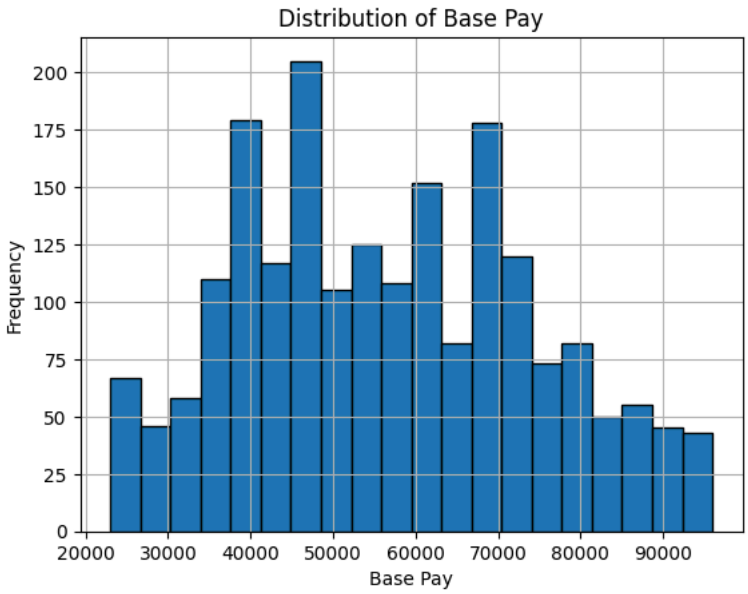
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df=pd.read_csv('/content/new_modified_dataset.csv')
# List of columns to scale
columns_to_scale = ['Grad', 'HSC', 'SSC']

# Divide each column by 2 to scale from 20 to 10
df[columns_to_scale] = df[columns_to_scale] / 2

# Optional: Round the values to eliminate any floating-point issues
df[columns_to_scale] = df[columns_to_scale].round(2)

df.head()
```

	Base Pay	Job Role	Skills	Base Pay Range	sex	age	Mother_education	Father_education	Mother_job	Father_job	studytime
0	72000	Teacher	Subject Knowledge, Communication, Patience, Cr...	30000-40000	Male	27	2	1	Health	Public	2
1	50000	Salesperson	Communication, Negotiation, Customer Service, ...	20000-30000	Male	20	1	0	Public	Health	4
2	38000	Salesperson	Communication, Negotiation, Customer Service, ...	20000-30000	Male	24	3	0	Teacher	Teacher	3
3	72000	Engineer	Technical Skills, Mathematics, Project Managem...	40000-50000	Male	26	0	2	Health	Public	3
4	65000	Engineer	Technical Skills, Mathematics, Project Managem...	40000-50000	Male	26	0	2	Public	Health	1

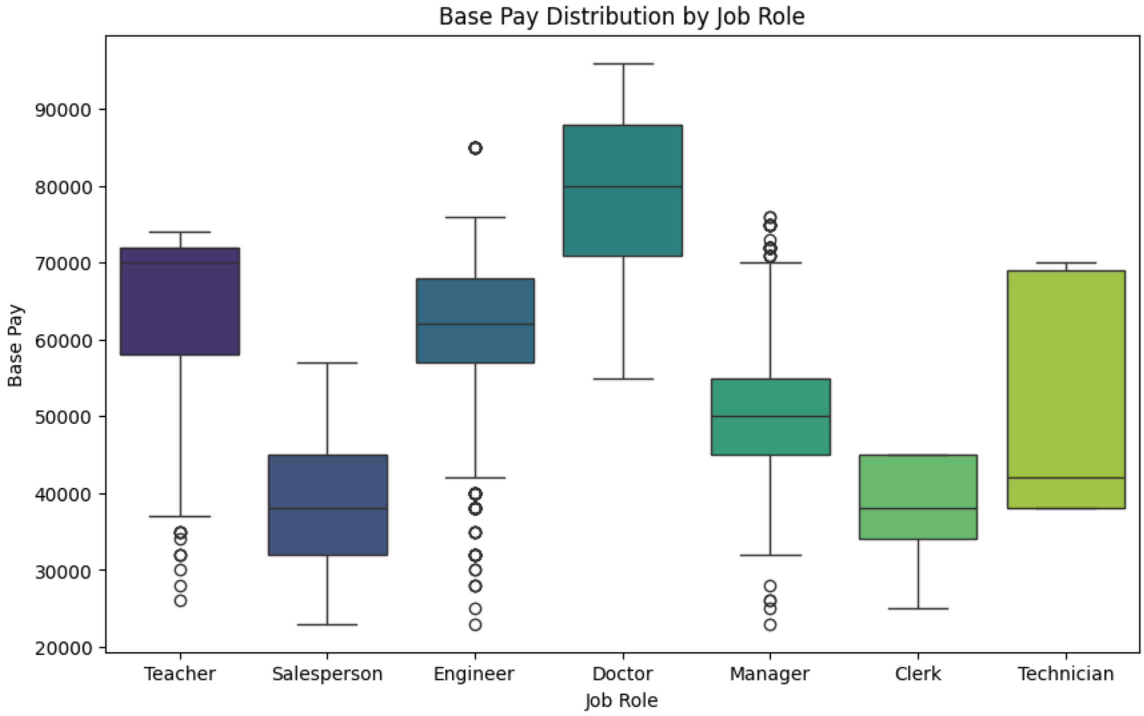
```
job_role_categories = pd.Categorical(df['Job Role'])
job_role_codes = job_role_categories.codes
job_role_names = job_role_categories.categories

# Create the scatter plot using job role codes for color mapping
scatter = plt.scatter(x=df['SSC'], y=df['HSC'],
                      c=job_role_codes,
                      cmap='viridis',
                      s=32, alpha=.8)

# Customize plot appearance
plt.gca().spines[['top', 'right']].set_visible(False)
plt.xlabel('SSC')
plt.ylabel('HSC')
plt.title('Scatter Plot of SSC vs. HSC by Job Role')

for role_code, role_name in enumerate(job_role_names):
    plt.scatter([], [], color=scatter.cmap(scatter.norm(role_code)), label=role_name)
plt.legend(title='Job Role', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout(rect=[0, 0, 0.85, 1])

