Importing Libraries

```
import warnings
warnings.filterwarnings('ignore')
```

```
import pandas as pd
import numpy as np

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

from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Loading Dataset

```
pd.set_option('display.max_columns', None)
burnoutDf=pd.read_csv('/content/drive/MyDrive/burnout. csv')
burnoutDf
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score
0	fffe32003000360033003200	2008-09-30	Female	Service	No	2.0	3.0	3.8
1	fffe3700360033003500	2008-11-30	Male	Service	Yes	1.0	2.0	5.0
2	fffe31003300320037003900	2008-03-10	Female	Product	Yes	2.0	NaN	5.8
3	fffe32003400380032003900	2008-11-03	Male	Service	Yes	1.0	1.0	2.6
4	fffe31003900340031003600	2008-07-24	Female	Service	No	3.0	7.0	6.9
...	...	...	...	...	...	...	...	...
22745	fffe31003500370039003100	2008-12-30	Female	Service	No	1.0	3.0	NaN
22746	fffe33003000350031003800	2008-	Female	Product	Yes	3.0	6.0	6.7

```
# convert into dateTime dataType
burnoutDf["Date of Joining"]= pd.to_datetime(burnoutDf["Date of Joining"])
```

```
# give the number of rows and columns
burnoutDf.shape
```

```
(22750, 9)
```

```
# general information
burnoutDf.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  float64
 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(4), object(4)
memory usage: 1.6+ MB
```

```
# show top 5 rows
burnoutDf.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	2.0	3.0	3.8	0.16
1	fffe3700360033003500	2008-11-30	Male	Service	Yes	1.0	2.0	5.0	0.36
2	fffe31003300320037003900	2008-	Female	Product	Yes	2.0	NaN	5.8	0.49

```
# extract all columns of the dataset
burnoutDf.columns
```

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

```
#check for null values
burnoutDf.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
```

```
# check the duplicate values
burnoutDf.duplicated().sum()
```

```
0
```

```
# calculate the mean , std, min, max and count of every attributes
burnoutDf.describe()
```

	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
count	22750.000000	21369.000000	20633.000000	21626.000000
mean	2.178725	4.481398	5.728188	0.452005
std	1.135145	2.047211	1.920839	0.198226
min	0.000000	1.000000	0.000000	0.000000
25%	1.000000	3.000000	4.600000	0.310000
50%	2.000000	4.000000	5.900000	0.450000
75%	3.000000	6.000000	7.100000	0.590000
max	5.000000	10.000000	10.000000	1.000000

```
# show the unique values
for i, col in enumerate(burnoutDf.columns):
  print(f"\n\n{burnoutDf[col].unique()}")
  print(f"\n{burnoutDf[col].value_counts()}\n\n")
```

```
['fffe32003000360033003200' 'fffe3700360033003500'
 'fffe31003300320037003900' ... 'fffe390032003000'
 'fffe33003300320036003900' 'fffe3400350031003800']

