MPP-E1180 Lecture 7: Web Scraping + Transforms

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Objectives for the week

- Assignments
- Review
- Intro to web scraping
- Processing strings, including an intro to regular expressions
- Data and data set transformations with dplyr

Assignment 2

I have marked Assignment 2 and aim to email you the feedback later this week.

Overall, everyone has made a **good first start**.

Minor: checkout these posts on GitHub:

- Problems compiling PDF: SyllabusAndLectures/issues/19
- Double spacing in R Markdown: SyllabusAndLectures/issues/20

Assignment 3

Purpose: Gather, clean, and analyse data

Deadline: 14 November 2015

You will submit a GitHub repo that:

- Gathers web-based data from at least **two sources**. Cleans and merges the data so that it is ready for statistical analyses.
- Conducts basic descriptive **and** inferential statistics with the data to address a relevant research question.
- Briefly describes the results including with **dynamically** generated tables and figures.
- Has a write up of **1,500 words maximum** that describes the data gathering and analysis, It also will use literate programming.

Assignment 3

This is ideally a **good first run** at the data gathering and analysis parts of your final project.

Review

What is open public data?

- Name one challenge and one opportunity presented by open public data.

What is a data API?

What are the characteristics of tidy data?

Why are unique observation IDs so important for data cleaning?

Caveat to Web scraping

I don't expect you to master the tools of web scraping in this course.

I just want you to know that these things are **possible**, so that you **know where to look** in future work.

Web scraping

Web scraping simply means gathering data from websites.

Last class we learned a particular form of web scraping: downloading explicitly structured data files/data APIs.

You can also download information that is not as well structured for statistical analysis:

- HTML tables
- Text on websites
- Information that requires you to navigate through web forms

To really master web scraping you need a good knowledge of HTML.

Key tools

The most basic tools for web scraping in R:

- httr: gather data + simple parsing
- XML: more advanced parsing
    - Parsing: the analysis of HTML (and other) markup so that each element is syntactically related in a **parse tree**.

Also take a look at rvest. It is a new package that aims to implement features from Python's popular Beautiful Soup.

Key steps:

1. **Look at** the HTML for the webpage you want to scrape (use Inspect Element in Chrome).
2. **Request** a URL with `GET`.
3. **Extract** the content from the request with `content`.
   - You can extract either the raw text with `as = 'text'` or parse the content with `as = 'parsed'`.
4. **Clean** content (there are many tools for this suited to a variety of problems).

Web scraping example

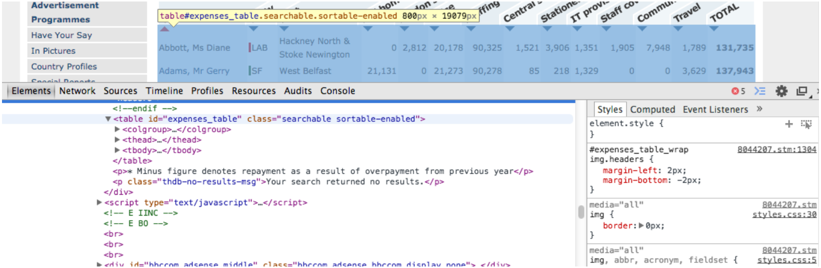
Scrape BBC's MP's Expenses table.

HTML markup marks tables using `<table>` tags.

We can use these to extract tabular information and convert them into data frames.

In particular, we want the table tag with the id `expenses_table`.

Viewing the web pages source



Web scraping example

```
library(httr)
library(dplyr)
library(XML)

URL <- 'http://news.bbc.co.uk/2/hi/uk_news/politics/804420

# Get and parse all tables on the webpage
tables <- URL %>% GET() %>%
            content(as = 'parsed') %>%
            readHTMLTable()

names(tables)
```

```
## [1] "NULL"            "NULL"            "NULL"
## [5] "expenses_table" "NULL"            "NULL"
```

Web scraping example

Now we just need to subset the *tables* list for the `expenses_table` data frame.

```
ExpensesTable <- tables[[5]]

head(ExpensesTable)[, 1:3]
```

```
##                         MP Party
## 1        Abbott, Ms Diane   LAB      Hackney North & Stok
## 2         Adams, Mr Gerry    SF                         W
## 3           Afriyie, Adam   CON
## 4            Ainger, Nick   LAB Carmarthen West & Pembroke
## 5    Ainsworth, Mr Peter   CON
## 6 Ainsworth, Rt Hon Bob   LAB                  Coventry
```

Processing strings

A (frustratingly) large proportion of time web scraping and doing data cleaning generally is taken up with **processing strings**.

