CODES ALONG WITH THE PLOTS

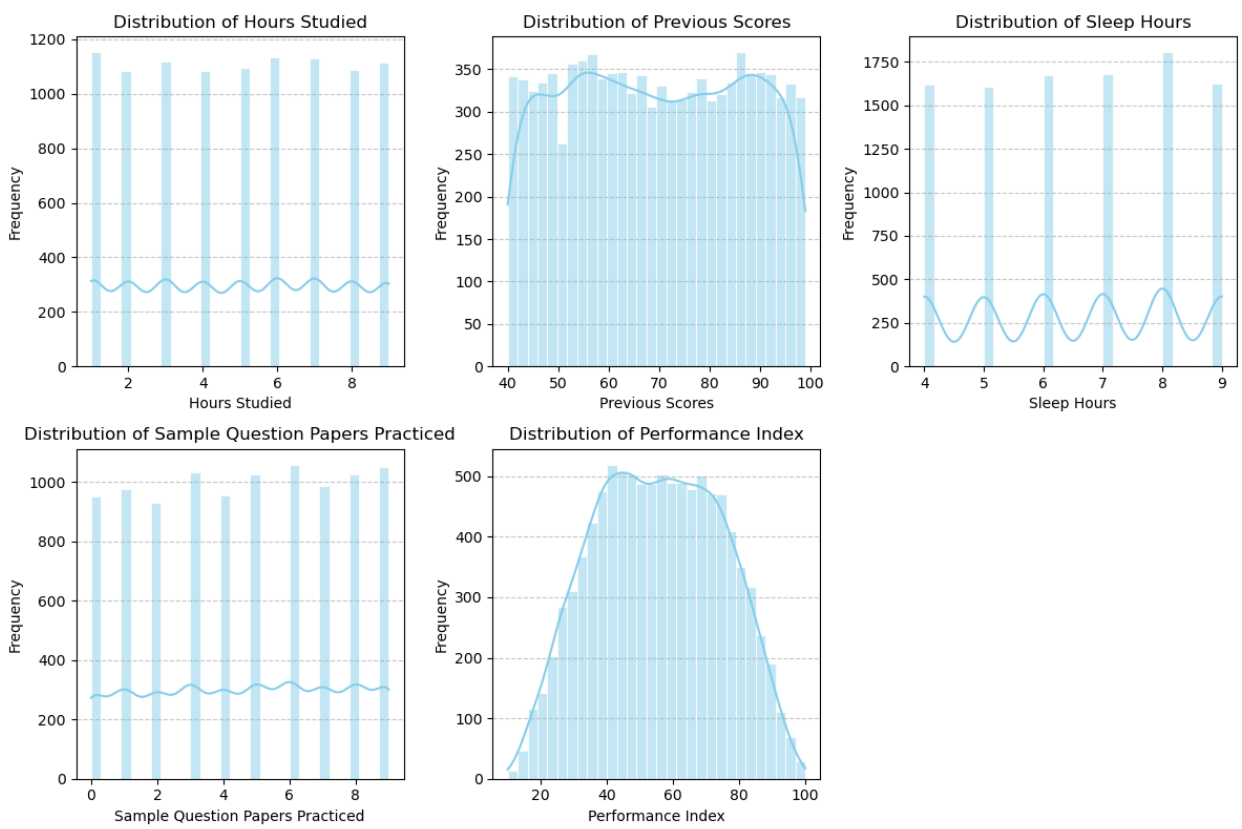
```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

import warnings
warnings.filterwarnings("ignore")
#to ignore unnecessary warnings


df=pd.read_excel("stud.xlsx")

df.describe() #a brief summary of the dataset
```

```
       Hours Studied  Previous Scores   Sleep Hours  \
count   10000.000000     10000.000000  10000.000000
mean        4.992900        69.445700      6.530600
std         2.589309        17.343152      1.695863
min         1.000000        40.000000      4.000000
25%         3.000000        54.000000      5.000000
50%         5.000000        69.000000      7.000000
75%         7.000000        85.000000      8.000000
max         9.000000        99.000000      9.000000

       Sample Question Papers Practiced  Performance Index
count                      10000.000000       10000.000000
mean                           4.583300          55.224800
std                            2.867348          19.212558
min                            0.000000          10.000000
25%                            2.000000          40.000000
50%                            5.000000          55.000000
75%                            7.000000          71.000000
max                            9.000000         100.000000
```

