SML 201 – Week 3

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Contents

Functions

Rationale

- Writing functions is a core activity of an R programmer. It represents the key step of the transition from a mere user to a developer who creates new functionality for R.
- Functions are often used to encapsulate a sequence of expressions that need to be executed numerous times, perhaps under slightly different conditions.
- Functions are also often written when code must be shared with others or the public.

From *R Programming for Data Science*

Defining a New Function

- Functions are defined using the `function()` directive
- They are stored as variables, so they can be passed to other functions and assigned to new variables
- Arguments and a final return object are defined

Example 1

```
> my_square <- function(x) {
+   x*x  # can also do return(x*x)
+ }
>
> my_square(x=2)
[1] 4
>
> my_fun2 <- my_square
> my_fun2(x=3)
[1] 9
```

Example 2

```
> my_square_ext <- function(x) {
+   y <- x*x
+   return(list(x_original=x, x_squared=y))
+ }
>
> my_square_ext(x=2)
$x_original
[1] 2

$x_squared
[1] 4
>
> z <- my_square_ext(x=2)
```

Example 3

```
> my_power <- function(x, e, say_hello) {
+   if(say_hello) {
+     cat("Hello World!")
+   }
+   x^e
+ }
>
> my_power(x=2, e=3, say_hello=TRUE)
Hello World!
[1] 8
>
> z <- my_power(x=2, e=3, say_hello=TRUE)
Hello World!
> z
[1] 8
```

Default Function Argument Values

Some functions have default values for their arguments:

```
> str(matrix)
function (data = NA, nrow = 1, ncol = 1, byrow = FALSE,
    dimnames = NULL)
```

You can define a function with default values by the following:

```
f <- function(x, y=2) {
  x + y
}
```

If the user types `f(x=1)` then it defaults to `y=2`, but if the user types `f(x=1, y=3)`, then it executes with these assignments.

The Ellipsis Argument

You will encounter functions that include as a possible argument the ellipsis: `...`

This basically holds arguments that can be passed to functions called within a function. Example:

```
> double_log <- function(x, ...) {
+   log((2*x), ...)
+ }
>
> double_log(x=1, base=2)
[1] 1
> double_log(x=1, base=10)
[1] 0.30103
```

Argument Matching

R Programming for Data Science spends several pages discussing how R deals with function calls when the arguments are not defined explicity. For example:

```
x <- matrix(1:6, nrow=2, ncol=3, byrow=TRUE)  # versus
x <- matrix(1:6, 2, 3, TRUE)
```

I strongly recommend that you define arguments explcitly. For example, I can never remember which comes first in `matrix()`, `nrow` or `ncol`.

Organizing Your Code

Suggestions

RStudio conveniently tries to automatically format your R code. We suggest the following in general.

1. No more than 80 characters per line (or fewer depending on how R Markdown compiles):

```
really_long_line <- my_function(x=20, y=30, z=TRUE,
                                a="Joe", b=3.8)
```

2. Indent 2 or more characters for nested commands:

```
for(i in 1:10) {
  if(i > 4) {
    print(i)
  }
}
```

Suggestions (cont'd)

3. Generously comment your code.

```
# a for-loop that prints the index
# whenever it is greater than 4
for(i in 1:10) {
  if(i > 4) {
    print(i)
  }
}
# a good way to get partial credit
# if something goes wrong :-)
```

4. Do not hesitate to write functions to organize tasks. These help to break up your code into more undertsandable pieces, and functions can often be used several times.

Where to Put Files

See *Elements of Data Analytic Style*, Chapter 12 ("Reproducibility") for suggestions on how to organize your files.

In this course, we will keep this relatively simple. We will try to provide you with some organization when distributing the projects.

Environment

Loading `.RData` Files

An `.RData` file is a binary file containing R objects. These can be saved from your current R session and also loaded into your current session.

```
> # generally...
> # to load:
> load(file="path/to/file_name.RData")
> # to save:
> save(file="path/to/file_name.RData")
```

```
> # assumes file in working directory
> load(file="project_1_R_basics.RData")
```

```
> # loads from our GitHub repository
> load(file=url("https://github.com/SML201/project1/raw/
+           master/project_1_R_basics.RData"))
```

Listing Objects

The objects in your current R session can be listed. An environment can also be specificied in case you have objects stored in different environments.

```
> ls()
[1] "num_people_in_precept"     "SML201_grade_distribution"
[3] "some_ORFE_profs"
>
> ls(name=globalenv())
[1] "num_people_in_precept"     "SML201_grade_distribution"
[3] "some_ORFE_profs"
>
> # see help file for other options
> ?ls
```

Removing Objects

You can remove specific objects or all objects from your R environment of choice.

```
> rm("some_ORFE_profs") # removes variable some_ORFE_profs
>
> rm(list=ls()) # Removes all variables from environment
```

Advanced

The R environment is there to connect object names to object values.

The *R Programming for Data Science* chapter titled "Scoping Rules of R" discussed environments and object names in more detail than we need for this course.

A useful discussion about environments can also be found on the *Advanced R* web site.