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

```
['2008-09-30T00:00:00.000000000' '2008-11-30T00:00:00.000000000'
 '2008-03-10T00:00:00.000000000' '2008-11-03T00:00:00.000000000'
 '2008-07-24T00:00:00.000000000' '2008-11-26T00:00:00.000000000'
 '2008-01-02T00:00:00.000000000' '2008-10-31T00:00:00.000000000'
 '2008-12-27T00:00:00.000000000' '2008-03-09T00:00:00.000000000'
 '2008-03-16T00:00:00.000000000' '2008-05-12T00:00:00.000000000'
 '2008-01-20T00:00:00.000000000' '2008-02-23T00:00:00.000000000'
 '2008-05-14T00:00:00.000000000' '2008-02-03T00:00:00.000000000'
 '2008-03-17T00:00:00.000000000' '2008-03-28T00:00:00.000000000'
 '2008-05-29T00:00:00.000000000' '2008-06-27T00:00:00.000000000'
 '2008-08-31T00:00:00.000000000' '2008-01-15T00:00:00.000000000'
 '2008-05-04T00:00:00.000000000' '2008-11-17T00:00:00.000000000'
 '2008-09-14T00:00:00.000000000' '2008-10-09T00:00:00.000000000'
 '2008-10-11T00:00:00.000000000' '2008-09-18T00:00:00.000000000'
 '2008-09-16T00:00:00.000000000' '2008-12-16T00:00:00.000000000'
 '2008-05-03T00:00:00.000000000' '2008-08-04T00:00:00.000000000'
 '2008-07-31T00:00:00.000000000' '2008-06-17T00:00:00.000000000'
 '2008-04-28T00:00:00.000000000' '2008-10-30T00:00:00.000000000'
 '2008-02-27T00:00:00.000000000' '2008-06-22T00:00:00.000000000'
 '2008-02-18T00:00:00.000000000' '2008-06-24T00:00:00.000000000'
 '2008-12-08T00:00:00.000000000' '2008-08-05T00:00:00.000000000'
 '2008-04-11T00:00:00.000000000' '2008-03-26T00:00:00.000000000'
 '2008-08-09T00:00:00.000000000' '2008-08-28T00:00:00.000000000'
 '2008-03-21T00:00:00.000000000' '2008-07-22T00:00:00.000000000'
 '2008-05-20T00:00:00.000000000' '2008-01-23T00:00:00.000000000'
 '2008-09-10T00:00:00.000000000' '2008-05-26T00:00:00.000000000'
 '2008-12-22T00:00:00.000000000' '2008-04-08T00:00:00.000000000'
 '2008-02-25T00:00:00.000000000' '2008-04-24T00:00:00.000000000'
 '2008-01-08T00:00:00.000000000' '2008-11-20T00:00:00.000000000'
 '2008-09-11T00:00:00.000000000' '2008-06-11T00:00:00.000000000'
 '2008-02-28T00:00:00.000000000' '2008-08-20T00:00:00.000000000'
 '2008-10-18T00:00:00.000000000' '2008-08-14T00:00:00.000000000'
 '2008-07-17T00:00:00.000000000' '2008-07-05T00:00:00.000000000'
 '2008-02-04T00:00:00.000000000' '2008-08-01T00:00:00.000000000'
 '2008-05-01T00:00:00.000000000' '2008-05-21T00:00:00.000000000'
 '2008-10-21T00:00:00.000000000' '2008-03-19T00:00:00.000000000'
```

```
# Drop irrelevant column
burnoutDf=burnoutDf.drop(['Employee ID'],axis=1)
```

```
# check the skewness of the attributes
intFloatburnoutDf=burnoutDf.select_dtypes([np.int, np.float])
for i, col in enumerate(intFloatburnoutDf.columns):
  if (intFloatburnoutDf[col].skew() >= 0.1):
    print("\n",col, "feature is Positively Skewed and value is: ", intFloatburnoutDf[col].skew())
  elif (intFloatburnoutDf[col].skew() <= -0.1):
      print("\n",col, "feature is Negatively Skewed and value is: ", intFloatburnoutDf[col].skew())
  else:
        print("\n",col, "feature is Normally Distributed and value is: ", intFloatburnoutDf[col].skew())
```

```
 Designation feature is Normally Distributed and value is:  0.09242138478903683

 Resource Allocation feature is Positively Skewed and value is:  0.20457273454318103

 Mental Fatigue Score feature is Negatively Skewed and value is:  -0.4308950578815428

 Burn Rate feature is Normally Distributed and value is:  0.045737370909640515
```

```
# Replace the null values with mean
burnoutDf['Resource Allocation'].fillna(burnoutDf['Resource Allocation'].mean(),inplace=True)
burnoutDf['Mental Fatigue Score'].fillna(burnoutDf['Mental Fatigue Score'].mean(),inplace=True)
burnoutDf['Burn Rate'].fillna(burnoutDf['Burn Rate'].mean(),inplace=True)
```

```
# check for null values
burnoutDf.isna().sum()
```

