```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statistics import mode
from scipy.stats import levene # Optional assumption for standard t-
test
from scipy.stats import ttest_ind  # To perform t-test

df = pd.read_csv("Apple_Store_Reviews.csv")
df
```

```
     Review_ID         App_Name  User_Age Review_Date  Rating  \
0            1  Candy Crush Saga        21  2023-01-16       4
1            2           Spotify        57  2024-02-01       1
2            3            TikTok        33  2023-11-30       5
3            4           Audible        40  2023-04-03       5
4            5           Spotify        44  2023-05-01       1
..         ...               ...       ...         ...     ...
995        996         Headspace        30  2023-11-15       3
996        997          Duolingo        19  2024-09-27       1
997        998          Duolingo        38  2023-06-07       5
998        999         Instagram        52  2024-03-04       4
999       1000           Audible        25  2024-02-20       2

                                      Review_Text  Likes Device_Type  \
0    Great game, but too many in-game purchases.     70   iPhone 12
1     Good, but has connection issues sometimes.     49   iPhone SE
2       Awesome app! Best entertainment content.     98   iPhone 12
3              Great app, but it's a bit pricey.     74   iPhone 13
4     Good, but has connection issues sometimes.     47   iPhone SE
..                                            ...    ...         ...
995  Good, but the premium content is expensive.     65   iPhone SE
996     Disappointing. Hard to follow and buggy.      4   iPhone SE
997            Excellent for learning new skills!     85   iPhone 11
998             Great app, but sometimes it lags.     55   iPhone 13
999   Terrible. Very limited selection of books.      7   iPhone 13

    Version_Used    Country  Purchase_Amount       Category
0       3.231.19  Australia             0.00          Games
1        4.102.9    Germany             7.15          Music
2         7.52.0    Germany             4.98  Entertainment
3       5.260.15  Australia             0.00          Books
4        4.50.18  Australia            14.31          Music
..           ...        ...              ...            ...
995     6.284.11         US             0.00         Health
996      6.293.8     Canada             7.25      Education
997    10.277.15     Mexico            13.33      Education
998      3.52.20         US             6.37         Social
999      9.150.8      India             8.32          Books
```

```
[1000 rows x 12 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Review_ID        1000 non-null   int64  
 1   App_Name         1000 non-null   object 
 2   User_Age         1000 non-null   int64  
 3   Review_Date      1000 non-null   object 
 4   Rating           1000 non-null   int64  
 5   Review_Text      1000 non-null   object 
 6   Likes            1000 non-null   int64  
 7   Device_Type      1000 non-null   object 
 8   Version_Used     1000 non-null   object 
 9   Country          1000 non-null   object 
 10  Purchase_Amount  1000 non-null   float64
 11  Category         1000 non-null   object 
dtypes: float64(1), int64(4), object(7)
memory usage: 93.9+ KB
```

```
df.isnull().sum()
```

```
Review_ID          0
App_Name           0
User_Age           0
Review_Date        0
Rating             0
Review_Text        0
Likes              0
Device_Type        0
Version_Used       0
Country            0
Purchase_Amount    0
Category           0
dtype: int64
```

```
df["Review_Date"] = pd.to_datetime(df["Review_Date"])
```

```
df["Rating"].describe()
```

```
count    1000.000000
mean        2.869000
std         1.467649
min         1.000000
25%         1.000000
50%         3.000000
```

```
75%          4.000000
max          5.000000
Name: Rating, dtype: float64
```

```
mean = df["Rating"].mean()
print(mean)
# Median - Robust to outliers and skewed distributions; provides a
better central tendency for non-symmetrical data.

median = df["Rating"].median()
print(median)

# Mode: Useful when the data has a prominent peak or category that
repeats frequently.

mode = df["Rating"].mode()
print(mode)
```

```
2.869
3.0
0    1
Name: Rating, dtype: int64
```

```
# Median - Robust to outliers and skewed distributions; provides a
better central tendency for non-symmetrical data.

