## Analysing College Admissions from SAT scores

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In a Data Science Program from 2019 (<u>link to</u> **Course and my Certificate of completion**), we were given various datasets to analyse and bring insights from, where one such data was on **College Admissions based on SAT scores** of students.

Using *Python*, we applied Logistic Regression on said data to find the probability of Admittance from SAT scores. Here we shall implement the same analysis using R.

The Data

Preview of our CSV data (of 168 rows):

SAT	Admitted	SAT	Admitted	Group
1363	No	1363	No	0
1792	Yes	1792	Yes	1
1954	Yes	1954	Yes	1
1653	No	1653	No	0
1593	No	1593	No	0
1755	Yes	1755	Yes	1

Table 1: Raw dataframe (left), New dataframe (right)

From the above, our raw data contains a numerical *SAT* column and a textual *Admitted* column of binary "No" and "Yes" responses. We modified this dataset to have a *Group* column of "No"/"Yes" values translated as numeric 0's and 1's (approxiate format for Logistic Regression).

Statistical summary of our Logisitic Regression:

```
# glm()'s family = "binomial", since our dependant variable is binary (0's and 1's).
admittance.SAT.logit = glm(Group ~ SAT, data = admittance.SAT, family = binomial)
logreg summary = summary(admittance.SAT.logit); logreg summary
##
## Call:
## glm(formula = Group ~ SAT, family = binomial, data = admittance.SAT)
##
## Deviance Residuals:
##
       Min 10
                        Median
                                      30
                                               Max
## -1.78661 -0.04825 0.00199 0.07157 1.80151
##
## Coefficients:
                Estimate Std. Error z value Pr(>|z|)
##
## (Intercept) -69.912802 15.735757 -4.443 8.87e-06 ***
## SAT
                0.042005
                          0.009431 4.454 8.43e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
      Null deviance: 230.511 on 167 degrees of freedom
##
## Residual deviance: 46.289 on 166 degrees of freedom
## AIC: 50.289
##
## Number of Fisher Scoring iterations: 8
Visualizing the Logisitic Regression
```

```
b0 = logreg_summary$coefficients[1,1] # Getting the coefficients to
b1 = logreg_summary$coefficients[2,1] # be used inside our ggplot
# Setting annotations for our Plot
text_1 = bquote(atop(italic(b[0]) == .(b0), italic(b[1]) == .(b1)))
text_2 = bquote(atop(
                    italic(log)(hat(odds)) == ~~.(b0) ~ + ~ .(b1)*X,
                    where ~~ hat(odds):~~ e^{(.(b0) ~ + ~ .(b1)*X}))
text_3 = bquote(and ~~ P(hat(Admitted)): ~~ hat(pi) == frac(hat(odds), 1+hat(odds)))
x_text = mean(admittance.SAT(SAT)*(1 + 1/9) # key x-position for the labels
# Plotting the Logistic Regression with fitted values
ggplot(admittance.SAT, aes(x = SAT, y = Group)) +
  geom_point(shape=1, position = position_jitter(width = .02, height = .02)) +
  stat_smooth(method = "glm", method.args = list(family = "binomial"), se = FALSE) +
  labs(y = "P(Admitted)") +
  annotate("text", x = x text, y = 0.7, label = text 1, cex = 4.5, col = "#7070fa") +
  annotate("text", x = x_text, y = 0.45, label = text_2, cex = 4.2, col = "#2424f2") +
  annotate("text", x = x_text, y = 0.15, label = text_3, cex = 4.2, col = "#0404b8")
```

