Predicting Employee Attrition

Hannah MacGinty[a]

[a]*Stellenbosch University, South Africa*

Abstract

This paper investigates employee attributes and attrition. Random forests are used to build a model to predict employee attrition based on key attributes, such as education, pay, gender, and age, among others.

1. Introduction

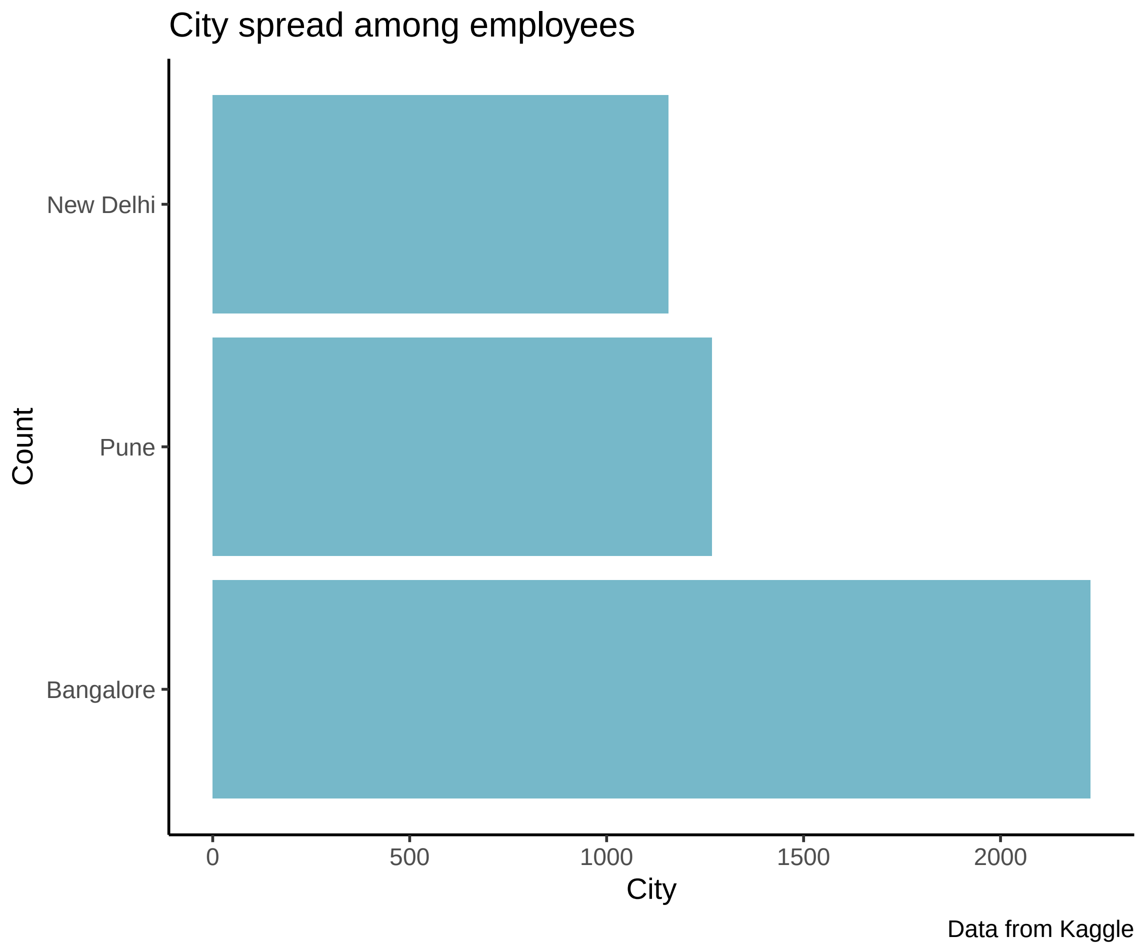
Losing employees can be costly for businesses. Predicting attrition and its key determinants or attributes can help estimate future employee turnover and attempt to reduce it.

