MONASH University

MONASH BUSINESS SCHOOL

ETC3250 Business Analytics: Data Wrangling

Week 7, class 2

Souhaib Ben Taieb, Di Cook

GROUP OF EIGHT AUSTRALIA

Web scraping data

- Example: NBA salaries
- ESPN provides basketball players' salaries for the 2013-2014 season at `http://espn.go.com/nba/salaries`

```
library(XML)
nba <- NULL
for (i in 1:11) {
  temp <- readHTMLTable(
    sprintf("http://espn.go.com/nba/salaries/_/page/%d",i))[[1
  nba <- rbind(nba, temp)
}
```

```
glimpse(nba)
#> Observations: 447
#> Variables: 4
#> $ RK     <fctr> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, RK, 11, 12,
#> $ NAME   <fctr> LeBron James, SF, Mike Conley, PG, Al Horf
#> $ TEAM   <fctr> Cleveland Cavaliers, Memphis Grizzlies, Bos
#> $ SALARY <fctr> $30,963,450, $26,540,100, $26,540,100, $25,
```

Working with strings

```
head(nba$SALARY)

# get rid of $ and , in salaries and convert to numeric:
gsub("[$,]", "", head(as.character(nba$SALARY)))
nba$SALARY <- as.numeric(gsub("[$,]", "",
  as.character(nba$SALARY)))

#> [1] $30,963,450 $26,540,100 $26,540,100 $25,000,000 $24,559
#> 313 Levels: $16,073,140 $16,393,443 $16,663,575 $16,957,900
#> [1] "30963450" "26540100" "26540100" "25000000" "24559380"
#> Warning: NAs introduced by coercion
```

- Where does the warning come from?

Cleaning NBA salaries data: hunting the warning

```
nba %>% filter(is.na(SALARY)) %>% head()
```

```
#>   RK NAME TEAM SALARY
#> 1 RK NAME TEAM     NA
#> 2 RK NAME TEAM     NA
#> 3 RK NAME TEAM     NA
#> 4 RK NAME TEAM     NA
#> 5 RK NAME TEAM     NA
#> 6 RK NAME TEAM     NA
```

- We don't need these rows - delete all of them

```
dim(nba)
nba <- nba[-which(nba$RK=="RK"),]
dim(nba)
```

```
#> [1] 447   4
#> [1] 416   4
```

Cleaning NBA data

- Separate names into first, last, and position

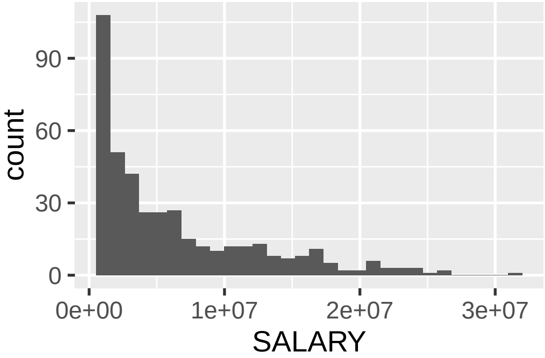
```
nba <- nba %>%
  mutate(NAME = as.character(nba$NAME)) %>%
  separate(NAME, c("full_name", "position"), ",") %>%
  separate(full_name, c("first", "last"), " ")
```

```
#>    RK   first      last position                     TEAM   SAL
#> 1   1  LeBron     James       SF     Cleveland Cavaliers 30963
#> 2   2    Mike    Conley       PG       Memphis Grizzlies 26540
#> 3   3      Al   Horford        C          Boston Celtics 26540
#> 4   4    Dirk Nowitzki       PF        Dallas Mavericks 25000
#> 5   5 Carmelo   Anthony       SF         New York Knicks 24559
#> 6   6  Damian   Lillard       PG Portland Trail Blazers 24328
```

Cleaned data . . . ?

- Numbers might still be wrong, but now we are in a position to check for that.

```
ggplot(data=nba, aes(x=SALARY)) + geom_histogram()
```



Reading different file formats: shapefiles

The Australian Electorate Commission publishes the boundaries of the electorates on their website at `http://www.aec.gov.au/Electorates/gis/gis_datadownload.htm`. Once the files (preferably the national files) are downloaded, unzip the file (it will build a folder with a set of files). We want to read the shapes contained in the `shp` file into R.

```r
library(maptools)

# shapeFile contains the path to the shp file:
shapeFile <- "../data/vic-esri-24122010/vic 24122010.shp"
sF <- readShapeSpatial(shapeFile)
class(sF)
#> [1] "SpatialPolygonsDataFrame"
#> attr(,"package")
#> [1] "sp"
```

sF is a spatial data frame containing all of the polygons. We use the rmapshaper package available from ateucher's github page to thin the polygons while preserving the geography:

```
library(rmapshaper)
```

```
sFsmall <- ms_simplify(sF, keep=0.05) # use instead of thinned
```

`keep` indicates the percentage of points we want to keep in the polygons. 5% makes the electorate boundary still quite recognizable, but reduce the overall size of the map considerably, making it faster to plot.

