

Quantitative social science with R

Get and manipulate data

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Outline

1. Import data

- .CSV
- .excel

2. Types of data

- factors
- strings
- dates

3. Manipulate data

- dplyr
- tidyr



Import data into R

Getting data

- There are two possible ways to input information:
 - **Manually**
 - **Import from somewhere**
- The majority of the analyses consist of data created externally
 - Data are delivered in different **formats**
 - Important to understand how information is **structured**

Step 1: Get started

The first commands consist of the following instructions intended to locate the project in the computer and load the set of functions needed for the analysis

- Working directory

```
# working directory  
setwd("/Users/my-file/my_document")
```

- Packages

```
install.packages() # for installing packages
```

- Library

```
library() # for loading libraries
```

Step 2: Load your data

- Various packages and libraries that allow for this
- Use depends on the type of data to be loaded

Function	Package	Format
<code>read.csv()</code>	base	Comma separated values
<code>read.dta()</code>	foreign	Stata files
<code>import()</code>	rio	All types
<code>read_csv()</code>	readr	Comma separated values
<code>read_xlsx()</code>	readr	Excel type
<code>read_excel()</code>	readxl	Excel files
<code>read_xml()</code>	xml2	XML files

Load data: csv files

- Comma separated files (csv) are quite common
- Values are separated by commas
- Base solution

```
# load data including working directory
my_df = read.csv("data/data_intro_r.csv",
                 sep = ",")

head(my_df)
```

##	location.id	location.region	date	jsa.fem
## 1	1-125058834	East of England	2010-10-01	55
## 2	1-125058834	East of England	2010-12-21	55
## 3	1-125058834	East of England	<NA>	55
## 4	1-125058834	East of England	<NA>	55
## 5	1-118532985	East of England	2010-10-01	40
## 6	1-118532985	East of England	2011-01-06	40

Load data: csv files

- There are other functions: `import()`...

```
# load data including working directory  
library(rio)  
my_df_import = import("data/data_intro_r.csv")  
  
head(my_df_import, 3)
```

```
##      location.id location.region      date jsa.fem  
## 1 1-125058834 East of England 2010-10-01      55  
## 2 1-125058834 East of England 2010-12-21      55  
## 3 1-125058834 East of England      <NA>      55
```

Load data: csv files

- ... and `read_csv()`

```
# load data including working directory
```

```
library(readr)
my_df_readr = read_csv("data/data_intro_r.csv")

head(my_df_readr)
```

```
## # A tibble: 6 x 4
##   location.id location.region      date jsa.fem
##         <chr>         <chr>    <date>   <int>
## 1 1-125058834 East of England 2010-10-01     55
## 2 1-125058834 East of England 2010-12-21     55
## 3 1-125058834 East of England      NA     55
## 4 1-125058834 East of England      NA     55
## 5 1-118532985 East of England 2010-10-01     40
## 6 1-118532985 East of England 2011-01-06     40
```

- Faster
- More flexible to read different types of variable (e.g. dates, times, currencies...)

Load data: excel files

- Excel files have been tedious to parse in R
- `readxl` works very well for this

```
# load data including working directory
```

```
library(readxl)  
my_excel = read_excel("data/r_intro.xlsx")
```

```
head(my_excel, 5)
```

```
## # A tibble: 5 x 13
```

```
##
```

```
`benefit payments - pension
```

```
##
```

```
## 1 ONS Crown Copyright Reserved [from Nomis on 14 September 2016]
```

```
## 2
```

```
## 3
```

```
## 4
```

```
## 5
```

```
## # ... with 12 more variables: X__1 <chr>, X__2 <chr>, X__3 <chr>, X__4 <chr>, X__5 <chr>, X__6 <chr>, X__7 <chr>, X__8 <chr>, X__9 <chr>, X__10 <chr>, X__11 <chr>, X__12 <chr>
```

```
## # X__4 <chr>, X__5 <chr>, X__6 <chr>, X__7 <chr>, X__8 <chr>, X__9 <chr>, X__10 <chr>, X__11 <chr>, X__12 <chr>
```

```
## # X__9 <chr>, X__10 <chr>, X__11 <chr>, X__12 <chr>
```

