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## 1. EDA

## 1.1 Univariate Analysis:

#### 1.1.1. Age:

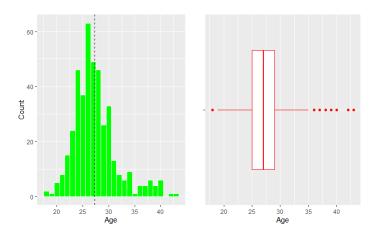
Minimum age is 18.

Maximum age is 43.

Average age is 27.33.

Outliers are present above and below the upper and lower limits.

Data slightly skewed to the right.



## 1.1.2. Work Experience:

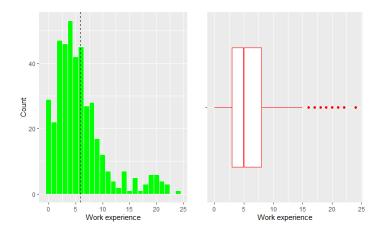
Some employees have no work experience.

Maximum work experience is 24 years.

Average is 5.873 years.

Outliers present above the upper limit.

Data skewed to the right.



#### 1.1.3. Salary:

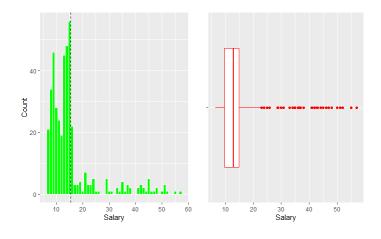
Minimum salary is \$6,500/year.

Maximum salary is \$57,000/year.

Average is \$15,418/year.

Outliers present above the upper limit.

Data skewed to the right.



#### 1.1.4. Distance from work:

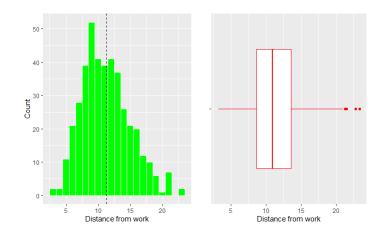
Minimum distance is 3.2 KM.

Maximum distance is 23.40 KM.

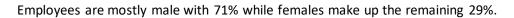
Average is 11.29 KM.

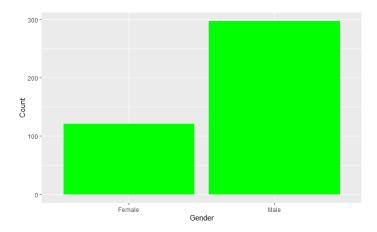
Outliers present above the upper limit.

Data skewed to the right.



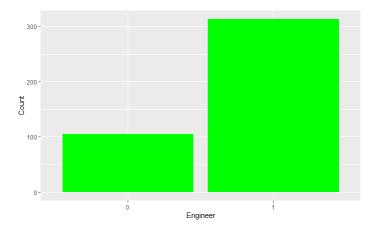
## 1.1.5. Gender:





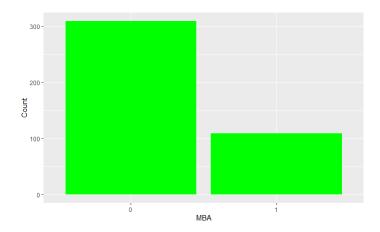
## 1.1.6. Engineering degrees:

75% of the employees have an engineering degree while the remaining 25% do not.



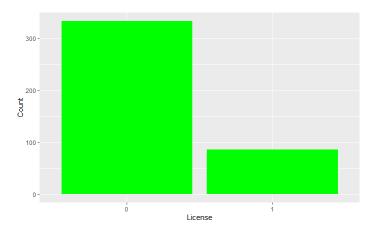
## 1.1.7. MBA degrees:

74% of the employees do not have an MBA degree. 26% do.



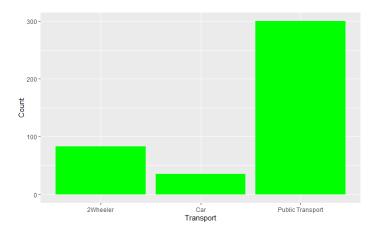
#### 1.1.8. License:

With about 80%, most of the employees do not have a license.



## 1.1.9. Mean of transport:

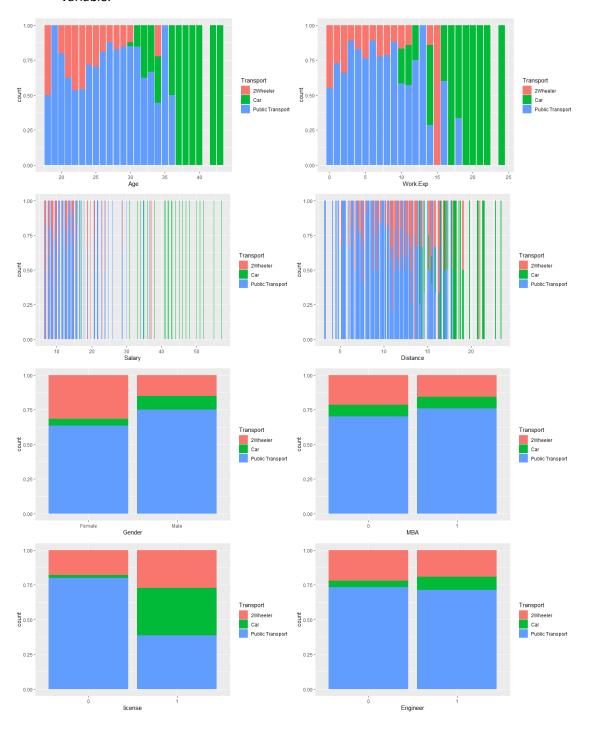
Most of the employees prefer taking public transport to go to work. About 20% use a 2 wheeler. With only 8% preferring to use their cars.



