Section 13: `data.table`

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Contents

1 Admin

1.1 Announcements

1. Today is our last section!
2. Office hours at usual time/place on Friday.
3. Whoever submits your problem set on bCourses has access to my comments. The solutions are also available for problem sets 1–3 (and 4 will be up shortly).
4. **From problem set 3**: Remember when you use the delta method that you need to take derivatives with respect to all of parameters in model. In the case of the problem in the problem set, each of the derivatives was equal to zero except one, but the derivation that many of you provided for the delta-method-based standard error of our estimator was no quite right.

1.2 Last section

In our previous section, we discussed spatial—focusing on one of the two major classes of spatial data: vector data, which include polygons, lines, and points.

1.3 This week

1.3.1 Spatial data

Today we will wrap up our discussion of spatial data, covering three topics:

1. **Raster data**: our remaining major class of spatial data
2. **Geocoding**: moving from addresses to geographic coordinates
3. **Leaflet**: an awesome tools for creating interactive maps

See Section 12b for this completion of spatial data.

1.3.2 `data.table`

In the second portion of this section, we will R's `data.table` package and its uses for cleaning/prepping datasets. `data.table` is particularly useful for large datasets, so we will use it on a fairly large dataset.

1.4 What you will need

Packages:

- New: `data.table`
- Old: magrittr‘

2 `data.table`

R's `data.table` package provides methods for fast (potentially grouped) manipulation of large datasets—aggregation, joins, modifications—without copying the dataset repeatedly. The syntax is not quite as clear as the "verbs" used by `dplyr` and the rest of the *hadleyverse*, but the efficiency benefits are substantial when you have large datsets.

2.1 R setup

Let's get started. First, set up R.

```
# General R setup ----
# Options
options(stringsAsFactors = F)
# Load packages
pacman::p_load(data.table, magrittr)
# Add an option for data.table
options(datatable.print.nrows = 20)
```

The option `options(datatable.print.nrows = 20)` tells R that we do not want to print the whole data table if it has more than 20 rows—a handy feature that prevents you from printing a billion rows to screen.[1]

[1] `tbl_dfs` have a similar feature. Plus, R will not actually let you print a billion rows to screen, but it will allow you to print 50,000, which is still a lot.

2.2 Creating a data table

Alright, let's create a data table.[2] To create a data table—or to convert an existing data frame or matrix to a data table—you use the `data.table()` function just as you would use the `data.frame()` function. Let's create a simple data table with 30 rows and four columns named `a`, `b`, `c`, and `d`. *Note*: I'm going to generally use the suffix `_dt` to denote data tables in our R scripts.

```
# Set the seed
set.seed(12345)
# Create our data table
our_dt <- data.table(
  a = 101:130,
  b = rnorm(30),
  c = runif(30),
  d = rep(1:5))
```

So what is this data table object that we just created?

```
# Check the class
our_dt %>% class()
```

```
## [1] "data.table" "data.frame"
```

```
# Check the dimensions, length, and names
our_dt %>% dim()
```

```
## [1] 30  4
```

```
our_dt %>% length()
```

```
## [1] 4
```

```
our_dt %>% names()
```

```
## [1] "a" "b" "c" "d"
```

This data table is still a `data.frame`, but it is also a `data.table`—similar to how we previously created objects that simultaneously had the classes `data.frame`, `tbl_df`, and `tbl`. The dimensions, length, and names are exactly what we expected them to be. Good.

Let's print the data table to screen.

```
# Print our_dt to screen
our_dt
```

```
##       a          b          c d
##  1: 101  0.5855288 0.79156780 1
##  2: 102  0.7094660 0.25868432 2
##  3: 103 -0.1093033 0.98598383 3
##  4: 104 -0.4534972 0.75687374 4
##  5: 105  0.6058875 0.97977825 5
## ---
```

[2] I'm going to write it "data table" rather than "data.table", since written English is a bit different than scripting/programming languages.

```
## 26: 126  1.8050975 0.30503175 1
## 27: 127 -0.4816474 0.82565686 2
## 28: 128  0.6203798 0.50234464 3
## 29: 129  0.6121235 0.80357263 4
## 30: 130 -0.1623110 0.06063998 5
```

I like this feature of data tables: you get to see the first and last five rows for each variable.

