Lab 3. Data Management

In Lab 2, it was mentioned that data visualization is a key part of EDA. The techniques for data management we'll discuss in this lab constitute the other important parts of EDA, which you should always do prior to modeling and analysis. In this lab, we will address what a factor variable is and how to use one, how to summarize your data numerically, how to combine, merge, and split datasets, and how to split and combine strings.

By the end of this lab, you will be able to:

- Create and reorder factor variables
- Generate pivot tables
- Aggregate data using the base and dplyr packages
- Use various methods to split, apply, and combine data in R
- Split character strings using the stringr package
- Merge and join different datasets using base R and the dplyr methods

Lab Environment

All packages have been installed. There is no requirement for any setup.

All datasets and examples are present in `~/Desktop/R-Programming/lesson3/` folder.

Factor Variables

Recall our discussion of variable classes and types from Lab 1. A factor variable will always be of class `factor`, but can be any type: `character`, `numeric`, `integer`, or otherwise. For example, a variable indicating month can have the months as type `character` (`"January"`, `"February"`, ...) or can be indicated with integers (`1`, `2`, `3`, ...).

Note:

You can access the class of an object, variable, dataset, or just about anything else in R using this code: `class(dataset$variable_name)` You can find out the type of the variable using this code: `typeof(dataset$variable_name)`

Let's learn more about what factor variables are and how to use them.

Let's return to the `mtcars` and `iris` datasets, both of which we've used previously. (They're very common examples of datasets that are used in R, if you haven't caught on to that yet!) After loading, let's examine each dataset with the method `str()`, as follows:

```
data("mtcars")
str(mtcars)
data("iris")
str(iris)
```

`mtcars` has no factor variables specified out of the box, but the Species variable in the `iris` dataset is explicitly declared to be a factor variable with three levels: `setosa`, `versicolor`, and, if we could see it, `virginica`. We can see all three by using the `levels()` function, as shown in the following screenshot:

```
> levels(iris$Species)
[1] "setosa"     "versicolor" "virginica"
>
```

Recall that in Lab 2, we examined plotting with factor variables: if you insert a factor into the generic `plot()` function, you get a bar chart instead of a scatter plot, where the bar chart shows counts of each observation at unique levels of the factor variable.

Since we've discussed what a factor variable is, let's go through some other questions you may have about factors.

Why Should You Use a Factor Variable?

For example, let's build a linear regression model to examine the relationship between the number of cylinders (`cyl`) and miles per gallon (`mpg`) in cars in the `mtcars` dataset. We'll use `cyl` both as an integer variable and as a factor variable.

We can use `cyl` as an integer variable as follows:

```
summary(lm(mpg ~ cyl, data = mtcars))
```

The output is as follows:

```
Call:
lm(formula = mpg ~ cyl, data = mtcars)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.9814 -2.1185  0.2217  1.0717  7.5186 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  37.8846     2.0738   18.27  < 2e-16 ***
cyl          -2.8758     0.3224   -8.92 6.11e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.206 on 30 degrees of freedom
Multiple R-squared:  0.7262,    Adjusted R-squared:  0.7171 
F-statistic: 79.56 on 1 and 30 DF,  p-value: 6.113e-10
```

We can use `cyl` as a factor variable as follows:

```
summary(lm(mpg ~ as.factor(cyl), data = mtcars))
```

The output is as follows:

```
Call:
lm(formula = mpg ~ as.factor(cyl), data = mtcars)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.2636 -1.8357  0.0286  1.3893  7.2364 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)      26.6636     0.9718  27.437  < 2e-16 ***
as.factor(cyl)6  -6.9208     1.5583  -4.441 0.000119 ***
as.factor(cyl)8 -11.5636     1.2986  -8.905 8.57e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.223 on 29 degrees of freedom
Multiple R-squared:  0.7325,    Adjusted R-squared:  0.714 
F-statistic:  39.7 on 2 and 29 DF,  p-value: 4.979e-09
```

However, only the output where we've used `cyl` as a factor variable is the correct model output. We want the model to know that that cylinder is a factor and measures the difference in miles per gallon between four and six cylinders and four and eight cylinders; this is the correct way to build the model.

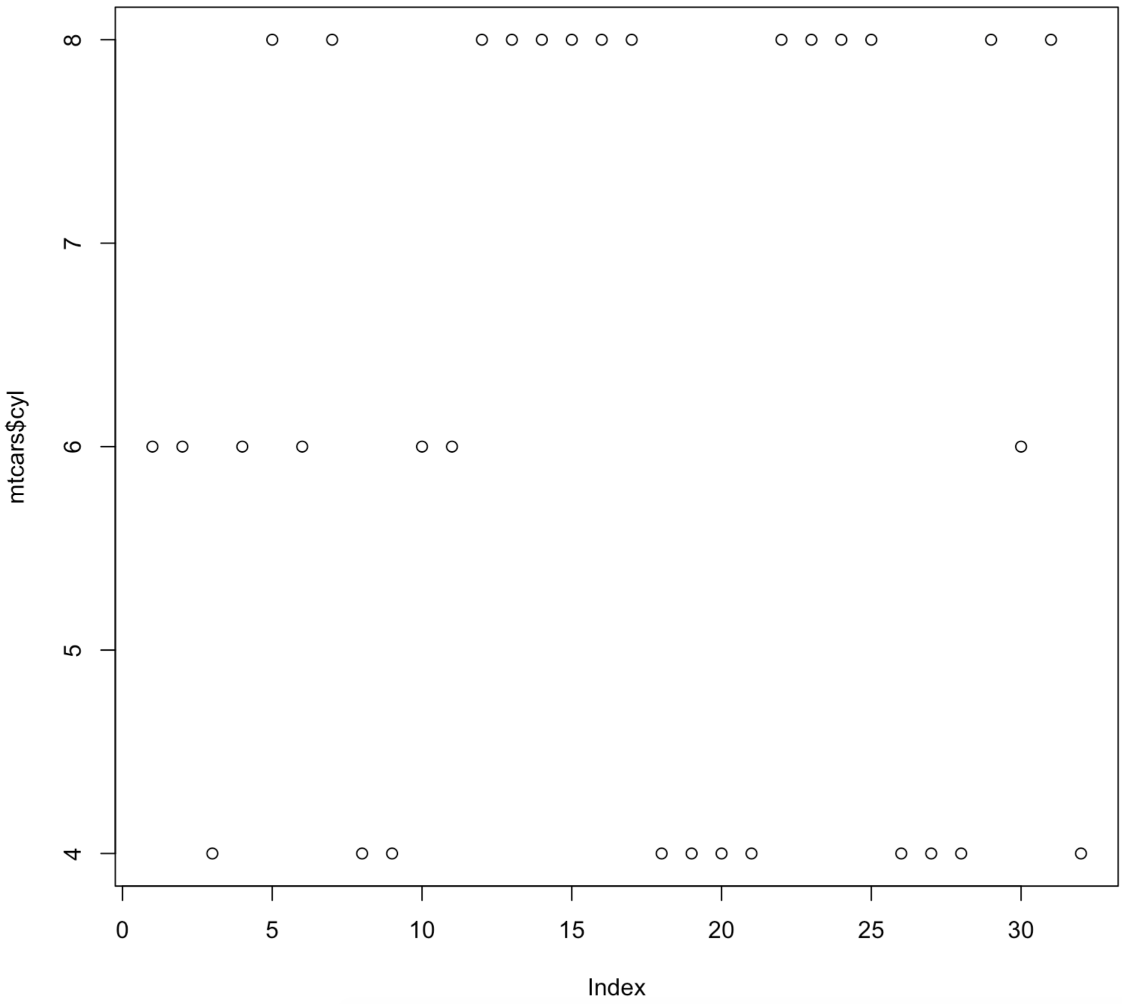
When a variable is categorical and is coded with text, for example, `Months = "January"`, `"February"`, `"March"`, and so on, modeling functions in R automatically treat the variable as categorical, but you should still code it as a factor variable. This is because of the second reason for using factors.

