Penny for Your Thoughts

Measuring the Impact of Funding on Educational Outcomes

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Objectives and Constraints

The goal of our project is to answer a research question investigating the relationship between funding and academic outcomes for public school students. Is there a direct relationship between funding for education and student achievement? What do we see when we examine the available data?

Answers to questions about educational funding are important to policymakers who determine where our tax money is spent, as well as to parents of school age children and their teachers. With ESSA replacing No Child Left Behind during the Obama Administration the role of evaluating schools and determining how to 'fix' them fell largely on each state. Pros and cons existed for each bill, but the question still remained, "How should we measure academic success or educational outcomes within the US?". With the Trump administration now overturning many of the educational bills passed during the Obama and Bush administration federal, state and local funding of public schools is in flux.

Changes made thus far include less strict review of teacher preparation programs and funding being cut to help states identify failing schools and development of plans to improve schools success rates. With less funding being aloted to reviewing different measures contributing to educational outcomes our team focused on creating an educational database focused on collecting factors that contribute to educational outcomes and develop measures to determine the success of students, and thus schools. For the purpose of this project we focused first on gathering funding and financial data along with any available educational factors related to public schools K-12. Due to time constraints and poor collection or data quality we settled on CCD and NAEP datasets.

Since this is a public interest topic, we wanted our results to be reproducible by others. So we made sure we used easily accessible publicly available data and a low cost solution. We also want the project to continue to be relevant in the future with the ability to incorporate future data sets.

How much of an impact funding has on children's success is debatable, but through this project we hope to give better insight on how public school funding is linked to a school's ability to output successful students. It is also an important question for the future of our country, as a well educated and informed society is better equipped to take a leadership role on the world stage.

Data Sources

To investigate our research question we required fiscal data measuring the revenue received by public schools annually in each state. We also needed a measure of academic performance. We obtained this data from two sources.

Common Core of Data

The Common Core of Data (CCD) is the Department of Education's database of public school data nationwide. It collected through surveys conducted annually. We used two data sets from the CCD:

- Fiscal provides details of school funding with breakdown into local/state/federal sources and expenses including teacher salaries and benefits
- Non fiscal includes total numbers of teachers and students for calculations such as pupil teacher ratios and funding per student

National Assessment of Educational Progress

The National Assessment of Educational Progress (NAEP) is the largest nationally representative and continuing assessment of student academic progress. Beginning with the 2003 assessments, national assessments are conducted every two years in reading and mathematics. Although the test was performed earlier, year 2003 was the first statewide full participation.

We chose to use the 8th Grade NAEP test scores as the data set was more complete. The NAEP test was first administered to 8th grade and then later added to 12th grade so there is a longer history of data for 8th grade.

We also considered using SAT data, but although we submitted a request for access to SAT data, we received no response. The NAEP data proved adequate for our purposes.

We chose to focus on statewide data to provide a more detailed analysis than federal level data would provide and we were able to leverage complete data sets that were available publicly.

We recognise that our definition of educational success is limited to factors measurable in a statistical survey. Outcomes such as teamwork, social leadership skills and a love of learning are difficult to quantify although they are undoubtedly valuable outcomes of a good education. We are also relying on educational assessment standards to measure success which do not necessarily provide a complete picture of academic achievement. Despite these limitations we felt we were able to provide good insight into the relationship between educational success and funding.

Architecture

Identifying which solution was best suited to our use case began with considering the following characteristics.

Data Characteristics

- Structured. The source data has a well defined structure with columns corresponding to property values and data types defined in the data layout document.
- Small size.
- Low sink latency and high source latency. Batch updates will occur annually, but we would like to be able to query the data as soon as it is imported.
- Medium quality. Most of the data quality issues are resolved in the transform scripts. Some filtering by constraints will be desirable.
- Complete data.