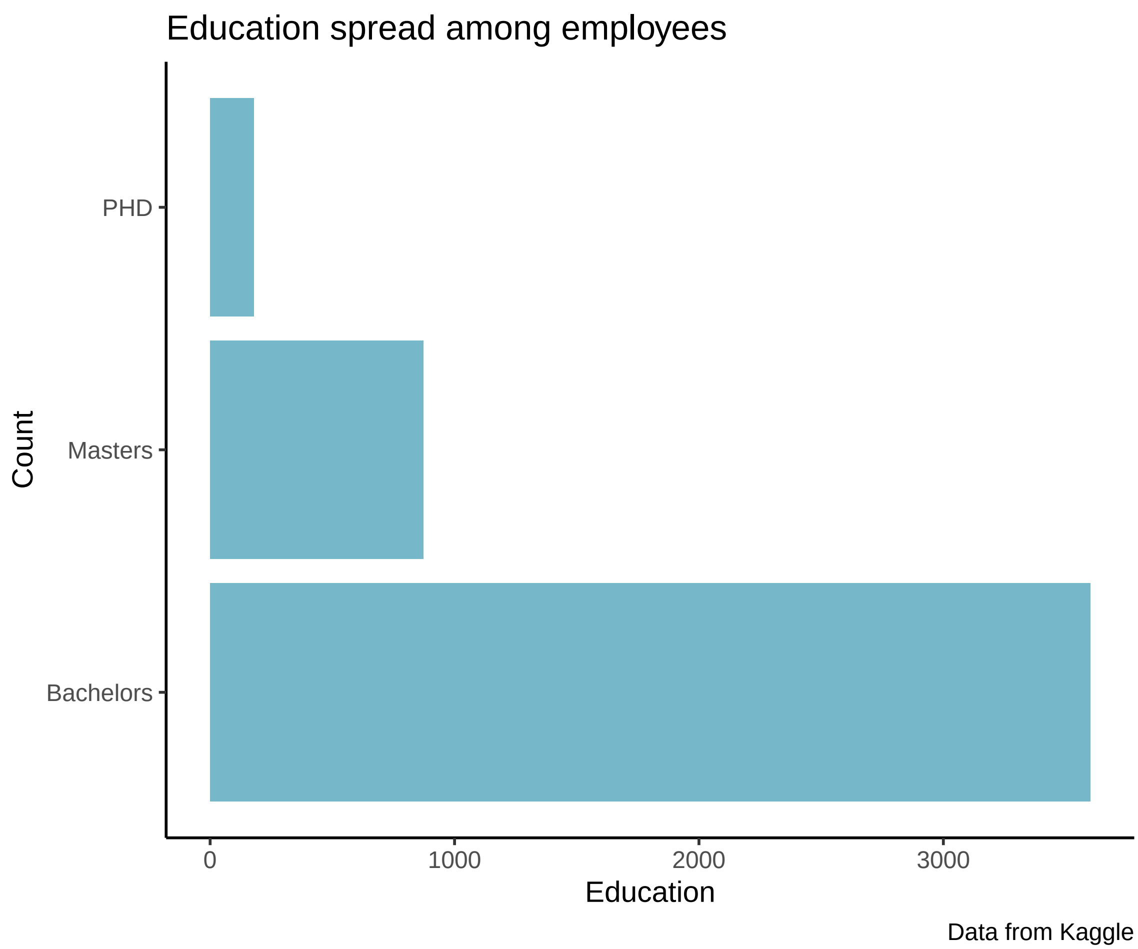
Exploratory Data Analaysis

The dataset contains information on 4653 employees and whether they attrited or not. The employee attributes available include demographic information such as age and gender. Employees are based in one of three major cities in India, namely Bangalore, Pune and New Delhi. The year an employee joined a company (Joining Year), ranging from 2014 to 2018, is also considered.

Given that earnings are generally an important determinant in whether an employee leaves their job, their payment tier, scaled from 1, being the highest, and 3, being the lowest, is included in the data. Additionally, years of experience in their current field is included as well as their highest level of education (Bachelor's, Master's, PhD). There is also information on whether an employee kept out of projects for 1 month or more, which could potentially indicates an employee's lack of interest in work or plans to leave the company.

*Corresponding author: Hannah MacGinty
Email address: `21082022@sun.ac.za` (Hannah MacGinty)

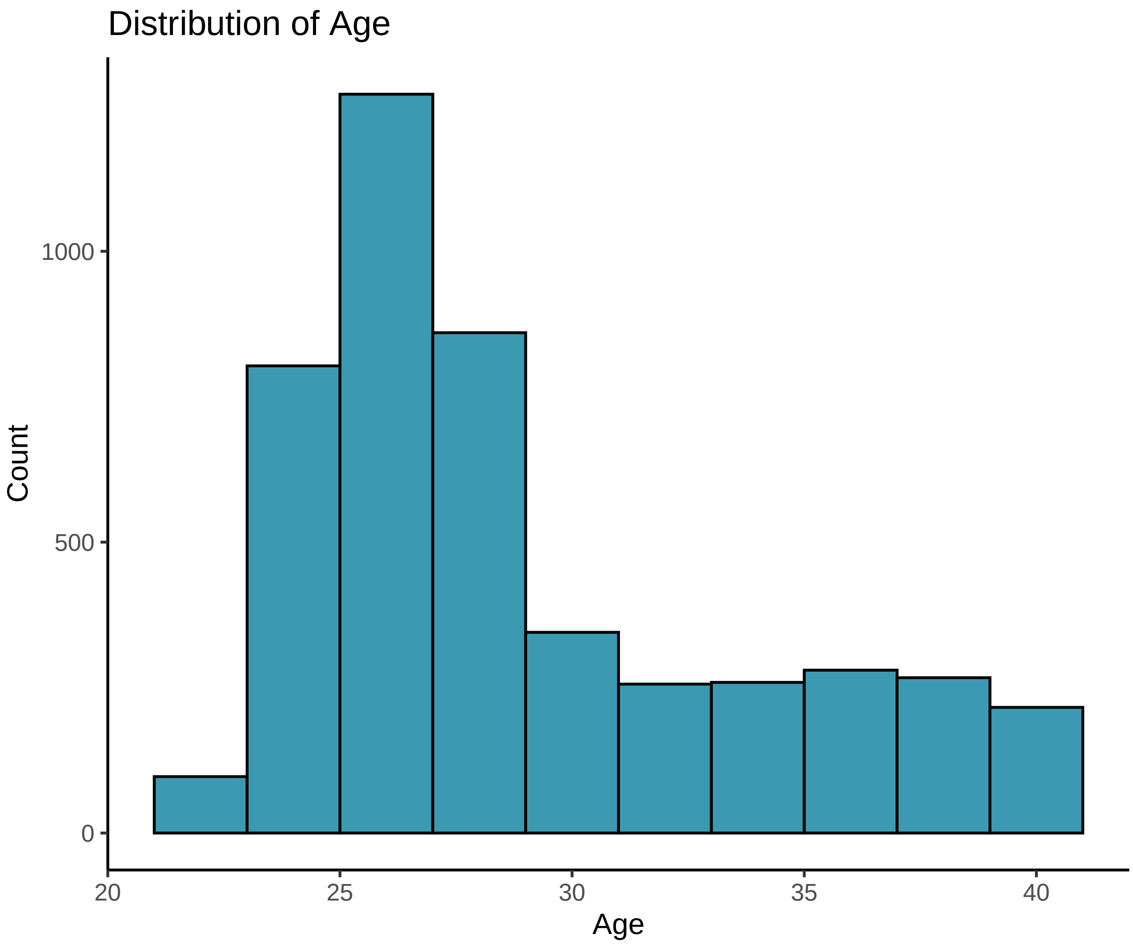

City spread among employees
New Delhi
Pune
Bangalore
Count
0
500
1000
1500
2000
City
Data from Kaggle