Plots will not render correctly with either base plots or `ggplot2` plots if you do not have your factor variables explicitly declared.

We can rerun the code to plot the `cyl` variable without transforming it into a factor, as follows:

```
plot(mtcars$cyl)
```

We get the scatterplot as an output, as shown in the following screenshot:



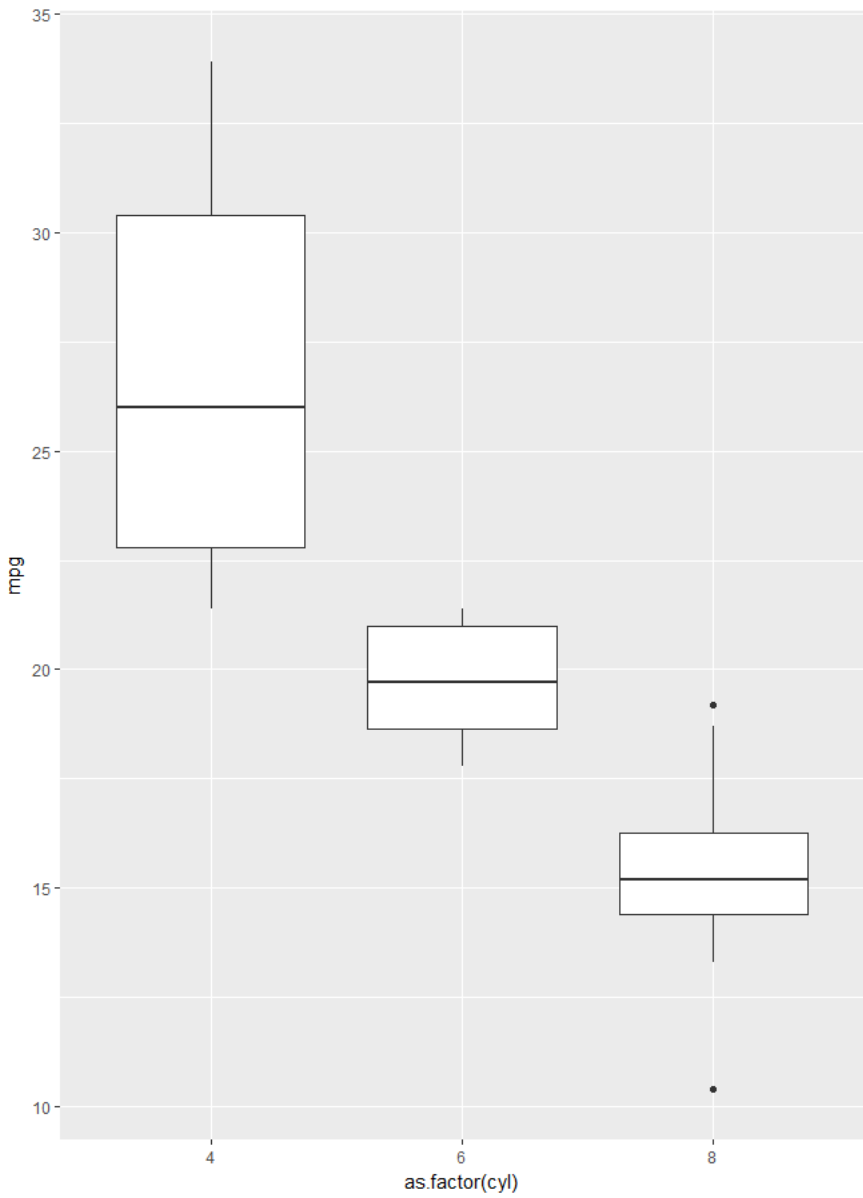
This doesn't really tell us anything about the variable. Similarly, if we try to create a graph using `ggplot2`, for example, by using a boxplot of `mpg` by `cyl` without transforming it into a factor, we'll get a warning:

```
> ggplot(mtcars, aes(cyl, mpg)) + geom_boxplot()
Warning message:
Continuous x aesthetic -- did you forget aes(group=...)?
```

The plot will be only one boxplot, because there's no group variable. Again, this is incorrect and uninformative. Thus, we should change `cyl` into a factor variable using `as.factor()`, as follows:

```
ggplot(mtcars, aes(as.factor(cyl), mpg)) + geom_boxplot()
```

Here is the boxplot we are looking for:



Now that we know when and why to use a factor variable, let's learn how to create one.

How Should You Create a Factor Variable?

We've seen many times in this lab and the preceding one that we can create factor variables using the `as.factor()` method. The input can be a variable from a dataset or a vector of values.

Typically, when you want to change a variable in a dataset to a factor, you overwrite the variable or create a second one. For example, to change the `cyl` variable in `mtcars` to a factor, you could either overwrite it or create another variable, as follows:

1. Overwrite the `cyl` variable and create it as a factor using the following code:

```
mtcars$cyl &lt;- as.factor(mtcars$cyl)
```

2. Create a second variable, `cyl2`, which will be a factor version of the original `cyl` variable as follows:

```
mtcars$cyl2 &lt;- as.factor(mtcars$cyl)
```

Note:

Whether you overwrite the original variable or create a second variable is up to you and will depend on the project, storage constraints, and your preferences. If you choose to overwrite the original variable, be sure to have a copy of the original dataset backed up in case something goes wrong!

Often, it will be the case that you'd like to transform more than one variable in your dataset into factor variables. To do this, you have a few options. For example, the variables `cyl`, `am`, and `gear` in the `mtcars` dataset are all categorical and should be transformed to factors. A good way to do this is by using the following code:

```
factors &lt;- c("cyl", "am", "gear")
mtcars[,factors] &lt;- data.frame(apply(mtcars[,factors], 2, as.factor))
```

Here, first, you create a vector of the names of variables you'd like to turn into factors, called `factors`. Then, using `data.frame()`, which creates a data frame, you apply the `as.factor()` function to only the desired columns of the dataset `mtcars`, which are accessed using `mtcars[,factors]`.

