Functions & Data Visualization

Fundamental Techniques in Data Science



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Outline

Functions

Data Visualization

Base R Graphics GGPlot Saving Graphics



FUNCTIONS



R Functions

Functions are the foundation of R programming.

- Other than data objects, almost everything else that you interact with when using R is a function.
- Any R command written as a word followed by parentheses, () , is a function.

```
o mean()
```

- o library()
- o mutate()
- Infix operators are aliased functions.

```
0 <-
```



We can define our own functions using the function() function.

```
square <- function(x) {
    out <- x^2
    out
}</pre>
```

After defining a function, we call it in the usual way.

```
square(5)
[1] 25
```

One-line functions don't need braces.

```
square <- function(x) x^2
square(5)
[1] 25</pre>
```

Function arguments are not strictly typed.

```
square(1:5)
[1] 1 4 9 16 25
square(pi)
[1] 9.869604
square(TRUE)
[1] 1
```

But there are limits.

```
square("bob") # But one can only try so hard
Error in x^2: non-numeric argument to binary operator
```

Functions can take multiple arguments.

```
mod <- function(x, y) x %% y
mod(10, 3)
[1] 1</pre>
```

Sometimes it's useful to specify a list of arguments.

```
getLsBeta <- function(datList) {
   X <- datList$X
   y <- datList$y
   solve(crossprod(X)) %*% t(X) %*% y
}</pre>
```

```
X <- matrix(runif(500), ncol = 5)
datList <- list(y = X %*% rep(0.5, 5), X = X)
getLsBeta(datList = datList)

    [,1]
[1,]    0.5
[2,]    0.5
[3,]    0.5
[4,]    0.5
[5,]    0.5</pre>
```

Functions are first-class objects in R.

We can treat functions like any other R object.

R views an unevaluated function as an object with type "closure".

```
class(getLsBeta)
[1] "function"
typeof(getLsBeta)
[1] "closure"
```

An evaluated functions is equivalent to the objects it returns.

```
class(getLsBeta(datList))
[1] "matrix" "array"
typeof(getLsBeta(datList))
[1] "double"
```

We can use functions as arguments to other operations and functions.

```
fun1 <- function(x, y) x + y
## What will this command return?
fun1(1, fun1(1, 1))
[1] 3</pre>
```

Why would we care?

```
s2 <- var(runif(100))
x <- rnorm(100, 0, sqrt(s2))</pre>
```

```
X[1:8,]
           [.1]
                     [.2] [.3]
                                          Γ.4]
                                                    [.5]
[1.] 0.52431382 0.67136447 0.28228726 0.7148383 0.54204681
[2.] 0.01926742 0.11693762 0.09148502 0.6929171 0.88371944
[3.] 0.05100735 0.18432074 0.43547799 0.6097462 0.09026598
[4.] 0.60566972 0.12944127 0.21000143 0.2441917 0.68141473
[5,] 0.48737303 0.94030405 0.23988619 0.4915910 0.36353771
[6.] 0.19941958 0.96670678 0.11455820 0.1243947 0.24253273
[7.] 0.95507804 0.38705829 0.49733535 0.2968470 0.81001800
[8.] 0.11093197 0.07731757 0.84923006 0.8653987 0.61914193
c(1, 3, 6:9, 12)
[1] 1 3 6 7 8 9 12
```

DATA VISUALIZATION



Setup

```
dataDir <- "../../data/"

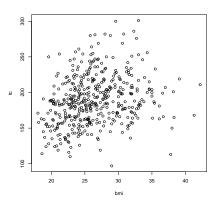
## Load some data:
diabetes <- readRDS(paste0(dataDir, "diabetes.rds"))
titanic <- readRDS(paste0(dataDir, "titanic.rds"))
bfi <- readRDS(paste0(dataDir, "bfi.rds"))

## Convert survival indicator to a numeric dummy code:
titanic <- titanic %-% mutate(survived = as.numeric(survived) - 1)</pre>
```