HISTOGRAM

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

numeric_columns = df.select_dtypes(include=['number']).columns
plt.figure(figsize=(12, 8))

# Looping through numeric columns and creating histograms with the kde
line
```

```
for i, col in enumerate(numeric_columns, 1):
    plt.subplot(2, 3, i)  # Adjust grid size if more columns exist
    sns.histplot(df[col], kde=True, bins=30, color="skyblue",
edgecolor="white")
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel("Frequency")
    plt.grid(axis="y", linestyle="--", alpha=0.7)

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



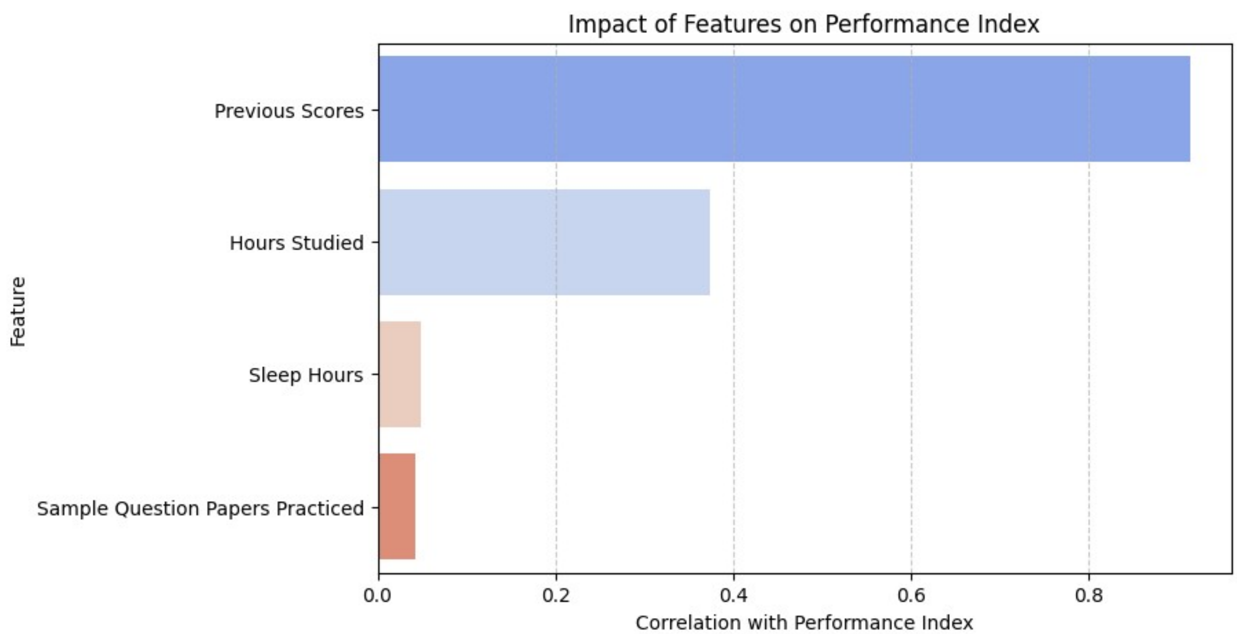
->Final Key Takeaways From the above histograms: 1) Balanced study hours 6-8 hours of sleep = Best performance 2) Practicing more sample papers can boost scores 3) If sleep hours are too low, cognitive performance may drop 4) If performance index is low despite high study hours, focus on quality over quantity

