In [1]:
```
# Initialize Otter
import otter
grader = otter.Notebook("hw2-seda.ipynb")
```

In [2]:
```
import numpy as np
import pandas as pd
import altair as alt
# disable row limit for plotting
alt.data_transformers.disable_max_rows()
# uncomment to ensure graphics display with pdf export
# alt.renderers.enable('mimetype')
```

Out[2]:
```
DataTransformerRegistry.enable('default')
```

Background

Gender achievement gaps in education have been well-documented over the years -- studies consistently find boys outperforming girls on math tests and girls outperforming boys on reading and language tests. A particularly controversial article was published in Science in 1980 arguing that this pattern was due to an 'innate' difference in ability (focusing on mathematics rather than on reading and language). Such views persisted in part because studying systematic patterns in achievement nationwide was a challenge due to differential testing standards across school districts and the general lack of availability of large-scale data.

It is only recently that data-driven research has begun to reveal socioeconomic drivers of achievement gaps. The Standford Educational Data Archive (SEDA), a publicly available database on academic achievement and educational opportunity in U.S. schools, has supported this effort. The database is part of a broader initiave aiming to improve educational opportunity by enabling researchers and policymakers to identify systemic drivers of disparity.

> SEDA includes a range of detailed data on educational conditions, contexts, and outcomes in school districts and counties across the United States. It includes measures of academic achievement and achievement gaps for school districts and counties, as well as district-level measures of racial and socioeconomic composition, racial and socioeconomic segregation patterns, and other features of the schooling system.

The database standardizes average test scores for schools 10,000 U.S. school districts relative to national standards to allow comparability between school districts and across grade levels and years. The test score data come from the U.S. Department of Education. In addition, multiple data sources (American Community Survey and Common

Core of Data) are integrated to provide district-level socioeconomic and demographic information.

A study of the SEDA data published in 2018 identified the following persistent patterns across grade levels 3 - 8 and school ears from 2008 through 2015:

- a consistent reading and language achievement gap favoring girls;
- *no* national math achievement gap on average; and
- local math achievement gaps that depend on the socioeconomic conditions of school districts.

You can read about the main findings of the study in this brief NY Times article.

Below, we'll work with selected portions of the database. The full datasets can be downloaded here.

Assignment objectives

In this assignment, you'll explore achievement gaps in California school districts in 2018, reproducing the findings described in the article above on a more local scale and with the most recent SEDA data. You'll practice the following:

- review of data documentation
- assessment of sampling design and scope of inference
- data tidying operations
  - slicing and filtering
  - merging multiple data frames
  - pivoting tables
  - renaming and reordering variables
- constructing exploratory graphics and visualizing trends
- data aggregations
- narrative summary of exploratory analysis

Import and assessment of datasets

You'll work with test data and socioeconomic covariates aggregated to the school district level. These data are stored in two separate tables. Here you'll examine them and review data documentation.

Test score data

The first few rows of the test data are shown below. The columns are:

Column name	Meaning
`sedalea`	District ID
`grade`	Grade level
`stateabb`	State abbreviation
`sedaleaname`	District name
`subject`	Test subject
`cs_mn_...`	Estimated mean test score
`cs_mnse_...`	Standard error for estimated mean test score
`totgyb_...`	Number of individual tests used to estimate the mean score

In [3]:
```
# import seda data
ca_main = pd.read_csv('data/ca-main.csv')
ca_cov = pd.read_csv('data/ca-cov.csv')

# preview test score data
ca_main.head(3)
```

Out[3]:

	sedalea	grade	stateabb	sedaleaname	subject	cs_mn_all	cs_mnse_all	totgyb_all	cs_
0	600001	4	CA	ACTON-AGUA DULCE UNIFIED ...	mth	-0.367007	0.108543	86.0	
1	600001	4	CA	ACTON-AGUA DULCE UNIFIED ...	rla	0.005685	0.117471	85.0	
2	600001	6	CA	ACTON-AGUA DULCE UNIFIED ...	rla	-0.000040	0.092172	114.0	

3 rows × 59 columns

The test score means for each district are named `cs_mn_...` with an abbreviation indicating subgroup (such as mean score for all `cs_mean_all`, for boys `cs_mean_mal`, for white students `cs_mn_wht`, and so on). Notice that these are generally small-ish: decimal numbers between -0.5 and 0.5.

These means are *estimated* from a number of individual student tests and *standardized* relative to national averages. They represent the number of standard deviations by which a district mean differs from the national average. So, for instance, the value `cs_mn_all = 0.1` indicates that the district average is estimated to be 0.1 standard deviations greater than the national average on the corresponding test and at the corresponding grade level.

Question 1: Interpreting test score values

Interpret the average math test score for all 4th grade students in Acton-Agua Dulce Unified School District (the first row of the dataset shown above).

The average math score for all 4th grade students in the Acton-Agua Dulce Unified School district is -0.36 from the national average. This can also be interpreted as the standard deviation, in which we can say the st deviation of math scores for 4th graders in the Acto-Agua Dulce Unified School District is 0.36 away from the average.

Covariate data

The first few rows of the covariate data are shown below. The column information is as follows:

Column name	Meaning
`sedalea`	District ID
`grade`	Grade level
`sedaleanm`	District name
`urban`	Indicator: is the district in an urban locale?
`suburb`	Indicator: is the district in a suburban locale?
`town`	Indicator: is the district in a town locale?
`rural`	Indicator: is the district in a rural locale?
`locale`	Description of district locale
Remaining variables	Demographic and socioeconomic measures

In [4]:
```
ca_cov.head(3)
```

Out[4]:

	sedalea	grade	sedaleanm	urban	suburb	town	rural	locale	perind	perasn	...
0	600001	4.0	ACTON-AGUA DULCE UNIFIED ...	0.0	0.0	0.0	1.0	Rural, Distant	0.003893	0.045901	...
1	600001	5.0	ACTON-AGUA DULCE UNIFIED ...	0.0	0.0	0.0	1.0	Rural, Distant	0.003788	0.046652	...
2	600001	6.0	ACTON-AGUA DULCE UNIFIED ...	0.0	0.0	0.0	1.0	Rural, Distant	0.003218	0.043657	...