Base R Graphics: Scatterplots

We can create a basic scatterplot using the plot() function.

```
diabetes %$% plot(y = tc, x = bmi)
```



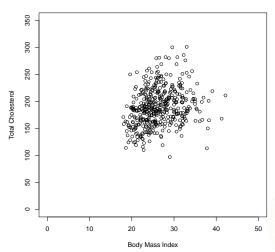


Base R Graphics: Scatterplots



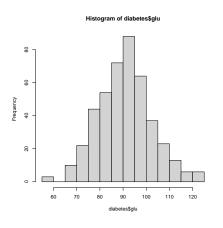
Base R Graphics: Scatterplots

Relation between BMI and Cholesterol



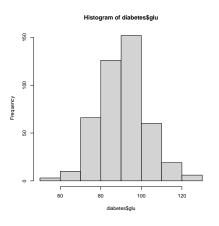
We can create a simple histogram with the <code>hist()</code> function.

hist(diabetes\$glu)



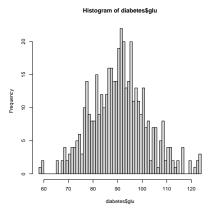


hist(diabetes\$glu, breaks = 5)



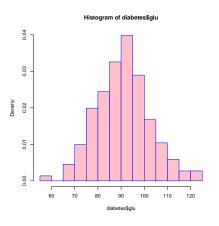


hist(diabetes\$glu, breaks = 50)





```
hist(diabetes$glu, col = "pink", border = "blue", probability = TRUE)
```

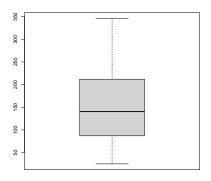




Base R Graphics: Boxplots

We can create simple boxplots via the <code>boxplot()</code> function.

boxplot(diabetes\$progress)



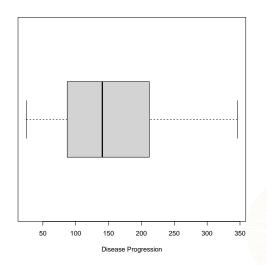


Base R Graphics: Boxplots

```
boxplot(diabetes$progress,
    horizontal = TRUE,
    range = 3,
    xlab = "Disease Progression")
```

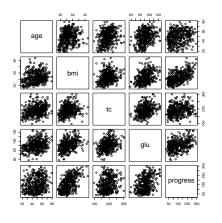


Base R Graphics: Boxplots



Plotting an entire data frame produces a scatterplot matrix.

diabetes %>% select(age, bmi, tc, glu, progress) %>% plot()

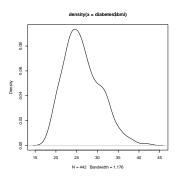




The density() function estimates the density of a variable.

• If we plot a density object, we get a kernel density plot.

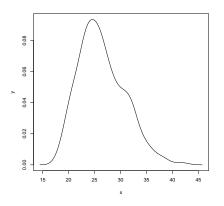
density(diabetes\$bmi) %>% plot()







d %% plot(y = y, x = x, type = "1")

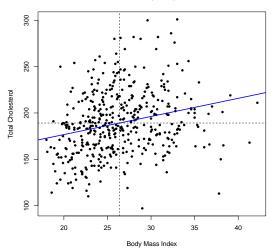




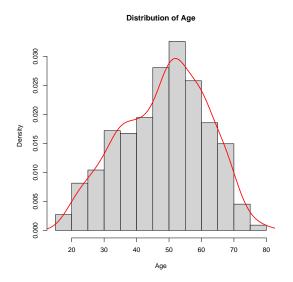
Base R graphics work by building up figures in layers.

```
## Start with a simple scatterplot:
diabetes %$% plot(y = tc, x = bmi, pch = 20, xlab = "", ylab = "")
## Use the abline() function to add lines representing the means of x and y:
abline(h = mean(diabetes$tc), v = mean(diabetes$bmi), ltv = 2)
## Add the best fit line from a linear regression of 'tc' onto 'bmi':
diabetes %$%
   lm(tc ~ bmi) %>%
   coef() %>%
   abline(coef = .. col = "blue", lwd = 2)
## Add titles:
title(main = "Total Cholesterol by Body Mass Index",
     vlab = "Total Cholesterol",
     xlab = "Body Mass Index")
```





Add a kernel density plot on top of a histogram.



