performance dataset

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[ ]:
```python
# import necessary libraries
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import pandas as pd
from sklearn.model_selection import train_test_split as split
from sklearn.preprocessing import StandardScaler
```

[ ]:
```python
# load the dataset
df = pd.read_csv("/content/employee_performance_pro.csv")
df.head(5)
```

[ ]:
```
   EmployeeID                 Name  Gender  Age Department          JobRole  \
0           1       Steven Barnett   Other   57    Finance          Auditor
1           2  Christopher Benson  Female   26      Sales  Sales Executive
2           3          Norman Lane   Other   59    Support         Helpdesk
3           4         Rita Walker  Female   43         HR     HR Executive
4           5          Judith Ware    Male   52      Sales  Account Manager

   EducationLevel JoiningDate  CountryCode  Country  …  LastLeaveDate  \
0               2  2016-05-05           91    India  …     2024-07-03
1               2  2014-08-20            1   Canada  …     2024-01-05
2               1  2010-05-17            1   Canada  …     2024-11-27
3               3  2015-06-20           49  Germany  …     2024-07-15
4               3  2019-08-20           49  Germany  …     2024-12-17

   LeaveDayName  ProjectsHandled  TrainingHours CustomerSatisfaction  \
0     Wednesday               13             16                  NaN
1        Friday               15             44                  8.0
2     Wednesday                7             62                  7.0
3        Monday               15              8                  NaN
4       Tuesday               10             57                  8.0

  LastPromotionYear  YearsAtCompany  WorkLifeBalanceScore  PerformanceRating  \
0              2020               9                  1.90                  4
1              2014              11                  5.03                  1
2              2012              15                  4.83                  4
```

```
3          2016          10             4.60              4
4          2022           6             3.73              4

   AttritionRisk
0             No
1            Yes
2             No
3             No
4             No

[5 rows x 24 columns]
```

[ ]:
```python
df.info() # check for null values and data types
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 24 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   EmployeeID             500 non-null    int64
 1   Name                   500 non-null    object
 2   Gender                 500 non-null    object
 3   Age                    500 non-null    int64
 4   Department             500 non-null    object
 5   JobRole                500 non-null    object
 6   EducationLevel         500 non-null    int64
 7   JoiningDate            500 non-null    object
 8   CountryCode            500 non-null    int64
 9   Country                500 non-null    object
 10  PhoneNumber            500 non-null    int64
 11  MonthlySalary          500 non-null    int64
 12  OvertimeHoursPerMonth  500 non-null    int64
 13  LeavesTaken            500 non-null    int64
 14  LastLeaveDate          500 non-null    object
 15  LeaveDayName           500 non-null    object
 16  ProjectsHandled        500 non-null    int64
 17  TrainingHours          500 non-null    int64
 18  CustomerSatisfaction   181 non-null    float64
 19  LastPromotionYear      500 non-null    int64
 20  YearsAtCompany         500 non-null    int64
 21  WorkLifeBalanceScore   500 non-null    float64
 22  PerformanceRating      500 non-null    int64
 23  AttritionRisk          500 non-null    object
dtypes: float64(2), int64(13), object(9)
memory usage: 93.9+ KB
```

