Analysis of socio-economic factors on national graduation rate

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1 Introduction:

The public, private, and home schools provide education in the United States. State governments set overall educational standards, often mandate standardized tests for K–12 public school systems, and supervise, usually through a board of regents, state colleges and universities. About 87% of school-age children attend public schools, about 10% attend private schools, and roughly 3% are home-schooled.

It has been alleged, since the 1950s and especially in recent years that American schooling is undergoing a crisis in which academic performance is behind other countries, such as Russia, Japan, or China, in core subjects. Every year, over 1.2 million students drop out of high school in the United States alone. That's a student every 26 seconds or 7,000 a day. About 25% of high school freshmen fail to graduate from high school on time. The U.S., which had some of the highest graduation rates of any developed country, now ranks 22nd out of 27 developed countries. In 2010, 38 states had higher graduation rates. Vermont had the highest rate, with 91.4% graduating. And Nevada had the lowest with 57.8% of students graduating.

For this project, my focus is on major educational issues in the United States and analyze various socio-economic factors on adjusted cohort graduation rate and provided a detailed report on the following:

1. A summarized visualization of adjusted cohort graduation rate by location
2. A comparison of adjusted cohort graduation rate for each state between school year 2011-12 and 2014-15
3. Identify the most salient features/variables used by the model for predicting most adjusted cohort graduation rate, within the limitations of my dataset
4. Building a predictive model of most adjusted cohort graduation rate in each district using machine learning

2 Potential Clients

There are two different types of clients that could be interested in the findings from this project. The first type of clients would be the US online and print media that cover socio-economic and urban issues. These clients are magazines that take an active interest in stories driven by socially

relevant issues and are backed by data analytics, for creating awareness within the public while simultaneously enhancing the quality of their readership. For example, US online media such as US News and Gates Foundation would fall under this category. I also anticipate interest from Government funded bodies and non-profits offering job placement services, and subsidized education services for youth and adults.

3 Datasets used, data wrangling, and data exploration

EDFacts[1] is a U.S. Department of Education (ED) initiative to collect, analyze, and promote the use of high-quality, pre-kindergarten through grade 12 data. I used two datasets from EDFacts portal consisting of District & school level statistics on graduation rates and performance on math & reading/language art assessments by race/ethnicity, gender, disability and economic status for two years 2011 and 2014.

The U.S. Census[2] Bureau's Small Area Income and Poverty Estimates program produces single-year estimates of income and poverty for all U.S. states and counties as well as estimates of school-age children in poverty for all 13,000+ school districts. I used two datasets from Census bureau which contains estimates of population and poverty for two years 2011 and 2014.

The Elementary/Secondary Information System[3] (ElSi) is an NCES web application that allows users to quickly view public and private school data and create custom tables and charts using data from the Common Core of Data (CCD) and Private School Survey (PSS). I used two datasets from ElSi website which contains basic statistical data on U.S. schools (Total Public Schools, Total Students, Pupil/Teacher Ratio and Secondary Teachers etc.) for two years 2011 and 2014.

3.1 Reading in data

Each dataset was provided as a raw dataset in CSV format for 2011 and 2014, which are imported as Pandas data frame. Each raw dataset resulted in two pandas data frames. Initially, I did not foresee any use for the graduation data as I felt that the adjusted cohort graduation rates (ACGR) datasets would be sufficient to address my problem. But later I had to merge other datasets to get all related variables in one dataset.

[1] https://www.ed.gov
[2] https://www.census.gov/programs-surveys/saipe.html
[3] https://nces.ed.gov/ccd/elsi/

The following formula provides an example of how the four-year adjusted cohort graduation rate would be calculated for the cohort entering 9th grade for the first time in the 2011-12 school year and graduating by the end of the 2014-15 school year:

Formula for Calculating the Four-Year Adjusted-Cohort Graduation Rate

$$\frac{\text{Number of cohort members who earned a regular high school diploma by the end of the 2014-15 school year}}{\text{Number of first-time 9th graders in fall 2011 (starting cohort) plus students who transferred in, minus students who transferred out, emigrated, or died during school years 2011-12, 2012-13, 2013-14, and 2014-15}}$$

3.2 Initial data exploration

After initial data exploration, I have found that adjusted cohort graduation rate is present in one dataset but there are 3 more datasets which has the remaining variables I am considering for analysis. Hence, I had to work on merging 4 datasets and coming up with a single dataset which can be used in the analysis.

I checked the first five rows in the adjusted cohort graduation rate data frames for both 2011 and 2014, and noticed that some columns are having suppressing data for very small groups of students to protect individual student's identity. I realized this would pose a challenge for making comparisons between 2011 and 2014.

The first five rows of the 2011 adjusted cohort graduation rates dataframe are shown below:

	STNAM	FIPST	LEAID	LEANM	ALL_COHORT_1112	ALL_RATE_1112	MAM_COHORT_1112	MAM_RATE_1112	MAS_COHORT_1112	MAS_RATE_1112	...
0	ALABAMA	01	0100005	Albertville City	268	83	NaN	NaN	NaN	NaN	...
1	ALABAMA	01	0100006	Marshall County	424	79	2	PS	1	PS	...
2	ALABAMA	01	0100007	Hoover City	1042	91	1	PS	71	85-89	...
3	ALABAMA	01	0100008	Madison City	836	91	4	PS	44	GE90	...
4	ALABAMA	01	0100011	Leeds City	117	70-74	NaN	NaN	NaN	NaN	...

3.3 Checking for missing values

Because it is often easy to identify specific individuals when data are presented for a very small number of students, the graduation rate has been suppressed for all subgroups for which there are 1-5 students in the cohort. These suppressions are identified by 'PS'. To further protect the privacy of students, and to prevent any data suppressed in Step One from being recalculated by subtracting other reported groups data from the "All Students" group, the Education Department has reported the graduation rates for all medium-sized groups as a range (e.g., <20% or 70-74%) The magnitude of the reported ranges is determined by the size of the group whose data are being reported. For example, subgroups with the fewest students (6-15) are reported with the

widest ranges (e.g., <50% or ≥50%). As the number of students in the group increases, the magnitude of the range decreases, until there are more than 300 students in a subgroup, at which point the graduation rate is reported as a whole number percentage. The ranges used for varying sized groups are presented in the following Table.

