Group Project I - College Scorecard Dataset

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College Scorecard Data Aggregation and Cleaning

Replace PrivacySuppressed

To view the R code for cleaning the College Scorecard Dataset, assessing the quality of the data, and adding latitude, longitude and rurality see the clean_all.R file.

We have chosen 65 columns to work with:

year id ope8_id ope6_id name city state zip location.lat location.lon	program_percentage.military program_percentage.multidiscipline program_percentage.parks_recreation_fitness program_percentage.philosophy_religious program_percentage.theology_religious_vocation program_percentage.physical_science program_percentage.science_technology program_percentage.psychology program_percentage.security_law_enforcement program_percentage.public_administration_social_service	
degrees_awarded.predominant_recoded degrees_awarded.predominant degrees_awarded.highest locale program_percentage.agriculture	program_percentage.social_science program_percentage.construction program_percentage.mechanic_repair_technology program_percentage.precision_production program_percentage.transportation	
program_percentage.resources program_percentage.architecture program_percentage.ethnic_cultural_gender program_percentage.communication program_percentage.communications_technology	program_percentage.visual_performing program_percentage.health program_percentage.business_marketing program_percentage.history attendance.academic_year	
program_percentage.computer program_percentage.personal_culinary program_percentage.education program_percentage.engineering program_percentage.engineering_technology	tuition.in_state tuition.out_of_state faculty_salary share_25_older share_firstgeneration	
program_percentage.language program_percentage.family_consumer_science program_percentage.legal program_percentage.english program_percentage.humanities	share_firstgeneration_parents.middleschool share_firstgeneration_parents.highschool share_firstgeneration_parents.somecollege demographics.age_entry demographics.over_23_at_entry	
program_percentage.library program_percentage.biological program_percentage.mathematics	demographics.first_generation rurality	

When analyzing the data, please keep in mind that not every year has good completeness of the data. Use completeness.by.year to explore the data before you begin visualization. Example:

completeness.by.year[, c("year", "locale")]

year	locale
1996_97	0.0000000
1997_98	0.0000000
1998_99	0.0000000
1999_00	0.0000000
2000_01	0.0000000
2001_02	0.0000000
2002_03	0.0000000
2003_04	0.0000000
2004_05	0.0000000
2005_06	0.0000000
2006_07	0.0000000
2007_08	0.0000000
2008_09	0.0000000
2009_10	0.0000000
2010_11	0.0000000
2011_12	0.0000000
2012_13	0.0000000
2013_14	0.0000000
2014_15	0.0000000
2015_16	0.9412617

Visualizing the College Scorecard Dataset

Please select a question (or come up with your own) and add some visualizations to display any relationships of interest. Most questions we came up with involved the rurality of the schools. The original dataset includes this information for the 2015-2016 school year in the "locale" column. For all the years, I've added a column of rurality to the dataset (original data can be found in ziprural.txt or downloaded here). The dictionary for explanations of these codes is as follows:

A1	Rural Urban Continuum Code		
Code	Description	Counties	2000 Population
Metro	Counties:		
1	Counties in metro areas of 1 million population or more	413	149,224,067
2	Counties in metro areas of 250,000 to 1 million population	325	55,514,159
3	Counties in metro areas of fewer than 250,000 population	351	27,841,714
Nonme	tro Counties:		
4	Urban population of 20,000 or more, adjacent to a metro area	218	14,442,161
5	Urban population of 20,000 or more, not adjacent to a metro area	105	5,573,273
6	Urban population of 2,500 to 19,999, adjacent to a metro area	609	15,134,357
7	Urban population of 2,500 to 19,999, not adjacent to a metro area	450	8,463,700
8	Completely rural or < 2,500 urban population, adjacent to a metro area	235	2,425,743
9	Completely rural or < 2,500 urban population, not adjacent to a metro area	435	2,802,732

Questions we discussed in class:

Rurality story: Where did they come from? Where did they go? Where did they come from, Cotton Eye Joe?

Do more rural schools show a higher percentage of returning adults than metro schools?

Do more rural schools have a higher percentage of first generation students?

How do the degrees awarded differ between rurality classes (do rural areas award more technical degrees)? Are more rural schools cheaper?

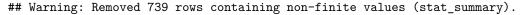
Other Questions How does the average faculty salary of a school scale with the cost of living in that area? (requires finding cost of living)

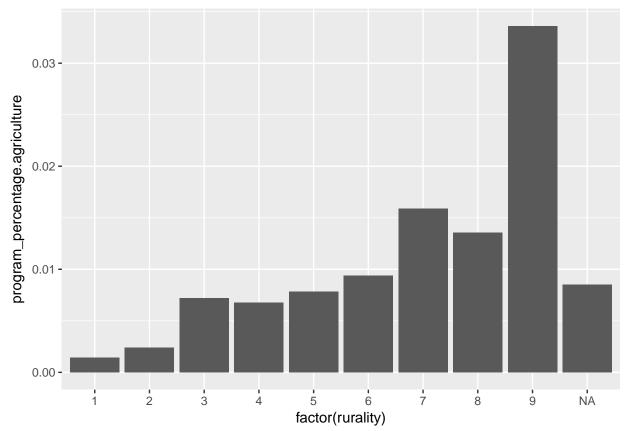
We can also ask some summary statistics of schools grouping by year: what has changed for schools in 20 years?

