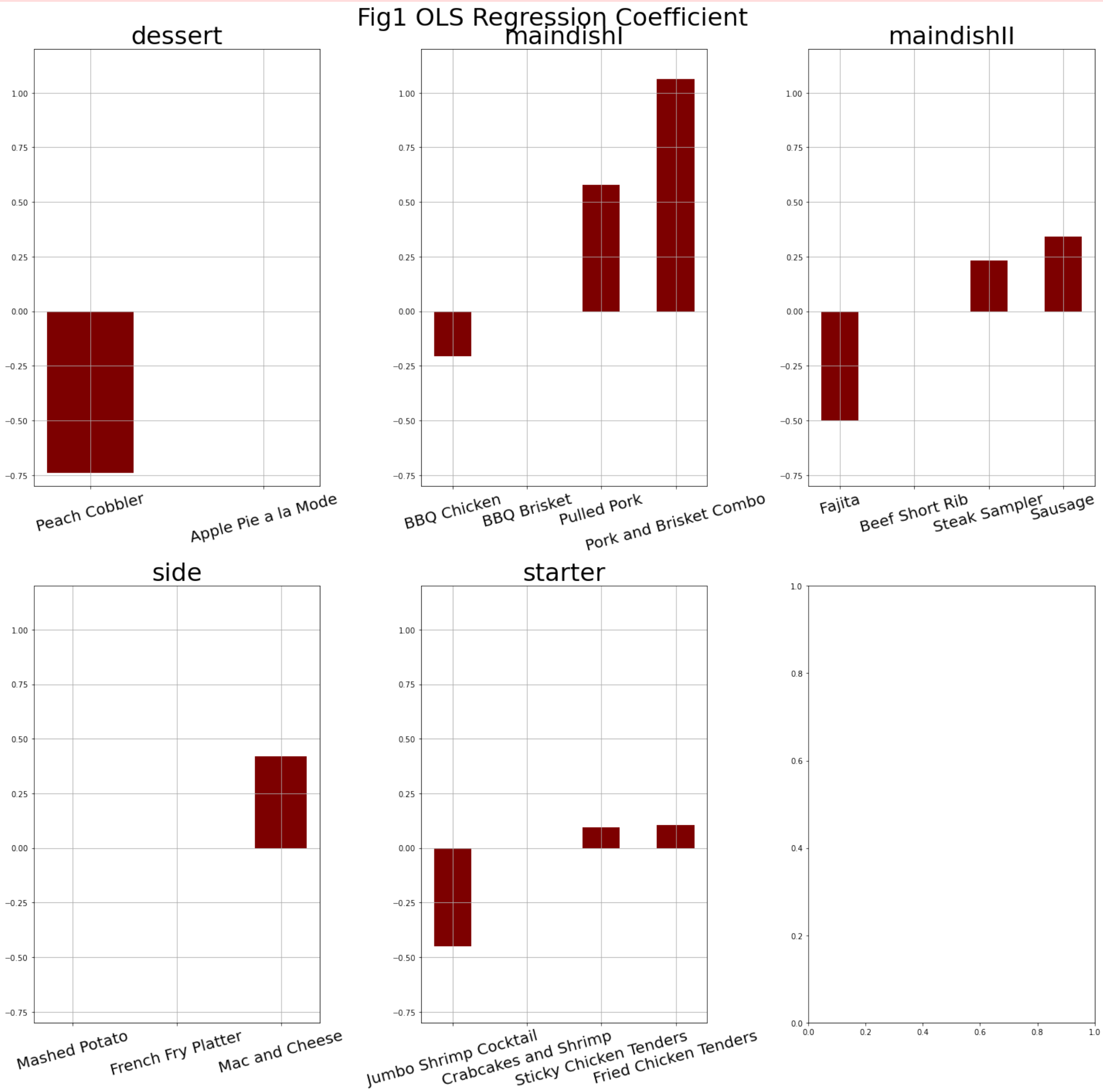
Out[46]:

	Coefficient	food_type	Item
dessert_Peach Cobbler	-0.739167	dessert	Peach Cobbler
dessert_Apple Pie a la Mode	0.000000	dessert	Apple Pie a la Mode
maindishI_BBQ Chicken	-0.207917	maindishI	BBQ Chicken
maindishI_BBQ Brisket	0.000000	maindishI	BBQ Brisket
maindishI_Pulled Pork	0.577188	maindishI	Pulled Pork
maindishI_Pork and Brisket Combo	1.063646	maindishI	Pork and Brisket Combo
maindishII_Fajita	-0.498312	maindishII	Fajita
maindishII_Beef Short Rib	0.000000	maindishII	Beef Short Rib
maindishII_Steak Sampler	0.232813	maindishII	Steak Sampler
maindishII_Sausage	0.342917	maindishII	Sausage
side_Mashed Potato	-0.002500	side	Mashed Potato
side_French Fry Platter	0.000000	side	French Fry Platter
side_Mac and Cheese	0.419687	side	Mac and Cheese
starter_Jumbo Shrimp Cocktail	-0.451771	starter	Jumbo Shrimp Cocktail
starter_Crabcakes and Shrimp	0.000000	starter	Crabcakes and Shrimp
starter_Sticky Chicken Tenders	0.093333	starter	Sticky Chicken Tenders
starter_Fried Chicken Tenders	0.103854	starter	Fried Chicken Tenders

In [47]:
```
fig, ax = plt.subplots(nrows=2, ncols=3,figsize=(20,20))
c=0
for num,item in coef_plot_df.groupby('food_type'):
    ax[c//3,c%3].bar(item.Item, item.Coefficient, color ='maroon',width = 0.5)
    ax[c//3,c%3].set_ylim(-0.8, 1.2)
    ax[c//3,c%3].grid()
    ax[c//3,c%3].set_title(num,fontsize=32)
```

```
    ax[c//3,c%3].set_xticklabels(item.Item,fontsize = 20,rotation=15)
    #ax[c//2,c%2].set_yticklabels(fontsize = 20)
    c+=1
fig.suptitle('Fig1 OLS Regression Coefficient', fontsize=32)
plt.tight_layout()
plt.show()

#
```

```
C:\Users\ranfe\AppData\Local\Temp/ipykernel_1128/4223688376.py:8: UserWarning:
FixedFormatter should only be used together with FixedLocator
  ax[c//3,c%3].set_xticklabels(item.Item,fontsize = 20,rotation=15)
```



In [48]:
```
#plt.figure(figsize=(10,10))
#sns.barplot(x=coef_plot_df.index,y='Coefficient',data=coef_plot_df)
#plt.gca().set_xticklabels(labels=coef_plot_df.index,rotation=90)
#plt.grid()
#plt.title('Fig1 OLS Regression Coefficient')
```