Number of Students in the Subgroup	Ranges Used for Reporting the Graduation Rate for that Subgroup
6-15	<50%, ≥50%
16-30	≤20%, 21-39%, 40-59%, 60-79% ≥80%
31-60	≤10%, 11-19%, 20-29%, 30-39%, 40-49%, 50-59%, 60-69%, 70-79%, 80-89%, ≥90%
61-300	≤5%, 6-9%, 10-14%, 15-19%, 20-24%, 24-29%, 30-34%, 35-39%, 40-44%, 45-49%, 50-54%, 55-59%, 60-64%, 65-69%, 70-74%, 75-79%, 80-84%, 85-89%, 90-94%, ≥95%
More than 300	≤1%, [whole number percentages] 2%, 3%, . . ., 98%, ≥99%

During data cleanup, I have used a random generator to replace the suppressed and missing values in the adjusted cohort graduation rates dataframe. This was done by generating a random number between the range given in the original dataframe and replace the corresponding value. In the final step of data wrangling I check the following to verify the data integrity:

1. If there are records with more than 100% graduation rate
2. If there are records with less than 0% graduation rate
3. If there are records with a non-integer graduation rate

I also checked to see if there were any record with adjusted cohort graduation rate as 0 and decided to drop these rows from my analysis. To do this, I dropped all the columns in the dataframes and checked to count after dropping the rows with values. After a comparison, I found that 142 & 128 records are dropped from the adjusted cohort graduation rates dataframe of 2011 and 2014 respectively.

3.4 Renaming column titles

The column titles of the adjusted cohort graduation rates dataframes for 2011 and 2014 are shown below.

2011 Columns	2014 Columns	Column Description	New Column Name
FIPST	FIPST	The two-digit State code	FIPCD
LEAID	LEAID	District NCES ID	LEAID
ALL_COHORT_1112	ALL_COHORT_1415	Total number of students within the four-year adjusted-cohort	ALLA
ALL_RATE_1112	ALL_RATE_1415	Rate of students who graduated within the four-year adjusted-cohort	ALLP
MAM_COHORT_1112	MAM_COHORT_1415	Total number of American Indian/Alaska Native students within the four-year adjusted-cohort	MAMA
MAM_RATE_1112	MAM_RATE_1415	Rate of American Indian/Alaska Native students who graduated within the four-year adjusted-cohort	MAMP
MAS_COHORT_1112	MAS_COHORT_1415	Total number of Asian/Pacific Islander students within the four-year adjusted-cohort	MASA

MAS_RATE_1112	MAS_RATE_1415	Rate of Asian/Pacific Islander students who graduated within the four-year adjusted-cohort	MASP
MBL_COHORT_1112	MBL_COHORT_1415	Total number of Black students within the four-year adjusted-cohort	MBLA
MBL_RATE_1112	MBL_RATE_1415	Rate of Black students who graduated within the four-year adjusted-cohort	MBLP
MHI_COHORT_1112	MHI_COHORT_1415	Total number of Hispanic students within the four-year adjusted-cohort	MHIA
MHI_RATE_1112	MHI_RATE_1415	Rate of Hispanic students who graduated within the four-year adjusted-cohort	MHIP
MTR_COHORT_1112	MTR_COHORT_1415	Total number of Multiracial students within the four-year adjusted-cohort	MTRA
MTR_RATE_1112	MTR_RATE_1415	Rate of Multiracial students who graduated within the four-year adjusted-cohort	MTRP
MWH_COHORT_1112	MWH_COHORT_1415	Total number of White students within the four-year adjusted-cohort	MWHA
MWH_RATE_1112	MWH_RATE_1415	Rate of White students who graduated within the four-year adjusted-cohort	MWHP
CWD_COHORT_1112	CWD_COHORT_1415	Total number of students with disabilities within the four-year adjusted-cohort	CWDA
CWD_RATE_1112	CWD_RATE_1415	Rate of students with disabilities who graduated within the four-year adjusted-cohort	CWDP
ECD_COHORT_1112	ECD_COHORT_1415	Total number of economically disadvantaged students within the four-year adjusted-cohort	ECDA
ECD_RATE_1112	ECD_RATE_1415	Rate of economically disadvantaged students who graduated within the four-year adjusted-cohort	ECDP
LEP_COHORT_1112	LEP_COHORT_1415	Total number of students with limited English proficiency within the four-year adjusted-cohort	LEPA
LEP_RATE_1112	LEP_RATE_1415	Rate of students with limited English proficiency who graduated within the four-year adjusted-cohort	LEPP

The column titles were very long with years as suffix. To make data access and data operations more manageable, I shortened all the column titles into smaller names by using a dictionary.

An example of shortened column titles for the 2011 adjusted cohort graduation rates data frame is shown below:

	YEAR	FIPCD	LEAID	ALLA	ALLP	ALLG	MAMA	MAMP	MAMG	MASA	MASP	MASG	MBLA	MBLP	MBLG
0	2011	01	0100005	268	83	222	0	0	0	0	0	0	6	97	6
1	2011	01	0100006	424	79	335	2	0	0	1	0	0	4	0	0

3.5 Normalizing Cohort data

I realized while doing some initial analysis that the adjusted cohort graduation rates dataframes does not have the % of students from different race which is an important variable in determining why students from some states are doing better. Hence, I calculated the following columns and added to the adjusted cohort graduation rates dataframes.

