Optimizing the Allocation of Public-School Funding

The Underprepared Undergrads

Introduction and Motivation

This project explores how U.S. public schools receive funding from the government. While each K-12 public school gets some amount of federal funding allocated to them, state and local governments also determine the amount of money each school receives. Papers like *Unequal School Funding in the United States* [4] discuss how the current models for allocating funds can neglect low income communities while other research, such as *Does Money Matter?* [5], is interested in the correlation between funding and scholastic achievement. This project looks to bring ideas in both these areas together to better understand how funding is allocated to schools in different need categories and analyze which social and school factors contribute to each categories' funding.

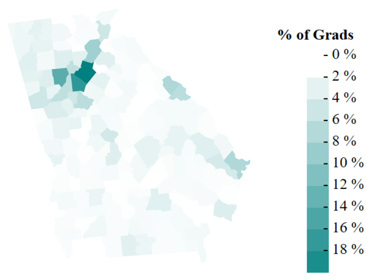


Figure 1: The percentage of Georgia high school graduates from each county, darker shading ⇒ more graduates

Figure 1 above shows that not all counties have equal academic outcomes and cannot be treated the same in terms of school funding.

The motivation behind this project comes from the fact that a quality public education is a "gateway to opportunity" for children of all backgrounds [19]. Equal access to this gateway is not yet a reality but is necessary to ensure a better society for future generations.

Problem Definition

The aim is to classify public schools in the United States into need categories based on factors like graduation rate for each school. Next step would be to create multiple models predicting funding for each need category. Finally, compare the prediction models between categories, identifying differences in funding for various need levels.

Literature Survey

Fairness of School Funding:

Is School Funding Fair? A National Report Card uses different measures to study "fairness" in school funding but does not look at scholastic achievement.

Unequal School Funding in the United States details how most school funding comes from local property taxes. The paper justifies the need for a more equitable funding model but does not investigate better ways to allocate funding.

Separate and Unequal: School District Financing… suggests that the financial support available to public schools affects quality of education but does not explore funding allocation.

The Role of Funding in Student Outcomes:

Does Money Matter? focuses on the effect of resources on scholastic achievement, reviewing multiple past studies.

Mind the Gap links school funding to class size and student-teacher ratios. The paper suggests that completely equal funding is undesirable because some areas need more support. The article focuses on achievement gaps.

Public school funding and performance… suggests that there is a significant positive relationship between school funding and academic performance.

Education Funding and Low-income Children: A Review of Current Research… suggests that student achievement is related to school funding. It discusses why there are conflicting views on the problem but does not identify better allocation methods.

The Role of School Factors in Student Outcomes:

Equality of Educational Opportunity evaluates different aspects of schools and their relation to academic achievement. This is useful because it identifies specific aspects of our model.

The Enduring Effects of Small Classes shows that students who attend small classes in grades K-3 are 2.5-5 months ahead in their education relative to peers in regular-sized classes, and this benefit continues for years.

Education Equity and School Structure analyzes what school size will work best for students and a school to achieve goals. Funding is not directly mentioned.

Reducing the Negative Effects of Large Schools looks into solutions for the large school problem. Funding is not a focal point.

Projections of Education Statistics to 2027 gives an overview of projected key education statistics. It details factors affecting the projections including student enrollment, teachers, graduates, and expenditures in elementary and secondary public and private schools.

Trends in High School Dropout and Completion Rates examines the characteristics of high school dropouts and completers. It depicts important trends based on 5 key indicators but does not examine the roles of these indicators.

Data Matters: Using Chronic Absence analyzes and provides the consequences of chronic absence in schools. It mentions how chronic absence data can help develop solutions.

Technical Prediction Methods:

School Funding Reform analyzes the current UK school funding formula that depends on factors like student poverty and cost of living. The paper gives us a framework for starting our own modeling but is specific to the UK system.

Geographic Resource Allocation… frames resource allocation as an optimization model, where an arbitrarily defined intervention effects variable is maximized through the use of binary decisions for each geographic area. Education is not a focus.

The geographic allocation… similarly frames resource allocation as a logarithmic regression model. In this case, features like population and income per capita are used to predict the financial need for poor/developing countries. Education is not directly mentioned.

