AAI_500_GROUP_12 (/github/BPALAN-USD/AAI_500_GROUP_12/tree/main)
/ TravelReviews.ipynb (/github/BPALAN-USD/AAI_500_GROUP_12/tree/main/TravelReviews.ipynb)

Travel Review Rating

Usecase & Description

We are using this Dataset to determine and categorize the Users Reviews on the different type of locations and potentially target the user based on location for positive review and travel opportunities.

We have combined the Travel Review Dataset with a Synthetic User Data that is generated to simulate the Real Problem & Statistical Analysis

1. Install & Import Required Libraries

Install Required Python Libraries if not exists

In [158…
```
!pip install faker pandas numpy matplotlib seaborn scikit-learn ucimlrepo scipy
```

Importing libraries

In [159…
```
## Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import display
from ucimlrepo import fetch_ucirepo
import warnings
import scipy.stats as stats
from faker import Faker
import os
import random
import pandas as pd
from datetime import datetime
from scipy.stats import skew, norm
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
warnings.filterwarnings('ignore')
```

2. Data Aquisition from UCI - Repository

Fetch Data from UCI ML Repository regarding Travel Reviews

In [160…

```
print(f""" Output Timestamp: {datetime.now()} \n""")

# fetch dataset
travel_review_ratings = fetch_ucirepo(id=485)

# data (as pandas dataframes)
X = travel_review_ratings.data.features
y = travel_review_ratings.data.targets

# variable information
display(travel_review_ratings.variables)
```

```
 Output Timestamp: 2025-06-20 21:51:02.207865
```

	name	role	type	demographic	description	units	missing_values
0	userid	ID	Categorical	None	None	None	no
1	churches	Feature	Continuous	None	None	None	no
2	resorts	Feature	Continuous	None	None	None	no
3	beaches	Feature	Integer	None	None	None	no
4	parks	Feature	Continuous	None	None	None	no
5	theatres	Feature	Continuous	None	None	None	no
6	museums	Feature	Continuous	None	None	None	no
7	malls	Feature	Continuous	None	None	None	no
8	zoos	Feature	Continuous	None	None	None	no
9	restaurants	Feature	Integer	None	None	None	no
10	pubs/bars	Feature	Continuous	None	None	None	no
11	local services	Feature	Continuous	None	None	None	no
12	burger/pizza shops	Feature	Continuous	None	None	None	no
13	hotels/other lodgings	Feature	Continuous	None	None	None	no
14	juice bars	Feature	Continuous	None	None	None	no
15	art galleries	Feature	Integer	None	None	None	no
16	dance clubs	Feature	Continuous	None	None	None	no
17	swimming pools	Feature	Continuous	None	None	None	no
18	gyms	Feature	Continuous	None	None	None	no
19	bakeries	Feature	Continuous	None	None	None	no
20	beauty & spas	Feature	Continuous	None	None	None	no
21	cafes	Feature	Continuous	None	None	None	no
22	view points	Feature	Continuous	None	None	None	no
23	monuments	Feature	Continuous	None	None	None	no
24	gardens	Feature	Continuous	None	None	None	no

Display the Data from Dataframe

In [162…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
## Convert the UCI ML Repo dataset to a pandas DataFrame
df_travel_review_ratings = travel_review_ratings.data.original
display(df_travel_review_ratings)
```

```
Output Timestamp: 2025-06-20 21:53:14.252692
```

	userid	churches	resorts	beaches	parks	theatres	museums	malls	zoos	restaurants
0	User 1	0.00	0.00	3.63	3.65	5.00	2.92	5.00	2.35	2.33
1	User 2	0.00	0.00	3.63	3.65	5.00	2.92	5.00	2.64	2.33
2	User 3	0.00	0.00	3.63	3.63	5.00	2.92	5.00	2.64	2.33
3	User 4	0.00	0.50	3.63	3.63	5.00	2.92	5.00	2.35	2.33
4	User 5	0.00	0.00	3.63	3.63	5.00	2.92	5.00	2.64	2.33
...	...	...	...	...	...	...	...	...	...	...
5451	User 5452	0.91	5.00	4.00	2.79	2.77	2.57	2.43	1.09	1.77
5452	User 5453	0.93	5.00	4.02	2.79	2.78	2.57	1.77	1.07	1.76
5453	User 5454	0.94	5.00	4.03	2.80	2.78	2.57	1.75	1.05	1.75
5454	User 5455	0.95	4.05	4.05	2.81	2.79	2.44	1.76	1.03	1.74
5455	User 5456	0.95	4.07	5.00	2.82	2.80	2.57	2.42	1.02	1.74

5456 rows × 25 columns

3. Generate User Demographics Data using Python Faker Library if the Data doesn't exist Locally

Check if the User Demographics Data/File exist locally. If Not, Generate Data else read the file into DataFrame

In [165…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
# Check if the file exists
if not os.path.exists('all_users.csv'):

    fake = Faker()
    num_users = 6000
    countries = ['US', 'UK', 'IN']
    genders = ['Male', 'Female']

    data = []
    for i in range(1, num_users + 1):
        first_name = fake.first_name()
        last_name = fake.last_name()
        email = fake.email()
        user = {
            'userid': f'User {i}',
            'first_name': first_name,
            'last_name': last_name,
            'email': email,
            'age': random.randint(18, 80),
            'gender': random.choice(genders),
            'country': random.choice(countries)
        }
        data.append(user)

    df_fake_users = pd.DataFrame(data)
    df_fake_users.to_csv('all_users.csv', index=False)
    print("all_users.csv generated.")
else:
    print("all_users.csv already exists.")
    df_user_demographics = pd.read_csv('all_users.csv', sep=',')
    display(df_user_demographics)
```

```
 Output Timestamp: 2025-06-20 21:53:43.389396

all_users.csv already exists.
```

	userid	first_name	last_name	email	age	gender	country
0	User 1	Daniel	Young	brentpearson@example.com	68	Female	US
1	User 2	Stacy	Morgan	sarah28@example.com	28	Male	US
2	User 3	Brittany	Henry	sheilacuevas@example.com	79	Male	UK
3	User 4	Christina	Delacruz	ssaunders@example.net	73	Female	UK
4	User 5	Ronald	Reynolds	jsmith@example.net	40	Male	UK
...	...	...	...	...	...	...	...
5995	User 5996	Walter	Smith	marshalljohn@example.com	78	Female	US
5996	User 5997	Victor	Jones	emilygardner@example.net	61	Female	IN
5997	User 5998	Michael	Aguilar	uoliver@example.org	32	Female	US
5998	User 5999	Jamie	Smith	cynthiatrujillo@example.com	69	Male	US
5999	User 6000	Steven	Brown	whiteadam@example.net	44	Male	US

6000 rows × 7 columns

4. Combine User Demographics Data with Travel Review Ratings

In [166…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
df_user_travel_reviews = pd.merge(df_user_demographics, df_travel_review_rating
display(df_user_travel_reviews.head())
```

```
 Output Timestamp: 2025-06-20 21:55:08.690850
```

	userid	first_name	last_name	email	age	gender	country	churches	re
0	User 1	Daniel	Young	brentpearson@example.com	68	Female	US	0.0	
1	User 2	Stacy	Morgan	sarah28@example.com	28	Male	US	0.0	
2	User 3	Brittany	Henry	sheilacuevas@example.com	79	Male	UK	0.0	
3	User 4	Christina	Delacruz	ssaunders@example.net	73	Female	UK	0.0	
4	User 5	Ronald	Reynolds	jsmith@example.net	40	Male	UK	0.0	

5 rows × 31 columns

Categorize the Age in DataFrame in Youth, Adult & Senior

In [167…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
# Define a function to categorize age
def categorize_age(age):
    if age < 18:
        return 'Youth'
    elif age < 60:
        return 'Adult'
    else:
        return 'Senior'

# Apply the function to create a new column
df_user_travel_reviews['age_group'] = df_user_travel_reviews['age'].apply(categ
display(df_user_travel_reviews.head())
```

```
 Output Timestamp: 2025-06-20 21:55:12.505874
```

	userid	first_name	last_name	email	age	gender	country	churches	re
0	User 1	Daniel	Young	brentpearson@example.com	68	Female	US	0.0	
1	User 2	Stacy	Morgan	sarah28@example.com	28	Male	US	0.0	
2	User 3	Brittany	Henry	sheilacuevas@example.com	79	Male	UK	0.0	
3	User 4	Christina	Delacruz	ssaunders@example.net	73	Female	UK	0.0	
4	User 5	Ronald	Reynolds	jsmith@example.net	40	Male	UK	0.0	

5 rows × 32 columns

Add Columns as Average Rating by Each Category

In [168…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
# Define column groups
natural_space_cols = ['parks', 'beaches', 'gardens', 'view points', 'monuments'
entertainment_cols = ['theatres', 'dance clubs', 'pubs/bars', 'zoos', 'resorts'
                      ,'hotels/other lodgings',
                      'gyms','beauty & spas']
food_space_cols = ['restaurants', 'burger/pizza shops', 'juice bars', 'cafes',
art_related_cols = ['museums', 'art galleries', 'churches','local services']

# Convert relevant columns to numeric (safely)
for col in natural_space_cols + entertainment_cols + art_related_cols:
    df_user_travel_reviews[col] = pd.to_numeric(df_user_travel_reviews[col], er

# Function to calculate mean ignoring 0 and NaN
def custom_mean(series):
    valid = series[(series != 0) & (~series.isna())]
    return valid.mean() if not valid.empty else np.nan

# Apply custom mean per row
df_user_travel_reviews['avg_natural_space'] = df_user_travel_reviews[natural_sp
df_user_travel_reviews['avg_entertainment'] = df_user_travel_reviews[entertainm
df_user_travel_reviews['avg_art_related'] = df_user_travel_reviews[art_related_
df_user_travel_reviews['avg_food_spaces'] = df_user_travel_reviews[food_space_c

display(df_user_travel_reviews.head())
```

Output Timestamp: 2025-06-20 21:55:46.409349

	userid	first_name	last_name	email	age	gender	country	churches	re
0	User 1	Daniel	Young	brentpearson@example.com	68	Female	US	0.0	
1	User 2	Stacy	Morgan	sarah28@example.com	28	Male	US	0.0	
2	User 3	Brittany	Henry	sheilacuevas@example.com	79	Male	UK	0.0	
3	User 4	Christina	Delacruz	ssaunders@example.net	73	Female	UK	0.0	
4	User 5	Ronald	Reynolds	jsmith@example.net	40	Male	UK	0.0	

5 rows × 36 columns

5. Exploratory Data Analysis

Perform the descriptive Statistics on the Dataframe

In [169…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
## Perform Descriptive Statistics on the DataFrame
## We can see
display(df_user_travel_reviews.describe(include='all'))
```

Output Timestamp: 2025-06-20 21:55:56.755947

	userid	first_name	last_name	email	age	gender	country	c
count	5456	5456	5456	5456	5456.000000	5456	5456	5456
unique	5456	613	928	5395	NaN	2	3	
top	User 1	Michael	Smith	osmith@example.net	NaN	Male	US	
freq	1	126	125	6	NaN	2787	1851	
mean	NaN	NaN	NaN	NaN	48.556268	NaN	NaN	1
std	NaN	NaN	NaN	NaN	18.093285	NaN	NaN	0
min	NaN	NaN	NaN	NaN	18.000000	NaN	NaN	0
25%	NaN	NaN	NaN	NaN	33.000000	NaN	NaN	0
50%	NaN	NaN	NaN	NaN	48.000000	NaN	NaN	1
75%	NaN	NaN	NaN	NaN	64.000000	NaN	NaN	1
max	NaN	NaN	NaN	NaN	80.000000	NaN	NaN	5

11 rows × 36 columns

Data Cleaning based on Null / Duplicate values and then check the descriptive statistics

In [170…

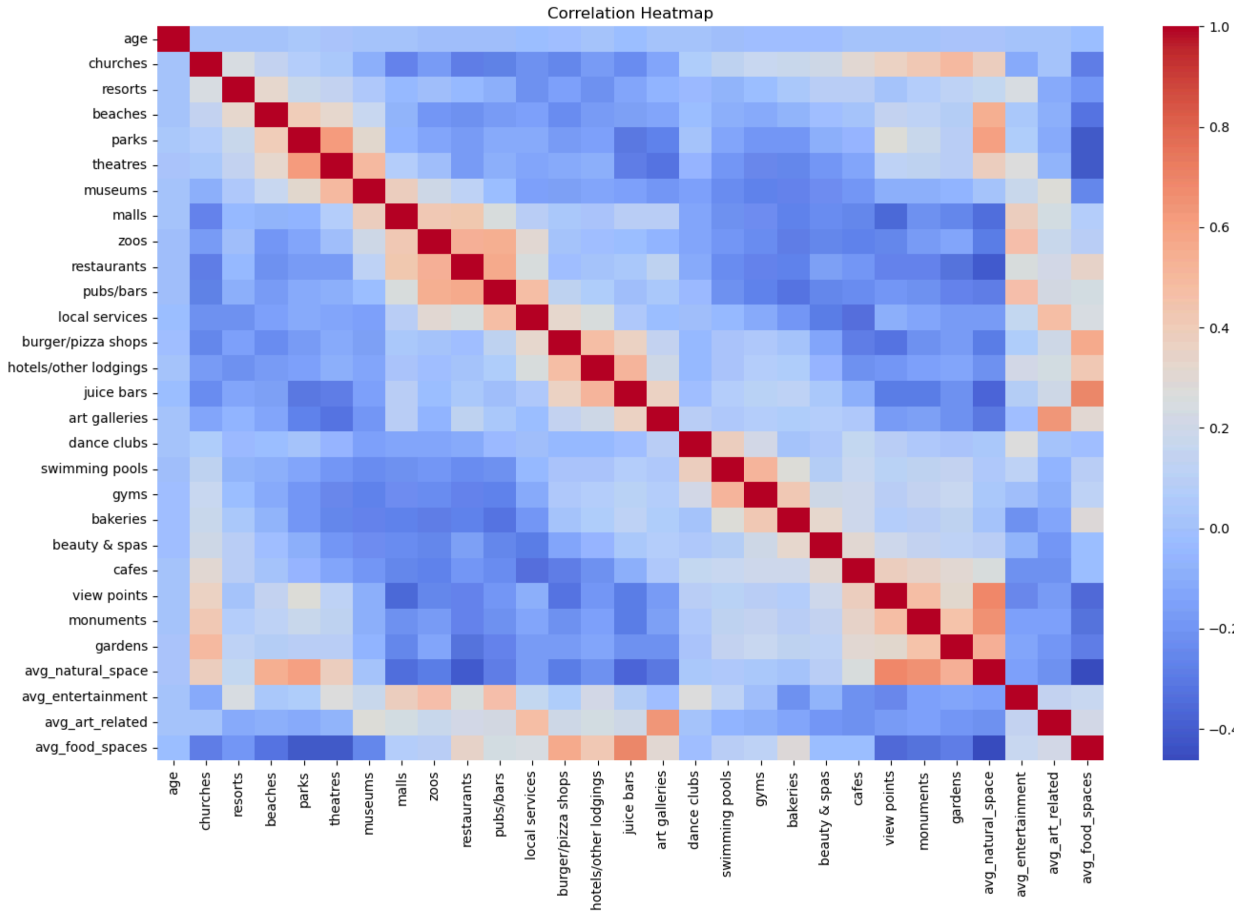
```
print(f""" Output Timestamp: {datetime.now()} \n""")
# Exploratory Data Analysis (EDA) and Cleanup for df_user_travel_reviews

# 1. Check for missing values
missing_counts = df_user_travel_reviews.isnull().sum()
print("Missing values per column:\n", missing_counts[missing_counts > 0])

# 2. Drop rows with missing values (if any)
df_user_travel_reviews_clean = df_user_travel_reviews.dropna().reset_index(drop

# 3. Check data types
print("\nData types:\n", df_user_travel_reviews_clean.dtypes)

# 4. Check for duplicates
duplicates = df_user_travel_reviews_clean.duplicated().sum()
print(f"\nNumber of duplicate rows: {duplicates}")

# 5. Drop duplicates if any
df_user_travel_reviews_clean = df_user_travel_reviews_clean.drop_duplicates().r

# 6. Basic statistics
display(df_user_travel_reviews_clean.describe(include='all'))

# 7. Value counts for categorical columns
for col in ['gender', 'country']:
    print(f"\nValue counts for {col}:")
    print(df_user_travel_reviews_clean[col].value_counts())

# 8. Correlation heatmap for numeric columns
plt.figure(figsize=(16, 10))
sns.heatmap(df_user_travel_reviews_clean.select_dtypes(include='number').corr()
plt.title('Correlation Heatmap')
plt.show()

# 9. Update the main dataframe variable for further analysis
df_user_travel_reviews = df_user_travel_reviews_clean
```

```
 Output Timestamp: 2025-06-20 21:56:02.492109

Missing values per column:
 local services        1
burger/pizza shops    1
gardens               1
dtype: int64

Data types:
 userid                    object
first_name               object
last_name                object
email                    object
age                       int64
gender                   object
country                  object
churches                float64
resorts                 float64
beaches                 float64
parks                   float64
theatres                float64
museums                 float64
malls                   float64
zoos                    float64
restaurants             float64
pubs/bars               float64
local services          float64
burger/pizza shops      float64
hotels/other lodgings   float64
juice bars              float64
art galleries           float64
dance clubs             float64
swimming pools          float64
gyms                    float64
bakeries                float64
beauty & spas           float64
cafes                   float64
view points             float64
monuments               float64
gardens                 float64
age_group                object
avg_natural_space       float64
avg_entertainment       float64
avg_art_related         float64
avg_food_spaces         float64
dtype: object

Number of duplicate rows: 0
```

	userid	first_name	last_name	email	age	gender	country	c
count	5454	5454	5454	5454	5454.000000	5454	5454	5454
unique	5454	613	928	5393	NaN	2	3	
top	User 1	Michael	Smith	osmith@example.net	NaN	Male	US	
freq	1	126	125	6	NaN	2786	1850	
mean	NaN	NaN	NaN	NaN	48.563073	NaN	NaN	1
std	NaN	NaN	NaN	NaN	18.092615	NaN	NaN	C
min	NaN	NaN	NaN	NaN	18.000000	NaN	NaN	0
25%	NaN	NaN	NaN	NaN	33.000000	NaN	NaN	0
50%	NaN	NaN	NaN	NaN	48.000000	NaN	NaN	1
75%	NaN	NaN	NaN	NaN	64.000000	NaN	NaN	1
max	NaN	NaN	NaN	NaN	80.000000	NaN	NaN	5