Key tools for processing strings:

- knowing your encoding and `iconv` function in base R
- `grep`, `gsub`, and related functions in base R
- Regular expressions
- stringr package

Character encoding: Motivation

Sometimes when you load text into R you will get weird symbols like (the replacement character) or other strange things will happen to the text.

NOTE: remember to always check your data when you import it!

This often happens when R is using the **wrong character encoding**.

Character encoding

All characters in a computer are **encoded** using some standardised system.

R can recognise latin1 and UTF-8.

- latin1 is fairly limited (mostly to the latin alphabet)
- UTF-8 covers a much wider range of characters in many languages

You may need to use the `iconv` function to convert a text to UTF-8 before trying to process it.

`grep`, `gsub`, and related functions

R (and many programming languages) have functions for **identifying** and **manipulating** strings.

Matching

You can use grep and grepl to find patterns in a vector.

```
pets <- c('cats', 'dogs', 'a big snake')

grep(pattern = 'cat', x = pets)
```

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

```
grepl(pattern = 'cat', pets)
```

```
## [1]  TRUE FALSE FALSE
```

```
# Subset vector
pets[grep('cats', pets)]
```

```
## [1] "cats"
```

Terminology

grep stands for: **G**lobally search a **R**egular **E**xpression and **P**rint

Manipulation

Use gsub to substitute strings.

```
gsub(pattern = 'big', replacement = 'small', x = pets)
```

```
## [1] "cats"              "dogs"              "a small snake"
```

Regular expressions

Regular expressions are a powerful tool for finding and manipulating strings.

They are special characters that can be used to search for text.

For example:

- find characters at only the beginning or end of a string
- find characters that follow or are preceded by a particular character
- find only the first or last occurrence of a character in a string

Many more possibilities.

Regular expressions examples

Examples modified from Robin Lovelace.

```
base <- c("cat16_24", "25_34cat", "35_44catch",
          "45_54Cat", "55_4fat$", 'colour', 'color')

## Find only all 'cat' regardles of case
grep('cat', base, ignore.case = T)
```

```
## [1] 1 2 3 4
```

Regular expressions examples

```
# Find only 'cat' at the end of the string with $
grep('cat$', base)
```

```
## [1] 2
```

```
# Find only 'cat' at the begining of the string with ^
grep('^cat', base)
```

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

Regular expressions examples

```
# Find zero or one of the preceeding character with ?
grep('colou?r', base)
```

```
## [1] 6 7
```

```
# Find one or more of the preceeding character with +
grep('colou+r', base)
```

```
## [1] 6
```

```
# Find '$' with the escape character \
grep('\\$', base)
```

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

Regular expressions examples

```
# Find string with any single character between 'c' and 'l
grep('c.l', base)
```

```
## [1] 6 7
```

```
# Find a range of numbers with [ - ]
grep('[1-3]', base)
```

```
## [1] 1 2 3
```

```
# Find capital letters
grep('[A-Z]', base)
```

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

Simple regular expressions cheatsheet

Character	Use
`$`	characters at the end of the string
`^`	characters at the beginning of the string
`?`	zero or more of the preceding character
`*`	zero or more of the preceding character
`+`	one or more of the preceding character
`\`	escape character use to find strings that are expressions
`.`	any single character
`[ - ]`	a range of characters

Simple regular expressions cheatsheet

You can also find the cheat-sheet at:
SyllabusAndLectures/Lecture7/README

String processing with stringer

The stringr package has many helpful functions that make dealing with strings a bit **easier**.

stringr examples

Remove leading and trailing **whitespace** (this can be a real problem when creating consistent variable values):

```r
library(stringr)

str_trim(' hello   ')
```

```
## [1] "hello"
```

stringr examples

Split strings (really useful for turning 1 variable into 2):

```r
trees <- c('Jomon Sugi', 'Huon Pine')

str_split_fixed(trees, pattern = ' ', n = 2)
```

```
##      [,1]    [,2]
## [1,] "Jomon" "Sugi"
## [2,] "Huon"  "Pine"
```

More data transformations with dplyr

The **dplyr** package has powerful capabilities to manipulate data frames quickly (many of the functions are written in the compiled language C++).