Packages

Rationale

"In R, the fundamental unit of shareable code is the package. A package bundles together code, data, documentation, and tests, and is easy to share with others. As of January 2015, there were over 6,000 packages available on the **C**omprehensive **R** **A**rchive **N**etwork, or CRAN, the public clearing house for R packages. This huge variety of packages is one of the reasons that R is so successful: the chances are that someone has already solved a problem that you're working on, and you can benefit from their work by downloading their package."

From http://r-pkgs.had.co.nz/intro.html by Hadley Wickham

Contents of a Package

- R functions
- R data objects
- Help documents for using the package
- Information on the authors, dependencies, etc.
- Information to make sure it "plays well" with R and other packages

Installing Packages

From CRAN:

```
install.packages("dplyr")
```

From GitHub (for advanced users):

```
library("devtools")
install_github("hadley/dplyr")
```

From Bioconductor (basically CRAN for biology):

```
source("https://bioconductor.org/biocLite.R")
biocLite("qvalue")
```

We will (probably) only be using packages from CRAN. Be *very* careful about dependencies when installing from GitHub.

Installing Packages (cont'd)

Multiple packages:

```
install.packages(c("dplyr", "ggplot2"))
```

Install all dependencies:

```
install.packages(c("dplyr", "ggplot2"), dependencies=TRUE)
```

Updating packages:

```
update.packages()
```

Loading Packages

Two ways to load a package:

```
library("dplyr")
library(dplyr)
```

I prefer the former.

Getting Started with a Package

When you install a new package and load it, what's next? I like to look at the help files and see what functions and data sets a package has.

```
library("dplyr")
help(package="dplyr")
```

Specifying a Function within a Package

You can call a function from a specific package. Suppose you are in a setting where you have two packages loaded that have functions with the same name.

```
dplyr::arrange(mtcars, cyl, disp)
```

This calls the `arrange` functin specifically from `dplyr`. The package `plyr` also has an `arrange` function.

More on Packages

We will be covering several highly used R packages in depth this semester, so we will continue to learn about packages, how they are organized, and how they are used.

You can download the "source" of a package from R and take a look at the contents if you want to dig deeper. There are also many good tutorials on creating packages, such as http://hilaryparker.com/2014/04/29/writing-an-r-package-from-scratch/.

Subsetting R Objects

Subsetting Vectors

```
> x <- 1:8
>
> x[1]          # extract the first element
[1] 1
> x[2]          # extract the second element
[1] 2
>
> x[1:4]        # extract the first 4 elements
[1] 1 2 3 4
>
> x[c(1, 3, 4)]  # extract elements 1, 3, and 4
[1] 1 3 4
> x[-c(1, 3, 4)] # extract all elements EXCEPT 1, 3, and 4
[1] 2 5 6 7 8
```

Subsetting Vectors

```
> names(x) <- letters[1:8]
> x
a b c d e f g h
1 2 3 4 5 6 7 8
>
> x[c("a", "b", "f")]
a b f
1 2 6
>
> s <- x > 3
> s
    a     b     c     d     e     f     g     h
FALSE FALSE FALSE  TRUE  TRUE  TRUE  TRUE  TRUE
> x[s]
d e f g h
4 5 6 7 8
```

Subsettng Matrices

```
> x <- matrix(1:6, nrow=2, ncol=3, byrow=TRUE)
> x
     [,1] [,2] [,3]
[1,]    1    2    3
[2,]    4    5    6
>
> x[1,2]
[1] 2
> x[1, ]
[1] 1 2 3
> x[ ,2]
[1] 2 5
```

Subsettng Matrices

```
> colnames(x) <- c("A", "B", "C")
>
> x[ , c("B", "C")]
     B C
[1,] 2 3
[2,] 5 6
>
> x[c(FALSE, TRUE), c("B", "C")]
B C
5 6
>
> x[2, c("B", "C")]
B C
5 6
```

Subsettng Matrices

```
> s <- (x %% 2) == 0
> s
         A     B     C
[1,] FALSE  TRUE FALSE
[2,]  TRUE FALSE  TRUE
>
> x[s]
[1] 4 2 6
>
> x[c(2, 3, 6)]
[1] 4 2 6
```

Subsetting Lists

```
> x <- list(my=1:3, favorite=c("a", "b", "c"),
+           course=c(FALSE, TRUE, NA))
>
> x[[1]]
[1] 1 2 3
> x[["my"]]
[1] 1 2 3
> x$my
[1] 1 2 3
```

```
> x[[c(3,1)]]
[1] FALSE
> x[[3]][1]
[1] FALSE
```

```
> x[c(3,1)]
$course
[1] FALSE  TRUE    NA

$my
[1] 1 2 3
```

Subsetting Data Frames

```
> x <- data.frame(my=1:3, favorite=c("a", "b", "c"),
+           course=c(FALSE, TRUE, NA))
>
> x[[1]]
[1] 1 2 3
> x[["my"]]
[1] 1 2 3
> x$my
[1] 1 2 3
```

```
> x[[c(3,1)]]
[1] FALSE
> x[[3]][1]
[1] FALSE
```

```
> x[c(3,1)]
  course my
1  FALSE  1
2   TRUE  2
3     NA  3
```

Subsetting Data Frames

```
> x <- data.frame(my=1:3, favorite=c("a", "b", "c"),
+            course=c(FALSE, TRUE, NA))
>
> x[1, ]
  my favorite course
1  1        a  FALSE
> x[ ,3]
[1] FALSE  TRUE    NA
> x[ ,"favorite"]
[1] a b c
Levels: a b c
```

```
> x[1:2, ]
  my favorite course
1  1        a  FALSE
2  2        b   TRUE
> x[ ,2:3]
  favorite course
1        a  FALSE
2        b   TRUE
3        c     NA
```

Note on Data Frames

R often converts character strings to factors unless you specify otherwise.