11 rows × 36 columns

```
Value counts for gender:
gender
Male      2786
Female    2668
Name: count, dtype: int64

Value counts for country:
country
US    1850
IN    1812
UK    1792
Name: count, dtype: int64
```

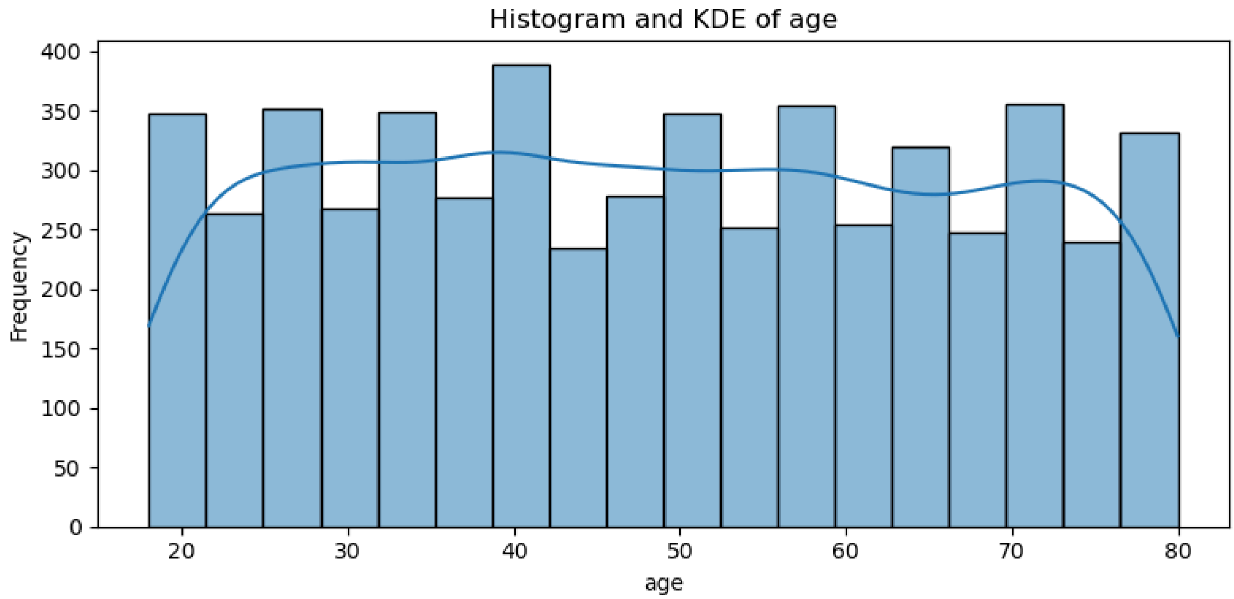


Display the Distribution of data and Some Inferences on it

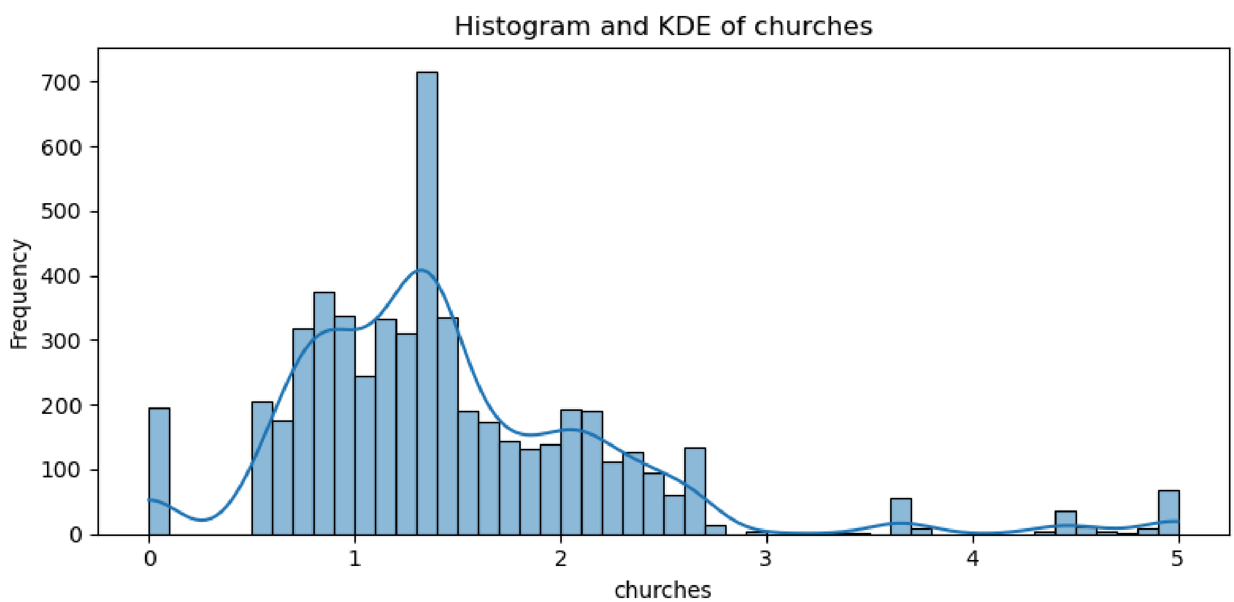
In [171…

```
print(f""" Output Timestamp: {datetime.now()} \n""")

# Plot Histogram and KDE with interpretation
for col in df_user_travel_reviews.select_dtypes(include=['float64', 'int64']).co
    data = df_user_travel_reviews[col].dropna()

    plt.figure(figsize=(8, 4))
    sns.histplot(data, kde=True)
    plt.title(f'Histogram and KDE of {col}')
    plt.xlabel(col)
    plt.ylabel("Frequency")
    plt.tight_layout()
    plt.show()

    # Inference based on skewness
    sk = skew(data)
    mean = data.mean()
    median = data.median()
    std = data.std()
    iqr = data.quantile(0.75) - data.quantile(0.25)
    outliers = data[(data < data.quantile(0.25) - 1.5 * iqr) | (data > data.quan

    if sk > 1:
        interpretation = "The distribution is highly right-skewed (positively sk
    elif sk > 0.5:
        interpretation = "The distribution is moderately right-skewed (positive
    elif sk < -1:
        interpretation = "The distribution is highly left-skewed (negatively ske
    elif sk < -0.5:
        interpretation = "The distribution is moderately left-skewed (negatively
    else:
        interpretation = "The distribution is approximately symmetric."

    print(f"Inference for {col}:\nSkewness: {sk:.2f} → {interpretation}\n")
    print(f"- Mean vs Median: {mean:.2f} vs {median:.2f} →", end=" ")
    if abs(mean - median) < 0.1 * std:
        print("Fairly symmetric central tendency.")
    else:
        print("Skewed central tendency.")
    print(f"- IQR (Interquartile Range): {iqr:.2f}")
    print(f"- Number of Outliers (1.5*IQR rule): {len(outliers)}")
```

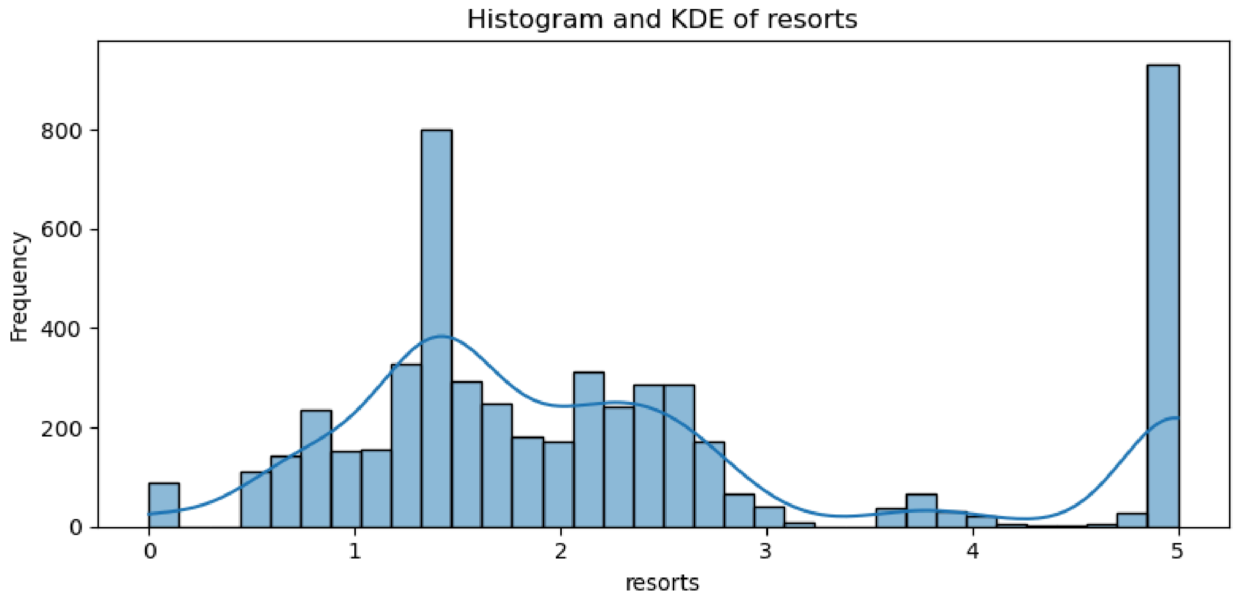
```
Output Timestamp: 2025-06-20 21:56:14.029347
```



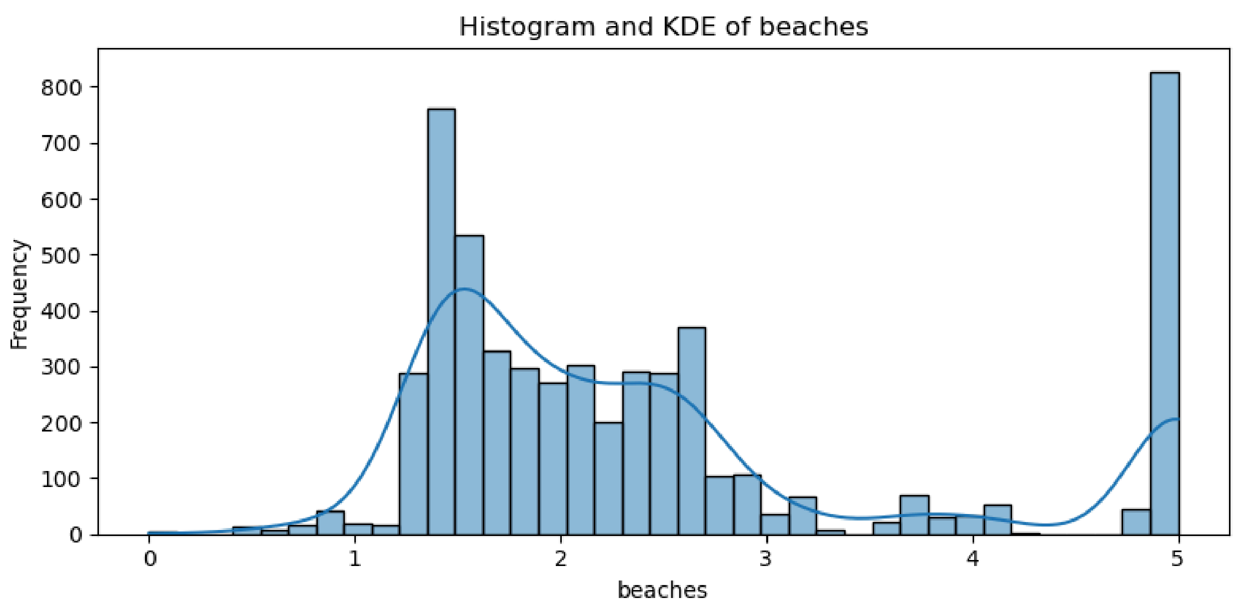

```
Inference for age:
Skewness: 0.04 → The distribution is approximately symmetric.

- Mean vs Median: 48.56 vs 48.00 → Fairly symmetric central tendency.
- IQR (Interquartile Range): 31.00
- Number of Outliers (1.5*IQR rule): 0
```



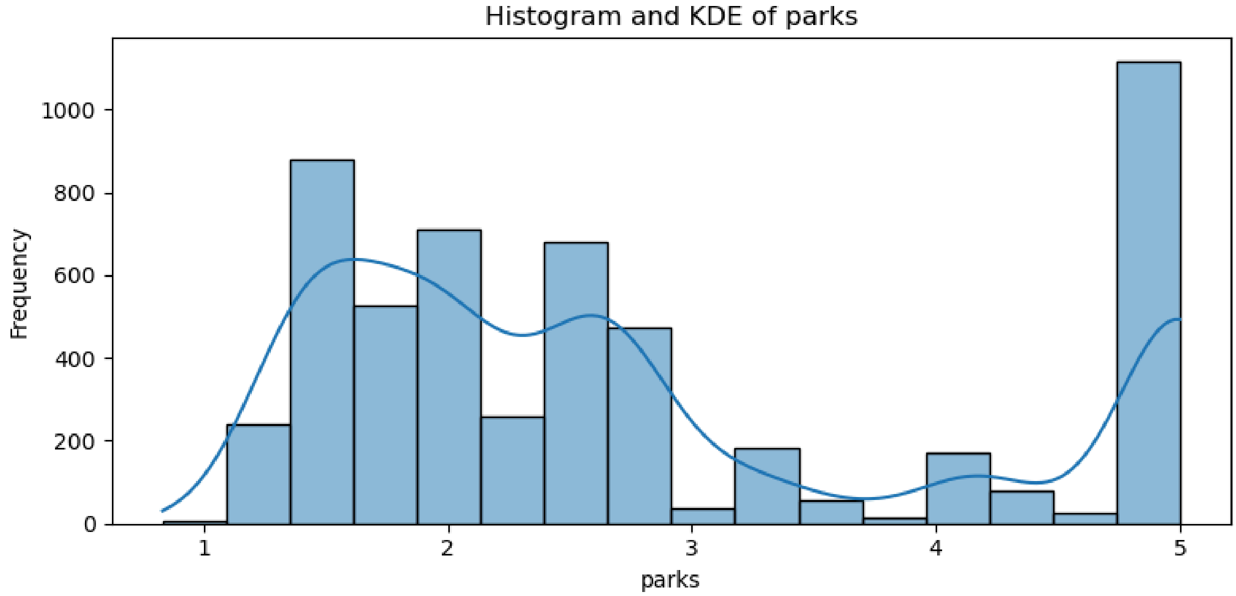

```
Inference for churches:
Skewness: 1.67 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 1.46 vs 1.34 → Skewed central tendency.
- IQR (Interquartile Range): 0.89
- Number of Outliers (1.5*IQR rule): 197
```



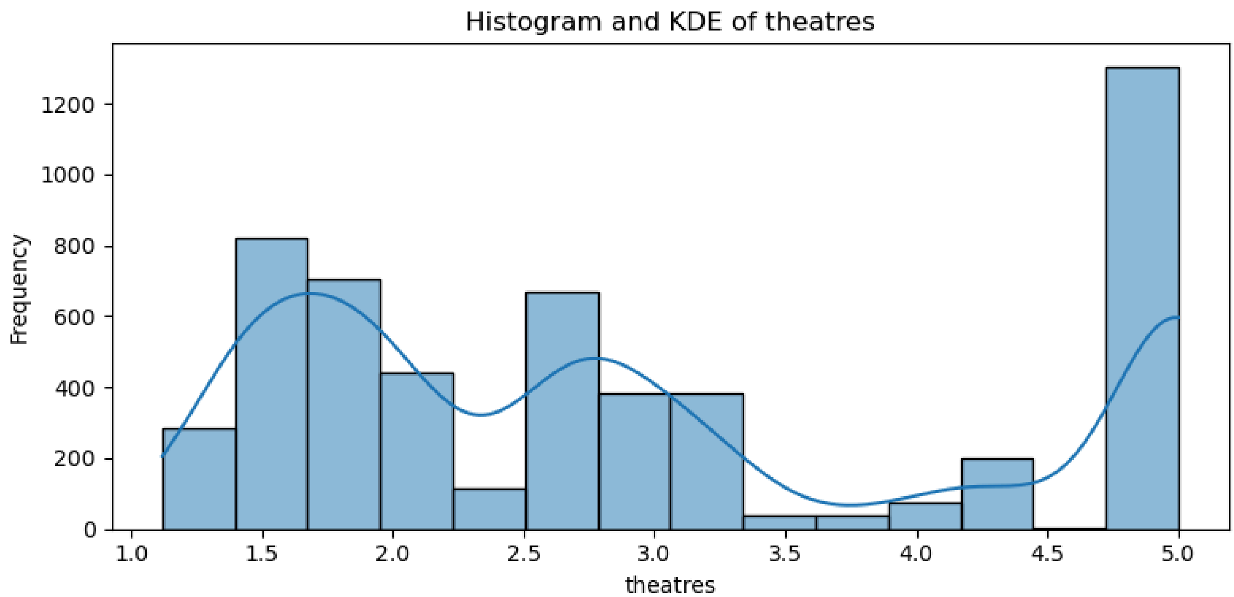

```
Inference for resorts:
Skewness: 0.88 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.32 vs 1.91 → Skewed central tendency.
- IQR (Interquartile Range): 1.33
- Number of Outliers (1.5*IQR rule): 966
```



