Double-click (or enter) to edit

EMPLOYEE BURNOUT PREDICTION

IMPORTING NECESSARY 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
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import pickle as pickle
import os
```

LOADING DATASET

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

Show hidden output

DATA OVERVIEW

```
data.head()
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
0	fffe32003000360033003200	2008-09-30	Female	Service	No	2	3.0	3.8	0.16
1	fffe3700360033003500	2008-11-30	Male	Service	Yes	1	2.0	5.0	0.36
2	fffe31003300320037003900	2008-03-10	Female	Product	Yes	2	NaN	5.8	0.49
3	fffe32003400380032003900	2008-11-03	Male	Service	Yes	1	1.0	2.6	0.20

```
data.tail(3)
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
22747	fffe390032003000	2008-11-05	Male	Service	Yes	3	7.0	NaN	0.72
22748	fffe33003300320036003900	2008-01-10	Female	Service	No	2	5.0	5.9	0.52

```
data.describe()
```

	Date of Joining	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
count	22750	22750.000000	21369.000000	20633.000000	21626.000000
mean	2008-07-01 09:28:05.274725120	2.178725	4.481398	5.728188	0.452005
min	2008-01-01 00:00:00	0.000000	1.000000	0.000000	0.000000
25%	2008-04-01 00:00:00	1.000000	3.000000	4.600000	0.310000
50%	2008-07-02 00:00:00	2.000000	4.000000	5.900000	0.450000
75%	2008-09-30 00:00:00	3.000000	6.000000	7.100000	0.590000
max	2008-12-31 00:00:00	5.000000	10.000000	10.000000	1.000000
std	NaN	1.135145	2.047211	1.920839	0.198226

```
data.columns.tolist()
```

```
['Employee ID',
 'Date of Joining',
```

```
 'Gender',
 'Company Type',
 'WFH Setup Available',
 'Designation',
 'Resource Allocation',
 'Mental Fatigue Score',
 'Burn Rate']
```

```
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
```

```
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.isnull().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
```

```
data.isnull().sum().values.sum()
```

```
4622
```

EXPLORATORY DATA ANALYSIS

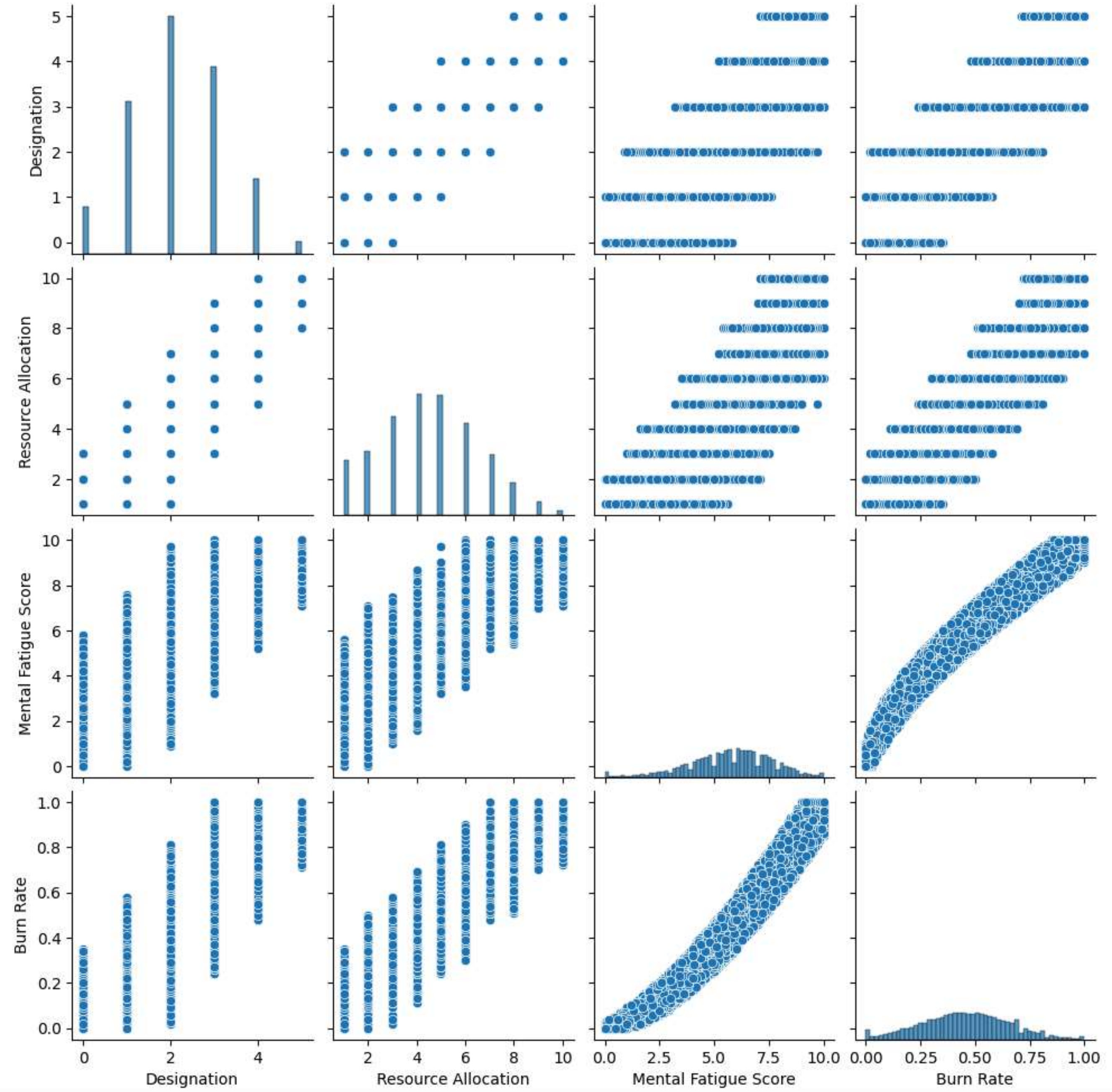
There are NaN values on our target ("Burn Rate") and also in Resource Allocation and Mental Fatigue Score columns. As we are going to perform Supervised Linear Regression, our target variable is needed to do so, Therefore this 1124 rows with NaN values must be dropped of our dataframe.

