Predicting Employee Attrition

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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.

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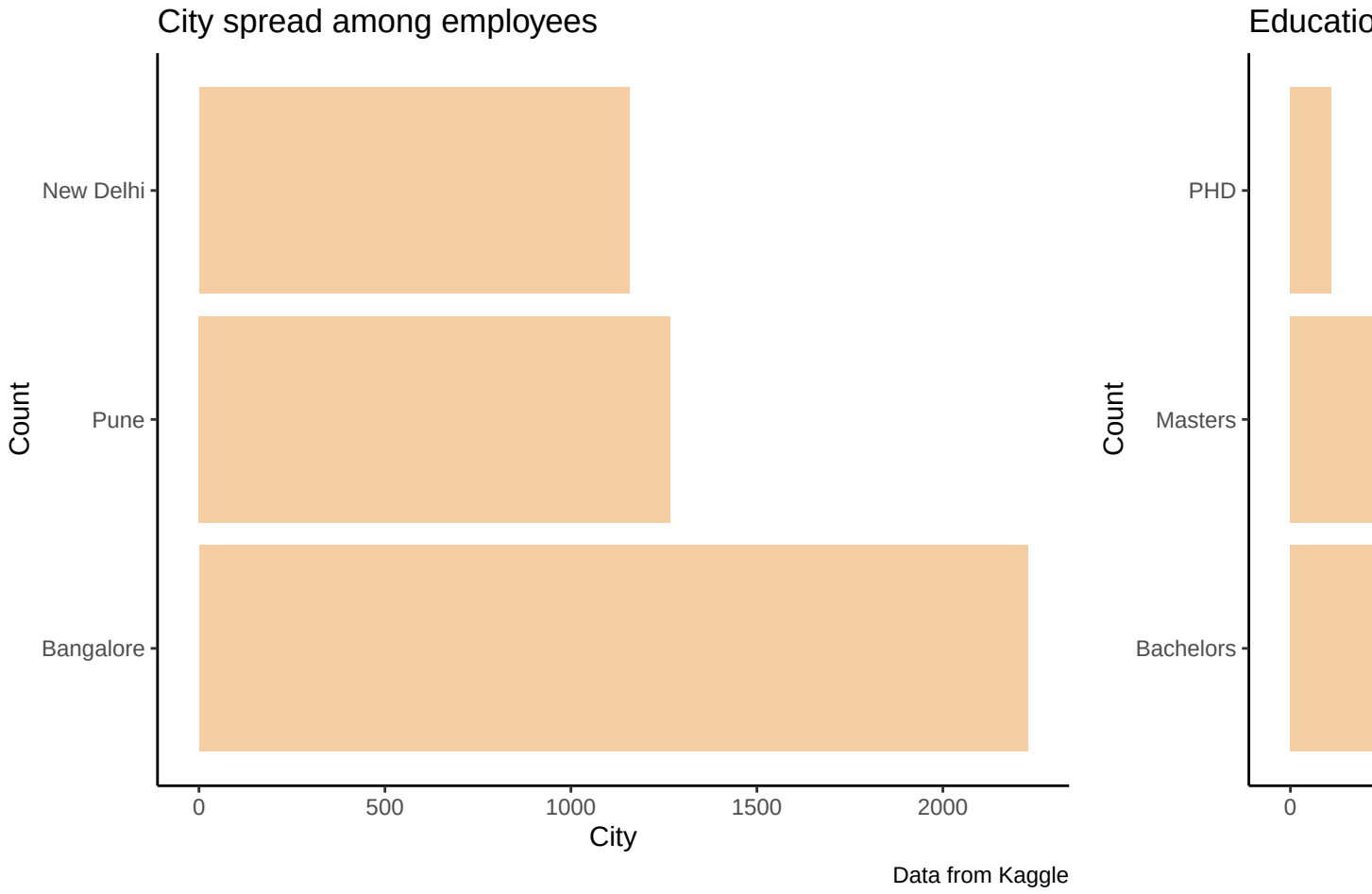
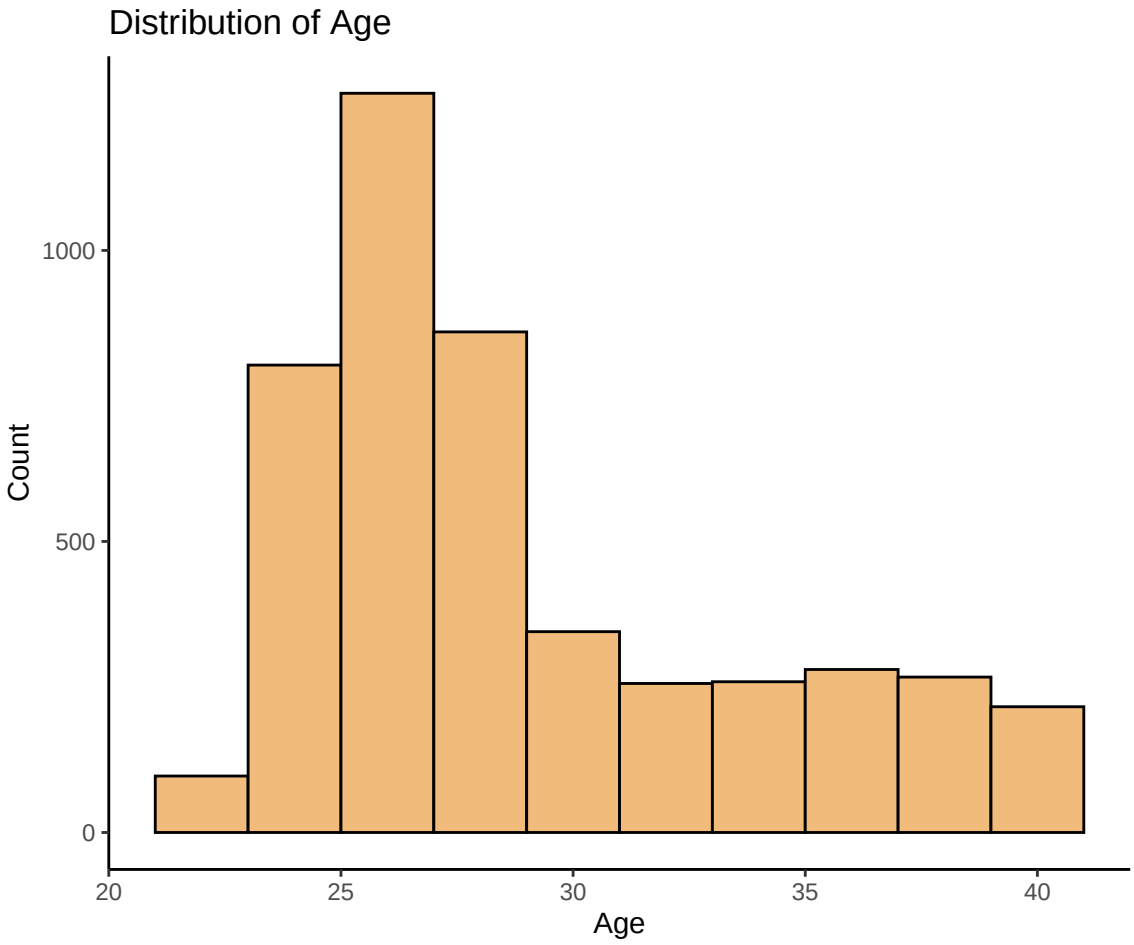
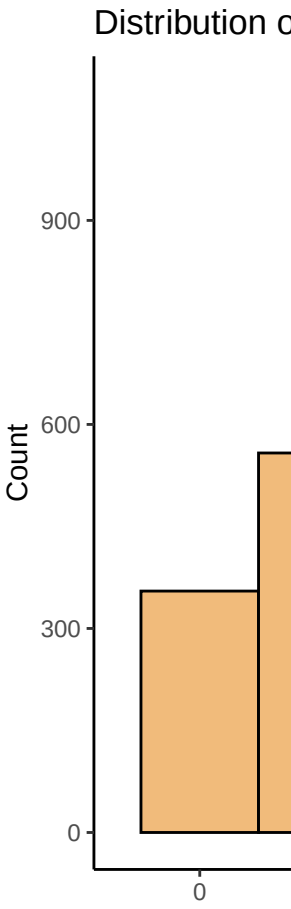


