# AD 654 Final project

Group MSSP

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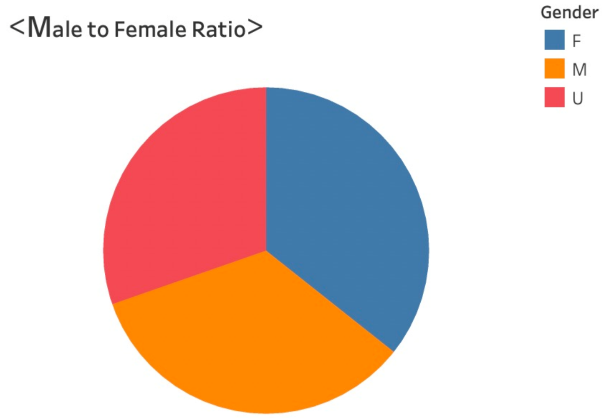
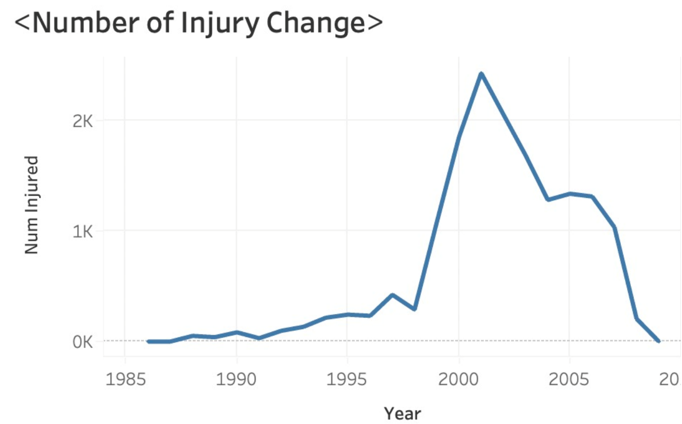
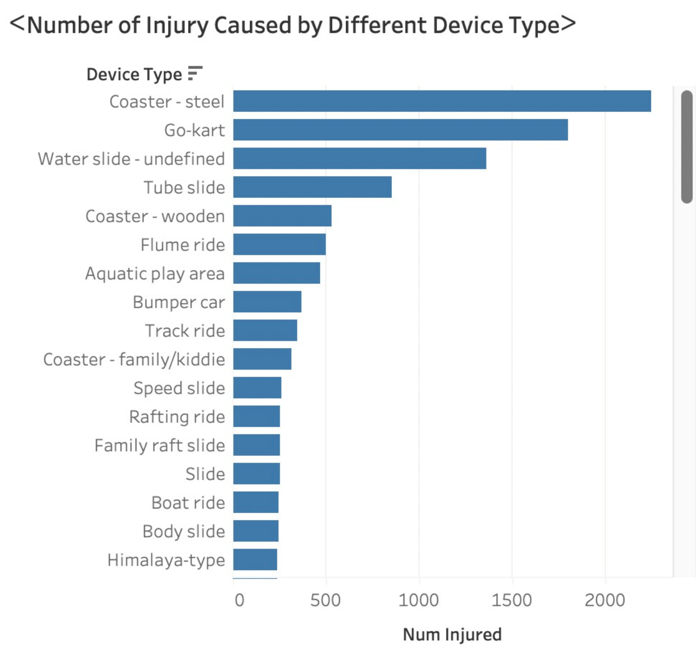
In [ ]:

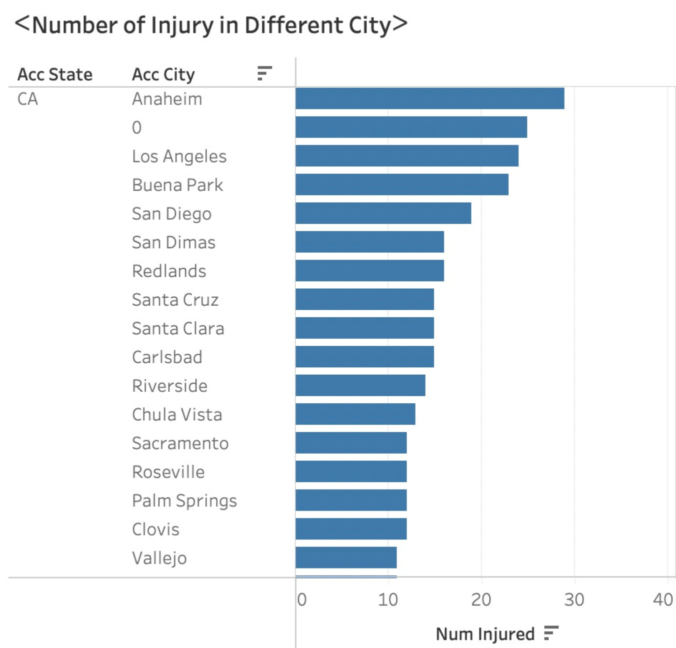
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA
from sklearn.cluster import KMeans
from sklearn.tree import DecisionTreeClassifier
from six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
```

# Data Visualization




# Summary Stats

In [2]:

```
df = pd.read_csv('park_accidents.csv')
promo_pics = pd.read_csv('promo_pics.csv')
#print(df.head())

