HR Analytics

Assignment 2

Group BA-18

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2, 992 words

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INTRODUCTION AND BACKGROUND

Employee turnover has been extensively examined, according to Shaw *et al.* (1998). However, there is no typical explanation for why employees leave a company. Employee turnover is the movement of workers within the labour market, between employers, positions, and professions, as well as between employment and unemployment (Abassi *et al*., 2000). According to Price (1989), "turnover" is the ratio of the average number of persons in an organisation for a certain period divided by the number of organisational members who have left during that same period. When a position is vacated, whether voluntarily or involuntarily, a new employee must be hired and trained. This entire process is referred to by management as turnover. Turnover is the term for this replacement cycle, Woods (1995). Employee turnover is a retrospective indicator of the employee retention behaviour of any organisation. Thus, turnover statistics can be used for describing and diagnosing the reasons of employee churn in an organisation.

Firth et al. (2004) summarised that workplace stress, lack of control of personal agency and economic disparity are some of the prime driving factors of employees leaving the organisation. Employees may become disengaged and dissatisfied with their jobs and careers, less committed to their organisations, and eventually display a propensity to leave the company if they are given insufficient information on how to perform the job adequately, unclear expectations of peers and supervisors, ambiguous performance evaluation methods, intense job pressures, and lack of consensus on job functions or duties (Ongori, 2007; Tor *et al.*, 1997). Hall (2019) argues that irrespective of the size of the business, employee turnover poses serious threats to the survival of a business. Turnovers can not only cause the company almost 32% of the employee's annual compensation but also affect the stock value of a firm in the free market (Libai and Muller, 2007).

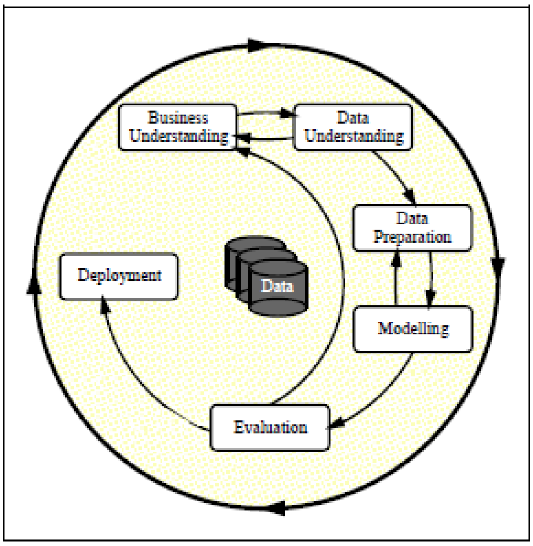
The pharmaceutical company in consideration is facing rising employee turnover and the past year's employee data extracted from their HR information system is to be considered in analysing the trends in turnover. Atif *et al.* (2011) analysed a similar scenario concerning six pharmaceutical companies who wanted to realise their reasons for employee turnover and retention. The results of the statistical analysis declared that lack of commitment to organisation was the most influential reason behind employee churn. Subsequently, compensation and adequate supervisory support greatly influenced organizational commitment, which thus influences the employee turnover in the companies.

The purpose of this paper is to investigate the factors that determine employee attrition in a Pharmaceutical company, including its impact on the organisation in order to provide appropriate solution for the future. The paper begins by reviewing extant literature in employee attrition to form the basis of the analyses. It will then go on to use the CRISP-DM approach to deal with data quality issues in the company dataset using KNIME and then visualised on Tableau to gain more insights in the data. After that, the decision tree model, which is a machine learning approach in predictive analytics is deployed to gain insights for the reason for staff attrition. The paper concludes by discussing the output from findings and provides recommendation to the company for implementation.

METHODOLOGY

CRISP-DM, short for CRoss Industry Standard Process for Data Mining has been used as a structure for carrying out the entire turnover analysis process for the scenario at hand. CRISP-DM is an industry independent model which can be followed for data mining (Wirth and Hipp, 2000). According to Chen et al. (1996), data mining can be concisely described as identifying and extracting patterns in large data sets using statistical and computational methods.

CRISP-DM initially breaks down an entire data mining cycle into four distinct levels. In the first level it organises the process into different phases and moves on to the second level where each phase shall be consisting of several generic tasks, which Wirth and Hipp (2000) suggested to be as complete and stable as possible. In the third level, the preceding tasks are applied to specific scenarios and insights are drawn from the findings of the analysis. The fourth level, also described as the process instance level essentially records the activities and insights of the model. According to Azevedo and Santos (2008), a CRISP-DM model once deployed, grows with the industry standards and sets sequential steps for iterative data mining. Thus, a model once deployed simply does not cease to function after a single iteration of function. It can be deployed throughout the business life cycle. The figure below depicts the cyclic nature of deployment of a general data mining model.

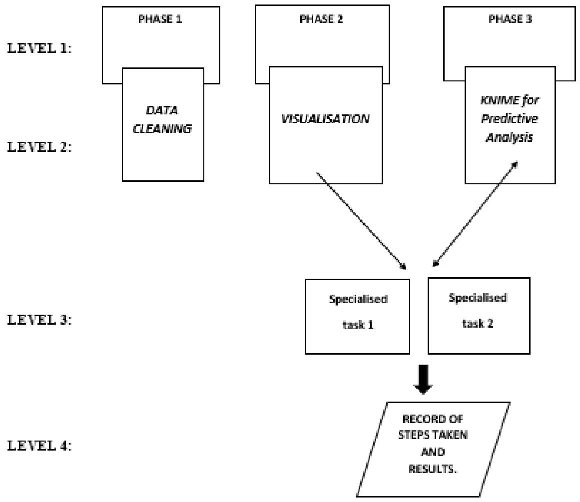


Source : Wirth and Hipp (2000)

The pharmaceutical company in consideration is facing an employee turnover which is the business problem that remains to be diagnosed.

The data containing employee details have been procured from the human resources information systems of the company for the previous year. A general overview of the dataset was taken to familiarise with the attributes presented in the dataset and proceed with defining the CRISP-DM model that will be specifically followed for analysing the trends of turnover in this company.

A diagrammatic representation of the CRISP-DM model that has been implemented for analysing this dataset has been provided below:



At the top level, the process has been divided into three distinct phases and every phase is assigned a second level generic task:

- Phase 1 – Cleaning and Preparing the dataset for further analysis using KNIME.
- Phase 2 – Generating visualisations for different control variables influencing attrition rate in the company and creating an organized dashboard to summarize the findings using Tableau.
- Phase 3 – Designing a KNIME workflow for predicting attrition causes using a decision tree model.

At the third level, the generic tasks in the model have been implemented for two specific scenarios to draw more insight from the analysis. The tasks conducted at each level are discussed in detail below.

RESULTS AND DISCUSSIONS

Level 1 and Level 2 tasks in Phases:

Phase 1-   Cleaning Dataset and fixing data quality issues.

Peng (2022) in his statistical analysis had also removed outliers concerning age greater than 60. The primary reason for removing outliers could be attributed to the findings of several researches, which have shown that organizations with younger employees show better growth (Andersson and Klepper 2013; Ouimet and Zarutskie 2011).

A KNIME workflow has been specifically designed to summarise the dataset, identify the data quality issues, and fix the same to obtain a dataset, fully prepared for further analysis. The workflow has been depicted below in Figure 1 and the functions of the various nodes have been explained.

