employe-burnout-prediction

February 18, 2025

bold text# ** Employee Burnout Prediction** Employee burnout is a state of physical, e ional and mental exhaustion caused by excessive and prolonged stress. It can have serious consequences on an individual's well-being and can lead to decreased productivity and job performance. In today's fast-paced and constantly connected world, it is increasingly important to recognize and address the signs of burnout in order to maintain the health and well-being of employees.

we will be exploring the use of regression techniques to predict employee burnout. By analyzing a dataset containing various factors that may contribute to burnout such as workload, mental fatigue job and work-life balance, we can develop a model to identify individuals who may be at risk of burnout. By proactively addressing these risk factors, organizations can help prevent burnout and promote the well-being of their employees. Dataset: Are Your Employees Burning Out?

1 This dataset consists of 9 columns as follows:

Employee ID: The unique ID allocated for each employee **(example: fffe390032003000)**

Date of Joining: The date-time when the employee has joined the organization **(example: 2008-12-30)**

Gender. The gender of the employee **(Male/Female)**

Company Type: The type of company where the employee is working **(Service/Product)**

WFH Setup Available: Is the work from home facility available for the employee (Yes/No)

Designation : The designation of the employee of work in the organization. In the range of [0.0, 5.0] bigger is higher designation.

Resource Allocation: The amount of resource allocated to the employee to work, ie. number of working hours. In the range of [1.0, 10.0] • Mental Fatigue Score: The level of fatigue mentally the employee is facing. In the range of [0.0, 10.0] where 0.0 means fatigue and 10.0 means completely fatigue.

Burn Rate: The value we need to predict to each employee telling the rate of Bur out while working. In the range of [0.0, 1.0] where the higher the value is more is the burn out.

2 IMPORTING LIBRARIES

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
```

3 LOADING DATASET

[ ]:
```
data=pd.read_excel("/content/employee_burnout_analysis-AI.xlsx")
```

4 DATA OVERVIEW

[ ]:
```
data.head()
```

[ ]:
```
                Employee ID Date of Joining  Gender Company Type  \
0  fffe32003000360033003200      2008-09-30  Female      Service
1      fffe3700360033003500      2008-11-30    Male      Service
2  fffe31003300320037003900      2008-03-10  Female      Product
3  fffe32003400380032003900      2008-11-03    Male      Service
4  fffe31003900340031003600      2008-07-24  Female      Service

  WFH Setup Available  Designation  Resource Allocation  Mental Fatigue Score  \
0                  No            2                  3.0                   3.8
1                 Yes            1                  2.0                   5.0
2                 Yes            2                  NaN                   5.8
3                 Yes            1                  1.0                   2.6
4                  No            3                  7.0                   6.9

   Burn Rate
0       0.16
1       0.36
2       0.49
3       0.20
4       0.52
```

[ ]:
```
data.tail()
```

[ ]:
```
                    Employee ID Date of Joining  Gender Company Type  \
22745  fffe31003500370039003100      2008-12-30  Female      Service
22746  fffe33003000350031003800      2008-01-19  Female      Product
22747          fffe390032003000      2008-11-05    Male      Service
```

```
22748  fffe3300330032003600390 0      2008-01-10  Female      Service
22749      fffe3400350031003800      2008-01-06    Male      Product

      WFH Setup Available  Designation  Resource Allocation  \
22745                  No            1                  3.0
22746                 Yes            3                  6.0
22747                 Yes            3                  7.0
22748                  No            2                  5.0
22749                  No            3                  6.0

       Mental Fatigue Score  Burn Rate
22745                   NaN       0.41
22746                   6.7       0.59
22747                   NaN       0.72
22748                   5.9       0.52
22749                   7.8       0.61
```

[ ]:
```python
data.shape
```

[ ]: `(22750, 9)`

4.1 Column Information

[ ]:
```python
data.columns.values
```

[ ]:
```
array(['Employee ID', 'Date of Joining', 'Gender', 'Company Type',
       'WFH Setup Available', 'Designation', 'Resource Allocation',
       'Mental Fatigue Score', 'Burn Rate'], dtype=object)
```

[ ]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22750 entries, 0 to 22749
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Employee ID           22750 non-null  object
 1   Date of Joining       22750 non-null  datetime64[ns]
 2   Gender                22750 non-null  object
 3   Company Type          22750 non-null  object
 4   WFH Setup Available   22750 non-null  object
 5   Designation           22750 non-null  int64
 6   Resource Allocation   21369 non-null  float64
 7   Mental Fatigue Score  20633 non-null  float64
 8   Burn Rate             21626 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(1), object(4)
memory usage: 1.6+ MB
```

[ ]:
```
data.dtypes
```

[ ]:
```
Employee ID                     object
Date of Joining         datetime64[ns]
Gender                          object
Company Type                    object
WFH Setup Available             object
Designation                      int64
Resource Allocation            float64
Mental Fatigue Score           float64
Burn Rate                      float64
dtype: object
```

[ ]:
```
data.describe()
```

[ ]:
```
                     Date of Joining   Designation  Resource Allocation  \
count                          22750  22750.000000         21369.000000
mean   2008-07-01 09:28:05.274725120      2.178725             4.481398
min              2008-01-01 00:00:00      0.000000             1.000000
25%              2008-04-01 00:00:00      1.000000             3.000000
50%              2008-07-02 00:00:00      2.000000             4.000000
75%              2008-09-30 00:00:00      3.000000             6.000000
max              2008-12-31 00:00:00      5.000000            10.000000
std                              NaN      1.135145             2.047211

       Mental Fatigue Score     Burn Rate
count          20633.000000  21626.000000
mean               5.728188      0.452005
min                0.000000      0.000000
25%                4.600000      0.310000
50%                5.900000      0.450000
75%                7.100000      0.590000
max               10.000000      1.000000
std                1.920839      0.198226
```

4.2 Finding Missing Values

data.isna().sum()

isna()//method to check any null values are there or missing values in the data set

sum() //calculate the count of null values in data

mean #median #mode #arbitarary #empty values

[ ]:
```
data.isna().sum().any()
```

[ ]: True

[ ]:
```
data.isna().sum()
```

[ ]:
```
Employee ID                0
Date of Joining            0
Gender                     0
Company Type               0
WFH Setup Available        0
Designation                0
Resource Allocation     1381
Mental Fatigue Score    2117
Burn Rate               1124
dtype: int64
```

5 Exploratory Data Analysis

There are NaN values on our target ("Burn Rate") eriti also in Resource Allocation and Mental Fatigue Score columns. As we are going to perform supervised linear regression, our target variable is needed to do so. Therefore, this 1124 rows with NaN values must be dropped off of our dataframe.

[ ]:
```
data.corr(numeric_only=True)['Burn Rate'][:-1]
```

[ ]:
```
Designation             0.737556
Resource Allocation     0.856278
Mental Fatigue Score    0.944546
Name: Burn Rate, dtype: float64
```

5.0.1 Inputting missing values with mostly appeared value i.e. 'S' for Resource Allocation column

[ ]:
```
data['Resource Allocation'].fillna(data['Resource Allocation'].mode()[0],␣
↪inplace=True)
```

5.0.2 Inputting missing values with mostly appeared value i.e. 'S' for Mental Fatigue Score column

[ ]:
```
data['Mental Fatigue Score'].fillna(data['Mental Fatigue Score'].mode()[0],␣
↪inplace=True)
```

5.0.3 Inputting missing values with mostly appeared value i.e. 'S' for Burn Rate column

[ ]:
```
data['Burn Rate'].fillna(data['Burn Rate'].mode()[0], inplace=True)
```

[ ]:
```
data.isna().sum()
```

[ ]:
```
Employee ID             0
Date of Joining         0
Gender                  0
Company Type            0
WFH Setup Available     0
Designation             0
Resource Allocation     0
Mental Fatigue Score    0
Burn Rate               0
dtype: int64
```

5.0.4 Calculate the all indivials values of categories in data set

[ ]:
```
print(data['Employee ID'].value_counts())
```

```
Employee ID
fffe32003000360033003200    1
fffe3600360035003500        1
fffe3800360034003400        1
fffe31003000310033003600    1
fffe31003400350031003700    1
                           ..
fffe33003400340032003400    1
fffe32003100370036003600    1
fffe31003900310035003800    1
fffe32003400320034003200    1
fffe3400350031003800        1
Name: count, Length: 22750, dtype: int64
```