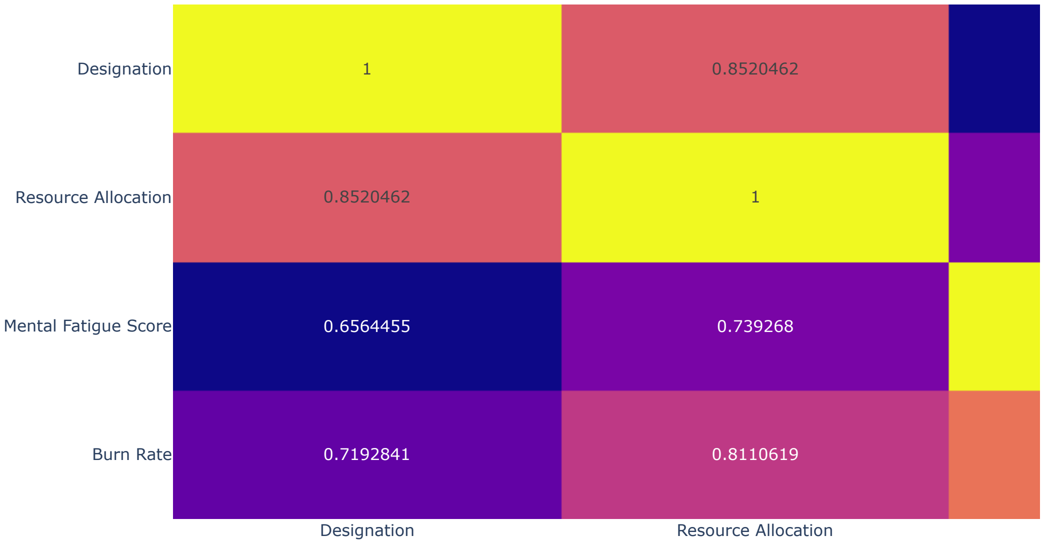
```
Date of Joining         0
Gender                  0
Company Type            0
WFH Setup Available     0
Designation             0
Resource Allocation     0
Mental Fatigue Score    0
Burn Rate               0
dtype: int64
```

```
# show the correlation
burnoutDf.corr()
```

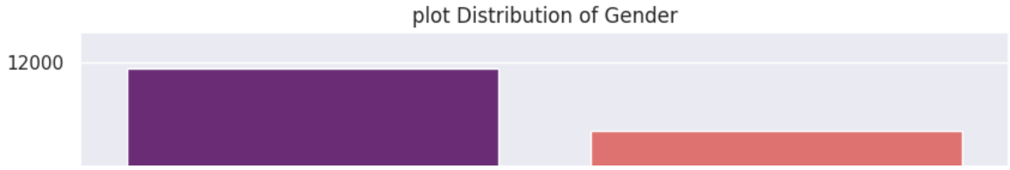
	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate
Designation	1.000000	0.852046	0.656445	0.719284
Resource Allocation	0.852046	1.000000	0.739268	0.811062
Mental Fatigue Score	0.656445	0.739268	1.000000	0.878217

Data Visualization

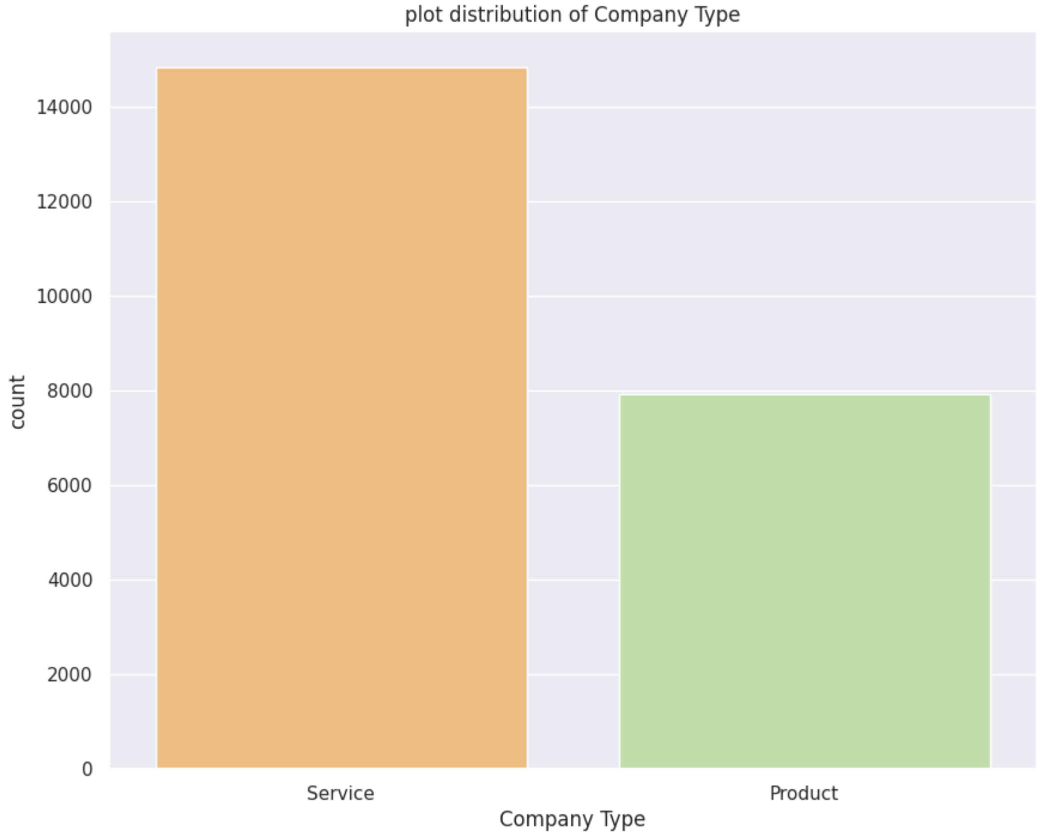
```
# Plotting Heat map to check correlation
corr=burnoutDf.corr()
sns.set(rc={'figure.figsize':(14,12)})
fig = px.imshow(corr, text_auto=True, aspect="auto")
fig.show()
```



