Introduction to Dplyr

Federal Reserve Board of Governors
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Introduction

- Last week - visualization with ggplot2
- Today - Dplyr
  - Data Analysis
  - Data Manipulation
- More background on this topic can be found in *R 4 Data Science* chapter 5 http://r4ds.had.co.nz/transform.html

Today's Question

- American Community Survey for the state of California
  - income, education, age, gender,
  - 2010-2014
- How does income differ for men and women?
- How does income differ by age?

Data

- `ca_acs.csv`
  - Read in this file as a data.frame and call it: "acs"
- Disclaimer: Data are taken from a random 20,000 subsample of the 5-year ACS Public Use data for California; results should be considered only as instructional exercises

Examining our Data

- How many columns?
- Names of our columns?
- Data is messy
- Install and attach the dplyr package

Guiding Question

- Easier to analyze data if you have a question/goal
- How do wages and income differ for men and women in California by age?
  - Line plot with age on the x-axis and dollars on the y-axis
- First step?

Analyzing our columns

- names are cryptic acronyms
  - Data dictionaries
  - Census provides a data dictionary for the ACS at www2.census.gov/programs-surveys/acs/tech_docs/pums/data_dict/PUMS_Data_Dictionary_2011-2015.pdf
- How do wages and income differ for men and women in California by age

Selecting our Columns

- Age (AGEP), Gender (SEX), wages (WAGP), income (PINCP)
  - inflation adjustment factor (ADJINC)
  - weighting factor (PWGTP)

dplyr::select

- `Select()` allows us to subset columns from data.frames
  - `select(.data, ...)`
  - `.data` = data.frame
  - `...` = columns
- `Select()` example

In class exercise: Select

- Now it's your turn, create a data.frame called `exercise_1_data` of the following columns from `acs`: `SEX`, `WKHP`, `ADJINC`, `PWGTP`, `WAGP`

Filtering our data

- Remove unusable observations
  - rows with NA values in them
- `filter()`
  - `filter(.data, ...)`
    - `.data` = data.frame
    - `...` = logical conditions (>, <, <=, >=, etc...)
- `Filter()` example 1

Boolean Logic

- Comparison statements that evalute to `TRUE` or `FALSE`
  - string multiple together with `&` (and) and `|` (or) operators
  - $3 < 4$ evaluates to TRUE,
  - $3 < 4$ & $5 > 7$ evaluates to FALSE
    - When making a statement with `&` remember: TRUE & TRUE = TRUE while any other combination = FALSE
  - However, the statement $3 < 4 \mid 5 > 7$ evaluates to TRUE
    - Only one statement must be TRUE when using `|` for the whole statement to be TRUE

Boolean logic: exercises

- Remember that == is “equal to” in R, since = also has assignment powers in R, like <-
- `%in%` is the “in” operator, for example, 2 %in% c(1, 2, 3) is TRUE
  - `filter(acs, AGEP < 30)`
  - `filter(acs, AGEP < 30 & SEX == 1)`
  - `filter(acs, AGEP < 25 | AGEP > 65)`
  - `filter(acs, Occ %in% c("Computer/Math", "Legal"))`

Back to Filter

- `filter()` can take multiple criteria
  - Example above use |
- Adding more conditions with , is the same as &

```
identical(filter(income_data, AGEP == 24 & SEX == 1),
    filter(income_data, AGEP == 24, SEX == 1))
```

Output: [1] TRUE

What do you think happens if you do not provide a search criterion to `filter()`?

In class exercise: Filter

- Re-assign your exercise_1_data data.frame to exercise_2_data and filter out any `NA` values in the columns
- Additionally, make sure that your WKHP variable is greater or equal to 10 and less than or equal to 60
- Your data should have the following dimensions:

8598, 5

Creating a Workflow

- Need to execute multiple steps
- One method: create new objects

```
object1 <- select(acs, AGEP, SEX, WAGP,
                  PINCP, ADJINC, PWGTP)

object2 <- filter(object1,
                  !(is.na(AGEP) | is.na(PINCP)))
```

Combining statements

- Creating new objects each time
  - Time consuming and confusing
- Nesting functions
  - $f(g(x)) = 5$

Nested Functions example

```
income_data_nest <- filter(select(acs, AGEP, SEX, WAGP,
                    PINCP, ADJINC, PWGTP),
                    !(is.na(AGEP) | is.na(PINCP)))

identical(object2, income_data_nest)
```

Output: [1] TRUE

Also confusing!