CORRELATION BARGRAPH

```
# Selected the numerical columns
numerical_columns = ["Hours Studied", "Previous Scores", "Sleep
Hours", "Sample Question Papers Practiced", "Performance Index"]
correlation_values = df[numerical_columns].corr()["Performance
Index"].drop("Performance Index")
```

```python
# Sorting it is descending order to get the one with highest
correlation
correlation_values = correlation_values.sort_values(ascending=False)
print("Correlation of each factor with Performance Index:\n")
print(correlation_values)

# Plotting the bar chart for visual representation
plt.figure(figsize=(8, 5))
sns.barplot(x=correlation_values.values, y=correlation_values.index,
palette="coolwarm")
plt.xlabel("Correlation with Performance Index")
plt.ylabel("Feature")
plt.title("Impact of Features on Performance Index")
plt.grid(axis="x", linestyle="--", alpha=0.7)
plt.show()
```

```
Correlation of each factor with Performance Index:

Previous Scores                     0.915189
Hours Studied                       0.373730
Sleep Hours                         0.048106
Sample Question Papers Practiced    0.043268
Name: Performance Index, dtype: float64
```



Feature : Correlation with Performance Index Hours Studied : Strong Positive (High) Previous Scores : Strong Positive (High) Sample Question Papers Practiced : Moderate Positive Sleep Hours : Weak Correlation (Almost None)

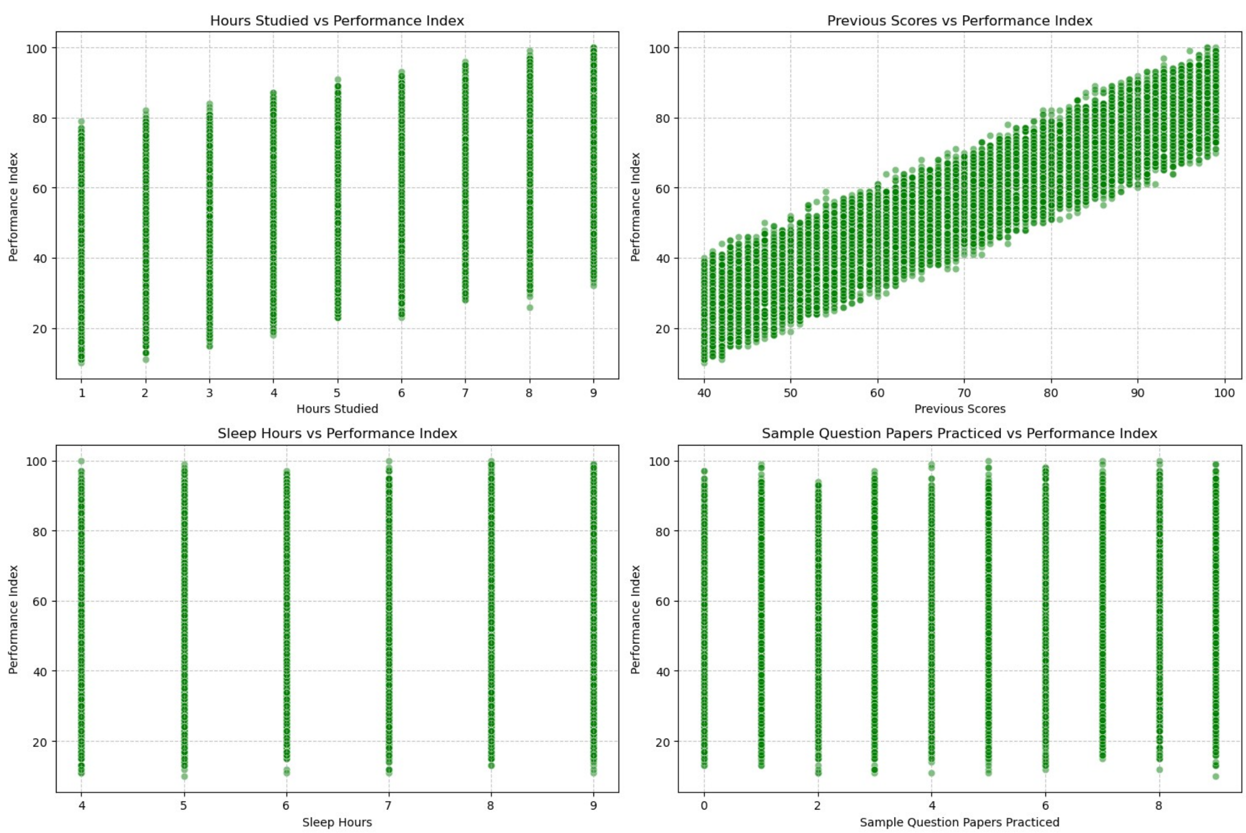
HEATMAP FOR THE CORRELATION

```
# Select numerical columns for correlation analysis
numerical_columns = ["Hours Studied", "Previous Scores", "Sleep
Hours", "Sample Question Papers Practiced", "Performance Index"]

# Compute correlation matrix
correlation_matrix = df[numerical_columns].corr()

# Plot correlation heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap="Spectral",
fmt=".2f", linewidths=0.5)
plt.title("Correlation Heatmap of Performance Index with Other
Features")
plt.show()
```