[ ]:
```
print(data['Date of Joining'].value_counts())
```

```
Date of Joining
2008-01-06    86
2008-05-21    85
2008-02-04    82
2008-07-16    81
2008-07-13    80
              ..
2008-06-27    44
2008-07-06    44
2008-07-04    43
2008-12-24    43
2008-12-07    39
Name: count, Length: 366, dtype: int64
```

[ ]:
```
print(data['Gender'].value_counts())
```

```
Gender
Female    11908
Male      10842
Name: count, dtype: int64
```

```
[ ]: print(data['Company Type'].value_counts())
```

```
Company Type
Service    14833
Product     7917
Name: count, dtype: int64
```

```
[ ]: print(data['WFH Setup Available'].value_counts())
```

```
WFH Setup Available
Yes    12290
No     10460
Name: count, dtype: int64
```

```
[ ]: print(data['Designation'].value_counts())
```

```
Designation
2    7588
3    5985
1    4881
4    2391
0    1507
5     398
Name: count, dtype: int64
```

```
[ ]: print(data['Resource Allocation'].value_counts())
```

```
Resource Allocation
4.0     5274
5.0     3861
3.0     3192
6.0     2943
2.0     2075
7.0     1965
1.0     1791
8.0     1044
9.0      446
10.0     159
Name: count, dtype: int64
```

```
[ ]: print(data['Mental Fatigue Score'].value_counts())
```

```
Mental Fatigue Score
```

```
6.0    2587
5.8     464
5.9     458
6.1     457
6.3     454
       …
0.5      24
0.2      23
0.4      19
0.1      17
0.3      13
Name: count, Length: 101, dtype: int64
```

[ ]:
```
print(data['Burn Rate'].value_counts())
```

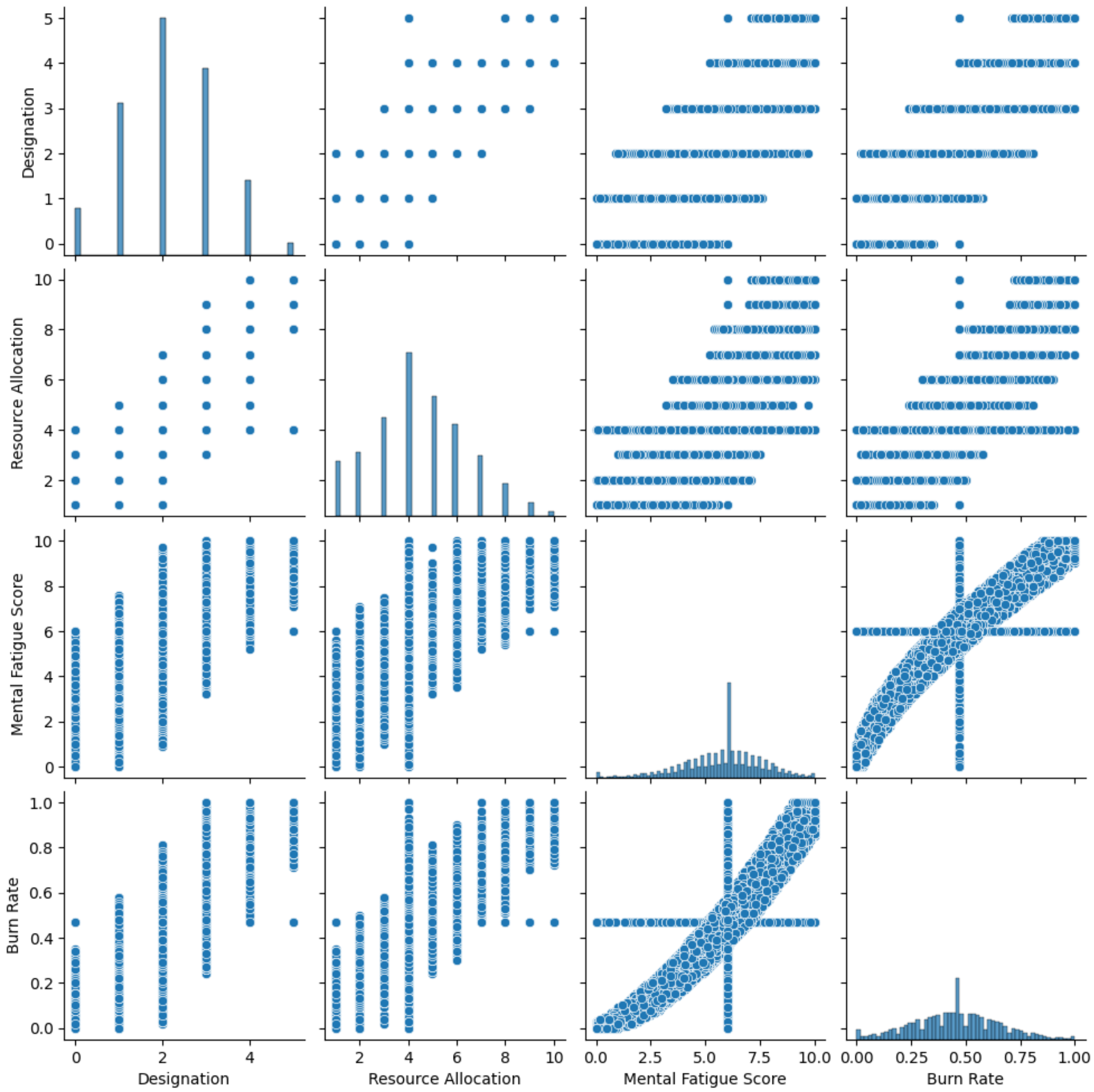
```
Burn Rate
0.47    1599
0.43     444
0.41     434
0.45     431
0.50     428
        …
0.98      18
0.97      17
0.95      17
0.96      13
0.99       8
Name: count, Length: 101, dtype: int64
```

[ ]:
```
data.nunique()
```

[ ]:
```
Employee ID             22750
Date of Joining           366
Gender                      2
Company Type                2
WFH Setup Available         2
Designation                 6
Resource Allocation        10
Mental Fatigue Score      101
Burn Rate                 101
dtype: int64
```