Processing Dimensions

- High to low selectivity. Some of our queries are highly selective and others are not.
- Short query time. We expect sub-second responses to our queries.
- Short processing time for batch jobs.
- Medium aggregation allowing us to aggregate over multiple dimensions.
- Advanced joins across multiple tables
- Exact precision handling numeric data

Other Characteristics

- Low cost. Open source preferred.
- Simple to configure and maintain.

Preferred Solution

These characteristics matched most closely with a relational database. Our desire for a low cost open source solution placed PostgreSQL at the top of our list. It is relatively easy to administer, stable and well maintained, and supports all the standard SQL constructs as well as some of the more advanced features. It also integrates with R, Tableau and other solutions we were considering as part of our implementation.

Scalability

Our data sets are small with the potential to grow over time. It is expected that the educational statistical data we use will continue to be generated every year for the foreseeable future. The annual increments impact the number of rows in the tables, but do not greatly increase storage

needs. We were able to store all of our database files locally, reducing the network overhead and cost of external storage solutions.

We chose to implement partitioning within the Postgres database to help ensure that query performance remained fast as the number of rows increased over time.

We also focused on appropriate indexing to ensure fast performance of our queries.

Cloud

We chose to implement our solution in an Amazon Web Services Linux image for ease of collaboration. We also used a github repository to share the solution implementation.

Schema

We are using third normal form schema on write with row based tables. Constraints are used to validate the data before persisting. The combination of state and year provides a common key to relate the tables. Indexes are defined for faster access. Partitioning is implemented for scalability.

Tables and Columns

Our Entity Relationship Diagram identified three classes of data - fiscal, nonfiscal and scores, where both fiscal and nonfiscal data influence the scores. For each table the year/state uniquely identifies the entity and provides a link to corresponding data in other tables.

Fiscal data

survey year	year
state	character
state revenue	numeric
local revenue	numeric
federal revenue	numeric
total revenue	numeric
teacher salaries	numeric
teacher benefits	numeric
current expenditures	numeric

Nonfiscal data

survey year	year
state	character
total teachers	numeric
grade 8 students	numeric
grade 12 students	numeric

total students	numeric

NAEP scores grade 8

test year	year
state	character
mathematics score	numeric
reading score	numeric

In addition, these values would allow us to perform queries to calculate the following:

- Total revenue per pupil as total revenue/total students
- Teacher compensation as (teacher salaries+teacher benefits)/total teachers
- Student teacher ratio as total students/total teachers

PostgreSQL has a remarkably enlightened approach to handling numeric data where it does not require the scale and precision to be defined in advance and will adapt based on the data input.

Constraints

In addition to “not null” modifiers, check constraints have been used to validate important values during import, including the following

- total revenue > 0
- total teachers > 0
- total students > 0
- mathematics and reading scores must be between 0 and 500

Furthermore, the insert trigger checks the state value and will only insert rows which match defined states.
We also defined a domain for the year data type with a constraint which checks that the value for year is valid.

Indexes

On each table, the combination of year and state has been defined as the primary key. This key relates the tables. It is also used in most of our queries and is therefore valuable for performance reasons.

Partitioning

We have divided the tables into five state range based partitions. Since most of our queries gather data per state, we implemented 5 range partitions with the states divided evenly.
Using state for the partition range also means that new years of data can be added without repartitioning.
The insert trigger function checks the value for state, and inserts the row into the appropriate partition table. If the state does not match a partition, a notice is issued and the row is skipped. This helps us ensure that only data from states common to all the data sets are imported.

Extract, Transform and Load

The first step was to look for existing tools which could be used to import the data into PostgreSQL.

- Unlike some of the more expensive commercial database products, Postgres does not provide full featured ETL tools.
- An open source tool called pgloader initially looked promising. It was able to download files from a website and import the csv contents into database tables. Upon closer examination however, it provided no functionality for extracting specific columns from a csv file.
- The PostgreSQL COPY command is generally considered to perform much better than other alternatives (including pandas for instance).

