```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
df = pd.read_csv('/content/walmart_data.txt')
df.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969

```
df.shape
```

```
(550068, 10)
```

```
df.dtypes
```

	0
User_ID	int64
Product_ID	object
Gender	object
Age	object
Occupation	int64
City_Category	object
Stay_In_Current_City_Years	object
Marital_Status	int64
Product_Category	int64
Purchase	int64

dtype: object

```
categorical_cols = ['Gender', 'Age', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_Status']
for col in categorical_cols:
    df[col] = df[col].astype('category')
```

```
df['Age'].unique()
```

```
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']
```

```
df['Marital_Status'].value_counts()
```

Marital_Status	count
0	324731
1	225337

dtype: int64

```
df['City_Category'].value_counts()
```

City_Category	count
B	231173
C	171175
A	147720

dtype: int64

```
df['Gender'].value_counts()
```

Gender	count
M	414259
F	135809

dtype: int64

```
df['Purchase'].describe()
```

	Purchase
count	550068.000000
mean	9263.968713
std	5023.065394
min	12.000000
25%	5823.000000
50%	8047.000000
75%	12054.000000
max	23961.000000

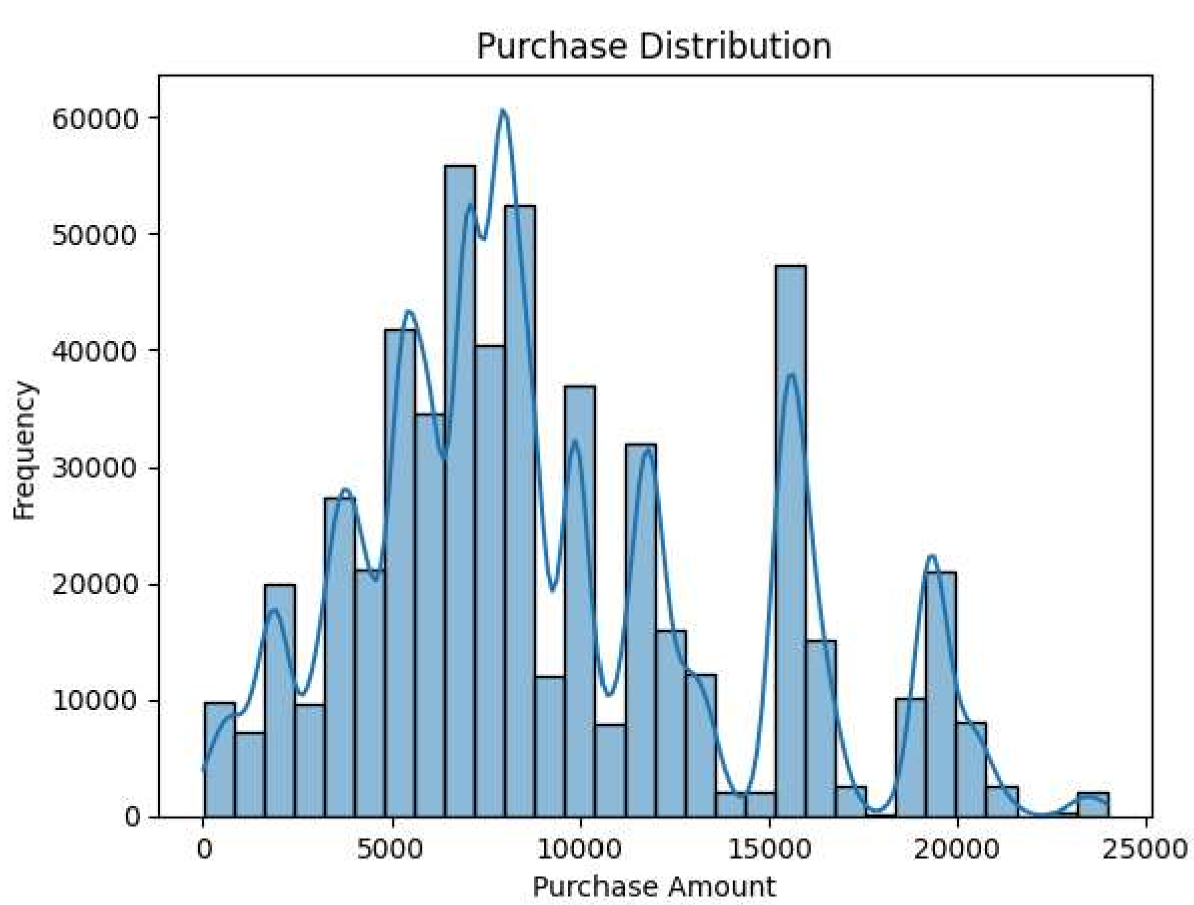
dtype: float64

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

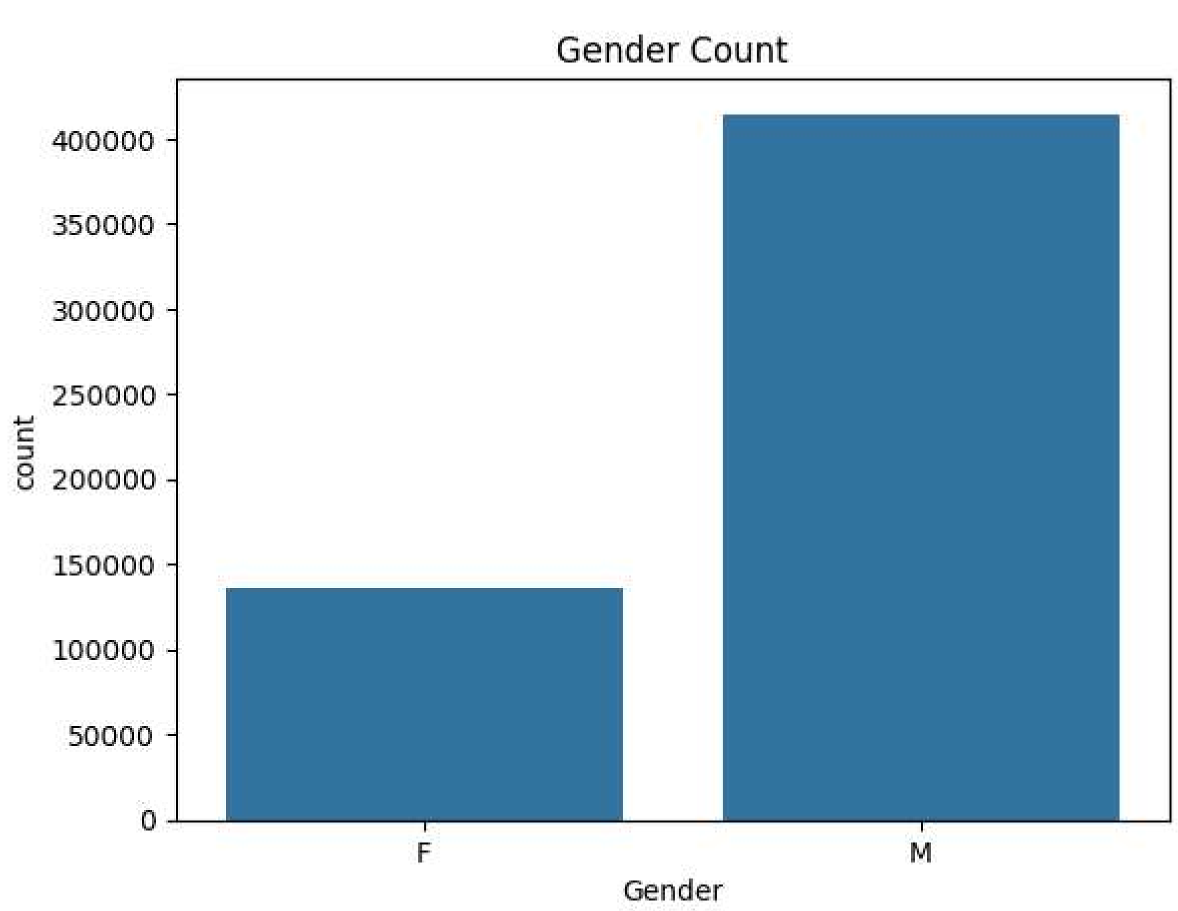
	0
User_ID	0
Product_ID	0
Gender	0
Age	0
Occupation	0
City_Category	0
Stay_In_Current_City_Years	0
Marital_Status	0
Product_Category	0
Purchase	0

dtype: int64

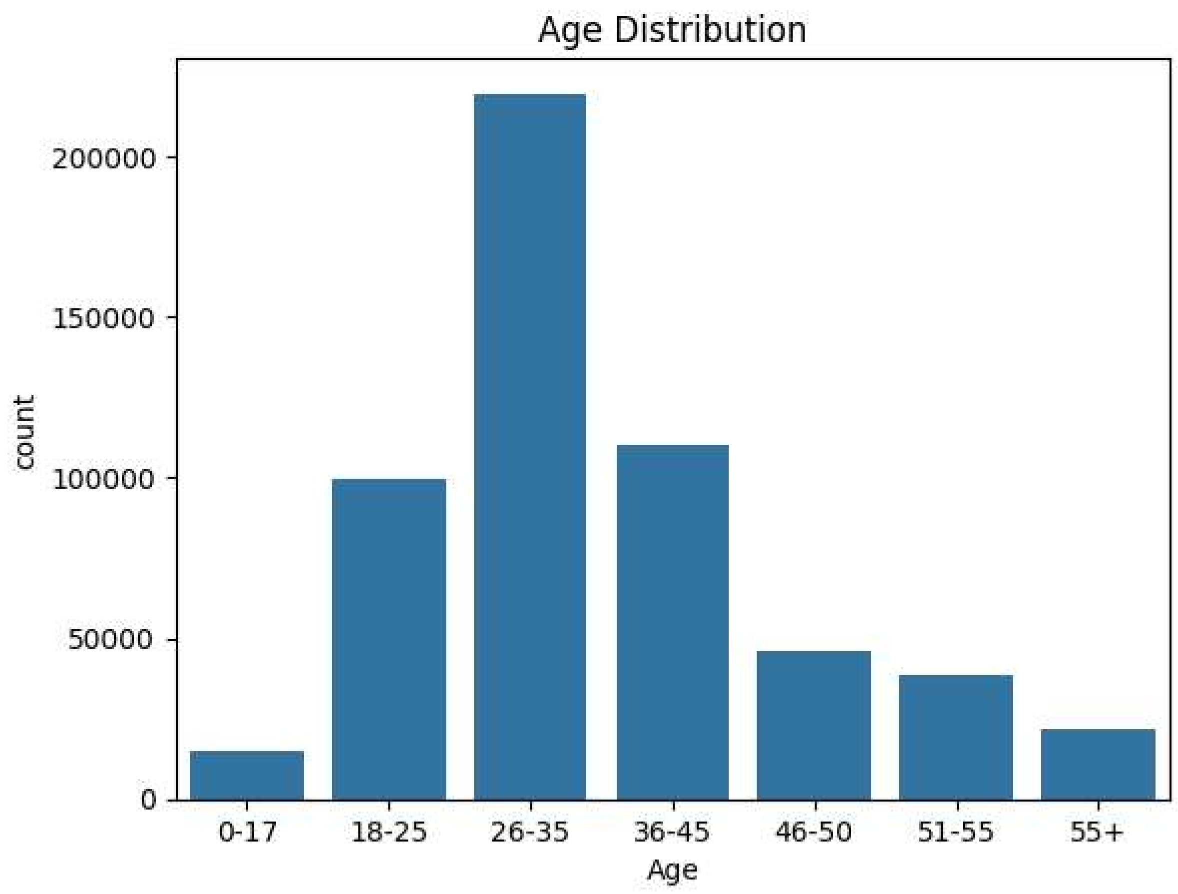
```
sns.histplot(df['Purchase'],kde = True,bins=30)
plt.title('Purchase Distribution')
plt.xlabel('Purchase Amount')
plt.ylabel('Frequency')
plt.show()
```



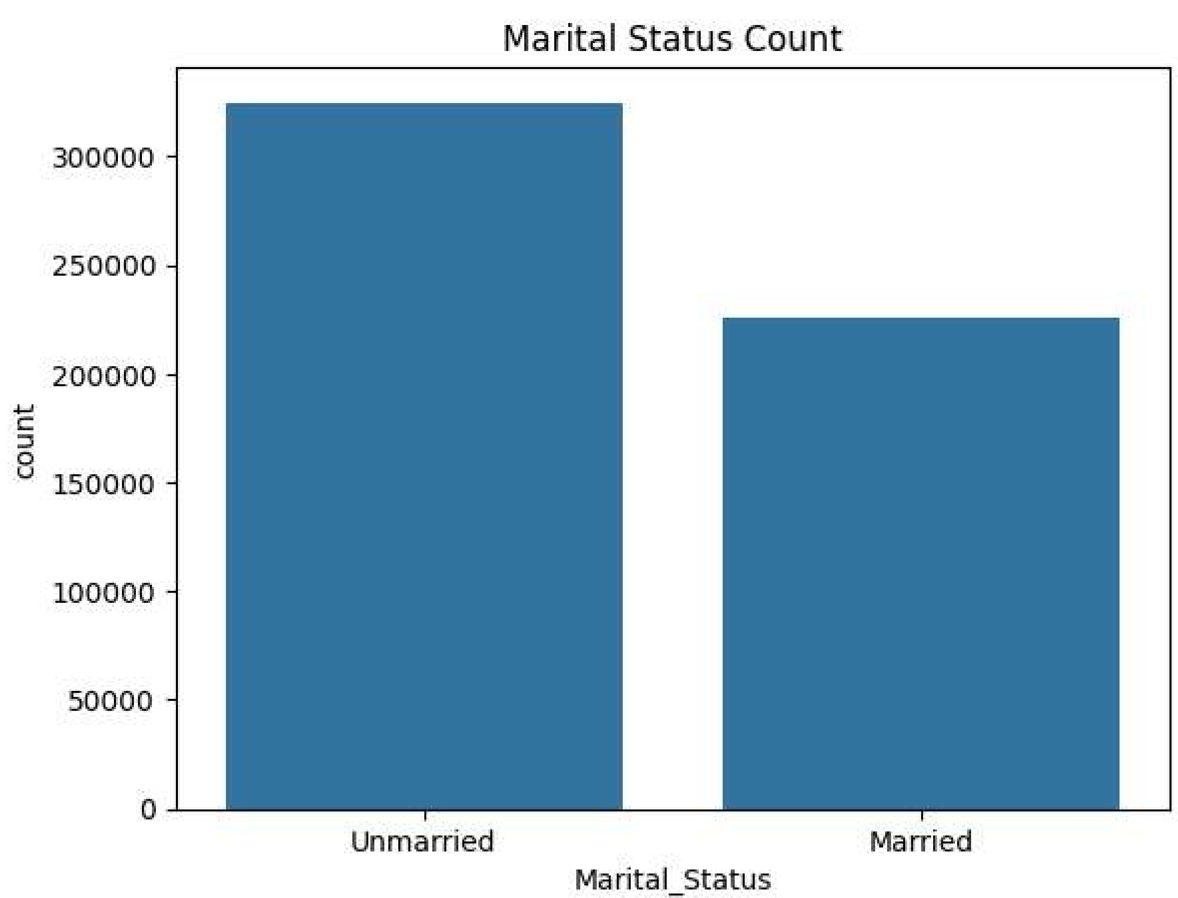