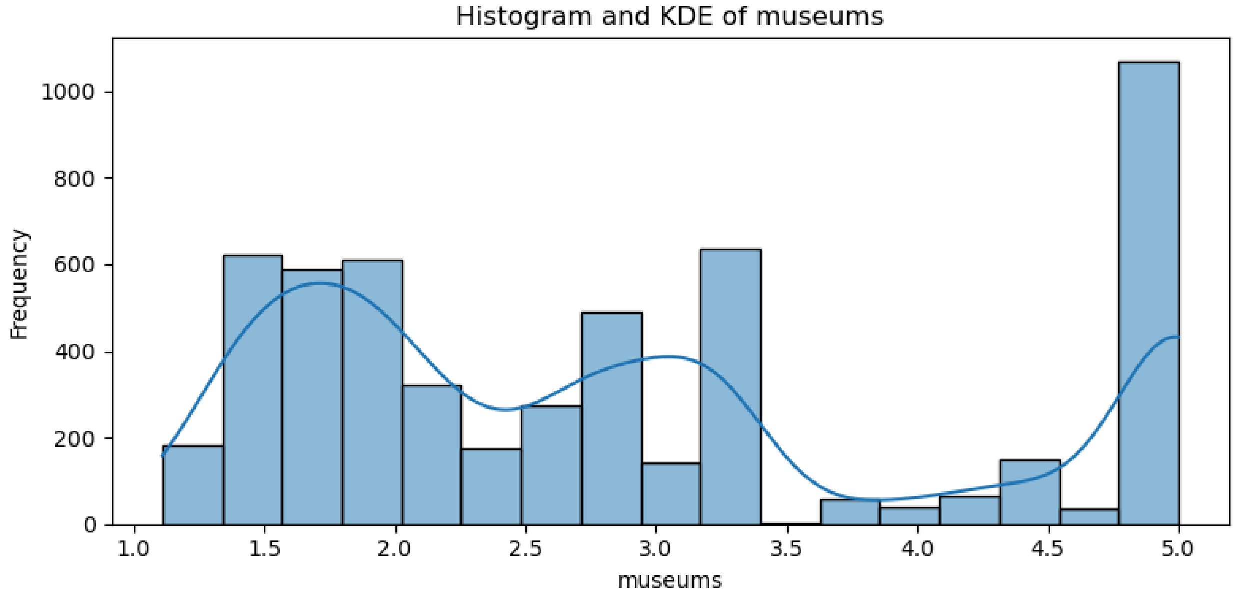

```
Inference for beaches:
Skewness: 1.09 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 2.49 vs 2.06 → Skewed central tendency.
- IQR (Interquartile Range): 1.20
- Number of Outliers (1.5*IQR rule): 872
```



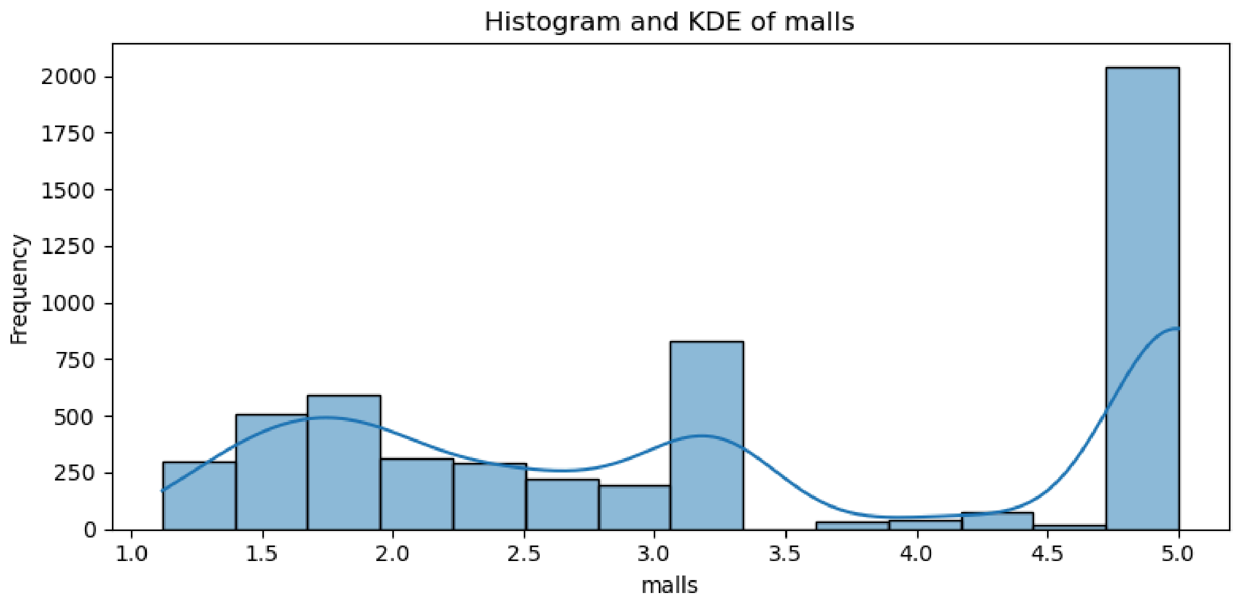

```
Inference for parks:
Skewness: 0.71 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.80 vs 2.46 → Skewed central tendency.
- IQR (Interquartile Range): 2.37
- Number of Outliers (1.5*IQR rule): 0
```



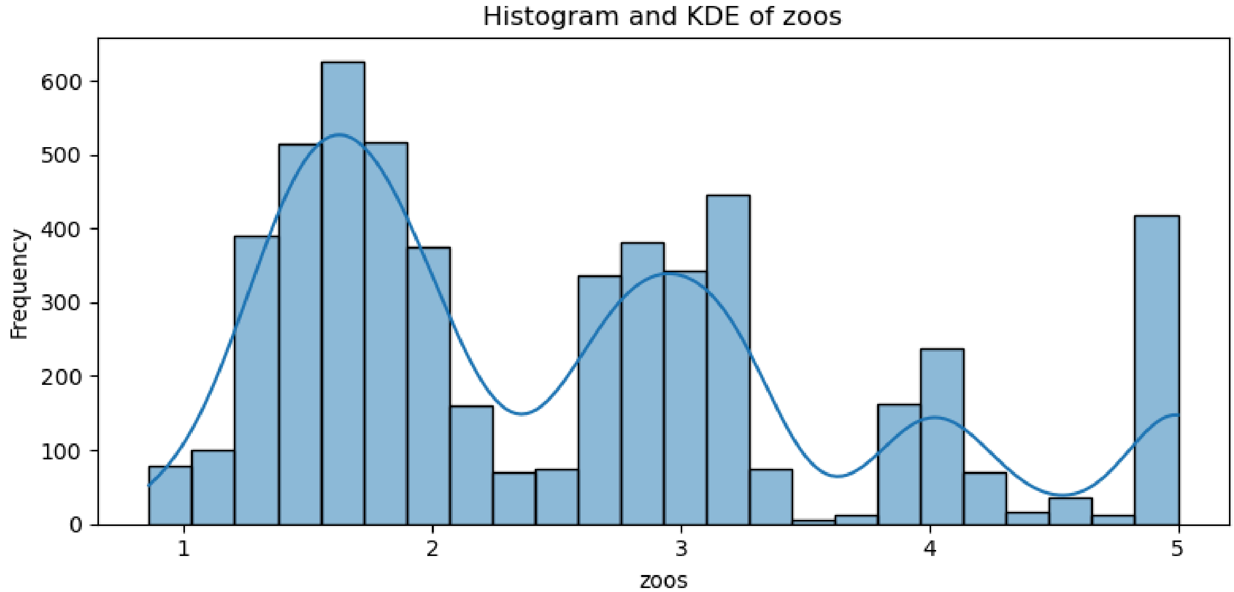

```
Inference for theatres:
Skewness: 0.49 → The distribution is approximately symmetric.

- Mean vs Median: 2.96 vs 2.67 → Skewed central tendency.
- IQR (Interquartile Range): 2.54
- Number of Outliers (1.5*IQR rule): 0
```



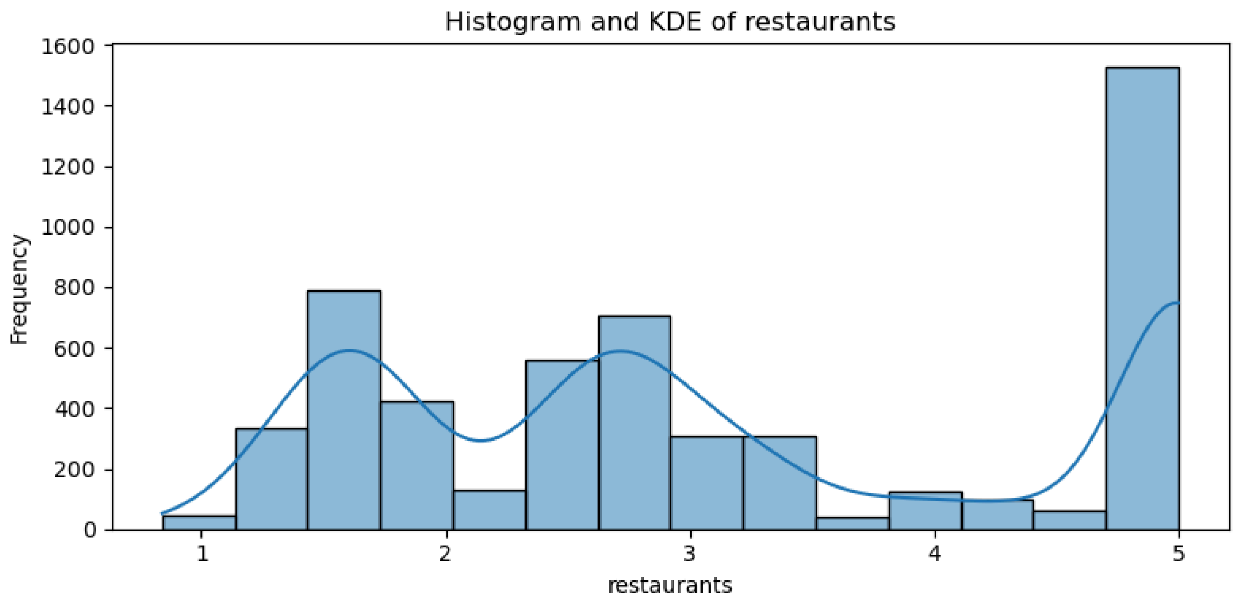

```
Inference for museums:
Skewness: 0.56 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.89 vs 2.68 → Skewed central tendency.
- IQR (Interquartile Range): 2.05
- Number of Outliers (1.5*IQR rule): 0
```



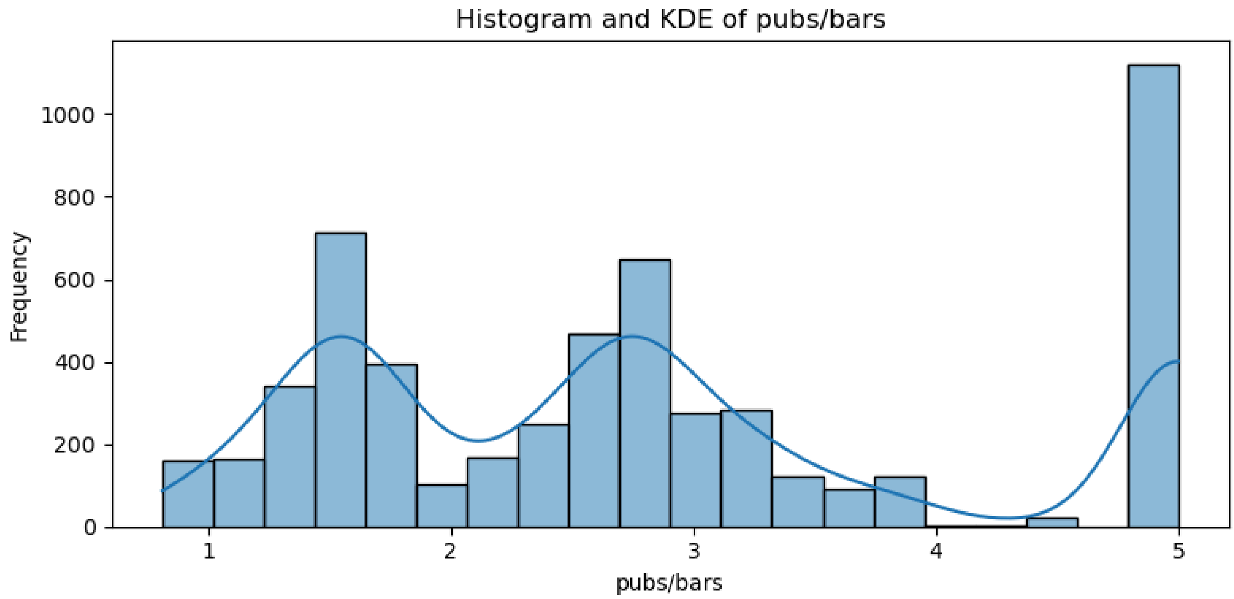

```
Inference for malls:
Skewness: 0.02 → The distribution is approximately symmetric.

- Mean vs Median: 3.35 vs 3.23 → Fairly symmetric central tendency.
- IQR (Interquartile Range): 3.07
- Number of Outliers (1.5*IQR rule): 0
```



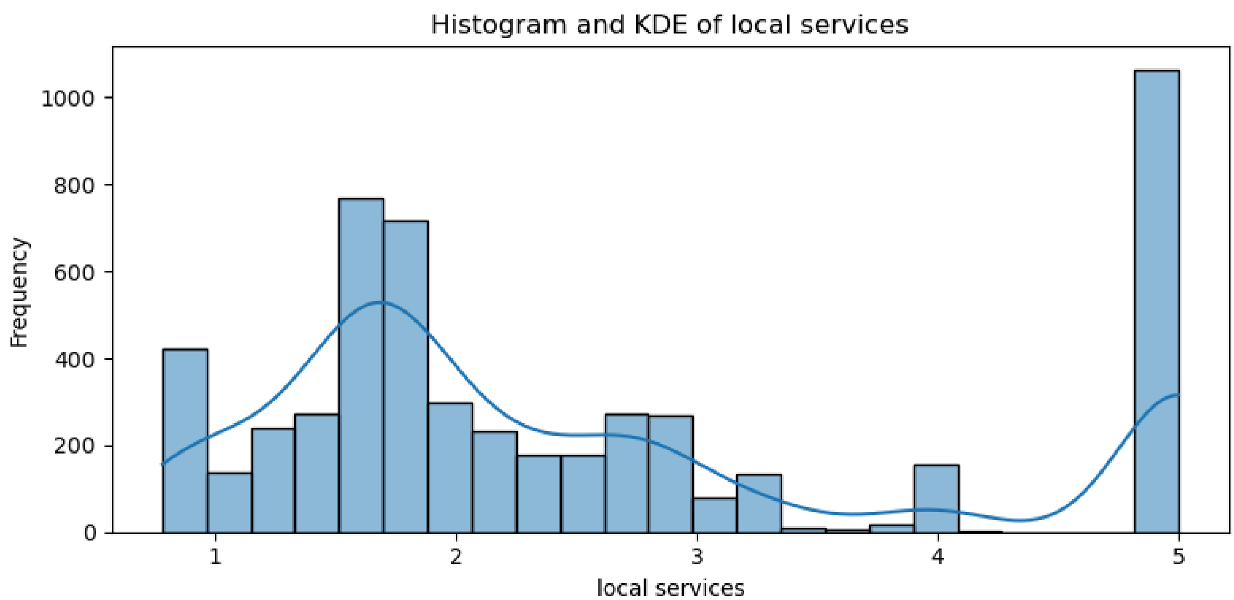

```
Inference for zoos:
Skewness: 0.77 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.54 vs 2.17 → Skewed central tendency.
- IQR (Interquartile Range): 1.57
- Number of Outliers (1.5*IQR rule): 0
```



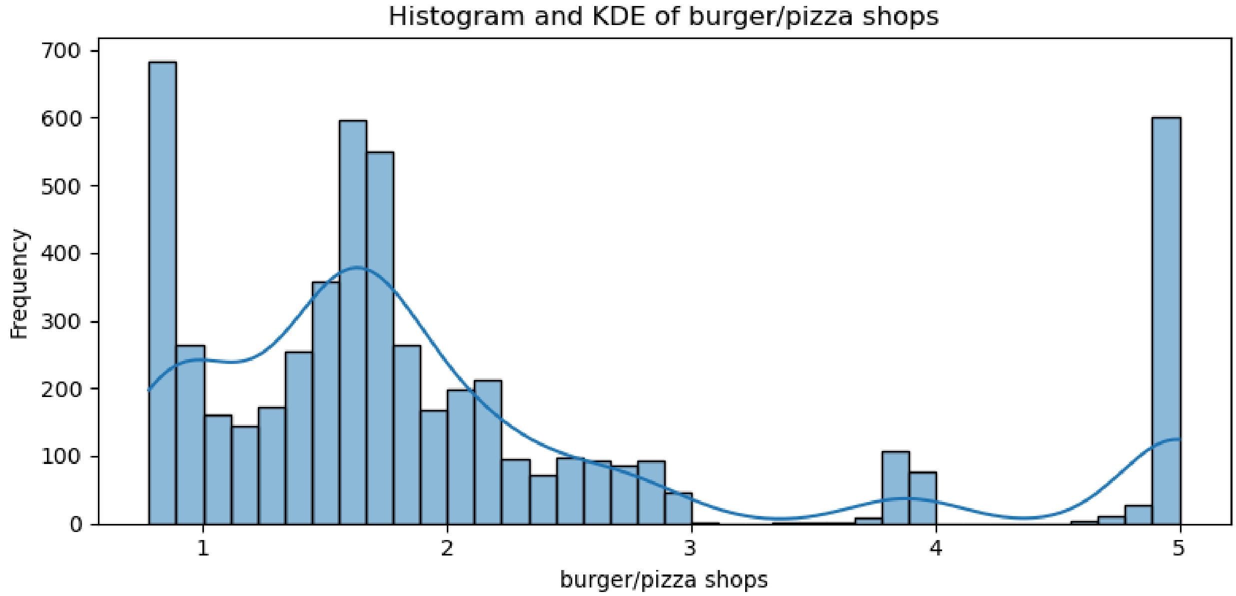

```
Inference for restaurants:
Skewness: 0.27 → The distribution is approximately symmetric.

- Mean vs Median: 3.13 vs 2.80 → Skewed central tendency.
- IQR (Interquartile Range): 3.20
- Number of Outliers (1.5*IQR rule): 0
```



