Education 240 Final Project

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Contents

1 - Introduction

In this project, I will be using statistical testing method, data visualization techniques, and content covered in lectures and readings to carry out an analysis on this dataset collected and made available by the University of California, Irvine Department of Machine Learning.

First, let's read and load the data. In this chunk, I will also load the libraries that I will need to perform the necessary analysis used in the rest of this report.

```r
schools <- read.csv("student-por.csv")

library(tidyverse)

## -- Attaching packages --------------------------------------- tidyverse 1.3.0 --

## v ggplot2 3.3.0     v purrr   0.3.3
## v tibble  3.0.0     v dplyr   0.8.5
## v tidyr   1.0.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
library(infer)
library(broom)
```

This dataset has 649 rows and 33 columns, meaning that the researchers took a sample of 649 students and collected information about them on 33 different variables. The original data was titled `Student Alcohol Consumption` as it categorizes students into different consumption levels from 1-5 both on workdays and weekends, as shown by the variables `dalc` and `walc` respectively.

However, this dataset also contains valuable insights into the students' academic performance as it contains their grades from year 1 to 3, shown in the variables `g1`, `g2`, and `g3` respectively. I will be creating a series of visualizations using this information and attempting to explain the trends I see using information learned in class and in my readings.

2 - The role of play

The first concept I want to investigate is Piaget's developmental theory on play. To do this, I will create a linear regression model of how the explanatory variables `goout`, `freetime` (categorical variables with levels of frequency from 1-5), and `activities` (binary variable of yes/no to extracirriculars) affect the response variable `g3` (final school grade).

2.1 - Data

```
lm_g3_play <- lm(G3 ~ goout + freetime + activities, data = schools)

tidy(lm_g3_play) %>%
  select(term, estimate)
```

```
## # A tibble: 4 x 2
##   term          estimate
##   <chr>            <dbl>
## 1 (Intercept)      13.3
## 2 goout           -0.150
## 3 freetime        -0.357
## 4 activitiesyes    0.530
```

2.2 - Interpretation

From this, we get a linear model in the form of $Y = m_1 X_1 + m_2 X_2 + m_3 X_3 + c$. The linear model from this regression is `G3 = 13.3 - 0.150 * goout - 0.357 * freetime + 0.530 * activities`.

By interpreting the signs of the coefficients, we see that both going out and having free time negatively correlates with the final course grade. Essentially, if an individual has a free time score of 5, his final course grade would be calculated by multiplying 5 with -0.357. The intercept means that, given all other variable values to be 0, would be 13.3 out of 20. This means that if a student had no activities nor free time and doesn't go out, the average score in that group would be 13.3.

Extracurricular activities, on the other hand, has the only positive coefficient in the model, suggesting a positive correlation between `G3` and `activities`. This means that when a student has extracirricular activities, their predicted final course grades are to increase by 0.530 points on average.

2.3 - Discussion

After understanding how different attributes affect this sample of students, we can now discuss how this supports or challenges Piaget's theories.

Scales, et al. (1991) defined play as "that absorbing activity in which healthy young children participate with enthusiasm and abandon," whereas Csikszentmihalyi (1981) described play as "a subset of life..., an arrangement in which one can practice behavior without dreading its consequence." In both cases, these researchers argue that play enables the learner to take on and understand simulated roles that they normally cannot be to expand their knowledge in different circumstances.

One reason, therefore, that could explain the effects of the variables in the model is the nature of the students' play. When they are engaged in extracurricular activities, it's often endorsed by the school, suggesting that there is a series of guidance provided by more knowledgeable others (MKO), whether that be a teacher, or older students. Their guidance is crucial in these students' learning of new knowledge, especially those that they have not mastered on their own. On the other hand, when students have `freetime`, or `goout`, this time might not be used productively and constructively to positively contribute towards their final grade.

3 - Does quality of family relationships affect academic performance?

We have previously discussed how every student faces a different challenge. Whether it's suffering from physical or mental disabilities or financial struggles, these factors could all affect a student's academic performance in school. One other factor that I will be investigating is whether the quality of relationships a student has with their family affect their academic performance. I will do this through simlulation-based hypothesis testing.

I think this is something that is worthy of investigating because a student spends a significant amount of time at home, spending time with their parents, who, for most, are their first models and source of enculuration as they enter this world. Especially, children should adopt most of their interpersonal behaviors from their parents, as their first person of contact and person of most frequent interaction at a young age is their parents.

