# Day32_Descriptive_Stats_Project

June 30, 2025

## 1 Agenda

In this project, we will perform Descriptive Statistical Analysis on a Household Income-Expense dataset. We will:

1. Import and understand the dataset
2. Perform basic descriptive statistics (mean, median, mode, std, var, IQR)
3. Visualize categorical and numerical data
4. Identify insights using group-by and correlation
5. Apply real-world use case: Coefficient of Variation for stock investment comparison

## 2 Import Required Libraries

We use: - `pandas` and `numpy` for data manipulation - `matplotlib` and `seaborn` for visualization - `scipy.stats` for skewness and kurtosis

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import skew, kurtosis
```

## 3 Load and Explore Dataset

This gives a quick preview of the dataset to understand the columns and values.

[3]:
```
# Load the CSV file
income_df=pd.read_csv("D:/Assignment Practice/M2/27 May/27 May/26th, 27th  -␣
 ↪Intro to Stats, Descriptive Stats/PROJECT/Inc_Exp_Data.csv")
# Display first 5 rows
income_df.head()
```

[3]:

| | Mthly_HH_Income | Mthly_HH_Expense | No_of_Fly_Members | Emi_or_Rent_Amt | \ |
|---|---|---|---|---|---|
| 0 | 5000 | 8000 | 3 | 2000 | |
| 1 | 6000 | 7000 | 2 | 3000 | |
| 2 | 10000 | 4500 | 2 | 0 | |
| 3 | 10000 | 2000 | 1 | 0 | |
| 4 | 12500 | 12000 | 2 | 3000 | |

| | Annual_HH_Income | Highest_Qualified_Member | No_of_Earning_Members |
|---|---|---|---|
| 0 | 64200 | Under-Graduate | 1 |
| 1 | 79920 | Illiterate | 1 |
| 2 | 112800 | Under-Graduate | 1 |
| 3 | 97200 | Illiterate | 1 |
| 4 | 147000 | Graduate | 1 |

## 4 Dataset Overview

`.info()` tells us about column names, data types, and missing values.
`.shape` gives number of rows and columns.

[4]:
```
# Check structure and types
income_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 7 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Mthly_HH_Income          50 non-null     int64
 1   Mthly_HH_Expense         50 non-null     int64
 2   No_of_Fly_Members        50 non-null     int64
 3   Emi_or_Rent_Amt          50 non-null     int64
 4   Annual_HH_Income         50 non-null     int64
 5   Highest_Qualified_Member 50 non-null     object
 6   No_of_Earning_Members    50 non-null     int64
dtypes: int64(6), object(1)
memory usage: 2.9+ KB
```

[5]:
```
# Check dimensions
income_df.shape
```

[5]: (50, 7)

## 5 Summary Statistics

This provides summary stats like count, mean, std, min, max, and quartiles for numerical columns.

[6]:
```
# Basic descriptive statistics
income_df.describe()
```

[6]:

| | Mthly_HH_Income | Mthly_HH_Expense | No_of_Fly_Members | Emi_or_Rent_Amt | \ |
|---|---|---|---|---|---|
| count | 50.000000 | 50.000000 | 50.000000 | 50.000000 | |
| mean | 41558.000000 | 18818.000000 | 4.060000 | 3060.000000 | |
| std | 26097.908979 | 12090.216824 | 1.517382 | 6241.434948 | |

```
min        5000.000000       2000.000000           1.000000          0.000000
25%       23550.000000      10000.000000           3.000000          0.000000
50%       35000.000000      15500.000000           4.000000          0.000000
75%       50375.000000      25000.000000           5.000000       3500.000000
max      100000.000000      50000.000000           7.000000      35000.000000
```

```
       Annual_HH_Income  No_of_Earning_Members
count      5.000000e+01              50.000000
mean       4.900190e+05               1.460000
std        3.201358e+05               0.734291
min        6.420000e+04               1.000000
25%        2.587500e+05               1.000000
50%        4.474200e+05               1.000000
75%        5.947200e+05               2.000000
max        1.404000e+06               4.000000
```

## 6 Check for Null Values

To ensure there are no missing values before performing analysis.

[7]:
```
income_df.isnull().sum()
```

[7]:
```
Mthly_HH_Income             0
Mthly_HH_Expense            0
No_of_Fly_Members           0
Emi_or_Rent_Amt             0
Annual_HH_Income            0
Highest_Qualified_Member    0
No_of_Earning_Members       0
dtype: int64
```

## 7 Measures of Central Tendency

Mean shows average, median shows middle value, and mode shows the most frequent value.

### 7.1 Mean of Monthly Household Expense

[9]:
```
mean_expense = income_df["Mthly_HH_Expense"].mean()
print(f"Mean Monthly Household Expense: {mean_expense:,.2f}")
```

