UCLA CS M148 Final Project - 24 Fall

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In this project, we explored a dataset that collected information about students and their test scores.
We wish to explore how these factors contribute to students improving their test scores

In [ ]:
```
%pip install pandas numpy matplotlib seaborn scikit-learn torch plotly
```

download the following dataset and store it in the same directory as this notebook as a csv named "StudentPerformanceFactors.csv"

https://www.kaggle.com/datasets/lainguyn123/student-performance-factors

i) Exploratory Data Analysis

in this section we will be exploring the our data

In [2]:
```
# imports
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import numpy as np
```

In [3]:
```
# loading data and taking sample
original_dataset_df = pd.read_csv("StudentPerformanceFactors.csv")
original_dataset_df.sample(10)
```

Out[3]:

	Hours_Studied	Attendance	Parental_Involvement	Access_to_Resources	Extracurricula
1873	25	98	Medium	Medium	
4437	18	61	Medium	Low	
6348	13	95	High	High	
6109	16	78	Medium	Medium	
3009	17	82	Low	Medium	
810	19	98	Medium	High	
2204	14	94	Low	Medium	
1287	23	63	Medium	Medium	
3757	32	61	High	Medium	
3890	24	80	Medium	High	

from : https://www.kaggle.com/datasets/lainguyn123/student-performance-factors

what does each var measure

the kaggle website includes a table of variables and what they measure

- however, some categorical variables do not clarify how category was determined or what they mean

About the Dataset

(https://www.kaggle.com/datasets/lainguyn123/student-performance-factors)

Attribute	Description
Hours_Studied	Number of hours spent studying per week.
Attendance	Percentage of classes attended.
Parental_Involvement	Level of parental involvement in the student's education (Low, Medium, High).
Access_to_Resources	Availability of educational resources (Low, Medium, High).
Extracurricular_Activities	Participation in extracurricular activities (Yes, No).
Sleep_Hours	Average number of hours of sleep per night.
Previous_Scores	Scores from previous exams.
Motivation_Level	Student's level of motivation (Low, Medium, High).

Attribute	Description
Internet_Access	Availability of internet access (Yes, No).
Tutoring_Sessions	Number of tutoring sessions attended per month.
Family_Income	Family income level (Low, Medium, High).
Teacher_Quality	Quality of the teachers (Low, Medium, High).
School_Type	Type of school attended (Public, Private).
Peer_Influence	Influence of peers on academic performance (Positive, Neutral, Negative).
Physical_Activity	Average number of hours of physical activity per week.
Learning_Disabilities	Presence of learning disabilities (Yes, No).
Parental_Education_Level	Highest education level of parents (High School, College, Postgraduate).
Distance_from_Home	Distance from home to school (Near, Moderate, Far).
Gender	Gender of the student (Male, Female).
Exam_Score	Final exam score.

how was data collected

according to documentation, it is synthetic data

observational units

each observation is a single student

data relevancy

Hours_Studied, Previous_Scores, Motivation_Level, Exam_Score are the most relevant fields for our exploration in.

Other variables we might want to explore include: parental involvement, access to resources, tutoring sessions, peer influence

questions, assumptions

- How is motivation level measured, what does it represent
- will motivation level be too correlated with other variables (hours studied)

Exploring data

In [4]:
```
# shape of df
original_dataset_df.shape
```

Out[4]: (6607, 20)

we have 20 variables and 6607 samples

In [5]:
```
original_dataset_df.describe()
```

Out[5]:

	Hours_Studied	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessions	Physi
count	6607.000000	6607.000000	6607.00000	6607.000000	6607.000000	6
mean	19.975329	79.977448	7.02906	75.070531	1.493719	
std	5.990594	11.547475	1.46812	14.399784	1.230570	
min	1.000000	60.000000	4.00000	50.000000	0.000000	
25%	16.000000	70.000000	6.00000	63.000000	1.000000	
50%	20.000000	80.000000	7.00000	75.000000	1.000000	
75%	24.000000	90.000000	8.00000	88.000000	2.000000	
max	44.000000	100.000000	10.00000	100.000000	8.000000	

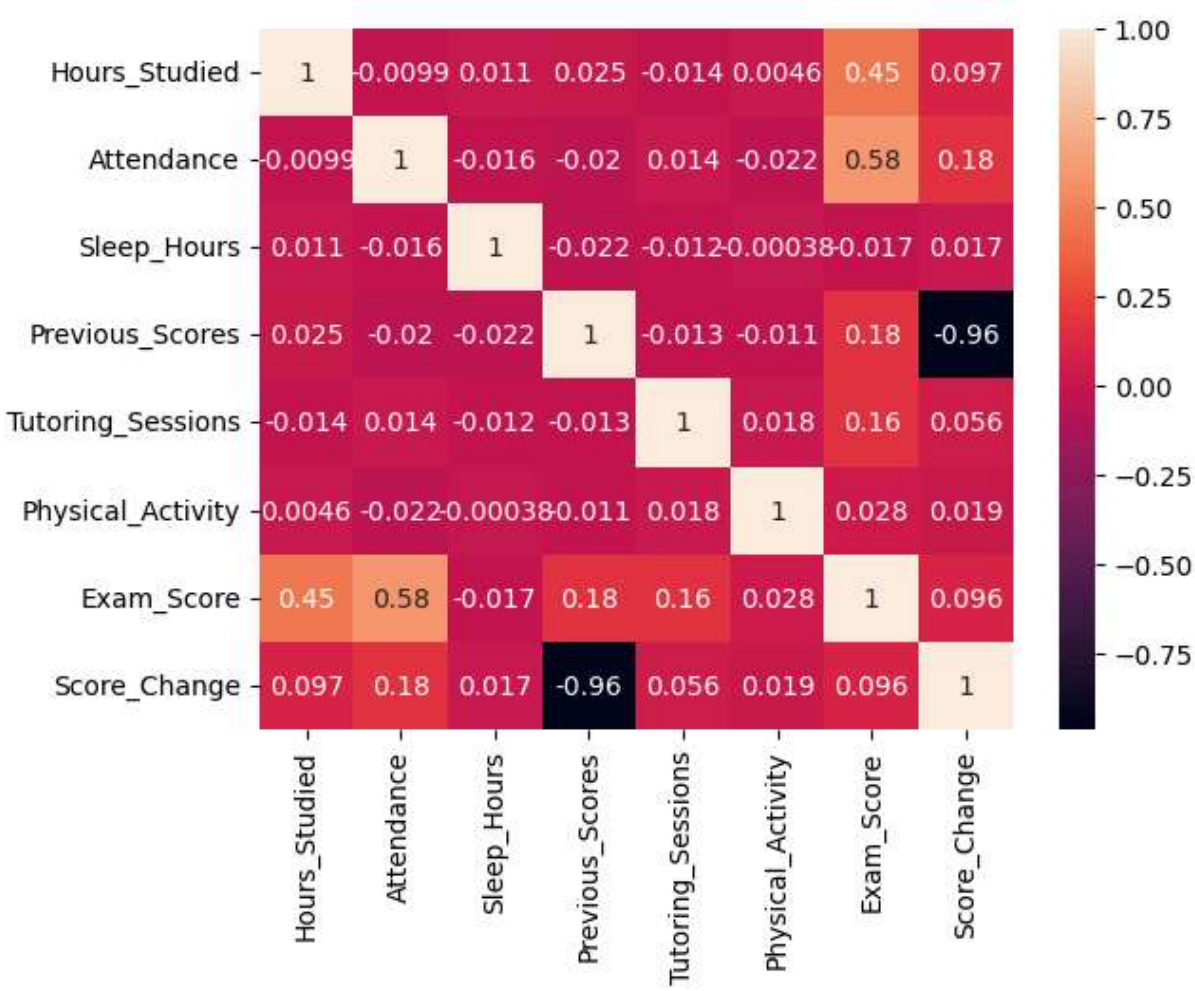
In [6]:
```
original_dataset_df[original_dataset_df['Exam_Score']>100]
```

Out[6]:

	Hours_Studied	Attendance	Parental_Involvement	Access_to_Resources	Extracurricula
1525	27	98	Low	Medium	

In [7]:
```
numerical_cols = original_dataset_df.select_dtypes(include=["int64"]).columns
corr_ds = original_dataset_df[numerical_cols].copy()
corr_ds["Score_Change"] = corr_ds["Exam_Score"] - corr_ds["Previous_Scores"]
sns.heatmap(corr_ds.corr(), annot=True)
```

Out[7]: <Axes: >



In [8]:
```
(original_dataset_df['Exam_Score'] <= original_dataset_df['Previous_Scores']).sum()
```

Out[8]: (4467, 2140)

Notes on distribution of data

- hours studies: the information seems reasonable though the max does seem high\
- exam scores : the max says there was an exam score of 101- this doesn't seem appropriate
  - because there was only one such outlier, we will remove it later
- hours studied and attendance have the highest correlation with exam scores
  - previous score are highly negatively correlated
- we have more examples of students not improving than students improving

In [9]:
```
for column in original_dataset_df.columns:
    print(f"Column: {column}, Data Type: {original_dataset_df[column].dtype}")
    if original_dataset_df[column].dtype == 'object':
        print(f"Categories: {original_dataset_df[column].unique()}")
    if original_dataset_df[column].dtype in ['int64', 'float64']:
        print(f"5-Number Summary: \n{original_dataset_df[column].describe()[['min',
        print(f"Mean: {original_dataset_df[column].mean():.5}")
        print(f"Standard Deviation: {original_dataset_df[column].std():.5}")
        print(f"Skewness: {original_dataset_df[column].skew():.5}")
```

```
        print(f"Kurtosis: {original_dataset_df[column].kurt():.5}")
    print("-" * 20)
```

```
Column: Hours_Studied, Data Type: int64
5-Number Summary:
min     1.0
25%    16.0
50%    20.0
75%    24.0
max    44.0
Name: Hours_Studied, dtype: float64
Mean: 19.975
Standard Deviation: 5.9906
Skewness: 0.013499
Kurtosis: 0.017771
--------------------
Column: Attendance, Data Type: int64
5-Number Summary:
min     60.0
25%     70.0
50%     80.0
75%     90.0
max    100.0
Name: Attendance, dtype: float64
Mean: 79.977
Standard Deviation: 11.547
Skewness: 0.013666
Kurtosis: -1.1944
--------------------
Column: Parental_Involvement, Data Type: object
Categories: ['Low' 'Medium' 'High']
--------------------
Column: Access_to_Resources, Data Type: object
Categories: ['High' 'Medium' 'Low']
--------------------
Column: Extracurricular_Activities, Data Type: object
Categories: ['No' 'Yes']
--------------------
Column: Sleep_Hours, Data Type: int64
5-Number Summary:
min     4.0
25%     6.0
50%     7.0
75%     8.0
max    10.0
Name: Sleep_Hours, dtype: float64
Mean: 7.0291
Standard Deviation: 1.4681
Skewness: -0.023805
Kurtosis: -0.5037
--------------------
Column: Previous_Scores, Data Type: int64
5-Number Summary:
min     50.0
25%     63.0
50%     75.0
75%     88.0
max    100.0
Name: Previous_Scores, dtype: float64
```

```
Mean: 75.071
Standard Deviation: 14.4
Skewness: -0.0037365
Kurtosis: -1.1911
--------------------
Column: Motivation_Level, Data Type: object
Categories: ['Low' 'Medium' 'High']
--------------------
Column: Internet_Access, Data Type: object
Categories: ['Yes' 'No']
--------------------
Column: Tutoring_Sessions, Data Type: int64
5-Number Summary:
min    0.0
25%    1.0
50%    1.0
75%    2.0
max    8.0
Name: Tutoring_Sessions, dtype: float64
Mean: 1.4937
Standard Deviation: 1.2306
Skewness: 0.81553
Kurtosis: 0.64372
--------------------
Column: Family_Income, Data Type: object
Categories: ['Low' 'Medium' 'High']
--------------------
Column: Teacher_Quality, Data Type: object
Categories: ['Medium' 'High' 'Low' nan]
--------------------
Column: School_Type, Data Type: object
Categories: ['Public' 'Private']
--------------------
Column: Peer_Influence, Data Type: object
Categories: ['Positive' 'Negative' 'Neutral']
--------------------
Column: Physical_Activity, Data Type: int64
5-Number Summary:
min    0.0
25%    2.0
50%    3.0
75%    4.0
max    6.0
Name: Physical_Activity, dtype: float64
Mean: 2.9676
Standard Deviation: 1.0312
Skewness: -0.031365
Kurtosis: -0.059439
--------------------
Column: Learning_Disabilities, Data Type: object
Categories: ['No' 'Yes']
--------------------
Column: Parental_Education_Level, Data Type: object
Categories: ['High School' 'College' 'Postgraduate' nan]
--------------------
Column: Distance_from_Home, Data Type: object
```

```
Categories: ['Near' 'Moderate' 'Far' nan]
--------------------
Column: Gender, Data Type: object
Categories: ['Male' 'Female']
--------------------
Column: Exam_Score, Data Type: int64
5-Number Summary:
min     55.0
25%     65.0
50%     67.0
75%     69.0
max    101.0
Name: Exam_Score, dtype: float64
Mean: 67.236
Standard Deviation: 3.8905
Skewness: 1.6448
Kurtosis: 10.575
--------------------
```

In [10]:

```
score_change = original_dataset_df["Exam_Score"] - original_dataset_df["Previous_Sc
print(f"5-Number Summary: \n{score_change.describe()[['min', '25%', '50%', '75%', '
print(f"Mean: {score_change.mean():.5}")
print(f"Standard Deviation: {score_change.std():.5}")
print(f"Skewness: {score_change.skew():.5}")
print(f"Kurtosis: {score_change.kurt():.5}")
```

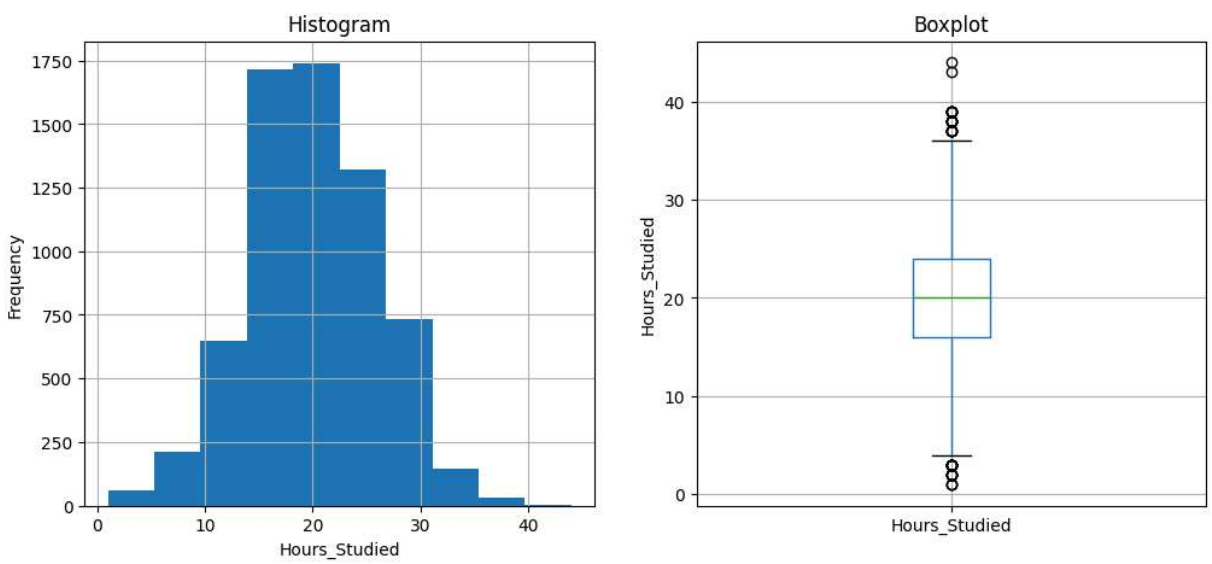
```
5-Number Summary:
min   -39.0
25%   -20.0
50%    -8.0
75%     4.0
max    41.0
dtype: float64
Mean: -7.8349
Standard Deviation: 14.243
Skewness: 0.036157
Kurtosis: -0.96563
```

In [10]:

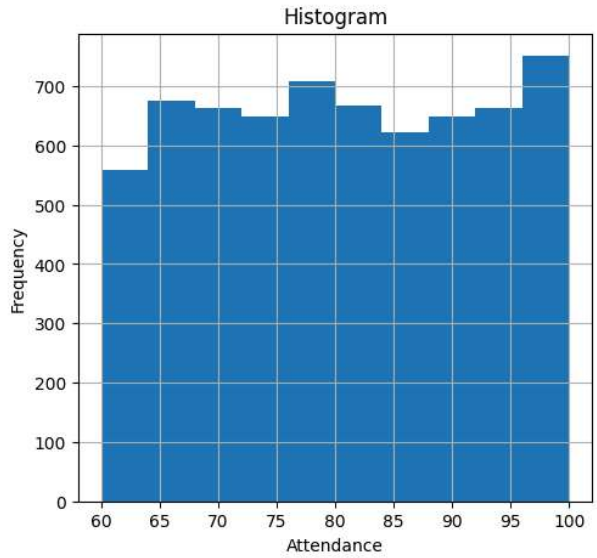
```
def explore_var(df, var):
  if df[var].dtype == "object":
    explore_cat(df, var)
  else:
    explore_num(df, var)


def explore_cat(df, var):
  print(df[var].value_counts())
  print("----")
  print(df[var].describe())
  print("----")
  sns.boxplot(x=var,y="Exam_Score", data=df)
  plt.show()


def explore_num(df, var):
  plt.figure(figsize=(12, 5))
```

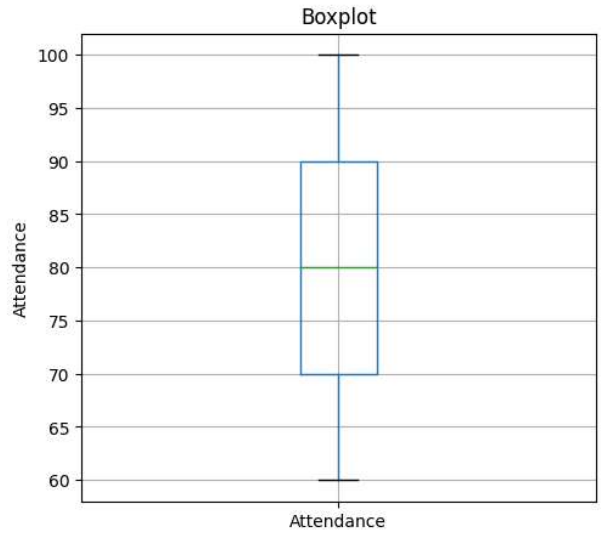
```
  print(df[var].describe())
  print("----")
  plt.subplot(1, 2, 1)
  df[var].hist()
  plt.xlabel(var)
  plt.ylabel('Frequency')
  plt.title('Histogram')

  plt.subplot(1, 2, 2)
  df.boxplot(column=var)
  plt.ylabel(var)
  plt.title('Boxplot')

  plt.show()

for c in original_dataset_df.columns:
  explore_var(original_dataset_df,c)
```

```
count    6607.000000
mean       19.975329
std         5.990594
min         1.000000
25%        16.000000
50%        20.000000
75%        24.000000
max        44.000000
Name: Hours_Studied, dtype: float64
----
```

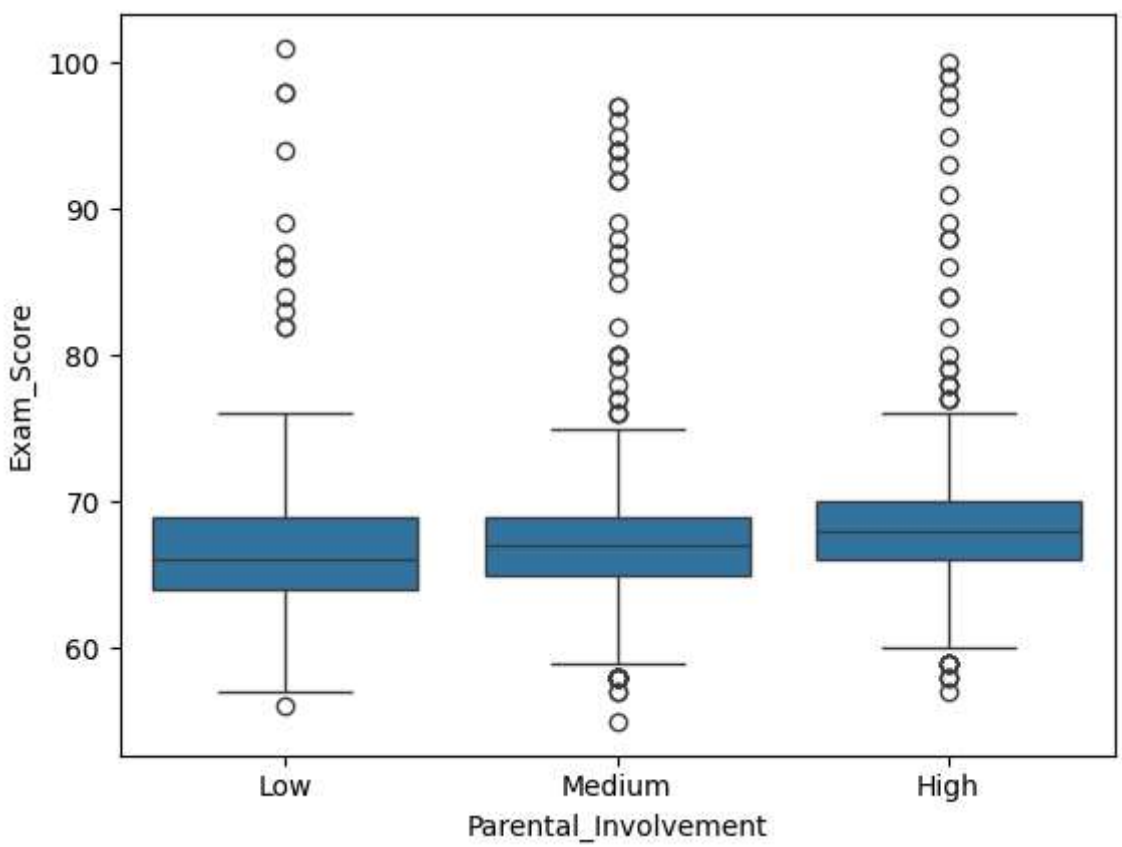



```
count    6607.000000
mean       79.977448
std        11.547475
min        60.000000
25%        70.000000
50%        80.000000
75%        90.000000
max       100.000000
Name: Attendance, dtype: float64
----
```