[ ]:
```python
df.shape # check the shape of the dataset
```

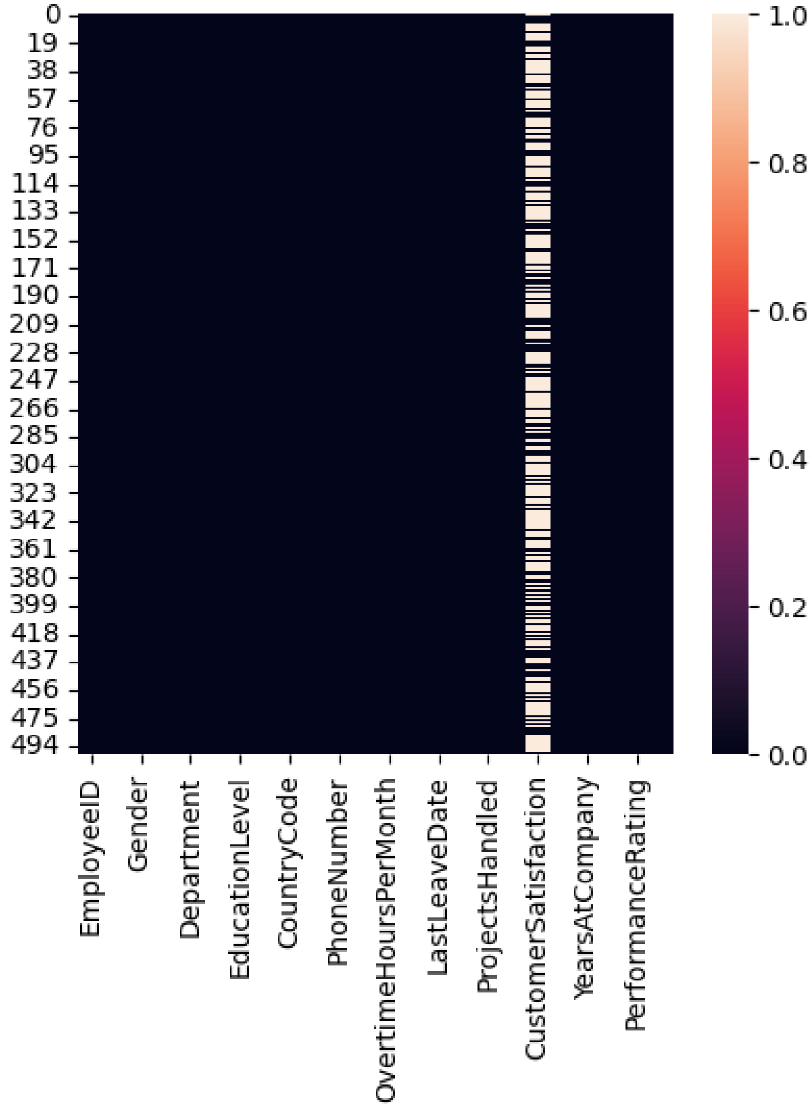
[ ]: (500, 24)

[ ]:
```
df.isnull().sum()   # check for null values in each column
```

[ ]:
```
EmployeeID                 0
Name                       0
Gender                     0
Age                        0
Department                 0
JobRole                    0
EducationLevel             0
JoiningDate                0
CountryCode                0
Country                    0
PhoneNumber                0
MonthlySalary              0
OvertimeHoursPerMonth      0
LeavesTaken                0
LastLeaveDate              0
LeaveDayName               0
ProjectsHandled            0
TrainingHours              0
CustomerSatisfaction     319
LastPromotionYear          0
YearsAtCompany             0
WorkLifeBalanceScore       0
PerformanceRating          0
AttritionRisk              0
dtype: int64
```

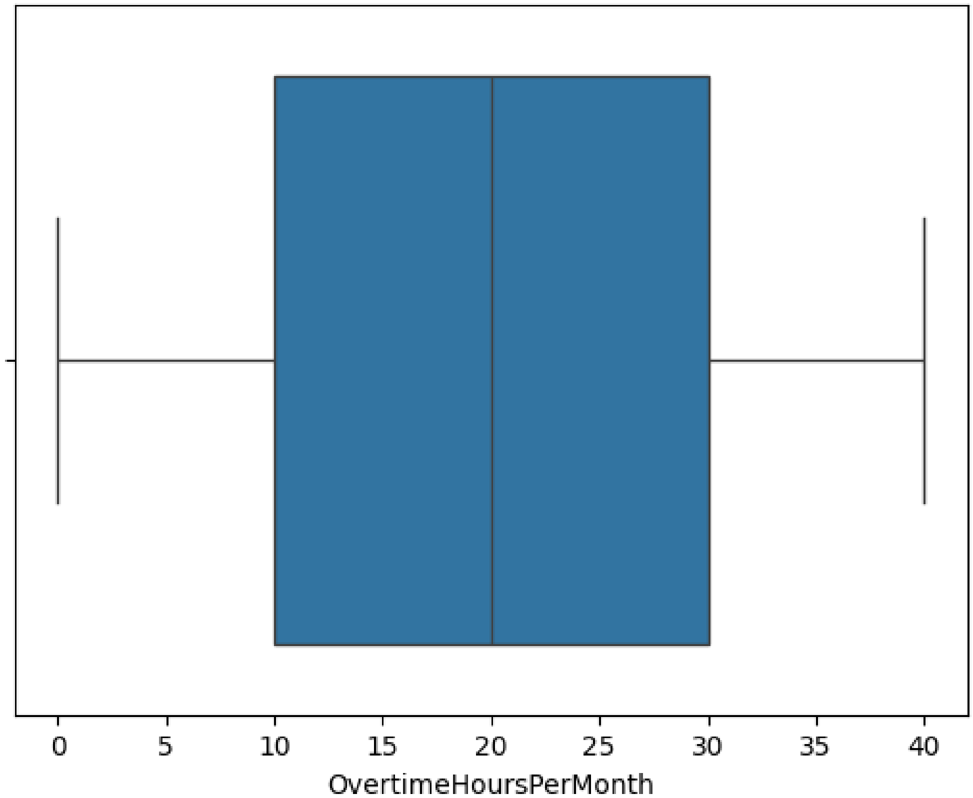
[ ]:
```
plt.figure(figsize = (5,5)) # visualize null values using heatmap
sns.heatmap(df.isnull()) # heatmap for null values
```

