Essential R Skills

UMN-Morris Statistics Discipline

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Contents

Chapter 1

Motivation

We have found that students enter our courses with wide variation in experience and comfort using statistical software for computation and making graphical displays. This document represents our expectations for the basic R skills that students should know upon completing an introductory course in statistics. Analysis methods may appear at times in this document, but the emphasis here is upon basic R usage for data wrangling, and exploratory data analysis using numeric and graphical methods.

Chapter 2

Getting Started

2.1 Packages

When you start R studio, basic functionality is initially available. However, in most projects we will want to use some special code and functions contained in packages that are not initially available whe R starts. Before packages can be used in our analyses, they must be installed in our R workspace. We presume that the R Studio development environment is being used by our students. Any package can be installed by clicking the "Packages" tab in the lower right panel of the R Studio workspace. Then click "Install" to produce an entry bar where you type the name of the desired package.

Once a package is installed into your R Studio environment, you make it available by loading with the `library()` command. For this document, some additional packages are needed, and are loaded in the next code block. The *knitr* and *tidyverse* packages have been previously installed. If you attempt to load a package (in this case zelig) that has not been installed, you will get an error message similar to this:

```
Error in library(zelig) : there is no package called ‘zelig’
```

```
# this block loads R packages that may be needed for the analysis.
library(knitr)
library(tidyverse)
```

2.2 The tidyverse Package

The tidyverse package is very special - it is a package of other packages. The tidyverse website tidyverse describes the tidyverse as: *The tidyverse is an opin-*

ionated collection of R packages designed for data science. All packages share an underlying design philosophy, grammar, and data structures.

The most important packages inside the tidyverse package for this document are: dplyr, magrittr, and ggplot2.

2.3 Gapminder Data:

This dataset (named gapminder) is contained in an R package called *gapminder*, and needs to be loaded before the dataset can be used.

```
library(gapminder)
```

2.4 Set Working Directory

In the "Files" tab in the lower right portion of the R Studio work area, you can choose where you want to store files and conduct your work by navigating to a suitable folder by making folders and sub-folders and then clicking to navigate to a suitable work area.

You should notify R Studio and the R software to this location called the working directory. Once you have navigated to where you want files, data, and results to reside, you notify R Studio by clicking the blue "More" gear and choose "set working directory." This will help R understand where to expect files and dat to be located.

One of the most common problems students experience is that they work on files in a location not specified as the "working directory."

2.5 Reading Data From a CSV File

The most common way to read data into R is from an excel spreadsheet that has been saved into a comma-separated-values (csv) file. This means that data elements are separated from each other by commas ",".

We consider a data file named (file.csv) that contains variable names in the first row of the file. Place this file in your working directory and read,

```
dataframe <- read.csv("file.csv",header=TRUE)
```

A frequent issue with `read.csv` is that character variables are automatically converted to factor/categorical variables. This may not be a good choice in many instances. To gain full control of how this is handled, you can prevent this kind of auto-conversion by using the `stringsAsFactors` option.

```
cardata <- read.csv(file = 'carspeeds.csv', stringsAsFactors = FALSE)
```

The *readr* package inside the *tidyverse* family of packages has a slightly nicer read csv function you should know about. We use the `readr::` prefix to inform readers that the `read_csv` function resides in the *readr* package. This read function will not auto-convert character variables to category/factor variables.

```
dataframe <- readr::read_csv("file.csv",col_names = TRUE)
```

Reading data directly from excel spreadsheets is more complex and you should read documentation for the *readxl* package.

Chapter 3

Overview of a Dataframe

Datasets in R are usually called dataframes or tibbles. The distinction between these names is not important for our purposes - we will usually refer to a dataset as a dataframe.

3.1 glimpse

Let's look at what is inside the gapminder dataset using the `glimpse` command from the *dplyr* package. The *dplyr* package is contained in the package "tidyverse" that was loaded previously. The `glimpse(gapminder)` command would have executed without any errors. We use the `dplyr::` prefix to inform readers that the glimpse function resides in the *dplyr* package.

```
# the next command would also execute if
# dplyr or tidyverse was loaded..
#glimpse(gapminder)
dplyr::glimpse(gapminder)
```

```
## Observations: 1,704
## Variables: 6
## $ country   <fct> Afghanistan, Afghanistan, Afghanistan, Afghanistan, Afghani…
## $ continent <fct> Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia,…
## $ year      <int> 1952, 1957, 1962, 1967, 1972, 1977, 1982, 1987, 1992, 1997,…
## $ lifeExp   <dbl> 28.801, 30.332, 31.997, 34.020, 36.088, 38.438, 39.854, 40.…
## $ pop       <int> 8425333, 9240934, 10267083, 11537966, 13079460, 14880372, 1…
## $ gdpPercap <dbl> 779.4453, 820.8530, 853.1007, 836.1971, 739.9811, 786.1134,…
```

This shows it contains economic and demographic information about different countries across years. There are 1704 rows (observations) and 6 columns (variables).

Each variable name is listed along with a variable type designation.

- fct: means a factor variable, also known as a categorical variable.
- int: means a quantitative variable that takes only integer or whole number values.
- dbl: means double precision, a quantitative variable that is essentially continuous - taking decimal values.

3.2 head

By default, the **head** command will show the first 6 rows of the dataset gapminder. Datasets in R are called “dataframes.” The gapminder dataframe is denoted as a “tibble” which is a type of dataframe.

Options to the head command can change the rows displayed.

```
# default is to show 6 rows
head(gapminder)
```

```
## # A tibble: 6 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Afghanistan Asia       1952    28.8  8425333      779.
## 2 Afghanistan Asia       1957    30.3  9240934      821.
## 3 Afghanistan Asia       1962    32.0 10267083      853.
## 4 Afghanistan Asia       1967    34.0 11537966      836.
## 5 Afghanistan Asia       1972    36.1 13079460      740.
## 6 Afghanistan Asia       1977    38.4 14880372      786.
```

```
# show only 4 rows...
head(gapminder,n=4)
```

```
## # A tibble: 4 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Afghanistan Asia       1952    28.8  8425333      779.
## 2 Afghanistan Asia       1957    30.3  9240934      821.
## 3 Afghanistan Asia       1962    32.0 10267083      853.
## 4 Afghanistan Asia       1967    34.0 11537966      836.
```

3.3 summary

This command shows a basic summary of the values in each variable.

```
# A basic, base R command
summary(gapminder)
```

```
##         country        continent        year         lifeExp
##  Afghanistan:  12   Africa  :624   Min.   :1952   Min.   :23.60
##  Albania    :  12   Americas:300   1st Qu.:1966   1st Qu.:48.20
##  Algeria    :  12   Asia    :396   Median :1980   Median :60.71
##  Angola     :  12   Europe  :360   Mean   :1980   Mean   :59.47
##  Argentina  :  12   Oceania : 24   3rd Qu.:1993   3rd Qu.:70.85
##  Australia  :  12                  Max.   :2007   Max.   :82.60
##  (Other)    :1632
##       pop              gdpPercap
##  Min.   :6.001e+04   Min.   :   241.2
##  1st Qu.:2.794e+06   1st Qu.:  1202.1
##  Median :7.024e+06   Median :  3531.8
##  Mean   :2.960e+07   Mean   :  7215.3
##  3rd Qu.:1.959e+07   3rd Qu.:  9325.5
##  Max.   :1.319e+09   Max.   :113523.1
##
```

The next command illustrates a "pipe" - here the dataframe gapminder is "piped" into the summary function to be processed. Note the same output is produce as using `summary(gapminder)`. Note, the pipe operation %>% is contained in tidyverse package: *magrittr* which is loaded when *tidyverse* is loaded.

```
# Same idea, but using tidyverse pipe
gapminder %>% summary()
```

```
##         country        continent        year         lifeExp
##  Afghanistan:  12   Africa  :624   Min.   :1952   Min.   :23.60
##  Albania    :  12   Americas:300   1st Qu.:1966   1st Qu.:48.20
##  Algeria    :  12   Asia    :396   Median :1980   Median :60.71
##  Angola     :  12   Europe  :360   Mean   :1980   Mean   :59.47
##  Argentina  :  12   Oceania : 24   3rd Qu.:1993   3rd Qu.:70.85
##  Australia  :  12                  Max.   :2007   Max.   :82.60
##  (Other)    :1632
##       pop              gdpPercap
##  Min.   :6.001e+04   Min.   :   241.2
##  1st Qu.:2.794e+06   1st Qu.:  1202.1
##  Median :7.024e+06   Median :  3531.8
##  Mean   :2.960e+07   Mean   :  7215.3
##  3rd Qu.:1.959e+07   3rd Qu.:  9325.5
##  Max.   :1.319e+09   Max.   :113523.1
##
```

3.4 Dataframe Details: funModeling package

The *funModeling* package contains the `df_status` command which also summarizes a dataframe - showing different aspects like missing values, percentage of zero values, and also the number of unique values.

```
funModeling::df_status(gapminder)
```

```
##    variable q_zeros p_zeros q_na p_na q_inf p_inf    type unique
## 1   country       0       0    0    0     0     0  factor    142
## 2 continent       0       0    0    0     0     0  factor      5
## 3      year       0       0    0    0     0     0 integer     12
## 4   lifeExp       0       0    0    0     0     0 numeric   1626
## 5       pop       0       0    0    0     0     0 integer   1704
## 6 gdpPercap       0       0    0    0     0     0 numeric   1704
```

```
di=funModeling::data_integrity(gapminder)
# returns a detailed summary of all variables
print(di)
```

```
## $vars_num_with_NA
## [1] variable q_na     p_na
## <0 rows> (or 0-length row.names)
##
## $vars_cat_with_NA
## [1] variable q_na     p_na
## <0 rows> (or 0-length row.names)
##
## $vars_cat_high_card
##   variable unique
## 1  country    142
##
## $MAX_UNIQUE
## [1] 35
##
## $vars_one_value
## character(0)
##
## $vars_cat
## [1] "country"   "continent"
##
## $vars_num
## [1] "year"      "lifeExp"   "pop"       "gdpPercap"
##
## $vars_char
## character(0)
##
## $vars_factor
## [1] "country"   "continent"
##
## $vars_other
## character(0)
```

3.5 Dataframe Details: skimr package

The *skimr* package contains many useful functions for summarizing a dataframe. When we supply a dataframe to the `skim_without_charts` function, dataframe details are separated by variable types.

```
gapminder %>%
  skimr::skim_without_charts()
```

```
##   Data Summary
##                            Values
## Name                       Piped data
## Number of rows             1704
## Number of columns          6
## _______________________
## Column type frequency:
##   factor                   2
##   numeric                  4
## ________________________
## Group variables            None
##
##   Variable type: factor
##   skim_variable n_missing complete_rate ordered n_unique
## 1 country               0             1 FALSE        142
## 2 continent             0             1 FALSE          5
##   top_counts
## 1 Afg: 12, Alb: 12, Alg: 12, Ang: 12
## 2 Afr: 624, Asi: 396, Eur: 360, Ame: 300
##
##   Variable type: numeric
##   skim_variable n_missing complete_rate       mean         sd    p0     p25
## 1 year                  0             1      1980.       17.3  1952   1966.
## 2 lifeExp               0             1       59.5       12.9  23.6    48.2
## 3 pop                   0             1  29601212. 106157897. 60011 2793664
## 4 gdpPercap             0             1      7215.      9857.  241.   1202.
##        p50       p75       p100
## 1    1980.     1993.       2007
## 2     60.7      70.8       82.6
## 3 7023596. 19585222. 1318683096
## 4    3532.     9325.    113523.
```

3.6 describe: Hmisc package

The *Hmisc* package contains the `describe` function that gives a helpful overview of numeric and categorical variables.

```r
gapminder %>%
  Hmisc::describe()
```

```
## .
##
##  6  Variables      1704  Observations
## --------------------------------------------------------------------------------
## country
##        n  missing distinct
##     1704        0      142
##
## lowest : Afghanistan        Albania            Algeria            Angola             Argentina
## highest: Vietnam            West Bank and Gaza Yemen, Rep.        Zambia             Zimbabwe
## --------------------------------------------------------------------------------
## continent
##        n  missing distinct
##     1704        0        5
##
## lowest : Africa   Americas Asia     Europe   Oceania
## highest: Africa   Americas Asia     Europe   Oceania
##
## Value        Africa Americas     Asia   Europe  Oceania
## Frequency       624      300      396      360       24
## Proportion    0.366    0.176    0.232    0.211    0.014
## --------------------------------------------------------------------------------
## year
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1704        0       12    0.993     1980    19.87     1952     1957
##      .25      .50      .75      .90      .95
##     1966     1980     1993     2002     2007
##
## lowest : 1952 1957 1962 1967 1972, highest: 1987 1992 1997 2002 2007
##
## Value       1952  1957  1962  1967  1972  1977  1982  1987  1992  1997  2002
## Frequency    142   142   142   142   142   142   142   142   142   142   142
## Proportion 0.083 0.083 0.083 0.083 0.083 0.083 0.083 0.083 0.083 0.083 0.083
##
## Value       2007
## Frequency    142
## Proportion 0.083
## --------------------------------------------------------------------------------
## lifeExp
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1704        0     1626        1    59.47    14.82    38.49    41.51
##      .25      .50      .75      .90      .95
##    48.20    60.71    70.85    75.10    77.44
##
## lowest : 23.599 28.801 30.000 30.015 30.331, highest: 81.701 81.757 82.000 82.208 82.603
## --------------------------------------------------------------------------------
## pop
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1704        0     1704        1 29601212 46384459   475459   946367
##      .25      .50      .75      .90      .95
##  2793664  7023596 19585222 54801370 89822054
##
## lowest :      60011      61325      63149      65345      70787
## highest: 1110396331 1164970000 1230075000 1280400000 1318683096
## --------------------------------------------------------------------------------
## gdpPercap
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##     1704        0     1704        1     7215     8573    548.0    687.7
##      .25      .50      .75      .90      .95
##   1202.1   3531.8   9325.5  19449.1  26608.3
##
## lowest :    241.1659    277.5519    298.8462    299.8503    312.1884
## highest:  80894.8833  95458.1118 108382.3529 109347.8670 113523.1329
## --------------------------------------------------------------------------------
```

Chapter 4

Introduction to Data Wrangling

In this chapter we present some very basic data handling and processing functions (data wrangline) that will be necessary for doing basic analyses, comparisons, and graphics. Most of the commands presented in this section stress the functions and R packages in the *tidyverse* - a set or family of packages that have similar syntax and behaviors.

4.1 Tidy Data

What is tidy data? Tidy data is a standard way of mapping the meaning of a dataset to its structure. A dataset is messy or tidy depending on how rows, columns and tables are matched up with observations, variables and types. In tidy data:

- Each variable forms a column.
- Each observation forms a row.
- Each type of observational unit forms a table.

4.2 Subset using filter

Suppose we wish to examine a subset of data for only one country, Jon's favorite country, Australia!! The following code starts by taking the gapminder dataset and then "pipes" it into the filtering (selecting rows) action so that only dataset rows from Australia are selected. The pipe function is %>% and is similar to a plumbing pipe that goes one direction: from left to right. After the "Australia" rows are selected, the result is “piped” into the head function for display. The head function says show the top 12 rows. When no rows are specified in the head function, the default is 6 rows. Note that the filter function resides in the *dplyr* package within the *tidyverse* family.