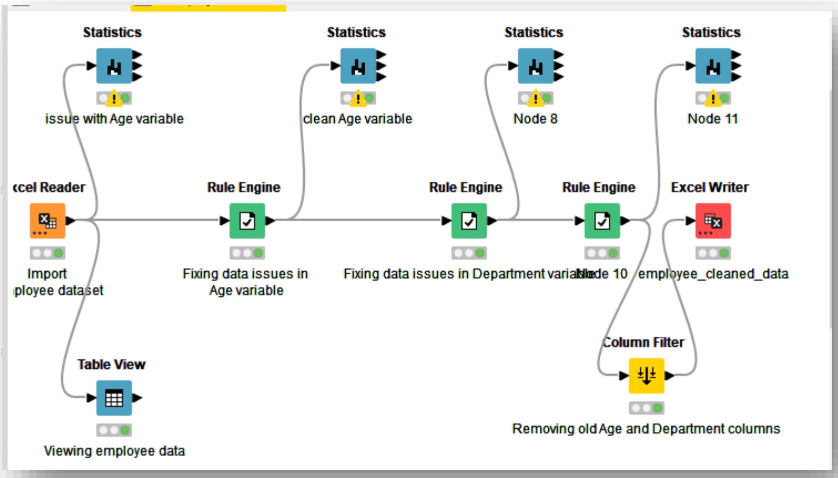


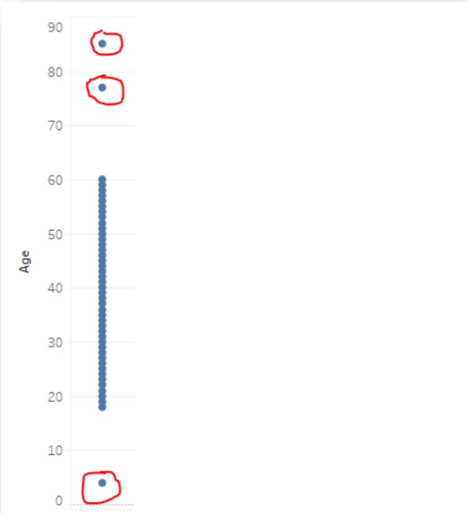
Figure 1

The dataset is first read into the Excel reader and then summarised using the statistics node. It was observed that the employee dataset has a minimum age of 4years and a maximum of 85 years, while the lower limit can be logically written off, the age limit has been restricted between 18 and 65.

Column	Min	Mean	Median	Max	Std. Dev.	Skewness	Kurtosis	No. Missing	No. +∞	No. -∞	Histogram
ID	1	734	?	1,467	423.6307	0.0	-1.2	0	0	0	1 1,467
Age	4	36.9646	?	85	9.3115	0.4951	0.2247	0	0	0	4 85
BillableRate	102	802.8957	?	1,499	403.5006	-0.0038	-1.2046	0	0	0	102 1,499
DistanceFromHome	1	9.2018	?	29	8.1118	0.9556	-0.2308	0	0	0	1 29
Education	1	2.9127	?	5	1.0252	-0.2889	-0.5642	0	0	0	

Figure 2

The summary statistics produced in KNIME for the employee dataset depicts the outliers in Age as shown in Figure 2 above.



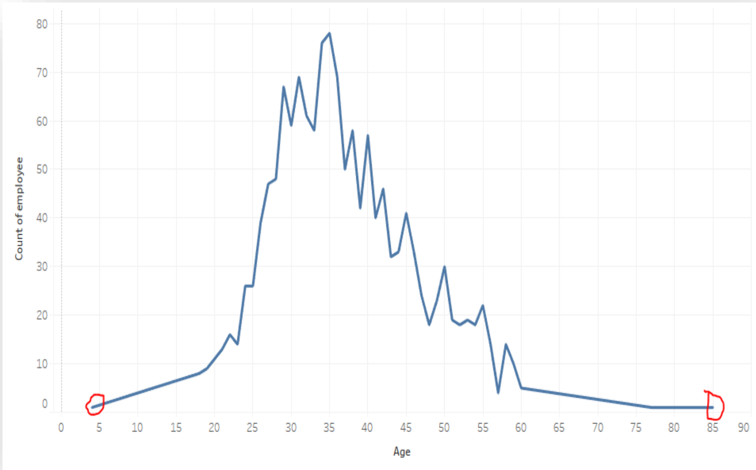


Figure 3(a) **Figure 3(b)**

The outliers in age can be spotted in the plots in figure 3(a) and 3(b) above. [Encircled Red].

It is also evident from the department wise employee strength graph in Figure 4 , that the human resource department attribute is duplicated. In order to fix the redundancy, the duplicated HR column has been merged with the human resources column.

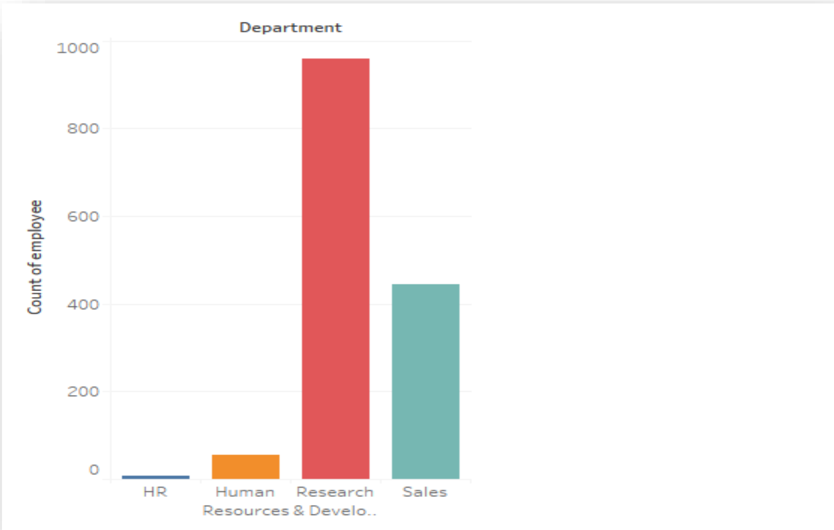


Figure 4

Phase 2- Visualisation and Insight

The clean dataset obtained from KNIME (See Figure 1) is loaded into Tableau for the purpose of visualisation. Atapattu et al. (2016) have emphasised in his analysis of employee attrition how efficient Tableau is an interactive graphical analytical tool. In this phase different control variables have been plotted against the attrition figures to understand more clearly the effect of various independent variables on attrition. Tableau facilitates a wide variety of data types (Deardoff, 2016) and is an excellent tool for visualising the story of an entire analysis cycle (Akhtar et al., 2020). The dashboard is a compelling feature in Tableau that allow for visualising and summarising the analysis and present key points to the viewer

with a general overview of the insights obtained on the business problem. The plots generated in Tableau for this particular analysis have been provided below with the insights derived from them described respectively.

The plot in Figure 5(a) compares the attrition rate by comparing the number of employees

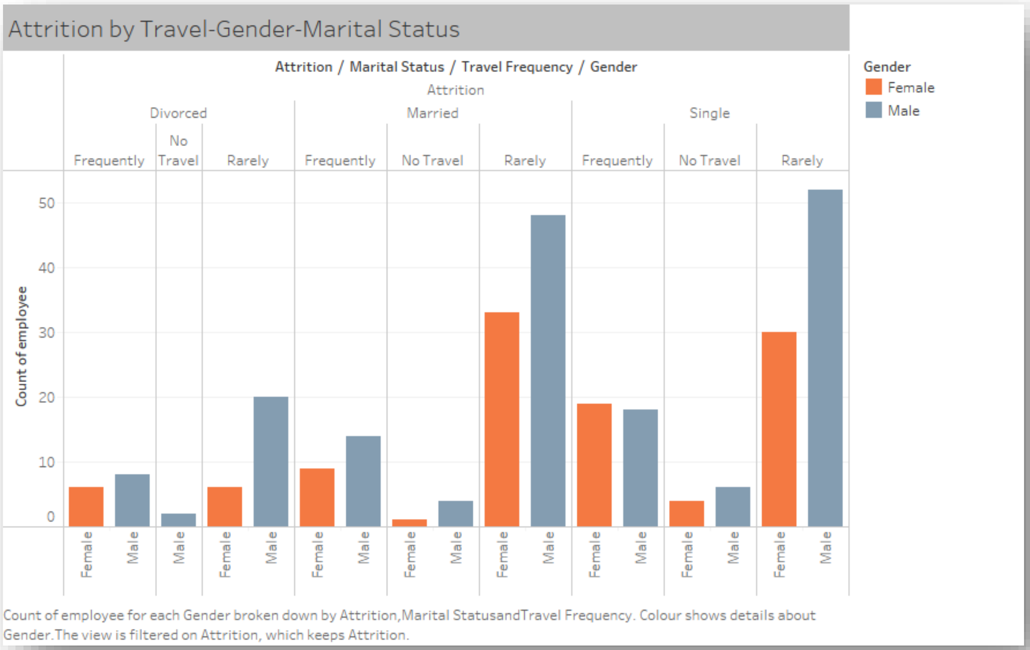


Figure 5(a)