In the previous slide, we saw it converted the “favorite” column to factors. Let’s fix that…

```
> x <- data.frame(my=1:3, favorite=c("a", "b", "c"),
+                  course=c(FALSE, TRUE, NA),
+                  stringsAsFactors=FALSE)
>
> x[ ,"favorite"]
[1] "a" "b" "c"
> class(x[ ,"favorite"])
[1] "character"
```

Missing Values

```
> data("airquality", package="datasets")
> head(airquality)
  Ozone Solar.R Wind Temp Month Day
1    41     190  7.4   67     5   1
2    36     118  8.0   72     5   2
3    12     149 12.6   74     5   3
4    18     313 11.5   62     5   4
5    NA      NA 14.3   56     5   5
6    28      NA 14.9   66     5   6
> dim(airquality)
[1] 153   6
```

```
> which(is.na(airquality$Ozone))
 [1]   5  10  25  26  27  32  33  34  35  36  37  39  42  43
[15]  45  46  52  53  54  55  56  57  58  59  60  61  65  72
[29]  75  83  84 102 103 107 115 119 150
> sum(is.na(airquality$Ozone))
[1] 37
```

Subsetting by Matching

```
> letters
 [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n"
[15] "o" "p" "q" "r" "s" "t" "u" "v" "w" "x" "y" "z"
> vowels <- c("a", "e", "i", "o", "u")
>
> letters %in% vowels
 [1]  TRUE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE  TRUE
[10] FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE
[19] FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE
> which(letters %in% vowels)
[1]  1  5  9 15 21
>
> letters[which(letters %in% vowels)]
[1] "a" "e" "i" "o" "u"
```

Advanced Subsetting

The *R Programming for Data Science* chapter titled “Subsetting R Objects” contains additional material on subsetting that you should know.

The *Advanced R* website contains more detailed information on subsetting that you may find useful.

Tidy Data

Definition

> Tidy datasets are easy to manipulate, model and visualize, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table.

From Wickham (2014), “Tidy Data”, *Journal of Statistical Software*

Definition (cont’d)

> A dataset is a collection of values, usually either numbers (if quantitative) or strings (if qualitative). Values are organized in two ways. Every value belongs to a variable and an observation. A variable contains all values that measure the same underlying attribute (like height, temperature, duration) across units. An observation contains all values measured on the same unit (like a person, or a day, or a race) across attributes.

From: Wickham H (2014), “Tidy Data”, *Journal of Statistical Software*

Example: Titanic Data

According to the `Titanic` data from the `datasets` package: 367 males survived, 1364 males perished, 344 females survived, and 126 females perished.

How should we organize these data?

Intuitive Format

	Survived	Perished
Male	367	1364
Female	344	126

Tidy Format

fate	sex	number
perished	male	1364
perished	female	126
survived	male	367
survived	female	344

Wide vs. Long Format

Tidy data come in wide and long formats.

Wide format data have a column for each variable and there is one observed unit per row.

The simplest long format data have two columns. The first column contains the variable names and the second colum contains the values for the variables. There are "wider" long format data that have additional columns that identify connections between observations.

Wide format data is useful for some analyses and long format for others.

`reshape2` Package

The `reshape` package has three important functions: `melt`, `dcast`, and `acast`. It allows one to move between wide and long tidy data formats.

```
> library("reshape2")
> library("datasets")
> data(airquality, package="datasets")
> names(airquality)
[1] "Ozone"   "Solar.R" "Wind"    "Temp"    "Month"   "Day"
> dim(airquality)
[1] 153   6
```

Air Quality Data Set

```
> head(airquality)
Source: local data frame [6 x 6]

  Ozone Solar.R  Wind  Temp Month   Day
  (int)   (int) (dbl) (int) (int) (int)
1    41     190   7.4    67     5     1
2    36     118   8.0    72     5     2
3    12     149  12.6    74     5     3
4    18     313  11.5    62     5     4
5    NA      NA  14.3    56     5     5
6    28      NA  14.9    66     5     6
```

```
> tail(airquality)
Source: local data frame [6 x 6]

  Ozone Solar.R  Wind  Temp Month   Day
  (int)   (int) (dbl) (int) (int) (int)
1    14      20  16.6    63     9    25
2    30     193   6.9    70     9    26
3    NA     145  13.2    77     9    27
4    14     191  14.3    75     9    28
5    18     131   8.0    76     9    29
6    20     223  11.5    68     9    30
```

