Who are the Winners in the 2019 Indian General Election?

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Introduction to Data Science

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Contents

The Lok Sabha, the lower house of the Parliament of India, is made up of Members of Parliament (MPs). Each MP, represents a single geographic constituency. There are currently 543 constituencies. The 17th Lok Sabha Election held in 2019 from April to May 2019 in 7 phase. Around 910 Million voters were eligible to vote and the voter turnout was 67%, this was the highest ever voting recorded by Election Commission of India. Voting percent of women's voters were also increased than previous Lok Sabha elections.

In this project, we will examine what attributes make a candidate successful in this election, and try to model the mechanism using supervised machine learning algorithms.

1. Understanding the Data Set

The dataset could be downloaded from Kaggle dataset with the link https://www.kaggle.com/prakrutchauhan/indian-candidates-for-general-election-2019. There are 19 variables in the original dataset: STATE, CONSTITUENCY, NAME, WINNER, PARTY, SYMBOL, GENDER, CRIMINAL CASES, AGE, CATEGORY, EDUCATION, ASSETS, LIABILITIES, GENERAL VOTES, POSTAL VOTES, TOTALVOTES, OVER TOTAL ELECTORS IN CONSTITUENCY, OVER TOTAL VOTES POLLED IN CONSTITUENCY, TOTAL ELECTORS. Using “summary” to display the properties of the dataset:

```
> summary(df)
          STATE           CONSTITUENCY                NAME          WINNER          PARTY                          SYMBOL
 Uttar Pradesh : 274   AURANGABAD :  14   NOTA            : 245   Min.   :0.0000   BJP    :420   Lotus                  :420
 Bihar         : 244   GAYA (SC)  :  12   Ajay Kumar      :   2   1st Qu.:0.0000   INC    :413   Hand                   :413
 Tamil Nadu    : 217   MAHARAJGANJ:   9   ATUL KUMAR SINGH:   2   Median :0.0000   NOTA   :245                          :245
 West Bengal   : 193   UJIARPUR   :   9   Rahul Gandhi    :   2   Mean   :0.2382   IND    :201   Elephant               :166
 Maharashtra   : 192   ARUKU      :   8   SANJAY KUMAR    :   2   3rd Qu.:0.0000   BSP    :163   Bicycle                : 65
 Andhra Pradesh: 121   BARAMULLA  :   8   SURENDRA RAM    :   2   Max.   :1.0000   CPI(M) :100   Hammer, Sickle and Star: 63
 (Other)       :1022   (Other)    :2203   (Other)         :2008                    (Other):721   (Other)                :891
    GENDER     CRIMINAL.CASES      AGE           CATEGORY                    EDUCATION                                ASSETS
        : 245   0      :1242   Min.   :25.00          : 245   Post Graduate         :502                                  : 245
 FEMALE: 258   1      : 313   1st Qu.:43.25   GENERAL:1392   Graduate              :441   Not Available                  :  22
 MALE  :1760           : 245   Median :52.00   SC     : 383   Graduate Professional:336   Nil                            :   3
               2      : 119   Mean   :52.27   ST     : 243   12th Pass             :256   Rs 1,75,000\n ~ 1 Lacs+        :   2
               3      : 104   3rd Qu.:61.00                                        :245   Rs 1,93,54,59,756\n ~ 193 Crore+:   2
               4      :  64   Max.   :86.00                   10th Pass             :196   Rs 11,95,43,561\n ~ 11 Crore+  :   2
               (Other): 176   NA's   :245                     (Other)               :287   (Other)                        :1987
                 LIABILITIES    GENERAL.VOTES      POSTAL.VOTES      TOTAL.VOTES      OVER.TOTAL.ELECTORS..IN.CONSTITUENCY
 Rs 0\n ~              : 634   Min.   :   1339   Min.   :    0.0   Min.   :   1342   Min.   : 0.09794
                       : 245   1st Qu.:  21035   1st Qu.:   57.0   1st Qu.:  21163   1st Qu.: 1.29652
 Not Available         :  22   Median : 153934   Median :  316.0   Median : 154489   Median :10.51055
 Rs 5,00,000\n ~ 5 Lacs+:  10   Mean   : 261599   Mean   :  990.7   Mean   : 262590   Mean   :15.81141
 Rs 1,00,000\n ~ 1 Lacs+:   8   3rd Qu.: 485804   3rd Qu.: 1385.0   3rd Qu.: 487232   3rd Qu.:29.46818
 Rs 50,000\n ~ 50 Thou+ :   8   Max.   :1066824   Max.   :19367.0   Max.   :1068569   Max.   :51.95101
 (Other)               :1336
 OVER.TOTAL.VOTES.POLLED..IN.CONSTITUENCY TOTAL.ELECTORS
 Min.   : 1.000                           Min.   :  55189
 1st Qu.: 1.899                           1st Qu.:1530014
 Median :16.222                           Median :1679030
 Mean   :23.191                           Mean   :1658016
 3rd Qu.:42.590                           3rd Qu.:1816857
 Max.   :74.412                           Max.   :3150313
```

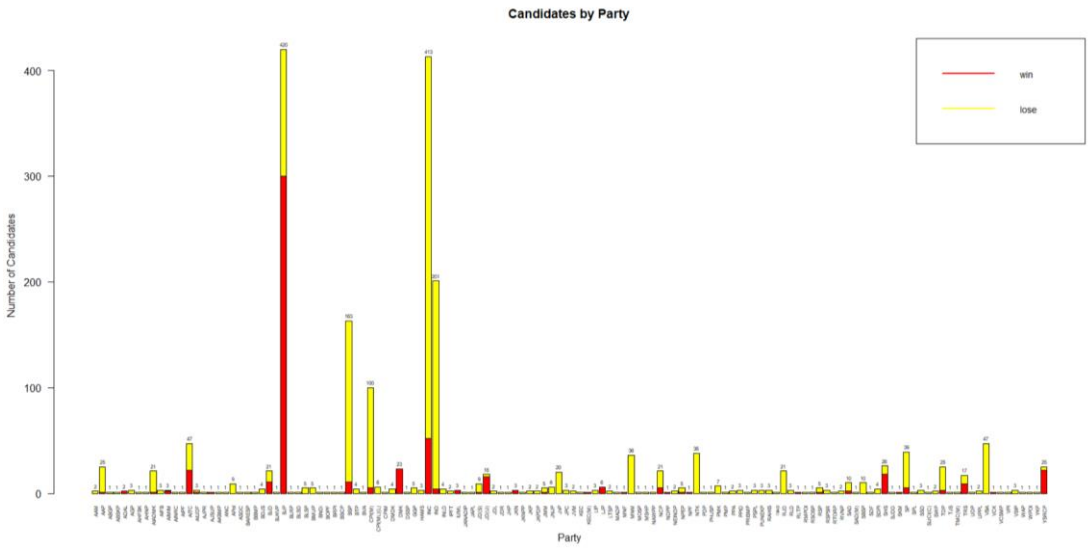
The Minimum age of the candidates was 25 whereas maximum age was 86. Average age of all the candidates who contested election was 52. As can be seen from the CATEGORY column, most candidates are GENERAL. General Category, also referred as Forward caste/General Class, is a term used in India to denote social groups that is ahead of other Indians on an average on economic and social front. Forward castes form about 18.8% of the population, the number varying by region.