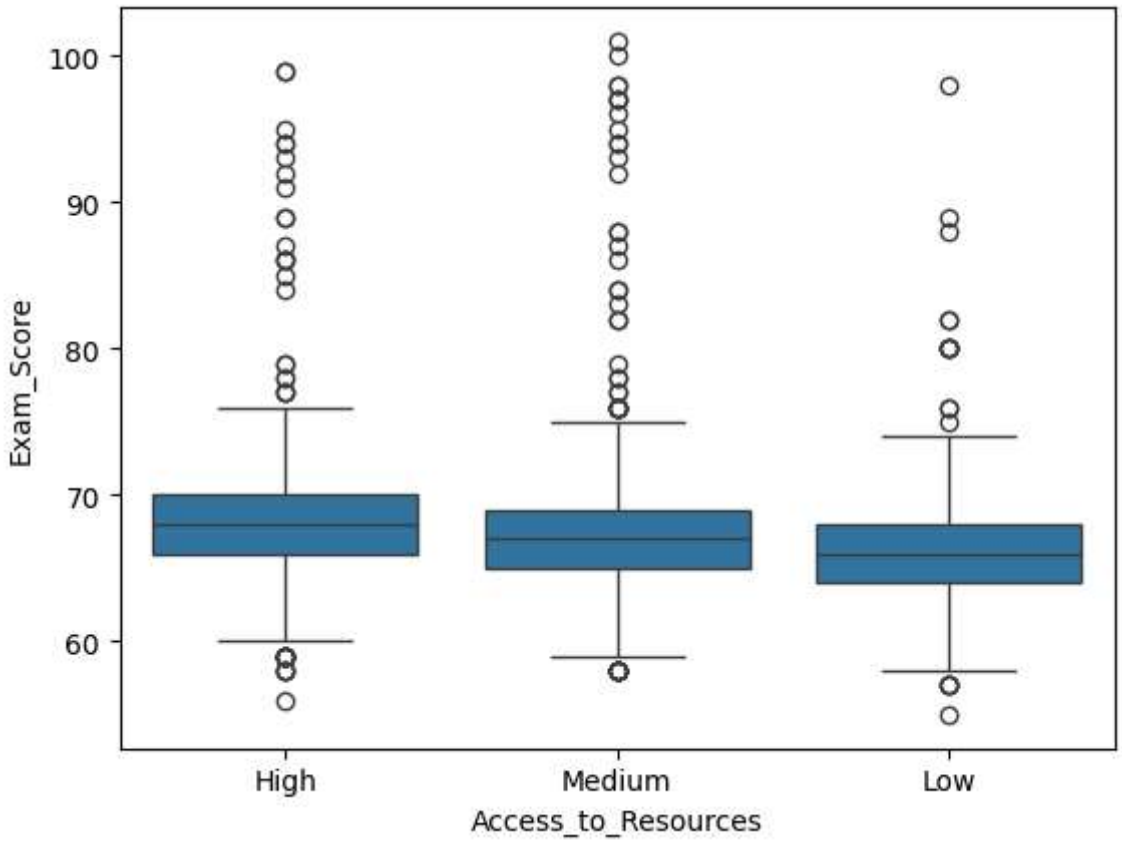




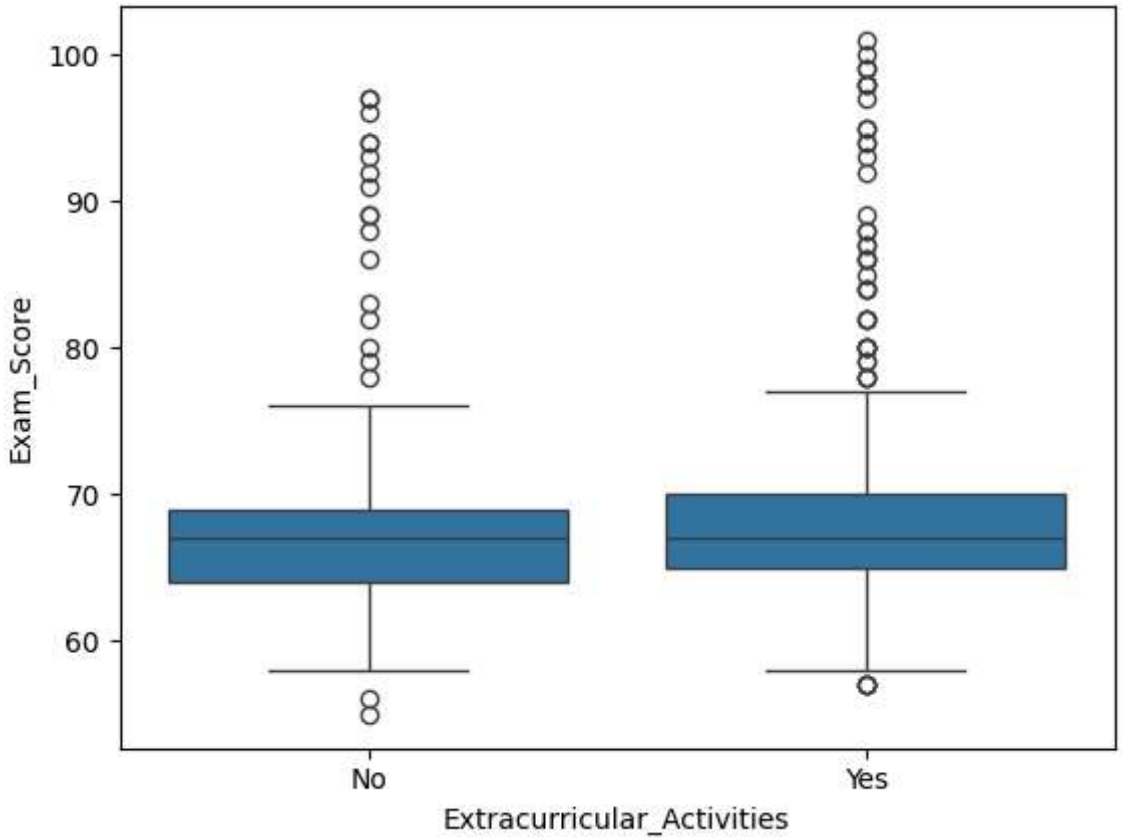

```
Parental_Involvement
Medium    3362
High      1908
Low       1337
Name: count, dtype: int64
----
count       6607
unique         3
top       Medium
freq        3362
Name: Parental_Involvement, dtype: object
----
```



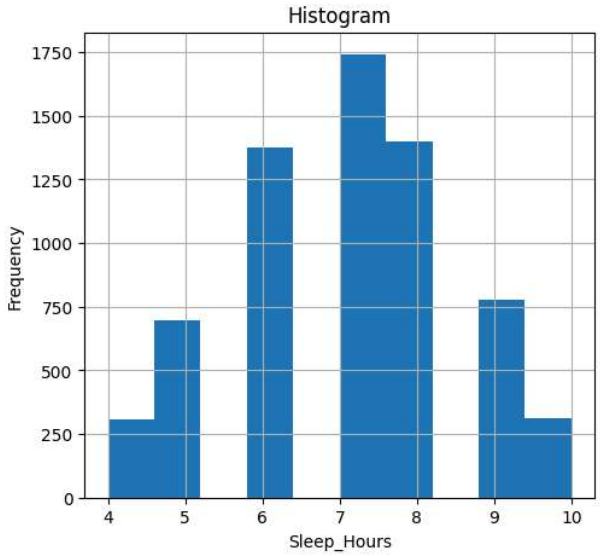
```
Access_to_Resources
Medium    3319
High      1975
Low       1313
Name: count, dtype: int64
----
count       6607
unique         3
top       Medium
freq        3319
Name: Access_to_Resources, dtype: object
----
```

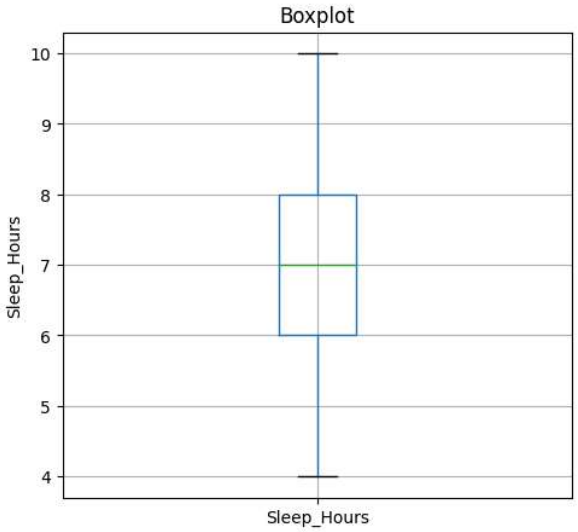



```
Extracurricular_Activities
Yes    3938
No     2669
Name: count, dtype: int64
----
count     6607
unique       2
top        Yes
freq      3938
Name: Extracurricular_Activities, dtype: object
----
```

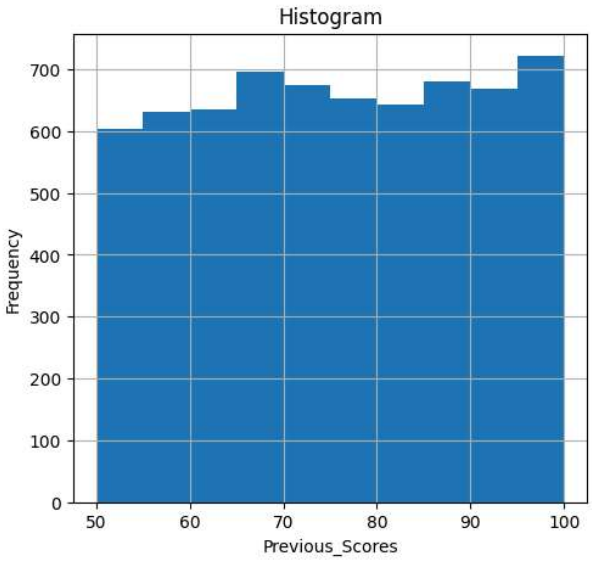


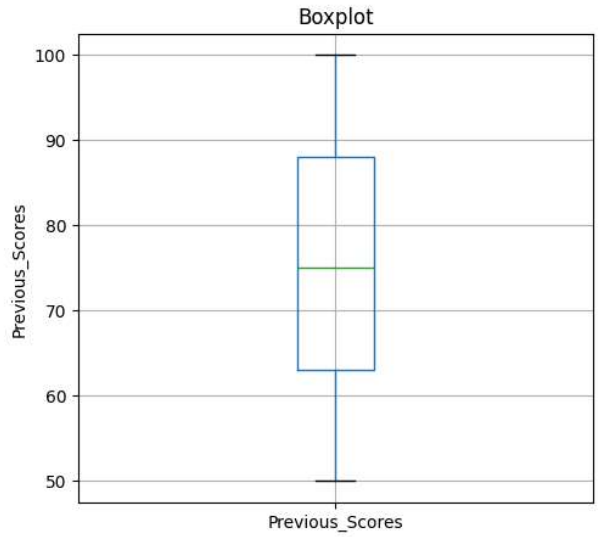

```
count    6607.00000
mean        7.02906
std         1.46812
min         4.00000
25%         6.00000
50%         7.00000
75%         8.00000
max        10.00000
Name: Sleep_Hours, dtype: float64
----
```



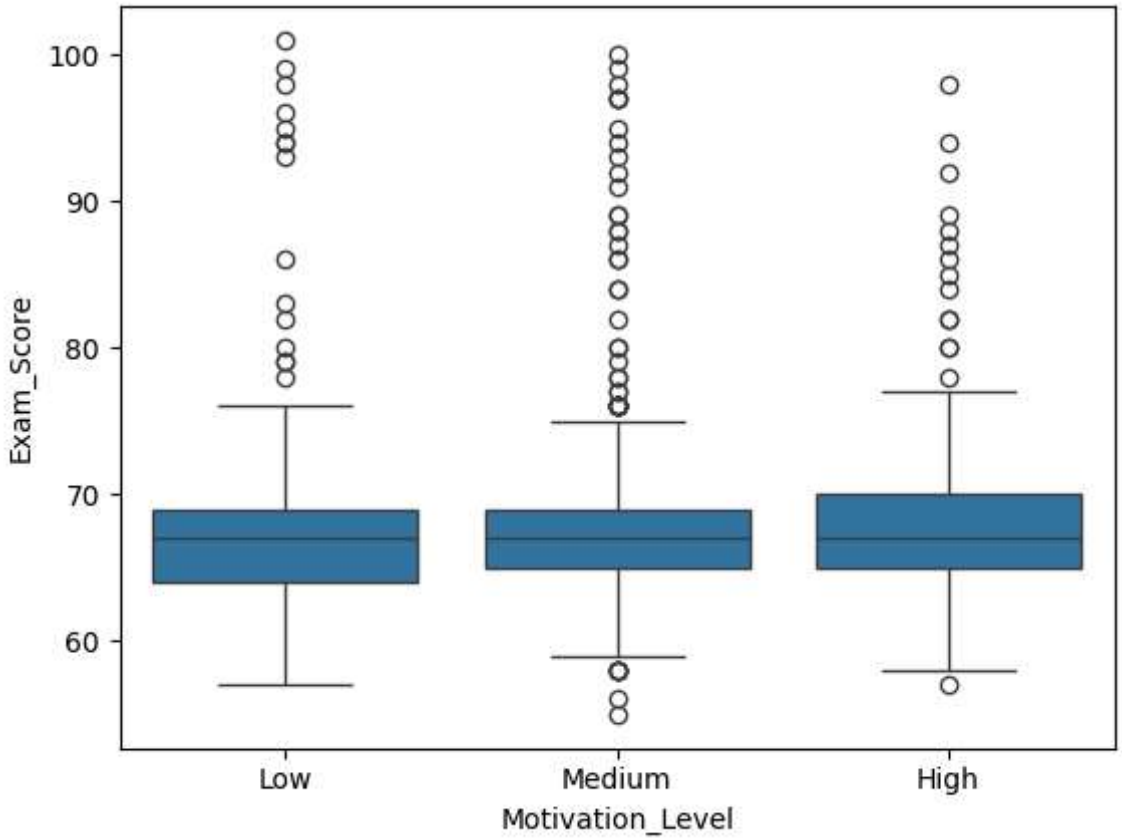


```
count    6607.000000
mean       75.070531
std        14.399784
min        50.000000
25%        63.000000
50%        75.000000
75%        88.000000
max       100.000000
Name: Previous_Scores, dtype: float64
----
```

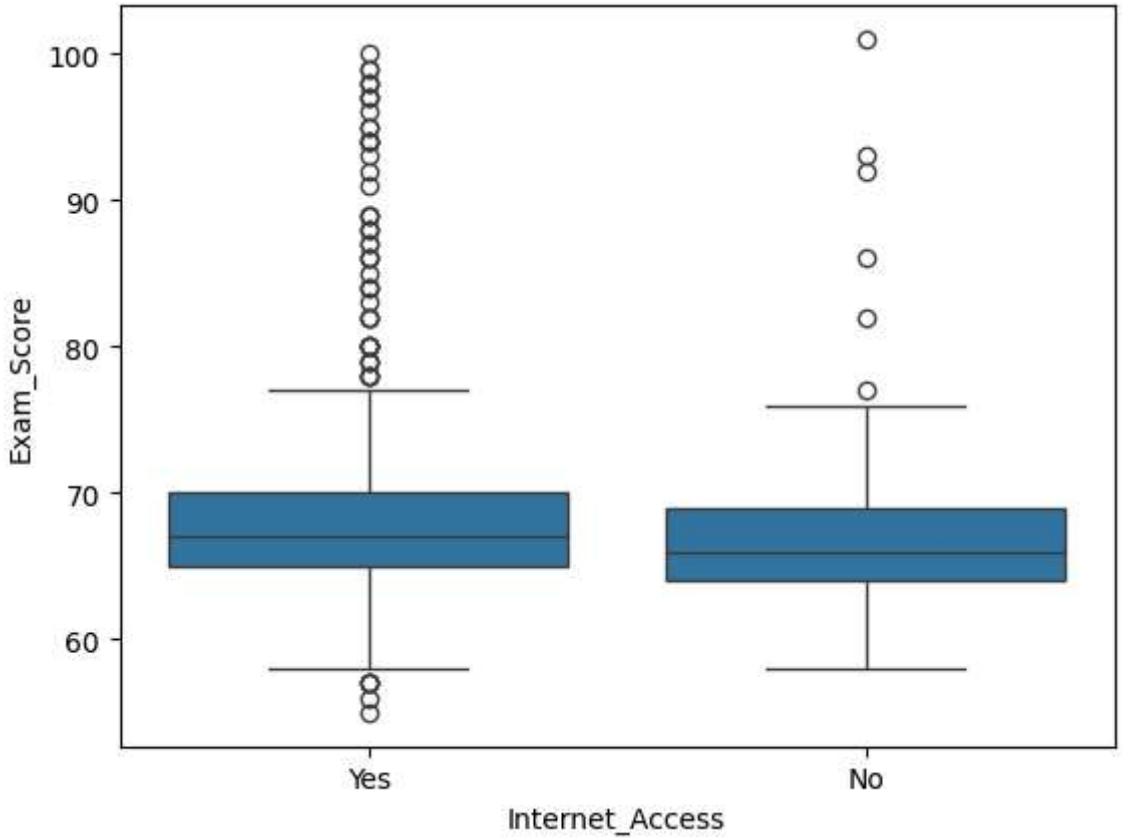




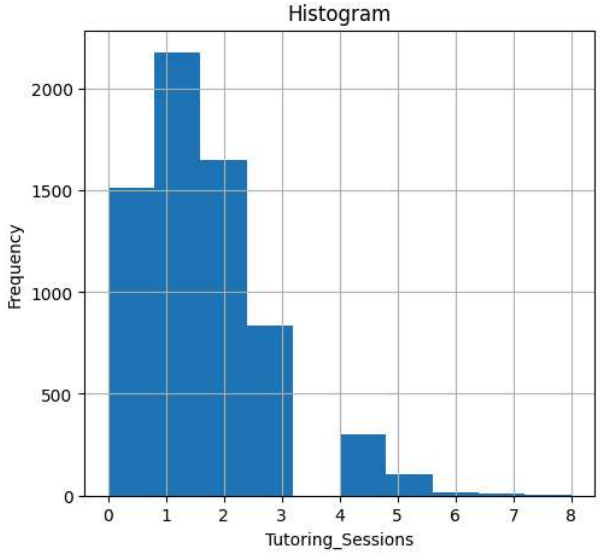

```
Motivation_Level
Medium    3351
Low       1937
High      1319
Name: count, dtype: int64
----
count       6607
unique         3
top       Medium
freq        3351
Name: Motivation_Level, dtype: object
----
```

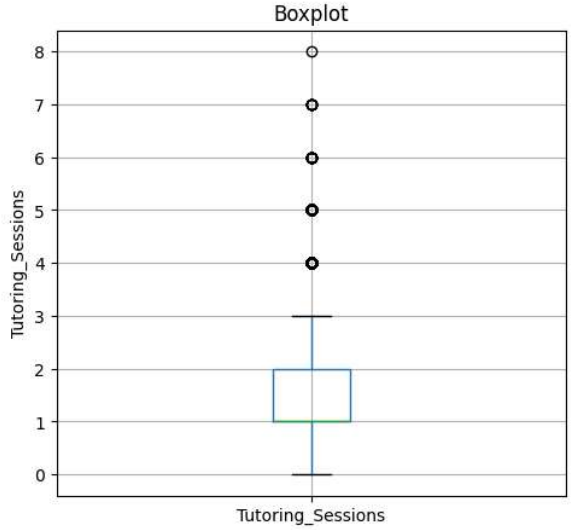



```
Internet_Access
Yes    6108
No      499
Name: count, dtype: int64
----
count     6607
unique       2
top        Yes
freq      6108
Name: Internet_Access, dtype: object
----
```

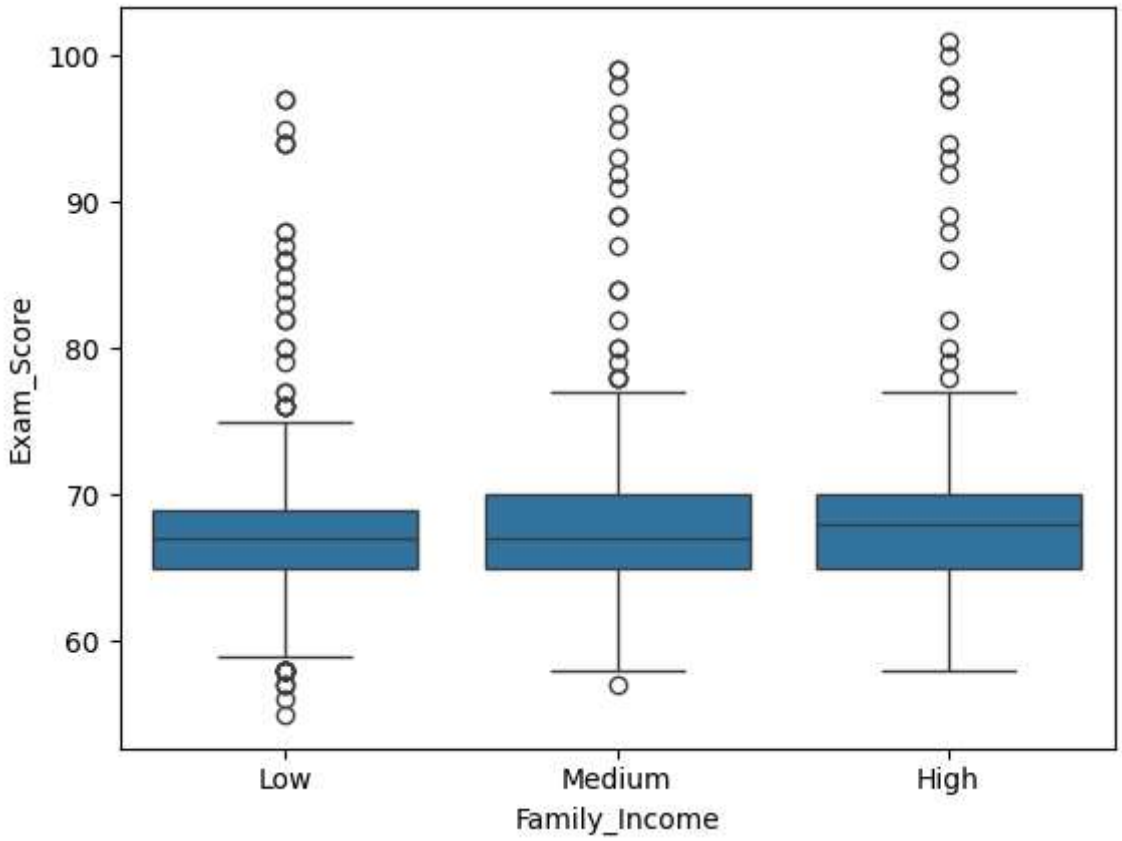



```
count    6607.000000
mean        1.493719
std         1.230570
min         0.000000
25%         1.000000
50%         1.000000
75%         2.000000
max         8.000000
Name: Tutoring_Sessions, dtype: float64
----
```