leaving the company with the Travel Frequency, Gender, and Martial Status. It has been observed that the highest attrition numbers are among single, and married men who rarely travel. Lunneborg and Lunneborg (1973) in their research had concluded that married men with children are more likely to switch jobs either to pursue a PhD or for enhancing their financial condition. It is also clear from the plot that married women who do not travel at all have the least attrition frequency. Additionally, it has been thoroughly researched that often, women are forced to sacrifice their career according to the social assumption that they should take up the primary responsibilities in domestic life (Rosser & Taylor, 2009; Xu, 2015) , the trend does not seem to hold up in this scenario.

In addition, the attrition frequency has been compared against the education field of the employees categorized by gender (see figure 5b. The highest number of attrition levels were that of male employees having a degree in life science, while the lowest was that of women from HR educational background.

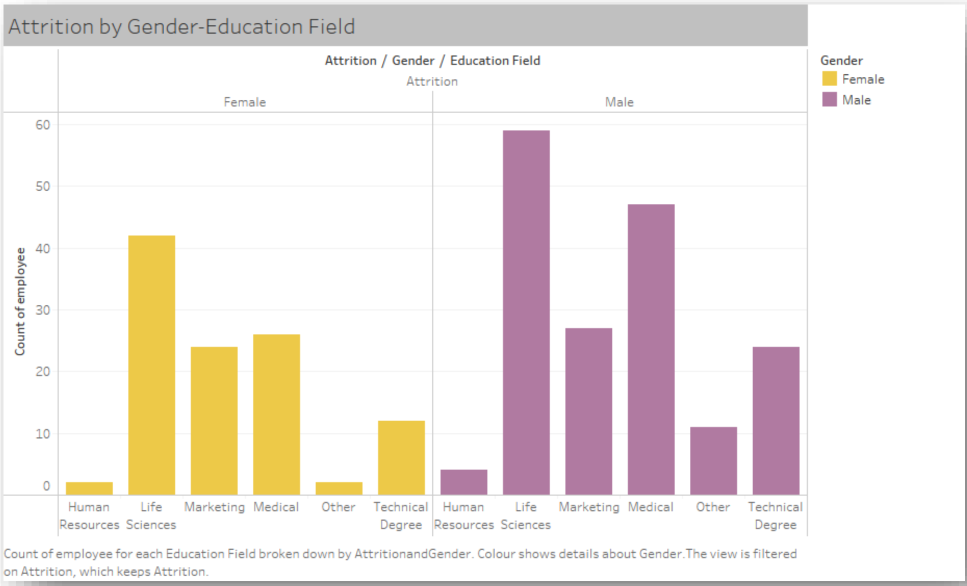


Figure 5 (b)

Furthermore, the attrition variable was plotted against total work experience of the employee as shown in Figure 5(c). The total work experience field was grouped into 7 categories to get a better understanding of the level of experience of the employees who are leaving the organization. The graph describes that the highest number of employee turnover has been among the employees with work experience between 5 and 10 years. The findings from the research of Kirschenbaum and Mano (2002) imply that disparities in turnover behaviour are caused by differences in occupation-dependent work histories and current job possibilities. It has been demonstrated that variations in employees' perceptions of opportunities, as affected by the "market viability" of the occupation, affect turnover. Thus, a moderate work experience may drive the employee to assess his/her value against the opportunities being provided by their

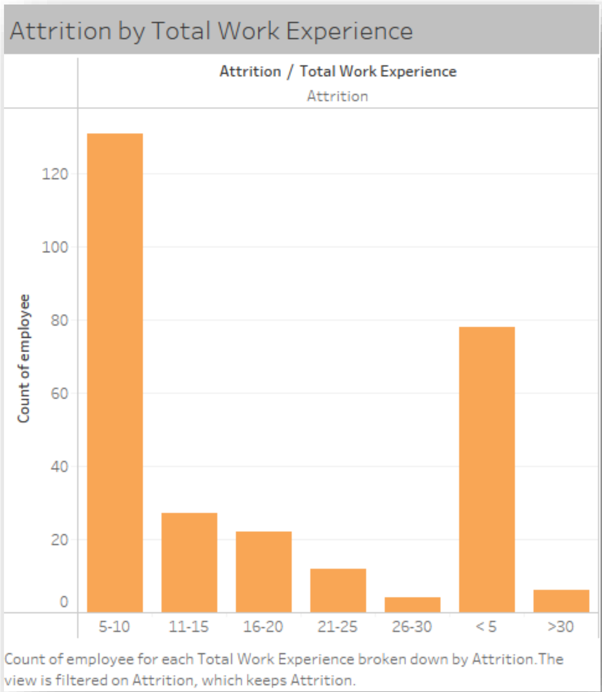


Figure 5(c)

current employer, which sets them at a higher potential to explore more employer options in the market elsewhere.

However, it was observed that the Research and Development department has the highest number of attritions in comparison to the remaining departments. Figure 5(d) shows how overtime duties and work life balance affect the attrition frequencies in the Research and Development department. An increasingly varied workforce and a higher need for employees to balance their professional and personal lives

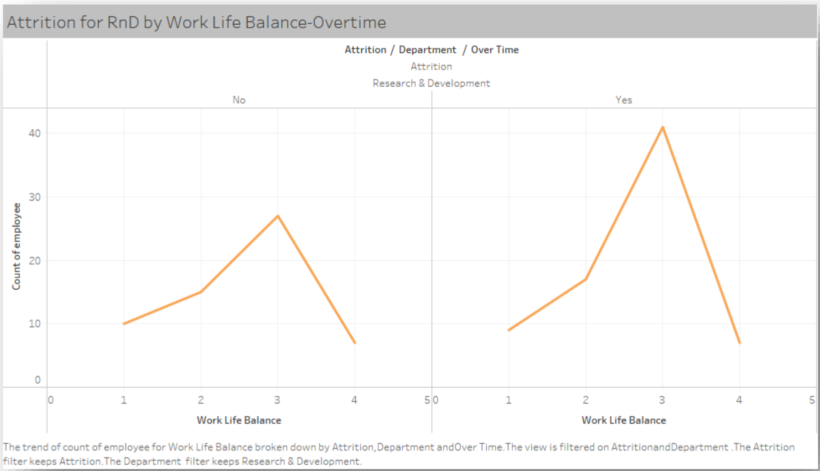


Figure 5(d)

are the results of demographic shifts, as evidenced by the rise in the number of women in the workforce and multiple career families (Baral and Bhargava, 2011; Bharat, 2003; Komarraju, 1997; Rajadhyaksha and Bhatnagar, 2000; Ramu, 1989). These factors have triggered the need for employers to introduce innovative practices to allow employees to achieve a greater work life balance (Friedman, Christensen, and DeGroot, 1998).

The plot shows that despite having a work life balance of '3' (which is interpreted as better), almost 21% more employees in the Research and Development department have left the company due to overtime work. Fallucchi et al. (2020) in their analysis discovered that over 30% of attrition could be attributed to overtime work. Bhuva and Srivastava (2018) also concluded that overtime work is one of the largest influencing factors of employee turnover.