```
sns.countplot(x='Gender', data=df)
plt.title('Gender Count')
plt.show()
```



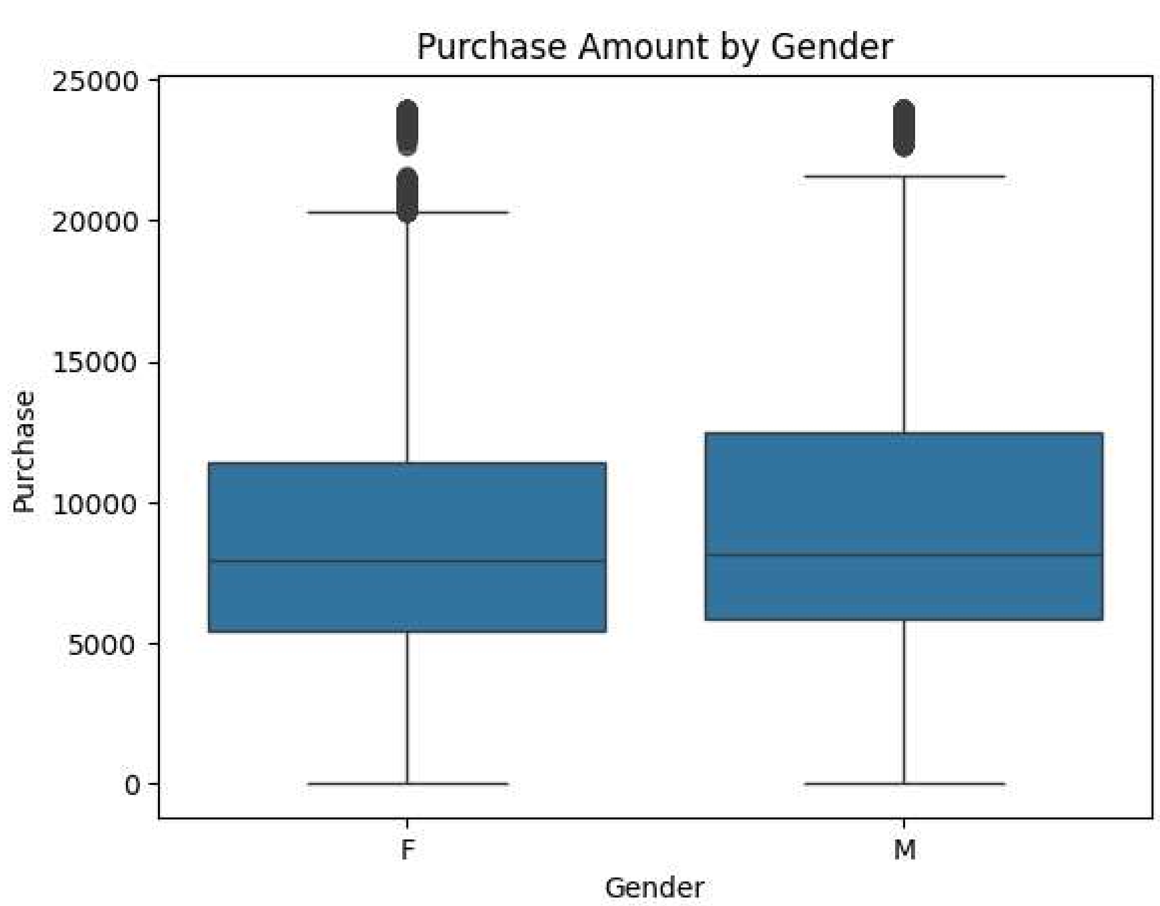