The `apply` family of functions provides an efficient way to perform another function on multiple rows or columns of a dataset at once. The input `2` indicates to `apply()` that `as.factor()` should be applied to columns of the dataset `mtcars`. If we had input `1`, `as.factor()` would be applied to rows of `mtcars` instead (and likely, this would have returned an error). Applying `as.factor()` by row doesn't really make sense if you think about a row of a dataset. A row of `mtcars` contains all of the information about the car: its `mpg`, `cyl`, `disp`, `hp`, and so on, and only some of these variables are factor/categorical variables. This logic will apply to most datasets you use!

We can check to be sure this worked by using `str()` as follows:

```
str(mtcars)
```

We see that the variables `cyl`, `am`, and `gear` are now all factor variables, as shown in the following screenshot:

```
> str(mtcars)
'data.frame':   32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : Factor w/ 3 levels "4","6","8": 2 2 1 2 3 2 3 1 1 2 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
 $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
 $ qsec: num  16.5 17 18.6 19.4 17 ...
 $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
 $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
 $ gear: Factor w/ 3 levels "3","4","5": 2 2 2 1 1 1 1 2 2 2 ...
 $ carb: Factor w/ 6 levels "1","2","3","4",..: 4 4 1 1 2 1 4 2 2 4 ...
```

Creating Factor Variables in a Dataset

Herein, we will create factor variables in a dataset both one at a time and by using a method that converts multiple variables at once. In order to do so, the following steps have to be executed:

1. Load the `datasets` library:

```
library(datasets)
```

2. Load the `midwest` dataset and examine it with `str()`:

```
data(midwest)
str(midwest)
```

3. Convert the `state` variable to a factor by using `as.factor()`:

```
midwest$state &lt;- as.factor(midwest$state)
```

4. Load the `band_instruments` dataset and examine it with `str()`:

```
data(band_instruments)
str(band_instruments)
```

5. Transform both variables in `band_instruments` to factor variables using `apply()`:

```
band_instruments &lt;- data.frame(apply(band_instruments, 2, as.factor))
```

6. Double-check that [*Step 5*] worked using `str()`:

```
str(band_instruments)
```

Output: The following is the output of the code mentioned in [*Step 2*]:

```
> str(midwest)
Classes ‘tbl_df’, ‘tbl’ and 'data.frame':       437 obs. of  28 variables:
 $ PID                 : int  561 562 563 564 565 566 567 568 569 570 ...
 $ county              : chr  "ADAMS" "ALEXANDER" "BOND" "BOONE" ...
 $ state               : chr  "IL" "IL" "IL" "IL" ...
 $ area                : num  0.052 0.014 0.022 0.017 0.018 0.05 0.017 0.027 0.024 0
.058 ...
 $ poptotal            : int  66090 10626 14991 30806 5836 35688 5322 16805 13437 17
3025 ...
 $ popdensity          : num  1271 759 681 1812 324 ...
 $ popwhite            : int  63917 7054 14477 29344 5264 35157 5298 16519 13384 146
506 ...
 $ popblack            : int  1702 3496 429 127 547 50 1 111 16 16559 ...
 $ popamerindian       : int  98 19 35 46 14 65 8 30 8 331 ...
 $ popasian            : int  249 48 16 150 5 195 15 61 23 8033 ...
```

The following is the output of the code mentioned in [*Step 4*]:

```
> str(band_instruments)
Classes ‘tbl_df’, ‘tbl’ and 'data.frame':       3 obs. of  2 variables:
 $ name : chr  "John" "Paul" "Keith"
 $ plays: chr  "guitar" "bass" "guitar"
```

The following is the output of the code mentioned in [*Step 5*]:

```
> str(band_instruments)
'data.frame':   3 obs. of  2 variables:
 $ name : Factor w/ 3 levels "John","Keith",..: 1 3 2
 $ plays: Factor w/ 2 levels "bass","guitar": 2 1 2
```

How Do You Know if Something is Already a Factor?

You can check if a variable or vector of values is already a factor by using `is.factor()`. It will return `TRUE` or `FALSE` accordingly. Alternatively, you can check the class using `class()` or use `str()` to view either the entire dataset's variable names and types (if you input the dataset name) or just the one variable (if you only input that):

```
> str(iris$Species)
 Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
```

What are the Levels of a Factor, and How Can You Change Them?

The levels of a factor are the particular categories for that variable. They are a special attribute of factor objects in R. You can view them with the `levels()` function, as shown in the following example:

```
levels(iris$Species)
```

It returns the three species of irises indicated in the `Species` variable column, as follows:

```
> levels(iris$Species)
[1] "setosa"     "versicolor" "virginica"
>
```

If we want to change the levels of the factor, we can do so in two ways:

- Using `ifelse()` statements
- Using the `recode()` function

Using ifelse() Statements

The following code will change the representation of the three species to numbers:

```
iris$Species2 &lt;- ifelse(iris$Species == "setosa", 1,
ifelse(iris$Species == "versicolor", 2, 3))
```

We can verify if it has worked by running the `table()` function as follows (more on this function in the next section!):

```
table(iris$Species)
```

Thus, we will get the following output:

```
Setosa    versicolor    verginica
  50          50           50
```

We can also execute the following code to verify whether the representation has changed:

```
table(iris$Species2)
```

Here is the output that we will get:

```
 1     2     3
50    50    50
```

Using the recode() Function

The `recode()` function, available in the `dplyr` package, can change the level of the factor by using more readable code, as follows:

```
library(dplyr)
iris$Species3 &lt;- recode(iris$Species,
                        "setosa" = 1,
                        "versicolor" = 2,
                        "virginica" = 3)
```

These are both valid options, and which one you use is up to you.

Examining and Changing the Levels of Pre-existing Factor Variables

Herein, we will create factor variables in a dataset both one at a time and by using a method that converts multiple variables at once. In order to do so, the following steps have to be executed:

1. Load the `dplyr` library. Use `levels()` to see how many levels of `band_instruments$plays` exist, as follows:

```
levels(band_instruments$plays)
```

2. Create a new variable, `plays2`, using `ifelse()` to change the levels bass and guitar to 1 and 2 using the following code:

```
band_instruments$plays2 &lt;- ifelse(band_instruments$plays == "bass", 1,
ifelse(band_instruments$plays == "guitar", 2, band_instruments$plays))
```

3. Use `levels()` to see how many levels of `midwest$state` exist as follows:

```
levels(midwest$state)
```

4. Load the `dplyr` library. Create a new variable, `state2`, by using `recode()` to change the levels of the state variable to the states' full names:

```
library(dplyr)
midwest$state2 &lt;- recode(midwest$state,
                         "IL" = "Illinois",
                         "IN" = "Indiana",
                         "MI" = "Michigan",
                         "OH" = "Ohio",
                         "WI" = "Wisconsin")
```

Output: The following is the output of the code mentioned in [*Step 1*]:

```
> levels(band_instruments$plays)
[1] "bass"   "guitar"
```

The following is the output of the code mentioned in [*Step 3*]:

```
> levels(midwest$state)
[1] "IL" "IN" "MI" "OH" "WI"
```

What about ordered categorical variables?