3.1 - Formalizing research hypothesis and operationalizing variables

Our research question can be boiled down to this: Does having a good relationship with family increase academic performance? In other words, the null hypothesis is to prove that academic performance measured by the variable `G3` and family relationship are independent events. The alternative hypothesis will be that the two variables are dependent.

To do this we will simulate by permutation. We will keep the same outcomes in response variable (grades), and permute the 'treatment' group, also known as the explanatory group, which in this case is family relationships. We will have to wrangle some data to change the target variables into categorical ones with two levels.

```
famsuccess_schools <- schools %>%
  mutate(categorized_famrel = case_when(
    famrel >= 4 ~ "high-quality",
    famrel < 4 ~ "low-quality"
)) %>%
  mutate(categorized_g3 = case_when(
    G3 >= 12 ~ "above average",
    G3 < 12 ~ "below average"
)) %>%
  mutate(categorized_famrel = as.factor(categorized_famrel)) %>%
  mutate(G3 = as.factor(G3))
```

We have changed `famrel` into `categorized_famrel` with levels of `high-quality` and `low-quality`. Any relationships marked with a level 4 or above was deemed `high-quality`.

Similarly, `G3` has been changed to `categorized_g3`, with students changed to whether they are above average or below average.

Next, we calculate the observed difference of proportion between above average students in two different groups of family relationships.

```
p_hat_diff <- famsuccess_schools %>%
  count(categorized_famrel, categorized_g3) %>%
  group_by(categorized_famrel) %>%
  mutate(p_hat = n / sum(n)) %>%
  filter(categorized_g3 == "above average") %>%
  pull(p_hat) %>%
  diff()

p_hat_diff
```

```
## [1] -0.1074208
```

3.2 - Simulating the sampling process

```
famgrade_dist <- famsuccess_schools %>%
  specify(response = categorized_g3, explanatory = categorized_famrel,
          success = "above average") %>%
  hypothesize(null = "independence") %>%
  generate(reps = 2500, type = "permute") %>%
  calculate(stat = "diff in props",
            order = c("low-quality", "high-quality"))
```

Since the p-value is the probability of observing our results or more extreme) if the null hypothesis were in fact true, we can visualize the p-value by plotting the observed difference and highlighting the areas that's greater than the value. The p-value can also be calculated directly to obtain as a figure. Unfortunately, the p-value is extremely high at `98.5%`, suggesting that there is no statistical significance in this causal relationship between academic performance and family relationships.

```
visualize(famgrade_dist) +
  shade_p_value(obs_stat = -0.107, direction = "greater")
```