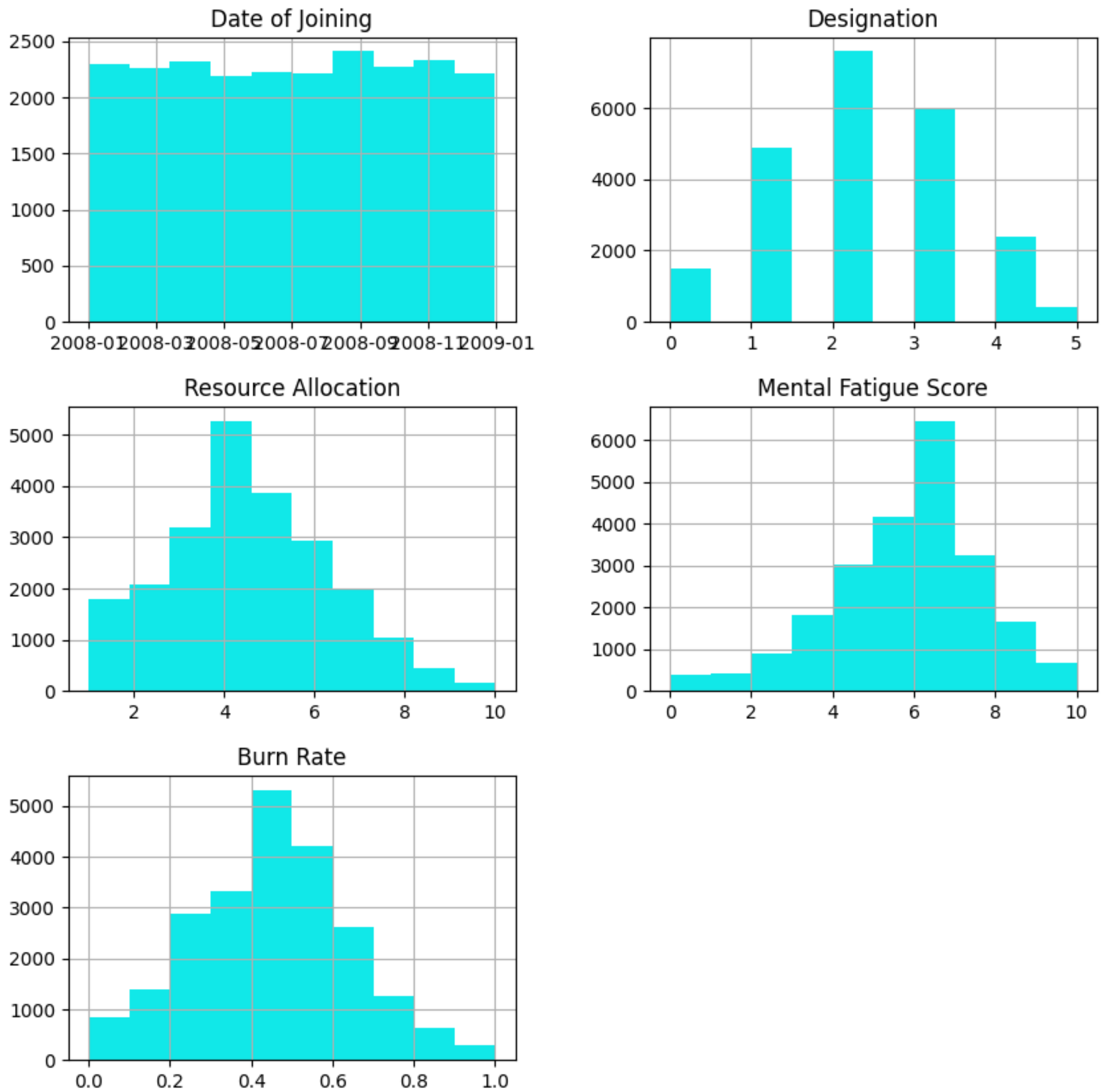
6 PAIRPLOTTING

[ ]:
```
sns.pairplot(data)
plt.show()
```



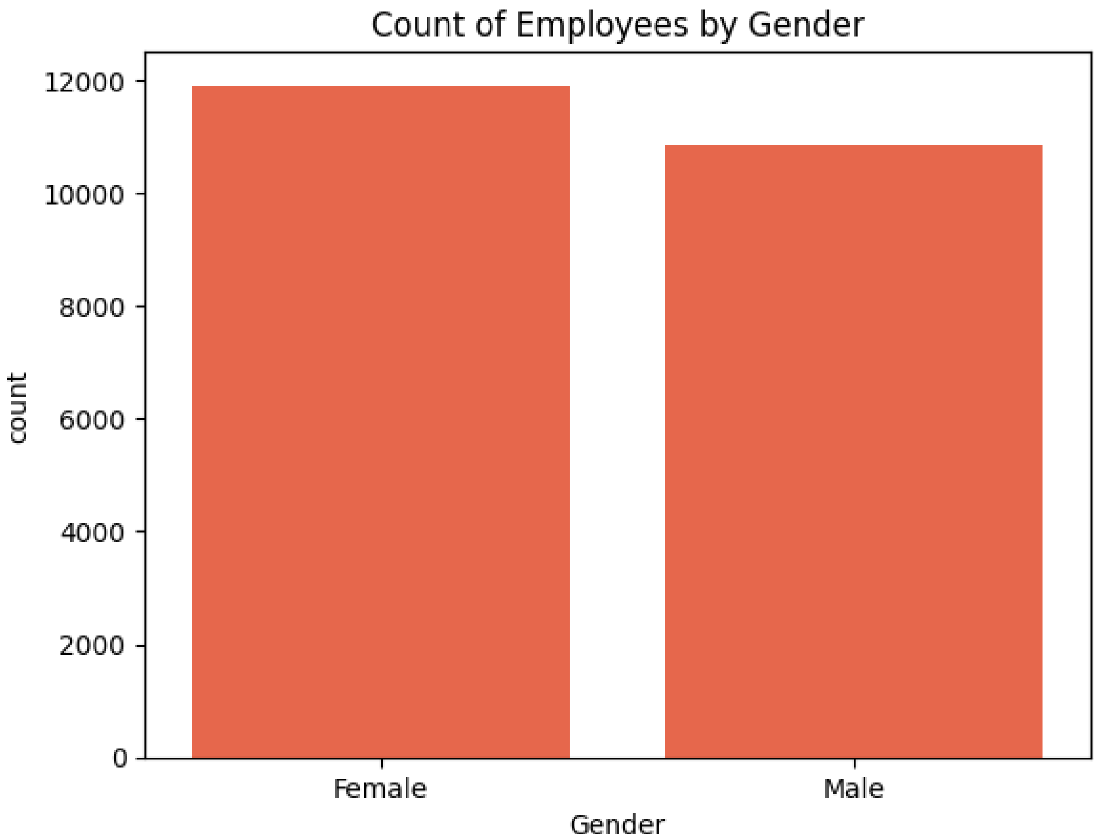
7 Plotting Hisplot

[ ]:
```
data.hist(figsize=(10,10),color='#11E8E8')
plt.show()
```

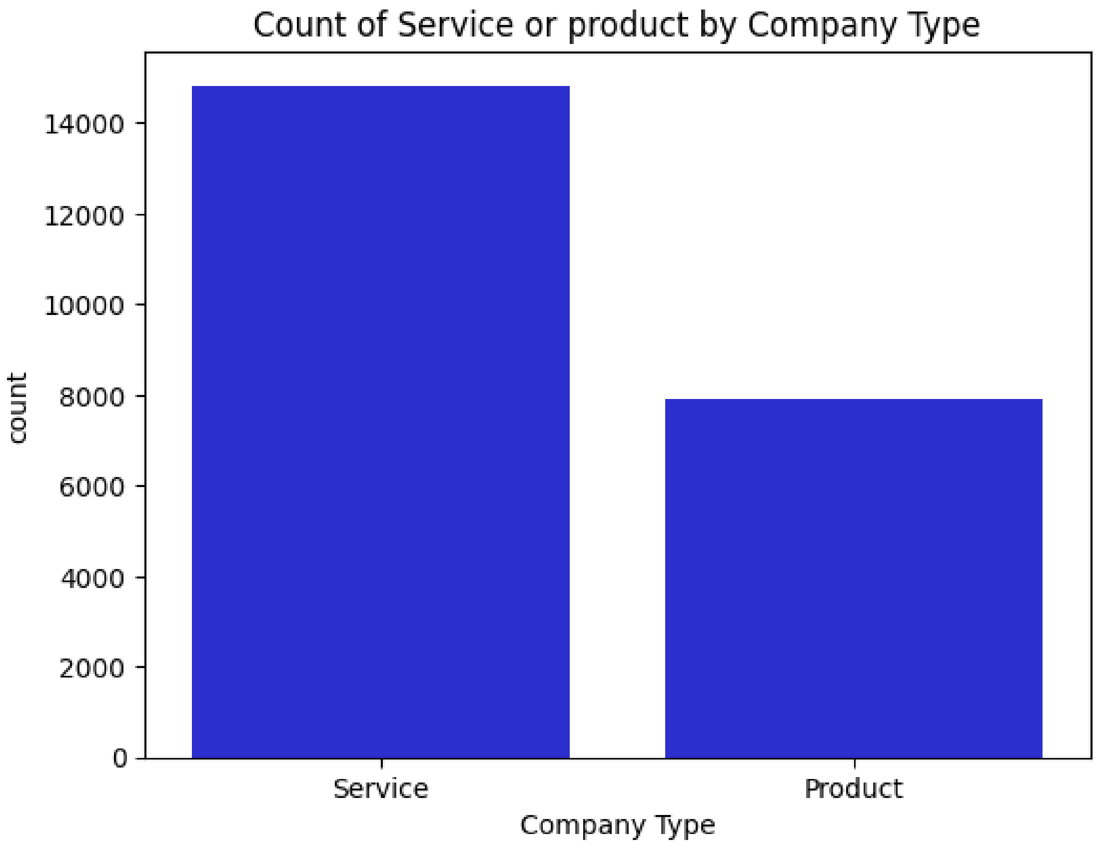


8 Bargraph plotting for different Categories

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming 'data' is your DataFrame containing 'Gender' column
sns.countplot(x='Gender', data=data,color='#FF5733')
plt.title('Count of Employees by Gender')
plt.show()
```

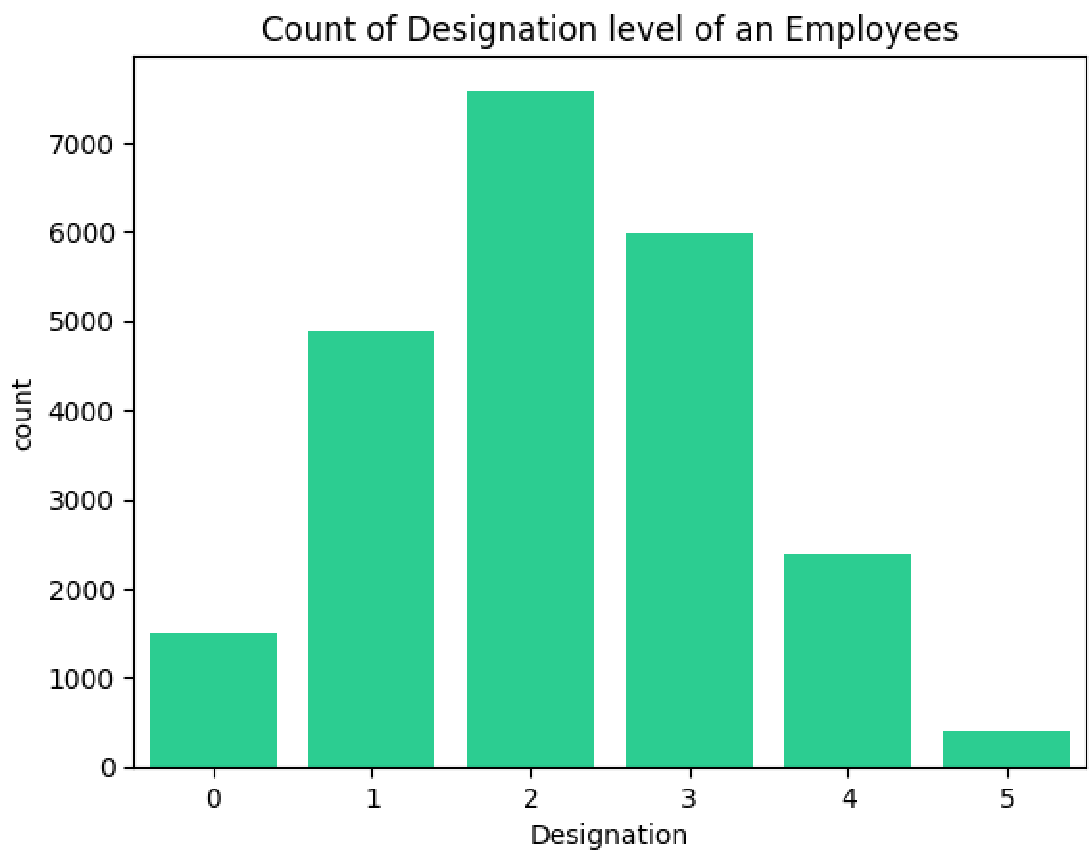


[ ]:
```
sns.countplot(x='Company Type', data=data,color='#1114E8')
plt.title('Count of Service or product by Company Type')
plt.show()
```

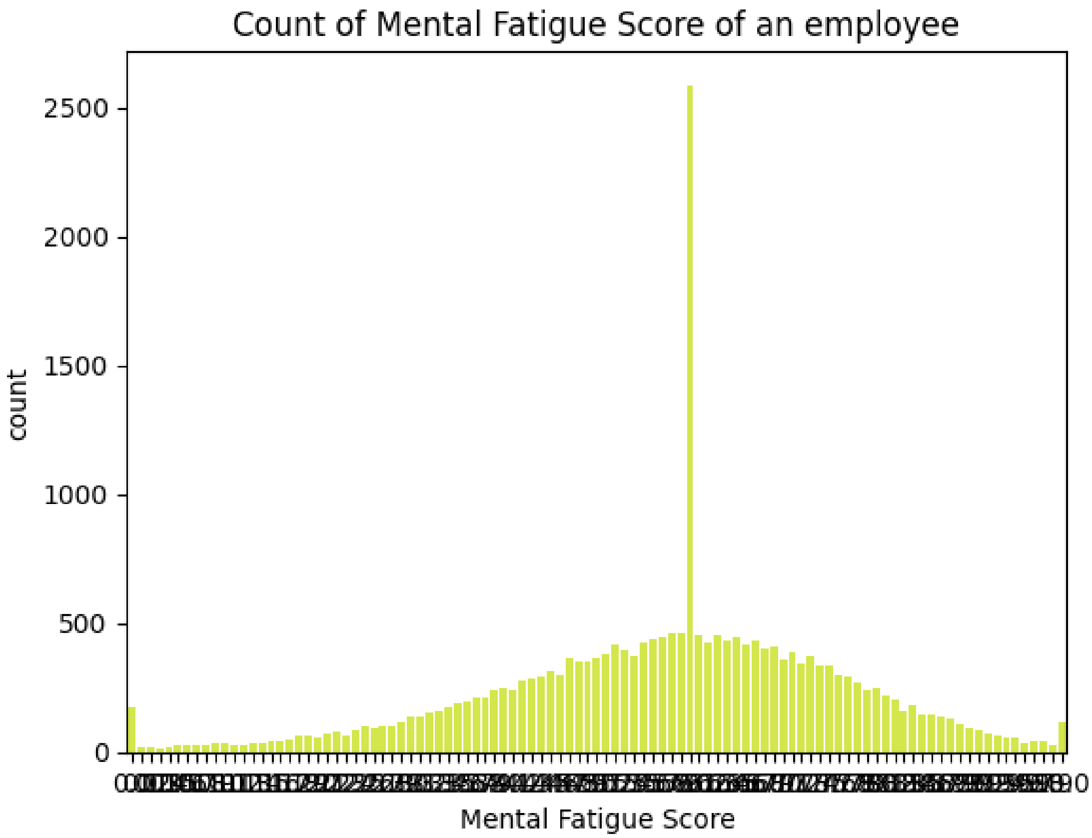


[ ]:
```