SCATTERPLOT

```
plt.figure(figsize=(15, 10))
```

```
features = ["Hours Studied", "Previous Scores", "Sleep Hours", "Sample
Question Papers Practiced"]
titles = ["Hours Studied vs Performance Index", "Previous Scores vs
Performance Index",
          "Sleep Hours vs Performance Index", "Sample Question Papers
Practiced vs Performance Index"]

#looping through the plots using subplots
for i, feature in enumerate(features, 1):
    plt.subplot(2, 2, i)
    sns.scatterplot(x=df[feature], y=df["Performance Index"],
alpha=0.5, color='green')
    plt.title(titles[i - 1])
    plt.xlabel(feature)
    plt.ylabel("Performance Index")
    plt.grid(True, linestyle="--", alpha=0.7)

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



1)plot1 - shows that the range of marks is going up as the number of people study more like there is about 40 mark difference in the lower limit of performance index

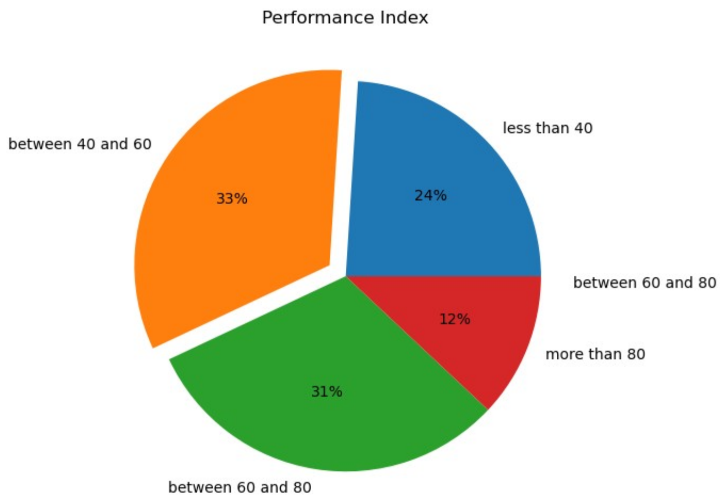
2)plot2 - shows almost a linear increase in the range of people who score high marks to the performance index the performance index is fairly high amongst those who got a almost perfect previous score

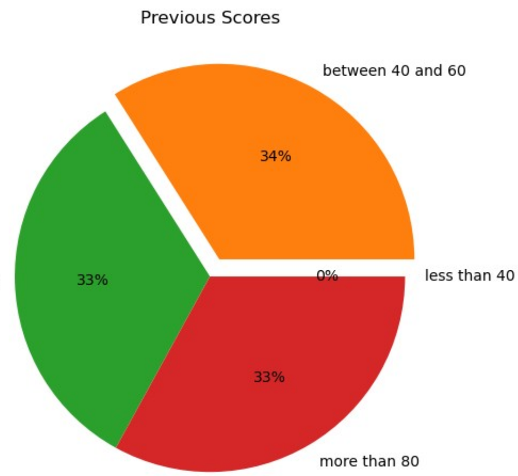
3)plot3 - in every category of sleep hour , there a people who get more than 80 marks and people who get less than 40 as well there is a fair share of varying performance index in each sleep hour

4)plot4 - follows a similar trend , one cannot tell anything about performance index even after having information on number of sample papers practiced

PIE CHART