We decided to write our own script to extract and transform the data and then use a sql script to create the schema and populate with data using the COPY command.

Download

The script downloads zip files containing the data from the CCD website. There is one fiscal and one nonfiscal zipped data file for each year.

The filenames of the data sets do not use a consistent naming pattern. An earlier version of the script attempted to use pattern matching to retrieve the filenames, but due to website redirects the script was attempting to access files not intended. As a safer approach, the script now uses text files containing the URLs of the data sets to be downloaded. Each year as new data is added to the CCD website, the text files can be updated to add the URLs of the new files.

Each file is downloaded to a temporary file, unzipped and extracted then deleted before the next file is retrieved. With this design we only need to store the extracted content of the files.

Extract and Transform

The most recent fiscal and nonfiscal data files are in tab delimited format with a header row. The extraction process reads each row of the file and parses the rows to output just the required columns into a comma delimited csv file.

We implemented the script to overcome the following challenges:

- the tab delimited data files contained null values
- some field values contained commas
- the format and columns of the nonfiscal data file changed. From 2003 to 2006 the files were in fixed width format. In 2007 the format changed to tab delimited. Starting in 2008 additional columns of demographic data were added to the files.
- the nonfiscal data files from 2003 to 2006 did not contain a header row but subsequent years did have column headers
- some files contained data for extra territories. The CCD include 56 states and territories including District of Columbia, American Samoa, Guam, Northern Mariana Islands, Puerto Rico, Virgin Islands. Some earlier years of nonfiscal data included DoD school

information while later years did not. The NAEP data includes 50 states plus District of Columbia and DoDEA (Department of Defense Education Activity military schools). We chose to use the overlapping data from the 50 states and District of Columbia in our analysis.

OpenRefine

The NAEP website provides an interactive form to generate csv file data which precludes the possibility of automating the download. The data file layout is designed for aesthetics not analysis:

- multiple header rows
- blank columns
- year values are provided in the first row of each table but not populated in subsequent rows

Fortunately the data for all years is included in a single file. This made it easy to quickly process the file in OpenRefine.The empty rows and columns were removed. The fill down tool was useful for populating the year value in rows where it was missing. The data was exported as a csv file.

Load

The SQL script which creates the database schema also loads the data from csv files into the tables using the COPY command. The data is checked by constraints on fiscal and state values.

Execution

The code for our scripts is available in the ETL folder of our project repository with a readme detailing steps for running the scripts.

1. Run ./extract_transform.sh

This process retrieves data files from the National Center for Educational Statistics website based on URLs recorded in the fiscal.txt and nonfiscal*.txt text files in the same directory. The output of the script is two csv files: fiscal.csv and nonfiscal.csv

While it is running, the extract_transform.sh script displays output as below.

```
[w205@ip-172-31-22-103 ETL]$ ./extract_transform.sh
--2017-08-15 05:12:21--  https://nces.ed.gov/ccd/data/zip/stfis14_1a.zip
Resolving nces.ed.gov... 63.145.228.23, 2001:428:7003:11::23
Connecting to nces.ed.gov|63.145.228.23|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 33374 (33K) [application/x-zip-compressed]
Saving to: `temp.zip'

100%[======================================================>] 33,374      44.6K/s   in 0.7s

2017-08-15 05:12:22 (44.6 KB/s) - `temp.zip' saved [33374/33374]

51 fiscal.csv
--2017-08-15 05:12:22--  https://nces.ed.gov/ccd/data/zip/stfis13_1a.zip
Resolving nces.ed.gov... 63.145.228.23, 2001:428:7003:11::23
Connecting to nces.ed.gov|63.145.228.23|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 34621 (34K) [application/x-zip-compressed]
Saving to: `temp.zip'

100%[======================================================>] 34,621      93.2K/s   in 0.4s

2017-08-15 05:12:23 (93.2 KB/s) - `temp.zip' saved [34621/34621]

102 fiscal.csv
--2017-08-15 05:12:23--  https://nces.ed.gov/ccd/data/zip/Stfis_1a_txt.zip
Resolving nces.ed.gov... 63.145.228.23, 2001:428:7003:11::23
Connecting to nces.ed.gov|63.145.228.23|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 35042 (34K) [application/x-zip-compressed]
Saving to: `temp.zip'
```

2. The load.sql script is executed within PostgreSQL: \i /home/w205/205_Project/ETL/load.sql

After creating the schema, the data is loaded from the csv files created by the previous step.