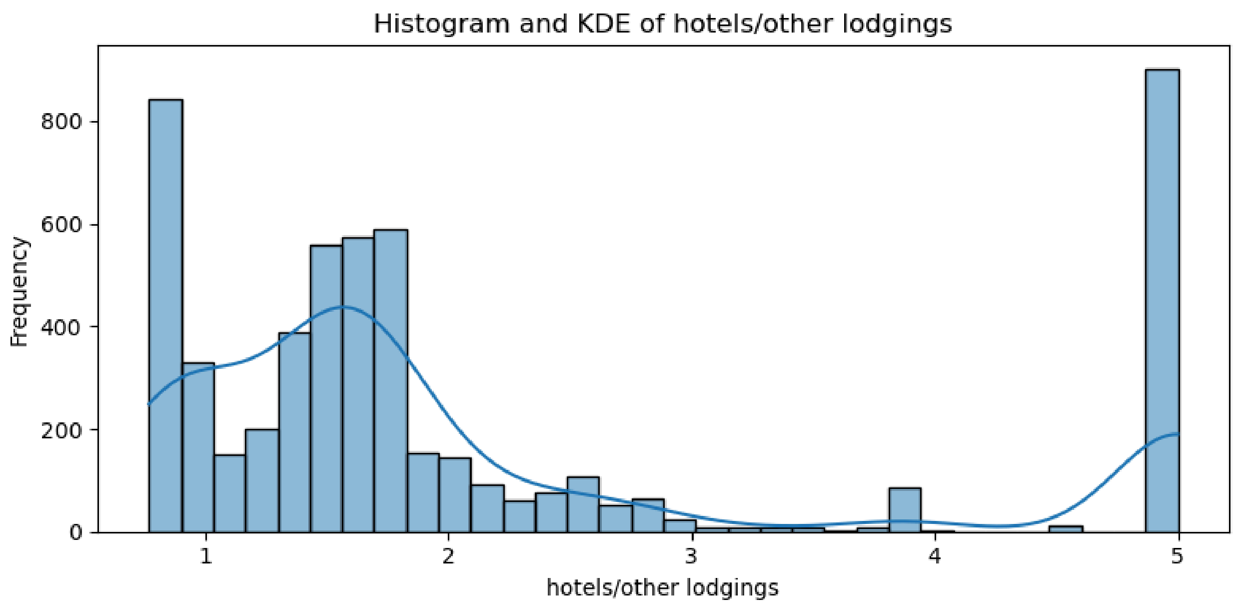

```
Inference for pubs/bars:
Skewness: 0.52 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.83 vs 2.68 → Skewed central tendency.
- IQR (Interquartile Range): 1.89
- Number of Outliers (1.5*IQR rule): 0
```



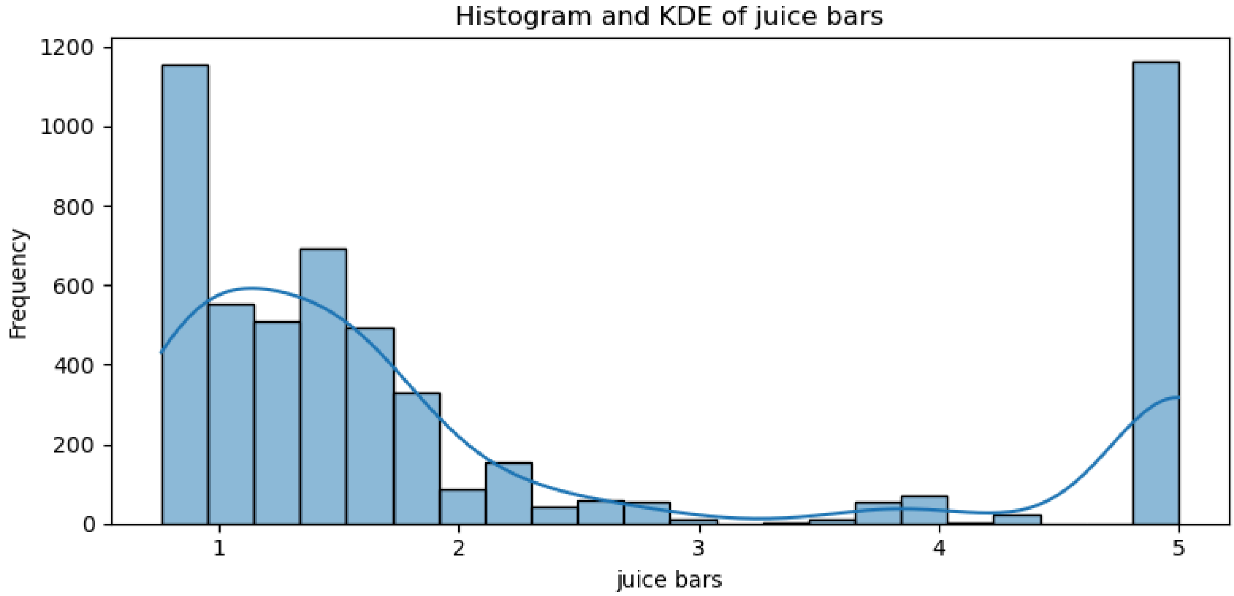

```
Inference for local services:
Skewness: 0.82 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.55 vs 2.00 → Skewed central tendency.
- IQR (Interquartile Range): 1.64
- Number of Outliers (1.5*IQR rule): 0
```



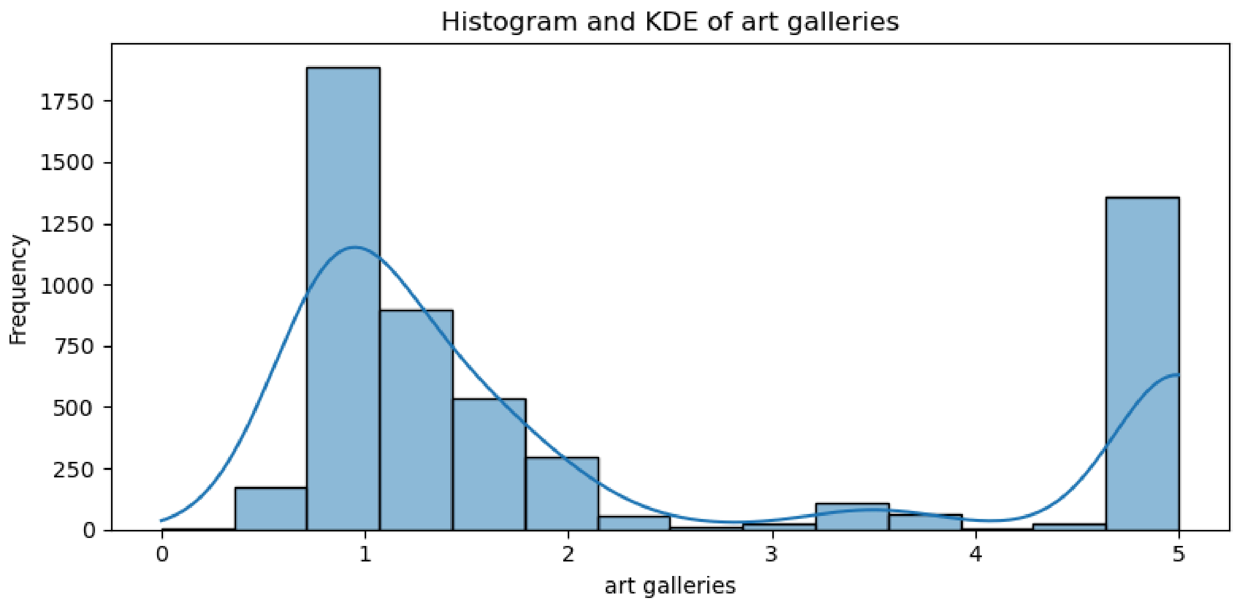

```
Inference for burger/pizza shops:
Skewness: 1.39 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 2.08 vs 1.69 → Skewed central tendency.
- IQR (Interquartile Range): 1.00
- Number of Outliers (1.5*IQR rule): 825
```



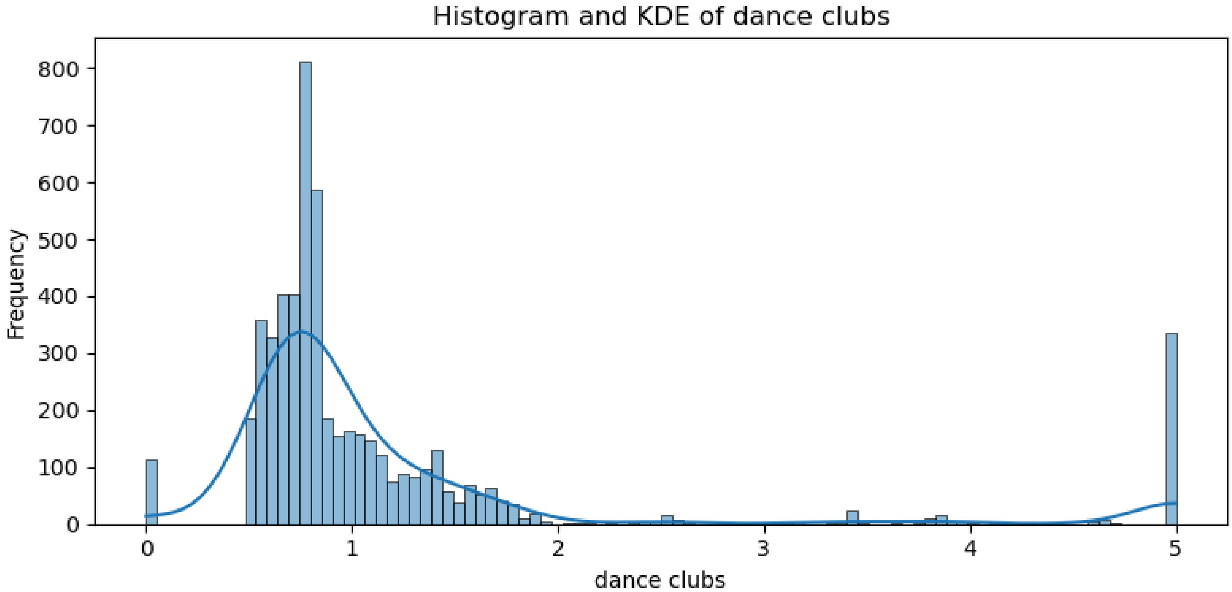

```
Inference for hotels/other lodgings:
Skewness: 1.26 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 2.13 vs 1.61 → Skewed central tendency.
- IQR (Interquartile Range): 1.17
- Number of Outliers (1.5*IQR rule): 915
```



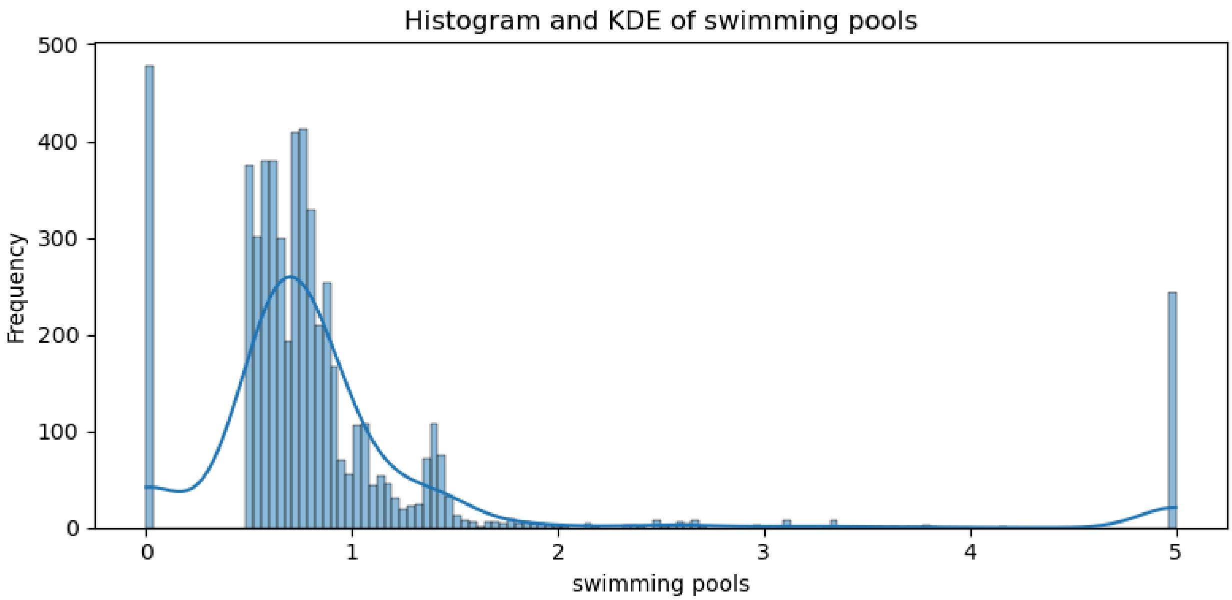

```
Inference for juice bars:
Skewness: 1.03 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 2.19 vs 1.49 → Skewed central tendency.
- IQR (Interquartile Range): 1.71
- Number of Outliers (1.5*IQR rule): 0
```



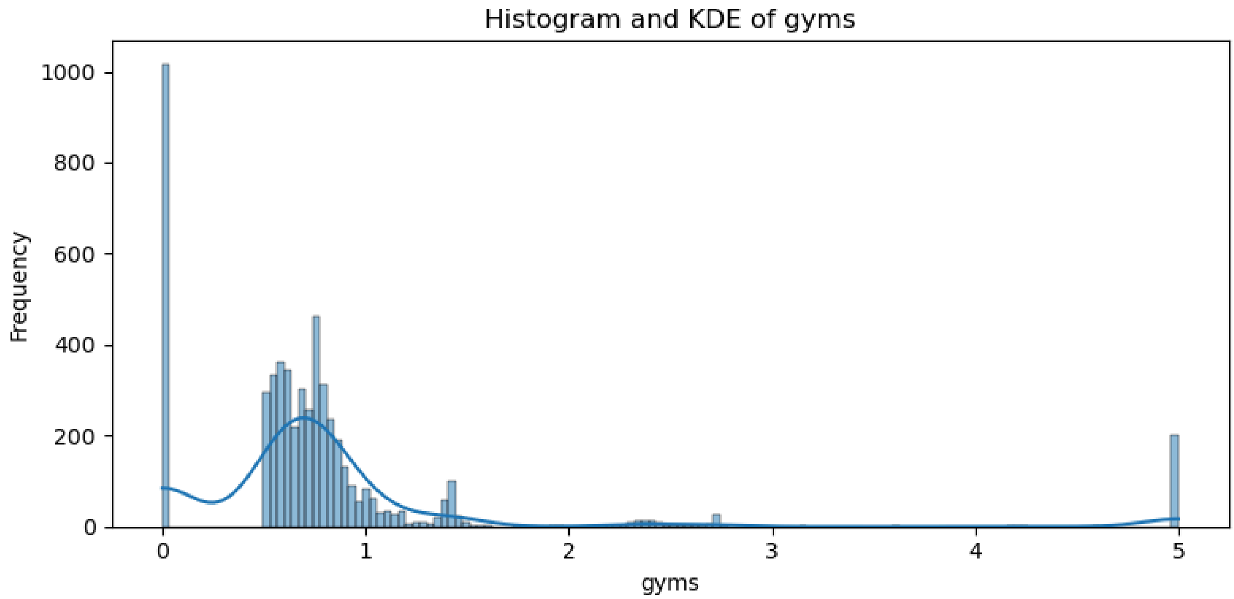

```
Inference for art galleries:
Skewness: 0.86 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.21 vs 1.33 → Skewed central tendency.
- IQR (Interquartile Range): 3.58
- Number of Outliers (1.5*IQR rule): 0
```