If the *tidyverse* or *dplyr* packages have been loaded, you don’t need to supply the `dplyr::` prefix to the `filter` command.

```
#gapminder %>% filter(country=="Australia") %>% head(n=12)
gapminder %>% dplyr::filter(country=="Australia") %>% head(n=12)
```

```
## # A tibble: 12 x 6
##    country   continent  year lifeExp      pop gdpPercap
##    <fct>     <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Australia Oceania    1952    69.1  8691212    10040.
##  2 Australia Oceania    1957    70.3  9712569    10950.
##  3 Australia Oceania    1962    70.9 10794968    12217.
##  4 Australia Oceania    1967    71.1 11872264    14526.
##  5 Australia Oceania    1972    71.9 13177000    16789.
##  6 Australia Oceania    1977    73.5 14074100    18334.
##  7 Australia Oceania    1982    74.7 15184200    19477.
##  8 Australia Oceania    1987    76.3 16257249    21889.
##  9 Australia Oceania    1992    77.6 17481977    23425.
## 10 Australia Oceania    1997    78.8 18565243    26998.
## 11 Australia Oceania    2002    80.4 19546792    30688.
## 12 Australia Oceania    2007    81.2 20434176    34435.
```

4.3 Subset using multiple conditions

Let’s select by contintent and year. The head function will then show some of the rows selected. Here the gapminder dataframe is piped to the `filter` function to select rows to be further piped to the `head()` function for display. The logical condtion inside `filter` restricts continent to “Oceania” AND (AND condition is “&”) year to be 1997. Both of these conditions must be TRUE for the row to enter the dataframe to displayed by the `head()` function.

```
gapminder %>%
  dplyr::filter(continent=="Oceania" & year==1997) %>%
  head()
```

```
## # A tibble: 2 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Australia   Oceania    1997    78.8 18565243    26998.
## 2 New Zealand Oceania    1997    77.6  3676187    21050.
```

The next example uses an "or" condition to specify the desired rows in the first `filter` expression - the next `filter` permits only observations from 1997.

```
gapminder %>%
  dplyr::filter(continent=="Oceania" | continent =="Americas") %>%
  dplyr::filter(year==1997) %>%
  head()
```

```
## # A tibble: 6 x 6
##   country   continent  year lifeExp       pop gdpPercap
##   <fct>     <fct>     <int>   <dbl>     <int>     <dbl>
## 1 Argentina Americas   1997    73.3  36203463    10967.
## 2 Australia Oceania    1997    78.8  18565243    26998.
## 3 Bolivia   Americas   1997    62.0   7693188     3326.
## 4 Brazil    Americas   1997    69.4 168546719     7958.
## 5 Canada    Americas   1997    78.6  30305843    28955.
## 6 Chile     Americas   1997    75.8  14599929    10118.
```

The next example selects observations/rows from a list of countries and also restricts year to 1997.

```
gapminder %>%
  filter(country %in% c("Australia", "New Zealand","Argentina") & year==1997) %>%
  head()
```

```
## # A tibble: 3 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Argentina   Americas   1997    73.3 36203463    10967.
## 2 Australia   Oceania    1997    78.8 18565243    26998.
## 3 New Zealand Oceania    1997    77.6  3676187    21050.
```

The next example selects observations by omitting one continent (Oceania is excluded) and then specifies a year. The code that causes "omit" is the "!=" syntax. In the code `year==1997`, the double equal sign `==` means make a logical check if year is 1997. Only rows where both aspects of the filter conditions pass through to be displayed by `head`. Again, the logical operator "AND" is expressed by the `&` expression.

```
gapminder %>%
  filter(continent!="Oceania" & year==1997) %>%
  head()
```

```
## # A tibble: 6 x 6
##   country     continent  year lifeExp      pop gdpPercap
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
## 1 Afghanistan Asia       1997    41.8 22227415      635.
## 2 Albania     Europe     1997    73.0  3428038     3193.
## 3 Algeria     Africa     1997    69.2 29072015     4797.
## 4 Angola      Africa     1997    41.0  9875024     2277.
## 5 Argentina   Americas   1997    73.3 36203463    10967.
## 6 Austria     Europe     1997    77.5  8069876    29096.
```

Please note that in all the above examples, the `filter` function accepts/rejects rows or observations in a dataframe according to the logical conditions specified inside the filter function.

4.4 Saving as a new dataframe

Here we save the the modified dataset as a new dataframe called gap97.

```
gap97 <- gapminder %>%
  filter(continent!="Oceania" & year==1997)
#
dplyr::glimpse(gap97)
```

```
## Observations: 140
## Variables: 6
## $ country   <fct> Afghanistan, Albania, Algeria, Angola, Argentina, Austria, …
## $ continent <fct> Asia, Europe, Africa, Africa, Americas, Europe, Asia, Asia,…
## $ year      <int> 1997, 1997, 1997, 1997, 1997, 1997, 1997, 1997, 1997, 1997,…
## $ lifeExp   <dbl> 41.763, 72.950, 69.152, 40.963, 73.275, 77.510, 73.925, 59.…
## $ pop       <int> 22227415, 3428038, 29072015, 9875024, 36203463, 8069876, 59…
## $ gdpPercap <dbl> 635.3414, 3193.0546, 4797.2951, 2277.1409, 10967.2820, 2909…
```

4.5 Subset using top_n

Let's make a dataset based on the countries in 1997 with highest gdp.

```
gapminder %>% filter(year==1997) %>%
  top_n(n = 10, wt = gdpPercap) %>%
  head(n=10)
```

```
## # A tibble: 10 x 6
##    country      continent  year lifeExp       pop gdpPercap
##    <fct>        <fct>     <int>   <dbl>     <int>     <dbl>
##  1 Austria      Europe     1997    77.5   8069876    29096.
##  2 Canada       Americas   1997    78.6  30305843    28955.
##  3 Denmark      Europe     1997    76.1   5283663    29804.
##  4 Japan        Asia       1997    80.7 125956499    28817.
##  5 Kuwait       Asia       1997    76.2   1765345    40301.
##  6 Netherlands  Europe     1997    78.0  15604464    30246.
##  7 Norway       Europe     1997    78.3   4405672    41283.
##  8 Singapore    Asia       1997    77.2   3802309    33519.
##  9 Switzerland   Europe     1997    79.4   7193761    32135.
## 10 United States Americas   1997    76.8 272911760    35767.
```

4.6 Subset using select

The `filter` function controls the rows of the dataframe. Sometimes we might want to include only a few of the variables (columns) in a dataset. We frequently want to create a data subset with only a few variables when the original dataset has hundreds of variables. The `select` function is used to select and rename variables.

```
# the next command selects three variables and renames two of them:
gapminder %>% dplyr::select(country, Year=year,LifeExp=lifeExp) %>% head()
```

```
## # A tibble: 6 x 3
##   country      Year LifeExp
##   <fct>       <int>   <dbl>
## 1 Afghanistan  1952    28.8
## 2 Afghanistan  1957    30.3
## 3 Afghanistan  1962    32.0
## 4 Afghanistan  1967    34.0
## 5 Afghanistan  1972    36.1
## 6 Afghanistan  1977    38.4
```

```
# to change the order of display, puts year first in the list of variables
gapminder %>% select(year,everything()) %>% head()
```

```
## # A tibble: 6 x 6
##    year country     continent lifeExp      pop gdpPercap
##   <int> <fct>       <fct>       <dbl>    <int>     <dbl>
## 1  1952 Afghanistan Asia         28.8  8425333      779.
## 2  1957 Afghanistan Asia         30.3  9240934      821.
## 3  1962 Afghanistan Asia         32.0 10267083      853.
## 4  1967 Afghanistan Asia         34.0 11537966      836.
## 5  1972 Afghanistan Asia         36.1 13079460      740.
## 6  1977 Afghanistan Asia         38.4 14880372      786.
```

The `profiling_num` command from the *funModeling* package produces a lot of output, some we might not want. We will show how to modify the output of this command here. The command produces a dataframe which has many columns we might not wish to display or consider further.

We begin by removing some columns of summary statistics that we wish to ignore. Selecting a list of column names with a “minus” - sign in front of the list will remove these items from the dataframe and keep the rest in place. The command below pipes the modified dataframe to the `kable` command in the *knitr* package for a more pleasing tabular display.

```
# Let's observe the contents of profiling_num:
funModeling::profiling_num(gapminder) %>% dplyr::glimpse()
```

```
## Observations: 4
## Variables: 16
## $ variable       <chr> "year", "lifeExp", "pop", "gdpPercap"
## $ mean           <dbl> 1.979500e+03, 5.947444e+01, 2.960121e+07, 7.215327e+03
## $ std_dev        <dbl> 1.726533e+01, 1.291711e+01, 1.061579e+08, 9.857455e+03
## $ variation_coef <dbl> 0.008722066, 0.217187544, 3.586268548, 1.366182632
## $ p_01           <dbl> 1952.0000, 33.4926, 154117.9200, 369.2201
## $ p_05           <dbl> 1952.0000, 38.4924, 475458.9000, 547.9964
## $ p_25           <dbl> 1965.750, 48.198, 2793664.000, 1202.060
## $ p_50           <dbl> 1979.5000, 60.7125, 7023595.5000, 3531.8470
## $ p_75           <dbl> 1.993250e+03, 7.084550e+01, 1.958522e+07, 9.325462e+03
## $ p_95           <dbl> 2007.000, 77.437, 89822054.500, 26608.333
## $ p_99           <dbl> 2.007000e+03, 8.023892e+01, 6.319900e+08, 3.678357e+04
## $ skewness       <dbl> 0.0000000, -0.2524798, 8.3328742, 3.8468819
## $ kurtosis       <dbl> 1.783217, 1.873099, 80.716151, 30.431702
## $ iqr            <dbl> 2.750000e+01, 2.264750e+01, 1.679156e+07, 8.123402e+03
## $ range_98       <chr> "[1952, 2007]", "[33.4926, 80.23892]", "[154117.92, 63…
## $ range_80       <chr> "[1957, 2002]", "[41.5108, 75.097]", "[946367.1, 54801…
```

```
# now remove unwanted columns from summary display
funModeling::profiling_num(gapminder) %>%
  select(-c("variation_coef","skewness","kurtosis","range_98","range_80","p_01","p_99"
  knitr::kable()
```

variable	mean	std_dev	p_05	p_25	p_50	p_
year	1.979500e+03	1.726533e+01	1952.0000	1965.750	1979.5000	1.993250e-
lifeExp	5.947444e+01	1.291711e+01	38.4924	48.198	60.7125	7.084550e-
pop	2.960121e+07	1.061579e+08	475458.9000	2793664.000	7023595.5000	1.958522e-
gdpPercap	7.215327e+03	9.857455e+03	547.9964	1202.060	3531.8470	9.325462e-

In the next command we take a different approach - we explicitly select the statistics (columns) we want to keep and display. The most commonly used summaries are chosen.

```
funModeling::profiling_num(gapminder) %>%
  select(c("variable","mean","std_dev","p_25","p_50","p_75")) %>%
  knitr::kable()
```

variable	mean	std_dev	p_25	p_50	p_75
year	1.979500e+03	1.726533e+01	1965.750	1979.5000	1.993250e+03
lifeExp	5.947444e+01	1.291711e+01	48.198	60.7125	7.084550e+01
pop	2.960121e+07	1.061579e+08	2793664.000	7023595.5000	1.958522e+07
gdpPercap	7.215327e+03	9.857455e+03	1202.060	3531.8470	9.325462e+03

4.7 Order using arrange

Sometimes we might want to know the countries with the largest or smallest values of some variables. In the following examples we sort/order by the values of life expectancy. In the code below, when we use the command `filter(year==1997)`, the double equal sign means make a logical check if year is 1997, and only allow dataframe rows where this is true to pass through to the next stage of the analysis pipeline.

```
# This command will show the countries with highest life expectancy because
# the data are arranged in descending order of life expectancy (larger to smaller)
gapminder %>%
  dplyr::filter(year==1997) %>%
  dplyr::select(country, continent, lifeExp) %>%
  dplyr::arrange(desc(lifeExp)) %>%
  head()
```

```
## # A tibble: 6 x 3
##   country          continent lifeExp
##   <fct>            <fct>       <dbl>
## 1 Japan            Asia         80.7
## 2 Hong Kong, China Asia         80
## 3 Sweden           Europe       79.4
## 4 Switzerland      Europe       79.4
## 5 Iceland          Europe       79.0
## 6 Australia        Oceania      78.8
```

```
# This command uses the default ascending (increasing) order with
# respect to life expectancy (order smaller to larger)
gapminder %>%
  filter(year==1997) %>%
  select(country, continent, lifeExp) %>%
  arrange(lifeExp) %>%
  head()
```

```
## # A tibble: 6 x 3
##   country      continent lifeExp
##   <fct>        <fct>       <dbl>
## 1 Rwanda       Africa       36.1
## 2 Sierra Leone Africa       39.9
## 3 Zambia       Africa       40.2
## 4 Angola       Africa       41.0
## 5 Afghanistan  Asia         41.8
## 6 Liberia      Africa       42.2
```

The `top_n` function from the *dplyr* package will select the n rows with the largest values of a variable. This is similar to the code above that orders the rows - then use `head` function to select the number of desired rows.

This first example uses the default alphabetical ordering of country name.

```r
gapminder %>%
  filter(year==1997) %>%
  select(country, continent, lifeExp) %>%
  dplyr::top_n(n=6,wt=lifeExp) %>%
  knitr::kable()
```

country	continent	lifeExp
Australia	Oceania	78.83
Hong Kong, China	Asia	80.00
Iceland	Europe	78.95
Japan	Asia	80.69
Sweden	Europe	79.39
Switzerland	Europe	79.37

The results can then be ordered by the life expectancy:

```r
gapminder %>%
  filter(year==1997) %>%
  select(country, continent, lifeExp) %>%
  dplyr::top_n(n=6,wt=lifeExp) %>%
  dplyr::arrange(desc(lifeExp)) %>%
  knitr::kable()
```

country	continent	lifeExp
Japan	Asia	80.69
Hong Kong, China	Asia	80.00
Sweden	Europe	79.39
Switzerland	Europe	79.37
Iceland	Europe	78.95
Australia	Oceania	78.83

The countries with the largest life expectancy can then be ordered by another variable like population. Here we find the 6 countries in 1997 with the highest life expectancy - then display them in order of population size.

```r
gapminder %>%
  filter(year==1997) %>%
  select(country, continent, lifeExp, pop) %>%
  dplyr::top_n(n=6,wt=lifeExp) %>%
  dplyr::arrange(desc(pop)) %>%
  knitr::kable()
```

country	continent	lifeExp	pop
Japan	Asia	80.69	125956499
Australia	Oceania	78.83	18565243
Sweden	Europe	79.39	8897619
Switzerland	Europe	79.37	7193761
Hong Kong, China	Asia	80.00	6495918
Iceland	Europe	78.95	271192

4.8 Grouped Filter

Another useful verb in the *tidyverse* is `group_by`. Suppose we wanted to view the two countries with the highest life expectancy in 1997, in each continent.

```r
gapminder %>%
  filter(year==1997) %>%
  select(country, continent, lifeExp, pop) %>%
  dplyr::group_by(continent) %>%
  dplyr::top_n(n=2,wt=lifeExp) %>%
  dplyr::arrange(continent) %>%
  knitr::kable()
```

country	continent	lifeExp	pop
Reunion	Africa	74.772	684810
Tunisia	Africa	71.973	9231669
Canada	Americas	78.610	30305843
Costa Rica	Americas	77.260	3518107
Hong Kong, China	Asia	80.000	6495918
Japan	Asia	80.690	125956499
Sweden	Europe	79.390	8897619
Switzerland	Europe	79.370	7193761
Australia	Oceania	78.830	18565243
New Zealand	Oceania	77.550	3676187

4.9 New Variables Using Mutate

In many problems we may wish to create a new variable based on an existing variable. Here we illustrate by making a new variable - the natural logarithm of population - based on the original variable `pop`.

```r
gapminder %>%
  dplyr::mutate(logpopulation = log(pop)) %>%
  dplyr::glimpse()
```

```
## Observations: 1,704
## Variables: 7
## $ country       <fct> Afghanistan, Afghanistan, Afghanistan, Afghanistan, Afg…
## $ continent     <fct> Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, A…
## $ year          <int> 1952, 1957, 1962, 1967, 1972, 1977, 1982, 1987, 1992, 1…
## $ lifeExp       <dbl> 28.801, 30.332, 31.997, 34.020, 36.088, 38.438, 39.854,…
## $ pop           <int> 8425333, 9240934, 10267083, 11537966, 13079460, 1488037…
## $ gdpPercap     <dbl> 779.4453, 820.8530, 853.1007, 836.1971, 739.9811, 786.1…
## $ logpopulation <dbl> 15.94675, 16.03915, 16.14445, 16.26115, 16.38655, 16.51…
```

If I want to change the name of the new variable from `logpopulation` to something shorter like `logPop`, we could re-run the `mutate` command, or use a `rename` function.

In addition we create a new version of the gapminder dataset that contains the new variable - called gapVers1. This dataframe is now available to be used in the ongoing analysis.

```r
gapVers1 <- gapminder %>%
  dplyr::mutate(logpopulation = log(pop)) %>%
  dplyr::rename(logPop=logpopulation)
#
  dplyr::glimpse(gapVers1)
```

```
## Observations: 1,704
## Variables: 7
## $ country   <fct> Afghanistan, Afghanistan, Afghanistan, Afghanistan, Afghani…
## $ continent <fct> Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia,…
## $ year      <int> 1952, 1957, 1962, 1967, 1972, 1977, 1982, 1987, 1992, 1997,…
## $ lifeExp   <dbl> 28.801, 30.332, 31.997, 34.020, 36.088, 38.438, 39.854, 40.…
## $ pop       <int> 8425333, 9240934, 10267083, 11537966, 13079460, 14880372, 1…
## $ gdpPercap <dbl> 779.4453, 820.8530, 853.1007, 836.1971, 739.9811, 786.1134,…
## $ logPop    <dbl> 15.94675, 16.03915, 16.14445, 16.26115, 16.38655, 16.51555,…
```

The next code uses a `mutate` command with logical conditions to make a new, two-level categorical variable region as a character variable. Then we use `mutate` again to convert `region` (character) to a factor variable named `regionf`. In statistical models, factor variables are preferred, but in data handling stages, character versions are probably easier to manipulate.

The `if_else` function from *dplyr* has the form ‘if_else(logical condition,value if TRUE, value if FALSE).