Pipe Operators

- %>% operator from dplyr
  - output of the left side becomes input on the right side

```
income_data_pipe <- acs %>%
    select(AGEP, SEX, WAGP, PINCP, ADJINC, PWGTP) %>%
    filter(!(is.na(AGEP) | is.na(PINCP)))

identical(income_data_nest, income_data_pipe)
```

Output: [1] TRUE

Pipes Explained

- By default the pipe operator takes the output from the left function and passes it to the right function **as the first argument**
  - Can change manually with the `.` operator

```
25 %>% seq(30, by = 1)
```

```
Output: [1] 25 26 27 28 29 30
```

```
25 %>% seq(30, ., by = -1)
```

```
Output: [1] 30 29 28 27 26 25
```

- The first example is `seq(25, 30, by = 1)` while the second is `seq(30, 25, by = -1)`

Mutating our data

- Adjust our income and wage data to be in constant 2014 USD
  - Move the decimal in ADJINC over
  - Recode our gender column to be “Male” and “Female”
  - Create buckets for our weekly hours column
- `mutate()`
  - calculate new columns, overwrite current columns, or delete columns
- `mutate()` example

Adjusting our adjuster

Can combine mutations into a single `mutate()` call

Updating Income and Wages

- Can refer to a column created earlier in a `mutate()` call within that same function call!
- `mutate()` example 2

Updating Gender

- Use a function within `mutate()`
  - ifelse()
  - plyr::round_any()
    - Need plyr installed

```
Output:    SEX gender WKHP Hours
Output: 1    2 Female   40    40
Output: 2    1   Male   40    40
Output: 3    2 Female   40    40
Output: 4    1   Male   60    60
Output: 5    2 Female   30    30
Output: 6    2 Female   45    45
```

In class Exercise: Mutate

- Now it's time to update your data: exercise_2_data
- Update SEX, ADJINC, and WKHP as seen previously
- Update WAGP to account for the adjustment factor

```
Output:    SEX WKHP   ADJINC PWGTP     WAGP Gender Hours
Output: 1   2   40 1.024037    15 23552.85 Female    40
Output: 2   1   40 1.024037    22 15360.56   Male    40
Output: 3   2   40 1.024037     7 38913.41 Female    40
Output: 4   1   60 1.008425    53 25412.31   Male    60
Output: 5   2   30 1.094136    10  5470.68 Female    30
Output: 6   2   45 1.008425    19 93783.52 Female    45
```

Deleting your columns

- using `mutate()` set your column = NULL

```
"SEX" %in% names(gender_hours_data)
```

```
Output: [1] TRUE
```

```
gender_hours_data <- gender_hours_data %>%
    mutate(SEX = NULL,
           WKHP = NULL)

"SEX" %in% names(gender_hours_data)
```

```
Output: [1] FALSE
```

The fun part: Summarize

- Generate our summary statistics
- Calculate functions over entire column(s) in a data.frame.
  - mean, median, etc...
- Summarise example

```
Output:      income    wages
Output: 1 54836.58 48077.21
```

Grouping

- Summarize by itself isn't all that useful
- Income for each gender/age combination.
- `group_by()`
  - When used in conjunction with summarize or other functions allows us to calculate statistics within different groups
- `ungroup()` resets our data

```r
income_data_summary <- gender_hours_data %>%
    group_by(AGEP, gender) %>%
    dplyr::summarise(income = weighted.mean(PINCP,
                                            PWGTP),
              wages = weighted.mean(WAGP, PWGTP))
head(income_data_summary, 3)
```

```
Output: Source: local data frame [3 x 4]
Output: Groups: AGEP [2]
Output:
Output: # A tibble: 3 x 4
Output:    AGEP gender   income     wages
Output:   <int>  <chr>    <dbl>     <dbl>
Output: 1    20 Female 10694.49  9342.122
Output: 2    20   Male 10492.21 10178.223
Output: 3    21 Female 11375.18 11053.704
```

dplyr::summarise()? weigthed.mean() instead of mean()?

