In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
train = pd.read_csv("Dataset/Train.csv")
test = pd.read_csv("Dataset/Test.csv")
```

In [3]:
```
print("Size of Train Data: ", len(train))
print("Size of Test Data: ", len(test))
```

```
Size of Train Data:  7000
Size of Test Data:  3000
```

In [4]:
```
print("List of Columns:", end = '\t')
print(list(train.columns))
print()
print("How many colums: ", len(list(train.columns)))
```

```
List of Columns:	['Employee_ID', 'Gender', 'Age', 'Education_Level', 'Re
lationship_Status', 'Hometown', 'Unit', 'Decision_skill_possess', 'Time_of_serv
ice', 'Time_since_promotion', 'growth_rate', 'Travel_Rate', 'Post_Level', 'Pay_
Scale', 'Compensation_and_Benefits', 'Work_Life_balance', 'VAR1', 'VAR2', 'VAR
3', 'VAR4', 'VAR5', 'VAR6', 'VAR7', 'Attrition_rate']

How many colums:  24
```

In [5]:
```
train.head()
```

Out[5]:

	Employee_ID	Gender	Age	Education_Level	Relationship_Status	Hometown	Unit	Dec
0	EID_23371	F	42.0	4	Married	Franklin	IT	
1	EID_18000	M	24.0	3	Single	Springfield	Logistics	
2	EID_3891	F	58.0	3	Married	Clinton	Quality	
3	EID_17492	F	26.0	3	Single	Lebanon	Human Resource Management	
4	EID_22534	F	31.0	1	Married	Springfield	Logistics	

5 rows × 24 columns

In [6]:
```
test.head()
```

Out[6]:

	Employee_ID	Gender	Age	Education_Level	Relationship_Status	Hometown	Unit	Decisic
0	EID_22713	F	32.0	5	Single	Springfield	R&D	
1	EID_9658	M	65.0	2	Single	Lebanon	IT	
2	EID_22203	M	52.0	3	Married	Springfield	Sales	
3	EID_7652	M	50.0	5	Single	Washington	Marketing	
4	EID_6516	F	44.0	3	Married	Franklin	R&D	

5 rows × 23 columns

Pre-processing Steps

- check for Nan Value and replace

In [7]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7000 entries, 0 to 6999
Data columns (total 24 columns):
Employee_ID                  7000 non-null object
Gender                       7000 non-null object
Age                          6588 non-null float64
Education_Level              7000 non-null int64
Relationship_Status          7000 non-null object
Hometown                     7000 non-null object
Unit                         7000 non-null object
Decision_skill_possess       7000 non-null object
Time_of_service              6856 non-null float64
Time_since_promotion         7000 non-null int64
growth_rate                  7000 non-null int64
Travel_Rate                  7000 non-null int64
Post_Level                   7000 non-null int64
Pay_Scale                    6991 non-null float64
Compensation_and_Benefits    7000 non-null object
Work_Life_balance            6989 non-null float64
VAR1                         7000 non-null int64
VAR2                         6423 non-null float64
VAR3                         7000 non-null float64
VAR4                         6344 non-null float64
VAR5                         7000 non-null int64
VAR6                         7000 non-null int64
VAR7                         7000 non-null int64
Attrition_rate               7000 non-null float64
dtypes: float64(8), int64(9), object(7)
memory usage: 1.3+ MB
```

In [8]:
```
train.isna().sum()
```

Out[8]:
```
Employee_ID                  0
Gender                       0
Age                        412
Education_Level              0
Relationship_Status          0
Hometown                     0
Unit                         0
Decision_skill_possess       0
Time_of_service            144
Time_since_promotion         0
growth_rate                  0
Travel_Rate                  0
Post_Level                   0
Pay_Scale                    9
Compensation_and_Benefits    0
Work_Life_balance           11
VAR1                         0
VAR2                       577
VAR3                         0
VAR4                       656
VAR5                         0
VAR6                         0
VAR7                         0
Attrition_rate               0
dtype: int64
```

In [9]:
```
train = train.drop('VAR2',axis=1)
test = test.drop('VAR2',axis=1)
train = train.drop('VAR4', axis=1)
test = test.drop('VAR4', axis=1)
```