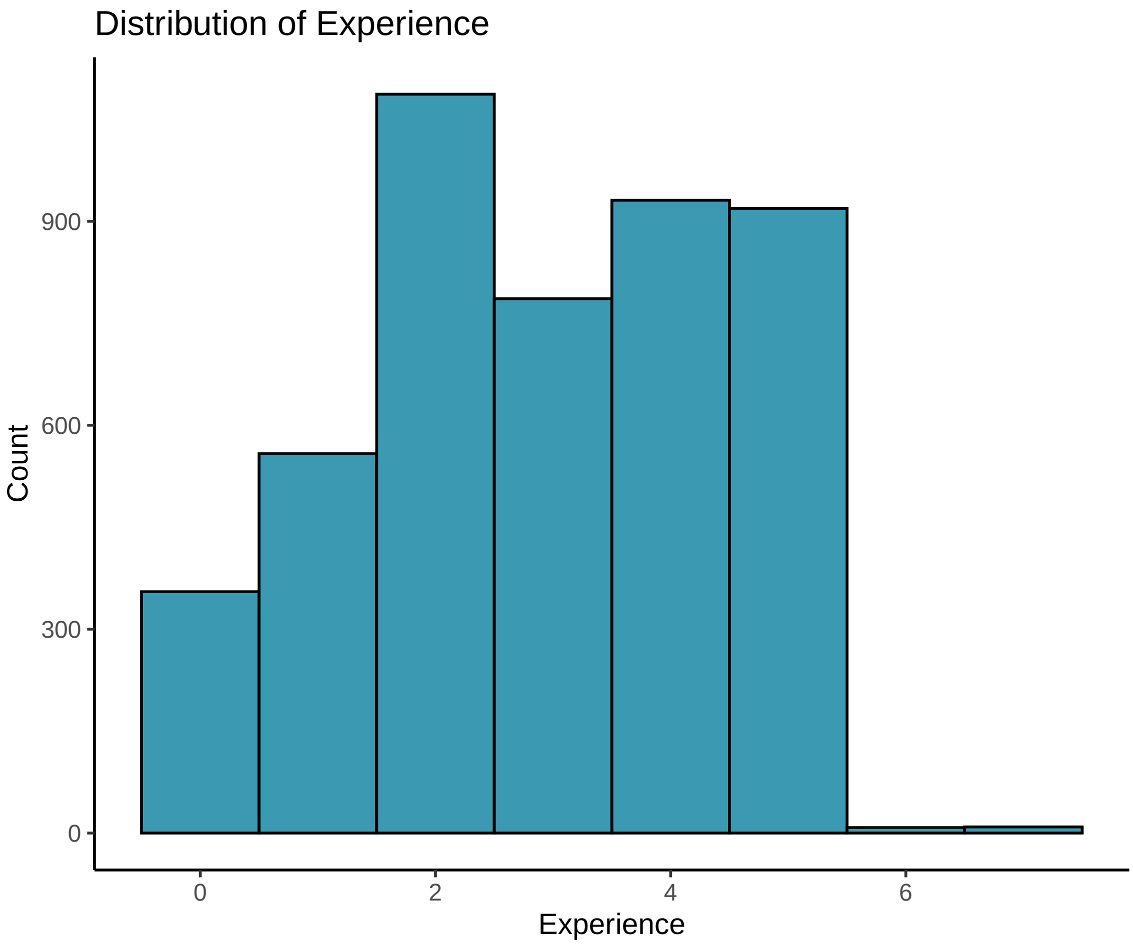


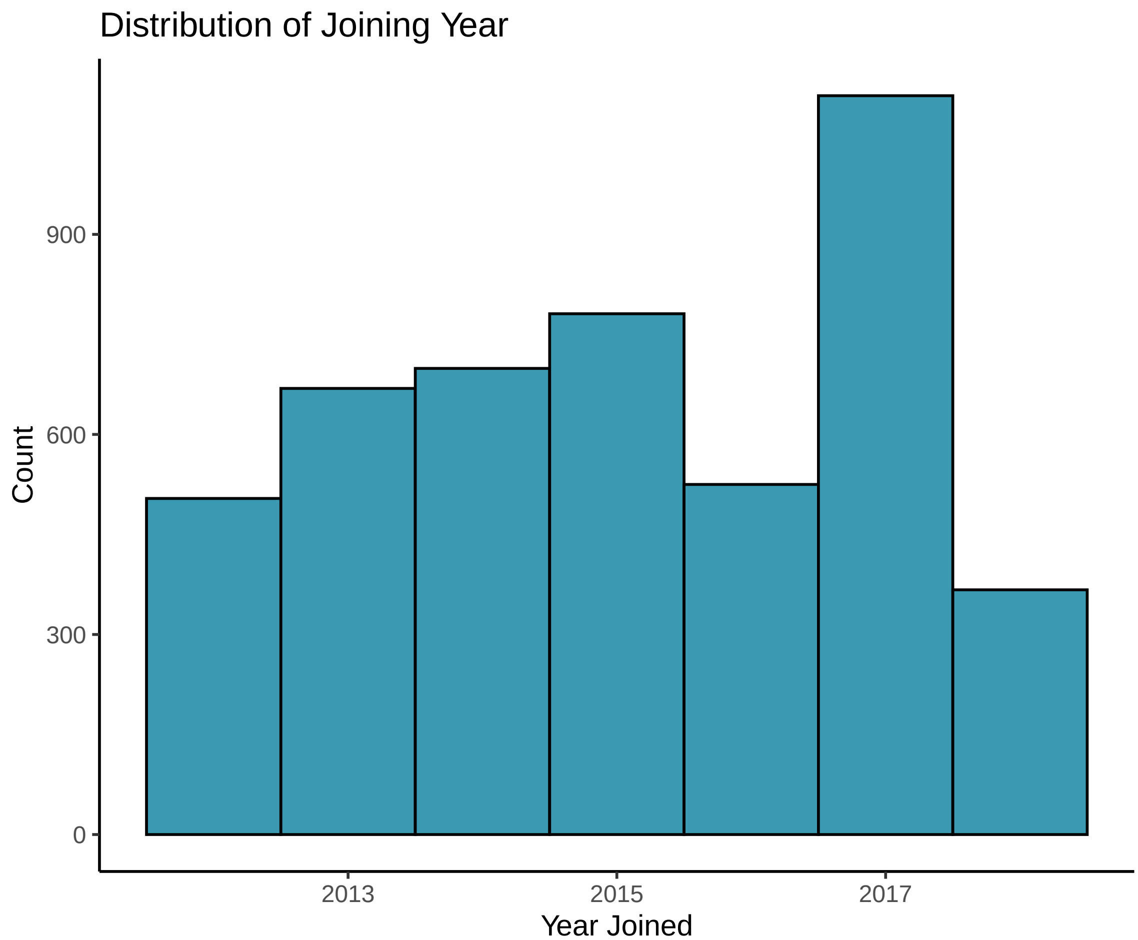
Spreading the data among city, most of the employees are from Bangalore. Additionally, most employees have a Bachelors degree. Only 179 employees have a PHD and 873 have Master's degrees. Looking at age, which ranges between 22 and 41, the majority of employees are in their mid to late twenties, skewing the distribution to right.