median = df["Rating"].median()
median
```

```
3.0
```

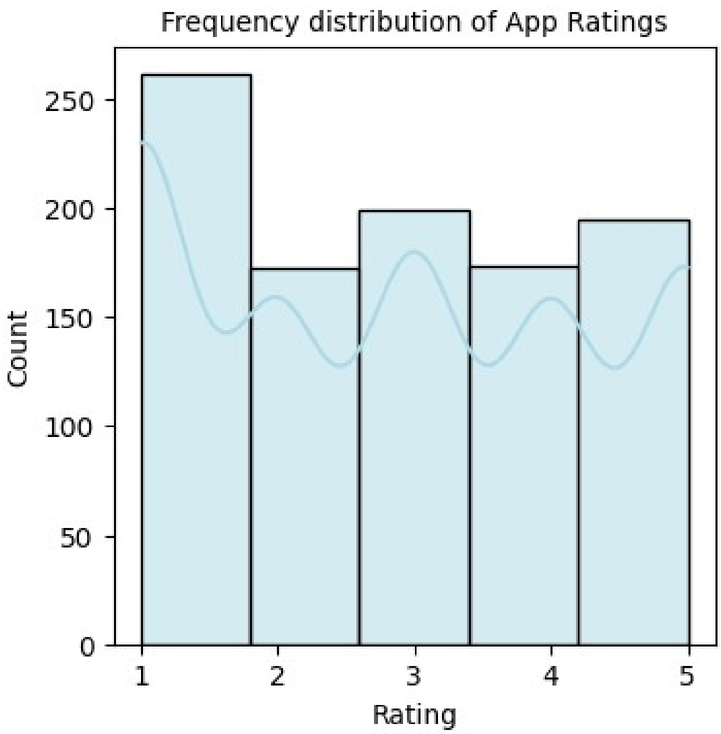
```
# Mode: Useful when the data has a prominent peak or category that
repeats frequently.

mode = mode(df["Rating"])
mode
```

```
1
```

```
df["Rating"].mode()
```

```
0    1
Name: Rating, dtype: int64
```

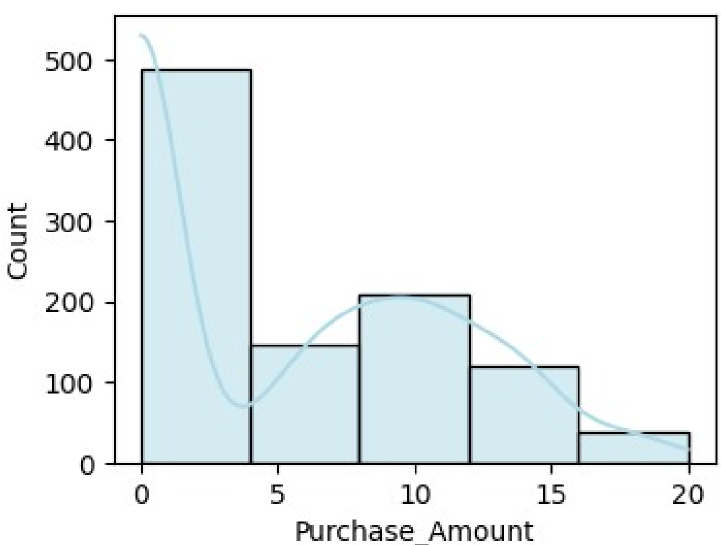
```
plt.figure(figsize = (4,4))
sns.histplot(data = df["Rating"], bins = 5, color = "lightblue",
edgecolor = "black", kde = True)
plt.title("Frequency distribution of App Ratings", fontsize = 10)
plt.show()
```




```
# Range = (min_value, max_value)
# IQR = Q3 - Q1(0.75 - 0.25)
'''
Conclusion :
The Range highlights the extreme values in the data, while the IQR
gives a more focused view of typical purchase behaviors.
Based on this, the dataset shows significant variability in purchase
amounts, with a notable cluster at lower values.

Insights:
- The data has a large spread, with some high-value purchases pushing
the maximum to $19.97. However, the low
Q1 shows a cluster of free or minimal-value purchases.
- The relatively high IQR ($10.19) compared to the Range ($19.97)
indicates that the variability in the middle 50% of data is
significant.
This implies diverse spending behaviors among users.