We have missing values in Age, Time_of_service and Work_Life_balance and all are of type float64

In [10]:
```
import math
work_life_fill = float(math.floor(train['Work_Life_balance'].mean()))
age_fill = float(math.ceil(train['Age'].mean()))
service_fill = float(math.floor(train['Time_of_service'].mean()))
```

In [11]:
```
print(work_life_fill,age_fill,service_fill)
```

```
2.0 40.0 13.0
```

In [12]:
```
train['Work_Life_balance'] = train['Work_Life_balance'].fillna(work_life_fill)
train['Age'] = train['Age'].fillna(age_fill)
train['Time_of_service'] = train['Time_of_service'].fillna(service_fill)
```

In [13]:
```
train.isna().sum() == 0
```

Out[13]:
```
Employee_ID                  True
Gender                       True
Age                          True
Education_Level              True
Relationship_Status          True
Hometown                     True
Unit                         True
Decision_skill_possess       True
Time_of_service              True
Time_since_promotion         True
growth_rate                  True
Travel_Rate                  True
Post_Level                   True
Pay_Scale                   False
Compensation_and_Benefits    True
Work_Life_balance            True
VAR1                         True
VAR3                         True
VAR5                         True
VAR6                         True
VAR7                         True
Attrition_rate               True
dtype: bool
```

In [14]:
```
test['Work_Life_balance'] = test['Work_Life_balance'].fillna(work_life_fill)
test['Age'] = test['Age'].fillna(age_fill)
test['Time_of_service'] = test['Time_of_service'].fillna(service_fill)
```

In [15]:
```
test.isna().sum()
```

Out[15]:
```
Employee_ID                 0
Gender                      0
Age                         0
Education_Level             0
Relationship_Status         0
Hometown                    0
Unit                        0
Decision_skill_possess      0
Time_of_service             0
Time_since_promotion        0
growth_rate                 0
Travel_Rate                 0
Post_Level                  0
Pay_Scale                   3
Compensation_and_Benefits   0
Work_Life_balance           0
VAR1                        0
VAR3                        0
VAR5                        0
VAR6                        0
VAR7                        0
dtype: int64
```

In [16]:
```
pay_fill = float(math.floor(train['Pay_Scale'].mean()))
test['Pay_Scale'] = test['Pay_Scale'].fillna(pay_fill)
train['Pay_Scale'] = train['Pay_Scale'].fillna(pay_fill)
```

In [17]:
```
train_ID = train['Employee_ID']
train = train.drop('Employee_ID',axis=1)
test_ID = test['Employee_ID']
test = test.drop('Employee_ID',axis=1)
```

