Human Resource Analytics

MGT7182

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Assignment 2

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Introduction

The purpose of this investigation is to uncover the primary variables attributing to attrition at the firm and present the insights derived from the dataset to the relevant HR managers. If the root cause of attrition is identified the HR managers can then implement tailored programs to prevent future attrition. Employee attrition is defined as the loss of employees for a variety of reasons, including low financial compensation and unsatisfactory working environment. (Alduayj & Rajpoot, 2018)

The challenge of employee retention is exacerbated by the global marketplace were employees are now connected by platforms such as LinkedIn, increasing exposure to the wider market creating higher rates of attrition (Qin, 2021)

Therefore, predicting employee attrition has become an integral component within HR analytics. The importance of retaining talented employees has become a focus not only due to the significant financial costs associated with rehiring but also lower productivity as a result of damaged team spirit. Maintaining long-term skilled employees is crucial for every company seeking a competitive advantage. (Carmeli and Weisberg, 2006) (Eduvie, et al, 2021).

This report utilizes the tools Tableau and KNIME to visualize and glean insights from the vast data providing context to the specific business problems. Using tableau, the data is explored visually to identify correlations and a dashboard created using the most insightful visualisations. KNIME will be used to split the data into 80:20 ratios and to then produce predictive models for attrition such as Decision Tree, Random Forest and Gradient Boost.

Literature review

There is an abundance of rich literature relating to employee attrition as demonstrated by numerous studies carried out to determine the primary drivers of attrition. One such study using random forest model found variables salary, previous number of companies worked and age as significant predictors of attrition. The regression model found employees who travelled frequently were twice as likely to leave. (Yang, Ravikumar and Shi, 2015)

A number of further studies found similar results that variables monthly income, age and job satisfaction are highly related to attrition (A Lao D et al, 2013) (Eduvie, et al, 2021) (Kashyap and Kriti, 2018), (Assel et al., 2021). In addition to income, Alhashmi found a significant positive correlation between working overtime and attrition. It (Alhashmi, 2019)

A limitation of past research is not addressing the problem of class imbalance that arises in real-world attrition data. (Alduayj & Rajpoot, 2018).

Methodology

A CRISP-DM (Cross Industry Standard Process for Data Mining) methodology is used for data mining which provides an overview of the data life cycle. The Aim behind using CRISP-DM model is to minimize the cost in large projects as it's more reliable, more repeatable, and faster to use.

Fig. Phases of CRISP-DM process model

Steps Performed in TABLEAU

- Step 1 gives a preview of the dataset; tableau makes an assumption of the data type but it's essential to double check the type above each field is correct such as date variables set correctly as date.
- Click on sheet 1 to start exploration of the data as shown in Step 3. The variable Attrition is a dimension which can be changed to a measure by either manually moving the dimension to the rows shelf and changing it to count.
- Alternatively, we can produce an attrition measure by creating a calculated field as in Step 4 & 5. By using the 'IF' function for when attrition is yes to equal 1 and when attrition is no to equal 0 as shown Step 6.
- We now have attrition as a dimension and a measure called 'AttritionYES' which can be used for any visualisation involving attrition as shown Step 7.

We can calculate relevant KPI’s to show the aggregate situation using the newly created ‘AttritionYES’ measure. This is done by filtering for relevant measure values as in Step 8.

- The default measure values will be given as a sum. However, the average of each value will give greater insight so this can be easily changed by changing the measure type as shown Step 9.
- If we wanted to investigate job satisfaction we move the pill across to the columns and attrition is moved across to rows. The attrition dimension is converted to measure(count). We want to distinguish between attrition count “yes” and “no” so we can filter by dragging attrition across to colour.
- As shown in Step 10 the largest number of attrition occurred from employees who had high job satisfaction with 83 employees leaving. The lowest number of attrition occurred from the medium category at only 53 employees leaving. However, this does not represent the full picture as the group sizes are significantly. It would be more interesting to express attrition as a percentage of total instead of count as shown Step 11.
- The computation must be changed from table(across) to table(down) as shown in Step 12. This step is important for all other visualisations that wish to calculate the % proportion of employees leaving from each group/category.
- This produces a much more useful visualization that shows 25.95% of employees within low group left the firm compared to only 15.25% who rated job satisfaction as very high as shown in Step 13. Surprisingly there is no significant difference in the % of total count of attrition between category high at 18.78% and medium at only marginally higher 18.93%.
- We can also assume that distance from work will be a variable that should be examined in greater detail to provide useful insights. Distance from work is a measure that ranges from 1 – 29 miles from work.
- It would be beneficial to categorize distance from work as either short distance or long distance. This is done by creating parameter for short distance and large distance as shown in Step 14. Short distance parameter is defined as minimum 1 and maximum 9miles. Large distance is categorised as larger than 10miles.
- Create calculated field for distance from home using the newly created parameters as in Step 15.
- We can now create visualisation for distance from home using the parameter short/large distance filter as shown in Step 16.

Data Preprocessing

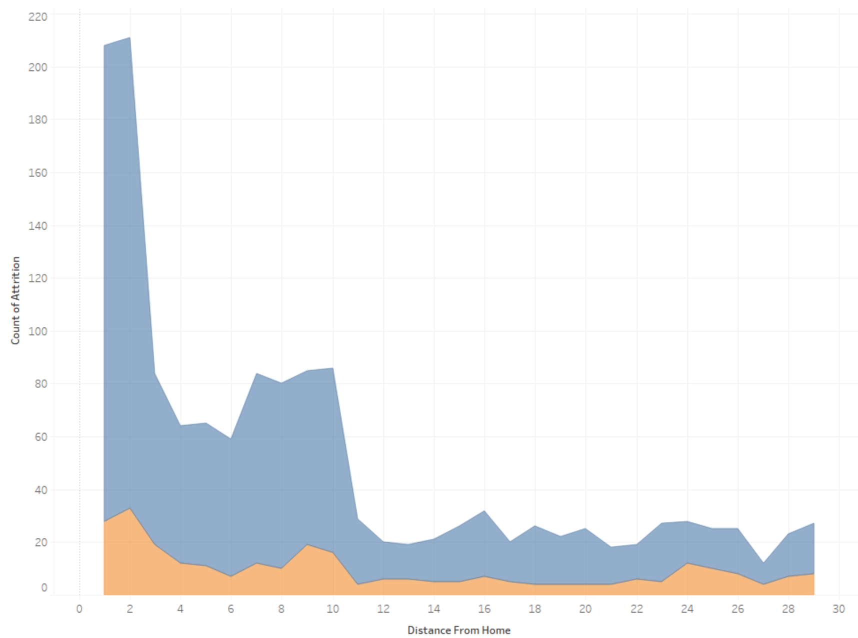
The dataset contains 1470 instances and 35 attributes of employee data from previous year. Within the 35 attributes is the target variable attrition. To determine the company's attrition rate, 'ID' is the unique indetifier, 'DOB' variable can be excluded as the variable age contains the same information. The variables 'Over18', 'StockOptionLevel' and 'Standard hours' can be excluded from further analysis as they lack variability and therefore provide zero insight. The statistics node is used to get the data's summary statistics.

- For data quality concerns, the age exceeding 65 years is removed using the 'Rule Engine' and 'Row filter' nodes in KNIME, and a new column called 'C_Age' is generated. This is due to 65yrs old being considered the age of retirement age in most companies.
- Using Rule Engine, travel frequency 0 is replaced with 'None,' and a new column 'C_TravelFreq' is generated.
- Few numerical variables like 'Education', 'EnvironmentalSatisfcation', 'JobInvolvement', 'Job Satisfaction', 'PerformanceRating', 'RelationshipSatisfaction' and 'WorkLifeBalance' are converted into categorical variable using 'Number to String' node.
- The cleaned data is then viewed using the 'Table View' node and then it is saved in the system using 'Excel Writer' node.
- On closer inspection of the target variable out of the 1470 instances 1190 were no and only 282 were yes for attrition. Therefore, the data has significant imbalance.
- We need to check for multicollinearity. As shown below monthly income and job level are highly correlated. It is unadvisable to use highly correlated variables together as it risks overfitting model.