The next example uses the “T-pipe” function `%T>%` to break the piping so that the result of the second `mutate` flows to both `glimpse` and to `head` - in this construction, it is understood the output of `glimpse` does not pipe to `head`, but rather the original data flow from the second `mutate`.

```r
gapminder %>%
  dplyr::mutate(region = if_else(country=="Oceania","Oceania","NotOceania")) %>%
  dplyr::mutate(regionf = as_factor(region)) %T>%
  dplyr::glimpse() %>%
  head()
```

```
## Observations: 1,704
## Variables: 8
## $ country   <fct> Afghanistan, Afghanistan, Afghanistan, Afghanistan, Afghani…
## $ continent <fct> Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia, Asia,…
## $ year      <int> 1952, 1957, 1962, 1967, 1972, 1977, 1982, 1987, 1992, 1997,…
## $ lifeExp   <dbl> 28.801, 30.332, 31.997, 34.020, 36.088, 38.438, 39.854, 40.…
## $ pop       <int> 8425333, 9240934, 10267083, 11537966, 13079460, 14880372, 1…
## $ gdpPercap <dbl> 779.4453, 820.8530, 853.1007, 836.1971, 739.9811, 786.1134,…
## $ region    <chr> "NotOceania", "NotOceania", "NotOceania", "NotOceania", "No…
## $ regionf   <fct> NotOceania, NotOceania, NotOceania, NotOceania, NotOceania,…
```

```
## # A tibble: 6 x 8
##   country     continent  year lifeExp      pop gdpPercap region     regionf
##   <fct>       <fct>     <int>   <dbl>    <int>     <dbl> <chr>      <fct>
## 1 Afghanistan Asia       1952    28.8  8425333      779. NotOceania NotOceania
## 2 Afghanistan Asia       1957    30.3  9240934      821. NotOceania NotOceania
## 3 Afghanistan Asia       1962    32.0 10267083      853. NotOceania NotOceania
## 4 Afghanistan Asia       1967    34.0 11537966      836. NotOceania NotOceania
## 5 Afghanistan Asia       1972    36.1 13079460      740. NotOceania NotOceania
## 6 Afghanistan Asia       1977    38.4 14880372      786. NotOceania NotOceania
```

4.10 Missing Values

If a variable is not complete and contains empty places, these are denoted in R as NA. We will often wish to create a dataframe without any missing values, or discover how many rows contain variables with missing values.

First let's create a small dataset with missing values:

```
x <- c(1,2,NA,4)
y <- c(11,12,13,NA)
z <- c(7,8,9,10)
tempdf <- data.frame(x,y,z)
tempdf
```

```
##    x  y  z
## 1  1 11  7
## 2  2 12  8
## 3 NA 13  9
## 4  4 NA 10
```

```
# count missing values for variable x
tempdf %>%
  dplyr::summarise(count = sum(is.na(x)))
```

```
##   count
## 1     1
```

```
# count rows with missing y
tempdf %>%
  dplyr::tally(is.na(y))
```

```
##   n
## 1 1
```

```
# subset of rows with complete data for specified columns
tempdf %>%
  dplyr::select(y,z) %>%
  tidyr::drop_na() %>%
  head()
```

```
##    y z
## 1 11 7
## 2 12 8
## 3 13 9
```

```
#   drop rows with missing values in all variables
tempdf %>%
  tidyr::drop_na() %>%
  head()
```

```
##   x  y z
## 1 1 11 7
## 2 2 12 8
```

Use base `is.na` function

```
tempdf %>%
  filter(!is.na(x),           # remove obs with missing x
         !is.na(y),  # remove obs with missing y
         !is.na(z))                 # remove obs with missing z
```

```
##   x  y z
## 1 1 11 7
## 2 2 12 8
```

Some code that will execute a filter that will permit only rows with entirely complete data in x to pass through to the dataset,

```
tempdf %>%
  filter(x %>% is.na() %>% magrittr::not()) %>%
  head()
```

```
##   x  y  z
## 1 1 11  7
## 2 2 12  8
## 3 4 NA 10
```

Chapter 5

Univariate Graphical Displays

In this section we will show examples of how to create graphical displays of a single variable - with examples for both quantitative and categorical variables. In each example, the first line creates the dataset to be graphed - followed by a command making the display. We will focus on graphical displays made by functions in the *ggplot2* family - that is, the *ggplot2* package which is also part of the *tidyverse* family of functions. If *tidyverse* is loaded, *ggplot2* functions will work without explicitly loading the *ggplot2* package.

5.1 Overview of ggplot

The *ggplot2* package uses the `ggplot` command - and builds a graphical display in steps and layers. We always start with the `ggplot` command which typically has two basic elements: a dataset to be used, and a list of mappings `aes` that is used to connect dataset variables to aspects of the plot like the vertical axis, horizontal axis, or perhaps the size of a point.

The kind of object being displayed is called a `geom`, and a plot can have several `geoms`, and they are added to a display in layers - connected by a `+` sign.

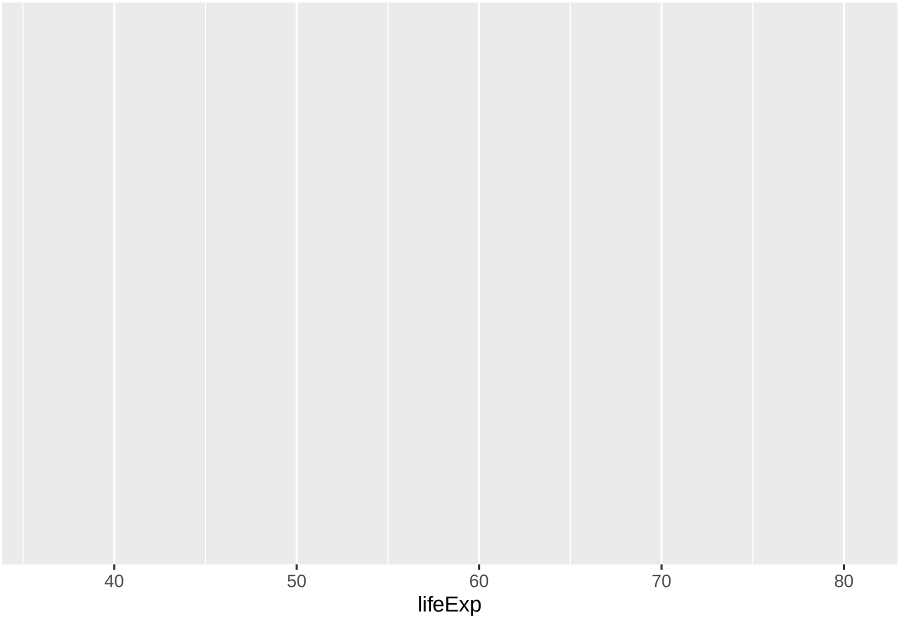
5.2 A Quantitative Variable

5.2.1 Dotplot

The next block of code takes the gapminder dataframe and "pipes" (%>%, a pipeline like plumbing) the data through a filter so that only data from year

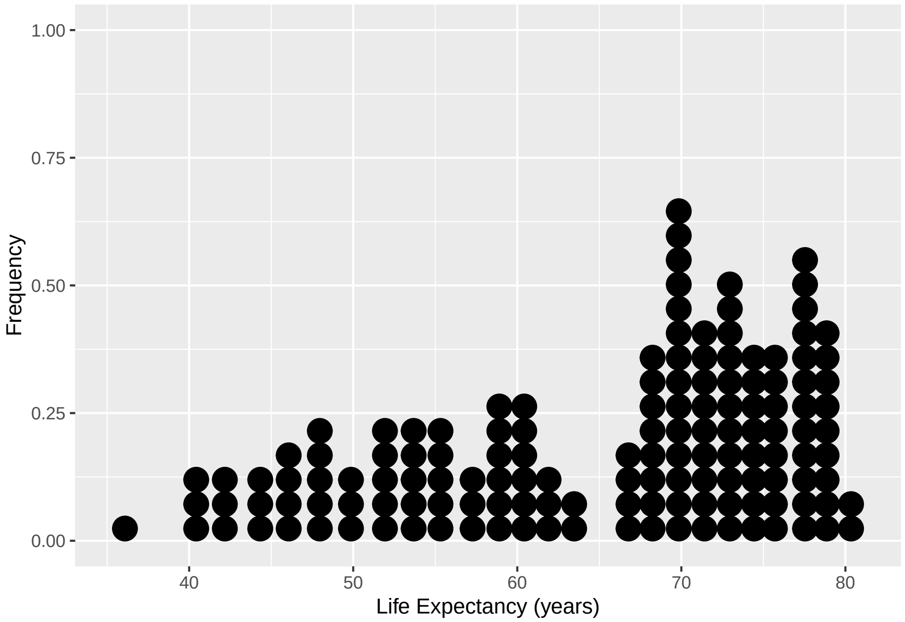
1997 flows through to define the new dataset named `ds`. The `ggplot` command uses dataset ds, and variable x life expectancy. The next example shows what using only the `ggplot` command produces an empty graphical region that is awaiting further instructions:

```
ds <- gapminder %>% filter(year==1997)
#
ggplot(data=ds, mapping=aes(x=lifeExp))
```



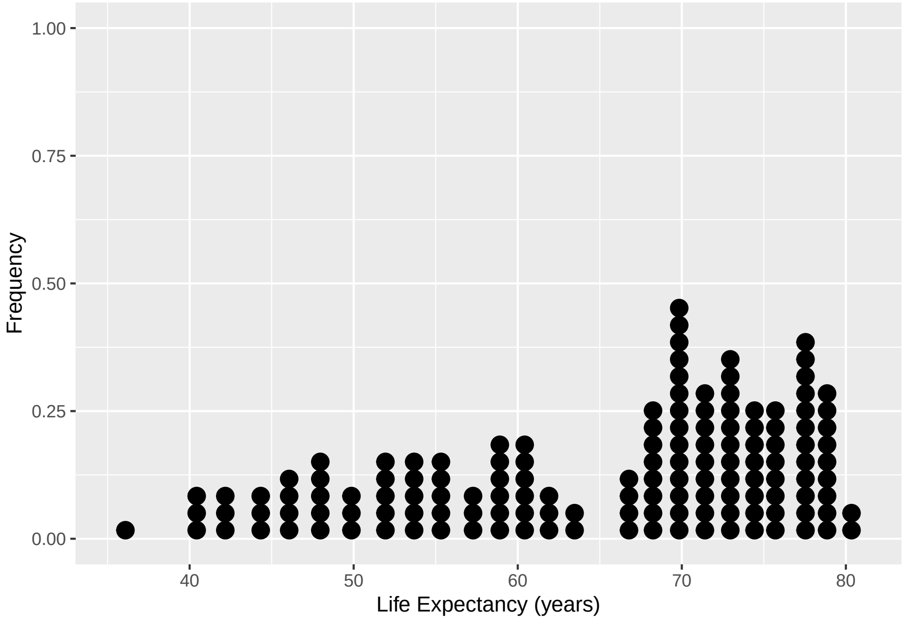
Now we use additional code to place the dotplot in the existing graphical region. In ggplot graphics we make graphical objects with a `geom` function - here a dotplot so we use `geom_dotplot()` to produce the dotplot specified using the variable mappings in the aesthetics command `aes` in the ggplot command.

```
ds <- gapminder %>% filter(year==1997)
#
ggplot(data=ds, mapping=aes(x=lifeExp)) +
  geom_dotplot() +
  xlab("Life Expectancy (years)") + ylab("Frequency")
```



Here we change the default size for the dots.

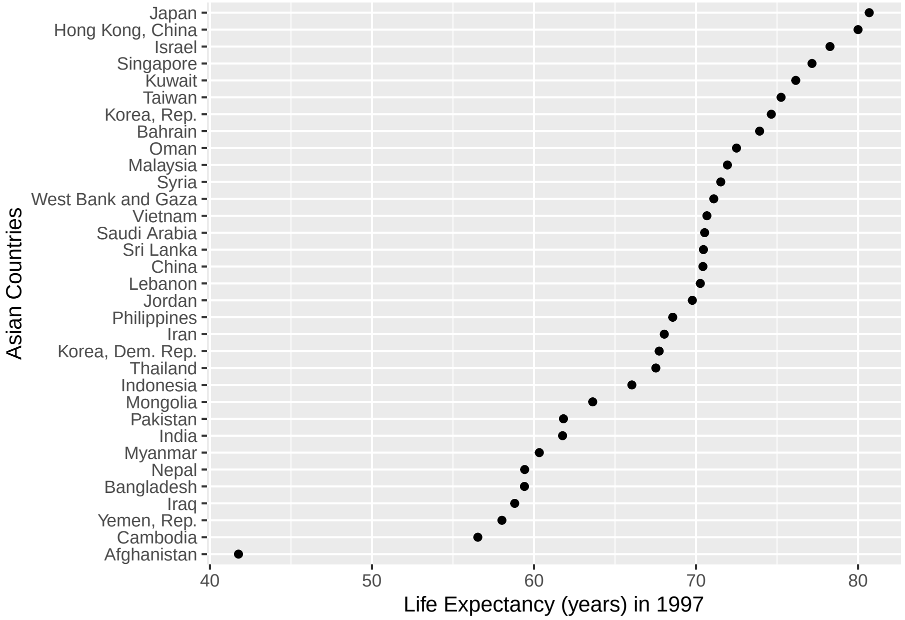
```
ds <- gapminder %>% filter(year==1997)
#
ggplot(data=ds, mapping=aes(x=lifeExp)) +
  geom_dotplot(dotsize=0.70) +
  xlab("Life Expectancy (years)") + ylab("Frequency")
```



5.2.1.1 Dotplot with observations identified and ordered

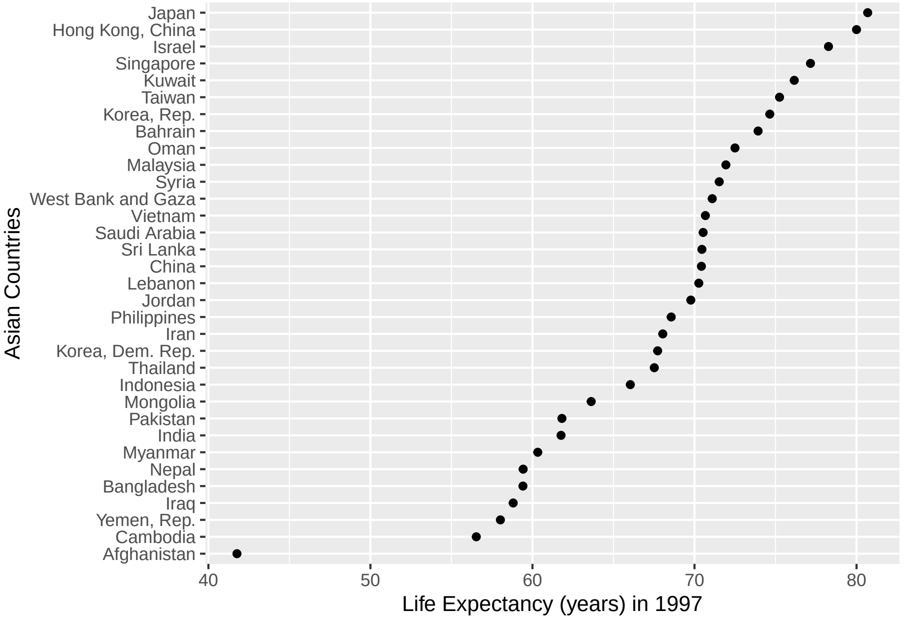
Here we produce a display so that life expectancy is displayed for each country in Asia, and the values are ordered.

```
ds <- gapminder %>% filter(continent=="Asia",year==1997)
#
ggplot(data=ds, mapping=aes(x=lifeExp, y= reorder(country,lifeExp))) +
  geom_point() +
  xlab("Life Expectancy (years) in 1997") +
  ylab("Asian Countries")
```



Notice that in the next example we simply pipe the modified dataset into the first argument of the `ggplot` command so that there is no need to save the modified dataset to make the display.