```
Mean Monthly Household Expense: 18,818.00
```

### 7.2 Median of Monthly Household Expense

[10]:
```
median_expense = income_df["Mthly_HH_Expense"].median()
print(f"Median Monthly Household Expense: {median_expense}")
```

```
Median Monthly Household Expense: 15500.0
```

## 8 Mode (most frequent expense)

[11]:
```
mode_expense = income_df["Mthly_HH_Expense"].mode()[0]
print(f"Most Frequent Monthly Expense: {mode_expense}")
```

```
Most Frequent Monthly Expense: 25000
```

## 9 Most Common Expense Value

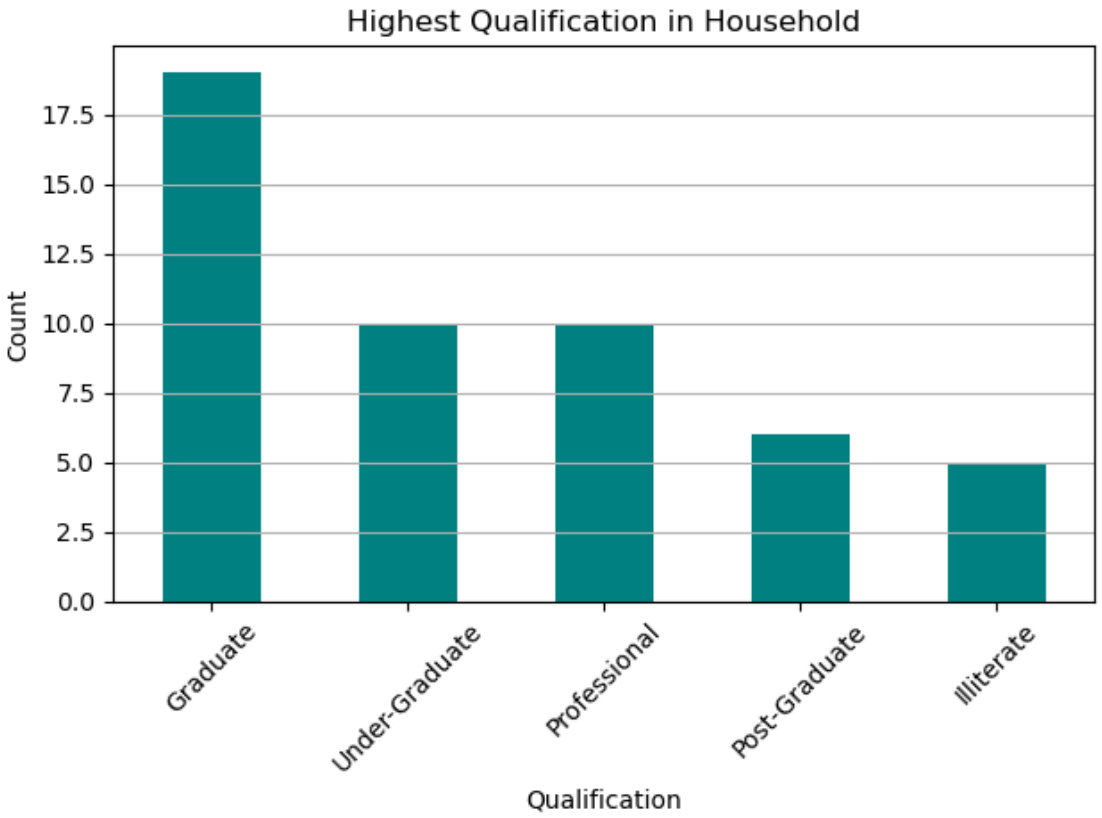
[12]:
```
most_common = income_df["Mthly_HH_Expense"].value_counts().idxmax()
print(f"The most common expense is: {most_common}")
```

```
The most common expense is: 25000
```

## 10 Visualize Categorical Variable

### 10.1 Highest Qualified Member

[13]:
```
income_df["Highest_Qualified_Member"].value_counts().plot(kind="bar",␣
 ↪color='teal')
plt.title("Highest Qualification in Household")
plt.xlabel("Qualification")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```




