CLEANING DATA IN R

Type conversions

Types of variables in R

- `character: "treatment", "123", "A"`
- `numeric: 23.44, 120, NaN, Inf`
- `integer: 4L, 1123L`
- `factor: factor("Hello"), factor(8)`
- `logical: TRUE, FALSE, NA`

Types of variables in R

```
> class("hello")
[1] "character"

> class(3.844)
[1] "numeric"

> class(77L)
[1] "integer"

> class(factor("yes"))
[1] "factor"

> class(TRUE)
[1] "logical"
```

Type conversions

```
> as.character(2016)
[1] "2016"

> as.numeric(TRUE)
[1] 1

> as.integer(99)
[1] 99

> as.factor("something")
[1] something
Levels: something

> as.logical(0)
[1] FALSE
```

Overview of lubridate

- Written by Garrett Grolemund & Hadley Wickham
- Coerce strings to dates

Dates with lubridate

```
# Load the lubridate package
> library(lubridate)

# Experiment with basic lubridate functions
> ymd("2015-08-25")
[1] "2015-08-25 UTC"
```

year-month-day

```
> ymd("2015 August 25")
[1] "2015-08-25 UTC"
```

year-month-day

```
> mdy("August 25, 2015")
[1] "2015-08-25 UTC"
```

month-day-year

```
> hms("13:33:09")
[1] "13H 33M 9S"
```

hour-minute-second

```
> ymd_hms("2015/08/25 13.33.09")
[1] "2015-08-25 13:33:09 UTC"
```

year-month-day hour-minute-second

CLEANING DATA IN R

Let's practice!

CLEANING DATA IN R

String manipulation

Overview of stringr

- R package written by Hadley Wickham
- Suite of helpful functions for working with strings
- Functions share consistent interface

Key functions in stringr for cleaning data

```
# Trim leading and trailing white space
> str_trim("  this is a test     ")
[1] "this is a test"
```

white space removed

```
# Pad string with zeros
> str_pad("24493", width = 7, side = "left", pad = "0")
[1] "0024493"
```

7 digits

```
# Create character vector of names
> friends <- c("Sarah", "Tom", "Alice")

# Search for string in vector
> str_detect(friends, "Alice")
[1] FALSE FALSE  TRUE

# Replace string in vector
> str_replace(friends, "Alice", "David")
[1] "Sarah" "Tom"   "David"
```

Key functions in stringr for cleaning data

- `str_trim()` - Trim leading and trailing white space
- `str_pad()` - Pad with additional characters
- `str_detect()` - Detect a pattern
- `str_replace()` - Find and replace a pattern

Other helpful functions in base R

- `tolower()` - Make all lowercase
- `toupper()` - Make all uppercase

```
# Make all lowercase
> tolower("I AM TALKING LOUDLY!!")
[1] "i am talking loudly!!"

# Make all uppercase
> toupper("I am whispering...")
[1] "I AM WHISPERING..."
```

CLEANING DATA IN R

Let's practice!

CLEANING DATA IN R

Missing and special values

Missing values

- May be random, but dangerous to assume
- Sometimes associated with variable/outcome of interest
- In R, represented as NA
- May appear in other forms
  - #N/A (Excel)
  - Single dot (SPSS, SAS)
  - Empty string

Special values

- `Inf` - "Infinite value" (indicative of outliers?)
  - `1/0`
  - `1/0 + 1/0`
  - `33333^33333`
- `NaN` - "Not a number" (rethink a variable?)
  - `0/0`
  - `1/0 - 1/0`

Finding missing values

```
# Create small dataset
> df <- data.frame(A = c(1, NA, 8, NA),
                   B = c(3, NA, 88, 23),
                   C = c(2, 45, 3, 1))
# Check for NAs
> is.na(df)
         A     B     C
[1,] FALSE FALSE FALSE
[2,]  TRUE  TRUE FALSE
[3,] FALSE FALSE FALSE
[4,]  TRUE FALSE FALSE

# Are there any NAs?
> any(is.na(df))
[1] TRUE

# Count number of NAs
> sum(is.na(df))
[1] 3
```