	MonthlyIncome	JobLevel	TotalWorkingYears	PerformanceRating	PercentSalaryHike
MonthlyIncome	1.00000000	0.95029991	0.754617479	-0.017120138	-0.02726859
JobLevel	0.95029991	1.00000000	0.763474224	-0.021222082	-0.03473049
TotalWorkingYears	0.75461748	0.76347422	1.000000000	0.003721072	-0.02547417
PerformanceRating	-0.01712014	-0.02122208	0.003721072	1.000000000	0.77355000
PercentSalaryHike	-0.02726859	-0.03473049	-0.025474169	0.773549996	1.00000000

Exploratory Data Analysis

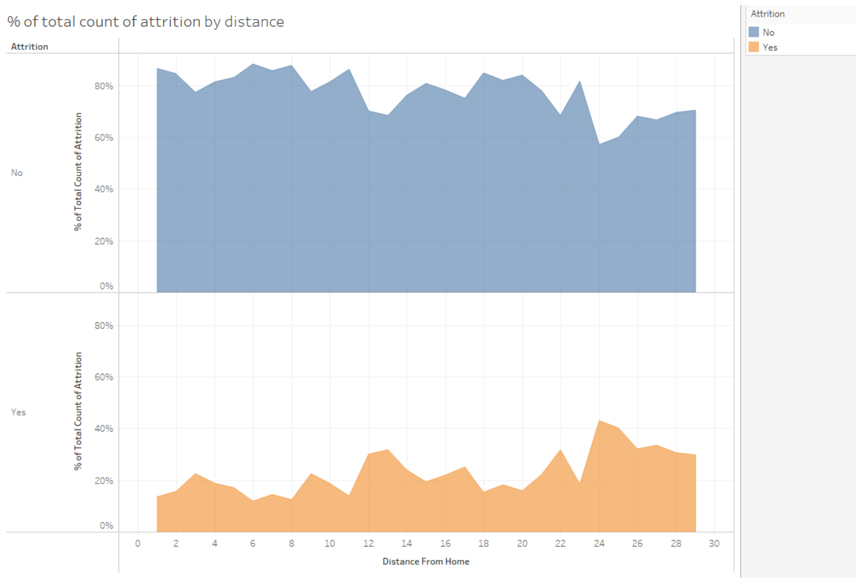
Attrition by distance from home



Intuitively it was expected that as distance from work increased so would the number of attrition as people are assumed to not like travelling to work. However, surprisingly we found that the opposite is true that the majority of employees leaving the company live within 2 miles from work.

It is possible due to the large number employees living within 2 miles of the office that it's not centrally located in a city and therefore not in a desirable location. Furthermore, as the workplace may not be near other facilities a recommendation would be to build a lounge area for employees.

However, the trend is arguably misleading as the majority of people live within 2miles it is then unsurprising that a larger count of attrition will occur from this group. More insightful is a visualization of the % proportion of people leaving from each unit distance from home.

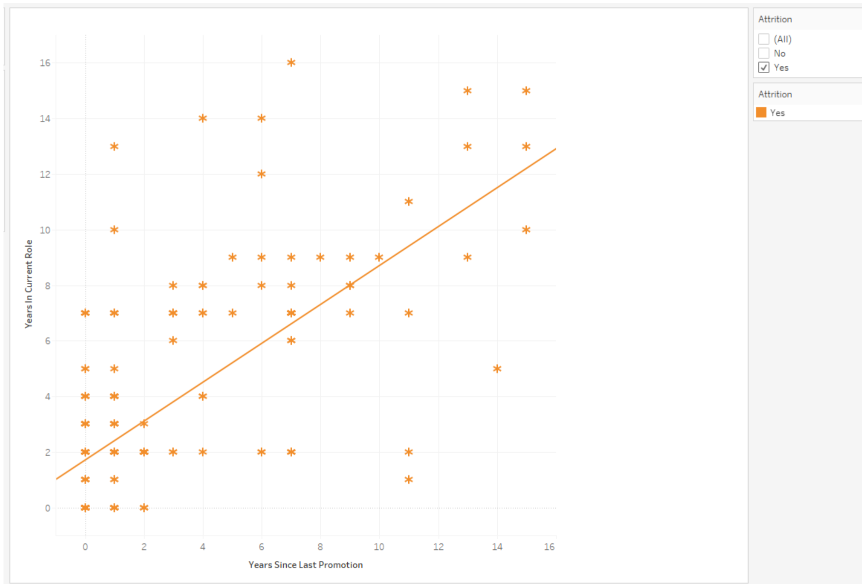


When accounting for the larger number of people who live near work, the trend is in line with expectations. The proportion of attrition increases as distance from home increases. Only 13.46% of people who live within one-mile work choose to leave whereas 42.86% of people who live 24miles away left the company.

Attrition by yrs. since last promotion

Interestingly high levels of attrition occur within one year of being promoted as shown by the dense cluster of stars (indicating attrition) in the 1yr since promotion and less than 4yrs in current role.

It appears new employees who have recently been promoted have the highest level of attrition as they potentially can now get higher salaries elsewhere. Seemingly employees stay until they have been promoted and then leave soon after. Furthermore, the cluster of attrition around 7-9yrs in current role and last promotion 4-7yrs is also concerning.



This result can be explained by examining years at company with promotion. The scatter plot for promotion and yrs. at company highlight an interesting correlation. From the trend line it is observed a positive relationship exists between years at company and years since last promotion.

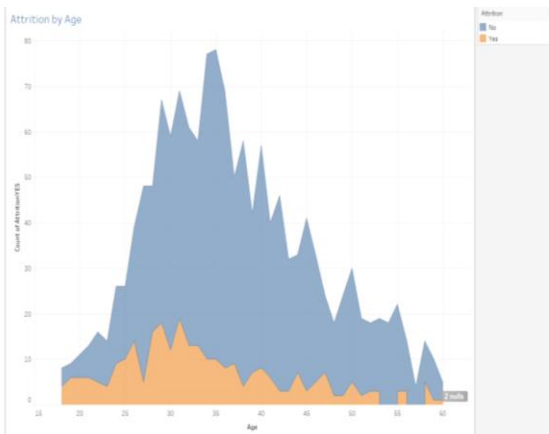
This is interesting as it indicates as employees stay longer at the company they receive fewer promotions. The longer employees stay at the firm the less likely they are to receive a promotion indicating stagnating employee development. This could explain why large number employees leave after receiving a promotion within the first few years.

Attrition by age

In line with expectations the highest count of attrition is relatively young at 31yrs old. Interestingly the attrition count decreases significantly from 40yrs onwards. The company should therefore focus on retaining employees below 40yrs old.

The below figure presents the full picture showing a clear trend that as age increases the proportion of attrition for each age decreases. The largest proportion of attrition is for 19yr olds with 66.67% of employees aged 19yrs leaving the company.

A number of possible reasons exist for this trend which is well documented in literature. Younger people are usually more ambitious and flexible to relocate elsewhere. The average monthly salary for younger age groups is significantly lower than older employees. Therefore, younger employees have decided to leave to either further their education credentials or seek higher salaries from rival firms.



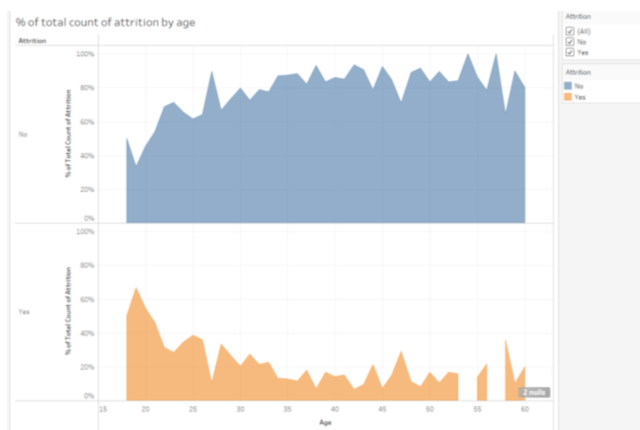


Fig 1 Attrition by Age

Fig 2 Percentage of total count of age

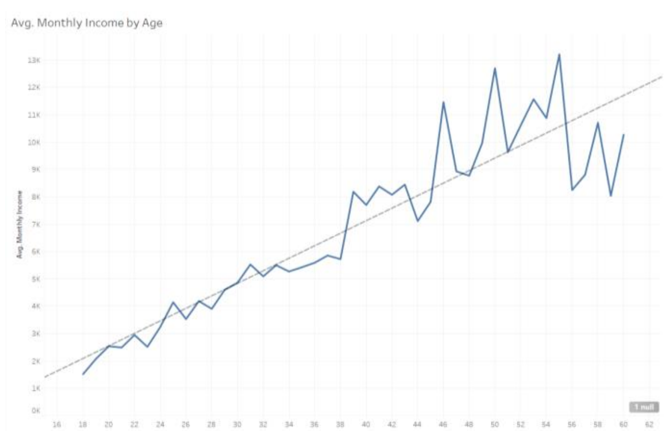


Fig3 positive correlation between age and salary

Number of companies worked

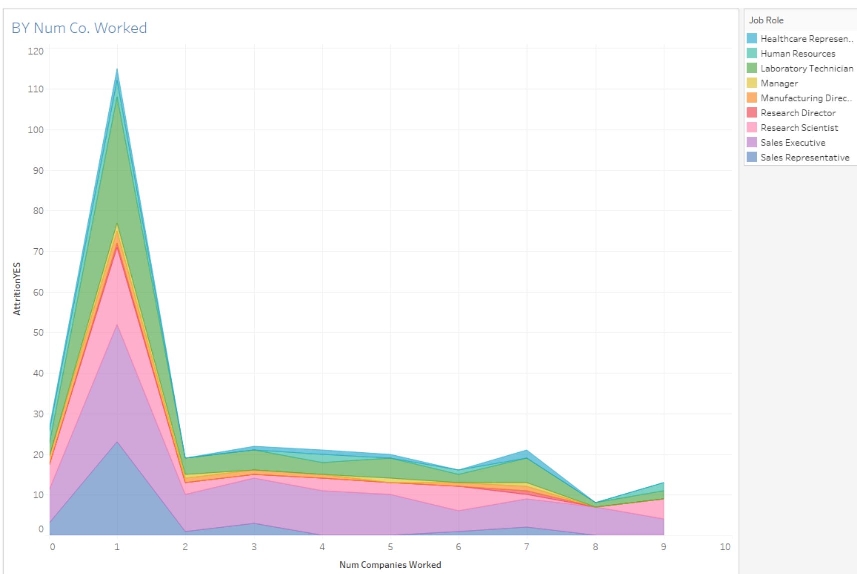


Fig. Number of companies worked

The highest level of attrition is amongst employees who have only worked at 1 previous company. This is likely related to age as younger employees will have had less experience and as a consequence lower salaries.