"None of the Above" (or NOTA) has been provided as an option to the voters of India in most elections since 2019. By expressing a preference for none of the above, a citizen can choose not to vote for any candidates who are contesting the elections. The vote does not hold any electoral value: even if a majority of votes were cast for NOTA, the candidate with the largest vote share would still be the winner. NOTA enables the voter to show their unacceptance for the fielded candidates. There are 245 NOTA (None of The Above) in NAME, and after we exclude them, there were 2018 candidates who contested 2019 LokSabha Election. Besides, after excluding NOTA, there is no missing values in the dataset anymore.

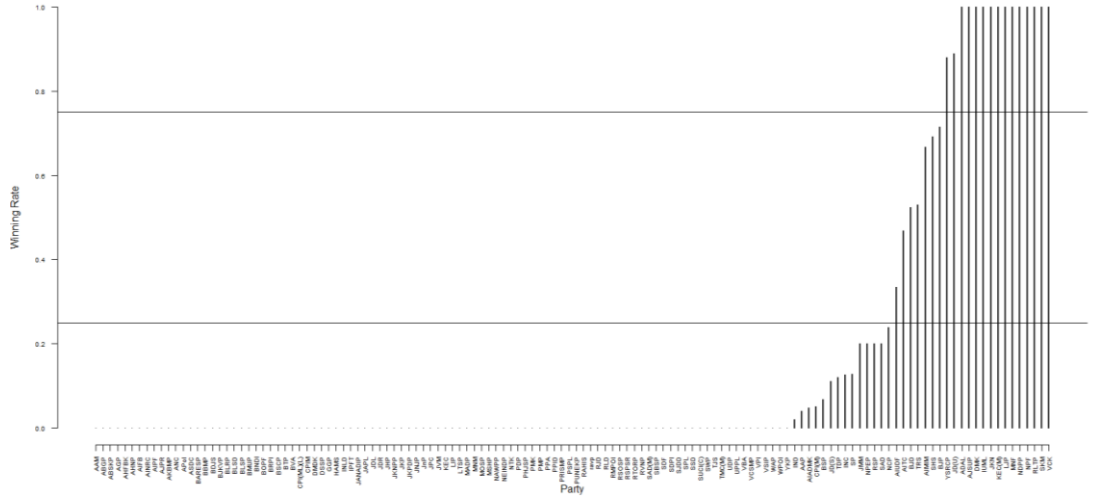
```
> summary(df1)
          STATE          CONSTITUENCY                   NAME          WINNER          PARTY                          SYMBOL
 Uttar Pradesh :251   AURANGABAD :  13   Ajay Kumar       :   2   Min.   :0.0000   BJP    :420   Lotus                    :420
 Bihar         :218   GAYA (SC)  :  11   ATUL KUMAR SINGH :   2   1st Qu.:0.0000   INC    :413   Hand                     :413
 Tamil Nadu    :189   CHATRA     :   8   Rahul Gandhi     :   2   Median :0.0000   IND    :201   Elephant                 :166
 Maharashtra   :175   MAHARAJGANJ:   8   SANJAY KUMAR     :   2   Mean   :0.2671   BSP    :163   Bicycle                  : 65
 West Bengal   :173   SHEOHAR    :   8   SURENDRA RAM     :   2   3rd Qu.:1.0000   CPI(M) :100   Hammer, Sickle and Star: 63
 Andhra Pradesh:101   SUPAUL     :   8   A N RADHAKRISHNAN:   1   Max.   :1.0000   AITC   : 47   Cup & Saucer             : 52
 (Other)       :911   (Other)    :1962   (Other)          :2007                    (Other):674   (Other)                  :839
    GENDER      CRIMINAL.CASES       AGE           CATEGORY                    EDUCATION                                  ASSETS
        :   0   0      :1242   Min.   :25.00          :   0   Post Graduate        :502   Not Available                    :  22
 FEMALE: 258   1      : 313   1st Qu.:43.25   GENERAL:1392   Graduate             :441   Nil                              :   3
 MALE  :1760   2      : 119   Median :52.00   SC     : 383   Graduate Professional:336   Rs 1,75,000\n ~ 1 Lacs+          :   2
               3      : 104   Mean   :52.27   ST     : 243   12th Pass            :256   Rs 1,93,54,59,756\n ~ 193 Crore+:   2
               4      :  64   3rd Qu.:61.00                  10th Pass            :196   Rs 11,95,43,561\n ~ 11 Crore+    :   2
               5      :  42   Max.   :86.00                  8th Pass             : 78   Rs 15,88,77,063\n ~ 15 Crore+    :   2
               (Other): 134                                  (Other)              :209   (Other)                          :1985
                 LIABILITIES    GENERAL.VOTES      POSTAL.VOTES     TOTAL.VOTES      OVER.TOTAL.ELECTORS..IN.CONSTITUENCY
 Rs 0\n ~              : 634   Min.   :   1339   Min.   :    0   Min.   :   1342   Min.   : 0.09794
 Not Available         :  22   1st Qu.:  30476   1st Qu.:   97   1st Qu.:  30744   1st Qu.: 1.95362
 Rs 5,00,000\n ~ 5 Lacs+:  10   Median : 284630   Median :  463   Median : 285525   Median :18.03686
 Rs 1,00,000\n ~ 1 Lacs+:   8   Mean   : 291190   Mean   : 1105   Mean   : 292295   Mean   :17.59681
 Rs 50,000\n ~ 50 Thou+ :   8   3rd Qu.: 505862   3rd Qu.: 1546   3rd Qu.: 507618   3rd Qu.:30.70811
 Rs 3,00,000\n ~ 3 Lacs+:   7   Max.   :1066824   Max.   :19367   Max.   :1068569   Max.   :51.95101
 (Other)               :1329
 OVER.TOTAL.VOTES.POLLED..IN.CONSTITUENCY TOTAL.ELECTORS
 Min.   : 1.000                           Min.   :  55189
 1st Qu.: 2.871                           1st Qu.:1530404
 Median :27.750                           Median :1679891
 Mean   :25.808                           Mean   :1660261
 3rd Qu.:44.350                           3rd Qu.:1823404
 Max.   :74.412                           Max.   :3150313
```

