

Project 3

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1 Abstract

This project consists of performing a virtual consulting analysis from College ScoreCard data. Specifically, our team members analyzed and interpreted the data by EDA analysis, regression model building and interactive shiny app to help a group of art institution administrators to compare themselves with similar schools in California, in terms of diversity of graduation rates.

2 Introduction

Data Analysis has been extensively used in different areas to explore, understand and predict our daily life. The motivation behind this project is to provide insights for higher education officials/policymakers to better assess how well institutions are providing access to diverse group of students. Our team decides to help a group of 4-year art institution administrators to compare themselves to similar schools in California, in terms of diversity and graduation rates.

The overall workflow can be summarized as followed: data cleaning (target schools that are 4-year art institutions located in California)–EDA Analysis(provide overall pictures of schools enrollment and graduation statistics)–Model Building()–Shiny App (interactive tool for user to visualize data with selected school and other criteria)–Presentation slides(share results with public). Each section of the workflow will be explored and explained in details.

3 Data Cleaning

The raw data used in this project comes from College ScoreCard, downloaded <https://ed-public-download.apps.cloud.gov/downloads/Most-Recent-Cohorts-All-Data-Elements.csv> where, developed by the U.S Department of Education. To select targeted school, we choose specifically four-year art schools in CA (these are indicated by the abbreviation "CCBASIC==30" and "STABBR=="CA" respectively in the raw data). We also extracted schools' location, zip code, website etc in similar way.



Figure 1: Average Age of Enrolled Students

Figure 1 shows enrollment rate vs average age. We can see two peaks at 22-24 and 28-30. It's expected that most people will choose to pursue a professional art degree after college, potentially as a way to change their career path (majority of universities/college don't have specialized art/design program). There's also a scenario where after working for several years, people decide to go back to school either for career switch or further their knowledge and skills.

There are several indicators for diversity, which we identified as gender, average family income, average age and ethnicity. For the dependent variables, we choose enrollment and graduation rates. We further divide enrollment based on ethnicity (enroll-white is percentage of enrolled people that are white etc), gender(enroll-men etc), graduation based on ethnicity(grad-rate-asian etc). Note that the raw data doesn't provide graduation based on gender. We also catalog schools based on their region (1 indicates North Cal, 2 Central Cal and 3 for South Cal).

Based on the criteria, 31 schools in total are selected and the finalized data is presented in "client-dat.csv".

4 EDA Analysis

As the first step of data analysis, EDA tries to provide a general picture of average school performance. A picture is worth a thousand words, so let's take a look at what information the data discloses.

For a more quantitative data summary, we also include "eda-output-enroll" and "eda-output-grad" in the data file if readers are interested.



Figure 2: Average Family Income of Enrolled Students

Figure 2 shows enrollment rate vs average family income. Again we can see relatively two prominent peaks at 20-30K and 60-70K. For people on the lower end of family income, studying art/design could be a relatively lucrative path given that arts, entertainment and design are big business in California. (Hollywood down South and Berkeley/Santa Clara up North). For people on the higher end of family income, it's possible that they have been receiving high quality cultural/artsy education since young and has adequate family financial support to pursue an artsy path.

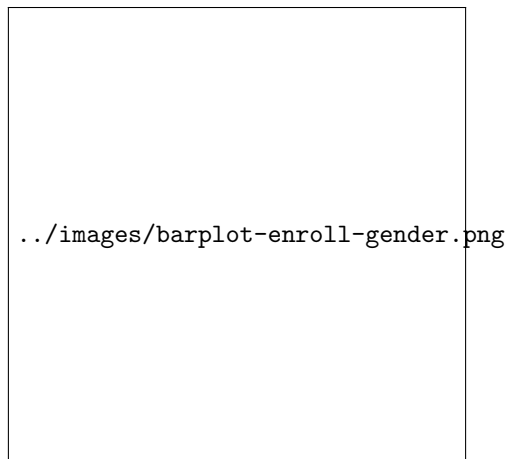


Figure 3: Gender Distribution of Enrolled Students

Figure 3 shows enrollment rate vs. gender, which simply indicates that for all 31 schools, female and male students populations are almost the same.

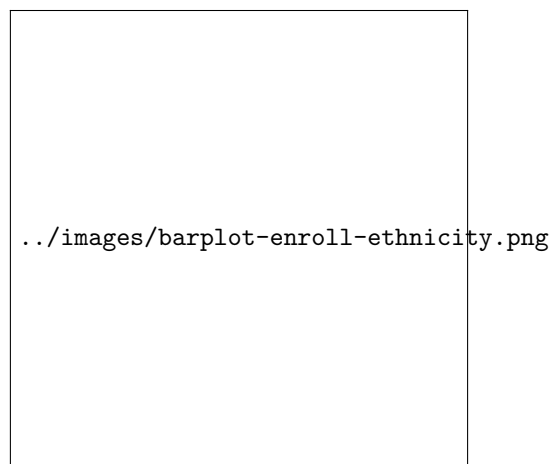


Figure 4: Ethnicity Distribution of Enrolled Students

Figure 4 shows enrollment ethnicity breakdown. The bar-plot indicates White and Hispanic make up half of the enrollment population. Since there aren't enough raw data available from College Scorecard (say ethnicity breakdown on average family income), it's difficult to extrapolate any other correlations (for example, could the 20-30K income peak corresponds to Hispanic enrollment?). Note that highest peak is "Other". This is because for simplicity, we combined all other race columns (except white, black, hispanic and asian) when producing the graphs. So "others" encompasses Indian-America, unknown, 2 or more race etc and thus the high percentage.