Now there are no missing values, Next step is to deal with categorical data

In [18]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7000 entries, 0 to 6999
Data columns (total 21 columns):
Gender                        7000 non-null object
Age                           7000 non-null float64
Education_Level               7000 non-null int64
Relationship_Status           7000 non-null object
Hometown                      7000 non-null object
Unit                          7000 non-null object
Decision_skill_possess        7000 non-null object
Time_of_service               7000 non-null float64
Time_since_promotion          7000 non-null int64
growth_rate                   7000 non-null int64
Travel_Rate                   7000 non-null int64
Post_Level                    7000 non-null int64
Pay_Scale                     7000 non-null float64
Compensation_and_Benefits     7000 non-null object
Work_Life_balance             7000 non-null float64
VAR1                          7000 non-null int64
VAR3                          7000 non-null float64
VAR5                          7000 non-null int64
VAR6                          7000 non-null int64
VAR7                          7000 non-null int64
Attrition_rate                7000 non-null float64
dtypes: float64(6), int64(9), object(6)
memory usage: 1.1+ MB
```

Categorical object with object type are : Gender, Relationship_Status, Hometown, Unit, Decision_skill_possess, Compensation_and_Benefits.

In [19]:
```
train['Gender'].value_counts()
```

Out[19]:
```
F    4114
M    2886
Name: Gender, dtype: int64
```

In [20]:
```
train['Gender'] = train['Gender'].map({'M':-1, 'F': 1})
test['Gender'] = test['Gender'].map({'M':-1, 'F': 1})
```

In [21]:
```
train['Relationship_Status'].value_counts()
```

Out[21]:
```
Married    4520
Single     2480
Name: Relationship_Status, dtype: int64
```

In [22]:
```
train['Relationship_Status'] = train['Relationship_Status'].map({'Married':1, 'S
test['Relationship_Status'] = test['Relationship_Status'].map({'Married':-1, 'Si
```

In [23]:
```
train['Hometown'].value_counts()
```

Out[23]:
```
Lebanon        2070
Springfield    1736
Franklin       1523
Washington     1106
Clinton         565
Name: Hometown, dtype: int64
```

In [24]:
```
train['Hometown'] = train['Hometown'].map({'Lebanon':4, 'Springfield': 3, 'Frankl
test['Hometown'] = test['Hometown'].map({'Lebanon':4, 'Springfield': 3, 'Frankli
```

In [25]:
```
train['Unit'].value_counts()
```

Out[25]:
```
IT                           1394
Logistics                    1173
Sales                         943
Operarions                    706
R&D                           680
Purchasing                    504
Accounting and Finance        496
Human Resource Management     344
Marketing                     212
Production                    211
Quality                       193
Security                      144
Name: Unit, dtype: int64
```

In [26]:
```
train['Unit'] = train['Unit'].map({'IT':11,'Logistics':10,'Sales':9,'Operarions'
test['Unit'] = test['Unit'].map({'IT':11,'Logistics':10,'Sales':9,'Operarions':8
```

In [27]:
```
train['Decision_skill_possess'].value_counts()
```

Out[27]:
```
Conceptual    1756
Analytical    1755
Directive     1753
Behavioral    1736
Name: Decision_skill_possess, dtype: int64
```

We will get_dummies for Decision_skill_possess

In [28]:
```
train['Compensation_and_Benefits'].value_counts()
```

Out[28]:
```
type2    3945
type3    2382
type4     353
type0     187
type1     133
Name: Compensation_and_Benefits, dtype: int64
```

In [29]:
```
train['Compensation_and_Benefits'] = train['Compensation_and_Benefits'].map({'ty
test['Compensation_and_Benefits'] = test['Compensation_and_Benefits'].map({'type
```

In [30]:
```
train.head()
```

Out[30]:

	Gender	Age	Education_Level	Relationship_Status	Hometown	Unit	Decision_skill_possess	Ti
0	1	42.0	4	1	2	11	Conceptual	
1	-1	24.0	3	-1	3	10	Analytical	
2	1	58.0	3	1	0	1	Conceptual	
3	1	26.0	3	-1	4	4	Behavioral	
4	1	31.0	1	1	3	10	Conceptual	

5 rows × 21 columns

In [31]:
```
train = pd.get_dummies(train)
test = pd.get_dummies(test)
```

In [32]:
```
train.head()
```

Out[32]:

	Gender	Age	Education_Level	Relationship_Status	Hometown	Unit	Time_of_service	Time_sin
0	1	42.0	4	1	2	11	4.0	
1	-1	24.0	3	-1	3	10	5.0	
2	1	58.0	3	1	0	1	27.0	
3	1	26.0	3	-1	4	4	4.0	
4	1	31.0	1	1	3	10	5.0	

5 rows × 24 columns

Feature Selection and Statistical Analysis

In [33]:
```
test.isna().sum()
```

Out[33]:
```
Gender                                0
Age                                   0
Education_Level                       0
Relationship_Status                   0
Hometown                              0
Unit                                  0
Time_of_service                       0
Time_since_promotion                  0
growth_rate                           0
Travel_Rate                           0
Post_Level                            0
Pay_Scale                             0
Compensation_and_Benefits             0
Work_Life_balance                     0
VAR1                                  0
VAR3                                  0
VAR5                                  0