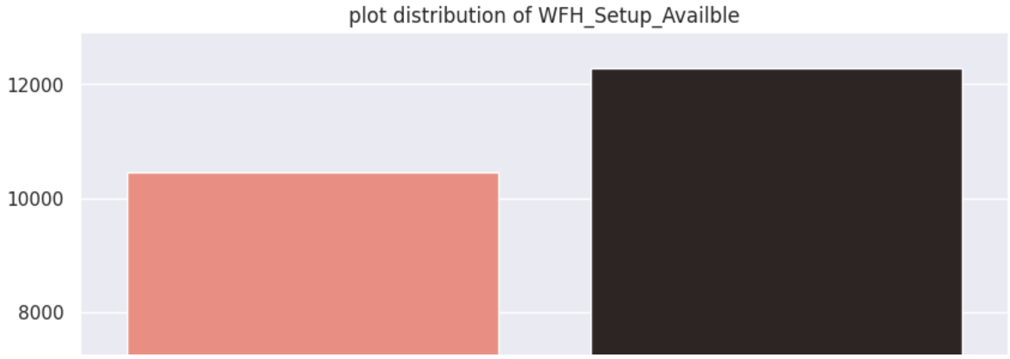

```
# Count plot Distribution of "Gender"
plt.figure(figsize=(10,8))
sns.countplot(x="Gender", data=burnoutDf, palette="magma")
plt.title("plot Distribution of Gender")
plt.show()
```




```
# Count plot distribution of "Company Type"
plt.figure(figsize=(10,8))
sns.countplot(x="Company Type", data=burnoutDf, palette="Spectral")
plt.title("plot distribution of Company Type")
plt.show()
```