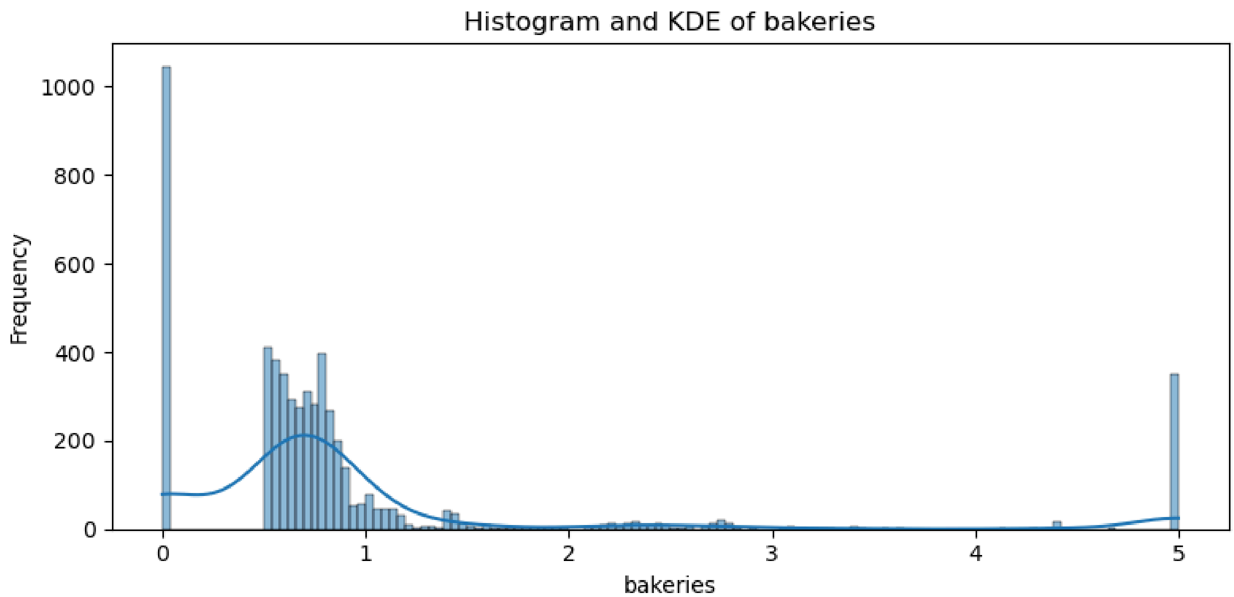

```
Inference for dance clubs:
Skewness: 2.69 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 1.19 vs 0.80 → Skewed central tendency.
- IQR (Interquartile Range): 0.47
- Number of Outliers (1.5*IQR rule): 501
```



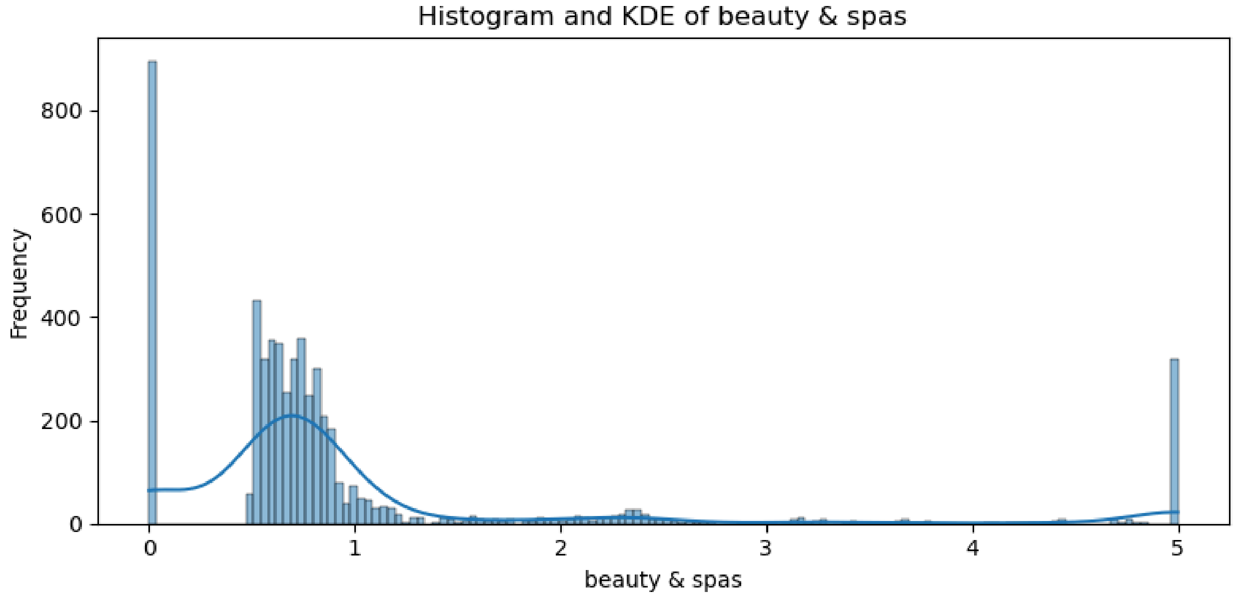

```
Inference for swimming pools:
Skewness: 3.27 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 0.95 vs 0.74 → Skewed central tendency.
- IQR (Interquartile Range): 0.33
- Number of Outliers (1.5*IQR rule): 1027
```



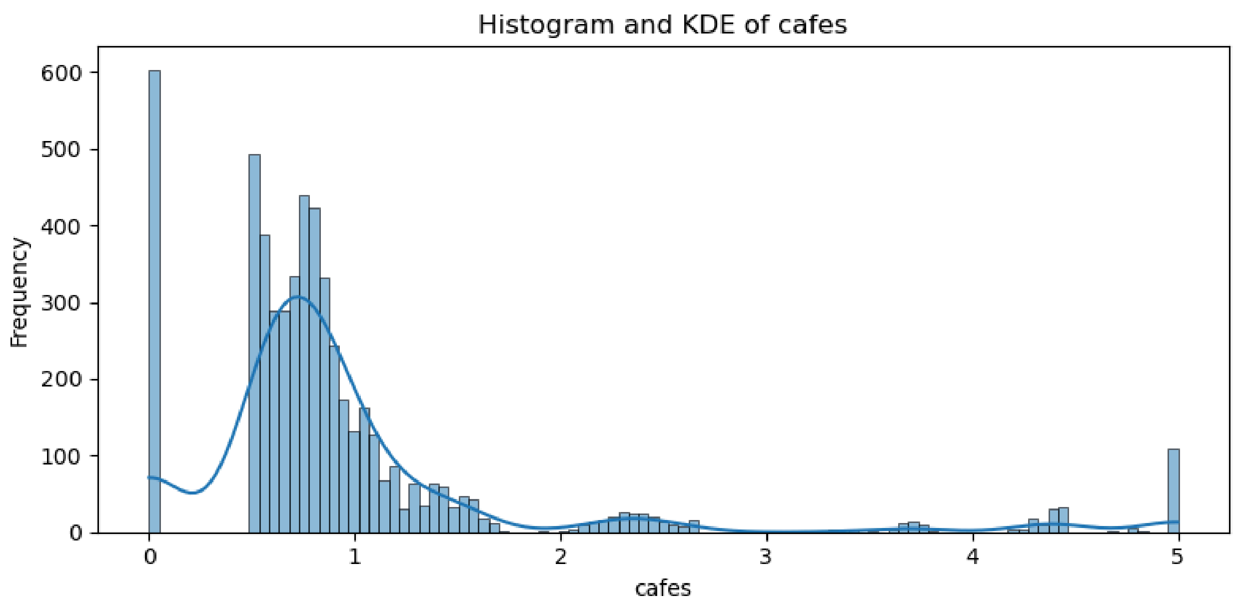

```
Inference for gyms:
Skewness: 3.28 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 0.82 vs 0.69 → Skewed central tendency.
- IQR (Interquartile Range): 0.31
- Number of Outliers (1.5*IQR rule): 1572
```



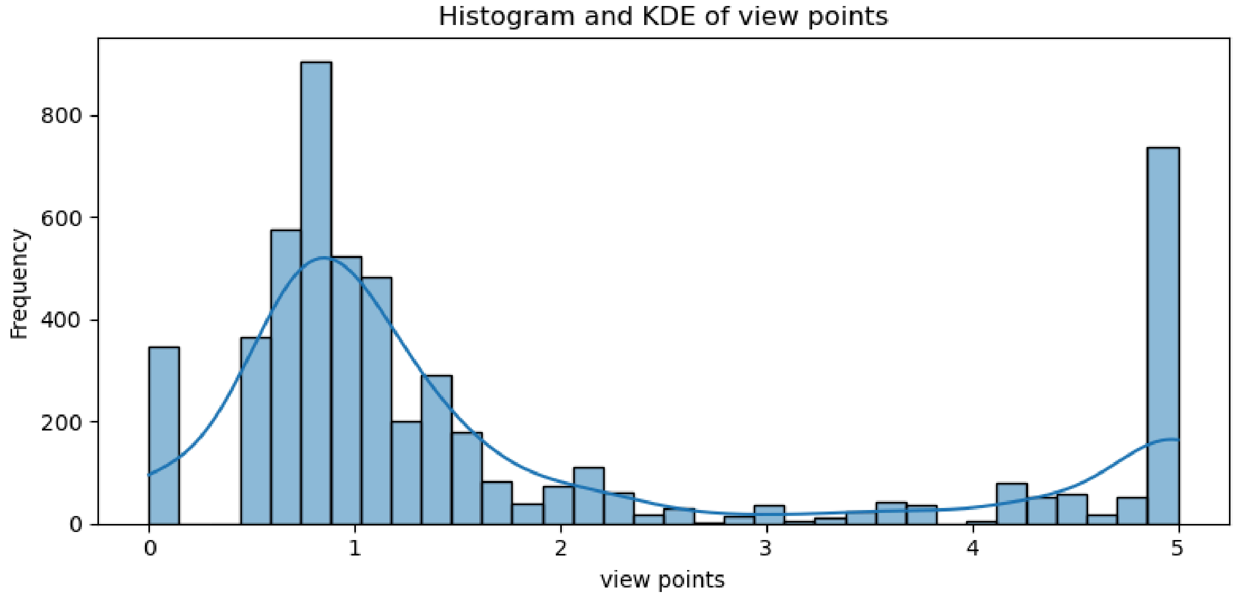

```
Inference for bakeries:
Skewness: 2.51 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 0.97 vs 0.69 → Skewed central tendency.
- IQR (Interquartile Range): 0.34
- Number of Outliers (1.5*IQR rule): 1769
```



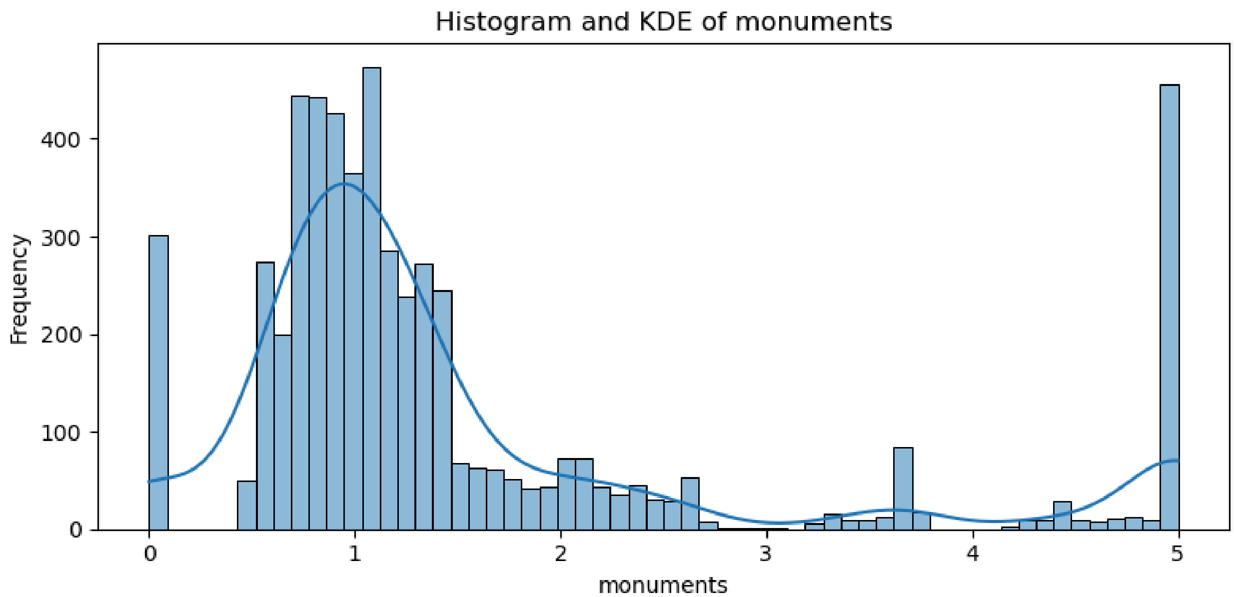

```
Inference for beauty & spas:
Skewness: 2.47 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 1.00 vs 0.69 → Skewed central tendency.
- IQR (Interquartile Range): 0.32
- Number of Outliers (1.5*IQR rule): 1653
```



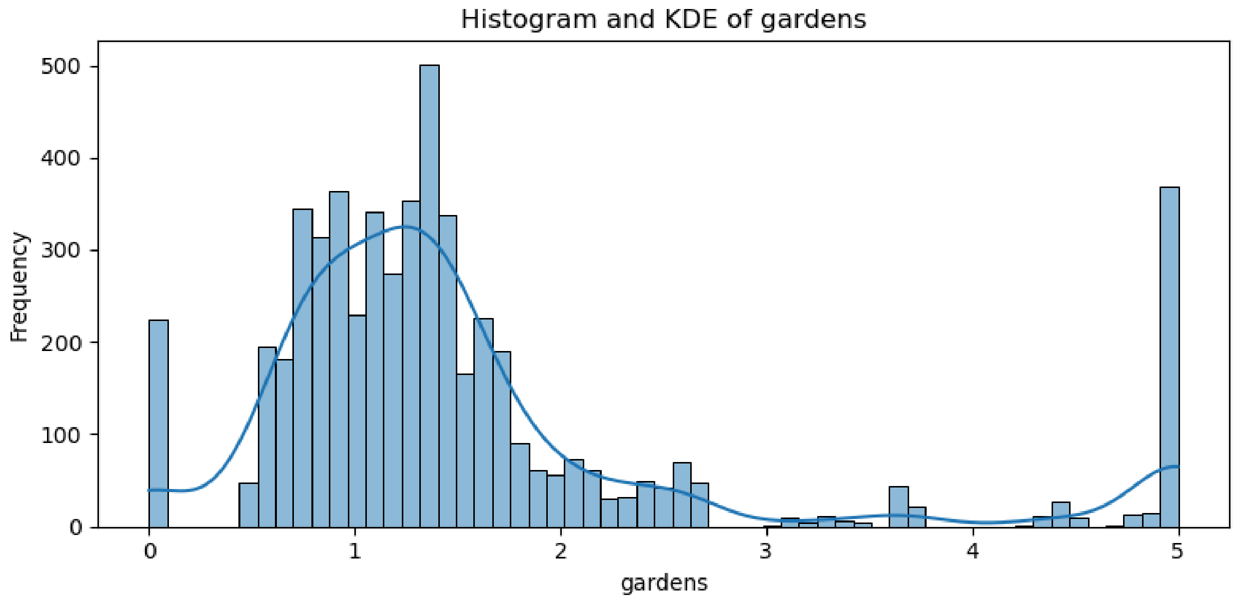

```
Inference for cafes:
Skewness: 2.82 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 0.97 vs 0.76 → Skewed central tendency.
- IQR (Interquartile Range): 0.43
- Number of Outliers (1.5*IQR rule): 485
```



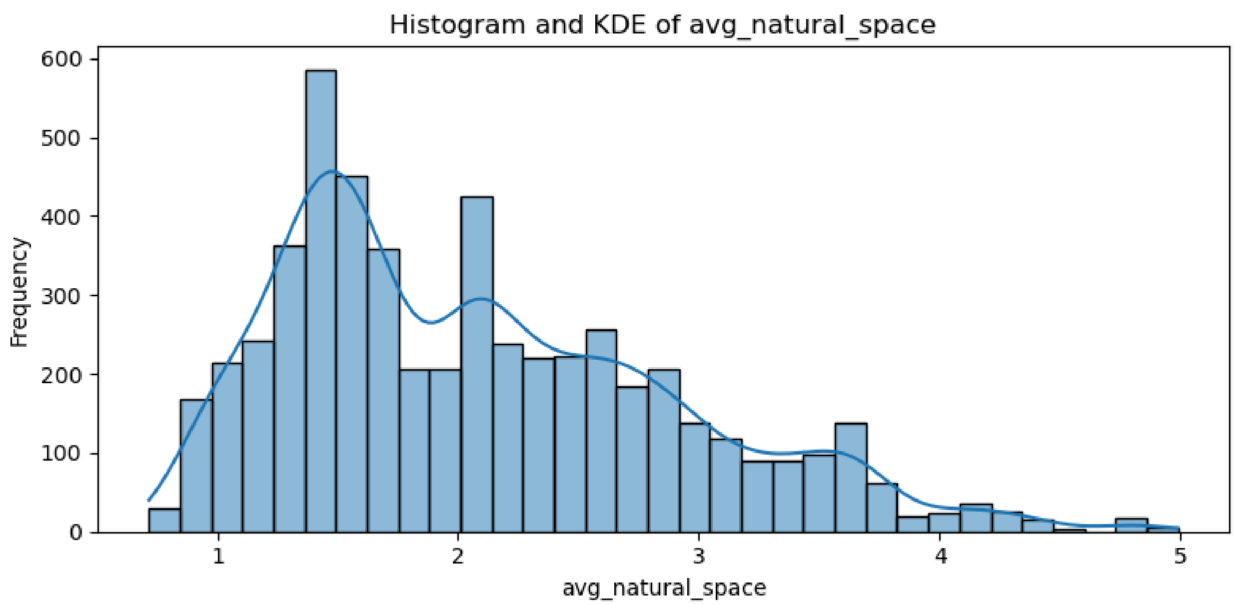

```
Inference for view points:
Skewness: 1.21 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 1.75 vs 1.03 → Skewed central tendency.
- IQR (Interquartile Range): 1.33
- Number of Outliers (1.5*IQR rule): 997
```