After digging through the data below, I'm not sure rurality is the best measure to look for differences in degrees awarded (9 the most rural has the highest percentage of history degrees?). Perhaps poverty levels would be more interesting.

I just threw together some simple ggplots, feel free to continue exploring anything that jumps out at you. I am by no means claiming all these for myself.

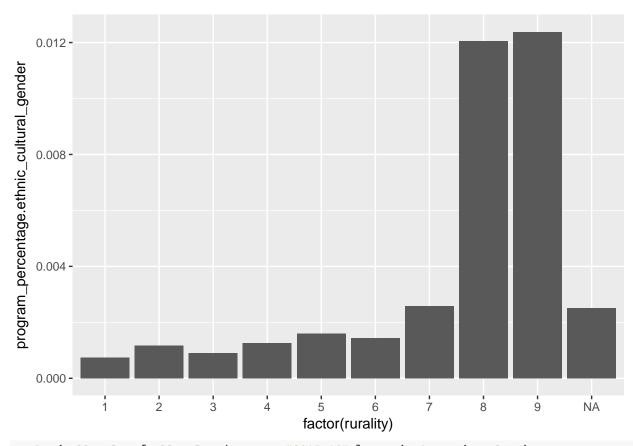
```
library(ggplot2)
ggplot(collegeData[collegeData$year == "2015_16",], aes(x=factor(rurality), y=program_percentage.agricu
```



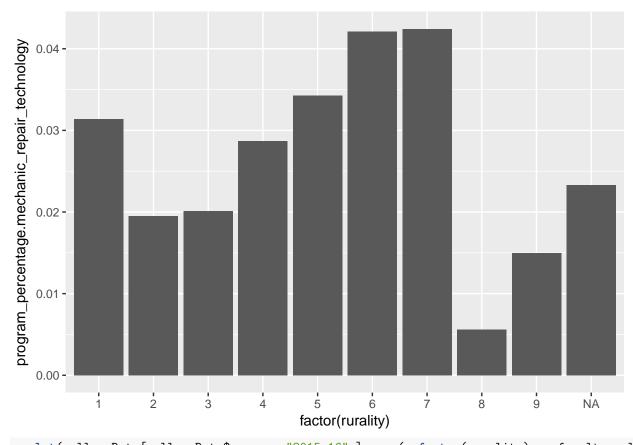


ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=program_percentage.ethnic

Warning: Removed 739 rows containing non-finite values (stat_summary).

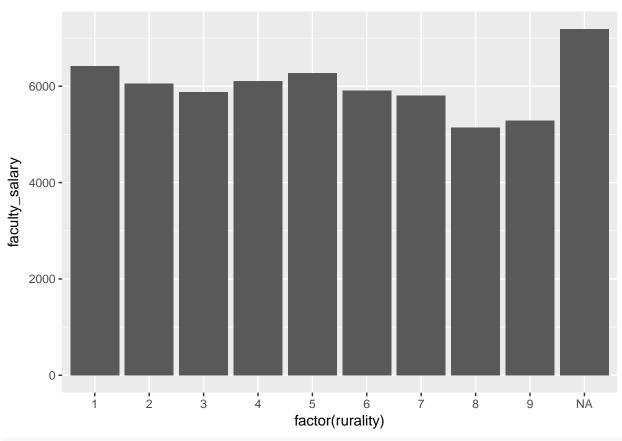


ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=program_percentage.mechan
Warning: Removed 739 rows containing non-finite values (stat_summary).



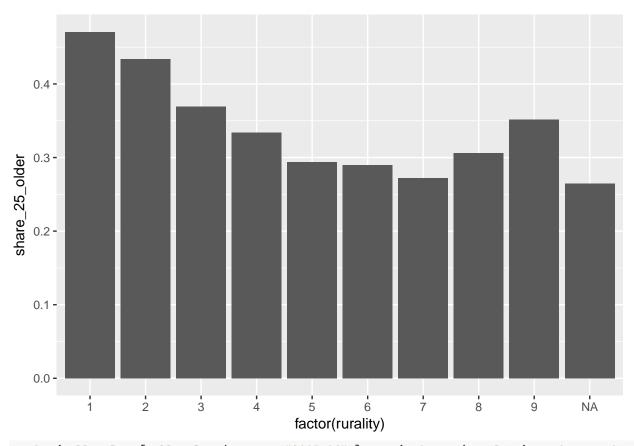
ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=faculty_salary)) + stat_s

Warning: Removed 3139 rows containing non-finite values (stat_summary).