4 rows, 3 columns

Same size: 4 rows, 3 columns

Finding missing values

```
# Use summary() to find NAs
> summary(df)
       A                B                C
 Min.   :1.00   Min.   : 3.0   Min.   : 1.00
 1st Qu.:2.75   1st Qu.:13.0   1st Qu.: 1.75
 Median :4.50   Median :23.0   Median : 2.50
 Mean   :4.50   Mean   :38.0   Mean   :12.75
 3rd Qu.:6.25   3rd Qu.:55.5   3rd Qu.:13.50
 Max.   :8.00   Max.   :88.0   Max.   :45.00
 NA's   :2      NA's   :1
```

Dealing with missing values

```
# Find rows with no missing values
> complete.cases(df)
[1]  TRUE FALSE  TRUE FALSE

# Subset data, keeping only complete cases
> df[complete.cases(df), ]
  A  B C
1 1  3 2
3 8 88 3

# Another way to remove rows with NAs
> na.omit(df)
  A  B C
1 1  3 2
3 8 88 3
```

CLEANING DATA IN R

Let's practice!

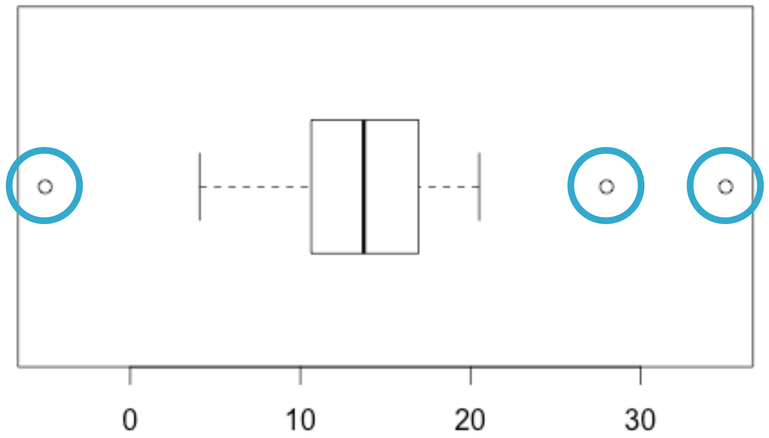
CLEANING DATA IN R

Outliers and obvious errors

Outliers

```
# Simulate some data
> set.seed(10)
> x <- c(rnorm(30, mean = 15, sd = 5), -5, 28, 35)

# View a boxplot
> boxplot(x, horizontal = TRUE)
```