3 rows × 60 columns

You will only be working with a handful of the demographic and socioeconomic measures, so you can put off getting acquainted with those until selecting a subset of variables.

Question 2: Data semantics

In the non-public data, observational units are students -- test scores are measured for each student. However, in the SEDA data you've imported, scores are *aggregated* to the district level by grade. Let's regard estimated test score means for each grade as distinct variables, so that an observation consists in a set of estimated means for different grade levels and groups. In this view, what are the observational units in the test score dataset? Are they the same or different for the covariate dataset?

The observational units in the dataset are district, it is the same for both datasets.

Question 3: Sample sizes

How many observational units are in each dataset? Count the number of units in the test dataset and the number of units in the covariate dataset separately. Store the values as `ca_cov_units` and `ca_main_units`, respectively.

(*Hint*: use `.nunique()`.)

In [5]:
```
ca_cov_units = ca_cov['sedalea'].nunique()
ca_main_units = ca_main['sedalea'].nunique()

print('units in covariate data: ', ca_cov_units)
print('units in test score data: ', ca_main_units)
```

```
units in covariate data:  913
units in test score data:  872
```

In [6]:
```
grader.check("q3")
```

Out[6]:

q3 passed! ✨

Question 4: Sample characteristics and scope of inference

Answer the questions below about the sampling design in a short paragraph. You do not need to dig through any data documentation in order to resolve these questions.

- (i) What is the relevant population for the datasets you've imported?
- (ii) About what proportion (to within 0.1) of the population is captured in the sample? (*Hint*: have a look at this website.)
- (iii) Considering that the sampling frame is not identified clearly, what kind of dataset do you suspect this is (*e.g.*, administrative, data from a 'typical sample', census, etc.)?
- (iv) In light of your description of the sample characteristics, what is the scope of inference for this dataset?

The data imported is from all the districts in claifornia that contain students from grades 3-8 and from the years of 2008 to 2015. The propertion captured is 84% of the population wiht 872 unique districts out of the 1037 school districts. The proportion ofht epopulation for the covariate data was 913/1037 school districts which is 88%. I believe pect the dataset to be an administrative sampling since a school administration wants to use what they can from this data to learn the most about the students in the school and what they can do to their sample size. Due to this ssample will be almost as large as the population which will allow the inferences to be made to a population and quite accurately.

Data tidying

Since you've already had some guided practice doing this in previous assignments, you'll be left to fill in a little bit more of the details on your own in this assignment. You'll work with the following variables from each dataset:

- **Test score data**
  - District ID
  - District name
  - Grade
  - Test subject
  - Estimated male-female gap
- **Covariate data**
  - District ID
  - Locale
  - Grade
  - Socioeconomic status (all demographic groups)
  - Log median income (all demographic groups)
  - Poverty rate (all demographic groups)
  - Unemployment rate (all demographic groups)
  - SNAP benefit receipt rate (all demographic groups)

Question 5: Variable names of interest

Download the codebooks by opening the 'data' directory from your Jupyter Lab file navigator and downloading the codebook files. Identify the variables listed above, and store the column names in lists named `main_vars` and `cov_vars`.

In [7]:
```
# store variable names of interest
main_vars = list(ca_main.columns[0:5])
cov_vars = list(ca_cov.columns[0:8])
```

In [8]:
```
grader.check("q5")
```

Out[8]:

q5 passed! 🍀

Question 6: Slice columns

Use your result from above to slice the columns of interest from the covariate and test score data. Store the resulting data frames as `main_sub` and `cov_sub` (for 'subset').

In [9]:
```
# slice columns to select variables of interest
main_sub = ca_main[main_vars]
cov_sub = ca_cov[cov_vars]
```

In [10]:
```
grader.check("q6")
```

Out[10]:

q6 passed! 🍀

In the next step you'll merge the covariate data with the test score data. In order to do this, you can use the `pd.merge(A, B, how = ..., on = SHARED_COLS)` function, which will match the rows of `A` and `B` based on the shared columns `SHARED_COLS`. If `how = 'left'`, then only rows in `A` will be retained in the output (so `B` will be merged *to* `A`); conversely, if `how = 'right'`, then only rows in `B` will be retained in the output (so `A` will be merged *to* `B`).

A simple example of the use of `pd.merge` is illustrated below:

In [11]:
```
# toy data frames
A = pd.DataFrame(
    {'shared_col': ['a', 'b', 'c'],
    'x1': [1, 2, 3],
    'x2': [4, 5, 6]}
)

B = pd.DataFrame(
    {'shared_col': ['a', 'b'],
    'y1': [7, 8]}
)
```

In [12]:
```
A
```

Out[12]:

	shared_col	x1	x2
0	a	1	4
1	b	2	5
2	c	3	6

In [13]:
```
B
```

Out[13]:

	shared_col	y1
0	a	7
1	b	8

Below, if `A` and `B` are merged retaining the rows in `A`, notice that a missing value is input because `B` has no row where the shared column (on which the merging is done) has value `c`. In other words, the third row of `A` has no match in `B`.

In [14]:
```
# left join
pd.merge(A, B, how = 'left', on = 'shared_col')
```

Out[14]:

	shared_col	x1	x2	y1
0	a	1	4	7.0
1	b	2	5	8.0
2	c	3	6	NaN

If the direction of merging is reversed, and the row structure of `B` is dominant, then the third row of `A` is dropped altogether because it has no match in `B`.

In [15]:
```
# right join
pd.merge(A, B, how = 'right', on = 'shared_col')
```

Out[15]:

	shared_col	x1	x2	y1
0	a	1	4	7
1	b	2	5	8

Question 7: Merge

Merge the covariate and test score data on both the ***district ID*** and ***grade level*** columns, and retain only the columns from the test score data (meaning, merge the covariate data *to* the test score data). Store the resulting data frame as `rawdata` and print the first four rows.