2.3 General syntax

The general syntax for data tables is slightly different from what we've seen so far. The main idea for the syntax of a data table is `DT[i, j, by]`, where `DT` is our data table, `i` references the rows that we want, `j` references the columns, and `by` provides the variables with which we want group our data. If you want all of the rows, simply omit `i` (but keep the comma). Likewise for `j`. And if you do not want to group your data, then omit `by` (you do not need to include the comma between `j` and `by` if you do not use the `by` argument).

2.4 Indexing columns

Let's talk about indexing columns/variables.

2.4.1 Accessing a column

You can still use the `$` to access columns, but this practice is discouraged because it is less efficient and generalizable than `data.table`'s other methods for accessing columns.

So how do you access columns? You define `j` as either the variable names or numbers. If we want to grab `b` (the second variable), we can define `j` as `b` or `"b"` or `2`. However, some of these methods will result in vector of the values in the `b` column, while others will result in a data table with only the column `b`. Finally, we can treat a data table (or data frame) as a list and reference a column with double square brackets and the column's name (*e.g.*, `our_dt[["b"]]`) or number.

Six options for grabbing the `b` variable:

```
our_dt$b
```

```
##  [1]  0.5855288  0.7094660 -0.1093033 -0.4534972  0.6058875 -1.8179560
##  [7]  0.6300986 -0.2761841 -0.2841597 -0.9193220 -0.1162478  1.8173120
## [13]  0.3706279  0.5202165 -0.7505320  0.8168998 -0.8863575 -0.3315776
## [19]  1.1207127  0.2987237  0.7796219  1.4557851 -0.6443284 -1.5531374
## [25] -1.5977095  1.8050975 -0.4816474  0.6203798  0.6121235 -0.1623110
```

```
our_dt[, b]
```

```
##  [1]  0.5855288  0.7094660 -0.1093033 -0.4534972  0.6058875 -1.8179560
##  [7]  0.6300986 -0.2761841 -0.2841597 -0.9193220 -0.1162478  1.8173120
## [13]  0.3706279  0.5202165 -0.7505320  0.8168998 -0.8863575 -0.3315776
## [19]  1.1207127  0.2987237  0.7796219  1.4557851 -0.6443284 -1.5531374
## [25] -1.5977095  1.8050975 -0.4816474  0.6203798  0.6121235 -0.1623110
```

```
our_dt[, "b"]
```

```
##              b
##  1:  0.5855288
##  2:  0.7094660
##  3: -0.1093033
##  4: -0.4534972
##  5:  0.6058875
## ---
## 26:  1.8050975
## 27: -0.4816474
## 28:  0.6203798
## 29:  0.6121235
## 30: -0.1623110
```

```
our_dt[, 2]
```

```
##              b
##  1:  0.5855288
##  2:  0.7094660
##  3: -0.1093033
##  4: -0.4534972
##  5:  0.6058875
## ---
## 26:  1.8050975
## 27: -0.4816474
## 28:  0.6203798
## 29:  0.6121235
## 30: -0.1623110
```

```
our_dt[["b"]]
```

```
##  [1]  0.5855288  0.7094660 -0.1093033 -0.4534972  0.6058875 -1.8179560
##  [7]  0.6300986 -0.2761841 -0.2841597 -0.9193220 -0.1162478  1.8173120
## [13]  0.3706279  0.5202165 -0.7505320  0.8168998 -0.8863575 -0.3315776
## [19]  1.1207127  0.2987237  0.7796219  1.4557851 -0.6443284 -1.5531374
## [25] -1.5977095  1.8050975 -0.4816474  0.6203798  0.6121235 -0.1623110
```

```
our_dt[[2]]
```

```
##  [1]  0.5855288  0.7094660 -0.1093033 -0.4534972  0.6058875 -1.8179560
##  [7]  0.6300986 -0.2761841 -0.2841597 -0.9193220 -0.1162478  1.8173120
## [13]  0.3706279  0.5202165 -0.7505320  0.8168998 -0.8863575 -0.3315776
## [19]  1.1207127  0.2987237  0.7796219  1.4557851 -0.6443284 -1.5531374
## [25] -1.5977095  1.8050975 -0.4816474  0.6203798  0.6121235 -0.1623110
```

Finally, imagine inside of a function, you have an object named `my_col`, which references `"b"`, and you want to grab the column referenced by `my_col`. You cannot grab the column `b` using `our_dt[,my_col]`, because `data.table` will think you are referencing a column named `my_col` rather than looking at the value assigned to `my_col`. To tell `data.table` to look at the value inside of `my_col`, you have three options:

- Use the list-style syntax: `our_dt[[my_col]]`
- Add the argument `with = F` to the end of your indexing: `our_dt[, .my_col, with = F]`
- Use double periods in front of `my_col`: `our_dt[, ..my_col]`

Again, which option you choose affects the type of object that `data.table` returns.

