

w1. INTRODUCTION

1.1 Overview

- The objective of this project is to predict the attrition rate for each employee, to find out who's more likely to leave the organization.
- It will help organization to find ways to prevent attrition or to plan in advance the hiring of new candidate.

1.2 Purpose

- Attrition proves to be costly and time consuming problem for the organization and it also leads to loss of productivity.
- The scope of the project extends to companies in all industries.

2. LITERATURE SURVEY

2.1 Existing Problem

Bill Gates was once quoted as saying,

" You take away our top 20 employees and we [Microsoft] become a mediocre company".

His statement cuts to the core of a **major problem: employee attrition**. An organization is only as good as its employees, and these people are the true source of its competitive advantage. **Organizations face huge costs resulting from employee turnover**. Some costs are tangible such as training expenses and the time it takes from when an employee starts to when they become a productive member. However, the most important costs are intangible. Consider what's lost when a productive employee quits: new product ideas, great project management, or customer relationships.

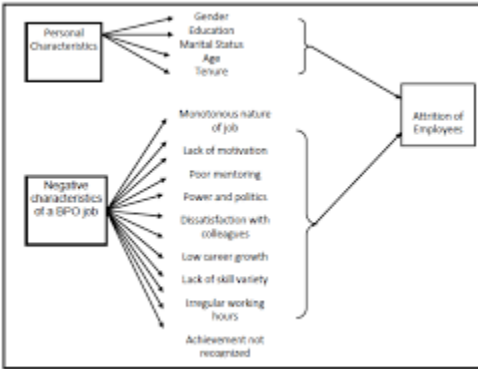
2.2 Proposed Solution

With advances in machine learning and data science, its possible to **not only predict employee attrition but to understand the key variables that influence turnover**.

3. THEORITICAL ANALYSIS

3.1 Block Diagram

The factors influencing the employee attrition in BPO can be illustrated as below:

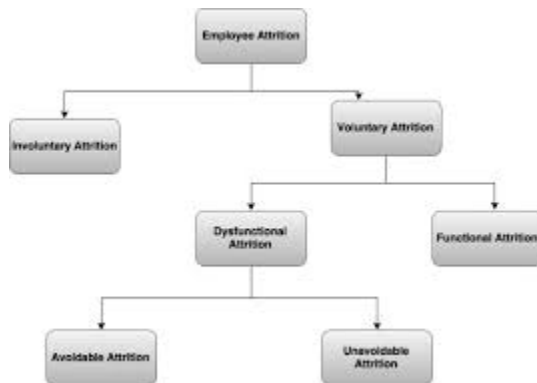


4. EXPERIMENTAL ANALYSIS

The dataset included various important features including average number of monthly hours, number of projects, years spent in the company and whether the employee received a promotion in the last five years. There were a total of nine features, out of which two were categorical and seven were numeric

- Data preprocessing
- Model Validation
- System Environment Specification

5. FLOWCHART



6. RESULT

- The dataset doesnot feature any missing values or any reductant features.
- The strongest positive correlations with the target features are Distance from home, Job Satisfaction, marital status ,overtime and business travel
- The strongest negative correlation with the target features are: Performance Rating and Training times last year.

7. ADVANTAGES AND DISADVANTAGES

Advantages

Not all turnovers are negative, we generally feel that an employee leaving the organization is detrimental to the organization, but there is a flip side to it.

Employees leaving an organization may lead to benefits. This type of job attrition is called 'healthy attrition' and is needed for growth and development of an organization

1. Higher manpower costs
2. Negative people effect
3. New Idea
4. Higher Performance
5. Setting the culture right

Disadvantages

When employees leave the organization it is a loss to the company, the team and the individuals.

Employees are the backbone of any organization and their departing may lead to lot of various losses to company on different aspects.

1. Decrease overall performance
2. Daily task management
3. Increased cost
4. Lack of knowledge employees
5. Create negative image
6. Employee development

8. CONCLUSION

Predictive Attrition Model helps in not only taking preventive measures but also into making better hiring decisions. Deriving trends in the candidate's performance out of past data is important in order to predict the future trends, as well as to board new employees. Moreover, HR can use the employee data to predict attrition, the possible reasons behind it and can take appropriate measures to prevent it.