GGPlot

Base R graphics are fine for quick-and-dirty visualizations (e.g., EDA, checking assumptions), but for publication quality graphics, you should probably use GGPlot.

 GGPlot uses the "grammar of graphics" and "tidy data" to build up a figure from modular components.

Describes all the non-data ink
Plotting space for the data
Statistical models & summaries
Rows and columns of sub-plots
Shapes used to represent the data
Scales onto which data is mapped
The actual variables to be plotted

Theme
Coordinates
Statistics
Facets
Geometries
Aesthetics
Data



GGPlot: Basic Setup

We start by calling the ggplot() function.

- We must define a data source.
- We must also give some aesthetic via the <code>aes()</code> function.

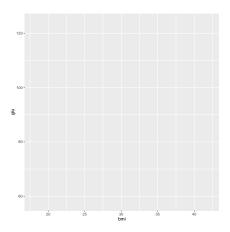
```
library(ggplot2)
p1 <- ggplot(data = diabetes, mapping = aes(x = bmi, y = glu))</pre>
```



GGPlot: Basic Setup

At this point, our plot is pretty boring.

p1

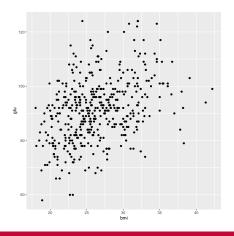




GGPlot: Geometries

We need to define some geometry via a geom_XXX() function.

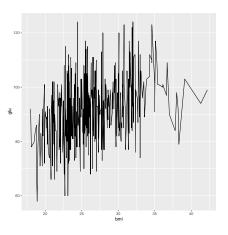
p1 + geom_point()





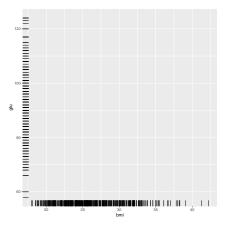
GGPlot: Geometries

p1 + geom_line()



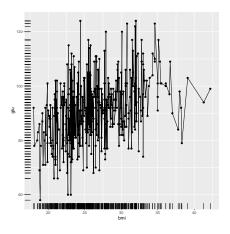


p1 + geom_rug()





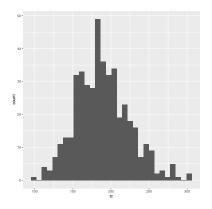
We can also combine different geometries into a single figure





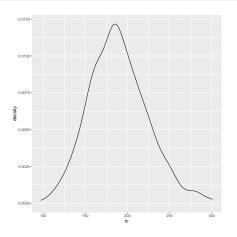
We can use different flavors of geometry for different types of data.

```
p2 <- ggplot(diabetes, aes(tc))
p2 + geom_histogram()</pre>
```



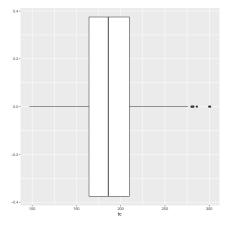


p2 + geom_density()



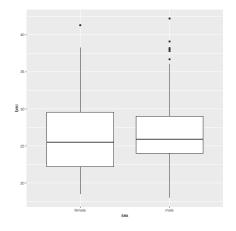


p2 + geom_boxplot()



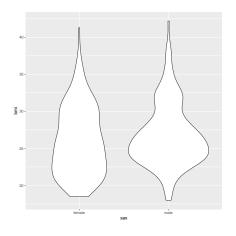


```
p3 <- ggplot(diabetes, aes(sex, bmi))
p3 + geom_boxplot()</pre>
```



