



# EMPLOYEE ATTRITION

IBM Dataset: Presentation

**Note:**

This presentation is in collaboration with 6 analysts. Authors can be provided by request..

The image features an aerial view of a city, likely Hong Kong, with a prominent mountain in the background. The entire scene is overlaid with a semi-transparent blue filter. A vertical teal bar is positioned on the right side of the image. The text 'Background & Objective' is centered in the middle of the image in a white, sans-serif font.

# Background & Objective

# Why Attrition Matters?



## REPLACEMENT COST

Direct Exit Cost  
Recruiting  
Training



## EMPLOYEE MORALE

Lost of Productivity  
Disengagement  
Domino Effect



## KNOWLEDGE LOST

Institutional Knowledge  
External Relationships  
Service Quality

**“For someone making \$40K a year, replacement cost is \$20K - \$30K in recruiting and training expenses.”**

*-- Society of Human Resource Management*

# Causes of Attrition

- Unsatisfying compensation and benefits
- Lack of development opportunity
- Lack of work-life balance
- Lack of recognition
- Poor management
- Poor work conditions





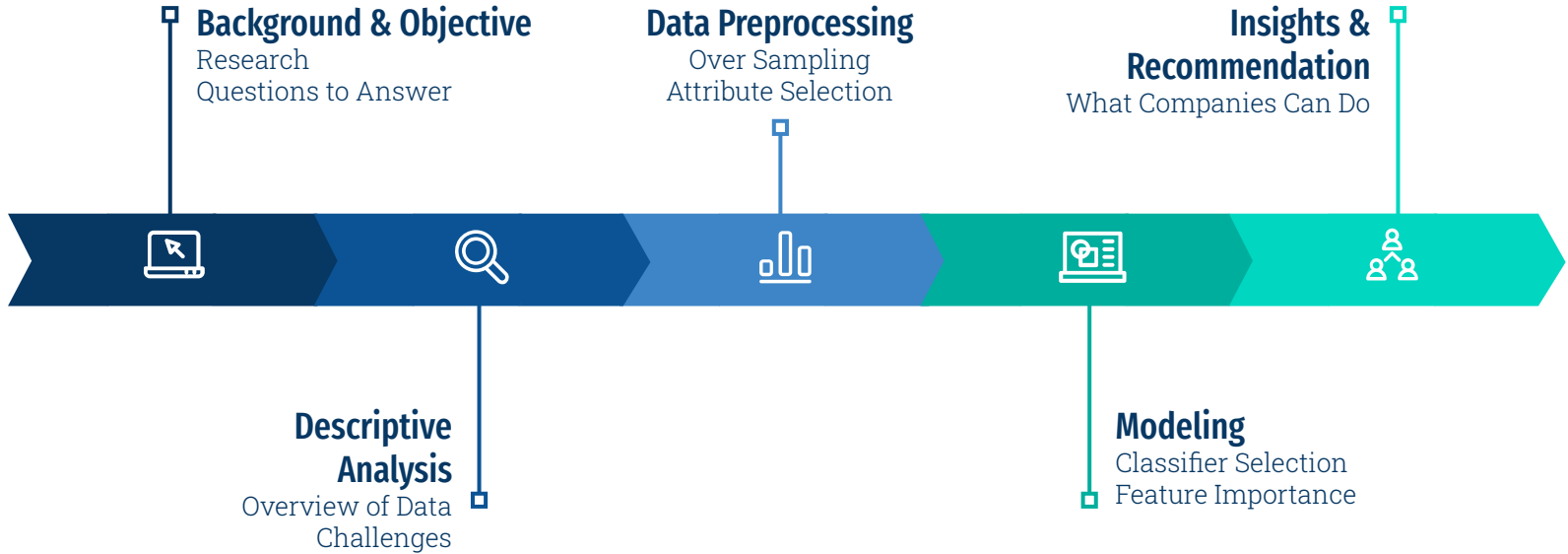
**We want to answer...**

Why do employees leave?

What factors characterize employee attrition?

What can companies do to prevent losing employees?

# Agenda



An aerial view of a city with a teal overlay and a vertical white line. The text 'Descriptive Analysis' is centered in white. The background shows a dense urban landscape with various buildings and a mountain in the distance.