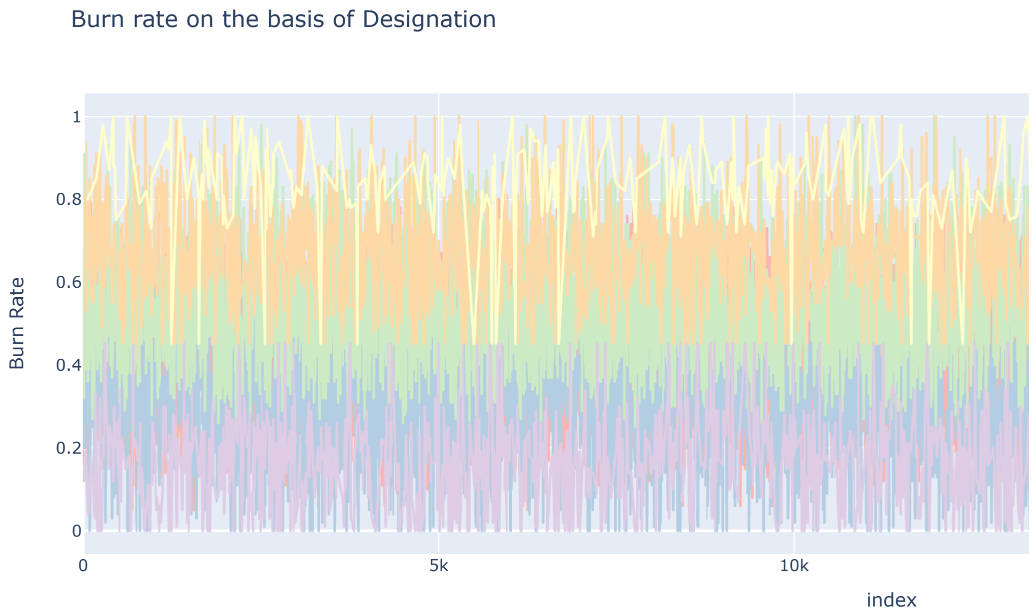



```
# Count plot distribution of "WFH Setup Available"
plt.figure(figsize=(10,8))
sns.countplot(x="WFH Setup Available", data=burnoutDf, palette="dark:salmon_r")
plt.title("plot distribution of WFH_Setup_Availble")
plt.show()
```

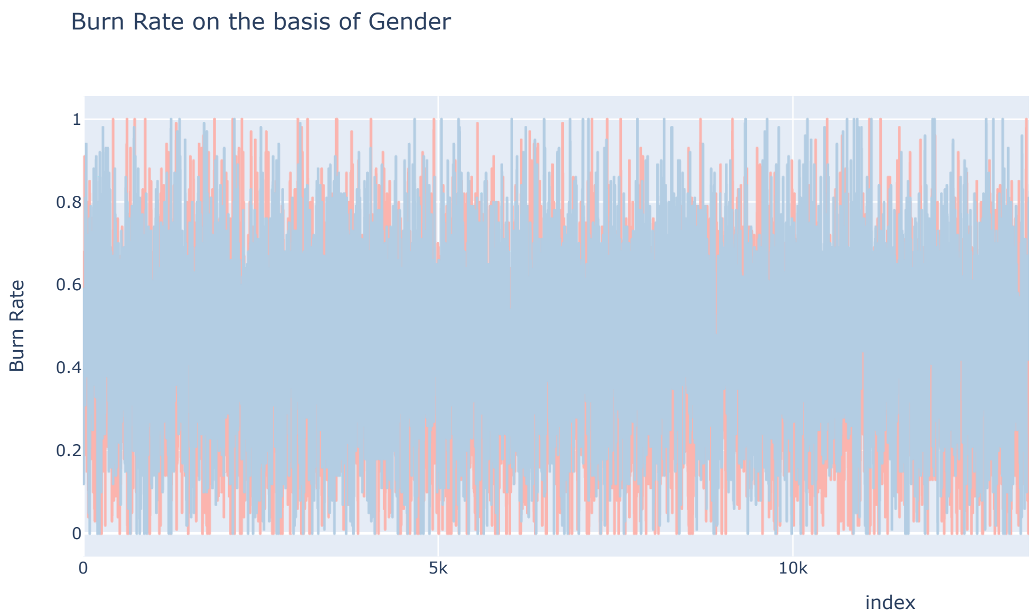



```
# Count-plot diaatribution of attributes with the help of Histogram
burn_st=burnoutDf.loc[:,'Date of Joining':'Burn Rate']
burn_st=burn_st.select_dtypes([int, float])
for i, col in enumerate(burn_st.columns):
    fig = px.histogram(burn_st, x=col, title="Plot Distribution of "+col, color_discrete_sequence=['indianred'])
    fig.update_layout(bargap=0.2)
    fig.show()
```