In [16]:
```
# merge covariates with gap data
rawdata = pd.merge(ca_main, ca_cov, on=['sedalea', 'grade'], how='left')

# print first four rows
rawdata.head(4)
```

Out[16]:

	sedalea	grade	stateabb	sedaleaname	subject	cs_mn_all	cs_mnse_all	totgyb_all	cs_
0	600001	4	CA	ACTON-AGUA DULCE UNIFIED ...	mth	-0.367007	0.108543	86.0	
1	600001	4	CA	ACTON-AGUA DULCE UNIFIED ...	rla	0.005685	0.117471	85.0	
2	600001	6	CA	ACTON-AGUA DULCE UNIFIED ...	rla	-0.000040	0.092172	114.0	
3	600001	8	CA	ACTON-AGUA DULCE UNIFIED ...	mth	-0.097702	0.103216	98.0	

4 rows × 117 columns

In [17]:
```
grader.check("q7")
```

Out[17]:

q7 passed! 🎉

Question 8: Rename and reorder columns

Now rename and rearrange the columns of `rawdata` so that they appear in the following order and with the following names:

- District ID, District, Locale, log(Median income), Poverty rate, Unemployment rate, SNAP rate, Socioeconomic index, Grade, Subject, Gender gap

Store the resulting data frame as `rawdata_mod1` and print the first four rows.

(*Hint*: first define a dictionary to map the old names to the new ones; then create a list of the new names specified in the desired order; then use `.rename()` and `.loc[]`. You can follow the renaming steps in HW1 as an example if needed.)

In [18]:
```
# define dictionary mapping for renaming columns
rename = {'sedalea': 'District ID',
          'sedaleaname': 'District',
          'locale': 'Locale',
          'lninc50all': 'log(Median income)',
          'povertyall': 'Poverty rate',
          'unempall': 'Unemployment rate',
          'snapall': 'SNAP rate',
          'sesall': 'Socioeconomic index',
          'grade': 'Grade',
          'subject': 'Subject',
          'cs_mn_mfg': 'Gender gap'}

# specify order of columns
order = ['District ID', 'District', 'Locale', 'log(Median income)', 'Poverty

# rename and reorder
rawdata_mod1 = rawdata.rename(columns=rename)[order]

# print first four rows
print(rawdata_mod1.head(4))
```

```
   District ID                                          District
0       600001  ACTON-AGUA DULCE UNIFIED                    ...  \
1       600001  ACTON-AGUA DULCE UNIFIED                    ...
2       600001  ACTON-AGUA DULCE UNIFIED                    ...
3       600001  ACTON-AGUA DULCE UNIFIED                    ...

            Locale  log(Median income)  Poverty rate  Unemployment rate
0  Rural, Distant           11.392048      0.091894           0.048886  \
1  Rural, Distant           11.392048      0.091894           0.048886
2  Rural, Distant           11.392048      0.091894           0.048886
3  Rural, Distant           11.392048      0.091894           0.048886

   SNAP rate  Socioeconomic index  Grade Subject  Gender gap
0   0.035165             1.237209      4     mth         NaN
1   0.035165             1.237209      4     rla         NaN
2   0.035165             1.237209      6     rla         NaN
3   0.035165             1.237209      8     mth   -0.562855
```

In [19]:
```
grader.check("q8")
```

Out[19]:

q8 passed! 🌈

Question 9: Pivot

Notice that the Gender gap column contains the values of two variables: the gap in estimated mean test scores for math tests, and the gap in estimated mean test scores for reading and language tests. To put the data in tidy format, use `.pivot` and `.rename()` to pivot the table so that the gender gap column is spread into two columns named `Math gap` and `Reading gap`. Store the result as `seda_data` and print the first four rows.

Hint: to avoid unweildy column indexing, make sure you specify a `values = ...` argument when using `.pivot()`. Doing so will result in the column index being named `Subject`; remove this name in your solution.

Aside: an alternative solution is to manipulate the indices and use `.unstack()`, but this method will produce a dataframe with hierarchical column indexing (you'll see) in which `Subject` is retained as a lower-level index; this will need to be collapsed in order to rename the columns as instructed using `MultiIndex.droplevel()` or similar.

In [20]:
```
# pivot to unstack gender gap (fixing tidy issue: multiple variables in one
seda_data = rawdata_mod1.set_index(order[0:10]).unstack(-1).reset_index()
multi_fix = seda_data.columns.droplevel(1)
multi_fix.values[9:11] = ['Math gap','Reading gap']
seda_data.columns = multi_fix

# print first four rows
seda_data.head(4)
```

Out[20]:

	District ID	District	Locale	log(Median income)	Poverty rate	Unemployment rate	SNAP rate	Socioecc
0	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	11.392048	0.091894	0.048886	0.035165	1.2
1	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	11.392048	0.091894	0.048886	0.035165	1.2
2	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	11.392048	0.091894	0.048886	0.035165	1.2
3	600006	ROSS VALLEY ELEMENTARY ...	Suburb, Large	11.607236	0.041418	0.048269	0.028006	1.5

In [21]:
```
grader.check("q9")
```

Out[21]:

q9 passed! 🌟

Your final dataset should match the dataframe below. You can use this to check your answer and revise any portions above that lead to different results.

In [22]:
```
# intended result
data_reference = pd.read_csv('data/tidy-seda-check.csv')
data_reference
```

Out[22]:

	District ID	District	Locale	log(Median income)	Poverty rate	Unemployment rate	SNAP rate	Socioeco
0	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	11.392048	0.091894	0.048886	0.035165	1.2
1	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	11.392048	0.091894	0.048886	0.035165	1.2
2	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	11.392048	0.091894	0.048886	0.035165	1.2
3	600006	ROSS VALLEY ELEMENTARY ...	Suburb, Large	11.607236	0.041418	0.048269	0.028006	1.5
4	600006	ROSS VALLEY ELEMENTARY ...	Suburb, Large	11.607236	0.041418	0.048269	0.028006	1.5
5	600006	ROSS VALLEY ELEMENTARY ...	Suburb, Large	11.607236	0.041418	0.048269	0.028006	1.5
6	600006	ROSS VALLEY ELEMENTARY ...	Suburb, Large	11.607236	0.041418	0.048269	0.028006	1.5
7	600011	FORT SAGE UNIFIED ...	Rural, Distant	10.704570	0.159981	0.066333	0.102054	-0.
8	600011	FORT SAGE UNIFIED ...	Rural, Distant	10.704570	0.159981	0.066333	0.102054	-0.
9	600011	FORT SAGE UNIFIED ...	Rural, Distant	10.704570	0.159981	0.066333	0.102054	-0.