```
#Now we go for a piechart of Performance Index and Previous Scores
names_list = ["Performance Index","Previous Scores"]
lab = ["less than 40","between 40 and 60","between 60 and 80","more 
than 80"]
plt.figure(figsize = (13,10))

for k in range(0,2):
    count = 0
    count_list = [0,0,0,0]
    range_list = [0,40,60,80,100]

    #loop to calculate the counts for each range

    for i in range(0,4):
        for j in df[names_list[k]]:
            if(range_list[i]<=j<range_list[i+1]):
                count_list[i]+=1
    total = sum(count_list)
    count_list = [round(i/total*100) for i in count_list]
    plt.subplot(1,2,k+1)

    #we processed data required for the pieplot till now for 
performance index

    plt.pie(x = count_list,labels = lab,explode = 
[0,0.1,0,0],autopct='%.0f%%',)
    plt.title(label = names_list[k])
plt.show()
```

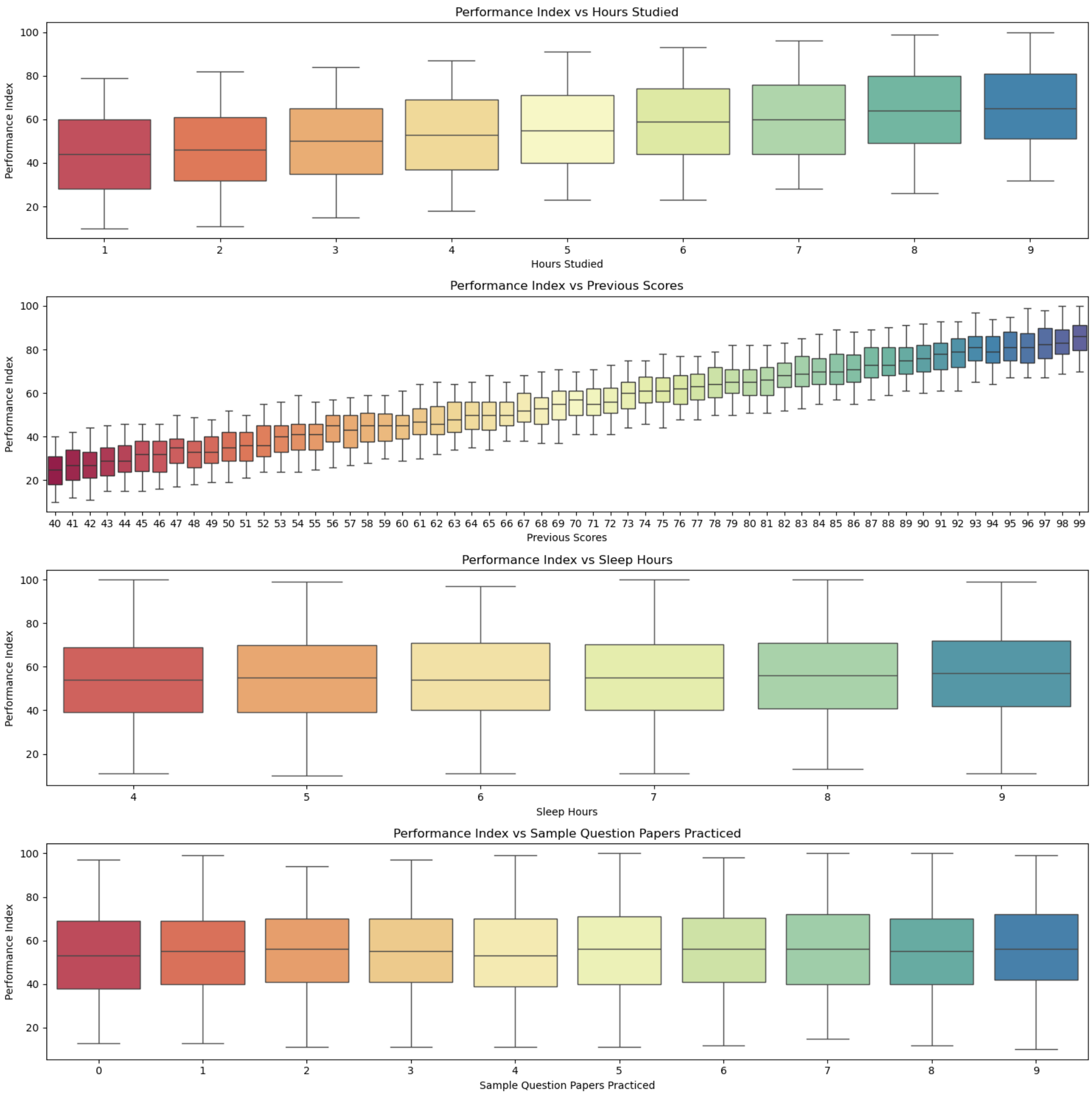




->**observation** - though the correlation is high but there is a significant difference between the percentage of people in each of the sections i.e there is almost no one under 40 maarks in this plot but around 25% people got less than 40 marks

BOX PLOT