# Show plot
plt.show()
```


```
df['Base Pay'].hist(bins=20, edgecolor='black')
plt.title('Distribution of Base Pay')
plt.xlabel('Base Pay')
plt.ylabel('Frequency')
plt.show()
```



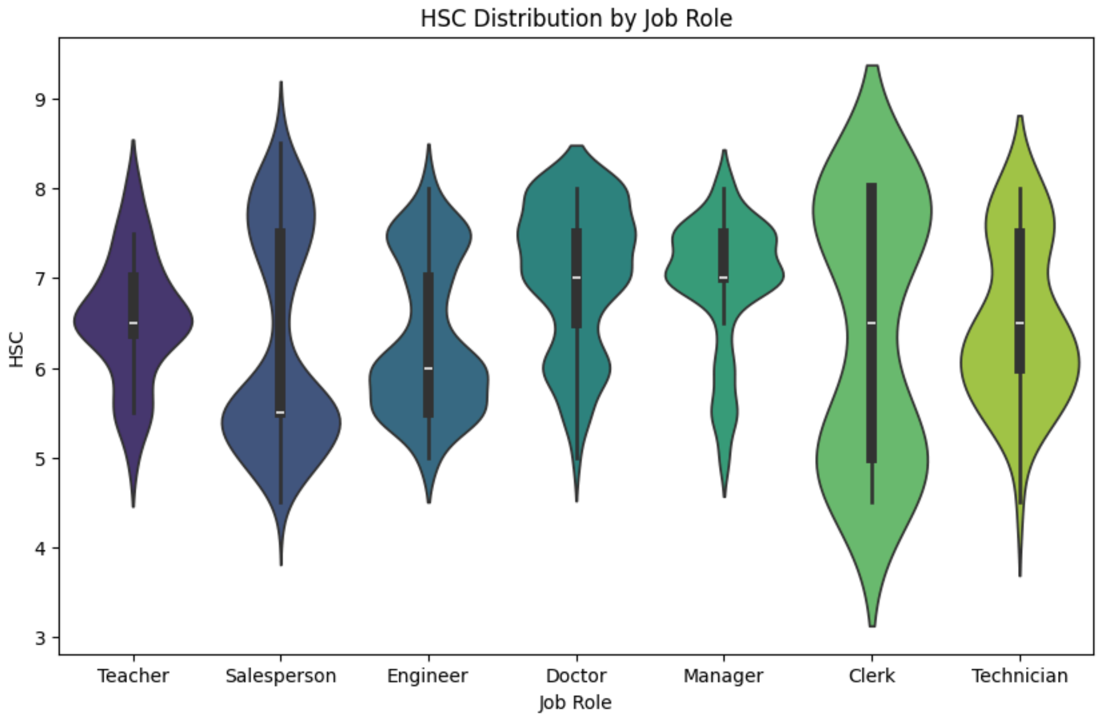

```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='Job Role', y='Base Pay', palette='viridis')
plt.title('Base Pay Distribution by Job Role')
plt.show()
```

```
<ipython-input-5-81334bad51fb>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue`

  sns.boxplot(data=df, x='Job Role', y='Base Pay', palette='viridis')
```

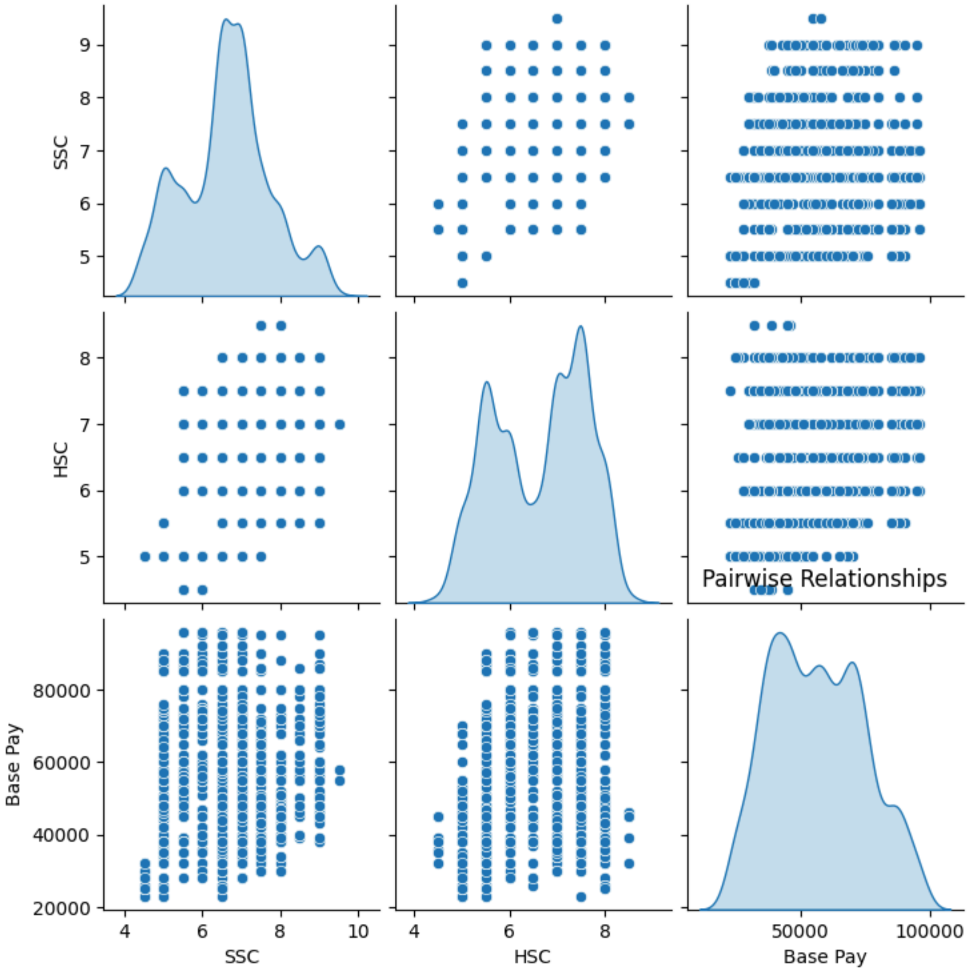



```
plt.figure(figsize=(10, 6))
sns.violinplot(data=df, x='Job Role', y='HSC', palette='viridis')
plt.title('HSC Distribution by Job Role')
plt.show()
```

```
<ipython-input-6-b37f067712f2>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue`

  sns.violinplot(data=df, x='Job Role', y='HSC', palette='viridis')
```

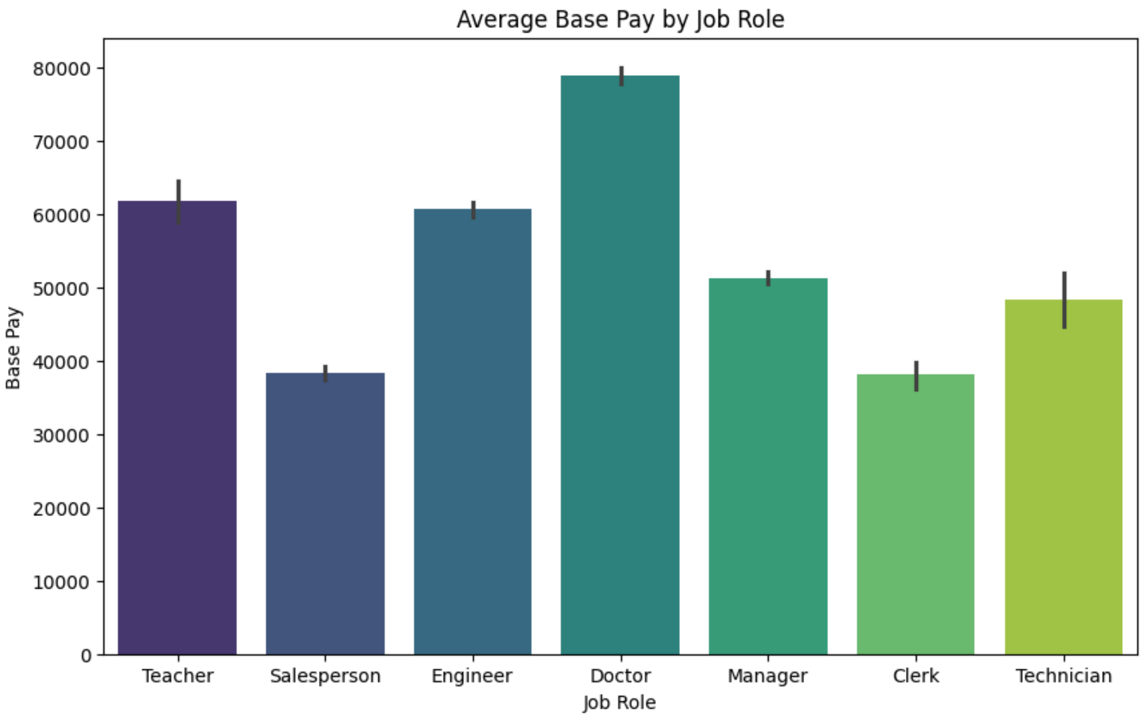