9. FUTURE SCOPE

1. Transportation should be provided to employees living in the same area.
2. Plan and allocate project in such a way to avoid the overtime.
3. Employees which hit their two-year anniversary should be identified as potentially having a higher risk of leaving.

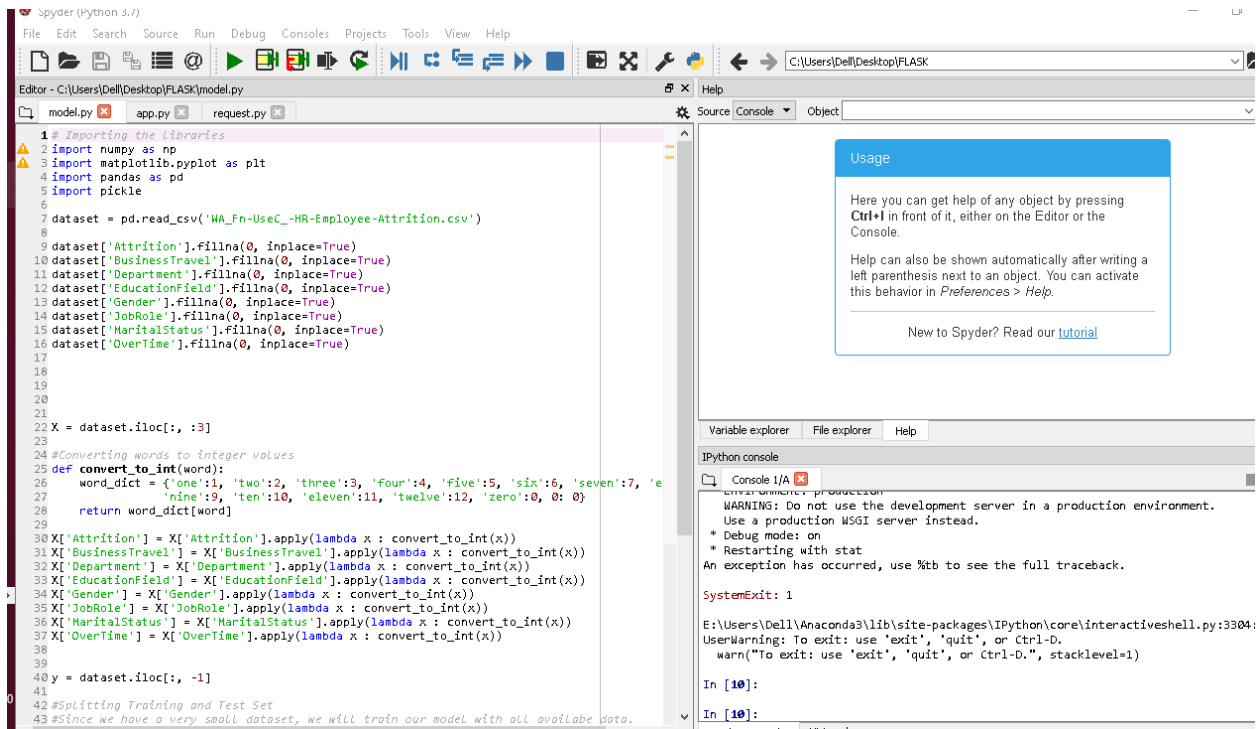
4. Gather information on industry benchmarks to determine if the company is providing competitive wages.

10. BIBLOGRAPHY

The content for this project report has taken from following links

1. <https://www.slideshare.net/ShrutiMohan5/predicting-employee-attrition-149113703>
2. <https://medium.com/analytics-vidhya/predict-employee-attrition-a34e2c5a972d>
3. <https://www.kaggle.com/c/1056lab-employee-attrition-prediction/>

SCREENSHOTS



Jupyter Employee Attrition Prediction final Last Checkpoint: Last Saturday at 5:00 PM (autosaved) Logout

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4 27 No Travel_Rarely 591 Research & Development 2 1 Medical 1 7 ...

1465 36 No Travel_Frequently 884 Research & Development 23 2 Medical 1 2061 ...

1466 39 No Travel_Rarely 613 Research & Development 6 1 Medical 1 2062 ...