VAR6                                  0
VAR7                                  0
Decision_skill_possess_Analytical     0
Decision_skill_possess_Behavioral     0
Decision_skill_possess_Conceptual     0
Decision_skill_possess_Directive      0
dtype: int64
```

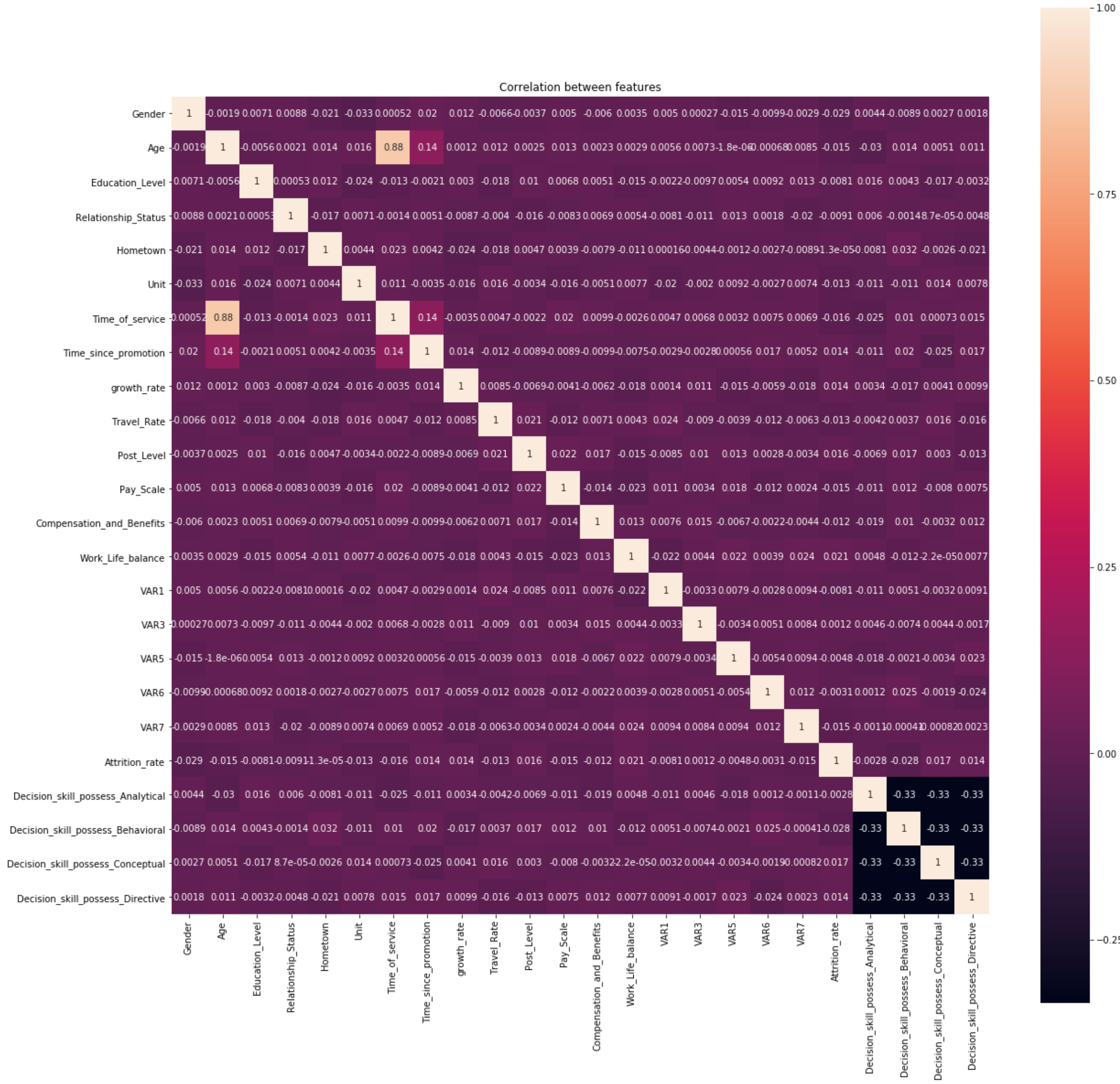
In [34]:
```
train.describe().T
```

Out[34]:

	count	mean	std	min	25%	50%	75
Gender	7000.0	0.175429	0.984562	-1.0000	-1.0000	1.00000	1.00
Age	7000.0	39.645000	13.200655	19.0000	28.0000	40.00000	51.00
Education_Level	7000.0	3.187857	1.065102	1.0000	3.0000	3.00000	4.00
Relationship_Status	7000.0	0.291429	0.956661	-1.0000	-1.0000	1.00000	1.00
Hometown	7000.0	2.520000	1.281229	0.0000	2.0000	3.00000	4.00
Unit	7000.0	7.727143	2.973735	0.0000	6.0000	9.00000	10.00
Time_of_service	7000.0	13.377143	10.257162	0.0000	5.0000	10.00000	20.00
Time_since_promotion	7000.0	2.367143	1.149395	0.0000	1.0000	2.00000	3.00
growth_rate	7000.0	47.064286	15.761406	20.0000	33.0000	47.00000	61.00
Travel_Rate	7000.0	0.817857	0.648205	0.0000	0.0000	1.00000	1.00
Post_Level	7000.0	2.798000	1.163721	1.0000	2.0000	3.00000	3.00
Pay_Scale	7000.0	6.006286	2.057112	1.0000	5.0000	6.00000	8.00
Compensation_and_Benefits	7000.0	3.402714	0.854273	0.0000	3.0000	4.00000	4.00
Work_Life_balance	7000.0	2.387286	1.122009	1.0000	1.0000	2.00000	3.00
VAR1	7000.0	3.098571	0.836377	1.0000	3.0000	3.00000	3.00
VAR3	7000.0	-0.013606	0.986933	-2.7762	-0.4537	-0.45370	0.70
VAR5	7000.0	2.834143	0.938945	1.0000	2.0000	3.00000	3.00
VAR6	7000.0	7.101286	1.164262	5.0000	6.0000	7.00000	8.00
VAR7	7000.0	3.257000	0.925319	1.0000	3.0000	3.00000	4.00
Attrition_rate	7000.0	0.189376	0.185753	0.0000	0.0704	0.14265	0.23
Decision_skill_possess_Analytical	7000.0	0.250714	0.433455	0.0000	0.0000	0.00000	1.00
Decision_skill_possess_Behavioral	7000.0	0.248000	0.431883	0.0000	0.0000	0.00000	0.00
Decision_skill_possess_Conceptual	7000.0	0.250857	0.433537	0.0000	0.0000	0.00000	1.00
Decision_skill_possess_Directive	7000.0	0.250429	0.433291	0.0000	0.0000	0.00000	1.00

In [35]:
```
plt.figure(figsize=(20,20))
corr = train.corr()
sns.heatmap(corr,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values, square=True,annot=True,linecolor="b
plt.title("Correlation between features")
```

Out[35]:
```
Text(0.5, 1.0, 'Correlation between features')
```



In [36]:
```
train = train.drop('Time_of_service',axis=1)
test = test.drop('Time_of_service',axis=1)
```

In [37]:
```
len(list(train.columns))
```

Out[37]:
```
23
```

In [38]:
```
corr_target = corr['Attrition_rate']
```

In [39]:
```
corr_target
relevant_features = corr_target[corr_target>-0.05]
relevant_features
```

Out[39]:
```
Gender                                -0.028544
Age                                   -0.015130
Education_Level                       -0.008143
Relationship_Status                   -0.009107
Hometown                              -0.000013
Unit                                  -0.013088
Time_of_service                       -0.016327
Time_since_promotion                   0.013880
growth_rate                            0.014247
Travel_Rate                           -0.012608
Post_Level                             0.016402
Pay_Scale                             -0.015221
Compensation_and_Benefits             -0.012186
Work_Life_balance                      0.020809
VAR1                                  -0.008073
VAR3                                   0.001245
VAR5                                  -0.004770
VAR6                                  -0.003130
VAR7                                  -0.015299
Attrition_rate                         1.000000
Decision_skill_possess_Analytical     -0.002822
Decision_skill_possess_Behavioral     -0.027524
Decision_skill_possess_Conceptual      0.016568
Decision_skill_possess_Directive       0.013680
Name: Attrition_rate, dtype: float64
```

In [40]:
```
train = train.drop('VAR1',axis=1)
train = train.drop('Travel_Rate',axis=1)
test = test.drop('VAR1',axis=1)
test = test.drop('Travel_Rate',axis=1)
```

In [41]:
```
len(list(train.columns))
```

Out[41]:
```
21
```

Missing Values Hadling, Categorical data handling and and feature selection is done.

###

Candidates for regression models :

- Linear Regression
- SVM regressor
- Lasso Regression
- Ridge Regression

In [42]:
```
from sklearn.utils import shuffle
dataset = shuffle(train)
dataset.head()
```

Out[42]:

	Gender	Age	Education_Level	Relationship_Status	Hometown	Unit	Time_since_promotion
972	-1	25.0	4	1	4	9	2
5381	1	30.0	4	1	4	11	4
4182	-1	48.0	4	1	4	5	4
4756	1	22.0	3	1	4	11	3
4071	-1	40.0	1	1	4	7	2

5 rows × 21 columns

In [43]:
```
label = dataset['Attrition_rate']
train = dataset.drop('Attrition_rate',axis=1)
```

Split Dataset and choose between SVM regressor and linear regression

In [44]:
```
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.linear_model import LinearRegression
```

In [45]:
```
len(train)
```

Out[45]:
```
7000
```

In [46]:
```
train_x,validation_x,train_y,validation_y = train_test_split(train,label,test_si
```

In [47]:
```
print("length of train data : ", len(train_x))
print("length of validation data : ", len(validation_x))
```