We've used an example of an ordered categorical variable a few times in this section: a categorical variable that indicates Low/Medium/High is considered ordered. Say we add a variable to the `mtcars` dataset that indicates the car's speed: low, medium, or high. We'll need to set this variable as a factor. When we do so, the code will be as follows:

```
speed &lt;- rep(c("low", "medium", "high"), times = 11)
speed &lt;- speed[-1]
mtcars$speed &lt;- factor(speed, levels = c("low", "medium", "high"), ordered = TRUE)
```

Now, when we view the class with the `class()` function, we see that it is now as follows:

```
[1] "ordered" "factor"
```

Any time you have a logical order to your factors, it's a good idea to set the `ordered = TRUE` argument.

Creating an Ordered Factor Variable

Herein, we will create an ordered factor variable in a dataset. In order to do so, the following steps need to be executed:

1. Create a vector called `gas_price` using the following code:

```
gas_price &lt;- rep(c("low", "medium", "high"), times = 146)
gas_price &lt;- gas_price[-1]
```

It will indicate if gas prices in that area are low, medium, or high on average.

2. Add the `gas_price` variable to the `midwest` dataset as follows:

```
midwest$gas_price &lt;- factor(gas_price,
                                levels = c("low", "medium", "high"),
                                ordered = TRUE)
```

3. Verify that the variable has been added to the dataset successfully using `table()` as follows:

```
table(midwest$gas_price)
```

Factor variables are a very important data type in R, since, as we learned previously, plots often won't render correctly unless the variable is explicitly declared to be a factor, and modeling will produce incorrect assumptions if a factor variable is not declared as such.

Activity: Creating and Manipulating Factor Variables

Scenario

You will not be able to avoid using factor variables in your work programming with R, so you set out to learn the best ways to create and manipulate them.

Aim

To recognize, create, and manipulate factor variables.

Prerequisites

Make sure you have R and RStudio installed on your machine.

Steps for Completion

1. Load the `datasets` library using `library(datasets)`.
2. Load the `diamonds` dataset:
   - Examine the dataset with `str()`.
   - How many factors are present, and what type are they?
   - Verify with `class()` that they are of the class shown.
3. Load the `midwest` dataset if it is not already loaded in your environment:
   - Examine the dataset with `str()`.
   - Turn all of the character variables into factor variables using the `apply()` method for changing many variables at once.
   - Check your work with `str()`.

Creating Different Tables Using the table() Function

Herein, we will use the `table()` function to create three different types of tables in R. In order to do so, the following steps need to be executed:

1. Load the `iris` dataset and create a one-way table of the `Species` variable using the following code:

```
table(iris$Species)
```

2. Load the `diamonds` dataset and create a two-way table of the cut and color variables using the following code:

```
table(diamonds$cut, diamonds$color)
```

3. Create a three-way table of the `cut`, `color`, and `clarity` variables from the diamonds dataset as follows:

```
table(diamonds$cut, diamonds$color, diamonds$clarity)
```

4. Load the `mtcars` dataset if it is not already loaded in your environment. Create a table of the `mpg` variable as follows:

```
table(mtcars$mpg)
```

Output: The following is the output we get as we execute the code mentioned in[*Step 1*]:

```
Setosa     versicolor     verginica
  50           50            50
```

The following is the output we get as we execute the code mentioned in [*Step 2*]:

```
              D    E    F    G    H    I    J
Fair        163  224  312  314  303  175  119
Good        662  933  909  871  702  522  307
Very Good  1513 2400 2164 2299 1824 1204  678
Premium    1603 2337 2331 2924 2360 1428  808
Ideal      2834 3903 3826 4884 3115 2093  896
```

The following is part of the output (it's very long) we get as we execute the code mentioned in [*Step 3*]:

```
, ,  = I1


             D   E   F   G   H   I   J
  Fair       4   9  35  53  52  34  23
  Good       8  23  19  19  14   9   4
  Very Good  5  22  13  16  12   8   8
  Premium   12  30  34  46  46  24  13
  Ideal     13  18  42  16  38  17   2

, ,  = SI2


             D   E   F   G   H   I   J
  Fair      56  78  89  80  91  45  27
  Good     223 202 201 163 158  81  53
  Very Good 314 445 343 327 343 200 128
  Premium  421 519 523 492 521 312 161
  Ideal    356 469 453 486 450 274 110
```

The following is the output we get as we execute the code mentioned in *Step 4*:

```
10.4 13.3 14.3 14.7   15 15.2 15.5 15.8 16.4 17.3 17.8 18.1 18.7 19.2 19.7   21
   2    1    1    1    1    2    1    1    1    1    1    1    1    2    1    2
21.4 21.5 22.8 24.4   26 27.3 30.4 32.4 33.9
   2    1    2    1    1    1    2    1    1
```

For any table above a two-way (or two - variable) table, you're better off turning to methods provided by the `dplyr` package. For example, if we wanted the counts for diamonds by `cut`, `color`, and `clarity`, it's easier to read a table that's been created with `dplyr` methods. `dplyr` will automatically print to the console, but if you'd like to access the tables you create later, you'll need to save the output to your environment. There is a lot of data summarizing that can be accomplished with the `dplyr` package. Let's learn some of the things it can accomplish in the section.

Using dplyr Methods to Create Data Summary Tables

We will utilize the `dplyr` verbs to create complex data summary tables. In order to do so, the following steps need to be executed:

1. Load the `diamonds` dataset using the following code:

```
data(diamonds)
```

2. Group the data by `cut`, `color`, and `clarity`, and find the number of observations at each combination of the three variables, as follows:

```
diamonds %&gt;% group_by(cut, color, clarity) %&gt;% summarise(n())
```

3. Find the mean and median price of diamonds by using the `dplyr` functions `group_by()` and `summarise()` as follows:

```
diamonds %&gt;% group_by(cut) %&gt;% summarise(mean = mean(price), median = median(price))
```

4. We can also filter out data we're not interested in quickly using `dplyr` methods. Say we don't want any diamonds with color `D` or `J`. We can find the mean price by cutting all of the diamonds left in the dataset after removing them:

```
diamonds %&gt;% filter(color != "D" & color != "J") %&gt;% group_by(cut) %&gt;% summarise(mean = mean(price))
```

Output: Data in the `diamonds` dataset grouped by `cut`, `color`, and `clarity` is as follows:

```
# A tibble: 276 x 4
# Groups: cut, color [?]
   cut   color clarity `n()`
   <ord> <ord> <ord>   <int>
 1 Fair  D     I1          4
 2 Fair  D     SI2        56
 3 Fair  D     SI1        58
 4 Fair  D     VS2        25
 5 Fair  D     VS1         5
 6 Fair  D     VVS2        9
 7 Fair  D     VVS1        3
 8 Fair  D     IF          3
 9 Fair  E     I1          9
10 Fair  E     SI2        78
# ... with 266 more rows
```

The mean and median price of diamonds is as follows:

```
# A tibble: 5 x 3
        cut     mean median
      <ord>    <dbl>  <dbl>
1      Fair 4358.758 3282.0
2      Good 3928.864 3050.5
3 Very Good 3981.760 2648.0
4   Premium 4584.258 3185.0
5     Ideal 3457.542 1810.0
```

The mean price by `cut` of all of the diamonds left in the dataset after removing them is as follows:

```
# A tibble: 5 x 2
        cut     mean
      <ord>    <dbl>
1      Fair 4311.788
2      Good 3966.567
3 Very Good 3983.078
4   Premium 4597.057
5     Ideal 3515.849
```

Summary tables are incredibly useful and you'll be building a lot of them as you do data science, both with the base `table()` function and with the `dplyr` package. The methods covered here are far from the only way to create data summaries, but are a great start.

