R for basic data analysis

Marcus W. Beck[1] Todd D. O'Brien[2]

[1]ORISE, USEPA NHEERL Gulf Ecology Division
Email: beck.marcus@epa.gov

[2]NOAA/NMFS COPEPOD Project
Email: todd.obrien@noaa.gov

What you'll learn about

- Data organization
- Data exploration and visualization
  - Common functions
  - Graphing tools
- Data analysis and hypothesis testing
  - Common functions
  - Evaluation of output
  - Graphing tools

Data organization

Start by opening R

The workspace is a group of objects that are loaded for our current session

Objects are loaded into the workspace by importing (or making within R) and assigning them to a variable object with a name of our choosing

We can see what's loaded in our workspace:

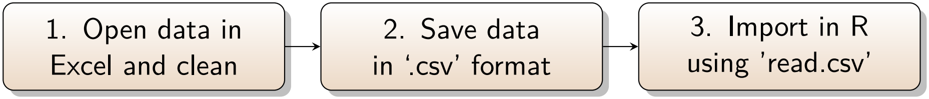
```
# create variable as a numeric vector
a <- c(1, 2)

# verify that its in our workspace
ls()

## [1] "a"
```

Data organization

Here's a workflow for importing data from Excel:


1. Open data in Excel and clean
2. Save data in '.csv' format
3. Import in R using 'read.csv'

- Column names should be simple
- Ensure all data will be easy to read

- File, Save as .csv
- Creates a comma separated file that looks like a spreadsheet
- One spreadsheet at a time

- header = T
- See ?read.csv for list of function options
- Remember to assign a name

Data organization

Excel files can also be imported directly into R without converting to a .csv file

However, this is not as intuitive as one would expect since .xls files are a proprietary format

There are several packages for importing excel files: Here's a nice summary

Try using the gdata package on your own, this also requires an installation of Strawberry Perl

Our workshop will not use methods that require direct import of Excel files - we will always use a .csv or .txt format for simplicity

Data organization

If the data you want to import are a text file... open it, how are the columns separated?

- comma... `sep = ','`
- tabs... `sep = '\t'`
- space... `sep = ''`
- arbitrary character

Use the read.table function and identify the column delimiter :

```
# data not loaded, only 'a' from before
ls()

## [1] "a"

# load data as comma separated, assign to dat
# make sure you are in the working directory for the toolkit
# e.g., setwd('C:/preworkshop_toolkit')
dat <- read.table('dat_example.txt',sep = ',', header = T)
ls()

## [1] "a"   "dat"
```

Data exploration

Now that the data are in our workspace, let's explore!

View the first six rows

```
head(dat)
```

```
##          datetimestamp do_mgl depth
## 1 2011-01-01 00:00:00     NA  1.54
## 2 2011-01-01 00:15:00     NA  1.53
## 3 2011-01-01 00:30:00     NA  1.52
## 4 2011-01-01 00:45:00     NA  1.51
## 5 2011-01-01 01:00:00     NA  1.50
## 6 2011-01-01 01:15:00     NA  1.48
```

View the last six rows

```
tail(dat)
```

```
##             datetimestamp do_mgl depth
## 2971 2011-01-31 22:30:00    9.6  1.49
## 2972 2011-01-31 22:45:00    9.8  1.50
## 2973 2011-01-31 23:00:00   10.7  1.50
## 2974 2011-01-31 23:15:00   10.8  1.51
## 2975 2011-01-31 23:30:00   10.8  1.52
## 2976 2011-01-31 23:45:00   10.8  1.52
```

Data exploration

What object class is the data?

```
class(dat)

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

What are the dimensions of the data frame?

```
dim(dat)

## [1] 2976    3

nrow(dat)

## [1] 2976

ncol(dat)

## [1] 3
```

The data contain 2976 rows and 3 columns, is this correct?

Data exploration

Can we get a summary of the data frame?

```
summary(dat)
```

```
##              datetimestamp       do_mgl          depth
##  2011-01-01 00:00:00:   1   Min.   : 7.5   Min.   :0.70
##  2011-01-01 00:15:00:   1   1st Qu.: 9.5   1st Qu.:1.02
##  2011-01-01 00:30:00:   1   Median :10.2   Median :1.21
##  2011-01-01 00:45:00:   1   Mean   :10.1   Mean   :1.19
##  2011-01-01 01:00:00:   1   3rd Qu.:10.7   3rd Qu.:1.36
##  2011-01-01 01:15:00:   1   Max.   :12.5   Max.   :1.69
##  (Other)            :2970   NA's   :431    NA's   :2
```

Summary returns different information depending on the class of each column

The first column is considered a ‘factor’ and simple counts are returned

The other two columns are ‘numeric’ and five number summaries are returned, including the number of observations with NA (or missing) values

Data exploration

Individual summmaries of variables are also possible

How do we obtain variables of interest?