```
length of train data :  5039
length of validation data :  1961
```

Linear Regression Baseline

In [48]:
```
model1 = LinearRegression()
```

In [49]:
```
train_x.isna().sum()
```

Out[49]:
```
Gender                             0
Age                                0
Education_Level                    0
Relationship_Status                0
Hometown                           0
Unit                               0
Time_since_promotion               0
growth_rate                        0
Post_Level                         0
Pay_Scale                          0
Compensation_and_Benefits          0
Work_Life_balance                  0
VAR3                               0
VAR5                               0
VAR6                               0
VAR7                               0
Decision_skill_possess_Analytical    0
Decision_skill_possess_Behavioral    0
Decision_skill_possess_Conceptual    0
Decision_skill_possess_Directive     0
dtype: int64
```

In [50]:
```
model1.fit(train_x,train_y)
```

Out[50]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [51]:
```
predict_y = model1.predict(validation_x)
```

In [52]:
```
def root_mean_squared_error(actual,predict):
    differences = [(x-y)**2 for (x,y) in zip(actual,predict)]
    return math.sqrt(sum(differences)/len(differences))
```

In [53]:
```
def performance(actual,predict):
    return 100*max(0,1-root_mean_squared_error(list(actual),predict.tolist()))
```

In [54]:
```
performance(validation_y,predict_y)
```

Out[54]:
```
81.51688348639816
```

SVR Baseline Model

In [55]:
```
model2 = svm.SVR()
model2.fit(train_x,train_y)
```