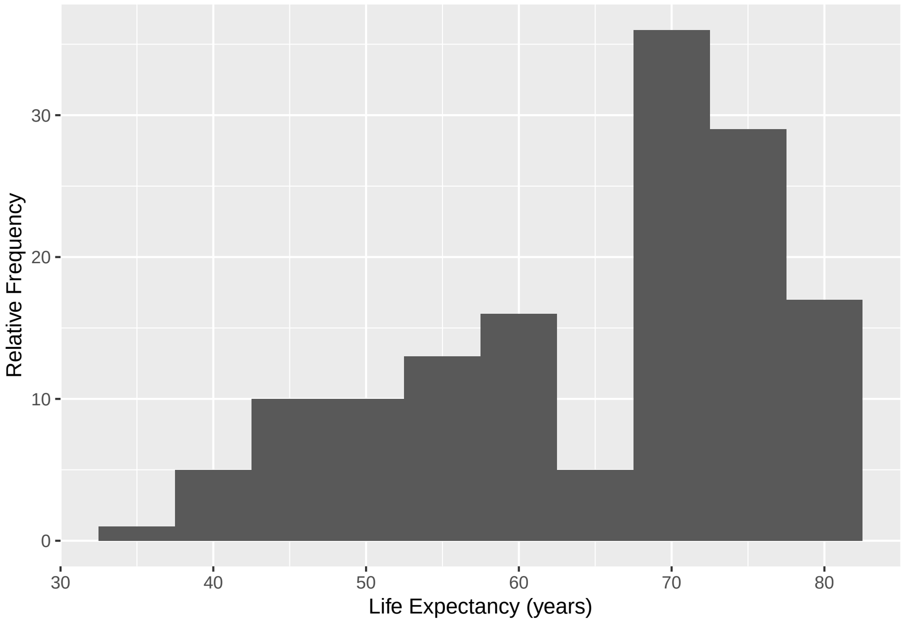
```
gapminder %>% filter(continent=="Asia",year==1997) %>%
ggplot( mapping=aes(x=lifeExp, y= reorder(country,lifeExp))) +
  geom_point() +
  xlab("Life Expectancy (years) in 1997") +
  ylab("Asian Countries")
```



5.2.2 Histogram

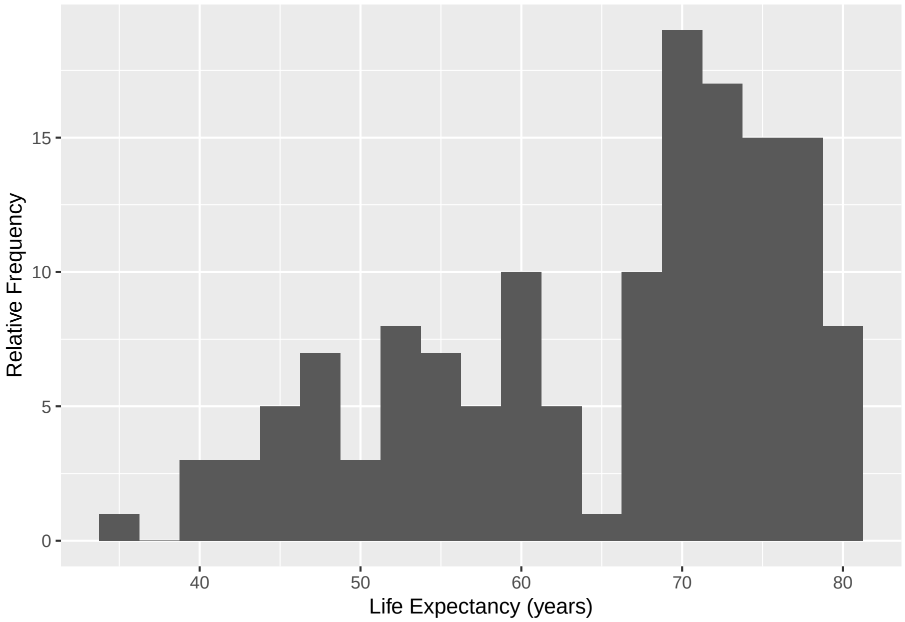
This code block is similar to the dotplot commands, but the geom_histogram function controls the bin width in units of the x variable - in this case 5 years.

```
gapminder %>% filter(year==1997) %>%
ggplot(mapping=aes(x=lifeExp)) +
  geom_histogram(binwidth=5) +
  xlab("Life Expectancy (years)") +
  ylab("Relative Frequency")
```



Here we change the binwidth:

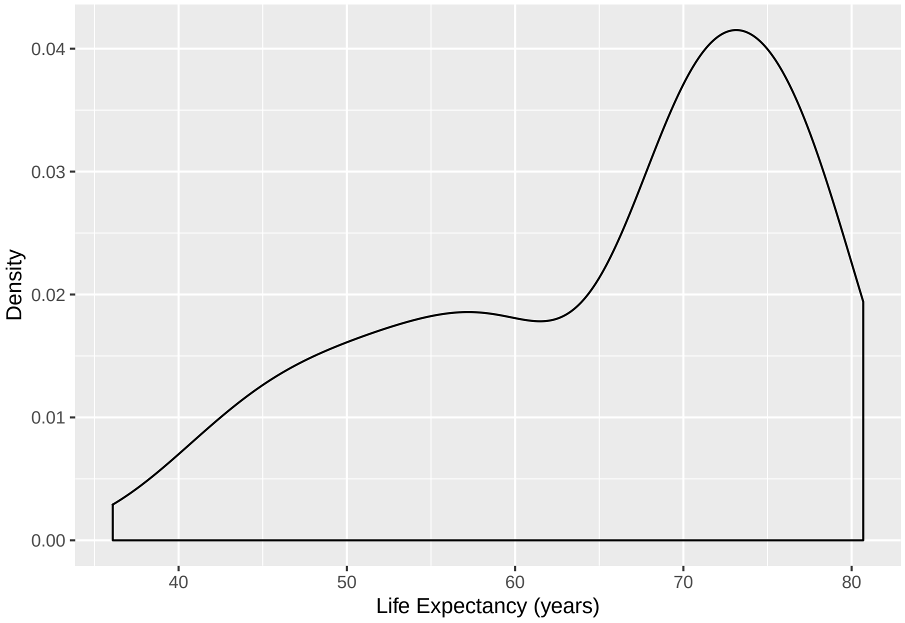
```
gapminder %>% filter(year==1997) %>%
ggplot(mapping=aes(x=lifeExp)) +
  geom_histogram(binwidth=2.5) +
  xlab("Life Expectancy (years)") +
  ylab("Relative Frequency")
```



5.2.3 Density Plot

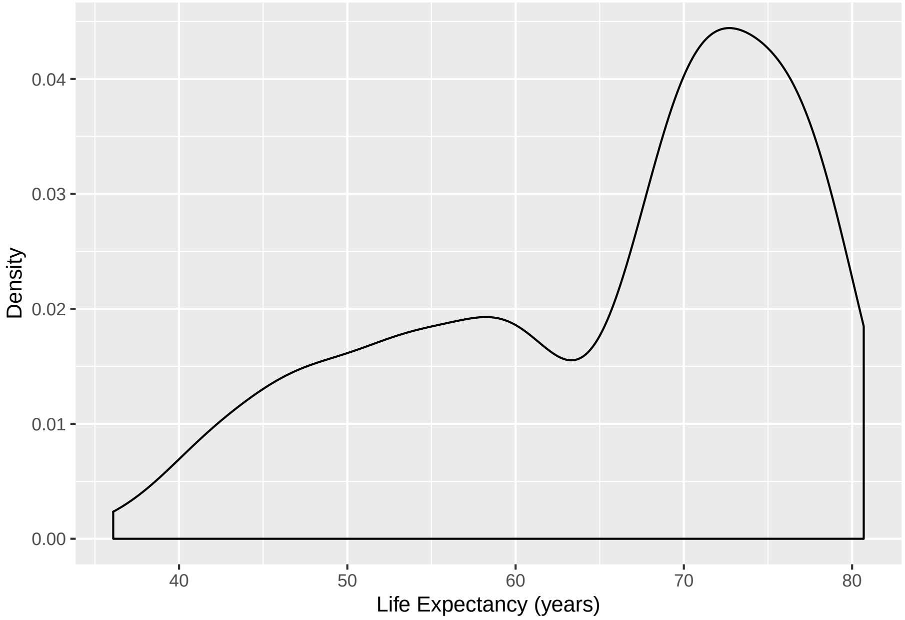
Density plots produces a smoothing of a histogram to display the distribution.

```
ds <- gapminder %>% filter(year==1997)
#
ggplot(data=ds, mapping=aes(x=lifeExp)) +
  geom_density() +
  xlab("Life Expectancy (years)") +
  ylab("Density")
```



The `adjust` option controls the amount of smoothing relative to a default value of 1. A smaller value gives less smoothing (more responsive line to small changes in the data distribution), and larger values will make a smoother curve that is less sensitive to the data pattern.

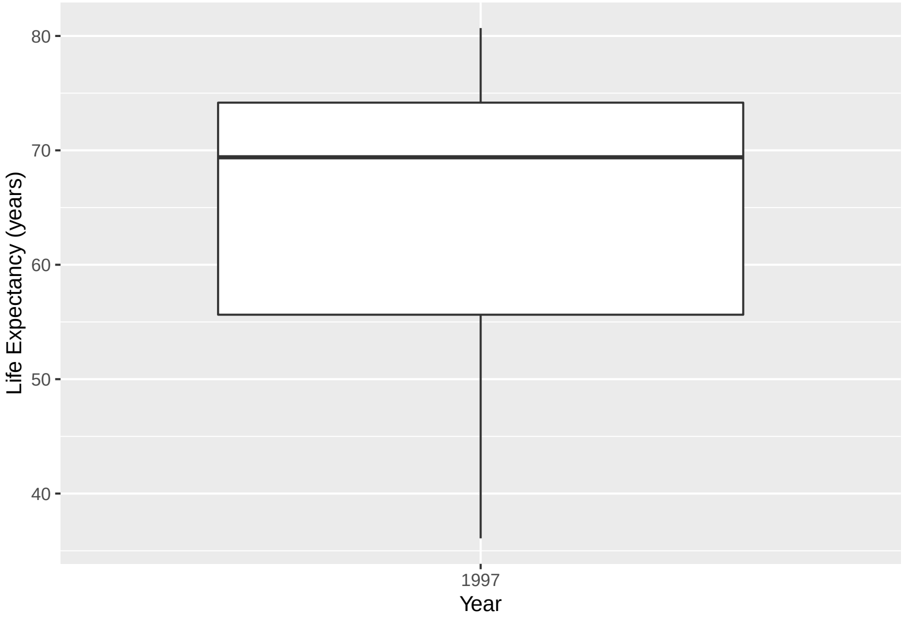
```
ds <- gapminder %>% filter(year==1997)
#
ggplot(data=ds, mapping=aes(x=lifeExp)) +
  geom_density(adjust=0.75) +
  xlab("Life Expectancy (years)") +
  ylab("Density")
```



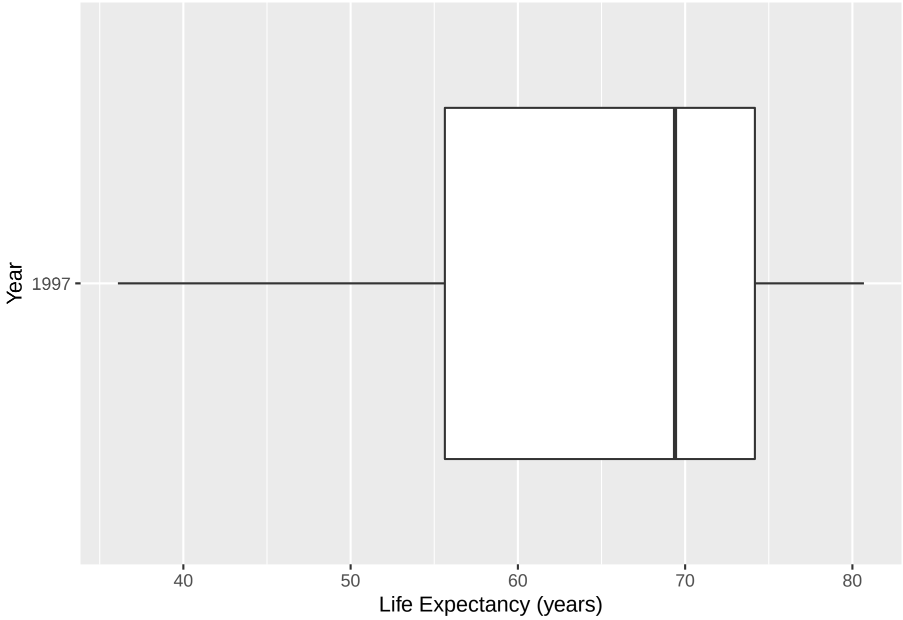
5.2.4 Boxplot

The boxplot display really needs only a single quantitative variable (here life expectancy) for the numeric axis. However, the other axis looks better with some sort of factor variable - so here we supply the year for the display, where the quantitative variable `year` has temporarily being used as a category/factor variable by being processed by the `factor` function before used in the graphic:

```
ds <- gapminder %>% filter(year==1997)
#
ggplot(data=ds, mapping=aes(x=factor(year),y=lifeExp)) +
 geom_boxplot() +
  labs(x="Year",y="Life Expectancy (years)")
```

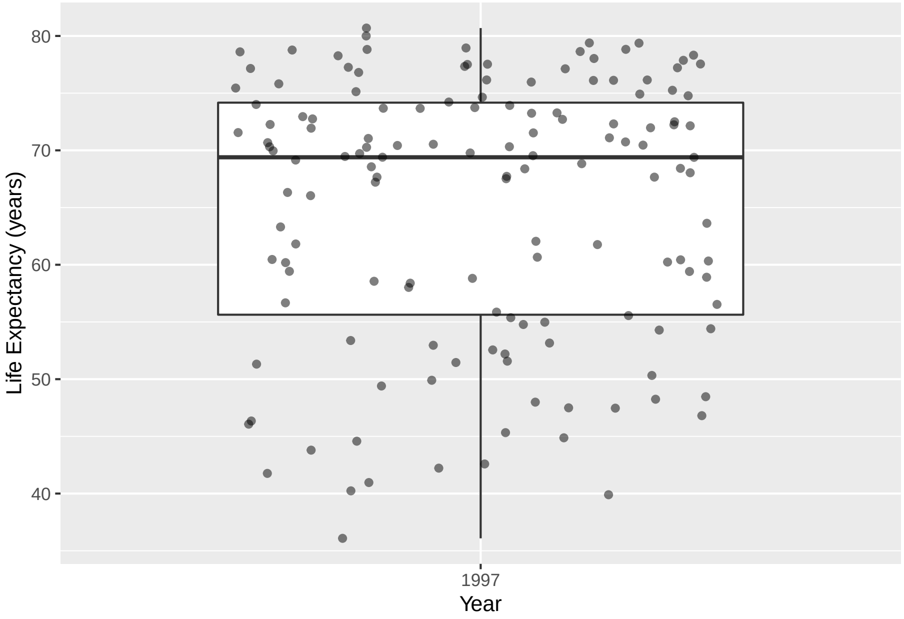


```
# Change orientation
ggplot(data=ds, mapping=aes(x=factor(year),y=lifeExp)) +
 geom_boxplot() +
  coord_flip() +
  labs(x="Year",y="Life Expectancy (years)")
```



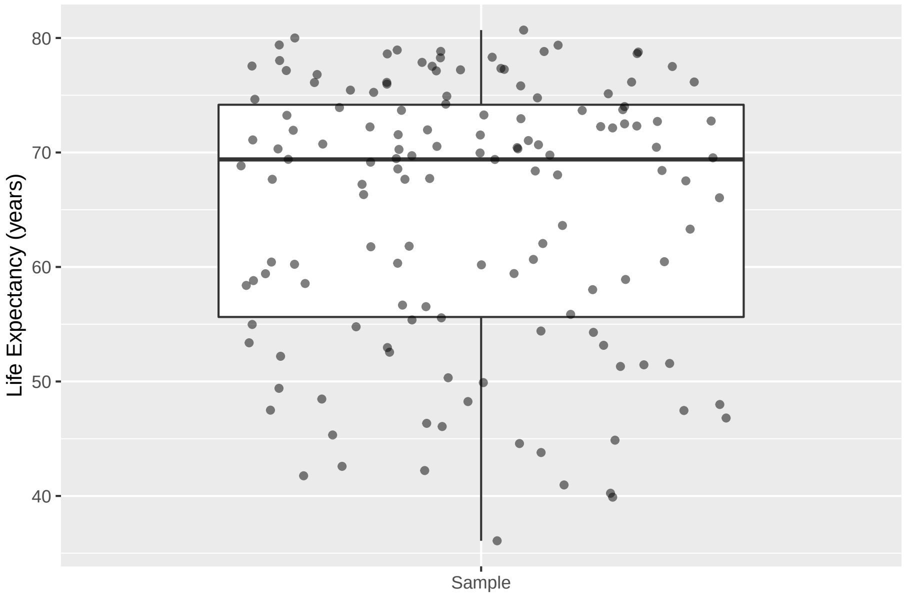
Now we overlay points on top of the boxplot display. Note the `geom_jitter` that overlays the points has an argument `alpha=0.5` signifying a slightly transparent plot symbol. An alpha value of 1 means the plot symbol is opaque, and a value of 0 is comletely transparent. Careful use of alpha in large datasets will enable the analyst to correctly perceive point density. Without using a smaller value of `alpha` the plot may be one large blob of ink - making it difficult to judge the density of points in the display.

```r
ds <- gapminder %>% filter(year==1997)
#
ggplot(data=ds, mapping=aes(x=factor(year),y=lifeExp)) +
 geom_boxplot(outlier.shape = NA) +
 geom_jitter(alpha=0.5, width=0.35) +
  labs(x="Year",y="Life Expectancy (years)")
```



If the dataframe has only one quantitative variable, we can make a character variable called “sample”, then this code will produce an acceptable display.