1467 27 No Travel_Rarely 155 Research & Development 4 3 Life Sciences 1 2064 ...

1468 49 No Travel_Frequently 1023 Sales 2 3 Medical 1 2065 ...

1469 34 No Travel_Rarely 628 Research & Development 8 3 Medical 1 2068 ...

1470 rows x 35 columns

In [5]: data1.head()

Out[5]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeNumber	...	RelationshipSatis
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	1	...	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	2	...	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	4	...	

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2 37 Yes Travel_Rarely 1373 Research & Development 2 2 Other 1 4 ...

3 33 No Travel_Frequently 1392 Research & Development 3 4 Life Sciences 1 5 ...

4 27 No Travel_Rarely 591 Research & Development 2 1 Medical 1 7 ...

5 rows x 35 columns

In [6]: data1.shape

Out[6]: (1470, 35)

In [7]: data1.isnull().sum()

Out[7]:

Age	0
Attrition	0
BusinessTravel	0
DailyRate	0
Department	0
DistanceFromHome	0
Education	0
EducationField	0
EmployeeCount	0
EmployeeNumber	0
EnvironmentSatisfaction	0
Gender	0
HourlyRate	0

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Restart

Code

Out

PerformanceRating0

RelationshipSatisfaction0

StandardHours0

StockOptionLevel0

TotalWorkingYears0

TrainingTimesLastYear0

WorkLifeBalance0

YearsAtCompany0

YearsInCurrentRole0

YearsSinceLastPromotion0

YearsWithCurrManager0

dtype: int64

In [8]: data1.isnull().any()

Out[8]:

AgeFalse

AttritionFalse

BusinessTravelFalse

DailyRateFalse

DepartmentFalse

DistanceFromHomeFalse

EducationFalse

EducationFieldFalse

EmployeeCountFalse

EmployeeNumberFalse

EnvironmentSatisfactionFalse

GenderFalse

HourlyRateFalse

JobInvolvementFalse

JobLevelFalse

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Run

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Code

Out

MonthlyIncomeFalse

MonthlyRateFalse

NumCompaniesWorkedFalse

Over18False

OverTimeFalse

PercentSalaryHikeFalse

PerformanceRatingFalse

RelationshipSatisfactionFalse

StandardHoursFalse

StockOptionLevelFalse

TotalWorkingYearsFalse

TrainingTimesLastYearFalse

WorkLifeBalanceFalse

YearsAtCompanyFalse

YearsInCurrentRoleFalse

YearsSinceLastPromotionFalse

YearsWithCurrManagerFalse

dtype: bool

In [9]:

from sklearn.preprocessing import LabelEncoder

labelencoder_y = LabelEncoder()

data1['Attrition'] = labelencoder_y.fit_transform(data1['Attrition'])

data1['BusinessTravel'] = labelencoder_y.fit_transform(data1['BusinessTravel'])

data1['Department'] = labelencoder_y.fit_transform(data1['Department'])

data1['EducationField'] = labelencoder_y.fit_transform(data1['EducationField'])

data1['Gender'] = labelencoder_y.fit_transform(data1['Gender'])

data1['JobRole'] = labelencoder_y.fit_transform(data1['JobRole'])

data1['MaritalStatus'] = labelencoder_y.fit_transform(data1['MaritalStatus'])

print(data1)

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	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	\
0	41	1	2	1102	2		1
1	49	0	1	279	1		8
2	37	1	2	1373	1		2
3	33	0	1	1392	1		3
4	27	0	2	591	1		2
...
1465	36	0	1	884	1		23
1466	39	0	2	613	1		6
1467	27	0	2	155	1		4
1468	49	0	1	1023	2		2
1469	34	0	2	628	1		8
	Education	EducationField	EmployeeCount	EmployeeNumber	...		\
0	2	1	1	1	1		...
1	1	1	1	1	2		...
2	2	4	1	1	4		...
3	4	1	1	1	5		...
4	1	3	1	1	7		...
...
1465	2	3	1	1	2061		...
1466	1	3	1	1	2062		...
1467	3	1	1	1	2064		...
1468	3	3	1	1	2065		...
1469	3	3	1	1	2068		...
	RelationshipSatisfaction	StandardHours	StockOptionLevel				\
0		1	80				0
1		4	80				1
2		2	80				0