# Descriptive Analysis

# Overview of Data

IBM HR Employee

<https://www.kaggle.com/pavansubhasht/ibm-hr-analytics-attrition-dataset>

## Structure

1470 observations

35 attributes

## Label - Attrition

"Yes": 237 (16%)

"No": 1233 (84%)

## Data Types

Numeric

Categorical

Ordinal/Scale



# Challenges

## Biased Dataset

The numbers of "Yes" and "No" are unbalanced

237 Yes  
1233 No

## Accuracy vs. Precision

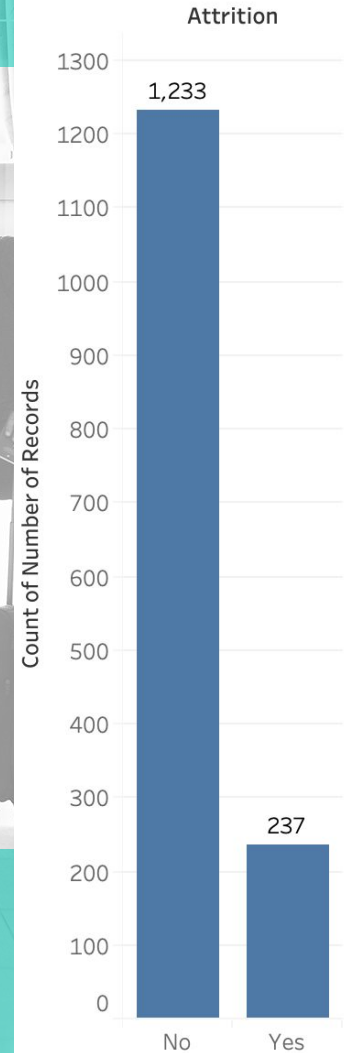
Need to focus on the number of 'Yes', instead of 'No'

$TP / (TP + FP)$

## Too Many Attributes

Problem with overfitting and redundancy

35 attributes



An aerial photograph of a city skyline, likely Hong Kong, featuring a prominent skyscraper (the Bank of China Tower) and a mountain in the background. The image is overlaid with a teal gradient and a white vertical line. The text "Data Preprocessing" is centered in white.

# Data Preprocessing

## Remove Single Unique Value

Employee ID

Employee Count

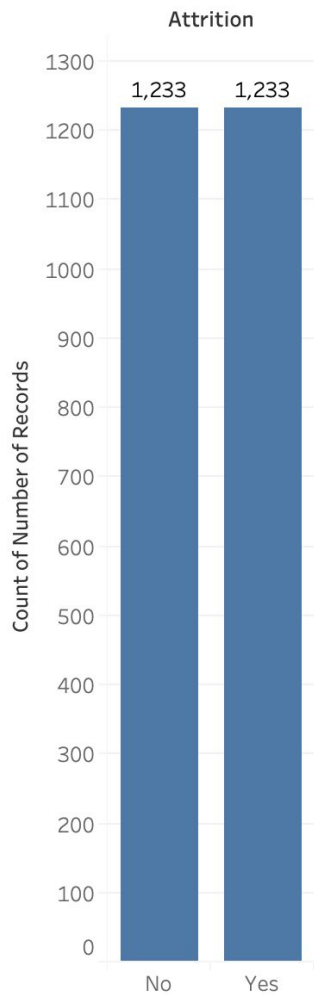
Over 18

Standard Hours

## Remove Highly Correlated Variables

	d.TotalWorkingYears	d.YearsAtCompany	d.YearsWithCurrManager	d.YearsInCurrentRole
d.TotalWorkingYears	1.0000000	0.6281332	0.4591884	0.4603646
d.YearsAtCompany	0.6281332	1.0000000	0.7692124	0.7587537
d.YearsWithCurrManager	0.4591884	0.7692124	1.0000000	0.7143648
d.YearsInCurrentRole	0.4603646	0.7587537	0.7143648	1.0000000
d.YearsSinceLastPromotion	0.4048578	0.6184089	0.5102236	0.5480562
	d.YearsSinceLastPromotion			
d.TotalWorkingYears	0.4048578			
d.YearsAtCompany	0.6184089			
d.YearsWithCurrManager	0.5102236			
d.YearsInCurrentRole	0.5480562			
d.YearsSinceLastPromotion	1.0000000			

	d.MonthlyIncome	d.JobLevel	d.TotalWorkingYears
d.MonthlyIncome	1.0000000	0.9502999	0.7728932
d.JobLevel	0.9502999	1.0000000	0.7822078
d.TotalWorkingYears	0.7728932	0.7822078	1.0000000



Over Sampling | The "Yes"

# Feature Selection

Top Features:

- Monthly Income
- Over Time
- Stock Option Level
- Years At Company
- Age
- Distance From Home

	Specs	Score
2	MonthlyIncome	411536.225257
5	YearsAtCompany	433.389238
0	Age	306.601455
1	DistanceFromHome	168.847410
13	OverTime	145.667368
14	StockOptionLevel	90.301831
12	MaritalStatus	52.232840
19	low_worklife_balance	31.705882
18	low_job_involvement	31.053763
17	frequent_travel	30.952381
9	EnvironmentSatisfaction	22.861395
3	NumCompaniesWorked	20.701826
11	JobSatisfaction	17.644864
16	low_relationship_satisfaction	10.695312
4	TrainingTimesLastYear	6.383004
6	Department	4.292568
10	Gender	1.063830
8	EducationField	0.805780
7	Education	0.453708
15	low_percentage_hike	0.326425



# Modeling

# Modeling with All Attributes

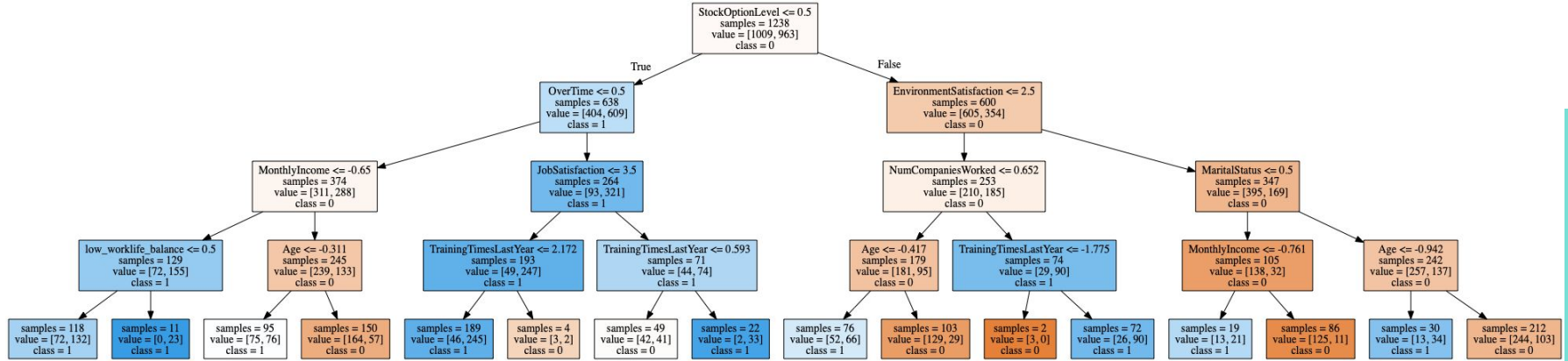
Model	Accuracy	Precision
Logistic Regression	74.2%	73%
Decision Tree	78.9%	73.7%
Random Forest	78.1%	79.1%
Gradient Boosting	95.9%	92.4%

# Modeling with Top Attributes from Feature Selection

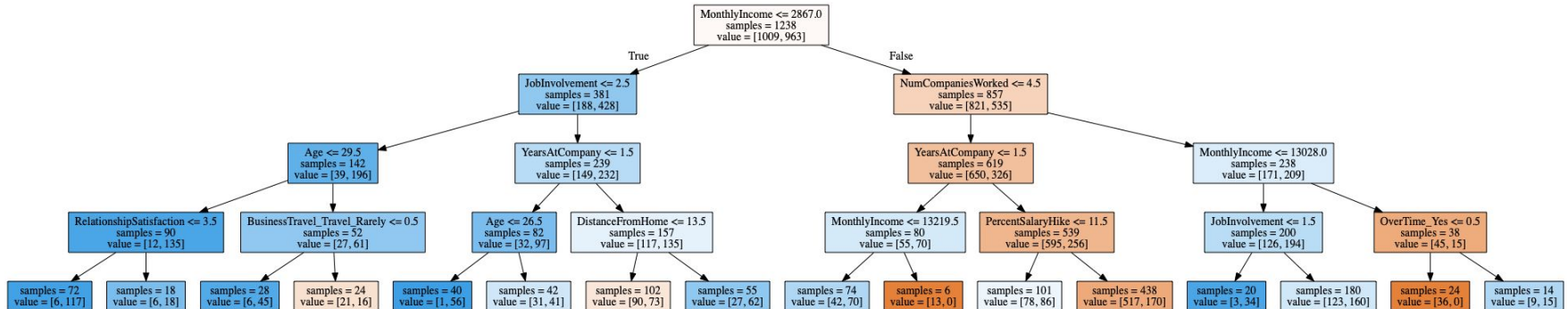
Model	Accuracy	Precision
Logistic Regression	69.4%	67%
Decision Tree	75.5%	78.3%
Random Forest	75.9%	77.7%
Gradient Boosting	92.9%	87.4%