Spreading the data among city, most of the employees are from Bangalore. Additionally, most employees have a Bachelors degree. Only 179 employees have a PHD and 873 have Master's degrees. Looking at age, which ranges between 22 and 41, the majority of employees are in their mid to late twenties, skewing 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 c
Count
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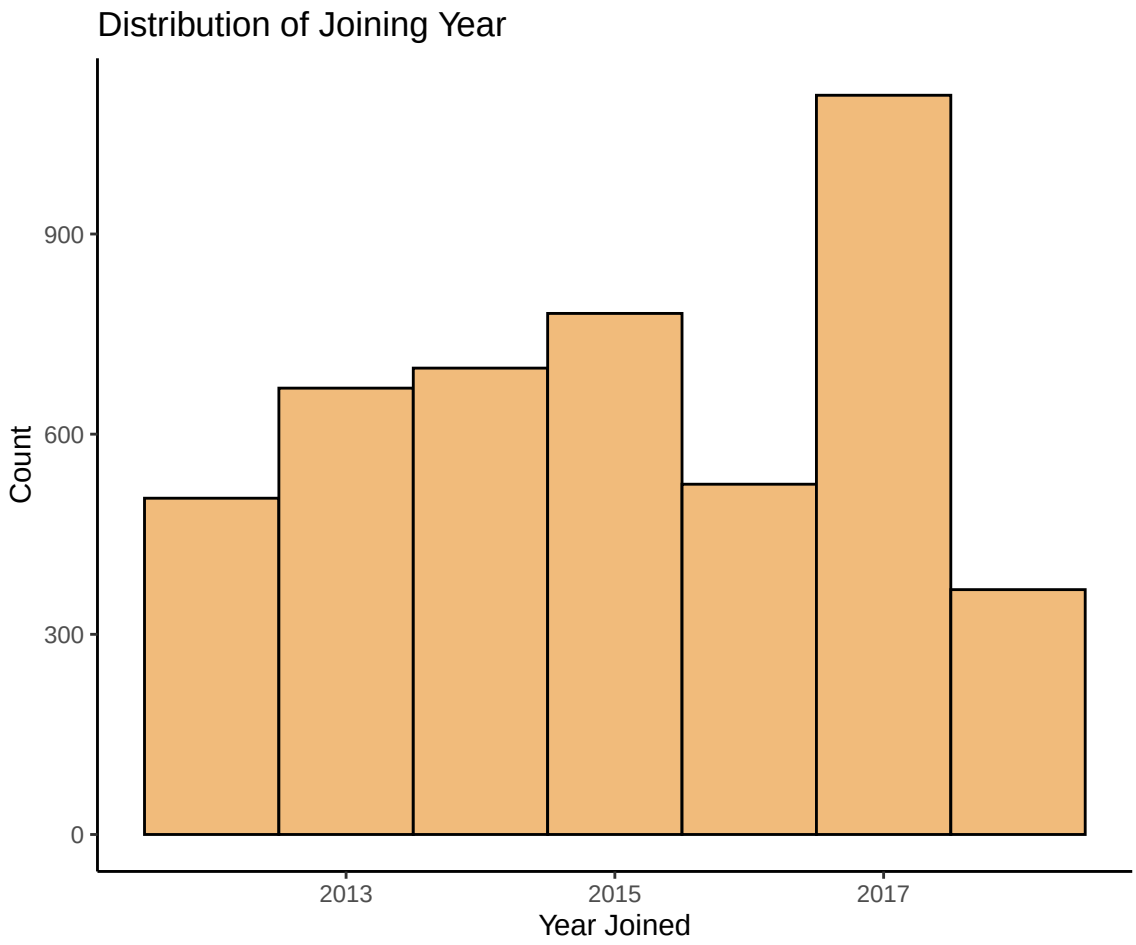
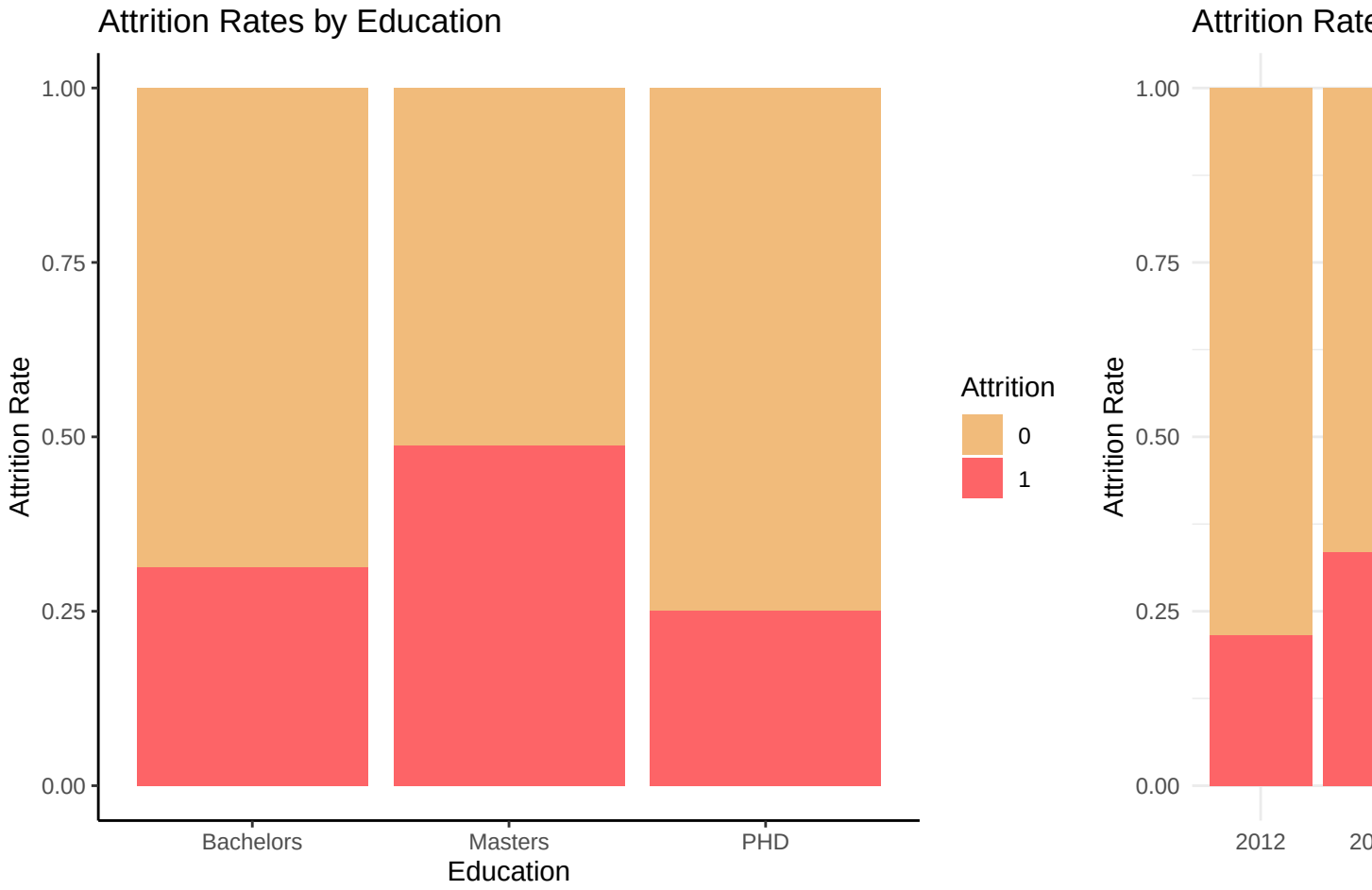
600
300
0
0



