STA130H1F

Class #3

Prof. Nathan Taback

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Welcome back to STA130 😆

Today's class

- Statistical data

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- Tidy data

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- Data wrangling

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Today's class

- Statistical data
- Tidy data
- Data wrangling
- Boxplots

Statistical data

What is statistical data?

- Statistical data is obtained by observing (random) variables.
- A random variable can be given a precise mathematical definition that we will cover later in the course.
- In this class we will discuss examples.

Observing a few variables on STA130 students

- What is your height?
- How many years have been at UofT?
- What is your sex (male or female)?

Collecting this data will generate three variables: `height`, `years`, and `eye_colour`.

Enter variables on STA130 students

```
height <- c()
years <- c()
eye_colour <- c()
```

Put the variables into an R data frame.

NB: `data_frame` is the `tidyverse` version of base R `data.frame`.

```
sta130_dat <- data_frame(height, years, eye_colour)
```

We could have entred this in a spreadsheet program like MS Excel, saved it as a CSV file, then imported the file into R.

Tidy data

There are three interrelated rules which make a dataset tidy:

1. Each variable must have its own column.
2. Each observation must have its own row.
3. Each value must have its own cell.

Suppose that a first year class of 250 students has the following distribution of eye colour.

Colour	N
Blue	105
Hazel	55
Green	75
Other	15

We can create a tidy data set with a categorical variable `eye_col`.

Suppose that a first year class of 250 students has the following distribution of eye colour.

Colour	N
Blue	105
Hazel	55
Green	75
Other	15

We can create a tidy data set with a categorical variable `eye_col`.

```
library(tidyverse)
blue_eye <- rep("Blue", 105)
hazel_eye <- rep("Hazel", 55)
green_eye <- rep("Green", 75)
other_eye <- rep("Other", 15)
eye_col = c(blue_eye, hazel_eye,
            green_eye, other_eye)
eye_data <- data_frame(stnum = 1:250, eye_col)
glimpse(eye_data)
```

```
## Observations: 250
## Variables: 2
## $ stnum   <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16,...
## $ eye_col <chr> "Blue", "Blue", "Blue", "Blue", "Blue", "Blue", "Blue",...
```

Tidy data

Which data set is tidy?

```
## # A tibble: 6 x 4
##   country      year  cases population
##   <chr>       <int>  <int>      <int>
## 1 Afghanistan  1999    745   19987071
## 2 Afghanistan  2000   2666   20595360
## 3 Brazil       1999  37737  172006362
## 4 Brazil       2000  80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>       <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

Tidy data

> "For a given dataset, it is usually easy to figure out what are observations and what are variables, but it is surprisingly difficult to precisely define variables and observations in general." (Wickham, 2014)

A general rule of thumb:

- It is easier to describe functional relationships between variables (e.g., z is a linear combination of x and y, density is the ratio of weight to volume) than between rows.
- It is easier to make comparisons between groups of observations (e.g., average of group a vs. average of group b) than between groups of columns.

(Wickham, 2014)

Data Wrangling

Data wrangling

- The `ggplot` library implements a **grammer of graphics**.
- Similarily the `dplyr` library presents a grammer for data wrangling.

The Economic Guide to Picking a Major

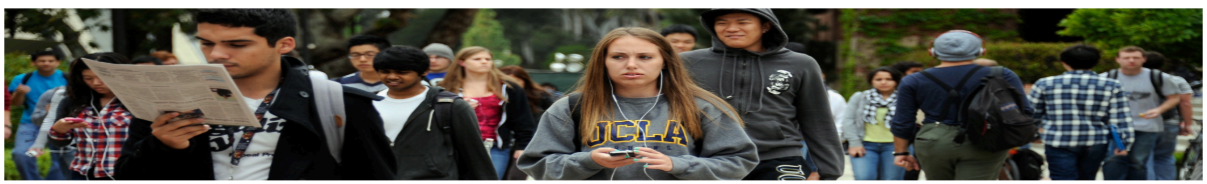
FiveThirtyEight

Politics | Sports | Science & Health | **Economics** | Culture

SEP. 12, 2014 AT 7:37 AM

The Economic Guide To Picking A College Major

By Ben Casselman
Filed under Higher Education
Get the data on GitHub



Students walk across the campus of UCLA in Los Angeles. KEVORK DJANSEZIAN / GETTY IMAGES

> "...A college degree is no guarantee of economic success. But through their choice of major, they can take at least some steps toward boosting their odds."

The Economic Guide to Picking a Major

- The data used in the article is from the American Community Survey 2010-2012 Public Use Microdata Series.
- We can use the `fivethirtyeight` library in R.

Data behind the article