```
sns.countplot(x='Age', data=df, order=sorted(df['Age'].unique()))
plt.title('Age Distribution')
plt.show()
```



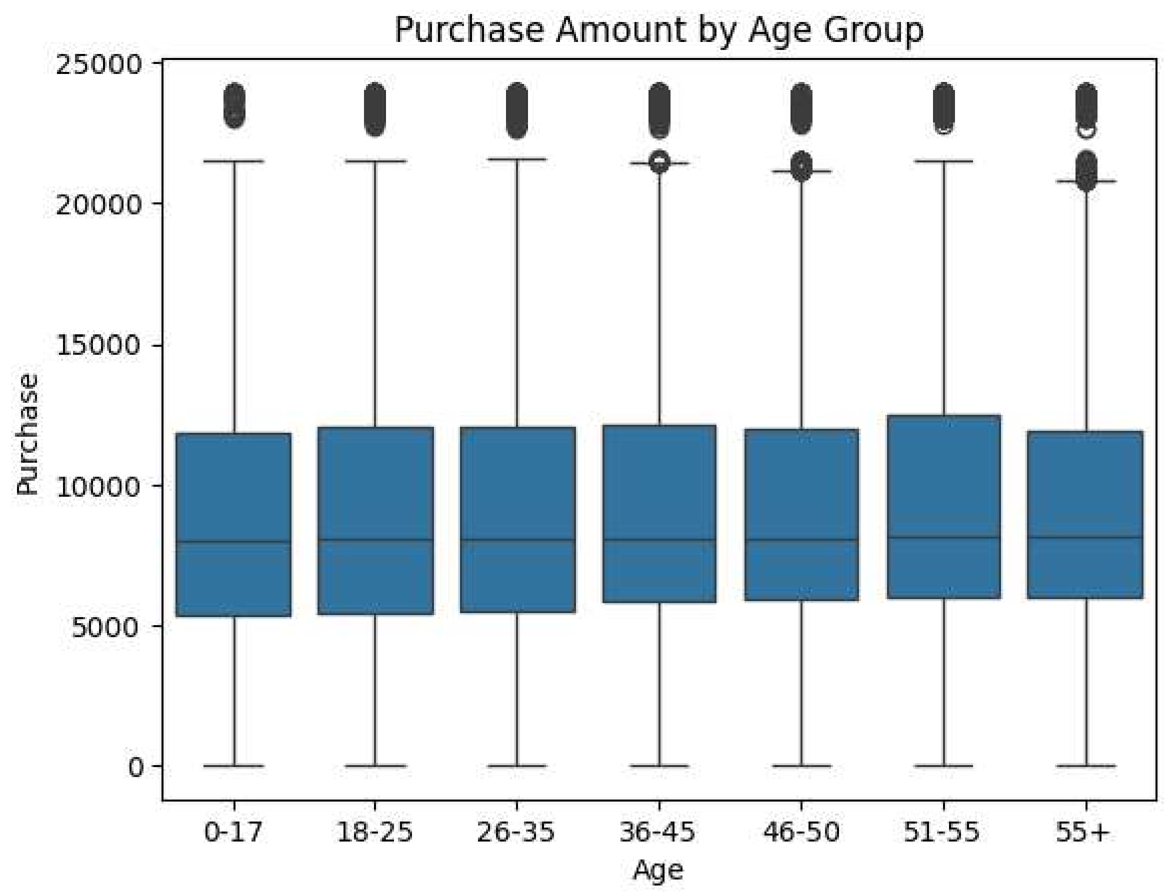