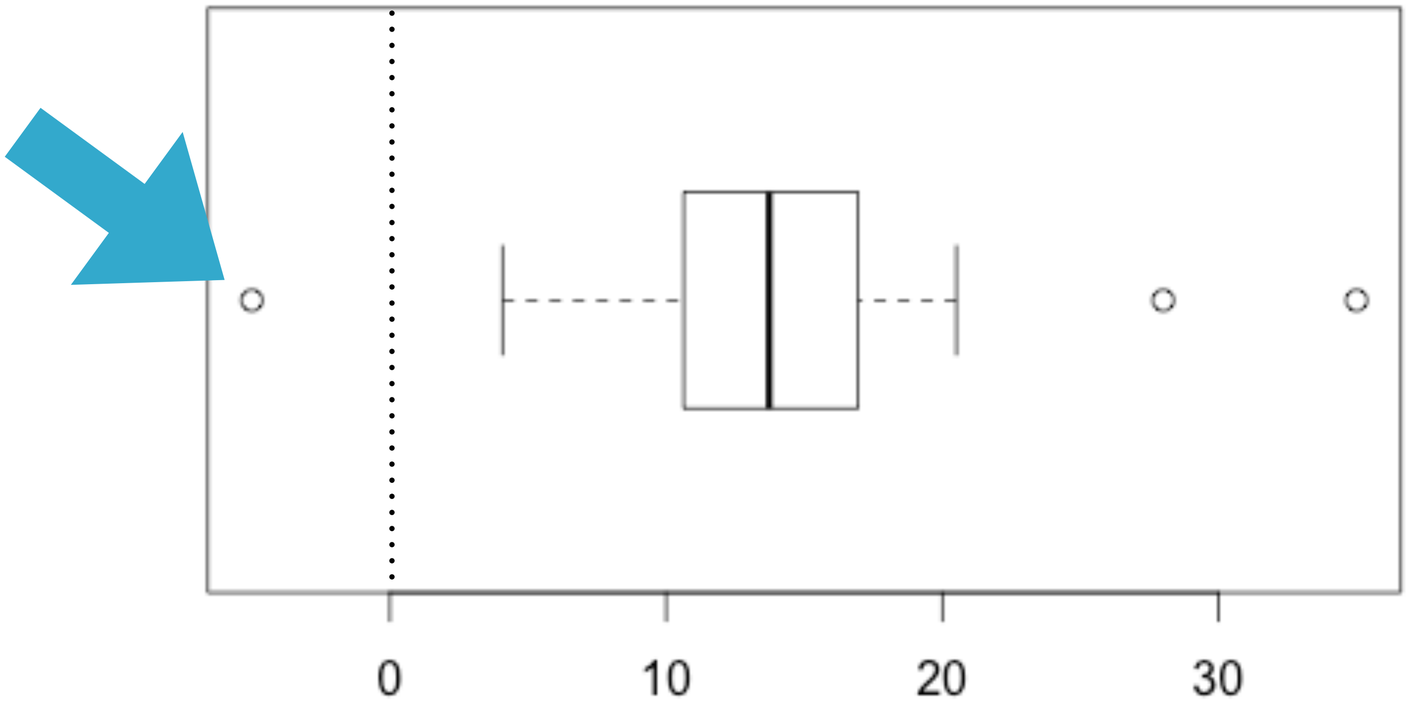
Outliers

Outliers

- Extreme values distant from other values
- Several causes
  - Valid measurements
  - Variability in measurement
  - Experimental error
  - Data entry error
- May be discarded or retained depending on cause

Obvious errors

What if these values are supposed to represent ages?



Obvious errors

- May appear in many forms
  - Values so extreme they can't be plausible (e.g. person aged 243)
  - Values that don't make sense (e.g. negative age)
- Several causes
  - Measurement error
  - Data entry error
  - Special code for missing data (e.g. -1 means missing)
- Should generally be removed or replaced