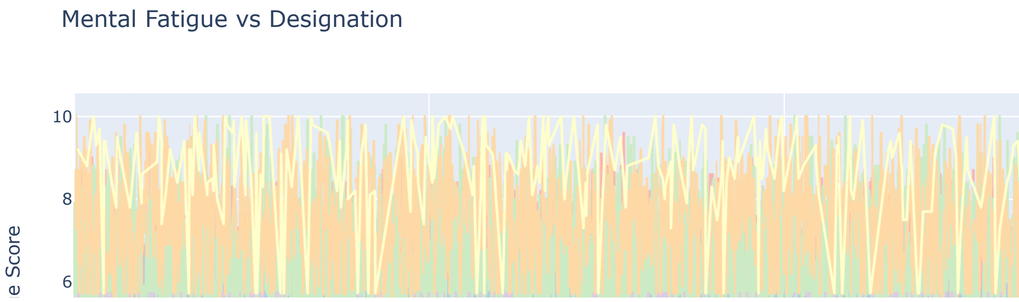
```
# Plot distribution of Burn rate on the basis of Designation
fig = px.line(burnoutDf, y="Burn Rate", color="Designation", title="Burn rate on the basis of Designation",color_discrete_sequence=px.col
fig.update_layout(bargap=0.1)
fig.show()
```




```
# Plot distribution of Burn Rate on the basis of Gender
fig = px.line(burnoutDf, y="Burn Rate", color="Gender", title="Burn Rate on the basis of Gender",color_discrete_sequence=px.colors.qualit
fig.update_layout(bargap=0.2)
fig.show()
```




```
# Plot distribution of mental fatigue score on the basis of Designation
fig = px.line(burnoutDf, y="Mental Fatigue Score", color="Designation", title="Mental Fatigue vs Designation",color_discrete_sequence=px.
fig.update_layout(bargap=0.2)
fig.show()
```




```
# plot distribution of "Designation vs mental fatigue"as per Company type , Burn rate and Gender
sns.relplot(
    data=burnoutDf, x="Designation", y="Mental Fatigue Score", col="Company Type",
    hue="Company Type", size="Burn Rate", style="Gender",
    palette=["g", "r"], sizes=(50, 200)
)
```

```
<seaborn.axisgrid.FacetGrid at 0x7ffaf00a8430>
```

Label Encoding

```
# label encoding and assign in new variable
from sklearn import preprocessing
Lable_encode = preprocessing.LabelEncoder()
```

```
# assign in new variable
burnoutDf['GenderLable'] = Lable_encode.fit_transform(burnoutDf['Gender'].values)
burnoutDf['Company_TypeLable'] = Lable_encode.fit_transform(burnoutDf['Company Type'].values)
burnoutDf['WFH_Setup_AvailableLable'] = Lable_encode.fit_transform(burnoutDf['WFH Setup Available'].values)
```

```
# check assigned values
gn = burnoutDf.groupby('Gender')
gn = gn['GenderLable']
gn.first()
```

```
Gender
Female    0
Male      1
Name: GenderLable, dtype: int64
```

```
# check assigned values
ct = burnoutDf.groupby('Company Type')
ct = ct['Compant_TypeLabel']
ct.first()
```

```
Company Type
Product    0
Service    1
Name: Compant_TypeLabel, dtype: int64
```

```
# check assigned values
wsa = burnoutDf.groupby('WFH Setup Available')
wsa = wsa['WFH_Setup_AvailableLable']
wsa.first()
```

```
WFH Setup Available
No     0
Yes    1
Name: WFH_Setup_AvailableLable, dtype: int64
```

```
# show last 10 rows
burnoutDf.tail(10)
```

	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Burn Rate	GenderLable	Co
22740	2008-09-05	Female	Product	No	3.0	6.0	7.300000	0.550000	0	
22741	2008-01-07	Male	Product	No	2.0	5.0	6.000000	0.452005	1	
22742	2008-07-28	Male	Product	No	3.0	5.0	8.100000	0.690000	1	
22743	2008-12-15	Female	Product	Yes	1.0	3.0	6.000000	0.480000	0	
22744	2008-05-27	Male	Product	No	3.0	7.0	6.200000	0.540000	1	
22745	2008-12-30	Female	Service	No	1.0	3.0	5.728188	0.410000	0	
22746	2008-01-19	Female	Product	Yes	3.0	6.0	6.700000	0.590000	0	
22747	2008-11-05	Male	Service	Yes	3.0	7.0	5.728188	0.720000	1	