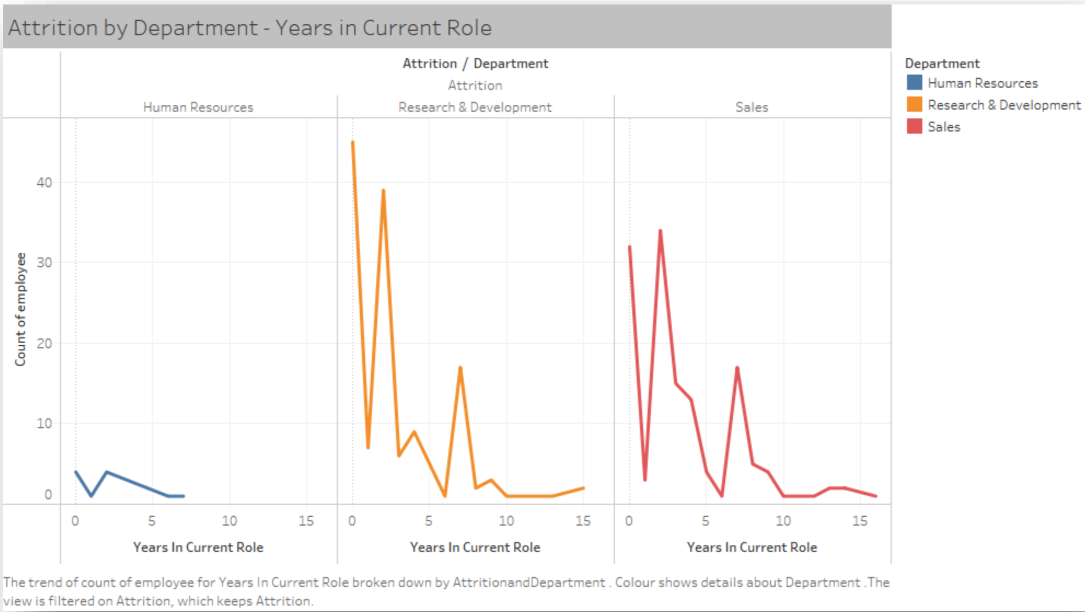


Figure 5(e)

In Figure 5(e) the attrition variable was plotted against years spent by the employee in their current role. There is a high tendency in attrition for both Sales, and Research and Development departments for employees who have spent less than 5 years in the same role.

Ultimately, the tableau dashboard, one of the most interactive and attractive visualisation tools for marketing purposes (Gounder et al., 2016) was used to tell the compelling story for the Pharmaceutical management team. This interactive dashboard has been created for this analysis (See Figure 6) and has been briefly explained below.

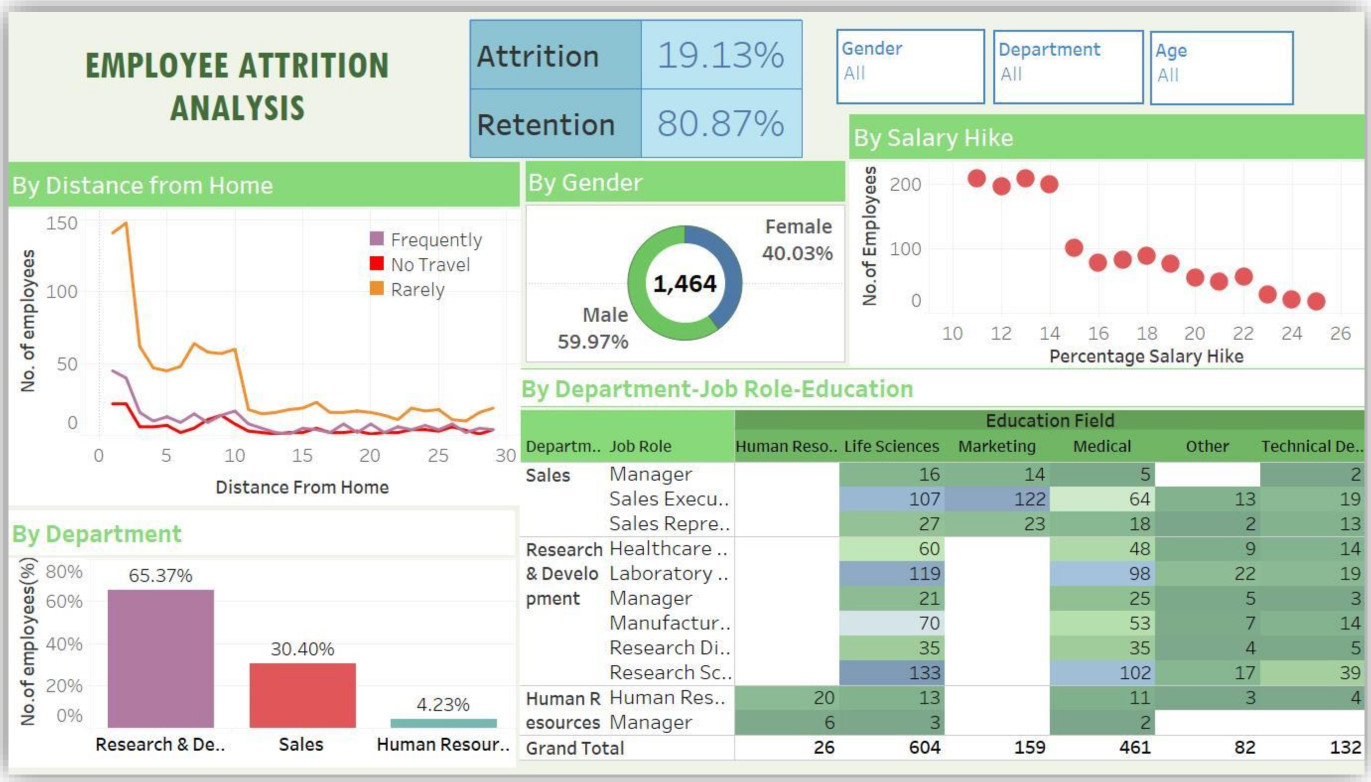


Figure 6

The insights obtained from this dashboard can be listed below:

- Almost 19% of the total employee strength of the company accounted for the entire turnover.
- Employees who rarely travelled had high attrition rates.
- Employees receiving a salary hike of less than 14% had high attrition rates.
- Research and Development department has the highest attrition numbers among all departments.
- Employees with an educational background in Life Sciences and Medical have high attrition frequency.
- Men are more likely to leave the company in comparison to women.

The dashboard also contains three universal filters: Gender, Department and Age. By selecting the respective options from the drop-down list of these filters, it is possible to filter all the graphs and charts in the dashboard. The insights obtained from the dashboard assists in identifying the factors that positively influence employee turnover.

Phase 3—Designing a KNIME workflow and predicting attrition causes using a decision tree model.

The decision tree algorithm is used for predictive analysis using KNIME. It is easy to use, clear of ambiguity, and resilient even in the face of missing information. The decision tree is one of the most efficient approaches for data mining and have been widely employed in many fields . It is simple to forecast the outcome for upcoming records using the decision tree model created from prior data (Song & Lu, 2015)**.** In KNIME, for a particular action, each node represents a processing point. A set of nodes that help complete a particular task is called a workflow. The task here is to predict the attrition of particular employees, which is represented by a character variable ('YES' value for employees who have left the organisation and 'NO' for employees who have not left the organisation).

First using an Excel Reader, the cleaned data is imported followed by the removal of two columns (ID and Over18) that are not required for analysis. In the Column Resorter node, the target variable was moved to the last column of the dataset for easy identification when comparing with the predictive values. The data is now ready for further analysis.

The model has been trained by partitioning it into a training and a test set. The training set contains 80% of the data and the 20% forms the test set. The data is sent to the decision tree learner node. The decision-tree predictor node is used to test the new model and to evaluate the performance. The confusion matrix, which can be accessed from the scorer produces the accuracy and error margin related to the performance of the model (see fig. 7) below.