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	<code>y = data1.iloc[:,3].values</code>						
In [11]:	<code>print(x[0],y[0])</code>						
	[41 1 2] 1102						
In [12]:	<code>from sklearn.compose import ColumnTransformer</code>						
In [13]:	<code>from sklearn.preprocessing import OneHotEncoder</code>						
In [14]:	<code>ct = ColumnTransformer(transformers=[("oh",OneHotEncoder(),[0])],remainder="passthrough")</code>						
In [15]:	<code>x=ct.fit_transform(x)</code>						
In [16]:	<code>print(x)</code>						
	(0, 23)	1.0					
	(0, 43)	1.0					
	(0, 44)	2.0					
	(1, 31)	1.0					
	(1, 44)	1.0					
	(2, 19)	1.0					
	(2, 43)	1.0					
	(2, 44)	2.0					
	(3, 15)	1.0					
	(3, 44)	1.0					
	(4, 9)	1.0					
	(4, 44)	2.0					

Jupyter Employee Attrition Prediction final Last Checkpoint: Last Saturday at 5:00 PM (autosaved)

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```
(1469, 44) 3.0064854641274565
```

```
In [18]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=10)
```

```
In [19]: print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)

(1029, 45)
(441, 45)
(1029,)
(441,)
```

```
In [20]: '''
classifier_reg = LogisticRegression()
classifier_reg.fit(x_train,y_train)

Commented out as LogReg is used for Classification and your task is Regression
'''

reg = LinearRegression()
reg.fit(x_train, y_train)
```

```
Out[20]: LinearRegression()
```

```
In [21]: y_pred=reg.predict(x_test)
```

```
In [22]: print(v_pred#.astype(int)) #Here rating are predicted as float(As obvious). if you want int values you can use .astype(int)
```

localhost:8888/notebooks/Desktop/remote internship 2020/data sets/Employee Attrition Prediction final.ip ...

Jupyter Employee Attrition Prediction final Last Checkpoint: Last Saturday at 5:00 PM (autosaved)

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```
770.20414698 870.12492948 791.75030311 803.09394314 690.34923104
873.55506943 844.9958983 700.26543995 729.52807371 947.77601121
799.25805454 740.14765209 902.26362546 844.9958983 666.8746855
874.98454982 880.66167847 798.98837332 873.55506943 834.80817992
819.88217514 838.66326789 740.14765209 782.84367849 797.15441215
740.14765209 772.1383769 962.70201599 791.45638511 815.40399893
844.9958983 731.53494547 753.05903372 746.0874228 872.04897185
858.4322226 966.65401446 878.12492948 864.42603518 740.14765209
834.80817992 797.15441215 790.64534792 796.68896486 676.04107515
821.43785465 744.45407848 857.75913658 774.43778536 1185.10476486
731.16141802]
```

```
In [23]: cols = ['Model','max_error','mean_squared_error','mean_squared_log_error',
'r2_score', 'mean_absolute_error','explained_variance_score']
models_report = pd.DataFrame(columns=cols)

print(models_report)

Empty DataFrame
Columns: [Model, max_error, mean_squared_error, mean_squared_log_error, r2_score, mean_absolute_error, explained_variance_score]
Index: []
```

```
In [24]: rows = np.array(["Linear Regression",
metrics.max_error(y_test, y_pred),
metrics.mean_squared_error(y_test, y_pred),
metrics.mean_squared_log_error(y_test, y_pred),
metrics.r2_score(y_test, y_pred),
metrics.mean_absolute_error(y_test, y_pred),
metrics.explained_variance_score(y_test, y_pred)])
```

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Run Code

```

770.26441696 870.12492948 731.43036311 800.09394314 696.37963104
873.55506943 844.9958983 700.26543995 729.52807371 947.77601121
799.25805454 740.14765209 902.26362546 844.9958983 666.8746855
874.98454982 880.66167847 798.98837332 873.55506943 834.80817992
819.88217514 838.66326789 740.14765209 782.84367849 797.15441215
740.14765209 772.1383769 962.70201599 791.45638511 815.40399893
844.9958983 731.53494547 753.05903372 746.0874228 872.04897185
858.4322226 966.65401446 878.12492948 864.42603518 740.14765209
834.80817992 797.15441215 790.64534792 796.68896486 676.04107515
821.43785465 744.45407848 857.75913658 774.43778536 1185.10476486
731.16141802]

In [23]: cols = ['Model', 'max_error', 'mean_squared_error', 'mean_squared_log_error',
               'r2_score', 'mean_absolute_error', 'explained_variance_score']
models_report = pd.DataFrame(columns=cols)

print(models_report)

Empty DataFrame
Columns: [Model, max_error, mean_squared_error, mean_squared_log_error, r2_score, mean_absolute_error, explained_variance_score]
Index: []

In [24]: rows = np.array(["Linear Regression",
                          metrics.max_error(y_test, y_pred),
                          metrics.mean_squared_error(y_test, y_pred),
                          metrics.mean_squared_log_error(y_test, y_pred),
                          metrics.r2_score(y_test, y_pred),
                          metrics.mean_absolute_error(y_test, y_pred),
                          metrics.explained_variance_score(y_test, y_pred)])

```

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Run Code

```

Reg_report = models_report.append(temp1, ignore_index = True)
Reg_report

Out[24]:

```

	Model	max_error	mean_squared_error	mean_squared_log_error	r2_score	mean_absolute_error	explained_variance_score
0	Linear Regression	1043.1047648598567	172301.8190985129	0.4940112052587489	-0.07772779874596614	349.3459593777875	-0.07523144662864523

```

In [25]: from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.linear_model import ElasticNet
pipe = Pipeline([
    ('rescale', StandardScaler(with_mean=False)),
    ('enet', ElasticNet())
])

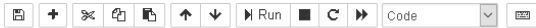
In [26]: pipe.fit(x_train, y_train)

Out[26]: Pipeline(steps=[('rescale', StandardScaler(with_mean=False)),
                          ('enet', ElasticNet())])

In [27]: y_predict=pipe.predict(x_test)
y_predict

Out[27]: array([ 886.16702856,  843.85302785,  883.58942605,  865.10801632,
                  753.27684107,  787.29736364,  787.20798184,  814.44553394,
                  813.05398632,  825.26424697,  784.5879239 ,  798.89068945,
                  813.05398632,  750.38048678,  825.26424697,  727.20301047,
                  861.61750506,  775.17280644,  768.27369459,  850.93244611,
                  806.92285558,  804.23770742,  813.05398632,  802.20327245])

```



```
826.89114903, 721.08187972, 855.49637432, 875.34831553,
707.14896884, 839.35453362, 825.26424697, 869.22718479,
826.89114903, 721.08187972, 855.49637432, 875.34831553,
```

```
In [28]: rows = np.array(["Elastic Net",
                           metrics.max_error(y_test, y_predict),
                           metrics.mean_squared_error(y_test, y_predict),
                           metrics.mean_squared_log_error(y_test, y_predict),
                           metrics.r2_score(y_test, y_pred),
                           metrics.mean_absolute_error(y_test, y_predict),
                           metrics.explained_variance_score(y_test, y_predict)])
temp2 = pd.Series(rows, index = cols)

Reg_report = Reg_report.append(temp2, ignore_index = True)
```

```
      Model      max_error  mean_squared_error \
0  Linear Regression  1043.1047648598567    172301.8190985129
1    Elastic Net    915.3322479071323    166560.77872274717

      mean_squared_log_error      r2_score  mean_absolute_error \
0    0.4940112052587489  -0.07772779874596614    349.3459593777875
1    0.4862341686303916  -0.07772779874596614    344.8101705846798

      explained_variance_score
0    -0.07523144662864523
1    -0.039109234859640685
```

```
In [29]: Reg_report
```

```
Out[29]:
```

	Model	max_error	mean_squared_error	mean_squared_log_error	r2_score	mean_absolute_error	explained_variance_score
0	Linear Regression	1043.1047648598567	172301.8190985129	0.4940112052587489	-0.07772779874596614	349.3459593777875	-0.07523144662864523
1	Elastic Net	915.3322479071323	166560.77872274717	0.4862341686303916	-0.07772779874596614	344.8101705846798	-0.039109234859640685