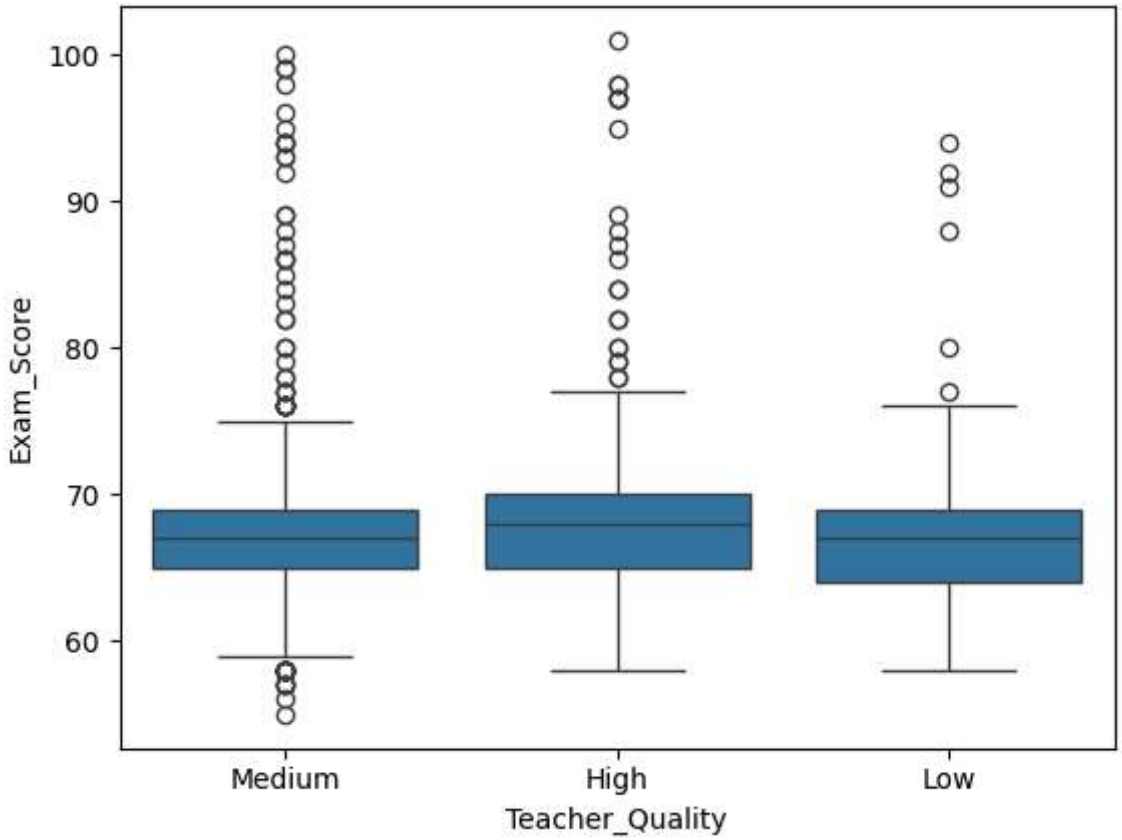




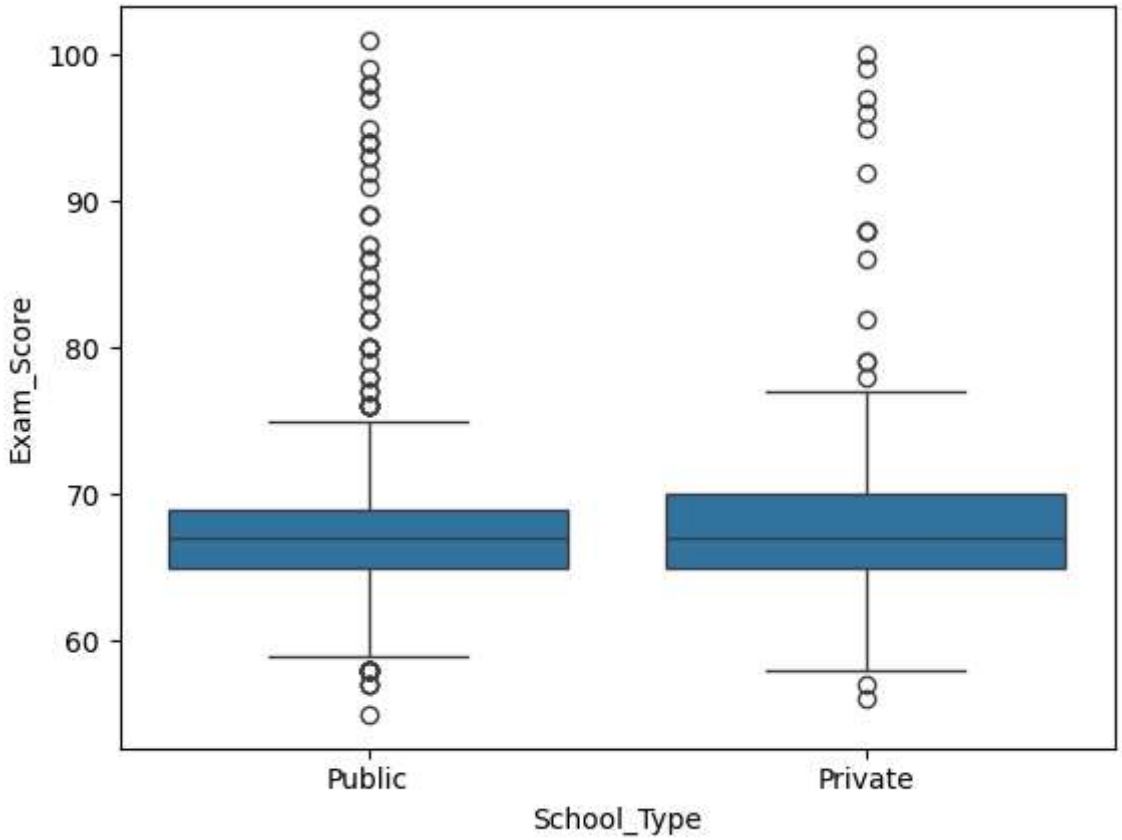
```
Family_Income
Low       2672
Medium    2666
High      1269
Name: count, dtype: int64
----
count     6607
unique       3
top        Low
freq      2672
Name: Family_Income, dtype: object
----
```



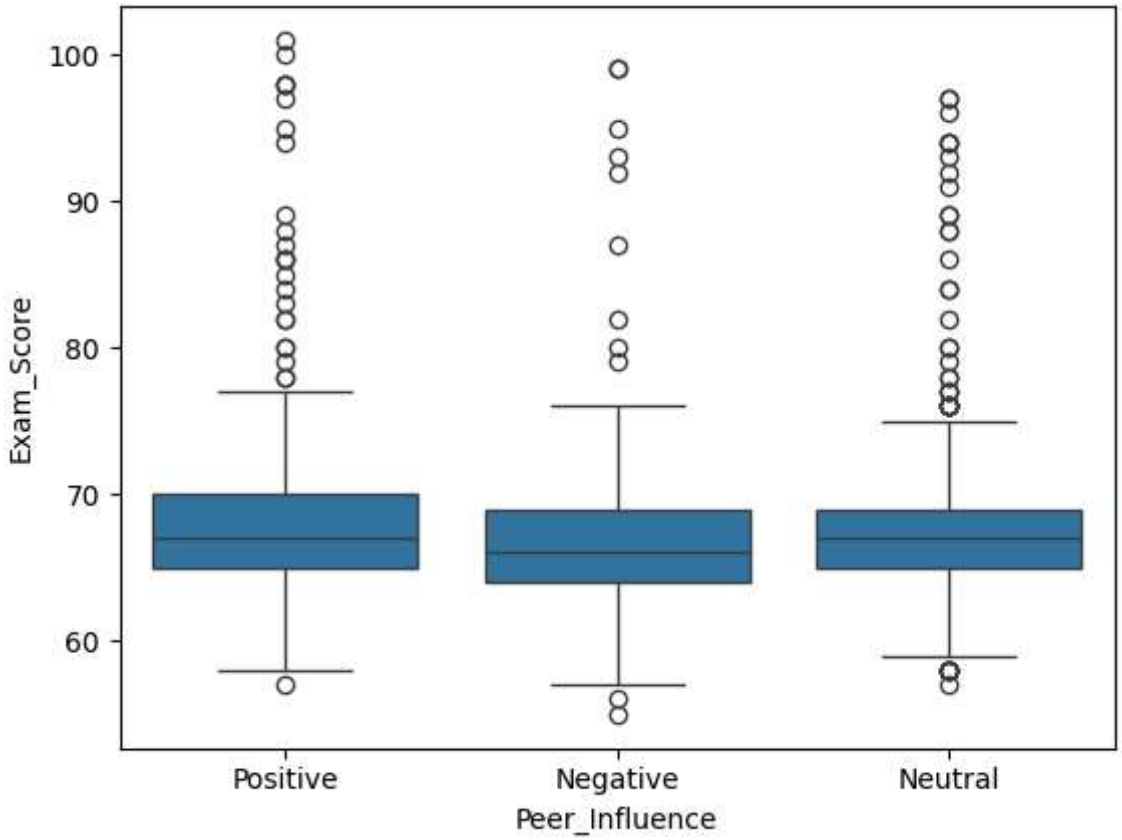

```
Teacher_Quality
Medium    3925
High      1947
Low        657
Name: count, dtype: int64
----
count       6529
unique         3
top       Medium
freq        3925
Name: Teacher_Quality, dtype: object
----
```



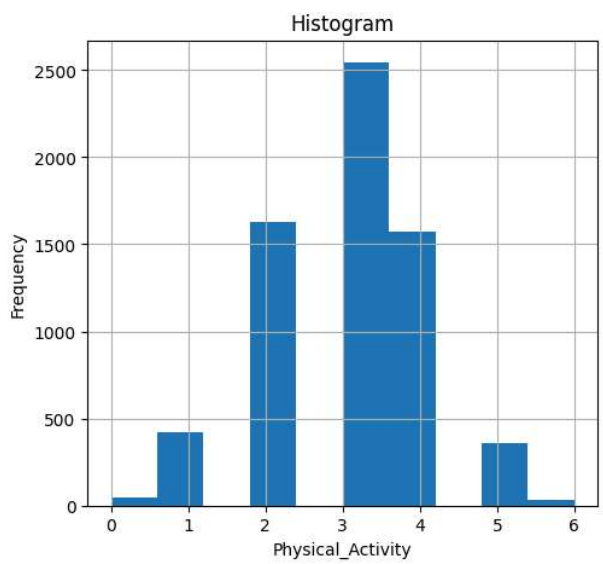

```
School_Type
Public     4598
Private    2009
Name: count, dtype: int64
----
count       6607
unique         2
top       Public
freq        4598
Name: School_Type, dtype: object
----
```

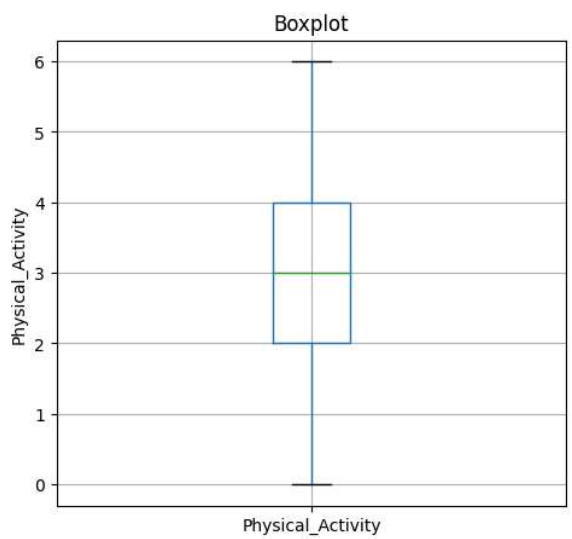



```
Peer_Influence
Positive    2638
Neutral     2592
Negative    1377
Name: count, dtype: int64
----
count         6607
unique           3
top       Positive
freq          2638
Name: Peer_Influence, dtype: object
----
```

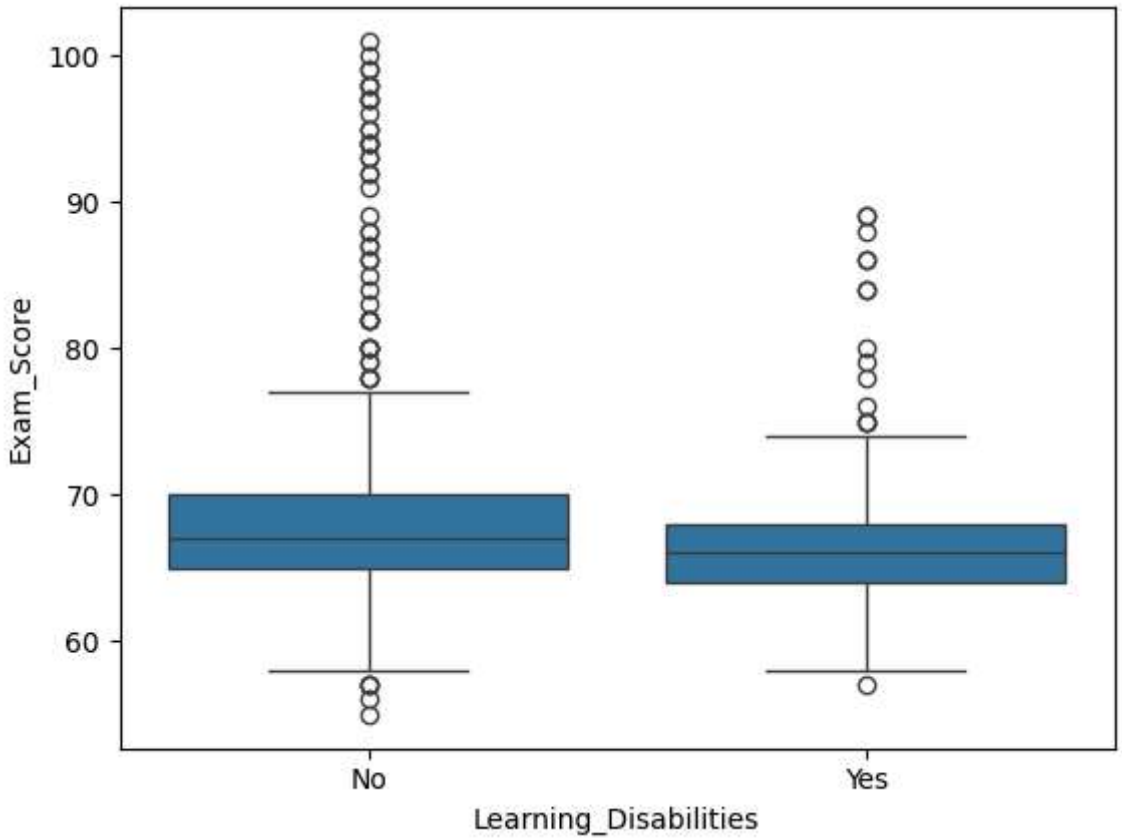



```
count    6607.000000
mean        2.967610
std         1.031231
min         0.000000
25%         2.000000
50%         3.000000
75%         4.000000
max         6.000000
Name: Physical_Activity, dtype: float64
----
```

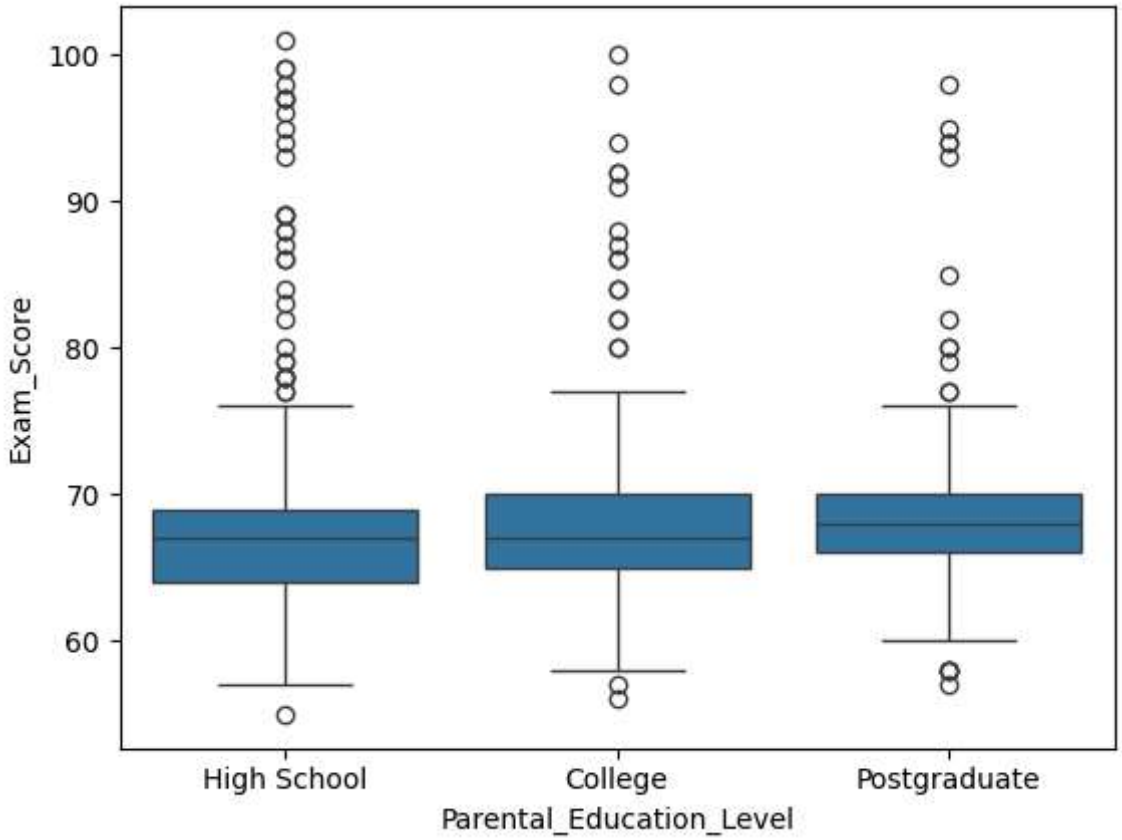




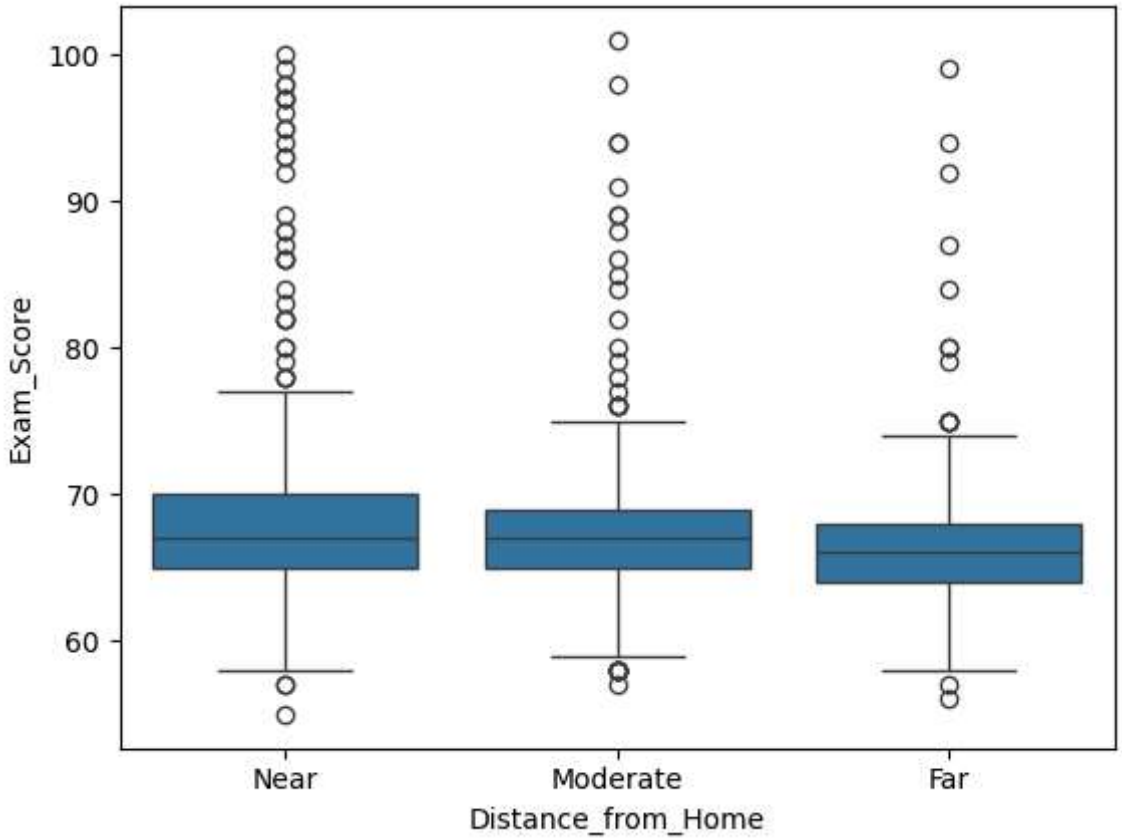
```
Learning_Disabilities
No     5912
Yes     695
Name: count, dtype: int64
----
count     6607
unique       2
top         No
freq      5912
Name: Learning_Disabilities, dtype: object
----
```