Column Name	Column Description	Column Rule
MAMR	% of American Indian/Alaska Native students appeared	MAMR = (MAMA/ALLA) * 100
MASR	% of Asian/Pacific Islander students appeared	MASR = (MASA/ALLA) * 100
MBLR	% of Black students appeared	MBLR = (MBLA/ALLA) * 100
MHIR	% of Hispanic students appeared	MHIR = (MHIA/ALLA) * 100
MTRR	% of Multiracial students with appeared	MTRR = (MTRA/ALLA) * 100
MWHR	% of White students appeared	MWHR = (MWHA/ALLA) * 100
CWDR	% of students appeared with disabilities	CWDR = (CWDA/ALLA) * 100
ECDR	% of economically disadvantaged students appeared	ECDR = (ECDA/ALLA) * 100
LEPR	% of students appeared with limited English proficiency	LEPR = (LEPA/ALLA) * 100

3.6 Assessment data exploration

I also wanted to consider the assessment data for 2011 and 2014 and decided to use the percentage of students in the district that scored at or above proficient in Math and Reading/Language Arts. Following a same procedure, I did with the adjusted cohort graduation rates data, I read the assessment data for 2011 and 2014 into separate Pandas data frames, selected only the most relevant columns: Total number of students that completed an assessment in Math & Reading/Language Arts, Percentage of students that scored at or above proficient in Math & Reading/Language Arts.

STATE	LEAID	ALL_MTH_PCT	ALL_RLA_PCT
ALABAMA	0100005	84	84
ALABAMA	0100006	90	82
ALABAMA	0100007	97	94
ALABAMA	0100008	95	93
ALABAMA	0100011	74	84

3.7 Poverty data exploration

Now I want to parse the small area income and poverty estimates for all district for 2011 and 2014. Following a same procedure, I read the poverty data for 2011 and 2014 into separate Pandas data frames, selected only the most relevant columns: Estimated Total Population(TOTP), Estimated Population between 5-17(CHLD) and Estimated number of relevant children 5 to 17 years old in poverty(CHIP).

I realized while doing some initial analysis that the poverty data has various number of relevant children 5 to 17 years old in poverty. Hence, I calculated the following columns and added to the poverty dataframes.

Column Name	Column Description	Column Rule
CHIR	% of Children per district	CHIR = (CHLD / TOTP) * 100
POVR	% of Children under poverty per district	MASR = (CHIP / CHLD) * 100

3.8 Elementary/Secondary data exploration

Now I want to parse the elementary/secondary data for all district for 2011 and 2014. Following a same procedure, I read the poverty data for 2011 and 2014 into separate Pandas data frames, selected only the most relevant columns. After renaming the column titles of the elementary/secondary dataframes for 2011 and 2014 are shown below.

2011 Columns	2014 Columns	Column Description	New Column Name
FIPST	FIPST	The two-digit State code	STATE
LEAID	LEAID	ANSI/FIPS State Code	LEAID
Total Schools	Total Schools	Total number of school per district	TOTSC
Total Charter Schools	Total Charter Schools	Total number of charter school per district	TOTCH

Total Public Schools	Total Public Schools	Total number of public charter school per district	TOTPS
Total Students	Total Students	Total number of Total Students per district	TOTS
Free and Reduced Lunch Students	Free and Reduced Lunch Students	Total of Free Lunch Eligible students and Reduced-price Lunch Eligible students	FRLS
Grade 12 Students - male	Grade 12 Students - male	Total number of male students in 12th grade	GR12M
Grade 12 Students - female	Grade 12 Students - female	Total number of female students in 12th grade	GR12F
Pupil/Teacher Ratio	Pupil/Teacher Ratio	Calculated Pupil Teacher Ratio	PTR
Full-Time Equivalent	Full-Time Equivalent	Total number of Full Time Equivalent teachers per district	FTE
Secondary Teachers	Secondary Teachers	Total number of secondary teachers per district	SET
Total Staff	Total Staff	Total number of staff per district	TOTSF
Secondary Guidance Counselors	Secondary Guidance Counselors	Total number of secondary guidance counselors per district	SEGC

I realized while doing some initial analysis that the elementary/secondary data is not normalized. Hence, I added to the elementary/secondary dataframes the following columns after normalization:

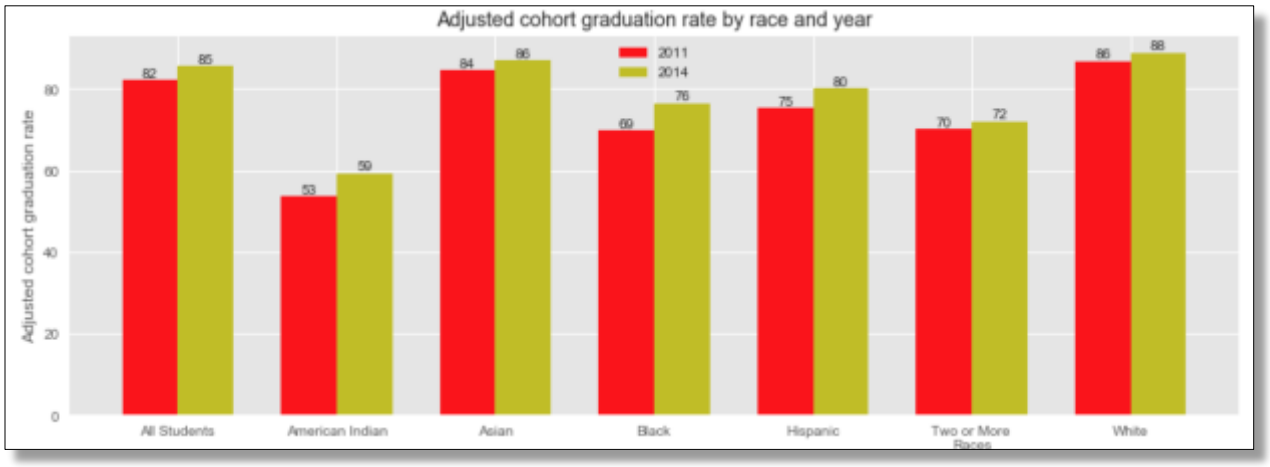
Column Name	Column Description	Column Rule
CHSR	% of Charter School	MAMR = (MAMA/TOTSC) * 100
MLSR	% of male students	MLSR = (GR12M /TOTS) * 100
FLSR	% of female students	FLSR = (GR12F/TOTS) * 100
FRLR	% of Students on free/reduced lunch	FRLR = (FRLS/TOTS) * 100
SETR	% of secondary teachers	SETR = (SET/FTE) * 100
SECR	% of secondary counselors	SECR = (SEGC/TOTSF) * 100