## 1.2. Bivariate Analysis:

# 1.2.1. Correlation between method of transport (the dependent variable) and the other variables:

All the variables appear to be correlated with the "Transport" variable except for the "Engineer" variable.



## 1.2.2. Correlation between numerical variables

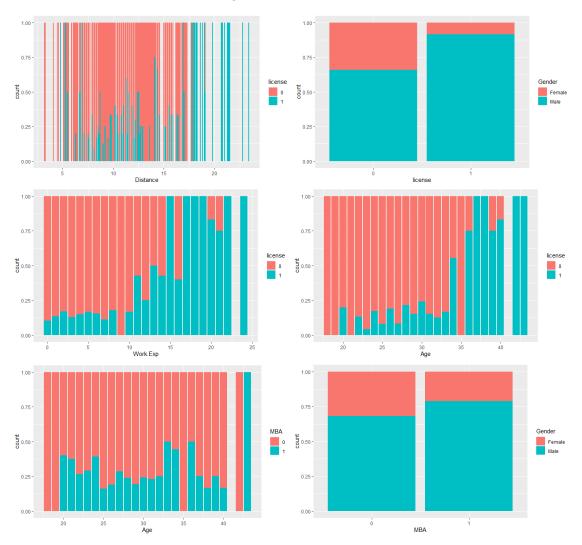
Age, Work Exp and Salary variables have a high correlation. Distance variable is not correlated with the others



#### 1.2.3. Important correlations between the remaining variables

License variable appear to have a significant correlation with Distance, Gender, Work Experience and Age variables.

While MBA variable seems to have a correlation with the Gender variable, it does not appear to have a correlation with the Age variable.



## 1.3. The most challenging aspects and methods used to deal with them

- 1) Dataset is highly imbalanced. SMOTE will be used to artificially oversample the minority
- 2) A new dependent variable will be created with only 2 levels, employees who use a car and those who do not. As the company is only interested in those who arrive by car.
- 3) Outliers are present in the numerical variables. So, the values will be capped.
- 4) Conversion of the Gender variable from a factor to a numerical variable by converting its values to 1s for males and 0s for females.

## 2. Modeling

#### 2.1. Logistic regression model performance (Without SMOTE)

After removing variables with multicollinearity and insignificant variables.

#### 2.1.1. Against train data:

Accuracy: 98.63% Sensitivity: 99.25% Specificity: 91.67%

#### 2.1.2. Against test data:

Accuracy: 97.62% Sensitivity: 97.39% Specificity: 100%

#### 2.2. Logistic regression model performance (With SMOTE)

#### 2.2.1. Against train data:

Accuracy: 99.37% Sensitivity: 99.23% Specificity: 99.65%

#### 2.2.2. Against test data:

Accuracy: 96.83% Sensitivity: 96.52% Specificity: 100%

#### 2.3. Naïve Bayes model performance (Without SMOTE)

#### 2.3.1. Against train data:

Accuracy: 99.32% Sensitivity: 99.63% Specificity: 95.83%

#### 2.3.2. Against test data:

Accuracy: 95.24% Sensitivity: 94.78% Specificity: 100%

## 2.4. Naïve Bayes model performance (With SMOTE)

#### 2.4.1. Against train data:

Accuracy: 98.11% Sensitivity: 99.76% Specificity: 94.91%

#### 2.4.2. Against test data:

Accuracy: 96.83% Sensitivity: 96.52% Specificity: 100%

#### 2.5. KNN model performance (Without SMOTE)

#### 2.5.1. Against train data:

Accuracy: 97.95% Sensitivity: 98.88% Specificity: 87.50%

#### 2.5.2. Against test data:

Accuracy: 96.03% Sensitivity: 98.26% Specificity: 72.73%

#### 2.6. KNN model performance (With SMOTE)

#### 2.6.1. Against train data:

Accuracy: 99.84% Sensitivity: 99.76% Specificity: 100%

#### 2.6.2. Against test data:

Accuracy: 96.03% Sensitivity: 97.39% Specificity: 81.82%

#### 2.7. Applying Random Forrest as a bagging technique (Without SMOTE)

#### 2.7.1. Against train data:

Accuracy: 100% Sensitivity: 100% Specificity: 100%

#### 2.7.2. Against test data:

Accuracy: 97.62% Sensitivity: 97.39% Specificity: 100%

#### 2.8. Random Forrest (With SMOTE)

#### 2.8.1. Against train data:

Accuracy: 100% Sensitivity: 100% Specificity: 100%

#### 2.8.2. Against test data:

Accuracy: 100% Sensitivity: 100% Specificity: 100%

## 2.9. Applying Extreme Gradient Boosting as a boosting technique (Without SMOTE)

#### 2.9.1. Against train data:

Accuracy: 100% Sensitivity: 100% Specificity: 100%

## 2.9.2. Against test data:

Accuracy: 98.41% Sensitivity: 98.26% Specificity: 100%

#### 2.10. Extreme Gradient Boosting (With SMOTE)

#### 2.10.1. Against train data:

Accuracy: 100% Sensitivity: 100% Specificity: 100%

#### 2.10.2. Against test data:

Accuracy: 100% Sensitivity: 100% Specificity: 100%

## 3. Conclusion

From the results we can see that:

- 1) With a 100% accuracy, sensitivity and specificity, the Extreme Gradient Boost and the Random Forrest models preformed perfectly after applying SMOTE.
- 2) Logistic regression and Naïve-Bayes models performed very well. But were worse than the Extreme Gradient Boost and Random Forrest models.
- 3) KNN model had a bad performance even after using SMOTE.
- 4) Most of the variables have a correlation with the Transport variable. But Age and Distance were found to be the best predictors.