While it is running the load.sql script displays output as below:

```
postgres=# \i /home/w205/205_Project/ETL/load.sql
DROP DATABASE
CREATE DATABASE
psql (8.4.20)
You are now connected to database "w205project".
CREATE DOMAIN
ALTER DOMAIN
CREATE LANGUAGE
ALTER LANGUAGE
SET
psql:/home/w205/205_Project/ETL/load.sql:42: NOTICE:  CREATE TABLE / PRIMARY KEY will create implicit
 index "fiscal_pkey" for table "fiscal"
CREATE TABLE
ALTER TABLE
CREATE TABLE
ALTER TABLE
CREATE TABLE
ALTER TABLE
CREATE TABLE
ALTER TABLE
CREATE TABLE
ALTER TABLE
CREATE TABLE
```

After the scripts are completed, the tables can be shown using the \dt command.

```
w205project=# \dt
            List of relations
 Schema |     Name      | Type  |  Owner
--------+---------------+-------+----------
 public | fiscal        | table | postgres
 public | fiscal_1      | table | postgres
 public | fiscal_2      | table | postgres
 public | fiscal_3      | table | postgres
 public | fiscal_4      | table | postgres
 public | fiscal_5      | table | postgres
 public | naep8         | table | postgres
 public | naep8_1       | table | postgres
 public | naep8_2       | table | postgres
 public | naep8_3       | table | postgres
 public | naep8_4       | table | postgres
 public | naep8_5       | table | postgres
 public | nonfiscal     | table | postgres
 public | nonfiscal_1   | table | postgres
 public | nonfiscal_2   | table | postgres
 public | nonfiscal_3   | table | postgres
 public | nonfiscal_4   | table | postgres
 public | nonfiscal_5   | table | postgres
(18 rows)
```

The columns, indexes, constraints and triggers for the fiscal table are displayed with \d fiscal.

```
w205project=# \d fiscal
                Table "public.fiscal"
       Column        |         Type         | Modifiers
---------------------+----------------------+-----------
 survey_year         | year                 | not null
 state               | character varying(2) | not null
 state_revenue       | numeric              | not null
 local_revenue       | numeric              | not null
 federal_revenue     | numeric              | not null
 total_revenue       | numeric              | not null
 teacher_salaries    | numeric              | not null
 teacher_benefits    | numeric              | not null
 current_expenditures | numeric             | not null
Indexes:
    "fiscal_pkey" PRIMARY KEY, btree (survey_year, state)
Check constraints:
    "fiscal_total_revenue_check" CHECK (total_revenue > 0::numeric)
Triggers:
    insert_fiscal_trigger BEFORE INSERT ON fiscal FOR EACH ROW EXECUTE PROCEDURE fiscal_insert_trigger()
```

The columns, indexes, constraints and triggers for the fiscal table are displayed with \d nonfiscal.

```
w205project=# \d nonfiscal
            Table "public.nonfiscal"
     Column      |         Type         | Modifiers
-----------------+----------------------+-----------
 survey_year     | year                 | not null
 state           | character varying(2) | not null
 total_teachers  | numeric              | not null
 grade8_students | integer              | not null
 total_students  | integer              | not null
Indexes:
    "nonfiscal_pkey" PRIMARY KEY, btree (survey_year, state)
Check constraints:
    "nonfiscal_grade8_students_check" CHECK (grade8_students > 0)
    "nonfiscal_total_students_check" CHECK (total_students > 0)
    "nonfiscal_total_teachers_check" CHECK (total_teachers > 0::numeric)
Triggers:
    insert_nonfiscal_trigger BEFORE INSERT ON nonfiscal FOR EACH ROW EXECUTE PROCEDURE nonfiscal_insert_trigger()
```