[ ]: <Axes: >



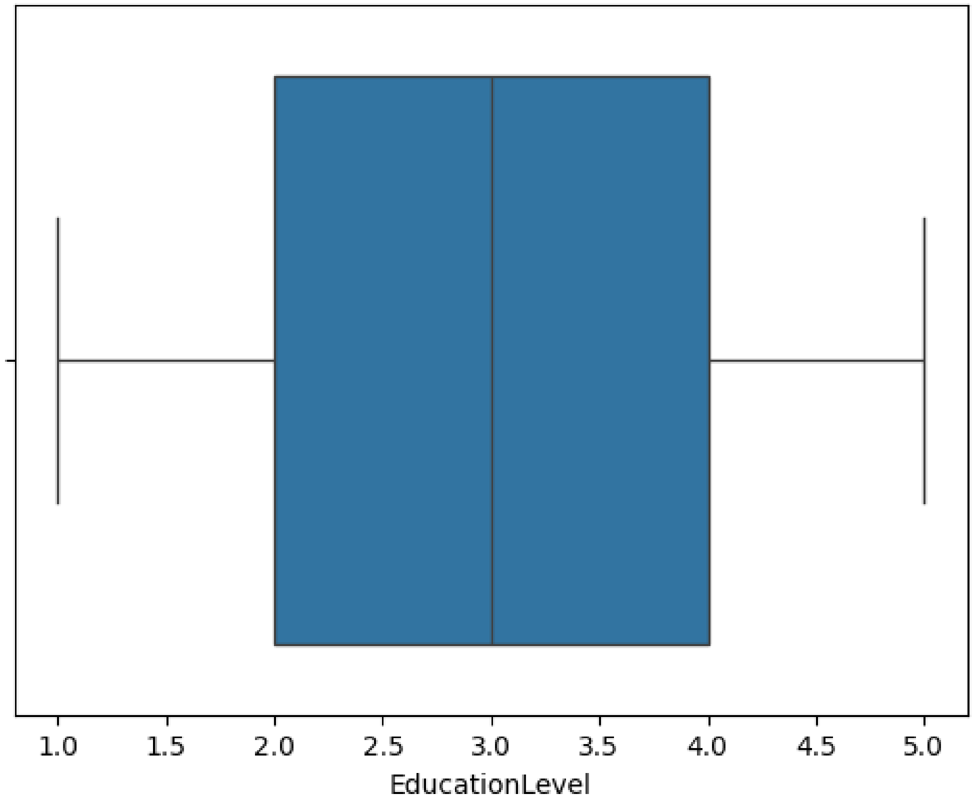
[ ]:
```
df['OvertimeHoursPerMonth'] = pd.to_numeric(df['OvertimeHoursPerMonth'], errors␣
↪= 'coerce') # convert to numeric, coercing errors to NaN

sns.boxplot(x = 'OvertimeHoursPerMonth' , data = df) # boxplot to visualize␣
↪outliers in OvertimeHoursPerMonth
```

