```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

TASK 1: POPULATION & SAMPLING

```python
# Load the dataset
df = pd.read_csv('sale_data.csv')
df.head()
```

```
   Product_ID   Sale_Date Sales_Rep Region  Sales_Amount
Quantity_Sold  \
0        1052  2023-02-03       Bob  North       5053.97
18
1        1093  2023-04-21       Bob   West       4384.02
17
2        1015  2023-09-21     David  South       4631.23
30
3        1072  2023-08-24       Bob  South       2167.94
39
4        1061  2023-03-24   Charlie   East       3750.20
13

  Product_Category  Unit_Cost  Unit_Price Customer_Type  Discount  \
0        Furniture     152.75      267.22     Returning      0.09
1        Furniture    3816.39     4209.44     Returning      0.11
2             Food     261.56      371.40     Returning      0.20
3         Clothing    4330.03     4467.75           New      0.02
4      Electronics     637.37      692.71           New      0.08

  Payment_Method Sales_Channel Region_and_Sales_Rep
0           Cash        Online            North-Bob
1           Cash        Retail             West-Bob
2  Bank Transfer        Retail          South-David
3    Credit Card        Retail            South-Bob
4    Credit Card        Online         East-Charlie
```

```python
# Inspect the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Product_ID            1000 non-null   int64
```

```
 1   Sale_Date              1000 non-null   object 
 2   Sales_Rep              1000 non-null   object 
 3   Region                 1000 non-null   object 
 4   Sales_Amount           1000 non-null   float64
 5   Quantity_Sold          1000 non-null   int64  
 6   Product_Category       1000 non-null   object 
 7   Unit_Cost              1000 non-null   float64
 8   Unit_Price             1000 non-null   float64
 9   Customer_Type          1000 non-null   object 
 10  Discount               1000 non-null   float64
 11  Payment_Method         1000 non-null   object 
 12  Sales_Channel          1000 non-null   object 
 13  Region_and_Sales_Rep   1000 non-null   object 
dtypes: float64(4), int64(2), object(8)
memory usage: 109.5+ KB
```

```
df.columns
```

```
Index(['Product_ID', 'Sale_Date', 'Sales_Rep', 'Region',
'Sales_Amount',
       'Quantity_Sold', 'Product_Category', 'Unit_Cost', 'Unit_Price',
       'Customer_Type', 'Discount', 'Payment_Method', 'Sales_Channel',
       'Region_and_Sales_Rep'],
      dtype='object')
```

```
# Treat the full dataset as Population
population_df = df.copy()

# Create a Sample dataset using Simple Random Sampling
sample_size = 100
sample_df = population_df.sample(n=sample_size, random_state=42)

# Display Population size and Sample size
population_size = population_df.shape[0]
print("Population Size:", population_size)
print("Sample Size:", sample_df.shape[0])
```

```
Population Size: 1000
Sample Size: 100
```

TASK 2: SAMPLING TECHNIQUES

```
# Create Random Sample
sample_size = 100
sample_df = population_df.sample(n=sample_size, random_state=42)
print(f'Size is', sample_df.shape[0])
sample_df.head()
```

```
Size is 100
```

```
     Product_ID   Sale_Date Sales_Rep Region  Sales_Amount  
Quantity_Sold  \
521        1100  2023-05-23       Bob   West       7667.96  
29   
737        1031  2023-03-23       Eve   East        433.40  
32   
740        1003  2023-07-25       Eve   West       5617.64  
5    
660        1017  2023-12-23     Alice   East        780.27  
33   
411        1042  2023-05-26       Bob   East        848.28  
1    

    Product_Category  Unit_Cost  Unit_Price Customer_Type  Discount  \
521             Food    3559.56     3607.15     Returning      0.21   
737         Clothing    3351.33     3711.47           New      0.16   
740             Food    2206.58     2490.47           New      0.28   
660             Food    1551.25     1994.01     Returning      0.08   
411      Electronics    1406.24     1535.57           New      0.08   

    Payment_Method Sales_Channel Region_and_Sales_Rep  
521           Cash        Retail             West-Bob  
737           Cash        Retail             East-Eve  
740           Cash        Online             West-Eve  
660           Cash        Online           East-Alice  
411    Credit Card        Retail             East-Bob  
```