Let's see these solutions in action:

```
# Define 'my_col' as "b"
my_col <- "b"
# The erroneous use
our_dt[, my_col]
```

```
## [1] "b"
```

```
# The list use
our_dt[[my_col]]
```

```
##  [1]  0.5855288  0.7094660 -0.1093033 -0.4534972  0.6058875 -1.8179560
##  [7]  0.6300986 -0.2761841 -0.2841597 -0.9193220 -0.1162478  1.8173120
## [13]  0.3706279  0.5202165 -0.7505320  0.8168998 -0.8863575 -0.3315776
## [19]  1.1207127  0.2987237  0.7796219  1.4557851 -0.6443284 -1.5531374
## [25] -1.5977095  1.8050975 -0.4816474  0.6203798  0.6121235 -0.1623110
```

```
# The 'with = F' option
our_dt[, my_col, with = F]
```

```
##              b
##  1:  0.5855288
##  2:  0.7094660
##  3: -0.1093033
##  4: -0.4534972
##  5:  0.6058875
## ---
## 26:  1.8050975
## 27: -0.4816474
## 28:  0.6203798
## 29:  0.6121235
## 30: -0.1623110
```

```
# The double-period option
our_dt[, ..my_col]
```

```
## Error in eval(expr, envir, enclos): object '..my_col' not found
```

2.4.2 Accessing multiple columns

The `[i,j,by]` syntax still applies for grabbing multiple columns, as does the `with = F` option. The big change here is that you do not want to use the `c()` function in conjunction with unquoted column names. Instead, use `list()` or simply `.()`. Let's grab the first two columns—`a` and `b`.

```
# Using 'list'
our_dt[, list(a, b)]
```

```
##       a          b
##  1: 101  0.5855288
```

```
##  2: 102  0.7094660
##  3: 103 -0.1093033
##  4: 104 -0.4534972
##  5: 105  0.6058875
## ---
## 26: 126  1.8050975
## 27: 127 -0.4816474
## 28: 128  0.6203798
## 29: 129  0.6121235
## 30: 130 -0.1623110
```

```
# Using the period
our_dt[, .(a, b)]
```

```
##       a          b
##  1: 101  0.5855288
##  2: 102  0.7094660
##  3: 103 -0.1093033
##  4: 104 -0.4534972
##  5: 105  0.6058875
## ---
## 26: 126  1.8050975
## 27: 127 -0.4816474
## 28: 128  0.6203798
## 29: 129  0.6121235
## 30: 130 -0.1623110
```

What about column numbers?

```
# List with numbers? No.
our_dt[, list(1, 2)]
```

```
##    V1 V2
## 1:  1  2
```

```
# c() with numbers and 'with = F'? Yes.
our_dt[, c(1, 2), with = F]
```

```
##       a          b
##  1: 101  0.5855288
##  2: 102  0.7094660
##  3: 103 -0.1093033
##  4: 104 -0.4534972
##  5: 105  0.6058875
## ---
## 26: 126  1.8050975
## 27: 127 -0.4816474
## 28: 128  0.6203798
## 29: 129  0.6121235
## 30: 130 -0.1623110
```

Again, if you want reference columns via another object, you need to use `with = F`.

```
# Define the object
my_cols <- c("a", "b")
# Access the columns using the object
our_dt[, my_cols, with = F]
```

```
##       a          b
##  1: 101  0.5855288
##  2: 102  0.7094660
##  3: 103 -0.1093033
##  4: 104 -0.4534972
##  5: 105  0.6058875
## ---
## 26: 126  1.8050975
## 27: 127 -0.4816474
## 28: 128  0.6203798
## 29: 129  0.6121235
## 30: 130 -0.1623110
```

2.5 Indexing rows

If you want to simply grab rows by their number, you can do so just as you would with an ordinary data frame:

```
# Grab some rows
our_dt[c(1, 5, 7, 10), ]
```

```
##      a          b         c d
## 1: 101  0.5855288 0.7915678 1
## 2: 105  0.6058875 0.9797782 5
## 3: 107  0.6300986 0.9487072 2
## 4: 110 -0.9193220 0.9464308 5
```