In [49]:
```
vendor_df.replace({'Jumbo Shrimp':'Jumbo Shrimp Cocktail',
                   'Pork & Brisket Combo':'Pork and Brisket Combo',
                   'Beef Short Ribs':'Beef Short Rib',
```

```
                         'French Fry Basket':'French Fry Platter'},inplace=True)
vendor_df
```

Out[49]:

	Item	Item Category	Cost Per Serving (Dollars)
0	Fried Chicken Tenders	Starters	3.40
1	Crabcakes and Shrimp	Starters	3.50
2	Sticky Chicken Tenders	Starters	2.90
3	Jumbo Shrimp Cocktail	Starters	4.60
4	BBQ Brisket	Main Dish I	5.70
5	Pulled Pork	Main Dish I	6.00
6	BBQ Chicken	Main Dish I	5.30
7	Pork and Brisket Combo	Main Dish I	6.10
8	Sausage	Main Dish II	5.30
9	Fajita	Main Dish II	4.70
10	Beef Short Rib	Main Dish II	6.00
11	Steak Sampler	Main Dish II	4.70
12	Mac and Cheese	Side	0.25
13	Mashed Potato	Side	0.10
14	French Fry Platter	Side	0.15
15	Peach Cobbler	Dessert	0.60
16	Apple Pie a la Mode	Dessert	0.90

In [50]:

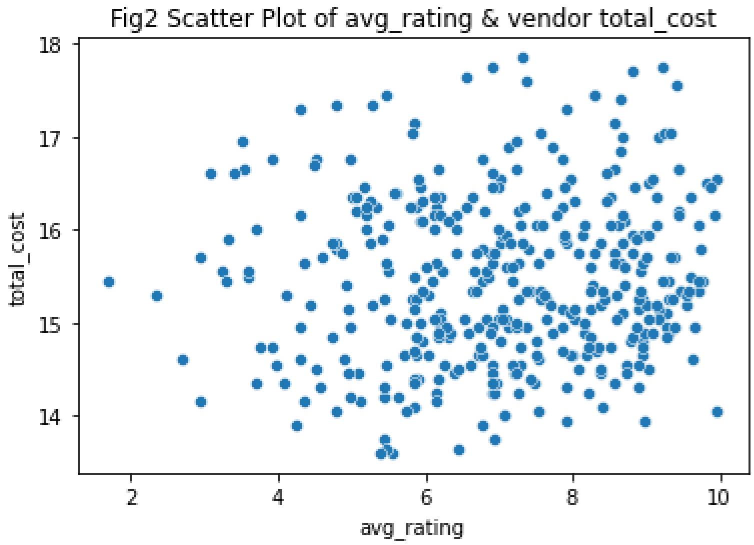
```
price_series = vendor_df.set_index('Item')['Cost Per Serving (Dollars)']
cost_df = pd.DataFrame()
for col in lake_df.columns[:-1]:
    one_price = lake_df[col].map(price_series)
    cost_df = pd.concat([cost_df,one_price],axis=1)
lake_df['total_cost'] = cost_df.sum(axis=1)
```

In [51]:

```
sns.scatterplot(x=lake_df.avg_rating, y=lake_df.total_cost)
plt.title('Fig2 Scatter Plot of avg_rating & vendor total_cost')
```

Out[51]:

```
Text(0.5, 1.0, 'Fig2 Scatter Plot of avg_rating & vendor total_cost')
```



In [52]:
```
lake_df.sort_values(by=['avg_rating'],ascending=False).head(8)
```

Out[52]:

bundleID	starter	maindishI	maindishII	side	dessert	avg_rating	pred	total_cost
90	Fried Chicken Tenders	Pork and Brisket Combo	Beef Short Rib	French Fry Platter	Apple Pie a la Mode	9.97	8.136146	16.55
260	Sticky Chicken Tenders	BBQ Chicken	Steak Sampler	Mac and Cheese	Apple Pie a la Mode	9.97	7.506562	14.05
41	Fried Chicken Tenders	Pulled Pork	Beef Short Rib	French Fry Platter	Peach Cobbler	9.93	6.910521	16.15
332	Jumbo Shrimp Cocktail	Pulled Pork	Steak Sampler	Mac and Cheese	Apple Pie a la Mode	9.89	7.746562	16.45
88	Fried Chicken Tenders	Pork and Brisket Combo	Beef Short Rib	Mashed Potato	Apple Pie a la Mode	9.81	8.133646	16.50
6	Fried Chicken Tenders	BBQ Brisket	Sausage	French Fry Platter	Apple Pie a la Mode	9.77	7.415417	15.45
76	Fried Chicken Tenders	Pork and Brisket Combo	Sausage	Mashed Potato	Apple Pie a la Mode	9.75	8.476563	15.80
92	Fried Chicken Tenders	Pork and Brisket Combo	Steak Sampler	Mac and Cheese	Apple Pie a la Mode	9.70	8.788646	15.35

In [53]:
```
lake_df.sort_values(by=['pred'],ascending=False).head(8)
```

Out[53]:

bundleID	starter	maindishI	maindishII	side	dessert	avg_rating	pred	total_cost
74	Fried Chicken Tenders	Pork and Brisket Combo	Sausage	Mac and Cheese	Apple Pie a la Mode	8.95	8.898750	15.95
266	Sticky Chicken Tenders	Pork and Brisket Combo	Sausage	Mac and Cheese	Apple Pie a la Mode	9.70	8.888229	15.45
170	Crabcakes and Shrimp	Pork and Brisket Combo	Sausage	Mac and Cheese	Apple Pie a la Mode	9.70	8.794896	16.05
92	Fried Chicken Tenders	Pork and Brisket Combo	Steak Sampler	Mac and Cheese	Apple Pie a la Mode	9.70	8.788646	15.35
284	Sticky Chicken Tenders	Pork and Brisket Combo	Steak Sampler	Mac and Cheese	Apple Pie a la Mode	9.28	8.778125	14.85
188	Crabcakes and Shrimp	Pork and Brisket Combo	Steak Sampler	Mac and Cheese	Apple Pie a la Mode	9.30	8.684792	15.45
86	Fried Chicken Tenders	Pork and Brisket Combo	Beef Short Rib	Mac and Cheese	Apple Pie a la Mode	7.23	8.555833	16.65
278	Sticky Chicken Tenders	Pork and Brisket Combo	Beef Short Rib	Mac and Cheese	Apple Pie a la Mode	7.78	8.545312	16.15

Memo

Fig1 shows the coefficient of the ratings-based conjoint analysis of the bundle options. Among starters, Fried Chicken Tenders and Sticky Chicken Tenders are more popular while the Jumbo Shrimp Cocktail is less popular. Among sides, Mac and Cheese is more popular while French Fry Platter and Mashed Potato is less popular. Among maindishI, Pork and Brisket Combo is the most popular and BBQ Chicken is the least popular. Among maindishII, Sausage and Steak Sampler are more popular while Fajita is less popular. Among desserts, Apple Pie a la Mode is more popular than Peach Cobbler.