Question 10: Sanity check

Ensure that your tidying did not inadvertently drop any observations: count the number of units in `seda_data`. Does this match the number of units represented in the original test score data `ca_main`? Store these values as `data_units` and `ca_main_units`, respectively.

(*Hint*: use `.nunique()`.)

In [23]:
```
# number of districts in tidied data compared with raw
data_units = seda_data['District ID'].nunique()
ca_main_units = ca_main['sedalea'].nunique()
```

In [24]:
```
grader.check("q10")
```

Out[24]:

q10 passed! 🎉

Question 11: Missing values

Gap estimates were not calculated for certain grades in certain districts due to small sample sizes (not enough individual tests recorded). Answer the following:

- (i) What proportion of rows are missing for each of the reading and math gap variables? Store these values as `math_missing` and `reading_missing`, respectively.
- (ii) What proportion of *districts* (not rows!) have missing gap estimates for one or both test subjects for at least one grade level?Store the value as `district_missing`.

In [25]:
```
# proportion of missing values
math_missing = seda_data['Math gap'].isna().mean()
reading_missing = seda_data['Reading gap'].isna().mean()

# proportion of districts with missing values
district_missing = seda_data.loc[seda_data['Math gap'].isna() | seda_data['R
                   .groupby('District ID')['Grade'] \
                   .nunique() \
                   .loc[lambda x: x >= 1] \
                   .shape[0] \
                   / seda_data['District ID'].nunique()
```

In [26]:
```
grader.check("q11")
```

Out[26]:

q11 passed! 🎉

Question 12: Missing mechanism

Do you expect that this missingness is more likely for some districts than for others? If so, explain; why is this, and is bias a concern if missing values are dropped?

I do belueve that there is missingness present in some districts more than others. Some distrits with a higher proportion of rich might not report every student to reduce the sample bias. Maybe schools may not report students that dont perform well as it could ruin their averages. Maybe some students filled out the forms wrong and so their data is not presented.

Exploratory graphics

For the purpose of visualizing the relationship between estimated gender gaps and socioeconomic variables, you'll find it more helpful to store a non-tidy version of the data. The cell below rearranges the dataset so that one column contains an estimated gap, one column contains the value of a socioeconomic variable, and the remaining columns record the gap type and variable identity.

Ensure that your results above match the reference dataset before running this cell.

In [27]:
```
name_order = seda_data.columns
# format data for plotting
plot_df = seda_data.melt(
    id_vars = name_order[0:9],
    value_vars = ['Math gap', 'Reading gap'],
    var_name = 'Gap type',
    value_name = 'Gap'
).melt(
    id_vars = ['District ID', 'District', 'Locale', 'Gap type', 'Gap', 'Grad
    value_vars = name_order[3:8],
    var_name = 'Socioeconomic variable',
    value_name = 'Measure'
)

# preview
plot_df.head()
```

Out[27]:

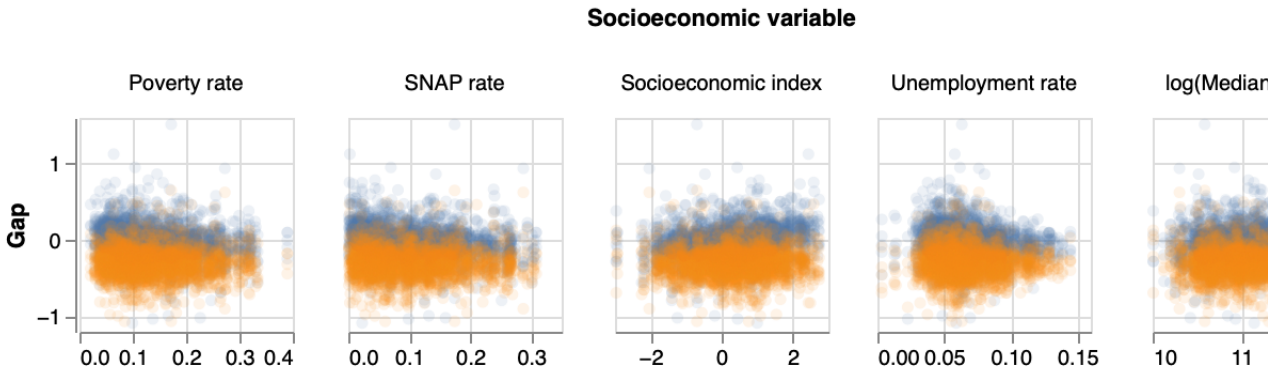
	District ID	District	Locale	Gap type	Gap	Grade	Socioeconomic variable	Measure
0	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	Math gap	NaN	4	log(Median income)	11.392048
1	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	Math gap	NaN	6	log(Median income)	11.392048
2	600001	ACTON-AGUA DULCE UNIFIED ...	Rural, Distant	Math gap	-0.562855	8	log(Median income)	11.392048
3	600006	ROSS VALLEY ELEMENTARY ...	Suburb, Large	Math gap	-0.025131	4	log(Median income)	11.607236
4	600006	ROSS VALLEY ELEMENTARY ...	Suburb, Large	Math gap	0.143163	5	log(Median income)	11.607236

Gender gaps and socioeconomic factors

The cell below generates a panel of scatterplots showing the relationship between estimated gender gap and socioeconomic factors for all grade levels by test subject. The plot suggests that the reading gap favors girls consistently across the socioeconomic spectrum -- in a typical district girls seem to outperform boys by 0.25 standard deviations of the national average. By contrast, the math gap appears to depend on socioeconomic factors -- boys only seem to outperform girls under *better* socioeconomic conditions.