An ordinal classification… discusses the remediation of environmentally damaged areas. Each area is classified into a different severity group with the use of a decision tree. This is not specific to education.

Proposed Method

Innovations

The literature survey indicates that regression models are not used to predict school funding within the United States. In addition, no previous work in this area has used machine learning methods to group schools into need categories. This allows us to look at inequality between groups in more detail instead of allowing trends in one group to affect a regression model. By comparing prediction models between categories, we will be able to see how different factors are taken into consideration when allocating school funding. Our research also uses graduation rate as a measure of academic achievement, which has not been seen previously in literature.

Data Collection and Processing

Data is combined from several sources including Kaggle (a website aggregation of databases) and the U.S. Department of Education. I used Excel's VLookup function to match school financial data with demographic data based on a school's name and district. I then stored the integrated data in an Excel spreadsheet.

YEAR	STNAM	LEANM	SCHNAM	ALL CO	ALL RATE	MA	MAM	MAS	MAS	MBL COH	MBL RATE	MHI COH	MHI R	MTR	MTR	MW	MWH	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	TCURINST	TCURSSVC	TCURONO	TCAPOUT
Not found	ALABAMA	Alabaster City	Thompson High School	311	93	.	.	2	PS	12	GE50	97	90-94	1	PS	199	90-94	Not found	Not found	Not found	Not found	Not found	Not found	Not found	Not found	Not found
2016	ALABAMA	Albertville City	Albertville High Sch	75	90-94	.	.	.	.	1	PS	25	GE80	.	.	48	GE90	49795	7277	28885	13633	46778	24173	15092	4435	1212
2016	ALABAMA	Alexander City	Alexander City Middle Sch	140	85-89	.	.	1	PS	3	PS	32	GE90	.	.	104	85-89	32454	3717	17018	11719	29642	17613	8768	2309	628
2016	ALABAMA	Alexander City	Benjamin Russell High Sch	121	90-94	.	.	.	.	2	PS	1	PS	1	PS	117	90-94	32454	3717	17018	11719	29642	17613	8768	2309	628
2016	ALABAMA	Andalusia City	Andalusia High Sch	95	85-89	.	.	.	.	2	PS	5	PS	1	PS	87	85-89	18650	2360	9571	6719	15978	9218	5193	1169	93
2016	ALABAMA	Anniston City	Anniston High Sch	743	92	.	.	39	GE9	200	90-94	52	70-79	29	GE80	422	94	23776	4344	11810	7622	24320	12649	9344	1890	413
2016	ALABAMA	Arab City	Arab High Sch	410	94	.	.	21	GE8	101	85-89	16	GE80	11	GE50	260	GE95	23606	1544	15096	6966	26202	14569	7328	1851	2325
2016	ALABAMA	Athens City	Athens High Sch	437	GE99	.	.	31	GE9	89	GE95	18	GE80	12	GE50	282	GE95	36442	2122	9735	24585	33757	20727	11281	746	796
2016	ALABAMA	Athens City	Athens Renaissance School	424	96	.	.	29	GE8	102	GE95	20	GE80	9	GE50	262	GE95	36442	2122	9735	24585	33757	20727	11281	746	796