```r
library(fivethirtyeight) # load the library
glimpse(college_recent_grads)
```

```
## Observations: 173
## Variables: 21
## $ rank                        <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,...
## $ major_code                  <int> 2419, 2416, 2415, 2417, 2405, 2418...
## $ major                       <chr> "Petroleum Engineering", "Mining A...
## $ major_category              <chr> "Engineering", "Engineering", "Eng...
## $ total                       <int> 2339, 756, 856, 1258, 32260, 2573,...
## $ sample_size                 <int> 36, 7, 3, 16, 289, 17, 51, 10, 102...
## $ men                         <int> 2057, 679, 725, 1123, 21239, 2200,...
## $ women                       <int> 282, 77, 131, 135, 11021, 373, 166...
## $ sharewomen                  <dbl> 0.1205643, 0.1018519, 0.1530374, 0...
## $ employed                    <int> 1976, 640, 648, 758, 25694, 1857, ...
## $ employed_fulltime           <int> 1849, 556, 558, 1069, 23170, 2038,...
## $ employed_parttime           <int> 270, 170, 133, 150, 5180, 264, 296...
## $ employed_fulltime_yearround <int> 1207, 388, 340, 692, 16697, 1449, ...
## $ unemployed                  <int> 37, 85, 16, 40, 1672, 400, 308, 33...
## $ unemployment_rate           <dbl> 0.018380527, 0.117241379, 0.024096...
## $ p25th                       <dbl> 95000, 55000, 50000, 43000, 50000,...
## $ median                      <dbl> 110000, 75000, 73000, 70000, 65000...
## $ p75th                       <dbl> 125000, 90000, 105000, 80000, 7500...
## $ college_jobs                <int> 1534, 350, 456, 529, 18314, 1142, ...
```

Select variables/columns using `select()`

To retrieve a data frame with only major, number of male and female graduates we use the `select()` function in the `dplyr` library.

```
select(college_recent_grads,major, men,women)
```

```
## # A tibble: 173 x 3
##    major                                    men women
##    <chr>                                  <int> <int>
##  1 Petroleum Engineering                   2057   282
##  2 Mining And Mineral Engineering           679    77
##  3 Metallurgical Engineering                725   131
##  4 Naval Architecture And Marine Engineering  1123   135
##  5 Chemical Engineering                   21239 11021
##  6 Nuclear Engineering                     2200   373
##  7 Actuarial Science                       2110  1667
##  8 Astronomy And Astrophysics               832   960
##  9 Mechanical Engineering                 80320 10907
## 10 Electrical Engineering                 65511 16016
## # ... with 163 more rows
```

Select observations/rows using `filter()`

If we want to retrieve only those observations (rows) that pertain to engineering majors then we need to specify that the value of the `major` variable is Electrical Engineering.

```
# == is a test for equality and is different than =.
EE <- filter(college_recent_grads,
             major == "Electrical Engineering")
glimpse(EE)
```

```
## Observations: 1
## Variables: 21
## $ rank                   <int> 10
## $ major_code             <int> 2408
## $ major                  <chr> "Electrical Engineering"
## $ major_category         <chr> "Engineering"
## $ total                  <int> 81527
## $ sample_size            <int> 631
## $ men                    <int> 65511
## $ women                  <int> 16016
## $ sharewomen             <dbl> 0.1964503
## $ employed               <int> 61928
## $ employed_fulltime      <int> 55450
```

Combine `select()` and `filter()`

- We can drill down to get certain pieces of information using `filter()` and `select()` together.
- The `median` variable is median salary.