In class exercise: group_by and summarize

- Using the `group_by()` and `summarize()` functions find the mean and median values for each gender/hour combination
- save your output as `exercise_4_data`
- Your data should look like the following:

```
Output: Source: local data frame [6 x 3]
Output: Groups: Gender [1]
Output:
Output: # A tibble: 6 x 3
Output:   Gender Hours     wages
Output:    <chr> <dbl>     <dbl>
Output: 1 Female    10  4640.393
Output: 2 Female    15 10555.757
Output: 3 Female    20 11856.598
Output: 4 Female    25 16512.445
Output: 5 Female    30 21234.293
Output: 6 Female    35 25792.914
```

Finding the top and bottom with arrange

- sorts rows
  - The default method is ascending sorting
  - descending is possible with the `desc()` function
- `arrange()` examples

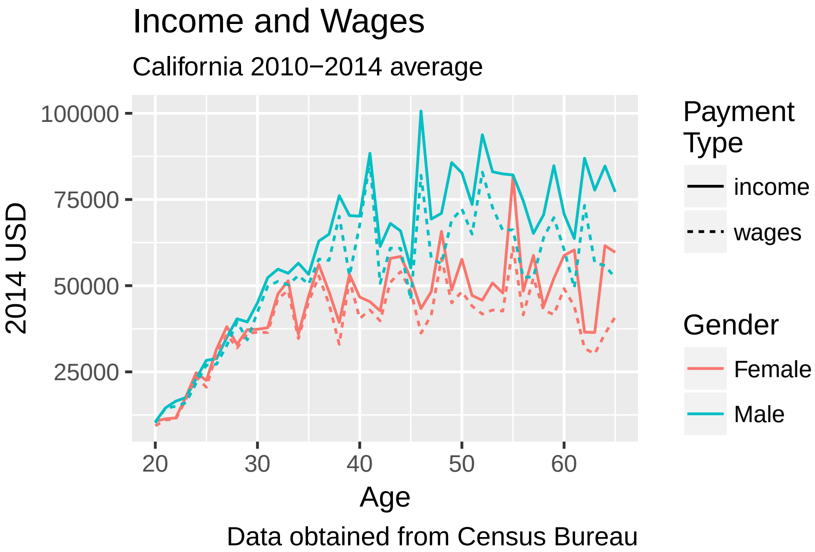
In Class Exercise: arrange

- Using your `exercise_4_data` find the bottom five observations for average wages
  - You do not have to save your output to a variable
  - what is their gender, the hours worked?

```
Output: Source: local data frame [5 x 3]
Output: Groups: Gender [2]
Output:
Output: # A tibble: 5 x 3
Output:   Gender Hours     wages
Output:    <chr> <dbl>     <dbl>
Output: 1 Female    10  4640.393
Output: 2   Male    10  5108.755
Output: 3   Male    15  8083.622
Output: 4   Male    20 10326.199
Output: 5 Female    15 10555.757
```

Answering our Question

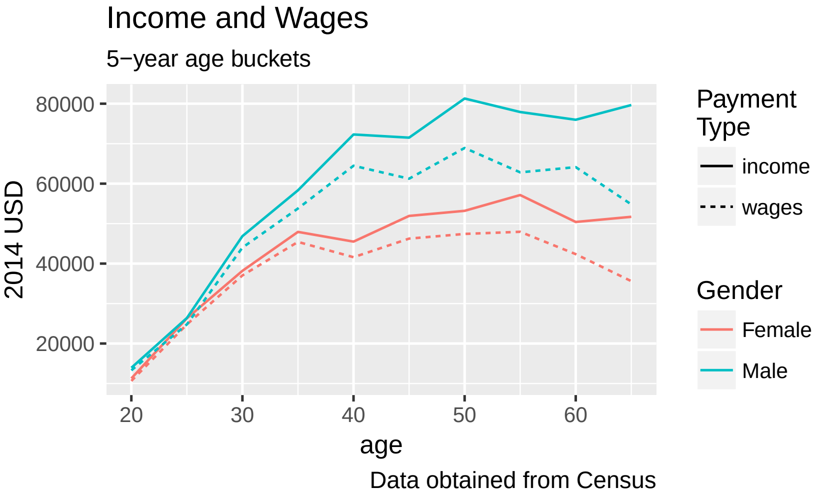
- Use ggplot to analyze our output



Understanding your analysis

- Difference between income and wages?
- Men and women?
  - What do we not take into account?
- Jagged peaks and valleys?
- Is this accurate?