Feature Selection

2008-

```
# feature selection
columns=['Designation', 'Resource Allocation', 'Mental Fatigue Score',
       'GenderLable', 'Company_TypeLable', 'WFH_Setup_Available']
x=burnoutDf[columns]
y=burnoutDf['Burn Rate']
```

```
print(x)
```

```
       Designation  Resource Allocation  Mental Fatigue Score  GenderLable  \
0              2.0             3.000000              3.800000            0
1              1.0             2.000000              5.000000            1
2              2.0             4.481398              5.800000            0
3              1.0             1.000000              2.600000            1
4              3.0             7.000000              6.900000            0
...            ...                  ...                   ...          ...
22745          1.0             3.000000              5.728188            0
22746          3.0             6.000000              6.700000            0
22747          3.0             7.000000              5.728188            1
22748          2.0             5.000000              5.900000            0
22749          3.0             6.000000              7.800000            1

       Company_TypeLable
0                      1
1                      1
2                      0
3                      1
4                      1
...                  ...
22745                  1
22746                  0
22747                  1
22748                  1
22749                  0

[22750 rows x 5 columns]
```

```
print(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
```

Implementing PCA

```
# principle component analysis
from sklearn.decomposition import PCA
pca = PCA(0.95)
x_pca = pca.fit_transform(x)
print("PCA shaoe of x is: ",x_pca.shape, "and original shape is: ", x.shape)
print("% of importance of selected features is:", pca.explained_variance_ratio_)
print("The number of features selected through PCA is:", pca.n_components_)
```

```
PCA shaoe of x is:  (22750, 4) and original shape is:  (22750, 5)
% of importance of selected features is: [0.80288084 0.11418113 0.03102338 0.0268774 ]
The number of features selected through PCA is: 4
```

Data Splitting

```
# Data Splitting in train and test
from sklearn.model_selection import train_test_split
x_train_pca, x_test, v_train, v_test = train_test_split(x_pca,y, test_size = 0.25, random_state=10)
```

```
# print the shape of splitted data
print(x_train_pca.shape, x_test.shape, v_train.shape, v_test.shape)
```

```
(17062, 4) (5688, 4) (17062,) (5688,)
```

MODEL IMPLEMENTATION

Random Forest Regressor

```
from sklearn.metrics import r2_score
```

```
# Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor()
rf_model.fit(x_train_pca, v_train)

train_pred_rf = rf_model.predict(x_train_pca)
train_r2 = r2_score(v_train, train_pred_rf)
test_pred_rf = rf_model.predict(x_test)
test_r2 = r2_score(v_test, test_pred_rf)
# Accuracy score
print("Accuracy score of train data: "+str(round(100*train_r2, 4))+" %")
print("Accuracy score of the test data: "+str(round(100*test_r2, 4))+" %")
```

```
Accuracy score of train data: 89.7017 %
Accuracy score of the test data: 84.4071 %
```

AdaBoost Regressor

```
# AdaBoost regressor
from sklearn.ensemble import AdaBoostRegressor
abr_model = AdaBoostRegressor()
abr_model.fit(x_train_pca, v_train)

train_pred_adboost = abr_model.predict(x_train_pca)
train_r2 = r2_score(v_train, train_pred_adboost)
test_pred_adaboost = abr_model.predict(x_test)
test_r2 = r2_score(v_test, test_pred_adaboost)

# Accuracy score
print("Accuracy score of train data: "+str(round(100*train_r2, 4))+" %")
print("Accuracy score of the test data: "+str(round(100*test_r2, 4))+" %")
```

```
Accuracy score of train data: 77.6054 %
Accuracy score of the test data: 77.2549 %
```

BURNOUT PREDICTION

```
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression, Ridge, Lasso

import warnings
warnings.filterwarnings(action='ignore')
```

```
burnoutDf=pd.read_csv('/content/drive/MyDrive/burnout. csv')
```

```
burnoutDf
```