The columns, indexes, constraints and triggers for the fiscal table are displayed with \d naep8.

```
w205project=# \d naep8
                Table "public.naep8"
    Column     |         Type         | Modifiers
---------------+----------------------+-----------
 test_year     | year                 | not null
 state         | character varying(2) | not null
 math_score    | numeric              |
 reading_score | numeric              |
Indexes:
    "naep8_pkey" PRIMARY KEY, btree (test_year, state)
Check constraints:
    "naep8_math_score_check" CHECK (math_score >= 0::numeric AND math_score <= 500::numeric)
    "naep8_reading_score_check" CHECK (reading_score >= 0::numeric AND reading_score <= 500::numeric)
Triggers:
    insert_naep8_trigger BEFORE INSERT ON naep8 FOR EACH ROW EXECUTE PROCEDURE naep8_insert_trigger()
```

After the data is loaded the database is small, justifying the storage choices we made.

```
w205project=# select pg_size_pretty(pg_database_size('w205project')) as size, pg_database_size('w205project') as bytes;
  size   |  bytes
---------+---------
 6294 kB | 6444816
(1 row)
```

Exploratory Data Analysis

We performed exploratory data analysis using R connected to the PostgreSQL database. This helped us better understand our data in preparation for later visualizations. For instance we noticed that there were some states with much higher revenue and that those were also the states with the highest numbers of students, so we decided to look at revenue per student in our visualizations. Similarly we found that remuneration per teacher made more sense that the raw salary plus benefits data given the different numbers of teachers per state. We also found that the data for DC included outlier values and not applicable values so we might want to focus on the 50 states in our final presentation for more consistent data.

The full data exploration report is available as pdf or as Rmd format file.

Visualization

The first step in the visualization process was deciding what kind of story our data wanted to tell and which queries would best enable us to reveal the information contained in the data. Our prior EDA proved helpful as a baseline for existing relationships. During the composition of our visualizations we reviewed 3 applications, R Shiny, Tableau Server, and Tableau Public, to output our analysis to the public. We resolved to use Tableau Public and posted our analysis on Tableau Public's site.

Choice of Visualization Product

For our project, all data is static and incremental uploads will take place every year to 2 years. We do not need to take into consideration streaming data, high velocity or data approaching 'big data' status at the moment. We as a team decided that the best way to output a response to the research question would be to create a dashboard and story documenting our analysis. The audience we foresee reviewing this analysis will be the public and our stakeholders, lay individuals with little to mild understanding of statistics. In accordance with our project constraints, we wished to make it possible for the public to leverage and build on our work.

We conducted an extensive analysis of visualization software. In addition to the summaries below we have two other documents with a description of our visualization output considerations and a detailed analysis of Tableau Server and R Shiny both of which can be found in the visualize folder of our GitHub repository.

R Shiny

R Shiny requires a small amount of time to learn how to code if you have experience with R, if you lack experience then it could take months. If working on a team that does not code in R; Plotly, Bokeh, Seaborn are other considerations for those who code in Python, while D3 visualizations take the same amount of time if able to create JavaScript, HTML, CSS. What it boils down to is building up a visualization or dashboard from code and packages. It requires one to know enough in one of the above languages and statistics to create a dashboard or visualization. Additional time and effort comes from coding each visualization and having to establish the composition of the dashboard with care.

Our team spent 48 hours working with both Tableau and R Shiny to create a base dashboard with visualizations to see what would be the best option for this current project. In R Shiny we were able to create a base functional dashboard with one visualization, while we were able to create a multitude of dashboards in Tableau.