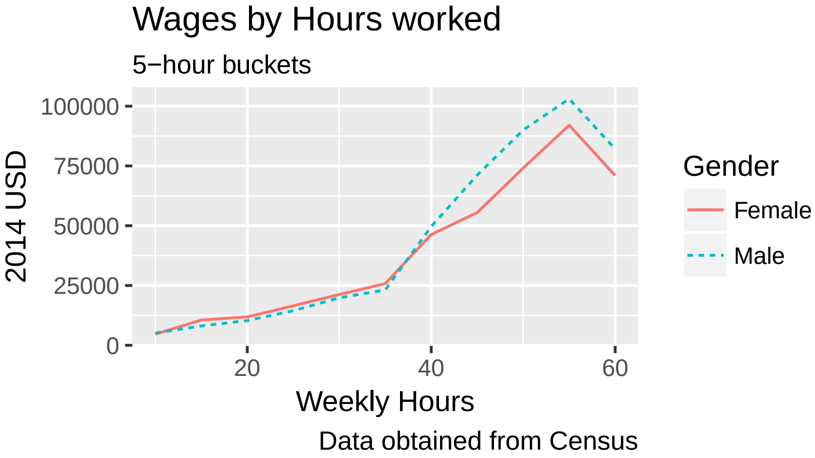
Widening our age ranges



What is the message of this chart compared with our first chart using only 1-year age buckets?

In Class Exercise

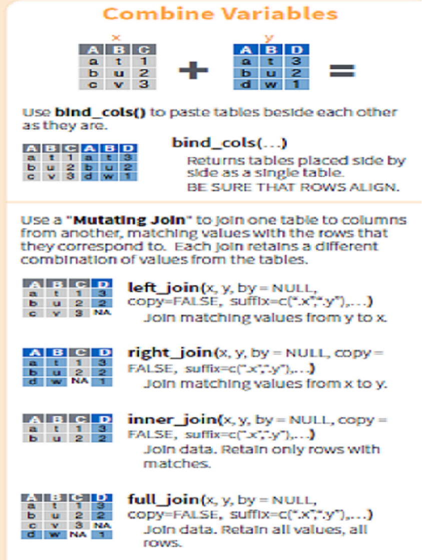
- Using the `exercise_3_data` create a chart showing mean wages for men and women by hours worked



What message does this chart show about wage inequality compared with our previous chart? What more questions do you have?

Joins

- Need multiple datasets to talk to each other



New Questions

- In what county do men have the highest wages? Women?
- In what county do men and women have the largest income ratio?
- Need to add county level data to our acs data
    - puma10_county_xwalk.csv

```
Output:   puma12   county
Output: 1    101 Alameda
Output: 2    102 Alameda
Output: 3    103 Alameda
```

Joining our Data

- We want to use an inner join

```
Output: [1] "AGEP"   "WAGP"   "PINCP"  "ADJINC" "PWGTP"
Output: [6] "PUMA10" "gender" "Hours"  "county"
```

County Level Statistics

- Which county has the highest male wages?

```
Output: # A tibble: 6 x 3
Output:           county    Female     Male
Output: *          <chr>     <dbl>    <dbl>
Output: 1          Marin 114325.96 69574.81
Output: 2         Placer  70621.52       NA
Output: 3 San Francisco   52621.21 98917.28
Output: 4      San Mateo  58002.22 93219.94
Output: 5    Santa Clara  56311.29 77299.68
Output: 6        Ventura        NA 70940.12
```