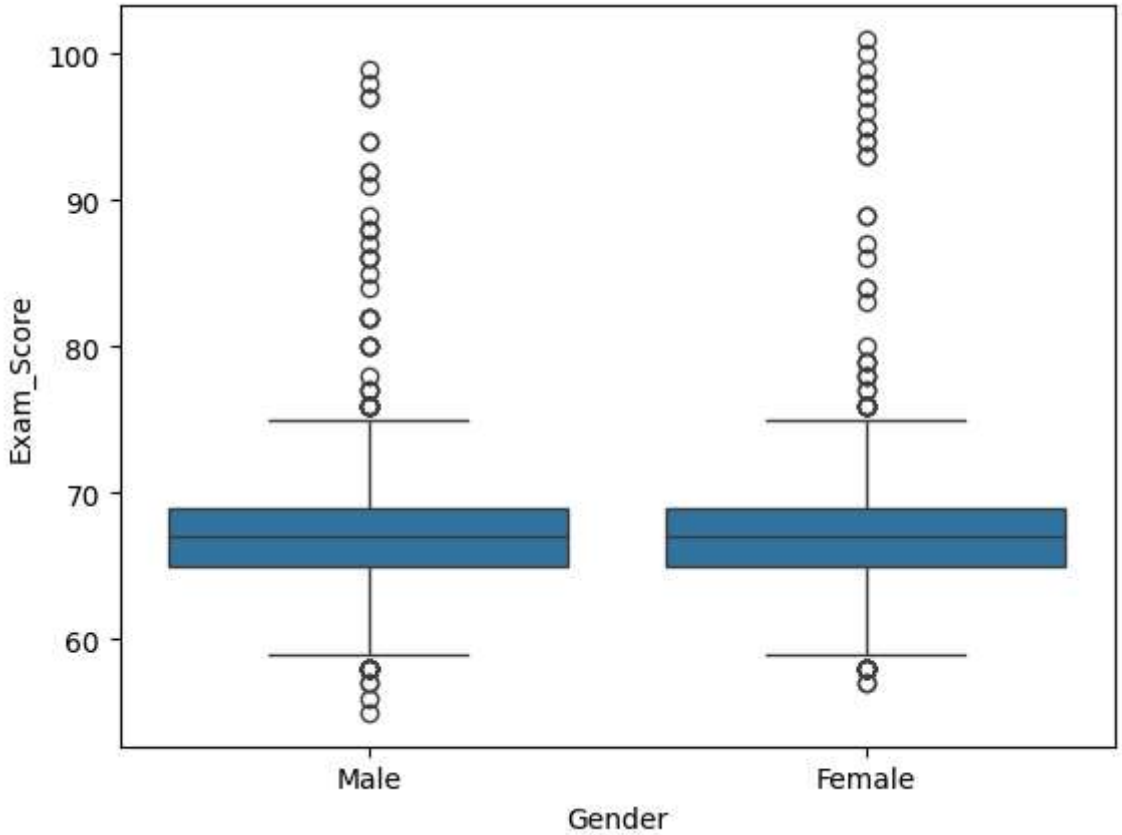

```
Parental_Education_Level
High School     3223
College         1989
Postgraduate    1305
Name: count, dtype: int64
----
count            6517
unique              3
top       High School
freq             3223
Name: Parental_Education_Level, dtype: object
----
```



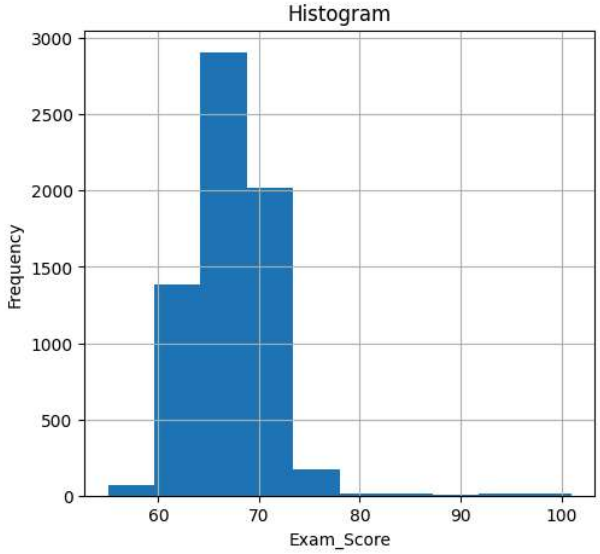

```
Distance_from_Home
Near        3884
Moderate    1998
Far          658
Name: count, dtype: int64
----
count     6540
unique       3
top       Near
freq      3884
Name: Distance_from_Home, dtype: object
----
```

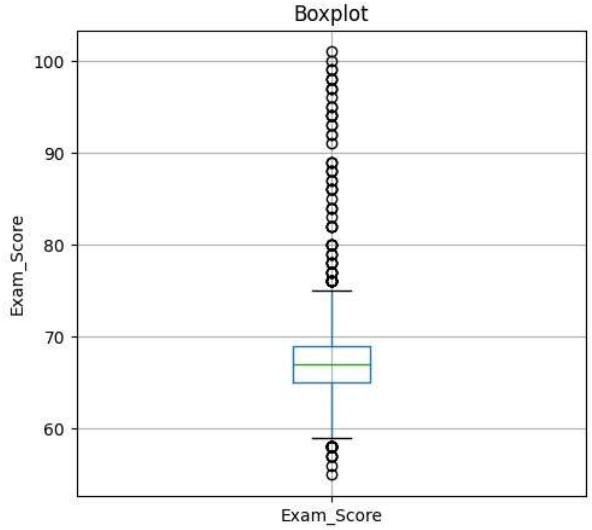



```
Gender
Male      3814
Female    2793
Name: count, dtype: int64
----
count     6607
unique       2
top       Male
freq      3814
Name: Gender, dtype: object
----
```




```
count    6607.000000
mean       67.235659
std         3.890456
min        55.000000
25%        65.000000
50%        67.000000
75%        69.000000
max       101.000000
Name: Exam_Score, dtype: float64
----
```





Missing Data

In [11]:
```
# number of nans in each column
nan = original_dataset_df.isna().sum()
nan[nan > 0]
```

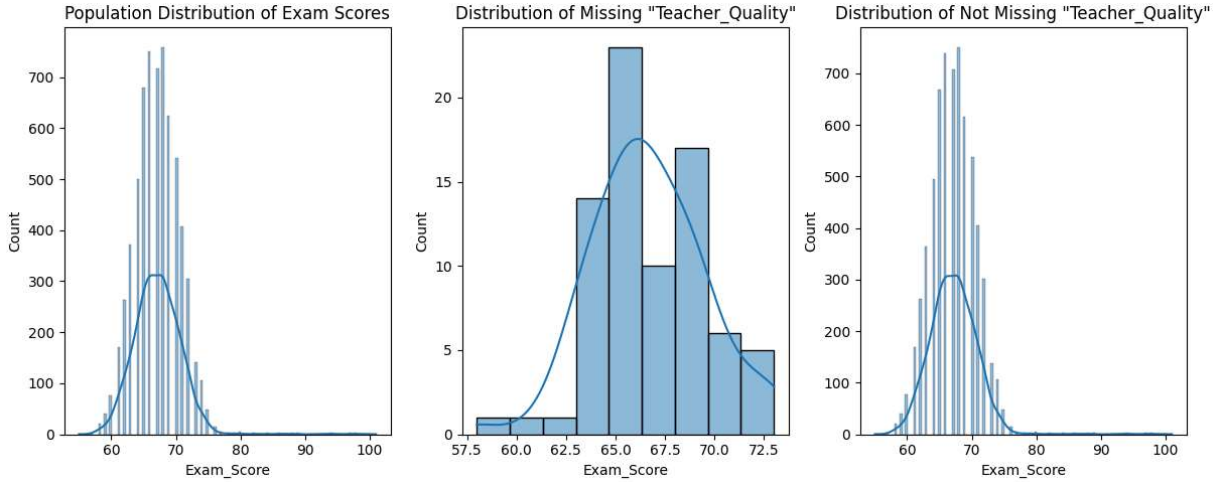
Out[11]:
```
Teacher_Quality             78
Parental_Education_Level    90
Distance_from_Home          67
dtype: int64
```

In [12]:
```
nan_rows = original_dataset_df.isna().any(axis=1)
count_nan_rows = nan_rows.sum()
count_nan_rows
```

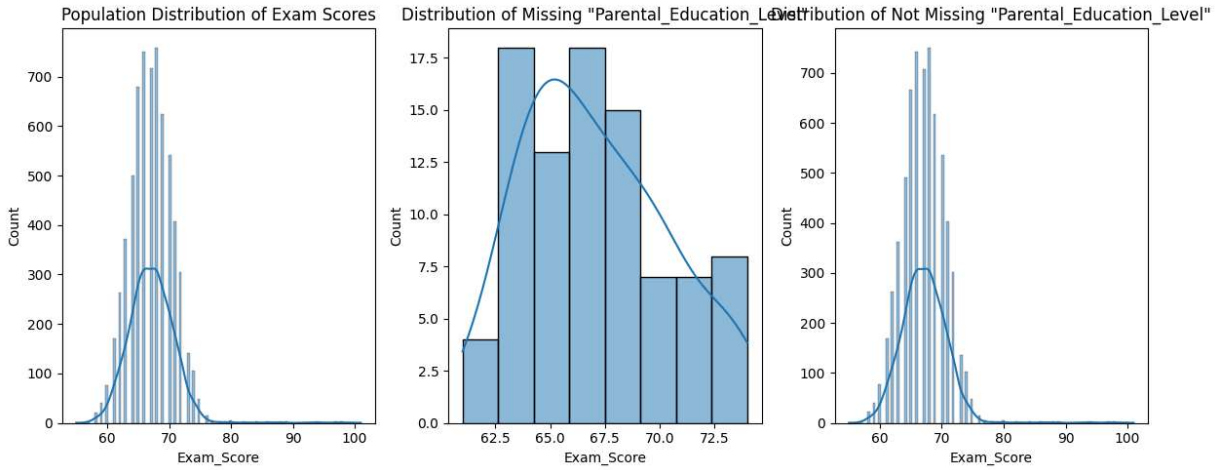
Out[12]:
```
229
```

we only have 229 data points with nans- a small proportion relative to the full 6607

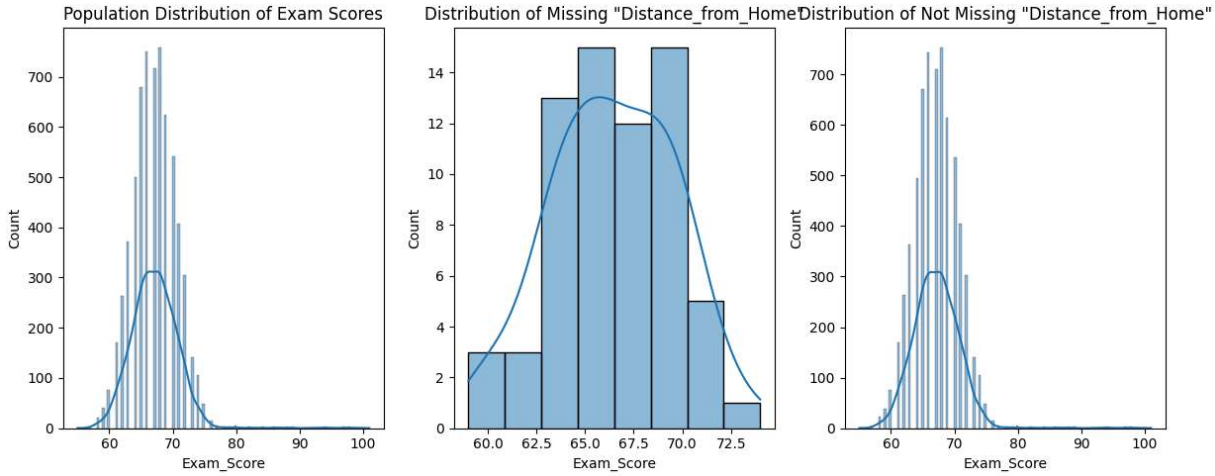
In [13]:
```
# Exploring the distributions between missing and non missing population
for column in original_dataset_df.columns:
    if original_dataset_df[column].isnull().any():  # Check for missing data in the
        # Create a figure and axes for the plots
        means = [0] * 3
        fig, axes = plt.subplots(1, 3, figsize=(12, 5))

        # Plot the distribution of exam scores for the population
        sns.histplot(original_dataset_df['Exam_Score'], ax=axes[0], kde=True)
        axes[0].set_title('Population Distribution of Exam Scores')
        means[0] = original_dataset_df["Exam_Score"].mean()

        # Plot the distribution of exam scores for the subset with missing data in
        subset = original_dataset_df[original_dataset_df[column].isnull()]
        sns.histplot(subset['Exam_Score'], ax=axes[1], kde=True)
        axes[1].set_title(f'Distribution of Missing "{column}"')
        means[1] = subset["Exam_Score"].mean()

        subset = original_dataset_df[~original_dataset_df[column].isnull()]
        sns.histplot(subset['Exam_Score'], ax=axes[2], kde=True)
        axes[2].set_title(f'Distribution of Not Missing "{column}"')
        means[2] = subset["Exam_Score"].mean()

        plt.tight_layout()
        plt.show()
        print(means)
```




```
[67.23565914938702, 66.64102564102564, 67.24276305712974]
```




```
[67.23565914938702, 67.05555555555556, 67.2381463863741]
```




```
[67.23565914938702, 66.43283582089552, 67.24388379204893]
```

for each column with missing values, we have created a histogram to explore the distribution of

- the entire population
- the part of a population with a missing value in the column
- the part of the population without a missing value

although the missing-population has a slightly lower mean value, the difference between the total population and the not-missing population is on the order of 1/100

- for this reason, we have chosen to drop the data with missing columns

ii) Data Preprocessing

In [14]:
```
import pandas as pd
```

We intend to perform the following transformations

- remove any row with NAN
- remove row with Exam Score > 100
- one-hot encode categorical variables
- create a column, improvement = Exam_Score - Previous_Scores
- rename other columns

Notes:

- 'duplicates' will be assumed to be separate students with the same metrics

In [15]:
```
original_dataset_df = pd.read_csv("StudentPerformanceFactors.csv")
original_dataset_df.sample(5)
```

Out[15]:

	Hours_Studied	Attendance	Parental_Involvement	Access_to_Resources	Extracurricula
6470	20	71	Low	High	
1365	19	71	High	Medium	
1569	17	69	Medium	Medium	
599	22	84	High	Medium	
1654	22	91	High	High	

remove nans

In [16]:
```
print("Original:\tany Nans?", original_dataset_df.isna().any().any())
no_nan_df = original_dataset_df.dropna()
print("New:\t\tany Nans?", no_nan_df.isna().any().any())
no_nan_df.sample(5)
```

```
Original:       any Nans? True
New:            any Nans? False
```

Out[16]:

	Hours_Studied	Attendance	Parental_Involvement	Access_to_Resources	Extracurricula
5863	9	93	High	Low	
4480	13	89	High	High	
3722	10	71	Medium	Low	
764	27	67	Low	Medium	
2769	19	87	High	High	

remove the Exam_Score > 100 because it is incorrect

In [17]:

```
print("Original:\t # Exam_Score>100", len(no_nan_df[no_nan_df['Exam_Score'] > 100])
no_gt100_df = no_nan_df.drop(no_nan_df[no_nan_df["Exam_Score"] > 100].index)
print("New:\t\t # Exam_Score>100", len(no_gt100_df[no_gt100_df['Exam_Score'] > 100]
no_gt100_df.sample(5)
```

```
Original:        # Exam_Score>100 1
New:             # Exam_Score>100 0
```

Out[17]:

	Hours_Studied	Attendance	Parental_Involvement	Access_to_Resources	Extracurricula
914	19	90	High	Medium	
3739	12	79	Medium	Low	
4288	29	90	Medium	Medium	
5529	19	78	Low	High	
1195	23	92	Medium	High	

rename columns and other transforms

In [18]:

```
renames = {
    "Hours_Studied" : "Hours_Studied_Per_Week"
}
transforms = {
    #"column name" : lamda x: transform(x)
}


rename_transformed_df = no_gt100_df.rename(columns=renames)
for k, v in transforms.items():
  rename_transformed_df[k] = rename_transformed_df[k].apply(v)

rename_transformed_df.sample(5)
```

Out[18]:

	Hours_Studied_Per_Week	Attendance	Parental_Involvement	Access_to_Resources	Ext
2381	14	88	Medium	Medium	
3863	19	81	Medium	High	
5654	15	68	Medium	High	
3607	26	72	Medium	Medium	
5638	18	63	High	High	

get dummy values for categorical data

In [19]:

```
oh_df = pd.get_dummies(rename_transformed_df, columns=rename_transformed_df.select_
oh_df.sample(5)
```

Out[19]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
1757	26	81	5	82	
2632	21	96	6	78	
3128	20	88	4	54	
6450	18	69	10	89	
3639	23	72	8	58	

5 rows × 41 columns

the naming of the new dummy variables seems intuitive enough that we do not feel that we need to rename them

adding score change column

In [20]:

```
diff_score_df = oh_df #this technically still is same df, just name to make it easi
diff_score_df["Score_Change"] = diff_score_df["Exam_Score"] - diff_score_df["Previo
diff_score_df.sample(5)
```

Out[20]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
153	21	86	5	51	
385	21	65	9	56	
5483	20	95	6	65	
1609	18	69	7	97	
5047	20	91	7	82	

5 rows × 42 columns

In [21]:
```
diff_score_df["Score_Change"].describe()
```

Out[21]:
```
count    6377.000000
mean       -7.816528
std        14.249124
min       -39.000000
25%       -20.000000
50%        -8.000000
75%         4.000000
max        41.000000
Name: Score_Change, dtype: float64
```

its interesting to se that the majority of students had their scores worsen

save data

In [22]:
```
df = diff_score_df
df.to_csv("transformed_data.csv", index=False)
```

In [23]:
```
df = pd.read_csv("transformed_data.csv")
df.sample(5)
```

Out[23]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
1080	13	68	6	79	
149	22	87	5	80	
3464	26	66	7	67	
2945	12	72	6	50	
6020	18	74	8	72	

5 rows × 42 columns

In [24]:
```
df.columns
```

Out[24]:
```
Index(['Hours_Studied_Per_Week', 'Attendance', 'Sleep_Hours',
       'Previous_Scores', 'Tutoring_Sessions', 'Physical_Activity',
       'Exam_Score', 'Parental_Involvement_High', 'Parental_Involvement_Low',
       'Parental_Involvement_Medium', 'Access_to_Resources_High',
       'Access_to_Resources_Low', 'Access_to_Resources_Medium',
       'Extracurricular_Activities_No', 'Extracurricular_Activities_Yes',
       'Motivation_Level_High', 'Motivation_Level_Low',
       'Motivation_Level_Medium', 'Internet_Access_No', 'Internet_Access_Yes',
       'Family_Income_High', 'Family_Income_Low', 'Family_Income_Medium',
       'Teacher_Quality_High', 'Teacher_Quality_Low', 'Teacher_Quality_Medium',
       'School_Type_Private', 'School_Type_Public', 'Peer_Influence_Negative',
       'Peer_Influence_Neutral', 'Peer_Influence_Positive',
       'Learning_Disabilities_No', 'Learning_Disabilities_Yes',
       'Parental_Education_Level_College',
       'Parental_Education_Level_High School',
       'Parental_Education_Level_Postgraduate', 'Distance_from_Home_Far',
       'Distance_from_Home_Moderate', 'Distance_from_Home_Near',
       'Gender_Female', 'Gender_Male', 'Score_Change'],
      dtype='object')
```

iii) regression analysis

In [25]:
```
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Lasso, LassoCV
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

In [26]:
```
df = pd.read_csv("transformed_data.csv")
```

we want to use our data to predict the difference in score

- we will try to predict this from {Hours_Studied, Attendance, Sleep_Hours, Motivation_Level_High, Motivation_Level_Medium, Motivation_Level_Low}

In [27]:
```
y = df["Score_Change"]
numerical_cols = ["Hours_Studied_Per_Week","Attendance","Sleep_Hours"]
dummy_cols = ["Motivation_Level_High","Motivation_Level_Medium","Motivation_Level_L
x = df[["Hours_Studied_Per_Week","Attendance","Sleep_Hours","Motivation_Level_High"
x.head()
```

Out[27]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Motivation_Level_High	Motivation_L
0	23	84	7	False	
1	19	64	8	False	
2	24	98	7	False	
3	29	89	8	False	
4	19	92	6	False	

In [28]:

```
# splitting data
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2)
```

In [29]:

```
# creating a model
model = LinearRegression()
model.fit(x_train, y_train)

# getting error
y_pred = model.predict(x_test)
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("test error")
print(f'MSE: {mse}, MAE: {mae}, R2: {r2}')

# print coefs
print("-"*10, )
print("intercept: ", model.intercept_)
for col, coef in zip(x.columns, model.coef_):
  print(f"{col}: {coef}")
```

```
test error
MSE: 205.82909735464398, MAE: 12.349619472151563, R2: 0.04573563190802821
----------
intercept:  -30.66957092078917
Hours_Studied_Per_Week: 0.24290415613199148
Attendance: 0.21483317336679378
Sleep_Hours: 0.10190376416215007
Motivation_Level_High: 0.1403957956508309
Motivation_Level_Medium: 0.31897688089020376
Motivation_Level_Low: -0.4593726765410314
```

this model does not seem well suited; our MSE is high and our R2 is close to 0
we will try scaling the X data

lets try using all the data and scaling the data

- we will mean center and scale the X; we will only standard deviation scale the y because we want to know if students are improving or not

In [30]:
```
y = df["Score_Change"]
y_scaled = y/y.std()

scaled_df = df.copy().drop(columns=["Exam_Score", "Score_Change"])
numerical_cols = scaled_df.select_dtypes(include=['int64']).columns
scaler = StandardScaler()
scaled_df[numerical_cols] = scaler.fit_transform(scaled_df[numerical_cols])

x_scaled = scaled_df
x_scaled.sample(5)
```

Out[30]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
2722	-2.001066	-0.434517	-1.386349	1.176267	2.84239
2437	0.505278	-1.387019	0.657282	-0.490557	1.22060
3751	-0.831439	0.691167	0.657282	-0.976714	0.40970
4415	-0.497260	0.691167	-0.023928	1.315169	0.40970
5882	-1.499797	1.643670	1.338492	0.898463	0.40970

5 rows × 40 columns

In [31]:
```
# splitting data
x_train, x_test, y_train, y_test = train_test_split(x_scaled,y_scaled, test_size=0.