Given the condition that a flat $\$15$ fee is decided to be charged for all visitors, we also need to pay attention to the cost of the food. Fig2 shows the scatterplot between avg_rating & total cost. Even though there may be some correlation between two variables, the increase of total cost doesn't necessarily help the increase of avg_rating. For one thing, we need to control the total cost under $\$15$, for another, higher avg_rating is important for dishes. The above two tables shows top 8 avg_rating bundles and top 8 predicted value bundles. There are some difference between two tables. If we control the toal cost below $\$15$, BundleID 260 has the high|est avg_rating in the first table; BundleID 284 has the highest predicted value in the second table. We will further discuss the BundleID 284 in that it is the result generated by the conjoint analysis model.

For BundleID 284,Apple Pie, Pork and Brisket Combo, Mac and Cheese are the most popular items among options in the dishes. Steak Sampler and Sticky Chicken Tenders are the second most popular items. If we take a close look to the option cost table, we can find that Steak Sampler's cost is lower than Sausage; Sticky Chicken Tenders's cost is lower than Fried Chicken Tenders. We regard it as the necessary compromise for the cost in that the popularity for the whole meal has been high enough for customers' satisfaction.

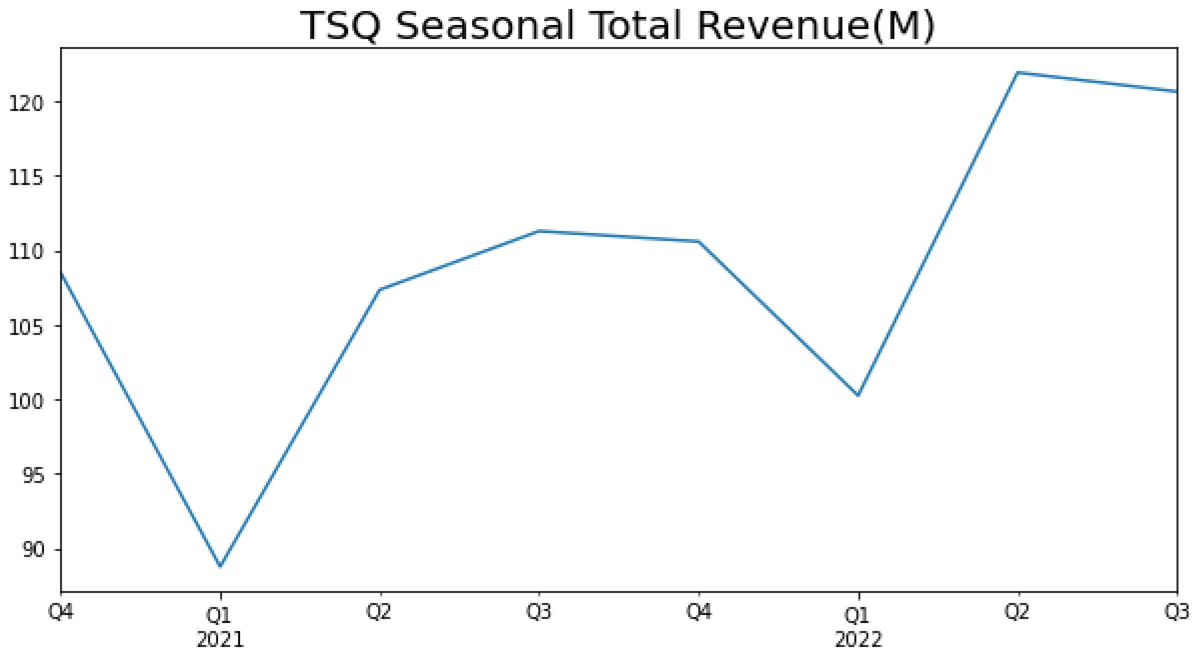
Our analysis also comes up with some limitations. First, there are some difference between avg_rating and predicted value. Some of the difference may influence our final decision. For example, BundleID 260 has high avg_rating but relative low predicted value. It is possible that there exists some interactions which change customers' rating for the whole meal. Second, if we have more information about demand and avg_rating relationship we may come up with other options. It is also possible that low avg_rating bundle is acceptable by many customers and the reduction of cost may also generate more profits for the Lobster Land. Third, Lobster Land also hopes that local beer vendors can sell beverages that will go well with the food choices. Therefore, we need extra analysis for the rating with the addition of beer. To delve further into this problem, we are still in need of more valuable information.

Overall, based on the current information we have, we recommend that Lobster Land should go with BundleID 284 (Starters: Sticky Chicken Tenders, MaindishI: Pork and Brisket Combo, MaindishII: Steak Sampler, Side: Mac and Cheese, Dessert: Apple Pie a la Mode). The BundleID 284 meets all the requirements and keep a perfect balance between rating and cost.

ForecastingTotal Revenue:

In [54]:
```
tsq = pd.read_excel('TSQ.xlsx',index_col=0)
tsq.sort_index(inplace=True)
plt.subplots(figsize=(10,5))
tsq['Total Revenue(M)'].plot()
plt.title('TSQ Seasonal Total Revenue(M)',fontsize=20)
```

Out[54]:
```
Text(0.5, 1.0, 'TSQ Seasonal Total Revenue(M)')
```



Method 1:

In [55]:
```
Q4 = tsq["Total Revenue(M)"].ewm(alpha=2/3,adjust=False).mean()
Q4.iloc[-1]
```

Out[55]: 119.01670324645633

In [56]:
```
Q4_est1 = tsq["Total Revenue(M)"].iloc[-3:].sum()+Q4.iloc[-1]
Q4_est1
```

Out[56]: 461.8167032464563

Method 2:

In [57]:
```
tsq = tsq.assign(gross = tsq['Gross Profit(M)']/tsq['Total Revenue(M)'])
```

In [58]:
```
Q4_profit = tsq["Gross Profit(M)"].ewm(alpha=2/3,adjust=False).mean().iloc[-1]
Q4_profit
```

Out[58]: 36.12957018747142

In [59]:
```
Q4_gross_rate = tsq["gross"].ewm(alpha=2/3,adjust=False).mean().iloc[-1]
Q4_gross_rate
```

Out[59]: 0.303074752396461

In [60]:
```
Q4_method2=Q4_profit/Q4_gross_rate
Q4_method2
```

Out[60]: 119.21009553514135

In [61]:
```
Q4_est2 = tsq["Total Revenue(M)"].iloc[-3:].sum()+Q4_method2
Q4_est2
```

Out[61]: 462.0100955351414

In [62]:
```
final_est = (Q4_est1+Q4_est2)/2
final_est
```

Out[62]: 461.9133993907989

Conclusion for ForecastingTotal Revenue

Both annual(from 2014 to 2021) and quarterly(from 2020-12-31 to 2022-09-30) income statements have limited data. Here we use the quarterly data. The plot shown below indicates that the total revenue has both trend and seasonality. Because of the limited data, the data isn't suitable for ARIMA model and Exponential Smoothing Methods.