In [28]:
```
# plot gap against socioeconomic variables by subject for all grades
fig1 = alt.Chart(plot_df).mark_circle(opacity = 0.1).encode(
    y = 'Gap',
    x = alt.X('Measure', scale = alt.Scale(zero = False), title = ''),
    color = 'Gap type'
).properties(
    width = 100,
    height = 100
).facet(
    column = alt.Column('Socioeconomic variable')
).resolve_scale(x = 'independent')

fig1
```

Out[28]:



Question 13: Relationships by grade level

Does the pattern shown in the plot above persist within each grade level? Modify the plot above to show these relationships by grade level: generate a panel of scatterplots of gap against socioeconomic measures by subject, where each column of the panel corresponds to one socioeconomic variable and each row corresponds to one grade level; the result should by a 5x5 panel. Resize the width and height of each facet so that the panel is of reasonable size. Keep a fixed axis scale for the variable of interest, but allow the axis scales for socioeconomic variables to vary independently. Store the plot as `fig2`; display the figure and provide an answer to the question of interest in the text cell.

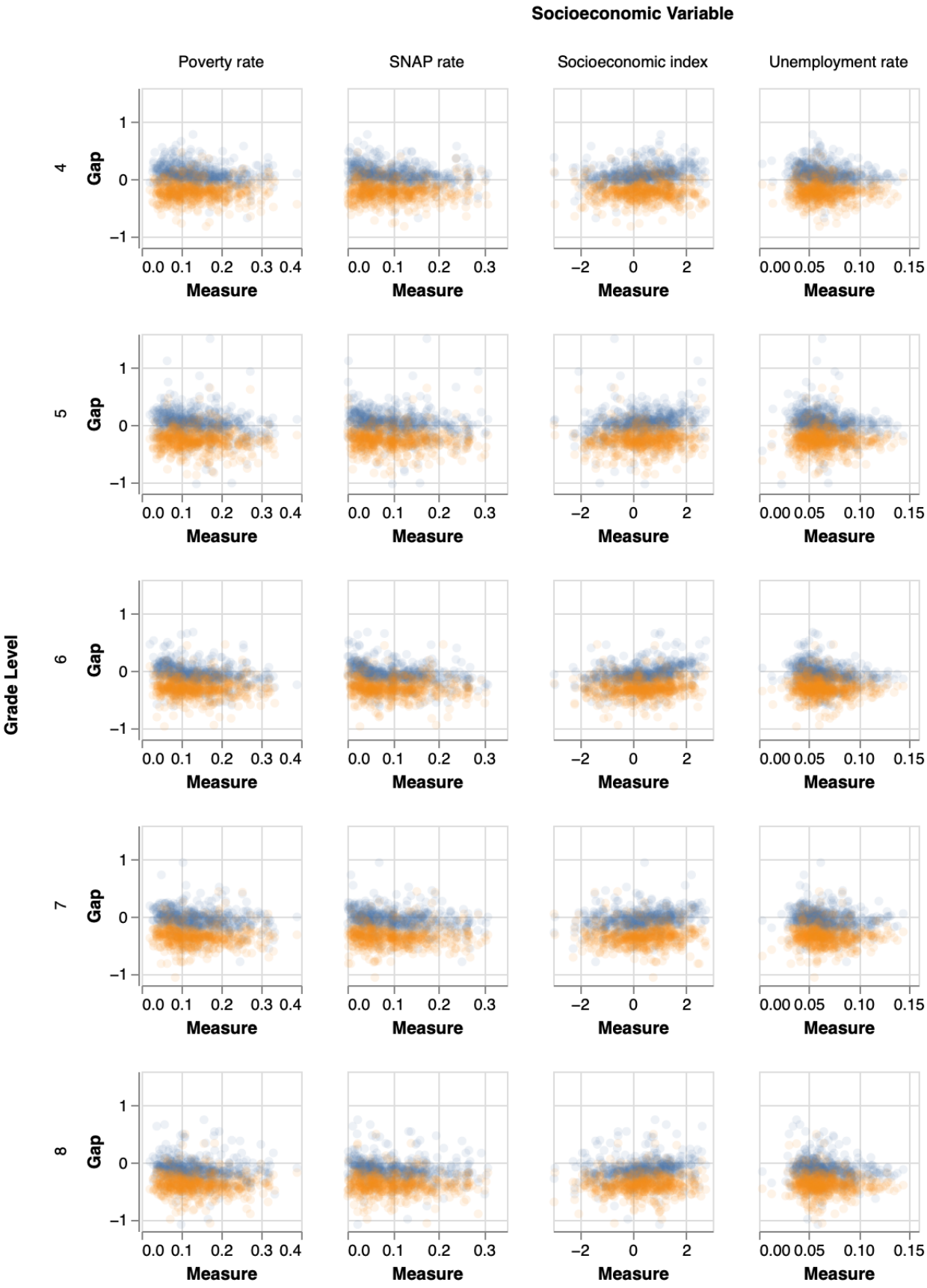
(*Hint*: you may find it useful to have a look at the altair documentation on compound charts, and lab 3, for examples to follow.)

Type your answer here, replacing this text.