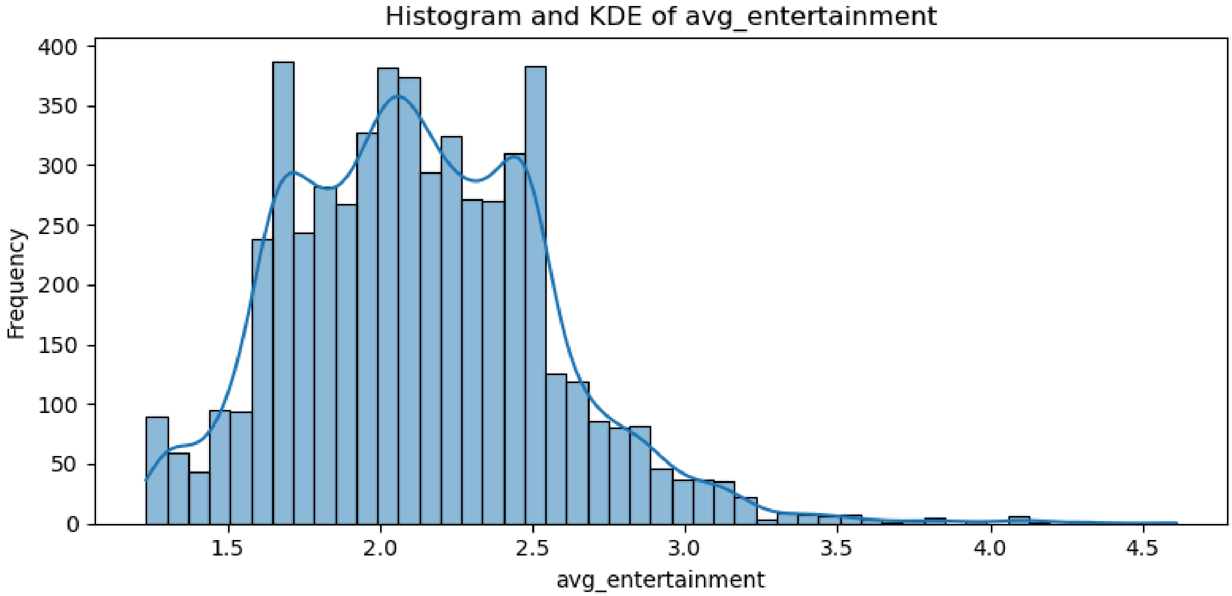

```
Inference for monuments:
Skewness: 1.71 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 1.53 vs 1.07 → Skewed central tendency.
- IQR (Interquartile Range): 0.77
- Number of Outliers (1.5*IQR rule): 717
```



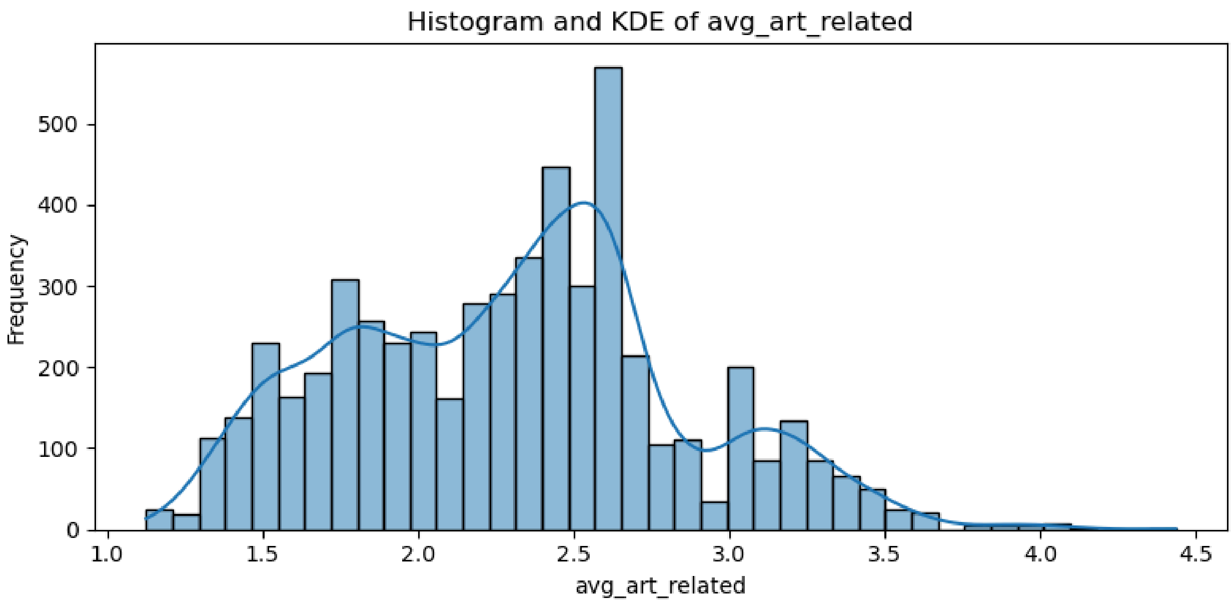

```
Inference for gardens:
Skewness: 1.87 → The distribution is highly right-skewed (positively skewed). M
ost values are concentrated on the left.

- Mean vs Median: 1.56 vs 1.29 → Skewed central tendency.
- IQR (Interquartile Range): 0.78
- Number of Outliers (1.5*IQR rule): 548
```



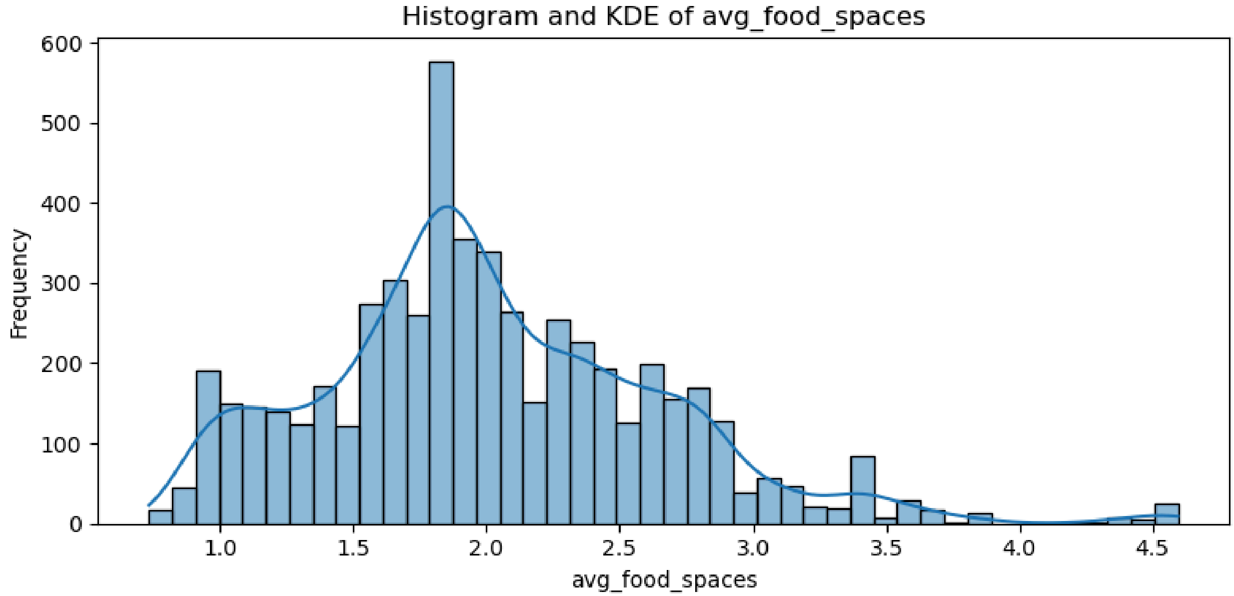

```
Inference for avg_natural_space:
Skewness: 0.76 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.08 vs 1.95 → Skewed central tendency.
- IQR (Interquartile Range): 1.17
- Number of Outliers (1.5*IQR rule): 36
```




```
Inference for avg_entertainment:
Skewness: 0.60 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.13 vs 2.10 → Fairly symmetric central tendency.
- IQR (Interquartile Range): 0.61
- Number of Outliers (1.5*IQR rule): 47
```




```
Inference for avg_art_related:
Skewness: 0.24 → The distribution is approximately symmetric.

- Mean vs Median: 2.30 vs 2.33 → Fairly symmetric central tendency.
- IQR (Interquartile Range): 0.76
- Number of Outliers (1.5*IQR rule): 27
```




```
Inference for avg_food_spaces:
Skewness: 0.67 → The distribution is moderately right-skewed (positively skewe
d).

- Mean vs Median: 2.01 vs 1.92 → Skewed central tendency.
- IQR (Interquartile Range): 0.79
- Number of Outliers (1.5*IQR rule): 94
```

Distribution Check - Normal, Gamma, Beta,

In [172…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
# === Define distributions to check ===
distributions = ['norm', 'gamma', 'beta']

# === Function to fit distributions and compute KS test ===
def analyze_distribution(series, dists):
    results = []
    data = series.dropna().values
    if len(data) < 10:
        return None  # Skip small samples
    for dist_name in dists:
        dist = getattr(stats, dist_name)
        try:
            params = dist.fit(data)
            D, p = stats.kstest(data, dist_name, args=params)
            results.append((dist_name, D, p))
        except Exception as e:
            continue  # Skip if fitting fails
    return sorted(results, key=lambda x: x[2], reverse=True)  # sort by p-value

# === Analyze all numeric columns ===
def analyze_dataframe_distributions(df, dists):
    numeric_cols = df.select_dtypes(include=['float64', 'int64']).columns
    summary = {}
    for col in numeric_cols:
        print(f"\nAnalyzing column: {col}")
        results = analyze_distribution(df[col], dists)
        if results:
            summary[col] = results
            for dist, D, p in results:
                print(f"  {dist:>8} | KS Stat = {D:.4f} | p = {p:.4f}")
        else:
            print("  Not enough data or fitting failed.")
    return summary

# === Run the analysis ===
distribution_summary = analyze_dataframe_distributions(df_user_travel_reviews, 
```

```
Output Timestamp: 2025-06-20 21:56:37.045058


Analyzing column: age
      beta | KS Stat = 0.0330 | p = 0.0000
     gamma | KS Stat = 0.0641 | p = 0.0000
      norm | KS Stat = 0.0648 | p = 0.0000

Analyzing column: churches
      beta | KS Stat = 0.0828 | p = 0.0000
     gamma | KS Stat = 0.0839 | p = 0.0000
      norm | KS Stat = 0.1358 | p = 0.0000

Analyzing column: resorts
     gamma | KS Stat = 0.1158 | p = 0.0000
      norm | KS Stat = 0.1530 | p = 0.0000
      beta | KS Stat = 0.3731 | p = 0.0000

Analyzing column: beaches
     gamma | KS Stat = 0.1165 | p = 0.0000
      norm | KS Stat = 0.1787 | p = 0.0000
      beta | KS Stat = 0.3150 | p = 0.0000

Analyzing column: parks
     gamma | KS Stat = 0.1291 | p = 0.0000
      norm | KS Stat = 0.1670 | p = 0.0000
      beta | KS Stat = 0.4697 | p = 0.0000

Analyzing column: theatres
     gamma | KS Stat = 0.1318 | p = 0.0000
      norm | KS Stat = 0.1624 | p = 0.0000
      beta | KS Stat = 0.3259 | p = 0.0000

Analyzing column: museums
     gamma | KS Stat = 0.1086 | p = 0.0000
      norm | KS Stat = 0.1413 | p = 0.0000
      beta | KS Stat = 0.1914 | p = 0.0000

Analyzing column: malls
     gamma | KS Stat = 0.2337 | p = 0.0000
      norm | KS Stat = 0.2338 | p = 0.0000
      beta | KS Stat = 0.3555 | p = 0.0000

Analyzing column: zoos
     gamma | KS Stat = 0.0777 | p = 0.0000
      norm | KS Stat = 0.1442 | p = 0.0000
      beta | KS Stat = 0.3092 | p = 0.0000

Analyzing column: restaurants
     gamma | KS Stat = 0.1614 | p = 0.0000
      norm | KS Stat = 0.1866 | p = 0.0000
      beta | KS Stat = 0.2703 | p = 0.0000

Analyzing column: pubs/bars
     gamma | KS Stat = 0.1215 | p = 0.0000
      norm | KS Stat = 0.1512 | p = 0.0000
      beta | KS Stat = 0.3106 | p = 0.0000
```

```
Analyzing column: local services
     gamma | KS Stat = 0.1189 | p = 0.0000
      norm | KS Stat = 0.1646 | p = 0.0000
      beta | KS Stat = 0.3197 | p = 0.0000

Analyzing column: burger/pizza shops
     gamma | KS Stat = 0.1060 | p = 0.0000
      norm | KS Stat = 0.1951 | p = 0.0000
      beta | KS Stat = 0.2908 | p = 0.0000

Analyzing column: hotels/other lodgings
     gamma | KS Stat = 0.1489 | p = 0.0000
      norm | KS Stat = 0.2536 | p = 0.0000
      beta | KS Stat = 0.5568 | p = 0.0000

Analyzing column: juice bars
     gamma | KS Stat = 0.1438 | p = 0.0000
      norm | KS Stat = 0.2591 | p = 0.0000
      beta | KS Stat = 0.5842 | p = 0.0000

Analyzing column: art galleries
     gamma | KS Stat = 0.1791 | p = 0.0000
      norm | KS Stat = 0.2453 | p = 0.0000
      beta | KS Stat = 0.6137 | p = 0.0000

Analyzing column: dance clubs
     gamma | KS Stat = 0.1866 | p = 0.0000
      beta | KS Stat = 0.1917 | p = 0.0000
      norm | KS Stat = 0.2646 | p = 0.0000

Analyzing column: swimming pools
      beta | KS Stat = 0.2521 | p = 0.0000
      norm | KS Stat = 0.2773 | p = 0.0000
     gamma | KS Stat = 0.4006 | p = 0.0000

Analyzing column: gyms
      beta | KS Stat = 0.2343 | p = 0.0000
      norm | KS Stat = 0.2835 | p = 0.0000
     gamma | KS Stat = 0.3080 | p = 0.0000

Analyzing column: bakeries
      norm | KS Stat = 0.3137 | p = 0.0000
     gamma | KS Stat = 0.3359 | p = 0.0000
      beta | KS Stat = 0.4047 | p = 0.0000

Analyzing column: beauty & spas
      norm | KS Stat = 0.3190 | p = 0.0000
     gamma | KS Stat = 0.6029 | p = 0.0000
      beta | KS Stat = 0.5404 | p = 0.0000

Analyzing column: cafes
     gamma | KS Stat = 0.2497 | p = 0.0000
      norm | KS Stat = 0.2501 | p = 0.0000
      beta | KS Stat = 0.2651 | p = 0.0000

Analyzing column: view points
```

```
      norm | KS Stat = 0.2486 | p = 0.0000
     gamma | KS Stat = 0.3599 | p = 0.0000
      beta | KS Stat = 0.5625 | p = 0.0000

Analyzing column: monuments
     gamma | KS Stat = 0.1645 | p = 0.0000
      norm | KS Stat = 0.2601 | p = 0.0000
      beta | KS Stat = 0.3319 | p = 0.0000

Analyzing column: gardens
     gamma | KS Stat = 0.1408 | p = 0.0000
      norm | KS Stat = 0.2224 | p = 0.0000
      beta | KS Stat = 0.3011 | p = 0.0000

Analyzing column: avg_natural_space
     gamma | KS Stat = 0.0463 | p = 0.0000
      beta | KS Stat = 0.0584 | p = 0.0000
      norm | KS Stat = 0.1086 | p = 0.0000

Analyzing column: avg_entertainment
     gamma | KS Stat = 0.0308 | p = 0.0001
      beta | KS Stat = 0.0312 | p = 0.0000
      norm | KS Stat = 0.0367 | p = 0.0000

Analyzing column: avg_art_related
      norm | KS Stat = 0.0525 | p = 0.0000
      beta | KS Stat = 0.0600 | p = 0.0000
     gamma | KS Stat = 0.0607 | p = 0.0000

Analyzing column: avg_food_spaces
      beta | KS Stat = 0.0481 | p = 0.0000
     gamma | KS Stat = 0.0488 | p = 0.0000
      norm | KS Stat = 0.0697 | p = 0.0000
```

In [173…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
display(df_user_travel_reviews.head())
```

```
 Output Timestamp: 2025-06-20 21:56:44.189359
```

	userid	first_name	last_name	email	age	gender	country	churches	re
0	User 1	Daniel	Young	brentpearson@example.com	68	Female	US	0.0	
1	User 2	Stacy	Morgan	sarah28@example.com	28	Male	US	0.0	
2	User 3	Brittany	Henry	sheilacuevas@example.com	79	Male	UK	0.0	
3	User 4	Christina	Delacruz	ssaunders@example.net	73	Female	UK	0.0	
4	User 5	Ronald	Reynolds	jsmith@example.net	40	Male	UK	0.0	

5 rows × 36 columns

6. Check if there is a relation between Gender and user Rating for Churches

Null Hypothesis (H0): There is no relationship between Gender and user rating for Churches.

Alternate Hypothesis (H1): There is a relationship between Gender and user rating for Churches.