2016	ALABAMA	Attalla City	Etowah High Sch	110	GE95	.	.	1	PS	32	GE90	15	GE50	7	GE50	55	80-89	16009	1940	10917	3152	17120	8944	4942	1409	1330
2016	ALABAMA	Auburn City	Auburn High Sch	170	85-89	.	.	4	PS	2	PS	29	GE80	5	PS	129	85-89	134959	4440	41613	88906	131695	44694	26933	5129	49074
2016	ALABAMA	Auburn City	Auburn Jr High Sch	341	98	.	.	9	GE5	40	GE90	6	GE50	10	GE50	275	GE95	134959	4440	41613	88906	131695	44694	26933	5129	49074
2016	ALABAMA	Autauga County	Billingsley High Sch	2	PS	.	.	.	.	2	PS	.	.	.	.	.	.	80867	7447	53842	19578	76672	43843	23941	6401	1506
2016	ALABAMA	Autauga County	Marbury Sch	215	90-94	.	.	.	.	74	90-94	9	GE50	.	.	132	90-94	80867	7447	53842	19578	76672	43843	23941	6401	1506
2016	ALABAMA	Autauga County	Prattville High Sch	110	GE95	.	.	3	PS	45	GE90	.	.	1	PS	61	GE95	80867	7447	53842	19578	76672	43843	23941	6401	1506
2016	ALABAMA	Autauga County	Autaugaville Sch	135	80-84	.	.	.	.	129	85-89	1	PS	2	PS	3	PS	80867	7447	53842	19578	76672	43843	23941	6401	1506
2016	ALABAMA	Baldwin County	Robertsdale High Sch	195	GE95	.	.	3	PS	1	PS	4	PS	.	.	186	GE95	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Baldwin County	Fairhope High Sch	232	91	.	.	6	GE5	58	80-89	27	GE80	6	GE50	133	90-94	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Baldwin County	Central Baldwin Middle Sch	181	85-89	.	.	.	.	17	21-39	2	PS	1	PS	160	90-94	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Baldwin County	Gulf Shores High Sch	193	85-89	.	.	.	.	21	GE80	14	GE50	14	GE50	144	85-89	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Baldwin County	Daphne High Sch	233	94	.	.	1	PS	35	GE90	3	PS	1	PS	189	90-94	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Baldwin County	Foley High Sch	54	80-89	.	.	.	.	44	80-89	1	PS	.	.	9	GE50	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Baldwin County	Baldwin Co High Sch	115	GE95	.	.	.	.	9	GE50	2	PS	1	PS	100	GE95	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Baldwin County	Spanish Fort High Sch	442	96	.	.	7	GE5	90	GE95	57	GE90	6	GE50	279	GE95	62065	10751	25552	25762	54609	31116	17108	4571	557
2016	ALABAMA	Barbour County	Barbour Co High Sch	232	92	.	.	3	PS	34	GE90	62	85-89	1	PS	130	90-94	10116	2342	5434	2340	10070	4907	3896	975	110
2016	ALABAMA	Bessemer City	Jess Lanier High Sch	615	95	.	.	84	GE9	133	90-94	25	GE80	2	PS	371	97	41288	7480	21905	11903	42030	20359	14741	4437	1717
2016	ALABAMA	Bibb County	Bibb Co High Sch	2	PS	.	.	.	.	2	PS	.	.	.	.	.	.	286129	44753	128031	113345	278372	136792	85868	17845	37763
2016	ALABAMA	Bibb County	West Blocton High Sch	54	80-89	.	.	.	.	14	GE50	.	.	.	.	40	80-89	286129	44753	128031	113345	278372	136792	85868	17845	37763
2016	ALABAMA	Birmingham City	Huffman High Sch-Magnet	122	85-89	.	.	2	PS	19	GE80	1	PS	.	.	100	85-89	273626	43262	125189	105175	272202	141114	96550	22760	8000