Load data: excel files

- Refine the information that can be loaded controlling for sheets, rows and columns
 - **sheet names**

```
# name of the sheet
library(readxl)
my_excel = read_excel("data/r_intro.xlsx", sheet
head(my_excel, 3)
```

```
## # A tibble: 3 x 13
##                               `benefit payments - pension
##
## 1 ONS Crown Copyright Reserved [from Nomis on 14 September
## 2
## 3
## # ... with 11 more variables: X__2 <chr>, X__3 <chr>, X__4
## #   X__5 <chr>, X__6 <chr>, X__7 <chr>, X__8 <chr>, X__9
## #   X__10 <chr>, X__11 <chr>, X__12 <chr>
```

Load data: excel files

- Refine the information that can be loaded controlling for sheets, rows and columns
 - **sheet position**

```
# name of the sheet
library(readxl)
my_excel = read_excel("data/r_intro.xlsx", sheet
head(my_excel, 2)
```

```
## # A tibble: 2 x 13
##                               `benefit payments - pension
##
## 1 ONS Crown Copyright Reserved [from Nomis on 14 September
## 2
## # ... with 11 more variables: X__2 <chr>, X__3 <chr>, X__4
## #   X__5 <chr>, X__6 <chr>, X__7 <chr>, X__8 <chr>, X__9
## #   X__10 <chr>, X__11 <chr>, X__12 <chr>
```

Load data: excel files

- Refine the information that can be loaded controlling for sheets, rows and columns
 - **rows**

```
# rows
library(readxl)
my_excel_clean = read_excel("data/r_intro.xlsx",
head(my_excel_clean, 3)
```

```
## # A tibble: 3 x 13
##
##
## 1 local authority: district / unitary (prior to April 2015)
## 2
## 3
## # ... with 11 more variables: X__3 <chr>, X__4 <chr>, X__5 <chr>,
## #   X__6 <chr>, X__7 <chr>, X__8 <chr>, X__9 <chr>, X__10 <chr>,
## #   X__11 <chr>, X__12 <chr>, X__13 <chr>
```

Load data: excel files

- Refine the information that can be loaded controlling for sheets, rows and columns
 - **columns**

```
library(readxl)
```

```
# columns
```

```
my_excel_clean_cols = read_excel("data/r_intro.xls")
```

```
head(my_excel_clean_cols, 3)
```

```
## # A tibble: 3 x 10
```

```
##   `August 2014` `November 2014` `February 2015` `May 2015`
```

```
##           <dbl>           <dbl>           <dbl>           <dbl>
```

```
## 1           2900           2860           2790           2790
```

```
## 2           6210           6150           6010           5980
```

```
## 3           4580           4530           4430           4430
```

```
## # ... with 5 more variables: `November 2015` <dbl>, `February 2016`
```

```
## #   `May 2016` <dbl>, `August 2016` <dbl>, `November 2016` <dbl>
```

Load data: excel files

- Refine the information that can be loaded controlling for sheets, rows and columns
 - **range**

```
library(readxl)
```

```
# range
```

```
my_excel_clean_range = read_excel("data/r_intro.x
```

```
head(my_excel_clean_range, 3)
```

```
## # A tibble: 3 x 13
```

```
##   `local authority: district / unitary (prior to April
```

```
##
```

```
## 1
```

```
## 2
```

```
## 3
```

```
## # ... with 11 more variables: `August 2014` <dbl>, `No
```

```
## #   `February 2015` <dbl>, `May 2015` <dbl>, `August 20
```

```
## #   `November 2015` <dbl>, `February 2016` <dbl>, `May
```

```
## #   `August 2016` <dbl>, `November 2016` <dbl>, `Febru
```


Exercise

Load information corresponding to 2015

##	#	A tibble: 6 x 4			
##		`February 2015`	`May 2015`	`August 2015`	`November 2015`
##		<dbl>	<dbl>	<dbl>	<dbl>
##	1	2790	2690	2640	2640
##	2	6010	5760	5670	5670
##	3	4430	4260	4210	4210
##	4	4530	4330	4270	4270
##	5	4950	4740	4670	4670
##	6	1740	1660	1640	1640

Types of data

factors

Data types: factors

- **Factors** refer to variables that represent different categories: gender, labour status, being treated or not, etc...
- What do we mean by categories?
 - fixed and known set of possible values
 - order in some cases



MySchizoBuddy commented on May 2, 2015



`col_factor()` requires a known set of factors. It should have a default option of reading the column as a factor without having to know in advance which factors are used in the file.



hadley commented on May 4, 2015

Owner



If you don't know in advance what the possible set of values are, it's not a factor.