```
names(dat)

## [1] "datetimestamp" "do_mgl"        "depth"
```

We can get a variable directly using $ or via indexing with [,]

```
# these all do the same thing

# get using $
dat$do_mgl

# get using [row, column] with variable name
dat[, 'do_mgl']

# get using [row, column] with column index
dat[, 2]
```

Data exploration

Just as we had summaries of the data frame, we can get summaries of individual variables

```
summary(dat$do_mgl)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##     7.5     9.5    10.2    10.1    10.7    12.5     431
```

Or specific information...

```
# note use of na.rm = T, you must specify how to handle missing values
mean(dat$do_mgl, na.rm = T)

## [1] 10.15

range(dat$do_mgl, na.rm = T)

## [1]  7.5 12.5

var(dat$do_mgl, na.rm = T)

## [1] 0.8342
```

Data exploration

Text-based summaries of our data are nice, but we should also visualize:

- How are our data distributed?
- Are there any outliers or extreme observations?
- How do our variables compare?

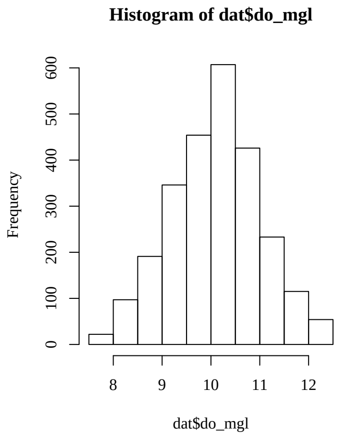
R has many built in functions for data exploration and plotting

- hist - plots a histogram (binned densities of continuous values)
- qqplot - comparison of a variable to a normal distribution
- barplot - for bar plots...
- plot - bivariate comparison of two variables
- Much, much more...

Data exploration

Let's examine the distribution of dissolved oxygen measurements

```r
hist(dat$do_mgl)
```

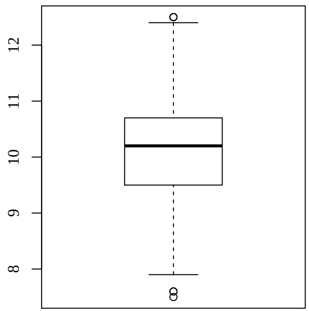


For example, $\approx$ 600 observations have DO values from, 10–10.5 mg L^{-1}

Data exploration

Boxplots are also useful for looking at a distribution

```r
boxplot(dat$do_mgl)
```

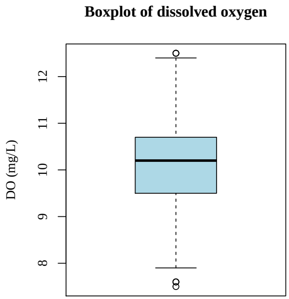


Let's make it look better...

Data exploration

Boxplots are also useful for looking at a distribution

```
# a nicer looking boxplot
boxplot(dat$do_mgl,
  ylab = 'DO (mg/L)',
  main = 'Boxplot of dissolved oxygen',
  col = 'lightblue'
  )
# see ?boxplot for all options
```



Data exploration

Values beyond the whiskers in a boxplot are considered outliers

We can use the boxplot function to identify outliers...

```r
# find the outliers using boxplot
myplot <- boxplot(dat$do_mgl, plot = F)
myplot$out

## [1]  7.6  7.6  7.5  7.6 12.5 12.5 12.5
```

This gives us the actual value, now we need to find them in our data

```r
# find the rows of the outliers
outlier <- myplot$out
out_row <- which(dat$do_mgl %in% outlier)
out_row #these are the row number of the outliers

## [1]  704 1001 1002 1003 1322 1440 1441
```

Data exploration

You can treat outliers as you wish

```
dat[out_row, ] # view the outliers

##             datetimestamp do_mgl depth
## 704  2011-01-08 07:45:00    7.6  1.20
## 1001 2011-01-11 10:00:00    7.6  1.32
## 1002 2011-01-11 10:15:00    7.5  1.31
## 1003 2011-01-11 10:30:00    7.6  1.30
## 1322 2011-01-14 18:15:00   12.5  1.28
## 1440 2011-01-15 23:45:00   12.5  1.38
## 1441 2011-01-16 00:00:00   12.5  1.37
```

Remove them...