# creating a model
model = LinearRegression()
model.fit(x_train, y_train)

# getting error
y_pred = model.predict(x_test)
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("test error")
print(f'MSE: {mse}, MAE: {mae}, R2: {r2}')

# print coefs
print("-"*10, )
print("intercept: ", model.intercept_)
for col, coef in zip(x_scaled.columns, model.coef_):
  print(f"{col}: {coef}")
```

```
test error
MSE: 0.019766990711776677, MAE: 0.03337006072913775, R2: 0.9799259714761407
----------
intercept:  -448548501256.897
Hours_Studied_Per_Week: 0.12393925259915912
Attendance: 0.15984805127968638
Sleep_Hours: -0.0009411387647689071
Previous_Scores: -0.9617544911277323
Tutoring_Sessions: 0.044107285153810946
Physical_Activity: 0.013221321917068098
Parental_Involvement_High: -1618571877524.8293
Parental_Involvement_Low: -1618571877524.9695
Parental_Involvement_Medium: -1618571877524.904
Access_to_Resources_High: 1306102016444.4604
Access_to_Resources_Low: 1306102016444.315
Access_to_Resources_Medium: 1306102016444.3887
Extracurricular_Activities_No: 57695194960.66548
Extracurricular_Activities_Yes: 57695194960.706985
Motivation_Level_High: -165346816952.3851
Motivation_Level_Low: -165346816952.46082
Motivation_Level_Medium: -165346816952.42056
Internet_Access_No: 101317609238.69751
Internet_Access_Yes: 101317609238.76944
Family_Income_High: 809662090001.5123
Family_Income_Low: 809662090001.4379
Family_Income_Medium: 809662090001.4717
Teacher_Quality_High: -372990802283.4702
Teacher_Quality_Low: -372990802283.5435
Teacher_Quality_Medium: -372990802283.5091
School_Type_Private: 704379455835.763
School_Type_Public: 704379455835.7655
Peer_Influence_Negative: 221358741712.23517
Peer_Influence_Neutral: 221358741712.272
Peer_Influence_Positive: 221358741712.3065
Learning_Disabilities_No: 522669201659.4296
Learning_Disabilities_Yes: 522669201659.3681
Parental_Education_Level_College: -726245084928.5894
Parental_Education_Level_High School: -726245084928.6274
Parental_Education_Level_Postgraduate: -726245084928.5591
Distance_from_Home_Far: 492043893932.69464
Distance_from_Home_Moderate: 492043893932.7167
Distance_from_Home_Near: 492043893932.75336
Gender_Female: -883525120839.7439
Gender_Male: -883525120839.746
```

this R2 Score is much better, but our coefficients are very high

we can also try using lasso regression to decrease the coefficients and identify the most important features

In [32]:
```
lasso_cv = LassoCV(alphas=np.logspace(-10, 0, 100), cv=5, random_state=183461)
lasso_cv.fit(x_train, y_train)

print(f"Best lambda: {lasso_cv.alpha_}")
```

```
Best lambda: 9.111627561154887e-05
```

this regularization constant is a little low

In [33]:
```
# seems like lasso isnt doing much
model = Lasso(alpha=lasso_cv.alpha_)
model.fit(x_train, y_train)
```

Out[33]:
```
Lasso
Lasso(alpha=9.111627561154887e-05)
```

In [34]:
```
# getting error
y_pred = model.predict(x_test)
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print("test error")
print(f'MSE: {mse}, MAE: {mae}, R2: {r2}')

# print coefs
print("-"*10, )
print("intercept: ", model.intercept_)
for col, coef in zip(x_scaled.columns, model.coef_):
  print(f"{col}: {coef}")
```

```
test error
MSE: 0.019771591496967063, MAE: 0.03339634810029263, R2: 0.9799212992276183
----------
intercept:  -0.608000117494527
Hours_Studied_Per_Week: 0.12381608557213386
Attendance: 0.1599829094388474
Sleep_Hours: -0.0007989977856626093
Previous_Scores: -0.9613937629530622
Tutoring_Sessions: 0.04403060155079752
Physical_Activity: 0.013165461313920202
Parental_Involvement_High: 0.0762318188334009
Parental_Involvement_Low: -0.06267171330684047
Parental_Involvement_Medium: -0.0
Access_to_Resources_High: 0.07126041495152156
Access_to_Resources_Low: -0.07274213607457758
Access_to_Resources_Medium: 0.0
Extracurricular_Activities_No: -0.04103437724550223
Extracurricular_Activities_Yes: 8.20234065795338e-18
Motivation_Level_High: 0.03571941525902418
Motivation_Level_Low: -0.039454674799415945
Motivation_Level_Medium: -0.0
Internet_Access_No: -0.07017783405145875
Internet_Access_Yes: 0.0
Family_Income_High: 0.039902071054296315
Family_Income_Low: -0.03393885968625626
Family_Income_Medium: -0.0
Teacher_Quality_High: 0.03895754055693672
Teacher_Quality_Low: -0.0340472413645821
Teacher_Quality_Medium: 0.0
School_Type_Private: -0.0014489054014801973
School_Type_Public: 0.0
Peer_Influence_Negative: -0.03621993163883001
Peer_Influence_Neutral: -0.0
Peer_Influence_Positive: 0.034230704277103036
Learning_Disabilities_No: 0.06012222147305471
Learning_Disabilities_Yes: -6.713893094584935e-16
Parental_Education_Level_College: -0.0
Parental_Education_Level_High School: -0.03776995276937811
Parental_Education_Level_Postgraduate: 0.030923052329697262
Distance_from_Home_Far: -0.020388231810637765
Distance_from_Home_Moderate: -0.0
Distance_from_Home_Near: 0.03651514297007487
Gender_Female: 0.002209727238433693
Gender_Male: -1.0444764358914529e-17
```

These coefficients seem much more reasonable while still having a very high R2-Score/Low MSE

What we can learn from our Lasso Regression model

- Sleep_hours does not seem to be relevant: our model has given it a very small coefficient
- Public vs Private Shools doesn't matter: both coefficients are very small

- Gender does not seem to matter much: both coefficients are very small
- At a first glance, Previous_Scores, Hours_Studied_Per_Week, and Attendance seem to have the highest impact: they have the largest coefficients

iv) Logistic Regression

In [35]:
```
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, roc_auc_score, f1_score
from sklearn.preprocessing import StandardScaler
from sklearn import metrics

import plotly.express as px
import matplotlib.pyplot as plt
import seaborn as sns
```

we will use logistic regression to try and predict if a students score will improve

In [36]:
```
df = pd.read_csv("transformed_data.csv")
df.sample(5)
```

Out[36]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
3525	23	74	4	67	
5464	16	61	8	54	
3038	23	94	8	86	
1292	27	91	5	75	
6193	23	99	8	95	

5 rows × 42 columns

In [37]:
```
y = df["Score_Change"] > 0
y.sample(5)
```

Out[37]:
```
2431    False
162      True
480      True
6219    False
1527    False
Name: Score_Change, dtype: bool
```

In [38]:
```
X = df.drop(columns=["Exam_Score", "Score_Change"])

scaled_df = df.copy().drop(columns=["Exam_Score", "Score_Change"])
```

```
numerical_cols = scaled_df.select_dtypes(include=['int64']).columns
scaler = StandardScaler()
scaled_df[numerical_cols] = scaler.fit_transform(scaled_df[numerical_cols])

x_scaled = scaled_df
x_scaled.head()
```

Out[38]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessions
0	0.505278	0.344803	-0.023928	-0.143302	-1.212085
1	-0.163081	-1.387019	0.657282	-1.115616	0.409708
2	0.672367	1.557079	-0.023928	1.106816	0.409708
3	1.507815	0.777759	0.657282	1.592974	-0.401188
4	-0.163081	1.037532	-0.705139	-0.698910	1.220605

5 rows × 40 columns

Train a Logistic regression Model

In [39]:
```
x_train, x_test, y_train, y_test = train_test_split(x_scaled,y, test_size=0.2)
```

In [40]:
```
cv_lrmodel = LogisticRegression(solver='liblinear', penalty='l2')
params = {"C":[1e-4, 1e-3, 1e-2, 1e-1, 1, 1e1, 1e2, 1e3, 1e4]}
grid_search = GridSearchCV(cv_lrmodel, params, cv=5, scoring='accuracy')
grid_search.fit(x_train, y_train)
grid_search.best_params_['C']
```

Out[40]: 1000.0

In [41]:
```
lrmodel = grid_search.best_estimator_

# print coefs
print("-"*10, )
print("intercept: ", lrmodel.intercept_)
for col, coef in zip(X.columns, lrmodel.coef_[0]):
  print(f"{col}: {coef}")
```

```
----------
intercept:  [-1.26830286]
Hours_Studied_Per_Week: 1.4936551604188484
Attendance: 1.9482708033426437
Sleep_Hours: -0.08079203086200018
Previous_Scores: -11.395856502690542
Tutoring_Sessions: 0.5600341438523275
Physical_Activity: 0.11609380661186093
Parental_Involvement_High: 0.39209496232775354
Parental_Involvement_Low: -1.0692828506989343
Parental_Involvement_Medium: -0.5911149684200111
Access_to_Resources_High: 0.5796801368127543
Access_to_Resources_Low: -1.2848603702422319
Access_to_Resources_Medium: -0.5631226233617969
Extracurricular_Activities_No: -0.8278468496030035
Extracurricular_Activities_Yes: -0.4404560071882762
Motivation_Level_High: -0.02832800655773072
Motivation_Level_Low: -0.9311341039659379
Motivation_Level_Medium: -0.3088407462676487
Internet_Access_No: -1.0904467049869135
Internet_Access_Yes: -0.17785615180442466
Family_Income_High: 0.09432335768707333
Family_Income_Low: -0.9646609698004105
Family_Income_Medium: -0.397965244677865
Teacher_Quality_High: -0.013591518369534488
Teacher_Quality_Low: -1.0734831272690024
Teacher_Quality_Medium: -0.18122821115271867
School_Type_Private: -0.5649221498567115
School_Type_Public: -0.7033807069346814
Peer_Influence_Negative: -0.9147305777558856
Peer_Influence_Neutral: -0.3828498443289013
Peer_Influence_Positive: 0.02927756529354097
Learning_Disabilities_No: -0.3810097239939827
Learning_Disabilities_Yes: -0.8872931327972627
Parental_Education_Level_College: -0.3678842097103063
Parental_Education_Level_High School: -1.0270083319537078
Parental_Education_Level_Postgraduate: 0.12658968487275643
Distance_from_Home_Far: -0.9431326410416012
Distance_from_Home_Moderate: -0.44320336927589343
Distance_from_Home_Near: 0.11803315352619405
Gender_Female: -0.591719776351234
Gender_Male: -0.676583080440074
```

Lets evaluate our Model

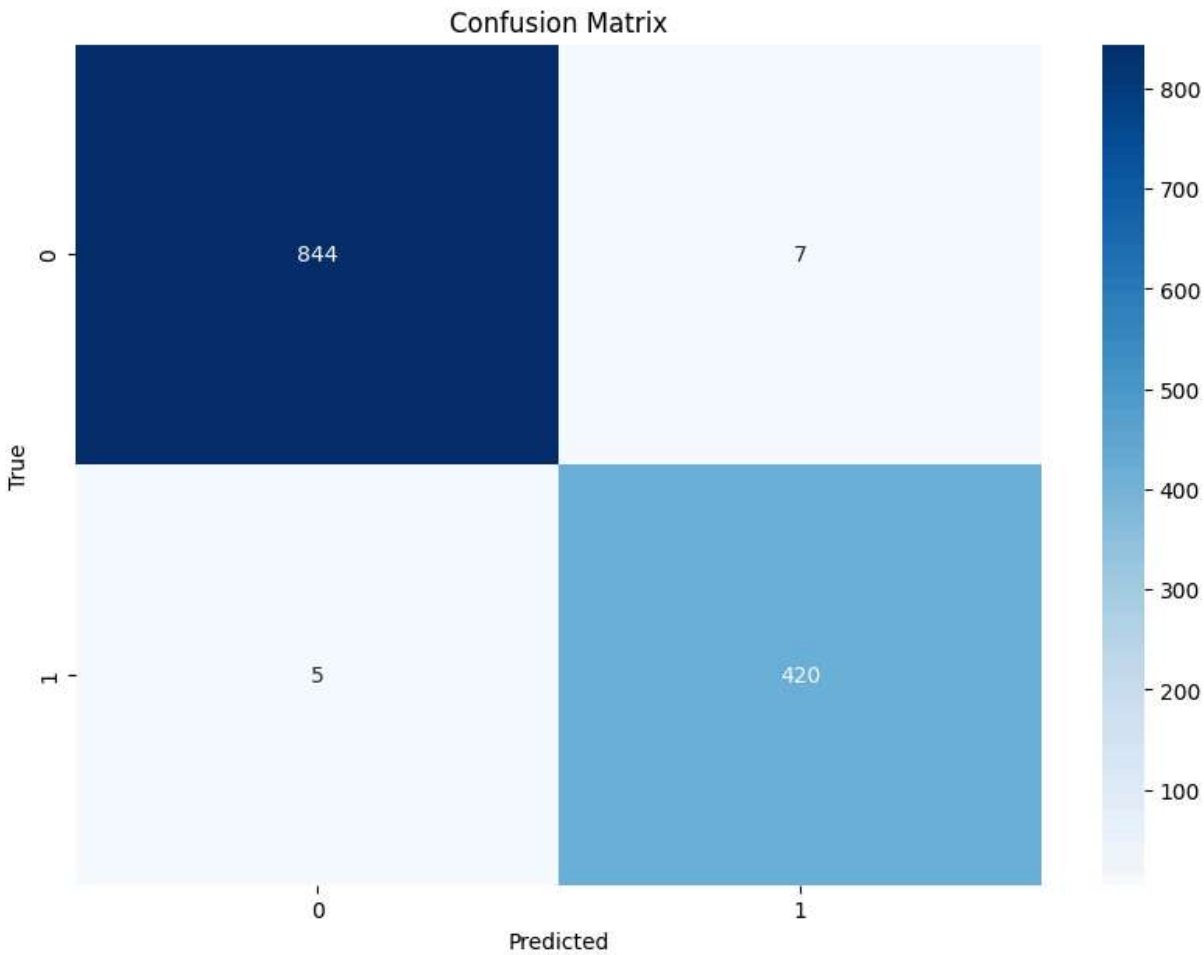
In [42]:
```
res = pd.DataFrame(dict(
  act = y_test,
  pred = lrmodel.predict(x_test),
  prob = lrmodel.predict_proba(x_test)[:,1]
))
res.sample(5)
```

Out[42]:

	act	pred	prob
5849	False	False	3.612138e-02
1212	False	False	1.712993e-07
3666	False	False	2.704404e-09
2450	False	False	3.764274e-08
6203	False	False	1.514773e-06

In [43]:

```
conf = confusion_matrix(res['act'], res['pred'])
#the count of true negatives is C_{0,0}, false negatives is C_{1,0}, true positives
plt.figure(figsize=(10, 7))
sns.heatmap(conf, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



In [44]:

```
#accuracy
metrics.accuracy_score(res['act'], res['pred'])
```

Out[44]: 0.9905956112852664

In [45]:
```
#prediction error =
1 - metrics.accuracy_score(res['act'], res['pred'])
```

Out[45]: 0.009404388714733591

In [46]:
```
#recall / tpr
metrics.recall_score(res['act'], res['pred'])
```

Out[46]: 0.9882352941176471

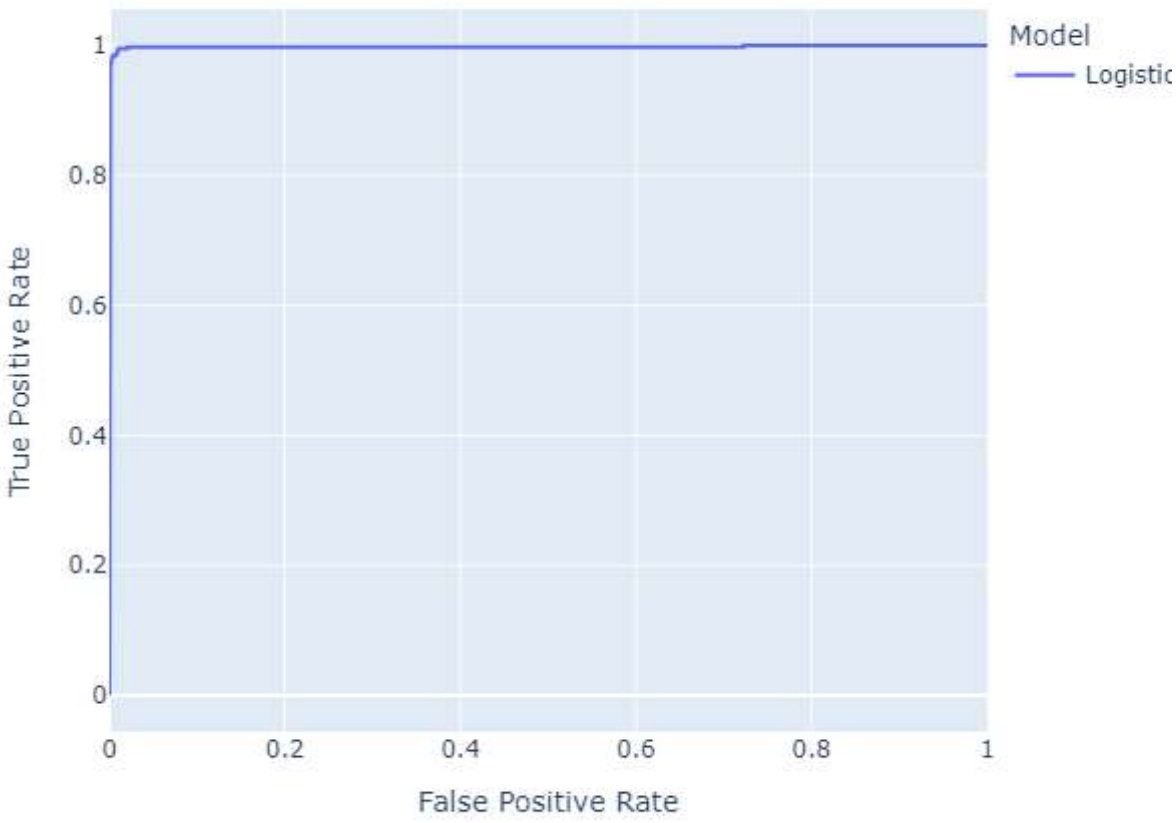
In [47]:
```
#tnr
(conf[0, 0]) / conf[0,:].sum()
```

Out[47]: 0.9917743830787309

In [48]:
```
#f1 score
f1_score(res['act'], res['pred'])
```

Out[48]: 0.9859154929577465

In [49]:
```
#ROC
lr_fpr_sample, lr_tpr_sample, lr_thresholds_sample = metrics.roc_curve(res['act'],

roc_lr_sample = pd.DataFrame({
    'False Positive Rate': lr_fpr_sample,
    'True Positive Rate': lr_tpr_sample,
    'Model': 'Logistic Regression'
}, index=lr_thresholds_sample)


roc_sample_df = pd.concat([roc_lr_sample])


px.line(roc_lr_sample, y='True Positive Rate', x='False Positive Rate',
        color='Model',
        width=700, height=500
)
```



In [50]:
```
roc_auc_score(res['act'], res['prob'] )
```

Out[50]: 0.9980756203774107

our model is doing very well, we have a high accuracy, recall, true negative rate, and our ROC curve looks very good

v) random forest and KNN

random forest

we will use a random forest classifier to predict if a student will improve their score or not

In [51]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, roc_auc_score
from sklearn import metrics
```

```
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
```

In [52]:
```
df = pd.read_csv("transformed_data.csv")
df.sample(5)
```

Out[52]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
2579	23	64	7	55	
3696	27	64	5	70	
3592	19	77	5	90	
6182	11	97	8	76	
2145	28	80	8	61	

5 rows × 42 columns

In [53]:
```
y = df["Score_Change"] > 0
y.sample(5)
```

Out[53]:
```
1668    False
2756    False
6316    False
3615     True
5990    False
Name: Score_Change, dtype: bool
```

In [54]:
```
X = df.drop(columns=["Exam_Score", "Score_Change"])
X.sample(5)
```

Out[54]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
3243	9	89	7	91	
860	28	94	7	80	
353	22	65	6	85	
5054	22	78	6	92	
5	19	88	8	89	

5 rows × 40 columns

In [55]:
```
x_train, x_test, y_train, y_test = train_test_split(X,y, test_size=0.2)
```

our model is doing very well, we have a high accuracy, recall, true negative rate, and our ROC curve looks very good

In [56]:
```
# Initialize the RandomForestClassifier
rf = RandomForestClassifier()

# Define a parameter grid for max_depth (tree depth)
param_grid = {
    'max_depth': [5, 10, 15, 20, 25, 30, None]  # None means no limit (<=40)
}

# Set up GridSearchCV to find the best max_depth using cross-validation
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring='accu

grid_search.fit(x_train, y_train)


best_model = grid_search.best_estimator_
best_model
```

Out[56]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=25)
```