Activity: Creating Data Summarization Tables

Scenario

You've been asked at work to dig deeper into the diamonds package because your boss is interested in investing company funds in diamonds. Create some explanatory data tables using base R and the `dplyr` methods.

Aim

To construct basic summary tables by recreating the ones given.

Prerequisites

You must have RStudio and R installed on your machine. The datasets package should also be installed.

Steps for Completion

1. Load the `dplyr` package.
2. Load the `diamonds` dataset, contained in the `datasets` package. Examine the dataset with `str()`:

```
# A tibble: 8 x 2
  clarity `median(depth)`
  <ord>             <dbl>
1 I1                 62.2
2 SI2                61.9
3 SI1                62.0
4 VS2                61.8
5 VS1                61.8
6 VVS2               61.8
7 VVS1               61.7
8 IF                 61.7
```

3. Recreate the following summary tables using the `table()` and `dplyr` methods.

The counts of the diamonds' clarity by price are as follows:

```
# A tibble: 56 x 3
# Groups: color [?]
   color clarity `median(price)`
   <ord> <ord>             <dbl>
 1 D     I1                 3774
 2 D     SI2                3468
 3 D     SI1                1759
 4 D     VS2                1688
 5 D     VS1                1860
 6 D     VVS2               1257
 7 D     VVS1               1427
 8 D     IF                 4632
 9 E     I1                 3296
10 E     SI2                3612
# ... with 46 more rows
```

The counts of the diamonds' clarity by color are as follows:

```
# A tibble: 5 x 2
  color `median(depth)`
  <ord>           <dbl>
1 E                61.8
2 F                61.8
3 G                61.8
4 I                61.9
5 J                62.0
```

Summarizing Data with the Apply Family

Let's look at a few examples of how to use the apply family to summarize data. One example of the use of the `apply()` function would be the following:

```
numbers &lt;- rbind(c(1:5), c(2:6)) apply(numbers, 2, mean)
```

The output that we get is the small matrix called numbers, which is represented as follows:

```
> numbers
     [,1] [,2] [,3] [,4] [,5]
[1,]    1    2    3    4    5
[2,]    2    3    4    5    6
```

The parameters passed to `apply()`, in this case, can be explained as follows:

1. The dataframe or matrix to apply a function on (here, `numbers`).
2. The digit indicating if the function is to be applied on columns or rows (here, 2, which in this case means the function will be applied over the columns of the data. If we wanted the mean of every row, we'd use 1 as an input instead.)
3. The function to apply, which in this case is `mean()`.

We used `apply()` here to calculate the mean of every column of the numbers matrix:

```
apply(numbers, 2, mean)
```

Thus, we get the output as follows:

```
[1] 1.5 2.5 3.5 4.5 5.5
```

You can also use multiple functions with `apply()`. Here's an example of that:

```
apply(numbers, 2, function(x) c(median(x), var(x)))
```

The output is as follows:

```
     [,1] [,2] [,3] [,4] [,5]
[1]  1.5  2.5  3.5  4.5  5.5
[2]  0.5  0.5  0.5  0.5  0.5
```

Using the apply() Function to Create Numeric Data Summaries

Herein, we will utilize the `apply()` function to summarize a dataset. In order to so, the following steps have to be executed:

1. Load the `iris` dataset using the following code:

```
data("iris")
```

2. Find the mean of all of the columns of the `iris` dataset except the fifth column (the Species column, which isn't numeric) with the following code:

```
apply(iris[,-c(5)], 2, FUN = mean)
```

3. Find the mean and variance of all of the columns of `iris` except the fifth column as follows:

```
apply(iris[,-c(5)], 2, function(x) c(mean(x), var(x)))
```

4. Find the mean of all the rows of `iris` as follows:

```
apply(iris[,-c(5)], 1, FUN = mean)
```

Output: The following is the output we get as we execute the code mentioned in the second step:

```
> apply(iris[,-c(5)], 2, FUN = mean)
Sepal.Length  Sepal.Width Petal.Length  Petal.Width
    5.843333     3.057333     3.758000     1.199333
```

The following is the output we get as we execute the code mentioned in the third step:

```
     Sepal.Length Sepal.Width Petal.Length Petal.Width
[1,]    5.8433333   3.0573333     3.758000   1.1993333
[2,]    0.6856935   0.1899794     3.116278   0.5810063
```

The following is the output we get as we execute the code mentioned in the second step:

```
  [1] 2.550 2.375 2.350 2.350 2.550 2.850 2.425 2.525 2.225 2.400 2.700 2.500
 [13] 2.325 2.125 2.800 3.000 2.750 2.575 2.875 2.675 2.675 2.675 2.350 2.650
 [25] 2.575 2.450 2.600 2.600 2.550 2.425 2.425 2.675 2.725 2.825 2.425 2.400
 [37] 2.625 2.500 2.225 2.550 2.525 2.100 2.275 2.675 2.800 2.375 2.675 2.350
 [49] 2.675 2.475 4.075 3.900 4.100 3.275 3.850 3.575 3.975 2.900 3.850 3.300
 [61] 2.875 3.650 3.300 3.775 3.350 3.900 3.650 3.400 3.600 3.275 3.925 3.550
 [73] 3.800 3.700 3.725 3.850 3.950 4.100 3.725 3.200 3.200 3.150 3.400 3.850
 [85] 3.600 3.875 4.000 3.575 3.500 3.325 3.425 3.775 3.400 2.900 3.450 3.525
 [97] 3.525 3.675 2.925 3.475 4.525 3.875 4.525 4.150 4.375 4.825 3.400 4.575
[109] 4.200 4.850 4.200 4.075 4.350 3.800 4.025 4.300 4.200 5.100 4.875 3.675
[121] 4.525 3.825 4.800 3.925 4.450 4.550 3.900 3.950 4.225 4.400 4.550 5.025
[133] 4.250 3.925 3.925 4.775 4.425 4.200 3.900 4.375 4.450 4.350 3.875 4.550
[145] 4.550 4.300 3.925 4.175 4.325 3.950
```

Activity: Implementing Data Summary

Scenario

You need to teach a coworker how to use apply functions. You write them a reproducible example using the `mtcars` dataset.

Aim

To summarize the variables in the `mtcars` data set using `apply()`.

Prerequisites

Make sure you have R and RStudio installed on your machine. The datasets package should be installed.

Steps for Completion

1. Load the `mtcars` dataset, if it currently isn't loaded in your R environment, and examine the data with `str()`.
2. Use `apply()` to summarize all of the variables in `mtcars` that are not categorical. Find the mean and variance of each.

Splitting, Combining, Merging, and Joining Datasets

Splitting Datasets into Lists and Then Back Again

Herein, we will utilize the `split()` and `unsplit()` functions to separate and recreate datasets, and then use `filter()` from `dplyr` to supplement knowledge of how to split data.