You can begin to see the power of `data.table` and its notation when you want to select rows using some criteria, as you would do with `filter()` in `dplyr`. Let's grab values of `b` below 0 and values of `c` above 0.5.

```
# Grab b < 0 and c > 0.5
our_dt[(b < 0) & (c > 0.5),]
```

```
##      a          b         c d
## 1: 103 -0.1093033 0.9859838 3
## 2: 104 -0.4534972 0.7568737 4
## 3: 109 -0.2841597 0.6003570 4
## 4: 110 -0.9193220 0.9464308 5
## 5: 111 -0.1162478 0.6883534 1
## 6: 117 -0.8863575 0.9614473 2
## 7: 118 -0.3315776 0.6549605 3
## 8: 127 -0.4816474 0.8256569 2
```

The parentheses here are not necessary—I just like them for ease of reading the code.

The `data.table` package also provides a handy function `between()` that helps you filter values between a min and a max. Rather than grabbing values of `b` less than 0, let's restrict our rows to values of `b` between -0.25

and 0.25. Finally, in addition to the rows we reference, let's grab only columns `a` and `c`.

```
# Grab b in [-0.25,0.25] and c > 0.5
our_dt[between(b, -0.25, 0.25) & (c > 0.5), .(a, c)]
```

```
##      a         c
## 1: 103 0.9859838
## 2: 111 0.6883534
```

To sample rows from your data table, you can apply R's `base` functions `sample()` and `sample.int()`. Sub-sampling[3] is a very useful tool when you are writing code to clean/analyze a huge dataset. Start on small subset of your data to write and test your code, then move up to the big leagues.

To sample 10 rows from our (already small) data table:

```
# Set the seed
set.seed(12345)
# Sample
our_dt[sample(10),]
```

```
##       a          b         c d
##  1: 108 -0.2761841 0.1494579 3
##  2: 110 -0.9193220 0.9464308 5
##  3: 107  0.6300986 0.9487072 2
##  4: 109 -0.2841597 0.6003570 4
##  5: 103 -0.1093033 0.9859838 3
##  6: 101  0.5855288 0.7915678 1
##  7: 102  0.7094660 0.2586843 2
##  8: 104 -0.4534972 0.7568737 4
##  9: 106 -1.8179560 0.2189478 1
## 10: 105  0.6058875 0.9797782 5
```

2.6 Adding/manipulating columns

You have two options for adding and manipulating columns in a data table.[4] The first is the rather strange syntax `:=`; the second is the function `set()`.

Let's start with `:=` route for creating and manipulating variables. Recall the `i,j` notation we discussed above. As `j` denotes columns, we will create and manipulate columns in the `j` place of our data table. Perhaps more clearly, if we want to create a column of ones called `ones` in our data table, we write:

```
# Define a column of ones
our_dt[, ones := 1]

# Check our data frame
our_dt
```

```
##       a          b          c d ones
##  1: 101  0.5855288 0.79156780 1    1
```

[3] Sampling? "Sub-sampling" seems redundant.

[4] You could also stick with `$`, but, again, it is inefficient. If you are switching to `data.table` for its efficiency/speed, it probably makes sense to avoid inefficient uses.

```
##  2: 102  0.7094660 0.25868432 2    1
##  3: 103 -0.1093033 0.98598383 3    1
##  4: 104 -0.4534972 0.75687374 4    1
##  5: 105  0.6058875 0.97977825 5    1
## ---
## 26: 126  1.8050975 0.30503175 1    1
## 27: 127 -0.4816474 0.82565686 2    1
## 28: 128  0.6203798 0.50234464 3    1
## 29: 129  0.6121235 0.80357263 4    1
## 30: 130 -0.1623110 0.06063998 5    1
```

Notice that there is no re-defining of the data table using `<-` or `%<>%`. We simple define a new column, and then the column exists. This change is part of `data.table`'s efficiency.