## 11 Interquartile Range (IQR)

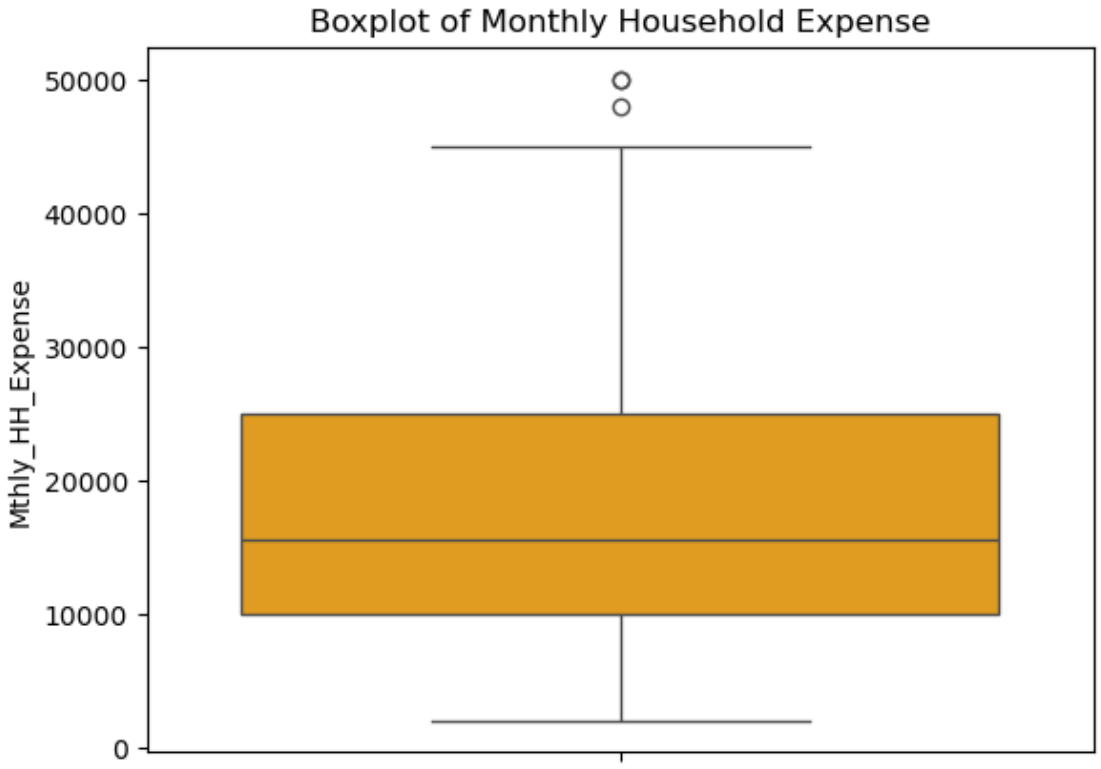
IQR helps us understand the spread of middle 50% data and detect outliers.

[24]:
```
Q1 = income_df["Mthly_HH_Expense"].quantile(0.25)
Q3 = income_df["Mthly_HH_Expense"].quantile(0.75)
IQR = Q3 - Q1
print("Q1 :",Q1)
print("Q3 :",Q3)
print(f"IQR for Monthly Household Expense: {IQR}")
```

```
Q1 : 10000.0
Q3 : 25000.0
IQR for Monthly Household Expense: 15000.0
```

## 12 Boxplot for Outliers

[15]:
```
sns.boxplot(y=income_df["Mthly_HH_Expense"], color='orange')
plt.title("Boxplot of Monthly Household Expense")
plt.show()
```




## 13 Standard Deviation and Variance

[16]:
```
# Std Dev for first 4 numeric columns
std_df = income_df.iloc[:, 0:4].std()
print("Standard Deviation:\n", std_df)
```

```
Standard Deviation:
 Mthly_HH_Income      26097.908979
Mthly_HH_Expense     12090.216824
No_of_Fly_Members        1.517382
Emi_or_Rent_Amt       6241.434948
dtype: float64
```