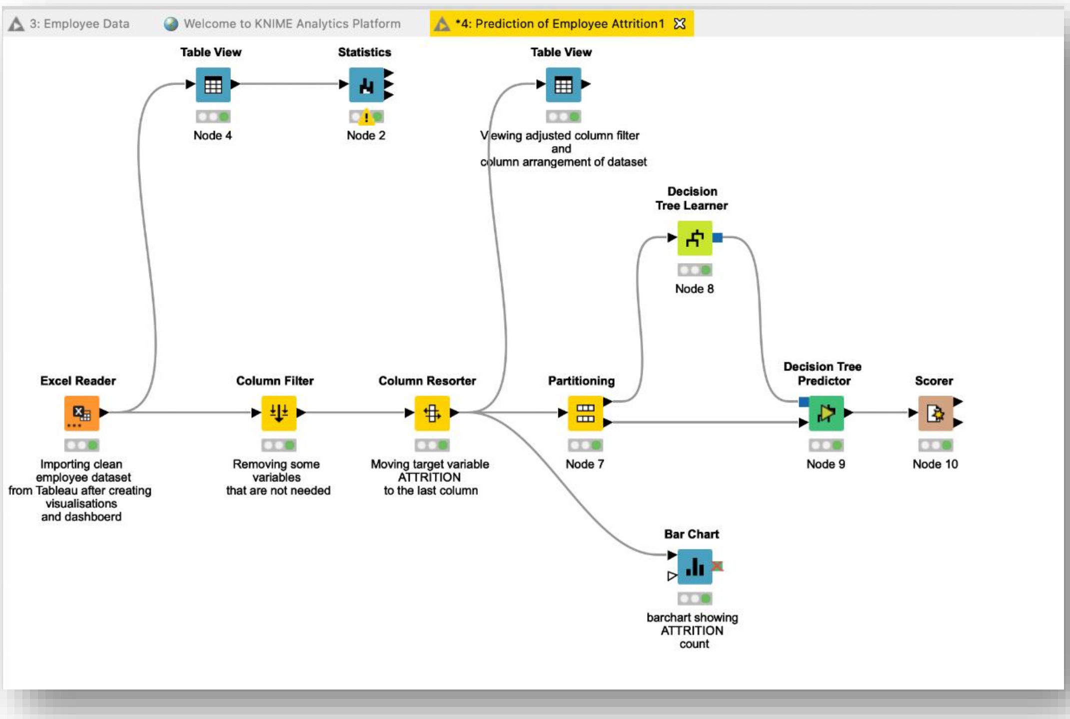


Figure 7

However, in other to evaluate the prediction accuracy, three models were carried out (models 1, 2, and 3). The third model is the most accurate and the final model that was used for implementation (see Appendix for models 1 and 2). As can be seen blow at figure 8, the minimum number of records per node is set to 6 and the number of threads to 8. Reduced error pruning has been implemented to reduce error rates of the decision tree.

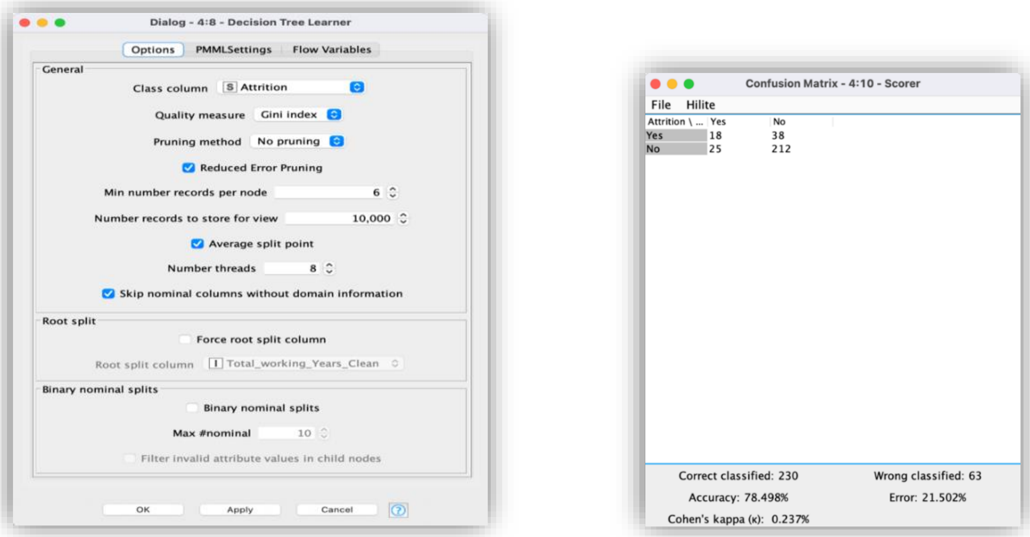


Figure 8

It is interesting to know that the confusion matrix above, for the final model has an accuracy of 78.49%. The model predicted 25 records of people who left the organization whereas the attrition value was "NO" for them. Alao & Adeyemo (2013) were able to achieve an accuracy of 0.74 in their analysis to estimate the possibility of employees leaving the organization based on historical data.

Level 3:

In the third level, the generalised tasks have been implemented for specific scenarios.

Two specific cases have been considered for this analysis:

1. Attrition levels of employees between the age of 22 to 38 years.

2. Attrition levels and causes of employees belonging to the Research and Development department.

Specialised Task KNIME Workflow 1

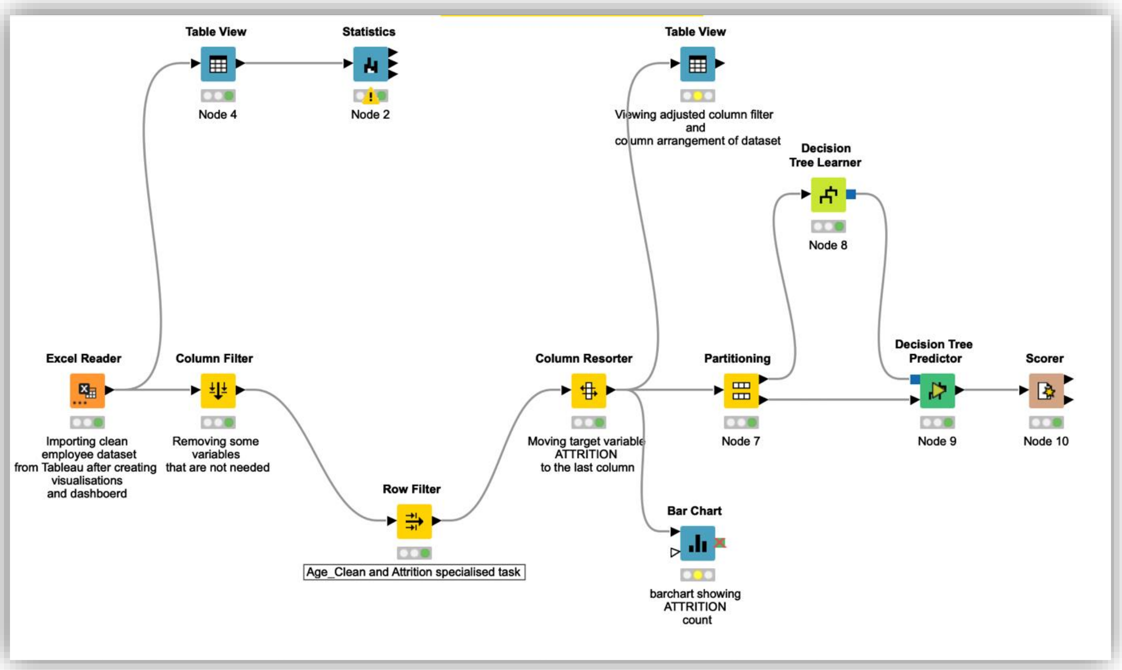
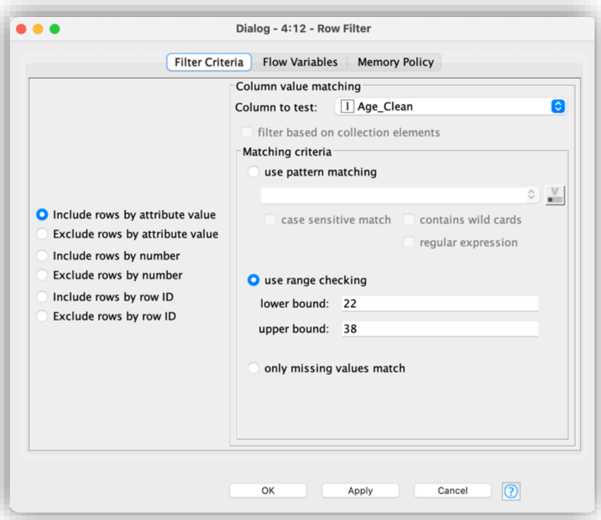