Melt

Melting can be thought of as melting a piece of solid metal (wide data), so it drips into long format.

```
> aql <- melt(airquality)
No id variables; using all as measure variables
> head(aql)
  variable value
1    Ozone    41
2    Ozone    36
3    Ozone    12
4    Ozone    18
5    Ozone    NA
6    Ozone    28
```

```
> tail(aql)
    variable value
913      Day    25
914      Day    26
915      Day    27
916      Day    28
917      Day    29
918      Day    30
```

Guided Melt

In the previous example, we lose the fact that a set of measurements occurred on a particular day and month, so we can do a guided melt to keep this information.

```
> aql <- melt(airquality, id.vars = c("Month", "Day"))
> head(aql)
  Month Day variable value
1     5   1    Ozone    41
2     5   2    Ozone    36
3     5   3    Ozone    12
4     5   4    Ozone    18
5     5   5    Ozone    NA
6     5   6    Ozone    28
```

```
> tail(aql)
    Month Day variable value
607     9  25     Temp    63
608     9  26     Temp    70
609     9  27     Temp    77
610     9  28     Temp    75
611     9  29     Temp    76
612     9  30     Temp    68
```

Casting

Casting allows us to go from long format to wide format data. It can be visualized as pouring molten metal (long format) into a cast to create a solid piece of metal (wide format).

Casting is more difficult because choices have to be made to determine how the wide format will be organized. It often takes some thought and experimentation for new users.

Let's do an example with `dcast`, which is casting for data frames.

dcast

```
> aqw <- dcast(aql, Month + Day ~ variable)
> head(aqw)
  Month Day Ozone Solar.R Wind Temp
1     5   1    41     190  7.4   67
2     5   2    36     118  8.0   72
3     5   3    12     149 12.6   74
4     5   4    18     313 11.5   62
5     5   5    NA      NA 14.3   56
6     5   6    28      NA 14.9   66
```

```
> tail(aqw)
    Month Day Ozone Solar.R Wind Temp
148     9  25    14      20 16.6   63
149     9  26    30     193  6.9   70
150     9  27    NA     145 13.2   77
151     9  28    14     191 14.3   75
152     9  29    18     131  8.0   76
153     9  30    20     223 11.5   68
```

Manipulating Data Frames

`dplyr` Package

`dplyr` is a package with the following description:

> A fast, consistent tool for working with data frame like objects, both in memory and out of memory.

This package offers a "grammar" for manipulating data frames.

Everything that `dplyr` does can also be done using basic R commands – however, it tends to be much faster and easier to use `dplyr`.

Grammar of `dplyr`

Verbs:

- `filter`: extract a subset of rows from a data frame based on logical conditions
- `arrange`: reorder rows of a data frame
- `rename`: rename variables in a data frame
- `select`: return a subset of the columns of a data frame, using a flexible notation

Partially based on *R Programming for Data Science*

Grammar of `dplyr`

Verbs (continued):

- `mutate`: add new variables/columns or transform existing variables
- `distinct`: returns only the unique values in a table
- `summarize`: generate summary statistics of different variables in the data frame, possibly within strata
- `group_by`: breaks down a dataset into specified groups of rows

Partially based on *R Programming for Data Science*

Example: Baby Names

```
> library("dplyr", verbose=FALSE)
> library("babynames")
> ls()
character(0)
> babynames <- babynames::babynames
> ls()
[1] "babynames"
```

`babynames` Object

```
> class(babynames)
[1] "tbl_df"     "tbl"        "data.frame"
> dim(babynames)
[1] 1792091       5
```

```
> babynames
Source: local data frame [1,792,091 x 5]

    year   sex      name     n       prop
   (dbl) (chr)     (chr) (int)      (dbl)
1   1880     F      Mary  7065 0.07238359
2   1880     F      Anna  2604 0.02667896
3   1880     F      Emma  2003 0.02052149
4   1880     F Elizabeth  1939 0.01986579
5   1880     F    Minnie  1746 0.01788843
6   1880     F  Margaret  1578 0.01616720
7   1880     F       Ida  1472 0.01508119
8   1880     F     Alice  1414 0.01448696
9   1880     F    Bertha  1320 0.01352390
10  1880     F     Sarah  1288 0.01319605
..   ...   ...       ...   ...        ...
```

Peek at the Data

```
> set.seed(201)
> sample_n(babynames, 10)
Source: local data frame [10 x 5]

    year   sex       name     n         prop
   (dbl) (chr)      (chr) (int)        (dbl)
1   1991     F      Sayra    29 1.426546e-05
2   1932     F    Wannell     5 4.520211e-06
3   1966     M        Rey    26 1.430083e-05
4   1905     F     Samuel     7 2.258975e-05
5   1992     F    Sherron    17 8.483034e-06
6   1927     F Pierrette     7 5.662116e-06
7   1907     M      Nolen     6 3.783293e-05
8   1967     F      Cheri  1305 7.602543e-04
9   1920     M      Tyson    11 9.991662e-06
10  1955     F        Gay   493 2.459665e-04
> # try also sample_frac(babynames, 6e-6)
```