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.



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.

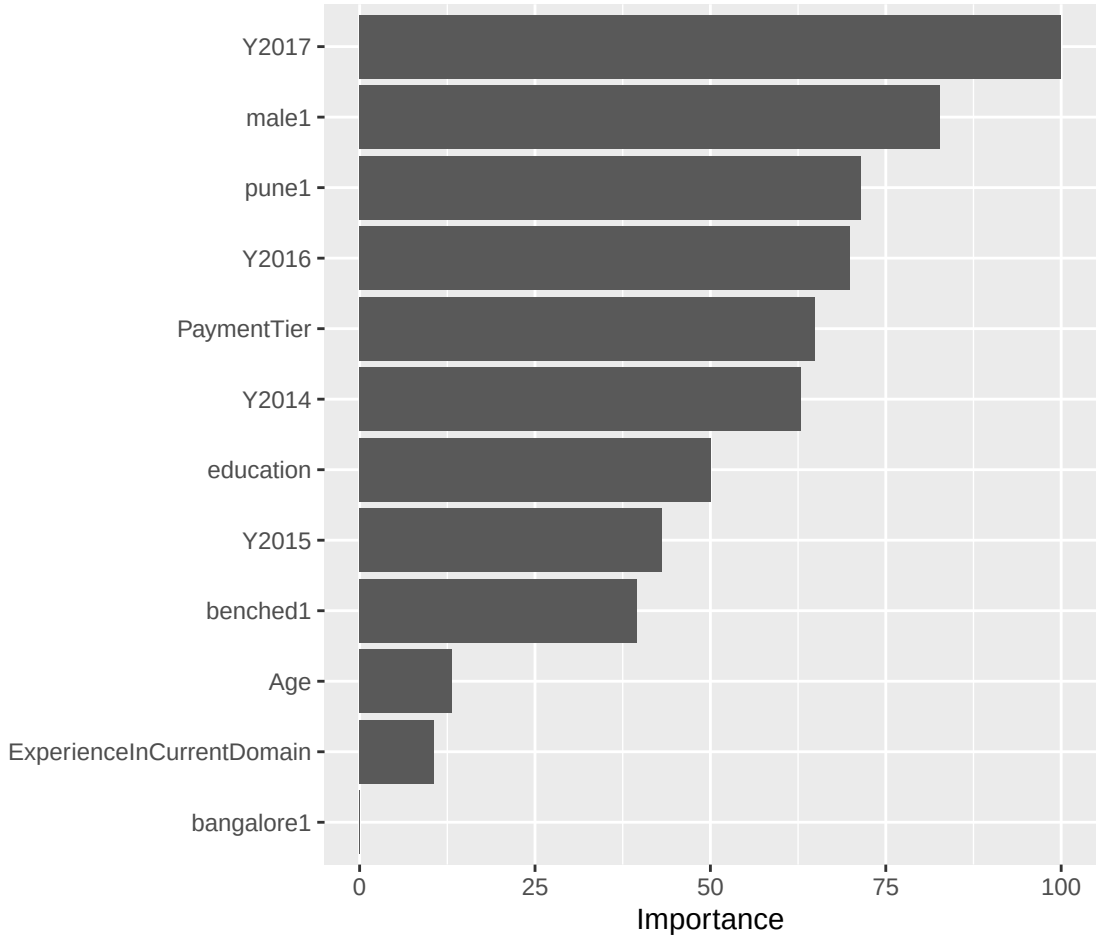
Logistic Regression

	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 1.1: Short Table Example

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.



	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 1.2: Logistic Regression Results

KNN

looking at a K-Nearest Neighbours approach, a grid-search is conducted to find the optimal level of K. The accuracy metric is used, given that is an appropriate metric for a classification problem. The grid search 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%.

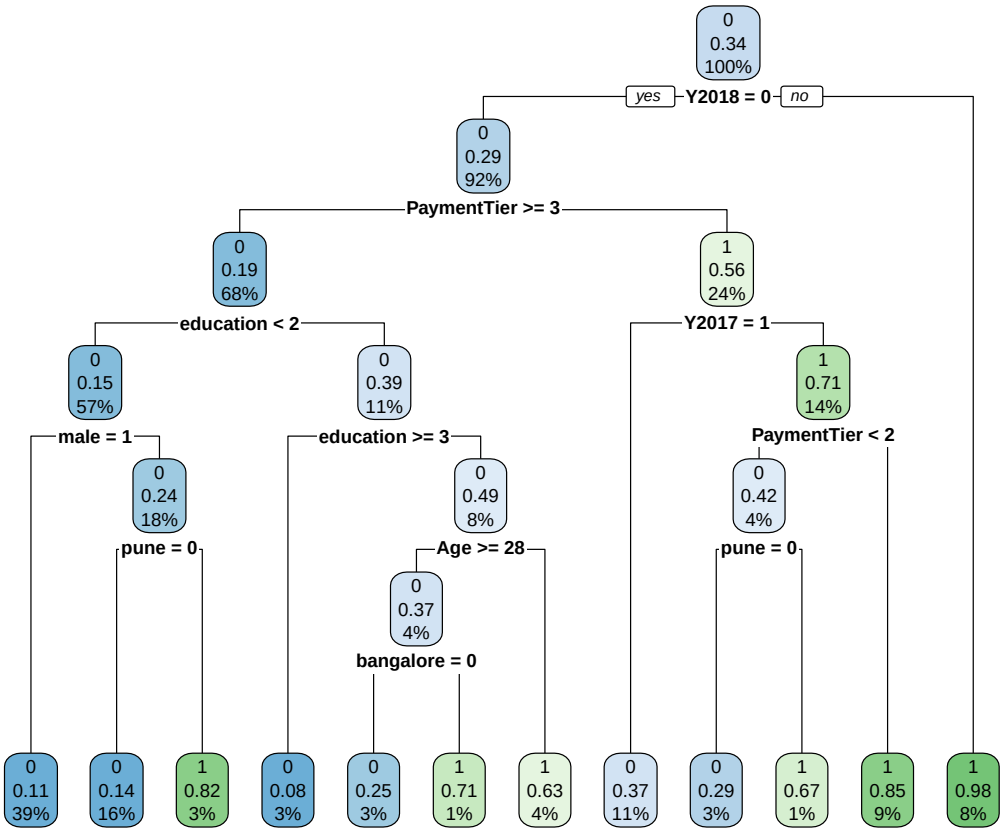
```
## [1] 0.7743553
```

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.