Attrition by overtime

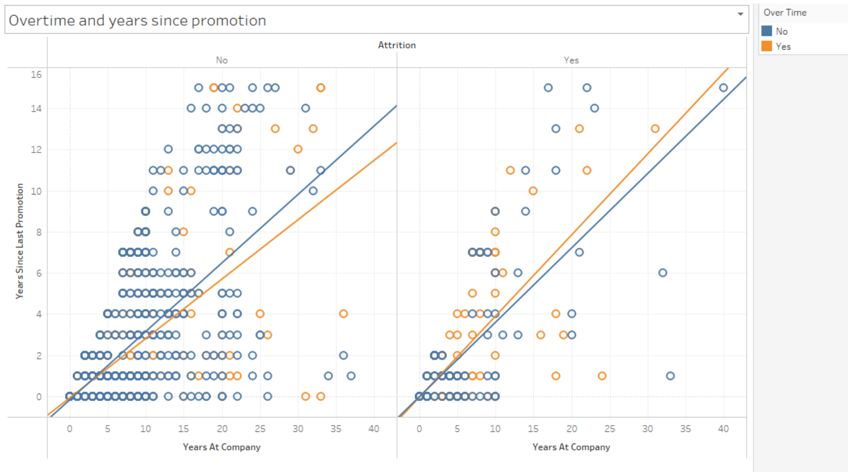
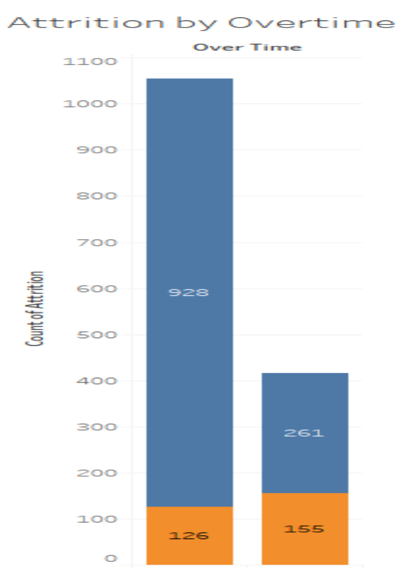


Fig. Scatterplot for Overtime and Year since promotion

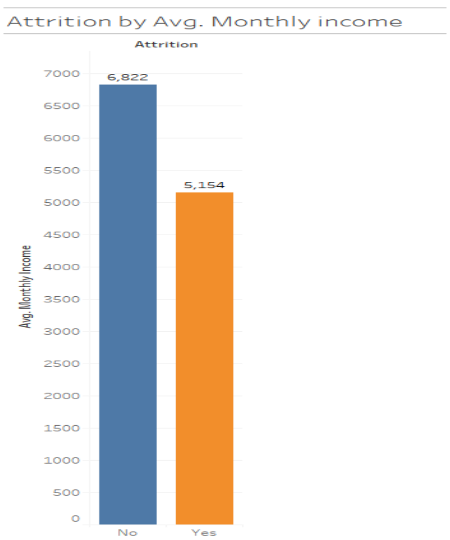
A very surprising insight can be gained from the scatter plots shown above. The scatterplots show that for hard-working employees who decide to help the company by working overtime on average receive fewer promotions. This is the opposite of what the firm should be doing which incentivizing hard work and not discouraging it. As the trend line for overtime amongst employees who decided to leave is steeper than for no-overtime thus indicating overtime employees must wait longer for a promotion.



It is therefore unsurprising that a larger count of employees who work over time leave the firm at 155 compared to 126.

Taking into account that a larger number of employees do not work overtime the proportion of employees who work overtime leaving the firm is 37.26% compared to only 11.95% of those who do not, this is due to the apparent unfairness that employees who don't work overtime get promoted faster

Attrition by monthly income



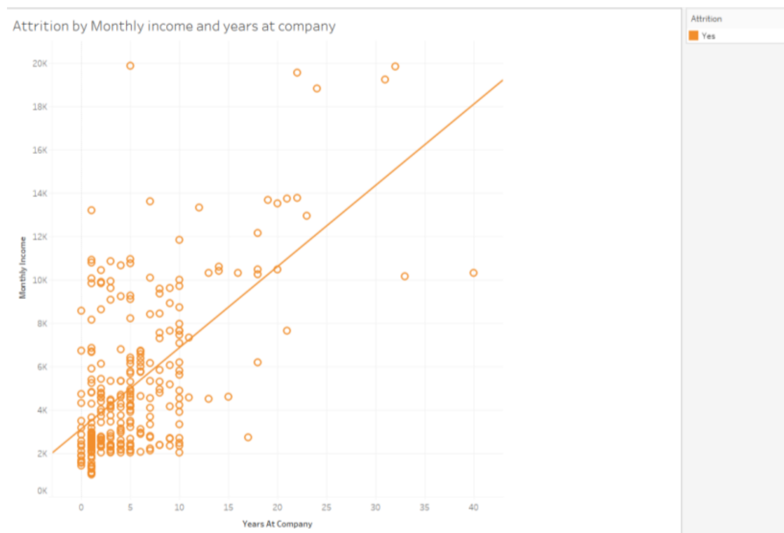


Fig. Attrition by Average monthly income

Fig. Attrition by monthly income and years at company

The average monthly income for people who leave is significantly less than for those who stay. This disparity is not surprising as income is a primary reason for attrition as most people make career choices based on monetary compensation. The enticement of potentially higher salaries from rival firms causes many employees to leave.

When attrition is filtered to show only yes (fig1) this presents a clearer insight as the attrition in the area less than 10yrs and below 6k monthly salary is very dense. This section accounts for the most attrition indicating most employees leave within the first 10yrs at monthly salary below 6k.

Furthermore, the attrition rate decreases for employees after 10yrs working at the firm. This could be due to employees being accustomed and comfortable at work and wish to remain until retirement.

Attrition by Job Role

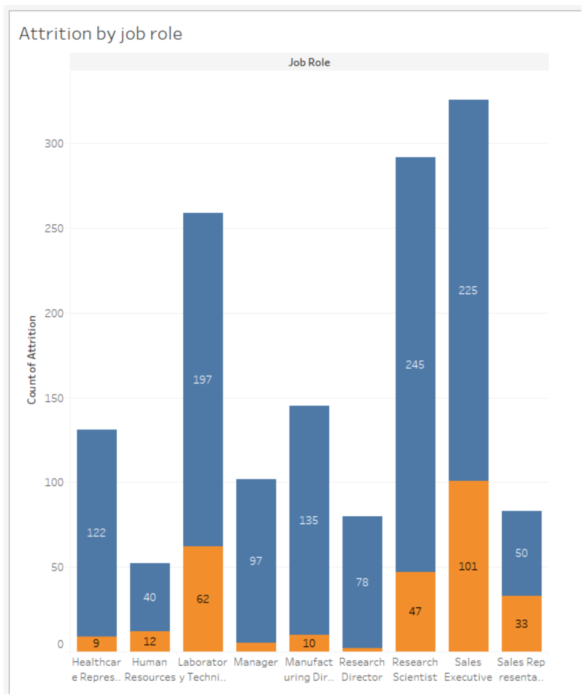


Fig. Attrition by Job Role

The largest count of attrition is sales executive with 101 employees leaving, followed by 62 laboratory technicians. The lowest count of attrition is research director at only 2. The company should remedy this by incentivizing the sales executives to remain as they are the largest group leaving.

Although the company should focus on the count of each job role leaving, more interestingly is the proportion of attrition with each role. As can be seen below the proportion of attrition is largest amongst sales representatives with 39.76% of this group leaving followed by sales executives at 30.98%. This insight highlights the need for change in the sales department to prevent such high levels of attrition.