County Income Ratio

- Male/Female income ratio (male wages/female wages)

```
Output: Source: local data frame [6 x 3]
Output: Groups: county [6]
Output:
Output: # A tibble: 6 x 3
Output:             county    ratio observations
Output:              <chr>    <dbl>        <int>
Output: 1         Imperial  2.644490          203
Output: 2 San Luis Obispo  2.471640          614
Output: 3          Ventura  2.376310         1591
Output: 4           Merced  2.292796          341
Output: 5             Yolo  2.120836          347
Output: 6             Lake  1.967070          217
```

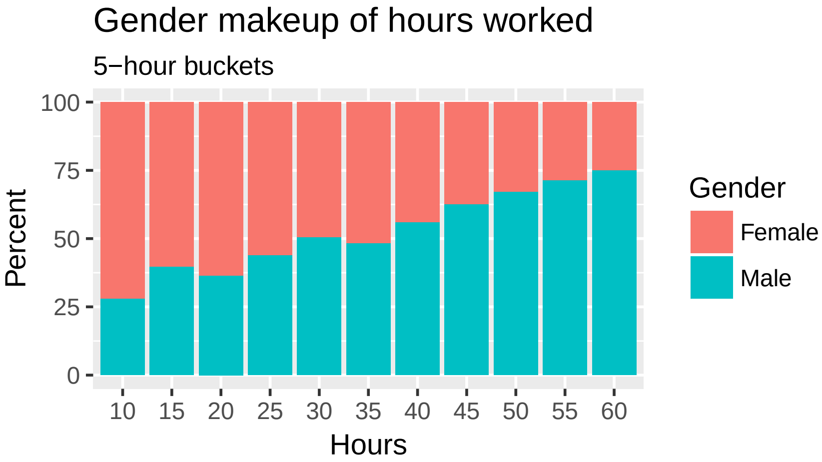
Let's now go back to how hours worked impacts wages

Challenge exercise 1

- Wages seem to increase dramatically with hours worked
- Next step: bar chart showing the percentage of men and women in each 5 hour bucket

1. Find the total number of observations in each hour/gender combination
   - group_by() and dplyr::summarise()
2. Change your grouping to just the hour buckets
   - use mutate to calculate the total number of observations in each bucket and the the percentage of men/women in each bucket
3. Plot with `ggplot()` and `geom_bar()` etc..., your `y` value should be the percentage
   - in the `geom_bar()` make sure to include `stat = "identity"`

Challenge Exercise 1 Answer

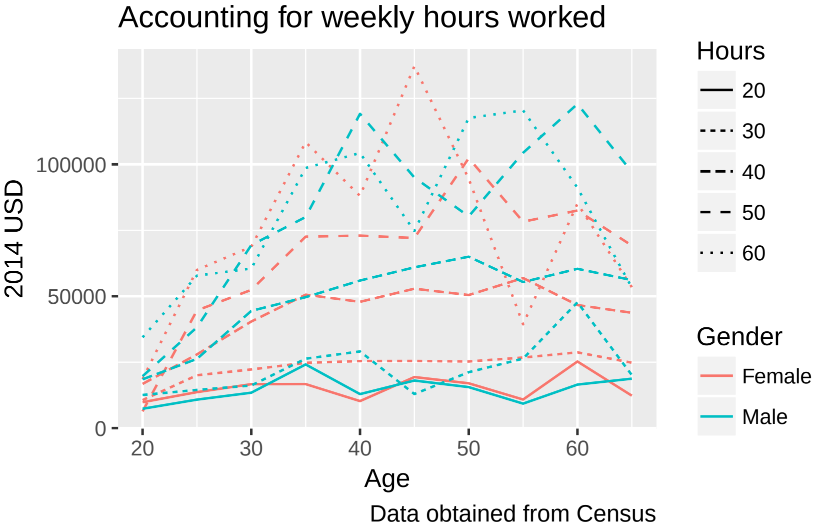


New insights? Further questions?

Challenge Exercise 2

- Using dplyr and ggplot analyze how wage (WAGP) changes over age between men and women
  - control for number of hours worked
    - 10 hour buckets instead of 5
    - Limit to people who work between 20 and 60 hours per week
  - Bucket sizes for age should be 5 years
- PWGTP
- You will need to start with the original ACS data to answer this

Challenge Exercise 2: Answer



Insights? Further Questions? Is this a “good” chart?