# WFH = (Work from Home)
sns.countplot(x='WFH Setup Available', data=data,color='#E811E5')
plt.title('Count of WFH Available For Employees')
plt.show()
```

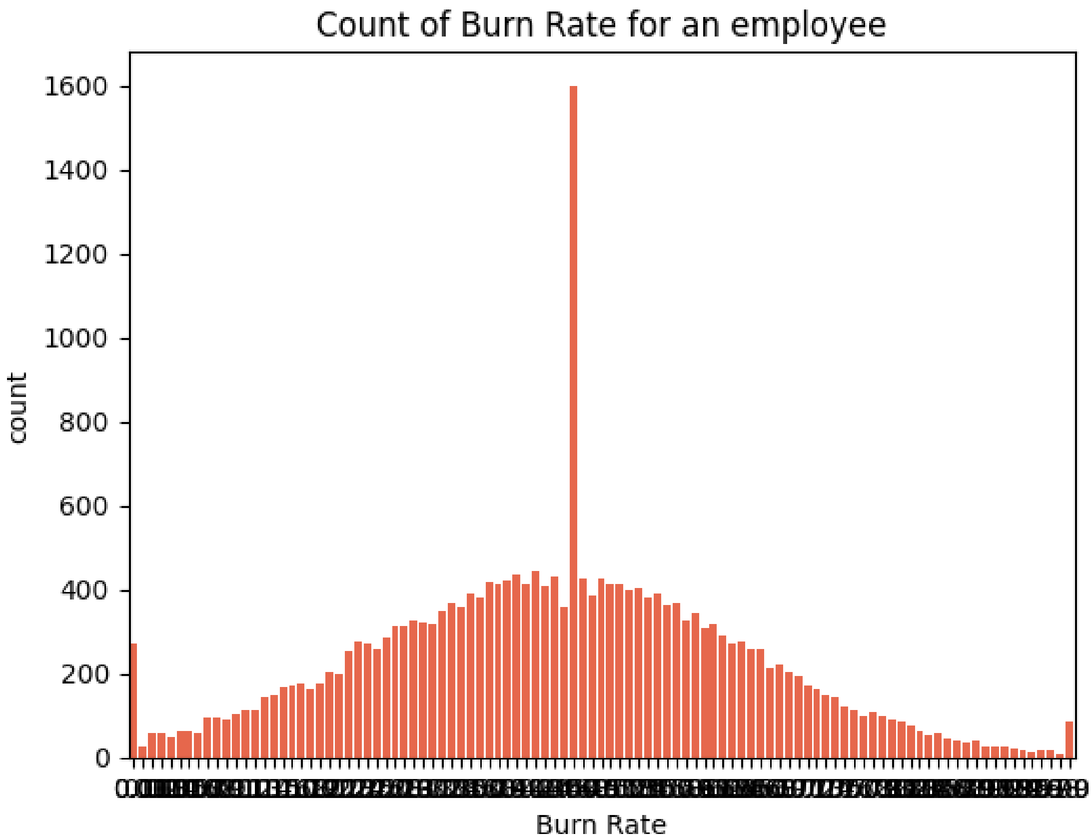
[ ]:
```
# designation of an employee refers to the job title or position held by the␣
↪employee within an organization.
sns.countplot(x='Designation', data=data,color='#11E898')
plt.title('Count of Designation level of an Employees')
plt.show()
```



[ ]:
```
# The term "Mental Fatigue Score" typically refers to a quantitative measure or
# rating that assesses the level of mental tiredness or exhaustion experienced␣
↪by an individual.
sns.countplot(x='Mental Fatigue Score', data=data,color='#E6FF33')
plt.title('Count of Mental Fatigue Score of an employee')
plt.show()
```