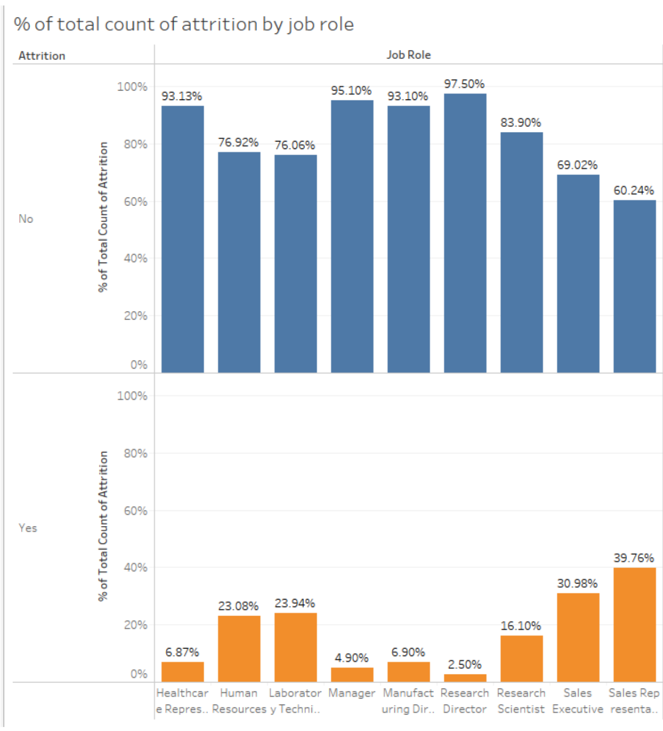
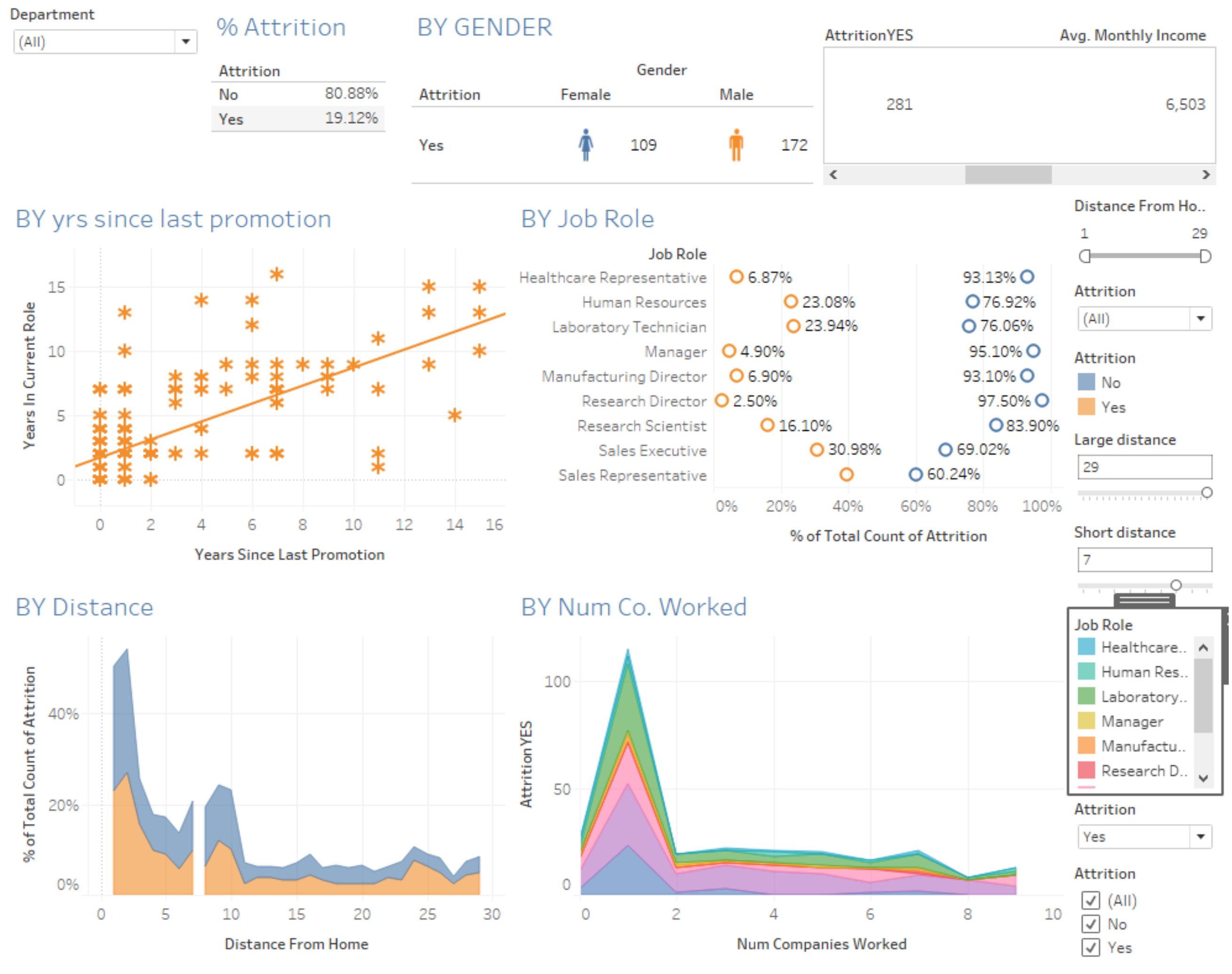


Fig. Percentage of total count of attrition by Job role

Job Role	
Healthcare Representative	6,811
Human Resources	3,093
Laboratory Technician	2,886
Manager	17,455
Manufacturing Director	6,447
Research Director	16,510
Research Scientist	2,888
Sales Executive	6,231
Sales Representative	2,579

Fig. Median monthly income by Job role

Dashboard



Department
(All)
% Attrition
Attrition
No 80.88%
Yes 19.12%
BY GENDER
Gender
Attrition Female Male
Yes 109 172
AttritionYES
Avg. Monthly Income
281
6,503
BY yrs since last promotion
Years In Current Role
Years Since Last Promotion
BY Job Role
Job Role
Healthcare Representative 6.87% 93.13%
Human Resources 23.08% 76.92%
Laboratory Technician 23.94% 76.06%
Manager 4.90% 95.10%
Manufacturing Director 6.90% 93.10%
Research Director 2.50% 97.50%
Research Scientist 16.10% 83.90%
Sales Executive 30.98% 69.02%
Sales Representative 60.24%
% of Total Count of Attrition
Distance From Ho..
1
29
Attrition
(All)
Attrition
No
Yes
Large distance
29
Short distance
7
BY Distance
% of Total Count of Attrition
Distance From Home
BY Num Co. Worked
Attrition YES
Num Companies Worked
Job Role
Healthcare..
Human Res..
Laboratory..
Manager
Manufactu..
Research D..
Attrition
Yes
Attrition
(All)
No
Yes

Data Modelling

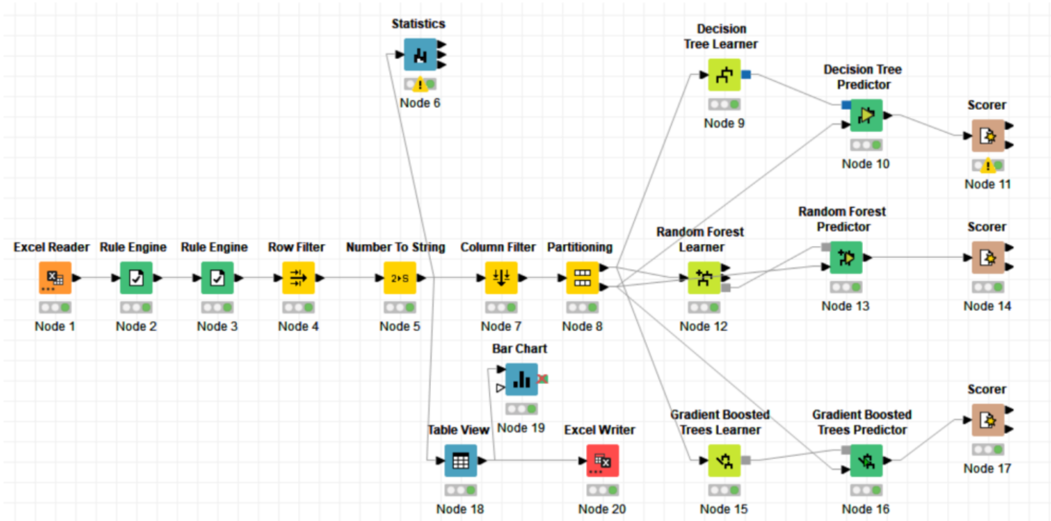


Fig 1. Model structures in KNIME

Decision Tree

The flowchart like structure made up of nodes and branches is a decision tree. Data splitting is performed at each node based on the input features of the data (KNIME, 2020). This splitting continues until all the data is split and belongs to same class or no further split is possible. This whole process generates the tree structure. Very first split is called the root node. The end nodes are called leaf nodes. Decision tree can only be used if the data is categorical. In this report decision tree leaner is used as we have identified if the employees had left the company or not.

The goal of using the decision tree is to split the training set until each split is pure.