%>% Operator

Originally from R package `magrittr`. Provides a mechanism for chaining commands with a forward-pipe operator, %>%.

```
> x <- 1:10
>
> x %>% log(base=10) %>% sum
[1] 6.559763
>
> sum(log(x,base=10))
[1] 6.559763
```

```
> babynames %>% sample_n(5)
Source: local data frame [5 x 5]

   year   sex   name     n         prop
  (dbl) (chr)  (chr) (int)        (dbl)
1  1978     M    Toy     8 4.681892e-06
2  1995     M Derron    32 1.591702e-05
3  1990     M  Jacob 22000 1.022964e-02
4  1979     F  Clara   342 1.985056e-04
5  1983     M  Jerid    35 1.879331e-05
```

`filter()`

```
> filter(babynames, year==1880, sex=="F")
Source: local data frame [942 x 5]

    year   sex       name     n       prop
   (dbl) (chr)      (chr) (int)      (dbl)
1   1880     F       Mary  7065 0.07238359
```

```
2   1880      F      Anna  2604 0.02667896
3   1880      F      Emma  2003 0.02052149
4   1880      F Elizabeth  1939 0.01986579
5   1880      F    Minnie  1746 0.01788843
6   1880      F  Margaret  1578 0.01616720
7   1880      F       Ida  1472 0.01508119
8   1880      F     Alice  1414 0.01448696
9   1880      F    Bertha  1320 0.01352390
10  1880      F     Sarah  1288 0.01319605
..   ...    ...       ...   ...        ...
> # same as filter(babynames, year==1880 & sex=="F")
```

```
> filter(babynames, year==1880, sex=="F", n > 5000)
Source: local data frame [1 x 5]

   year   sex  name     n       prop
  (dbl) (chr) (chr) (int)      (dbl)
1  1880     F  Mary  7065 0.07238359
```

arrange()

```
> arrange(babynames, name, year, sex)
Source: local data frame [1,792,091 x 5]

    year   sex       name     n         prop
   (dbl) (chr)      (chr) (int)        (dbl)
1   2007     M      Aaban     5 2.260668e-06
2   2009     M      Aaban     6 2.835010e-06
3   2010     M      Aaban     9 4.392374e-06
4   2011     M      Aaban    11 5.433940e-06
5   2012     M      Aaban    11 5.447022e-06
6   2013     M      Aaban    14 6.998380e-06
7   2011     F      Aabha     7 3.625123e-06
8   2012     F      Aabha     5 2.590107e-06
9   2003     M      Aabid     5 2.381787e-06
10  2008     F Aabriella     5 2.405002e-06
..   ...   ...        ...   ...          ...
```

arrange()

```
> arrange(babynames, desc(name), desc(year), sex)
Source: local data frame [1,792,091 x 5]

    year   sex       name     n         prop
   (dbl) (chr)      (chr) (int)        (dbl)
1   2010     M      Zzyzx     5 2.440208e-06
2   2010     F    Zyyanna     6 3.068790e-06
3   2009     M     Zyvion     5 2.362508e-06
4   2010     M Zytavious     6 2.928249e-06
```

```
5   2009     M Zytavious     7 3.307511e-06
6   2007     M Zytavious     6 2.712801e-06
7   2006     M Zytavious     7 3.197154e-06
8   2005     M Zytavious     5 2.353078e-06
9   2004     M Zytavious     6 2.841921e-06
10  2002     M Zytavious     6 2.905729e-06
..   ...   ...       ...   ...          ...
```

rename()

```
> rename(babynames, number=n)
Source: local data frame [1,792,091 x 5]

    year   sex      name number       prop
   (dbl) (chr)     (chr)  (int)      (dbl)
1   1880     F      Mary   7065 0.07238359
2   1880     F      Anna   2604 0.02667896
3   1880     F      Emma   2003 0.02052149
4   1880     F Elizabeth   1939 0.01986579
5   1880     F    Minnie   1746 0.01788843
6   1880     F  Margaret   1578 0.01616720
7   1880     F       Ida   1472 0.01508119
8   1880     F     Alice   1414 0.01448696
9   1880     F    Bertha   1320 0.01352390
10  1880     F     Sarah   1288 0.01319605
..   ...   ...       ...    ...        ...
```

select()

```
> select(babynames, sex, name, n)
Source: local data frame [1,792,091 x 3]

     sex      name     n
   (chr)     (chr) (int)
1      F      Mary  7065
2      F      Anna  2604
3      F      Emma  2003
4      F Elizabeth  1939
5      F    Minnie  1746
6      F  Margaret  1578
7      F       Ida  1472
8      F     Alice  1414
9      F    Bertha  1320
10     F     Sarah  1288
..   ...       ...   ...
> # same as select(babynames, sex:n)
```