Similarly, if we want create a column named `abc` that is the product of the columns `a`, `b`, and `c`, then we write

```
# Define abc
our_dt[, abc := a * b * c]

# Check our data frame
our_dt
```

```
##       a          b          c d ones       abc
##  1: 101  0.5855288 0.79156780 1    1  46.81206
##  2: 102  0.7094660 0.25868432 2    1  18.71983
##  3: 103 -0.1093033 0.98598383 3    1 -11.10044
##  4: 104 -0.4534972 0.75687374 4    1 -35.69697
##  5: 105  0.6058875 0.97977825 5    1  62.33171
## ---
## 26: 126  1.8050975 0.30503175 1    1  69.37712
## 27: 127 -0.4816474 0.82565686 2    1 -50.50478
## 28: 128  0.6203798 0.50234464 3    1  39.89049
## 29: 129  0.6121235 0.80357263 4    1  63.45325
## 30: 130 -0.1623110 0.06063998 5    1  -1.27953
```

You can manipulate a column in the same way that you define a column, *e.g.*,

```
# Re-define the column
our_dt[, ones := 111]

# Check our data frame
our_dt
```

```
##       a          b          c d ones       abc
##  1: 101  0.5855288 0.79156780 1  111  46.81206
##  2: 102  0.7094660 0.25868432 2  111  18.71983
##  3: 103 -0.1093033 0.98598383 3  111 -11.10044
##  4: 104 -0.4534972 0.75687374 4  111 -35.69697
##  5: 105  0.6058875 0.97977825 5  111  62.33171
## ---
## 26: 126  1.8050975 0.30503175 1  111  69.37712
## 27: 127 -0.4816474 0.82565686 2  111 -50.50478
```

```
## 28: 128  0.6203798 0.50234464 3  111  39.89049
## 29: 129  0.6121235 0.80357263 4  111  63.45325
## 30: 130 -0.1623110 0.06063998 5  111  -1.27953
```

To delete a column, you redefine the column as `NULL`. Let's delete the column `ones`.

```
# Delete 'ones'
our_dt[, ones := NULL]
```

```
our_dt
```

```
##       a          b          c d       abc
##  1: 101  0.5855288 0.79156780 1  46.81206
##  2: 102  0.7094660 0.25868432 2  18.71983
##  3: 103 -0.1093033 0.98598383 3 -11.10044
##  4: 104 -0.4534972 0.75687374 4 -35.69697
##  5: 105  0.6058875 0.97977825 5  62.33171
## ---
## 26: 126  1.8050975 0.30503175 1  69.37712
## 27: 127 -0.4816474 0.82565686 2 -50.50478
## 28: 128  0.6203798 0.50234464 3  39.89049
## 29: 129  0.6121235 0.80357263 4  63.45325
## 30: 130 -0.1623110 0.06063998 5  -1.27953
```

If you want to define/manipulate multiple columns, you add parentheses to `:=` and separate the new columns with commas. Let's delete `abc` and at the same time add the two-way products `ab` and `ac`.

```
our_dt[, `:=`(
  abc = NULL,
  ab = a * b,
  ac = a *c
  )]
```

```
our_dt
```

```
##       a          b          c d        ab         ac
##  1: 101  0.5855288 0.79156780 1  59.13841  79.948348
##  2: 102  0.7094660 0.25868432 2  72.36553  26.385800
##  3: 103 -0.1093033 0.98598383 3 -11.25824 101.556335
##  4: 104 -0.4534972 0.75687374 4 -47.16371  78.714869
##  5: 105  0.6058875 0.97977825 5  63.61818 102.876716
## ---
## 26: 126  1.8050975 0.30503175 1 227.44229  38.434001
## 27: 127 -0.4816474 0.82565686 2 -61.16922 104.858422
## 28: 128  0.6203798 0.50234464 3  79.40861  64.300114
## 29: 129  0.6121235 0.80357263 4  78.96393 103.660869
## 30: 130 -0.1623110 0.06063998 5 -21.10043   7.883198
```

As I mentioned above, you can also define and manipulate columns using the `data.table` function `set()`. `set()` also uses the `i,j` syntax. `set()` takes the following arguments:

- `x`: the name of data table
- `i`: the row numbers which you want to receive the new values (omit for all rows)

- `j`: the name (or number) of the column
- `value`: the value to assign

Let's use `set()` to add back our column of ones… and then delete it.

```
# Add column of ones using 'set'
set(x = our_dt, j = "ones", value = 1)
# Delete column of ones using 'set'
set(x = our_dt, j = "ones", value = NULL)
```

`set()` is very helpful within a function, since it allows you to easily define the rows, column name (as a character), and values.