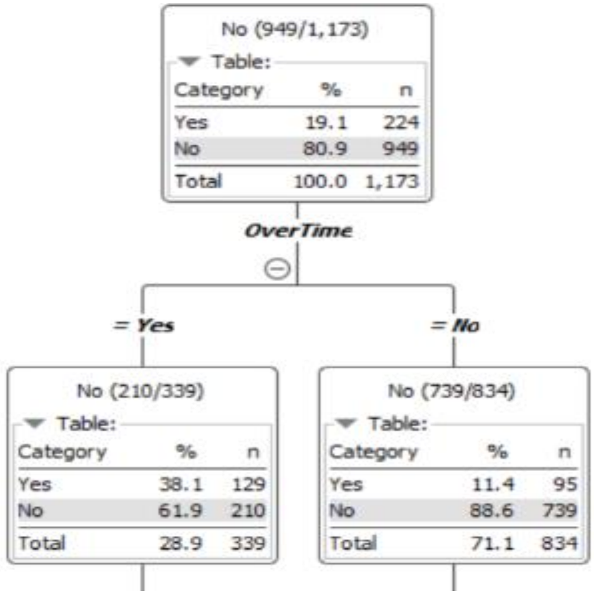


Fig 2. 1st Split

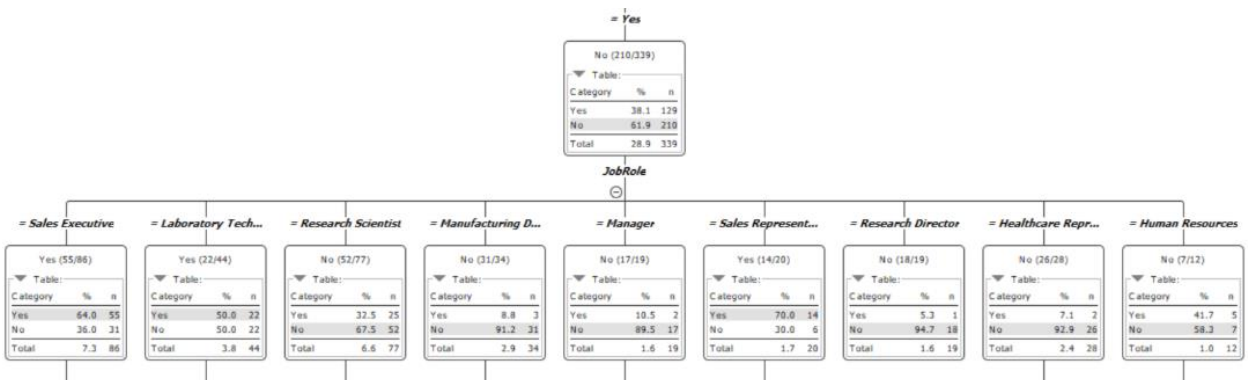


Fig 3. 2nd Split

Fig 2. Shows the 1st split that involves 'OverTime' and partition the input subset in two subsets "Yes" or "No" this represents that 38.1% of the total employees who left the company worked overtime and only 11.4% of the employees left the company who didn't worked overtime. Later the employees who worked overtime and left the company are split using 'JobRole'. Upon further observation it can be observed that the data is split according to the role types of the employee like 'Sales Executive', 'Laboratory technicians', 'Research Scientist', 'Sales Representatives', 'Manufacturing Director', 'Manager', 'Research Director', 'Healthcare representative' and 'Human Resources'. Moreover, from the Fig 3. it can be seen that the job roles with maximum attrition rate are 'Sales representative' with 70% followed by 'Sale Executive' with 64%, 'Laboratory technicians' with 50% and 'Research Scientists' with

32.5%. The least attrition rate is observed at administrative level i.e. 'Manufacturing Director', 'Research Director', 'Manager' and 'Healthcare Representative'.

Factors responsible for employee attrition according to job role are

- Sales Representatives who are less than or equal to 33.5yrs of age and working overtime are most likely to leave the company with attrition rate of 100%.
- Managers with monthly rate above 21,114.5 working overtime are more likely to leave the company with attrition rate of 66.7%.
- Laboratory technicians with monthly income below 3806 working overtime are more likely to leave the company with attrition rate of 67.9%.
- Research Scientists with monthly income below 2476 working overtime are more likely to leave the company with attrition rate of 65.4%.
- Human Resource with low level of job satisfaction and working overtime are most likely to leave the organization with attrition rate of 41.7%.

Upon further prediction the accuracy of the model comes to 78.76% whereas the Cohen's kappa comes at 0.324 which is above 0.3 meaning the prediction of the model is good.

Attrition \...	Yes	No
Yes	26	30
No	32	204

Correct classified: 230 Wrong classified: 62

Accuracy: 78.767 % Error: 21.233 %

Cohen's kappa (κ) 0.324

Fig 3. Confusion matrix for Decision Tree

Random Forest

As many different trees can produce the accurate predictions than just one tree Random forest is used. It is a supervised classification algorithm and builds number of trees which are trained slightly different and are considered for the final decision. Every decision trees are trained using random sampling with replacement of the original dataset (KNIME, 2020).

Attrition \ Prediction (Attrition)	Yes	No
Yes	17	39
No	10	228

Correct classified: 245 Wrong classified: 49

Accuracy: 83.333 % Error: 16.667 %

Cohen's kappa (κ) 0.326

Fig 4. Confusion matrix for Random Forest

The accuracy of the model comes to 83.33% whereas the Cohen's kappa comes at 0.326 which is greater than 0.3 meaning the prediction of the model is good as well. Furthermore, to increase the accuracy and kappa Gradient boosted tree is used.

Gradient Boosted Tree

Gradient Boosting is a powerful technique for building the predictive model and provides the best predictive accuracy (Github.io, 2017).

The original dataset is split using 'Partitioning' node into 'Gradient Boosted Trees Learner' and 'Gradient Boosted Trees Predictor'. The next step is to train the model using learner node were 80% of the data is used 20% data is used in prediction of the model. The GBM model is ran and resulting model parameters are used in the predictor node. Predictor node then pulls the test data and produces the result. Going forward to interpret the result 'Scorer' node is used which produces the below output.

Attrition \ Prediction (Attrition)	Yes	No
Yes	23	33
No	15	223

Correct classified: 246 Wrong classified: 48

Accuracy: 83.673 % Error: 16.327 %

Cohen's kappa (κ) 0.396

Fig 5. Confusion matrix for Gradient Boosted Tree

The accuracy of the model comes to 83.67% whereas the Cohen's kappa comes at 0.396 which is near by 0.4 which means this is the best prediction model.

Furthermore, the number of trees in this model can be pruned by using Out of bag approach.

Result

Models	Accuracy	Kappa
Decision Tree	78.76	0.324
Random Forest	83.44	0.326
Gradient Boost Tree	83.67	0.396

Table 1. Shows Accuracy and Kappa Value of prediction models

Recommendation

- They could recompense those who travel far distances by paying for their fuel to get to work.
- They can introduce programs that facilitate the development of high performing employees who have recently joined the company by setting out a clear progression pathway for their future career.
- They should introduce higher reward incentives for sales people.
- Overtime policy should be inspected and changes introduced that benefit hard-working employees
- There should be an increase in average monthly salary of younger people.

Conclusion

In conclusion the analysis performed using KNIME identify overtime and job role are the main predictors responsible for Employee attrition. These factors should be investigated further by the HR team to improve the attrition rate of the organization. Managers need to recognize that by additional overtime the company is losing more money through attrition than gained by extra work. The focus should be placed on the mental health of their employees by ensuring they are comfortable doing overtime and accordingly compensated. Employees are more likely to leave a job if the role's responsibilities are not as expected. Monthly Income, promotion, and job satisfaction levels are the secondary factors which needs to be addressed by providing incentives such as good performance pay. The managers of the company must be motivating and supportive. It is clear from the investigation employees are more concerned with monetary benefits rather than how happy/satisfied they are when deciding on whether to leave.

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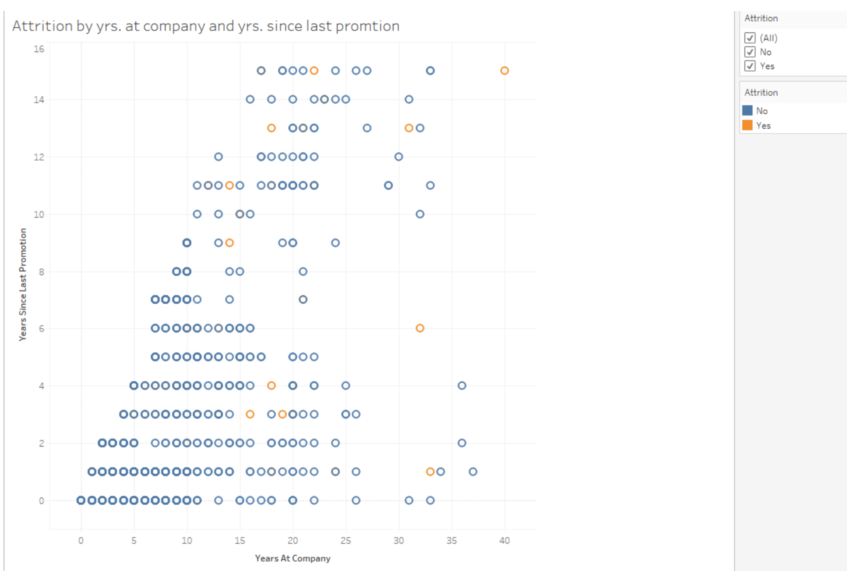
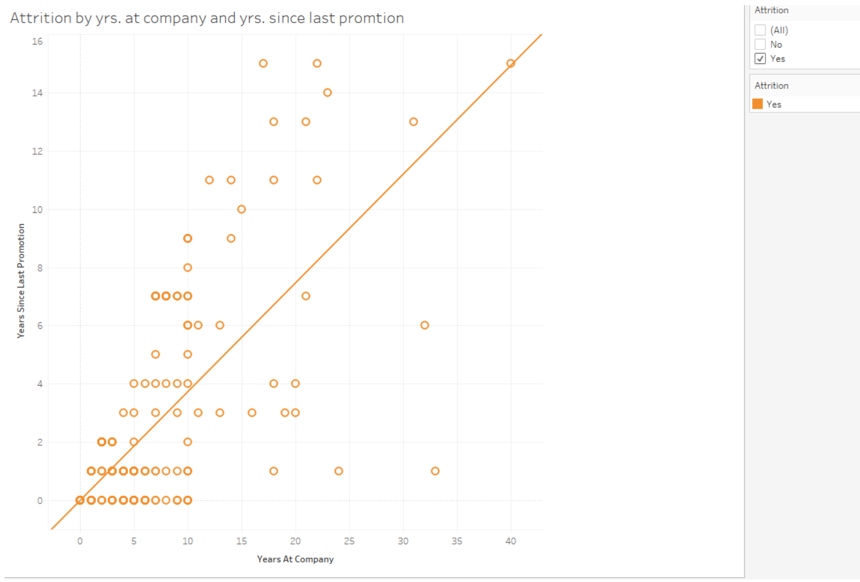
Appendix