2. Exploratory Data Analysis

2.1 Candidates by Party

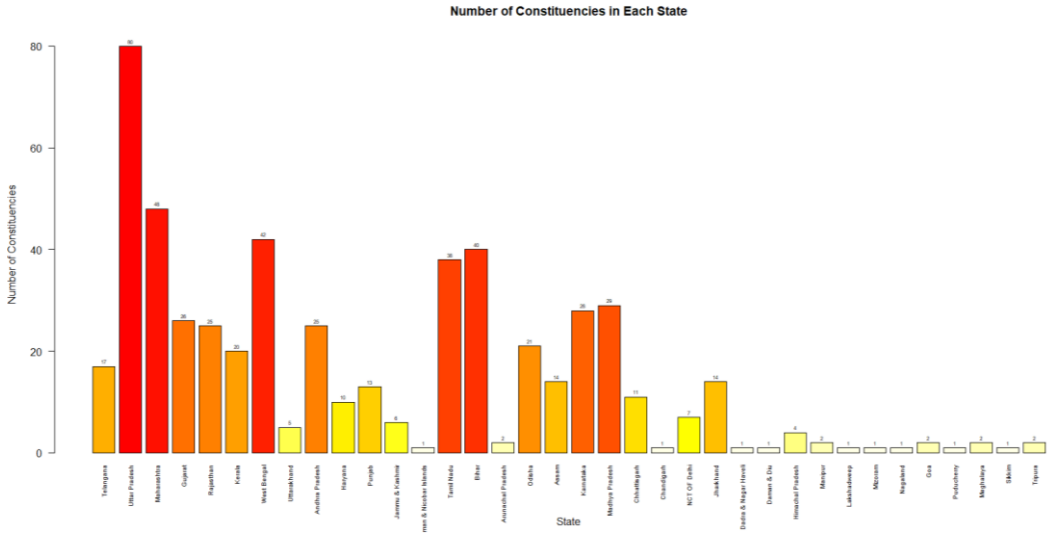


India has a multi-party system with recognition accorded to national and state and district level parties. There were 133 parties involving in 2019 Lok Sabha election. BJP had the largest number, 420, of candidates contesting the election, followed by INC 413 candidates. However, BJP achieved a landslide victory winning 300 seats out of 539 seats whereas INC won only 52 seats. Candidates in the party INC had much lower winning rate than in the BJP. Some parties, such as DMK, YSRCP, LJP, etc., had very high winning rates in spite of low numbers of candidates.

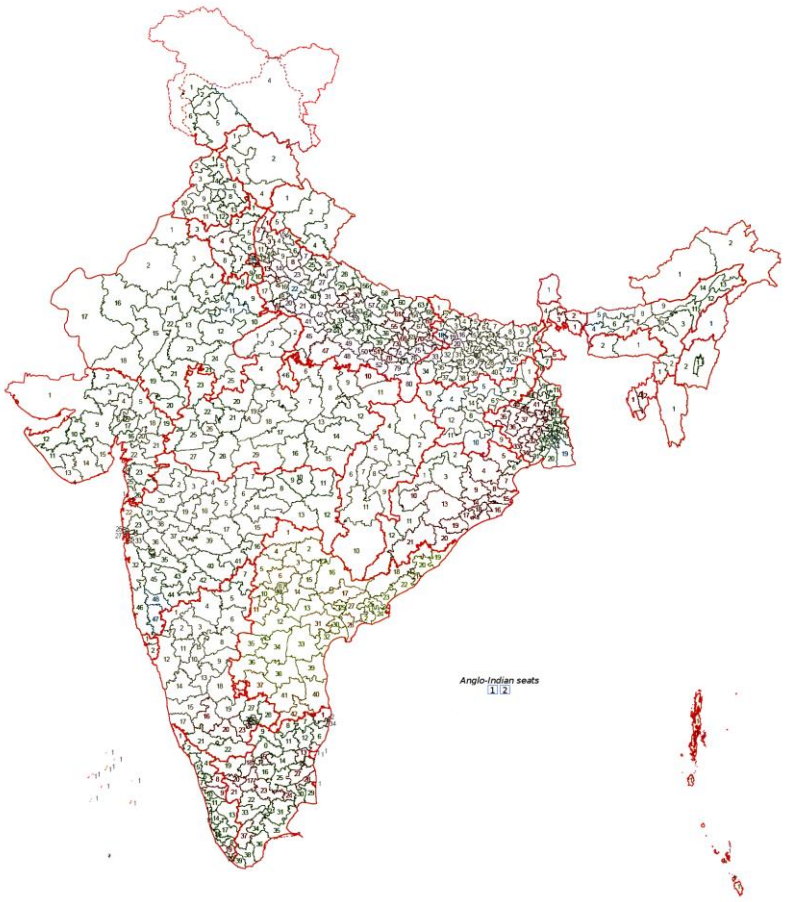


In order to consider parties as a factor in predicting winning rates, we classify 133 parties into three categories based on their winning rates. Winning rates higher than 75% (The third quantile), higher than 25% and lower than and equal to 75%, and lower than 25% (The first quantile) are classified as “high”, “medium”, and “low” respectively. As a result, there are 88 parties in “high”, 1393 in “medium”, and 537 in “low”.

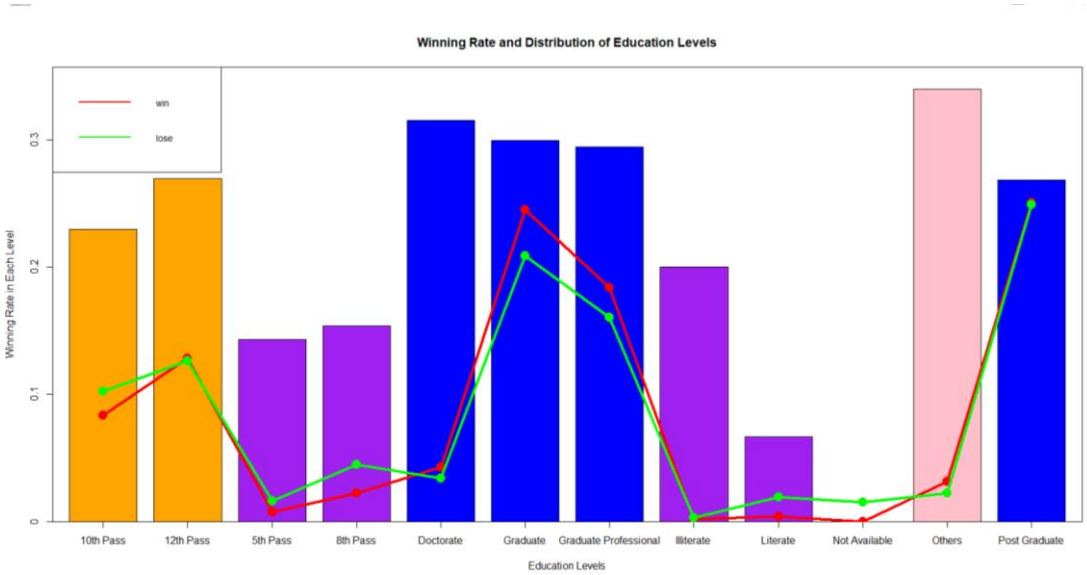
2.2 Number of Constituencies in Each State



There are 36 states and 539 constituencies shown in the data set. India is a federal union comprising 28 states and 8 union territories, for a total of 36 entities. There are 5 categories of states and union territories: 5 Very Big, 7 Big, 6 Average, 4 Small, rest14 are categorized as Tiny. The constituencies are delimited in a manner that the population of each Parliamentary and Assembly Constituency in a State so far as practicable be the same throughout the State. The following graph shows the delineation of constituencies across India.



2.3 Winning Rate and Distribution of Education Levels



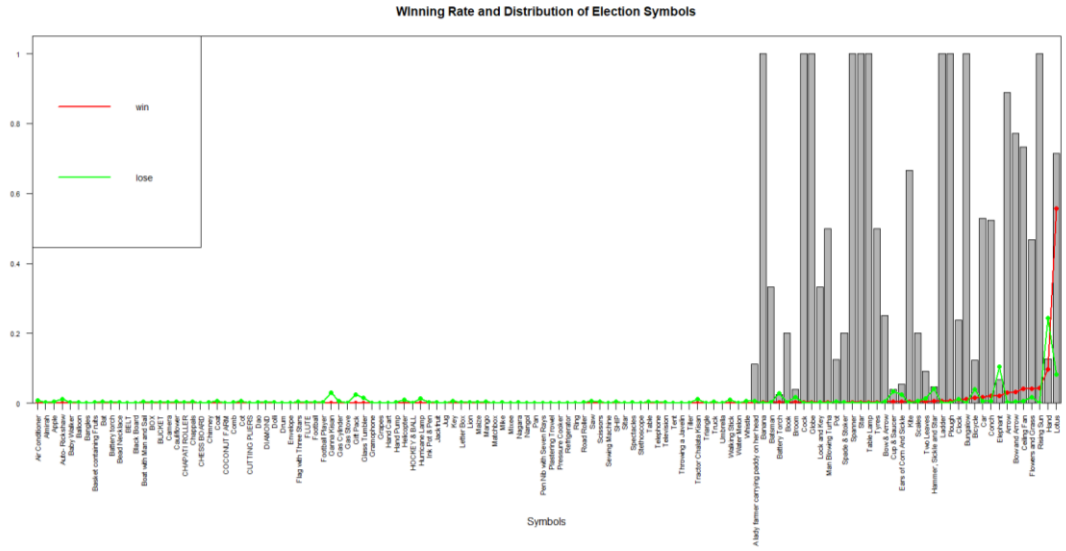
Based on the education level, we divide 12 levels of education into 5 groups and use different colors to distinguish them. There are 1353 candidates possessing advanced education (Adv_edu) including Doctorate, Graduate, Graduate Professional, Post Graduate; 452 candidates having high level education (High_edu) including 10^{th} Pass and 12^{th} Pass; 163 candidates with low level education (Low_edu) including 5^{th} Pass, 8^{th} Pass, Literate, Illiterate, Not Available; and Others (Others_edu). It can be seen that candidates running for India's lower house of parliament are generally highly educated.

Shown in the Figure, people with Others or graduate level of education had relatively higher winning rates whereas those with a low level of education had a low probability of winning. Though people with graduate levels of education composed the highest proportion of winning and losing candidates, a higher percentage of the winning candidates were graduate, graduate professional and doctorate, and a higher percentage of the losing candidates had lower educational levels such as 10th Pass, 5th pass, 8th pass, Literate, and Not Available.

2.4 Election Symbols Distribution

When India held its first national election in 1951-52, almost 3 in 4 voters were illiterate. To help them identify the party of their choice, visual symbols were allotted to parties and candidates. While literacy levels have increased dramatically since, the abiding appeal of party symbols has not faded.

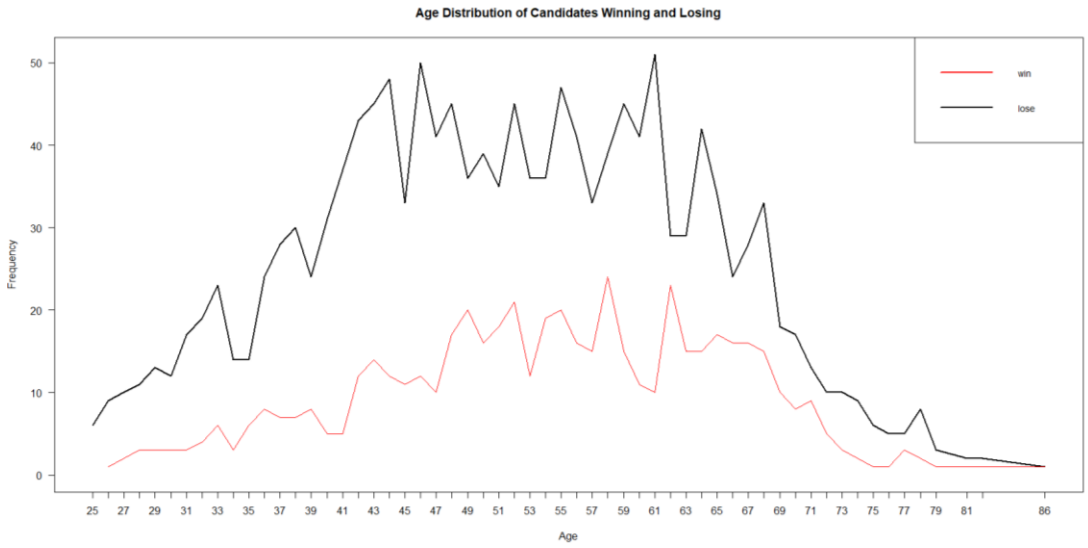
All registered parties contesting elections need to choose a symbol from a list of available symbols offered by the Election Commission of India. If a party is recognized as a national or state party, its symbol is reserved for its exclusive use in the country or in the state. For example, India's national flower, the lotus, is the symbol of the ruling Bharatiya Janata Party, or BJP. The lotus is associated with the Hindu goddess of knowledge and symbolizes the party's link to Hinduism and its traditions. While India's seven national parties and 64 state parties have fixed symbols, the Election Commission also has a pool of "free" symbols that can be used by thousands of smaller, lesser-known organizations.



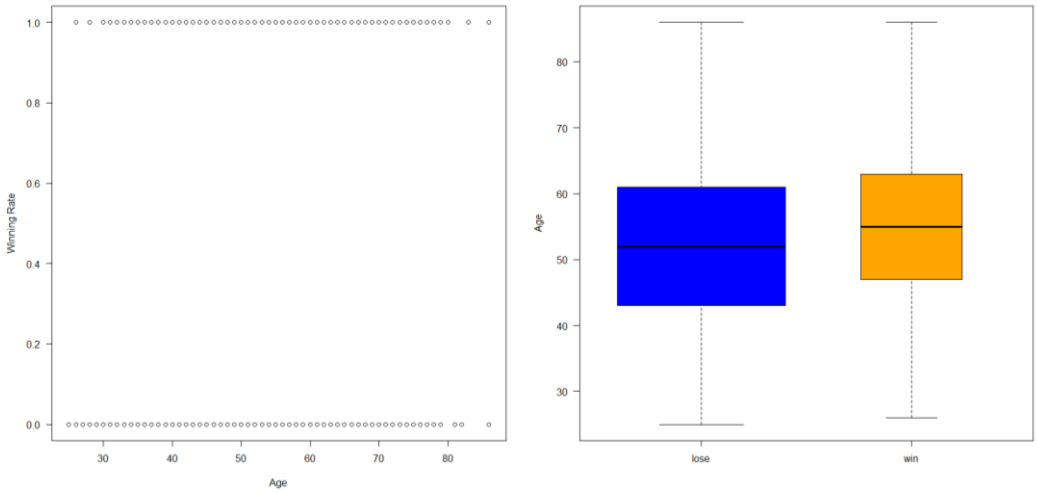
There were 127 symbols contested in the 2019 Lok Sobha, but only a few parties won seats. Among the winning candidates, the biggest share came from the lotus party, the BJP, followed by the Indian National Congress, symbolized by the hand. However, Indian National Congress also had the highest number of losing candidates as reflected by the highest green point in the figure. The fact also shows in the low bar chart of hand symbol party.

Disregarding those symbols that had 100 percent winning rate because only one or two candidates ran and won, candidates in the parties symbolized by lotus, rising sun, flowers and grass, ceiling fan, bow and arrow, and arrow had a higher probability of winning.

2.5 Age Distribution of Candidates



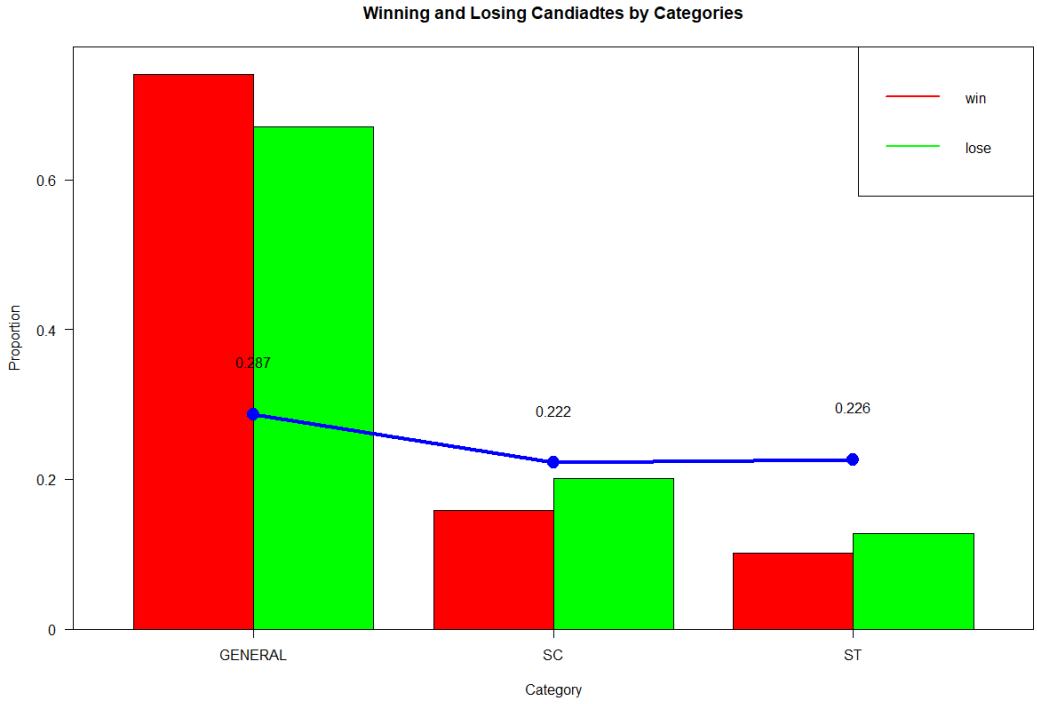
The winning and losing candidates had very similar age distribution, with most being between 40 and 60 years old.



According to the scatter plot and the boxplot, age cannot differentiate winning rate. Therefore, we do not consider age as a predictor in our prediction models.

2.6 Winning and Losing Candidates by Categories

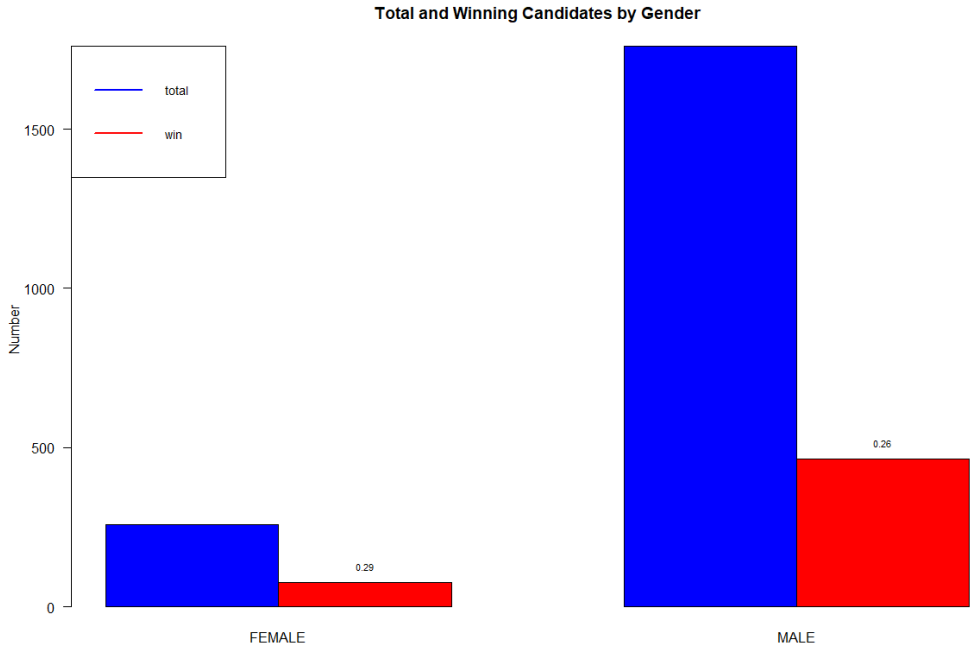
The Scheduled Caste (SCs) and Scheduled Tribes (STs) are officially designated groups of people in India. For much of the period of British rule in the Indian subcontinent, they were known as the Depressed Classes. In modern literature, the Scheduled Castes are sometimes referred to as Dalit, meaning "broken/scattered" in Sanskrit. The Scheduled Castes and Scheduled Tribes comprise about 16.6% and 8.6%, respectively, of India's population (according to the 2011 census). The Constitution (Scheduled Castes) Order, 1950 lists 1,108 castes across 29 states in its First Schedule, and the Constitution (Scheduled Tribes) Order, 1950 lists 744 tribes across 22 states in its First Schedule. The Constitution lays down the general principles of positive discrimination for SCs and STs. Since the independence of India, the Scheduled Castes and Scheduled Tribes were given Reservation status, guaranteeing political representation.



The highest proportion of the winning and losing candidates was of the General

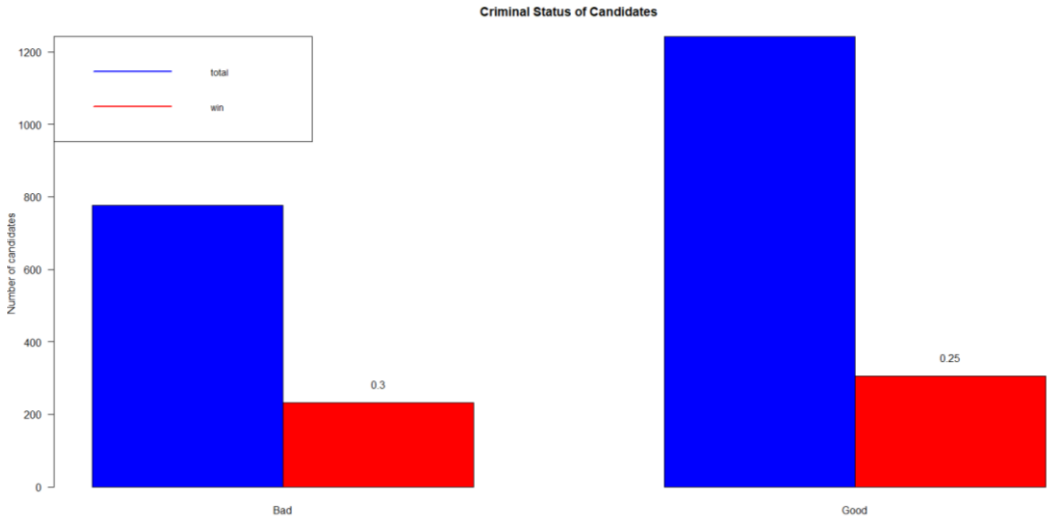
Category/Forward caste, suggesting that the majority of political participation was still caste related. Forward caste had a higher probability (0.287) of winning than SC and ST, which can also be seen from the higher red bar of General and the lower red bars of SC and ST than green bars.

2.7 Candidates by Gender

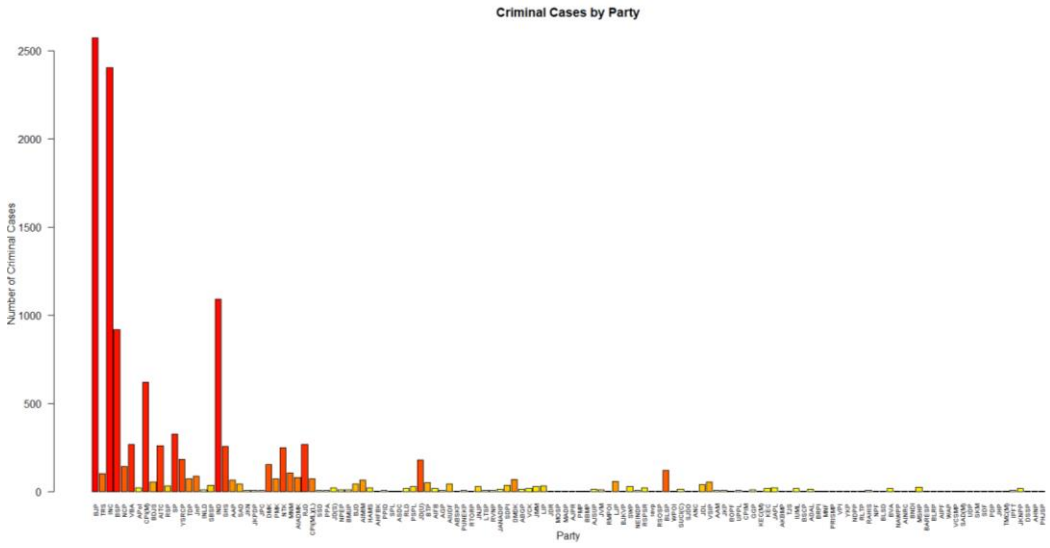


Among the total candidates, there were far more men than women. Also, there is a very clear gap between number of male and female representatives in the assembly. However, female had a slightly higher winning percentage (0.29).

2.8 Criminal Cases against Candidates



We classify candidates with no criminal case as Good, otherwise as Bad. Among the total candidates, a greater proportion had no criminal history. However, the winning candidates were almost evenly divided between the Good and Bad. Candidates with criminal cases even had a higher probability of winning (0.3)! It looks like having criminal cases made no difference to the outcome of the election.



BJP and INC gained the most seats in the 2019 Lok Sabha election, even though BJP Candidates had highest number of criminal cases against them and INC candidates were not too far behind.

3. Winner Prediction using Machine Learning Algorithms

In order to predict the target variable "WINNER", we first split the dataset into training set (around 60%) and test set (around 40%). Since the number of winning candidates (539) were much less than losing candidates (1,479), this dataset is imbalanced. Therefore, we select 60% of the 539 winning candidates and 60% of the1479 losing candidates to be our training data, and the remaining 40% of the 539 winning candidates and the remaining 40% of the 1,479 losing candidates become test dataset.

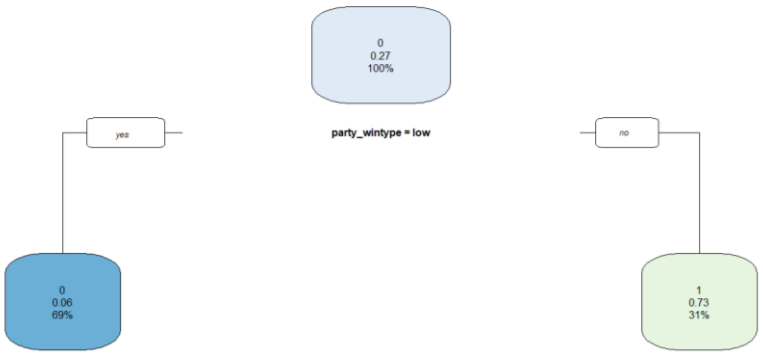
```
> idx_win <- which(df1$WINNER == 1)
> idx_lose <- which(df1$WINNER == 0)
> train_rate <- 0.6
> set.seed(1)
> train_idx <- c(sample(idx_win, size = floor(length(idx_win)*train_rate), re
place = FALSE), sample(idx_lose, size = floor(length(idx_lose)*train_rate), r
eplace = FALSE))
> df1_train <- df1[train_idx,]
> df1_test <- df1[-train_idx,]
```

Based on the previous visualization analysis, we select GENDER, CATEGORY, Criminal Status, Education Levels, Types of Parties as the variables for prediction,

3.1 Decision Tree

Decision tree is a classification model which works on the concept of information gain at every node. For all the data points, decision tree will try to classify data points at each of the nodes and check for information gain at each node. It will then classify at the node where information gain is maximum. It will follow this process subsequently until all the nodes are exhausted or there is no further information gain. Though Decision tree model is simple and of low predictive power, but the variables nodes pick are good hints for interpretation.

```
> fit <- rpart(WINNER~., data = df1_fac, method = 'class')
> rpart.plot(fit, extra = 106)
```



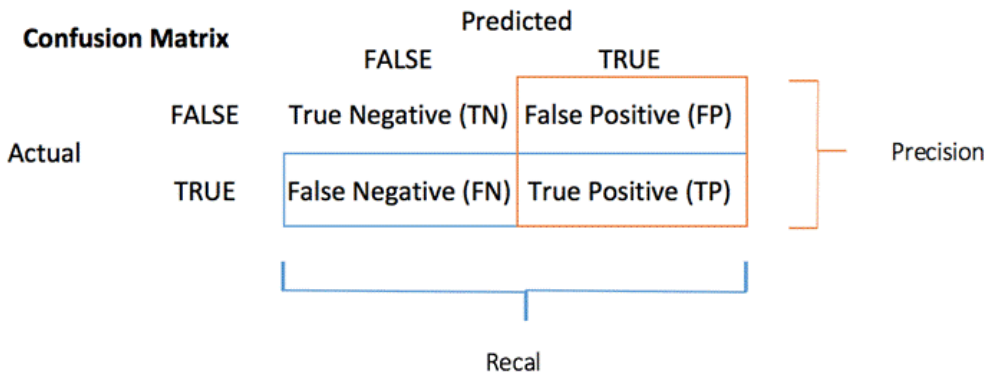
We start at the root node (the top of the graph): At the top, it is the overall probability of winning. It shows the proportion of candidates that won the election, 27 percent of total candidates. Then this node asks whether the party of the candidate is of low winning rate type. If yes, then the chance of winning is only 6%. rpart() function uses the Gini impurity measure to split the note. The higher the Gini coefficient, the more different instances within the node.

Next we can predict our test dataset, and create a table to count how many candidates are classified as winners and lost compared to the correct classification.

```
> predict_unseen <-predict(fit, df1_fact, type = 'class')
> table_mat <- table(df1_fact$WINNER, predict_unseen)
> table_mat
   predict_unseen
      0   1
  0 515  77
  1  41 175
```

The model correctly predicts 515 losing candidates but classified 41 winners as losers. By analogy, the model misclassifies 77 candidates as winners while they turned out to be losers.

To measure the model performance, we can compute an accuracy measure for classification task with the confusion matrix. The general idea is to count the number of times True instances are classified are False.



Each row in a confusion matrix represents an actual target, while each column represents a predicted target. The first row of this matrix considers losing candidates (the False class): 515 were correctly classified as losers (True negative), while the remaining 77 was wrongly classified as winners (False positive). The second row considers the winners, the positive class were 175 (True positive), while the False negative was 41.

The accuracy test from the confusion matrix is the proportion of true positive and true negative over the sum of the matrix.

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

```
> accuracy_Test <- sum(diag(table_mat)) / sum(table_mat)
> accuracy_Test
[1] 0.8539604
```

We have a score of 85 percent for the test set.

3.2 Random Forest

Random Forest is one such very powerful ensembling machine learning algorithm which works by creating multiple decision trees and then combining the output generated by each of the decision trees. Random Forest works on the same principle as Decision Tress; however, it does not select all the data points and variables in each of the trees. It randomly samples data points and variables in each of the tree that it creates and then combines the output at the end. It removes the bias that a decision tree model might introduce in the system. Also, it improves the predictive power significantly.