```python
# Create Systematic Sample (every nth record)
n = 10  # Every 10th record
systematic_sample_df = population_df.iloc[::n]
print(f'Size is', systematic_sample_df.shape[0])
systematic_sample_df.head()
```

```
Size is 100

    Product_ID   Sale_Date Sales_Rep Region  Sales_Amount  
Quantity_Sold  \
0         1052  2023-02-03       Bob  North       5053.97  
18   
10        1088  2023-11-16       Eve  North       8518.45  
13   
20        1002  2023-04-22       Eve  North       6551.23  
9    
30        1091  2023-09-04   Charlie  South        675.11  
44   
40        1062  2023-03-16     David   West       4195.06  
45   

   Product_Category  Unit_Cost  Unit_Price Customer_Type  Discount  \
0         Furniture     152.75      267.22     Returning      0.09  
```

```
10        Furniture    2440.11     2517.60           New      0.23
20      Electronics    4398.16     4439.12           New      0.18
30             Food    2085.46     2406.58     Returning      0.06
40        Furniture    4849.60     5166.72     Returning      0.25

   Payment_Method Sales_Channel Region_and_Sales_Rep
0            Cash        Online            North-Bob
10  Bank Transfer        Retail            North-Eve
20  Bank Transfer        Online            North-Eve
30  Bank Transfer        Retail        South-Charlie
40    Credit Card        Online           West-David
```

```
# Compare Mean of population and Mean of samples

# Assuming we're using 'Sales_Amount' as the numerical column for
means
population_mean = population_df['Sales_Amount'].mean()

print("Population Mean (Sales_Amount):", population_mean)
population_df['Sales_Amount'].head()
```

```
Population Mean (Sales_Amount): 5019.265229999999

0    5053.97
1    4384.02
2    4631.23
3    2167.94
4    3750.20
Name: Sales_Amount, dtype: float64
```

```
random_sample_mean = sample_df['Sales_Amount'].mean()

print("Random Sample Mean (Sales_Amount):", random_sample_mean)
sample_df['Sales_Amount'].head()
```

```
Random Sample Mean (Sales_Amount): 5073.0229

521    7667.96
737     433.40
740    5617.64
660     780.27
411     848.28
Name: Sales_Amount, dtype: float64
```

```
systematic_sample_mean = systematic_sample_df['Sales_Amount'].mean()

print("Systematic Sample Mean (Sales_Amount):",
systematic_sample_mean)
systematic_sample_df['Sales_Amount'].head()
```

```
Systematic Sample Mean (Sales_Amount): 4499.2767
```

```
0     5053.97
10    8518.45
20    6551.23
30     675.11
40    4195.06
Name: Sales_Amount, dtype: float64
```

```
# Write a short note on Difference between population and sample
results
print("Note on Difference:")
print("""The population mean represents the true average of all data
points. Sample means approximate this but may differ due to sampling
variability.
Random sampling tends to be unbiased, while systematic sampling might
introduce bias if there's a pattern every nth row. In this case, the
differences
are small, indicating good representation.""")
```