```
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
```

These two variables are strongly correlated with target variable, therefore, important to estimate it.

```
sns.pairplot(data)
plt.show()
```



Drop off all observations with NaN values of our dataframe.

```
data = data.dropna()
```

To check whether data is dropped off or Not

```
data.shape
```

```
(18590, 9)
```

Analyzing Data Type of each variable

```
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
```

The Employee ID doesn't provide any useful information and,therefore, they must be dropped.

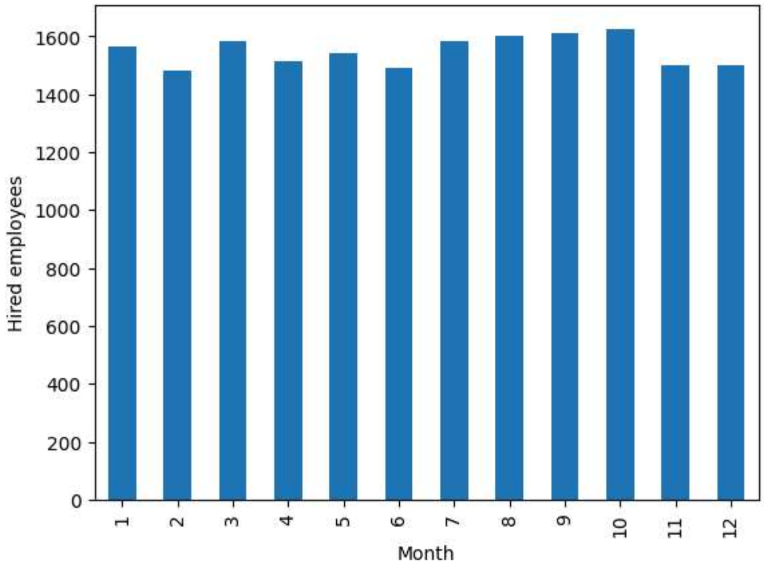
```
data = data.drop('Employee ID', axis = 1)
```

Checking the correlation of Date of Joining with Target Variable