```
sns.pairplot(df[['SSC', 'HSC', 'Base Pay']], diag_kind='kde')
plt.title('Pairwise Relationships')
plt.show()
```




```
plt.figure(figsize=(10, 6))
sns.barplot(data=df, x='Job Role', y='Base Pay', palette='viridis')
plt.title('Average Base Pay by Job Role')
plt.show()
```

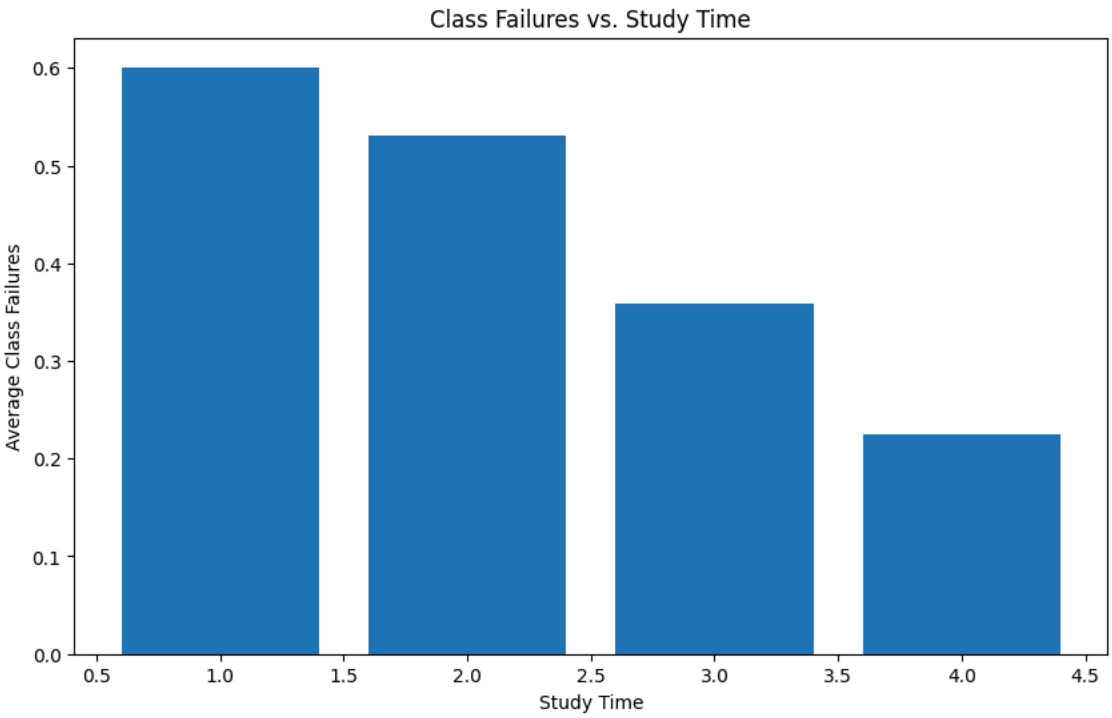
```
<ipython-input-8-1bdf2e4f01df>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue`

  sns.barplot(data=df, x='Job Role', y='Base Pay', palette='viridis')
```



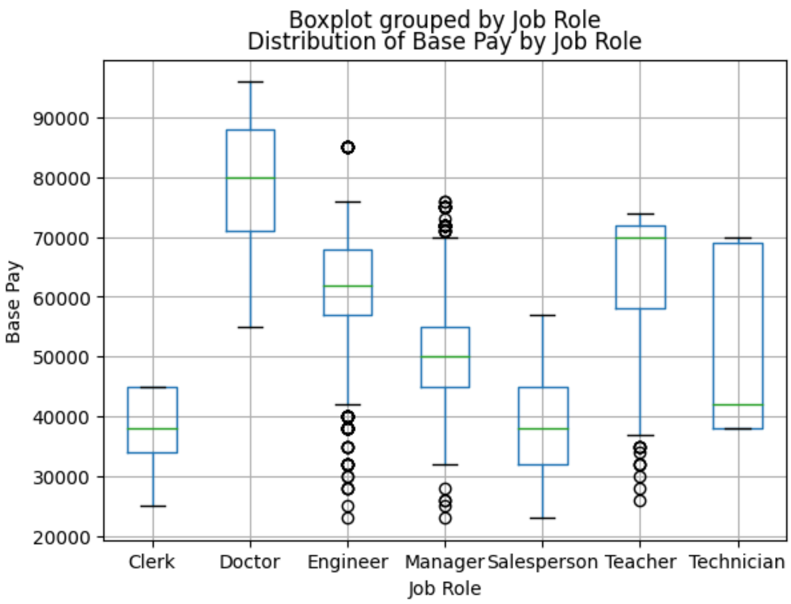
```
df.columns
```

```
Index(['Base Pay', 'Job Role', 'Skills', 'Base Pay Range', 'sex', 'age',
       'Mother_education', 'Father_education', 'Mother_job', 'Father_job',
       'studytime', 'backlogs', 'tuition', 'pursue_higher_studies',
       'Internet_usage', 'absences', 'SSC', 'HSC', 'Grad'],
      dtype='object')
```

```
study_time_groups = df.groupby('studytime')['backlogs'].mean()

plt.figure(figsize=(10, 6))
plt.bar(study_time_groups.index, study_time_groups.values)
plt.xlabel('Study Time')
plt.ylabel('Average Class Failures')
_ = plt.title('Class Failures vs. Study Time')
```




```
df.boxplot(column='Base Pay', by='Job Role')
plt.xlabel('Job Role')
plt.ylabel('Base Pay')
_ = plt.title('Distribution of Base Pay by Job Role')
```




```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 19 columns):
```

```
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Base Pay               2000 non-null   int64  
 1   Job Role               2000 non-null   object 
 2   Skills                 2000 non-null   object 
 3   Base Pay Range         2000 non-null   object 
 4   sex                    2000 non-null   object 
 5   age                    2000 non-null   int64  
 6   Mother_education       2000 non-null   int64  
 7   Father_education       2000 non-null   int64  
 8   Mother_job             2000 non-null   object 
 9   Father_job             2000 non-null   object 
 10  studytime              2000 non-null   int64  
 11  backlogs               2000 non-null   int64  
 12  tuition                2000 non-null   object 
 13  pursue_higher_studies  2000 non-null   object 
 14  Internet_usage         2000 non-null   object 
 15  absences               2000 non-null   int64  
 16  SSC                    2000 non-null   float64
 17  HSC                    2000 non-null   float64
 18  Grad                   2000 non-null   float64
dtypes: float64(3), int64(7), object(9)
memory usage: 297.0+ KB
```