Here we take two estimations and take the means of the two estimations as the final result. The first estimation is to take the exponentially weighted moving average for the total revenue. Alpha is set as 2/3 and the adjust is set as False. The second estimation is to take the exponentially weighted moving average for the gross profit and gross profit rate and then use both of them get the total revenue. Alpha is set as 2/3 and the adjust is set as False. After having the two estimations for Q4 total revenue, we can predict the estimation for the 2022 total revenue by adding Q4 total revenue estimation with previous three quarter total revenue. Since we have two methods for estimation. we can take the means of two estimation as the final estimation.

Classification

In [63]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn import tree
from sklearn.tree import export_graphviz
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

Data Processing

In [65]:
```
carnival = pd.read_csv("carnival_visitors.csv")
carnival.head()
```

Out[65]:

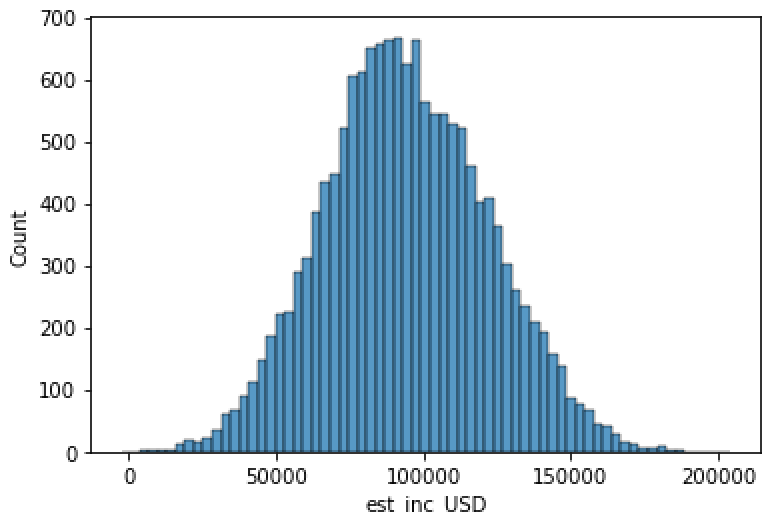
	householdID	est_inc_USD	est_netw_USD	hhold_field	hhold_oldest	hhold_pax	hhold_youn
0	23	59245	381931	Govt	48	2	
1	27	116628	457159	Tech	51	5	
2	36	65835	394803	Services	50	4	
3	41	132483	429296	Tech	54	2	
4	44	83444	488210	Education	51	7	

In [66]:
```
carnival.describe()
```

Out[66]:

	householdID	est_inc_USD	est_netw_USD	hhold_oldest	hhold_pax	hhold_young
count	15000.000000	15000.000000	15000.000000	15000.000000	15000.000000	15000.000
mean	7500.500000	94350.965000	466169.094800	45.327400	4.458933	14.984
std	4330.271354	27826.069636	71050.877531	4.966017	1.796106	8.361
min	1.000000	-2537.000000	180540.000000	25.000000	1.000000	1.000
25%	3750.750000	75246.750000	418090.500000	42.000000	3.000000	11.000
50%	7500.500000	93209.500000	466061.000000	45.000000	4.000000	13.000
75%	11250.250000	113346.250000	514245.250000	49.000000	6.000000	16.000
max	15000.000000	204057.000000	774358.000000	66.000000	12.000000	62.000

In [67]:
```
sns.histplot(x = "est_inc_USD", data = carnival);
```



In [68]:
```
carnival.corr()
```

Out[68]:

	householdID	est_inc_USD	est_netw_USD	hhold_oldest	hhold_pax	hhold_you
householdID	1.000000	0.000139	-0.007308	-0.011543	-0.008880	0.0
est_inc_USD	0.000139	1.000000	0.564164	0.005654	0.007785	-0.0
est_netw_USD	-0.007308	0.564164	1.000000	0.007206	-0.009177	0.0
hhold_oldest	-0.011543	0.005654	0.007206	1.000000	-0.070359	0.0
hhold_pax	-0.008880	0.007785	-0.009177	-0.070359	1.000000	-0.4
hhold_youngest	0.005873	-0.031581	0.002547	0.097418	-0.448442	1.0
stream_subs	-0.002836	-0.009212	-0.008941	-0.007161	-0.006198	-0.0
primary	0.001270	-0.086437	0.004245	-0.238336	0.069625	-0.0

In [69]:
```
carnival = carnival.drop("est_netw_USD", axis=1)
carnival.isnull().sum()
```

Out[69]:
```
householdID         0
est_inc_USD         0
hhold_field         0
hhold_oldest        0
hhold_pax           0
hhold_youngest      0
homeState           0
hhold_car         551
stream_subs         0
primary             0
dtype: int64
```

In [70]:
```
carnival = carnival.dropna()
```

Logistic Regression Model

In [71]:
```
carnival_log = carnival.copy()
carnival_log["est_inc_USD"] = carnival_log["est_inc_USD"].apply(lambda x: x/10(
```

In [72]:
```
carnival_log["est_inc_USD"]
```

Out[72]:
```
0         5.9245
1        11.6628
2         6.5835
3        13.2483
4         8.3444
          ...
14995     9.6786
14996    11.3057
14997    10.3937
14998    13.7577
14999     5.7796
Name: est_inc_USD, Length: 14449, dtype: float64
```

Iteration 1

In [73]:
```
carnival_1 = pd.get_dummies(carnival_log, drop_first=True, columns=['hhold_fie
carnival_1.columns
```

Out[73]:
```
Index(['householdID', 'est_inc_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 Hampshir
e',
       '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 [74]:
```
X1 = carnival_1[['est_inc_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_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']]
y1 = carnival_1['primary']
X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size=0.4,

logit_model1 = sm.Logit(y1_train, sm.add_constant(X1_train))
result1 = logit_model1.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.611247
         Iterations 5
```

```
D:\app\anaconda\lib\site-packages\statsmodels\tsa\tsatools.py:142: FutureWarni
ng: In a future version of pandas all arguments of concat except for the argum
ent 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [75]:
```
result1.summary()
```

Out[75]:

Logit Regression Results

Dep. Variable:	primary	**No. Observations:**	8669
Model:	Logit	**Df Residuals:**	8643
Method:	MLE	**Df Model:**	25
Date:	Tue, 13 Dec 2022	**Pseudo R-squ.:**	0.1136
Time:	17:32:03	**Log-Likelihood:**	-5298.9
converged:	True	**LL-Null:**	-5977.7
Covariance Type:	nonrobust	**LLR p-value:**	4.346e-271

	coef	std err	z	P>|z|	[0.025	0.975]
const	5.3323	0.358	14.910	0.000	4.631	6.033
est_inc_USD	-0.0443	0.010	-4.408	0.000	-0.064	-0.025
hhold_oldest	-0.1144	0.005	-22.555	0.000	-0.124	-0.104
hhold_pax	0.0376	0.015	2.552	0.011	0.009	0.066
hhold_youngest	-0.0094	0.003	-2.895	0.004	-0.016	-0.003
stream_subs	0.2414	0.014	17.229	0.000	0.214	0.269
hhold_field_Finance	-0.9406	0.088	-10.680	0.000	-1.113	-0.768
hhold_field_Govt	-0.9951	0.081	-12.313	0.000	-1.154	-0.837
hhold_field_Manufacturing	-0.5526	0.152	-3.638	0.000	-0.850	-0.255
hhold_field_Other	-0.3742	0.159	-2.361	0.018	-0.685	-0.064
hhold_field_Services	0.1518	0.091	1.664	0.096	-0.027	0.331
hhold_field_Tech	-0.5232	0.091	-5.721	0.000	-0.703	-0.344
homeState_Connecticut	-0.0274	0.257	-0.106	0.915	-0.531	0.477
homeState_Maine	-0.1155	0.214	-0.540	0.589	-0.535	0.304
homeState_Massachusetts	-0.2546	0.236	-1.077	0.281	-0.718	0.209
homeState_New Hampshire	-0.2328	0.221	-1.052	0.293	-0.666	0.201
homeState_New York	-0.0719	0.230	-0.312	0.755	-0.523	0.380
homeState_Ontario	-0.2212	0.232	-0.953	0.341	-0.676	0.234
homeState_Quebec	-0.0696	0.232	-0.300	0.764	-0.525	0.385
homeState_Rhode Island	-0.2778	0.240	-1.155	0.248	-0.749	0.193
homeState_US_Other	-0.2100	0.242	-0.868	0.385	-0.684	0.264
homeState_Vermont	-0.1254	0.224	-0.559	0.576	-0.565	0.314
hhold_car_LuxurySedan	0.3422	0.093	3.678	0.000	0.160	0.525
hhold_car_Pickup	0.0981	0.107	0.917	0.359	-0.112	0.308
hhold_car_SUV	0.0937	0.088	1.071	0.284	-0.078	0.265
hhold_car_Sedan	0.3089	0.095	3.243	0.001	0.122	0.496

Iteration 2

From iteration 1, we can see high p-value(>0.5) for all levels of `homeState` variables. Therefore, I drop the categorical variable in iteration 2.

In [76]:
```
X2_train = X1_train.drop(labels=['homeState_Connecticut',
       'homeState_Maine', 'homeState_Massachusetts', 'homeState_New Hampshire'
       'homeState_New York', 'homeState_Ontario', 'homeState_Quebec',
       'homeState_Rhode Island', 'homeState_US_Other', 'homeState_Vermont'], ax
X2_test = X1_test.drop(labels=['homeState_Connecticut',
       'homeState_Maine', 'homeState_Massachusetts', 'homeState_New Hampshire'
       'homeState_New York', 'homeState_Ontario', 'homeState_Quebec',
       'homeState_Rhode Island', 'homeState_US_Other', 'homeState_Vermont'], ax
y2_train = y1_train.copy()
y2_test = y1_test.copy()
```

In [77]:
```
logit_model2 = sm.Logit(y2_train, sm.add_constant(X2_train))
result2 = logit_model2.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.611718
         Iterations 5
```

```
D:\app\anaconda\lib\site-packages\statsmodels\tsa\tsatools.py:142: FutureWarni
ng: In a future version of pandas all arguments of concat except for the argum
ent 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

In [78]:
```
result2.summary()
```

Out[78]:

Logit Regression Results

Dep. Variable:	primary	**No. Observations:**	8669
Model:	Logit	**Df Residuals:**	8653
Method:	MLE	**Df Model:**	15
Date:	Tue, 13 Dec 2022	**Pseudo R-squ.:**	0.1129
Time:	17:32:03	**Log-Likelihood:**	-5303.0
converged:	True	**LL-Null:**	-5977.7
Covariance Type:	nonrobust	**LLR p-value:**	1.249e-278

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	5.1690	0.287	17.999	0.000	4.606	5.732
est_inc_USD	-0.0444	0.010	-4.425	0.000	-0.064	-0.025
hhold_oldest	-0.1141	0.005	-22.524	0.000	-0.124	-0.104
hhold_pax	0.0385	0.015	2.620	0.009	0.010	0.067
hhold_youngest	-0.0093	0.003	-2.882	0.004	-0.016	-0.003
stream_subs	0.2418	0.014	17.281	0.000	0.214	0.269
hhold_field_Finance	-0.9400	0.088	-10.686	0.000	-1.112	-0.768
hhold_field_Govt	-0.9941	0.081	-12.312	0.000	-1.152	-0.836
hhold_field_Manufacturing	-0.5524	0.151	-3.646	0.000	-0.849	-0.255
hhold_field_Other	-0.3766	0.158	-2.378	0.017	-0.687	-0.066
hhold_field_Services	0.1525	0.091	1.674	0.094	-0.026	0.331
hhold_field_Tech	-0.5231	0.091	-5.729	0.000	-0.702	-0.344
hhold_car_LuxurySedan	0.3388	0.093	3.647	0.000	0.157	0.521
hhold_car_Pickup	0.0955	0.107	0.894	0.371	-0.114	0.305
hhold_car_SUV	0.0896	0.087	1.025	0.305	-0.082	0.261
hhold_car_Sedan	0.3071	0.095	3.227	0.001	0.121	0.494

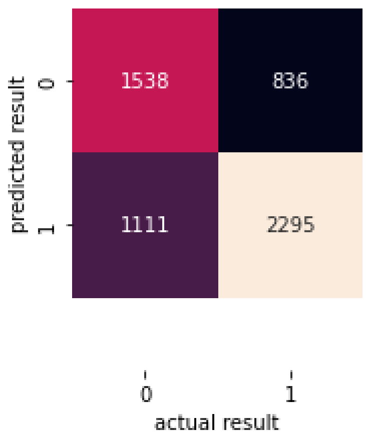
In [79]:
```
logmodel = LogisticRegression(random_state = 2000, max_iter=1000)
```

In [80]:
```
logmodel.fit(X2_train, y2_train)
```

Out[80]:
```
LogisticRegression(max_iter=1000, random_state=2000)
```

In [81]:
```
# against the test set
predictions_logit = logmodel.predict(X2_test)
mat_logit = confusion_matrix(predictions_logit, y2_test)
sns.heatmap(mat_logit,square = True, fmt = 'g', annot = True, cbar = False)
plt.xlabel('actual result')
plt.ylabel('predicted result')
a,b = plt.ylim()
a+=0.5
b-=0.5
```