```
Note on Difference:
The population mean represents the true average of all data points.
Sample means approximate this but may differ due to sampling
variability.
Random sampling tends to be unbiased, while systematic sampling might
introduce bias if there's a pattern every nth row. In this case, the
differences
are small, indicating good representation.
```

TASK 3: CENTRAL LIMIT THEOREM (CLT)

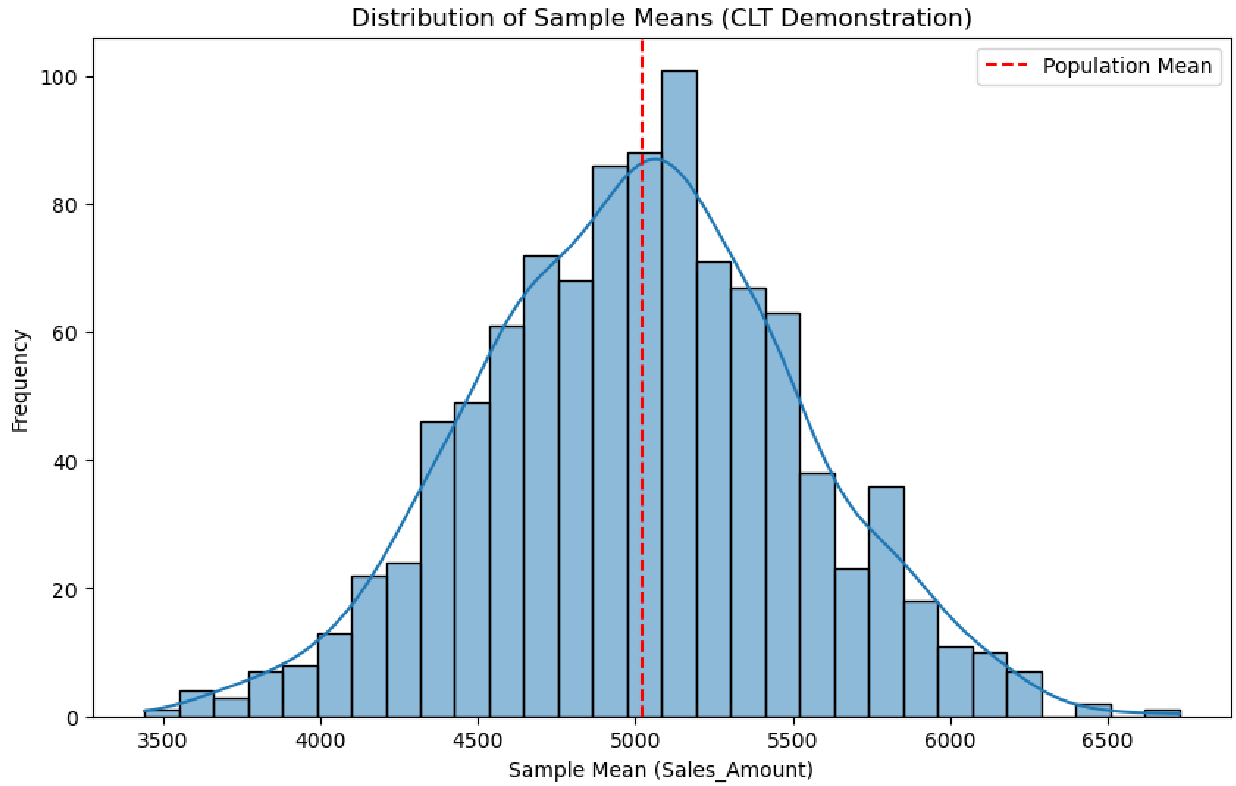
```
# Take multiple samples of size 30
num_samples = 1000  # Number of samples
sample_means = []

# Calculate the mean of each sample
for _ in range(num_samples):
    sample = population_df['Sales_Amount'].sample(n=30,
random_state=np.random.randint(10000))
    sample_means.append(sample.mean())

# Store sample means
sample_means_df = pd.DataFrame({'Sample_Mean': sample_means})

# Plot the distribution of sample means
plt.figure(figsize=(10, 6))
sns.histplot(sample_means_df['Sample_Mean'], kde=True, bins=30)
plt.title('Distribution of Sample Means (CLT Demonstration)')
plt.xlabel('Sample Mean (Sales_Amount)')
plt.ylabel('Frequency')
plt.axvline(population_mean, color='r', linestyle='--',
```

```
label='Population Mean')
plt.legend()
plt.show()
```




```
# Observe and explain
print("Observation on Distribution:")
print("""The distribution of sample means is approximately normal
(bell-shaped), centered around the population mean. This holds even if
the
original data isn't normal, as per CLT.""")

Observation on Distribution:
The distribution of sample means is approximately normal (bell-
shaped), centered around the population mean. This holds even if the
original data isn't normal, as per CLT.

print("Relation to CLT:")
print("""CLT states that for large enough sample sizes (n=30 here),
the sampling distribution of the mean approaches a normal
distribution,
regardless of the population's distribution. This enables inference
about the population from samples.""")