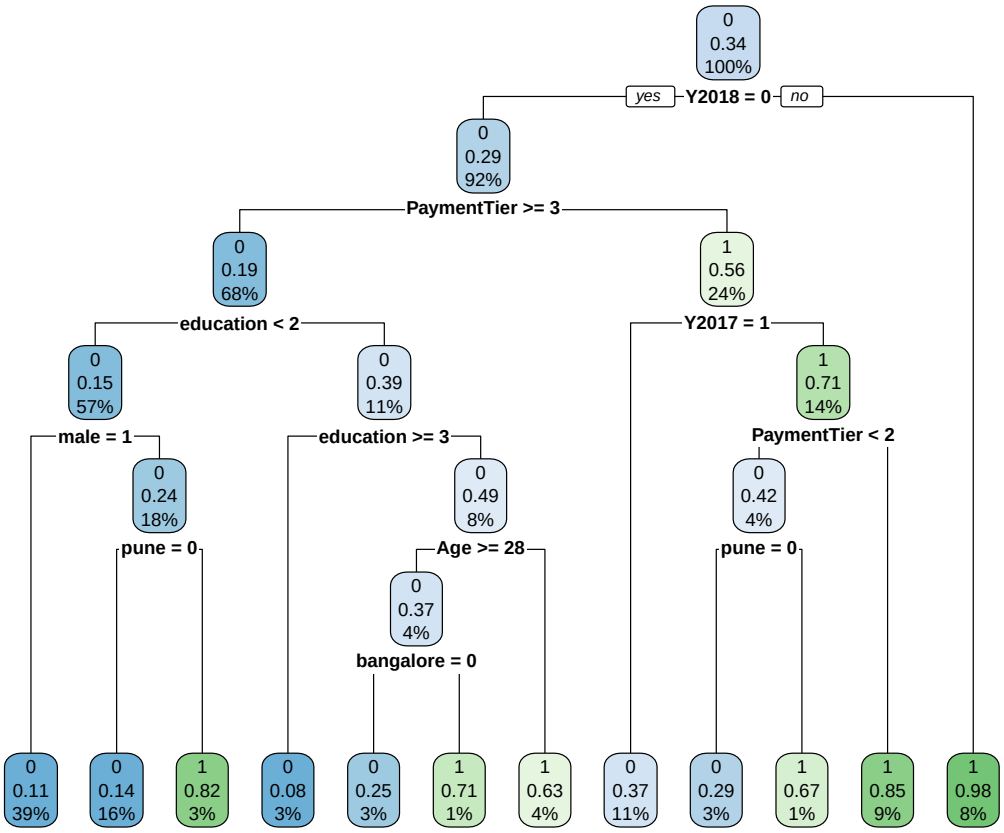
Decision tree

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



#ranger - model$confusionmatrix

```
## Accuracy: 82.80802 %
```



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.

```
## [1] 0.3898466
```

	Metric	Value
1	Accuracy	0.85
2	F1 Score	0.73
3	Recall	0.62
4	Precision	0.90
5	AUC ROC	0.79

Table 1.3: Metrics 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	0.84
3	Training Error	0.12
4	Test Error	0.16

Table 1.4: 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.