In order to do so, the following steps have to be executed:

1. Load the `iris` dataset if it is not currently loaded using the following code:

```
data(iris)
```

2. Split the `iris` dataset by species. This creates three lists of dataframes, each of which will only contain the information about one species of iris represented in the data. Verify that `iris_species` is a list by checking its type and check the class of `iris_species[[1]]`. This can be done with the help of the following code:

```
iris_species &lt;- split(iris, iris$Species)
typeof(iris_species)
class(iris_species[[1]])
```

3. Print the head of the second dataframe, which contains all the versicolor iris data using the following code:

```
head(iris_species[[2]])
```

4. Assign each dataframe into its own separate data object. Name the dataframes after the species of iris contained inside, as follows:

```
iris_setosa &lt;- iris_species[[1]]
iris_versicolor &lt;- iris_species[[2]]
iris_virginica &lt;- iris_species[[3]]
```

5. Use `unsplit()` to recombine `iris_species` into `iris_back`, which should be identical to the original `iris` dataset. Verify that they are identical using `all_equal()` from `dplyr`, which compares every aspect of the two dataframes. It can be done using the following code:

```
iris_back &lt;- unsplit(iris_species, iris$Species)
library(dplyr)
all_equal(iris, iris_back)
```

6. Since `dplyr` is now loaded, recreate the three different `iris` datasets using `filter()` on `iris` to retain only one species of iris at a time. This method involves less code than using `split()` to create a list of dataframes by allowing you to create each dataframe directly:

```
iris_setosa_2 &lt;- iris %&gt;% filter(Species == "setosa")
iris_versicolor_2 &lt;- iris %&gt;% filter(Species == "versicolor")
iris_virginica_2 &lt;- iris %&gt;% filter(Species == "virginica")
```

7. Rejoin the three new iris dataframes by using `rbind.as.data.frame()`, and verify that it's the same as iris by using `all_equal()`:

```
iris_back_2 &lt;- rbind.data.frame(iris_setosa_2, iris_versicolor_2, iris_virginica_2)
all_equal(iris, iris_back_2)
```

Output: The following is the output we get as we execute the code from the second step:

```
[1]  "list"

[1]  "dat.frame"
```

The following is the output we get as we execute the code from the third step:

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
51	7.0	3.2	4.7	1.4	versicolor
52	6.4	3.2	4.5	1.5	versicolor
53	6.9	3.1	4.9	1.5	versicolor
54	5.5	2.3	4.0	1.3	versicolor
55	6.5	2.8	4.6	1.5	versicolor
56	5.7	2.8	4.5	1.3	versicolor

The following is the output we get as we execute the code mentioned in the sixth step:

```
[1]   TRUE
```

The following is the output we get as we execute the code mentioned in the seventh step:

```
[1]   TRUE
```

Combining Data

`rbind()` and `cbind()` are two major combining functions you can use in R. We just used the `rbind.data.frame()` function to recombine the iris datasets, and you may recall that we covered both of these functions in [*Lab 1], [Introduction to R*], in detail. As a reminder, they combine data by row and column, respectively. As a quick review, let's combine some data in the next section.

Combining Data with rbind()

Herein, we will demonstrate the power of `rbind()` for combining data. In order to do so, the following steps need to be executed:

1. Install and load the `ggplot2` package, as it contains the `midwest` dataset:

```
install.packages("ggplot2") library(ggplot2)
```

2. Load the `midwest` data and examine its contents with `str()` :

```
data("midwest") str(midwest)
```

3. We'll first need to split the data in order to combine it. Let's split it evenly, in half, to create `midwest_1` and `midwest_2` . We can calculate directly in our subsetting method to get half of the number of rows of `midwest` in each dataset:

```
midwest1 &lt;- midwest[1:round(nrow(midwest)/2),]
midwest2 &lt;-
midwest[(round(nrow(midwest)/2)+1):nrow(midwest),]
```

4. Recombine `midwest` into `midwest_back` using `rbind()` to combine by rows (because we split in half by rows!):

```
midwest_back &lt;- rbind(midwest1, midwest2)
```

5. Check to see if `midwest_back` is the same as `midwest` using `all_equal()` , like we did previously:

```
all_equal(midwest, midwest_back)
```

Output: The following is the output we get as we execute the code mentioned in [*Step 2*]:

```
Classes 'tbl_df', 'tbl' and 'data.frame':      437 obs. of  28 variables:
 $ PID                 : int  561 562 563 564 565 566 567 568 569 570 ...
 $ county              : chr  "ADAMS" "ALEXANDER" "BOND" "BOONE" ...
 $ state               : chr  "IL" "IL" "IL" "IL" ...
 $ area                : num  0.052 0.014 0.022 0.017 0.018 0.05 0.017 0.027 0.024 0.058 ...
 $ poptotal            : int  66090 10626 14991 30806 5836 35688 5322 16805 13437 173025 ...
 $ popdensity          : num  1271 759 681 1812 324 ...
 $ popwhite            : int  63917 7054 14477 29344 5264 35157 5298 16519 13384 146506 ...
 $ popblack            : int  1702 3496 429 127 547 50 1 111 16 16559 ...
 $ popamerindian       : int  98 19 35 46 14 65 8 30 8 331 ...
 $ popasian            : int  249 48 16 150 5 195 15 61 23 8033 ...
 $ popother            : int  124 9 34 1139 6 221 0 84 6 1596 ...
 $ percwhite           : num  96.7 66.4 96.6 95.3 90.2 ...
 $ percblack           : num  2.575 32.9 2.862 0.412 9.373 ...
 $ percamerindan       : num  0.148 0.179 0.233 0.149 0.24 ...
 $ percasian           : num  0.3768 0.4517 0.1067 0.4869 0.0857 ...
 $ percother           : num  0.1876 0.0847 0.2268 3.6973 0.1028 ...
 $ popadults           : int  43298 6724 9669 19272 3979 23444 3583 11323 8825 95971 ...
 $ perchsd             : num  75.1 59.7 69.3 75.5 68.9 ...
 $ percollege          : num  19.6 11.2 17 17.3 14.5 ...
 $ percprof            : num  4.36 2.87 4.49 4.2 3.37 ...
 $ poppovertyknown     : int  63628 10529 14235 30337 4815 35107 5241 16455 13081 154934 ...
 $ percpovertyknown    : num  96.3 99.1 95 98.5 82.5 ...
 $ percbelowpoverty    : num  13.15 32.24 12.07 7.21 13.52 ...
 $ percchildbelowpovert: num  18 45.8 14 11.2 13 ...
 $ percadultpoverty    : num  11.01 27.39 10.85 5.54 11.14 ...
 $ percelderlypoverty  : num  12.44 25.23 12.7 6.22 19.2 ...
 $ inmetro             : int  0 0 0 1 0 0 0 0 0 1 ...
 $ category            : chr  "AAR" "LHR" "AAR" "ALU" ...
```

The following is the output we get as we execute the code mentioned in [*Step][5*]:

```
[1] TRUE
```

Note:

If you use `rbind()` to combine data, you'll need the same amount of columns in the data you are combining. If you use `cbind()`, you'll need to have the same number of rows in the data you're combining.