```
sns.countplot(x='Marital_Status', data=df)
plt.title('Marital Status Count')
plt.xticks([0, 1], ['Unmarried', 'Married'])
plt.show()
```



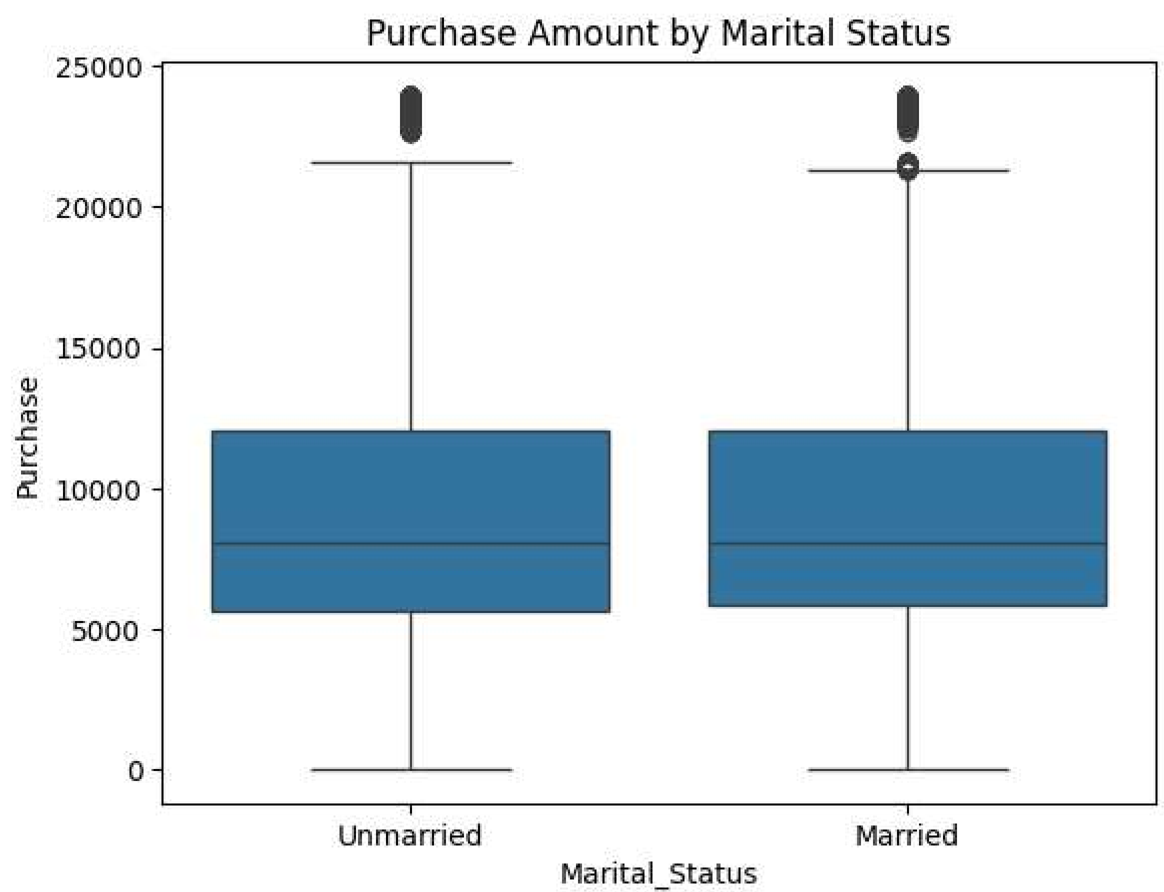