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] 0.3741739
```

```
## [1] 0.8495702
```

```
## [1] 0.875
```

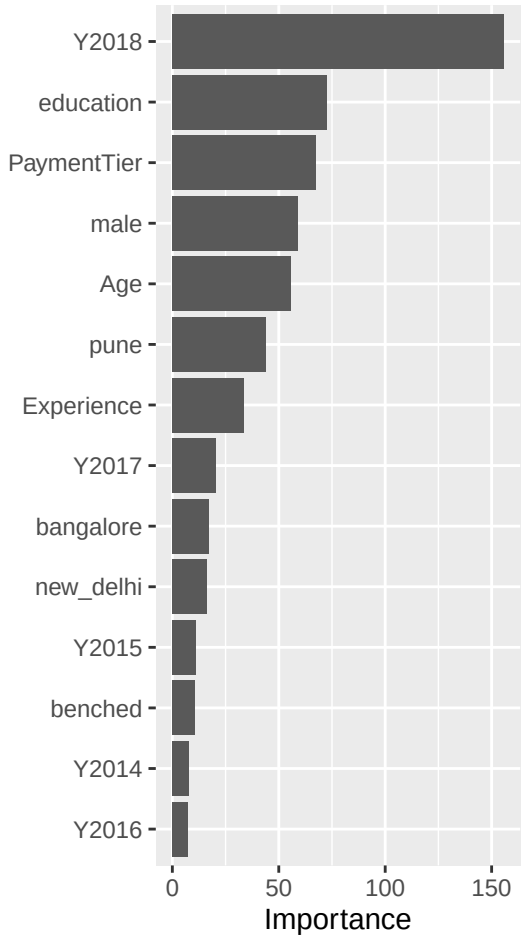
```
## [1] 0.65625
```

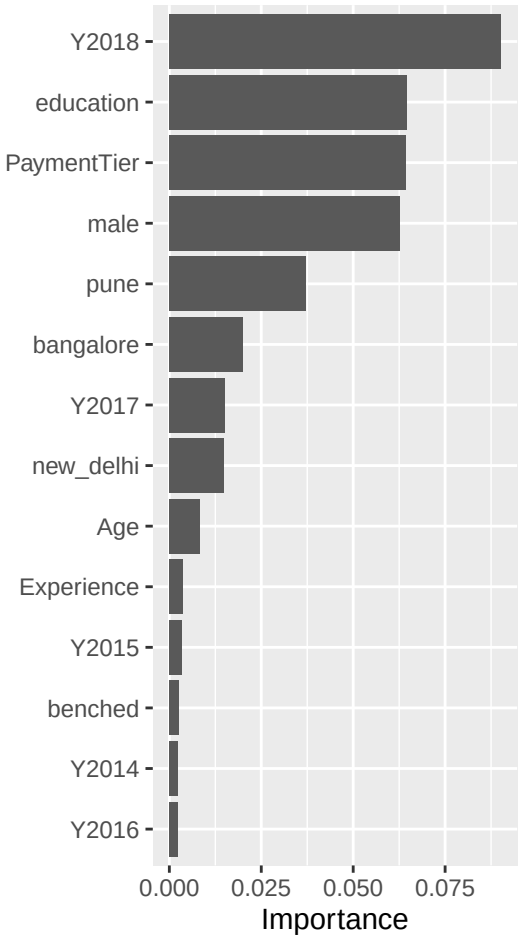
```
## [1] 0.75
```