3.9 Exploration of Combined Dataset

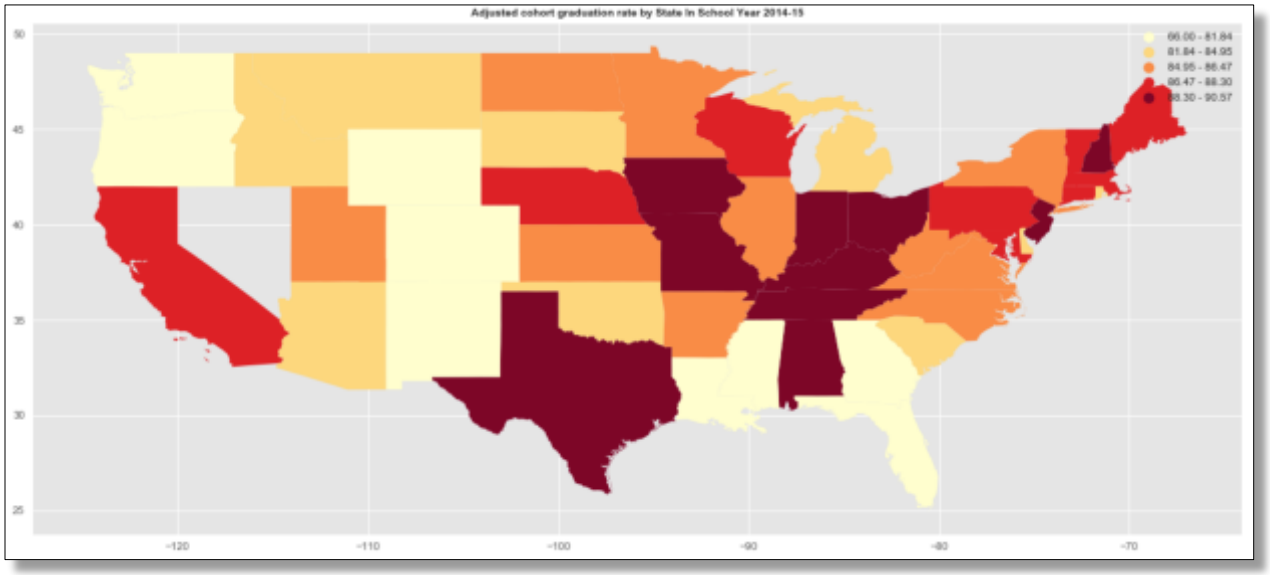
After normalizing the cohort dataset, assessment dataset, poverty dataset and elementary secondary dataset, these datasets are merged and generated a combined dataframe. Now we will try to analyze the statement made by Department of Education that "In school year 2014-15, the adjusted cohort graduation rate (ACGR) for public high school students rose to 83%."

After verifying the clean regulatory adjusted cohort graduation rate for all district, we can see that in school year 2014-15 the graduation rate at the national level is 85%, an increase from 82% in 2011-12.

After calculating the cohort graduation rate for major racial and ethnic groups, we can see that in school year 2014–15 white students have the highest ACGR of 88.0%, followed by Asian/Pacific Islander 86.0%, Hispanic 80.0%, Black 76.0%, Two or more races 72% and American Indian/Alaska Native 59.0%.



From the Adjusted cohort graduation rate by race and year we can conclude that the increase in the overall cohort graduation rate is contributed by each race but they may not have contributed at the same rate. Later we will analyze which race has more impact on the overall graduation rate. Now check the states which are doing better than other state. In order to, have a better visual representation we have plotted the chloropleth map with the data from school year 2014-15 after removing Hawaii and Alaska.



From the above heat map, it is very clear that the school district in Northeast and South region is doing better than the school district in Midwest and west region. Now check how these states are doing over time.

3.10 Further exploration

Next, I compared the means of all the critical factors which can impact the adjusted cohort graduation rates in 2011 with 2014. I found that the % of American Indian, Hispanic and Asian

students are increased in 2014 and the % of Black and White students is decreased in 2014. The % of students, who are proficient in Math and ELA were the two most significant factors that can contribute towards the adjusted cohort graduation rate. This finding perhaps justifies why the nationwide adjusted cohort graduation rate is moved from 82.25% to 84.26%.

The mean of each normalized critical factor impacting the adjusted cohort graduation rates data for 2011 and 2014:

Critical Factor	2011	2014	% of change
% Appeared - American Indian	1.90	2.60	36.84
% Appeared - Asian	1.89	1.98	4.76
% Appeared - Black	8.41	7.81	-7.13
% Appeared - Hispanic	10.66	11.72	9.94
% Appeared - White	75.72	73.95	-2.34
% Appeared - Two or More Races	1.20	1.82	51.67
% Appeared - Children with disabilities	12.98	12.59	-3.00
% Appeared - Economically disadvantaged	40.44	43.75	8.18
% Appeared - Limited English proficient	2.68	2.76	2.99
% Proficient - Math	64.19	51.52	-19.74
% Proficient - ELA	73.76	61.71	-16.34
% of Children Population	16.91	16.68	-1.36
% of Children under poverty	18.97	18.76	-1.11
% of Charter School	1.08	1.02	-5.56
Pupil/Teacher Ratio	14.48	14.55	0.48
% of male students in G12	4.12	4.04	-1.94
% of female students in G12	3.93	3.85	-2.04
% of Students on free/reduced lunch	43.12	44.16	2.41
% of secondary teachers	44.74	44.36	-0.85
% of secondary counselors	0.89	0.88	-1.12

3.11 Comparison of states having most and least Cohort rate

The state wise mean adjusted cohort graduation rate in 2011 and 2014 (i.e., ALLP) were sorted to find the top five state having lowest graduation rate for both these years.