In [57]:
```
best_rf = best_model
best_rf.fit(x_train, y_train)
```

Out[57]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=25)
```

our cross validation says that a depth of 5 produces the best result

evaluating our random forest

In [58]:
```
res = pd.DataFrame(dict(
  act = y_test,
  pred = best_rf.predict(x_test),
  prob = best_rf.predict_proba(x_test)[:,1]
))
res.sample(5)
```

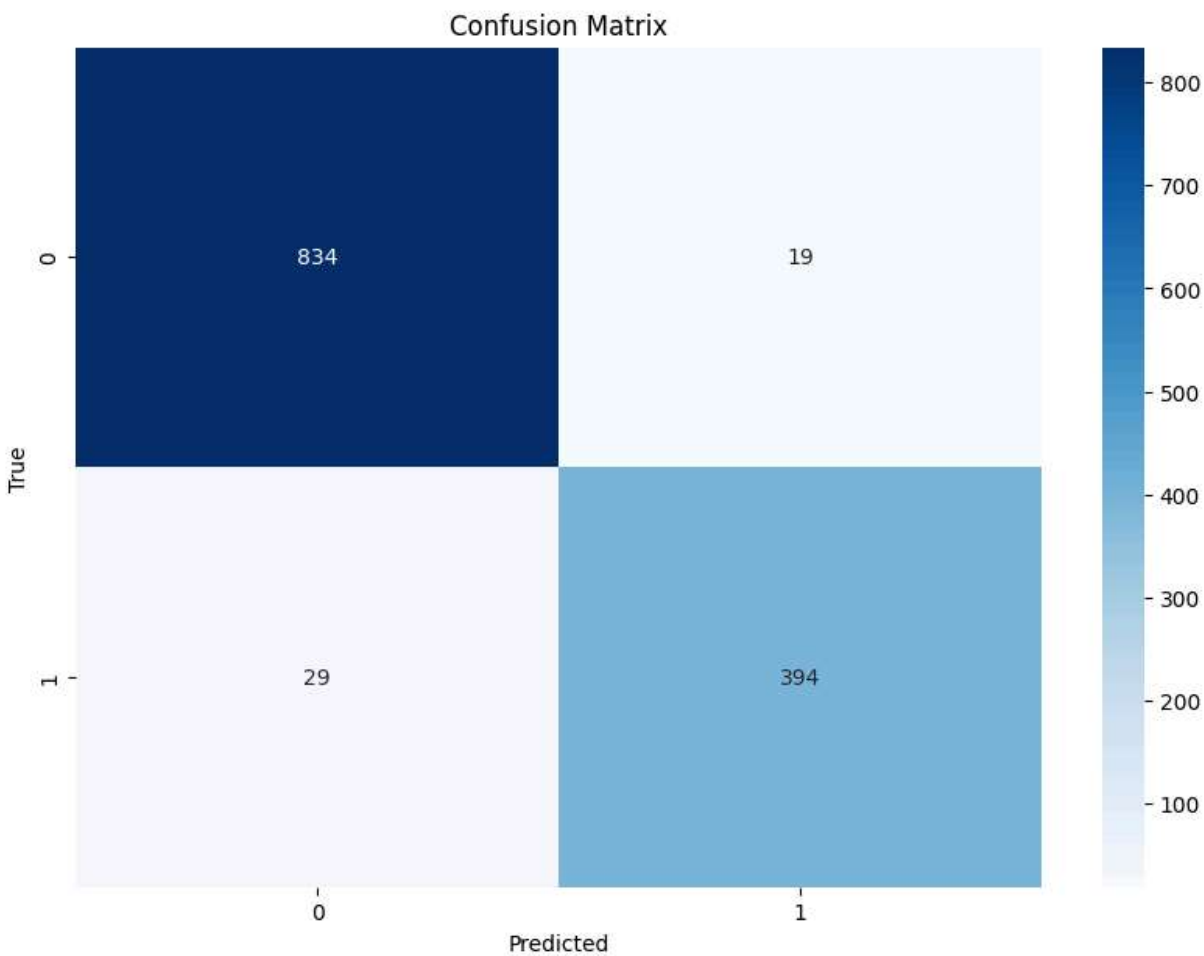
Out[58]:

	act	pred	prob
5433	False	False	0.09
3381	True	True	0.73
1993	True	True	0.80
4929	False	False	0.15
1152	True	False	0.45

In [59]:
```
best_rf.score(x_test, y_test)
```

Out[59]:
```
0.9623824451410659
```

In [60]:
```
conf = confusion_matrix(res['act'], res['pred'])
#the count of true negatives is C_{0,0}, false negatives is C_{1,0}, true positives
plt.figure(figsize=(10, 7))
sns.heatmap(conf, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



In [61]:
```
#accuracy
metrics.accuracy_score(res['act'], res['pred'])
```

Out[61]: 0.9623824451410659

In [62]:
```
#prediction error =
1 - metrics.accuracy_score(res['act'], res['pred'])
```

Out[62]: 0.037617554858934144

In [63]:
```
#recall / tpr
metrics.recall_score(res['act'], res['pred'])
```

Out[63]: 0.9314420803782506

In [64]:
```
#tnr
(conf[0, 0]) / conf[0,:].sum()
```

Out[64]: 0.977725674091442

In [65]:
```
#f1 score
metrics.f1_score(res['act'], res['pred'])
```

Out[65]: 0.9425837320574163

In [66]:
```
#ROC
lr_fpr_sample, lr_tpr_sample, lr_thresholds_sample = metrics.roc_curve(res['act'],

roc_lr_sample = pd.DataFrame({
    'False Positive Rate': lr_fpr_sample,
    'True Positive Rate': lr_tpr_sample,
    'Model': 'Random Forest'
}, index=lr_thresholds_sample)


roc_sample_df = pd.concat([roc_lr_sample])


px.line(roc_lr_sample, y='True Positive Rate', x='False Positive Rate',
        color='Model',
        width=700, height=500
)
```

In [67]:
```
roc_auc_score(res['act'], res['prob'] )
```

Out[67]: 0.9896166776139838

Our Random Forest's performance is comparable to logistic regression, albeit slightly worse.

KNN

In [68]:
```
import pandas as pd

from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import roc_auc_score, confusion_matrix


import matplotlib.pyplot as plt
import plotly.express as px
```

In [69]:
```
df = pd.read_csv("transformed_data.csv")
df.sample(5)
```

Out[69]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
2534	28	87	4	62	
1294	11	84	6	76	
4203	14	97	5	83	
2865	22	84	8	90	
3288	19	65	9	60	

5 rows × 42 columns

In [70]:
```
y = df["Score_Change"] > 0

X = df.drop(columns=["Exam_Score", "Score_Change"])

scaled_df = df.copy().drop(columns=["Exam_Score", "Score_Change"])
numerical_cols = scaled_df.select_dtypes(include=['int64']).columns
scaler = StandardScaler()
scaled_df[numerical_cols] = scaler.fit_transform(scaled_df[numerical_cols])

x_scaled = scaled_df
x_scaled.head()
```

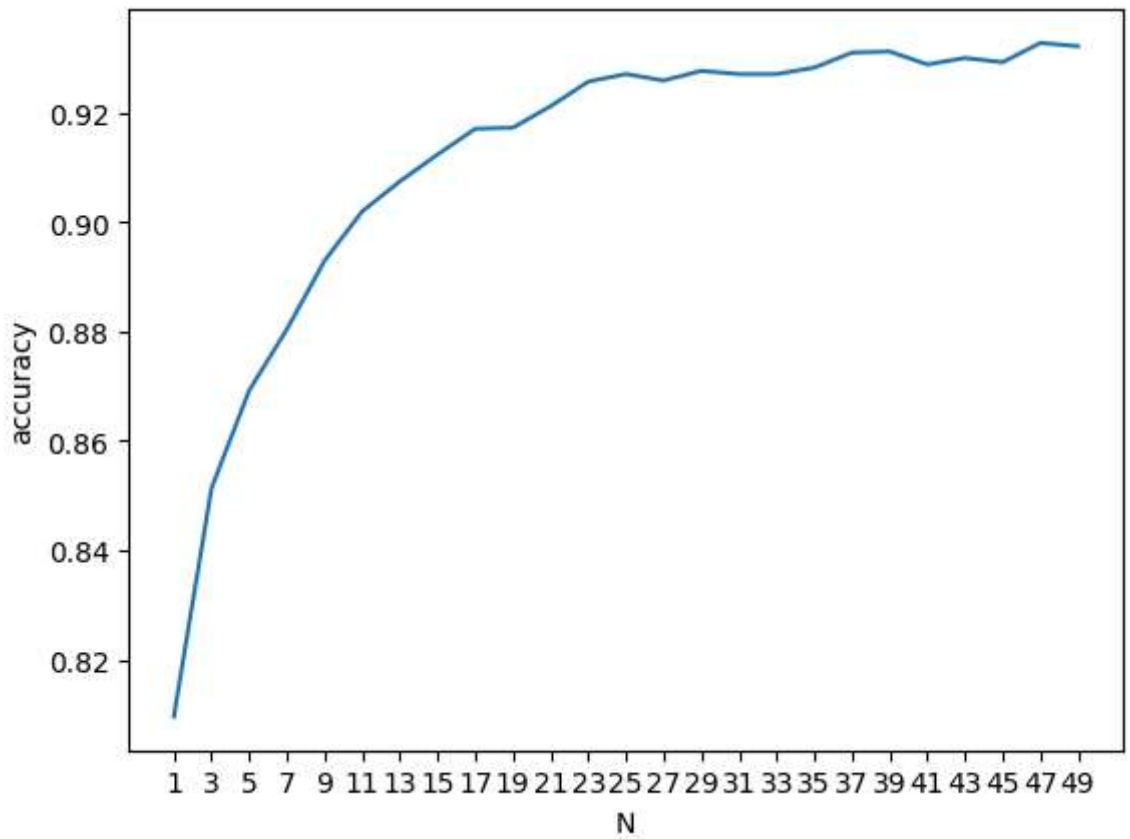
Out[70]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessions
0	0.505278	0.344803	-0.023928	-0.143302	-1.212085
1	-0.163081	-1.387019	0.657282	-1.115616	0.409708
2	0.672367	1.557079	-0.023928	1.106816	0.409708
3	1.507815	0.777759	0.657282	1.592974	-0.401188
4	-0.163081	1.037532	-0.705139	-0.698910	1.220605

5 rows × 40 columns

In [71]:
```
x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.2)
```

In [72]:
```
k_vals = range(1,51,2) # range from 1 to 50 neighbors (step size of 2)

cv_score = []

# Perform CV
for k in k_vals:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, x_train, y_train, cv=5, scoring='accuracy')  # 5-
    cv_score.append(np.mean(scores))

# Plot the cross-validation results
plt.plot(k_vals, cv_score)
plt.xlabel("N")
plt.xticks(k_vals)
plt.ylabel("accuracy")
plt.show()

# Find the optimal k (the value with the lowest negative MSE)
optimal_k = k_vals[np.argmax(cv_score)]
print(f"Optimal number of neighbors (K): {optimal_k}")
```




```
Optimal number of neighbors (K): 47
```

In [73]:
```
knn = KNeighborsClassifier(n_neighbors=optimal_k)

knn.fit(x_train, y_train)
```

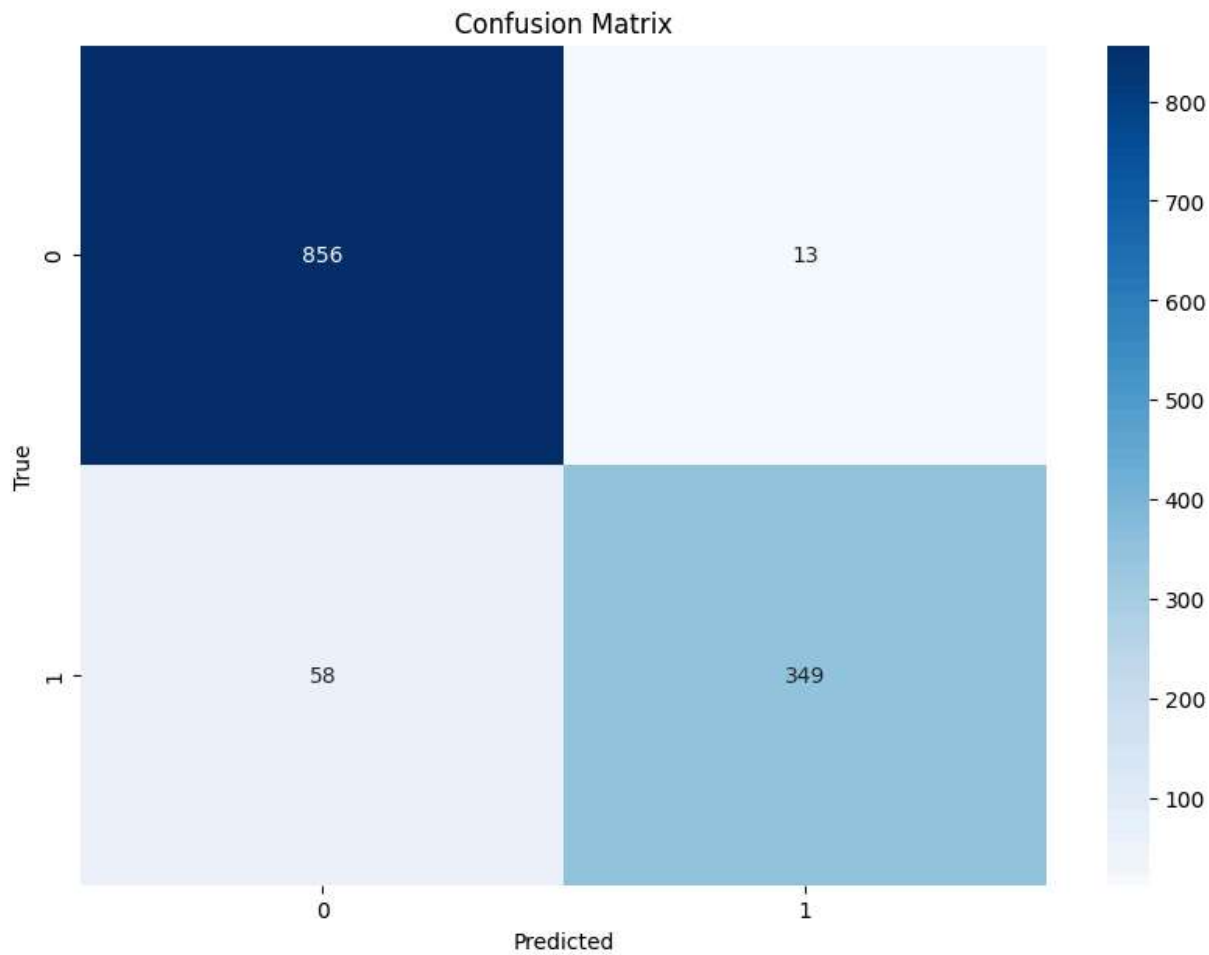
Out[73]:
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=47)
```

In [74]:
```
res = pd.DataFrame(dict(
  act = y_test,
  pred = knn.predict(x_test),
  prob = knn.predict_proba(x_test)[:,1]
))
res.sample(5)
```

Out[74]:

	act	pred	prob
2647	False	False	0.127660
3115	True	True	0.936170
2008	False	False	0.361702
802	True	True	0.531915
395	True	True	0.829787

In [75]:
```
conf = confusion_matrix(res['act'], res['pred'])
#the count of true negatives is C_{0,0}, false negatives is C_{1,0}, true positives
plt.figure(figsize=(10, 7))
sns.heatmap(conf, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



In [76]:
```
#accuracy
metrics.accuracy_score(res['act'], res['pred'])
```

Out[76]: 0.9443573667711599

In [77]:
```
#prediction error =
1 - metrics.accuracy_score(res['act'], res['pred'])
```

Out[77]: 0.05564263322884011

In [78]:
```
#recall / tpr
metrics.recall_score(res['act'], res['pred'])
```

Out[78]: 0.8574938574938575

In [79]:
```
#tnr
(conf[0, 0]) / conf[0,:].sum()
```

Out[79]:
```
0.9850402761795167
```

In [80]:
```
#f1 score
metrics.f1_score(res['act'], res['pred'])
```

Out[80]:
```
0.9076723016905072
```

In [81]:
```
#ROC
lr_fpr_sample, lr_tpr_sample, lr_thresholds_sample = metrics.roc_curve(res['act'],

roc_lr_sample = pd.DataFrame({
    'False Positive Rate': lr_fpr_sample,
    'True Positive Rate': lr_tpr_sample,
    'Model': 'KNN'
}, index=lr_thresholds_sample)


roc_sample_df = pd.concat([roc_lr_sample])


px.line(roc_lr_sample, y='True Positive Rate', x='False Positive Rate',
        color='Model',
        width=700, height=500
)
```

In [82]:
```
roc_auc_score(res['act'], res['prob'] )
```

Out[82]:
```
0.9858489098995429
```

similar to Random Forest, KNN does a good job at fitting the data, but is slightly worse than logistic regression

vi) PCA and Clustering

In [12]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
import pandas as pd
import plotly.express as px
```

In [13]:
```
df = pd.read_csv("transformed_data.csv")
df.sample(5)
```

Out[13]:

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
2465	15	74	8	76	
1963	26	91	7	57	
2782	7	64	9	70	
1984	17	76	7	81	
2049	20	86	7	53	

5 rows × 42 columns

PCA

we will perform pca on our prediction data

- we will mean center and standard-deviation scale our data (excluding categorical variables)

In [14]:
```
# important that we drop our response variable
scaled_df = df.copy().drop(columns=["Exam_Score", "Score_Change"])

numerical_cols = scaled_df.select_dtypes(include=['int64']).columns
scaler = StandardScaler()
scaled_df[numerical_cols] = scaler.fit_transform(scaled_df[numerical_cols])
# setting one-hot columns to ints
scaled_df[scaled_df.select_dtypes(include=['bool']).columns] = scaled_df.select_dty
scaled_df.sample(5)
```

Out[14]:

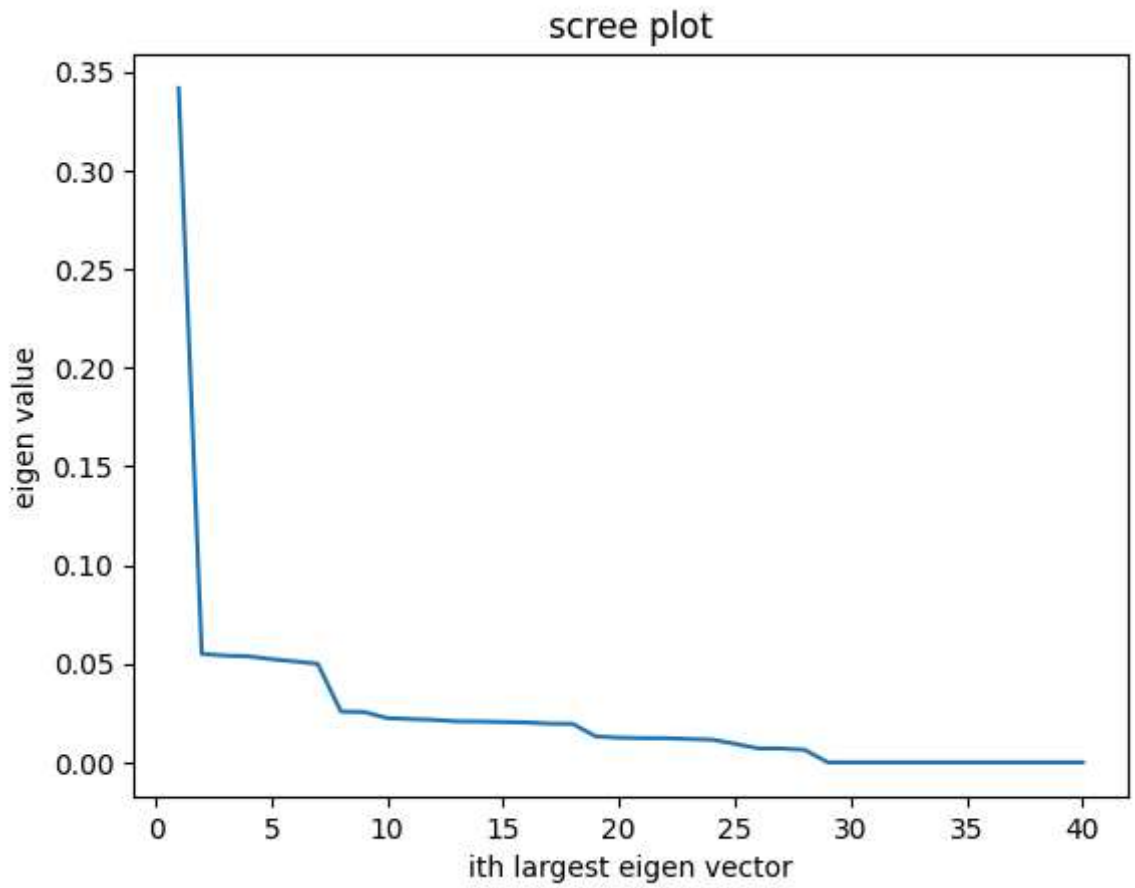
	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
95	0.338188	-1.387019	-0.023928	1.592974	-0.40118
2945	-1.332708	-0.694291	-0.705139	-1.740675	-0.40118
2578	-0.664349	0.864350	-0.705139	1.037365	0.40970
2042	-0.998529	0.085030	0.657282	-0.282204	-0.40118
3380	0.004009	-0.001562	-0.023928	-1.185067	-1.21208

5 rows × 40 columns

In [15]:
```
u,s,vh = np.linalg.svd(scaled_df)
v = vh.T
```

In [16]:
```
vars = np.square(s)
total_var = np.sum(vars)
"total variance", total_var
percent_var = vars/total_var
plt.plot(range(1, len(percent_var) + 1), percent_var)
plt.title("scree plot")
plt.ylabel("eigen value")
plt.xlabel("ith largest eigen vector")
list(enumerate(percent_var))
```

Out[16]:
```
[(0, 0.34164038591161594),
 (1, 0.054980265136858955),
 (2, 0.054105467500842254),
 (3, 0.053757040115614364),
 (4, 0.05229492277328973),
 (5, 0.051204281680537304),
 (6, 0.04992622714839374),
 (7, 0.0257939572878531),
 (8, 0.0255166732602858),
 (9, 0.022419319023245815),
 (10, 0.02196114883364197),
 (11, 0.021553872465941273),
 (12, 0.02080358687271321),
 (13, 0.02069495589560597),
 (14, 0.020452909291477094),
 (15, 0.020240841605596346),
 (16, 0.01964549663184825),
 (17, 0.01948570514261525),
 (18, 0.013152406051659385),
 (19, 0.012541141418314264),
 (20, 0.012293992222875721),
 (21, 0.012246264589144969),
 (22, 0.011841568381625566),
 (23, 0.011521646616405085),
 (24, 0.009414940418501033),
 (25, 0.007083543138350393),
 (26, 0.00704908036024405),
 (27, 0.006378360224903195),
 (28, 6.737668602257329e-32),
 (29, 6.348469833783414e-33),
 (30, 5.606404457244697e-33),
 (31, 3.5803746434875684e-33),
 (32, 2.7414215619206324e-33),
 (33, 2.5343221491236437e-33),
 (34, 2.395452805479779e-33),
 (35, 1.8437247903183755e-33),
 (36, 1.8437247903183755e-33),
 (37, 1.8437247903183755e-33),
 (38, 1.8437247903183755e-33),
 (39, 1.0803223469619167e-33)]
```



from our scree plot, we see that first principal component has the highest variation while most others have less variation.

In [17]:
```
sum(percent_var[:16])
```

Out[17]: 0.857345854803513

to reduce the dimensionality of the data, we will only use principal components with a proportion of variance >=0.2: the first 16 PC's account for 86 % of the variability

In [18]:
```
# put the loadings for PC1 in a data frame
loadings1 = pd.DataFrame(
    {"feature": scaled_df.columns,
     "pc1_loading": vh[0]
     })
# look at the 10 largest (absolute value) loadings for PC1 but print out the signed
loadings1.reindex(loadings1["pc1_loading"].abs().sort_values(ascending=False).index
    .head(10)
```

Out[18]:

	feature	pc1_loading
18	Internet_Access_Yes	-0.364970
30	Learning_Disabilities_No	-0.354694
26	School_Type_Public	-0.277202
24	Teacher_Quality_Medium	-0.240007
37	Distance_from_Home_Near	-0.238291
13	Extracurricular_Activities_Yes	-0.236386
39	Gender_Male	-0.229028
8	Parental_Involvement_Medium	-0.203650
16	Motivation_Level_Medium	-0.202746
11	Access_to_Resources_Medium	-0.200517

In [19]:

```
# put the loadings for PC2 in a data frame
loadings2 = pd.DataFrame(
    {"feature": scaled_df.columns,
     "pc2_loading": vh[1]
     })
# look at the 10 largest (absolute value) loadings for PC2 but print out the signed
loadings2.reindex(loadings2["pc2_loading"].abs().sort_values(ascending=False).index
    .head(10)
```

Out[19]:

	feature	pc2_loading
1	Attendance	-0.530130
0	Hours_Studied_Per_Week	0.489049
3	Previous_Scores	0.482920
4	Tutoring_Sessions	-0.431940
2	Sleep_Hours	0.228748
5	Physical_Activity	0.075047
33	Parental_Education_Level_High School	0.021219
32	Parental_Education_Level_College	-0.013745
37	Distance_from_Home_Near	-0.013512
21	Family_Income_Medium	0.011317

In [20]:

```
vh_k = vh[:16]
vh_k.shape #expect 16x #features
```

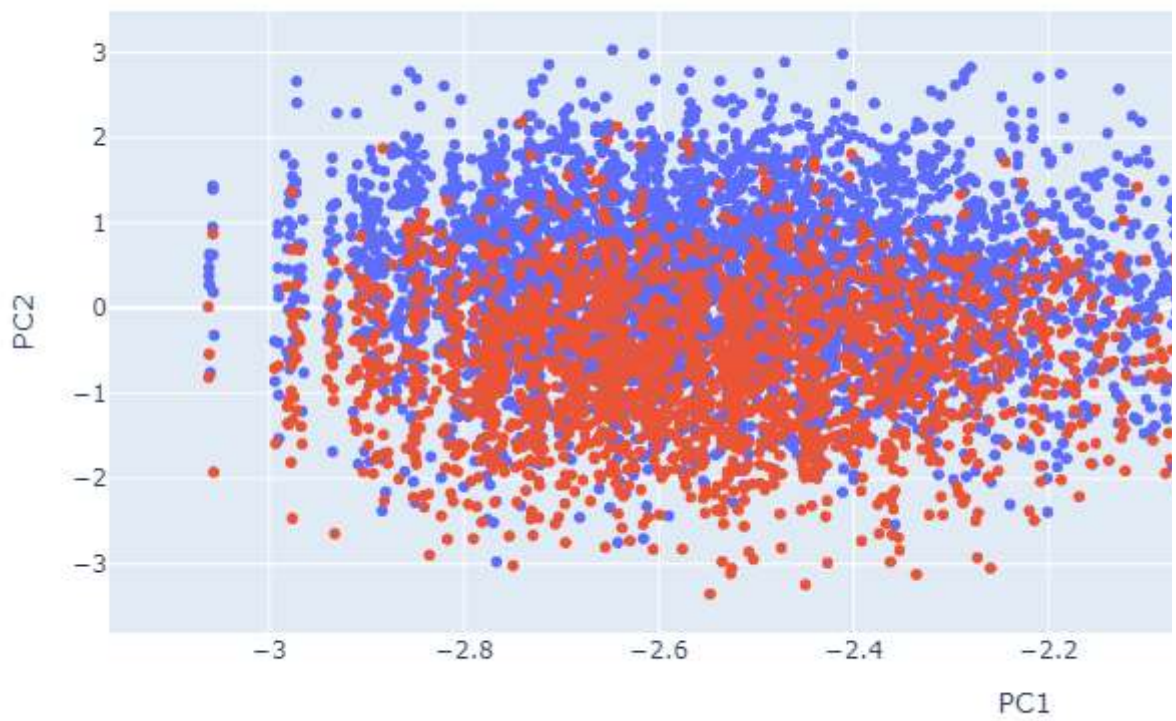
Out[20]: (16, 40)

In [21]:
```
pca_scaled= scaled_df @ vh_k.T
pca_scaled.columns = ["PC" + str(1 + col) for col in pca_scaled.columns]
pca_scaled.head()
```

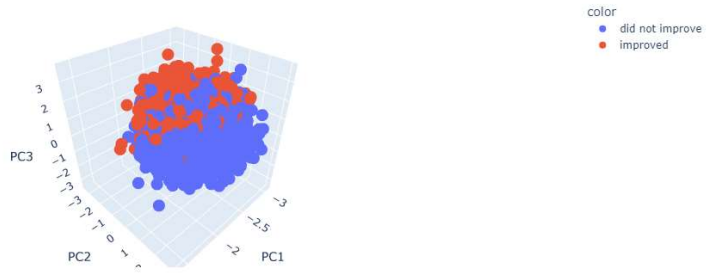
Out[21]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	
0	-2.676485	0.538157	-0.440957	0.559043	-0.057349	1.041448	-0.069853	-0.092106	0
1	-2.414635	0.186480	2.128333	-0.071981	0.288688	-0.080515	-0.576401	-1.095563	0
2	-2.936074	-0.092377	-0.536675	-0.868524	-1.384697	0.527511	1.464263	0.721905	0
3	-2.734005	1.526738	-0.349569	-0.467300	-1.456618	0.592148	1.408511	0.816131	-0
4	-2.783703	-1.587723	0.466373	-0.972204	-0.841322	0.419609	0.165178	-0.422203	-0

In [22]:
```
colors = ["improved" if a else "did not improve" for a in df["Score_Change"] > 0]
px.scatter(pca_scaled, x="PC1", y="PC2", color = colors)
```



In [23]:
```
colors = ["improved" if a else "did not improve" for a in df["Score_Change"] > 0]
px.scatter_3d(pca_scaled, x="PC1", y="PC2", z="PC3", color = colors)
```



There seems to be decent separated with a bit of overlap

- however, this might be because we are projecting into a smaller dimension. The data might be better separated in the higher dimensional space

Clustering

In [24]:
```
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.metrics import silhouette_score, rand_score, adjusted_rand_score
```

we will cluster the PCA-Transformed data

- we have already seen in our 3d scatter of the PC's that the data has begun to seperate, so using the PCA-transformed data should help

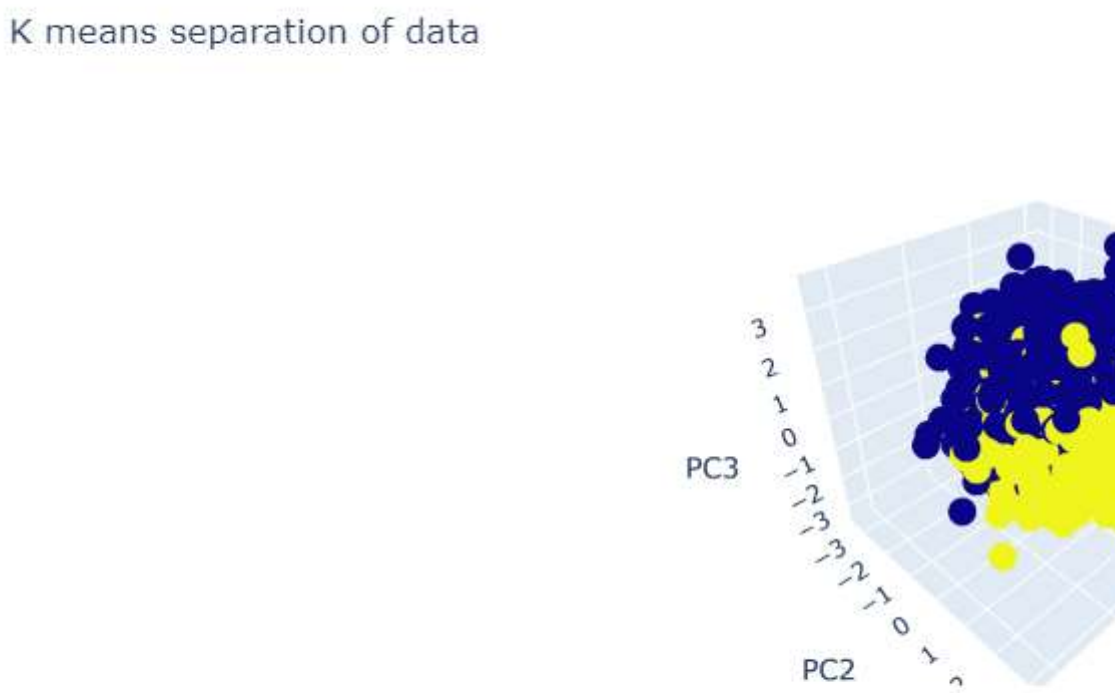
We know that our data should have two distinct clusters - "improved score" and "did not improve score", so we will use two clusters

- we will compare the quality of kmeans and agglomerative clustering and how well they relate to the actual labels

In [25]:
```
kmeans = KMeans(n_clusters=2)
y_kmeans = kmeans.fit_predict(pca_scaled)
kmeans.cluster_centers_
```

Out[25]:
```
array([[-2.53992877e+00,  5.14763132e-01,  3.67532164e-01,
        -1.37913821e-01,  3.39467822e-01, -2.39369884e-01,
        -3.54835887e-01, -1.96113167e-03, -8.17050444e-03,
        -2.12644467e-02,  1.18784967e-02,  5.87918094e-03,
        -1.58009468e-02,  1.29689158e-02, -7.29620469e-04,
        -2.33729503e-03],
       [-2.53539940e+00, -5.40171057e-01, -3.85618318e-01,
         1.47059586e-01, -3.55628740e-01,  2.48173415e-01,
         3.73396075e-01, -2.11069235e-02,  9.26495987e-03,
        -1.50984442e-03,  1.95059720e-02, -2.62770940e-03,
        -1.94111932e-02,  5.38456718e-03,  6.90001677e-04,
        -1.53396043e-02]])
```

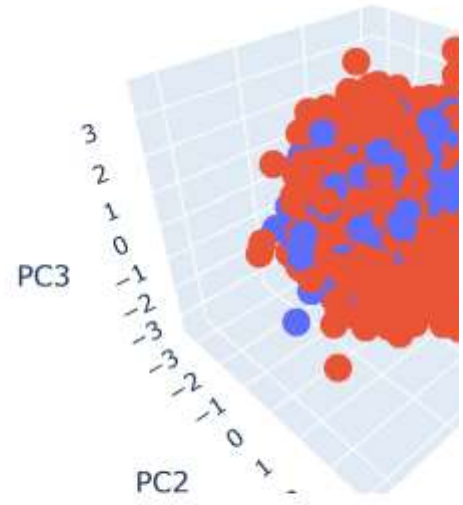
In [26]:
```
px.scatter_3d(pca_scaled, x="PC1", y="PC2", z="PC3", color=y_kmeans, title="K means
```



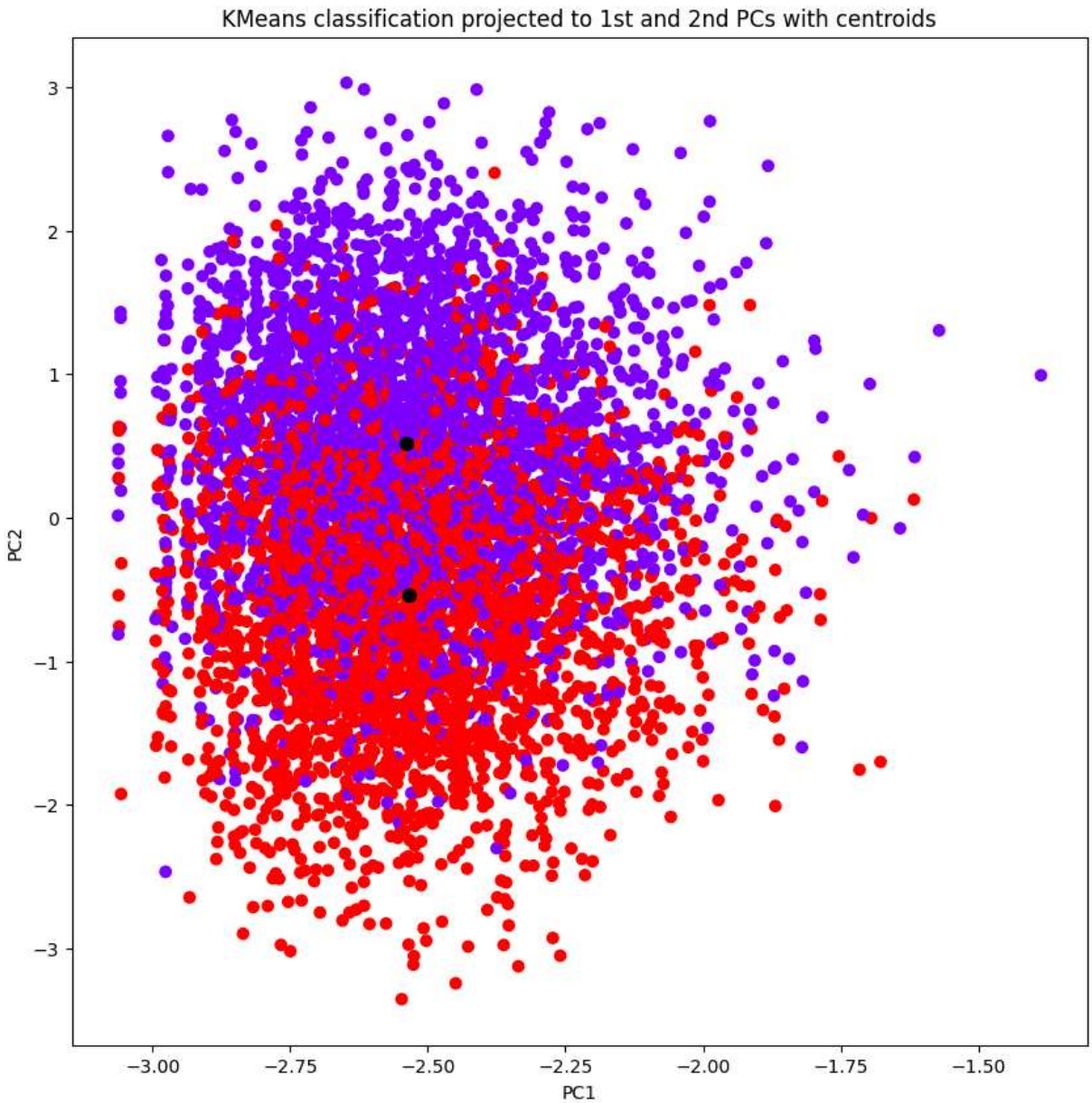
In [27]:
```
same_diff = y_kmeans==(df["Score_Change"] > 0).astype('int')
prop = sum(same_diff)/len(same_diff)
print(max(prop, 1-prop))
same_diff = ["same" if s else "diff" for s in same_diff]
px.scatter_3d(pca_scaled, x="PC1", y="PC2", z="PC3", color=same_diff, title="KMeans
```

```
0.5640583346401129
```

KMeans consistency with data (should expect one color dominan



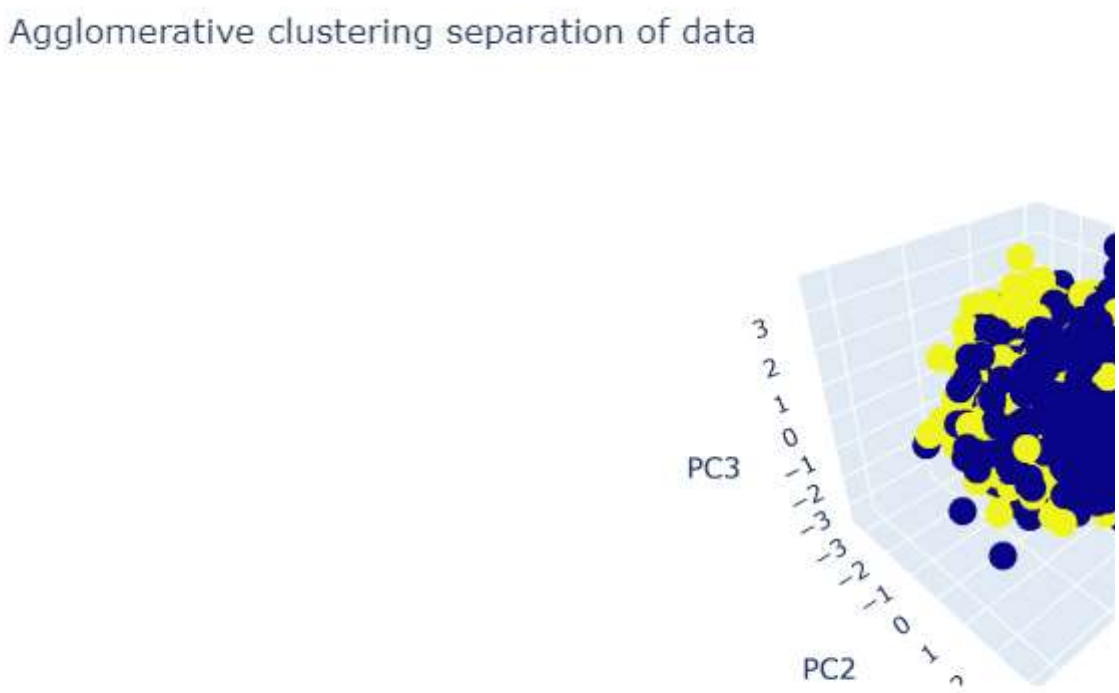
In [28]:
```
plt.figure(figsize=(10,10))
# Using average drive and fairway p
plt.scatter(pca_scaled['PC1'], pca_scaled['PC2'], c = y_kmeans, cmap='rainbow')
centroids = kmeans.cluster_centers_
plt.scatter(centroids [:, 0], centroids[:, 1], c='black', s=50)
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.title("KMeans classification projected to 1st and 2nd PCs with centroids")
plt.show()
```



k means has done a good job of separating the data. Furthermore, since we have the labels we can also see that the clustering has done a good job of creating clusters that actually reflect the labels (which we did not provide)

In [29]:
```
hclust = AgglomerativeClustering(n_clusters=2, metric='euclidean', linkage='ward')
hclust_labels = hclust.fit(pca_scaled).labels_
```

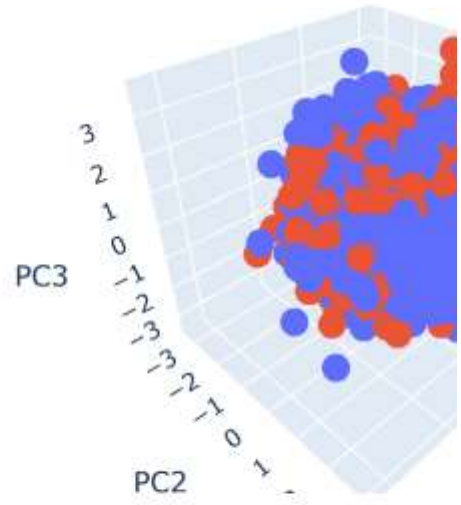
In [30]:
```
px.scatter_3d(pca_scaled, x="PC1", y="PC2", z="PC3", color=hclust_labels, title="Ag
```



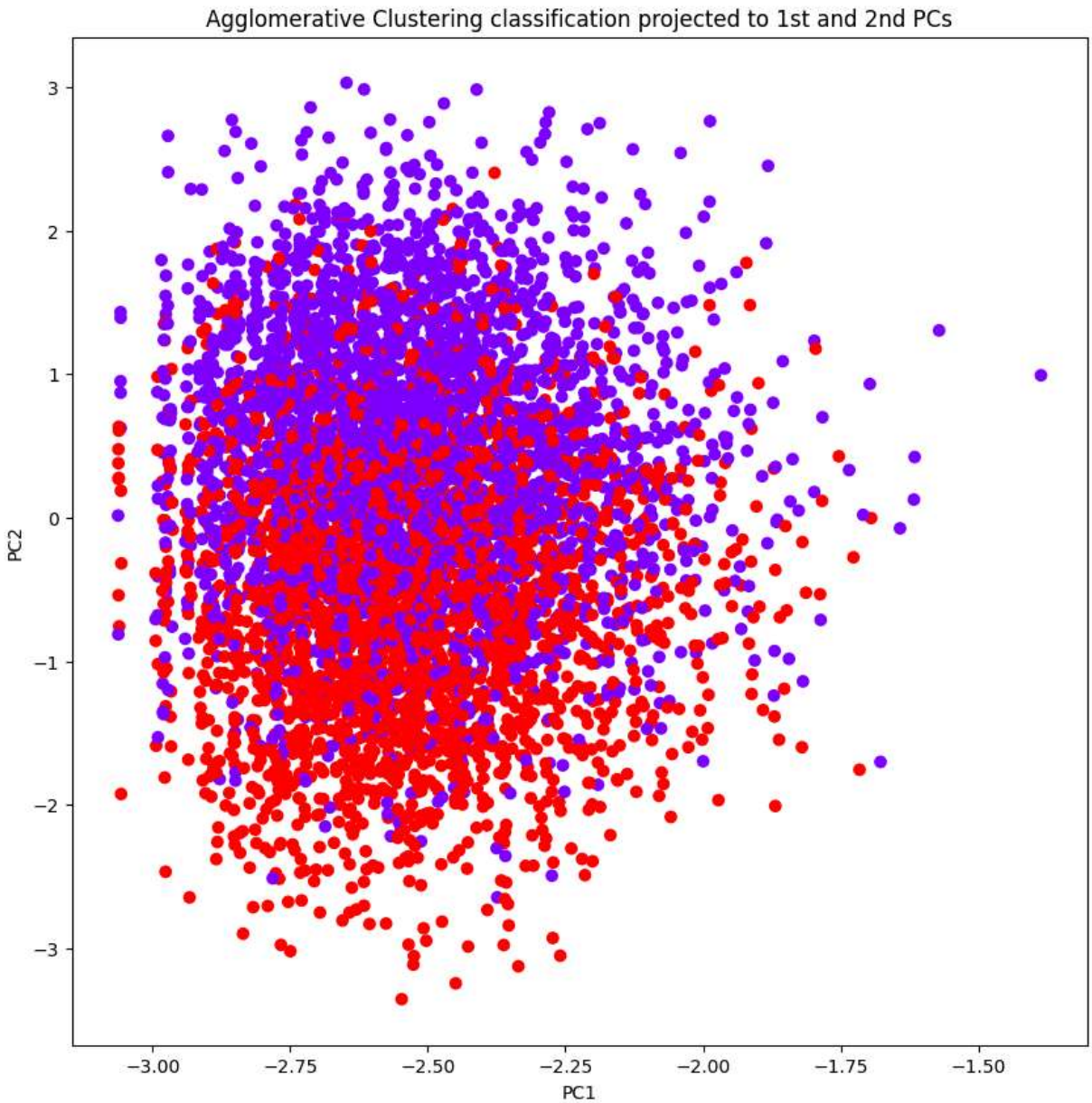
In [31]:
```
same_diff = hclust_labels==(df["Score_Change"] > 0).astype('int')
prop = sum(same_diff)/len(same_diff)
print(max(prop, 1-prop))
same_diff = ["same" if s else "diff" for s in same_diff]
px.scatter_3d(pca_scaled, x="PC1", y="PC2", z="PC3", color=same_diff, title="Agglom
```