Simulation–Based Null Distribution
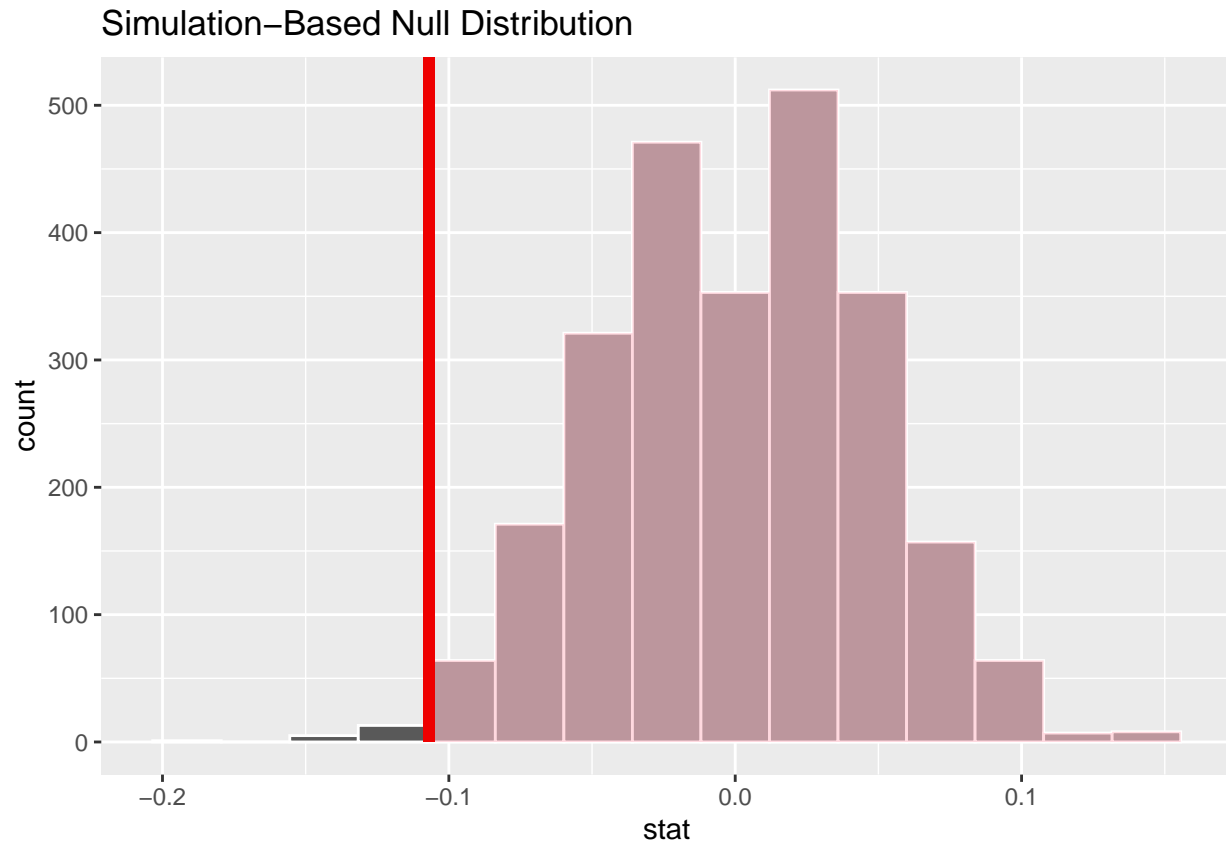

```
famgrade_dist %>%
  filter(stat >= -0.107) %>%
  summarise(p_value = n() / nrow(famgrade_dist))
```

```
## # A tibble: 1 x 1
##   p_value
##     <dbl>
## 1   0.987
```

3.3 - Alternative method of investigating causes for academic performance

This method involves the use of linear regression as discussed in Section 2. Instead of only picking two variables, however, we create a linear model that has one response variable, G3, and a lot of explanatory variables. Within these explanatory variables, we aim to find what combination of them has the highest adjusted R^2 value, a statistical measure of how much the variability in the response variable is due to the explanatory variable after taking into account the number of explanators used.

```
lm_full <- lm(G3 ~ school + G1 + studytime + higher + internet + famrel +
              health + absences, data = schools) # creating model
```

Once the model has been created, the function `step()` automates a backward-selection process and ends the output with the combination of variables with the highest adjusted R^2 value. It essentially brute-forces the process by starting with the full model, records the $adj.R^2$, removes one variable, determines whether the $adjR^2$ is higher without that variable. If it is higher, the current model becomes the 'best model', until removing another variable yields a higher value.

```
best_model <- step(lm_full) # using the step function
```

```
## Start:  AIC=772.2
## G3 ~ school + G1 + studytime + higher + internet + famrel + health +
##     absences
##
##              Df Sum of Sq     RSS     AIC
## - internet   1       2.7  2077.4  771.06
## - absences   1       4.7  2079.3  771.67
## - studytime  1       5.3  2079.9  771.85
## - famrel     1       5.5  2080.2  771.93
## <none>                    2074.6  772.20
## - school     1       7.3  2081.9  772.48
## - higher     1      13.7  2088.3  774.47
## - health     1      24.7  2099.3  777.89
## - G1         1    3196.9  5271.5 1375.42
##
## Step:  AIC=771.06
## G3 ~ school + G1 + studytime + higher + famrel + health + absences
##
##              Df Sum of Sq     RSS     AIC
## - absences   1       5.1  2082.4  770.65
## - studytime  1       5.2  2082.5  770.68
## - famrel     1       6.2  2083.6  771.00
## <none>                    2077.4  771.06
## - school     1       9.5  2086.9  772.03
## - higher     1      14.0  2091.3  773.41
## - health     1      25.4  2102.8  776.96
## - G1         1    3225.3  5302.6 1377.24
##
## Step:  AIC=770.65
## G3 ~ school + G1 + studytime + higher + famrel + health
##
##              Df Sum of Sq     RSS     AIC
## - studytime  1       4.3  2086.7  769.98
## - famrel     1       5.4  2087.8  770.31
## <none>                    2082.4  770.65
## - higher     1      12.7  2095.1  772.59
## - school     1      13.8  2096.3  772.93
## - health     1      26.6  2109.1  776.89
## - G1         1    3259.6  5342.0 1380.04
##
## Step:  AIC=769.98
## G3 ~ school + G1 + higher + famrel + health
##
##            Df Sum of Sq     RSS     AIC
## - famrel   1       5.2  2091.9  769.59
## <none>                  2086.7  769.98
## - higher   1      14.5  2101.2  772.47
## - school   1      14.9  2101.6  772.60
## - health   1      27.8  2114.5  776.58
## - G1       1    3421.4  5508.2 1397.92
##
## Step:  AIC=769.59
## G3 ~ school + G1 + higher + health
##
```

```
##           Df Sum of Sq    RSS     AIC
## <none>                  2091.9  769.59
## - higher  1      15.0 2107.0  772.24
## - school  1      15.1 2107.0  772.26
## - health  1      25.5 2117.5  775.47
## - G1       1    3436.2 5528.2 1398.27
```

```
tidy(best_model) # displaying in a tidy manner
```

```
## # A tibble: 5 x 5
##   term        estimate std.error statistic   p.value
##   <chr>          <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)    1.43     0.405      3.52 4.55e-  4
## 2 schoolMS      -0.336    0.156     -2.15 3.16e-  2
## 3 G1             0.931    0.0286    32.5  5.07e-138
## 4 higheryes      0.528    0.245      2.15 3.18e-  2
## 5 health        -0.138    0.0492    -2.80 5.19e-  3
```

From the output of `best_model`, we get a linear model of

```
final period grade = 1.43 - 0.336 * MS + 0.931 * first period grade + 0.528 * higher -
                                   0.138 * health
```

Comparing this to the full model we started with, the variables `studytime`, `internet`, `famrel`, and `absences` were all discarded from the best model. From the code below, we see that approximately 68.9% of the variability in the response variable `G3` can be explained by the response variables.

```
glance(best_model) %>%
  select(adj.r.squared)
```

```
## # A tibble: 1 x 1
##   adj.r.squared
##         <dbl>
## 1       0.689
```

It is indeed a bit unfortunate that the variable that I hypothesized in the beginning of this section will directly cause variances in the final course grade did not even make this final correlational model. This goes to say that, at least in this sample, the quality of relationships with family does not play a relatively big role in affecting students' final academic performances. This also explains why the p-value we obtained in the previous statistical test is so ridiculously high.

3.4 - Discussion

The discussion in this section will mainly focus on the remaining variables in `best_model`. Interestingly, we see that a students' health conditions is negatively correlating with their final grade. Albeit the coefficient being small, being at one higher level of health actually decreases the predicted final grade by 0.138.

We also see that the biggest factor in the students' final grade is their `G1` value, which is their first period grade. It seems to be the case that if a student performs well on their first period exam, they tend to find success on their final exam. One reason for this is that they may be motivated by their previous success, as motivation is something that "energizes, directs, and sustains behavior; it gets people moving, points them in a particular direction, and keeps them going." (Ormrod, p. 405) Also, as students succeed, it is likely that students will adopt a growth mindset and see increases in their self-efficacy, now believing that they are more capable in their cognitive abilities.

Further, the variable `higher` also has a positive correlation. In the dataset, this variable reveals whether the student has aspirations for higher education. For a student with aspirations, their average predicted final grade is approximately 0.5 points higher. I argue that this is again associated with the motivation of a

student, specifically being another source. Setting realistic goals and pursuing them is a great way to promote high expectancies in a classroom setting (Ormrod, p.458). When a student knows what they are working towards by setting clear goals, they are more motivated to achieve it, leading to a better final grade.

Finally, the school that students attend also plays a role in their academic performance. In the model, we see that the code displays `schoolMS`. This means that if the student goes to the school coded as `MS`, this value is `1`, meaning that the average predicted final score decreases by `0.34`. This suggests that the other school in the dataset, `GP`, is the better school in terms of final grades. There are a plethora of reasons as to why `GP` could be a better school. It could be that teachers are more qualified and prepared for class, students are exposed to small group learning experiences, a wider range of extracurricular offerings, and etc. Unfortunately, this dataset does not offer any explicit details on this.