Relation to CLT:
CLT states that for large enough sample sizes (n=30 here), the
```

```
sampling distribution of the mean approaches a normal distribution,
regardless of the population's distribution. This enables inference
about the population from samples.
```

TASK 4: NORMAL DISTRIBUTION ANALYSIS

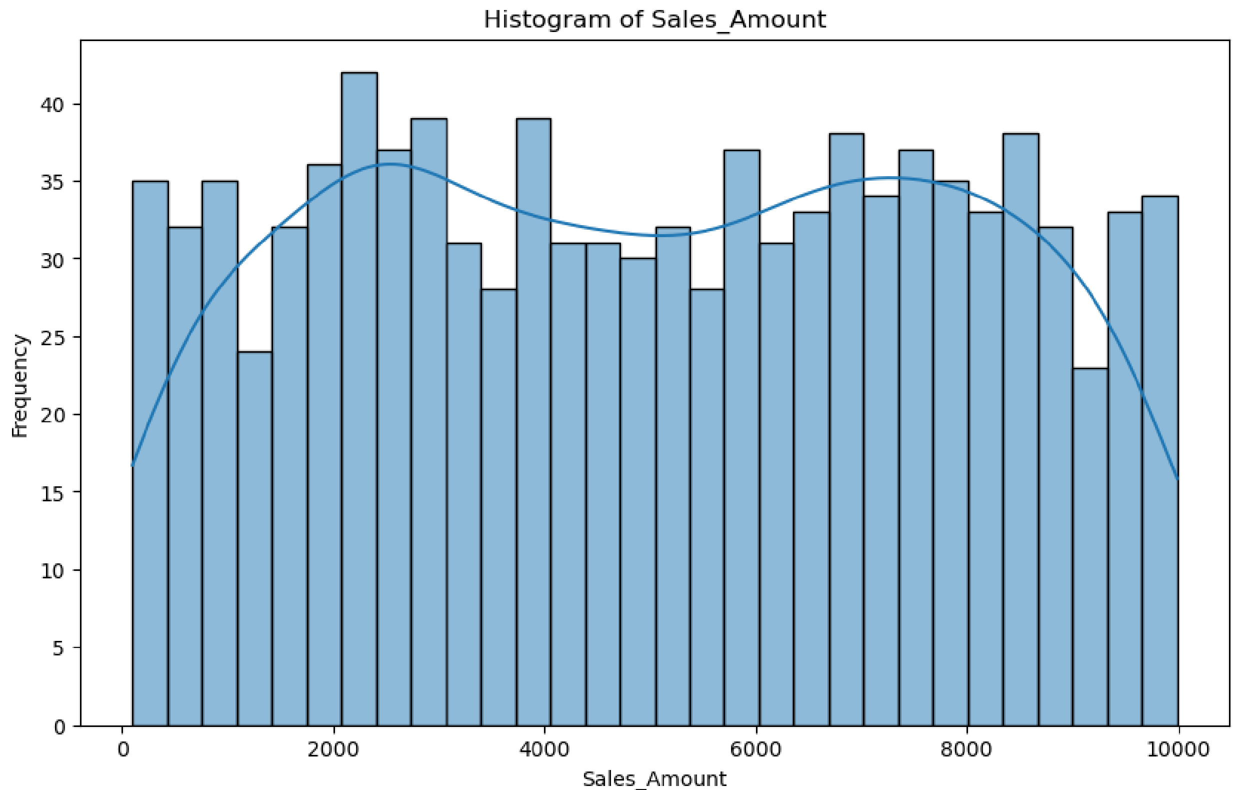
```python
# Using 'Sales_Amount' column
column = 'Sales_Amount'

# Calculate Mean and Standard Deviation
mean = population_df[column].mean()
std_dev = population_df[column].std()

print("Mean (Sales_Amount):", mean)
print("Standard Deviation (Sales_Amount):", std_dev)
```

```
Mean (Sales_Amount): 5019.265229999999
Standard Deviation (Sales_Amount): 2846.7901256682326
```