[ ]: <Axes: xlabel='OvertimeHoursPerMonth'>



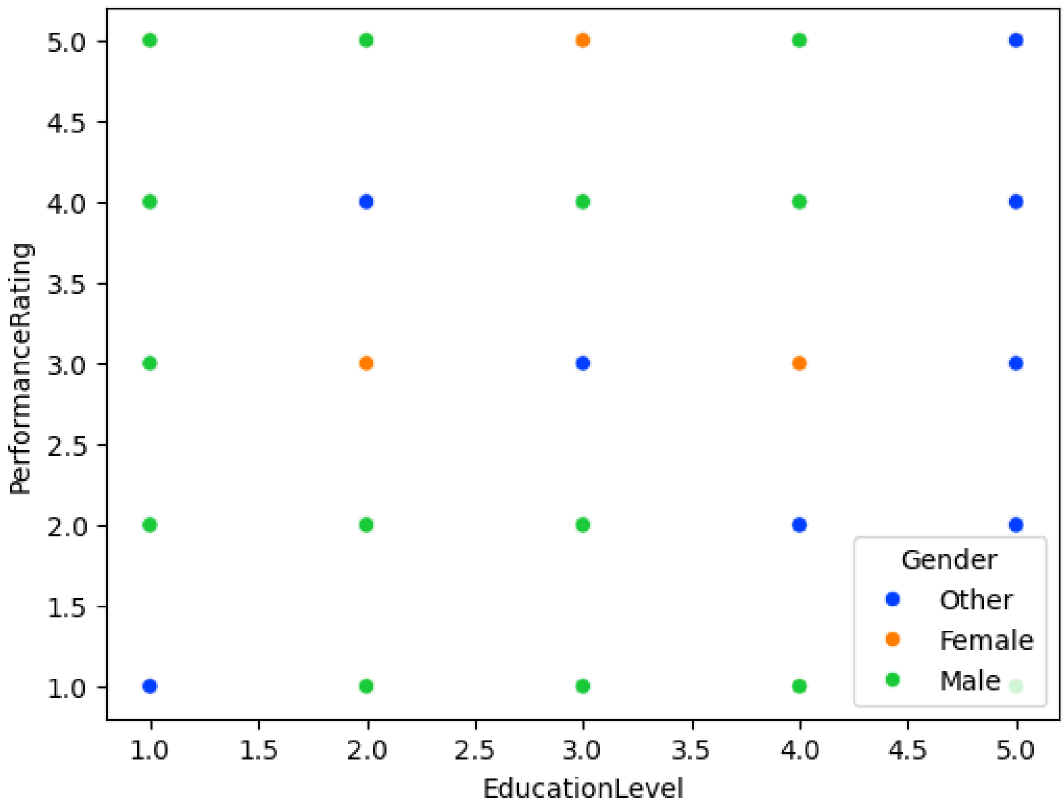

```
[ ]: df['EducationLevel'] = pd.to_numeric(df['EducationLevel'], errors = 'coerce') #␣
      ↪convert EducationLevel to numeric
     sns.boxplot(x = 'EducationLevel' , data = df) # boxplot to visualize outliers␣
      ↪in EducationLevel
```

```
[ ]: <Axes: xlabel='EducationLevel'>
```



[ ]:
```
# scatter plot to visualize relationship between EducationLevel and␣
↪PerformanceRating
sns.scatterplot(data=df , x = 'EducationLevel' , y = 'PerformanceRating' , hue␣
↪= 'Gender', palette ='bright')
```

[ ]:
```
<Axes: xlabel='EducationLevel', ylabel='PerformanceRating'>
```



[ ]:
```
# Identify outliers in OvertimeHoursPerMonth using IQR method
df['OvertimeHoursPerMonth'] = pd.to_numeric(df['OvertimeHoursPerMonth'], errors␣
↪= 'coerce')
data = df.dropna(subset = ["OvertimeHoursPerMonth"])
Q1 = np.percentile(data["OvertimeHoursPerMonth"] , 25)
Q3 = np.percentile(data["OvertimeHoursPerMonth"] , 75)
IQR = Q3 - Q1
# Calculate bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
# Filter out the outliers
outliers = data[(df["OvertimeHoursPerMonth"]< lower_bound) | (data␣
↪["OvertimeHoursPerMonth"] > upper_bound)]

print("outliers :\n" , outliers)
```

```
outliers :
 Empty DataFrame
Columns: [EmployeeID, Name, Gender, Age, Department, JobRole, EducationLevel,
JoiningDate, CountryCode, Country, PhoneNumber, MonthlySalary,
OvertimeHoursPerMonth, LeavesTaken, LastLeaveDate, LeaveDayName,
```

```
ProjectsHandled, TrainingHours, CustomerSatisfaction, LastPromotionYear,
YearsAtCompany, WorkLifeBalanceScore, PerformanceRating, AttritionRisk]
Index: []

[0 rows x 24 columns]
```