Figure 5: Ethnicity Distribution of Graduated Students

And finally, Figure 5 shows graduation rate ethnicity breakdown. Several things that need special attention. First, similar to Figure 4, the "Other" category includes multiple race options (it would be impractical to plot 12 bars into a single graph). Second, the total percentage of all bars don't add up to 1 due to nature of the clean data. For "Total" categories, it means the percentage of students that graduated within 4 years in total enrolled population. However, for "White", "Black", "Hispanic", "Asian" categories, it shows the percentage of students that graduated within their own racial category. (e.g about 45% of white students graduated within 4 years in all white enrolled students). We comment that Hispanic and Asians have more than 50% graduation rate while Black students suffer from low graduation rate. Again similar to Figure 4, due to deficiency of relevant data (e.g ethnicity vs average income), no other definitive conclusions can be drawn from the plot.

5 Conclusion

In conclusion, through EDA analysis, we are able to provide a general overview of selected art institution in California regarding enrollment and graduation data. Through model building, we are able to show that there is a linear relationship between diversity variables and graduation rate in these art schools. Finally, we build an interactive shiny App for school administrators to visualize our analysis results

6 Methods

We built various linear models from the *client-data.csv* data set. We predicted the variable ‘Grad_Rate’ in terms of eight predictors: proportion of White students enrolled, proportion of Black students enrolled, proportion of Hispanic students enrolled, proportion of Asian students enrolled, proportion of Women enrolled, Average age of enrolled students, Average Family Income and Total Enrollment.

We created 5 different scripts for running various regression methods: Ordinary Least Squares, Ridge regression, Lasso Regression, Principal Components Regression, and Partial Least Squares Regression.

Our first method, was a simple linear model, Ordinary Least Squares. In **ols_regression.R**, using the `lm()` where the y variable is Balance and the x variable is the combination of the the rest of the variables, the results from the OLS regression methods are output. This script’s outputs will be used as a basis for all other regression models to compare to. We read in the scaled data set, which in turn is used for the regression model.

Our next two methods, Ridge and Lasso regression, are shrinkage methods. The script, **Ridge_regression.R**, performs a ridge regression and **Lasso_regression.R** performs a lasso regression. The steps for these two methods are nearly identical:

1. Load *scaled-client.csv*, and `library(glmnet)` and set the seed, for reproducibility sake.
2. Create a ‘x’ and ‘y’ variable from the training set, read in from my Rdata file containing training and testing set indices.
3. Run `cv.glmnet()` which performs 10-fold cross-validation and outputs an intercept term and standardizes the variables by default. For ridge regression we use ‘alpha =0’ and for lasso we use ‘alpha =1’.
4. `cv.glmnet()` will output a list of models. We decide the best one based of the minimum lambda and then save this lambda value as well as the coefficients associated with it.
5. Next we plot the model and save it to a png.
6. Once we identified the best model we use the `test_set` to calculate the test MSE, which will eventually help us compare the performances of all the models.

7. Finally we refit the model to the *scaled-client.csv* which is our entire data set using the lambda from step 4. We save the coefficient estimates and use it in the *Results* section of the report.

Our next two methods, Principal Components(PCR) and Partial Least Squares regression(PLSR) are dimension reduction methods performed by **PC_regression.R** and **PLS_regression.R** respectively. The steps for these two regression are very similar to those above, so naturally this outline will not go into as much detail.

1. Load *scaled-client.csv*, and `library(glmnet)` and set the seed, for reproducibility sake.

2. Create a `x` and `y` variable from the training set, read in from the Rdata file containing training and testing set indices.

3. Run `pcr()` or `pls()` depending on which model you want, and use arguments `GradRate` `.`, `data=train_set`, `validation = CV` and `scale = TRUE`.

4. We decide the best model using `which.min(MODELvalidationPRESS)` where `MODEL` is the name of the pcr or pls model depending on the script.

5. Next we plot the model and save it to a png.

6. Once we identified the best model we use the `test_set` to calculate the test MSE, which will eventually help us compare the performances of all the models.

7. Finally we refit the model to the *scaled-client.csv* which is our entire data set using the lambda from step 4. We save the coefficient estimates and use it in the *Results* section of the report.

7 Shiny App

In order to gain more insight into our data set on California art schools, we made a shiny app that would facilitate users to understand the difference of certain statistics between each school and how they correlate to higher graduation rates. Using the shiny app, we are able to construct bar charts and pie charts that would give visual aid to readers on which school is the better of a certain pair. The following class types are the main indicators and predictors we used for our regression models: gender, ethnicity, graduation rate, average age, and median income. The selected groups consist of not only specific academic institutions, but also the three separated regions in California: Northern, Central, and Southern. Given an insufficient data set, there is no clean data for the art schools in Central California, so the charts are not shown.

One piece of information to consider is how graduation rates in Southern California are relatively higher than the rates in Northern California. Especially in graduation rates for the white race, the graduation rate in Southern California is higher by approximately two-fold. From the ethnicity class type, we can see that Asians and Hispanics are enrolled more in Southern California. This case may be related to a regions demographic information, but it may be an indicator that having more Asians or Hispanics can lead to a higher graduation rate. In addition, comparing two schools from Southern and Northern California (Argosy University in San Diego and the San Francisco Conservatory

of Music), we can see that the average age is relatively higher in San Diego while the median income is relatively lower in San Diego. A high average age with low median income can be related to lower graduation rates; however, a higher age group is more matured in terms of careers and academics, so a higher age group can be correlated to higher graduation rates.