df.groupby('category').agg({'acc_date': 'count','num_injured': 'sum','age_youngest': 'mear
```

Out[2]:

| category | acc_date | num_injured | age_youngest |
|---|---|---|---|
| **Abrupt stop/drop/lurch** | 108 | 232 | 22.537037 |
| **Awkward landing** | 1 | 1 | 0.000000 |
| **Body pain (normal motion)** | 1422 | 1438 | 22.277075 |
| **Burn (includes friction burn)** | 88 | 90 | 12.693182 |
| **Choking, water inhalation, suffocation** | 28 | 29 | 8.821429 |
| **Collision: go-kart crashed (no further description)** | 14 | 14 | 12.142857 |
| **Collision: go-kart or bumper car hit stationary object** | 434 | 441 | 11.783410 |
| **Collision: operator-controlled vehicles** | 142 | 374 | 17.176056 |

| | acc_date | num_injured | age_youngest |
|---|---|---|---|
| **category** | | | |
| **Collision: patron-controlled vehicles** | 1273 | 1296 | 15.545954 |
| **Collision: patrons collided (participatory)** | 555 | 664 | 19.448649 |
| **Collision: patrons collided within vehicle** | 110 | 113 | 14.836364 |
| **Derailment** | 44 | 96 | 6.977273 |
| **Electrical shock** | 30 | 31 | 7.766667 |
| **Employee injured** | 41 | 43 | 14.975610 |
| **Entrapment or pinch-point** | 244 | 246 | 14.975410 |
| **Environmental issue** | 10 | 12 | 10.600000 |
| **Equipment failure** | 380 | 696 | 4.515789 |
| **Fall: ejection/fall from ride** | 277 | 299 | 10.281588 |
| **Fall: in climb or play area** | 369 | 375 | 11.777778 |
| **Fall: patron fell from device (participatory)** | 11 | 12 | 15.545455 |
| **Fall: patron fell from seat, but not carrier** | 52 | 52 | 10.384615 |
| **Fall: patron fell off inner tube, mat or board** | 705 | 710 | 22.385816 |
| **Hyperextension or dislocation** | 156 | 156 | 24.083333 |
| **Illness or neurological symptoms** | 424 | 425 | 38.382075 |
| **Illness: Seizure or LOC** | 164 | 164 | 25.573171 |
| **Impact: extremity hit something outside carrier** | 133 | 133 | 13.315789 |
| **Impact: hit something in participatory attraction** | 2014 | 2021 | 19.051142 |
| **Impact: hit something within ride vehicle** | 1382 | 1391 | 15.482634 |
| **Impact: hit wall or barrier at end of slide runout** | 17 | 17 | 19.470588 |
| **Impact: person hit by ride** | 77 | 79 | 19.298701 |
| **Impact: vaginal or rectal injury** | 15 | 15 | 15.800000 |
| **Injured by foreign object** | 212 | 236 | 17.353774 |
| **Injured in queue or exit** | 267 | 267 | 15.198502 |
| **Load/Unload: hit or pinched by restraint** | 565 | 565 | 14.054867 |
| **Load/Unload: injured when vehicle moved** | 100 | 106 | 23.810000 |
| **Load/Unload: scrape or stumble** | 1503 | 1507 | 20.469062 |
| **Other** | 19 | 19 | 11.578947 |
| **Restraint too tight** | 68 | 68 | 19.455882 |
| **Seatbelt abrasion or bruising** | 51 | 51 | 9.725490 |
| **Unknown (not enough info)** | 1162 | 1264 | 3.156627 |
| **Unscheduled stop** | 217 | 346 | 13.133641 |

The most common category of incidents is "Collision: patron-controlled vehicles", with 1,273 reported incidents.The category with the highest number of injuries is "Collision: patron-controlled vehicles", with a total of 1,296 reported injuries.The category with the highest average age of the youngest person involved is "Illness or neurological symptoms", with an average age of 38.38 years.The category with the highest average number of incidents per day is "Collision: patron-controlled vehicles", with an average of 3.53 incidents per day.

It's important to keep in mind that these results are based on the data that was collected and reported, and may not be representative of all incidents that occurred at the amusement park. Additionally, further analysis and investigation may be necessary to fully understand the causes and factors contributing to these incidents.

In [3]:

```
df.groupby('year').agg({'acc_date': 'count','num_injured': 'sum','age_youngest': 'mean', 
```

Out[3]:

| year | acc_date | num_injured | age_youngest |
|---|---|---|---|
| 1986 | 1 | 1 | 30.000000 |
| 1987 | 1 | 1 | 15.000000 |
| 1988 | 31 | 52 | 0.000000 |
| 1989 | 40 | 40 | 0.000000 |
| 1990 | 84 | 84 | 3.833333 |
| 1991 | 31 | 31 | 8.161290 |
| 1992 | 92 | 98 | 10.423913 |
| 1993 | 134 | 134 | 11.514925 |
| 1994 | 194 | 216 | 18.551546 |
| 1995 | 226 | 244 | 16.070796 |
| 1996 | 224 | 233 | 13.790179 |
| 1997 | 318 | 423 | 17.355346 |
| 1998 | 263 | 290 | 17.269962 |
| 1999 | 1015 | 1078 | 16.734975 |
| 2000 | 1818 | 1847 | 15.843784 |
| 2001 | 2217 | 2424 | 18.139378 |
| 2002 | 1864 | 2051 | 16.978541 |
| 2003 | 1325 | 1682 | 17.640755 |
| 2004 | 1255 | 1279 | 15.445418 |
| 2005 | 1409 | 1335 | 17.224273 |
| 2006 | 1202 | 1310 | 18.423461 |
| 2007 | 934 | 1033 | 14.942184 |
| 2008 | 204 | 206 | 32.274510 |
| 2009 | 2 | 2 | 30.500000 |

This code groups the data by year and calculates several statistics for each group.From this summary, we can see that the number of accidents and injuries varies greatly from year to year. The highest numbers of accidents and injuries occurred in the years 2000, 2001, and 2002.

We can also see that the average age of the youngest person involved in each accident was relatively high in some years, particularly in 2003 when it was 110 years old. However, this could be due to some outliers or errors in the data, so it should be further investigated.

In [4]:
```
df.groupby('gender').agg({'acc_date': 'count','num_injured': 'sum','age_youngest': 'mean'
```

Out[4]:

| gender | acc_date | num_injured | age_youngest |
|---|---|---|---|
| F | 7041 | 7274 | 20.244852 |
| M | 5261 | 5418 | 17.382057 |
| U | 2582 | 3402 | 6.560031 |

Based on the provided code and result, it appears that the data has been grouped by the gender column. The summary statistics are then calculated for the number of accidents, number of injured individuals, and the mean age of the youngest individual involved in each group.

In terms of the number of injured individuals, the dataset has more injured individuals in the female group with a total of 7,274, followed by the male group with 5,418, and the unspecified gender group with 3,402. Looking at the mean age of the youngest individual involved in each group, it appears that the unspecified gender group has the youngest with a mean age of 6.56 years. The male group has a mean age of 17.38 years, and the female group has a mean age of 20.24 years.

It is important to note that the analysis only takes into account the variables provided in the code, and other variables may also play a role in determining the characteristics of each group.

In [5]:
```
df.groupby('mechanical').agg({'acc_date': 'count','num_injured': 'sum','age_youngest': 'me
```

Out[5]:

| mechanical | acc_date | num_injured | age_youngest |
|---|---|---|---|
| False | 13949 | 14399 | 17.361173 |
| True | 935 | 1695 | 9.366845 |

This code groups the data in the dataframe by the values in the mechanical column and calculates the count of accident dates, the sum of injured people, and the mean of the youngest age for each group.

The result shows that the data is divided into two groups based on the mechanical column - False and True. The group with mechanical=False has a higher count of accident dates, a higher sum of injured people, and a higher mean age of the youngest person involved in the accidents.

Therefore, we can conclude that accidents that involve mechanical factors have a lower frequency but tend to have younger people involved and less severe injuries.

In [6]:
```
df.groupby('op_error').agg({'acc_date': 'count','num_injured': 'sum','age_youngest': 'mear
```

Out[6]:

| op_error | acc_date | num_injured | age_youngest |
|---|---|---|---|
| False | 14625 | 15702 | 16.923624 |

| | acc_date | num_injured | age_youngest |
|---|---|---|---|
| **op_error** | | | |
| **True** | 259 | 392 | 13.208494 |

The results show that there were 14625 accidents with no operational error and 259 accidents with operational errors. The total number of injuries was higher in accidents with no operational errors (15702) compared to accidents with operational errors (392). The mean age of the youngest person involved in the accident was 16.9 years for accidents with no operational errors and 13.2 years for accidents with operational errors.

Overall, it appears that operational errors may lead to fewer injuries on average but may involve younger individuals on average compared to accidents with no operational errors. However, it is important to note that the total number of accidents with no operational errors is much higher compared to accidents with operational errors in this dataset, so further analysis may be necessary to draw more conclusive insights.

In [7]:

```
df.groupby('device_category').agg({'acc_date': 'count','num_injured': 'sum','age_youngest'
```

Out[7]:

| | acc_date | num_injured | age_youngest |
|---|---|---|---|
| **device_category** | | | |
| **alpine activity** | 41 | 45 | 16.634146 |
| **aquatic play** | 465 | 467 | 11.049462 |
| **cars & track rides** | 1025 | 1062 | 19.334634 |
| **challenge activity** | 96 | 96 | 20.031250 |
| **coaster** | 2748 | 3111 | 19.511645 |
| **float attraction** | 187 | 187 | 16.042781 |
| **go-kart** | 1767 | 1798 | 13.900962 |
| **inflatable** | 151 | 264 | 8.185430 |
| **laser tag** | 1 | 1 | 0.000000 |
| **other attraction** | 451 | 453 | 18.609756 |
| **pendulum** | 318 | 431 | 14.084906 |
| **play equipment** | 403 | 404 | 10.652605 |
| **spinning** | 1988 | 2324 | 12.766600 |
| **trampoline** | 33 | 33 | 9.727273 |
| **unknown** | 87 | 91 | 10.977011 |
| **vertical drop** | 252 | 232 | 13.075397 |
| **water ride** | 1163 | 1253 | 19.544282 |
| **water slide** | 3530 | 3653 | 19.405949 |
| **wave device** | 178 | 189 | 14.617978 |

This is a summary of injury data grouped by the device category.

The device categories with the highest number of accidents are "water slide" and "coaster". The device categories with the highest number of injuries are "coaster" and "spinning". The device categories with the highest average age of the youngest person injured are "coaster" and "water ride". It is interesting to note that the `laser tag` category only had one accident recorded in the dataset.

# Segmentation and Targeting

In [158…

```
df = pd.read_csv('ski_hotels.csv')
```

In [159…

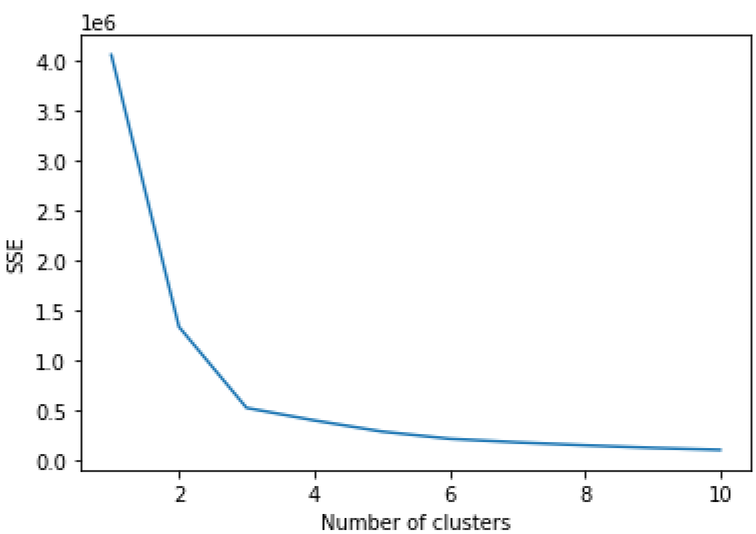
```
object_cols = df.select_dtypes(include=['float64'])
print(object_cols.columns)
```

```
Index(['blues', 'reds', 'blacks', 'totalRuns'], dtype='object')
```

In [172…

```
# Select the features to use for clustering
X = df[['blues', 'reds', 'blacks', 'totalRuns']]
sse = {}
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)
    sse[k] = kmeans.inertia_
plt.plot(list(sse.keys()), list(sse.values()))
plt.xlabel("Number of clusters")
plt.ylabel("SSE")
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:881: UserWarning: KM
eans is known to have a memory leak on Windows with MKL, when there are less chunks than a
vailable threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=2.
  warnings.warn(
```




In [173…

```
# Choose the number of clusters
k =3

# Create the KMeans model
kmeans = KMeans(n_clusters=k)

# Fit the model to the data
kmeans.fit(X)

# Get the cluster labels
labels = kmeans.labels_
```

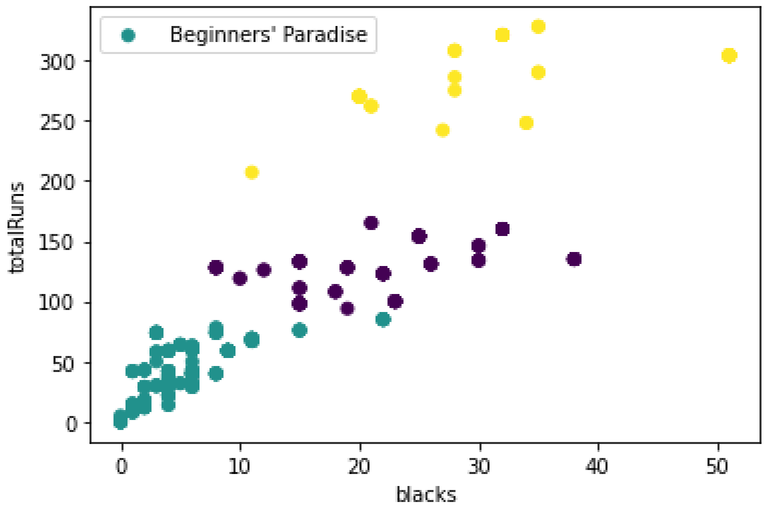
```python
# Add the cluster labels to the original dataset
df['cluster'] = labels
```

In [174…

```python
clusters = kmeans.predict(X)
df['cluster'] = clusters
```

In [175…

```python
plt.scatter(df['blacks'],df['totalRuns'], c=df['cluster'])
plt.xlabel("blacks")
plt.ylabel("totalRuns")