In [174…

```
from scipy.stats import ttest_ind
from scipy.stats import f_oneway

print(f""" Output Timestamp: {datetime.now()} \n""")

# We will perform a t-test to check if there is a significant relationship betw
# Extract relevant columns for the t-test

church_ratings_by_gender = df_user_travel_reviews[['gender', 'churches']].dropn

# Independent t-test
male_group = church_ratings_by_gender[church_ratings_by_gender['gender'] == 'Ma
female_group = church_ratings_by_gender[church_ratings_by_gender['gender'] == '
stat, p_value = ttest_ind(male_group, female_group, equal_var=False)
print(f"T-test statistic: {stat:.4f}, p-value: {p_value:.4e}")

if p_value < 0.05:
    print("Reject the null hypothesis: There is a significant relationship betw
else:
    print("Fail to reject the null hypothesis: No significant relationship betw
```

```
 Output Timestamp: 2025-06-20 21:56:50.092255

T-test statistic: 0.9204, p-value: 3.5742e-01
Fail to reject the null hypothesis: No significant relationship between Gender
and user rating for Churches.
```

In [175…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
display(df_user_travel_reviews.head())
```

```
 Output Timestamp: 2025-06-20 21:56:54.155530
```

	userid	first_name	last_name	email	age	gender	country	churches	re
0	User 1	Daniel	Young	brentpearson@example.com	68	Female	US	0.0	
1	User 2	Stacy	Morgan	sarah28@example.com	28	Male	US	0.0	
2	User 3	Brittany	Henry	sheilacuevas@example.com	79	Male	UK	0.0	
3	User 4	Christina	Delacruz	ssaunders@example.net	73	Female	UK	0.0	
4	User 5	Ronald	Reynolds	jsmith@example.net	40	Male	UK	0.0	

5 rows × 36 columns

7. Determine if the User is overall reviewing only during Positive Experiance or Negative Experiance

Adding Column to get the average for all the review ratings from Non-Zero or Valid Values

In [176…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
# Select only the review rating columns (exclude non-rating columns)
rating_cols = [
    'churches', 'resorts', 'beaches', 'parks', 'theatres', 'museums', 'malls',
    'restaurants', 'pubs/bars', 'burger/pizza shops', 'hotels/other lodgings',
    'art galleries', 'dance clubs', 'swimming pools', 'gyms', 'bakeries', 'beau
    'cafes', 'view points', 'monuments', 'gardens'
]

def avg_nonzero(row):
    vals = row[rating_cols]
    vals = pd.to_numeric(vals, errors='coerce')
    vals = vals[(vals != 0) & (~vals.isnull())]
    return vals.mean() if not vals.empty else np.nan

df_user_travel_reviews['reviewed_average'] = df_user_travel_reviews.apply(avg_n
display(df_user_travel_reviews[['userid', 'reviewed_average']].head())
```

```
Output Timestamp: 2025-06-20 21:56:57.512943
```

	userid	reviewed_average
0	User 1	2.397333
1	User 2	2.417333
2	User 3	2.415333
3	User 4	2.277500
4	User 5	2.415333

Calculate Mean, Median and Standard Deviation along with Additional Statistics

In [177…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
# Calculate mean, median, and standard deviation for 'reviewed_average'
mean_reviewed = df_user_travel_reviews['reviewed_average'].mean()
median_reviewed = df_user_travel_reviews['reviewed_average'].median()
std_reviewed = df_user_travel_reviews['reviewed_average'].std()


# Additional statistics
min_reviewed = df_user_travel_reviews['reviewed_average'].min()
max_reviewed = df_user_travel_reviews['reviewed_average'].max()
q1 = df_user_travel_reviews['reviewed_average'].quantile(0.25)
q3 = df_user_travel_reviews['reviewed_average'].quantile(0.75)
```

```
Output Timestamp: 2025-06-20 21:57:02.872018
```

Inference from the Statistics are as below

In [178…

```
print(f""" Output Timestamp: {datetime.now()} \n""")
# Inference from the reviewed_average statistics

print("Inference on User Review Behavior:")
print(f"- The mean of reviewed_average is {mean_reviewed:.2f}, with a median of
print(f"- The minimum reviewed_average is {min_reviewed:.2f}, and the maximum i
print(f"- The 25th percentile (Q1) is {q1:.2f}, and the 75th percentile (Q3) is

if mean_reviewed > (max_reviewed + min_reviewed) / 2:
    print("- On average, users tend to give more positive reviews.")
elif mean_reviewed < (max_reviewed + min_reviewed) / 2:
    print("- On average, users tend to give more negative reviews.")
else:
    print("- On average, user reviews are balanced between positive and negativ

print("- The relatively small standard deviation suggests that most users' aver
```

```
 Output Timestamp: 2025-06-20 21:57:06.557094

Inference on User Review Behavior:
- The mean of reviewed_average is 2.10, with a median of 2.08 and a standard de
viation of 0.26.
- The minimum reviewed_average is 1.42, and the maximum is 3.21.
- The 25th percentile (Q1) is 1.91, and the 75th percentile (Q3) is 2.26.
- On average, users tend to give more negative reviews.
- The relatively small standard deviation suggests that most users' average rat
ings are close to the mean, indicating consistent review behavior across users.
```

7. Check the Influence of Age Group on Average Reviews by Natura Space, Entertainment, Art Related and Food Spaces

We are going to Perform ANOVA Test and not t-test since we have 3 Age Groups and t-test is applicable for 2 groups.

In [179…

```
import pandas as pd
from scipy.stats import f_oneway

print(f""" Output Timestamp: {datetime.now()} \n""")

# Columns to review for Significance Testing
review_cols = [
    'avg_natural_space',
    'avg_entertainment',
    'avg_art_related',
    'avg_food_spaces'
]

# Drop rows with NaNs in relevant columns
df_user_travel_reviews_clean = df_user_travel_reviews.dropna(subset=['age_group

# Group by age_group
grouped = df_user_travel_reviews_clean.groupby('age_group')

# Perform ANOVA for each column
anova_results = {}
for col in review_cols:
    # Extract list of values per age group
    groups = [group[col].dropna().values for name, group in grouped if len(grou
    if len(groups) > 1:
        f_stat, p_val = f_oneway(*groups)
        anova_results[col] = {'F-statistic': f_stat, 'p-value': p_val}
    else:
        anova_results[col] = {'F-statistic': None, 'p-value': None}

# Print results
for col, result in anova_results.items():
    if result['p-value'] <= 0.05:
        print(f""" for column '{col}': Age Group has a significant effect on re
    else:
        print(f""" for column '{col}': Age Group does not has a significant eff
```

```
 Output Timestamp: 2025-06-20 21:57:11.425635

 for column 'avg_natural_space': Age Group does not has a significant effect on
reviews since p-value: 0.31 is greater than 0.05
 for column 'avg_entertainment': Age Group does not has a significant effect on
reviews since p-value: 0.25 is greater than 0.05
 for column 'avg_art_related': Age Group does not has a significant effect on r
eviews since p-value: 0.85 is greater than 0.05
 for column 'avg_food_spaces': Age Group does not has a significant effect on r
eviews since p-value: 0.05 is greater than 0.05
```

8. Calculate Confidence Interval for each user with 95% Confidence

In [180…

```
print(f""" Output Timestamp: {datetime.now()} \n""")

# 95% confidence
z = norm.ppf(0.975)

def compute_ci(row):
    values = row[review_cols].dropna()
    values = values[values > 0]  # exclude zero if needed
    n = len(values)
    if n <= 1:
        return pd.Series([np.nan, np.nan])

    mean = values.mean()
    std = values.std()
    se = std / np.sqrt(n)

    lower = mean - z * se
    upper = mean + z * se
    return pd.Series([lower, upper])

df_user_travel_reviews[['reviewed_ci_lower', 'reviewed_ci_upper']] = df_user_tr

display(df_user_travel_reviews[['userid', 'reviewed_average', 'reviewed_ci_lowe
# Save the final DataFrame to a CSV file
```

```
 Output Timestamp: 2025-06-20 21:57:21.040734
```

	userid	reviewed_average	reviewed_ci_lower	reviewed_ci_upper
0	User 1	2.397333	1.602412	3.327588
1	User 2	2.417333	1.611679	3.339750
2	User 3	2.415333	1.613190	3.332524
3	User 4	2.277500	1.542321	3.260179
4	User 5	2.415333	1.613190	3.332524

9. Identify top 5 Users who are tend to give high reviews based on Confidence Interval

We are going to use CI Upper Bound and then target Top 20 Users to send email for Giving Reviews when any location needs to be given review

In [181…

```
print(f""" Output Timestamp: {datetime.now()} \n""")

# Sort users by the lower bound of their confidence interval in descending orde
top_reviewers = df_user_travel_reviews.sort_values(by='reviewed_ci_upper', asce

# Pick top 5 users
top_20_users = top_reviewers.head(20)

# Display selected columns
print(top_20_users[['userid', 'reviewed_average', 'reviewed_ci_lower', 'reviewe
```

```
Output Timestamp: 2025-06-20 21:57:25.788897
```

	userid	reviewed_average	reviewed_ci_lower	reviewed_ci_upper
960	User 961	2.399565	1.007291	4.384959
1865	User 1867	2.400870	1.038591	4.321409
951	User 952	2.714348	1.528104	4.261396
4606	User 4609	2.378261	1.099549	4.247201
516	User 517	2.240000	1.046944	4.218556
607	User 608	3.212222	1.779521	4.193145
953	User 954	2.412609	1.032372	4.184128
2848	User 2851	2.213043	0.640418	4.157582
661	User 662	2.973125	1.558561	4.156856
2832	User 2835	2.497826	1.363002	4.149748
1556	User 1558	2.363000	1.156398	4.136519
512	User 513	2.305217	1.113897	4.132603
1872	User 1874	2.259565	1.037468	4.128282
653	User 654	2.711667	1.330654	4.127680
664	User 665	2.916250	1.534438	4.125145
1552	User 1554	2.355500	1.148242	4.124008
1559	User 1561	2.343000	1.131464	4.122786
1558	User 1560	2.355000	1.150150	4.122767
1560	User 1562	2.432632	1.195205	4.121184
952	User 953	2.529130	1.438364	4.110386

Observation from Above:

Users with Wide Variability including lower near 1 but high upper bound impacts our Target User who we want to determine that is likely going to give positive review is not accurate.

So we should consider CI Midscore to focus on High CI Lower & High CI Upper.

In [182…

```python
print(f""" Output Timestamp: {datetime.now()} \n""")

# Create a midpoint score for the confidence interval
df_user_travel_reviews['ci_score'] = (df_user_travel_reviews['reviewed_ci_lower

# Sort by this score in descending order
top_20_balanced = df_user_travel_reviews.sort_values(by='ci_score', ascending=Fa

# Display relevant columns
display(top_20_balanced[['userid', 'reviewed_average', 'reviewed_ci_lower', 're
```

```
Output Timestamp: 2025-06-20 21:57:29.940036
```

	userid	reviewed_average	reviewed_ci_lower	reviewed_ci_upper	ci_score
642	User 643	3.136471	2.022619	4.045089	3.033854
1343	User 1344	2.949444	2.533656	3.457713	2.995685
607	User 608	3.212222	1.779521	4.193145	2.986333
1362	User 1364	2.803333	2.711124	3.186585	2.948854
5443	User 5446	2.824348	2.291179	3.591571	2.941375
3923	User 3926	2.852174	2.412730	3.468770	2.940750
623	User 624	3.047647	2.049616	3.826467	2.938042
626	User 627	2.691176	1.905228	3.955355	2.930292
2088	User 2090	2.777391	1.946408	3.890092	2.918250
628	User 629	2.687222	1.815902	3.997979	2.906940
951	User 952	2.714348	1.528104	4.261396	2.894750
391	User 392	2.905909	2.343520	3.444480	2.894000
1340	User 1341	2.949444	2.131270	3.647718	2.889494
2075	User 2077	2.733478	2.296276	3.470474	2.883375
643	User 644	2.974706	1.909980	3.846270	2.878125
386	User 387	2.763636	2.151330	3.604170	2.877750
1373	User 1375	2.792941	2.585503	3.166997	2.876250
3905	User 3908	2.764348	2.041399	3.709351	2.875375
602	User 603	3.061667	1.887571	3.862179	2.874875
1909	User 1911	2.727895	2.437264	3.309986	2.873625

10. Lets check if there is any influence of Age Group + Gender combined on the Average Ratings using two way ANOVA analysis

In [183…
```
import pandas as pd
import statsmodels.api as sm
from statsmodels.formula.api import ols

print(f""" Output Timestamp: {datetime.now()} \n""")

# Drop rows with missing data in any of the relevant columns
df_user_travel_reviews_anova = df_user_travel_reviews.dropna(subset=['reviewed_a

# Perform Two-Way ANOVA
model = ols('reviewed_average ~ C(age_group) + C(gender) + C(age_group):C(gende
anova_table = sm.stats.anova_lm(model, typ=2)

print(anova_table)
```

```
Output Timestamp: 2025-06-20 21:57:36.473442

                             sum_sq      df         F    PR(>F)
C(age_group)               0.072087     1.0  1.067856  0.301476
C(gender)                  0.010126     1.0  0.150005  0.698546
C(age_group):C(gender)     0.051603     1.0  0.764410  0.381990
Residual                 367.911374  5450.0       NaN       NaN
```

Observation:

Based on the above since P Value signifact more than 0.05, we can conclude that neither Age Group, gender nor their Interaction has a statistically Significant impact on Average Reviews

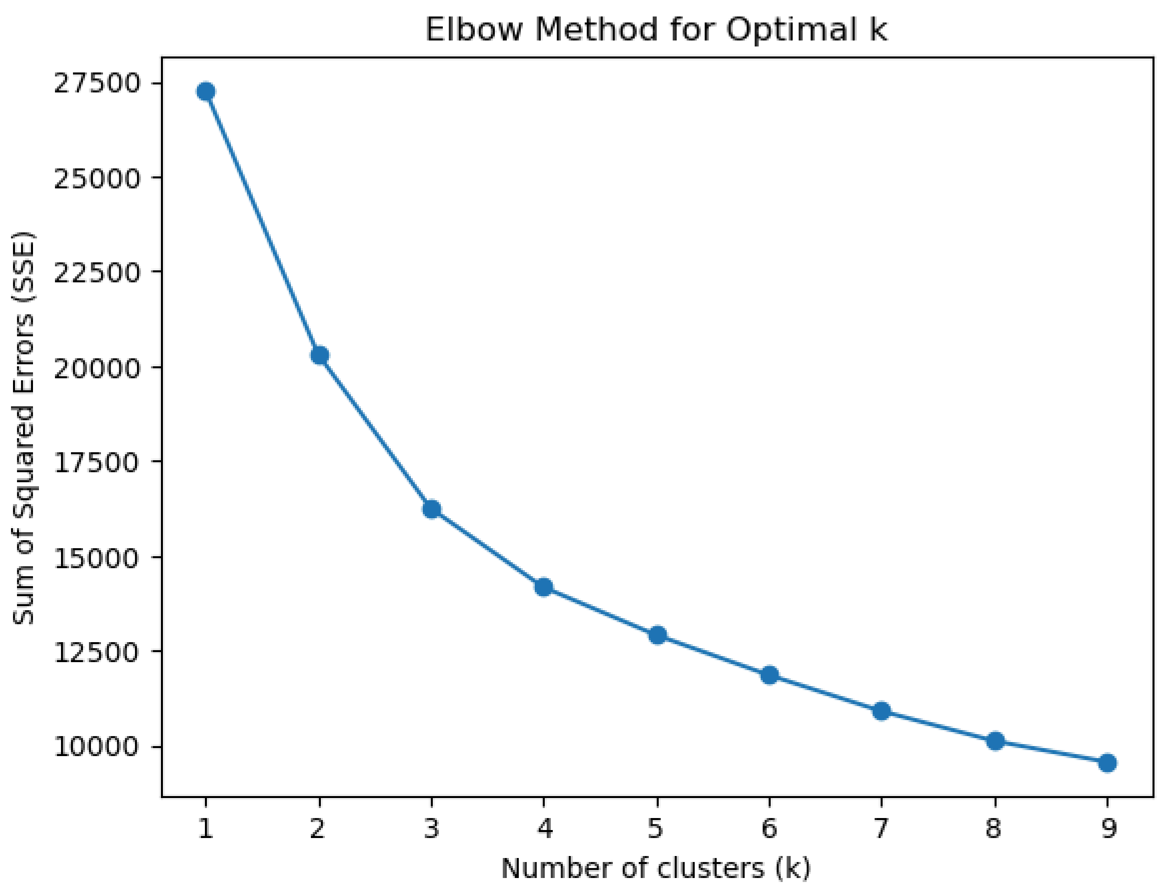
11. Perform the K-Mean Clustering on Users based on Average Reviews

In [184…

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

print(f""" Output Timestamp: {datetime.now()} \n""")

# Select relevant features for clustering
features = df_user_travel_reviews[['avg_natural_space', 'avg_entertainment', 'av

# Drop rows with NaN or zeros (assuming zeros mean "no data" or not meaningful)
features = features[(features != 0).all(axis=1)].dropna()

# Standardize features to have mean=0 and std=1 for fair clustering
scaler = StandardScaler()
X_scaled = scaler.fit_transform(features)

# Use the Elbow Method to find optimal number of clusters by plotting SSE (Sum o
sse = []
for k in range(1, 10):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    sse.append(kmeans.inertia_)

plt.plot(range(1, 10), sse, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Sum of Squared Errors (SSE)')
plt.show()

# Based on elbow plot, we select k=4 clusters (for example)
k = 4
kmeans = KMeans(n_clusters=k, random_state=42)
clusters = kmeans.fit_predict(X_scaled)

# Assign cluster labels back to original dataframe (only rows that were used)
df_user_travel_reviews.loc[features.index, 'user_cluster'] = clusters

# Calculate and print silhouette score to evaluate clustering quality
sil_score = silhouette_score(X_scaled, clusters)
print(f"Silhouette Score for k={k} clusters: {sil_score:.3f}")
# Silhouette closer to 1 means well-separated clusters, closer to 0 means overla

# Analyze cluster centroids in original feature scale to interpret clusters
centroids = scaler.inverse_transform(kmeans.cluster_centers_)
centroids_df = pd.DataFrame(centroids, columns=features.columns)
print("\nCluster centroids (mean feature values) for each cluster:")
print(centroids_df)

# Inferences:
print("\nInferences:")
for i, row in centroids_df.iterrows():
    print(f"\nCluster {i}:")
    print(f"- avg_natural_space: {row['avg_natural_space']:.2f}")
    print(f"- avg_entertainment: {row['avg_entertainment']:.2f}")
    print(f"- avg_art_related: {row['avg_art_related']:.2f}")
```

```
    print(f"- avg_food_spaces: {row['avg_food_spaces']:.2f}")
    print(f"- reviewed_average: {row['reviewed_average']:.2f}")


# Assign cluster labels back to original dataframe (only rows that were used)
df_user_travel_reviews.loc[features.index, 'user_cluster'] = clusters

# Count users per cluster
cluster_counts = df_user_travel_reviews['user_cluster'].value_counts().sort_ind
print("\nNumber of users in each cluster:")
print(cluster_counts)
```

```
Output Timestamp: 2025-06-20 21:57:44.461513
```



```
Silhouette Score for k=4 clusters: 0.214

Cluster centroids (mean feature values) for each cluster:
   avg_natural_space  avg_entertainment  avg_art_related  avg_food_spaces  \
0           3.142936           1.744589         2.044848         1.376106
1           1.444952           2.078455         2.788095         2.646660
2           2.426606           2.606564         2.365679         2.038773
3           1.637452           2.020001         2.057005         1.904399

   reviewed_average
0          2.010016
1          2.139710
2          2.398341
3          1.894602

Inferences:

Cluster 0:
- avg_natural_space: 3.14
- avg_entertainment: 1.74
- avg_art_related: 2.04
- avg_food_spaces: 1.38
- reviewed_average: 2.01

Cluster 1:
- avg_natural_space: 1.44
- avg_entertainment: 2.08
- avg_art_related: 2.79
- avg_food_spaces: 2.65
- reviewed_average: 2.14

Cluster 2:
- avg_natural_space: 2.43
- avg_entertainment: 2.61
- avg_art_related: 2.37
- avg_food_spaces: 2.04
- reviewed_average: 2.40

Cluster 3:
- avg_natural_space: 1.64
- avg_entertainment: 2.02
- avg_art_related: 2.06
- avg_food_spaces: 1.90
- reviewed_average: 1.89

Number of users in each cluster:
user_cluster
0.0    1053
1.0    1256
2.0    1373
3.0    1772
Name: count, dtype: int64
```