```
sns.boxplot(x='Gender', y='Purchase', data=df)
plt.title('Purchase Amount by Gender')
plt.show()
```




```
sns.boxplot(x='Age', y='Purchase', data=df, order=sorted(df['Age'].unique()))
plt.title('Purchase Amount by Age Group')
plt.show()
```




```
sns.boxplot(x='Marital_Status', y='Purchase', data=df)
plt.title('Purchase Amount by Marital Status')
plt.xticks([0, 1], ['Unmarried', 'Married'])
plt.show()
```




```
import numpy as np

# Filter by gender
female_purchases = df[df['Gender'] == 'F']['Purchase']
male_purchases = df[df['Gender'] == 'M']['Purchase']

# Random samples (adjust n later)
female_sample = female_purchases.sample(n=1000, random_state=1)
male_sample = male_purchases.sample(n=1000, random_state=1)
```

```
import scipy.stats as stats

def confidence_interval(data, confidence=0.95):
    mean = data.mean()
    std_err = stats.sem(data)  # standard error
    margin = std_err * stats.t.ppf((1 + confidence) / 2., len(data) - 1)
    return mean, (mean - margin, mean + margin)
```

```
female_mean, female_ci = confidence_interval(female_sample, confidence=0.95)
male_mean, male_ci = confidence_interval(male_sample, confidence=0.95)

print(f"Female Avg: ₹{female_mean:.2f}, 95% CI: {female_ci}")
print(f"Male Avg: ₹{male_mean:.2f}, 95% CI: {male_ci}")
```

```
Female Avg: ₹8935.67, 95% CI: (np.float64(8634.688107142785), np.float64(9236.655892857216))
Male Avg: ₹9506.05, 95% CI: (np.float64(9190.017274719046), np.float64(9822.072725280954))
```

```
#married vs unmarried
married = df[df['Marital_Status'] == 1]['Purchase']
unmarried = df[df['Marital_Status'] == 0]['Purchase']
```

```
sample_married = married.sample(n=1000, random_state=42)
sample_unmarried = unmarried.sample(n=1000, random_state=42)
```

```
married_mean, married_ci = confidence_interval(sample_married, confidence=0.95)
unmarried_mean, unmarried_ci = confidence_interval(sample_unmarried, confidence=0.95)

print(f"Married Avg: ₹{married_mean:.2f}, 95% CI: {married_ci}")
print(f"Unmarried Avg: ₹{unmarried_mean:.2f}, 95% CI: {unmarried_ci}")
```