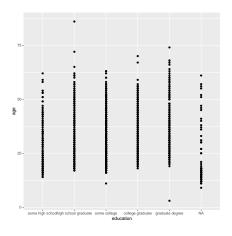


p3 + geom_violin()



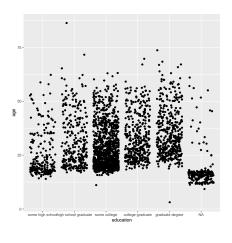


```
p4 <- ggplot(bfi, aes(education, age))
p4 + geom_point()</pre>
```





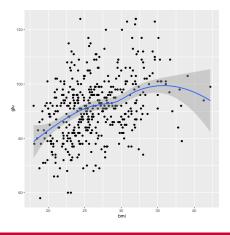
p4 + geom_jitter()



GGPlot: Statistics

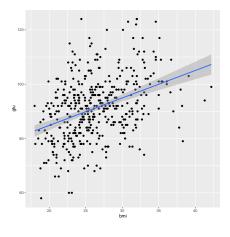
We can also add statistical summaries of the data.

p1 + geom_point() + geom_smooth()



GGPlot: Statistics

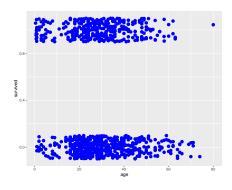
```
p1 + geom_point() + geom_smooth(method = "lm")
```





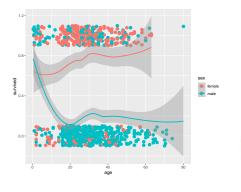
Changing style options outside of the <code>aes()</code> function applies the styling to the entire plot.

```
p5 <- ggplot(titanic, aes(age, survived))
p5 + geom_jitter(color = "blue", size = 3, height = 0.1)</pre>
```



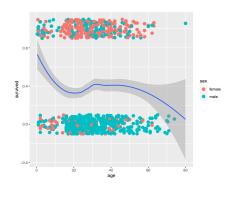
We can also apply styles as a function of variables by defining the style within the aes() function.

```
p6.1 <- ggplot(titanic, aes(age, survived, color = sex))
p6.1 + geom_jitter(size = 3, height = 0.1) + geom_smooth()</pre>
```



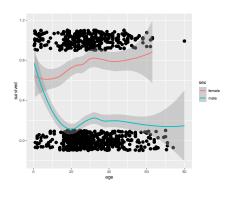


```
p6.2 <- ggplot(titanic, aes(age, survived))
p6.2 + geom_jitter(aes(color = sex), size = 3, height = 0.1) +
    geom_smooth()</pre>
```



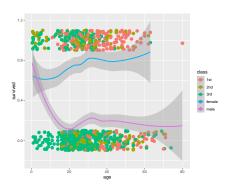


```
p6.2 + geom_jitter(size = 3, height = 0.1) +
    geom_smooth(aes(color = sex))
```



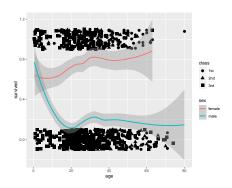


```
p6.2 + geom_jitter(aes(color = class), size = 3, height = 0.1) +
    geom_smooth(aes(color = sex))
```



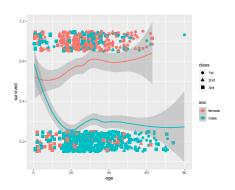


```
p6.2 + geom_jitter(aes(shape = class), size = 3, height = 0.1) +
  geom_smooth(aes(color = sex))
```



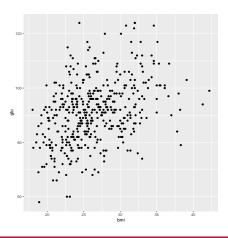


```
p6.1 + geom_jitter(aes(shape = class), size = 3, height = 0.1) +
    geom_smooth()
```

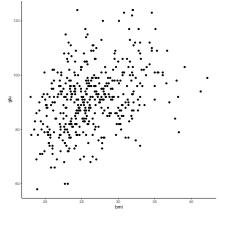




We can apply canned themes to adjust a plot's overall appearance.