```
[ ]: # "Burn Rate" can refer to the rate at which the body burns calories during␣
     ↪physical activity.
     sns.countplot(x='Burn Rate', data=data,color='#FF5733')
     plt.title('Count of Burn Rate for an employee')
     plt.show()
```



8.1 Droping Cabing Column

[ ]:
```
#we are removing one of the colum from edution to reducary we need remove␣
↪education because machine canoot recogonice all the
#catogriacal values into numerical values for machine learning
#redundant info to remove
data=data.drop(columns=['Resource Allocation'])
```

[ ]:
```
data
```

[ ]:
```
                          Employee ID Date of Joining  Gender Company Type  \
0       fffe32003000360033003200      2008-09-30  Female      Service
1           fffe3700360033003500      2008-11-30    Male      Service
2       fffe31003300320037003900      2008-03-10  Female      Product
3       fffe32003400380032003900      2008-11-03    Male      Service
4       fffe31003900340031003600      2008-07-24  Female      Service
…                            …             …     …            …
22745   fffe31003500370039003100      2008-12-30  Female      Service
22746   fffe33003000350031003800      2008-01-19  Female      Product
```

```
22747           fffe390032003000      2008-11-05    Male      Service
22748   fffe3300330032003600 3900      2008-01-10  Female      Service
22749       fffe3400350031003800      2008-01-06    Male      Product

      WFH Setup Available  Designation  Mental Fatigue Score  Burn Rate
0                      No            2                   3.8       0.16
1                     Yes            1                   5.0       0.36
2                     Yes            2                   5.8       0.49
3                     Yes            1                   2.6       0.20
4                      No            3                   6.9       0.52
…                     …          …                    …        …
22745                  No            1                   6.0       0.41
22746                 Yes            3                   6.7       0.59
22747                 Yes            3                   6.0       0.72
22748                  No            2                   5.9       0.52
22749                  No            3                   7.8       0.61

[22750 rows x 8 columns]
```

9 Converting non-numeric data into binary categorical data

[ ]:
```
# Identify columns with non-numeric data
non_numeric_columns = data.select_dtypes(include=['object']).columns
print(non_numeric_columns)
```

```
Index(['Employee ID', 'Gender', 'Company Type', 'WFH Setup Available'],
dtype='object')
```

[ ]:
```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder

# Example: Label Encoding for binary categorical data
label_encoders = {}
for column in non_numeric_columns:
    le = LabelEncoder()
    data[column] = le.fit_transform(data[column])
    label_encoders[column] = le

# Example: One-Hot Encoding for multi-class categorical data
# Uncomment the following line if you have multi-class categorical columns
# data = pd.get_dummies(data, columns=non_numeric_columns)
```

[ ]:
```
data
```

[ ]:
```
       Employee ID Date of Joining  Gender  Company Type  WFH Setup Available  \
0             7722      2008-09-30       0             1                    0
1            21062      2008-11-30       1             1                    1
```

```
2           2381      2008-03-10       0             0                    1
3          10790      2008-11-03       1             1                    1
4           6810      2008-07-24       0             1                    0
…            …              …     …         …                 …
22745       4208      2008-12-30       0             1                    0
22746      14934      2008-01-19       0             0                    1
22747      22181      2008-11-05       1             1                    1
22748      16875      2008-01-10       0             1                    0
22749      18847      2008-01-06       1             0                    0

       Designation  Mental Fatigue Score  Burn Rate
0                2                   3.8       0.16
1                1                   5.0       0.36
2                2                   5.8       0.49
3                1                   2.6       0.20
4                3                   6.9       0.52
…            …                   …         …
22745            1                   6.0       0.41
22746            3                   6.7       0.59
22747            3                   6.0       0.72
22748            2                   5.9       0.52
22749            3                   7.8       0.61

[22750 rows x 8 columns]
```

10 Converting datetime columns intoto numeric columns

[ ]:
```python
# Identify columns with non-numeric data
non_numeric_columns = data.select_dtypes(include=['object', 'datetime64']).
 ↪columns
print(non_numeric_columns)
```

```
Index(['Date of Joining'], dtype='object')
```

[ ]:
```python
# Convert datetime columns to numeric
for column in data.select_dtypes(include=['datetime64']).columns:
    data[f'{column}_year'] = data[column].dt.year
    data[f'{column}_month'] = data[column].dt.month
    data[f'{column}_day'] = data[column].dt.day
    data = data.drop(columns=[column])
```

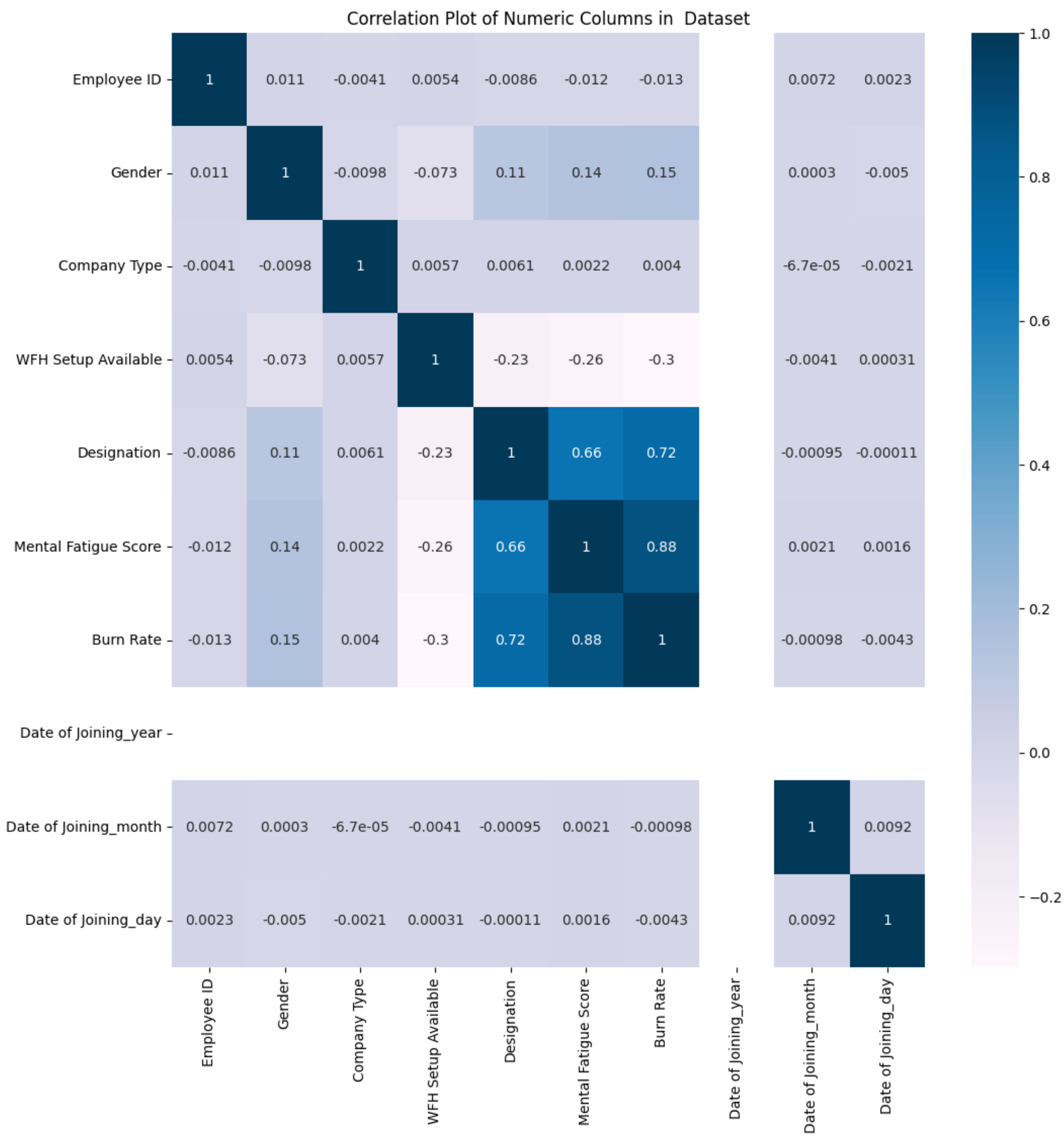
[ ]:
```python
data
```

[ ]:
```
       Employee ID  Gender  Company Type  WFH Setup Available  Designation  \
0             7722       0             1                    0            2
1            21062       1             1                    1            1
```