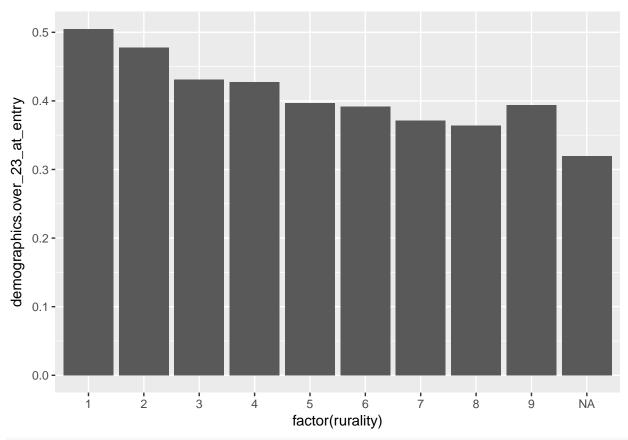
Looks like metro areas have more return adults
ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=share_25_older)) + stat_s

Warning: Removed 805 rows containing non-finite values (stat_summary).



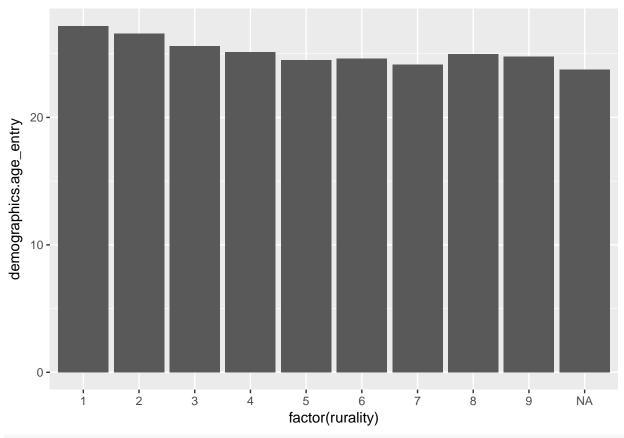
ggplot(collegeData[collegeData\$year == "2005_06",], aes(x=factor(rurality), y=demographics.over_23_at_e.

Warning: Removed 285 rows containing non-finite values (stat_summary).



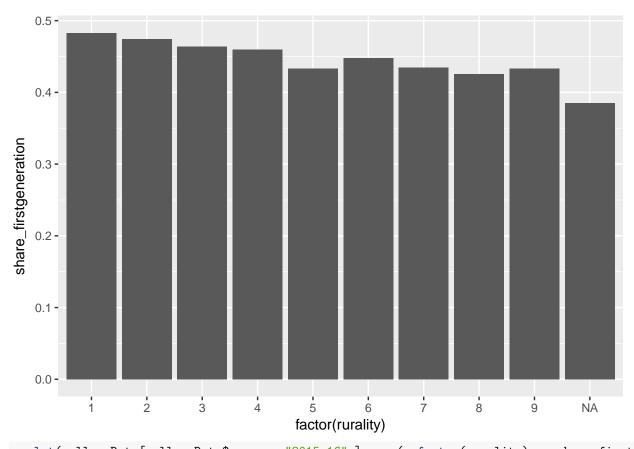
But average age remains in the 20s across ruralities
ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=demographics.age_entry))

Warning: Removed 333 rows containing non-finite values (stat_summary).



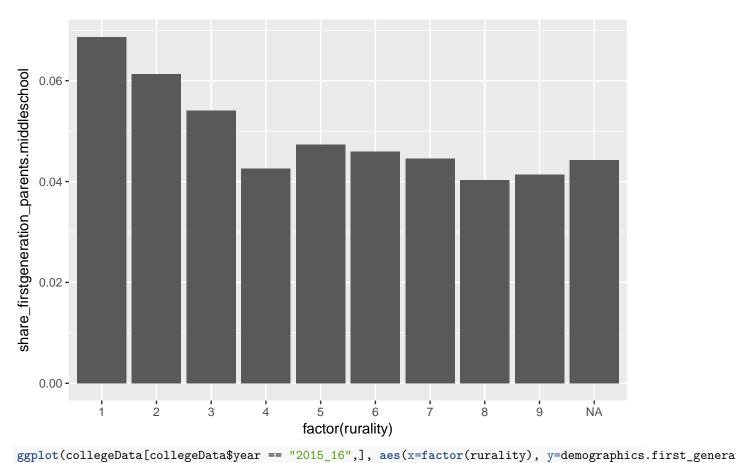
 ${\tt ggplot(collegeData[collegeData\$year == "2015_16",], \ aes(x=factor(rurality), \ y=share_firstgeneration)) + to the property of the proper$

Warning: Removed 1118 rows containing non-finite values (stat_summary).