We construct 500 decision trees for this random forest to achieve good performance. In addition, for each bagged tree in this forest, only two variables are randomly sampled as candidates at each split.

```
> rf <- randomForest(WINNER ~ . , data=df1_fac, ntree=500,
+                    mtry=2,importance=TRUE)

> rf

Call:
 randomForest(formula = WINNER ~ ., data = df1_fac, ntree = 500,      mtry = 2, importance = TRUE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 12.73%
Confusion matrix:
    0   1 class.error
0 785 102   0.1149944
1  52 271   0.1609907
```

Error rate is 12.73%. Then we use the model to predict on the test dataset and calculate misclassification error rate.

```
> df1_fact <- df1_test %>% mutate_if(is.character, as.factor)
> df1_fact$WINNER <- as.factor(df1_fact$WINNER)
> df1_fact <- df1_fact[,c(4,10,20,21,22)]
> prediction <- predict(rf, newdata=df1_fact, type="class")
```

```
> table(prediction, df1_fact$WINNER)
prediction   0   1
         0   516  43
         1    76 173
> misclassification_error_rate <- sum(df1_fact$WINNER != prediction) /
+   nrow(df1_fact)*100
> misclassification_error_rate
[1] 14.72772
```

The misclassification rate on the test dataset is 14.7%. Finally, we got the list of variable importance measures. Party type is the most important feature.

```
> importance(rf)
                        0         1 MeanDecreaseAccuracy MeanDecreaseGini
CATEGORY        0.9880136  -6.429692           -5.628332         5.129235
party_wintype 148.2875485 158.642633          162.781975       223.384412
edu_level      -6.5485540   3.007133           -1.111387         8.116682
crim_class      0.4978169  -5.008002           -5.070179         3.495069
```

We achieved an accuracy of about 85.3% using Random Forest Classifier.

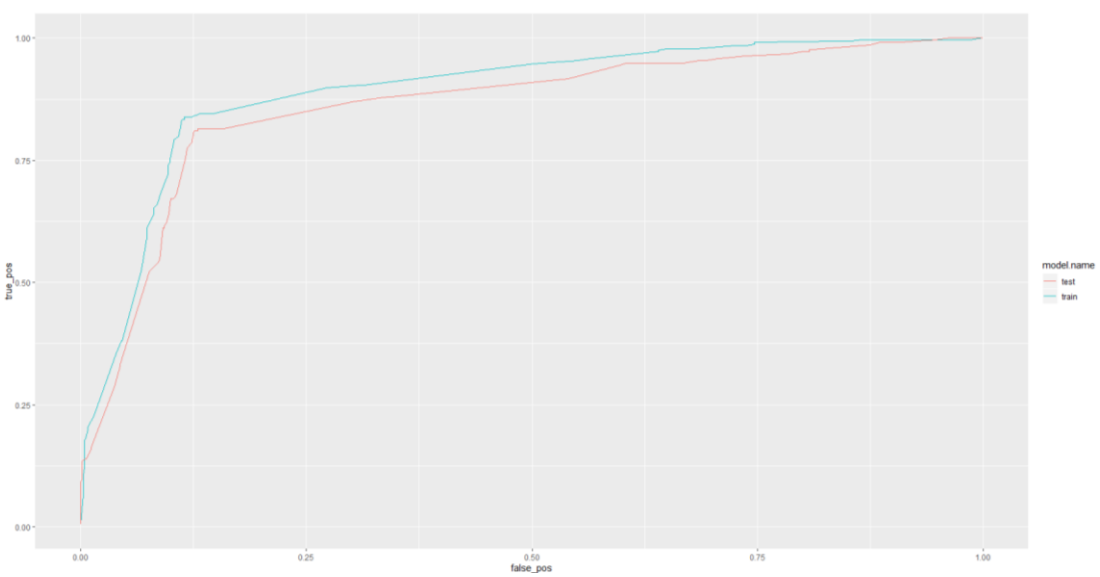
3.3 Logistic Regression

```
> glm1 <- glm(WINNER ~ crim_class + edu_level + party_wintype + GENDER + CATEG
ORY, data = df1_train, family = binomial)
> summary(glm1)

Call:
glm(formula = WINNER ~ crim_class + edu_level + party_wintype +
    GENDER + CATEGORY, family = binomial, data = df1_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3695  -0.3830  -0.3405   0.3529   2.7400

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)         2.77589    0.58208   4.769 1.85e-06 ***
crim_classGood     -0.03704    0.19202  -0.193 0.847020
edu_levelHigh_edu  -0.05494    0.22153  -0.248 0.804140
edu_levelLow_edu   -0.87653    0.43819  -2.000 0.045463 *
edu_levelOthers_edu 0.33503    0.50355   0.665 0.505841
party_wintypelow   -5.28349    0.53986  -9.787  < 2e-16 ***
party_wintypemed   -1.83229    0.53425  -3.430 0.000604 ***
GENDERMALE         -0.03100    0.26856  -0.115 0.908102
CATEGORYSC         -0.27785    0.25264  -1.100 0.271433
CATEGORYST         -0.24310    0.28737  -0.846 0.397579
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1404.07  on 1209  degrees of freedom
Residual deviance:  800.96  on 1200  degrees of freedom
AIC: 820.96

Number of Fisher Scoring iterations: 5
```

Types of parties and low education level have small p-value, meaning they are significant in explaining winning possibility. We then use the model to predict winning rate in the test dataset, and

calculate the Receiver Operating Characteristics (ROC) curve from predicted probabilities and the ground truth for both training and testing data.

```
> prob <- predict(glm1, newdata = df1_test, type = "response")
```




```
> ROCs %>% group_by(model.name) %>%
+   mutate(delta=false_pos-lag(false_pos)) %>%
+   summarize(AUC=sum(delta*true_pos, na.rm=T)) %>%
+   arrange(desc(AUC))
# A tibble: 2 x 2
  model.name   AUC
  <fct>      <dbl>
1 train      0.905
2 test       0.876
```

Test error of the model obtained: AUC = 0.876 for test data set. The training and the test sets have very similar and high AUC, the model can make well predictions.

4. Conclusion

In this report, we conduct exploratory data analysis and winning rate prediction using Machine Learning algorithms on the 2019 Lok Sabha election data. Some stylized facts are forward caste and highly educated people made up the majority of the candidates; the likelihood of winning was independent of age or gender; only a few parties won the majority seats and criminal cases had no adverse effect on the election result.

We applied the methods of Decision Tree, Random Forest, and Logistic Regression to the train data and make prediction on the test data. Logistic regression achieved the highest accuracy of about 87.6%.