Data types: factors

```
##      location.id location.region      date jsa.fem
## 1 1-125058834 East of England 2010-10-01      55
## 2 1-125058834 East of England 2010-12-21      55
## 3 1-125058834 East of England      <NA>      55
## 4 1-125058834 East of England      <NA>      55
## 5 1-118532985 East of England 2010-10-01      40
## 6 1-118532985 East of England 2011-01-06      40
## 7 1-118532985 East of England      <NA>      40
```

Data types: factors

```
glimpse(my_data)
```

```
## Observations: 97,416
```

```
## Variables: 4
```

```
## $ location.id      <chr> "1-125058834", "1-125058834", "
```

```
## $ location.region  <chr> "East of England", "East of Eng
```

```
## $ date             <date> 2010-10-01, 2010-12-21, NA, NA
```

```
## $ jsa.fem          <int> 55, 55, 55, 55, 40, 40, 40, 40
```

Data types: factors

- How can we transform characters into factors?
- Base solution: combination of `$` and `as.factor()`

```
my_data$location.id = as.factor(my_data$location.  
glimpse(my_data)
```

```
## Observations: 97,416  
## Variables: 4  
## $ location.id      <fctr> 1-125058834, 1-125058834, 1-125058834,  
## $ location.region  <chr> "East of England", "East of England",  
## $ date             <date> 2010-10-01, 2010-12-21, NA, NA,  
## $ jsa.fem          <int> 55, 55, 55, 55, 40, 40, 40, 40
```

- We will see other alternatives further on

Data types: factors

- The categories of the factor can be retrieve with `levels()`
- *What are the regions of the locations?*

```
# transform into a factor
my_data$location.region = as.factor(my_data$location)

# get level
levels(my_data$location.region)
```

```
##      [1] "East Midlands"          "East of England"
##      [3] "London"                 "North East"
##      [5] "North West"             "South East"
##      [7] "South West"             "Unspecified"
##      [9] "West Midlands"          "Yorkshire and The Huml"
```

Data types: factors

- Levels can be renamed
- *Define "Unspecified" as "no_name"*

```
library(forcats)

# transform into a factor
my_data$location.region = as.factor(my_data$location.region)

# get region levels
regions = levels(my_data$location.region)

fct_recode(regions, no_name = "Unspecified")
```

```
##   [1] East Midlands      East of England
##   [3] London             North East
##   [5] North West         South East
##   [7] South West         no_name
##   [9] West Midlands      Yorkshire and The Humber
##  10 Levels: East Midlands East of England London North
```


Data types: factors

- Levels can be summarised
- *How many observations do we have in each region?*

```
table(my_data$location.region)
```

```
##
##           East Midlands           East of England
##                9100                10180
##           North East           North West
##                5560                11508
##           South West           Unspecified
##                12928                16
## Yorkshire and The Humber
##                9188
```

Exercise

Create a variable called `regions.recoded` where "Unspecified" regions are recoded as "No Name"

```
##      location.id location.region      date jsa.fem region
## 1 1-125058834 East of England 2010-10-01      55 East of
## 2 1-125058834 East of England 2010-12-21      55 East of
## 3 1-125058834 East of England      <NA>      55 East of
## 4 1-125058834 East of England      <NA>      55 East of
## 5 1-118532985 East of England 2010-10-01      40 East of
## 6 1-118532985 East of England 2011-01-06      40 East of

##
##      East Midlands      East of England
##      9100      10180
##      North East      North West
##      5560      11508
##      South West      No name
##      12928      16
## Yorkshire and The Humber
##      9188
```

Types of data

strings

Data types: strings

- Text can be analysed as data
- Text data are becoming more frequent: tweets, reviews, news...
- Text may appear in your data
 - remove a given character in the names of your variables
 - replace a given character in your data
 - extract a given character in your data

Data types: strings

- Strings can be manipulated in multiple ways
- **stringr** package is a complete tool

Function	Description
str_c()	string concatenation
str_length()	number of characters
str_sub()	extracts substrings
str_dup()	duplicates characters
str_trim()	removes leading and trailing whitespace pads a string