It is also useful for transforming data from **grouped observations**, e.g. countries, households.

dplyr

Set up for examples

```
# Create fake grouped data
library(randomNames)
library(dplyr)
library(tidyr)

people <- randomNames(n = 1000)
people <- sort(rep(people, 4))
year <- rep(2010:2013, 1000)
trend_income <- c(30000, 31000, 32000, 33000)
income <-  replicate(trend_income + rnorm(4, sd = 20000),
                     n = 1000) %>%
            data.frame() %>%
            gather(obs, value, X1:X1000)
income$value[income$value < 0] <- 0
data <- data.frame(people, year, income = income$value)
```

dplyr

```r
head(data)
```

```
##                     people year    income
## 1           Aafedt, Kiana 2010 19952.244
## 2           Aafedt, Kiana 2011 56902.582
## 3           Aafedt, Kiana 2012  1852.227
## 4           Aafedt, Kiana 2013 38193.546
## 5 Abdalla, Christopher 2010     0.000
## 6 Abdalla, Christopher 2011 10124.599
```

Simple dplyr

Select rows

```
higher_income <- filter(data, income > 60000)

head(higher_income)
```

```
##                              people year   income
## 1                   Alarid, Istiaq 2010 88154.13
## 2 Alvarez Valentin, Nyamekye 2011 72603.13
## 3                        An, David 2011 62778.21
## 4                     An, Maleaque 2013 93621.39
## 5                  Anderson, Long 2010 64670.36
## 6                  Angel, Savannah 2012 85927.05
```

Simple dplyr

Select columns

```r
people_income <- select(data, people, income)

# OR

people_income <- select(data, -year)

head(people_income)
```

```
##                   people    income
## 1          Aafedt, Kiana 19952.244
## 2          Aafedt, Kiana 56902.582
## 3          Aafedt, Kiana  1852.227
## 4          Aafedt, Kiana 38193.546
## 5 Abdalla, Christopher     0.000
## 6 Abdalla, Christopher 10124.599
```

dplyr with grouped data

Tell dplyr what the groups are in the data with group_by.

```
group_data <- group_by(data, people)
head(group_data)[1:5, ]
```

```
## Source: local data frame [5 x 3]
## Groups: people
##
##                     people year    income
## 1          Aafedt, Kiana 2010 19952.244
## 2          Aafedt, Kiana 2011 56902.582
## 3          Aafedt, Kiana 2012  1852.227
## 4          Aafedt, Kiana 2013 38193.546
## 5 Abdalla, Christopher 2010     0.000
```

Note: all of the following functions work on **non-grouped data** as well.

dplyr with grouped data

Now that we have declared the data as grouped, we can do operations on each group.

For example, we can extract the highest and lowest income years for each person:

```
min_max_income <- summarize(group_data,
                            min_income = min(income),
                            max_income = max(income))
head(min_max_income)[1:3, ]
```

```
## Source: local data frame [3 x 3]
##
##                  people min_income max_income
## 1         Aafedt, Kiana   1852.227   56902.58
## 2 Abdalla, Christopher      0.000   40540.83
## 3          Adams, Elaine     0.000   29517.42
```

dplyr with grouped data

We can sort the data using `arrange`.

```
# Sort highest income for each person in ascending order
ascending <- arrange(min_max_income, max_income)
head(ascending)[1:3, ]
```

```
## Source: local data frame [3 x 3]
##
##                              people min_income max_income
## 1                   Bluford, Sharad      0.000   14676.98
## 2 Rollins-Niblet, Kawaileolani      0.000   15333.53
## 3                     Moreno, Joana   8884.431   15531.44
```

dplyr with grouped data

Add desc to sort in descending order

```
descending <- arrange(min_max_income, desc(max_income))
head(descending)[1:3, ]
```

```
## Source: local data frame [3 x 3]
##
##                 people min_income max_income
## 1 O'Donnell, Jessie   14340.89  101775.40
## 2  Williams, Joseph   16497.90   98596.13
## 3      An, Maleaque   22941.06   93621.39
```

dplyr with grouped data

`summarize` creates a new data frame with the summarised data.

We can use `mutate` to add new columns to the original data frame.

```
data <- mutate(group_data,
               min_income = min(income),
               max_income = max(income))
head(data)[1:3, ]
```

```
## Source: local data frame [3 x 5]
## Groups: people
##
##          people year    income min_income max_income
## 1 Aafedt, Kiana 2010 19952.244   1852.227   56902.58
## 2 Aafedt, Kiana 2011 56902.582   1852.227   56902.58
## 3 Aafedt, Kiana 2012  1852.227   1852.227   56902.58
```

Seminar: Web scraping and data transformations

Scrape and **clean** the Medal Table from `http://www.bbc.com/sport/winter-olympics/2014/medals/countries`.

- Also, sort by total medals in **descending order**.

Work on **gathering data and cleaning** for **Assignment 3**.