[ ]:
```
df.shape # check the shape of the dataset
```

[ ]:
```
(500, 24)
```

[ ]:
```
df.info() # check for null values and data types
```

```
<class 'pandas.core.frame.DataFrame'>
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Data columns (total 24 columns):
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 0   EmployeeID             500 non-null    int64
 1   Name                   500 non-null    object
 2   Gender                 500 non-null    object
 3   Age                    500 non-null    int64
 4   Department             500 non-null    object
 5   JobRole                500 non-null    object
 6   EducationLevel         500 non-null    int64
 7   JoiningDate            500 non-null    object
 8   CountryCode            500 non-null    int64
 9   Country                500 non-null    object
 10  PhoneNumber            500 non-null    int64
 11  MonthlySalary          500 non-null    int64
 12  OvertimeHoursPerMonth  500 non-null    int64
 13  LeavesTaken            500 non-null    int64
 14  LastLeaveDate          500 non-null    object
 15  LeaveDayName           500 non-null    object
 16  ProjectsHandled        500 non-null    int64
 17  TrainingHours          500 non-null    int64
 18  CustomerSatisfaction   181 non-null    float64
 19  LastPromotionYear      500 non-null    int64
 20  YearsAtCompany         500 non-null    int64
 21  WorkLifeBalanceScore   500 non-null    float64
 22  PerformanceRating      500 non-null    int64
 23  AttritionRisk          500 non-null    object
dtypes: float64(2), int64(13), object(9)
memory usage: 93.9+ KB
```

[ ]:
```
X = df.drop(columns = ['OvertimeHoursPerMonth']) # features
y = df[['OvertimeHoursPerMonth']] # target variable
```

[ ]:
```
X.columns # check feature columns
```

[ ]:
```
Index(['EmployeeID', 'Name', 'Gender', 'Age', 'Department', 'JobRole',
       'EducationLevel', 'JoiningDate', 'CountryCode', 'Country',
       'PhoneNumber', 'MonthlySalary', 'LeavesTaken', 'LastLeaveDate',
       'LeaveDayName', 'ProjectsHandled', 'TrainingHours',
       'CustomerSatisfaction', 'LastPromotionYear', 'YearsAtCompany',
       'WorkLifeBalanceScore', 'PerformanceRating', 'AttritionRisk'],
      dtype='object')
```

[ ]:
```python
y.columns # check target variable column
```

[ ]:
```
Index(['OvertimeHoursPerMonth'], dtype='object')
```

[ ]:
```python
y.head(2) # display first 2 rows of target variable
```

[ ]:

	OvertimeHoursPerMonth
0	33
1	24

[ ]:
```python
# split the dataset into training and testing sets
X_train , X_test , y_train , y_test = split(X, y , train_size = 0.8 ,␣
↪random_state = 42)
X_train.shape
```

[ ]:
```
(400, 23)
```

[ ]:
```python
# check the shape of the target variable training set
y_train.shape
```

[ ]:
```
(400, 1)
```

[ ]:
```python
# print the shapes of training and testing sets
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(400, 23)
(100, 23)
(400, 1)
(100, 1)
```

[ ]:
```python
# alternative way to split the dataset using train_test_split
from sklearn.model_selection import train_test_split
X = df[['OvertimeHoursPerMonth']]
y = df[['EducationLevel']]
X_train , X_test , y_train , y_test = train_test_split(X , y , test_size = 0.2␣
↪, random_state = 42)
```

[ ]:
```
# feature scaling using StandardScaler
sc = StandardScaler()
X_train_sc = sc.fit_transform(X_train)
X_test_sc = sc.fit_transform(X_test)
```

[ ]:
```
# import DecisionTreeRegressor
from sklearn.tree import DecisionTreeRegressor
```

[ ]:
```
# create Decision Tree Regressor model
model = DecisionTreeRegressor()
```

[ ]:
```
# fit the model on training data
model.fit(X_train , y_train)
```

[ ]:
```
DecisionTreeRegressor()
```

[ ]:
```
# make predictions on the test set
y_pred = model.predict(X_test)
```

[ ]:
```
# evaluate the model using R-squared metric
from sklearn.metrics import r2_score
```

[ ]:
```
# calculate R-squared score
r2_score(y_test , y_pred)*100
```

[ ]:
```
1.3608422144420484
```

[ ]:
```
# import LinearRegression
from sklearn.linear_model import LinearRegression
```