Source: *"Handling and Processing Strings in R"* (Sánchez, 2014)

Data types: strings

- Create a new variable that includes a particular string to a variable - for example "region_"
- Make it lower case

```
library(stringr)
```

```
# transform and add the string
```

```
my_data$new_region = str_c("region", my_data$locat
```

```
# make it lower
```

```
my_data$new_region = tolower(my_data$new_region)
```

```
head(my_data$new_region)
```

```
## [1] "region_east of england" "region_east of england"  
## [3] "region_east of england" "region_east of england"  
## [5] "region_east of england" "region_east of england"
```

Data types: strings

```
glimpse(my_data)
```

```
## Observations: 97,416
## Variables: 6
## $ location.id      <fctr> 1-125058834, 1-125058834, 1-125058834, ...
## $ location.region   <fctr> East of England, East of England, East of Engl...
## $ date              <date> 2010-10-01, 2010-12-21, NA, NA, NA, NA, NA, NA, NA, NA, ...
## $ jsa.fem           <int> 55, 55, 55, 55, 40, 40, 40, 40, 40, 40, 40, 40, 40, 40, 40, 40, ...
## $ regions.recoded    <fctr> East of England, East of England, East of England, East of Engla...
## $ new_region         <chr> "region_east of england", "region_east of england", "region_east of england", ...
```

Data types: strings

- Extract region_ from the variable new_region

```
library(stringr)
```

```
my_data$new_region2 = str_sub(my_data$new_region,  
head(my_data$new_region2, 10)
```

```
## [1] "region_" "region_" "region_" "region_" "region_"  
## [8] "region_" "region_" "region_"
```

- Drop "_" from new_region variable

```
library(stringr)
```

```
my_data$new_region2 = gsub("_", " ", my_data$new_  
head(my_data$new_region2)
```

```
## [1] "region east of england" "region east of england"  
## [3] "region east of england" "region east of england"  
## [5] "region east of england" "region east of england"
```


Data types: strings

- Identify those observations whose region contains the word East

```
my_data$region.east = str_detect(my_data$location,  
table(my_data$region.east))
```

```
##  
## FALSE TRUE  
## 54164 43252
```

- Extract East from the names of the regions

```
my_data$region.east2 = as.factor(str_extract(my_d  
summary(my_data$region.east2))
```

```
## East NA's  
## 43252 54164
```

Types of data

dates and times

Data types: dates and times

- Dates can be considered differently depending on various issues
 - is there information on time? "2002-06-09 12:45:40"
 - does it have time zones? (POSIXct and POSIXlt classes)

```
dates <- c("02/27/92", "02/27/92", "01/14/92", "01/14/92")
times <- c("23:03:20", "22:29:56", "01:03:30", "01:03:30")
x <- data.frame(dates, times, dates_times = paste(dates, times))
```

- **lubridate** allows for great flexibility when dealing with both types of data.

Data types: dates

- Transform to date format: `mdy_hms()`

```
library(lubridate)
str(x)
```

```
## 'data.frame':    5 obs. of  3 variables:
## $ dates          : Factor w/ 4 levels "01/14/92","02/01/92","02/01/92","02/01/92": 1 2 3 4
## $ times          : Factor w/ 5 levels "01:03:30","16:56:20","16:56:20","16:56:20","16:56:20": 1 2 3 4 5
## $ dates_times    : Factor w/ 5 levels "01/14/92 01:03:30","02/01/92 01:03:30","02/01/92 16:56:20","02/01/92 16:56:20","02/01/92 16:56:20": 1 2 3 4 5
```

```
# transform to "date format"
```

```
x$new_datetime = mdy_hms(x$dates_times)
str(x)
```

```
## 'data.frame':    5 obs. of  4 variables:
## $ dates          : Factor w/ 4 levels "01/14/92","02/01/92","02/01/92","02/01/92": 1 2 3 4
## $ times          : Factor w/ 5 levels "01:03:30","16:56:20","16:56:20","16:56:20","16:56:20": 1 2 3 4 5
## $ dates_times    : Factor w/ 5 levels "01/14/92 01:03:30","02/01/92 01:03:30","02/01/92 16:56:20","02/01/92 16:56:20","02/01/92 16:56:20": 1 2 3 4 5
## $ new_datetime   : POSIXct, format: "1992-02-27 23:03:20" "1992-02-27 23:03:20" "1992-02-27 23:03:20" "1992-02-27 23:03:20" "1992-02-27 23:03:20"
```