Distance Fr..	Attrition No	Yes
1	86.54%	13.46%
2	84.36%	15.64%
3	77.38%	22.62%
4	81.25%	18.75%
5	83.08%	16.92%
6	88.14%	11.86%
7	85.71%	14.29%
8	87.50%	12.50%
9	77.65%	22.35%
10	81.40%	18.60%
11	86.21%	13.79%
12	70.00%	30.00%
13	68.42%	31.58%
14	76.19%	23.81%
15	80.77%	19.23%
16	78.12%	21.88%
17	75.00%	25.00%
18	84.62%	15.38%
19	81.82%	18.18%
20	84.00%	16.00%
21	77.78%	22.22%
22	68.42%	31.58%
23	81.48%	18.52%
24	57.14%	42.86%
25	60.00%	40.00%
26	68.00%	32.00%
27	66.67%	33.33%
28	69.57%	30.43%
29	70.37%	29.63%

Fig. table showing proportion of attrition by each unit of distance

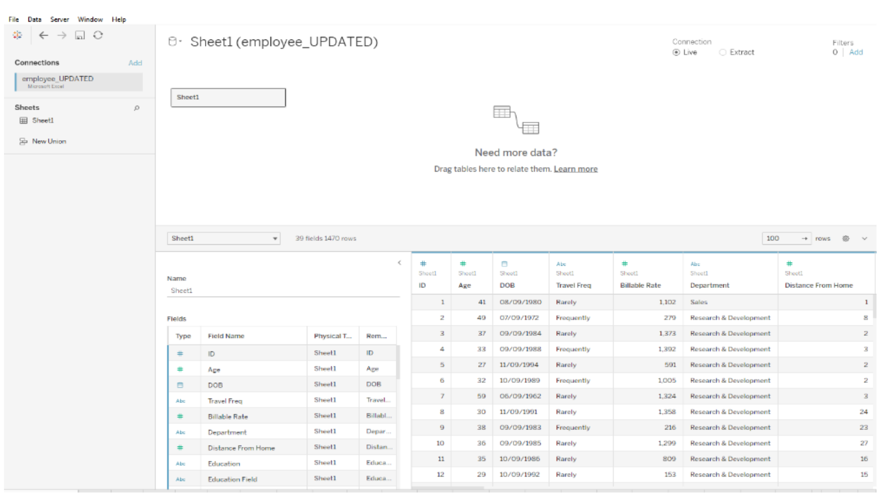




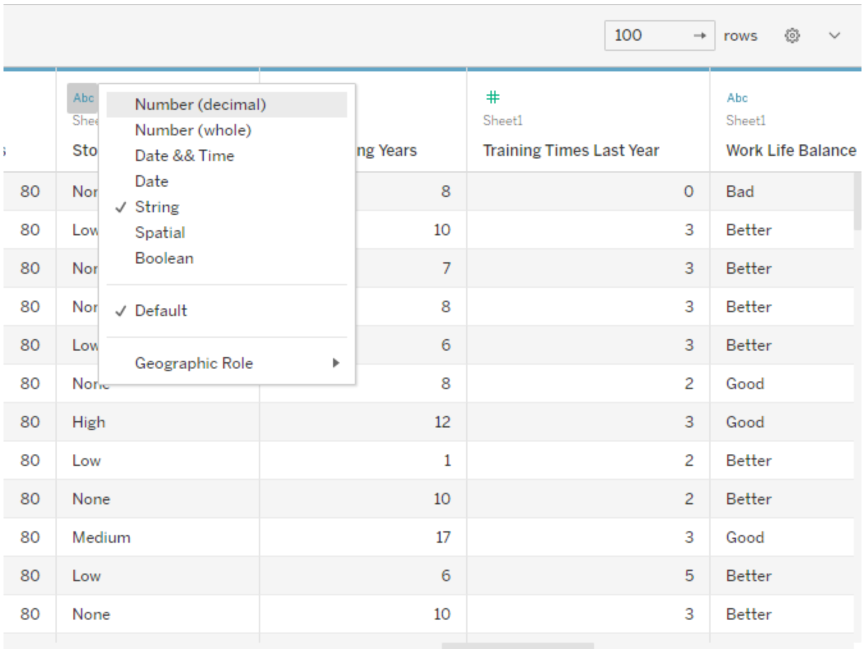
% of total Attrition by Overtime

	Over Time	
Attrition	No	Yes
No	88.05%	62.74%
Yes	11.95%	37.26%

Fig. Percentage of total attrition by overtime



Step 1


100 rows
Number (decimal)
Number (whole)
Date && Time
Date
String
Spatial
Boolean
Default
Geographic Role
ng Years
Sheet1
Training Times Last Year
Sheet1
Work Life Balance
High
Low
None
Medium
Bad
Better
Good

Step 2

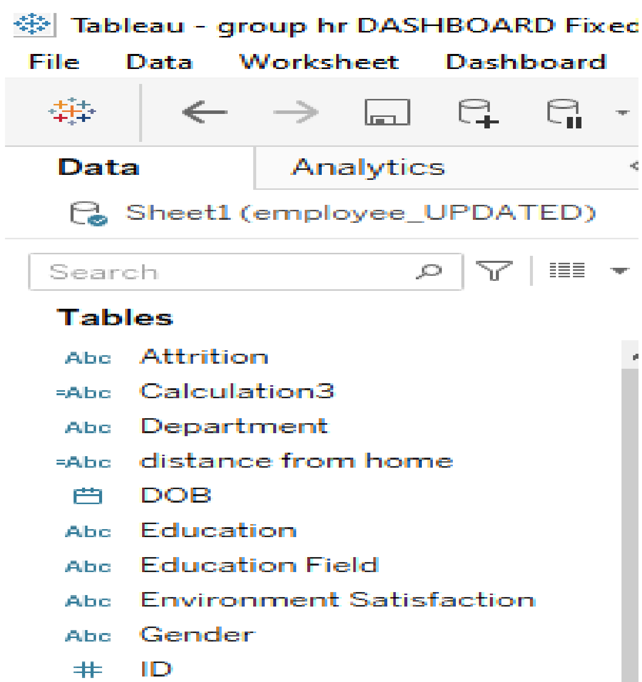


Tableau - group hr DASHBOARD Fixec
File Data Worksheet Dashboard
Data
Analytics
Sheet1 (employee_UPDATED)
Search
Tables
Attrition
Calculation3
Department
distance from home
DOB
Education
Education Field
Environment Satisfaction
Gender
ID