Figure 9

Settings used and confusion matrix 1



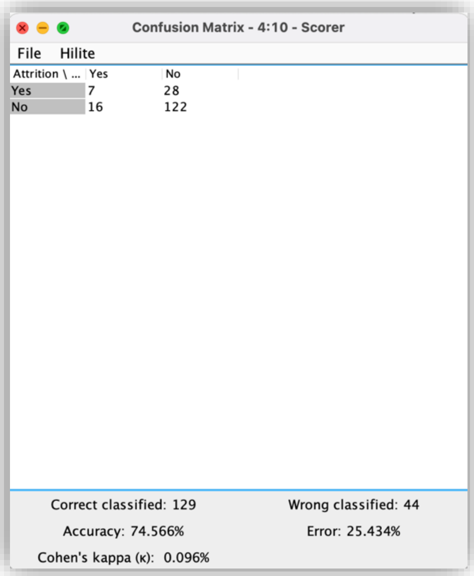
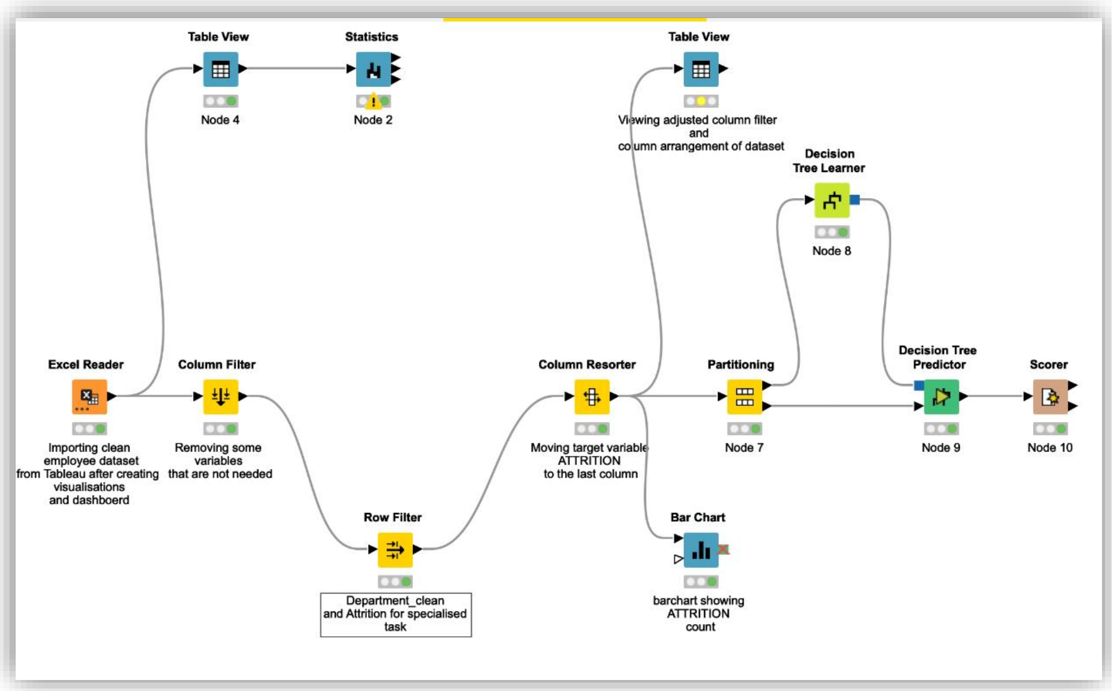


Figure 10

<u>Result of specialized task 1:</u>

As per the confusion matrix above (see Figure 10), the accuracy obtained is 74.56%. So, it can be inferred that employees in the age range of 22 to 38 years old have a higher tendency of leaving. Active involvement in the job, monthly income, and travel distance seem to be important reasons for employees quitting belonging to this age range (see Appendix).

Specialised Task KNIME Workflow 2



<u>Figure 11</u>

Settings used and confusion matrix 2

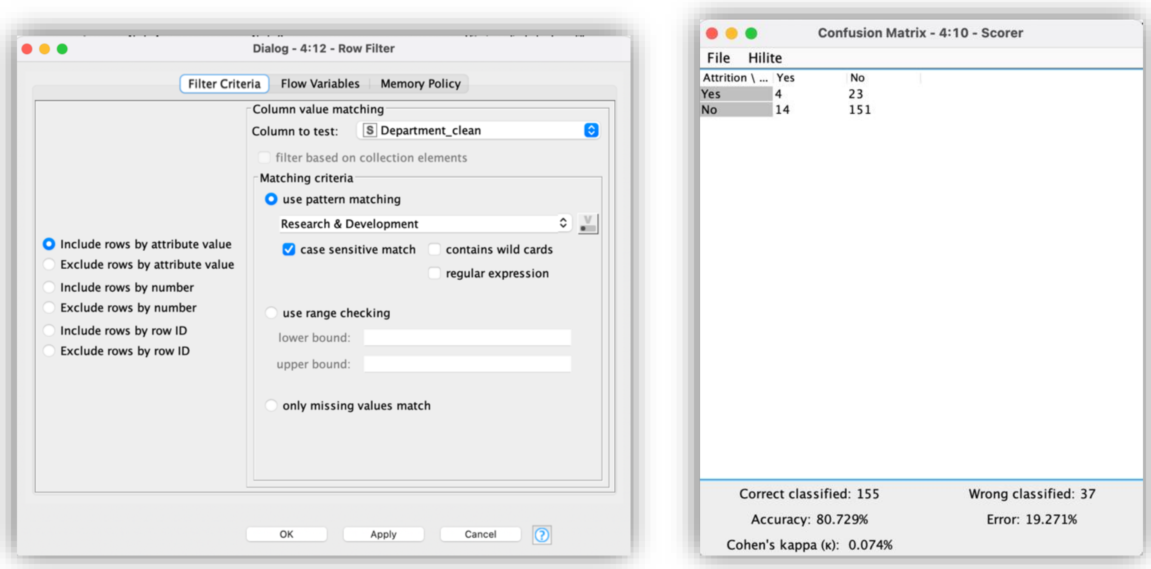


Figure 12

Result of specialized task 2:

As per the confusion matrix above (see figure 12), the accuracy obtained is 80.72%. So, it can be inferred that employees in the Research and Development have a higher tendency of leaving. Monthly income and overtime seem to be the main reasons for employees quitting belonging to this department (see Appendix).

Phase 4—Overall result

From the results obtained in this analysis using Tableu and Knime, it has been observed that overtime hours, increase in travel distance and amount received as monthly income seem to have great influence on Employee Attrition rate. These should be carefully considered by the company in future to diminish Attrition.

CONCLUSIONS

As per this analysis, it can be inferred that employees who have worked overtime, they show a higher tendency of leaving the organization despite having a better work-life balance. In such cases, the hourly pay rate can be increased to lower the rate of attrition. As people younger than the age of 40 show a higher tendency of leaving due to travel distance, hybrid mode of working can be adopted by the organisation. Employees with an educational background in life sciences or medical should be carefully evaluated before assigning them to the sales or marketing department as it increases the chances of them leaving the company.