In [29]:

```
# plotting codes here
fig13 = alt.Chart(plot_df).mark_circle(opacity=0.1).encode(
    x='Measure',
    y=alt.Y('Gap', scale=alt.Scale(zero=False)),
    color='Gap type'
).properties(
    width=100,
    height=100
).facet(
    column=alt.Column('Socioeconomic variable', title='Socioeconomic Variabl
    row=alt.Column('Grade', title='Grade Level')
).resolve_scale(x='independent')

# display
fig13
```

Out[29]:


Socioeconomic Variable
Poverty rate
SNAP rate
Socioeconomic index
Unemployment rate
Grade Level
4
5
6
7
8
Gap
Measure
1
0
−1
0.0 0.1 0.2 0.3 0.4
0.0 0.1 0.2 0.3
−2 0 2
0.00 0.05 0.10 0.15

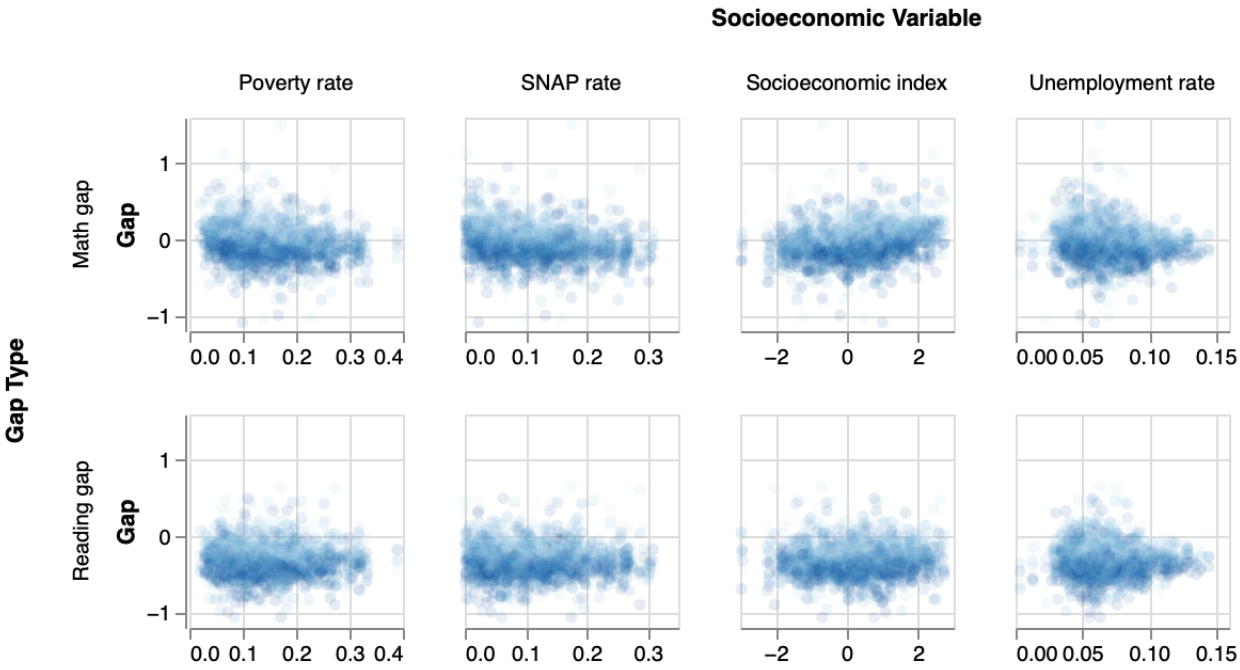
Question 14: Association with grade level

Do gaps shift across grade levels? It's not so easy to tell from the last figure. Construct a 2x5 panel of scatterplots showing estimated achievement gap against each of the 5 socioeconomic variables, with one row per test subject. Display grade level using a color gradient. Store the plot as `fig3`; display the figure and answer the question of interest in a short sentence or two in the text cell provided.

Type your answer here, replacing this text.

In [30]:
```
# plotting codes here
fig14 = alt.Chart(plot_df).mark_circle(opacity=0.1).encode(
    y='Gap',
    x=alt.X('Measure', scale=alt.Scale(zero=False), title=''),
    color='Grade'
).properties(
    width=100,
    height=100
).facet(
    column=alt.Column('Socioeconomic variable', title='Socioeconomic Variabl
    row=alt.Column('Gap type', title='Gap Type')
).resolve_scale(x='independent')

# display
fig14
```

Out[30]:



While the magnitude of the achievement gaps seems to depend very slightly on grade level (figure 3), the form of relationship between achievement gap and socioeconomic factors does not differ from grade to grade (figure 2).

Given that the relationships between achievement gaps and socioeconomic factors don't change drastically across grade levels, it is reasonable to look at the average relationship between estimated achievement gap and median income after aggregating across grade.

Question 15: Aggregation across grade levels

Compute the mean estimated achievement gap in each subject across grade levels by district using `District ID` and retain the district-level socioeconomic variables. Store the resulting data frame as `seda_data_agg`.

Note: best practice here would be to aggregate just the test scores by district and then re-merge the result with the district-level socioeconomic variables. However, since the district-level socioeconomic variables do not differ by grade within a district, averaging them across grade levels by district together with the test scores will simply return their unique values; so the aggregation can be applied across *all* columns for a fast-and-loose way to obtain the desired result.

In [31]:
```
# Aggregate data across grades
seda_data_agg = seda_data.drop(columns="Locale").groupby(["District ID", "Di

# Preview first few rows
print(seda_data_agg.head())
```

```
   District ID                                          District
0       600001  ACTON-AGUA DULCE UNIFIED                    ...  \
1       600006  ROSS VALLEY ELEMENTARY                      ...
2       600011  FORT SAGE UNIFIED                           ...
3       600012  TWIN RIDGES ELEMENTARY                      ...
4       600013  ROCKLIN UNIFIED                             ...

   log(Median income)  Poverty rate  Unemployment rate  SNAP rate
0           11.392048      0.091894           0.048886   0.035165  \
1           11.607236      0.041418           0.048269   0.028006
2           10.704570      0.159981           0.066333   0.102054
3           10.589787      0.179102           0.059158   0.074903
4           11.399662      0.060338           0.045533   0.035016

   Socioeconomic index  Grade  Math gap  Reading gap
0             1.237209    6.0 -0.562855    -0.785321
1             1.912972    5.5  0.061163    -0.242572
2            -0.478127    6.0 -0.015417    -0.191400
3            -0.096379    6.0       NaN          NaN
4             1.398133    6.0  0.054454    -0.312638
```

In [32]:
```
grader.check("q15")
```

Out[32]:

q15 passed! 🍀

Question 16: Melt aggregated data for plotting

Similar to working with the disaggregated data, it will be helpful for plotting to melt the two gap variables into a single column. Follow the example above at the beginning of this section to melt *only the test score gap columns* (not the district-level variables -- we will not create scatterplot panels as before). Name the new columns `Subject` and `Average estimated gap`; store the resulting data frame as `agg_plot_df` and print the first four rows.