```
print(f"Min date {data['Date of Joining'].min()}")
print(f"Max date {data['Date of Joining'].max()}")
data_month = data.copy()

data_month["Date of Joining"] = data_month['Date of Joining'].astype("datetime64[ns]")  #specify time unit as nanoseconds
data_month["Date of Joining"].groupby(data_month['Date of Joining'].dt.month).count().plot(kind="bar" , xlabel='Month' , ylabel='Hired e
```

```
Min date 2008-01-01 00:00:00
Max date 2008-12-31 00:00:00
<Axes: xlabel='Month', ylabel='Hired employees'>
```



The date of joining is uniformly distributed with values between 2008-01-01 and 2008-2-31. So in order to create a new feature which represents the labour sanity, we could create a variable with de days worked.

```
data_2008 = pd.to_datetime(["2008-01-01"]*len(data))
data["Days"] = data['Date of Joining'].astype("datetime64[ns]").sub(data_2008).dt.days
data.Days
```

```
0        273
1        334
3        307
4        205
5        330
        ...
22743    349
22744    147
22746     18
22748      9
22749      5
Name: Days, Length: 18590, dtype: int64
```

```
#select only numeric columns before calculating correlation.
numeric_data = data.select_dtypes(include=['number'])
correlation = numeric_data.corr()['Burn Rate']
print(correlation)
```

```
Designation             0.736412
Resource Allocation     0.855005
Mental Fatigue Score    0.944389
Burn Rate               1.000000
Days                    0.000309
Name: Burn Rate, dtype: float64
```

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

```
Designation             0.736412
Resource Allocation     0.855005
Mental Fatigue Score    0.944389
Burn Rate               1.000000
```

```
Days                    0.000309
Name: Burn Rate, dtype: float64
```

We observed that there is no strong correlation between Date of Joining and Burn Rate. So, we are dropping the column date Date of joining.

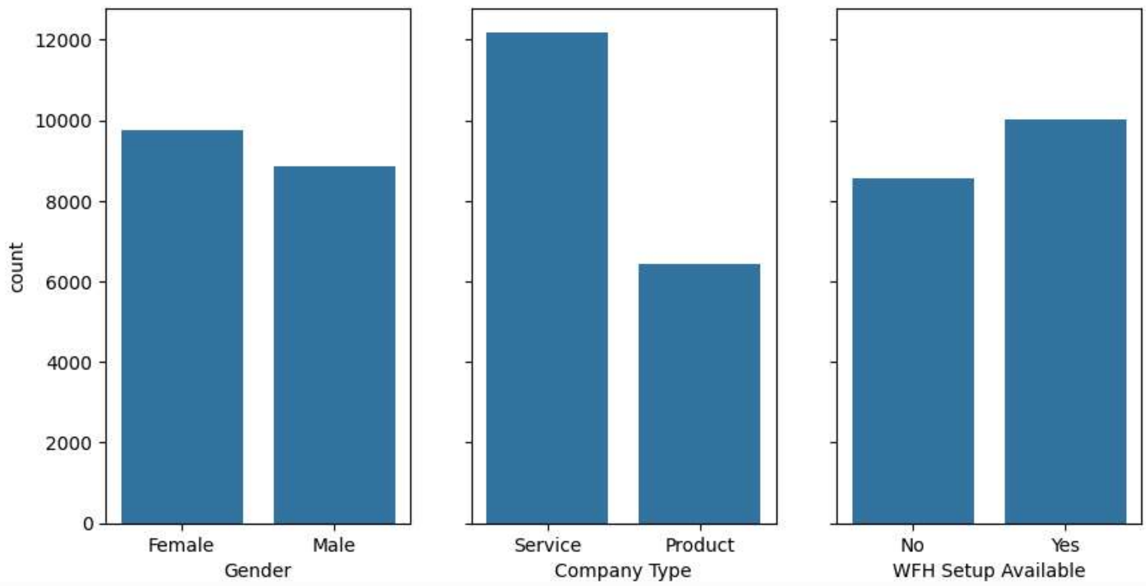
```
data = data.drop(['Date of Joining','Days'], axis = 1)
```