```
C:\Users\alsrivas\AppData\Local\Continuum\anaconda3\lib\site-packages\sklearn\s
vm\base.py:196: FutureWarning: The default value of gamma will change from 'aut
o' to 'scale' in version 0.22 to account better for unscaled features. Set gamm
a explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

Out[55]:
```
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
  gamma='auto_deprecated', kernel='rbf', max_iter=-1, shrinking=True,
  tol=0.001, verbose=False)
```

In [56]:
```
predict_svr = model2.predict(validation_x)
```

In [57]:
```
performance(validation_y,predict_svr)
```

Out[57]:
```
79.84926551422757
```

Ridge Regression Baseline:

In [58]:
```
from sklearn.linear_model import Ridge
```

In [59]:
```
model3 = Ridge()
```

In [60]:
```
model3.fit(train_x,train_y)
```

Out[60]:
```
Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='auto', tol=0.001)
```

In [61]:
```
predict_ridge = model3.predict(validation_x)
performance(validation_y,predict_ridge)
```

Out[61]:
```
81.5168993256991
```

Lasso Model Baseline

In [62]:
```
from sklearn.linear_model import Lasso
```

In [63]:
```
model4 = Lasso()
```

In [64]:
```
model4.fit(train_x,train_y)
```

Out[64]:
```
Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
   normalize=False, positive=False, precompute=False, random_state=None,
   selection='cyclic', tol=0.0001, warm_start=False)
```