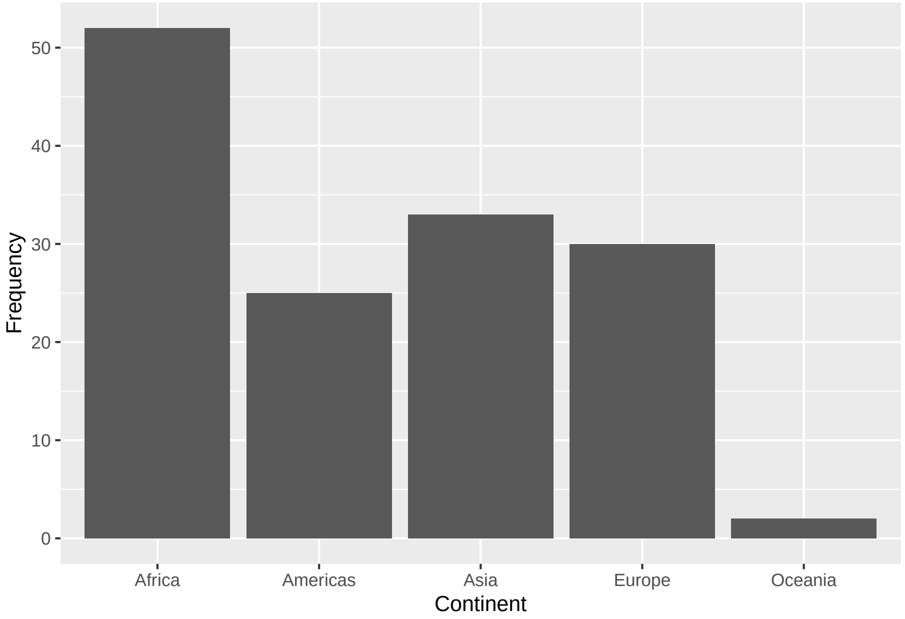
```
ds <- gapminder %>% filter(year==1997) %>%
  mutate(sample="Sample")
#
ggplot(data=ds, mapping=aes(x=sample,y=lifeExp)) +
 geom_boxplot(outlier.shape = NA) +
 geom_jitter(alpha=0.5, width=0.35) +
  labs(x="",y="Life Expectancy (years)")
```



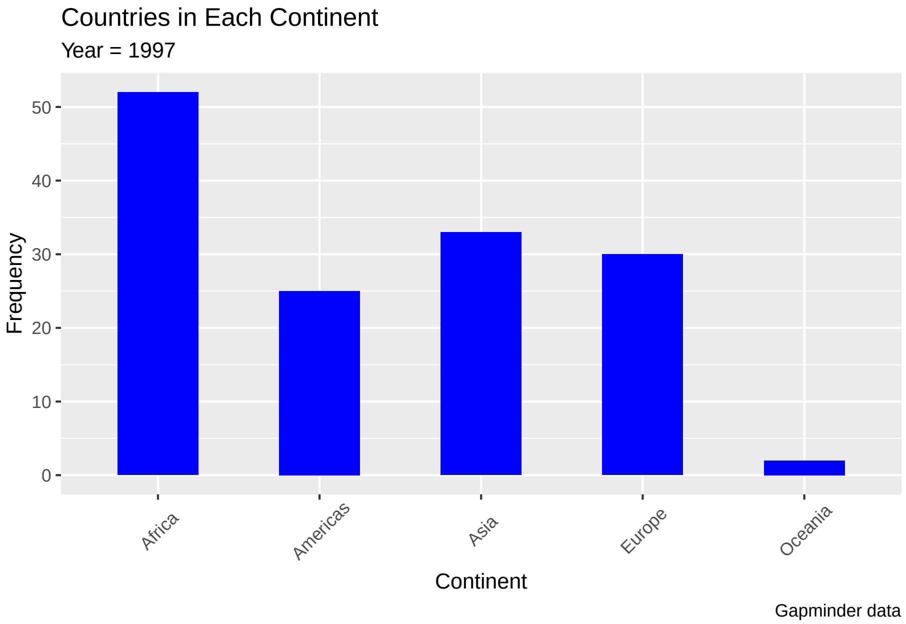
5.3 Displays of a Categorical Variable

5.3.1 Bar Graph

```
ds <- gapminder %>%
  filter(year==1997) %>%
  group_by(continent)
# Frequency of countries in each continent in 1997.
ggplot(data=ds, mapping=aes(x=continent)) +
  geom_bar() +
  labs(x="Continent", y="Frequency")
```

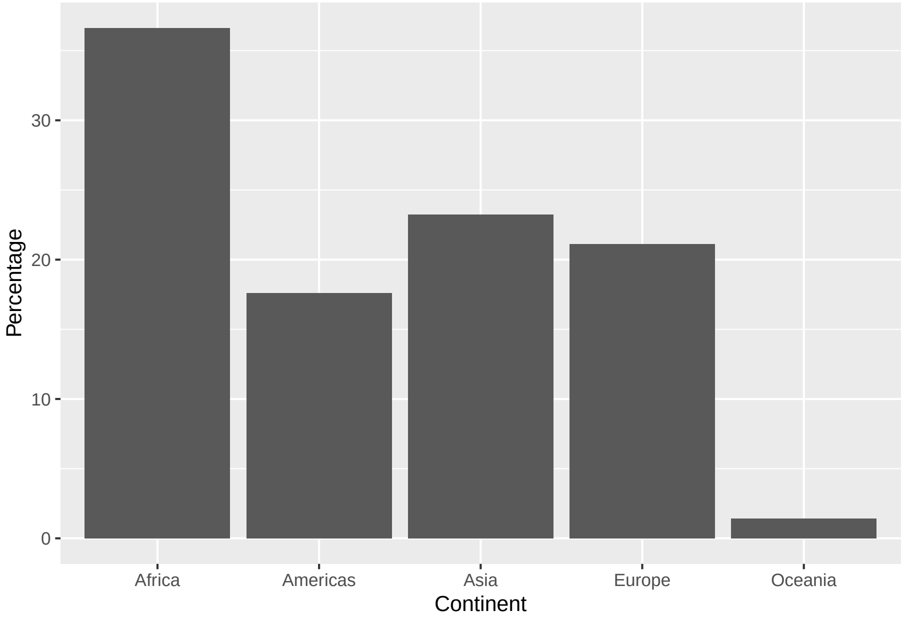


```
#
ggplot(data=ds, mapping=aes(x=continent)) +
  geom_bar(width=0.5,fill="blue") +
  labs(title="Countries in Each Continent",
       subtitle = "Year = 1997",
       caption = "Gapminder data",
       x="Continent",
       y="Frequency") +
  theme(axis.text.x = element_text(angle=45,vjust = 0.6))
```

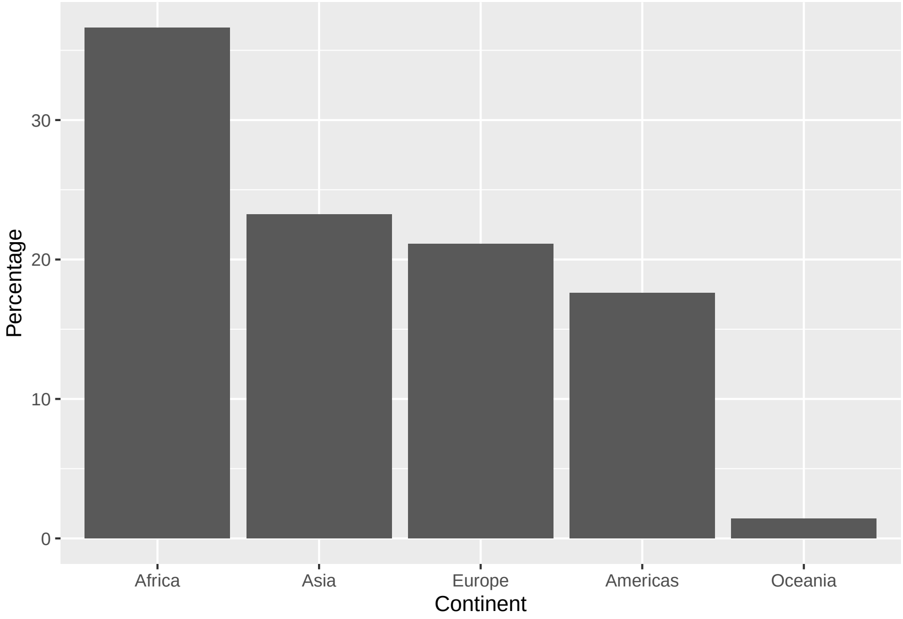


Bar graph with percentages on vertical axis.

```
ds <- gapminder %>%
  filter(year==1997) %>%
  group_by(continent)  %>%
  summarise (n = n()) %>%
  mutate(pct = 100*n / sum(n))
#
ggplot(data=ds, mapping=aes(x = continent, y = pct)) +
  geom_bar(stat = "identity") +
  xlab("Continent") + ylab("Percentage")
```

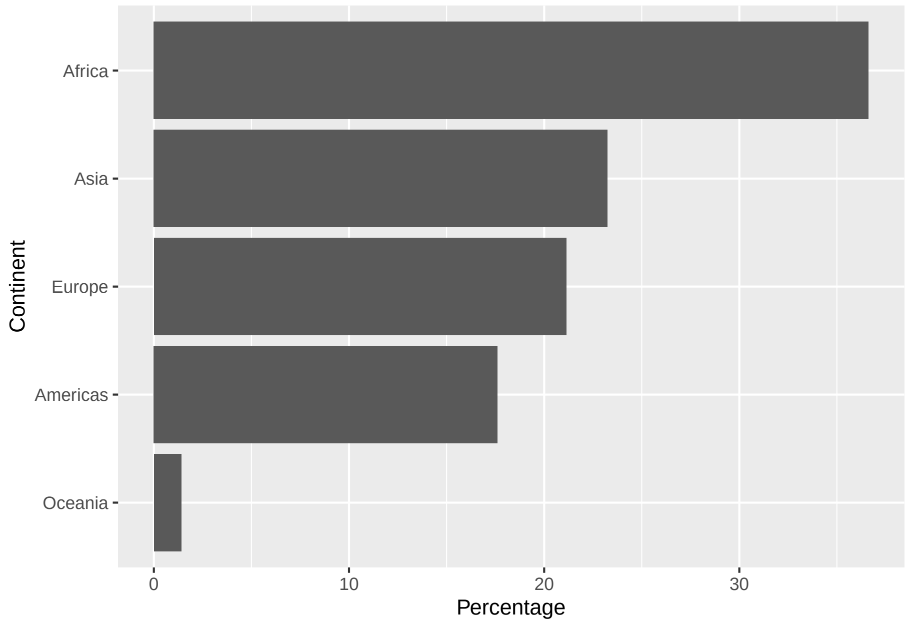


```
# change order of continents in decreasing frequency order
ggplot(data=ds, mapping=aes(x = reorder(continent, -pct), y = pct)) +
  geom_bar(stat = "identity") +
  xlab("Continent") + ylab("Percentage")
```



Sometimes it is more convenient to have the bars oriented horizontally. Notice we set up the aesthetic mappings as usual and then flip the axes with the `coord_flip` command.

```
ds <- gapminder %>%
  filter(year==1997) %>%
  group_by(continent)  %>%
  summarise (n = n()) %>%
  mutate(pct = 100*n / sum(n))
#
ggplot(data=ds, mapping=aes(x = reorder(continent, pct), y = pct)) +
  geom_bar(stat = "identity") +
  coord_flip() +
  xlab("Continent") + ylab("Percentage")
```

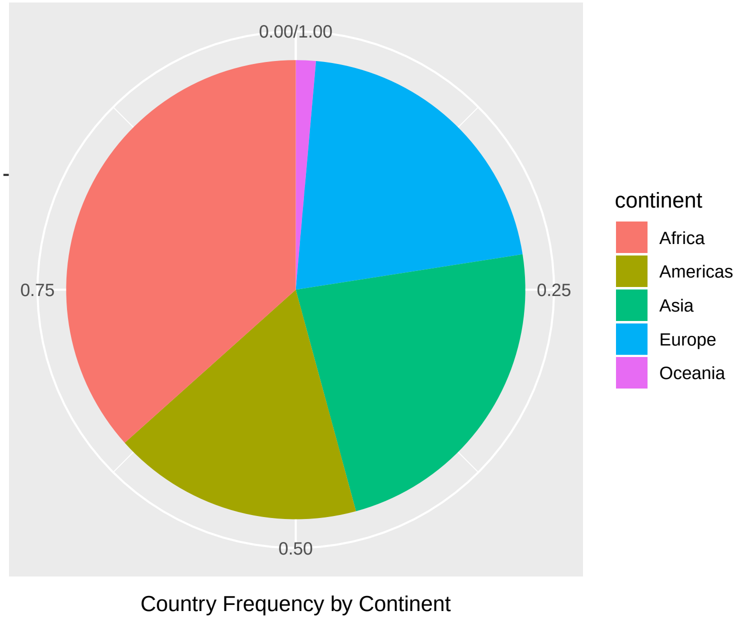


5.3.2 Pie Graph

Pie graphs are not recommended, but the code needed to make one is given here.

```
contin.prop<- gapminder %>%
  group_by(continent) %>%
  summarise (n = n()) %>%
  mutate(freq = n / sum(n))
#
```

```
ggplot(data=contin.prop, mapping=aes(x="",y=freq,fill=continent)) +
  geom_bar(width=1,stat="identity") +
  coord_polar("y",start=0) +
  xlab("") + ylab("Country Frequency by Continent")
```



Chapter 6

Summary Statistics For One Variable

6.1 One Quantitative Variable

6.1.1 Using base R summary function

```
gapminder %>% filter(year==1997) %>% select(lifeExp) %>% summary()
```

```
##     lifeExp
##  Min.   :36.09
##  1st Qu.:55.63
##  Median :69.39
##  Mean   :65.01
##  3rd Qu.:74.17
##  Max.   :80.69
```

6.1.2 Using dplyr summarise function

It is often helpful to create data summaries during preliminary phases of examination. Here is how to use the summarise command in the analysis pipeline system.

```
gapminder %>% filter(year==1997) %>%
      dplyr::summarise(meanLE=mean(lifeExp,na.rm=TRUE),
                       medLE=median(lifeExp,na.rm=TRUE),
                       sd=sd(lifeExp,na.rm=TRUE),
                       iqr=IQR(lifeExp,na.rm=TRUE),
                      Q1=quantile(lifeExp,probs=0.25,na.rm=TRUE),
                      Q3=quantile(lifeExp,probs=0.75),
                      n=n())
```

```
## # A tibble: 1 x 7
##   meanLE medLE    sd   iqr    Q1    Q3     n
##    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <int>
## 1   65.0  69.4  11.6  18.5  55.6  74.2   142
```

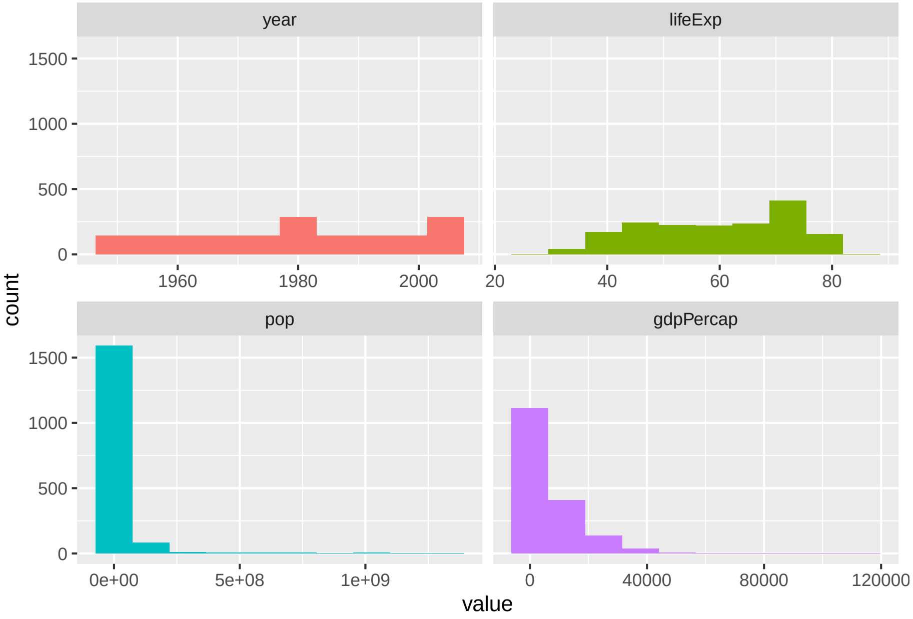
6.1.3 Summary Statistics Using funModeling package