One nice feature of the functions `rbind()` and `cbind()` is that they can combine more than two items to create a new dataset.

Combining Matrices of Objects into Dataframes

Herein, we will use `rbind()` and `cbind()`, plus their associated `data.frame` methods, to combine multiple R objects into dataframes. In order to do so, the following steps have to be executed:

1. Create one, two, three, and four, which are all vectors of sequential numbers:

```
one &lt;- 1:15
two &lt;- 16:30
three &lt;- 31:45
four &lt;- 46:60
```

2. Create `all1` and `all2` from one, two, three, and four. `all1` should be combined by rows, while `all2` should be combined by columns:

```
all1 &lt;- rbind(one, two, three, four)
all2 &lt;- cbind(one, two, three, four)
```

3. Check the class of `all1`:

```
class(all1)
```

4. Recombine one, two, three, and four into `data.frames` and look at the class of `all3`:

```
all3 &lt;- rbind.data.frame(one, two, three, four)
all4 &lt;- cbind.data.frame(one, two, three, four)
class(all3)
```

Output: The following is the output we get as we execute the code `class(all1)`:

```
[1] "Matrix"
```

The following is the output we get as we execute the code mentioned in the last [*Step 4*]:

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

Splitting Strings

One other useful type of splitting is the ability to split strings. While this isn't a data splitting and unsplitting method, it will often be useful to do the following to manipulate variables in a dataset. The most efficient way to accomplish string splitting in R is to use the `stringr` package, which contains a variety of functions that make working with strings far simpler than alternative methods in base, which include `subset()` and `gsub()`. We won't cover these methods here, however the `stringr` methods are highly recommended, are far more versatile, and often don't require you to write complicated regex patterns for matching.

Note:

A [*regex*], or regular expression, is a search method used to match certain things in text. Look up regex on the search engine of your choice and read more about them if you're interested.

From the `stringr` package, the `str_split()` function in particular is useful. Let's dive in and look at some different ways it can be used.

Using stringr Package to Manipulate a Vector of Names

Herein, we will utilize the `str_split()` function to learn how to split character strings in R. In order to do so, the following steps need to be executed:

1. Install and then load the `stringr` package:

```
install.packages("stringr") library(stringr)
```

2. Create the names vector, a list of various names, and check its length to see how many names it contains:

```
names &lt;- c("Danelle Lewison", "Reyna Wieczorek", "Jaques Sola", "Marcus Huling", "Elvis Driver", "Chandra Picone", "Alejandro Caffey", "Shawnna Lomato", "Masako Hice", "Wally Ota", "Phillip Batten", "Denae Rizzuto", "Joseph Merlos", "Maurice Debelak", "Carina Gunning", "Tama Moody") length(names)
```

3. Use `str_split()` to separate each name into first name and surname and save it as an object called `names_split`. `str_split()` takes two arguments: the vector (or character string) you plan to split, and a pattern to split on:

```
names_split &lt;- str_split(names, pattern = " ")
```

4. Examine the first split name in `names_split`. Then, look at the first name. Remember to use list indexing, as `names_split` is a list of the split first names and surnames:

```
names_split[[1]]
names_split[[1]][1]
```

5. Split create `names_split_a`, which splits names at any as in each name. You only have to change one of the inputs to `str_split()` that you used previously:

```
names_split_a &lt;- str_split(names, pattern = "a")
```

6. Examine the first split name and the second half of the first split name in `names_split_a` once more. How has it been split differently?

```
names_split_a[[1]] names_split_a[[1]][2]
```

7. Now, examine the fifth split name from `names_split_a`. What happened with this name that has no a in it?

```
names_split_a[[5]]
```

Output: The following is the output we get upon executing the code mentioned in [*Step 2*]:

```
[1] 16
```

The following is the output we get upon executing the code mentioned in *Step 4*:

```
[1] "Danelle" "lewison"
[1] "Danelle"
```

The following is the output we get upon executing the code mentioned in *Step 6*:

```
[1] "Elvis Driver"
```

Combining Strings Using Base R Methods

Herein, we will use `paste()` and `paste0()` with character objects, character strings, and integers. In order to do so, the following steps have to be executed:

1. Create variables `a`, `b`, and `c`, which contain character strings:

```
a &lt;- "R" b &lt;- "is" c &lt;- "fun"
```

2. Use `paste()` to combine `a`, `b`, and `c` with an exclamation mark:

```
paste(a, b, c, "!")
```

3. Use `paste0()` to do the same, but without spaces between `a`, `b`, `c`, and the exclamation mark:

```
paste0(a, b, c, "!")
```

4. Use `paste()` to create the string `"R is fun x 10"` with the objects you've created:

```
paste(a, b, c, "x", 10)
```

Output: The following is the output we get upon executing the code mentioned in [*Step 2*]:

```
[1] "R is fun !"
```

The following is the output we get upon executing the code mentioned in [*Step 3*]:

```
[1] "Risfun!"
```

The following is the output we get upon executing the code mentioned in *Step 4*:

```
[1] "R is fun x 10"
```

Splitting and combining both data and character strings are important skills for programming with R. Often, they'll be used as part of a workflow known as split-apply-combine, where you split a dataset as needed, apply various summaries and other functions to it, and then recombine the summarized data, now transformed and exactly how you need it.

Activity: Demonstrating Splitting and Combining Data

Scenario

You need to split the `mtcars` dataset by cylinder type for a project. You also want to recombine the datasets to understand the power of combining data in R.

Aim

To get comfortable with both splitting and combining datasets.

Prerequisites

Make sure you have R and RStudio installed on your machine.

Steps for completion

1. Load the `mtcars` dataset.
2. Split the data by the `cyl` variable.
3. Create a dataset for each level of `cyl` .
4. Recreate `mtcars` by unsplitting the split version of the data.
5. Create the following two datasets by combining the data:

`letters1` dataset:

letters1 ×

Filter

	c..a....e....i....m....q..	c..b....f....j....n....r..	c..c....g....k....o....s..	c..d....h....l....p....t..
1	a	b	c	d
2	e	f	g	h
3	i	j	k	l
4	m	n	o	p
5	q	r	s	t

`letters2` dataset:

letters2 ×

Filter

	l1	l2	l3	l4	l5
1	a	e	i	m	q
2	b	f	j	n	r
3	c	g	k	o	s
4	d	h	l	p	t

Demonstrating Merges and Joins in R

Herein, we will use the base R `merge()` function and the `dplyr` join functions to work out how to merge and join data in R, comparing and contrasting the two functions throughout.