```
# Defining numerical features for comparison
numeric_features = ["Hours Studied", "Previous Scores", "Sleep Hours",
"Sample Question Papers Practiced"]

plt.figure(figsize=(15, 15))

# Creating box plots to anaylyze the relationship of each feature vs
Performance Index
for i, feature in enumerate(numeric_features, 1):
    plt.subplot(4, 1, i)  # Arrange in a 4x1 grid
    sns.boxplot(x=df[feature], y=df["Performance Index"],
palette="Spectral")
    plt.title(f"Performance Index vs {feature}")
    plt.xlabel(feature)
    plt.ylabel("Performance Index")

# Optimize layout
plt.tight_layout()
plt.show()
```



Observations: 1) Hours Studied - More study hours generally lead to higher scores. Some outliers suggest that a few students study a lot but still score low.

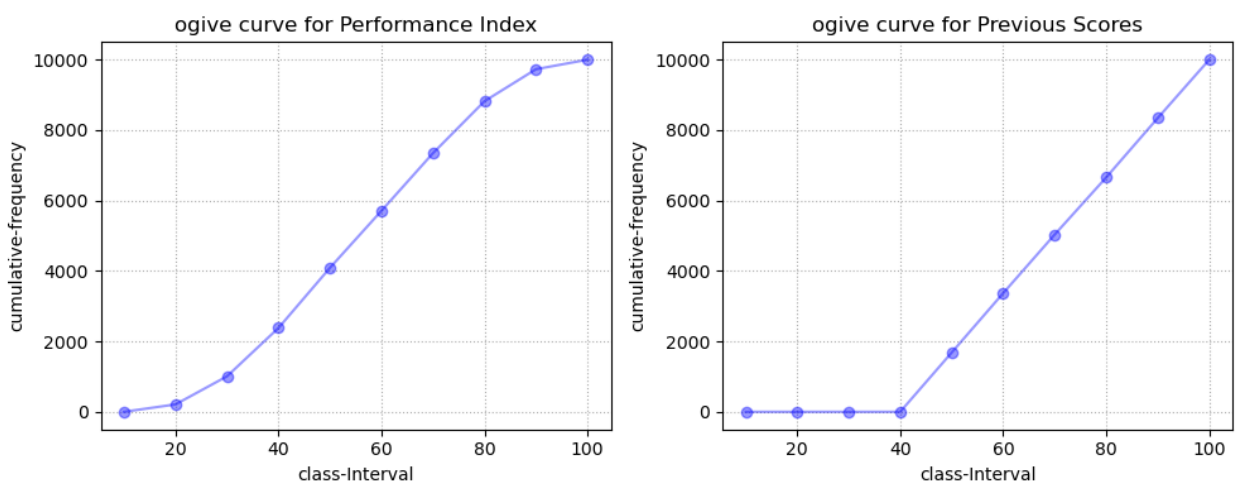
2) Previous Scores- Strong correlation: Students with higher past scores tend to perform well. A few students with low past scores performed exceptionally well!

3) Sleep Hours - No clear pattern, suggesting sleep hours have less impact on performance. Some students sleep a lot and still score high.

4) Sample Question Papers Practiced - More practice papers seem to slightly help performance. Some students who practiced a lot still have low scores, indicating other factors at play.

LESS THAN OGIVE