Data types: dates

- Extract relevant information - e.g: *hours, day of the week*

```
library(lubridate)
```

```
# hours
```

```
x$hour = hour(x$new_datetime)
```

```
# week-day to "date format"
```

```
x$weekday = wday(x$new_datetime, label = TRUE)
```

```
x
```

```
##          dates      times      dates_times      new_datet
## 1 02/27/92 23:03:20 02/27/92 23:03:20 1992-02-27 23:03
## 2 02/27/92 22:29:56 02/27/92 22:29:56 1992-02-27 22:29
## 3 01/14/92 01:03:30 01/14/92 01:03:30 1992-01-14 01:03
## 4 02/28/92 18:21:03 02/28/92 18:21:03 1992-02-28 18:21
## 5 02/01/92 16:56:26 02/01/92 16:56:26 1992-02-01 16:56
```

Data types: dates

- Arithmetic operations
 - what's the average date and time?
 - what are the max and min date and time?

```
library(lubridate)
```

```
summary(x$new_datetime)
```

```
##                Min.                1st Qu.
## "1992-01-14 01:03:30" "1992-02-01 16:56:26" "1992-02-21 16:56:26"
##                Mean                3rd Qu.
## "1992-02-13 21:10:51" "1992-02-27 23:03:20" "1992-02-28 23:03:20"
```

Manipulation of data

`dplyr` and `tidyr`

Data manipulation: dplyr

- **dplyr** is the backbone of the grammar for data manipulation
- Compatibility with the pipes: **%>%**
- Main functions associated with different tasks

Function	Description
mutate()	adds new variables that are functions of existing variables
select()	picks variables based on their names.
filter()	picks cases based on their values.
summarise()	reduces multiple values down to a single summary.
arrange()	changes the ordering of the rows.

Source: tidyverse

Data manipulation: dplyr

- Working example
 - create a variable that reflects the level of female unemployment in the region of the location. Less than 30 claimants is below the average, 30-35 is in the average and more than 35 is above the average.

```
library(rio)
library(dplyr)

my_data = import("data/data_intro_r.csv")

my_data = my_data %>% mutate(unemp_level = ifelse(
  jsa.fem < 30, "below",
  ifelse(jsa.fem >= 30 & jsa.fem <= 35, "average",
  ifelse(jsa.fem > 35, "above", NA)))

head(my_data, 4)
```

##	location.id	location.region	date	jsa.fem	unemp.
## 1	1-125058834	East of England	2010-10-01	55	
## 2	1-125058834	East of England	2010-12-21	55	
## 3	1-125058834	East of England	<NA>	55	
## 4	1-125058834	East of England	<NA>	55	

Data manipulation: dplyr

- Select locations in the South East and South West and order by date.

```
library(dplyr)

regions_south = c("South East", "South West")

my_data_south = my_data %>%
  filter(location.region %in% regions_south) %>%
  arrange(date)

head(my_data_south, 7)
```

##	location.id	location.region	date	jsa.fem	unemp.
## 1	RX229	South East	2010-04-01	10	
## 2	RX2Y5	South East	2010-04-01	25	
## 3	RXXDL	South East	2010-04-01	10	
## 4	RXXDM	South East	2010-04-01	10	
## 5	RXXY3	South East	2010-04-01	10	
## 6	RXXEC	South East	2010-04-01	30	
## 7	RXXY2	South East	2010-04-01	5	

Data manipulation: dplyr

- What's the average, max and min number of claimants in each region?

```
sum_jsa = my_data %>%  
  group_by(location.region) %>%  
  summarise(mean_jsa = mean(jsa.fem),  
            min_jsa = min(jsa.fem),  
            max_jsa = max(jsa.fem))
```

```
sum_jsa
```

```
## # A tibble: 10 x 4  
##       location.region mean_jsa min_jsa max_jsa  
##       <chr>         <dbl>   <dbl>   <dbl>  
## 1      East Midlands 38.54505     0    200  
## 2    East of England 33.36542     0    250  
## 3         London 42.06765     0    160  
## 4      North East 51.70144     0    265  
## 5      North West 39.80883     0    320  
## 6      South East 26.16772     0    375  
## 7      South West 27.69028     0    210  
## 8      Unspecified 13.75000     5     25  
## 9      West Midlands 43.99924     0    235  
## 10 Yorkshire and The Humber 45.05660     0    270
```