'''


minimum = df["Purchase_Amount"].min()
maximum = df["Purchase_Amount"].max()

q1 = df["Purchase_Amount"].quantile(0.25)
q3 = df["Purchase_Amount"].quantile(0.75)

Range = maximum - minimum
```

```python
IQR = q3 -q1

print("Maximum Purchase Amount :",maximum)
print("Minimum Purchase Amount : ",minimum)
print("Q1 (25th percentile): ",q1)
print("Q3 (75th percentile):",q3)
print("Range (Max - Min):", Range)
print("Interquartile Range (IQR = Q3 - Q1):", IQR)

plt.figure(figsize = (4,3))
sns.histplot(data = df["Purchase_Amount"], kde = True, bins = 5, color
= "lightblue",edgecolor = "black")
plt.show()
```

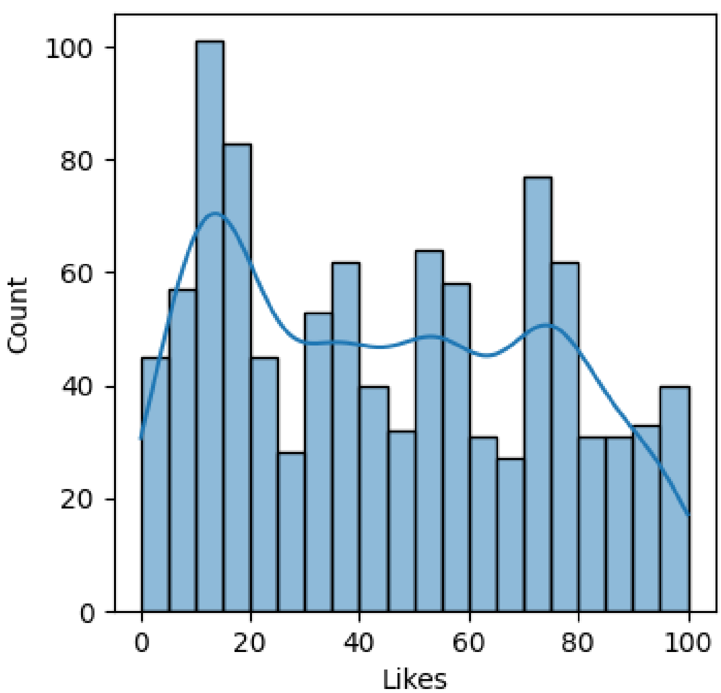
```
Maximum Purchase Amount : 19.97
Minimum Purchase Amount :  0.0
Q1 (25th percentile):  0.0
Q3 (75th percentile): 10.192499999999999
Range (Max - Min): 19.97
Interquartile Range (IQR = Q3 - Q1): 10.192499999999999
```




```python
'''
Standard Deviation (28.69):
The standard deviation indicates a moderate level of variability in
the number of likes.
Most reviews tend to receive likes that are within a range of
approximately 28.69 likes above or below the mean.
This suggests that while some reviews perform better or worse than
average, the majority of reviews have a fairly consistent level of
engagement.

Variance (822.85):
```

```
The variance, being the square of the standard deviation, quantifies
the spread of the data but in squared units.
The relatively high value confirms the presence of variability, though
it is less intuitive to interpret compared to the standard deviation.

Conclusion :
The combination of moderate standard deviation and variance highlights
that while there are variations in the number of likes received,
most reviews tend to perform within a predictable range around the
average.
'''



std = df["Likes"].std()
print("Standard deviation : ",std)
var = df["Likes"].var()
print("Variance : ",var)

plt.figure(figsize  = (4,4))
sns.histplot(data= df["Likes"], kde = True, bins = 20)
plt.show()
```

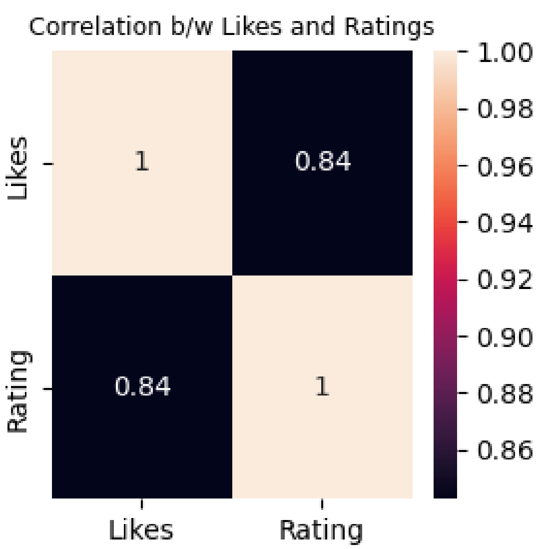
```
Standard deviation :  28.685443672334557
Variance :  822.8546786786787
```




```
'''
Interpretation of the Correlation:
```

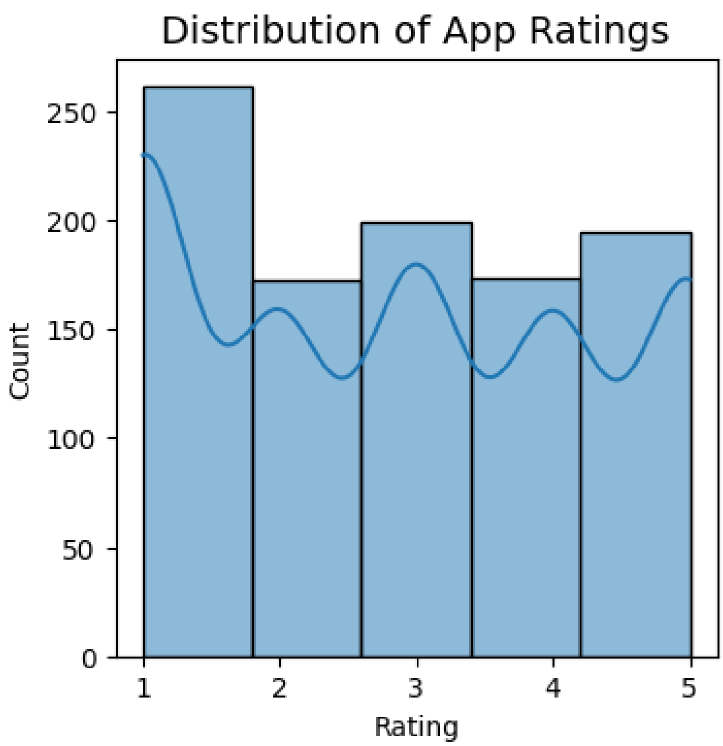
```
Value of Correlation (0.8425):

Correlation values range from -1 to 1:
+1: Perfect positive correlation.