```
select(filter(college_recent_grads, median <= 25000 ),
       major, men, women)
```

(1) Which students, and (2) variables are in this data frame?

Respond at **PollEv.com/nathantaback**
Text **NATHANTABACK** to **37607** once to join, then **A, B, C, or D**

(1) 50% of the students in the original data set that earn 25,000; (2) three variables: major, men, women	**A**
(1) All students in the original data set in a major where the median salary is at least 25,000; (2) all variables in the data set.	**B**
(1) 50% of the students in the original data set that earn at most 25,000; (2) three variables: major, men, women	**C**
(1) All students in the original data set in a major where the median salary is at most 25,000; (2) three variables: major, men, women	**D**

The pipe operator %>%

In the code:

```
select(filter(college_recent_grads, median >= 60000),
       major,men,women)
```

filter is nested inside select.

The pipe operator allows is an alternative to nesting and yields easier to read code.

The same expression can be written with the pipe operator

```
college_recent_grads %>%
  filter(median >= 60000) %>%
  select(major, men, women)
```

Create new variables from existing variables using `mutate()`

What percentage of graduates from each major where the median earnings is at least $60,000 are men ?

```
college_recent_grads %>%
  filter(median >= 60000) %>%
  select(major, men, women) %>%
  mutate(total = men + women,
         pct_male = round((men / total)*100, 2))
```

Compare to nested code:

```
  mutate(select(filter(college_recent_grads,median >= 60000),
                major, men, women),
         total = men + women,
         pct_male = round((men / total)*100, 2))
```

Create new variables from existing variables using `mutate()`

```
knitr::kable(college_recent_grads %>%
  filter(median >= 60000) %>%
  select(major, men, women) %>%
  mutate(total = men + women,
         pct_male = round((men / total)*100, 2)),
  format = "html")
```

major	men	women	total	pct_male
Petroleum Engineering	2057	282	2339	87.94
Mining And Mineral Engineering	679	77	756	89.81
Metallurgical Engineering	725	131	856	84.70
Naval Architecture And Marine Engineering	1123	135	1258	89.27
Chemical Engineering	21239	11021	32260	65.84
Nuclear Engineering	2200	373	2573	85.50

Create new variables from existing variables using `mutate()` and `ifelse()`

- Suppose that we would like to create a categorical variable to identify majors with between 45% and 55% women (ie., approximately equal numbers of males and females).

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The format of an `ifelse()` statement in R is:

```
ifelse(test, yes, no)
```

Create new variables from existing variables using `mutate()` and `ifelse()`

- Suppose that we would like to create a categorical variable to identify majors with between 45% and 55% women (ie., approximately equal numbers of males and females).

- We can use `ifelse()` in a `mutate()` statement.

The format of an `ifelse()` statement in R is:

```
ifelse(test, yes, no)
```

```
people <- c("Jamie", "Lei", "Francois", "Fanny")
ifelse(people == "Lei" | people == "Fanny", "Female", "Male")
```

```
## [1] "Male"   "Female" "Male"   "Female"
```

```r
college_recent_grads %>%
  select(major, men, women) %>%
  mutate(total = men + women,
         pct_female = round((women / total)*100, 2),
         sex.equal = ifelse(pct_female >= 45 & pct_female <= 55,
                            "Yes","No")) %>%
  select(major,sex.equal)
```

```
## # A tibble: 173 x 2
##    major                                     sex.equal
##    <chr>                                     <chr>
##  1 Petroleum Engineering                     No
##  2 Mining And Mineral Engineering            No
##  3 Metallurgical Engineering                 No
##  4 Naval Architecture And Marine Engineering No
##  5 Chemical Engineering                      No
##  6 Nuclear Engineering                       No
##  7 Actuarial Science                         No
##  8 Astronomy And Astrophysics                Yes
##  9 Mechanical Engineering                    No
## 10 Electrical Engineering                    No
## # ... with 163 more rows
```

Rename variables using `rename()`

- It's considered bad practice in R to use periods in variable names.
- We can use `rename()` to change the name of `sex.equal` to `sex_equal`.