Data manipulation: dplyr

```
sum_jsa = my_data %>%  
  group_by(location.region) %>%  
  summarise(mean_jsa = mean(jsa.fem),  
            min_jsa = min(jsa.fem),  
            max_jsa = max(jsa.fem)) %>%  
  filter(location.region != "Unspecified")  
  
sum_jsa
```

```
## # A tibble: 9 x 4  
##       location.region mean_jsa min_jsa max_jsa  
##       <chr>         <dbl>   <dbl>   <dbl>  
## 1      East Midlands 38.54505     0    200  
## 2   East of England 33.36542     0    250  
## 3         London 42.06765     0    160  
## 4     North East 51.70144     0    265  
## 5     North West 39.80883     0    320  
## 6     South East 26.16772     0    375  
## 7     South West 27.69028     0    210  
## 8     West Midlands 43.99924     0    235  
## 9 Yorkshire and The Humber 45.05660     0    270
```

Data manipulation: dplyr

- Change the types of variables

```
glimpse(my_data)
```

```
## Observations: 97,416
## Variables: 5
## $ location.id      <chr> "1-125058834", "1-125058834",
## $ location.region  <chr> "East of England", "East of En
## $ date             <chr> "2010-10-01", "2010-12-21", NA
## $ jsa.fem          <int> 55, 55, 55, 55, 40, 40, 40, 40
## $ unemp_level      <chr> "high", "high", "high", "high"
```

- `location.region` and `unemp_level` are represent categories. `date` represents dates.

```
my_data = my_data %>%
  mutate_at(vars(location.region, unemp_level), f
  mutate_at(vars(date), funs(as.Date)))
```

Data manipulation: dplyr

```
glimpse(my_data)
```

```
## Observations: 97,416
## Variables: 5
## $ location.id      <chr> "1-125058834", "1-125058834",
## $ location.region  <fctr> East of England, East of Engl
## $ date             <date> 2010-10-01, 2010-12-21, NA, NA
## $ jsa.fem          <int> 55, 55, 55, 55, 40, 40, 40, 40
## $ unemp_level      <fctr> high, high, high, high, high,
```

Data manipulation: dplyr

- `dplyr` has functions for linking datasets

Function	Description
<code>inner_join()</code>	return all rows from x where there are matching values in y, and all columns from x and y
<code>left_join()</code>	return all rows from x, and all columns from x and y
<code>right_join()</code>	return all rows from y, and all columns from x and y
<code>semi_join()</code>	return all rows from x where there are matching values in y, keeping just columns from x
<code>anti_join()</code>	return all rows from x where there are not matching values in y, keeping just columns from x
<code>full_join()</code>	return all rows and all columns from both x and y

Data manipulation: dplyr

- Linking two datasets

```
library(dplyr)
library(rio)

d1 = import("data/pop_link.csv")
d2 = import("data/claim_link.csv")
```


Data manipulation: dplyr

```
glimpse(d1)
```

```
## Observations: 326
## Variables: 8
## $ `Local Authority` <chr> "Babergh", "Basildon", "Bedf
## $ oslaua <chr> "E07000200", "E07000066", "E
## $ `All Ages` <int> 88845, 180521, 163924, 14998
## $ `Aged 65-69` <int> 6947, 9808, 8600, 9443, 9917
## $ `Aged 70-74` <int> 5045, 6816, 6223, 6461, 7249
## $ `Aged 75-79` <int> 3907, 5850, 5177, 4864, 5977
## $ `Aged 80-84` <int> 2856, 4493, 4000, 3561, 4358
## $ `Aged 85+` <int> 2961, 3844, 3910, 3886, 4225
```

```
glimpse(d2)
```

```
## Observations: 326
## Variables: 6
## $ `Local Authority` <chr> "Babergh", "Basildon", "Bedf
## $ code_la <chr> "E07000200", "E07000066", "E
## $ `2014` <int> 88845, 180521, 163924, 14998
## $ `2015` <int> 88990, 181859, 166167, 15094
## $ `2016` <int> 89237, 183308, 168303, 15197
## $ `2017` <int> 89549, 184789, 170394, 15303
```