Renaming with select()

```
> select(babynames, sex, name, number=n)
Source: local data frame [1,792,091 x 3]

     sex      name number
   (chr)     (chr)  (int)
1      F      Mary   7065
2      F      Anna   2604
3      F      Emma   2003
4      F Elizabeth   1939
5      F    Minnie   1746
6      F  Margaret   1578
7      F       Ida   1472
8      F     Alice   1414
9      F    Bertha   1320
10     F     Sarah   1288
..   ...       ...    ...
```

mutate()

```
> mutate(babynames, total_by_year=round(n/prop))
Source: local data frame [1,792,091 x 6]

    year   sex      name     n       prop total_by_year
   (dbl) (chr)     (chr) (int)      (dbl)         (dbl)
1   1880     F      Mary  7065 0.07238359         97605
2   1880     F      Anna  2604 0.02667896         97605
3   1880     F      Emma  2003 0.02052149         97605
4   1880     F Elizabeth  1939 0.01986579         97605
5   1880     F    Minnie  1746 0.01788843         97605
6   1880     F  Margaret  1578 0.01616720         97605
7   1880     F       Ida  1472 0.01508119         97605
8   1880     F     Alice  1414 0.01448696         97605
9   1880     F    Bertha  1320 0.01352390         97605
10  1880     F     Sarah  1288 0.01319605         97605
..   ...   ...       ...   ...        ...           ...
> # see also transmutate
```

No. Individuals by Year and Sex

Let's put a few things together now adding the function distinct()...

```
> babynames %>% mutate(total_by_year=round(n/prop)) %>%
+   select(sex, year, total_by_year) %>% distinct
Source: local data frame [268 x 3]

     sex  year total_by_year
   (chr) (dbl)         (dbl)
1      F  1880         97605
```

```
2       M  1880        118400
3       F  1881         98857
4       M  1881        108285
5       F  1882        115698
6       M  1882        122032
7       F  1883        120065
8       M  1883        112481
9       F  1884        137588
10      M  1884        122742
..    ...   ...           ...
```

summarize()

```
> summarize(babynames, mean_n = mean(n), median_n = median(n),
+           number_sex = n_distinct(sex),
+           distinct_names = n_distinct(name))
Source: local data frame [1 x 4]

    mean_n median_n number_sex distinct_names
     (dbl)    (int)      (int)          (int)
1 186.0496       12          2          92600
```

group_by()

```
> babynames %>% group_by(year, sex)
Source: local data frame [1,792,091 x 5]
Groups: year, sex [268]

    year   sex      name     n       prop
   (dbl) (chr)     (chr) (int)      (dbl)
1   1880     F      Mary  7065 0.07238359
2   1880     F      Anna  2604 0.02667896
3   1880     F      Emma  2003 0.02052149
4   1880     F Elizabeth  1939 0.01986579
5   1880     F    Minnie  1746 0.01788843
6   1880     F  Margaret  1578 0.01616720
7   1880     F       Ida  1472 0.01508119
8   1880     F     Alice  1414 0.01448696
9   1880     F    Bertha  1320 0.01352390
10  1880     F     Sarah  1288 0.01319605
..   ...   ...       ...   ...        ...
```

No. Individuals by Year and Sex

```
> babynames %>% group_by(year, sex) %>%
+   summarize(total_by_year=sum(n))
Source: local data frame [268 x 3]
```

```
Groups: year [?]

    year   sex total_by_year
   (dbl) (chr)         (int)
1   1880     F         90993
2   1880     M        110491
3   1881     F         91954
4   1881     M        100746
5   1882     F        107850
6   1882     M        113687
7   1883     F        112322
8   1883     M        104630
9   1884     F        129022
10  1884     M        114446
..   ...   ...           ...
```

Compare to earlier slide. Why the difference?

How Many Distinct Names?

```
> babynames %>% group_by(sex) %>%
+   summarize(mean_n = mean(n),
+             distinct_names_sex = n_distinct(name))
Source: local data frame [2 x 3]

    sex   mean_n distinct_names_sex
  (chr)    (dbl)              (int)
1     F 155.5683              64089
2     M 230.4324              38601
```

Most Popular Names

```
> top_names <- babynames %>% group_by(year, sex) %>%
+   summarize(top_name = name[which.max(n)])
>
> head(top_names)
Source: local data frame [6 x 3]
Groups: year [3]

   year   sex top_name
  (dbl) (chr)    (chr)
1  1880     F     Mary
2  1880     M     John
3  1881     F     Mary
4  1881     M     John
5  1882     F     Mary
6  1882     M     John
```

Most Popular Names

Recent Years

```
> tail(top_names, n=10)
Source: local data frame [10 x 3]
Groups: year [5]

    year   sex top_name
   (dbl) (chr)    (chr)
1   2009     F Isabella
2   2009     M    Jacob
3   2010     F Isabella
4   2010     M    Jacob
5   2011     F   Sophia
6   2011     M    Jacob
7   2012     F   Sophia
8   2012     M    Jacob
9   2013     F   Sophia
10  2013     M     Noah
```

Most Popular Female Names

1990s

```
> top_names %>% filter(year >= 1990 & year < 2000, sex=="F")
Source: local data frame [10 x 3]
Groups: year [10]

    year   sex top_name
   (dbl) (chr)    (chr)
1   1990     F  Jessica
2   1991     F   Ashley
3   1992     F   Ashley
4   1993     F  Jessica
5   1994     F  Jessica
6   1995     F  Jessica
7   1996     F    Emily
8   1997     F    Emily
9   1998     F    Emily
10  1999     F    Emily
```