```
0.569233181746903
```

Agglomerative clustering consistency with data (should expect o



In [32]:
```
plt.figure(figsize=(10,10))
# Using average drive and fairway p
plt.scatter(pca_scaled['PC1'], pca_scaled['PC2'], c = hclust_labels, cmap='rainbow'
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.title("Agglomerative Clustering classification projected to 1st and 2nd PCs")
plt.show()
```



agglomerative clustering seems to do a worse job of seperating data and matching the labels

comparing clustering

In [33]:
```
kmeans.inertia_
```

Out[33]: 58001.86698717489

In [34]:
```
silhouette_score(pca_scaled, y_kmeans)
```

Out[34]: 0.07507644406826537

In [35]:
```
silhouette_score(pca_scaled, hclust_labels)
```

Out[35]: 0.04615634225246989

both have low silhouette scores implying the clusters are close together, mixed

- this reflects what we saw in graphs

In [36]:
```
rand_score(y_kmeans, hclust_labels)
```

Out[36]:
```
0.6788974020303912
```

In [37]:
```
adjusted_rand_score(y_kmeans, hclust_labels)
```

Out[37]:
```
0.35779417090727367
```

a high rand score implies they are clustering in similar ways

conclusion

Clustering can be useful in cases where we do not have labels for unsupervised machine learning methods. When clustering our data, it was interesting to see that clustering the PCA-transformed data was able to create clusters that matched up well with our dataset. However, since we do have labels for our data, clustering is not a very appropriate tool to be using.

PCA has proven to be much more useful. With PCA, we are able to reduce the dimension of our data from 40 features to 16 principal components. Furthermore these principal components help separate the data for us too. PCA is useful to reduce computation costs and process the data

vii)viii) Neural Networks and hyperparameter tuning

In [109…
```
import numpy as np
import pandas as pd
import plotly.express as px

import torch
import torch.nn as nn
import torch.optim as optim

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, KFold
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

from sklearn import metrics
```

In [110…
```
df = pd.read_csv("transformed_data.csv")
df.sample(5)
```

Out[110…

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessior
545	17	83	7	70	
5140	20	68	8	88	
6086	19	93	7	84	
3749	21	63	7	63	
2652	21	72	9	80	

5 rows × 42 columns

we will create a NN for predicting if a students score improves or not

In [111…

```
y = (df["Score_Change"] > 0).astype('int')
y_tensor = torch.tensor(y.values.reshape(-1, 1), dtype=torch.float32)
y_tensor
```

Out[111…

```
tensor([[0.],
        [1.],
        [0.],
        ...,
        [1.],
        [0.],
        [0.]])
```

In [112…

```
X = df.drop(columns=["Exam_Score", "Score_Change"])

scaled_df = df.copy().drop(columns=["Exam_Score", "Score_Change"])
numerical_cols = scaled_df.select_dtypes(include=['int64']).columns
scaler = StandardScaler()
scaled_df[numerical_cols] = scaler.fit_transform(scaled_df[numerical_cols])
scaled_df[scaled_df.select_dtypes(include=['bool']).columns] = scaled_df.select_dty

x_scaled = scaled_df
x_tensor = torch.tensor(x_scaled.values, dtype=torch.float32)
x_scaled.head()
```

Out[112…

	Hours_Studied_Per_Week	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessions
0	0.505278	0.344803	-0.023928	-0.143302	-1.212085
1	-0.163081	-1.387019	0.657282	-1.115616	0.409708
2	0.672367	1.557079	-0.023928	1.106816	0.409708
3	1.507815	0.777759	0.657282	1.592974	-0.401188
4	-0.163081	1.037532	-0.705139	-0.698910	1.220605

5 rows × 40 columns

In [113…

```
x_train, x_test, y_train, y_test = train_test_split(x_tensor, y_tensor)
```

In [114…

```
class SimpleNN(nn.Module):
    def __init__(self, insize, hidden_size):
        super(SimpleNN, self).__init__()
        self.hidden1 = nn.Linear(insize, hidden_size)
        self.relu1 = nn.ReLU()
        self.out = nn.Linear(hidden_size, 1)
        self.sigmoid_out = nn.Sigmoid()
    def forward(self, x):
        zh = self.hidden1(x)
        ah = self.relu1(zh)
        z_out = self.out(ah)
        a_out = self.sigmoid_out(z_out)
        return a_out
```

In [115…

```
n_features = x_tensor.shape[1]
model = SimpleNN(n_features, int(n_features**(1/2))) #geo mean hidden layer size
loss_fn = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr = 0.01)
```

In [116…

```
def train(model, loss_fn, optimizer, epochs=100):
    for epoch in range(epochs):
      prediction = model(x_train)
      loss = loss_fn(prediction, y_train)
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

      if(epoch + 1) % 10 == 0:
        print(f"Epoch [{epoch + 1}/{epochs}], Loss: {loss.item():.4f}")

train(model, loss_fn, optimizer)
```

```
Epoch [10/100], Loss: 0.5546
Epoch [20/100], Loss: 0.4776
Epoch [30/100], Loss: 0.3983
Epoch [40/100], Loss: 0.3240
Epoch [50/100], Loss: 0.2611
Epoch [60/100], Loss: 0.2150
Epoch [70/100], Loss: 0.1828
Epoch [80/100], Loss: 0.1604
Epoch [90/100], Loss: 0.1443
Epoch [100/100], Loss: 0.1323
```

this is our simple model, we will now select hyper parameters

In [117…

```
kf = KFold(n_splits=5, shuffle=True)
learning_rates = [1e-5,1e-4,1e-3,1e-2,1e-1,1]
hidden_layer_options = range(6,41,4) # 40 input, 1 ouput, considering on range [in
```

In [118…

```
best_score = np.inf
def train_and_evaluate(hidden_dim, learning_rate):
    fold_scores = []
    for train_idx, val_idx in kf.split(x_tensor):
        X_train, X_val = x_tensor[train_idx], x_tensor[val_idx]
        y_train, y_val = y_tensor[train_idx], y_tensor[val_idx]

        # create model, loss, optimizer
        model = SimpleNN(X.shape[1], hidden_dim)
        criterion = nn.BCELoss()
        optimizer = optim.Adam(model.parameters(), lr=learning_rate)

        # Training
        for epoch in range(10):
            model.train()
            optimizer.zero_grad()
            predictions = model(X_train)
            loss = criterion(predictions, y_train)
            loss.backward()
            optimizer.step()

        # Validation
        model.eval()
        with torch.no_grad():
            val_predictions = model(X_val)
            val_loss = criterion(val_predictions, y_val).item()
            fold_scores.append(val_loss)

    return np.mean(fold_scores)


for hidden_dim in hidden_layer_options:
    for lr in learning_rates:
            avg_score = train_and_evaluate(hidden_dim, lr)
            print(f"Params: hidden_dim={hidden_dim}, lr={lr}, avg_score={avg_score:

            # get min loss/score
            if avg_score < best_score:
```

```
                best_score = avg_score
                best_params = {'hidden_dim': hidden_dim, 'lr': lr}

# Best hyperparameters
print(f"Best Params: {best_params} with score: {best_score:.4f}")
```

```
Params: hidden_dim=6, lr=1e-05, avg_score=0.6878
Params: hidden_dim=6, lr=0.0001, avg_score=0.7434
Params: hidden_dim=6, lr=0.001, avg_score=0.6766
Params: hidden_dim=6, lr=0.01, avg_score=0.5662
Params: hidden_dim=6, lr=0.1, avg_score=0.3899
Params: hidden_dim=6, lr=1, avg_score=14.3315
Params: hidden_dim=10, lr=1e-05, avg_score=0.6954
Params: hidden_dim=10, lr=0.0001, avg_score=0.6958
Params: hidden_dim=10, lr=0.001, avg_score=0.6672
Params: hidden_dim=10, lr=0.01, avg_score=0.5554
Params: hidden_dim=10, lr=0.1, avg_score=0.2963
Params: hidden_dim=10, lr=1, avg_score=13.1200
Params: hidden_dim=14, lr=1e-05, avg_score=0.6973
Params: hidden_dim=14, lr=0.0001, avg_score=0.7304
Params: hidden_dim=14, lr=0.001, avg_score=0.6706
Params: hidden_dim=14, lr=0.01, avg_score=0.5328
Params: hidden_dim=14, lr=0.1, avg_score=0.3412
Params: hidden_dim=14, lr=1, avg_score=39.6469
Params: hidden_dim=18, lr=1e-05, avg_score=0.7029
Params: hidden_dim=18, lr=0.0001, avg_score=0.6962
Params: hidden_dim=18, lr=0.001, avg_score=0.6465
Params: hidden_dim=18, lr=0.01, avg_score=0.5208
Params: hidden_dim=18, lr=0.1, avg_score=0.4113
Params: hidden_dim=18, lr=1, avg_score=32.4912
Params: hidden_dim=22, lr=1e-05, avg_score=0.7333
Params: hidden_dim=22, lr=0.0001, avg_score=0.7182
Params: hidden_dim=22, lr=0.001, avg_score=0.6432
Params: hidden_dim=22, lr=0.01, avg_score=0.5025
Params: hidden_dim=22, lr=0.1, avg_score=0.3996
Params: hidden_dim=22, lr=1, avg_score=32.4919
Params: hidden_dim=26, lr=1e-05, avg_score=0.6901
Params: hidden_dim=26, lr=0.0001, avg_score=0.6928
Params: hidden_dim=26, lr=0.001, avg_score=0.6609
Params: hidden_dim=26, lr=0.01, avg_score=0.5019
Params: hidden_dim=26, lr=0.1, avg_score=0.2835
Params: hidden_dim=26, lr=1, avg_score=39.0645
Params: hidden_dim=30, lr=1e-05, avg_score=0.7200
Params: hidden_dim=30, lr=0.0001, avg_score=0.7045
Params: hidden_dim=30, lr=0.001, avg_score=0.6421
Params: hidden_dim=30, lr=0.01, avg_score=0.5045
Params: hidden_dim=30, lr=0.1, avg_score=0.3166
Params: hidden_dim=30, lr=1, avg_score=32.4918
Params: hidden_dim=34, lr=1e-05, avg_score=0.6911
Params: hidden_dim=34, lr=0.0001, avg_score=0.6823
Params: hidden_dim=34, lr=0.001, avg_score=0.6764
Params: hidden_dim=34, lr=0.01, avg_score=0.4673
Params: hidden_dim=34, lr=0.1, avg_score=0.4501
Params: hidden_dim=34, lr=1, avg_score=32.4919
Params: hidden_dim=38, lr=1e-05, avg_score=0.7122
Params: hidden_dim=38, lr=0.0001, avg_score=0.7288
Params: hidden_dim=38, lr=0.001, avg_score=0.6568
Params: hidden_dim=38, lr=0.01, avg_score=0.4511
Params: hidden_dim=38, lr=0.1, avg_score=0.3539
Params: hidden_dim=38, lr=1, avg_score=32.4919
Best Params: {'hidden_dim': 26, 'lr': 0.1} with score: 0.2835
```

In [119…

```
model = SimpleNN(x_tensor.shape[1], best_params['hidden_dim'])
loss_fn = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=best_params['lr'])
train(model, loss_fn, optimizer)
```

```
Epoch [10/100], Loss: 0.4954
Epoch [20/100], Loss: 0.3177
Epoch [30/100], Loss: 0.2005
Epoch [40/100], Loss: 0.1376
Epoch [50/100], Loss: 0.1059
Epoch [60/100], Loss: 0.0922
Epoch [70/100], Loss: 0.0853
Epoch [80/100], Loss: 0.0814
Epoch [90/100], Loss: 0.0790
Epoch [100/100], Loss: 0.0774
```

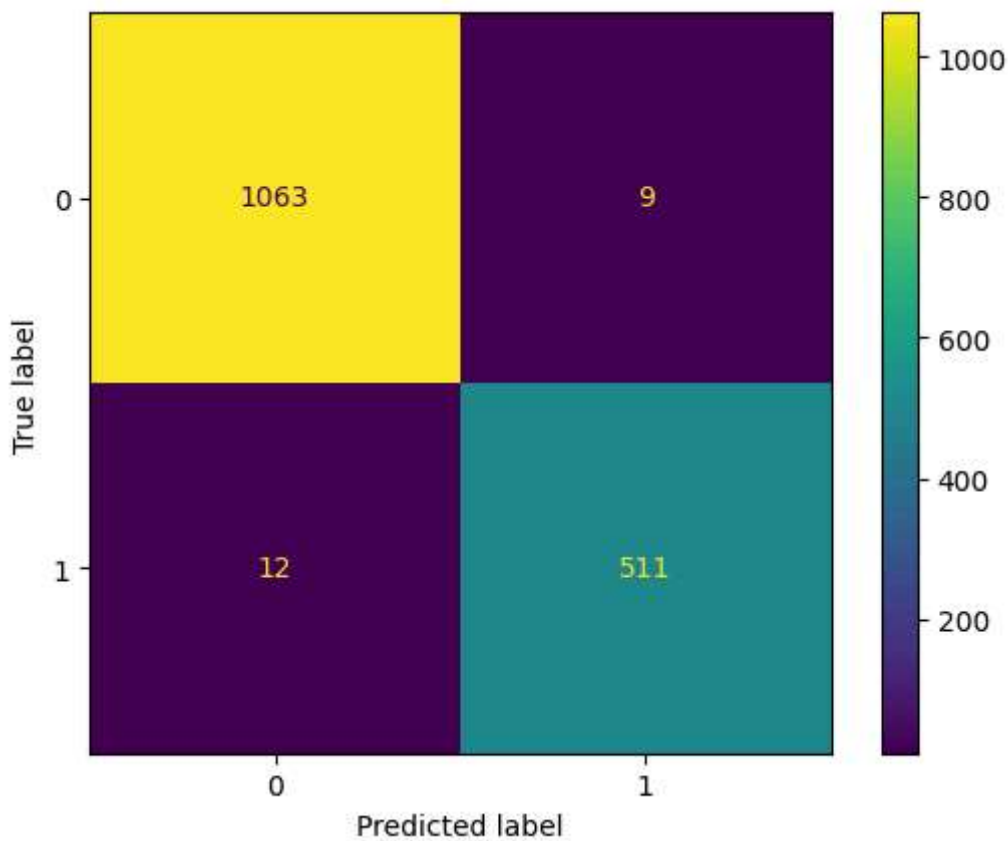
evaluating model

In [120…

```
with torch.no_grad():
    pred = model(x_test)
pred_class = pred > 0.5
metrics.ConfusionMatrixDisplay(confusion_matrix(y_test==1, pred_class)).plot()
```

Out[120…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x24b781e38f0>
```



In [121…

```
accuracy_score(y_test, pred_class )
```

Out[121…

```
0.986833855799373
```

In [122…
```
precision_score(y_test, pred_class)
```

Out[122…
```
0.9826923076923076
```

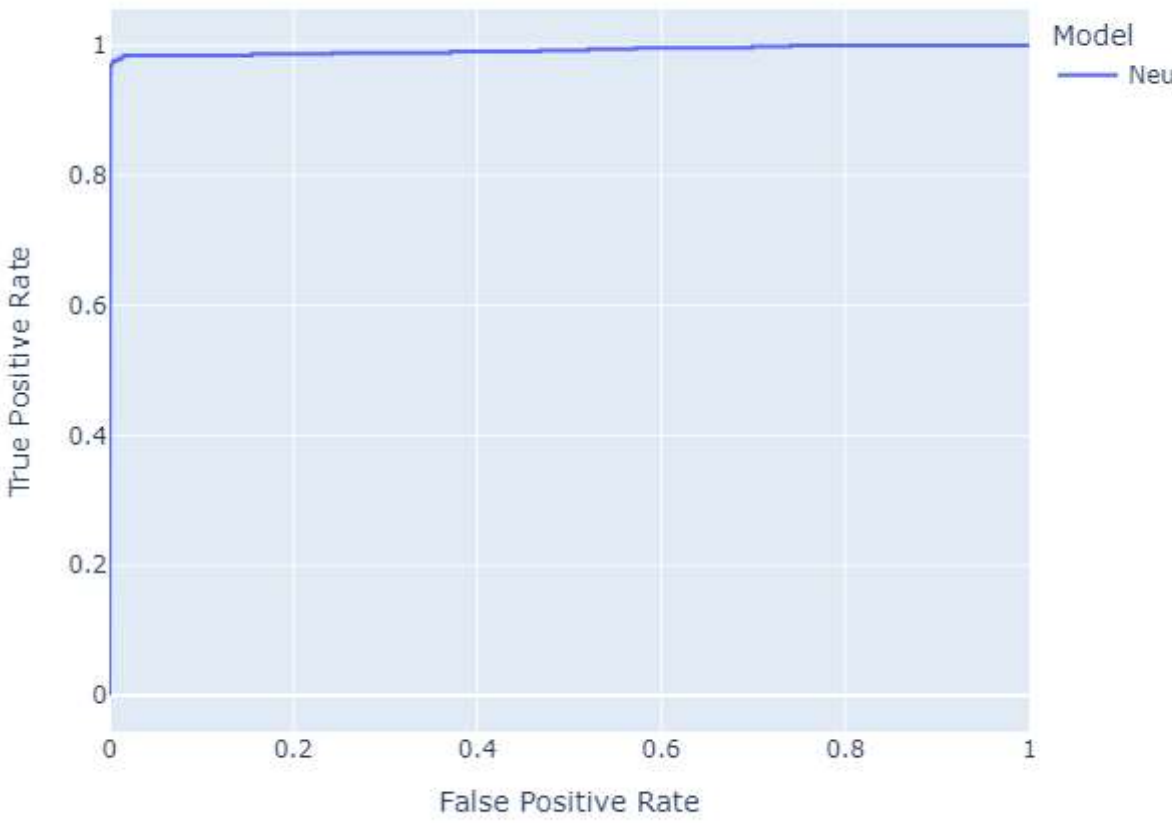
In [123…
```
recall_score(y_test, pred_class)
```

Out[123…
```
0.9770554493307839
```

In [124…
```
f1_score(y_test, pred_class)
```

Out[124…
```
0.9798657718120806
```

In [125…
```
#ROC
lr_fpr_sample, lr_tpr_sample, lr_thresholds_sample = metrics.roc_curve(y_test, pred

roc_lr_sample = pd.DataFrame({
    'False Positive Rate': lr_fpr_sample,
    'True Positive Rate': lr_tpr_sample,
    'Model': 'Neural Network'
}, index=lr_thresholds_sample)


roc_sample_df = pd.concat([roc_lr_sample])


px.line(roc_lr_sample, y='True Positive Rate', x='False Positive Rate',
        color='Model',
        width=700, height=500
)
```



In [126…
```
roc_auc_score(y_test, pred)
```

Out[126… 0.9926568163009047

our NN performs very well, but also on par with our logistic regression method.