In [65]:
```
predict_lasso = model4.predict(validation_x)
```

In [66]:
```
performance(validation_y,predict_lasso)
```

Out[66]:
```
81.52189003116348
```

We will choose Lasso Regression for parameter search

In [67]:
```
alpha_lasso = [0.001,0.01, 0.1, 1, 10, 100]
fit_lasso = [True, False]
selection_lasso = ['cyclic', 'random']
model_performance = []
```

In [68]:
```
best_model = None
best_performance = None
for i in alpha_lasso:
    for j in fit_lasso:
        for k in selection_lasso:
            model = Lasso(alpha=i,fit_intercept=j,selection=k)
            model.fit(train_x,train_y)
            predictY = model.predict(validation_x)
            model_per = performance(validation_y,predictY)
            model_performance.append((model_per,model))
            if best_model is None:
                best_model = model
                best_performance = model_per
            elif best_performance < model_per:
                best_performance = model_per
                best_model = model
```

In [69]:
```
best_performance
```

Out[69]:
```
81.52266080805572
```

In [70]:
```
selected_model_lasso = sorted(model_performance, key=lambda x: x[0],reverse=True
```

In [71]:
```
selected_model_lasso
```

Out[71]:
```
(81.52266080805572,
 Lasso(alpha=0.001, copy_X=True, fit_intercept=True, max_iter=1000,
    normalize=False, positive=False, precompute=False, random_state=None,
    selection='random', tol=0.0001, warm_start=False))
```

Parameter search for Ridge

In [72]:
```
alpha_ridge = [0.0001,0.001,0.01,0.1,1,10,100,1000,10000]
fit_ridge = [True, False]
solver_ridge = ['auto','svd','cholesky','lsqr','sparse_cg','sag','saga']
model_performance_ridge = []
```

In [73]:
```
best_model = None
best_performance = None
for i in alpha_ridge:
    for j in fit_ridge:
        for k in solver_ridge:
            model = Ridge(alpha=i,fit_intercept=j,solver=k)
            model.fit(train_x,train_y)
            predictY = model.predict(validation_x)
            model_per = performance(validation_y,predictY)
            model_performance_ridge.append((model_per,model))
            if best_model is None:
                best_model = model
                best_performance = model_per
            elif best_performance < model_per:
                best_performance = model_per
                best_model = model
```

In [74]:
```
best_performance
```

Out[74]:
```
81.52456328587276
```

In [75]:
```
selected_model_ridge = sorted(model_performance_ridge, key=lambda x: x[0],revers
```

In [76]:
```
selected_model_ridge
```

Out[76]:
```
(81.52456328587276,
 Ridge(alpha=10000, copy_X=True, fit_intercept=True, max_iter=None,
    normalize=False, random_state=None, solver='lsqr', tol=0.001))
```

So, Selected model is ridge

In [77]:
```
print("RMSE on validation data using selected ridge model is : ", selected_model_
```

```
RMSE on validation data using selected ridge model is :  81.52456328587276
```

In [78]:
```
selected_model = Ridge(alpha=10000, copy_X=True, fit_intercept=True, max_iter=Nor
    normalize=False, random_state=None, solver='sag', tol=0.001)
```

In [79]:
```
selected_model.fit(train,label)
```

Out[79]:
```
Ridge(alpha=10000, copy_X=True, fit_intercept=True, max_iter=None,
   normalize=False, random_state=None, solver='sag', tol=0.001)
```

In [80]:
```
predict_test = selected_model.predict(test).tolist()
```

In [81]:
```
type(predict_test)
```

Out[81]:
```
list
```

In [82]:
```
print(len(test_ID), " ", len(predict_test))
```

```
3000   3000
```

In [83]:
```
import csv
with open('submission.csv', 'w', newline='') as file:
    writer = csv.writer(file)
    writer.writerow(["Employee_ID", "Attrition_rate"])
    for i in range(3000):
        writer.writerow([test_ID[i],predict_test[i]])
```