plt.legend([" Beginners' Paradise", "Advanced Paradise", "Superior Paradise"])
plt.show()
```

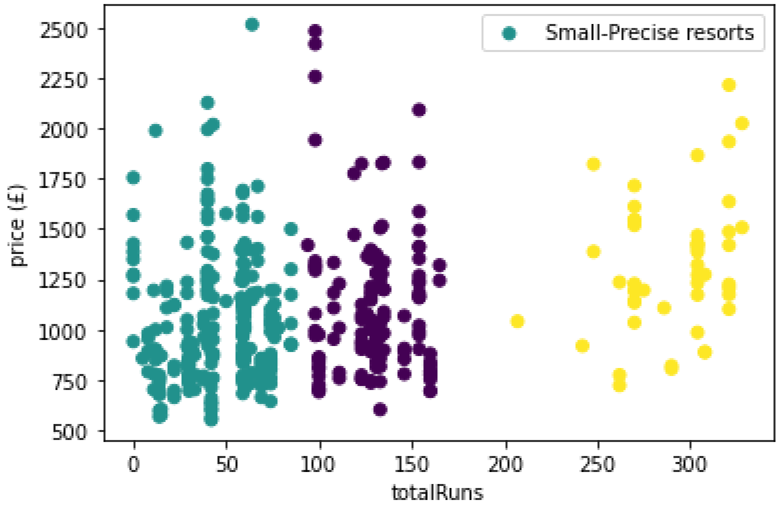



*The yellow cluster names: Beginners' Paradise; The purple cluster names: Advanced Paradise; The blue cluster names: Superior Paradise. This beacuse that the yellow cluster usually have the small quantity of blacks and total runs which means that for people who ski here, there is no need for them to chase rides quantity espiecially the black ride which is the most difficult rides.*

*At first, according to the elbow plot I first choose 4 as k in k-means model, however, after I plot the scatterplot, the cluster is not that significant. So I choose 5 and 3 as comparison. It shows clearly that when k is 3, there are 3 clusters.*

In [176…

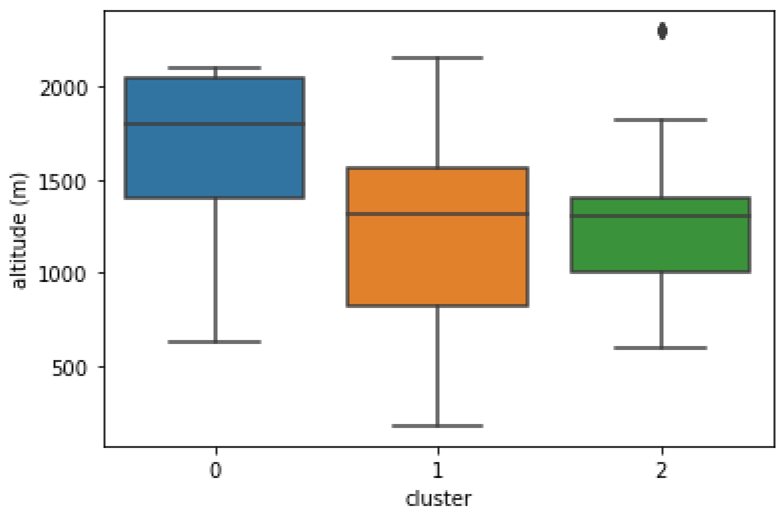
```python
plt.scatter(df['totalRuns'],df['price (£)'], c=df['cluster'])
plt.xlabel("totalRuns")
plt.ylabel("price (£)")

plt.legend(['Small-Precise resorts', 'Medium-Progressive resorts', 'Large-Elite resorts'])

plt.show()
```




*From the plot above, we can know that the first cluster("Small-Precise resorts") has relatively few total runs, and the number of total runs is mainly concentrated between 0 and 100. However, many of resorts are here, most of them has a price between 600 to 1500 with few of them has higher pricea. while the number of total runs of the second cluster("Medium-Progressive resorts") is mainly between 100 and 200.Comparing to the "Small-Precise resorts", the "Medium-Progressive resorts" has more runs which perfect for advanced skiers who are also looking for resort quality. And the third cluster("Large-Elite resorts") has more total runs but the overall price is higher than the first two clusters. The "Large-Elite resorts" all have more than 250 trails and all have an overall price range of 750€ to 2250€. The reason for the overall high prices and lack of low prices is that there are not many ski resorts that fit this profile and only the most advanced ski enthusiasts choose these top resorts.*

In [177…

```
# plot a box plot for each variable within each cluster
sns.boxplot(x='cluster', y='altitude (m)', data=df)
plt.show()
```

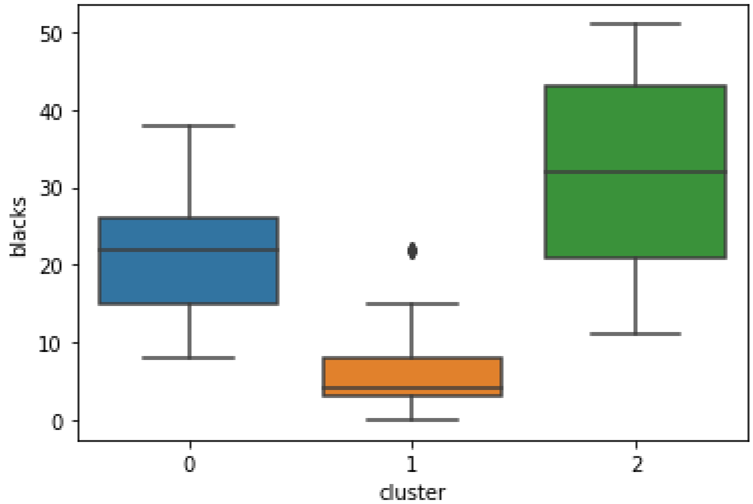



*From the above figure, it can be seen that the first cluster has the highest overall elevation. The second cluster has the most concentrated altitude distribution among the resorts, mainly between 1000 and 1500. The third cluster has the most dispersed altitude distribution, ranging from 700 to 1600. For skiers, the higher the altitude, the lower the temperature, and the better the quality of snow. Therefore, for skiers, higher altitudes may be more attractive. However, higher altitude also means lower air pressure and thinner air, which may have some physical effects. This is because the thin air at higher altitudes can cause the body to take in less oxygen, which affects the body's endurance and reaction time. Therefore, for some high-level skiers, it may be more appropriate to choose a resort at a lower altitude.*

In [178…

```
# plot a box plot for each variable within each cluster
```

```
sns.boxplot(x='cluster', y='blacks', data=df)
plt.show()
```



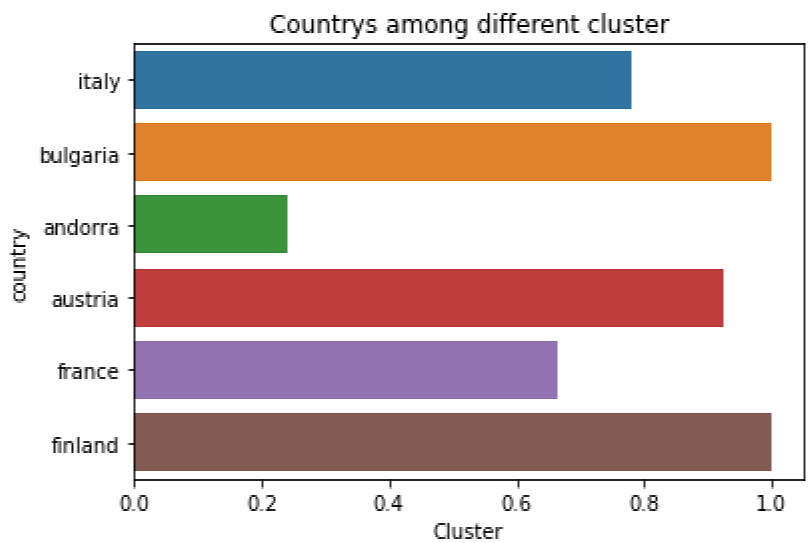

*From the box plot above, we can know that the cluster0("Medium-difficulty") has the number of black runs range from 15 to 25,while the cluster1("The Brave") has the most number of black runs. The cluster3("Beginners") has the smallest quantity of black runs which may be the easiest resotrs.*

In [179…