```
data.head()
```

	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
0	Female	Service	No	2	3.0	3.8	0.16
1	Male	Service	Yes	1	2.0	5.0	0.36
3	Male	Service	Yes	1	1.0	2.6	0.20
4	Female	Service	No	3	7.0	6.9	0.52
5	Male	Product	Yes	2	4.0	3.6	0.29

Now Analyzing the categorical variables

```
cat_columns = data.select_dtypes(object).columns
fig, ax = plt.subplots(nrows=1, ncols=len(cat_columns), sharey=True, figsize=(10, 5))
for i, c in enumerate(cat_columns):
    sns.countplot(x=c, data=data, ax=ax[i])
plt.show()
```



The number of observations of each category on each variable is equally distributed, except to the Company_Type where the number of service jobs its almost twice that of product ones.

One-Hot Encoding for categorical features

```
#check if columns exits before applying get_dummies
if all(col in data.columns for col in ['Company Type', 'WFH Setup Available', 'Gender']):
   data=pd.get_dummies(data, columns=['Company Type', 'WFH Setup Available', 'Gender'], drop_first=True)
   data.head()
   encoded_columns = data.columns
else:
    print("Error: One or more of the specified columns are not present in the DataFrame.")
    print(data.columns)
```

PRE PROCESSING

```
# Split df into X and y
y = data['Burn Rate']
X = data.drop('Burn Rate', axis=1)
```

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.7, shuffle=True, random_state=1)

# Scale X
scaler = StandardScaler()
scaler.fit(X_train)
X_train = pd.DataFrame(scaler.transform(X_train), index=X_train.index, columns=X_train.columns)
X_test = pd.DataFrame(scaler.transform(X_test), index=X_test.index, columns=X_test.columns)
```

```
X_train
```

	Designation	Resource Allocation	Mental Fatigue Score	Company Type_Service	WFH Setup Available_Yes	Gender_Male
8977	0.723327	0.250185	-0.061773	0.724706	-1.082297	1.051505
14115	-0.159330	0.250185	-0.941481	0.724706	-1.082297	-0.951018
8797	0.723327	0.250185	0.973179	0.724706	-1.082297	-0.951018
1173	-1.041987	-1.214568	-0.579248	-1.379869	-1.082297	-0.951018
1941	-0.159330	0.738436	1.180169	-1.379869	0.923961	1.051505
...	...	...	...	...	...	...
13453	0.723327	1.226687	1.645897	-1.379869	0.923961	-0.951018
21179	0.723327	0.250185	-1.044976	0.724706	0.923961	1.051505
6327	0.723327	0.250185	0.093470	0.724706	-1.082297	1.051505
14933	-0.159330	0.250185	0.714441	0.724706	-1.082297	1.051505
288	-0.159330	0.250185	1.076674	-1.379869	-1.082297	-0.951018

13013 rows × 6 columns

```
y_train
```

```
8977     0.41
14115    0.34
8797     0.61
1173     0.35
1941     0.61
         ...
13453    0.78
21179    0.30
6327     0.42
14933    0.54
288      0.57
Name: Burn Rate, Length: 13013, dtype: float64
```

MODEL BUILDING

LINEAR REGRESSION

```
linear_regression_model = LinearRegression()
linear_regression_model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
#Linear Regression Model Performance Metrics

print("Linear Regression Model Performance Metrics:\n")

#make predictions on the test set
y_pred = linear_regression_model.predict(X_test)

#Calculate mean squared error
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error", mse)

#Calculate root mean squared error
rmse = mean_squared_error(y_test, y_pred, squared=False)
print("Root Mean Squared Error", rmse)

#Calculate mean absolute error
mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error", mae)

#Calculate R-squared score
r2 = r2_score(y_test, y_pred)
print("R-squared score", r2)
```

```
Linear Regression Model Performance Metrics:

Mean Squared Error 0.0031569779113610717
Root Mean Squared Error 0.0561869905882231
Mean Absolute Error 0.04595032032644773
R-squared score 0.918822674247248
```

OUR FINAL OBSERVATION

> Based on the evaluation metrics, the linear regression model appears to be the best model for predicting burnout analysis.

> It has the lowest mean squared error, root mean squared error, and mean absolute error, indicating the better accuracy and precision in its predictions.