Regarding experience, very few individuals have 6 or 7 years experience (only 16 employees in total) in their current field of work, most likely due to the young employee base. Most commonly, individuals have 2 years experience.

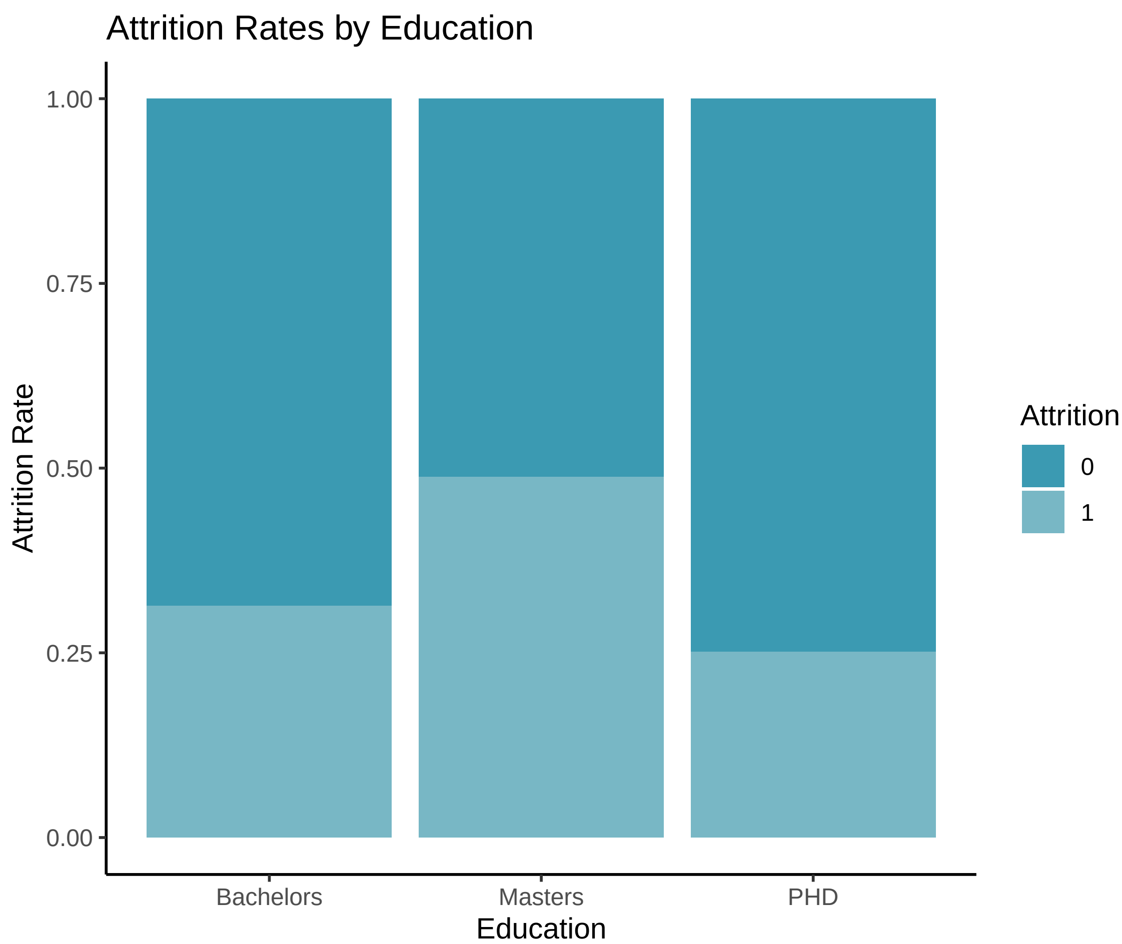
2017 saw the most employees join the company. There was a substantial fall in employees joining in 2018. Only 367 employees joined in 2018, compared to 1180 in 2017.