[ ]:
```
# create Linear Regression model
model = LinearRegression()
model.fit(X_train_sc , y_train)
```

[ ]:
```
LinearRegression()
```

[ ]:
```
# make predictions on the test set
X_train_sc = sc.fit_transform(X_train)
X_test_sc = sc.fit_transform(X_test)
```

[ ]:
```
# display first 10 rows of X_train

X_train[:10]
```

[ ]:
```
     OvertimeHoursPerMonth
249                      5
433                     19
19                       2
```

```
322                    34
332                    16
56                     16
301                     5
229                     4
331                    10
132                    22
```

[ ]:
```
# check the dataframe info

df.info()
```

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 5   JobRole                 500 non-null    object
 6   EducationLevel          500 non-null    int64
 7   JoiningDate             500 non-null    object
 8   CountryCode             500 non-null    int64
 9   Country                 500 non-null    object
 10  PhoneNumber             500 non-null    int64
 11  MonthlySalary           500 non-null    int64
 12  OvertimeHoursPerMonth   500 non-null    int64
 13  LeavesTaken             500 non-null    int64
 14  LastLeaveDate           500 non-null    object
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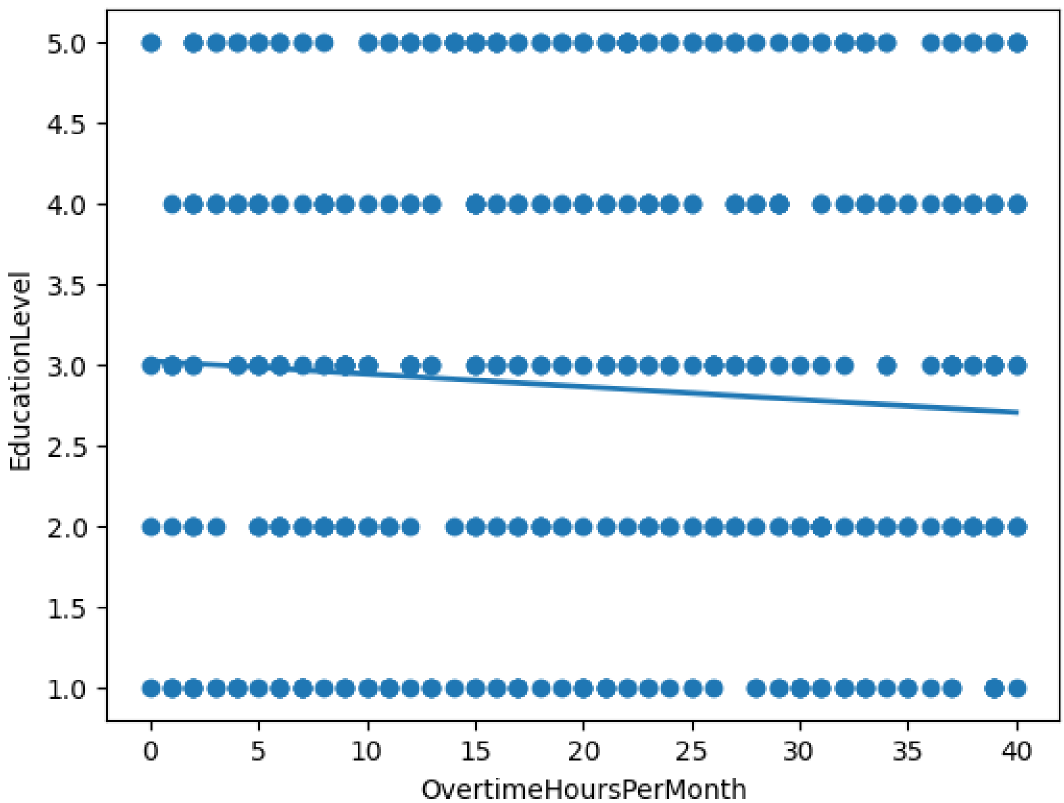
dtypes: float64(2), int64(13), object(9)
memory usage: 93.9+ KB
```

[ ]:
```
# visualize the regression results
plt.scatter(X.values , y.values  , label = "Actual data")
x_line = np.linspace(X.min().item(), X.max().item(), 100).reshape(-1,1)