```
Married Avg: ₹9142.70, 95% CI: (np.float64(8830.967685363708), np.float64(9454.426314636292))
Unmarried Avg: ₹9388.18, 95% CI: (np.float64(9075.420653796173), np.float64(9700.939346203828))
```

```
# Age
```

```
age_results = {}

for age_group in df['Age'].cat.categories:
    group_data = df[df['Age'] == age_group]['Purchase']
    sample = group_data.sample(n=1000, random_state=42)
    mean, ci = confidence_interval(sample)
    age_results[age_group] = {'Mean': mean, 'CI': ci}
```

```
for age, stats in age_results.items():
    print(f"{age}: Avg = ₹{stats['Mean']:.2f}, CI = {stats['CI']}")
```

```
0-17: Avg = ₹8791.89, CI = (np.float64(8462.271535328842), np.float64(9121.510464671157))
18-25: Avg = ₹9311.40, CI = (np.float64(8990.95031010509), np.float64(9631.84168989491))
26-35: Avg = ₹9003.25, CI = (np.float64(8689.999136436514), np.float64(9316.492863563484))
36-45: Avg = ₹9584.51, CI = (np.float64(9276.549964694934), np.float64(9892.464035305065))
46-50: Avg = ₹9348.86, CI = (np.float64(9041.923462502853), np.float64(9655.806537497147))
51-55: Avg = ₹9351.78, CI = (np.float64(9036.258477817235), np.float64(9667.297522182766))
55+: Avg = ₹9383.91, CI = (np.float64(9070.378358206763), np.float64(9697.443641793237))
```

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Final Insights

✅ Gender-Based

- Males spend more on average than females, and their confidence intervals do not overlap, indicating a statistically significant difference.
- This suggests that marketing high-value items toward men during Black Friday could boost revenue.

✅ Marital Status

- Although unmarried customers spent slightly more on average, their confidence intervals do overlap with married customers.
- Spending habits are statistically similar—Walmart should consider lifestyle-based targeting rather than relationship status.

✅ Age-Based

- Customers aged 36–45 spend the most per transaction, and their upper CI edges close to ₹9900.
- Under-18 customers spend the least, with a CI that doesn't overlap much with other groups—this is a clear behavioral split.

Double-click (or enter) to edit

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Actionable Recommendations for Walmart :

Segment & Target by Age Group ▶

- 36–45: Offer premium product bundles and exclusive loyalty perks.
- 18–25: Use digital-first campaigns (social media, app notifications) for gadgets and fashion deals.
- 0–17: Design "gift for kids" bundles marketed to parents.

Optimize for Gender Behavior ▶

- Males lean toward higher-value purchases—feature high-ticket electronics or tools more prominently.
- Females could be encouraged via bundled savings offers or loyalty incentives.

Rethink Marital Segmentation ▶

- Since spending behavior isn't significantly different, segment more meaningfully by life-stage or product interest.

Personalize Marketing ▶

- Use historical purchasing and demographic data to generate custom Black Friday deals per user segment.
- Leverage Walmart's e-commerce + in-store omnichannel power to push recommendations.

Visual Dashboard ▶

- Build a live dashboard in Power BI or Excel showing average purchase amounts by demographic—empowering real-time decision-making during campaigns.

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Executive Summary

Walmart's Black Friday transactional data was analyzed to explore customer spending behavior across gender, marital status, and age groups. Through statistical sampling and confidence interval estimation, we discovered that:

- Men spend more per transaction than women, with non-overlapping confidence intervals, making the difference statistically meaningful.
- Marital status does not significantly affect spending, suggesting lifestyle segmentation may be more actionable than relationship status.
- Customers aged 36–45 emerge as the highest spenders, while 0–17 age group consistently lags in transaction size. These insights were backed by exploratory data analysis, CLT-driven confidence intervals, and clear visual evidence.

Walmart can leverage this to create hyper-targeted promotions, optimize product placement, and align digital campaigns with customer life stages.

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