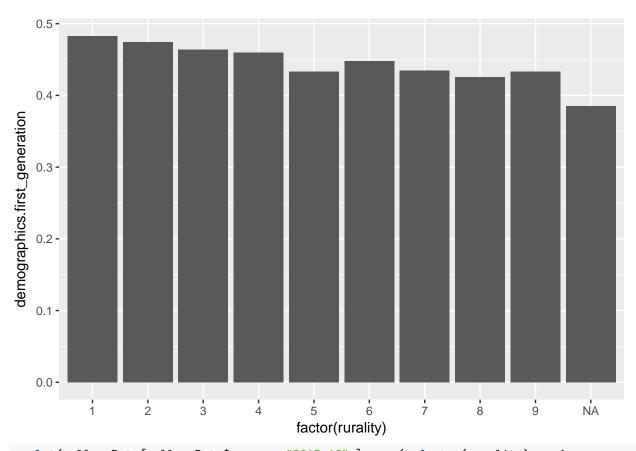


ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=share_firstgeneration_parameter)

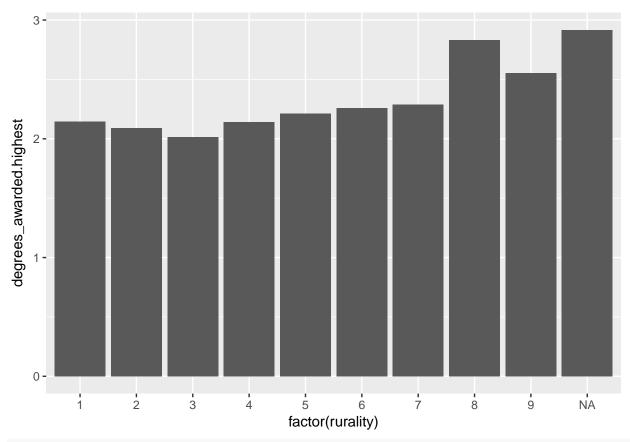
Warning: Removed 2595 rows containing non-finite values (stat_summary).



Warning: Removed 1118 rows containing non-finite values (stat_summary).

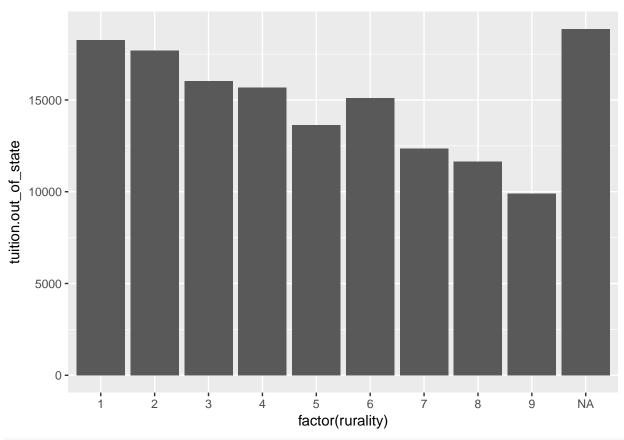


ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=degrees_awarded.highest))



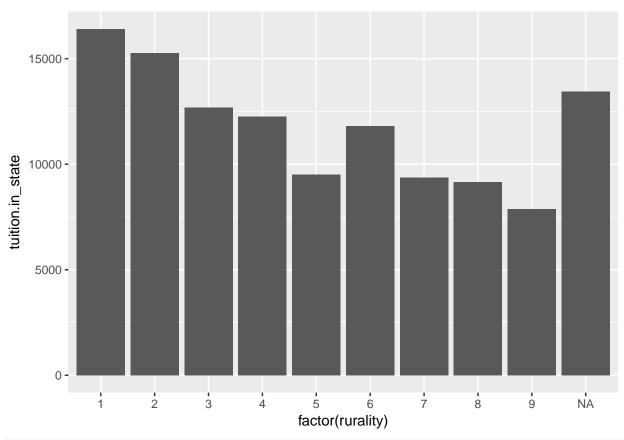
ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=tuition.out_of_state)) +

Warning: Removed 3504 rows containing non-finite values (stat_summary).



ggplot(collegeData[collegeData\$year == "2015_16",], aes(x=factor(rurality), y=tuition.in_state)) + stat

Warning: Removed 3290 rows containing non-finite values (stat_summary).



 ${\tt ggplot(collegeData[collegeData\$year == "2015_16",], \ aes(x=factor(rurality), \ y=attendance.academic_year))}$

 $\hbox{\tt \#\# Warning: Removed 3673 rows containing non-finite values (stat_summary).}$