In [33]:
```
# format for plotting
agg_plot_df = pd.melt(
    seda_data_agg,
    id_vars=seda_data_agg.columns[0:7],
    value_vars=['Math gap', 'Reading gap'],
    var_name='Subject',
    value_name='Average estimated gap'
).drop("District", axis=1)

# print four rows
agg_plot_df.head(4)
```

Out[33]:

	District ID	log(Median income)	Poverty rate	Unemployment rate	SNAP rate	Socioeconomic index	Subject	Aver estima
0	600001	11.392048	0.091894	0.048886	0.035165	1.237209	Math gap	-0.562
1	600006	11.607236	0.041418	0.048269	0.028006	1.912972	Math gap	0.06
2	600011	10.704570	0.159981	0.066333	0.102054	-0.478127	Math gap	-0.01
3	600012	10.589787	0.179102	0.059158	0.074903	-0.096379	Math gap	

In [34]:
```
grader.check("q16")
```

Out[34]:

q16 passed! ✨

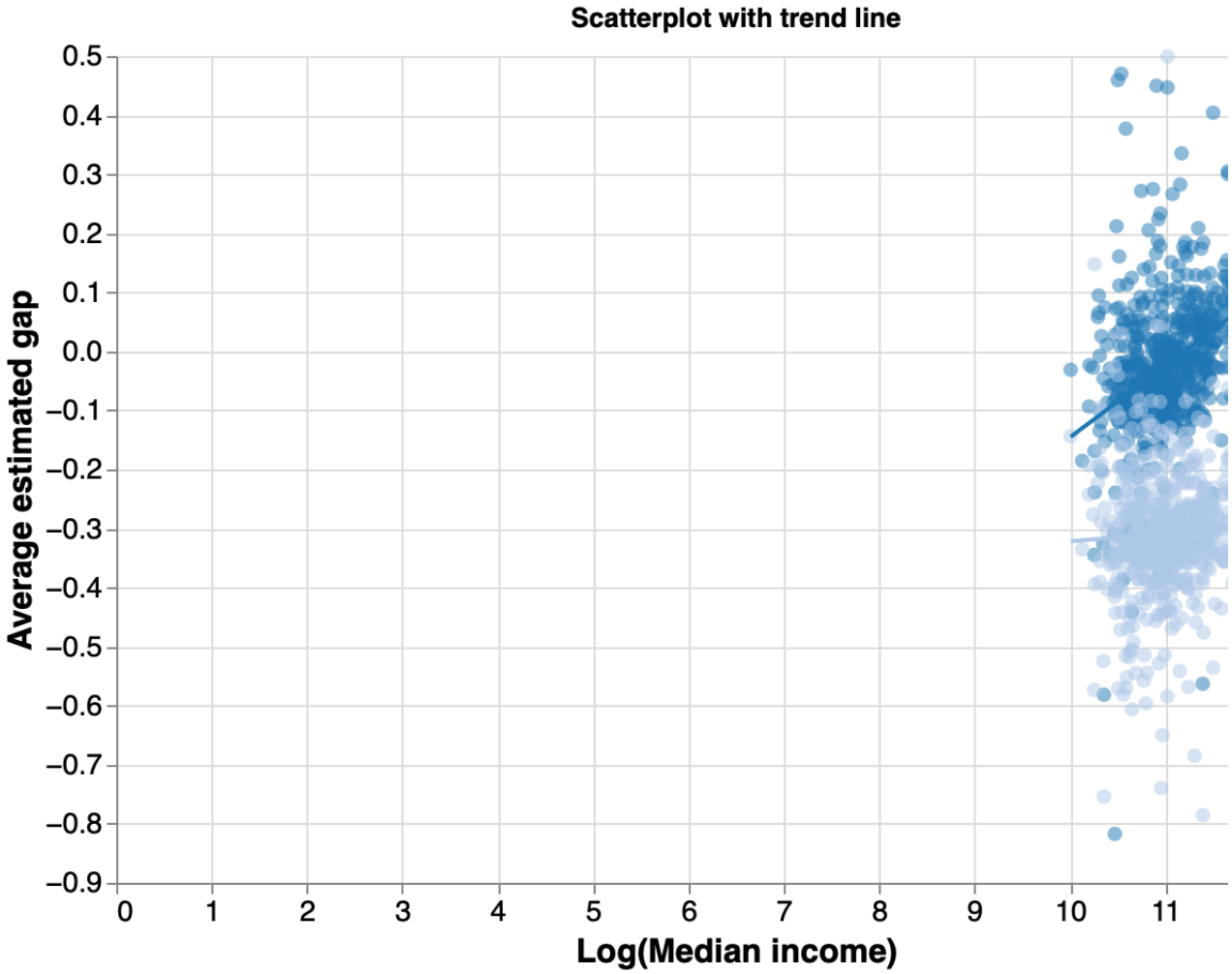
Question 17: District average gaps

Construct a scatterplot of the average estimated gap against log(Median income) by subject for each district and add trend lines (see lab 4). Store the plot as `fig4`. Describe and interpret the plot in a few sentences.

Type your answer here, replacing this text.