Figure 2: A snapshot of the working data. Some columns are hidden for ease of viewing.

Demographic factors in our data include number of students and graduation rate in total as well as the count and graduation rate for Native American students, Asian/Pacific Islander students, Black students, Hispanic students, Multiracial students, White students, students with disabilities, economically disadvantaged students, and students with limited English proficiency.

Financial factors are total school revenue, revenue coming from federal sources, revenue coming from state sources, revenue coming from local sources, total expenditures, expenditures outside of instruction, expenditures minus support services, and other spending. All of these financial factors are measured in dollars. Our final data ranges from 2010-2016 and is 15 MB with 37 features and 145,000 rows.

Classification

Initially, I classified each school based on graduation rate and created equally sized groups. However, after further testing of our models, I decided that k-means clustering with 5 groups based on all school features better represented the "need level" of each school. Since many of the features used in prediction are moderately correlated with each other, principal component analysis was used to reduce overfitting.

STNAM	LEAID	CLASS_SIZ	%_FEDRE\	%_STREV	%_LOCRE\	TOTALEXP	TOTALEXP	TCURINST,	TCURSSVC	TCURONO	TCAPOUT/	ALL_RATE_	clusters
MONTANA	3016290	9.333333	0	0.111111	0.888889	1.6	0.470004	0	0.857143	0	0	75	2
MONTANA	3016290	14.66667	0	0.5	0.5	1.8	0.587787	0	0.613636	0	0	75	2
MAINE	2304895	33.68421	0	0	1	2.714286	0.998529	0	0.296875	0	0	95	1
ARIZONA	400142	9.333333	0.5	0	0.5	3	1.098612	0.214286	0.428571	0	0	75	2
MICHIGAN	2627240	20	0	0.271739	0.728261	3	1.098612	0	1.65	0	0	75	2
MONTANA	3021000	8	0	0.235294	0.764706	3	1.098612	0	1.5	0	0	75	2
MICHIGAN	2627240	146.3415	0	0.271739	0.728261	3	1.098612	0	0.2255	0	0	82	4
MICHIGAN	2627240	152.1739	0	0.271739	0.728261	3	1.098612	0	0.216857	0	0	92	1
MICHIGAN	2627240	47.36842	0	0.271739	0.728261	3	1.098612	0	0.696667	0	0	95	1
PENNSYLVAN	4204080	139.0805	0	0.19382	0.80618	3.857143	1.349927	0.194132	0	0	0	87	4
ARIZONA	400142	20	0.714286	0	0.285714	4	1.386294	0.15	0.25	0	0	75	2
VERMONT	5008248	78.04878	0	1	0	4.142857	1.421386	0	0.038438	0	0	82	4

Figure 3: A snapshot of the classified data. The farthest right column shows the "group" or "cluster" that the school belongs to.

Below is a table of groups and average graduation rates from our final clustered data.

Group	Average Graduation Rate
3	28.6%
0	54.0%
2	73.6%
4	86.7%
1	95.0%

From this clustering, we can identify group 3 as the highest-need group and group 1 as the lowest-need group.

Regression Models
After classification, I used the linear_model. Lasso function that is part of the sklearn module in Python to fit a linear regression model to each of the need groups. Lasso regression is used to screen for important variables in order to create simple yet effective models with low multicollinearity. The response variable was total school expenditures, while the independent variables were all of the other columns in our data.

After initial model training and evaluation, I performed data transformations. Instead of passing absolute dollar amounts of funding into our model, I changed total federal revenue into percentage of total revenue coming from the federal level and did the same for state and local levels. In addition, total school expenditures showed an exponential trend when I plotted values against predictor variable values, so I decided to take the natural logarithm of total expenditures to make the trend more linear.

Random Forests
Another algorithm I used for predicting funding based on need group was the Random Forest Regressor in Python's sklearn module. I created five RandomForestRegressor models, one for each need group. I then used GridSearchCV with 10-fold cross-validation to tune the max_depth hyperparameter in each of the five models.

Visualization
In order to visualize our results from our predictions, I created an interactive chloropleth map of the US using the d3 library for Javascript. I used a TopoJSON file detailing states across the US to map average prediction error for each state. This allowed me to see which geographic areas deviated the most from our funding prediction models.

Experiments and Evaluation

I evaluated and adapted linear regression methods using common error metrics for regression, and evaluated random forest models using cross-validation.
I also wanted to use our prediction methods to answer the questions below, related to broader study goals:

- Is there any relation between funding and academic achievement (i.e. graduation rate)?
- Is school funding allocated comparably based on achievement level of a school?
- If there are significant distinctions between need groups, are the factors that differ changeable?

Details: Regression Models

Testing accuracy scores and MSE values for the five linear regression models are below. The groups are sorted from lowest need to highest need.

Group	Accuracy Score	MSE
3	0.1722	3.473
0	0.1384	3.2507
2	0.1014	2.5563
4	0.18	1.9935
1	0.0925	1.9874

R^2 values for each of these models are approximately 15%. While these R^2 values are very low for a traditional linear regression, the MSE was ~25% lower than other higher R^2 models I found, showing improvement when modeling with lasso regression. A discussion of the actual predictors selected with this technique follows later.

There appears to be a pattern in the mean squared error values, with high-need schools having high errors and low-need schools with low errors. This could be due to sample size, as there are fewer schools in the high-need categories.