```
2           2381      0          0                 1         2
3          10790      1          1                 1         1
4           6810      0          1                 0         3
…             …    …       …             …     …
22745       4208      0          1                 0         1
22746      14934      0          0                 1         3
22747      22181      1          1                 1         3
22748      16875      0          1                 0         2
22749      18847      1          0                 0         3

       Mental Fatigue Score  Burn Rate  Date of Joining_year  \
0                       3.8       0.16                  2008
1                       5.0       0.36                  2008
2                       5.8       0.49                  2008
3                       2.6       0.20                  2008
4                       6.9       0.52                  2008
…                     …        …                   …
22745                   6.0       0.41                  2008
22746                   6.7       0.59                  2008
22747                   6.0       0.72                  2008
22748                   5.9       0.52                  2008
22749                   7.8       0.61                  2008

       Date of Joining_month  Date of Joining_day
0                          9                   30
1                         11                   30
2                          3                   10
3                         11                    3
4                          7                   24
…                        …                   …
22745                     12                   30
22746                      1                   19
22747                     11                    5
22748                      1                   10
22749                      1                    6

[22750 rows x 10 columns]
```

11 Plotting Correlation

[ ]:
```
# Plot the heatmap
plt.figure(figsize=(12,12))
sns.heatmap(data.corr(), annot=True, cmap='PuBu')
plt.title('Correlation Plot of Numeric Columns in  Dataset')
plt.show()
```



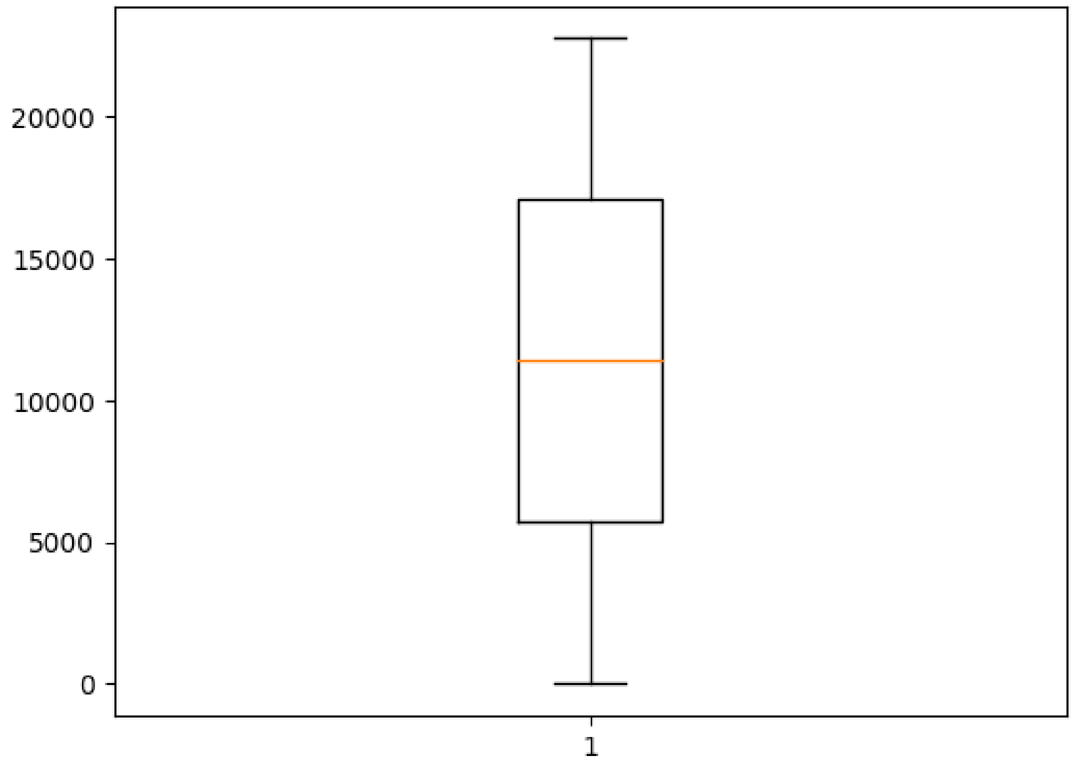
12 Plotting Box Plots(Out Layers)

outlayers = it is deviating our results or it is extream data point soo we need to remove this with folloing sntaxa

circles are the outlayers are represent by circles from 80 to 90 because those cant work box represent most useful info

line for least useful info # average for most useful info is the **orange line**

[ ]:
```
import matplotlib.pyplot as plt # visualization technic to undrestand data set
plt.boxplot(data['Employee ID']) #numerical values
plt.show()
```

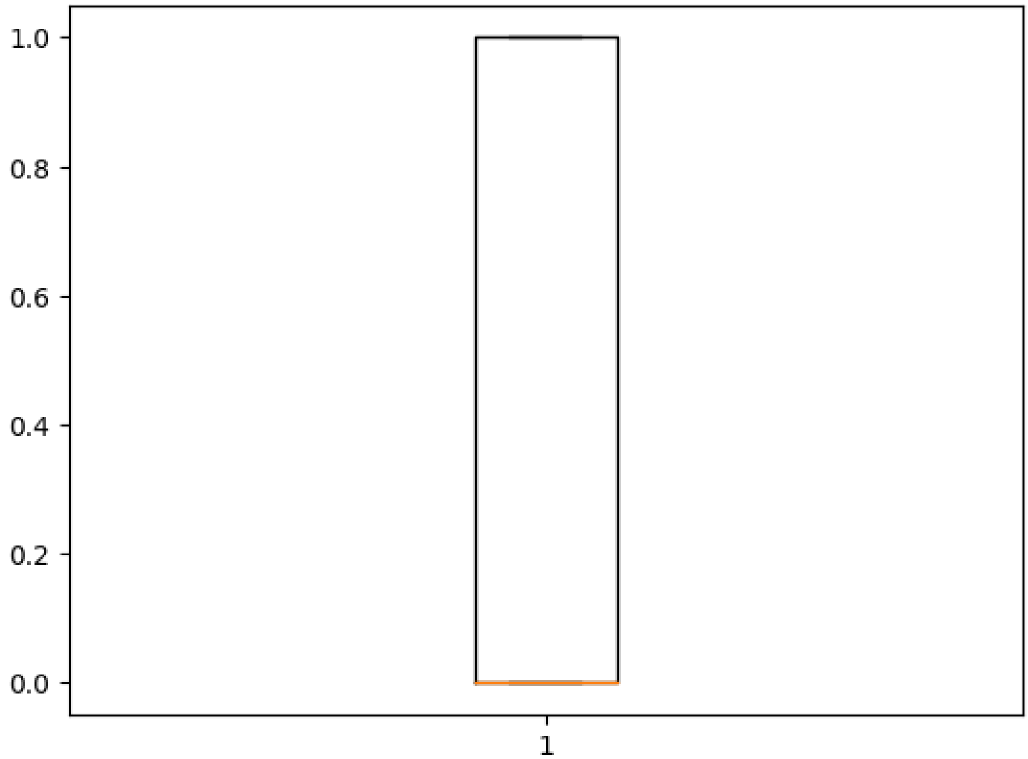


[ ]:
```
data.head(2)
```

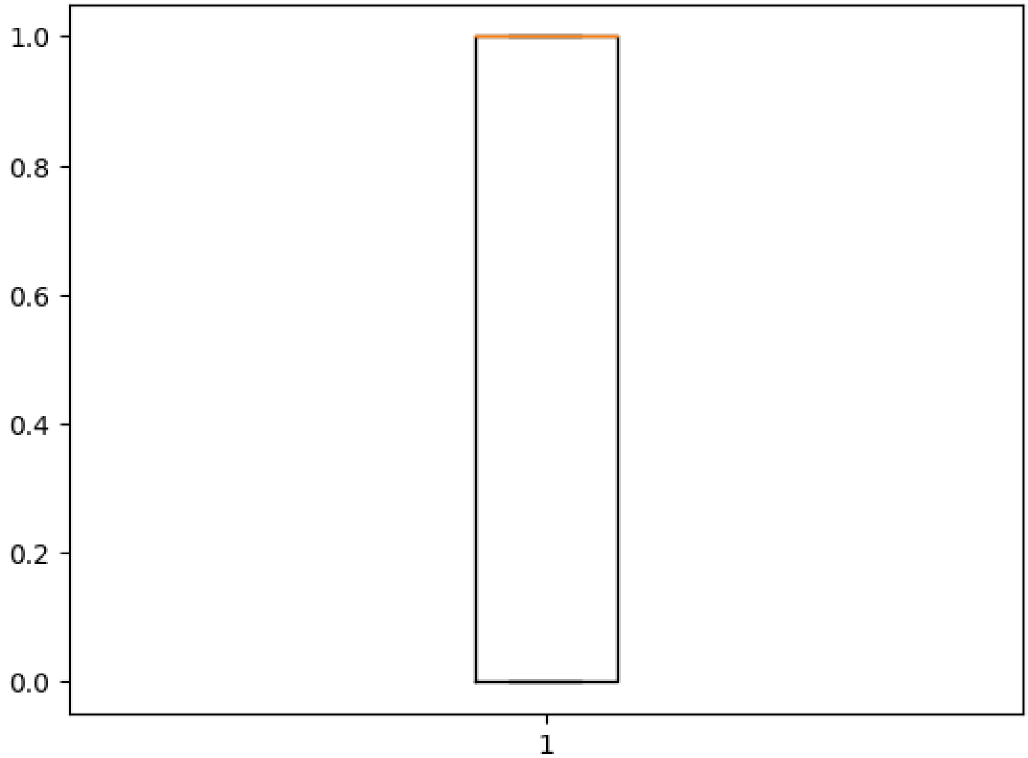
[ ]:
```
   Employee ID  Gender  Company Type  WFH Setup Available  Designation  \
0         7722       0             1                    0            2
1        21062       1             1                    1            1