Data manipulation: dplyr

- Add information from d2 to d1

```
new_data = left_join(d1, d2, by = c("Local Authority"  
glimpse(new_data)
```

```
## Observations: 326  
## Variables: 13  
## $ `Local Authority` <chr> "Babergh", "Basildon", "Bedf  
## $ oslaia <chr> "E07000200", "E07000066", "E  
## $ `All Ages` <int> 88845, 180521, 163924, 14998  
## $ `Aged 65-69` <int> 6947, 9808, 8600, 9443, 9917  
## $ `Aged 70-74` <int> 5045, 6816, 6223, 6461, 7249  
## $ `Aged 75-79` <int> 3907, 5850, 5177, 4864, 5977  
## $ `Aged 80-84` <int> 2856, 4493, 4000, 3561, 4358  
## $ `Aged 85+` <int> 2961, 3844, 3910, 3886, 4225  
## $ code_la <chr> "E07000200", "E07000066", "E  
## $ `2014` <int> 88845, 180521, 163924, 14998  
## $ `2015` <int> 88990, 181859, 166167, 15094  
## $ `2016` <int> 89237, 183308, 168303, 15197  
## $ `2017` <int> 89549, 184789, 170394, 15303
```

Data manipulation: dplyr

- Add information from d2 to d1

```
new_data = left_join(d1, d2,  
                     by = c("Local Authority" = "  
                           "oslaua" = "c  
  
glimpse(new_data)
```

```
## Observations: 326  
## Variables: 12  
## $ `Local Authority` <chr> "Babergh", "Basildon", "Bedf  
## $ oslaua <chr> "E07000200", "E07000066", "E  
## $ `All Ages` <int> 88845, 180521, 163924, 14998  
## $ `Aged 65-69` <int> 6947, 9808, 8600, 9443, 9917  
## $ `Aged 70-74` <int> 5045, 6816, 6223, 6461, 7249  
## $ `Aged 75-79` <int> 3907, 5850, 5177, 4864, 5977  
## $ `Aged 80-84` <int> 2856, 4493, 4000, 3561, 4358  
## $ `Aged 85+` <int> 2961, 3844, 3910, 3886, 4225  
## $ `2014` <int> 88845, 180521, 163924, 14998  
## $ `2015` <int> 88990, 181859, 166167, 15094  
## $ `2016` <int> 89237, 183308, 168303, 15197  
## $ `2017` <int> 89549, 184789, 170394, 15303
```

Data manipulation: tidyr

- **Tidyr** is helpful for creating **tidy datasets**
 - each variable is in a column
 - each observation is in a row
 - each value in a cell.
- Useful for reshaping data from wide to long formats and also for visualisations
 - `gather()`: it makes “wide” data longer
 - `spread()`: it makes “long” data wider

Data manipulation: tidyr

- Working example
 - transform a wide data frame into a long

```
library(rio)
library(tidyr)
library(dplyr)

d1 = import("data/pop_link.csv")

head(d1)
```

```
##   Local Authority      oslaue All Ages Aged 65-69 Aged 70+
## 1      Babergh E07000200    88845    6947      5
## 2      Basildon E07000066   180521    9808      0
## 3      Bedford E06000055   163924    8600      0
## 4      Braintree E07000067   149985    9443      0
## 5      Breckland E07000143   133986    9917      7
## 6      Brentwood E07000068    75645    4464      3
##   Aged 80-84 Aged 85+
## 1      2856    2961
## 2      4493    3844
## 3      4000    3910
## 4      3561    3886
## 5      4358    4225
## 6      2368    2361
```

Data manipulation: tidyr

```
d1 %>% gather(age, number, `All Ages`: `Aged 85+`
```