# Decision Tree (Decision Nodes)



# Random Forest (Decision Nodes)





# Insights & Recommendation

# Why do employees leave?

## Theory of Organizational Equilibrium

An Employee will stay with an organization:

- If attributes such:
  - Satisfactory **Pay**
  - Working **Conditions**
  - Developmental **Opportunities**
- Are equal to or greater than:
  - Time / Effort

# What we found influences Employees to Leave

## Overtime

Time/effort

## Monthly Salary

Satisfactory Pay

## Job Involvement

Development

## Age

Development

## Stock Options

Satisfactory Pay

## Years With Company

Working Conditions

# Most Important Attributes

- Overtime
- Age
- Monthly Income
- Years At Company
- Stock Options

# How to address?

- Training/Skills & Promotions
- Manage Age 26-34
- Promotions Opps. For Income  
below \$2960
- First few years are Highest Risk
- Offer higher stock options

# Characteristics of Attrition by Department

## Insight 1

Employees with **technical degrees** are more likely to leave when working for **HR Department**.

85%

## Insight 2

Employees from **all departments** are roughly twice as likely to leave when **working overtime**.

2X

## Insight 3

Employees from all departments benefit from **High Job Involvement**.

73%  
/37%

# Future of Employee Management

Employees that show signs of leaving...will **not only** be dealt with by managers and HR.... but by **solutions groups**, something IBM is already using today.

IBM has saved nearly **\$300 million in retention costs** using similar AI and predictive techniques.

A background image showing a close-up of two hands shaking in a firm grip. The image is overlaid with a semi-transparent blue filter. The hands are positioned in the center-right of the frame, with the left hand slightly lower than the right. The background is out of focus, showing what appears to be an office setting with papers and a desk.

# THANKS

## Q&A



# Appendix

# Initial Modeling

Our Best Models:

1. Support Vector Machine
2. Random Forest
3. Decision Tree
4. Gradient Boosting

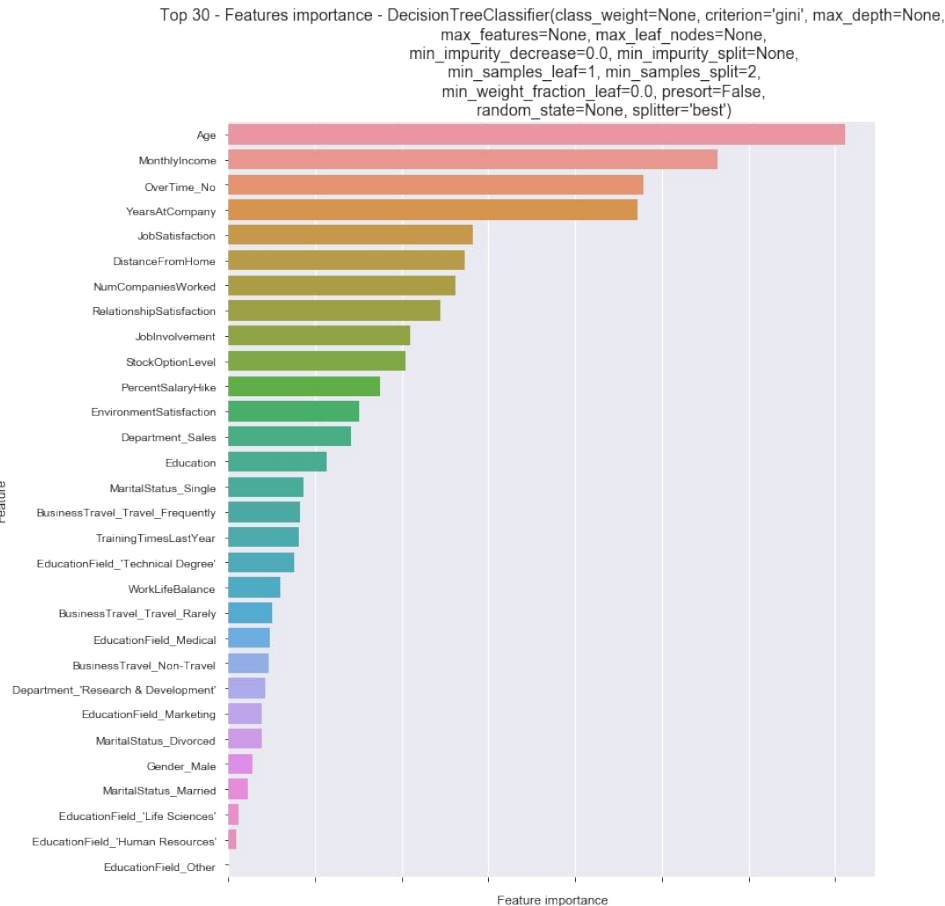
	<b>Classifiers</b>	<b>Crossval Mean Scores</b>
0	Logistic Reg.	0.743309
1	SVC	0.982157
2	KNN	0.744120
3	Dec Tree	0.912003
4	Grad B CLF	0.874696
5	Rand FC	0.964315
6	Neural Classifier	0.572182
7	Naives Bayes	0.572182