Step 3

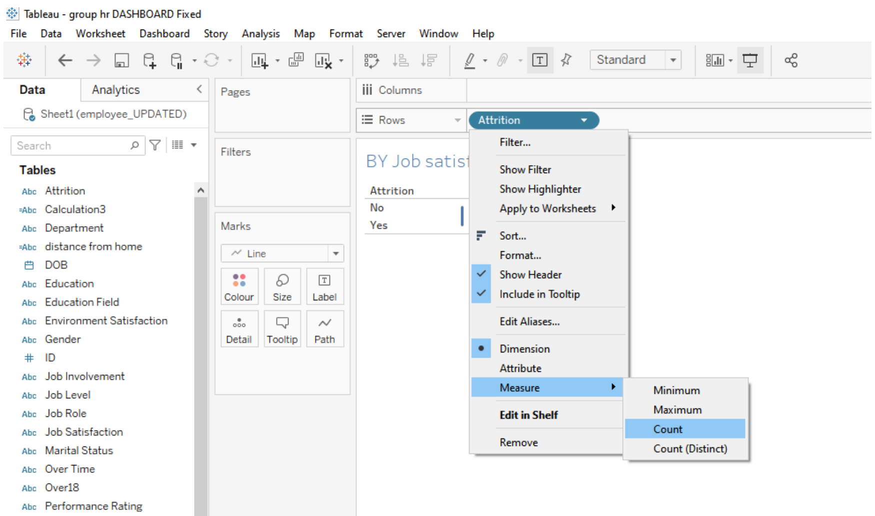


Tableau - group hr DASHBOARD Fixed
File Data Worksheet Dashboard Story Analysis Map Format Server Window Help
Standard
Data
Analytics
Sheet1 (employee_UPDATED)
Search
Tables
Attrition
Calculation3
Department
distance from home
DOB
Education
Education Field
Environment Satisfaction
Gender
ID
Job Involvement
Job Level
Job Role
Job Satisfaction
Marital Status
Over Time
Over18
Performance Rating
Pages
Filters
Marks
Line
Colour
Size
Label
Detail
Tooltip
Path
Columns
Rows
Attrition
BY Job satis
Attrition
No
Yes
Filter...
Show Filter
Show Highlighter
Apply to Worksheets
Sort...
Format...
Show Header
Include in Tooltip
Edit Aliases...
Dimension
Attribute
Measure
Edit in Shelf
Remove
Minimum
Maximum
Count
Count (Distinct)

Step 4

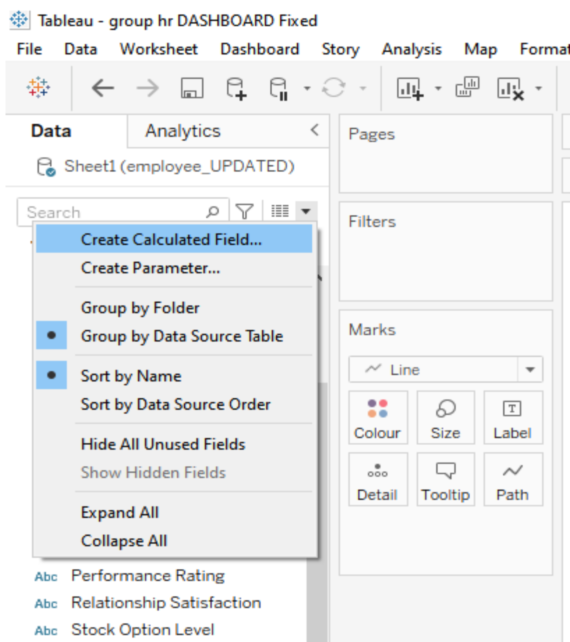
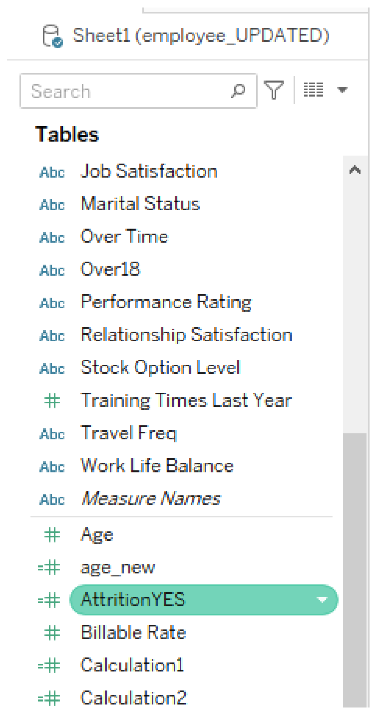


Tableau - group hr DASHBOARD Fixed
File Data Worksheet Dashboard Story Analysis Map Format
Data
Analytics
Sheet1 (employee_UPDATED)
Search
Create Calculated Field...
Create Parameter...
Group by Folder
Group by Data Source Table
Sort by Name
Sort by Data Source Order
Hide All Unused Fields
Show Hidden Fields
Expand All
Collapse All
Performance Rating
Relationship Satisfaction
Stock Option Level
Pages
Filters
Marks
Line
Colour
Size
Label
Detail
Tooltip
Path

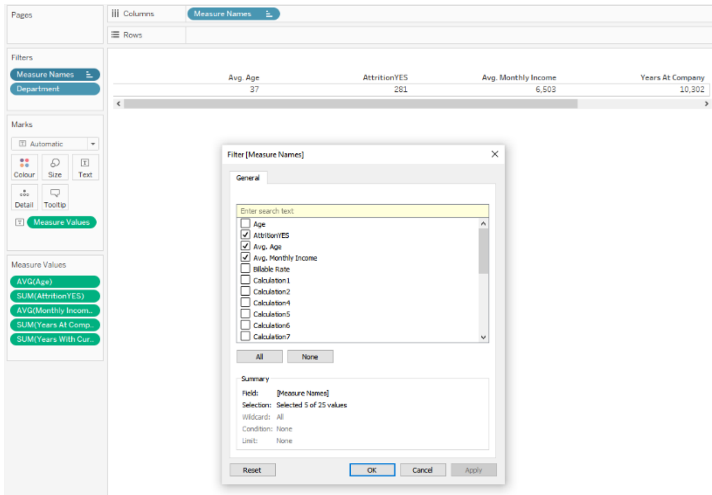
Step 5


AttritionYES
IF [Attrition] = "Yes" THEN 1
ELSE 0
END
The calculation is valid.
4 Dependencies
Apply
OK
All
Search
ABS
ACOS
AND
AREA
ASCII
ASIN
ATAN
ATAN2
ATTR
AVG
BUFFER

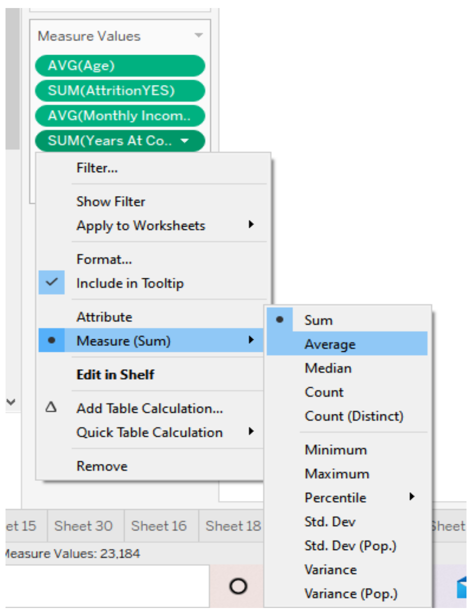
Step 6


Sheet1 (employee_UPDATED)
Search
Tables
Job Satisfaction
Marital Status
Over Time
Over18
Performance Rating
Relationship Satisfaction
Stock Option Level
Training Times Last Year
Travel Freq
Work Life Balance
Measure Names
Age
age_new
AttritionYES
Billable Rate
Calculation1
Calculation2

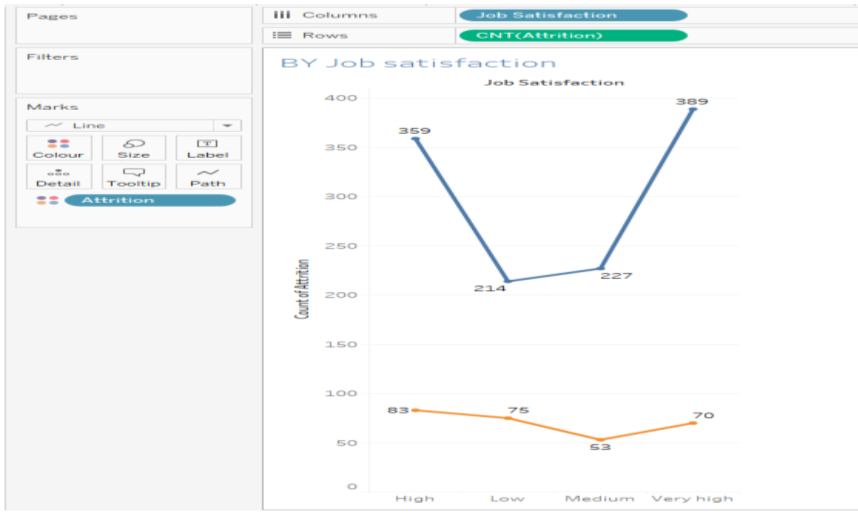
Step 7


Pages
Columns
Measure Names
Rows
Filters
Measure Names
Department
Avg. Age
AttritionYES
Avg. Monthly Income
Years At Company
37
281
6,503
10,302
Marks
Automatic
Colour
Size
Text
Detail
Tooltip
Measure Values
Measure Values
AVG(Age)
SUM(AttritionYES)
AVG(Monthly Incom..
SUM(Years At Comp..
SUM(Years With Cur..
Filter [Measure Names]
General
Enter search text
Age
AttritionYES
Avg. Age
Avg. Monthly Income
Billable Rate
Calculation1
Calculation2
Calculation4
Calculation5
Calculation6
Calculation7
All
None
Summary
Field: [Measure Names]
Selection: Selected 5 of 25 values
Wildcard: All
Condition: None
Limit: None
Reset
OK
Cancel
Apply