```python
# Plot Histogram of the data
plt.figure(figsize=(10, 6))
sns.histplot(population_df[column], kde=True, bins=30)
plt.title('Histogram of Sales_Amount')
plt.xlabel('Sales_Amount')
plt.ylabel('Frequency')
plt.show()
```




```
# Normality test (Shapiro-Wilk on full data since n=1000 ≤ 5000)
stat, p_value = stats.shapiro(population_df[column])
print(f"Shapiro-Wilk Test p-value: {p_value:.2e}")
print("Data does not appear normal (p-value << 0.05). The distribution
is likely uniform or close to uniform based on the range and stats.")
```

```
Shapiro-Wilk Test p-value: 5.78e-17
Data does not appear normal (p-value << 0.05). The distribution is
likely uniform or close to uniform based on the range and stats.
```

```
# 68-95-99.7 rule check
within_1sd = np.mean((population_df[column] >= mean - std_dev) &
(population_df[column] <= mean + std_dev)) * 100
within_2sd = np.mean((population_df[column] >= mean - 2*std_dev) &
(population_df[column] <= mean + 2*std_dev)) * 100
within_3sd = np.mean((population_df[column] >= mean - 3*std_dev) &
(population_df[column] <= mean + 3*std_dev)) * 100

print("68-95-99.7 Rule Results (for reference):")
print(f"Within 1 SD: {within_1sd:.2f}% (Normal expects ~68%)")
print(f"Within 2 SD: {within_2sd:.2f}% (Normal expects ~95%)")
print(f"Within 3 SD: {within_3sd:.2f}% (Normal expects ~99.7%)")
print("Deviations confirm the data is not normally distributed (closer
to uniform behavior).")
```

```
68-95-99.7 Rule Results (for reference):
Within 1 SD: 58.60% (Normal expects ~68%)
Within 2 SD: 100.00% (Normal expects ~95%)
Within 3 SD: 100.00% (Normal expects ~99.7%)
Deviations confirm the data is not normally distributed (closer to
uniform behavior).
```

TASK 5: Z-SCORE CALCULATION

```
population_df['Z_Score'] = (population_df[column] - mean) / std_dev

population_df['Outlier'] = np.where((population_df['Z_Score'].abs() >
3), 'Yes', 'No')

print("Number of Outliers (|Z| > 3):", (population_df['Outlier'] ==
'Yes').sum())
if (population_df['Outlier'] == 'Yes').sum() > 0:
    print(population_df[population_df['Outlier'] == 'Yes']
[['Product_ID', column, 'Z_Score']])
else:
    print("No extreme outliers detected.")

Number of Outliers (|Z| > 3): 0
No extreme outliers detected.
```

TASK 6: BUSINESS INSIGHTS

```
print("Business Insights:\n")

print("1. Why is sampling required in real-world data analysis?")
print("   Sampling saves time and resources when the full population
is too large to analyze. "
      "It provides reliable insights if done properly.")

print("2. How does CLT help in analytics?")
print("   CLT allows us to use normal-based statistics (like
confidence intervals) on sample means, "
      "even if the original data isn't normal, making inference
easier.")

print("3. Why is normal distribution important before hypothesis
testing?")
print("   Many tests assume normality for accurate results. If data
isn't normal, we may need transformations "
      "or non-parametric tests to avoid wrong conclusions.")

print("4. How does Z-Score help in identifying unusual values?")
```

```python
print("   Z-Score shows how far a value is from the mean in standard deviations. "
      "Values with |Z| > 3 are rare and flagged as potential outliers for review.")
```

```
Business Insights:

1. Why is sampling required in real-world data analysis?
   Sampling saves time and resources when the full population is too large to analyze. It provides reliable insights if done properly.
2. How does CLT help in analytics?
   CLT allows us to use normal-based statistics (like confidence intervals) on sample means, even if the original data isn't normal, making inference easier.
3. Why is normal distribution important before hypothesis testing?
   Many tests assume normality for accurate results. If data isn't normal, we may need transformations or non-parametric tests to avoid wrong conclusions.
4. How does Z-Score help in identifying unusual values?
   Z-Score shows how far a value is from the mean in standard deviations. Values with |Z| > 3 are rare and flagged as potential outliers for review.
```