# Top Features Decision Tree

**Feature Importance:**  
Based on Gini Index

Top Five

1. Age
2. Monthly Income
3. Overtime\_No
4. Years at Company
5. Job Satisfaction



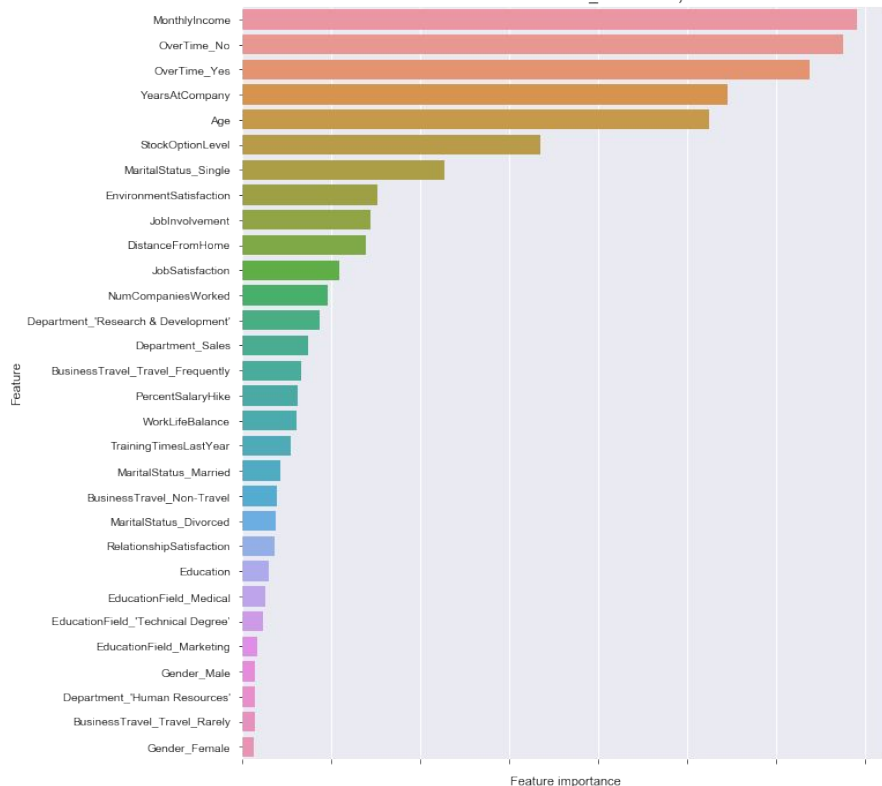
# Top Features Random Forest

## Feature Importance Based on Gini Index

### Top Five

1. Monthly Income
2. Overtime\_No
3. Overtime\_Yes
4. Years at Company
5. Age

Top 30 - Features importance - RandomForestClassifier(bootstrap=True, class\_weight=None, criterion='gini', max\_depth=4, max\_features='sqrt', max\_leaf\_nodes=None, min\_impurity\_decrease=0.0, min\_impurity\_split=None, min\_samples\_leaf=2, min\_samples\_split=2, min\_weight\_fraction\_leaf=0.0, n\_estimators=1000, n\_jobs=-1, oob\_score=False, random\_state=345, verbose=0, warm\_start=False)