y_line = model.predict(x_line)
```

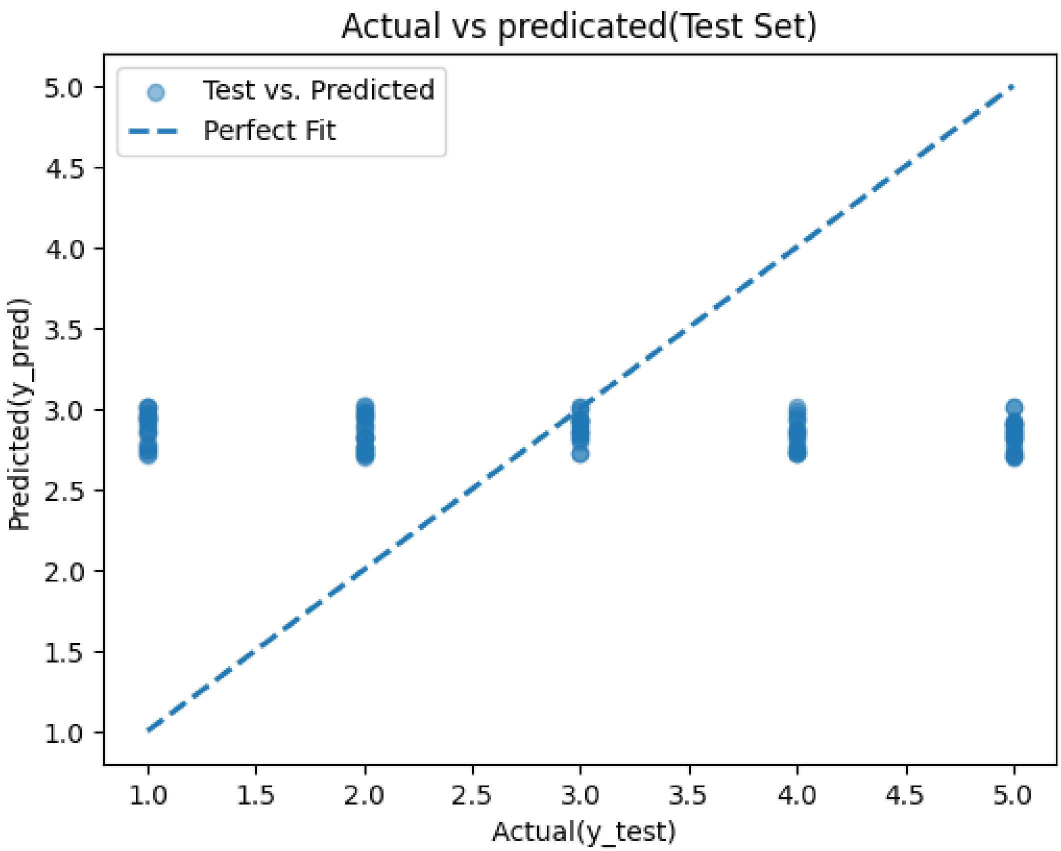
```
plt.plot(x_line , y_line , linewidth = 2 , label = "Regression line")
plt.xlabel("OvertimeHoursPerMonth")
plt.ylabel("EducationLevel")
plt.show()
```



This plot shows that Education Level does not meaningfully change with Overtime Hours. The points are spread evenly across all education levels, and the trend line is almost flat. This means there is no real relationship—employees with any education level work similar amounts of overtime.

[ ]:
```
# visualize Actual vs Predicted for test set
y_pred_test = model.predict(X_test).ravel()
plt.scatter(y_test.values.ravel(), y_pred_test , alpha = 0.5 , label = "Test vs.
 ↪ Predicted")
mn,mx = y_test.values.min() , y_test.values.max()
plt.plot([mn , mx], [mn , mx], linestyle = "--", linewidth = 2, label =␣
 ↪"Perfect Fit")
plt.xlabel(" Actual(y_test)")
plt.ylabel("Predicted(y_pred)")
plt.title("Actual vs predicated(Test Set)")
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.12/dist-packages/sklearn/utils/validation.py:2732:
UserWarning: X has feature names, but LinearRegression was fitted without
feature names
  warnings.warn(
```



This plot shows that the model's predictions are almost the same value every time, no matter what the actual education level is. The points cluster around ~3.0 instead of following the perfect-fit line. This means the model cannot learn the relationship and simply predicts the average for all cases — indicating very poor predictive performance.