Top five states having lowest graduation rate in 2011 and 2014:

2011	
STATE	% Graduated
DISTRICT OF COLUMBIA	54.01
NEVADA	64.38
OREGON	69.01
ALASKA	69.08
GEORGIA	70.60

2014	
STATE	% Graduated
DISTRICT OF COLUMBIA	66.00
NEW MEXICO	69.81
OREGON	74.62
ALASKA	75.33
FLORIDA	77.88

Four of the top five states having lowest graduation rate matched in 2011 and 2014.

Next, I compared the top five states having highest graduation rate for these two years.

Top five states having highest graduation rate in 2011 and 2014:

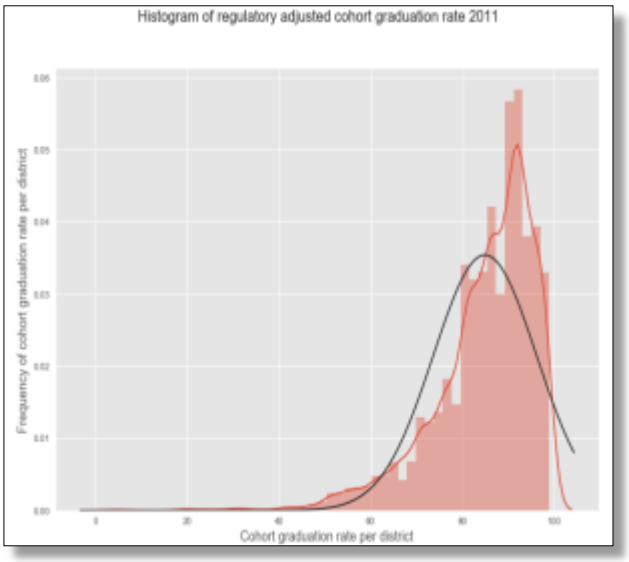
2011

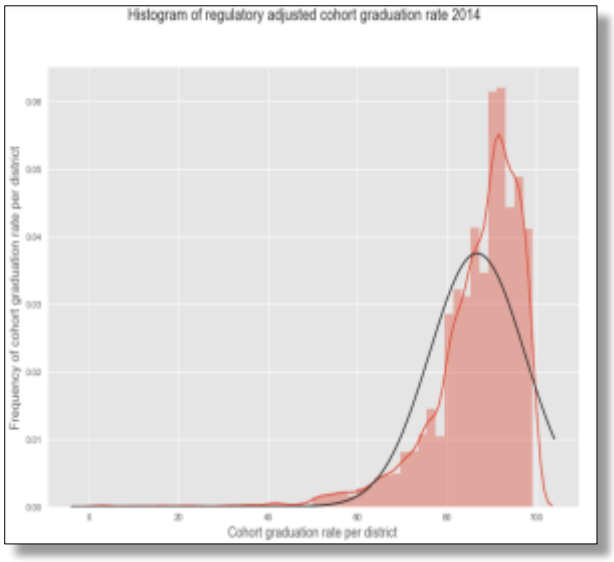
2014

STATE	% Graduated
WISCONSIN	87.29
VERMONT	87.78
OHIO	88.13
IOWA	88.67
TEXAS	88.98

STATE	% Graduated
MISSOURI	89.76
INDIANA	89.87
IOWA	89.91
TEXAS	90.25
TENNESSEE	90.57

Again, I noticed that two of the top five states having highest graduation match in 2011 and 2014. Next, I plotted a few visualizations of the adjusted cohort graduation rates data. I compared graduation rate per district in 2011 and 2014 as univariate distributions using Seaborn by plotting a histogram and a kernel density estimate. A kernel density estimation allows us to estimate the probability density function of a random variable from a finite set of data. So, it allows us to look at the adjusted cohort graduation data as a continuous probability distribution rather than a

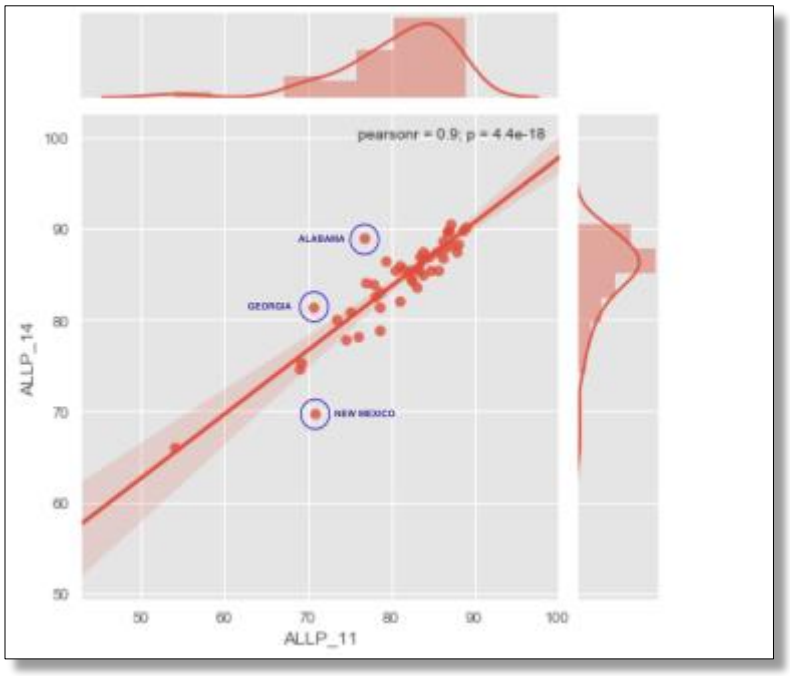




histogram.