##	Local Authority	oslaua	age
## 1	Babergh	E07000200	All Ages
## 2	Basildon	E07000066	All Ages
## 3	Bedford	E06000055	All Ages
## 4	Braintree	E07000067	All Ages
## 5	Breckland	E07000143	All Ages
## 6	Brentwood	E07000068	All Ages
## 7	Broadland	E07000144	All Ages
## 8	Broxbourne	E07000095	All Ages
## 9	Cambridge	E07000008	All Ages
## 10	Castle Point	E07000069	All Ages
## 11	Central Bedfordshire	E06000056	All Ages
## 12	Chelmsford	E07000070	All Ages
## 13	Colchester	E07000071	All Ages
## 14	Dacorum	E07000096	All Ages
## 15	East Cambridgeshire	E07000009	All Ages
## 16	East Hertfordshire	E07000242	All Ages
## 17	Epping Forest	E07000072	All Ages
## 18	Fenland	E07000010	All Ages
## 19	Forest Heath	E07000201	All Ages
## 20	Great Yarmouth	E07000145	All Ages
## 21	Harlow	E07000073	All Ages
## 22	Hertsmere	E07000098	All Ages
## 23	Huntingdonshire	E07000011	All Ages
## 24	Ipswich	E07000202	All Ages
## 25	King's Lynn and West Norfolk	E07000146	All Ages
## 26	Luton	E06000032	All Ages
## 27	Maldon	E07000074	All Ages
## 28	Mid Suffolk	E07000203	All Ages
## 29	North Hertfordshire	E07000099	All Ages
## 30	North Norfolk	E07000147	All Ages
## 31	Norwich	E07000148	All Ages
## 32	Peterborough	E06000031	All Ages

Data manipulation: tidyr

- tidyr and dplyr

```
d1 %>% gather(age, number, `All Ages`: `Aged 85+`  
  arrange(`Local Authority`))
```

##	Local Authority	oslaua	age
## 1	Adur	E07000223	All Ages
## 2	Adur	E07000223	Aged 65-69
## 3	Adur	E07000223	Aged 70-74
## 4	Adur	E07000223	Aged 75-79
## 5	Adur	E07000223	Aged 80-84
## 6	Adur	E07000223	Aged 85+
## 7	Allerdale	E07000026	All Ages
## 8	Allerdale	E07000026	Aged 65-69
## 9	Allerdale	E07000026	Aged 70-74
## 10	Allerdale	E07000026	Aged 75-79
## 11	Allerdale	E07000026	Aged 80-84
## 12	Allerdale	E07000026	Aged 85+
## 13	Amber Valley	E07000032	All Ages
## 14	Amber Valley	E07000032	Aged 65-69
## 15	Amber Valley	E07000032	Aged 70-74
## 16	Amber Valley	E07000032	Aged 75-79
## 17	Amber Valley	E07000032	Aged 80-84
## 18	Amber Valley	E07000032	Aged 85+
## 19	Arun	E07000224	All Ages
## 20	Arun	E07000224	Aged 65-69
## 21	Arun	E07000224	Aged 70-74
## 22	Arun	E07000224	Aged 75-79
## 23	Arun	E07000224	Aged 80-84
## 24	Arun	E07000224	Aged 85+
## 25	Ashfield	E07000170	All Ages
## 26	Ashfield	E07000170	Aged 65-69
## 27	Ashfield	E07000170	Aged 70-74
## 28	Ashfield	E07000170	Aged 75-79
## 29	Ashfield	E07000170	Aged 80-84

Exercise

- Create a data frame that contains information on the district regarding the number of inhabitants associated with each age range and the information corresponding to each year

##	Local Authority	oslaua	age	number	year	cla
## 1	Adur	E07000223	All Ages	63176	2014	
## 2	Adur	E07000223	All Ages	63176	2015	
## 3	Adur	E07000223	All Ages	63176	2016	
## 4	Adur	E07000223	All Ages	63176	2017	
## 5	Adur	E07000223	Aged 65-69	4310	2014	
## 6	Adur	E07000223	Aged 65-69	4310	2015	

Exercise

```
new_df_long = new_data %>%
  select(oslaua, `2014`:`2017`) %>%
  gather(year, claimants, `2014`:`2017`)

d1_long = d1 %>% gather(age, number, `All Ages`:
  arrange(`Local Authority`)

exercise = left_join(d1_long, new_df_long, by = "
head(exercise)
```

##	Local Authority	oslaua	age	number	year	cla
## 1	Adur	E07000223	All Ages	63176	2014	
## 2	Adur	E07000223	All Ages	63176	2015	
## 3	Adur	E07000223	All Ages	63176	2016	
## 4	Adur	E07000223	All Ages	63176	2017	
## 5	Adur	E07000223	Aged 65-69	4310	2014	
## 6	Adur	E07000223	Aged 65-69	4310	2015	

Thanks!

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