Observation:

Cluster 0 : Users in this cluster likely prefer Natural Spaces and have overall low reviewed average meaning their reviews are mostly dis-satisfied related. Number of Users in this Category / Cluster are lowest compare to other 3 clusters

Cluster 1 : This Group Prefer Art & Food related Spaces. Low Review in Natural Space suggest that they dont prefer natural space

Cluster 2 : User has generally Balanced Interest across all category with little less into the Food Space meaning they could be picky in the food choices or doesn't like to eat out.

Cluster 3 : This cluster of users are generally less satisfied in all the categories and most likely prefer to give -ve reviews. Also this cluster has the highest number of users meaning More users give -ve Reviews compare to Positive.

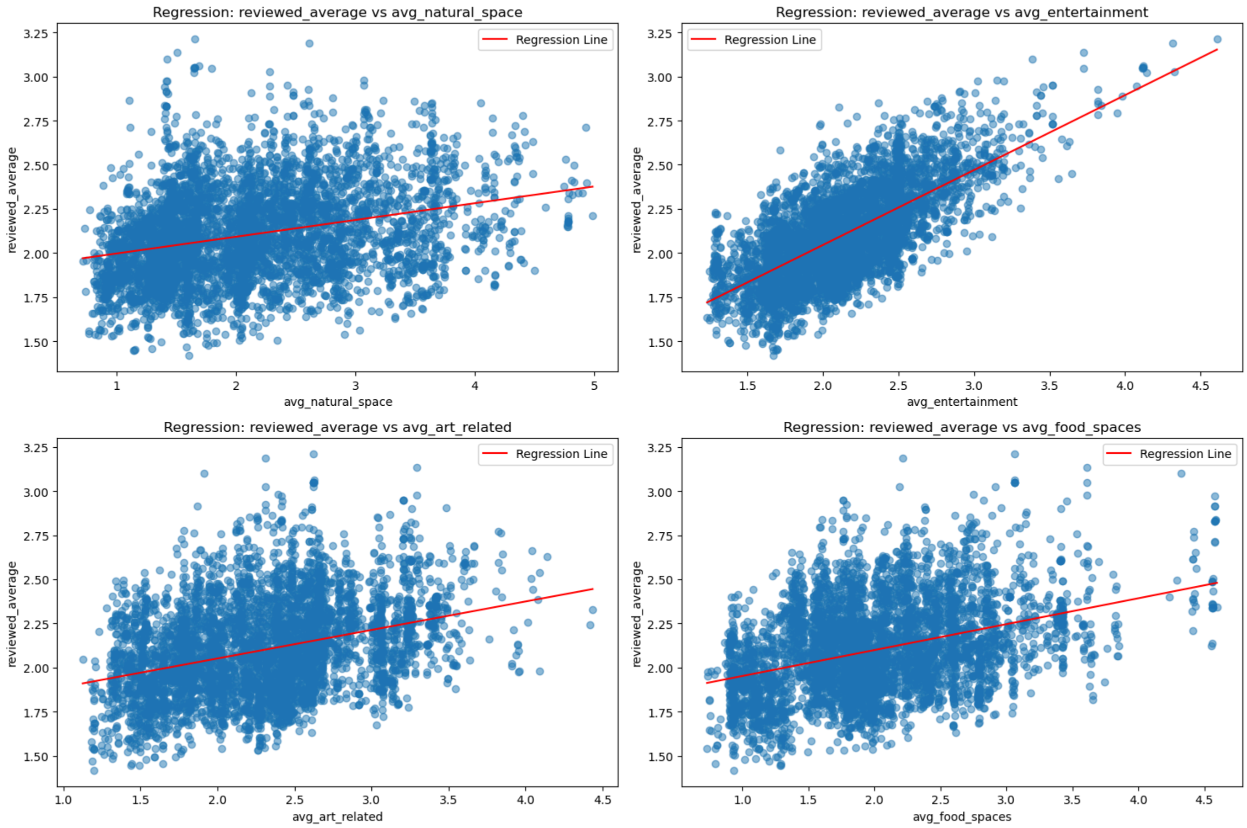
12. Linear Regression of Average Review by Categories of Places

In [185…

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

print(f""" Output Timestamp: {datetime.now()} \n""")

features = ['avg_natural_space', 'avg_entertainment', 'avg_art_related', 'avg_f
target = 'reviewed_average'

fig, axs = plt.subplots(2, 2, figsize=(15, 10))
axs = axs.flatten()

for i, feature in enumerate(features):
    X = df_user_travel_reviews[[feature]]
    y = df_user_travel_reviews[target]

    model = LinearRegression().fit(X, y)

    print(f"{feature}: intercept = {model.intercept_:.4f}, slope = {model.coef_


    # Predict line
    x_line = np.linspace(X.min().values[0], X.max().values[0], 100).reshape(-1,
    y_line = model.predict(x_line)

    # Plot
    axs[i].scatter(X, y, alpha=0.5)
    axs[i].plot(x_line, y_line, color='red', label='Regression Line')
    axs[i].set_xlabel(feature)
    axs[i].set_ylabel(target)
    axs[i].legend()
    axs[i].set_title(f'Regression: {target} vs {feature}')

plt.tight_layout()
plt.show()
```

```
Output Timestamp: 2025-06-20 21:57:52.591675
```

```
avg_natural_space: intercept = 1.9021, slope = 0.0949
avg_entertainment: intercept = 1.1968, slope = 0.4244
avg_art_related: intercept = 1.7285, slope = 0.1615
avg_food_spaces: intercept = 1.8052, slope = 0.1468
```



Observation:

From the above it seems that Entertainment Category has a strongest Impact on Average Reviews compare to other categories and the weakest is the Natural Places which is visible from the Slope Values.

13. Classification of User Group/Cluster based on Reviews in each Categories

In [186…

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

print(f""" Output Timestamp: {datetime.now()} \n""")

features = ['avg_natural_space', 'avg_entertainment', 'avg_art_related', 'avg_fo
X = df_user_travel_reviews[features]
y = df_user_travel_reviews['user_cluster']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

clf = RandomForestClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

print(classification_report(y_test, y_pred))
```

```
 Output Timestamp: 2025-06-20 21:57:57.917301

              precision    recall  f1-score   support

         0.0       0.98      0.99      0.98       218
         1.0       0.96      0.94      0.95       248
         2.0       0.94      0.95      0.95       269
         3.0       0.96      0.96      0.96       356

    accuracy                           0.96      1091
   macro avg       0.96      0.96      0.96      1091
weighted avg       0.96      0.96      0.96      1091
```

Observation:

From above, we can see that we have 96% Accuracty and similar F1-Score and Recall in this Model and it indicates it performing really well.

14. In Section 12, we realized that Entertainment category has the significant impact on the overall average review. Performing Bootstrapping to estimate Confidence Interval (Non-Parametric) on Entertainment Category by resampling users and also performing Hypothesis Testing to see if gender has any influence on this category

In [192…

```
# Example: Bootstrap CI for avg_entertainment
n_iterations = 1000
boot_means = []

sample = df_user_travel_reviews['avg_entertainment'].dropna().values

for _ in range(n_iterations):
    boot_sample = np.random.choice(sample, size=len(sample), replace=True)
    boot_means.append(np.mean(boot_sample))

ci_lower = np.percentile(boot_means, 2.5)
ci_upper = np.percentile(boot_means, 97.5)

print(f"Bootstrapped CI for avg_entertainment: ({ci_lower:.2f}, {ci_upper:.2f})'
```

```
Bootstrapped CI for avg_entertainment: (2.12, 2.14)
```

In [194…

```
male_scores = df_user_travel_reviews[df_user_travel_reviews['gender'] == 'Male'
female_scores = df_user_travel_reviews[df_user_travel_reviews['gender'] == 'Fem

# Observed difference
obs_diff = male_scores.mean() - female_scores.mean()

# Bootstrap
boot_diffs = []
for _ in range(1000):
    boot_male = np.random.choice(male_scores, size=len(male_scores), replace=Tr
    boot_female = np.random.choice(female_scores, size=len(female_scores), repl
    boot_diffs.append(np.mean(boot_male) - np.mean(boot_female))

# P-value
p_val = np.mean(np.abs(boot_diffs) >= abs(obs_diff))
print(f"Bootstrapped p-value for gender difference: {p_val:.3f}")
```

```
Bootstrapped p-value for gender difference: 0.688
```

Observation:

The Average Entertainment Category rating is statistically likely to lie between 2.12 and 2.14 across users with 95% confidence. Also this narrow interval in CI - Lower & Upper suggests that data is consistent and sample size is large enough.

Since the p-value is > 0.05, it kinds of highlight that that is no statistically signifanct difference in rating given by Gender Male or Female on the Entertainment Category

In [195…

```
df_user_travel_reviews.columns.tolist()
```

Out[195]:
```
['userid',
 'first_name',
 'last_name',
 'email',
 'age',
 'gender',
 'country',
 'churches',
 'resorts',
 'beaches',
 'parks',
 'theatres',
 'museums',
 'malls',
 'zoos',
 'restaurants',
 'pubs/bars',
 'local services',
 'burger/pizza shops',
 'hotels/other lodgings',
 'juice bars',
 'art galleries',
 'dance clubs',
 'swimming pools',
 'gyms',
 'bakeries',
 'beauty & spas',
 'cafes',
 'view points',
 'monuments',
 'gardens',
 'age_group',
 'avg_natural_space',
 'avg_entertainment',
 'avg_art_related',
 'avg_food_spaces',
 'reviewed_average',
 'reviewed_ci_lower',
 'reviewed_ci_upper',
 'ci_score',
 'user_cluster']
```

15. Get top 10 users details in each Category to Target for Reviews & Opportunities

In [205…
```
# Get top 10 users overall likely to give best entertainment reviews
top_entertainment_users = (
    df_user_travel_reviews
    .dropna(subset=['user_cluster', 'avg_entertainment'])
    .query('avg_entertainment > 0')
    .sort_values('avg_entertainment', ascending=False)
    .head(10)
)

print("\nTop 10 users most likely to give high entertainment reviews (across al
display(top_entertainment_users[['userid', 'first_name', 'last_name', 'email',
```

```
Top 10 users most likely to give high entertainment reviews (across all cluster
s):
```

	userid	first_name	last_name	email	user_cluster	avg_entertainmen
607	User 608	William	Parsons	harrysimmons@example.org	2.0	4.60833
1333	User 1334	Bernard	Sanchez	paul97@example.org	2.0	4.32833
1332	User 1333	Shawn	Martinez	wjohnson@example.org	2.0	4.31428
608	User 609	Nancy	Williams	moranlisa@example.com	2.0	4.14333
602	User 603	Brooke	Peters	phillipsdanielle@example.net	2.0	4.12000
604	User 605	Lisa	Castillo	danielscynthia@example.com	2.0	4.11833
605	User 606	Evan	Cox	april86@example.org	2.0	4.11833
606	User 607	James	Brown	beth40@example.org	2.0	4.11666
603	User 604	Vickie	Anderson	charles46@example.com	2.0	4.11666
1344	User 1345	Julie	Massey	timothy46@example.net	2.0	4.07428

In [204…

```python
# Get top 10 users overall likely to give best Natural Space reviews
top_nature_users = (
    df_user_travel_reviews
    .dropna(subset=['user_cluster', 'avg_natural_space'])
    .query('avg_natural_space > 0')
    .sort_values('avg_natural_space', ascending=False)
    .head(10)
)

print("\nTop 10 users most likely to give high Natural Space reviews (across al
display(top_nature_users[['userid', 'first_name', 'last_name', 'email', 'user_c
```

```
Top 10 users most likely to give high Natural Space reviews (across all cluster
s):
```

	userid	first_name	last_name	email	user_cluster	avg_natural_spac
2848	User 2851	Kathleen	Haynes	samuelcarter@example.net	0.0	4.98
960	User 961	Julie	Ferguson	chandlerallison@example.net	0.0	4.93
951	User 952	Annette	Drake	jessicagalloway@example.net	2.0	4.93
2833	User 2836	Kara	James	ayersandrea@example.com	0.0	4.90
4605	User 4608	Michaela	Sandoval	paynecaroline@example.com	0.0	4.86
2832	User 2835	Martha	Wise	tara96@example.org	0.0	4.83
1865	User 1867	Mike	Tucker	brose@example.com	0.0	4.83
2831	User 2834	Darlene	Willis	alexis53@example.org	0.0	4.82
953	User 954	Steven	Silva	qmoreno@example.com	0.0	4.80
1866	User 1868	Jennifer	Poole	aprilwalters@example.org	0.0	4.79

In [206…

```
# Get top 10 users overall likely to give best Art Space reviews
top_art_users = (
    df_user_travel_reviews
    .dropna(subset=['user_cluster', 'avg_art_related'])
    .query('avg_art_related > 0')
    .sort_values('avg_art_related', ascending=False)
    .head(10)
)

print("\nTop 10 users most likely to give high Art Space reviews (across all cl
display(top_art_users[['userid', 'first_name', 'last_name', 'email', 'user_clus
```

```
Top 10 users most likely to give high Art Space reviews (across all clusters):
```

	userid	first_name	last_name	email	user_cluster	avg_art_related
389	User 390	Matthew	Morales	chenamy@example.org	1.0	4.4350
516	User 517	Cindy	Trevino	clarkgeorge@example.com	0.0	4.4150
980	User 981	Chad	Bailey	mathewwhite@example.net	1.0	4.1400
394	User 395	Alyssa	Osborne	hurleynoah@example.com	2.0	4.0925
395	User 396	Christopher	Rodriguez	parkjennifer@example.net	1.0	4.0900
574	User 575	Christopher	Sanchez	phillipsdavid@example.com	1.0	4.0800
581	User 582	Andrew	Hill	yharris@example.org	1.0	4.0450
582	User 583	Francisco	Harris	grimesscott@example.com	1.0	4.0400
272	User 273	Jean	Sharp	ucarter@example.com	1.0	4.0375
427	User 428	Lori	Mcclure	deborahhopkins@example.com	1.0	4.0150

In [207…

```
# Get top 10 users overall likely to give best Food Space reviews
top_food_users = (
    df_user_travel_reviews
    .dropna(subset=['user_cluster', 'avg_food_spaces'])
    .query('avg_food_spaces > 0')
    .sort_values('avg_food_spaces', ascending=False)
    .head(10)
)

print("\nTop 10 users most likely to give high Food Space reviews (across all cl
display(top_food_users[['userid', 'first_name', 'last_name', 'email', 'user_clu
```

```
Top 10 users most likely to give high Food Space reviews (across all clusters):
```

	userid	first_name	last_name	email	user_cluster	avg_food_spaces
1559	User 1561	Brent	White	lisaanderson@example.net	1.0	4.5950
652	User 653	Brian	Williams	jamesmejia@example.org	1.0	4.5825
658	User 659	Becky	Mckenzie	erikakeith@example.com	1.0	4.5825
661	User 662	Alyssa	Hartman	bowerscheryl@example.com	2.0	4.5800
665	User 666	Fernando	Powell	burchantonio@example.org	2.0	4.5800
663	User 664	Amanda	Howard	allisonblack@example.com	1.0	4.5800
662	User 663	Jessica	Chen	barronmichael@example.net	1.0	4.5800
664	User 665	Paul	Oconnor	laurenfinley@example.org	2.0	4.5800
660	User 661	Scott	Gomez	justinbean@example.org	1.0	4.5800
659	User 660	Justin	White	brobles@example.org	1.0	4.5800