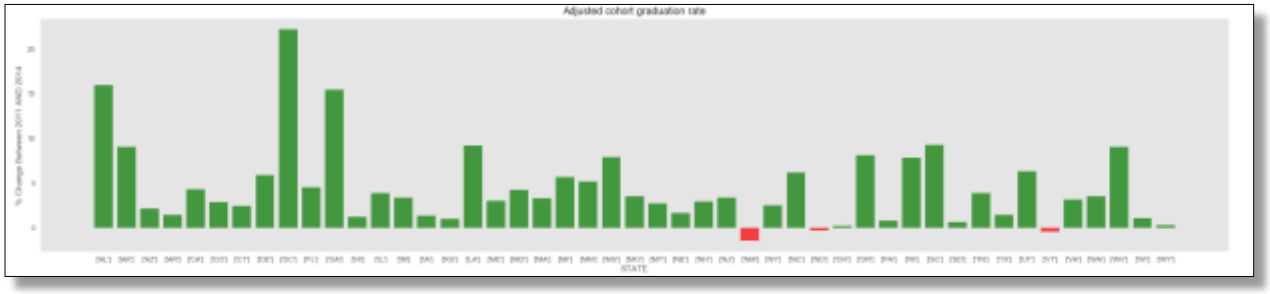
I realized that an easier way to compare both years would be to show the adjusted cohort graduation rate in a scatterplot. This also showed how correlated both were. In the plot below, 2011 adjusted cohort graduation rates data is on the x-axis and 2014 adjusted cohort graduation rates data is on the y-axis.

As expected, there was a strong correlation of 0.9 in adjusted cohort graduation rates for both years. In addition to outliers in the plot, I also noticed three points, which did not fall along the general trend. These two points refer to the adjusted cohort graduation rate in three states. I found that these three states were New Mexico, Georgia and Alabama. Among these three states New Mexico is the only state which is showing negative growth in adjusted cohort graduation rate.



3.12 States with maximum change in Cohort rate

I calculated the percentage of increase or decrease in adjusted cohort graduation rate from 2011 to 2014 by (a) computing the difference in adjusted cohort graduation rate between the two years for each state, (b) dividing this difference with the adjusted cohort graduation rate in 2011 for that state, and (c) converting this value into a percentage.



From the above histogram, it is clear that most states shown positive growth in cohort graduation rate.

But NEW MEXICO, NORTH DAKOTA, VERMONT are the states showing negative growth in cohort graduation rate.

Positive values of percentage change in graduation rate from 2011 to 2014 indicate an increase in graduation rate and negative values indicate a decrease in graduation rate, from 2011 to 2014.

I wanted to know how these states with the most increase and decrease in adjusted cohort

graduation rate compared against some of the top and bottom states based on graduation states for 2014.

4 Prediction Using Machine Learning

We'll next explore how this data can be modeled to predict future graduation rate using EDFacts data.

4.1 Linear Regression Analysis

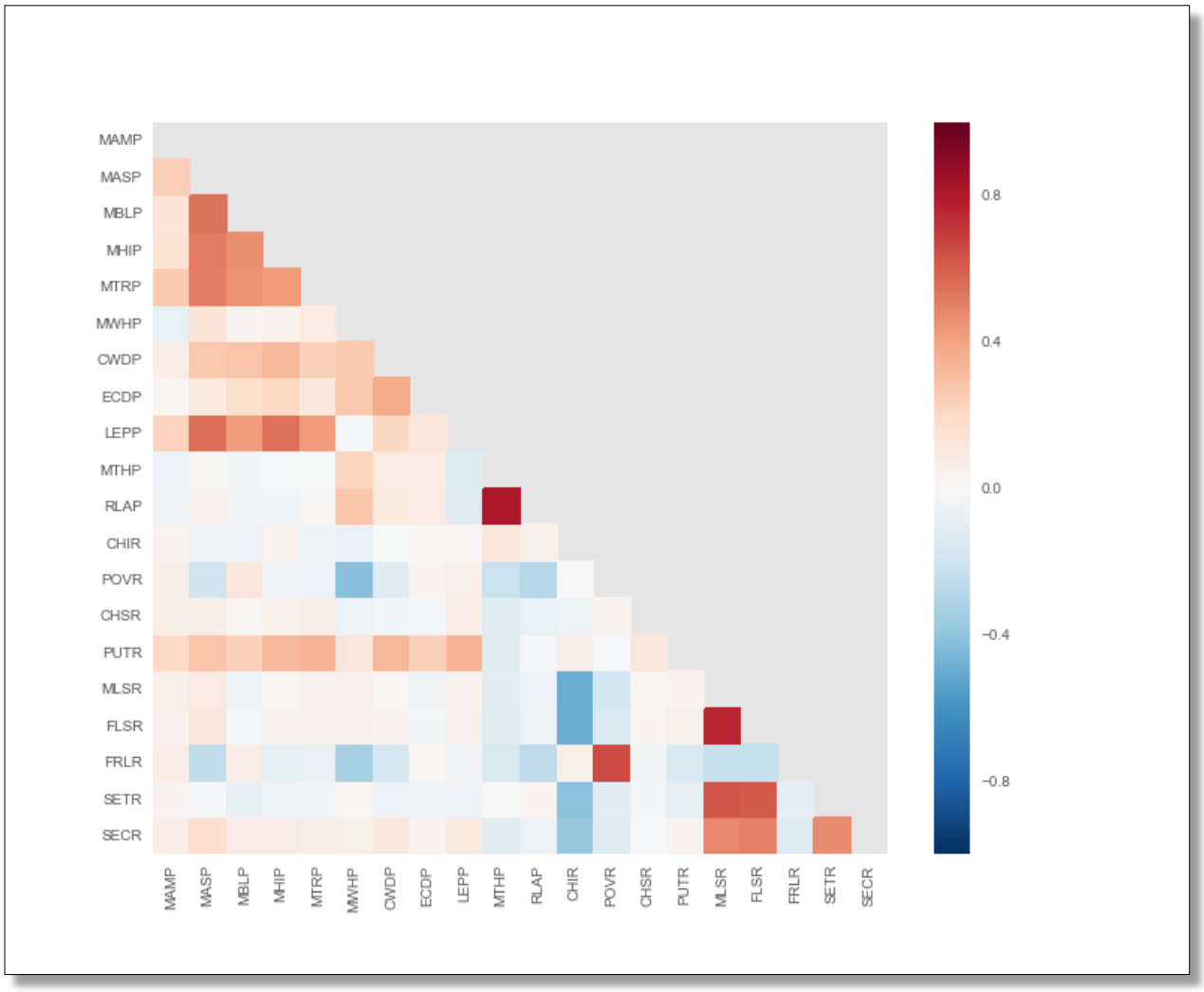
To generate a linear regression model, I merged the cohort dataset, assessment dataset, poverty dataset and elementary secondary dataset, for each district separately. This resulted in obtaining two data frames with 21 columns – 20 features/independent variables, and 1 dependent variable. We will attempt to build a model using only the data to predict the graduation rate.