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score
0	fffe32003000360033003200	2008-09-30	Female	Service	No	2.0	3.0	3.8
1	fffe3700360033003500	2008-11-30	Male	Service	Yes	1.0	2.0	5.0
2	fffe31003300320037003900	2008-03-10	Female	Product	Yes	2.0	NaN	5.8
3	fffe32003400380032003900	2008-11-03	Male	Service	Yes	1.0	1.0	2.6
4	fffe31003900340031003600	2008-07-24	Female	Service	No	3.0	7.0	6.9
...	...	...	...	...	...	...	...	...
22745	fffe31003500370039003100	2008-12-30	Female	Service	No	1.0	3.0	NaN
22746	fffe33003000350031003800	2008-	Female	Product	Yes	3.0	6.0	6.7

```
burnoutDf.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  object
 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  float64
 6   Resource Allocation   21369 non-null  float64
 7   Mental Fatigue Score  20633 non-null  float64
 8   Burn Rate             21626 non-null  float64
dtypes: float64(4), object(5)
memory usage: 1.6+ MB
```

```
def preprocess_inputs(df):
    df = df.copy()

    # Drop Employee ID column
    df = df.drop('Employee ID', axis=1)

    # Drop rows with missing target values
    missing_target_rows = df.loc[df['Burn Rate'].isna(), :].index
    df = df.drop(missing_target_rows, axis=0).reset_index(drop=True)

    # Fill remaining missing values with column means
    for column in ['Resource Allocation', 'Mental Fatigue Score']:
        df[column] = df[column].fillna(df[column].mean())

    # Extract date features
    df['Date of Joining'] = pd.to_datetime(df['Date of Joining'])
    df['Join Month'] = df['Date of Joining'].apply(lambda x: x.month)
    df['Join Day'] = df['Date of Joining'].apply(lambda x: x.day)
```

```
    df = df.drop('Date of Joining', axis=1)

    # Binary encoding
    df['Gender'] = df['Gender'].replace({'Female': 0, 'Male': 1})
    df['Company Type'] = df['Company Type'].replace({'Product': 0, 'Service': 1})
    df['WFH Setup Available'] = df['WFH Setup Available'].replace({'No': 0, 'Yes': 1})

    # Split df into X and y
    y = df['Burn Rate']
    X = df.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)

    return X_train, X_test, y_train, y_test
```

```
X_train, X_test, y_train, y_test = preprocess_inputs(burnoutDf)
```

```
X_train
```

	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Join Month	Join Day
8275	-0.954022	-1.379211	-1.087295	0.725025	0.768001	0.475128	0.433442	-0.649693
21284	1.048194	0.725052	-1.087295	1.604608	1.270205	1.131455	1.596251	-0.536187
16802	1.048194	0.725052	-1.087295	-0.154557	0.768001	0.420434	1.305549	0.371860
3271	1.048194	-1.379211	-1.087295	1.604608	2.274612	1.733089	0.142739	1.620424
5302	-0.954022	-1.379211	-1.087295	-0.154557	-0.236406	0.475128	0.724144	-0.422682
...	...	...	...	...	...	...	...	...
10955	-0.954022	0.725052	-1.087295	-0.154557	0.768001	0.803292	-1.020070	-1.444234
17289	-0.954022	0.725052	0.919713	0.725025	-0.236406	-0.509363	-0.147963	0.712377
5192	-0.954022	0.725052	0.919713	0.725025	0.265797	-1.165690	1.014847	0.031342
12172	1.048194	-1.379211	0.919713	-1.913723	-1.743017	-1.220384	0.433442	-1.671246
235	-0.954022	0.725052	-1.087295	-1.913723	-1.743017	-2.861202	-0.729368	0.031342

```
y_train
```

```
8275     0.61
21284    0.81
16802    0.62
3271     0.73
5302     0.43
         ...
10955    0.58
17289    0.39
5192     0.24
12172    0.18
235      0.00
Name: Burn Rate, Length: 15138, dtype: float64
```

```
models = {
    "                     Linear Regression": LinearRegression(),
    " Linear Regression (L2 Regularization)": Ridge(),
    " Linear Regression (L1 Regularization)": Lasso(),
    "                         Decision Tree": DecisionTreeRegressor()
}

for name, model in models.items():
    model.fit(X_train, y_train)
    print(name + " trained.")
```

```
                     Linear Regression trained.
 Linear Regression (L2 Regularization) trained.
 Linear Regression (L1 Regularization) trained.
                         Decision Tree trained.
```

```
for name, model in models.items():
    print(name + " R^2 Score: {:.5f}".format(model.score(X_test, y_test)))
```

```
                         Linear Regression R^2 Score: 0.87075
      Linear Regression (L2 Regularization) R^2 Score: 0.87075
      Linear Regression (L1 Regularization) R^2 Score: -0.00001
                             Decision Tree R^2 Score: 0.81926
```