```
my_college_dat <- college_recent_grads %>%
  select(major, men, women, median) %>%
  mutate(total = men + women,
         pct_female = round((women / total)*100, 2),
         sex.equal = ifelse(pct_female >= 45 &
                                     pct_female <= 55, "Yes","No")) %>%
  select(major,sex.equal, median)

my_college_dat <- my_college_dat %>%
  rename(sex_equal = sex.equal, salary_median = median)
glimpse(my_college_dat)
```

```
## Observations: 173
## Variables: 3
## $ major         <chr> "Petroleum Engineering", "Mining And Mineral Eng...
## $ sex_equal     <chr> "No", "No", "No", "No", "No", "No", "No", "Yes",...
## $ salary_median <dbl> 110000, 75000, 73000, 70000, 65000, 65000, 62000...
```

Sort a data frame using `arrange()`

```
my_college_dat %>%
  select(major, salary_median) %>%
  arrange(desc(salary_median))
```

```
## # A tibble: 173 x 2
##    major                                    salary_median
##    <chr>                                            <dbl>
##  1 Petroleum Engineering                           110000
##  2 Mining And Mineral Engineering                   75000
##  3 Metallurgical Engineering                        73000
##  4 Naval Architecture And Marine Engineering        70000
##  5 Chemical Engineering                             65000
##  6 Nuclear Engineering                              65000
##  7 Actuarial Science                                62000
##  8 Astronomy And Astrophysics                       62000
##  9 Mechanical Engineering                           60000
## 10 Electrical Engineering                           60000
## # ... with 163 more rows
```

Summarize a data frame using `summarize()`

The average number of female grads and the total number of majors in the data set.

```
college_recent_grads %>%
  select(major, men, women) %>%
  summarise(femgrad_mean = mean(women, na.rm = T), N = n())
```

```
## # A tibble: 1 x 2
##   femgrad_mean     N
##          <dbl> <int>
## 1       22647.   173
```

Summarize groups in a data frame using `summarize()` and `group_by()`

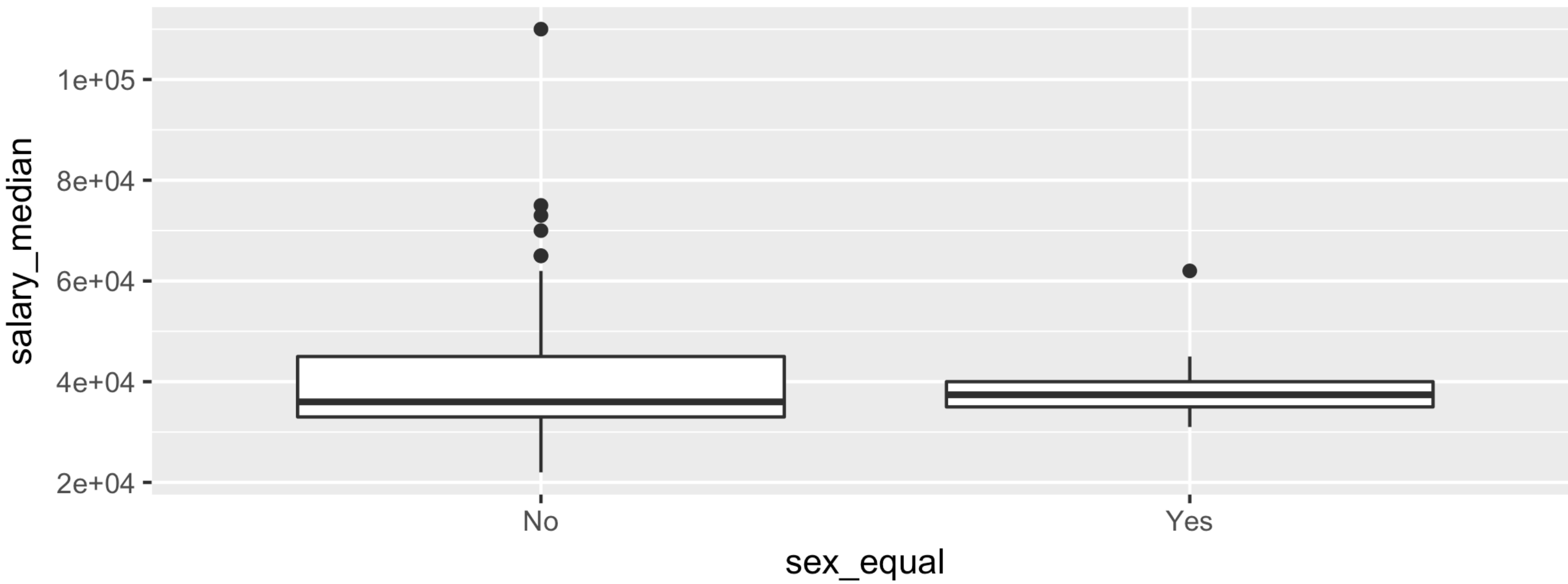
The median salary in majors with 45%-55% female students.