Distribution of Age
Count
1000
500
0
20
25
30
35
40
Age

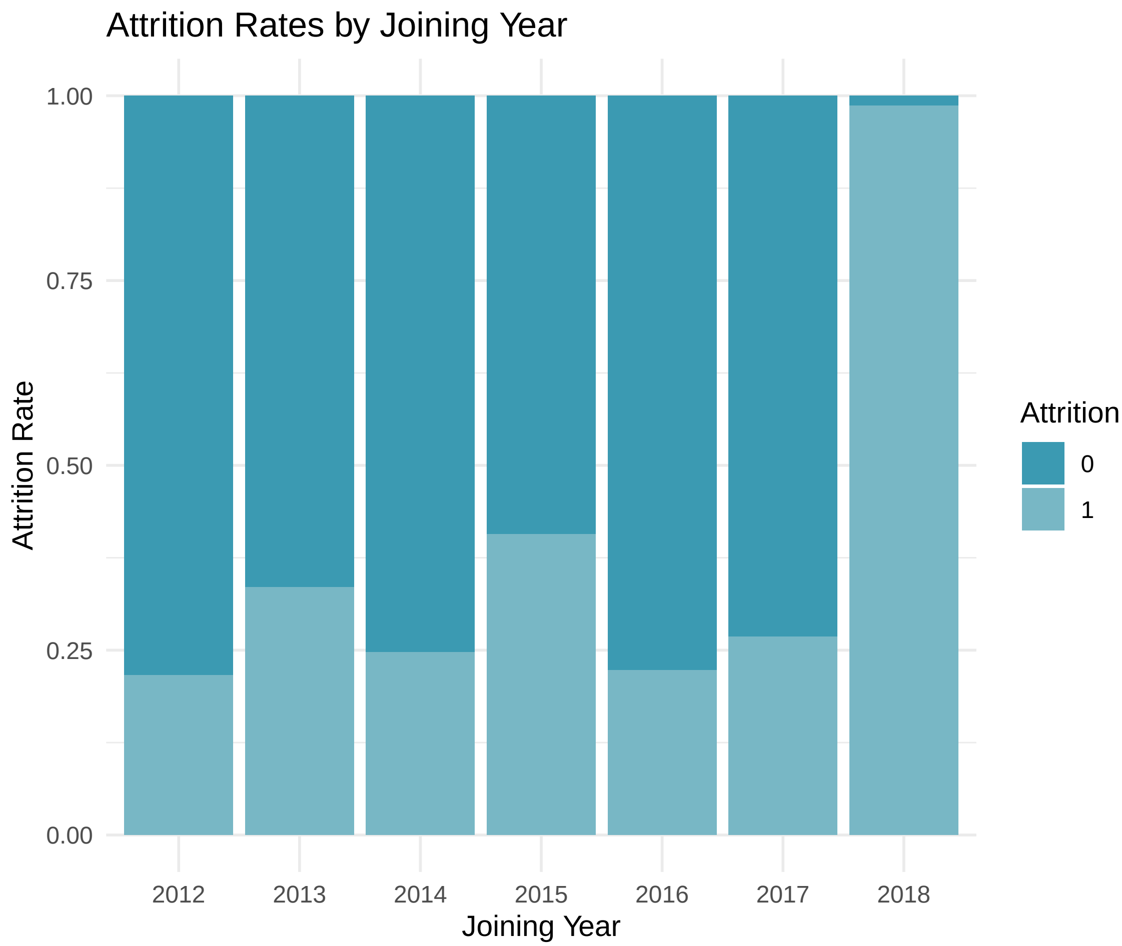

Distribution of Experience
Count
900
600
300
0
0
2
4
6
Experience



Attrition rates are highest among those with Master's degrees. Nearly fifty percent of those with Master's degrees left their job. When looking across joining year, almost all the employees that joined in 2018 resigned. It is possible that some event occurred in 2018 that caused that cohort to leave within the next two years.



Attrition Rates by Education
Attrition Rate
1.00
0.75
0.50
0.25
0.00
Bachelors
Masters
PHD
Education
Attrition
0
1



The table below presents the attrition rate across education, gender, city, joining year, experience, and pay level. Attrition rates are particularly high for individuals who joined in 2018 (98%), matching the graphical analysis. It is also high for those earning a mid-tier salary (almost 60%). This is followed by 50% of those from Pune attriting.

	Variable	Category	Attrition.Rate
1	Education	Bachelors	31.35
2	Education	Masters	48.80
3	Education	PHD	25.14
4	City	Bangalore	26.71
5	City	New Delhi	31.63
6	City	Pune	50.39
7	Gender	Female	47.15
8	Gender	Male	25.77
9	Year	2012	21.63
10	Year	2013	33.48
11	Year	2014	24.75
12	Year	2015	40.72
13	Year	2016	22.29
14	Year	2017	26.81
15	Year	2018	98.64
16	Pay	1	36.63
17	Pay	2	59.91
18	Pay	3	27.52

Table 1.1: Attrition Rate Across Categories

Feature and Target Engineering

Since my predictor variable (Leave or Not) is binary, there is no need for target engineering.

Regarding feature engineering, most of the features are categorical. Gender and whether a person benched or not (removed themselves from projects in the lst month) are transformed into dummies. Joining year is one-hot encoded, resulting in binary variables for each of the 5 joining years.

Education is label encoded as it can be ordered (Bachelors being the lowest level of education, Master's one higher and PHD being the highest level of education). Payment Tier and experience in the current domain were already label encoded and thus do not require further engineering.

Since age is numeric and random forests are able to handle both numeric and categorical variables, it is not altered.

Logistic Regression

Logistic regression is often used for binary classification problems.

Using logistic regression, three models are estimated to assess the accuracy of predicting employee attrition. Model 1 regresses employee attrition on education level. Model 2 adds payment tier as another feature. Model 3 regresses employee attrition on all available features.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
1	0.63	0.64	0.65	0.64	0.66	0.66	0.00
2	0.60	0.62	0.63	0.63	0.65	0.66	0.00
3	0.70	0.72	0.74	0.74	0.75	0.76	0.00