```
plt.ylim(a,b)
plt.show()
```



In [82]:
```
predictions2 = logmodel.predict(X2_train)
accuracy_score(y2_train, predictions2)
```

Out[82]: 0.674933671703772

In [83]:
```
accuracy_logmodel = (mat_logit[1,1]+mat_logit[0,0])/sum(sum(mat_logit))
print('The logistic regression model has a accuracy of: ', accuracy_logmodel)
```

The logistic regression model has a accuracy of: 0.6631487889273356

In [84]:
```
sensitivity_logmodel = mat_logit[1,1]/(mat_logit[1,1]+mat_logit[0,1])
print('The logistic regression model has a sensitivity of: ', sensitivity_logmo
```

The logistic regression model has a sensitivity of: 0.7329926541041201

In [85]:
```
specificity_logmodel = mat_logit[0,0]/(mat_logit[0,0]+mat_logit[1,0])
print('The logistic regression model has a specificity of: ', specificity_logmo
```

The logistic regression model has a specificity of: 0.5805964514911287

In [86]:
```
precision_logmodel = mat_logit[1,1]/(mat_logit[1,1]+mat_logit[1,0])
print('The logistic regression model has a precision of: ', precision_logmodel
```

The logistic regression model has a precision of: 0.673810921902525

Random Forest Model

In [87]:
```
carnival_3 = pd.get_dummies(carnival, drop_first=False, columns=['hhold_field'
carnival_3.columns
```

Out[87]:
```
Index(['householdID', 'est_inc_USD', 'hhold_oldest', 'hhold_pax',
       'hhold_youngest', 'stream_subs', 'primary', 'hhold_field_Education',
       'hhold_field_Finance', 'hhold_field_Govt', 'hhold_field_Manufacturing',
       'hhold_field_Other', 'hhold_field_Services', 'hhold_field_Tech',
       'homeState_Can_Other', '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_Compact/Hybrid', 'hhold_car_LuxurySedan', 'hhold_car_Picku
p',
       'hhold_car_SUV', 'hhold_car_Sedan'],
      dtype='object')
```

In [88]:
```
X3 = carnival_3[['est_inc_USD', 'hhold_oldest',
       'hhold_pax', 'hhold_youngest', 'stream_subs',
       'hhold_field_Education', 'hhold_field_Finance', 'hhold_field_Govt',
       'hhold_field_Manufacturing', 'hhold_field_Other',
       'hhold_field_Services', 'hhold_field_Tech', 'homeState_Can_Other',
       '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_Compact/Hybrid',
       'hhold_car_LuxurySedan', 'hhold_car_Pickup',
       'hhold_car_SUV', 'hhold_car_Sedan']]
y3 = carnival_3['primary']
X3_train, X3_test, y3_train, y3_test = train_test_split(X3, y3, test_size=0.4,
```

In [89]:
```
clf=RandomForestClassifier()
param_grid1 = {
    'n_estimators' : [150],
    'max_depth' : [9,10, 11],
    'max_features' : [10,11,12],
    'min_samples_split' : [4, 5, 6]
}
travel_rfc = GridSearchCV(estimator = clf, param_grid = param_grid1, cv = 5)
travel_rfc.fit(X1_train, y1_train)
print(travel_rfc.best_params_)
```

```
{'max_depth': 10, 'max_features': 11, 'min_samples_split': 6, 'n_estimators':
150}
```

In [90]:
```
clf=RandomForestClassifier(max_depth=10, max_features=11, min_samples_split= 5
clf.fit(X3_train,y3_train)
```

Out[90]:
```
RandomForestClassifier(max_depth=10, max_features=11, min_samples_split=5,
                       n_estimators=150, random_state=2000)
```

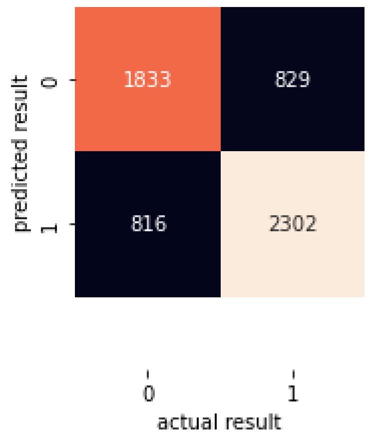
In [91]:
```
feature_imp_df = pd.DataFrame(list(zip(clf.feature_importances_, X3_train)))
feature_imp_df.columns = ['feature importance', 'feature']
feature_imp_df = feature_imp_df.sort_values(by='feature importance', ascending=
feature_imp_df
```

Out[91]:

	feature importance	feature
1	0.262284	hhold_oldest
4	0.184424	stream_subs
0	0.142079	est_inc_USD
3	0.092947	hhold_youngest
2	0.055545	hhold_pax
10	0.041402	hhold_field_Services
5	0.030394	hhold_field_Education
7	0.028976	hhold_field_Govt
6	0.023026	hhold_field_Finance
27	0.011566	hhold_car_Sedan
11	0.011087	hhold_field_Tech
25	0.010446	hhold_car_Pickup
26	0.009645	hhold_car_SUV
14	0.009424	homeState_Maine
22	0.008460	homeState_Vermont
23	0.008300	hhold_car_Compact/Hybrid
24	0.008284	hhold_car_LuxurySedan
16	0.007795	homeState_New Hampshire
18	0.007384	homeState_Ontario
15	0.006790	homeState_Massachusetts
17	0.006679	homeState_New York
19	0.006105	homeState_Quebec
20	0.005734	homeState_Rhode Island
21	0.005280	homeState_US_Other
8	0.005125	hhold_field_Manufacturing
9	0.004232	hhold_field_Other
13	0.004213	homeState_Connecticut
12	0.002372	homeState_Can_Other

In [92]:

```
predictions_rfm = clf.predict(X3_test)
mat_rfm = confusion_matrix(predictions_rfm, y3_test)
sns.heatmap(mat_rfm,square = True, fmt = 'g', annot = True, cbar = False)
plt.xlabel('actual result')
plt.ylabel('predicted result')
a,b = plt.ylim()
a+=0.5
b-=0.5
plt.ylim(a,b)
plt.show()
```



In [93]:
```
predictions1 = clf.predict(X3_train)
accuracy_score(y3_train, predictions1)
```

Out[93]:
```
0.7983619794670666
```

In [94]:
```
accuracy_rfm = (mat_rfm[1,1]+mat_rfm[0,0])/sum(sum(mat_rfm))
print('The random forest model has a accuracy of: ', accuracy_rfm)
```

```
The random forest model has a accuracy of:  0.7153979238754326
```

In [95]:
```
sensitivity_rfm = mat_rfm[1,1]/(mat_rfm[1,1]+mat_rfm[0,1])
print('The random forest model has a sensitivity of: ', sensitivity_rfm)
```