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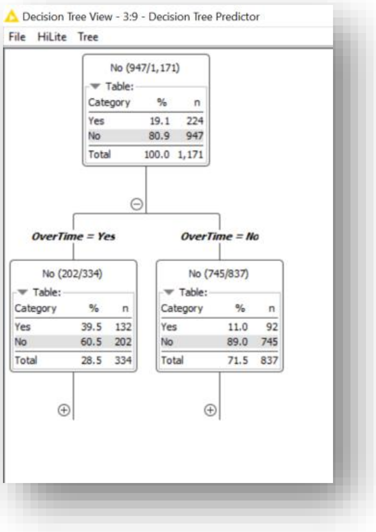
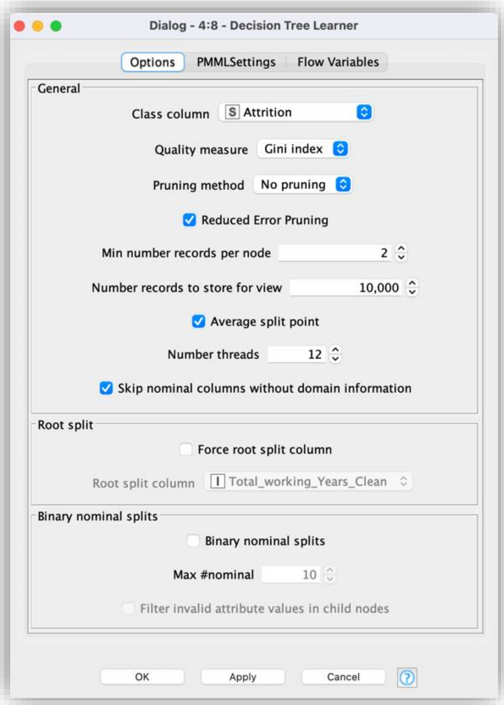
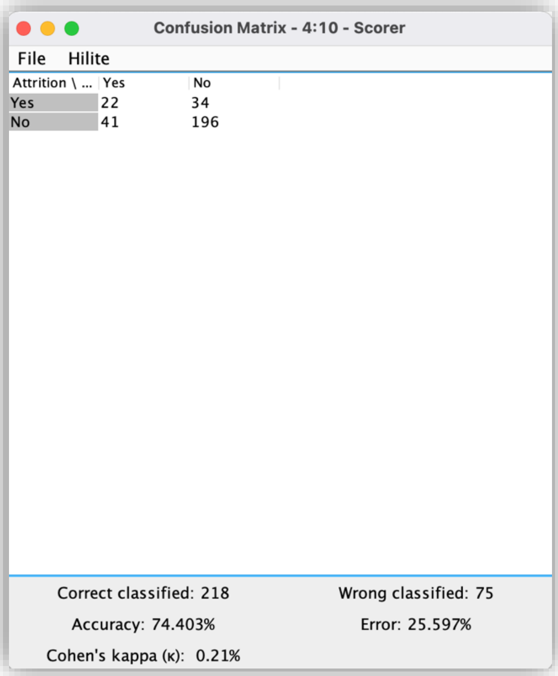
APPENDIX