```
df.describe()
```

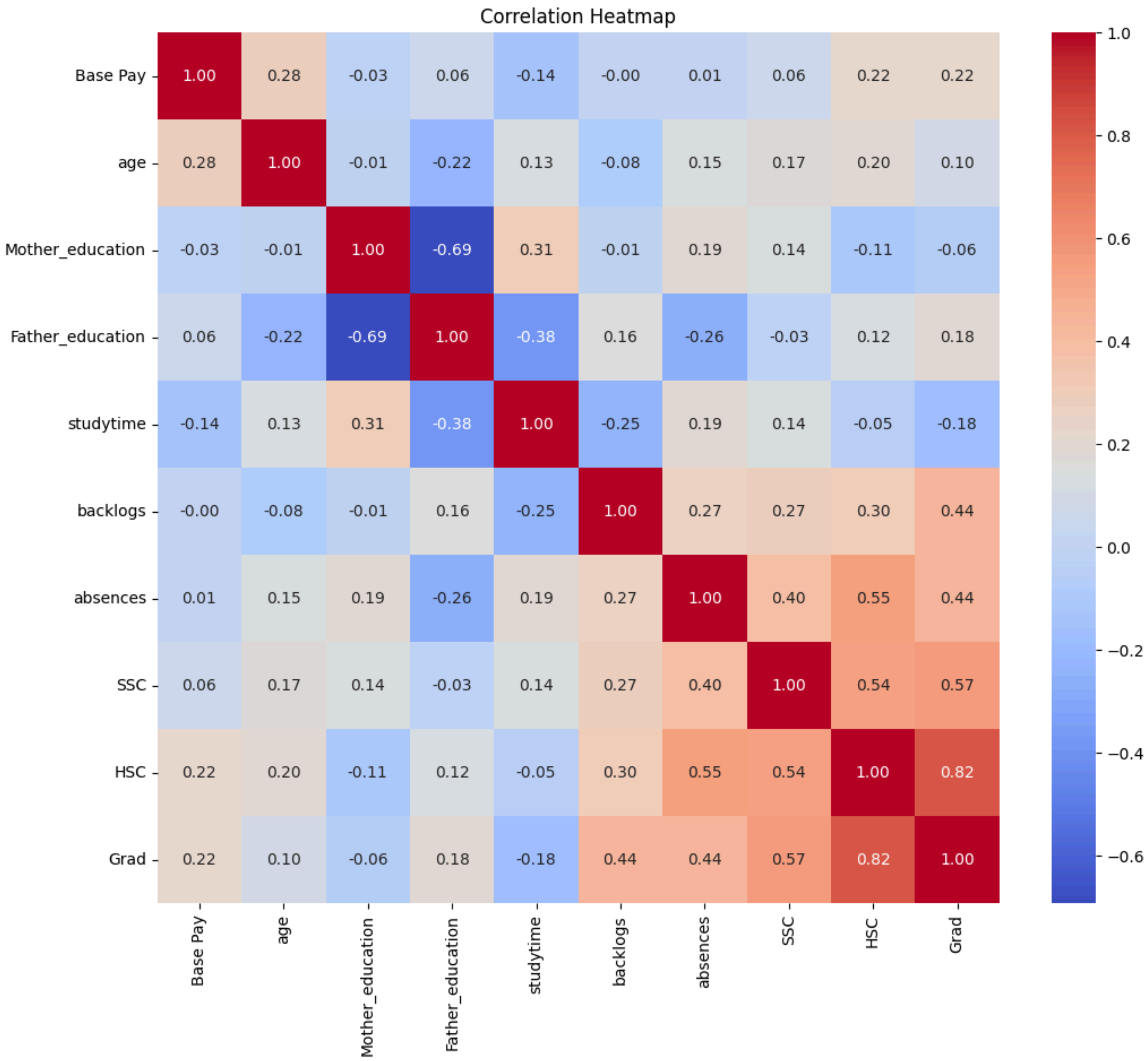
	Base Pay	age	Mother_education	Father_education	studytime	backlogs	absences	SSC	HS
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.00000
mean	56594.500000	25.849000	1.407500	1.451000	2.133000	0.475500	6.365500	6.619750	6.63125
std	17880.350198	2.426962	1.041627	0.937571	1.000906	0.508457	3.563602	1.099723	0.96507
min	23000.000000	20.000000	0.000000	0.000000	1.000000	0.000000	0.000000	4.500000	4.50000
25%	42000.000000	24.000000	1.000000	1.000000	1.000000	0.000000	3.000000	6.000000	5.50000
50%	55000.000000	26.000000	1.000000	1.000000	2.000000	0.000000	6.000000	6.500000	7.00000
75%	70000.000000	28.000000	2.000000	2.000000	3.000000	1.000000	9.000000	7.000000	7.50000
max	96000.000000	31.000000	3.000000	3.000000	4.000000	2.000000	15.000000	9.500000	8.50000

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

	0
Base Pay	0
Job Role	0
Skills	0
Base Pay Range	0
sex	0
age	0
Mother_education	0
Father_education	0
Mother_job	0
Father_job	0
studytime	0
backlogs	0
tuition	0
pursue_higher_studies	0
Internet_usage	0
absences	0
SSC	0
HSC	0
Grad	0

dtype: int64

```
# from sklearn.preprocessing import LabelEncoder
# label_encoder = LabelEncoder()

# for column in df.columns:
#   if df[column].dtype == 'object':  # Check if the column is categorical
#     df[column] = label_encoder.fit_transform(df[column])


# df.head()


numerical_df = df.select_dtypes(include=np.number)

# Calculate correlation matrix
corr_matrix = numerical_df.corr()

# Create heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```




```
df.duplicated().value_counts()
```

	count
False	1488
True	512

dtype: int64

```
df['Job Role'].value_counts()
```

Job Role	count
Engineer	472
Salesperson	460
Manager	449
Doctor	425
Teacher	108
Technician	49
Clerk	37

dtype: int64

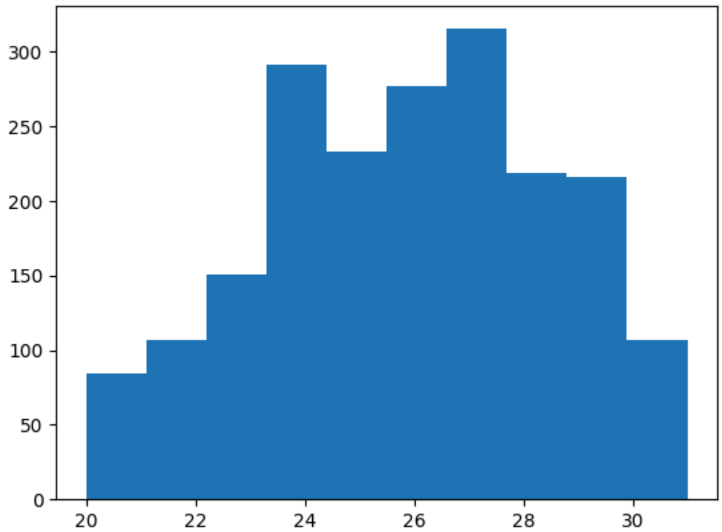
```
df['Base Pay Range'].value_counts()
```