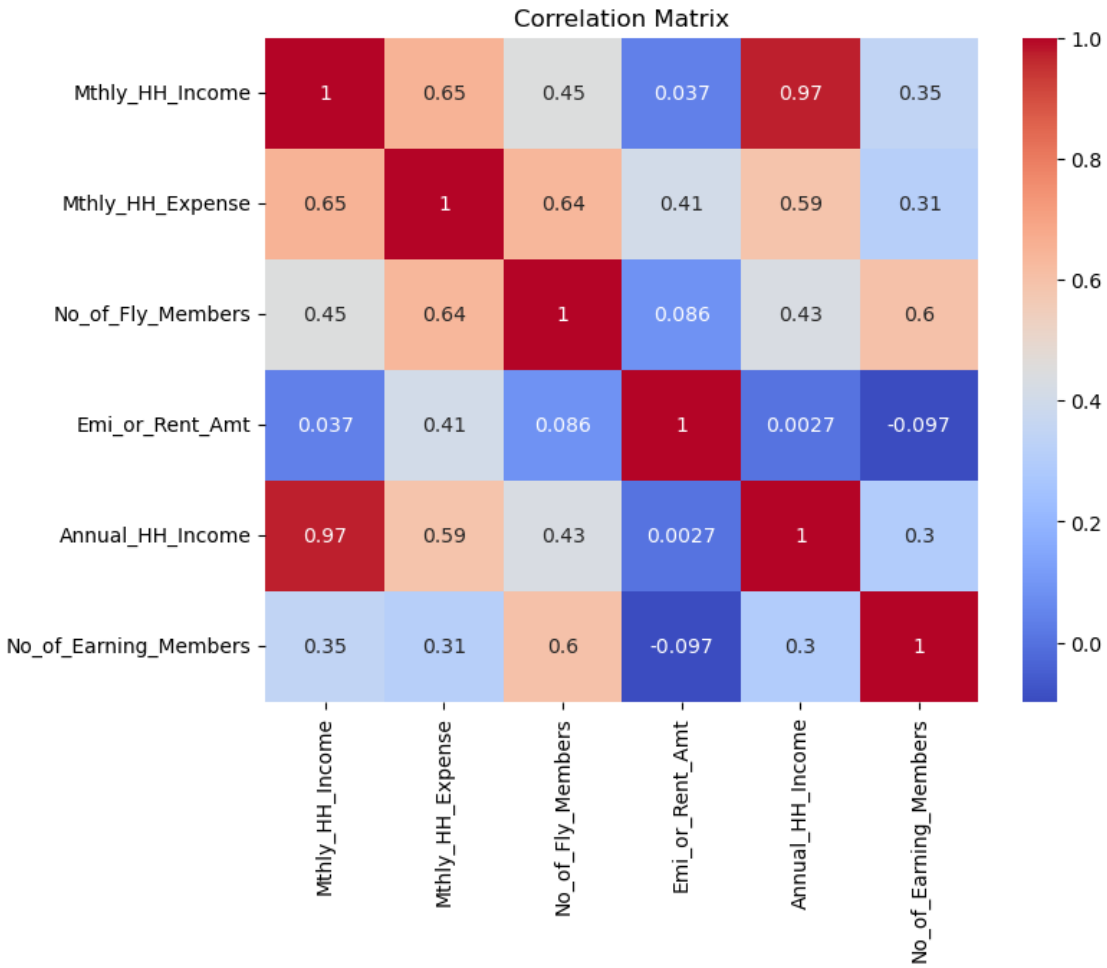
[23]:
```
# Variance for first 4 numeric columns
var_df = income_df.iloc[:, 0:4].var()
print("\nVariance:\n",var_df )
```

```
Variance:
 Mthly_HH_Income       6.811009e+08
Mthly_HH_Expense      1.461733e+08
No_of_Fly_Members     2.302449e+00
Emi_or_Rent_Amt       3.895551e+07
dtype: float64
```

## 14 Correlation Matrix

This shows how strongly variables are related.
e.g., income and expense might have a positive correlation.