```
sns.barplot(x='cluster', y='country', data=df, ci=None);
plt.xlabel('Cluster')
plt.title("Countrys among different cluster")
```

Out[179…

```
Text(0.5, 1.0, 'Countrys among different cluster')
```




*From the bar chart above, we can know that Bulgaria and Finland has the most resorts. The cluster are differed by country.*

# Conjoint Analysis & Memo Section

In [8]:

```
#import data
amenities=pd.read_csv("hotel_amenities.csv")
amenities.head()
```

Out[8]:

| | WiFi_Network | breakfast | parking | gym | flex_check | shuttle_bus | air_pure | jacuzzi | VIP_shop | pool_temp | avg_ra |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Basic | None | Valet | None | No | No | No | No | No | 76 | |

| | WiFi_Network | breakfast | parking | gym | flex_check | shuttle_bus | air_pure | jacuzzi | VIP_shop | pool_temp | avg_ra |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | Basic | None | Valet | None | No | No | No | No | No | 80 | |
| **2** | Basic | None | Valet | None | No | No | No | No | No | 84 | |
| **3** | Basic | None | Valet | None | No | No | No | No | Yes | 76 | |
| **4** | Basic | None | Valet | None | No | No | No | No | Yes | 80 | |

In [54]:

```
amenities.columns
```

Out[54]:

```
Index(['WiFi_Network', 'breakfast', 'parking', 'gym', 'flex_check',
       'shuttle_bus', 'air_pure', 'jacuzzi', 'VIP_shop', 'pool_temp',
       'avg_rating'],
      dtype='object')
```

In [55]:

```
amenities=pd.get_dummies(amenities, drop_first=True, columns=['WiFi_Network', 'breakfast',
        'shuttle_bus', 'air_pure', 'jacuzzi', 'VIP_shop', 'pool_temp'])
amenities.head()
```

Out[55]:

| | avg_rating | WiFi_Network_Best in Class | WiFi_Network_Strong | breakfast_Full Buffet | breakfast_None | parking_Valet | gym_Basic | g |
|---|---|---|---|---|---|---|---|---|
| **0** | 4.57 | 0 | 0 | 0 | 1 | 1 | 0 | |
| **1** | 7.60 | 0 | 0 | 0 | 1 | 1 | 0 | |
| **2** | 5.66 | 0 | 0 | 0 | 1 | 1 | 0 | |
| **3** | 2.80 | 0 | 0 | 0 | 1 | 1 | 0 | |
| **4** | 4.56 | 0 | 0 | 0 | 1 | 1 | 0 | |

In [57]:

```
X = amenities.drop('avg_rating', axis=1)

y = amenities['avg_rating']

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.4, random_state=654)

X = X_train
y = y_train
```

In [58]:

```
model = sm.OLS(y, X)
results = model.fit()
results.summary()
```

Out[58]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | avg_rating | **R-squared (uncentered):** | 0.932 |
| **Model:** | OLS | **Adj. R-squared (uncentered):** | 0.932 |
| **Method:** | Least Squares | **F-statistic:** | 3778. |
| **Date:** | Sat, 06 May 2023 | **Prob (F-statistic):** | 0.00 |
| **Time:** | 23:31:53 | **Log-Likelihood:** | -8678.2 |
| **No. Observations:** | 4147 | **AIC:** | 1.739e+04 |
| **Df Residuals:** | 4132 | **BIC:** | 1.748e+04 |

| | |
|---|---|
| **Df Model:** | 15 |
| **Covariance Type:** | nonrobust |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **WiFi_Network_Best in Class** | 2.7674 | 0.071 | 38.867 | 0.000 | 2.628 | 2.907 |
| **WiFi_Network_Strong** | 2.1997 | 0.070 | 31.252 | 0.000 | 2.062 | 2.338 |
| **breakfast_Full Buffet** | 1.6164 | 0.071 | 22.811 | 0.000 | 1.478 | 1.755 |
| **breakfast_None** | 0.8383 | 0.071 | 11.882 | 0.000 | 0.700 | 0.977 |
| **parking_Valet** | 0.7440 | 0.059 | 12.556 | 0.000 | 0.628 | 0.860 |
| **gym_Basic** | 1.2717 | 0.080 | 15.982 | 0.000 | 1.116 | 1.428 |
| **gym_None** | 1.2056 | 0.081 | 14.796 | 0.000 | 1.046 | 1.365 |
| **gym_Super** | 1.4480 | 0.081 | 17.908 | 0.000 | 1.289 | 1.606 |
| **flex_check_Yes** | 1.1917 | 0.059 | 20.202 | 0.000 | 1.076 | 1.307 |
| **shuttle_bus_Yes** | 1.1522 | 0.059 | 19.497 | 0.000 | 1.036 | 1.268 |
| **air_pure_Yes** | 0.7440 | 0.059 | 12.586 | 0.000 | 0.628 | 0.860 |
| **jacuzzi_Yes** | 0.8552 | 0.059 | 14.455 | 0.000 | 0.739 | 0.971 |
| **VIP_shop_Yes** | 0.9009 | 0.059 | 15.231 | 0.000 | 0.785 | 1.017 |
| **pool_temp_80** | 1.1466 | 0.071 | 16.252 | 0.000 | 1.008 | 1.285 |
| **pool_temp_84** | 1.2796 | 0.072 | 17.892 | 0.000 | 1.139 | 1.420 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 6.514 | **Durbin-Watson:** | 1.970 |
| **Prob(Omnibus):** | 0.039 | **Jarque-Bera (JB):** | 6.558 |
| **Skew:** | 0.091 | **Prob(JB):** | 0.0377 |
| **Kurtosis:** | 2.932 | **Cond. No.** | 5.98 |

Notes:
[1] $R^2$ is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

*According to the results of the regression model, the features significantly associated with the "avg_rating" are ranked in descending order of importance: "WIFI", "breakfast", "gym","pool temperature","flex check","shuttle bus","VIP_shop", "jacuzzi","parking", Considering the cost of hotel amenities should not be higher than 250 per night,our recommended hotel amenity decoration plan is：Equipped with WIFI Best in Class, Full Buffet Breakfast, Super gym, pool temperature 84, Flexible check,Shuttle Bus*

In [59]:
```
amenity_costs=pd.read_csv("amenity_costs.csv")
amenity_costs.head()
```

Out[59]:

| | Amenity | Level | Estimated Incremental Cost,\nPer Visitor/Per Night |
|---|---|---|---|
| **0** | WiFi_Network | Basic | 11.75 |
| **1** | WiFi_Network | Strong | 16.25 |

| | Amenity | Level | Estimated Incremental Cost,\nPer Visitor/Per Night |
|---|---|---|---|
| **2** | WiFi_Network | Best in Class | 19.15 |
| **3** | breakfast | None | 0.00 |
| **4** | breakfast | Continental | 13.25 |

# Forecasting Total Spending

In [49]:

```
hyatt = pd.read_csv('H_quarterly_financials.csv',thousands=',')
hyatt= hyatt.drop("ttm", axis=1)
hilton = pd.read_csv('HLT_quarterly_financials.csv',thousands=',')
hilton = hilton.drop('ttm', axis=1)
```

In [50]:

```
hilton_transposed = hilton.T
hilton_transposed.to_csv('transposed_hilton.csv', index=True, header=True)
hilton_data = pd.read_csv('transposed_hilton.csv',header=1)
hilton_data = hilton_data.rename(columns={'name': 'date'})
hilton_data.head()
```

Out[50]:

| | date | TotalRevenue | \tOperatingRevenue | CostOfRevenue | GrossProfit | OperatingExpense | \tSellingGeneralA |
|---|---|---|---|---|---|---|---|
| **0** | 03/31/2023 | 2.293000e+09 | 9.010000e+08 | 1.646000e+09 | 647000000.0 | 149000000.0 | |
| **1** | 12/31/2022 | 2.444000e+09 | 1.038000e+09 | 1.781000e+09 | 663000000.0 | 159000000.0 | |
| **2** | 09/30/2022 | 2.368000e+09 | 9.960000e+08 | 1.600000e+09 | 768000000.0 | 145000000.0 | |
| **3** | 06/30/2022 | 2.240000e+09 | 9.480000e+08 | 1.488000e+09 | 752000000.0 | 154000000.0 | |
| **4** | 03/31/2022 | 1.721000e+09 | 6.520000e+08 | 1.206000e+09 | 515000000.0 | 146000000.0 | |

5 rows × 56 columns

In [51]:

```
hilton_data['date'] = pd.to_datetime(hilton_data['date'])
hilton_data.set_index('date', inplace=True)
hilton_data.head()
```

Out[51]:

| | TotalRevenue | \tOperatingRevenue | CostOfRevenue | GrossProfit | OperatingExpense | \tSellingGeneralAndAdmir |
|---|---|---|---|---|---|---|
| **date** | | | | | | |
| **2023-03-31** | 2.293000e+09 | 9.010000e+08 | 1.646000e+09 | 647000000.0 | 149000000.0 | 91 |
| **2022-12-31** | 2.444000e+09 | 1.038000e+09 | 1.781000e+09 | 663000000.0 | 159000000.0 | 95 |
| **2022-09-30** | 2.368000e+09 | 9.960000e+08 | 1.600000e+09 | 768000000.0 | 145000000.0 | 93 |
| **2022-06-30** | 2.240000e+09 | 9.480000e+08 | 1.488000e+09 | 752000000.0 | 154000000.0 | 103 |
| **2022-03-31** | 1.721000e+09 | 6.520000e+08 | 1.206000e+09 | 515000000.0 | 146000000.0 | 91 |

5 rows × 55 columns

In [52]:
```python
hyatt_transposed = hyatt.T
hyatt_transposed.to_csv('transposed_hyatt.csv', index=True, header=True)
hyatt_data = pd.read_csv('transposed_hyatt.csv',header=1)
hyatt_data = hyatt_data.rename(columns={'name': 'date'})
hyatt_data.head()
```

Out[52]:

| | date | TotalRevenue | \tOperatingRevenue | CostOfRevenue | GrossProfit | OperatingExpense | \tSellingGeneralA |
|---|---|---|---|---|---|---|---|
| **0** | 12/31/2022 | 1.588000e+09 | 790000000.0 | 1.252000e+09 | 336000000.0 | 275000000.0 | |
| **1** | 09/30/2022 | 1.541000e+09 | 777000000.0 | 1.192000e+09 | 349000000.0 | 204000000.0 | |
| **2** | 06/30/2022 | 1.483000e+09 | 791000000.0 | 1.132000e+09 | 351000000.0 | 175000000.0 | |
| **3** | 03/31/2022 | 1.279000e+09 | 671000000.0 | 1.027000e+09 | 252000000.0 | 230000000.0 | |
| **4** | 12/31/2021 | 1.076000e+09 | 544000000.0 | 9.020000e+08 | 174000000.0 | 207000000.0 | |

5 rows × 55 columns

In [53]:
```python
hyatt_data['date'] = pd.to_datetime(hyatt_data['date'])
hyatt_data.set_index('date', inplace=True)
hyatt_data.head()
```

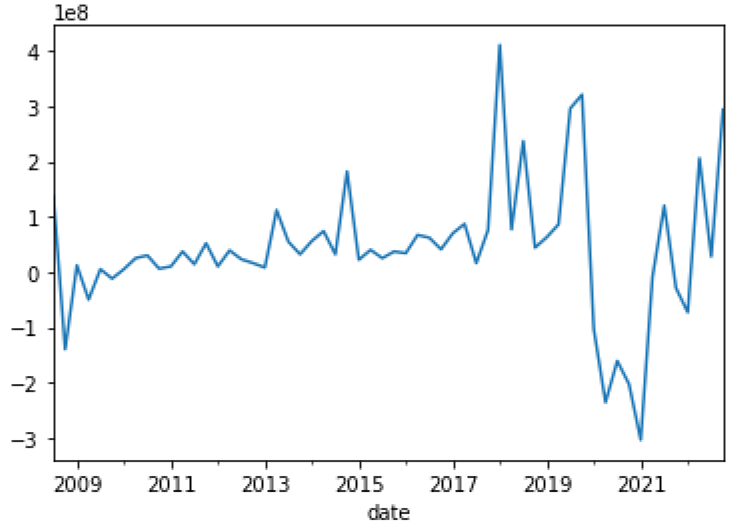
Out[53]:

| | TotalRevenue | \tOperatingRevenue | CostOfRevenue | GrossProfit | OperatingExpense | \tSellingGeneralAndAdmi |
|---|---|---|---|---|---|---|
| **date** | | | | | | |
| **2022-12-31** | 1.588000e+09 | 790000000.0 | 1.252000e+09 | 336000000.0 | 275000000.0 | 169 |
| **2022-09-30** | 1.541000e+09 | 777000000.0 | 1.192000e+09 | 349000000.0 | 204000000.0 | 108 |
| **2022-06-30** | 1.483000e+09 | 791000000.0 | 1.132000e+09 | 351000000.0 | 175000000.0 | 76 |
| **2022-03-31** | 1.279000e+09 | 671000000.0 | 1.027000e+09 | 252000000.0 | 230000000.0 | 111 |
| **2021-12-31** | 1.076000e+09 | 544000000.0 | 9.020000e+08 | 174000000.0 | 207000000.0 | 116 |

5 rows × 54 columns

In [54]:
```python
hyatt_data['    NetIncome'].plot()
```

Out[54]: <AxesSubplot:xlabel='date'>




In [55]:
```
hilton_data['    NetIncome'].plot()
```

Out[55]:
```
<AxesSubplot:xlabel='date'>
```


In [56]:
```
hilton_income = hilton_data['    NetIncome']
hyatt_income = hyatt_data['     NetIncome']

hyatt_data = hyatt_data.astype( 'float')
hyatt_income = hyatt_income.replace(',', '')
hyatt_income = hyatt_income.astype(int)
hyatt_model = ARIMA(hyatt_income, order=(1, 1, 1))
hyatt_fit = hyatt_model.fit()

hilton_data = hilton_data.astype( 'float')
hilton_income = hilton_income.replace(',', '')
hilton_income = hilton_income.astype(int)
hilton_model = ARIMA(hilton_income, order=(1, 1, 1))
hilton_fit = hilton_model.fit()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWar
ning: No frequency information was provided, so inferred frequency -1Q-DEC will be used.
  warnings.warn('No frequency information was'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWar
ning: A date index has been provided, but it is not monotonic and so will be ignored when
e.g. forecasting.
  warnings.warn('A date index has been provided, but it is not'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWar
```