We can use base graphics to plot this map:

```
plot(sFsmall)
```

Extracting the electorate information

A spatial polygons data frame consists of both a data set with information on each of the entities (in this case, electorates), and a set of polygons for each electorate (sometimes multiple polygons are needed, e.g. if the electorate has islands). We want to extract both of these parts.

```r
nat_data <- sF@data
head(nat_data)
#>   GEODB_OID OBJECTID DIV_NUMBER ELECT_DIV NUMCCDS ACTUAL P
#> 0         1        1          1     Aston     190  92370
#> 1         2        2          2  Ballarat     274  95003
#> 2         3        3          3    Batman     265  96909
#> 3         4        4          4   Bendigo     284  95729
#> 4         5        5          5     Bruce     226  95472
#> 5         6        6          6   Calwell     214  99031
#>   POPULATION OVER_18 AREA_SQKM SORTNAME                  MAP_
#> 0          0       0   98.9337    Aston Final Divisional Bo
#> 1          0       0 4651.6400 Ballarat Final Divisional Bo
#> 2          0       0   65.6887   Batman Final Divisional Bo
#> 3          0       0 6255.0000  Bendigo Final Divisional Bo
#> 4          0       0   72.6900    Bruce Final Divisional Bo
#> 5          0       0  174.7130  Calwell Final Divisional Bo
#>       LENGTH SHAPE_AREA
#> 0   58422.89   99056594
#> 1 417555.12 4652896627
```

The row names of the data file are identifiers corresponding to the polygons - we want to make them a separate variable:

```
nat_data$id <- row.names(nat_data)
```

Extracting the polygon information

The fortify function in the ggplot2 package extracts the polygons into a data frame.

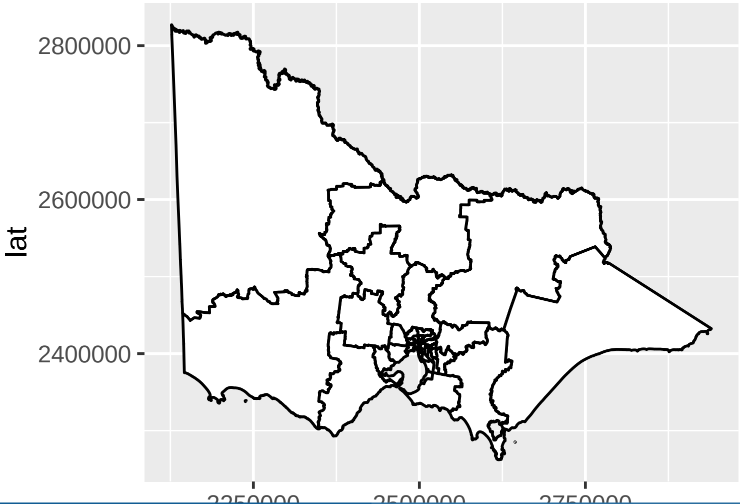
```
nat_map <- ggplot2::fortify(sFsmall)
head(nat_map)
#>      long     lat order  hole piece id group
#> 1 2525287 2407463     1 FALSE     1  0   0.1
#> 2 2525840 2407413     2 FALSE     1  0   0.1
#> 3 2527187 2406561     3 FALSE     1  0   0.1
#> 4 2527167 2406442     4 FALSE     1  0   0.1
#> 5 2527987 2406306     5 FALSE     1  0   0.1
#> 6 2527967 2406186     6 FALSE     1  0   0.1
```

We need to make sure that group and piece are kept as factor variables - if they are allowed to be converted to numeric values, it messes things up, because as factor levels 9 and 9.0 are distinct, whereas they are not when interpreted as numbers ...

```
nat_map$group <- paste("g",nat_map$group,sep=".")
nat_map$piece <- paste("p",nat_map$piece,sep=".")
head(nat_map)
#>      long     lat order  hole piece id group
#> 1 2525287 2407463     1 FALSE   p.1  0 g.0.1
#> 2 2525840 2407413     2 FALSE   p.1  0 g.0.1
#> 3 2527187 2406561     3 FALSE   p.1  0 g.0.1
#> 4 2527167 2406442     4 FALSE   p.1  0 g.0.1
#> 5 2527987 2406306     5 FALSE   p.1  0 g.0.1
#> 6 2527967 2406186     6 FALSE   p.1  0 g.0.1
```

Plot it

```r
ggplot(nat_map, aes(x=long, y=lat, group=group)) +
  geom_polygon(fill="white", colour="black")
```



Handling missing values

- Need to know how the missings are coded, hopefully clearly missing, treated as NA in R, not 0, or -9, or -9999, or . Recode as need be.
- Study the distribution of missing vs not missing, which will help determine how to handle them.

What ways can these affect analysis?

- If missings happen when conditions are special, eg sensor tends to stop when temperature drops below 3 degrees Celsius, estimation of model parameters may not reflect the population parameters
- Some techniques, particularly multivariate methods like many used in data mining require complete records over many variables. Just a few missing numbers can mean a lot of cases that cannot be used.

Terminology

- missing completely at random (MCAR) means that values that are missing appaear to be independent of everything else, just sporadically occur
- missing at random (MAR) means that missings can dependent on other known information, eg temperature, and this information can be used to help estimate values to substitute the missing values
- missing not at random (MNAR) means that the missings are dependent on something else, but we may not have that information, which makes it impossible to appropriately estimate substitute values.

Making it Easy - MissingDataGUI

- Methods for summarising missings in a data set
- Ways to plot to examine dependence between missing vs not missing
- Imputation methods to substitute missings

```
library(MissingDataGUI)
data(tao)
MissingDataGUI(tao)
```

References

- eechida package vignettes
- AEC electorate polygons
- Paper on the MissingDataGUI

Share and share alike