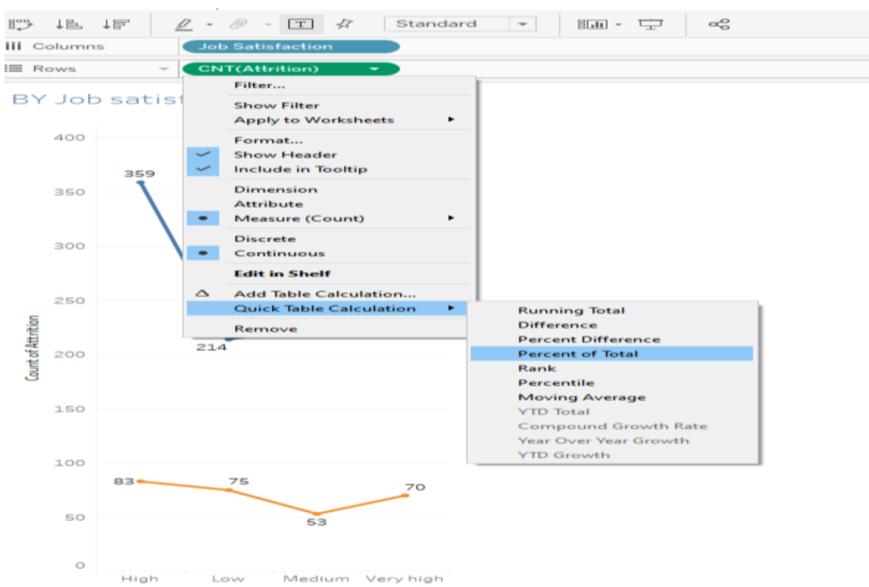
Step 8


Measure Values
AVG(Age)
SUM(AttritionYES)
AVG(Monthly Incom..
SUM(Years At Co..
Filter...
Show Filter
Apply to Worksheets
Format...
Include in Tooltip
Attribute
Measure (Sum)
Edit in Shelf
Add Table Calculation...
Quick Table Calculation
Remove
Sum
Average
Median
Count
Count (Distinct)
Minimum
Maximum
Percentile
Std. Dev
Std. Dev (Pop.)
Variance
Variance (Pop.)
et 15
Sheet 30
Sheet 16
Sheet 18
heet
leasure Values: 23,184

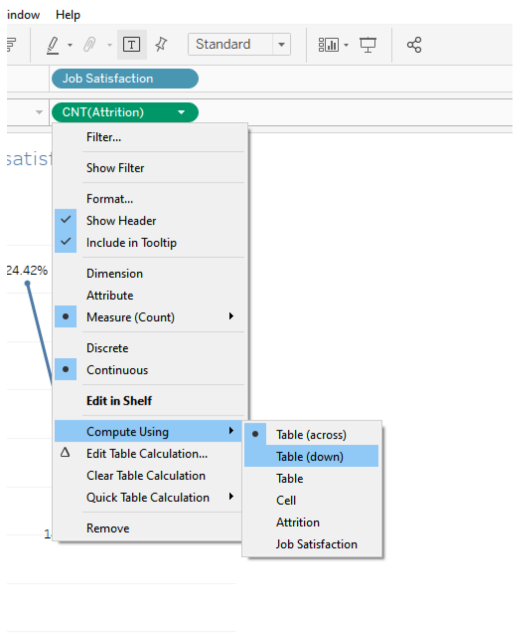
Step 9



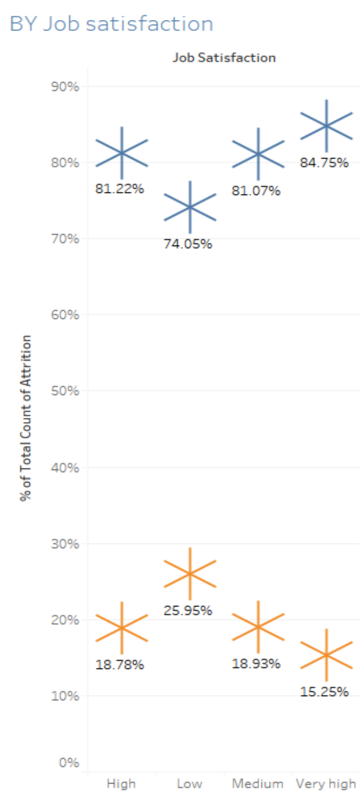
Step 10



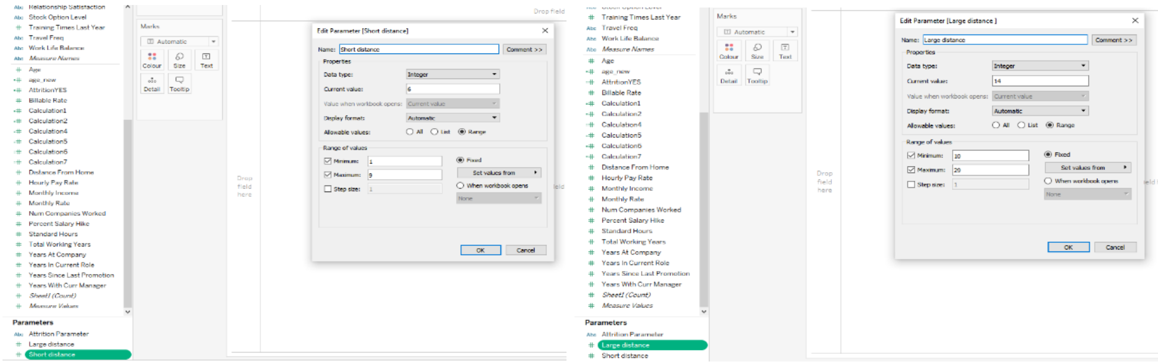
Step 11



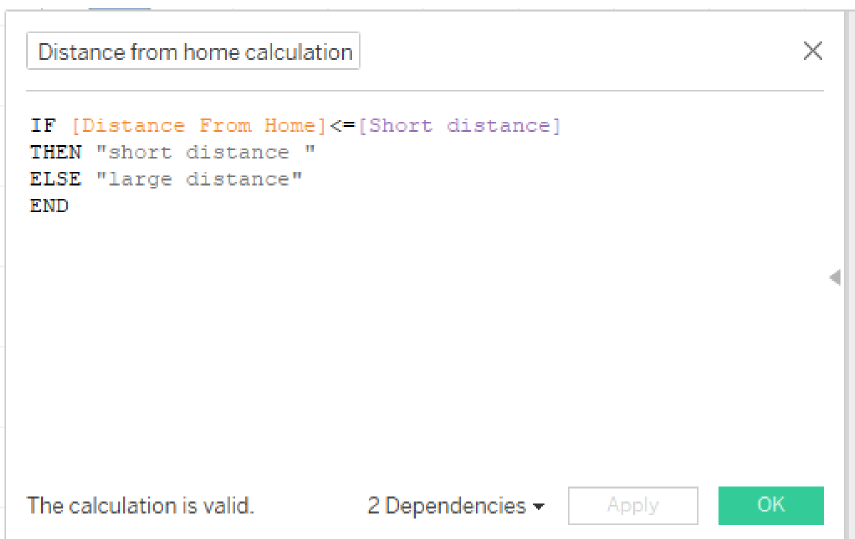
Step 12



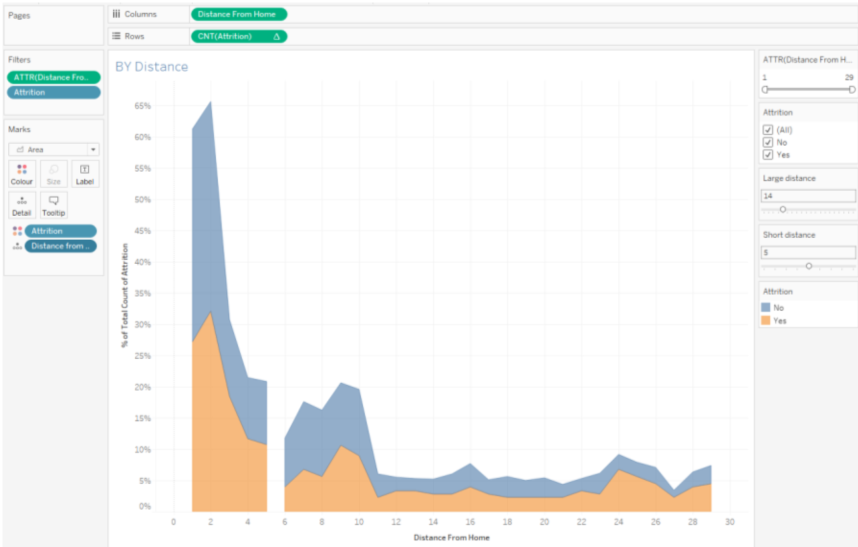
Step 13



Step 14



Step 15


Pages
Columns
Distance From Home
Rows
CNT(Attrition)
Filters
ATTR(Distance Fro...
Attrition
Marks
Area
Colour
Size
Label
Detail
Tooltip
Attrition
Distance from ...
BY Distance
% of Total Count of Attrition
Distance From Home
ATTR(Distance From H...
1
29
Attrition
(All)
No
Yes
Large distance
14
Short distance
5
Attrition
No
Yes

Step 16