0: No correlation.
-1: Perfect negative correlation.
A correlation of 0.8425 is close to +1, suggesting a strong positive
relationship.
What It Means:

As the rating of a review increases, the number of likes it receives
also tends to increase.
High ratings are strongly associated with high engagement (likes),
indicating that users are more likely to like reviews they perceive as
positive or useful.
'''

corr = df[["Likes","Rating"]].corr()
print("Correlation : ", corr)


plt.figure(figsize = (3,3))
sns.heatmap(data = corr, annot = True)
plt.title("Correlation b/w Likes and Ratings", fontsize = 9)
plt.show()
```

```
Correlation :             Likes    Rating
Likes   1.000000  0.842541
Rating  0.842541  1.000000
```




```
'''
A skewness value close to 0 indicates that the distribution is
```

```
approximately symmetrical.

Skewness Value: The skewness of the app ratings is 0.1018
0.1018, which is close to zero. This indicates an approximately
symmetrical distribution with a slight positive skew.

The histogram confirms this, as most ratings are clustered near the
mean with a small rightward tail.

Conclusion: The nearly symmetrical distribution suggests balanced user
satisfaction.
This indicates that the app performs moderately well in meeting user
expectations.

'''



plt.figure(figsize=(4,4))
sns.histplot(data = df["Rating"], bins = 5, kde = True, edgecolor =
"black")
plt.title("Distribution of App Ratings", fontsize=14)
plt.show()
skew = df["Rating"].skew()
print("Skewness : ",skew)
```



```
Skewness :  0.10182054838079216
```

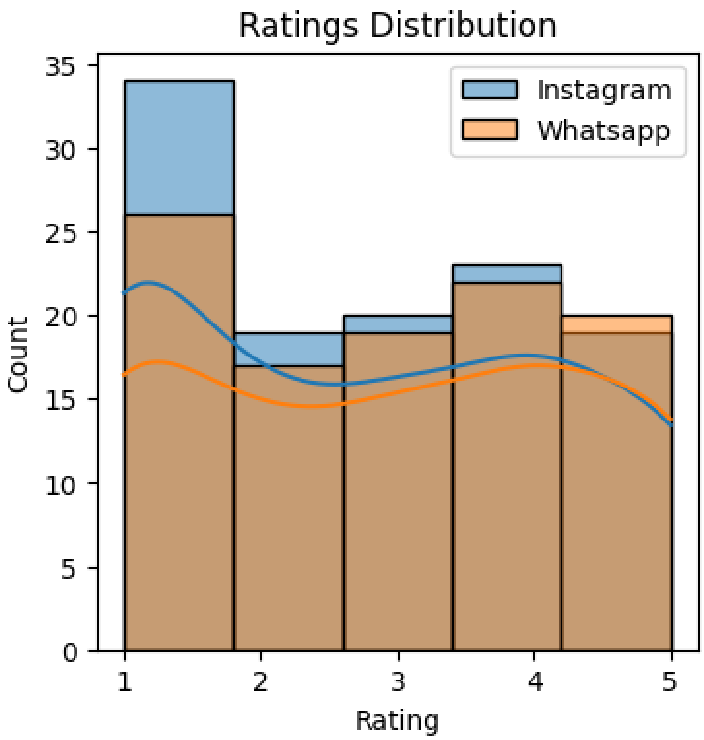
```python
#Hypothesis testing

instagram_ratings = df[df["App_Name"] == "Instagram"]["Rating"]
whatsapp_ratings = df[df["App_Name"] == "WhatsApp"]["Rating"]
instagram_ratings.describe()
```

```
count    115.000000
mean       2.773913
std        1.475299
min        1.000000
25%        1.000000
50%        3.000000
75%        4.000000
max        5.000000
Name: Rating, dtype: float64
```

```python