Details: Random Forest Models

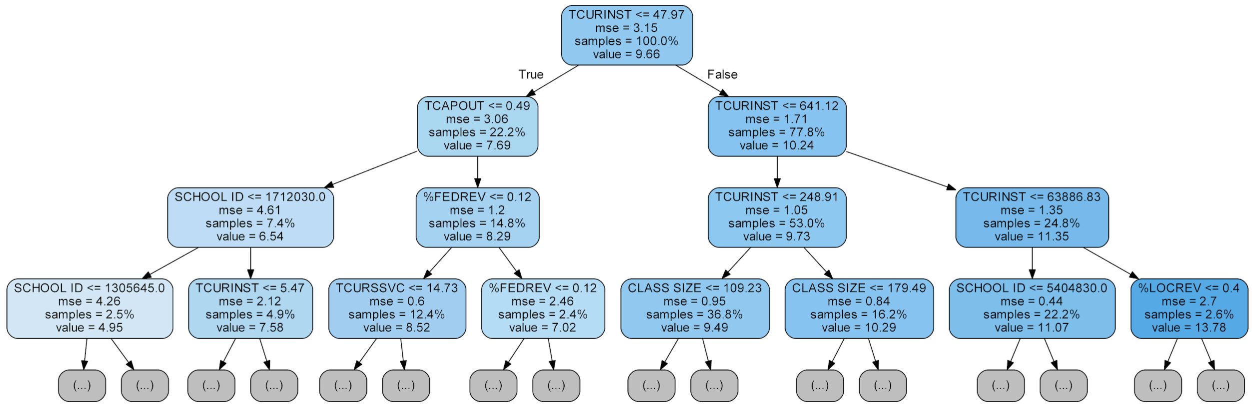
I used GridSearchCV in order to find the best possible models for each of the need groups and perform cross-validation on the models.

Cross-validation scores and MSE for the five random forest regressor models are:

Group	Score	MSE
3	0.7934	.3769
0	0.8031	.2903
2	0.8324	.2071
4	0.8537	.1481
1	0.8581	.1461

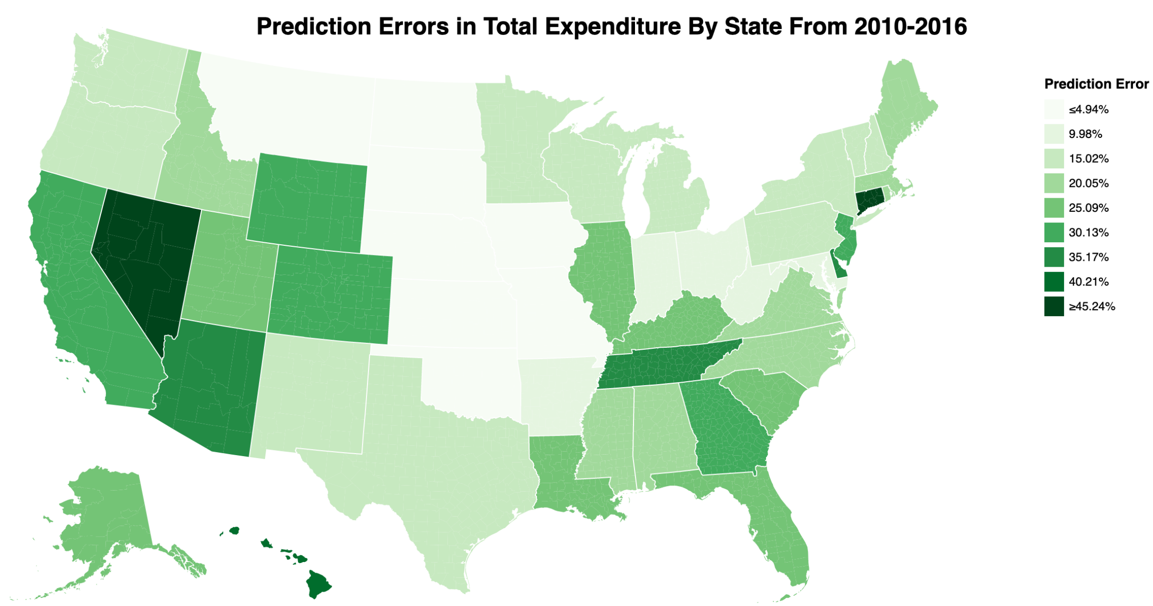
These scores are much higher than those for linear regression. However, the results still show lower accuracy and higher error for higher-need schools. This indicates that models for higher-

need schools, even when they have been tuned to try and achieve maximum accuracy, still perform more poorly.
Below is a visual of one decision tree used in our random forest model:



This diagram indicates that the most important factors in this model are financial and not demographic.