   Mental Fatigue Score  Burn Rate  Date of Joining_year  \
0                   3.8       0.16                  2008
1                   5.0       0.36                  2008

   Date of Joining_month  Date of Joining_day
0                      9                   30
1                     11                   30
```

13 Plotting Under Some different conditions

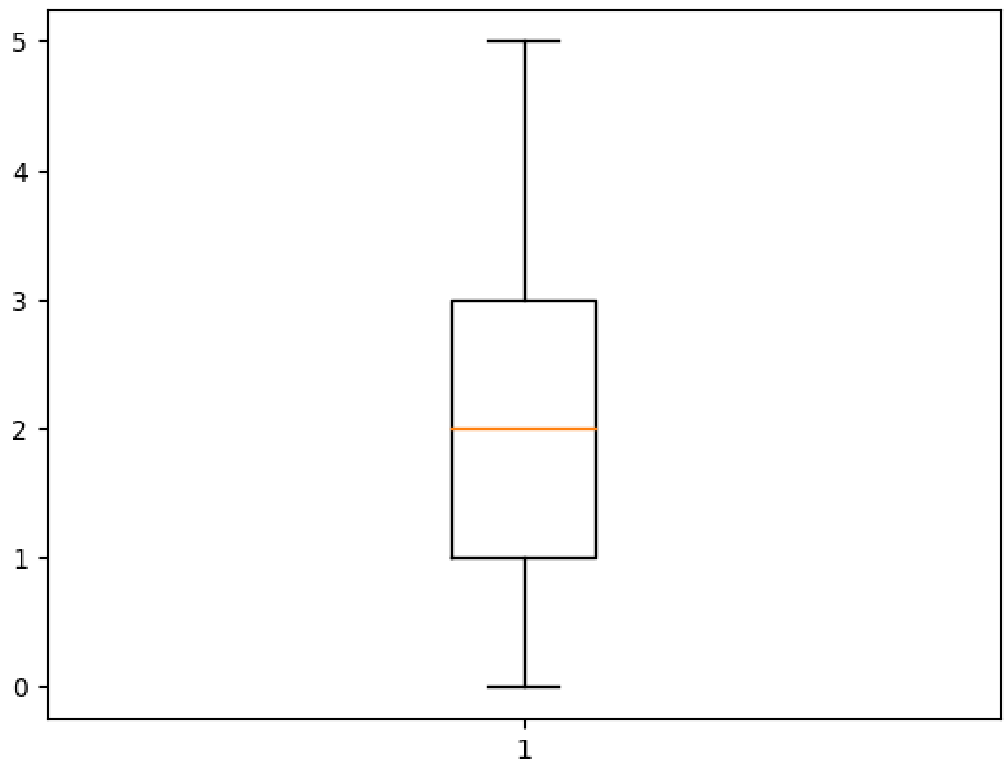
[ ]:
```
import matplotlib.pyplot as plt # visualization technic to undrestand data set
plt.boxplot(data['Gender']) #numerical values
plt.show()
```



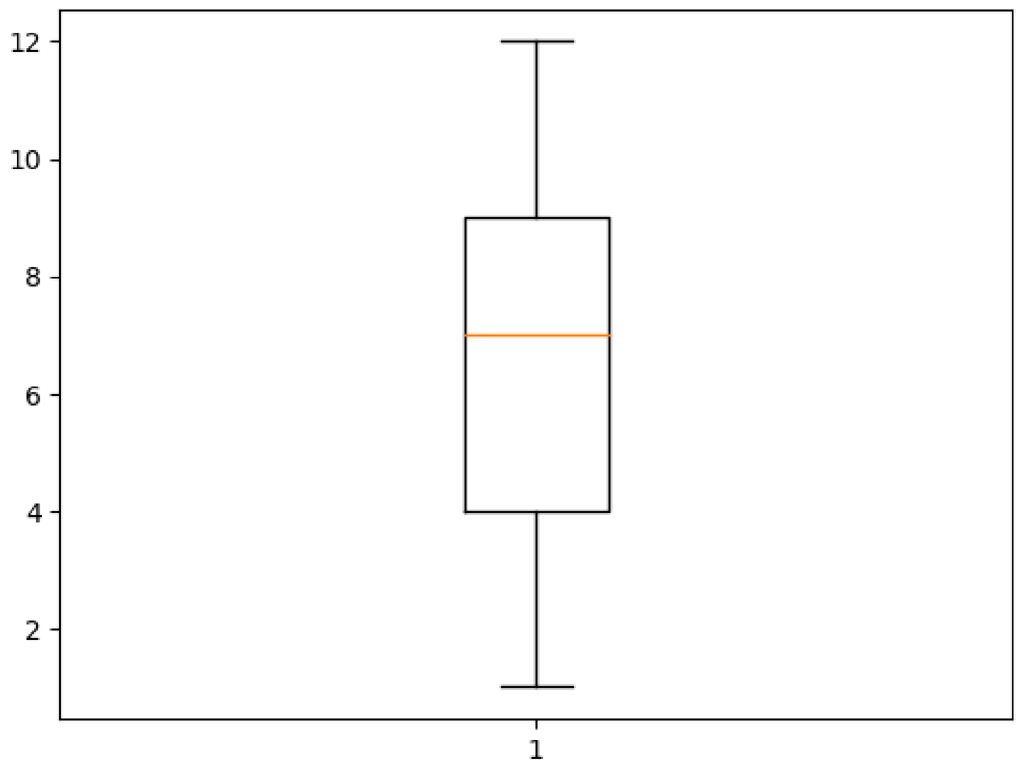
[ ]:
```
plt.boxplot(data['Company Type']) #numerical values
plt.show()
```



[ ]:
```
plt.boxplot(data['Designation']) #numerical values
plt.show()
```



[ ]:
```
plt.boxplot(data['Date of Joining_month']) #numerical values
plt.show()
```



[ ]:
```
# we have 8 columns input and output
#feed my machine -- input and output separatly
#soo now i have to do
#7 columns as input
#income column as out put
x=data.drop(columns=['Burn Rate']) # input
```

[ ]:
```
x
```

[ ]:

	Employee ID	Gender	Company Type	WFH Setup Available	Designation \
0	7722	0	1	0	2
1	21062	1	1	1	1
2	2381	0	0	1	2
3	10790	1	1	1	1
4	6810	0	1	0	3
…	…	…	…	…	…
22745	4208	0	1	0	1
22746	14934	0	0	1	3
22747	22181	1	1	1	3
22748	16875	0	1	0	2
22749	18847	1	0	0	3