2.7 Setting names

Continuing in the spirit of `set()`, `data.table` also provides a function to set column names. Why? Because `names(our_dt) <-`… is, again, an inefficient way to set the column names: it when you use `<-`, you are copying the entire data frame to simply change a few names.

Let's imagine that we want to change all of our variable names to all capital letters. The function `toupper()` changes characters to uppercase, so we could write `names(our_dt) <- toupper(names(our_dt))`, but we want to be efficient, so let's use `setnames()`.

```
# Change names to uppercase
setnames(our_dt, toupper(names(our_dt)))
```

What if we only want to change a single name? `setnames()` still works! It accepts the arguments `old` and `new`, so we can single out the `old` variable name and replace it with a `new` name. Let's change `"AB"` to `"ab"`.

```
# Change 'AB' to 'ab'
setnames(our_dt, old = "AB", new = "ab")
# Check our data table
our_dt
```

```
##       A          B          C D        ab         AC
##  1: 101  0.5855288 0.79156780 1  59.13841  79.948348
##  2: 102  0.7094660 0.25868432 2  72.36553  26.385800
##  3: 103 -0.1093033 0.98598383 3 -11.25824 101.556335
##  4: 104 -0.4534972 0.75687374 4 -47.16371  78.714869
##  5: 105  0.6058875 0.97977825 5  63.61818 102.876716
## ---
## 26: 126  1.8050975 0.30503175 1 227.44229  38.434001
## 27: 127 -0.4816474 0.82565686 2 -61.16922 104.858422
## 28: 128  0.6203798 0.50234464 3  79.40861  64.300114
## 29: 129  0.6121235 0.80357263 4  78.96393 103.660869
## 30: 130 -0.1623110 0.06063998 5 -21.10043   7.883198
```

Finally, let's change the names back to lowercase, using `tolower()`.

```
# Change names back to lowercase
setnames(our_dt, tolower(names(our_dt)))
```

2.8 Summarizing columns

`data.table`'s `i,j,by` syntax also allows you to quickly summarize variables. For instance, if you want to take the means of `a` and `b`:

```
# Mean of 'a' and 'b'
our_dt[, .(mean(a), mean(b))]
```

```
##       V1         V2
## 1: 115.5 0.07880701
```

However, `V1` and `V2` are not the more informative names. With a few more keystrokes, we can add names:

```
# Mean of 'a' and 'b', named
our_dt[, .(mean_a = mean(a), mean_b = mean(b))]
```

```
##    mean_a     mean_b
## 1:  115.5 0.07880701
```

Nice, right?

What if we want to take the means of `a` and `b`, grouped by the variable `d` (which takes on the values 1, 2, 3, 4, and 5)? Enter the `by` part of `i,j,by`!

```
# Mean of 'a' and 'b' grouped by 'd'
our_dt[, .(mean_a = mean(a), mean_b = mean(b)), by = d]
```

```
##    d mean_a       mean_b
## 1: 1  113.5  0.342157388
## 2: 2  114.5  0.540776135
## 3: 3  115.5 -0.061730962
## 4: 4  116.5 -0.006290287
## 5: 5  117.5 -0.420877223
```

Hopefully you are starting to get on board with this `data.table` thing.

`data.table` has a few special commands that are only accessible inside of the square brackets of a data table. One of them is `.N`, which gives the number of observations for the given data table/group. For instance, we can access the final observation of a data table using

```
# Last observation
our_dt[.N,]
```

```
##      a         b          c d        ab       ac
## 1: 130 -0.162311 0.06063998 5 -21.10043 7.883198
```

We can also use `.N` as a summary statistic to count the number of observations within each group:

```
our_dt[, .N, by = d]
```

```
##    d N
## 1: 1 6
## 2: 2 6
## 3: 3 6
## 4: 4 6
```

```
## 5: 5 6
```

You can also add summaries back into the data table, using the same notation we used above. For instance, if we wan to add the mean of `a`, using `d` to group, we simply type:

```
# Add means of 'a', grouped by 'd'
our_dt[, mean_a_by_d := mean(a), by = d]
```

```
##       a          b          c d        ab         ac mean_a_by_d
##  1: 101  0.5855288 0.79156780 1  59.13841  79.948348       113.5
##  2: 102  0.7094660 0.25868432 2  72.36553  26.385800       114.5
##  3: 103 -0.1093033 0.98598383 3 -11.25824 101.556335       115.5
##  4: 104 -0.4534972 0.75687374 4 -47.16371  78.714869       116.5
##  5: 105  0.6058875 0.97977825 5  63.61818 102.876716       117.5
## ---
## 26: 126  1.8050975 0.30503175 1 227.44229  38.434001       113.5
## 27: 127 -0.4816474 0.82565686 2 -61.16922 104.858422       114.5
## 28: 128  0.6203798 0.50234464 3  79.40861  64.300114       115.5
## 29: 129  0.6121235 0.80357263 4  78.96393 103.660869       116.5
## 30: 130 -0.1623110 0.06063998 5 -21.10043   7.883198       117.5
```