Final decision tree structure-

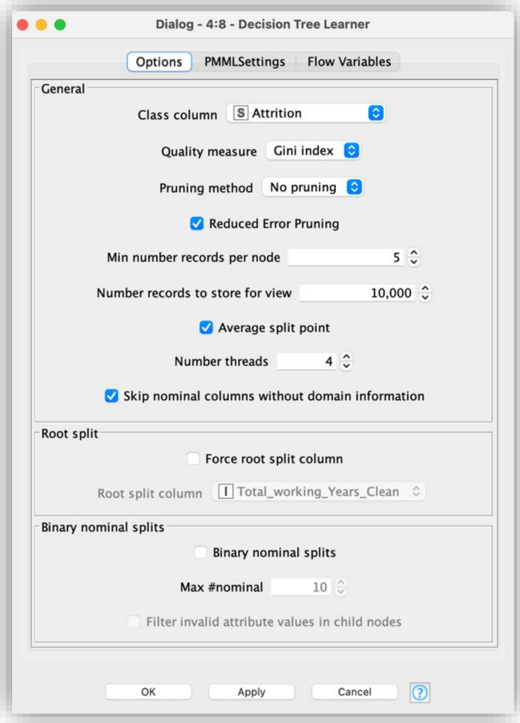


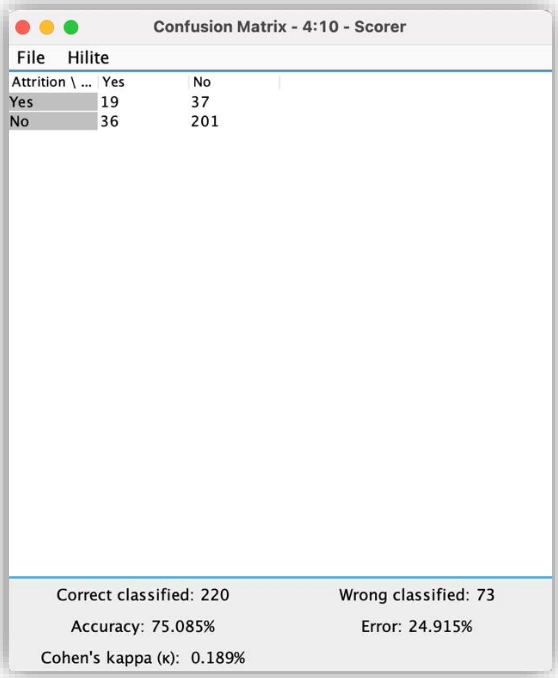
Decision Tree 1



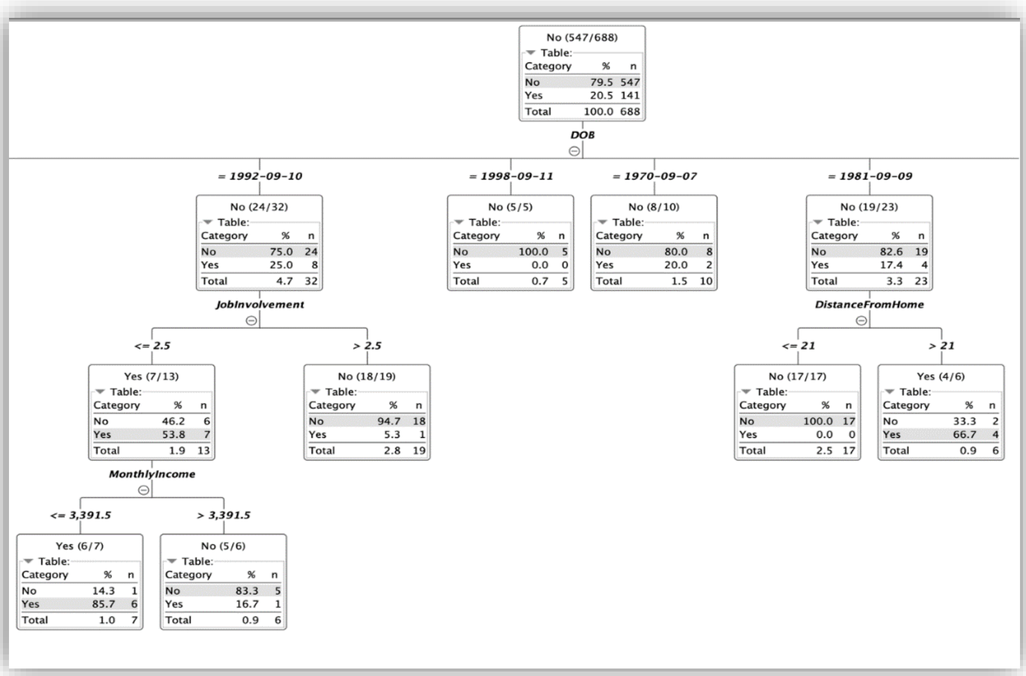


Decision tree 2

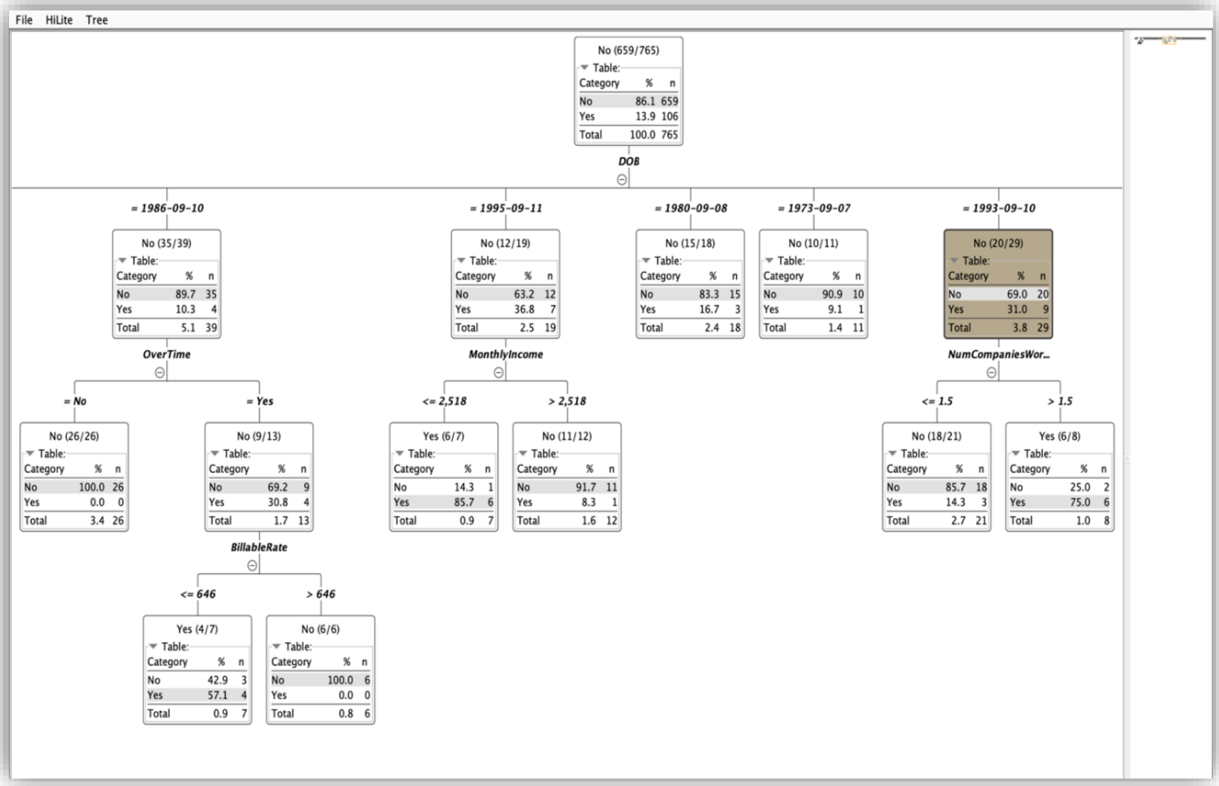




Specialized task 1 decision tree



Specialised task 2 decision tree



Appendix – Minutes of Meetings

Date: 23/11/22 **<u>MGT_7182 HR Analytics A2 Session 1</u>**

Members present: Chukwekwu Musei, Oindrila Mukherjee, Tathagata Chakraborty, Aravind Kumar Devarajan Geetha

<u>Meeting minutes:</u>

- Discussion on structure of assignment.
- Basic objectives of project and project report.
- General planning, group meeting schedule until submission.
- Addressing Data Quality issues.

<u>Tentative structure of meeting schedule:</u>

- Minimum of 6 group sessions required before submission of report
- Session 1 and 2 – Data Quality and Visualisation
- Session 3 and 4 – Analysis and Dashboard
- Session 5 and 6 – Report preparation and quality management

**Additional sessions may be added as and when needed depending on situational demand.

Important:

- All Group members are expected to contribute to the development of the project.
- Group members must be open to constructive criticism of their work by their colleagues.
- Any grievances or conflicts should be addressed in the group WhatsApp or group official mail trail.
- Inability to attend group meetings physically should be intimated to the group at least 24hrs before scheduled time. Recurring absence will be interpreted as non-compliance and member may be excluded from the group following a consensus. In case of extenuating circumstances, group members are advised to let all know about their availability.

<u>TASKS TO DO BEFORE NEXT SESSION</u>

- Check Data Quality Issues on KNIME of the entire dataset.
- Perform at least 4 visualisations on Tableau.
- READ the practical guidelines and manual sent by Byron thoroughly.

Session 2 – 28 /11/22 (Monday) 10:30AM

Venue – Room will be booked at Library/Grad School.

Date: 28/11/22 **MGT_7182 HR Analytics A2 Session 2**

Members present: Chukwekwu Musei, Oindrila Mukherjee, Tathagata Chakraborty, Aravind Kumar Devarajan Geetha

Meeting minutes:

- Discussing visualisation results.
- Handling Data Quality issues using KNIME.
- General planning, group meeting schedule until submission.
- Making Dashboard prototypes.
- Selecting independent variables for further analysis

TASKS TO DO BEFORE NEXT SESSION

- Finalise Dashboard.
- Analyse regression process finalisation.
- READ the practical guidelines and manual sent by Byron thoroughly.
- Start analysis on KNIME workflow.

Session 3 – 30 /11/22 (Wednesday) 2:30 PM

Venue – Room will be booked at Library/Grad School.

Date: 30/11/22 **MGT_7182 HR Analytics A2 Session 3**

Members present: Chukwekwu Musei, Oindrila Mukherjee, Tathagata Chakraborty, Aravind Kumar Devarajan Geetha

Meeting minutes:

- Finalising visualisations for report.
- Designing the dashboard using clean data.
- General planning, group meeting schedule until submission.

TASKS TO DO BEFORE NEXT SESSION

- Go through decision tree formation process in Knime

Session 4 – 11 /12/22 (Sunday) 3:00 PM

Venue – Room will be booked at Library/Grad School.

Date: 11/12/22 **MGT_7182 HR Analytics A2 Session 4**

Members present: Chukwekwu Musei, Oindrila Mukherjee, Tathagata Chakraborty, Aravind Kumar Devarajan Geetha

Meeting minutes:

- Working on Knime decision tree
- Finalised the dashboard using clean data.
- Division of report writing and research for references.

TASKS TO DO BEFORE NEXT SESSION

- Collect references for report structure

Session 5 – 14 /12/22 (Wednesday) 01:00 PM

Venue – Room will be booked at Library/Grad School.

Date: 14/12/22 **MGT_7182 HR Analytics A2 Session 5**

Members present: Chukwekwu Musei, Oindrila Mukherjee, Tathagata Chakraborty, Aravind Kumar Devarajan Geetha

Meeting minutes:

- Started report writing and completed upto half of it
- Finalised Knime decision tree

TASKS TO DO BEFORE NEXT SESSION

- Collect snapshots for appendix
- Finish report results writing as assigned to team members

Session 6 – 15 /12/22 (Thursday) 10:00 AM

Venue – Room will be booked at Library/Grad School.

Date: 15/12/22 **MGT_7182 HR Analytics A2 Session 6**

Members present:

Chukwekwu Musei,

Oindrila Mukherjee,

Tathagata Chakraborty,

Aravind Kumar Devarajan Geetha

Meeting minutes:

- Completed report writing
- Completed addition of appendix to the report
- Next session to be held in case of any addition required to the report

DECLARATION

We hereby declare that the group assignment submitted to Queens' University, Belfast by Group BA- 18 with four members is an original work done for the fulfillment of the requirements of Human Resource Analytics (MGT7182) module in Business Analytics (M.Sc). All four students contributed equally to the assignment, and it is understood that each member will be awarded the same mark for the assignment.

- Chukwekwu Musei,

Oindrila Mukherjee,

Tathagata Chakraborty,

Aravind Kumar Devarajan Geetha