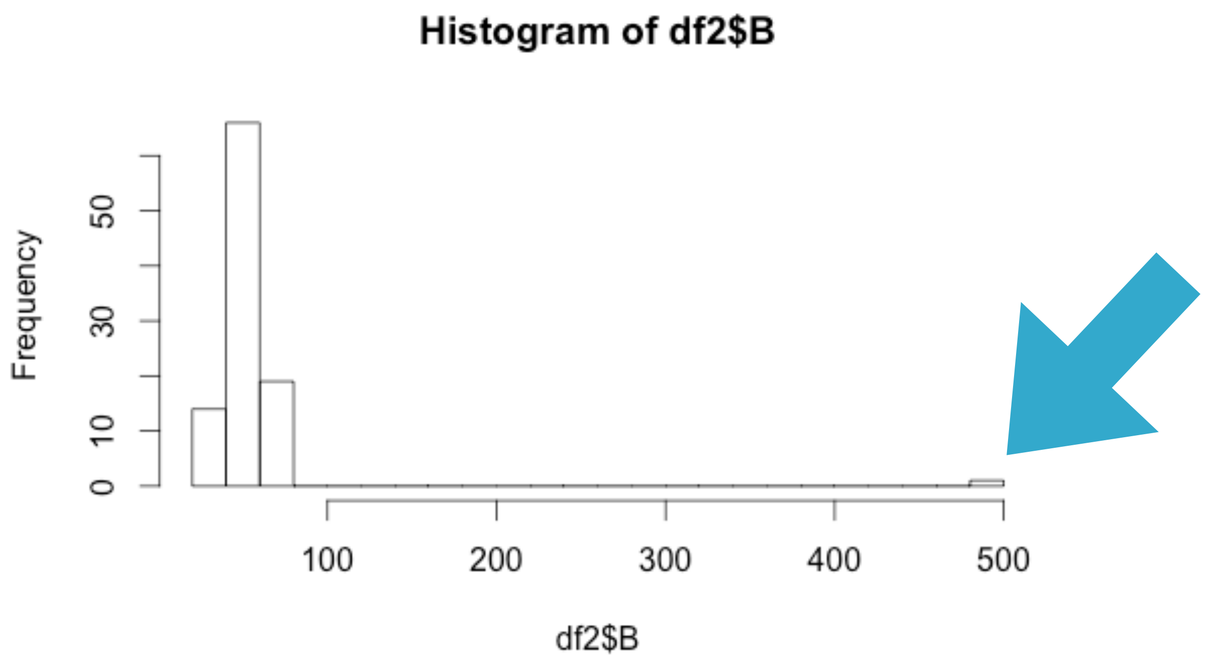
Finding outliers and errors

```
# Create another small dataset
> df2 <- data.frame(A = rnorm(100, 50, 10),
                    B = c(rnorm(99, 50, 10), 500),
                    C = c(rnorm(99, 50, 10), -1))

# View a summary
> summary(df2)
       A                B                C
 Min.   :23.7   Min.   : 26.9   Min.   :-1.0
 1st Qu.:43.7   1st Qu.: 43.7   1st Qu.:40.3
 Median :51.9   Median : 49.8   Median :48.5
 Mean   :50.4   Mean   : 54.9   Mean   :47.8
 3rd Qu.:56.9   3rd Qu.: 56.6   3rd Qu.:56.3
 Max.   :77.2   Max.   :500.0   Max.   :75.1
```

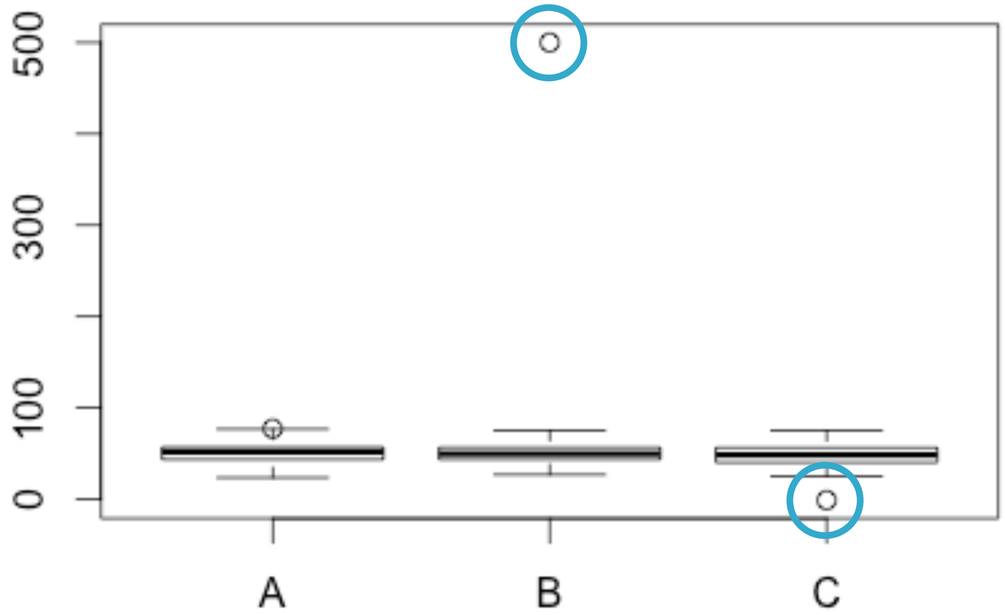
Finding outliers and errors

```
# View a histogram
> hist(df2$B, breaks = 20)
```



Finding outliers and errors

```
# View a boxplot
> boxplot(df2)
```



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Let's practice!