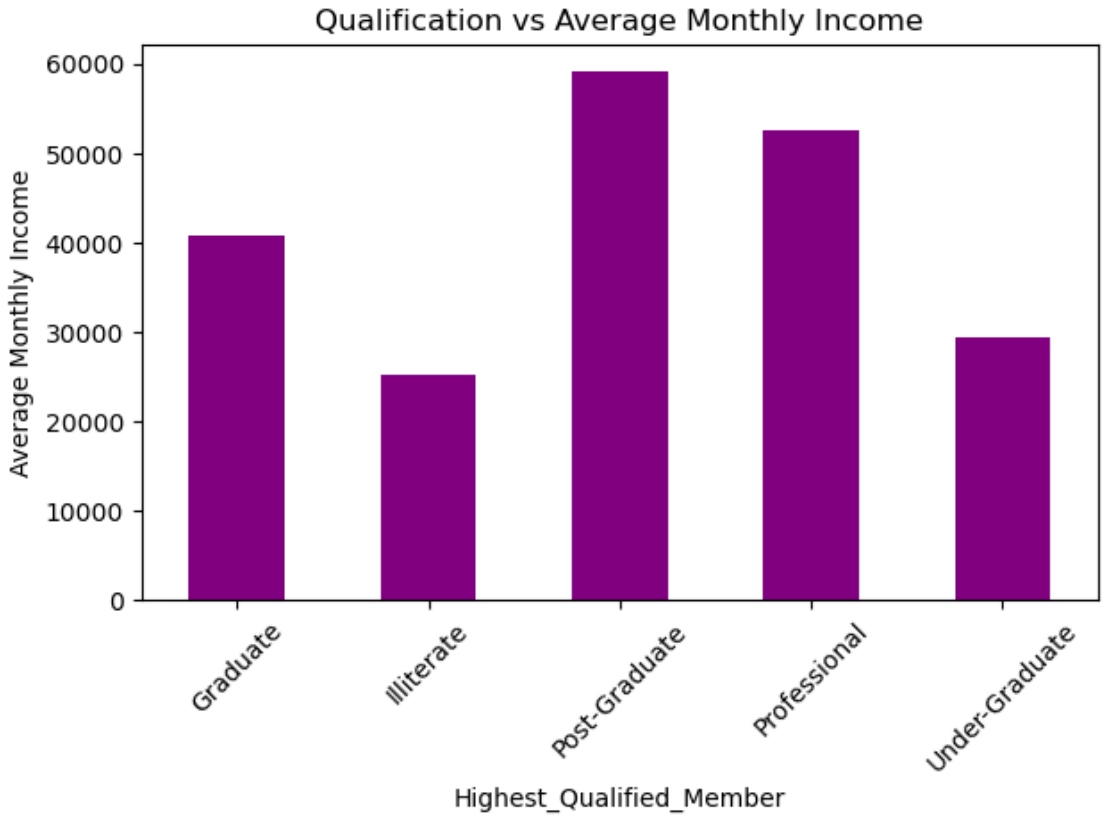
[19]:
```
plt.figure(figsize=(8, 6))
sns.heatmap(income_df.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
```



## 15 Group Analysis – Qualification vs Income

Group-by helps analyze how income varies with education level.

[20]:
```
income_df.groupby("Highest_Qualified_Member")["Mthly_HH_Income"].mean().
↪plot(kind="bar", color='purple')
plt.ylabel("Average Monthly Income")
plt.title("Qualification vs Average Monthly Income")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```




## 16 Skewness and Kurtosis

- Skewness tells if data is symmetric (0 = perfect)
- Kurtosis tells if data has heavy/light tails compared to normal distribution

[21]:
```
print("Skewness of Monthly Expense:", skew(income_df["Mthly_HH_Expense"]))
print("Kurtosis of Monthly Expense:", kurtosis(income_df["Mthly_HH_Expense"]))
```

```
Skewness of Monthly Expense: 1.1631728469608633
```

```
Kurtosis of Monthly Expense: 0.7331960636897663
```

## 17 Coefficient of Variation (Real-life stock example)

Lower Coefficient of Variation (CV) is better.
Stock B is more stable (CV = 0.5) than Stock A (CV = 0.67), so it's a better investment.

[22]:
```python
# Coefficient of variation = std / mean
std_A, mean_A = 10, 15
std_B, mean_B = 5, 10

cv_A = std_A / mean_A
cv_B = std_B / mean_B

print(f"Stock A CV: {cv_A:.2f}")
print(f"Stock B CV: {cv_B:.2f}")
```

```
Stock A CV: 0.67
Stock B CV: 0.50
```

## 18 Conclusion:

- The average monthly household expense is around 18,818.
- Most households have 1 earning member and qualification affects income.
- Monthly expenses are slightly skewed and have visible outliers.
- Stock B is less risky and more efficient based on CV.

This analysis used core descriptive statistics techniques, suitable for understanding household patterns and making informed decisions.