```
The random forest model has a sensitivity of:  0.735228361545832
```

In [96]:
```
specificity_rfm = mat_rfm[0,0]/(mat_rfm[0,0]+mat_rfm[1,0])
print('The random forest model has a specificity of: ', specificity_rfm)
```

```
The random forest model has a specificity of:  0.6919592298980748
```

In [97]:
```
precision_rfm = mat_rfm[1,1]/(mat_rfm[1,1]+mat_rfm[1,0])
print('The random forest model has a precision of: ', precision_rfm)
```

```
The random forest model has a precision of:  0.7382937780628608
```

Conclusion for Classification

We used the carnival_visitors dataset to build a model to classify whether a particular household prefers "consume" or "entertain". Firstly, to get data prepared, we drop the NaNs value in hhold_car as there are only 551 (about 3.7%) rows containing NaNs. Meanwhile, we accessed the correlations of the data, where `est_inc_USD` and `est_netw_USD` has a strong correlation(>0.5). So we drop `est_netw_USD`, considering the total income could have a stronger impact on the decision than the net worth. Secondly, we fitted a logistic regression model and access its performance. In this part, we divided `est_inc_USD` by 10000 as the range of it is too large. We didn't use the log transformation since it is quite symmetric. Finally, we fitted a logistic regression model and access its performance as well to compare with the logistic regression model.

For the logistic regression model, the accuracy of the training set is 67.5% and of the testing set is 66.3% -- quite close, which means there are no overfitting situations. The sensitivity is 73.3% but the specificity is 58.1%, which means this model is better at identifying those who prefer entertainment, but worse at identifying those who prefer consumption. For the random forest model, the accuracy of the training set is 79.8% and for the testing set is 71.5%. This model exist a slight overfit but performs better than the logistic regression model. The sensitivity is 73.5% and the specificity is 69.2%, both are higher than the logistic one. Therefore, we think the random forest model could be better used by Lobster Land management to make the classification.

Furthermore, when we built the logistic regression model, we dropped the `homeStates` since it is statistically insignificant at all levels -- It is not important at all. It can be also seen by the feature important table of the random forest model. Actually, the random forest model thinks the most three important factors when a household chooses their preference are the age of the oldest people, the number of streaming entertainment service subscriptions, and the total income. Even though the random forest model is non-linear, we can see the overall trends through the logistic regression model -- the older age and higher income will make households more likely to choose consumption, and more streaming entertainment service subscriptions will make the household more likely to choose entertainment. Therefore advertisements for eating, drinking, and shopping, should aim at older people and high-income households. And advertisements for live shows, performance acts, concerts, comedy, and live competitions should aim at younger people, low-income households, and streaming lovers.

A/B Testing

In [98]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy import stats
dt = pd.read_csv("snowmobile_pics.csv")
# dt.head()
```

Data Visualization

In [99]:
```
# check the balance distribution of 3 pictures
dt.groupby('pic_seen').describe().round(2).spend
```

Out[99]:

pic_seen	count	mean	std	min	25%	50%	75%	max
Racers in Action	1110.0	16.78	0.86	14.30	16.20	16.80	17.40	19.20
Sharp Turn	1142.0	18.61	2.43	10.42	17.02	18.62	20.22	27.12
Starting Line	1148.0	14.02	2.11	7.40	12.60	14.00	15.50	20.90

The "count" column shows that the dataset is balanced, which helps avoid confounding risks, and we assume the test was conducted by randomly assigning users to each picture grounp.

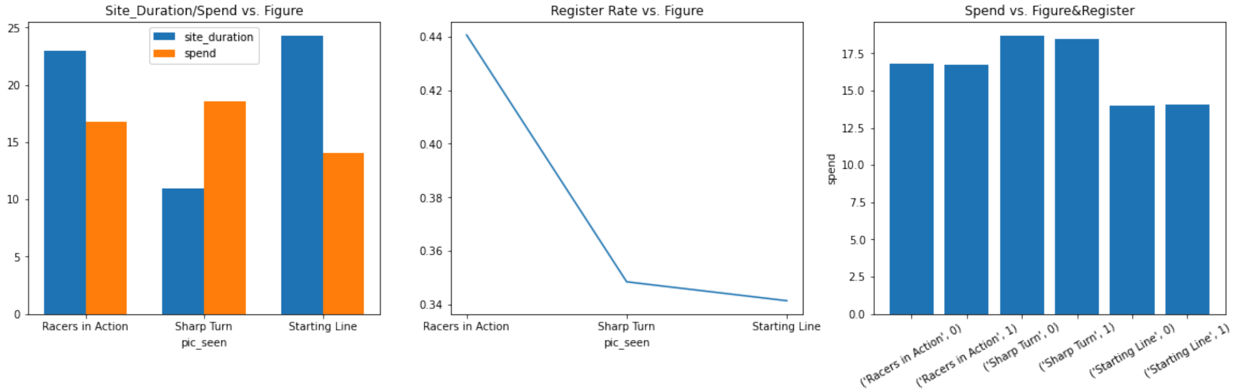
In [100…

```
temp1 = dt.groupby('pic_seen')[['site_duration','spend']].mean()
fig, ax = plt.subplots(nrows=1, ncols=3,figsize=(20,5))
labels = temp1.index
width = 0.35
x = np.arange(len(labels))
rects1 = ax[0].bar(x - width/2, temp1.site_duration.values,width,label='site_du
rects2 = ax[0].bar(x + width/2, temp1.spend.values,width,label='spend')
ax[0].set_xticks(x)
ax[0].set_xticklabels(labels)
ax[0].set_title("Site_Duration/Spend vs. Figure")
ax[0].set_xlabel(temp1.index.name)
ax[0].legend()

ax[1].plot(dt.groupby('pic_seen')['register'].mean())
ax[1].set_title("Register Rate vs. Figure")
ax[1].set_xlabel(temp1.index.name)

temp2 = dt.groupby(['pic_seen','register'])['spend'].mean()
plot_index = [str(i) for i in temp2.index]
ax[2].bar(plot_index,temp2.values)
ax[2].set_ylabel("spend")
ax[2].set_title("Spend vs. Figure&Register")
ax[2].set_xticklabels(plot_index,rotation=30)
```

```
C:\Users\ranfe\AppData\Local\Temp/ipykernel_1128/1866388807.py:23: UserWarnin
g: FixedFormatter should only be used together with FixedLocator
  ax[2].set_xticklabels(plot_index,rotation=30)
```

Out[100]:

```
[Text(0, 0, "('Racers in Action', 0)"),
 Text(1, 0, "('Racers in Action', 1)"),
 Text(2, 0, "('Sharp Turn', 0)"),
 Text(3, 0, "('Sharp Turn', 1)"),
 Text(4, 0, "('Starting Line', 0)"),
 Text(5, 0, "('Starting Line', 1)")]
```



From the "Site_Duration/Spend vs. Figure" plot, we can see the "Sharpt Turn" figure has the largest conversion rate in consumer purchasing behavior.