The `profiling_num` and `plot_num` functions from the *funModeling* package help give a concise numeric and visual overview of the numeric variables in the dataframe.

```
funModeling::profiling_num(gapminder)
```

```
##    variable         mean      std_dev variation_coef        p_01        p_05
## 1      year 1.979500e+03 1.726533e+01    0.008722066   1952.0000   1952.0000
## 2   lifeExp 5.947444e+01 1.291711e+01    0.217187544     33.4926     38.4924
## 3       pop 2.960121e+07 1.061579e+08    3.586268548 154117.9200 475458.9000
## 4 gdpPercap 7.215327e+03 9.857455e+03    1.366182632    369.2201    547.9964
##          p_25         p_50         p_75         p_95         p_99   skewness
## 1    1965.750    1979.5000 1.993250e+03     2007.000 2.007000e+03  0.0000000
## 2      48.198      60.7125 7.084550e+01       77.437 8.023892e+01 -0.2524798
## 3 2793664.000 7023595.5000 1.958522e+07 89822054.500 6.319900e+08  8.3328742
## 4    1202.060    3531.8470 9.325462e+03    26608.333 3.678357e+04  3.8468819
##    kurtosis          iqr                       range_98
## 1  1.783217 2.750000e+01                 [1952, 2007]
## 2  1.873099 2.264750e+01            [33.4926, 80.23892]
## 3 80.716151 1.679156e+07  [154117.92, 631990000.000002]
## 4 30.431702 8.123402e+03 [369.220127794, 36783.5723707]
##                      range_80
## 1                [1957, 2002]
## 2           [41.5108, 75.097]
## 3      [946367.1, 54801369.5]
## 4 [687.71836128, 19449.138209]
```

```
funModeling::plot_num(gapminder)
```

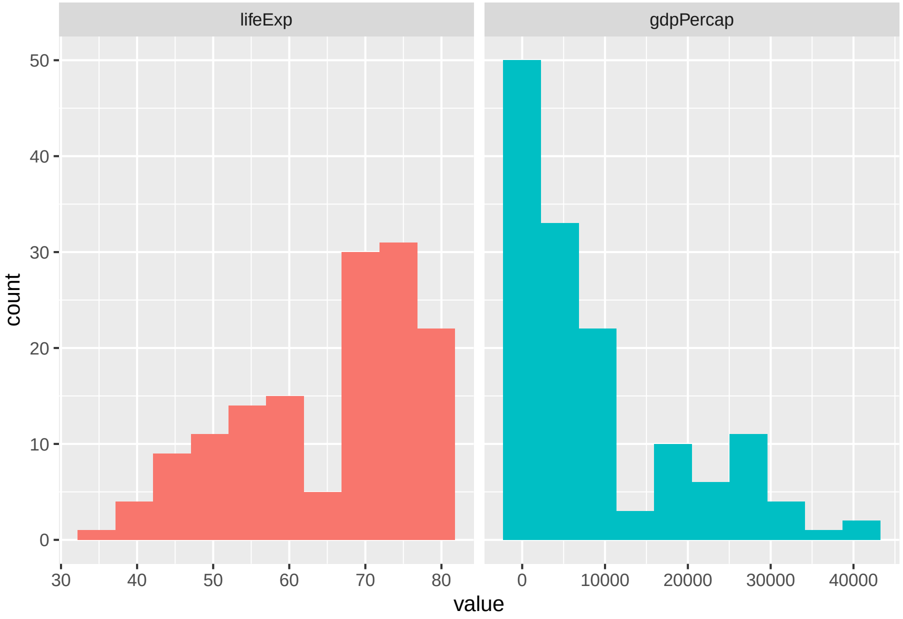


This example shows summary statistics for two quantitative variables. For only one variable, simply use `select` for only one variable.

```
gapminder %>%
  filter(year==1997) %>%
  select(lifeExp,gdpPercap) %>%
funModeling::profiling_num()
```

```
##    variable       mean     std_dev variation_coef      p_01      p_05
## 1   lifeExp   65.01468    11.55944      0.1777974  40.03681  43.83415
## 2 gdpPercap 9090.17536 10171.49326      1.1189546 434.72721 590.90598
##         p_25     p_50        p_75       p_95       p_99   skewness kurtosis
## 1   55.63375   69.394    74.16975    78.7635    79.7499 -0.6427906 2.218599
## 2 1366.83796 4781.825 12022.86719 29088.8709 38442.0133  1.2979366 3.604446
##          iqr                       range_98                     range_80
## 1     18.536            [40.03681, 79.7499]            [47.4671, 77.548]
## 2  10656.029 [434.727210598, 38442.0133187] [789.29339925, 26905.596049]
```

```
#
gapminder %>%
  filter(year==1997) %>%
  select(lifeExp,gdpPercap) %>%
funModeling::plot_num()
```



6.1.4 Summary Statistics: skimr package

The *skimr* package produces summary statistics about variables and overviews for dataframes. It is easy to manipulate and use pipes, select, and filter from the tidyverse family of packages.

The next code supplies a dataframe that contains both categorical variables (continent), and numeric variables (lifeExp, gdpPercap). Numeric variables are chosen with the `yank` function, then some attributes are omitted from the display (n_missing, complete_rate) using the `select` function from dplyr.

```
varlist <- c("n_missing","complete_rate")
gapminder %>% filter(year==1997) %>%
  select(-year, -country, -pop) %>%
  skimr::skim_without_charts() %>%
  skimr::yank("numeric") %>%
  dplyr::select(-one_of(varlist))
```

Variable type: numeric

skim_variable	mean	sd	p0	p25	p50	p75	p100
lifeExp	65.01	11.56	36.09	55.63	69.39	74.17	80.69
gdpPercap	9090.18	10171.49	312.19	1366.84	4781.83	12022.87	41283.16

6.2 One Categorical Variable

6.2.1 Counting Values

The next command counts the number of rows in the dataset for each continent - then we show a variant which pipes the output into the kable function for a more attractive table.

```
gapminder %>% count(continent)
```

```
## # A tibble: 5 x 2
##   continent     n
##   <fct>     <int>
## 1 Africa      624
## 2 Americas    300
## 3 Asia        396
## 4 Europe      360
## 5 Oceania      24
```

```
#
gapminder %>%  count(continent) %>% knitr::kable()
```

continent	n
Africa	624
Americas	300
Asia	396
Europe	360
Oceania	24

```
#
gapminder %>%  count(continent, sort=TRUE) %>% knitr::kable()
```

continent	n
Africa	624
Asia	396
Europe	360
Americas	300
Oceania	24

The previous code tells us how many lines (rows) for each continent, but many rows are repeated for each country - just different years.

```
gapminder %>% filter(year==1997 | year==1967) %>%
  dplyr::group_by(continent) %>%
  dplyr::summarise(n = n(), n_countries = n_distinct(country)) %>% knitr::kable()
```

continent	n	n_countries
Africa	104	52
Americas	50	25
Asia	66	33
Europe	60	30
Oceania	4	2

6.2.2 Categorical variable: skimr package

Here we summarize a categorical variable (continent), and observe it has 5 unique values (levels) and the most frequent values are displayed.

```
gapminder %>% filter(year==1997) %>%
  select(lifeExp,continent) %>%
  skimr::skim_without_charts() %>%
  skimr::yank("factor") %>%
  dplyr::select(-n_missing,-ordered,-complete_rate)
```

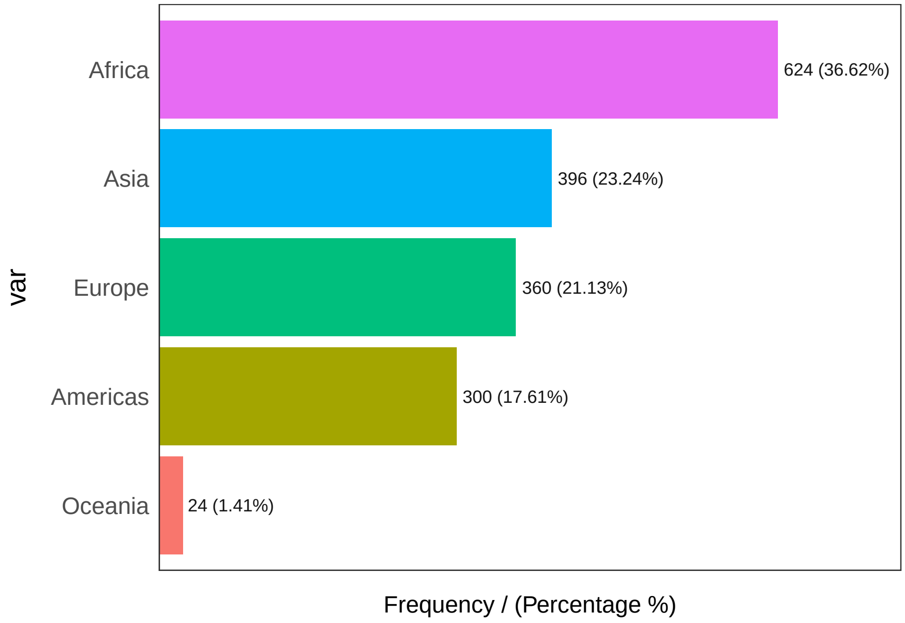
Variable type: factor

skim_variable	n_unique	top_counts
continent	5	Afr: 52, Asi: 33, Eur: 30, Ame: 25

6.2.3 Categorical variable: funModeling package

The *funModeling* package gives an easy way to learn about categorical variables of types: character and factor. There are two categorical variables in the gapminder dataframe: country and continent. There are a lot of countries, so we demonstrate this command for only the continent variable.

```
# Frequency distribution of entire dataframe
# will produce lots of output and warnings
#funModeling::freq(gapminder)
# next command for one category variable:  continent
funModeling::freq(gapminder$continent)
```



```
##        var frequency percentage cumulative_perc
## 1   Africa       624      36.62           36.62
## 2     Asia       396      23.24           59.86
## 3   Europe       360      21.13           80.99
## 4 Americas       300      17.61           98.60
## 5  Oceania        24       1.41          100.00
```

There are a lot of observations (rows) for Africa and very few for Oceania (Australia, New Zealand, etc).

6.2.4 Categorical variable: janitor package

Let's begin with the base R function `table`:

```
gapminder %>%
  filter(year==1997) %>%
  select(continent) %>%
  table()
```

```
## .
##   Africa Americas     Asia   Europe  Oceania
##       52       25       33       30        2
```

Now contrast with the `tabyl` function from the *janitor* package:

```
gapminder %>%
  filter(year==1997) %>%
  janitor::tabyl(continent,sort=TRUE) %>%
  knitr::kable()
```

continent	n	percent
Africa	52	0.3661972
Americas	25	0.1760563
Asia	33	0.2323944
Europe	30	0.2112676
Oceania	2	0.0140845

```
#
gapminder %>%
  filter(year==1997) %>%
  janitor::tabyl(continent,sort=TRUE) %>%
  janitor::adorn_pct_formatting(digits=2,affix_sign = TRUE) %>%
  knitr::kable()
```

continent	n	percent
Africa	52	36.62%
Americas	25	17.61%
Asia	33	23.24%
Europe	30	21.13%
Oceania	2	1.41%

Chapter 7

Exploratory Data Analysis For One Quantitative Variable: by Groups

It is often helpful to create data summaries of a quantitative variable for each level of a grouping variable.

7.1 Summary Statistics: dplyr

Using *dplyr* and *tidyverse* for summary statistics across the levels of a group variable (of type factor/categorical) requires the use of the verb `group_by`. Here we produce summary statistics of life expectancy across the levels of continent.

```
# Output presented in initial continent order (alphabetic)
gapminder %>% filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent) %>%
  summarise(meanLE=mean(lifeExp,na.rm=TRUE),
            medLE=median(lifeExp,na.rm=TRUE),
            sd=sd(lifeExp,na.rm=TRUE),
            iqr=IQR(lifeExp,na.rm=TRUE),
            Q1=quantile(lifeExp, probs=0.25,na.rm=TRUE),
            Q3=quantile(lifeExp,probs=0.75),
            n=n())
```

```
## # A tibble: 4 x 8
##   continent meanLE medLE    sd   iqr    Q1    Q3     n
##   <fct>      <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <int>
## 1 Africa      53.6  52.8  9.10 11.9   47.3  59.2    52
## 2 Americas    71.2  72.1  4.89  4.83  69.4  74.2    25
## 3 Asia        68.0  70.3  8.09 10.7   61.8  72.5    33
## 4 Europe      75.5  76.1  3.10  4.97  73.0  78.0    30
```

```
#
# Output rows ordered by decreasing values of a statistic (mean Life Expectancy):
gapminder %>% filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent) %>%
  summarise(meanLE=mean(lifeExp,na.rm=TRUE),
            medLE=median(lifeExp,na.rm=TRUE),
            sd=sd(lifeExp,na.rm=TRUE),
            iqr=IQR(lifeExp,na.rm=TRUE),
            min=min(lifeExp),
            max=max(lifeExp),
            n=n())  %>%
  arrange(desc(meanLE))
```

```
## # A tibble: 4 x 8
##   continent meanLE medLE    sd   iqr   min   max     n
##   <fct>      <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <int>
## 1 Europe      75.5  76.1  3.10  4.97  68.8  79.4    30
## 2 Americas    71.2  72.1  4.89  4.83  56.7  78.6    25
## 3 Asia        68.0  70.3  8.09 10.7   41.8  80.7    33
## 4 Africa      53.6  52.8  9.10 11.9   36.1  74.8    52
```

Next, we save the statistics table to an object called statstable, then we use the `kable` function for display.

```
statstable <- gapminder %>% filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent) %>%
  summarise(meanLE=mean(lifeExp,na.rm=TRUE),
            medLE=median(lifeExp,na.rm=TRUE),
            sd=sd(lifeExp,na.rm=TRUE),
            iqr=IQR(lifeExp,na.rm=TRUE),
            min=min(lifeExp),
            max=max(lifeExp),
            n=n())  %>%
  arrange(desc(meanLE))
#
knitr::kable(statstable)
```

continent	meanLE	medLE	sd	iqr	min	max	n
Europe	75.50517	76.116	3.104677	4.96625	68.835	79.390	30
Americas	71.15048	72.146	4.887584	4.83500	56.671	78.610	25
Asia	68.02052	70.265	8.091171	10.68100	41.763	80.690	33
Africa	53.59827	52.759	9.103387	11.92825	36.087	74.772	52

7.2 Summary Statistics: skimr

Here we implement the `group_by` function to display descriptive statistics for numeric variables by continent, for two quantitative variables using functions from the *skimr* package.

```
gapminder %>% filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent) %>%
  skimr::skim_without_charts() %>%
  skimr::yank("numeric") %>%
  dplyr::filter(skim_variable %in% c("lifeExp","gdpPercap")) %>%
  knitr::kable()
```

skim_variable	continent	n_missing	complete_rate	mean	sd	p0	p25
lifeExp	Africa	0	1	53.59827	9.103387	36.0870	47.30025
lifeExp	Americas	0	1	71.15048	4.887584	56.6710	69.38800
lifeExp	Asia	0	1	68.02052	8.091171	41.7630	61.81800
lifeExp	Europe	0	1	75.50517	3.104677	68.8350	73.02350
gdpPercap	Africa	0	1	2378.75956	2820.728117	312.1884	791.90197
gdpPercap	Americas	0	1	8889.30086	7874.225145	1341.7269	4684.31381
gdpPercap	Asia	0	1	9834.09330	11094.180481	415.0000	1902.25210
gdpPercap	Europe	0	1	19076.78180	10065.457716	3193.0546	9946.59931

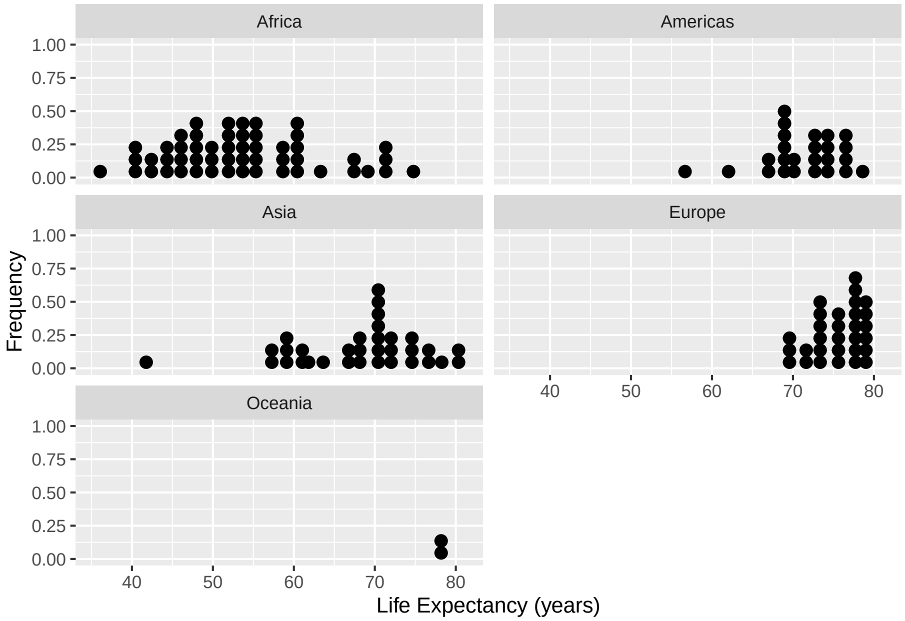
7.3 Graphical Displays of a quantitative variable, separated by groups

In each example, the first lines create the dataset to be graphed - followed by a `ggplot` command making the display. Several of the examples make use of the principle of "small-multiples" so that each level of the factor variable has a separarate panel for the quantitative variable display.