```
my_college_dat %>%
  group_by(sex_equal) %>%
  summarise(median(salary_median))
```

```
## # A tibble: 3 x 2
##   sex_equal `median(salary_median)`
##   <chr>                       <dbl>
## 1 No                          36000
## 2 Yes                         37400
## 3 <NA>                        53000
```

Boxplots to compare distribution of salary in males versus females

```
my_college_dat %>% filter(is.na(sex_equal) == FALSE) %>%
  ggplot(aes(x = sex_equal, y = salary_median)) + geom_boxplot()
```



Anatomy of a Boxplot

A boxplot summarizes the distribution of a quantitative variable using five statistics while plotting unusual observations (*outliers*).

Anatomy of a Boxplot

A boxplot summarizes the distribution of a quantitative variable using five statistics while plotting unusual observations (*outliers*).

The five statistics are:

- $Q_1 = 25^{th}$ percentile (first quartile)
- Median = 50^{th} percentile
- $Q_3 = 75^{th}$ percentile (third quartile)
- lower whisker = $Q_1 - 1.5 \times IQR$
- upper whisker = $Q_3 + 1.5 \times IQR$

NB: $IQR = Q_3 - Q_1$ is called the inter-quartile range.

Anatomy of a Boxplot

An **outlier** in is defined as any value of the quantitative variable that is either:

less than $Q_1 - 1.5 \times IQR$ or greater than $Q_3 + 1.5 \times IQR$.

Anatomy of a Boxplot

An **outlier** in is defined as any value of the quantitative variable that is either:

less than $Q_1 - 1.5 \times IQR$ or greater than $Q_3 + 1.5 \times IQR$.

The whiskers of the boxplot capture data outside the box, but not more than $1.5 \times IQR$.

```r
x
```

```
##  [1] 0.14 0.15 0.15 0.44 0.54 0.76 0.96 1.18 1.23 2.89
```

```r
quantile(x, 0.25)
```

```
##    25% 
## 0.2225
```

```r
quantile(x, 0.50)
```

```
##  50% 
## 0.65
```

```r
quantile(x, 0.75)
```

```
##   75% 
## 1.125
```

```r
quantile(x, 0.75) - quantile(x, 0.25) # IQR
```

```
##    75% 
## 0.9025
```

The boxplot of the data ...

```
data_frame(x) %>%
  ggplot(aes(x = "", y = x)) +
  geom_boxplot()
```