```
ning: No frequency information was provided, so inferred frequency -1Q-DEC will be used.
  warnings.warn('No frequency information was'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWar
ning: A date index has been provided, but it is not monotonic and so will be ignored when
e.g. forecasting.
  warnings.warn('A date index has been provided, but it is not'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWar
ning: No frequency information was provided, so inferred frequency -1Q-DEC will be used.
  warnings.warn('No frequency information was'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWar
ning: A date index has been provided, but it is not monotonic and so will be ignored when
e.g. forecasting.
  warnings.warn('A date index has been provided, but it is not'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWar
ning: No frequency information was provided, so inferred frequency -1Q-DEC will be used.
  warnings.warn('No frequency information was'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWar
ning: A date index has been provided, but it is not monotonic and so will be ignored when
e.g. forecasting.
  warnings.warn('A date index has been provided, but it is not'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWar
ning: No frequency information was provided, so inferred frequency -1Q-DEC will be used.
  warnings.warn('No frequency information was'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWar
ning: A date index has been provided, but it is not monotonic and so will be ignored when
e.g. forecasting.
  warnings.warn('A date index has been provided, but it is not'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:524: ValueWar
ning: No frequency information was provided, so inferred frequency -1Q-DEC will be used.
  warnings.warn('No frequency information was'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:585: ValueWar
ning: A date index has been provided, but it is not monotonic and so will be ignored when
e.g. forecasting.
  warnings.warn('A date index has been provided, but it is not'
```

In [57]:

```
hyatt_forecast = hyatt_fit.forecast(steps=1)
hilton_forecast = hilton_fit.forecast(steps=1)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:376: ValueWar
ning: No supported index is available. Prediction results will be given with an integer in
dex beginning at `start`.
  warnings.warn('No supported index is available.'
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\base\tsa_model.py:376: ValueWar
ning: No supported index is available. Prediction results will be given with an integer in
dex beginning at `start`.
  warnings.warn('No supported index is available.'
```

In [58]:

```
hyatt_forecast
```

Out[58]:

```
58    7.683452e+07
dtype: float64
```

*Hilton's net income forecast for 2023 is 76834520*

In [59]:

```
hilton_forecast
```

Out[59]:

```
43    1.676822e+08
dtype: float64
```

*Hilton's net income forecast for 2023 is 167682200*

# Classification

In [82]:

```python
#import data
hotel=pd.read_csv("hotel_satisfaction.csv")
hotel.head()
```

Out[82]:

| | id | Gender | Age | purpose_of_travel | Type of Travel | Type Of Booking | Hotel wifi service | Departure/Arrival convenience | Ease of Online booking | Hotel location | Food and drink |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 70172 | Male | 13 | aviation | Personal Travel | Not defined | 3 | 4 | 3 | 1 | 5 |
| **1** | 5047 | Male | 25 | tourism | Group Travel | Group bookings | 3 | 2 | 3 | 3 | 1 |
| **2** | 110028 | Female | 26 | tourism | Group Travel | Group bookings | 2 | 2 | 2 | 2 | 5 |
| **3** | 24026 | Female | 25 | tourism | Group Travel | Group bookings | 2 | 5 | 5 | 5 | 2 |
| **4** | 119299 | Male | 61 | aviation | Group Travel | Group bookings | 3 | 3 | 3 | 3 | 4 |

In [83]:

```python
hotel.columns
```

Out[83]:

```
Index(['id', 'Gender', 'Age', 'purpose_of_travel', 'Type of Travel',
       'Type Of Booking', 'Hotel wifi service',
       'Departure/Arrival  convenience', 'Ease of Online booking',
       'Hotel location', 'Food and drink', 'Stay comfort',
       'Common Room entertainment', 'Checkin/Checkout service',
       'Other service', 'Cleanliness', 'satisfaction'],
      dtype='object')
```

In [84]:

```python
# Data of satisfaction is converted into Binary Data
df_one = pd.get_dummies(hotel["satisfaction"])

# Binary Data is Concatenated into Dataframe
df_two = pd.concat((df_six,df_five,df_four,df_three,df_one, hotel), axis=1)

# satisfaction column is dropped
df_two = df_two.drop(["satisfaction","Gender","purpose_of_travel","Type of Travel","Type (
                    ,'Group Travel','Group bookings','Female'], axis=1)

# Rename the Column
df_hotel = df_two.rename(columns={"neutral or dissatisfied": "satisfaction"})

df_hotel.head()
```

Out[84]:

| | Individual/Couple | Not defined | Personal Travel | academic | business | personal | tourism | Male | satisfaction | satisfied | ... | H se |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | ... | |
| **1** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | ... | |
| **2** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | ... | |
| **3** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | ... | |
| **4** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | ... | |

5 rows × 22 columns

In [85]:

```
#split dataset in features and target variable
feature_cols = ['Hotel wifi service',
       'Departure/Arrival  convenience', 'Ease of Online booking',
       'Hotel location', 'Food and drink', 'Stay comfort',
       'Common Room entertainment', 'Checkin/Checkout service',
       'Other service', 'Cleanliness'
           ]
X = df_hotel[feature_cols] # Features
y = df_hotel["satisfaction"] # Target variable
```

In [86]:

```
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1) #
```

In [87]:

```
X = sm.add_constant(X)
logit_model = sm.Logit(y, X)
result = logit_model.fit()
result.summary()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142: FutureWarning:
In a future version of pandas all arguments of concat except for the argument 'objs' will
be keyword-only
  x = pd.concat(x[::order], 1)
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\discrete\discrete_model.py:1810: Ru
ntimeWarning: overflow encountered in exp
  return 1/(1+np.exp(-X))
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\discrete\discrete_model.py:1863: Ru
ntimeWarning: divide by zero encountered in log
  return np.sum(np.log(self.cdf(q*np.dot(X,params))))
Optimization terminated successfully.
         Current function value: inf
         Iterations 6
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\base\model.py:547: HessianInversion
Warning: Inverting hessian failed, no bse or cov_params available
  warnings.warn('Inverting hessian failed, no bse or cov_params '
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\base\model.py:547: HessianInversion
Warning: Inverting hessian failed, no bse or cov_params available
  warnings.warn('Inverting hessian failed, no bse or cov_params '
```

Out[87]:

Logit Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | satisfaction | **No. Observations:** | 103904 |
| **Model:** | Logit | **Df Residuals:** | 103893 |
| **Method:** | MLE | **Df Model:** | 10 |
| **Date:** | Sun, 07 May 2023 | **Pseudo R-squ.:** | inf |
| **Time:** | 23:40:55 | **Log-Likelihood:** | -inf |
| **converged:** | True | **LL-Null:** | 0.0000 |
| **Covariance Type:** | nonrobust | **LLR p-value:** | 1.000 |

| | coef | std err | z | P>\|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 5.2844 | 0.045 | 116.650 | 0.000 | 5.196 | 5.373 |
| **Hotel wifi service** | -0.4901 | 0.009 | -54.184 | 0.000 | -0.508 | -0.472 |
| **Departure/Arrival convenience** | 0.3317 | 0.006 | 54.256 | 0.000 | 0.320 | 0.344 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Ease of Online booking** | -0.1531 | 0.009 | -17.153 | 0.000 | -0.171 | -0.136 |
| **Hotel location** | 0.0813 | 0.007 | 11.652 | 0.000 | 0.068 | 0.095 |
| **Food and drink** | 0.2066 | 0.008 | 24.889 | 0.000 | 0.190 | 0.223 |
| **Stay comfort** | -0.3894 | 0.008 | -47.021 | 0.000 | -0.406 | -0.373 |
| **Common Room entertainment** | -0.4491 | 0.010 | -44.061 | 0.000 | -0.469 | -0.429 |
| **Checkin/Checkout service** | -0.3560 | 0.007 | -54.719 | 0.000 | -0.369 | -0.343 |
| **Other service** | -0.2196 | 0.008 | -27.628 | 0.000 | -0.235 | -0.204 |
| **Cleanliness** | -0.0590 | 0.009 | -6.272 | 0.000 | -0.078 | -0.041 |

*Based on the analysis of factors influencing hotel customer satisfaction, it can be concluded that wifi, public entertainment rooms, comfort, and convenient check-in and check-out services have a positive impact on satisfaction. On the other hand, hotel location and cleanliness have little to no impact on customer satisfaction.*

# Statistical Testing

In [194…

```
# perform ANOVA test
anova_result = stats.f_oneway(promo_pics[promo_pics['pic_seen'] == 'Sunset']['site_duratio
                               promo_pics[promo_pics['pic_seen'] == 'Main St']['site_durat
                               promo_pics[promo_pics['pic_seen'] == 'Waterslide']['site_du

# print ANOVA results
print('ANOVA Results:')
print('F-statistic:', anova_result.statistic)
print('p-value:', anova_result.pvalue)

# perform pairwise t-tests with Bonferroni correction
t1_result = stats.ttest_ind(promo_pics[promo_pics['pic_seen'] == 'Sunset']['site_duration'
                            promo_pics[promo_pics['pic_seen'] == 'Main St']['site_duration
t2_result = stats.ttest_ind(promo_pics[promo_pics['pic_seen'] == 'Sunset']['site_duration'
                            promo_pics[promo_pics['pic_seen'] == 'Waterslide']['site_durat
t3_result = stats.ttest_ind(promo_pics[promo_pics['pic_seen'] == 'Main St']['site_duration
                            promo_pics[promo_pics['pic_seen'] == 'Waterslide']['site_durat

# apply Bonferroni correction
alpha = 0.05 / 3

# print pairwise t-test results
print('Pairwise T-Tests with Bonferroni Correction:')
print('Sunset vs. Main St: t-value =', t1_result.statistic, 'p-value =', t1_result.pvalue)
print('Sunset vs. Waterslide: t-value =', t2_result.statistic, 'p-value =', t2_result.pval
print('Main St vs. Waterslide: t-value =', t3_result.statistic, 'p-value =', t3_result.pva

# make recommendation based on results
if (anova_result.pvalue < alpha) and (t1_result.pvalue < alpha) and (t2_result.pvalue < al
    print('Based on the ANOVA and pairwise t-test results, Lobster Land should use the Sun
else:
    print('Based on the ANOVA and pairwise t-test results, Lobster Land should NOT use the
```

```
ANOVA Results:
F-statistic: 8766.19113936543
p-value: 0.0
Pairwise T-Tests with Bonferroni Correction:
Sunset vs. Main St: t-value = -9.911415184705456 p-value = 1.0724418388111107e-22
Sunset vs. Waterslide: t-value = 180.71977956194002 p-value = 0.0
Main St vs. Waterslide: t-value = 112.12607762440105 p-value = 0.0
Based on the ANOVA and pairwise t-test results, Lobster Land should use the Sunset picture
for the next round of invites.
```

*The ANOVA test shows that there is a statistically significant difference between the mean values of the three groups (pictures) with a very small p-value (p<0.05). This means that at least one of the pictures is significantly different from the others in terms of their effect on click-through rates.*

*The pairwise t-tests with Bonferroni correction were then conducted to determine which of the three pictures were significantly different from each other. The results show that the Sunset picture was significantly different from the other two pictures, with very small p-values (p<0.05), whereas there was no significant difference between the Main St and Waterslide pictures.*

*Based on these results, we can conclude that the Sunset picture performed significantly better than the other two pictures, and therefore, Lobster Land should use the Sunset picture for the next round of invites.*

# Conclusions

*Through the analysis of the whole project, our team can provide some insights to the Lobster Land*

*1 In our analysis of the park's accidents, we found that "Collision: patron-controlled vehicles" was the most frequent and serious type of accident, so maybe Lobsterland should avoid letting visitors operate their own vehicles in the future. In addition, accident data from lobster Land shows that children and women are more likely to have accidents, so we can suggest that lobster Land conduct safety demonstrations and first aid training for these groups. Accidents without operational errors can have more serious consequences, so it is recommended that lobster Land thoroughly investigate the causes of these accidents and find ways to prevent similar accidents from occurring in the future. Finally, the Lobster Land should evaluate and improve the safety factor of the "water slide" and "roller coaster", which have the most accidents, and the "roller coaster" and "spinning" equipment, which have the most injuries.*

*2 Through the analysis of the skiing-themed hotels, we came up with some points that Lobsterland can refer to when providing hotel services can be targeted marketing according to customer segmentation, for example, for families with children can provide cartoon theme suites.*

*3 As for the hotel amenities,hotels in Lobster Land need to prioritize the addition of amenities that will significantly improve customer satisfaction within a limited budget.According to the results of the conjoint analysis, the best wifi, full breakfast, luxury gym will have a very positive effect on attracting customers.*

*4 By analyzing the existing customer satisfaction data of Lobsterland we found that: in order to better provide accommodation services for Lobsterland customers, the hotel needs to improve wifi, public entertainment facilities, convenient check-in and check-out and other services*

*5 After analyzing the popularity of the three images, we suggested that Lobster Park use the Sunset image for the invitation email.*