Base Pay Range	count
40000-50000	472
20000-30000	460
70000-90000	449
60000-80000	425
30000-40000	108
10000-20000	49
10000-15000	37

dtype: int64

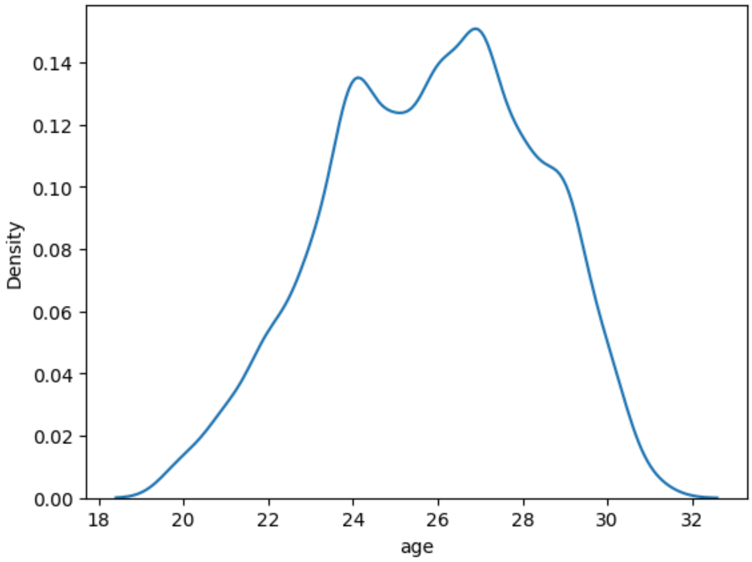
```
plt.hist(df['age'])
```

```
(array([ 84., 107., 151., 291., 233., 277., 315., 219., 216., 107.]),
 array([20. , 21.1, 22.2, 23.3, 24.4, 25.5, 26.6, 27.7, 28.8, 29.9, 31. ]),
 <BarContainer object of 10 artists>)
```



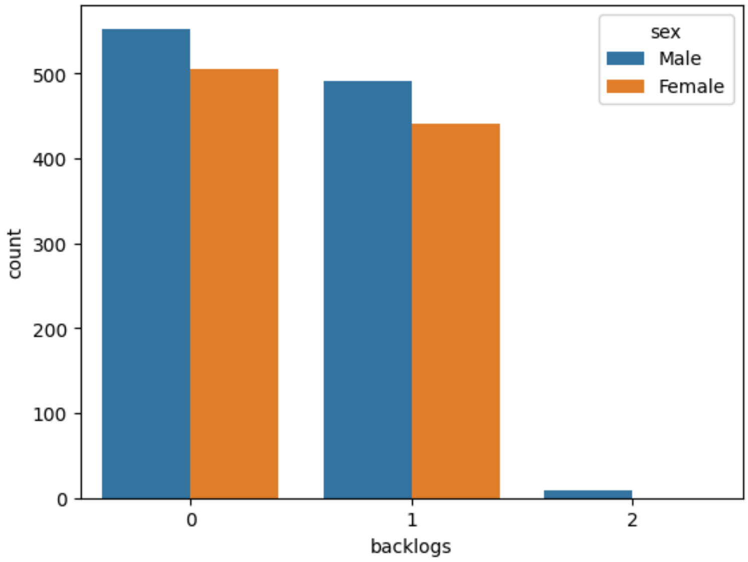

```
sns.kdeplot(df['age'])
```

```
<Axes: xlabel='age', ylabel='Density'>
```



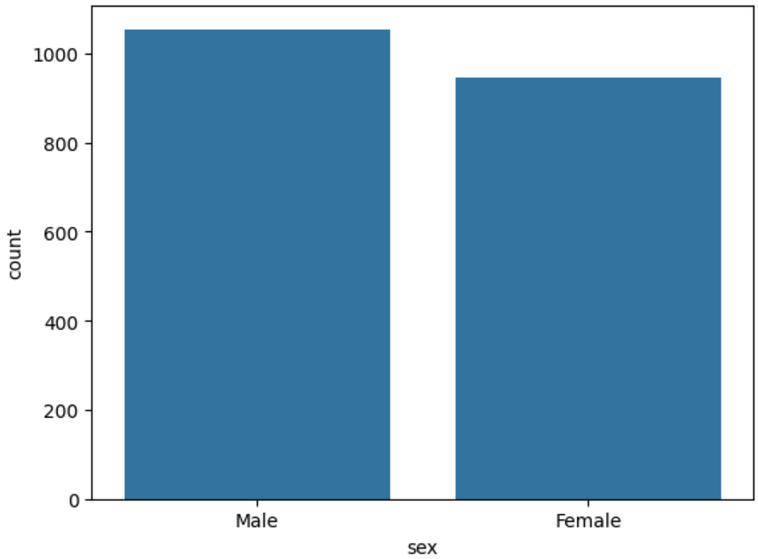

```
sns.countplot(data=df, x="backlogs", hue="sex")
```

```
<Axes: xlabel='backlogs', ylabel='count'>
```



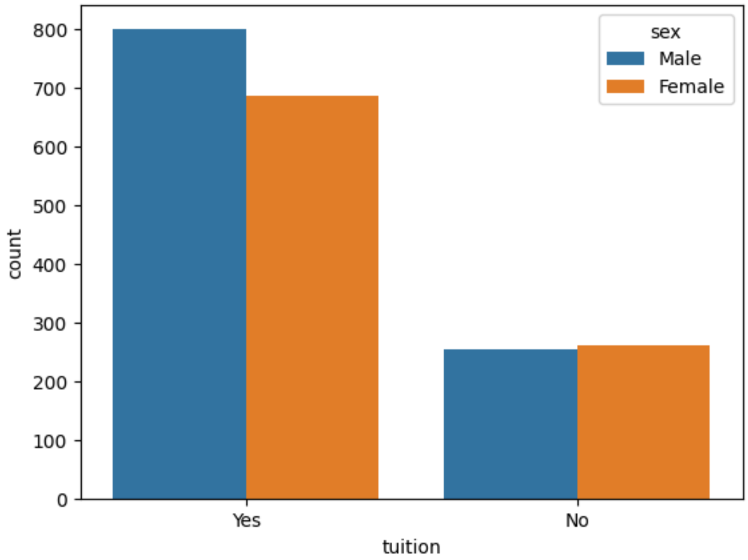

```
sns.countplot(data=df, x="sex")
```

```
<Axes: xlabel='sex', ylabel='count'>
```




```
sns.countplot(data=df, x="tuition", hue="sex")
```

```
<Axes: xlabel='tuition', ylabel='count'>
```

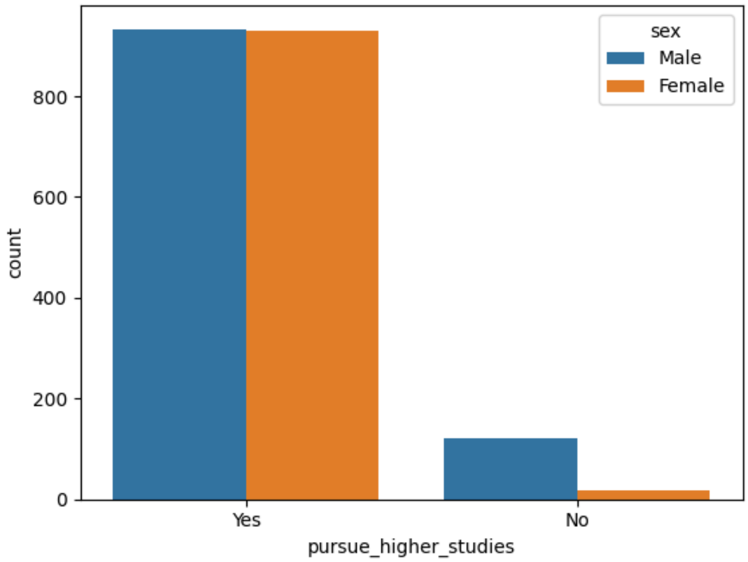



```
df.columns
```

```
Index(['Base Pay', 'Job Role', 'Skills', 'Base Pay Range', 'sex', 'age',
       'Mother_education', 'Father_education', 'Mother_job', 'Father_job',
       'studytime', 'backlogs', 'tuition', 'pursue_higher_studies',
       'Internet_usage', 'absences', 'SSC', 'HSC', 'Grad'],
      dtype='object')
```

