

Turing Admissions and Outcomes Analysis

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Springboard - Foundations of Data Science

TURING SCHOOL OF SOFTWARE & DESIGN

Overview of problem

Using compiled data from enroll, apply, and our internal records, I sought to answer the following questions:

- 1. Students with which demographic characteristics are most likely to drop out? (race, gender, logic scores, payment plan)
- 2. Are there factors which make a student more likely to repeat?
- 3. Can we calculate a student's likelihood of repeating and support them accordingly?
- 4. What are the "success rates" of different interviewers?
- 5. Are students with higher logic scores more likely to be successful completing the program?

Logistic regression models

Based on the data available, I built two prediction models that allowed me to answer these questions:

- 1. What is the likelihood of graduation for students from various demographic groups based on their initial logic score?
- 2. Are there factors which make a student more likely to repeat?

Initial statistical analysis

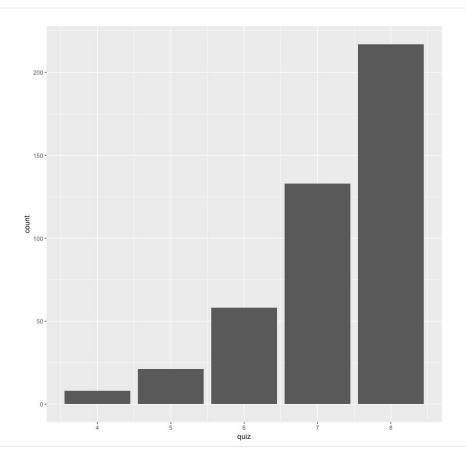
Data set: alldata_safe1

Compiled from enroll, apply, demographic surveys

A count of application quiz scores among enrolled students.

Most accepted students have higher quiz scores.

ggplot(alldata_safe1\$status, aes(quiz)) +
 geom_bar()

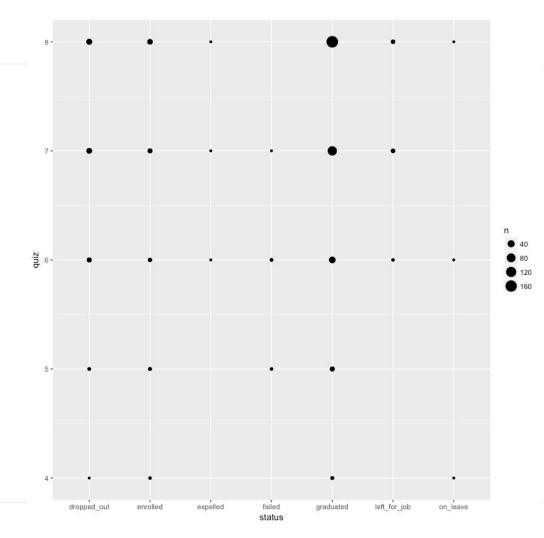


Statistical Analysis

Initial quiz scores compared to graduation status.

No students with 4 or 5 have been expelled, and no students with 8 have failed.

ggplot(alldata_safe1, aes(status, quiz)) +
 geom_count()



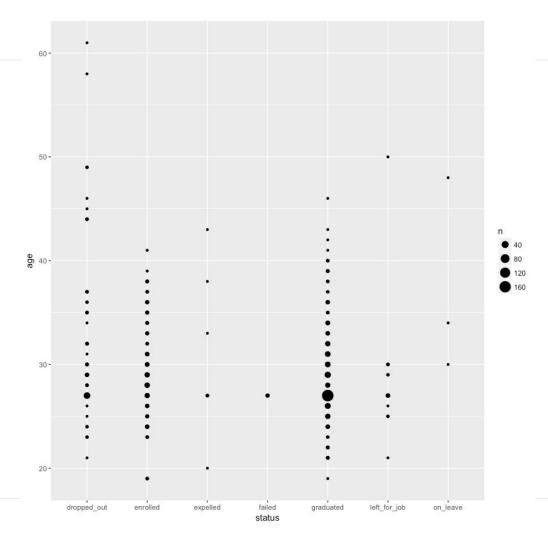


Statistical Analysis

Age and status

Older students have higher incidences of dropping out.

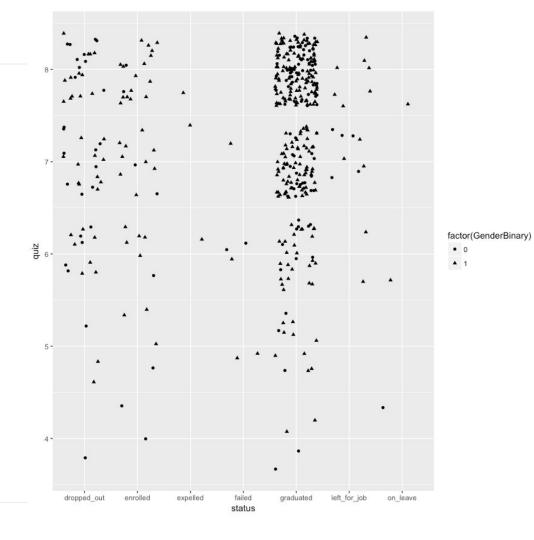
ggplot(alldata_safe1, aes(status, age)) +
 geom_count()





Quiz, gender and status

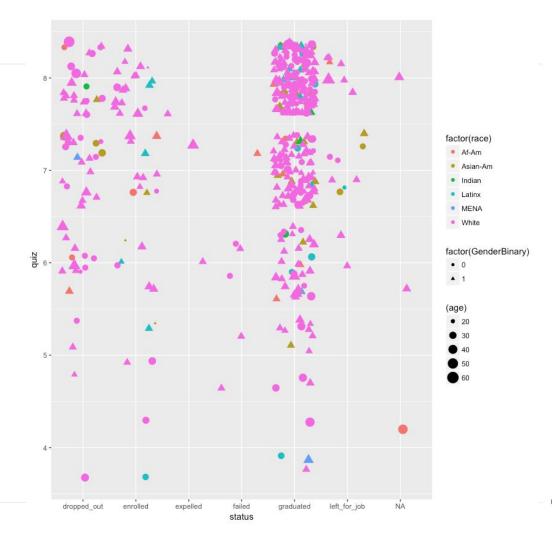
ggplot(alldata_safe1, aes(x = status, y = quiz, shape = factor(GenderBinary))) + geom_jitter()





Quiz, race, gender, age and status

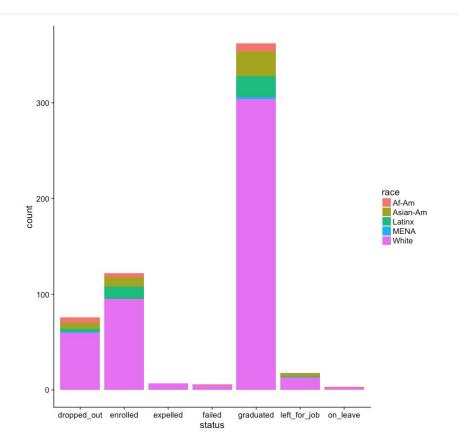
ggplot(alldata_safe1, aes(x = status, y = quiz, col
= factor(race), shape = factor(GenderBinary),
size = (age))) + geom_jitter()





Status count by race

ggplot(alldata_safe1, aes(x=status, fill=race)) +
geom_bar()



Applying the prediction model

What is the likelihood of graduation for students from various demographic groups based on their initial logic score?

I created a logistic regression model using the dependent variable 'graduated', where graduated = 1, and every other status = 0.

glm(graduated~age+quiz+GenderBinary+White+veterans+BE+int_logic_score+enrollments, data=alldata_safe1, family="binomial")

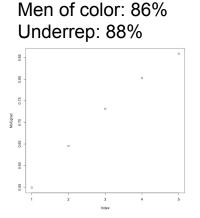
```
183
                                     glm(formula = graduated ~ age + quiz + GenderBinary + White +
                              184
                                           veterans + BE + int_logic_score + enrollments, family = "binomial",
Logistic Regression Code
                              185
                                         data = alldata_safe1)
                              186
                              187
                                   Deviance Residuals:
                              188
                                     Min
                                               10 Median
                                                                30
                                                                        Max
                                   -3.2680 -0.3566 0.4492
                              189
                                                              0.5757
                                                                       1.8671
                              190
                                   Coefficients:
                                     Estimate Std. Error z value Pr(>|z|)
                                                              1.83012 -4.341 1.42e-05 ***
                              193
                                   (Intercept)
                                                  -7.94399
                              194
                                                    -0.02190
                                                                0.02931 -0.747 0.45509
                                     age
                                   auiz
                                                   0.40282
                                                              0.14299
                                                                      2.817 0.00485 **
                                                                0.30797
                              196
                                     GenderBinary
                                                     0.20024
                                                                          0.650 0.51558
                                   White
                                                              0.35764
                                                   0.47126
                                                                       1.318 0.18761
                                                              0.99086
                                                                       -0.384 0.70088
                              198
                                   veterans
                                                   -0.38063
                              199
                                   BE
                                                   -0.44465
                                                              0.38311
                                                                       -1.161 0.24578
                              200
                                   int_logic_score 0.16355
                                                              0.10257
                                                                       1.595 0.11080
                                   enrollments
                                                                        9.453 < 2e-16 ***
                              201
                                                   1.30982
                                                              0.13857
                              202
                                     Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 ', 0.1 ' 1
                              203
                              204
                              205
                                   (Dispersion parameter for binomial family taken to be 1)
                              206
                                   Null deviance: 530.29 on 436 degrees of freedom
                              207
                              208
                                   Residual deviance: 343.17 on 428 degrees of freedom
                                   (157 observations deleted due to missingness)
                              210
                                   AIC: 361.17
                              211
                                   Number of Fisher Scoring iterations: 5
```

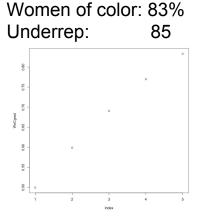
cull.

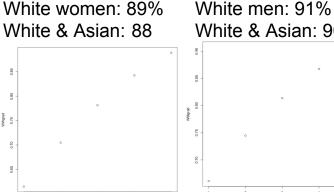
Predictions

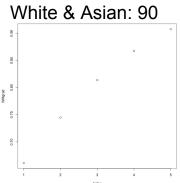
Using this model, I wanted to predict the likelihood of graduation based on an applicant's race, gender, and initial quiz score. I got an array of numbers that looked like this. This basically shows a positive correlation to graduation rates for all groups.

Likelihood of graduating with a quiz score of 8:









Predictions - positive outcomes

Using this model, I wanted to predict the likelihood of graduation based on an applicant's race, gender, and initial quiz score. I got an array of numbers that looked like this. This basically shows a positive correlation to graduation rates for all groups.

Likelihood of positive outcomes with a guiz score of 8:

Men of color: 93%

Underrep: 94

Women of color: 91%

Underrep: 92

White women: 93%

White & Asian: 93

White men: 94%

White & Asian: 94

Let's try it! Predict a student's likelihood of graduating from Turing:

The factors available in this model are:

- Age
- Gender (0=F, 1=M)
- Race (1=white or 0=PoC in this model)
- Quiz score (4 through 8)
- Vet status
- Program
- Interview Logic Score (6-14)
- Number of enrollments (4-7)

Basic code to make a prediction

- new.pred <- data.frame(age=XX, White=X, GenderBinary=X, quiz=c(4:8), veterans=X, BE=X, int_logic_score=XX, enrollments=X)
- predict(log.reg.white, new.pred, type = "response")

Recommendations

- Continue using the logic test as an admissions tool. This is strongly correlated with student success and likelihood to graduate. Require all applicants to take the logic test, refining the Fast Track process to include the logic test.
- 2. Collect anecdotal, qualitative data from students of color and female students who graduated and those who did not in order to deepen the analysis and determine why students from underrepresented groups are less likely to graduate.
- Based on results of surveys above, offer support immediately to underrepresented students who score a 7 or 8 on their initial logic evaluation.

Ideas for further research

Idea 1: For the second prediction model, I wanted to answer the following question: *Are there factors which make a student more likely to repeat?* I built another model using repeats as the dependent variable, but haven't analyzed it in depth.

Idea 2: Further research that would be valuable for our admissions process would be to review the success rates of various interviewers (question 4 above). This would require some data wrangling to make the list of interviewers into a readable format for logistic or linear regression. I would probably make new binary columns or assign each interviewer a number then run a similar regression model to the one above.

Idea 3: Create a linear regression model by scaling the 'behavior' column from 1-5, then backtracking that to interview red flags (this would require significantly more data collection than is currently available).