Most Popular Male Names

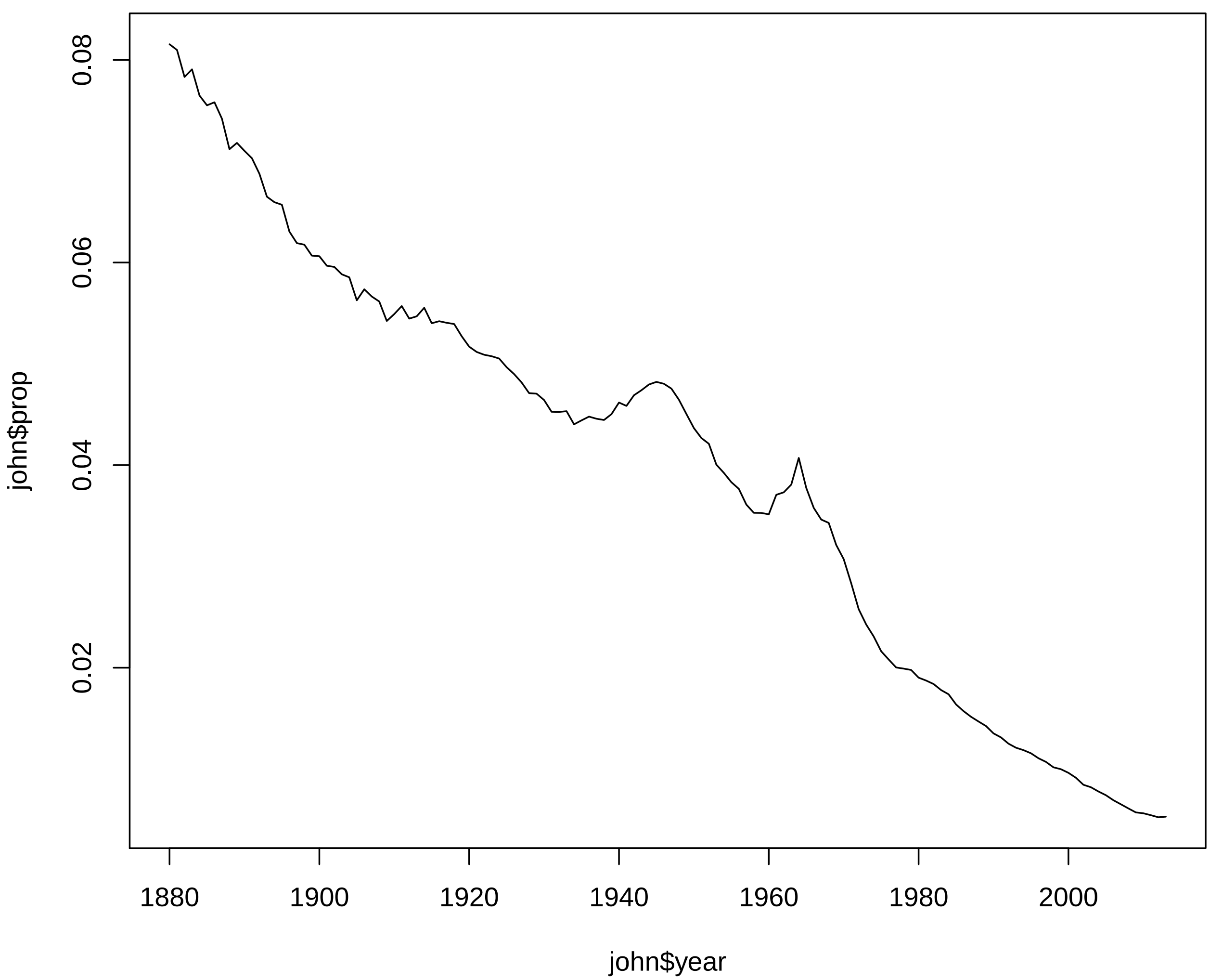
1990s

```
> top_names %>% filter(year >= 1990 & year < 2000, sex=="M")
Source: local data frame [10 x 3]
```

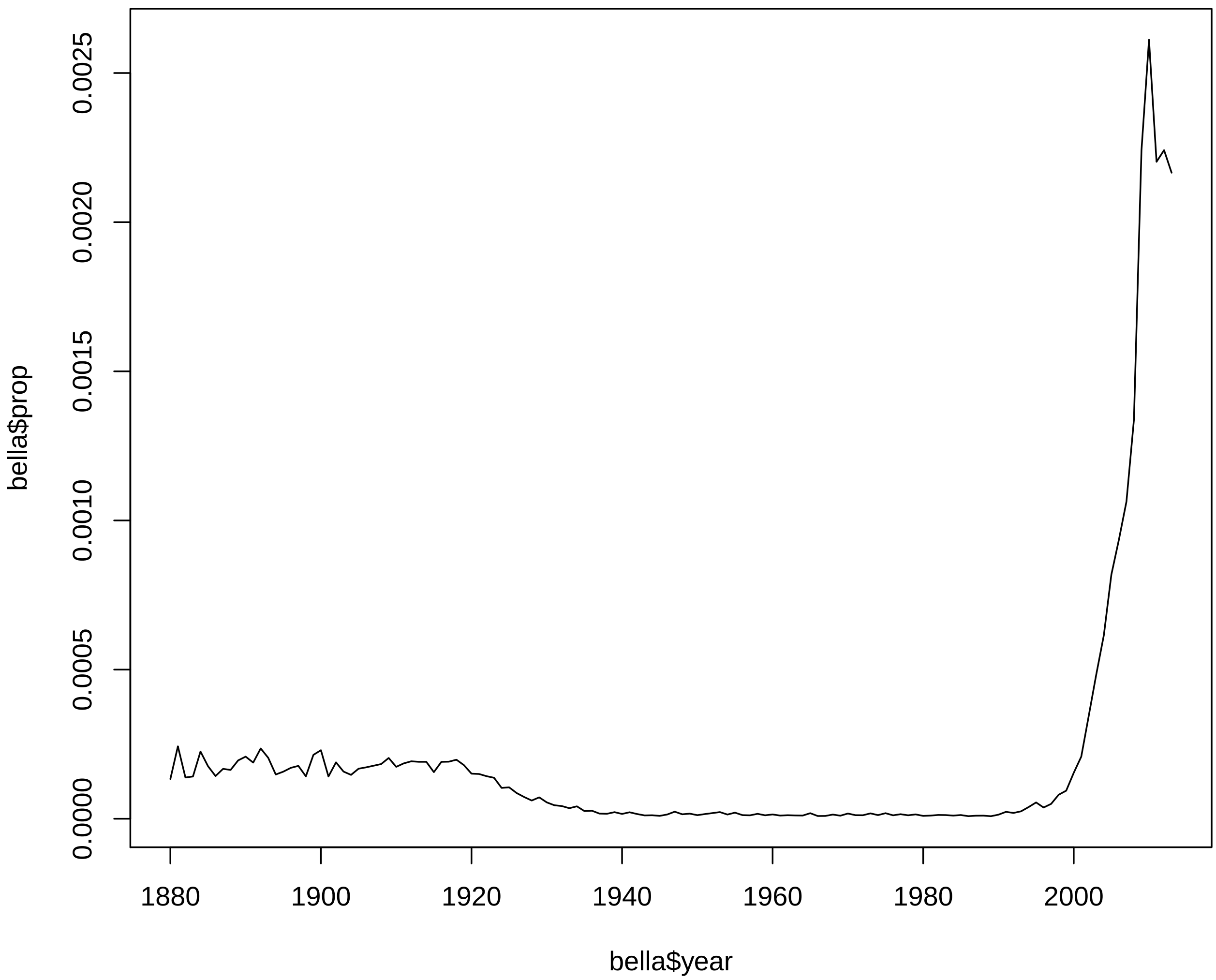
```
Groups: year [10]

    year   sex top_name
   (dbl) (chr)    (chr)
1   1990     M  Michael
2   1991     M  Michael
3   1992     M  Michael
4   1993     M  Michael
5   1994     M  Michael
6   1995     M  Michael
7   1996     M  Michael
8   1997     M  Michael
9   1998     M  Michael
10  1999     M    Jacob
```

```
> # Analyzing the name 'John'
> john <- babynames %>% filter(sex=="M", name=="John")
> plot(john$year, john$prop, type="l")
```



```
> # Analyzing the name 'Bella'
> bella <- babynames %>% filter(sex=="F", name=="Bella")
> plot(bella$year, bella$prop, type="l")
```



Additional Examples

You should study additional tutorials of `dplyr` that utilize other data sets:

- Read the `dplyr` introductory vignette
- Read the examples given in *R Programming for Data Science*, the "Managing Data Frames with the `dplyr` Package" chapter

Additional `dplyr` Features

- We've only scratched the surface – many interesting demos of `dplyr` can be found online
- `dplyr` can work with other data frame backends such as SQL databases

- There is an SQL interface for relational databases via the `DBI` package
- `dplyr` can be integrated with the `data.table` package for large fast tables
- There is a healthy rivalry between `dplyr` and `data.table`

Extras

Source Code

https://github.com/SML201/lectures/tree/master/week3

Session Information

```
> sessionInfo()
R version 3.2.3 (2015-12-10)
Platform: x86_64-apple-darwin13.4.0 (64-bit)
Running under: OS X 10.11.3 (El Capitan)

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods
[7] base

other attached packages:
[1] babynames_0.1   dplyr_0.4.3     reshape2_1.4.1
[4] knitr_1.12.3    devtools_1.10.0

loaded via a namespace (and not attached):
 [1] Rcpp_0.12.3     assertthat_0.1  digest_0.6.9
 [4] R6_2.1.2        plyr_1.8.3      DBI_0.3.1
 [7] formatR_1.2.1   magrittr_1.5    evaluate_0.8
[10] highr_0.5.1     stringi_1.0-1   lazyeval_0.1.10
[13] rmarkdown_0.9.2 tools_3.2.3     stringr_1.0.0
[16] parallel_3.2.3  yaml_2.1.13     memoise_0.2.1
[19] htmltools_0.3
```