Tableau

Tableau for our team provided an easier solution for the creation of visualizations and

dashboard. We were able to create three dashboards and over ten visualizations. Tableau won in speed of creation over R Shiny. Additionally, in a real world setting we would be able to create new visuals quickly and easily to present to stakeholders. R Shiny would be able to create more detailed visuals with more options for statistical analysis. If this was not a project we would take into consideration in more detail what our stakeholders were requesting and if the analysis required more advanced statistics we would most likely move to R Shiny or create an additional layer (possibly presentation layer) in R Studio before outputting the data to Tableau.

Maintenance

R Shiny:
Open Source requires constant updates on an as needed basis of packages. This may require for someone to constantly monitor and update the code for the dashboard and your analysis.

Tableau:
Unless we wanted to upgrade we would only to update when necessary aka something being deprecated.

Flexibility

R Shiny:
R Shiny has more options for making visuals and bringing in multiple sources, but building up and making changes is harder.

Tableau:
Tableau is limited to what the software is able to do, but very easy to build and change visualizations on the fly. We did not foresee the creation of overly complex visualizations of the data.

Cost of Development

R Shiny:
*Free open source version, no user limit
*Upgrade to RStudio Shiny Server Pro with licensing on a concurrent user basis, require RStudio support, improved tuning and scaling Cost: Starts at $9,995, as you add users jumps to $14,990-$24,990 large concurrent users will increase pricing

Tableau:
*Currently using free Tableau Student and Tableau Public version
*Upgrade to Tableau Server or Tableau Desktop would require additional cost. Our team foresees Tableau Server being the best option if permissions, higher volume or data and traffic require us to move on from Tableau Public. Cost per Tableau Desktop: $1,500 -2,500 depending on number of licenses, Cost Monthly for Tableau Server: $300 –Dependent on use-case

Solution: Product	Solution: Host	Expected Cost	Expected Benefit	Verdict
Tableau Server	t2.xlarge	$82 + $125 $207 / mo	Unified workbook Relatively known technology Available to the public	✓ Attempt
Tableau Server	m4.xlarge	$138 + $125 $263 / mo	Unified workbook Relatively known technology Available to the public	X Do not attempt
Tableau Server	m4.2xlarge	$184 + $125 $309 / mo (Runs < 12 hours a day)	Unified workbook Relatively known technology Available to the public	X Do not attempt
Shiny	None, host on DB	Cost folded into data base cost	Available to the public Unified Workbook	✓ Attempt
Tableau Public	None	0	Available to the public Relatively known technology	✓ Attempt

Advanced Analytics

R Shiny:
R Shiny is able to create more advanced analytics than tableau, R is the language for statistics.

Tableau:
Tableau is not quite as advanced as R Shiny, but it is advancing. You can now create calculations in R and Python, and Tableau now allows for kmeans clustering through its analysis tab.

Traffic

R Shiny:
The R Shiny Pro base licence has a limitation of 20 users which could create issues for our project because we hoped to share this with the public. The free R Shiny server does not have this limitation but does restrict available features.

Tableau:
Tableau Public has no restriction on number of users.

Automation

R Shiny:
R is a programming language and thus the majority of the steps required for automation are documented in the process of creation. If the file format changes or new variables are added the code will need to be updated.

Tableau:
Tableau can document the steps of what will need to be done to the data through calculations, parameters and groups, BUT lacks the abilities of R to cleanse and data mine. Please note that Tableau has recently released TabPy which adds an unknown amount of automation potential to Tableau.

Summary

We chose Tableau over R Shiny due to time constraints, not knowing if the visualizations we made would need to be completely reworked and to build off of existing, functional, and refined work done in Tableau. The free Tableau Public solution was the most cost effective and easy to use both for us and anyone else wishing to contribute to our project.

Designing and Building Dashboards

Building the dashboards required an understanding of the visualization capabilities of Tableau and how we wanted to probe into the data to uncover the answer to our research question.