Visualizations:
A choropleth map was created to help show how average prediction errors for all schools in a state from 2010-2016 vary geographically.



The three states with the highest percent errors were Nevada with 50.28%, Connecticut with 42.01%, and Hawaii with 37.26%. We know from our background research that states allocate funding to public schools very differently, so this map confirms that regional differences are significant when examining funding.

Questions Answered:

- Is there any relation between funding and academic achievement (i.e. graduation rate)?

The results from the regression models indicate that each group of schools can be modeled similarly, since lasso regression selected the same variables to be included in each model. However, there are greater inaccuracies in modeling “needier” groups of schools, which implies less equitable funding in poorer areas. While random forest models were much more accurate on average, the MSE is still higher for the higher-need groups. Despite the fact that random forests serve as a much better regressor, they are still less accurate in predicting the required funding for “needier” schools and thus may require further information.

I recognize the MSE may be higher for higher-need groups because of their lower sample size, but what that indicates is a bias against higher-need groups in general. Because there are fewer higher-need schools, funding tends to be more unpredictable. This is a significant issue for these schools, since consistent and stable funding is vital for teacher retention, student aid programs, and other factors needed to improve student outcomes. This finding confirms the idea that systemic reform in public school funding is needed in order to give high-need schools more consistency and stability.

- Is school funding allocated comparably based on need level of a school?

In linear models, the majority of the variables identified as significant for regression were financial factors, including funding structure and expenditures per student in different categories. The only non-financial factor was average class size. From this, I conclude that demographic factors such as number of economically disadvantaged students and number of students with disabilities are not as significant in predicting school funding compared to financial factors.

I had initially assumed from our previous research into the UK school funding system that these metrics were primary indicators of school need and would be the most important factors when determining funding. The fact that these student population metrics are not significant indicates that the US public school funding allocation system does not sufficiently and completely account for school need.

- If there are significant distinctions, are the factors that differ changeable?

The significant factors that determine school expenditures were mostly financial: funding structure, non-teaching expenses per student, non-support service expenses per student, and capital outlays for building improvements. Theoretically, these factors are changeable, since school budgets can be modified year to year. A deeper analysis of how funding structure, expenditures, and school need are related could shed greater light on how changing school funding and expense structure influences student outcomes.

Conclusion and Discussion

Discussion of Results

The answers to the questions above indicate that there is a relationship between school funding, school need level, and academic success and that the significant factors in this relationship are ones that can be changed. Results also confirm previous research that schools with poorer academic outcomes receive less funding than other schools. I have innovated in this area by finding that higher-need schools also receive more inconsistent and unpredictable funding year-to-year, which can be detrimental for academic outcome improvement. Since there are fewer high-need schools compared to other need categories, the same models used for other groups cannot be used to predict funding, since the smaller sample size creates larger and more frequent errors. In addition, demographic factors like number of economically disadvantaged students are important determinants of school need and currently do not influence how much funding a school receives. A more equitable model would also incorporate demographic factors.

One important point is that these results do not imply causation between predictor variables and response variable. Conclusion remains that certain correlations exist between our predictors and total expenditures and that those correlations seem to differ when looking at different need categories.

Further Research

One way to expand this research would be from a public policy point of view, in order to determine why funding and expense structure distinctions between need categories exist. One hypothesis could be that state funding has different requirements and regulations than local funding, so schools have to spend the money from these sources in different ways. This research could also be taken further in terms of technical approaches, and additional prediction and classification algorithms could be used to more clearly identify the most important factors in the relationship between school funding, school need, and academic achievement.

Conclusion

By analyzing school funding and demographic data using classification and prediction algorithms, I found that there are meaningful differences in how funding is allocated to schools that have different levels of need. To truly ensure that every child has the opportunity to get a quality public education, we need to look carefully at how our current methods are perpetuating inequality in school systems and make meaningful changes for future generations. School funding is a small part of the problem, but each step we take towards fully understanding and fixing these issues is vital.

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