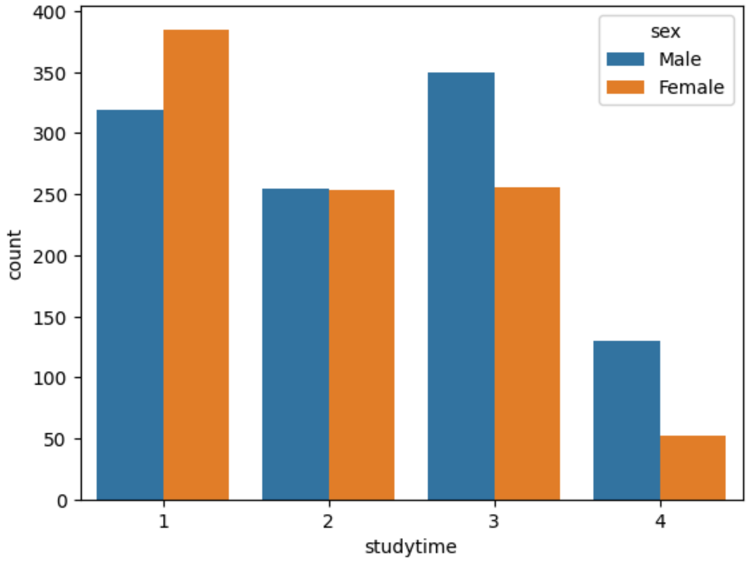
```
sns.countplot(data=df, x="pursue_higher_studies", hue="sex")
```

```
<Axes: xlabel='pursue_higher_studies', ylabel='count'>
```

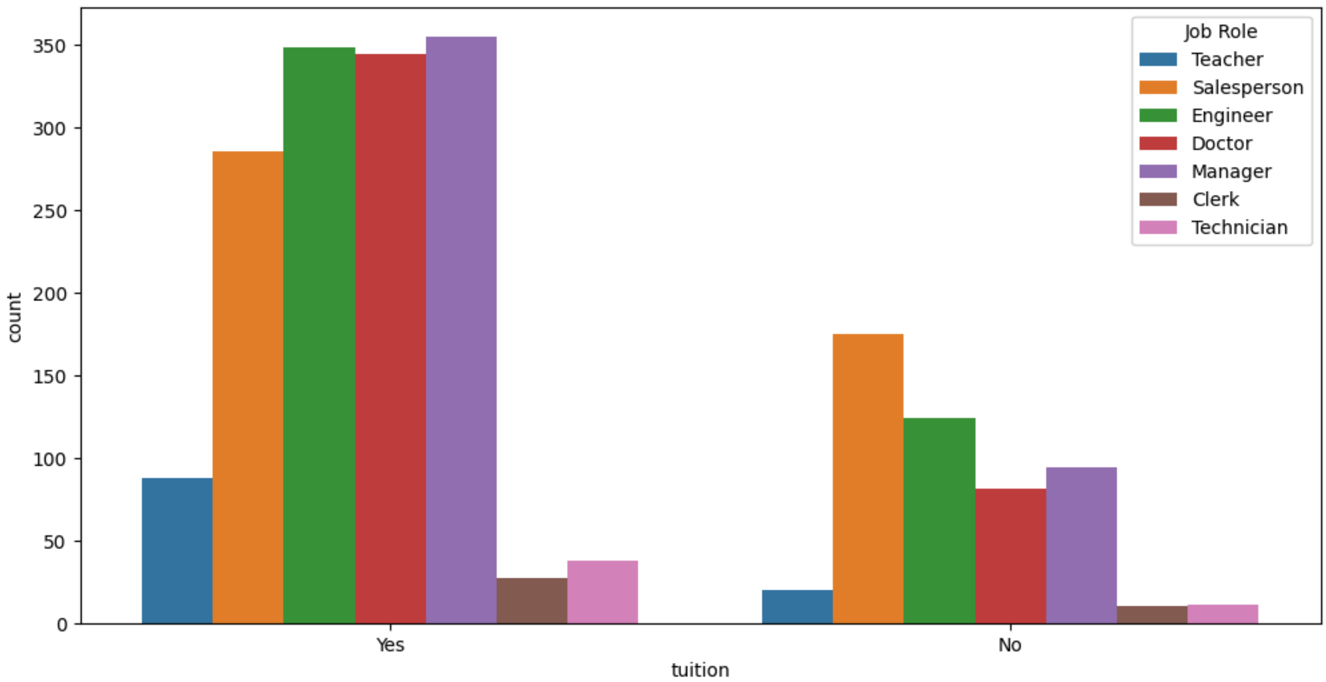



```
sns.countplot(data=df, x="studytime", hue="sex")
```

```
<Axes: xlabel='studytime', ylabel='count'>
```

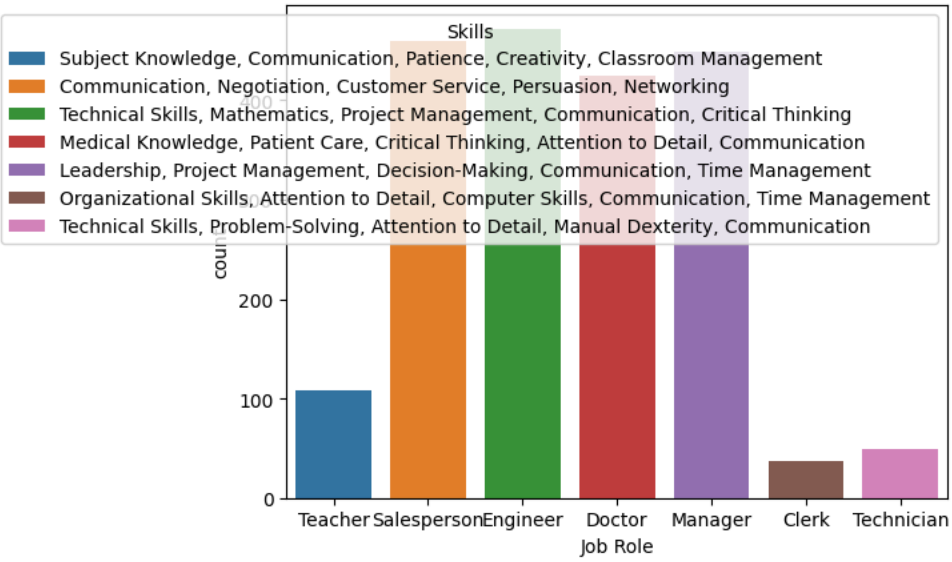



```
plt.figure(figsize=(12, 6))

# Create the countplot
sns.countplot(data=df, x="tuition", hue="Job Role")

# Show the plot
plt.show()
```