4.1.1 Feature selection

Twenty columns were originally chosen as possible features of interest that might impact graduation rate; their names and descriptions are listed below.

Full Name	2011 Column	2014 Column
% Passed - American Indian	MAMP	MAMP
% Passed - Asian	MASP	MASP
% Passed - Black	MBLP	MBLP
% Passed - Hispanic	MHIP	MHIP
% Passed - White	MWHP	MWHP
% Passed - Two or More Races	MTRP	MTRP
% Passed - Children with disabilities	CWDP	CWDP
% Passed - Economically disadvantaged	ECDP	ECDP
% Passed - Limited English proficient	LEPP	LEPP
% Proficient - Math	MTHP	MTHP
% Proficient - ELA	RLAP	RLAP
% of Children Population	CHIR	CHIR
% of Children under poverty	POVR	POVR
% of Charter School	CHSR	CHSR
Pupil/Teacher Ratio	PUTR	PUTR
% of male students in G12	MLSR	MLSR
% of female students in G12	FLSR	FLSR
% of Students on free/reduced lunch	FRLR	FRLR
% of secondary teachers	SETR	SETR
% of secondary counselors	SECR	SECR

A correlation plot of all the above features is shown below to gain a better understanding into the dependencies between these variables.



We can see that there are several highly-correlated pairs of features. For example, the % Passed - Economically disadvantaged is very positively correlated with % of Children under poverty while the % Passed - White is negatively correlated. The % of male students in G12 is associated with the % of female students in G12 — an unsurprising result that both male and female students are contributing towards overall graduation rate. Additionally, we can see that % Proficient - Math are highly correlated with % Proficient - ELA. After looking at the co-relation matrix I have selected the following features for analysis.

Full Name	
% Passed - American Indian	% Passed - Limited English proficient
% Passed - Asian	% Proficient - Math
% Passed - Black	% Proficient - ELA
% Passed - Hispanic	% of Children under poverty
% Passed - White	% of Students on free/reduced lunch
% Passed - Economically disadvantaged	% of secondary teachers

4.1.2 Linear Regression Results on Graduation Rate

The LinearRegression class from sklearn was used to fit the model with ordinary least squares (OLS) linear regression. The data showing students data from the 10593 district and the graduation rate vector were split into a training (70%) and a test (30%) set, and the model was fit on the training data after normalizing the features. However, the adjusted R-squared value for this model is only 0.45, a moderate number that may indicate that a linear relationship is not the right fit for this dataset.

We next look at the mean squared error (MSE), which is almost similar on the training data (MSE = 63.76) and for the test data (MSE = 64.42). To limit the effects of overfitting, we can use k-fold cross-validation (k = 5), but this procedure calculates a high MSE of 66.35, indicating that the Graduation rate is not an excellent candidate for linear regression.

Below, we've plotted the actual vs. predicted response times using the fitted model. The scatterplot does seem to line up well in a linear fashion. On the right, we can see the residuals for both the training and test set are distributed uniformly around zero.

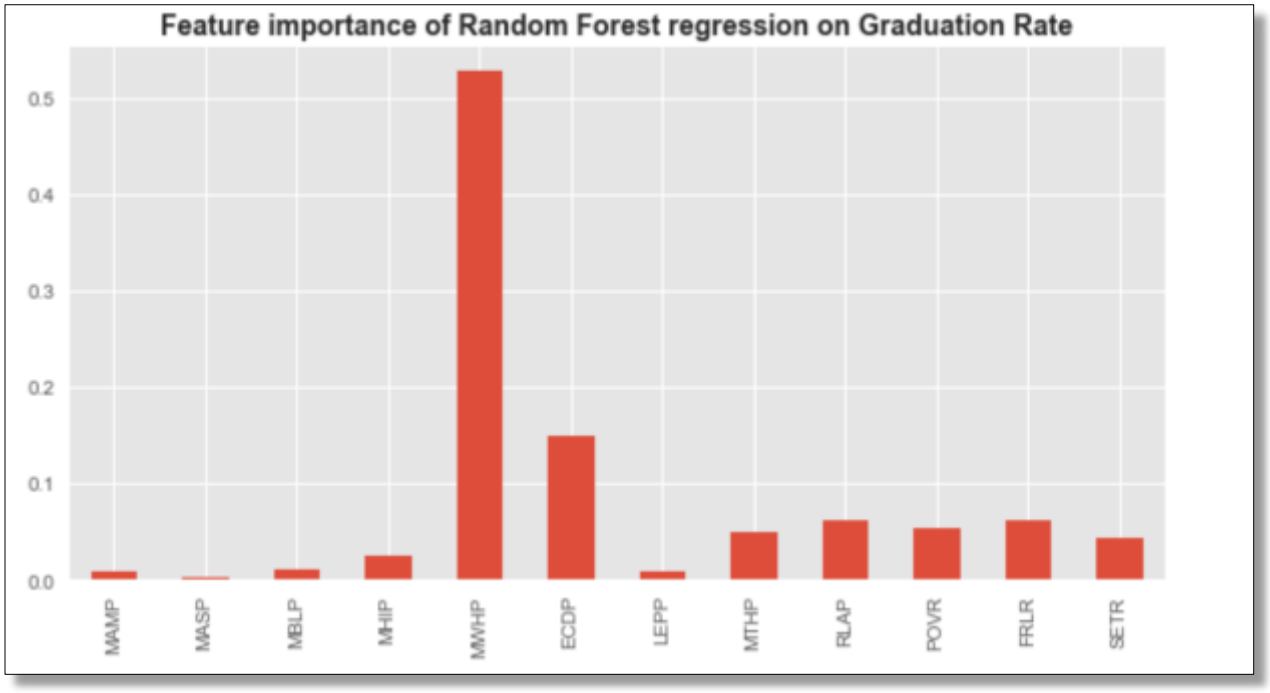
4.2 Random Forest Regression

After linear regression produced a subpar model for the graduation rate, we can turn to random forest regression using the same training and test sets from linear regression.

