Review of R/RStudio and EDA

Overview of R Markdown files

In this course we will often work with R markdown files in class.

Try executing this chunk by clicking the *Run* button within the chunk or by placing your cursor inside it and pressing *Cmd/Cntrl+Shift+Enter*.

```
1:10
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

Add a new chunk by clicking the *Insert Chunk* button on the toolbar or by pressing *Cmd/Cntrl+Option+I*.

When you save the notebook, a file containing the code **and** output will be saved alongside it (click the *Preview* button or press *Cmd+Shift+K* to preview the PDF file; you may need to change the output type to HTML or Word if you don't have LaTeX installed on your computer).

Your First R session

While you are learning the R language, remember that you are learning a new language; thus, we will start rather simply with small analysis tasks and build up to more complicated tasks. Also, you will not remember everything immediately—that's OK, it's a natural part of learning a language!

Installing and loading R packages

R does not enable all of its functionality when you open it. To enable additional functionality we need to load *R packages*. In this class we will often use the `dplyr` R package to enable better tools for data manipulation and the `ggformula` package to enable better tools for plotting. Below is an example of installation and loading:

```
# You only need to install a package once
# If you use the server, then these packages are already installed
install.packages("dplyr")
install.packages("ggformula")
```

```
# You will need to load the package in each R markdown notebook
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 3.5.1
```

```
library(ggformula)
```

Note: I added the `message = FALSE` argument to this code chunk to avoid unnecessary messages

Loading data and assignment

Regression models are fit to data sets, so data will play a central role in this course. There are multiple ways to load data sets (and we'll learn more about them later), but we often need to load a `.csv` (comma separated value) file.

Today, we'll look at a data set containing information on health evaluation and linkage to primary care.

```r
# Load the data and assign it a name
HELPrct <- read.csv("https://aloy.rbind.io/data/HELPrct.csv")
```

Data frames

The `HELPrct` object is our first example of a data frame, which is essentially a list of vectors. We can get a first glimpse of our data set in a few ways:

```r
# Printing the first 6 rows
# Note that missing values are denoted by NA
head(HELPrct)
```

```r
# Looking at the number of rows and columns
dim(HELPrct)
```

```r
# Looking at the structure
str(HELPrct)
```

```r
# looking at quick summary statistics
summary(HELPrct)
```

Exploring the Data

In this course, we'll work with data sets that have a combination of quantitative and categorical variables. Oftentimes, an important first step (before doing any analysis) is to explore the data. Here are some plots and summary statistics that are frequently used to visually display the data.

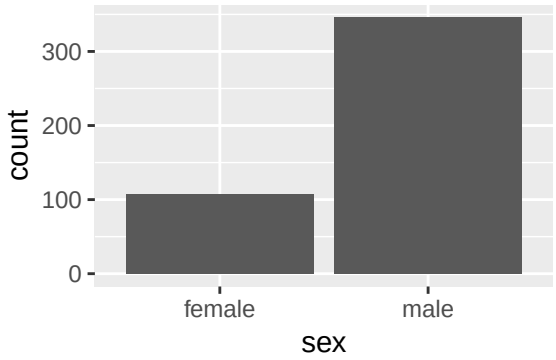
Univariate summaries

Categorical variables

```r
table(HELPrct$sex)
```

```
##
## female   male
##    107    346
```

```r
gf_bar(~ sex, data = HELPrct)
```



Quantitative variables

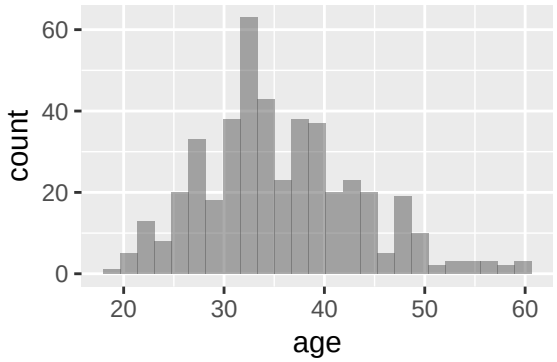
```
summary(HELPrct$age)
```

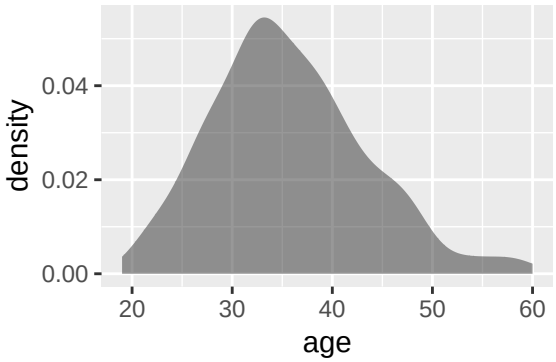
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   19.00   30.00   35.00   35.65   40.00   60.00
```

```
sd(HELPrct$age)
```

```
## [1] 7.710266
```

```
gf_histogram(~ age, data = HELPrct)
gf_density(~ age, data = HELPrct)
```