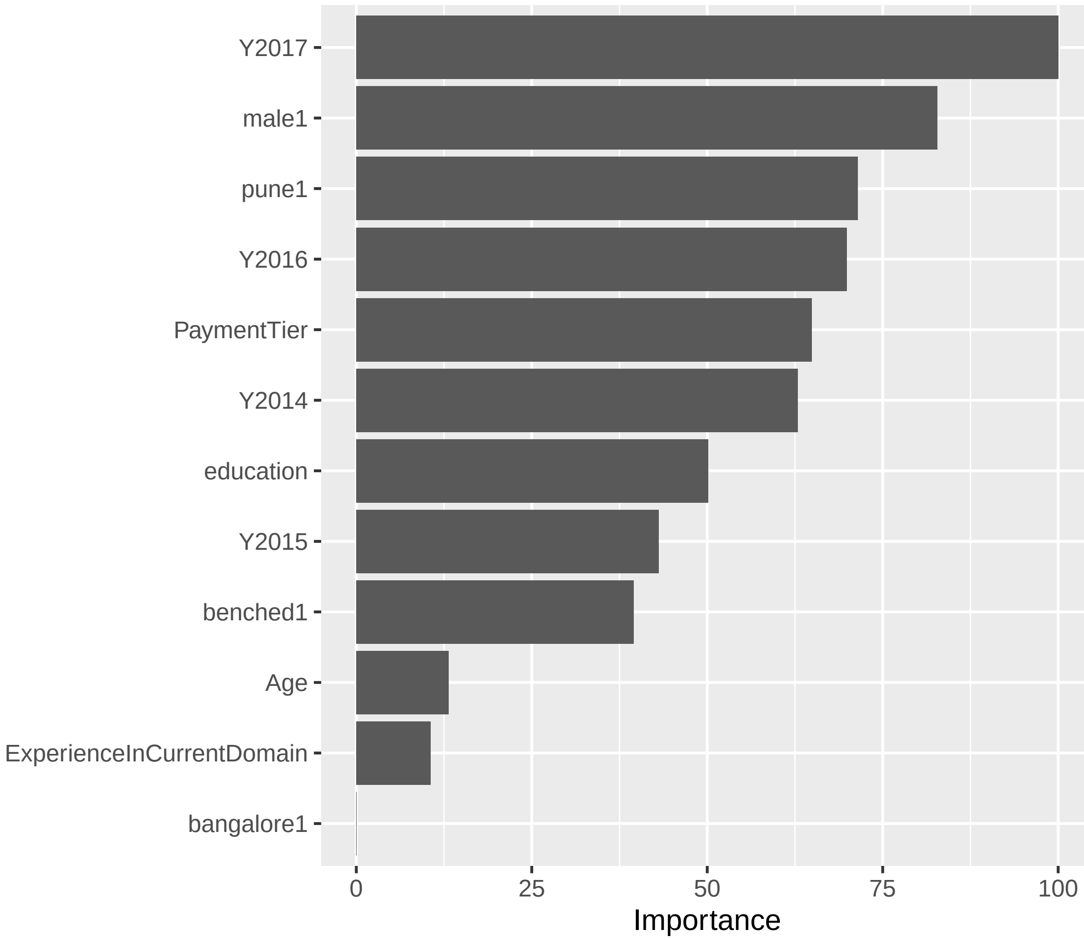
Table 1.2: Accuracy across logistic models

From the logistic regression, model accuracy ranges from 70 and 76 percent for the full model. The weakest model is model 1, which regresses attrition on education, has an accuracy rate between 63 and 66 percent.

In terms of the most important features, gender and the joining year of 2017 are the most important predictive features. Most of the other variables do carry some level of importance, therefore the model is not overly reliant on gender and joining year. This also provides an indication that the variance of the model is not too high. While the model suffers some level of bias, given that the accuracy is the model is approximately 74 percent, it does not suffer from high bias.

	Reference	Prediction	Count
1	1	1	483
2	1	0	637
3	0	1	204
4	0	0	1933

Table 1.3: Confusion Matrix for Logistic Model



	Metric	Value
1	Accuracy	0.74
2	F1 Score	0.53
3	Recall	0.43
4	Precision	0.70

Table 1.4: Metrics for Logistic Regression

	Metric	Value
1	Training Accuracy	0.74
2	Test Accuracy	0.71
3	Training Error	0.26
4	Test Error	0.29

Table 1.5: More Metrics for Logistic Regression

	term	estimate	std.error	statistic	p.value
1	(Intercept)	1.86	0.39	4.79	0.00
2	Age	-0.02	0.01	-2.73	0.01
3	male1	-0.81	0.09	-9.48	0.00
4	benched1	0.67	0.13	5.29	0.00
5	ExperienceInCurrentDomain	-0.07	0.03	-2.48	0.01
6	bangalore1	0.17	0.12	1.45	0.15
7	pune1	0.99	0.12	8.38	0.00
8	education	0.53	0.08	6.31	0.00
9	PaymentTier	-0.60	0.08	-7.75	0.00
10	Y2014	-0.97	0.13	-7.56	0.00
11	Y2015	-0.69	0.12	-5.63	0.00
12	Y2016	-1.23	0.15	-8.23	0.00
13	Y2017	-1.30	0.12	-11.16	0.00

Table 1.6: Logistic Regression Results

KNN

The K-nearest neighbour (KNN) algorithm predicts each observation based on its similarity to other observations. It identifies “k” observations that are most similar .. and uses the most common class of those k observations as the predicted output ().

Using the KNN approach, a grid-search is conducted to find the optimal level of K. Low values of K makes the model sensitive to noise and less generalisable while large values can lead to oversmoothing.

The accuracy metric is used, given that is an appropriate metric for a classification problem. The grid search uses cross-validation techniques to looks for the optimal level of K between 2 and 25. The model selects k =3 as the optimal value. The accuracy rate for k=3 is 78.3%. For the testing data, the model’s accuracy is slightly lower at 77%.

Alongside the model’s accuracy, the precision, recall and F1 score are also examined. Precision measures the proportion of correctly predicted positive instances, also called true positives, out of all instances predicted as positive. A high precision indicates few false positives. In this case the precision is 74%, which is relatively high.

Recall, also known as the model’s sensitivity, measures the proportion of correctly predicted positive instances out of all actual positives instances. In other words, it is the proportion of true positives out of both the true positives and false negatives. A higher recall indicates few false negatives. In this instance, the recall is much lower (52%). This indicates that the model has a higher false negative rate than false positive rate.

The F1 score balances both the precision and recall, and provides an indication of the overall performance of the model. The F1 score for the optimal K-nearest neighbours model is 61.2%, indicating that the model is somewhat adequate.

	Reference	Prediction	Count
1	1	1	250
2	1	0	230
3	0	1	86
4	0	0	830

Table 1.7: Confusion Matrix for KNN Model

	Metric	Value
1	Accuracy	0.77
2	F1 Score	0.62
3	Recall	0.53
4	Precision	0.74

Table 1.8: Metrics for KNN Model

	Metric	Value
1	Training Accuracy	0.84
2	Test Accuracy	0.77
3	Training Error	0.16
4	Test Error	0.23

Table 1.9: More Metrics for KNN Model

	Metric	Value
1	Accuracy	0.77
2	F1 Score	0.62
3	Recall	0.53
4	Precision	0.74

Table 1.10: Metrics for KNN

KNN models are very sensitive to feature scaling. Results can easily become biased as variables with larger scales can dominate the distance to calculation.