We focussed on the following:

1.Strength of relationship between funding per student and test scores in math and reading per state

2. Regional variation and differences of strong vs weak funding and academic outcome relationships

3.Outliers

Visualizations

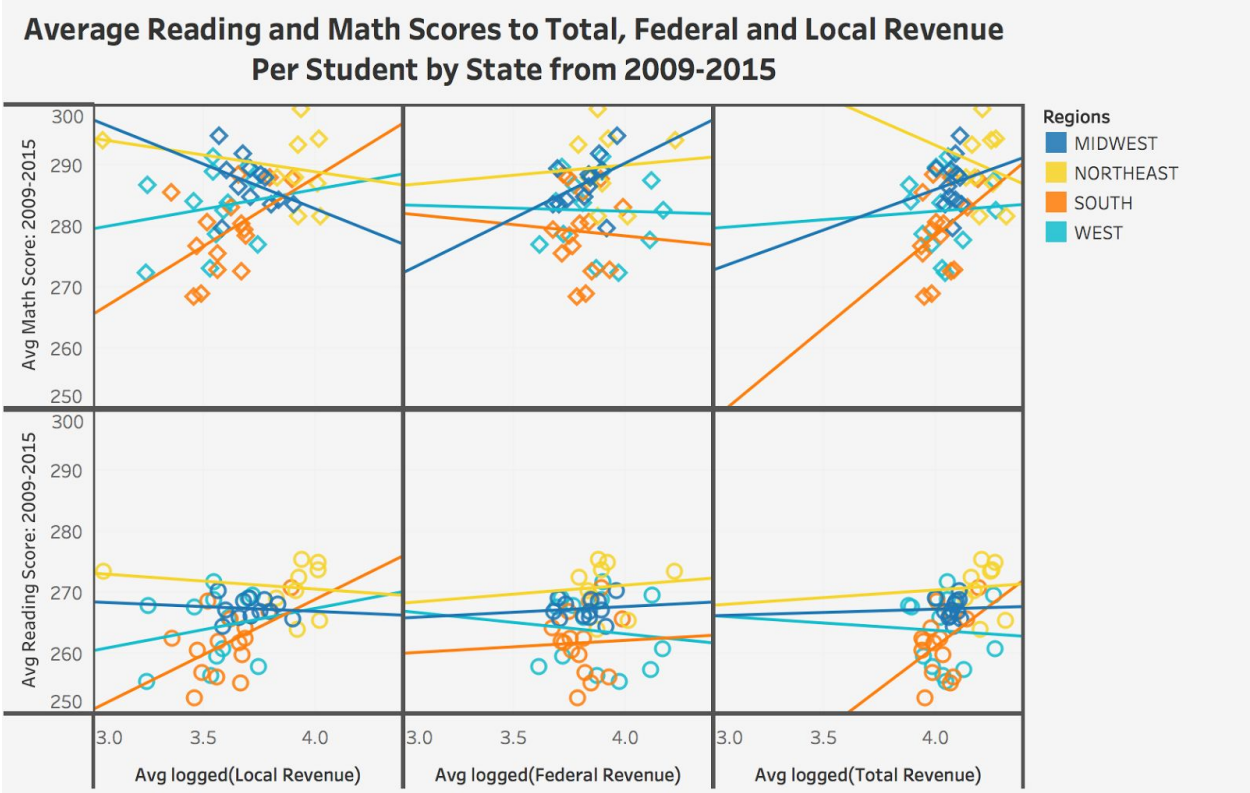
We enriched our visualizations with proficiency and percentile rankings for both reading and math scores, US Regions and US districts. Additionally, we filtered and excluded fields and instances with poor data quality within Tableau and then implemented in our Postgres tables.