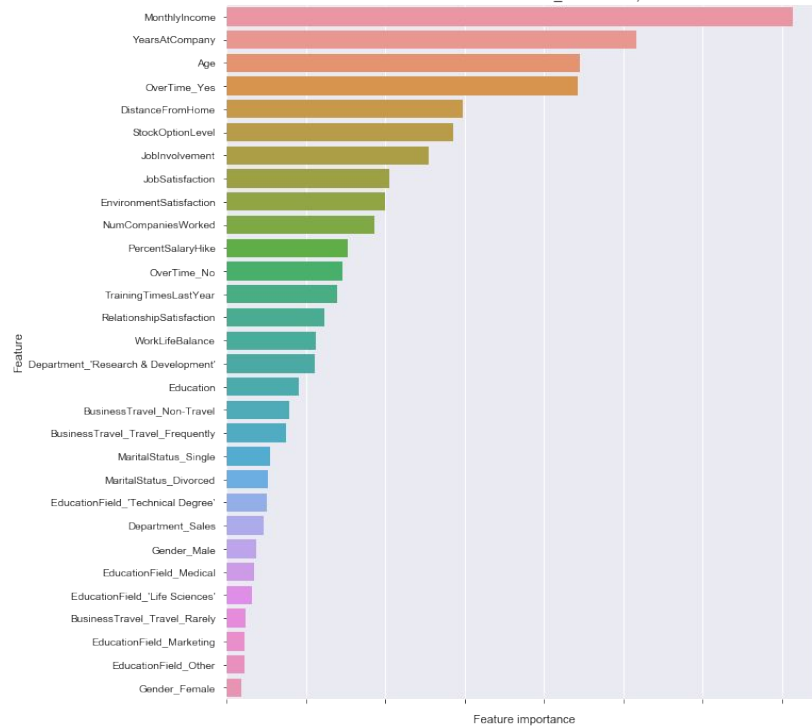
# Top Features Gradient Boosting

**Feature Importance:**  
Based on Friedman

Top Five

1. Monthly Income
2. Years At Company
3. Age
4. Overtime\_Yes
5. Distance From Home

Top 30 - Features importance - GradientBoostingClassifier(criterion='friedman\_mse', init=None, learning\_rate=0.25, loss='deviance', max\_depth=4, max\_features='sqrt', max\_leaf\_nodes=None, min\_impurity\_decrease=0.0, min\_impurity\_split=None, min\_samples\_leaf=2, min\_samples\_split=2, min\_weight\_fraction\_leaf=0.0, n\_estimators=1500, n\_iter\_no\_change=None, presort='auto', random\_state=345, subsample=1, tol=0.0001, validation\_fraction=0.1, verbose=0, warm\_start=False)



# Highest Attrition Ratio

Attrition	No	Yes	All	YesToNo	YesOverTot
TotalWorkingYears					
40	0	2	2	inf	100.00
1	41	40	81	97.56	49.38
0	6	5	11	83.33	45.45
2	22	9	31	40.91	29.03
37	4	0	4	0.00	0.00
38	1	0	1	0.00	0.00

The highest ratio of attrition is in the first three years with the company. Between 30%-50% attrition.

The highest turnover rate is between the ages of 18-20 with an average turnover of 57%. Ages 59-60 saw no turnover, while 58 saw a turnover of 35%.

Attrition	No	Yes	All	YesRatNo	YesRatio
Age					
19	3	6	9	200.00	66.67
20	5	6	11	120.00	54.55
18	4	4	8	100.00	50.00
58	9	5	14	55.56	35.71
59	10	0	10	0.00	0.00
60	5	0	5	0.00	0.00

# Largest Disparity

The greatest disparity in turnout is within Job Role, Age, and Job Level.

For Job Role there is difference of up to 6x between “Sales Representative” and “Healthcare Representative”.

Attrition	No	Yes	All	YesToNo	YesOverTot
JobRole					
Sales Representative	50	33	83	66.00	39.76
Laboratory Technician	197	62	259	31.47	23.94
Human Resources	40	12	52	30.00	23.08
Sales Executive	269	57	326	21.19	17.48
Research Scientist	245	47	292	19.18	16.10
Healthcare Representative	122	9	131	7.38	6.87

Attrition	No	Yes	All	YesRatio	YesRatNo
JobLevel					
1	400	143	543	26.34	35.75
2	482	52	534	9.74	10.79
5	64	5	69	7.25	7.81
4	101	5	106	4.72	4.95

For Job Level, there is difference of up to 7x between “Level 1” and “Level 4”.