```
#class_interval,data_points for ogive

names_list = ["Performance Index","Previous Scores"]
plt.figure(figsize = (10,4))
for i in range(0,2):
    class_interval = list(range(0,110,10))
    main_data = df[names_list[i]]
    plt.subplot(1,2,i+1)
    #returns class intervals and frequency
    frequency,class_interval = np.histogram(main_data,class_interval)

    #returns cumulative frequency of the frequency list
    cumulative_frequency = np.cumsum(frequency)

    #we plot the ogive now
    plt.plot(class_interval[1:],cumulative_frequency,marker =
'o',color = 'blue',alpha = 0.4)
    plt.grid(True,linestyle = ":")
    plt.xlabel("class-Interval")
    plt.ylabel("cumulative-frequency")
    plt.title(f"ogive curve for {names_list[i]}")
plt.tight_layout()
plt.show()
```

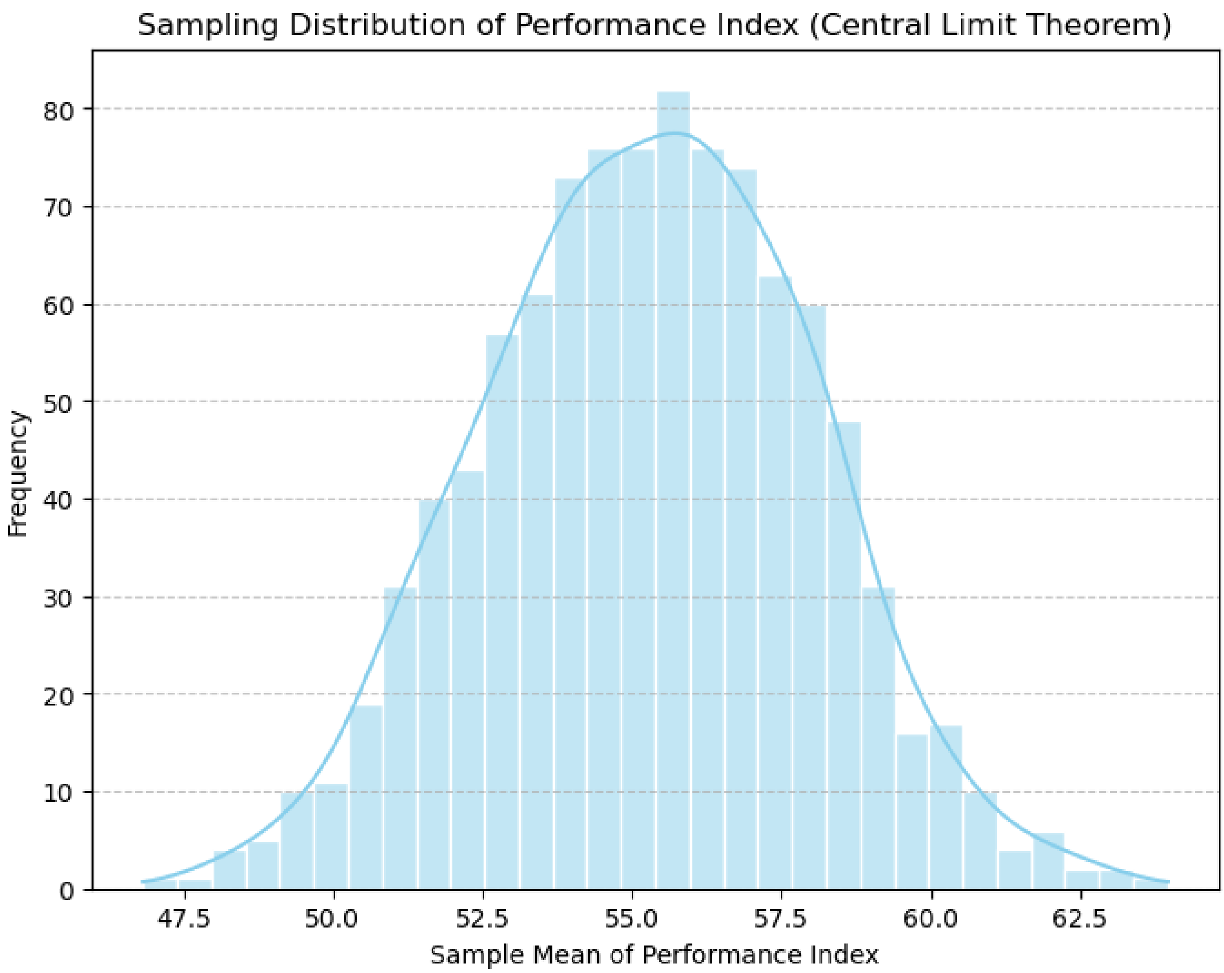


Key Insights from the Ogive Graph 1: 1) The curve rises steeply between 40-80, meaning most students have a Performance Index in this range. 2) The cumulative frequency reaches near 100% at 100, indicating very few students have a perfect score. 3) The lower range (0-40) has a slow increase, showing fewer students fall into the "Low Performance" category.

-> For the second graph 1)The curve starts flat with little to no increase in frequency up to around the 40 mark. 2)After this point, there is a steep upward trend, indicating that most of the scores fall in the higher ranges. 3)The conclusion is that a significant portion of the data is concentrated in the upper class intervals, leading to a rapid rise in cumulative frequency.

CENTRAL LIMIT APPROXIMATION