Metrics to note created in Tableau/Postgres:
Average Math and Reading Score across 2009-2013
Logged Total Revenue per Student
Logged Federal Revenue per Student
Logged Local Revenue per Student
Correlation between Math, Reading, Local Revenue and Total Revenue per Student
Teacher to Student Ratio
Revenue per Teacher

Results

Our analysis found that there is a complex relationship between funding and academic outcomes. With evidence of a positive linear trend between total revenue and math/reading scores across states it would be unreasonable to dismiss funding as factor in academic outcomes for students. However this relationship was not statistically significant, but it is practically significant.

After a thorough review of the data through EDA and descriptive stats we formed the following conclusions:
While a relationship between between state funding and math/reading scores exists it is not a strong one due to unique outliers such as HI, AR, and AK, but there are strong and variable relationships between regional US educational funding and math/reading scores.



Additional resources were added to the dashboard to enrich the analysis:

- NAEP ranking of percentile
- Basic-proficient rank score
- US regions

- US Districts

Considered for future enrichment:

- Attributes of students, teachers, districts and states
- Median income of each state
- Political leanings of each state and district
- Ranked educational laws by state, region and country

Our research raised some additional questions:

Why are states like Alaska, Hawaii, Arkansas and Vermont outliers in local and total funding?
While the south has shown the most improvement over the years, why, according to our data, is it consistently behind in math/reading scores and funding from other states?
The western states seem to be divided into high performing Northwestern states to low performing southwestern states in regards to math/reading scores. When thinking of policy changes should this region be subdivided at all times to ensure that we do not ultimately create laws that would increase performance from the southwest, but decrease performance from the northwest?
Could the Northwest be shown as performing better than the other regions due to a larger population and while it tends to allot more revenue for teachers than other regions could this be due to a higher standard income than other regions?

Future Evolution of the Project

Given the opportunity to expand on our existing project, we would look at additional factors which contribute to academic outcome unrelated to educational funding as well as drilling down into more specific uses of educational funding to obtain insight.

Identifying Other Factors Influencing Academic Outcomes

In this project we focused on local, state and federal revenue sources and test scores as our primary metrics. We also looked at class sizes and teacher salaries as results of funding contributing to academic success. It would be useful to examine other ways in which funding is used. Some examples include:

- property expenditure and maintenance
- facilities acquisition
- food services
- staff training
- support staff type and numbers

Incorporating Additional Data Sources

Enrichment data sets which could provide some further insights include demographic data which may be obtained from the Center for Economic Studies census bureau or the Bureau of Labor Statistics Consumer Expenditure Survey to provide additional context to the educational outcomes.

Handling an Evolving Dataset

When our project expands, we need to ensure our visualization infrastructure can handle any changes which might occur in data size as well as data variety. Assuming our project were to continue, we would likely onboard a variety of data sources which would provide us both finer-grained data as well as new data sources. These have been identified as the primary projects for how our data could change, that is, we expect changes in both volume and variety.

As our data grows more nuanced, access to a UI could prove useful to discovering new trends in our data. Due to this, if our data variety increases, Tableau variants pose substantial benefit due to Tableau's high accessibility and ease of creating dashboards.

If our data were to grow in volume, Tableau variants are likely able to bear the brunt up due to how Tableau handles data, especially in-memory data. If we reach a point, however, that the amount of memory Tableau consumes renders Tableau an unusable solution, we could opt for other solutions. For instance, we might find it useful to pre-compute some of our data to reduce the memory footprint.

Analyzing Our Data in New Ways

Finer-grained data means we have more methods to analyze our data. Notably, it could be of use to employ more advanced cluster analysis methods and algorithms to identify trends which are not so readily available via the methods we use today. For instance, we might find it prudent to cluster students by socioeconomic data and check if there are other overarching trends present among those clusters which can be used to further refine our models.

We might also find use in the apriori algorithm as a niche alternative to traditional methods. If the apriori algorithm proves useful, Neo4j could also come into play to data mine our associations and how they interplay with each other.

Sources

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