In [35]:
```
# scatterplot
agg_plot_df["log(Median income)"] = np.array(agg_plot_df["log(Median income)

scatter = alt.Chart(agg_plot_df).mark_circle(opacity=0.5, size=50).encode(
    x=alt.X('log(Median income)', title='Log(Median income)'),
    y=alt.Y('Average estimated gap', title='Average estimated gap'),
    color=alt.Color('Subject', legend=None, scale=alt.Scale(scheme='category
).properties(
    title='Scatterplot with trend line',
    width=600,
    height=400
)

# trend line
trend = scatter.transform_regression(
    on='log(Median income)',
    regression='Average estimated gap',
    groupby=['Subject']
).mark_line(color='black', strokeWidth=2)

# combine layers
fig4 = (scatter + trend)

# display
fig4.configure_axis(labelFontSize=14, titleFontSize=16)
```

Out[35]:



Now let's try to capture this pattern in *tabular* form. The cell below adds an `Income bracket` variable by cutting the median income into 8 contiguous intervals using `pd.cut()`, and tabulates the average socioeconomic measures and estimated gaps across districts by income bracket. Notice that with respect to the gaps, this displays the pattern that is shown visually in the figures above.

In [36]:
```
seda_data_agg['Income bracket'] = pd.cut(np.e**seda_data_agg['log(Median inc
seda_data_agg.groupby('Income bracket').mean(numeric_only= True).drop(columr
```

Out[36]:

Income bracket	Poverty rate	Unemployment rate	SNAP rate	Socioeconomic index	Grade	Math gap	R
(21980.176, 46455.372]	0.194870	0.072689	0.155061	-0.651999	5.994241	-0.070284	-0.
(46455.372, 70736.321]	0.134078	0.063788	0.095303	0.291085	5.978134	-0.034061	-0.
(70736.321, 95017.269]	0.088713	0.052785	0.048242	1.110433	5.944277	0.004239	-0.
(95017.269, 119298.218]	0.064131	0.046848	0.030548	1.640159	5.907738	0.050006	-0
(119298.218, 143579.167]	0.050315	0.044343	0.011023	2.167272	5.722222	0.090138	-0.
(143579.167, 167860.115]	0.043896	0.042379	0.008451	2.382258	6.000000	0.084683	-0.
(167860.115, 192141.064]	0.040552	0.040120	0.010159	2.652906	5.833333	0.175793	-0.
(192141.064, 216422.013]	0.047097	0.054055	0.002555	2.588499	6.000000	0.267301	-0.

Question 18: Proportion of districts with a math gap

What proportion of districts in each income bracket have an average estimated math achievement gap favoring boys? Answer this question by performing the following steps:

- Append an indicator variable `Math gap favoring boys` to `seda_data_agg` that records whether the average estimated math gap favors boys by more than 0.1 standard deviations relative to the national average.
- Compute the proportion of districts in each income bracket for which the indicator is true: group by bracket and take the mean. Store this as `income_bracket_boys_favored`

In [37]:
```
# define indicator
seda_data_agg['Math gap favoring boys'] = np.where(seda_data_agg['Math gap']

# proportion of districts with gap favoring boys, by income bracket
income_bracket_boys_favored = (seda_data_agg.groupby('Income bracket')['Math
                               .value_counts(normalize=True).mul(100)
                               .reset_index(name='percentage')
                               .loc[lambda x: x['Math gap favoring boys']==Tr
                               [['Income bracket', 'percentage']])
# print result
print(income_bracket_boys_favored)
```

```
                Income bracket  percentage
1      (21980.176, 46455.372]    3.658537
3      (46455.372, 70736.321]    6.122449
5      (70736.321, 95017.269]    8.433735
7     (95017.269, 119298.218]   23.214286
9    (119298.218, 143579.167]   38.888889
11   (143579.167, 167860.115]   44.444444
13   (167860.115, 192141.064]   50.000000
14   (192141.064, 216422.013]  100.000000
```

In [38]:
```
grader.check("q18")
```

Out[38]:

q18 passed! 🌟

Question 19: Statewide averages

To wrap up the exploration, calculate a few statewide averages to get a sense of how some of the patterns above compare with the state as a whole.

- (i) Compute the statewide average estimated achievement gaps. Store the result as `state_avg`.
- (ii) Compute the proportion of districts in the state with a math gap favoring boys. Store this result as `math_boys_proportion`
- (iii) Compute the proportion of districts in the state with a math gap favoring girls. You will need to define a new indicator within `seda_data_agg` to perform this calculation.

In [39]:
```
# statewide average
state_avg = seda_data_agg[['Math gap', 'Reading gap']].mean()

# proportion of districts in the state with a math gap favoring boys
math_boys_proportion = seda_data_agg['Math gap'].apply(lambda x: x > 0.1).me

# proportion of districts in the state with a math gap favoring girls
seda_data_agg['Math gap favoring girls'] = seda_data_agg['Math gap'].apply(l
math_girls_proportion = seda_data_agg['Math gap favoring girls'].mean()
```

In [40]:
```
grader.check("q19")
```

Out[40]:

q19 passed! 🌈

Communicating results

Take a moment to review and reflect on your findings and consider what you have learned from the analysis.

Question 20: Summary

Write a brief summary of your exploratory analysis. What have you discovered about educational achievement gaps in California school districts? Aim to answer in 3-5 sentences or less.

Based on teh data, there is a noticable change in subjgect gap and gender gap in direct relationship towards the incom.. As the income increases, the gap in, mathematics and english, both increase for males, however this gap stays similar for females. This could be that females are more academically driven, maybe families with more money wish to spend more money on their child so the men have a direct increase. There could also be some old gender norms playing a role in which the family wants the men of the family to be educated and will spend more money on them to perform better.

Submission

1. Save the notebook.
2. Restart the kernel and run all cells. (**CAUTION**: if your notebook is not saved, you will lose your work.)
3. Carefully look through your notebook and verify that all computations execute correctly. You should see **no errors**; if there are any errors, make sure to correct them before you submit the notebook.
4. Download the notebook as an `.ipynb` file. This is your backup copy.
5. Export the notebook as PDF and upload to Gradescope.

In [44]:
```
grader.check_all()
```

Out[44]:
```
q10 results: All test cases passed!

q11 results: All test cases passed!

q15 results: All test cases passed!

q16 results: All test cases passed!

q18 results: All test cases passed!

q19 results: All test cases passed!

q3 results: All test cases passed!

q5 results: All test cases passed!

q6 results: All test cases passed!

q7 results: All test cases passed!

q8 results: All test cases passed!

q9 results: All test cases passed!
```