whatsapp_ratings.describe()
```

```
count    104.000000
mean       2.932692
std        1.469855
min        1.000000
25%        1.750000
50%        3.000000
75%        4.000000
max        5.000000
Name: Rating, dtype: float64
```

```python
# plot for ratings distribution

plt.figure(figsize = (4,4))
sns.histplot(data = instagram_ratings, bins= 5, kde= True, label =
"Instagram")
sns.histplot(data = whatsapp_ratings, bins= 5, kde= True, label =
"Whatsapp")
plt.title("Ratings Distribution")
plt.legend()
plt.show()
```

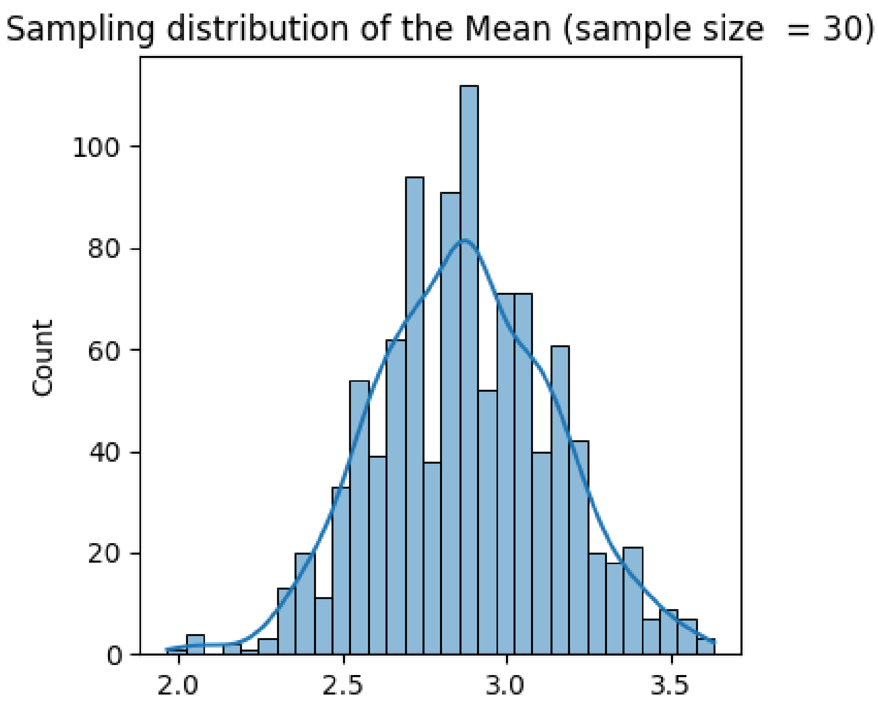



```
stat, p = levene(instagram_ratings, whatsapp_ratings)
print("Levene's Test P-Value:", p)
print("--------------------------")
t_stat, p_value = ttest_ind(instagram_ratings, whatsapp_ratings,
alternative='greater')

print("T-Statistic:", t_stat)
print("P-Value:", p_value)
```

```
Levene's Test P-Value: 0.7874164357527333
--------------------------
T-Statistic: -0.79674231444911
P-Value: 0.786764229580496
```

```
#Performing CLT

#Parameters
sample_size = 30
num_samples = 1000

# Population data = Ratings column
population = df["Rating"]

# Step -1 ; Taking randome samples and calculating their means
sample_means = []
for i in range (num_samples):
    sample = np.random.choice(population,size = sample_size, replace =
```

```
True)
    sample_means.append(np.mean(sample))

#step -2 ; Creating sampling distribution
plt.figure(figsize = (4,4))
sns.histplot(data = sample_means,bins = 30, edgecolor = "black", kde =
True)
plt.title("Sampling distribution of the Mean (sample size  = 30)",
fontsize = 12)
plt.show()

#Step - 3 ; Comparing Population mean with Sampling mean
population_mean = np.mean(population)
sampling_mean = np.mean(sample_means)
sampling_std = np.std(sample_means)

print("Population Mean:", population_mean)
print("Sampling Mean:", sampling_mean)
print("Standard Error:", sampling_std)
```




```
Population Mean: 2.869
Sampling Mean: 2.8728000000000002
Standard Error: 0.2718294890388295
```