From the "Register Rate vs. Figure" plot, we can see the "Racers in Action" figure leads to more registration for the snowmobile race.

From the "Spend vs. Figure&Register" plot, we can see registration seems does not have relationship with purchasing behaviors.

A/B Test for "Spend"

In [101…

```
t, p = stats.ttest_ind(dt.loc[dt['pic_seen'] == 'Racers in Action', 'spend'].va
                       dt.loc[dt['pic_seen'] == 'Sharp Turn', 'spend'].values,
                       equal_var=False)
print("For Figure(Racers in Action) vs. Figure(Sharp Turn): t-statistics=", t.
```

```
For Figure(Racers in Action) vs. Figure(Sharp Turn): t-statistics= -23.86 , p-
value= 0.0 .
```

In [102…

```
t, p = stats.ttest_ind(dt.loc[dt['pic_seen'] == 'Racers in Action', 'spend'].va
                       dt.loc[dt['pic_seen'] == 'Starting Line', 'spend'].valu
                       equal_var=False)
print("For Figure(Racers in Action) vs. Figure(Starting Line): t-statistics=",
```

```
For Figure(Racers in Action) vs. Figure(Starting Line): t-statistics= 41.03 ,
p-value= 0.0 .
```

In [103…

```
t, p = stats.ttest_ind(dt.loc[dt['pic_seen'] == 'Starting Line', 'spend'].value
                       dt.loc[dt['pic_seen'] == 'Sharp Turn', 'spend'].values,
                       equal_var=False)
print("For Figure(Starting Line) vs. Figure(Sharp Turn): t-statistics=", t.rou
```

```
For Figure(Starting Line) vs. Figure(Sharp Turn): t-statistics= -48.18 , p-val
ue= 0.0 .
```

We first selected "Spend" as our desired goal to compare the effectiveness of three different figures on purchasing behavior. Since our goal is to drive revenue through our snowmobile race, we chose "Spend" as our measure of success. The results of our t-tests showed that, for all three groups, the p-value of the t-test was smaller than 0.05 (assuming an alpha value of 0.05 for statistical tests). This indicates that the variation in purchasing behavior among members who received different figures is not due to random chance. In other words, the figures do have a statistically significant effect on purchasing behavior.

A/B Test for "Register"

In [104…
```
t, p = stats.ttest_ind(dt.loc[dt['pic_seen'] == 'Racers in Action', 'register']
                       dt.loc[dt['pic_seen'] == 'Sharp Turn', 'register'].valu
                       equal_var=False)
print("For Figure(Racers in Action) vs. Figure(Sharp Turn): t-statistics=", t.
```

```
For Figure(Racers in Action) vs. Figure(Sharp Turn): t-statistics= 4.48 , p-va
lue= 0.0 .
```

In [105…
```
t, p = stats.ttest_ind(dt.loc[dt['pic_seen'] == 'Racers in Action', 'register']
                       dt.loc[dt['pic_seen'] == 'Starting Line', 'register'].va
                       equal_var=False)
print("For Figure(Racers in Action) vs. Figure(Starting Line): t-statistics=",
```

```
For Figure(Racers in Action) vs. Figure(Starting Line): t-statistics= 4.84 , p
-value= 0.0 .
```

In [106…
```
t, p = stats.ttest_ind(dt.loc[dt['pic_seen'] == 'Starting Line', 'register'].va
                       dt.loc[dt['pic_seen'] == 'Sharp Turn', 'register'].valu
                       equal_var=False)
print("For Figure(Starting Line) vs. Figure(Sharp Turn): t-statistics=", t.rou
```

```
For Figure(Starting Line) vs. Figure(Sharp Turn): t-statistics= -0.35 , p-valu
e= 0.72 .
```

Considering more registeration can creat a bustling atmosphere at the festival which can attract more people to participate with the aim of lift revenue. We also conducted an A/B test to compare the effectiveness of different figures on "Register" and found that Figure (Starting Line) significantly promoted registration compared to the other two figures. There was no meaningful difference in registration between groups that received Figure (Starting Line) versus Figure (Sharp Turn), as indicated by the p-value of our t-test being larger than 0.05. Our results suggest that Figure (Starting Line) is the most effective figure for promoting registration.

Conclusion for A/B Test

The management at Lobster Land must weigh the trade-offs between focusing on maximizing spending or increasing registration for holding the snowmobile race, similar to balance profit oriented or revenue oriented when pricing. Our data suggests that Figure (Sharp Turn) is more effective at promoting spending, while Figure (Racers in Action) is more effective at promoting registration. Based on this information, the management can make an informed decision on which figure to use in order to achieve their desired goal.

Total Conclusion

Summary Stats

Based on angle_market data, the lobster land did hold a well organized market for their business. If the lobster land has estimate hourly sales, it would be better for them to select more appropriate vendors for the carnival. Last but not least, Lobster Land might consider narrow down the size of loval vendors. With competition comes advancement.

Segmentation and Targeting

Our team has applied K-Means clustering to create 5 clusters of Maine families based on their spending habits and characteristics, each with a featured name, and targeted with a tailored strategy for park management,such as sending more marketing emails and Ads with deals and coupons, holding games and events for large families, etc. These approachs can help to effectively market the park and increase revenue.

Conjoint Analysis

We recommend that Lobster Land should go with BundleID 284 (Starters: Sticky Chicken Tenders, MaindishI: Pork and Brisket Combo, MaindishII: Steak Sampler, Side: Mac and Cheese, Dessert: Apple Pie a la Mode). The BundleID 284 meets all the requirements and keep a perfect balance between rating and cost.

Forecasting

We apply exponentially weighted moving average to estimate the total revenue in 2022 for TSQ. Two approaches are used in the estimation. The first approach is to use season total revenue to get the estimation. The second is to use season gross profit and gross profit rate to get the estimation. We take the mean of two estimations as the final output and our final estimation for TSQ’s total revenue in 2022 is about 461.91M.estimation.

Classification

We built a random forest model to classify whether a particular household prefers "consumption" or "entertainment". The model acurracy is 71.5% and implies that older age and higher income will make households more likely to choose consumption, and more streaming entertainment service subscriptions will make the household more likely to choose entertainment.

A/B Testing

Our A/B Testing result suggest that Figure (Sharp Turn) is more effective at promoting spending, while Figure (Racers in Action) is more effective at promoting registration. The management at Lobster Land must weigh the trade-offs between focusing on maximizing spending or increasing registration for holding the snowmobile race.

Case Analysis

The success of Qingdao International Beer Festival can be attributed to its cultural uniqueness and organization structure. Therefore, we suggest that Lobster Land works on both the cultural and organizational aspects, incorporating unique local cultural elements such as lobster into the carnival, and working with the local government to ensure financial support so that it can meet the goal to hold a regular and annual carnival.