```
sample_size = 50   # Each sample will have 50 students
num_samples = 1000  # Number of samples to take

sample_means = []

for _ in range(num_samples):
    sample = df["Performance Index"].sample(n=sample_size,
replace=True)  # Random sampling with replacement
    sample_means.append(sample.mean())

# Plotting the sampling distribution of sample means
plt.figure(figsize=(8, 6))
sns.histplot(sample_means, bins=30, kde=True, color="skyblue",
edgecolor="white")
plt.title("Sampling Distribution of Performance Index (Central Limit
Theorem)")
plt.xlabel("Sample Mean of Performance Index")
plt.ylabel("Frequency")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()

print(f"Mean of Population: {df['Performance Index'].mean():.2f}")
print(f"Mean of Sample Means: {np.mean(sample_means):.2f}")
print(f"Standard Deviation of Population: {df['Performance
Index'].std():.2f}")
print(f"Standard Deviation of Sample Means: {np.std(sample_means,
ddof=1):.2f}")  # Standard error approximation
```




```
Mean of Population: 55.22
Mean of Sample Means: 55.26
Standard Deviation of Population: 19.21
Standard Deviation of Sample Means: 2.73
```

-> Key Insights from CLT Application 1) Normal Shape → The sampling distribution is approximately normal, even if the original data is not. 2) Sample Mean ≈ Population Mean → The average of all sample means is close to the true population mean. 3) Standard Deviation Decreases → The standard deviation of sample means (standard error) is smaller than the population standard deviation. 4) Larger Samples Improve Accuracy → Increasing the sample size (e.g., from 50 to 100) makes the distribution even tighter and more normal.