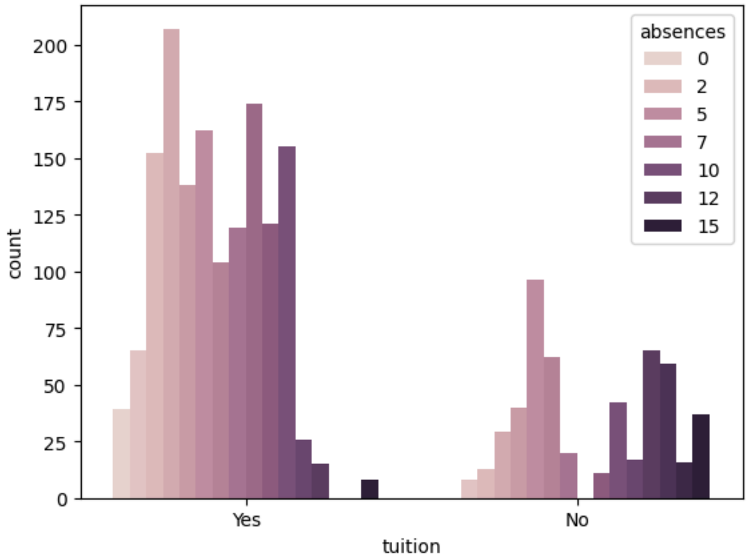

```
sns.countplot(data=df, x="Job Role", hue="Skills")
```

```
<Axes: xlabel='Job Role', ylabel='count'>
```




```
sns.countplot(data=df, x="tuition", hue="absences")
```

```
<Axes: xlabel='tuition', ylabel='count'>
```




```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['Job Role'] = le.fit_transform(df['Job Role'])
```

```
label_encoder = LabelEncoder()

for column in df.columns:
  if df[column].dtype == 'object':  # Check if the column is categorical
    df[column] = label_encoder.fit_transform(df[column])
```

PREDICTING JOB ROLE BASED ON STUDENT DEMOGRAPHICS

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

```
X = df.drop(columns=['Job Role'])
y = df['Job Role']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100)

# Train the model
rf_classifier.fit(X_train, y_train)
```

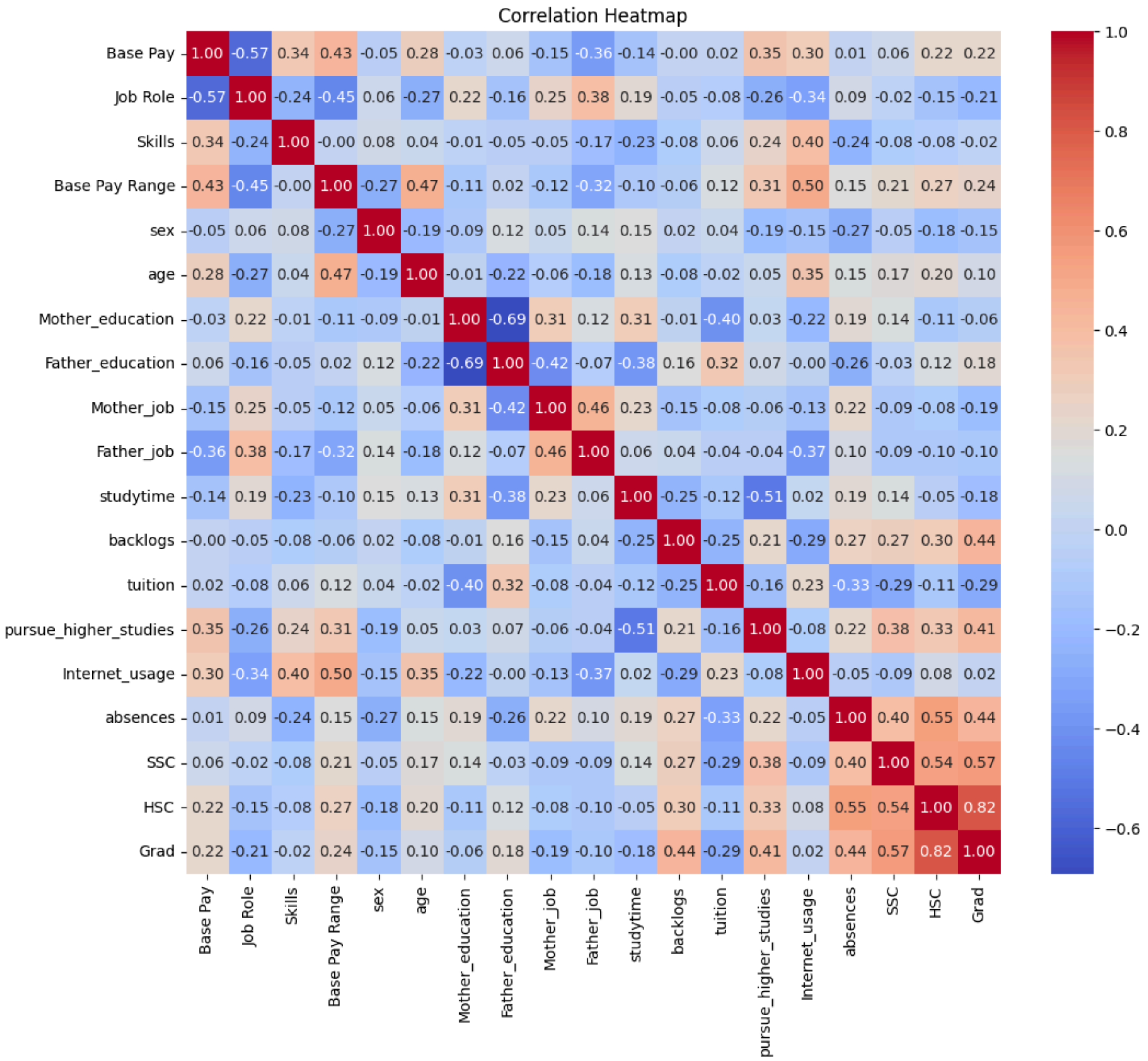
```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
# Predict on the test set
y_pred = rf_classifier.predict(X_test)
```

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')

# Classification report
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Accuracy: 1.00

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         9
           1       1.00      1.00      1.00        82
           2       1.00      1.00      1.00        79
           3       1.00      1.00      1.00        93
           4       1.00      1.00      1.00        96
           5       1.00      1.00      1.00        29
           6       1.00      1.00      1.00        12

    accuracy                           1.00       400
   macro avg       1.00      1.00      1.00       400
weighted avg       1.00      1.00      1.00       400


Confusion Matrix:
[[ 9  0  0  0  0  0  0]
 [ 0 82  0  0  0  0  0]
 [ 0  0 79  0  0  0  0]
 [ 0  0  0 93  0  0  0]
 [ 0  0  0  0 96  0  0]
 [ 0  0  0  0  0 29  0]
 [ 0  0  0  0  0  0 12]]
```

```
corr_matrix = df.corr()

# Create heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```




```
df.shape
```

```
(2000, 19)
```

PREDICTING THE MONTHLY INCOME BASED ON VARIOUS STUDENT DEMOGRAPHIES

```
df.columns
```

```
Index(['Base Pay', 'Job Role', 'Skills', 'Base Pay Range', 'sex', 'age',
       'Mother_education', 'Father_education', 'Mother_job', 'Father_job',
       'studytime', 'backlogs', 'tuition', 'pursue_higher_studies',
       'Internet_usage', 'absences', 'SSC', 'HSC', 'Grad'],
      dtype='object')
```

```
X1 = df.drop(columns=['Base Pay Range'])
y1 = df['Base Pay Range']

# Split the data into training and testing sets
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.2)
```

```
# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100)

# Train the model
rf_classifier.fit(X_train1, y_train1)
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