```
## Area under the curve: 0.7914
```

	Metric	Value
1	Accuracy	0.85
2	F1 Score	0.75
3	Recall	0.66
4	Precision	0.88
5	AUC ROC	0.79

Table 1.5: Metrics for Tuned Random Forest





2. Results

Tables can be included as follows. Use the *xtable* (or kable) package for tables. Table placement = H implies Latex tries to place the table Here, and not on a new page (there are, however, very many ways to skin this cat. Luckily there are many forums online!).

To reference calculations **in text**, *do this:* From table 1.5 we see the average value of mpg is 20.98.

Including tables that span across pages, use the following (note that I add below the table: "continue on the next page' '). This is a neat way of splitting your table across a page.

Use the following default settings to build your own possibly long tables. Note that the following will fit on one page if it can, but cleanly spreads over multiple pages:

Table 2.1: Long Table Example

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
	21.00	6.00	160.00	110.00	3.90	2.62	16.46	0.00	1.00	4.00	4.00
	21.00	6.00	160.00	110.00	3.90	2.88	17.02	0.00	1.00	4.00	4.00
	22.80	4.00	108.00	93.00	3.85	2.32	18.61	1.00	1.00	4.00	1.00
	21.40	6.00	258.00	110.00	3.08	3.21	19.44	1.00	0.00	3.00	1.00
	18.70	8.00	360.00	175.00	3.15	3.44	17.02	0.00	0.00	3.00	2.00
	18.10	6.00	225.00	105.00	2.76	3.46	20.22	1.00	0.00	3.00	1.00
	14.30	8.00	360.00	245.00	3.21	3.57	15.84	0.00	0.00	3.00	4.00
	24.40	4.00	146.70	62.00	3.69	3.19	20.00	1.00	0.00	4.00	2.00
	22.80	4.00	140.80	95.00	3.92	3.15	22.90	1.00	0.00	4.00	2.00
	19.20	6.00	167.60	123.00	3.92	3.44	18.30	1.00	0.00	4.00	4.00
	17.80	6.00	167.60	123.00	3.92	3.44	18.90	1.00	0.00	4.00	4.00
	16.40	8.00	275.80	180.00	3.07	4.07	17.40	0.00	0.00	3.00	3.00
	17.30	8.00	275.80	180.00	3.07	3.73	17.60	0.00	0.00	3.00	3.00
	15.20	8.00	275.80	180.00	3.07	3.78	18.00	0.00	0.00	3.00	3.00
	10.40	8.00	472.00	205.00	2.93	5.25	17.98	0.00	0.00	3.00	4.00
	10.40	8.00	460.00	215.00	3.00	5.42	17.82	0.00	0.00	3.00	4.00
	14.70	8.00	440.00	230.00	3.23	5.34	17.42	0.00	0.00	3.00	4.00
	32.40	4.00	78.70	66.00	4.08	2.20	19.47	1.00	1.00	4.00	1.00
	30.40	4.00	75.70	52.00	4.93	1.61	18.52	1.00	1.00	4.00	2.00
	33.90	4.00	71.10	65.00	4.22	1.83	19.90	1.00	1.00	4.00	1.00
	21.50	4.00	120.10	97.00	3.70	2.46	20.01	1.00	0.00	3.00	1.00
	15.50	8.00	318.00	150.00	2.76	3.52	16.87	0.00	0.00	3.00	2.00
	15.20	8.00	304.00	150.00	3.15	3.44	17.30	0.00	0.00	3.00	2.00
	13.30	8.00	350.00	245.00	3.73	3.84	15.41	0.00	0.00	3.00	4.00
	19.20	8.00	400.00	175.00	3.08	3.85	17.05	0.00	0.00	3.00	2.00
	27.30	4.00	79.00	66.00	4.08	1.94	18.90	1.00	1.00	4.00	1.00
	26.00	4.00	120.30	91.00	4.43	2.14	16.70	0.00	1.00	5.00	2.00
	30.40	4.00	95.10	113.00	3.77	1.51	16.90	1.00	1.00	5.00	2.00
	15.80	8.00	351.00	264.00	4.22	3.17	14.50	0.00	1.00	5.00	4.00
	19.70	6.00	145.00	175.00	3.62	2.77	15.50	0.00	1.00	5.00	6.00
	15.00	8.00	301.00	335.00	3.54	3.57	14.60	0.00	1.00	5.00	8.00
	21.40	4.00	121.00	109.00	4.11	2.78	18.60	1.00	1.00	4.00	2.00

2.1. Huxtable

Huxtable is a very nice package for making working with tables between Rmarkdown and Tex easier.

This cost some adjustment to the Tex templates to make it work, but it now works nicely.

See documentation for this package here. A particularly nice addition of this package is for making the printing of regression results a joy (see here). Here follows an example:

If you are eager to use huxtable, comment out the Huxtable table in the Rmd template, and uncomment the colortbl package in your Rmd's root.

Note that I do not include this in the ordinary template, as some latex users have complained it breaks when they build their Rmds (especially those using tidytex - I don't have this problem as I have the full Miktex installed on mine). Up to you, but I strongly recommend installing the package manually and using huxtable. To make this work, uncomment the *Adding additional latex packages* part in yaml at the top of the Rmd file. Then comment out the huxtable example in the template below this line. Reknit, and enjoy.

Table 2.2: Regression Output

	Reg1	Reg2	Reg3
(Intercept)	-2256.361 ***	5763.668 ***	4045.333 ***
	(13.055)	(740.556)	(286.205)
carat	7756.426 ***		7765.141 ***
	(14.067)		(14.009)
depth		-29.650 *	-102.165 ***
		(11.990)	(4.635)
N	53940	53940	53940
R2	0.849	0.000	0.851

*** p $<$ 0.001; ** p $<$ 0.01; * p $<$ 0.05.

FYI - R also recently introduced the gt package, which is worthwhile exploring too.

3. Lists

To add lists, simply using the following notation

- This is really simple
  - Just note the spaces here - writing in R you have to sometimes be pedantic about spaces...
- Note that Rmarkdown notation removes the pain of defining LaTeXenvironments!

4. Conclusion

I hope you find this template useful. Remember, stackoverflow is your friend - use it to find answers to questions. Feel free to write me a mail if you have any questions regarding the use of this package. 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.

Appendix

Appendix A

Some appendix information here

Appendix B