4.2.1 Random Forest Regression Results on Graduation Rate

The R-squared value from the fitted random forest regression on the response data is much higher than the linear model is 0.67. However, while the MSE on the training set is 7.71, the MSE for the test set jumped significantly to 38.89. The regression for the response data is over fit. Performing a k-fold cross validation with 5 folds still showed a higher MSE of 43.85. We can conclude that neither linear or random forest regression is a good fit to model this data.

However, the feature importance are shown below to give a sense of which variables the model found to have the largest impact on mean decrease node impurity during the training. We can see that % Pass - White and % Passed - Economically disadvantaged were more important than the other students variables in decreasing node impurity.



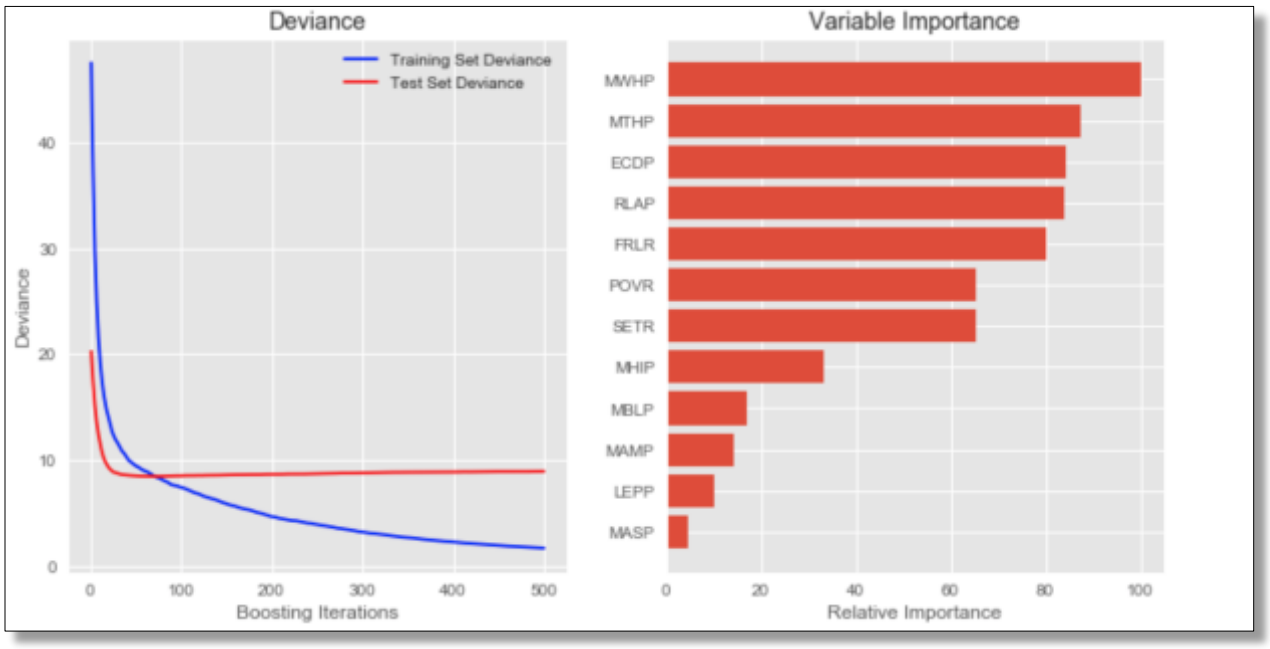
4.3 Gradient Boosting Regression

After random forest regression produced a subpar model for the graduation rate, we can turn to Gradient Boosting regression using the same training and test sets from linear regression.

4.3.1 Gradient Boosting Regression Results on Graduation Rate

The R-squared value from the fitted gradient boosting regression on the response data is much higher than the random forest model, is 0.70. However, while the MSE on the training set is 4.88, the MSE for the test set jumped significantly to 35.95. The regression for the response data is over fit. Performing a k-fold cross validation with 5 folds still showed a higher MSE of 39.28. We can conclude that neither linear, random forest regression or gradient boosting regression is a good fit to model this data.

However, the variable importance are shown below to give a sense of which variables the model found to have the largest impact. We can see that % Pass - White and % Proficient - Math were more important than the other variables.



4.4 Conclusions and Future Work

While the correlations shown in this paper are certainly intriguing, the real value of this analysis lies in the predictive models' application to new data points. US Department of Education can use ED.gov to access similar student's data in narrower geographies of interest (cohort dataset, assessment dataset, poverty dataset, elementary secondary dataset, etc.) and predict graduation rate per district.

Recommendations for further action based on this analysis:

• For the District:

Conduct a study to determine the root cause why the school district in Northeast and South region is doing better than the school district in Midwest and west region. Is there any evidence that re-zoning these districts will allow the overall graduation rate to increase further?

• For State:

Investigate why New Mexico, North Dakota, Vermont are showing negative growth in graduation rate. Using smaller geographic areas as suggested above, plot graduation rate to determine if these states are showing any trend by location. Use this data to create a corrective action to improve the graduation rate.

Future opportunities to continue this work include further training of the regression model on smaller district areas with more accurate dataset to determine if the regional division holds on a larger data set. Incorporating income data may also add accuracy to the regressions, allowing Department of Education to pinpoint the graduation rate for any district. We can also determine if these correlations are standardized across district by applying the regression models to similar district from other states.