```
# Predict on the test set
# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100)

# Train the model
rf_classifier.fit(X_train1, y_train1)


# Evaluate the model
accuracy = accuracy_score(y_test1, y_pred1)
print(f'Accuracy: {accuracy:.2f}')

# Classification report
print("\nClassification Report:")
print(classification_report(y_test1, y_pred1))

# Confusion matrix
print("\nConfusion Matrix:")
print(confusion_matrix(y_test1, y_pred1))
```

```
Accuracy: 1.00

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         7
           2       1.00      1.00      1.00        85
           3       1.00      1.00      1.00        15
           4       1.00      1.00      1.00       100
           5       1.00      1.00      1.00        92
           6       1.00      1.00      1.00        91

    accuracy                           1.00       400
   macro avg       1.00      1.00      1.00       400
weighted avg       1.00      1.00      1.00       400


Confusion Matrix:
[[ 10   0   0   0   0   0   0]
 [  0   7   0   0   0   0   0]
 [  0   0  85   0   0   0   0]
 [  0   0   0  15   0   0   0]
 [  0   0   0   0 100   0   0]
 [  0   0   0   0   0  92   0]
 [  0   0   0   0   0   0  91]]
```

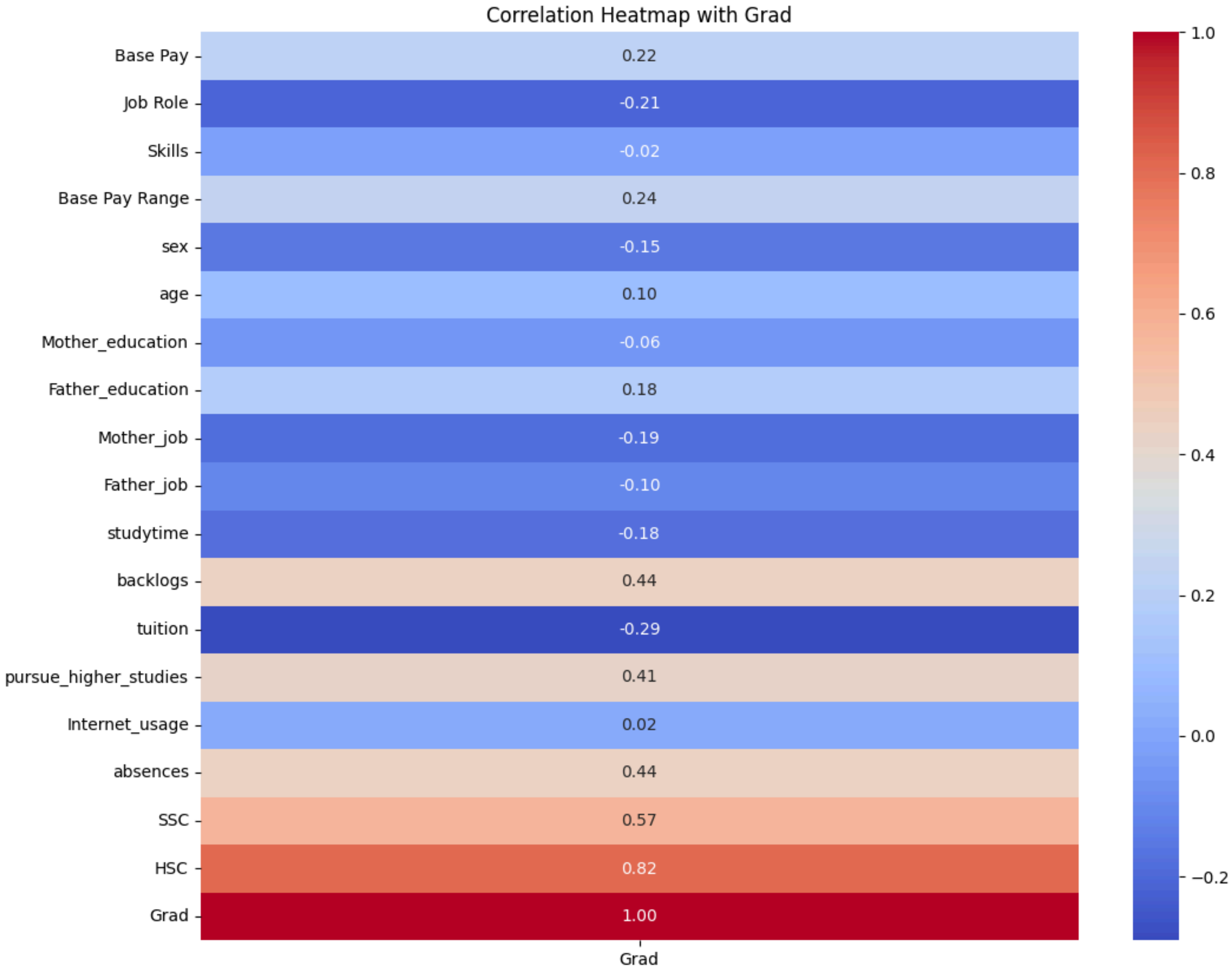
PREDICTING GRADUATION MARKS

```
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Recalculate VIF after ensuring data is clean and numeric
vif_data = pd.DataFrame()
vif_data["Feature"] = df.columns
vif_data["VIF"]  = [variance_inflation_factor(df.values, i) for i in range(df.shape[1])]

print(vif_data.sort_values(by="VIF", ascending=False))
```

```
                 Feature         VIF
18                  Grad  242.578630
17                   HSC  210.758367
5                    age   95.155822
16                   SSC   84.359774
13  pursue_higher_studies   39.498286
0               Base Pay   22.294241
3         Base Pay Range   17.866512
14        Internet_usage   15.111155
10             studytime   13.044033
15              absences    9.681854
8             Mother_job    9.511199
7       Father_education    9.180028
1               Job Role    8.365285
```

```
6        Mother_education    6.842893
12                tuition    6.028220
9              Father_job    5.543742
2                  Skills    4.751360
11               backlogs    3.045521
4                     sex    2.810284
```

```
corr_matrix = df.corr()
# Create heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix[['Grad']], annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap with Grad')
plt.show()
```



```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

X2 = df[['backlogs', 'pursue_higher_studies', 'absences', 'SSC', 'HSC']]
y2 = df['Grad']

# Split the data into training and testing sets
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.2)

# Initialize and train the model
model = LinearRegression()
model.fit(X_train2, y_train2)

# Make predictions
y_pred2 = model.predict(X_test2)

# Evaluate the model
mse = mean_squared_error(y_test2, y_pred2)
rmse = np.sqrt(mse)
```

Inferences from the Data Analysis:

Correlation Between SSC and HSC Performance:

Inference: Students who perform well in SSC tend to also perform well in HSC, indicating that early academic success is a strong predictor of future academic performance. This correlation suggests that consistent academic diligence from early education stages can influence career trajectories positively.

Salary Distribution Across Job Roles:

Inference: The majority of jobs have a salary below ₹50,000, with the exception of the doctor profession, which is the highest-paying, typically earning above ₹90,000. This highlights the financial benefits of pursuing a career in medicine.

Impact of Study Time on Academic Success: