

# Human Resources: A Study of Attrition

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# Data

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 1480 entries, 0 to 1479
```

```
Data columns (total 38 columns):
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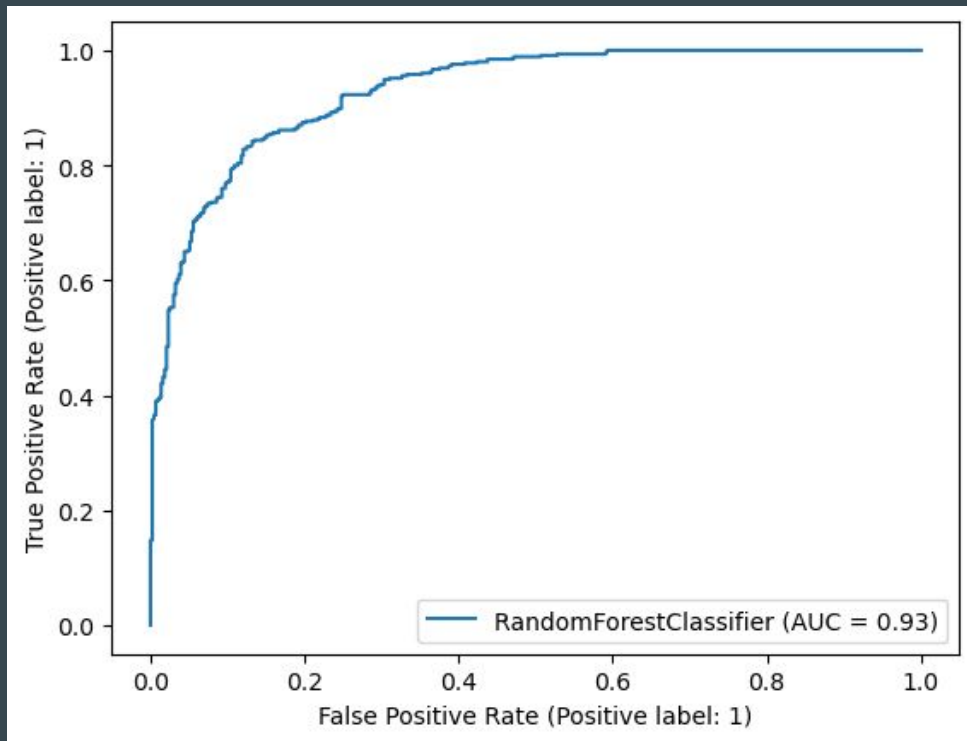
#	Column	Non-Null Count	Dtype
0	EmpID	1480 non-null	object
1	Age	1480 non-null	int64
2	AgeGroup	1480 non-null	object
3	Attrition	1480 non-null	object
4	BusinessTravel	1480 non-null	object
5	DailyRate	1480 non-null	int64
6	Department	1480 non-null	object
7	DistanceFromHome	1480 non-null	int64
8	Education	1480 non-null	int64
9	EducationField	1480 non-null	object
10	EmployeeCount	1480 non-null	int64
11	EmployeeNumber	1480 non-null	int64
12	EnvironmentSatisfaction	1480 non-null	int64
13	Gender	1480 non-null	object
14	HourlyRate	1480 non-null	int64
15	JobInvolvement	1480 non-null	int64
16	JobLevel	1480 non-null	int64
17	JobRole	1480 non-null	object
18	JobSatisfaction	1480 non-null	int64
19	MaritalStatus	1480 non-null	object
20	MonthlyIncome	1480 non-null	int64
21	SalarySlab	1480 non-null	object
22	MonthlyRate	1480 non-null	int64
23	NumCompaniesWorked	1480 non-null	int64
24	Over18	1480 non-null	object
25	OverTime	1480 non-null	object
26	PercentSalaryHike	1480 non-null	int64
27	PerformanceRating	1480 non-null	int64
28	RelationshipSatisfaction	1480 non-null	int64
29	StandardHours	1480 non-null	int64

- 38 Columns
- 1480 Observations
- Gender, Marital Status, Monthly Income, and YearsinCurrentRole were all target variables

# Data Organization

- Balance data
- One Hot Encode variables
- Train Test Set
- Models: Random Forest is the baseline model
- Additional Models: Logistic Regression, Decision Tree Classifier, and Multinomial
- Hyperparameters were added for more iterations and then higher tolerance with confusion matrix
- SMOTE function
- Linear Regression - Target variables were Monthly Income and YearsInCurrentRole
- Multi-class Regression - Target variable was Marital Status

# Baseline Model - Random Forest Regressor



➤ Accuracy score is 0.93 on the train data

# Additional Models - Classification Report

Model 1 – Accuracy: 0.5033783783783784

Classification Report:

	precision	recall	f1-score	support
0	0.55	0.45	0.49	159
1	0.47	0.57	0.51	137
accuracy			0.50	296
macro avg	0.51	0.51	0.50	296
weighted avg	0.51	0.50	0.50	296

Model 2 – Accuracy: 0.5236486486486487

Classification Report:

	precision	recall	f1-score	support
0	0.56	0.53	0.54	159
1	0.49	0.52	0.50	137
accuracy			0.52	296
macro avg	0.52	0.52	0.52	296
weighted avg	0.53	0.52	0.52	296

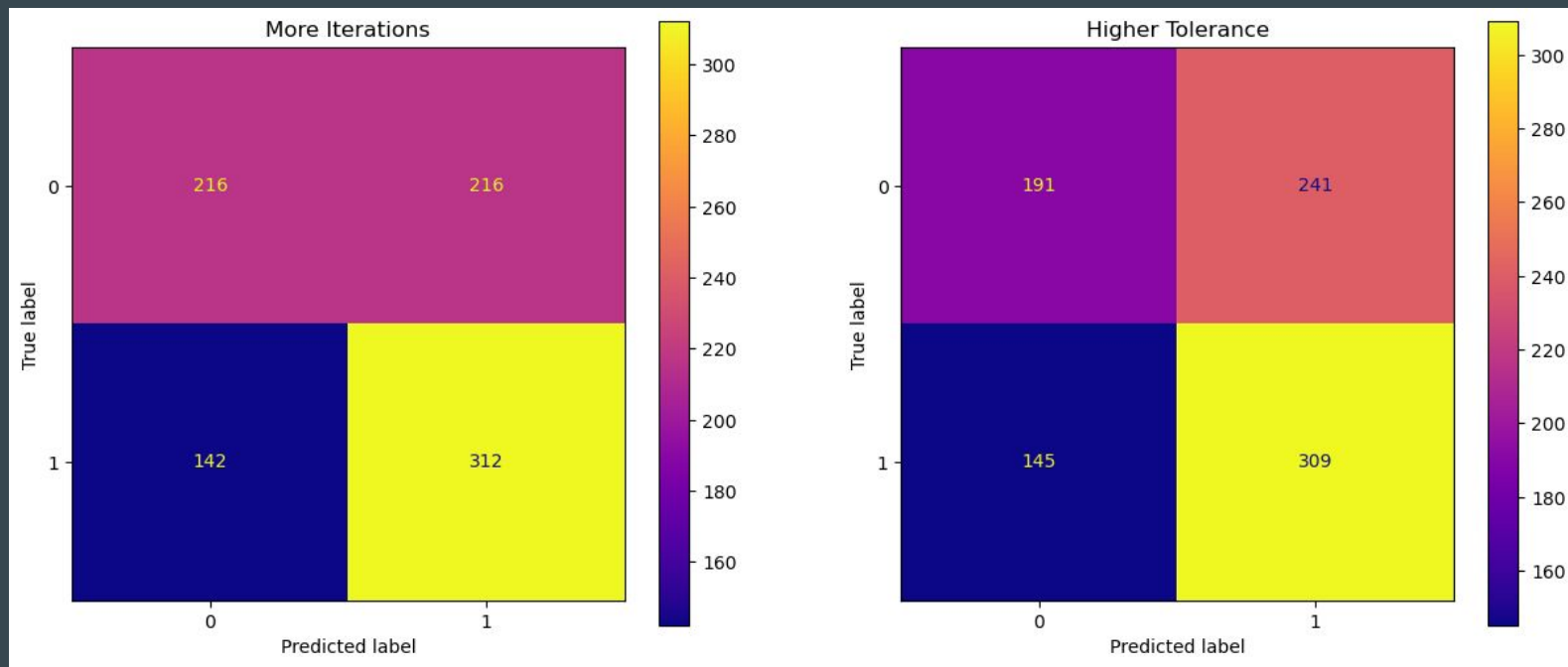
Model 3 – Accuracy: 0.543918918918919

Classification Report:

	precision	recall	f1-score	support
0	0.60	0.45	0.52	159
1	0.51	0.65	0.57	137
accuracy			0.54	296
macro avg	0.55	0.55	0.54	296
weighted avg	0.56	0.54	0.54	296

- Model 1 - Logistic Regression
- Model 2 - Decision Tree Classifier
- Model 3 - Multinomial
- Scores were lower for these models
- Baseline Random Forest Regressor Model had highest results

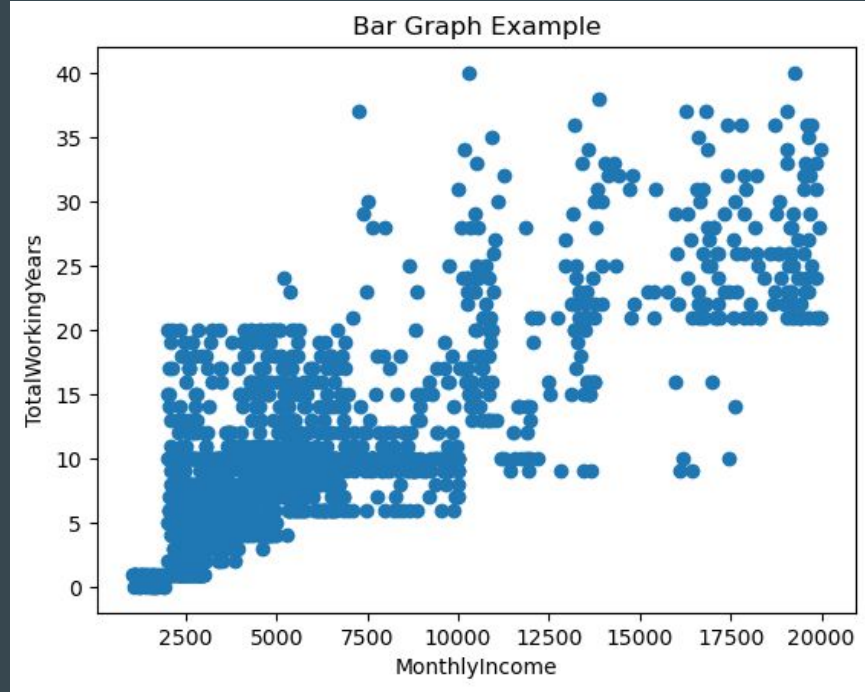
# Hyperparameters for Logistic Regression



➤ Confusion Matrix for More Parameters and higher Tolerance

# Scatter Plot for Linear Regression

- Monthly Income on X Axis
- TotalWorkingHours on Y Axis
- Positive Correlation



# Linear Regression

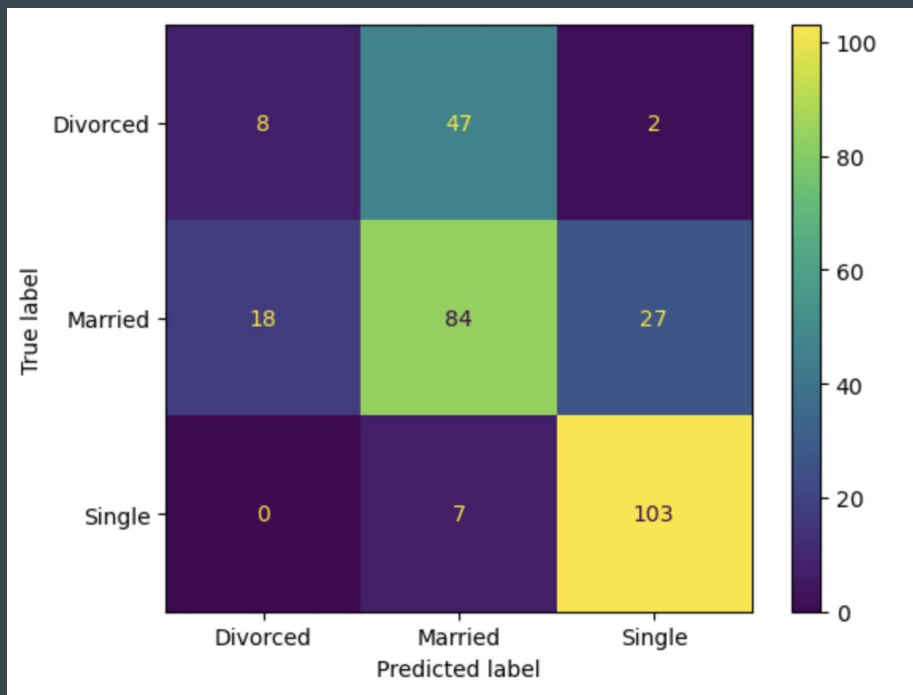
OLS Regression Results						
Dep. Variable:	MonthlyIncome	R-squared:	0.248			
Model:	OLS	Adj. R-squared:	0.247			
Method:	Least Squares	F-statistic:	388.2			
Date:	Mon, 06 Nov 2023	Prob (F-statistic):	6.10e-75			
Time:	13:02:28	Log-Likelihood:	-11322.			
No. Observations:	1182	AIC:	2.265e+04			
Df Residuals:	1180	BIC:	2.266e+04			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	3306.6715	162.684	20.326	0.000	2987.490	3625.853
YearsAtCompany	384.5406	19.516	19.704	0.000	346.250	422.831
Omnibus:	371.198	Durbin-Watson:	1.752			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1066.059			
Skew:	1.602	Prob(JB):	3.22e-232			
Kurtosis:	6.373	Cond. No.	13.4			

OLS Regression Results						
=====						
Dep. Variable:	MonthlyIncome	R-squared:	0.539			
Model:	OLS	Adj. R-squared:	0.535			
Method:	Least Squares	F-statistic:	171.1			
Date:	Tue, 07 Nov 2023	Prob (F-statistic):	5.72e-191			
Time:	10:57:47	Log-Likelihood:	-11033.			
No. Observations:	1182	AIC:	2.208e+04			
Df Residuals:	1173	BIC:	2.213e+04			
Df Model:	8					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	1720.0221	803.853	2.140	0.033	142.872	3297.172
YearsAtCompany	50.2819	30.385	1.655	0.098	-9.333	109.897
YearsSinceLastPromotion	-5.7712	34.943	-0.165	0.869	-74.330	62.787
TrainingTimesLastYear	-18.2800	61.511	-0.297	0.766	-138.964	102.404
TotalWorkingYears	419.1931	15.541	26.974	0.000	388.703	449.684
PerformanceRating	-39.4628	221.465	-0.178	0.859	-473.974	395.048
MonthlyRate	0.0154	0.011	1.368	0.172	-0.007	0.037
YearsInCurrentRole	-23.4194	38.020	-0.616	0.538	-98.014	51.175
HourlyRate	-4.6900	3.956	-1.186	0.236	-12.451	3.071
=====						
Omnibus:	85.957	Durbin-Watson:	2.050			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	166.524			
Skew:	0.485	Prob(JB):	6.92e-37			
Kurtosis:	4.562	Cond. No.	1.65e+05			
=====						

- Linear Regression for Monthly Income with one dependent variable
- Other Linear Regression is result with multiple dependent variables
- R\*\*2 values varied - 0.25 and 0.539



# Multi-Class Regression



	precision	recall	f1-score	support
Divorced	0.14	0.31	0.19	26
Married	0.65	0.61	0.63	138
Single	0.94	0.78	0.85	132
accuracy			0.66	296
macro avg	0.58	0.57	0.56	296
weighted avg	0.73	0.66	0.69	296

- Married and Single categories had highest scores

# Recommendations

- Sort the data for specific genders to better understand how it is driving attrition rates - Random Forest Regressor had high scores on the train data
- The multi-Class Regression study had high scores for the specific categories of Single and Married so could filter the data for these categories to better understand how it is driving attrition rates
- For the Linear Regression Study filtering for the variables that were found to be significant at the 1% level would also be a solid indicator of what is driving attrition levels.
- These recommendations would be very helpful to companies because of how high levels of attrition are. Companies lose revenue when there's high turnover so understanding how to interpret data for attrition is a big step toward raising revenue levels