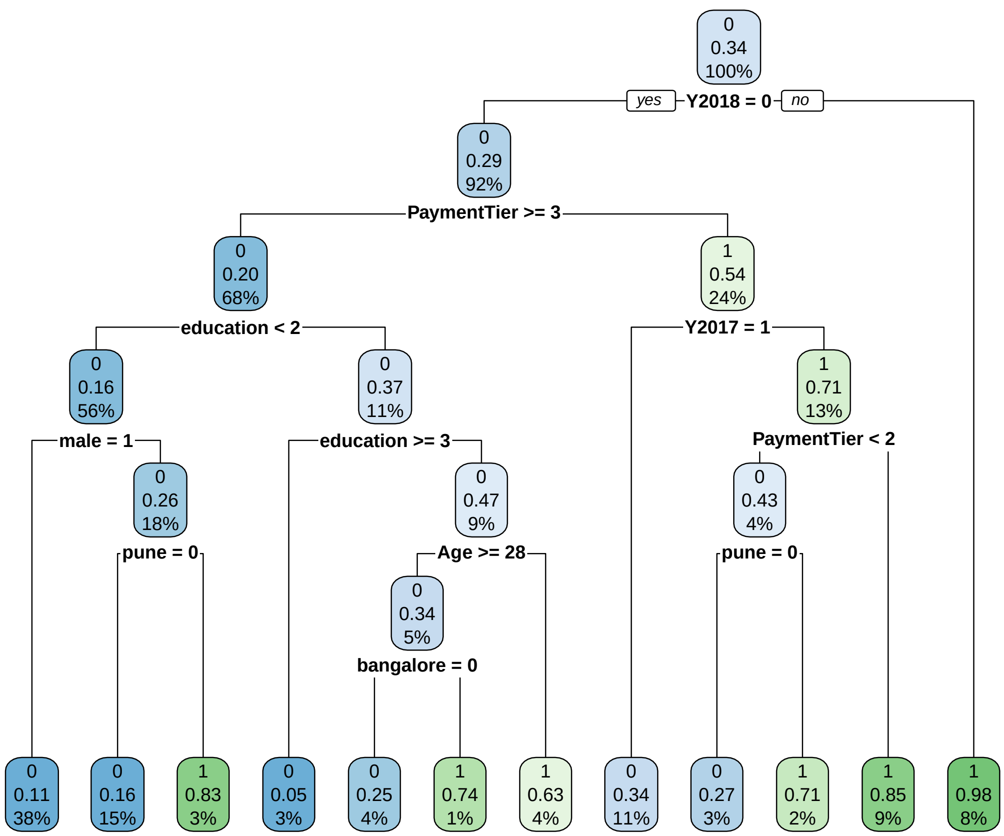
On the other hand, KNN is appropriate for small datasets such as this one.

Random Forests

Random forests are powerful out-of the box algorithms that generally have very good predictive accuracy (). The come with the benefits of decision trees and bagging but greatly reduce instability and between-tree correlation.

Decision tree

Following the general rule-of-thumb, there is a 70:30 split among the training and testing data.



1.1. Baseline Random Forest

The results from the baseline random forest are presented below. Random Forests help to reduce tree correlation. It does so by using split-variable randomisation. In the baseline model, number of trees are set to 500 by default. It is possible to alter the m(try) parameter, but currently it is set to the square root of the number of parameters, given that this standard when doing a classification problem.

	Metric	Value
1	Accuracy	0.85
2	F1 Score	0.75
3	Recall	0.64
4	Precision	0.91
5	AUC ROC	0.80

Table 1.11: Metrics for Baseline Random Forest

	Reference	Prediction	Count
1	1	1	308
2	1	0	172
3	0	1	23
4	0	0	893

Table 1.12: Confusion Matrix for Baseline Random Forest

Comparing the training and testing error, the test error (15.1%) is slightly higher than the training error (11.8%). This may indicate that there is some level of overfitting, given that the training data performs better, however it does not appear to be substantial. The model's performance is still reasonably good.

To continue to examine the bias-variance tradeoff, the learning curve is plotted. At small sample sizes, it can be seen that the test accuracy is much lower than the training dataset. The high accuracy for the training set at lower sample sizes indicates overfitting. Once the sample size reaches over 2000, the accuracy between the training and the testing set begin to converge, reducing the bias-variance tradeoff.

	Metric	Value
1	Training Accuracy	0.88
2	Test Accuracy	0.85
3	Training Error	0.12
4	Test Error	0.15

Table 1.13: More Metrics for Baseline Random Forest

There are several hyper-parameters to consider in this model, including the number of trees, the number of features to consider at a given split, the complexity of each tree, the sampling scheme, and the splitting rule to use during tree construction.

The first parameter I adjust is the number of trees. If I have 15 variables, I will make 150 trees. The default above was 500 trees.

Adjusting the number of trees down from 500 to 150 increases the accuracy of the model, but marginally. Accuracy increased from 84.81% to 84.96%.

Following the baseline random forest model, a grid search is conducted over a range of hyperparameters in an attempt to select the optimal model.

The default sampling scheme for a random forest is one with replacement.

Sample size influences how many observations are drawn for the training of each tree. Decreasing the sample size leads to more diverse trees and less between-tree correlation, which has a positive effect on predictive accuracy. Having a few features that

Having many categorical features with varying number of levels, such as experience or education in this case, or unbalanced categories, then sampling with replacement can lead to biased results. Sampling without replacement can thus lead to a less biased use of all the levels across the trees in the random forest.

I included the number of trees in the search. As a rule of thumb, the number of trees is 100, 150 and 250 were selected as possibilities.

To select the best model, the grid search finds the out-of-bag error for each possible model. The model with the lowest RMSE is chosen as the best model. Comappring the RMSE of the baseline model to the tuned model the tuned model is a 1.9 percent improvement over the baseline model. Although this increase is small, the greater accuracy in predicting employee attrition, the better.

The best model selected is one with m(try) set to 4, a number of trees as 250, a node size of 1, sample without replacement, and a sample fraction of 0.63.

```
## [1] 0.3838944
```

	Reference	Prediction	Count
1	1	1	318
2	1	0	162
3	0	1	30
4	0	0	886

Table 1.14: Confusion Matrix for Tuned Random Forest

	Metric	Value
1	Accuracy	0.86
2	F1 Score	0.76
3	Recall	0.67
4	Precision	0.88
5	AUC ROC	0.80

Table 1.15: Metrics for Tuned Random Forest

Bias-Variance Trade-off

It is also important to consider the bias-variance trade-off. Prediction errors are generally a result of either bias or variance. In general, decreasing bias will almost always lead to greater variance. Bias is the difference between the expected prediction and the correct value (linear models have high levels of bias).

Variance error is the variability of a model prediction for a given data point. Some models can potentially overfit the training data, resulting in accurate results against the training data but typically poor results against the test data. In other words, the model does not generalise well.

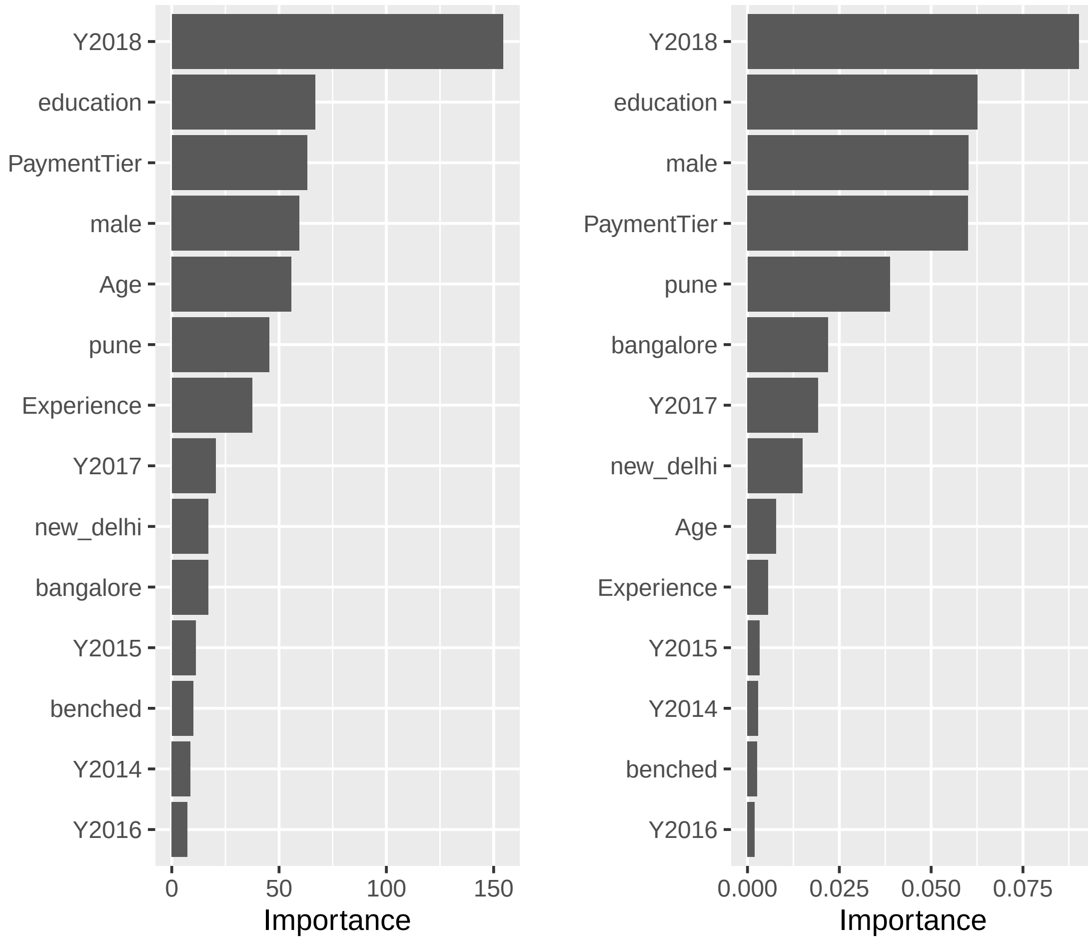
We can adjust the model hyperparameters to achieve the best mix of bias and variance.

	Metric	Value
1	Training Accuracy	0.89
2	Test Accuracy	0.86
3	Training Error	0.11
4	Test Error	0.14

Table 1.16: More Metrics for Tuned Random Forest

Assessing variable importance gives an indication of the variance in the model. If the model relies heavily on a few features, then this indicates high variance and over-fitting. Comparing the two graphs below, it can be seen that with impurity-based variable importance, the model heavily relies on the joining year, specifically, those who joined the company in 2018. This is most likely due to the high attrition rate seen in the exploratory data analysis. Under permutation-based variable importance, there is grater emphasis on more features such as education, payment tier and gender, despite joining year being the most important predictive feature.

Comparing the graphs below to the variable importance plot for the logistic regression, the random forest model appears to suffer from higher variance due to its heavier reliance on certain features. This shows a clear example of the bias-variance trade-off, given the improved accuracy of the random forrest model compared to the logistic model.



2. Conclusion

In order to predict employee attrition, various models and their accuracy levels are assessed.

The best model in predicting is the random forest model after hyperparameter tuning. This model achieves an accuracy rate of 86 percent.

When assessing the bias-variance tradeoff…

To cite this package, simply type citation("Texevier") in Rstudio to get the citation for Katzke (2017) (Note that uncited references in your bibtex file will not be included in References).

References

Katzke, N.F. 2017. *Texevier: Package to create elsevier templates for rmarkdown.* Stellenbosch, South Africa: Bureau for Economic Research.