7.3.1 Dotplots

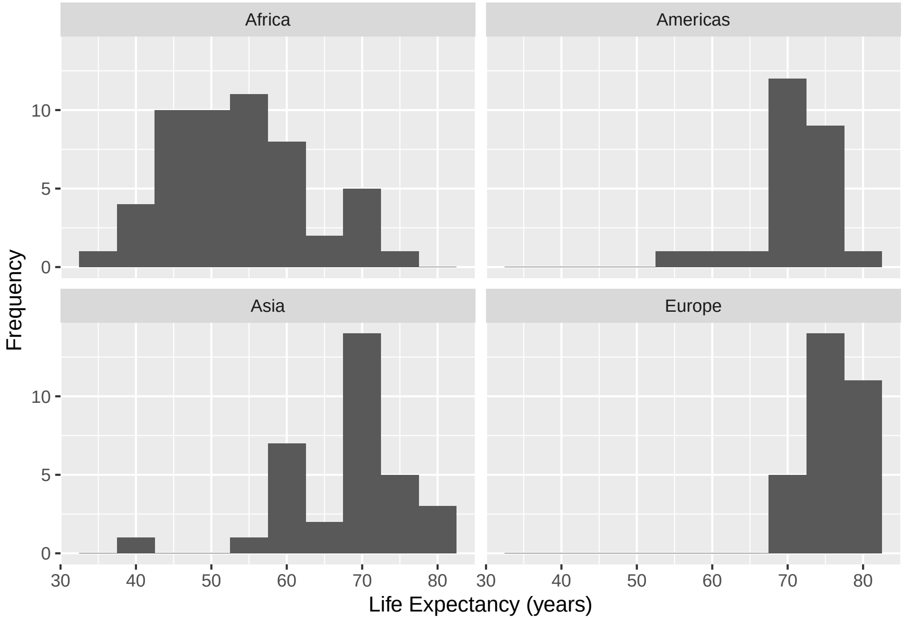
```
ds <- gapminder %>% filter(year==1997)
#
```

```
ggplot(data=ds,mapping=aes(x=lifeExp)) +
  geom_dotplot() +
  facet_wrap( ~ continent,ncol=2) +
  xlab("Life Expectancy (years)") +
  ylab("Frequency")
```



7.3.2 Histograms

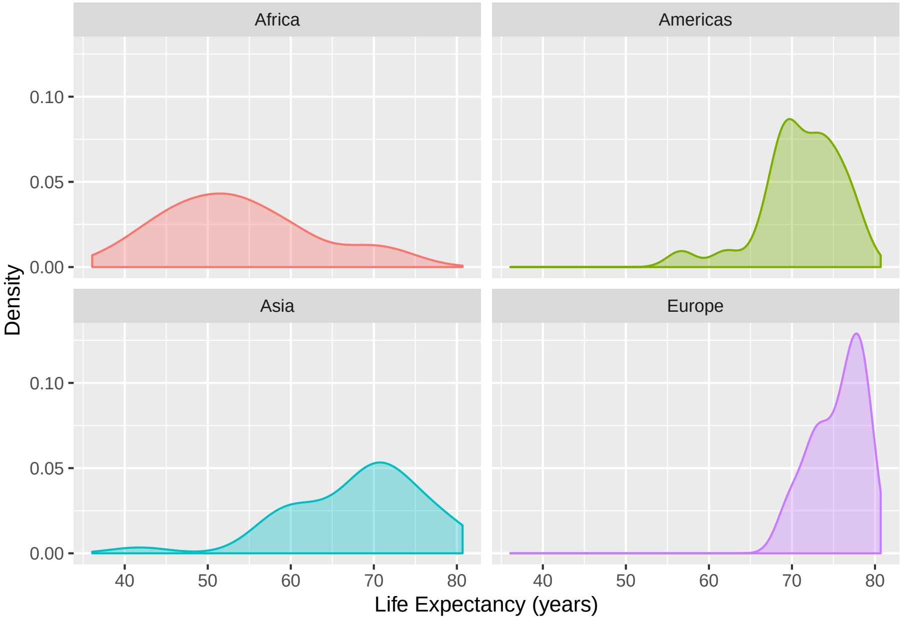
```
ds <- gapminder %>%
  filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent)
#
ggplot(data=ds, mapping=aes(x=lifeExp)) +
  geom_histogram(binwidth=5) +
  facet_wrap( ~ continent,ncol=2) +
  xlab("Life Expectancy (years)") +
  ylab("Frequency")
```



7.3.3 Density Plots in Facets

The code given here shows how to produce a density plot in separate panels for each continent.

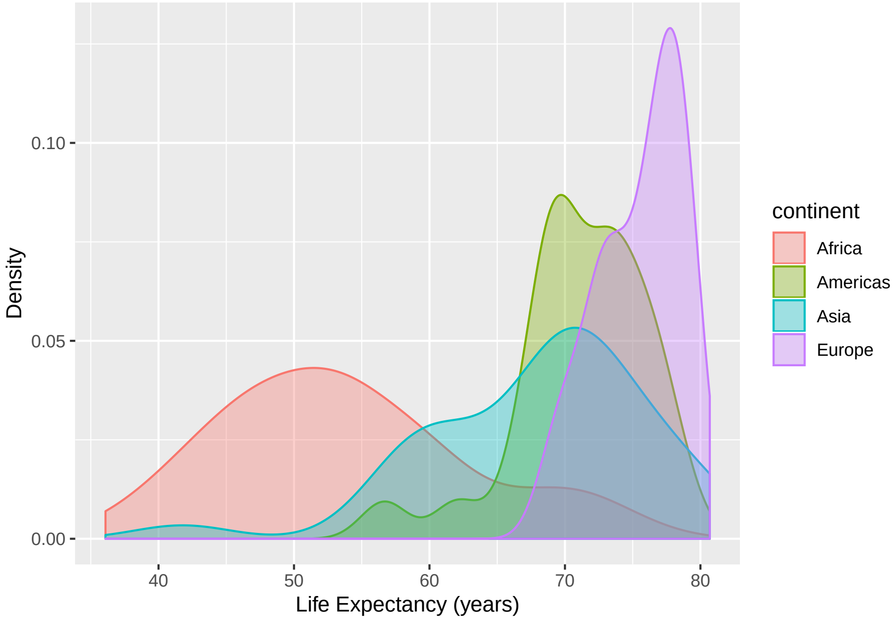
```
ds <- gapminder %>%
  filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent)
#
ggplot(data=ds, mapping=aes(x=lifeExp, colour=continent, fill=continent)) +
  geom_density(alpha = 0.35) +
  xlab("Life Expectancy (years)") +
  ylab("Density") +
  facet_wrap( ~ continent, ncol = 2) +
  theme(legend.position = "none")
```



7.3.4 Overlaid Density Plots

The initial command below takes the gapminder data and consider only observations (rows) from 1997, but exclude all observations from Oceania. The `alpha` setting controls the amount of transparency in the densities for each continent - smaller values of `alpha` (between 0 and 1) are more transparent.

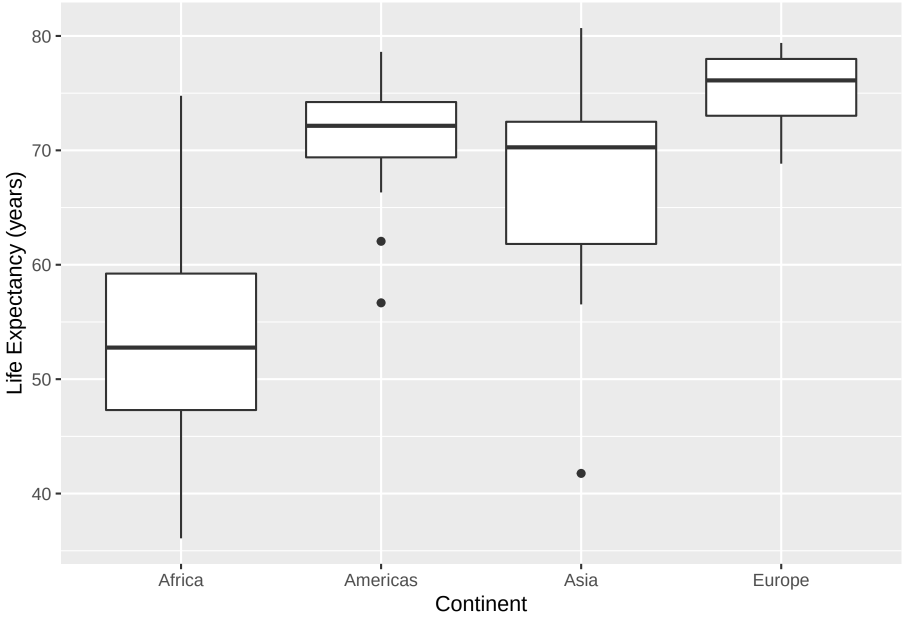
```
gapminder %>%
  filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent) %>%
ggplot(mapping=aes(x=lifeExp, colour=continent, fill=continent)) +
  geom_density(alpha = 0.35) +
  xlab("Life Expectancy (years)") +
  ylab("Density")
```



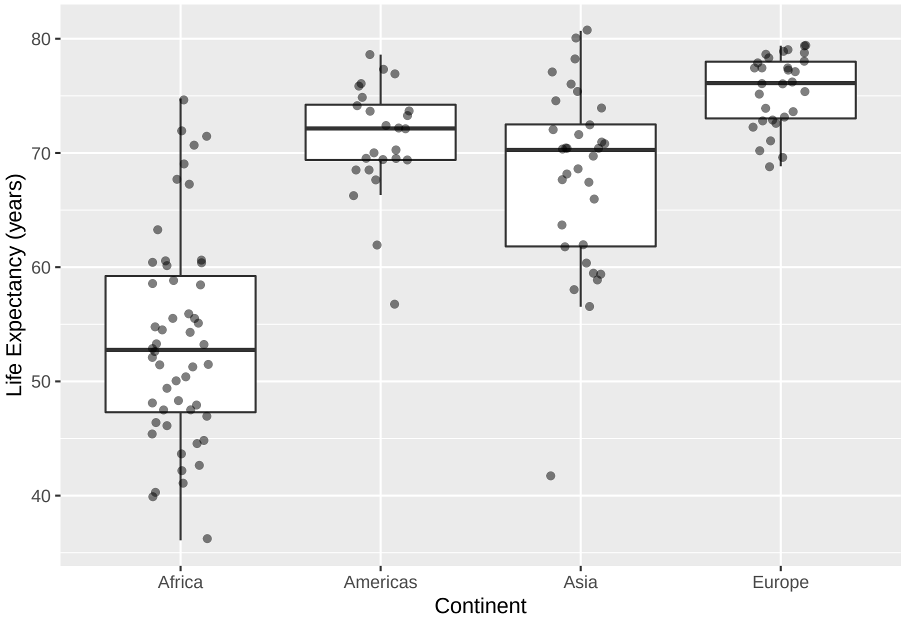
7.3.5 Boxplots, Grouped Data

In the code below, the `alpha` value again controls the transparency of the points alpha=1 means opaque, alpha=0 means completely see-through. When there is a lot of data, use a smaller value of alpha.

```
ds <- gapminder %>%
  filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent)
#
ggplot(data=ds, mapping=aes(x=continent,y=lifeExp)) +
 geom_boxplot() +
  labs(x="Continent",y="Life Expectancy (years)")
```



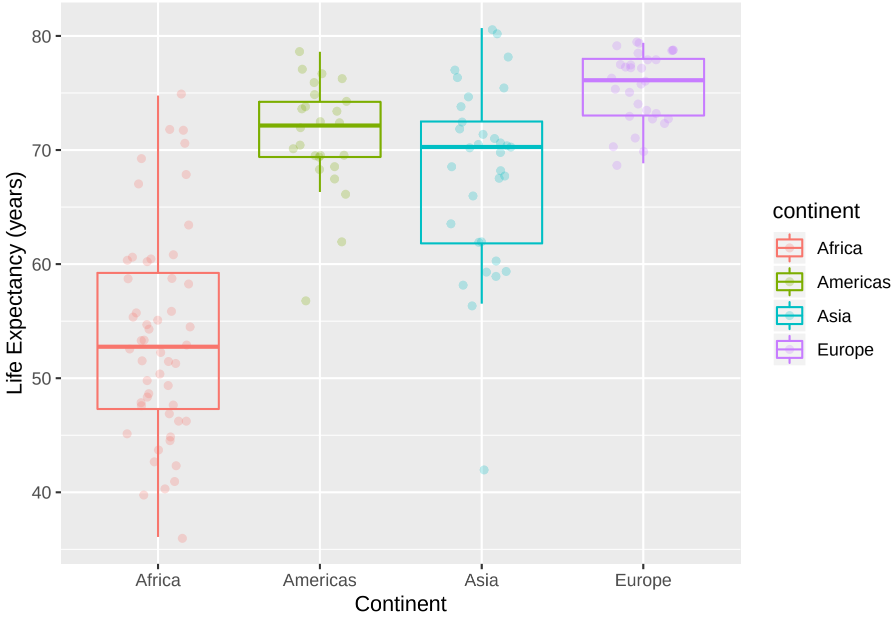
```r
#
ggplot(data=ds, mapping=aes(x=continent,y=lifeExp)) +
 geom_boxplot(outlier.colour = NA) +
 geom_point(position = position_jitter(width = 0.15, height = 0.15),alpha=.50) +
  labs(x="Continent",y="Life Expectancy (years)")
```



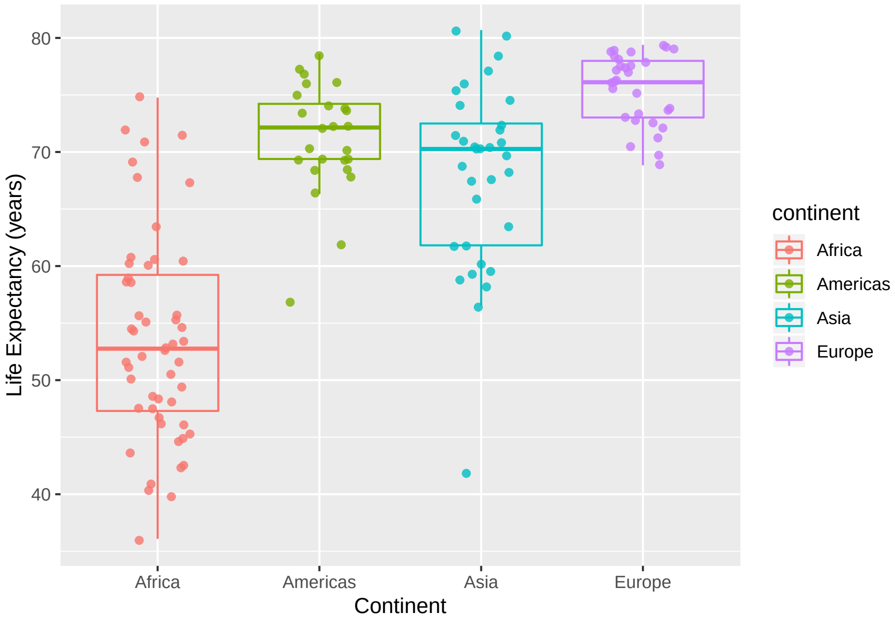
7.3.6 Boxplots, overlay points on the boxplots with color control

In the code below, the alpha value controls the transparency of the points alpha=1 means opaque, alpha=0 means completely see-through.

```
ds <- gapminder %>%
  filter(year==1997) %>%
  filter(continent != "Oceania") %>%
  group_by(continent)
#
ggplot(data=ds, mapping=aes(x=continent,y=lifeExp, colour=continent)) +
  geom_point(position = position_jitter(width = 0.2, height = 0.2),alpha=.25) +
 geom_boxplot(outlier.colour = NA, fill = NA) +
  labs(x="Continent",y="Life Expectancy (years)")
```



```
#
ggplot(data=ds, mapping=aes(x=continent,y=lifeExp, colour=continent)) +
  geom_point(position = position_jitter(width = 0.2, height = 0.2),alpha=.80) +
 geom_boxplot(outlier.colour = NA, fill = NA) +
  labs(x="Continent",y="Life Expectancy (years)")
```


80
70
60
50
40
Life Expectancy (years)
Africa
Americas
Asia
Europe
Continent
continent
Africa
Americas
Asia
Europe

Chapter 8

Analysis of One Categorical Variable by another categorical variable

To demonstrate graphical displays of two categorical variables, we need a new dataset with two categorical variables. We use the `congress_age` dataframe from the *fivethirtyeight* package. In these displays we will use categorical variables:

- party affiliation (party) with values: D, I, R.
- congressional chamber (chamber) with values: house, senate

We will restrict ourselves to the 113th congress, a meeting of the legislative branch of the United States federal government, from January 3, 2013, to January 3, 2015, during the fifth and sixth years of Barack Obama's presidency.