Finally, `data.table` as a useful function named `uniqueN()`, which is pretty much the combination of `unique()` and `length()`—it tells you the number of unique observations for whatever object you feed it.

How many unique values of `d` do we have?

```
# Count the unique values of 'd'
our_dt[,d] %>% uniqueN()
```

```
## [1] 5
```

2.9 Ordering

Last—also in the spirit of `set()` and `setnames()`—you can set the order of rows using `setorder()` and the order of columns using `setcolorder()`.

Let's order the rows of `our_dt` (*arrange*, in the `dplyr` world) by `d` and then by the reverse order (largest to smallest) of `a`:

```
# Order by 'd' and then reversed 'a'
setorder(our_dt, d, -a)
# Check work
our_dt
```

```
##       a          b          c d         ab         ac mean_a_by_d
##  1: 126  1.8050975 0.30503175 1  227.44229  38.434001       113.5
##  2: 121  0.7796219 0.87044788 1   94.33425 105.324194       113.5
##  3: 116  0.8168998 0.61894754 1   94.76038  71.797915       113.5
##  4: 111 -0.1162478 0.68835336 1  -12.90351  76.407223       113.5
##  5: 106 -1.8179560 0.21894784 1 -192.70333  23.208471       113.5
## ---
## 26: 125 -1.5977095 0.14451190 5 -199.71369  18.063988       117.5
```

```
## 27: 120  0.2987237 0.15009821 5   35.84684  18.011785       117.5
## 28: 115 -0.7505320 0.04825135 5  -86.31118   5.548906       117.5
## 29: 110 -0.9193220 0.94643075 5 -101.12542 104.107383       117.5
## 30: 105  0.6058875 0.97977825 5   63.61818 102.876716       117.5
```

Again, there is no <- re-definition—the function does all of the work.

For ordering columns, you give `setcolorder()` the name of the data table and a character vector (or vector of integers for indexes) of the column names in your desired order. Let's re-arrange our columns arbitrarily.

```
# Change column order
setcolorder(our_dt,
  c("a", "ab", "ac", "mean_a_by_d", "b", "c", "d"))
# Check work
our_dt
```

```
##       a         ab         ac mean_a_by_d          b          c d
##  1: 126  227.44229  38.434001       113.5  1.8050975 0.30503175 1
##  2: 121   94.33425 105.324194       113.5  0.7796219 0.87044788 1
##  3: 116   94.76038  71.797915       113.5  0.8168998 0.61894754 1
##  4: 111  -12.90351  76.407223       113.5 -0.1162478 0.68835336 1
##  5: 106 -192.70333  23.208471       113.5 -1.8179560 0.21894784 1
## ---
## 26: 125 -199.71369  18.063988       117.5 -1.5977095 0.14451190 5
## 27: 120   35.84684  18.011785       117.5  0.2987237 0.15009821 5
## 28: 115  -86.31118   5.548906       117.5 -0.7505320 0.04825135 5
## 29: 110 -101.12542 104.107383       117.5 -0.9193220 0.94643075 5
## 30: 105   63.61818 102.876716       117.5  0.6058875 0.97977825 5
```

Note that if you forget names, the function does not work.

2.10 More?

We're only scratching the surface of the `data.table` package. The package also includes really efficient joins/merges (see `?data.table::merge`). The `merge()` function has some cool properties—left joins, right joins, cartesian products, *etc.*—and you are also able to run rolling joins (using a different notation), which are awesome. Want more? You can add `leads` and `lags` easily with `shift()`, and the package includes `fread()` function for *fast reading* (though I think `readr` is a bit more stable and at least as fast, in general). And there are still more features.

`data.table` provides a number of great resources for learning:

- DataCamp
- Introduction vignette
- Frequently asked questions regarding `data.table`
- More vignettes

I'm also happy to chat if you have questions, and I like coffee.[5]

[5] Wink, wink.