```
       Mental Fatigue Score  Date of Joining_year  Date of Joining_month  \
0                       3.8                  2008                      9
1                       5.0                  2008                     11
2                       5.8                  2008                      3
3                       2.6                  2008                     11
4                       6.9                  2008                      7
…                      …                    …                      …
22745                   6.0                  2008                     12
22746                   6.7                  2008                      1
22747                   6.0                  2008                     11
22748                   5.9                  2008                      1
22749                   7.8                  2008                      1

       Date of Joining_day
0                       30
1                       30
2                       10
3                        3
4                       24
…                     …
22745                   30
22746                   19
22747                    5
22748                   10
22749                    6

[22750 rows x 9 columns]
```

[ ]:
```
y=data['Burn Rate'] #output
```

[ ]:
```
y
```

[ ]:
```
0        0.16
1        0.36
2        0.49
3        0.20
4        0.52
         …
22745    0.41
22746    0.59
22747    0.72
22748    0.52
22749    0.61
Name: Burn Rate, Length: 22750, dtype: float64
```

[ ]:
```
data
```

[ ]:

```
       Employee ID  Gender  Company Type  WFH Setup Available  Designation  \
0             7722       0             1                    0            2
1            21062       1             1                    1            1
2             2381       0             0                    1            2
3            10790       1             1                    1            1
4             6810       0             1                    0            3
…              …      …           …                    …        …
22745         4208       0             1                    0            1
22746        14934       0             0                    1            3
22747        22181       1             1                    1            3
22748        16875       0             1                    0            2
22749        18847       1             0                    0            3

       Mental Fatigue Score  Burn Rate  Date of Joining_year  \
0                       3.8       0.16                  2008
1                       5.0       0.36                  2008
2                       5.8       0.49                  2008
3                       2.6       0.20                  2008
4                       6.9       0.52                  2008
…                     …          …                    …
22745                   6.0       0.41                  2008
22746                   6.7       0.59                  2008
22747                   6.0       0.72                  2008
22748                   5.9       0.52                  2008
22749                   7.8       0.61                  2008

       Date of Joining_month  Date of Joining_day
0                          9                   30
1                         11                   30
2                          3                   10
3                         11                    3
4                          7                   24
…                       …                   …
22745                     12                   30
22746                      1                   19
22747                     11                    5
22748                      1                   10
22749                      1                    6

[22750 rows x 10 columns]
```

[ ]:

```
if y.dtype.kind in 'fc':
    y = pd.cut(y, bins=2, labels=[0, 1])
```

[ ]:

```
from sklearn.model_selection import train_test_split #training and testing 80-20
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.
↪2,random_state=23,stratify=y)
```

```
[ ]: xtrain
```

```
[ ]:        Employee ID  Gender  Company Type  WFH Setup Available  Designation  \
     18956         3391       1             1                    0            4
     2560          3729       0             0                    1            2
     9607          9199       0             1                    0            3
     15942         5155       1             1                    1            0
     15061         5118       1             1                    0            1
     …              …     …           …                   …          …
     12902        18740       1             0                    0            3
     11751         1918       0             1                    1            2
     18695        17171       0             0                    1            0
     22202         1537       0             1                    0            3
     19702        10714       1             1                    1            1

            Mental Fatigue Score  Date of Joining_year  Date of Joining_month  \
     18956                   9.2                  2008                     10
     2560                    4.4                  2008                      5
     9607                    5.4                  2008                      4
     15942                   3.3                  2008                      7
     15061                   6.1                  2008                      5
     …                     …                   …                     …
     12902                   5.4                  2008                      1
     11751                   5.1                  2008                     10
     18695                   3.7                  2008                      1
     22202                   5.1                  2008                      8
     19702                   6.2                  2008                     10

            Date of Joining_day
     18956                   12
     2560                     6
     9607                     7
     15942                   16
     15061                    8
     …                     …
     12902                    6
     11751                   31
     18695                   25
     22202                    7
     19702                   11

     [18200 rows x 9 columns]
```

```
[ ]: ytrain
```

```
[ ]: 18956    1
     2560     0
```

```
9607     0
15942    0
15061    1
        ..
12902    0
11751    0
18695    0
22202    0
19702    1
Name: Burn Rate, Length: 18200, dtype: category
Categories (2, int64): [0 < 1]
```

14 Data Prediction Methods

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
# Create an instance of KNeighborsClassifier
knn = KNeighborsClassifier()
# Fit the model using the training data
knn.fit(xtrain, ytrain)
#training dataset
```

[ ]:
```
KNeighborsClassifier()
```

[ ]:
```
predict1=knn.predict(xtest)  #testing input
predict1
```

[ ]:
```
array([1, 0, 0, …, 0, 1, 0])
```

[ ]:
```
from sklearn.metrics import accuracy_score
accuracy_score(ytest,predict1) #actual ouput vs predicted o/p
```

[ ]:
```
0.5835164835164836
```

[ ]:
```
from sklearn.neural_network import MLPClassifier #image dataset - cnn
clf=MLPClassifier(solver='adam',alpha=1e-5,hidden_layer_sizes=(5,2),random_state=1,max_iter=30
clf.fit(xtrain,ytrain)
```

[ ]:
```
MLPClassifier(alpha=1e-05, hidden_layer_sizes=(5, 2), max_iter=3000,
              random_state=1)
```

[ ]:
```
predict2=clf.predict(xtest)  #testing input
predict2
```

[ ]:
```
array([0, 0, 0, …, 0, 0, 0])
```

[ ]:
```
from sklearn.metrics import accuracy_score
accuracy_score(ytest,predict2) #actual ouput vs predicted o/p
```

[ ]: 0.621978021978022

[ ]:
```
#creating model set prdection process or binary cllassification process
# regression is to
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
lr.fit(xtrain,ytrain)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[ ]: LogisticRegression()

[ ]:
```
predict3=lr.predict(xtest)
predict3
```

[ ]: array([0, 0, 1, …, 0, 0, 0])

[ ]:
```
from sklearn.metrics import accuracy_score
accuracy_score(ytest,predict3) #actual ouput vs predicted o/p
```

[ ]: 0.8876923076923077

15 Conclusion

Burnout syndrome is a common and important problem among health professionals that also has adverse effects on people's daily life, especially increasing the incidence of infection and trauma. "When workers are suffering from burnout, their productivity drops, and they may become less innovative and more likely to make errors