8.1 Tables

```
congage <- fivethirtyeight::congress_age
ds1 <- congage %>% filter(congress > 112) %>% select(congress,chamber,state,party,incumbent,age)
#  We declare party and chamber as factor/categorical variables, and control their levels.
ds1 <- ds1 %>% mutate(party = factor(party,levels=c("D","I","R")),
                     chamber = factor(chamber))
ds1 <- ds1 %>% na.omit()
ds <- ds1
#
table(ds$chamber,ds$party)
```

```
##
##            D   I   R
##   house  202   0 237
##   senate  57   2  46
```

```
#
mytable <- table(ds$chamber,ds$party)
#
prop.table(mytable) # cell percentages
```

```
##
##                    D           I           R
##   house  0.371323529 0.000000000 0.435661765
##   senate 0.104779412 0.003676471 0.084558824
```

```
prop.table(mytable, 1) # row percentages
```

```
##
##                   D          I          R
##   house  0.46013667 0.00000000 0.53986333
##   senate 0.54285714 0.01904762 0.43809524
```

```
prop.table(mytable, 2) # column percentages
```

```
##
##                  D         I         R
##   house  0.7799228 0.0000000 0.8374558
##   senate 0.2200772 1.0000000 0.1625442
```

```
ds %>%  janitor::tabyl(chamber, party)
```

```
##  chamber   D I   R
##    house 202 0 237
##   senate  57 2  46
```

```
#
t2 <- ds %>%  janitor::tabyl(chamber, party)
t2 %>%
  janitor::adorn_percentages("row") %>%
  janitor::adorn_pct_formatting(digits = 2) %>%
  janitor::adorn_ns()
```

```
##  chamber            D         I            R
##    house 46.01% (202) 0.00% (0) 53.99% (237)
##   senate 54.29%  (57) 1.90% (2) 43.81%  (46)
```

```
# column percentages
t2 %>%
  janitor::adorn_percentages("col") %>%
  janitor::adorn_pct_formatting(digits = 2) %>%
  janitor::adorn_ns()
```

```
##   chamber              D            I             R
##     house 77.99% (202)   0.00% (0) 83.75% (237)
##    senate 22.01%  (57) 100.00% (2) 16.25%  (46)
```

```
# both row and column percentages
t2 %>%
  janitor::adorn_percentages("all") %>%
  janitor::adorn_pct_formatting(digits = 2) %>%
  janitor::adorn_ns()
```

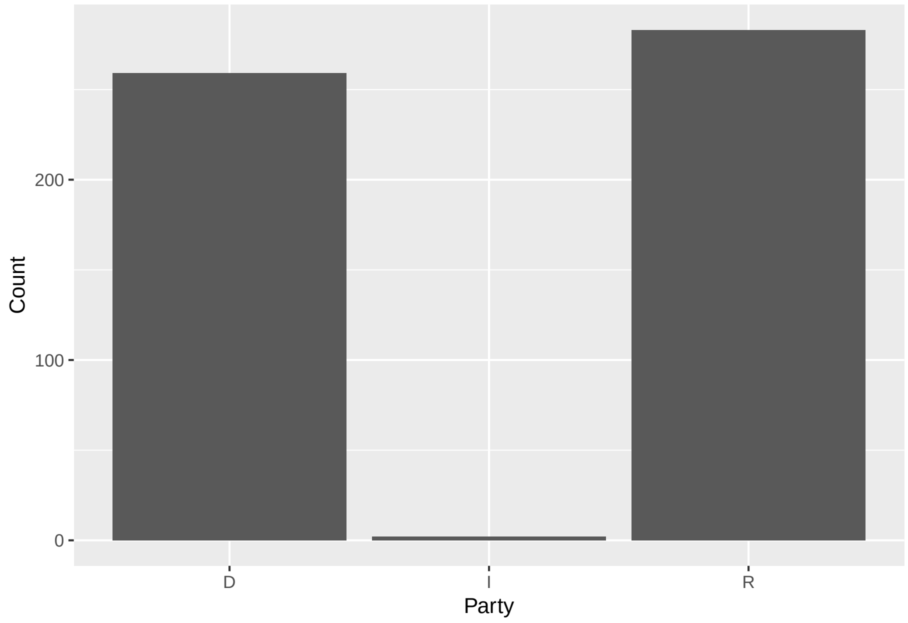
```
##   chamber              D          I             R
##     house 37.13% (202) 0.00% (0) 43.57% (237)
##    senate 10.48%  (57) 0.37% (2)  8.46%  (46)
```

```
congage <- fivethirtyeight::congress_age
ds1 <- congage %>% filter(congress > 112) %>% select(congress,chamber,state,party,incumbent,age)
#  We declare party and chamber as factor/categorical variables, and control their levels.
ds1 <- ds1 %>% mutate(party = factor(party,levels=c("D","I","R")),
                    chamber = factor(chamber))
ds1 <- ds1 %>% na.omit()
ds <- ds1
ds %>% group_by(chamber,party) %>%
  dplyr::count() %>%
  tidyr::pivot_wider(names_from = party, values_from = n)
```

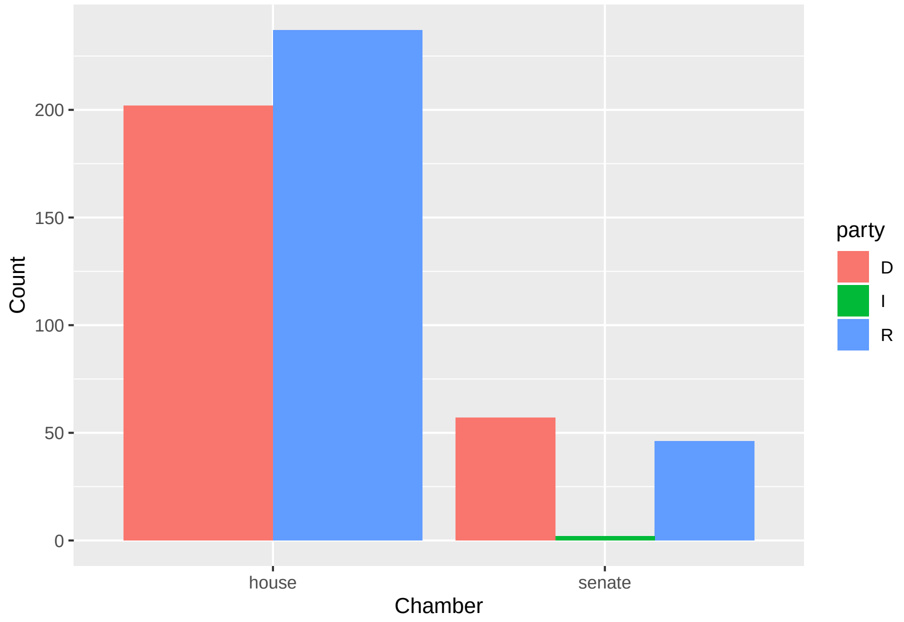
```
## # A tibble: 2 x 4
## # Groups:   chamber [2]
##   chamber     D     R     I
##   <fct>   <int> <int> <int>
## 1 house     202   237    NA
## 2 senate     57    46     2
```

8.2 Graphical Displays

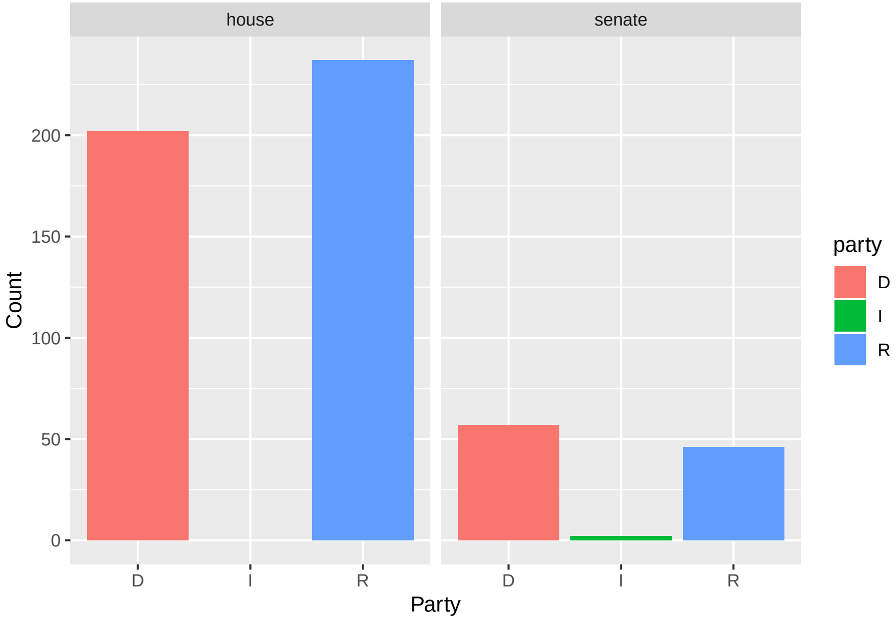
```
# basic bar plot of party affiliation
ggplot(data=ds, aes(x=party)) + geom_bar() +
  labs(x="Party", y="Count")
```



```
ds <- ds1 %>% group_by(party,chamber)
#
ggplot(data=ds, aes(x=chamber)) + geom_bar(aes(fill=party),position="dodge") +
  labs(x="Chamber", y="Count")
```



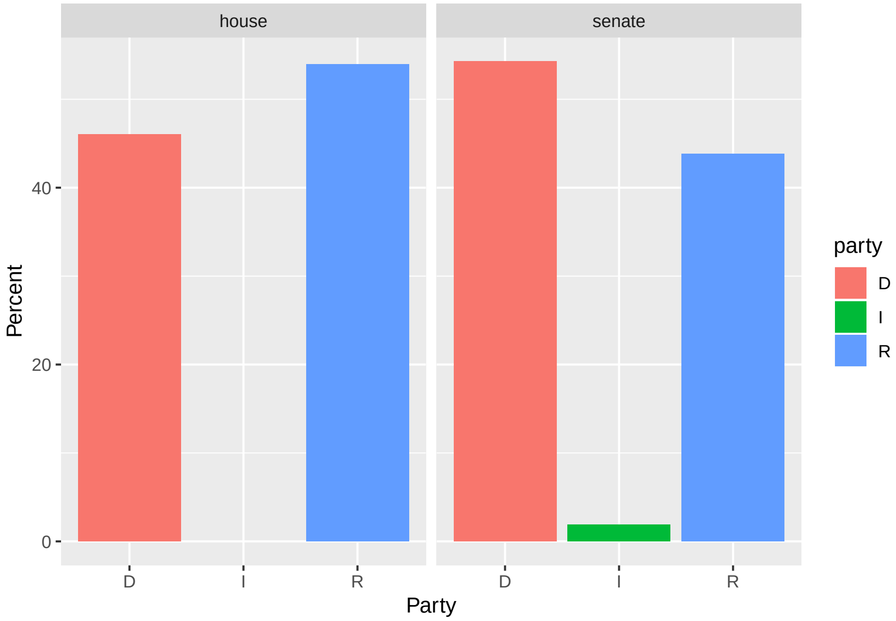
```
#
ggplot(data=ds, aes(x=party)) +
  geom_bar(aes(fill=party)) +
  facet_wrap( ~ chamber) +
  labs(x="Party", y="Count")
```



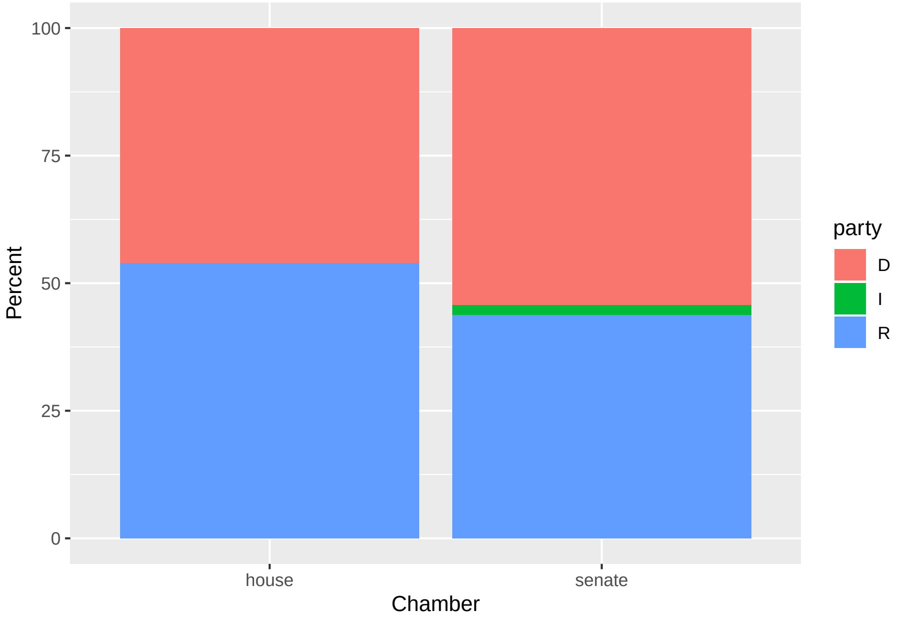
```
#  The next display attempts to use percentages on the vertical axis defined within chamber.
# This means the next command must list chamber as the FIRST group_by variable.
ds <- ds1 %>% group_by(chamber,party)  %>%
   summarise (n = n()) %>%
  mutate(pct = 100*n / sum(n))
#
ds
```

```
## # A tibble: 5 x 4
## # Groups:   chamber [2]
##   chamber party     n   pct
##   <fct>   <fct> <int> <dbl>
## 1 house   D       202 46.0
## 2 house   R       237 54.0
## 3 senate  D        57 54.3
## 4 senate  I         2  1.90
## 5 senate  R        46 43.8
```

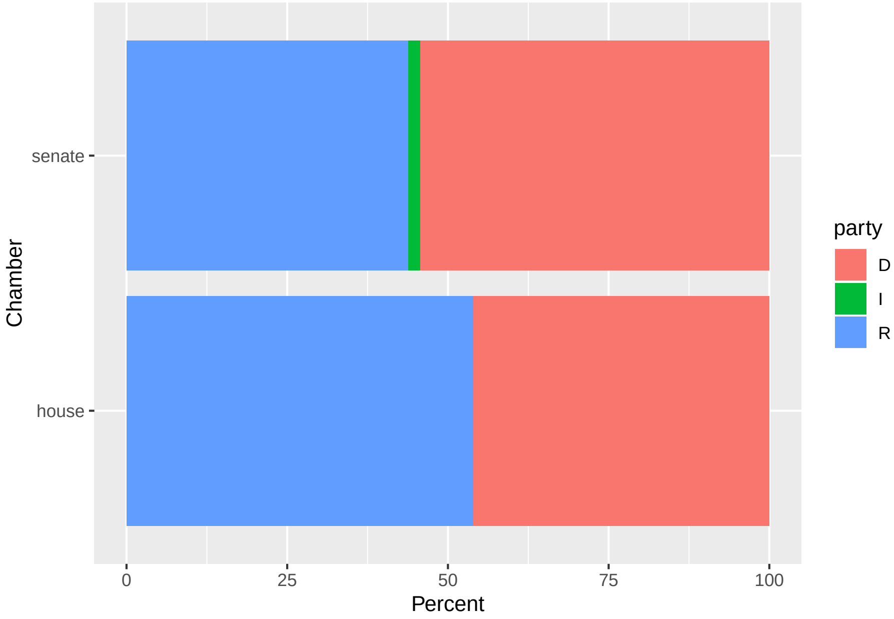
```
#
ggplot(data=ds, aes(x=party, y=pct)) + geom_bar(aes(fill=party),stat="identity") +
  facet_wrap( ~ chamber) +
  labs(x="Party", y="Percent")
```



```
ds1 <- congage %>% filter(congress > 112) %>% select(congress,chamber,state,party,incu
 mutate(party = factor(party,levels=c("D","I","R")),
                    chamber = factor(chamber)) %>%
  na.omit()
#
ds <- ds1 %>% group_by(chamber,party)  %>%
   summarise (n = n()) %>%
  mutate(pct = 100*n / sum(n))
#
ggplot(data=ds, mapping=aes(x=chamber,y=pct,fill=party)) +
  geom_col() +
  labs(x="Chamber", y="Percent")
```



```
ds1 <- congage %>% filter(congress > 112) %>% select(congress,chamber,state,party,incumbent,age)
 mutate(party = factor(party,levels=c("D","I","R")),
                    chamber = factor(chamber)) %>%
  na.omit()
#
ds1 %>% group_by(chamber,party)  %>%
   summarise (n = n()) %>%
  mutate(pct = 100*n / sum(n)) %>%
ggplot( mapping=aes(x=chamber,y=pct,fill=party)) +
  geom_col() +
  coord_flip() +
  labs(x="Chamber", y="Percent")
```


senate
house
Chamber
0
25
50
75
100
Percent
party
D
I
R