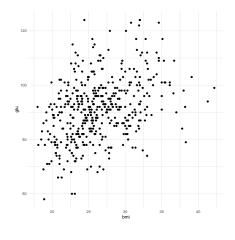


p1.1 + theme_classic()



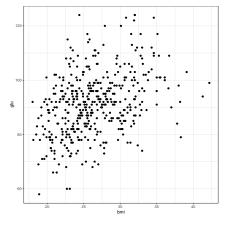


p1.1 + theme_minimal()





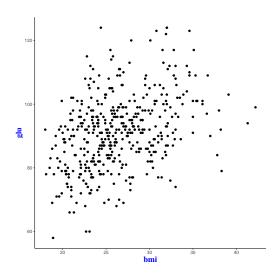
p1.1 + theme_bw()





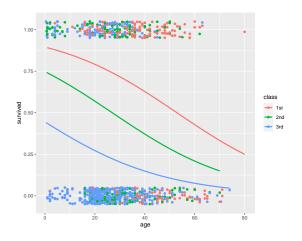
We can also modify individual theme elements.



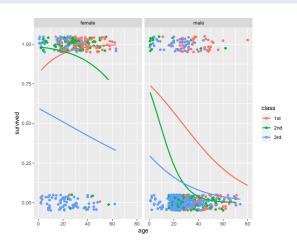


Faceting allow us to make arrays of conditional plots.

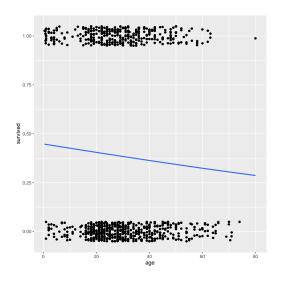




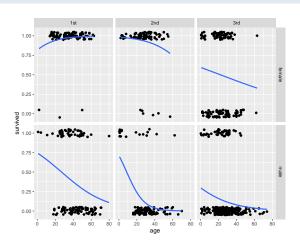
p7 + facet_wrap(vars(sex))







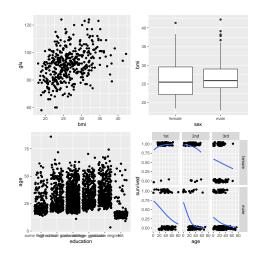
p8 + facet_grid(vars(sex), vars(class))



GGPlot: Joining Multiple Figures

If we want to paste several different plots into a single figure (without faceting), we can use the utilities in the **gridExtra** package.

GGPlot: Joining Multiple Figures



Saving Graphics

To save a graphic that we've created in R, we simply redirect the graphical output to a file using an appropriate function.

```
figDir <- "figures/"

## Save as PDF
pdf(paste0(figDir, "example_plot.pdf"))
p7 + facet_wrap(vars(sex))
dev.off()
pdf
2</pre>
```

Saving Graphics

```
## Save as IPEG
jpeg(paste0(figDir, "example_plot.jpg"))
p7 + facet_wrap(vars(sex))
dev.off()
pdf
  2
## Saue as PNG
png(pasteO(figDir, "example_plot.png"))
p7 + facet_wrap(vars(sex))
dev.off()
pdf
  2
```

Saving Graphics

With PDF documents, we can save multiple figures to a single file.

```
pdf(paste0(figDir, "example_plot2.pdf"))
p6.1 + geom_jitter(size = 3, height = 0.1) + geom_smooth()
p7 + facet_wrap(vars(sex))
p8 + facet_grid(vars(sex), vars(class))
dev.off()
pdf
2
```