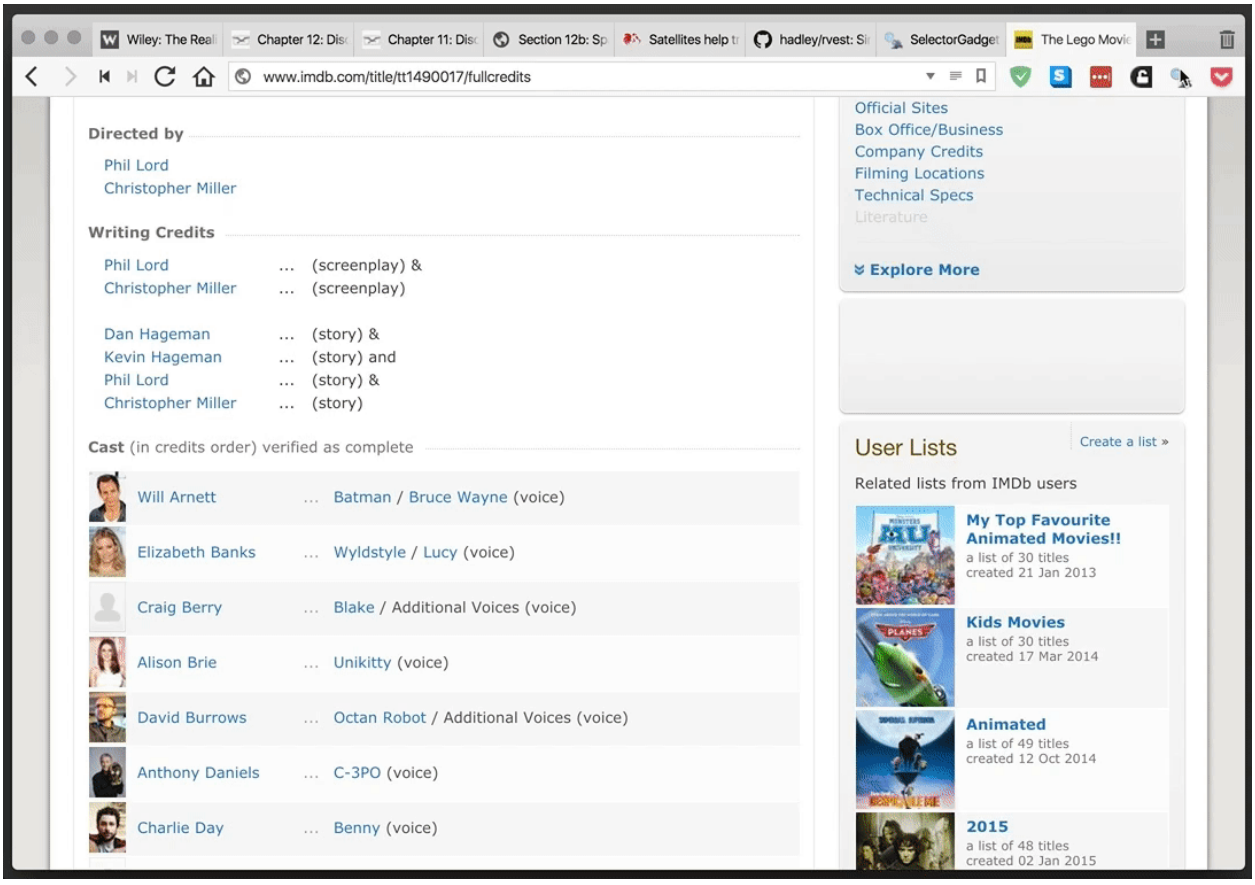
3 Other nice tools for R

Here are a few more nice tools for R/research.

- New documentation website for `ggplot2`!
- A nicer way to read/search R's documentation files.
- For administrative boundary shapefiles—includes `.rds` format for reading straight into R!

4 Fun tools: SelectorGadget and `rvest`

`rvest` provides a simple and powerful package for webscraping in R. SelectorGadget provides an even more simple—and yet tremendously helpful—browser extension for finding CSS and xpath selectors. They make a great team.



SelectorGadget in action: selecting the table of cast members for The Lego Movie from IMDB.

Bonus feature: Vivalid is a vastly customizable browser providing tab management and a host of other features not common to many other browsers.