```
dat[out_row, 'do_mgl'] <- NA
```

Replace with mean...

```
dat[out_row, 'do_mgl'] <- mean(dat$do_mgl, na.rm = T)
```

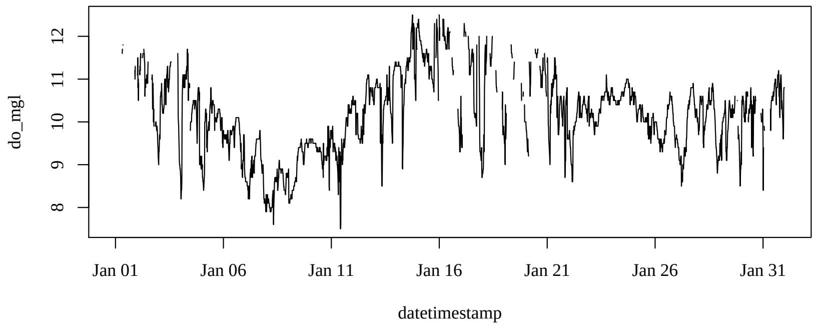
Or do nothing...

Data exploration

The time series can be plotted to evaluate trends

```r
#first we have to convert the datetimestamp column
dat$datetimestamp <- as.POSIXct(dat$datetimestamp)

# plot the time series, y vs x syntax
plot(do_mgl ~ datetimestamp, data = dat, type = 'l')
```

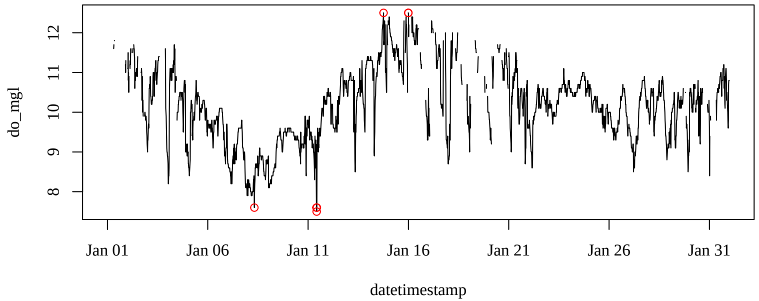


Data exploration

We can also add our outliers to the plot

```
# plot the time series
plot(do_mgl ~ datetimestamp, data = dat, type = 'l')

# use the out_row object from earlier to subset
x <- dat[out_row, 'datetimestamp']
y <- dat[out_row, 'do_mgl']
points(x, y, col = 'red')
```



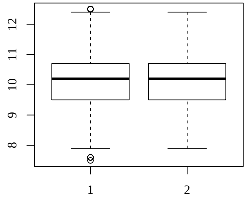
Data exploration

What effect do these outliers have on the mean DO value for the time series?

```
# the original dataset
dat_orig <- dat$do_mgl

# dataset with outliers removed
dat_remove <- dat$do_mgl
dat_remove[out_row] <- NA

# a boxplot comparison of the two datasets
boxplot(dat_orig, dat_remove)
```



Data exploration

We can test these differences more formally using a standard statistical test

```
# a t-test, evaluates the null that the difference in means is zero
t.test(dat_orig, dat_remove)


##
##  Welch Two Sample t-test
##
## data:  dat_orig and dat_remove
## t = -0.05, df = 5081, p-value = 0.9602
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.05128  0.04873
## sample estimates:
## mean of x mean of y
##     10.15     10.15
```

There is a 96.02% probability that the difference in means between the datasets is equal to zero, due to random chance

We should leave the outliers in the dataset...

Conclusions

The previous examples are simple approaches to exploratory data analysis with R

These were designed to get you comfortable using the R command-line

The workshop will provide a comprehensive guide to exploring and working with time series data from SWMP

Please see the additional resources slide in 'intro_to_r.pdf' for more training information

Questions: contact Marcus Beck (beck.marcus@epa.gov) or Todd O'Brien (todd.obrien@noaa.gov)