Bivariate summaries

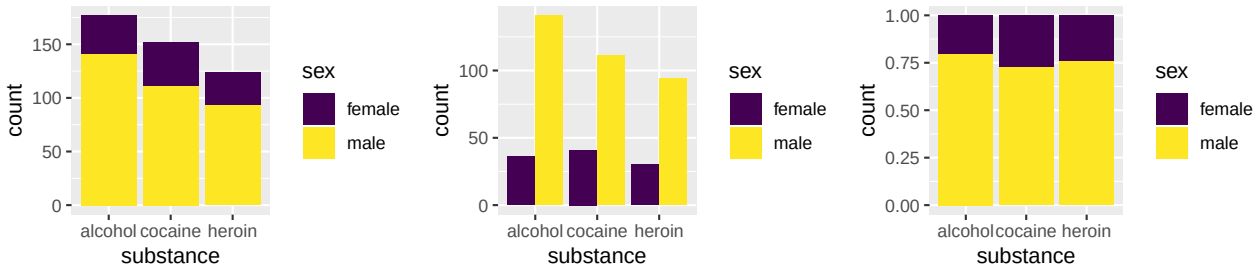
Categorical vs. categorical

```
table(HELPrct$sex, HELPrct$substance)
```

```
##
##          alcohol cocaine heroin
##   female      36      41     30
##   male       141     111     94
```

```
gf_bar( ~ substance, data = HELPrct, fill = ~sex)
gf_bar( ~ substance, data = HELPrct, fill = ~sex, position = position_dodge())
gf_bar( ~ substance, data = HELPrct, fill = ~sex, position = position_fill())
```

```
## Loading required package: viridisLite
```

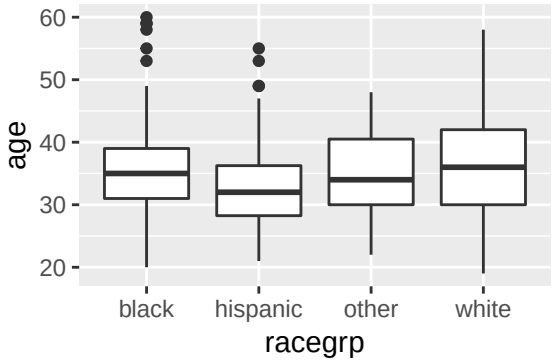


Quantitative vs. categorical

```
# Using dplyr
HELPrct %>%
  group_by(racegrp) %>%
  summarize(min = min(age),
            Q1 = quantile(age, prob = .25),
            median = median(age),
            Q3 = quantile(age, prob = .75),
            max = max(age),
            mean = mean(age),
            sd = sd(age),
            n = length(age))
```

```
## # A tibble: 4 x 9
##   racegrp    min    Q1 median    Q3   max  mean    sd     n
##   <fct>    <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl> <dbl> <int>
## 1 black       20  31       35  39      60  35.7  7.08   211
## 2 hispanic    21  28.2     32  36.2    55  33.2  7.99    50
## 3 other       22  30       34  40.5    48  35.0  7.66    26
## 4 white       19  30       36  42      58  36.5  8.28   166
```

```
gf_boxplot(age ~ racegrp, data = HELPrct)
```

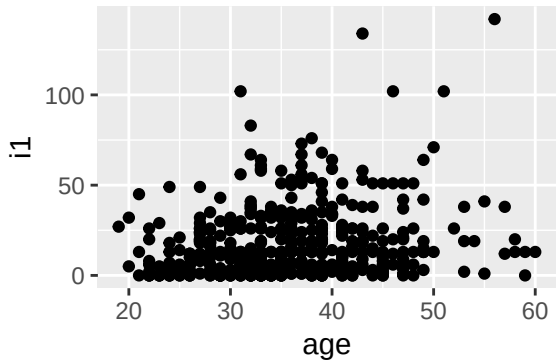


Quantitative vs. Quantitative

```
cor(HELPrct$i1, HELPrct$age)
```

```
## [1] 0.2069538
```

```
gf_point(i1 ~ age, data = HELPrct)
```


i1
100
50
0
20
30
40
50
60
age