In order to do so, the following steps need to be executed:

1. Install and load the `readr` package, which contains functions that read in data much faster than the `baseR` data read functions:

```
install.packages("readr") library(readr)
```

2. Download the `students` and `students2` datasets from the GitHub repository:

```
students &lt;- read_csv("https://raw.githubusercontent.com/
fenago/R-Programming/master/lesson3/students.csv")
```

```
students2 &lt;- read_csv("https://raw.githubusercontent.com/
fenago/R-Programming/master/lesson3/students2.csv")
```

3. Examine both datasets using `str()` . Verify that they each has an `ID` variable, and take note that students has information about 20 students (20 observations), while `students2` has information on five additional students (25 observations):

```
str(students) str(students2)
```

4. Create `students_combined` by merging the two datasets by `ID` . Check the dimensions of students combined to see how many students' information is retained on this inner join. There should only be 20 matches on ID between the two datasets on this default inner join:

```
students_combined &lt;- merge(students, students2, by = "ID") dim(students_combined)
```

5. Create `students_combined2` , this time performing a right join using `merge()` , which should retain all of the possible students' information. Check the dimensions to see how much of students' information is in the combined dataset. Does it match up with your expectations?

```
students_combined2 &lt;- merge(students, students2, by = "ID", all.y = TRUE) dim(students_combined2)
```

You'll see the following output:

~/R_directory/packt_introDSR/BeginningDSwRCodeFiles - master - RStudio Source Editor

students_combined

Filter

	ID	Height_inches	Weight_lbs	EyeColor	HairColor	USMensShoeSize	Gender	Grade	Sport
1	1	65	120	Blue	Brown	9	F	9	Basketball
2	2	55	135	Brown	Blond	5	F	9	Track
3	3	60	166	Hazel	Black	6	M	12	Tennis
4	4	61	154	Brown	Brown	7	M	11	None
5	5	62	189	Green	Blond	8	M	10	Tennis
6	6	66	200	Green	Red	9	F	12	Tennis
7	7	69	250	Blue	Red	10	F	12	None
8	8	54	122	Blue	Brown	5	M	9	Basketball
9	9	57	101	Blue	Brown	6	F	12	Basketball
10	10	58	178	Brown	Black	4	F	10	Track
11	11	59	199	Hazel	Blond	8	F	10	Track
12	12	59	260	Green	Black	9	F	9	Track
13	13	60	145	Blue	Brown	10	M	11	None
14	14	60	158	Brown	Blond	11	M	10	Basketball
15	15	57	197	Brown	Black	12	M	11	None
16	16	66	126	Blue	Red	6	F	10	Track
17	17	67	278	Green	Brown	5	F	12	Track
18	18	68	225	Hazel	Black	9	F	10	Track
19	19	69	103	Blue	Blond	7	M	11	Basketball
20	20	70	111	Blue	Red	5	M	10	None
21	21	NA	NA	NA	NA	NA	M	9	Tennis
22	22	NA	NA	NA	NA	NA	M	11	Basketball
23	23	NA	NA	NA	NA	NA	M	10	Basketball
24	24	NA	NA	NA	NA	NA	M	11	None
25	25	NA	NA	NA	NA	NA	M	11	Basketball

Showing 1 to 25 of 25 entries

6. Install and load the `dplyr` package, if you have not done either of these already:

```
install.packages("dplyr") library(dplyr)
```

7. Create `students_right_join` , performing another right join, but this time using the `dplyr` join methods. Check the dimensions to verify the number of students' information in the joined dataset:

```
students_right_join &lt;- right_join(students, students2, by = "ID")
dim(students_right_join)
```

8. Create `students_anti_join` similarly and check the dimensions. Based on the preceding table, is the output what you expected?

```
students_anti_join &lt;- anti_join(students, students2, by = "ID") dim(students_anti_join)
```

9. If the by variables are named the same things, you can actually do both merges and joins without specifying a by variable:

```
students_merge_noby &lt;- merge(students, students2)
students_join_noby &lt;- right_join(students, students2)
```

10. Rename the `ID` variable on students to be called `StudentID`. Now, merge and join the data using the slightly different by variable names to see how powerful merge and join functions truly are:

```
colnames(students)[6] &lt;- "StudentID"
students_merge_diff &lt;- merge(students, students2, by.x = "StudentID", by.y = "ID")
students_join_diff &lt;- right_join(students, students2, by = c("StudentID" = "ID"))
```

Output: The following is the `students` dataset as an output:

```
Classes 'tbl_df', 'tbl' and 'data.frame': 20 obs. of 6 variables: $ Height_inches : int 65 55 60 61 62 66 69 54 57 58 ... $
Weight_lbs : int 120 135 166 154 189 200 250 122 101 178 ... $ EyeColor : chr "Blue" "Brown" "Hazel" "Brown" ... $ HairColor : chr
"Brown" "Blond" "Black" "Brown" ... $ USMensShoeSize: int 9 5 6 7 8 9 10 5 6 4 ... $ ID : int 1 2 3 4 5 6 7 8 9 10 ...
```

The following is the `students2` dataset as an output:

```
'data.frame': 25 obs. of 4 variables: $ ID : int 1 2 3 4 5 6 7 8 9 10 ... $ Gender: Factor w/ 2 levels "F","M": 1 1 1 1 1 1 1 1 1
2 ... $ Grade : num 10 10 9 10 12 9 12 12 11 10 ... $ Sport : Factor w/ 4 levels "Basketball","None",..: 4 3 3 1 1 4 4 3 4 3 ...
4. [1] 20 9 5. [1] 25 9 7. [1] 25 9 8. [1] 0 6 9b. Joining, by = "ID"
```

Activity: Merging and Joining Data

Scenario

You work at a school, where you've been tasked with updating the data for one of the high school English classes. Use your merging and joining skills to get the data in the final state your boss requires.

Aim

To practice merging and joining datasets. Prerequisites Make sure that R and RStudio are installed on your machine.

Steps for Completion

1. Re-import the `students` dataset from the repository on GitHub. The best way to do this is by using the following code:

```
read_csv("https://github.com/fenago/R-Programming/blob/master/lesson1/students.csv")
```

Note:

To use this code, you have to load the `readr` package!

Add an `id` variable to students equal to the number of rows of students.

2. Navigate to `lesson3_activityC2.R` on GitHub to get the code you need to create the second and third students datasets.
3. Merge the three datasets until you arrive at one with 16 rows and 12 variables:

The variables should be in the following order: `StudentID`, `Height_inches`, `Weight_lbs`, `EyeColor`, `HairColor`, `USMensShoeSize`, `Gender`, `Grade`, `Sport`, `HomeroomTeacher`, `ACTScore`, `CollegePlans`.

4. Join the datasets until you arrive at one with 25 rows and 12 variables:

The variables should be in the following order: `Height_inches`, `Weight_lbs`, `EyeColor`, `HairColor`, `USMensShoeSize`, `StudentID`, `HomeroomTeacher`, `ACTScore`, `CollegePlans`, `Gender`, `Gr`

Summary

Data management is a crucial skill needed for working with data in R, and we have covered many of the basics in this lab. One thing to keep in mind is that there is no prescribed order in which to conduct data management, cleaning, and data visualization. Rather, it will be an iterative process that likely won't end, even if you continue with your data and perform data analysis projects. You will probably run across more questions about your data if you use it to build statistical models.

This course has taken you through variable types, basic flow control, data import and export, data visualization with base plots and ggplot2, summarizing and aggregating data, plus joins and merging to help you build a foundation for how to use R to work with data.