Lab 1 | Introduction to Data Visualization

ST 437 Data Visualization

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Learning Objectives

1. Identify the components of a Quarto document.
2. Write and run code chunks from a Quarto document.
3. Render a Quarto document to both HTML and PDF.
4. Create basic visualizations using both base R and 'gglot2' functions.

Using Quarto

What is a Quarto document?

This is a quarto document! A quarto document (.qmd) is a special kind of file that combines code and plain text to produce polished, shareable reports and presentations. In this class we'll use Quarto documents to record our work.

There are three main components to Quarto document:

1. The YAML header
2. Code blocks
3. Markdown text

The YAML Header

Every Quarto document begins with the YAML header that appears inside three dashes `---`. The header controls document level settings, such as the document type, the title, and the author.

Code Blocks

We can write, store, and run code entirely within a Quarto document. Code blocks start and end with three back ticks ```` ``` ````. After the first set of back ticks, we indicate that we're using R code by specifying `{r}`. If we don't included `{r}` at the start of the code block, Quarto won't recognize the content as code. See the two examples below.

```
# Not executable code
3+4
```

```r
# Executable code
3+4
```

```
[1] 7
```

Markdown text

Anything else in the document outside of the YAML header and the code blocks is interpreted as Markdown - a syntax for controlling the text of the document.

For example, to indicate a header, use `#`. To indicate a subheader, use `##`, and so on.

For help with Markdown syntax, check out https://quarto.org/docs/authoring/markdown-basics.html.

Source vs. Visual Editing

When working in a .qmd file in RStudio, you have the option of editing your file in *Source* mode or *Visual* mode. In the top left corner of your .qmd file, take a look at both options by clicking the Source and Visual buttons. *Source* provides a more raw markdown format and *Visual* is bit more what-you-see-is-what-you-get and may be easier to navigate if this is your first time working in a Quarto document. Use whichever option you prefer!

Installing R-packages

In this lab, we'll rely on a few functions that aren't a part of Base R. Instead, they are dependent on a package - a collection of code, data, and documentation typically used to run more advanced functions. Here, we'll need the`ggplot2` and `AER` packages.

You may have received a warning at the start of your .qmd file that says `Package ggplot2 is required but is not installed.` If you see this warning, you can easily install the package by clicking the `Install` option. You can also install packages using `install.packages('Name of Package')`. Careful! Package names are case sensitive, so install.packages('GGplot2') will not work, but `install.packages('ggplot2')` will.

You only need to install a package once, so instead of including the code to install `ggplot2` and `AER` as a code chunk, navigate to the **Console** of your RStudio window, type `install.packages(c('ggplot2', 'AER'))` and hit enter. Give R a moment to install the packages.

> ❗ Loading Packages
>
> Once you have installed a package, you won't need to install it again. You will; however, need to load any necessary packages with each new iteration of RStudio. The code chunk below loads the `ggplot2` package for us.

```r
library(ggplot2)
```

Running Code from a Quarto File

The .qmd file is simply a static document. If we want to actually run code from the document, we need to send the code from the .qmd code block to the RStudio console.

> Running Code Block Shortcuts
>
> `Mac users`: Use + return to run single or highlighted line(s). Use + shift + return to run entire code block
> `Windows users`: Use ctrl + enter to run single or highlighted line(s). Use ctrl + shift + enter to run entire code block

```r
# This code block stores the values
# 10 in x and 15 in y.
# Try running this code!
x <- 10
y <- 15
```

```r
# Now trying adding x to y. Run your code.

# By the way, this is a comment! Anything prefaced by
# the # symbol in an R code chunk won't be treated as code.
```

Rendering a Quarto Document

Up until this point, you've likely been reading this document directly in your RStudio window. Typically, we want to **render** our Quarto documents so that they are presentable and easily shareable. If you scroll back up to the YAML, you'll see we set the format of this document to HTML. If you need to render your document as a PDF or docx document, I recommend holding off on changing the format, until you are done editing your document. The rendering speed is much faster for HTML.

To render and preview your document, click the Render option in the horizontal menu across the top of your .qmd file. If a preview of your document does not appear in the Viewer pane on the right side of your RStudio window, click the gear icon next to the Render option and make sure Preview in Viewer Pane is selected.

Rendering to PDF

To render your document to PDF, change the format option in the YAML from `html` to `pdf`.

In order to create PDFs you will need to install a recent distribution of TeX. We recommend the use of TinyTeX, which you can install by running the following command in the **Terminal**. To open the Terminal, select the tab just to the right of the Console below. Simply type the following three words and hit return/enter.

```
quarto install tinytex
```

Now try rendering your .qmd file as a PDF.

Exploring Data with Visualizations

For the remainder of this lab, we'll use a variety of visualization techniques to explore data. If we're interested in creating visualizations solely to get a quick-and-dirty understanding of our data, we may not need to spend a lot of time creating pretty visualizations. If that's the case, it may be more efficient to create visualizations using R's base graphics. If instead, we want to create visualizations to share with others, we should spend a little more time crafting nicer visualizations using the `ggplot2` package. In the following exercises, we'll do both!

Start by loading the `AER` package. The dataset we'll use for the following exercises, `CASchools`, is stored in this package.

```r
library(AER)
```

When a dataset (or function) is stored as a part of an R package, we can read more about it by opening the help documentation. Help documentation can be found by searching in the **Help** tab on the right-hand side of the RStudio window or by using a `?` as the prefix for the object you want to learn about.

Did you notice the additional argument at the start of the code chunk above? What do you think this argument does? Hint: render your document and try to locate this code chunk.

To let R know that we want to use the `CASchools`, call in into your **Environment** by using the `data()` function.

```
data(CASchools)
```

Next week, we'll look at how to import and use data that aren't already stored in an R function.

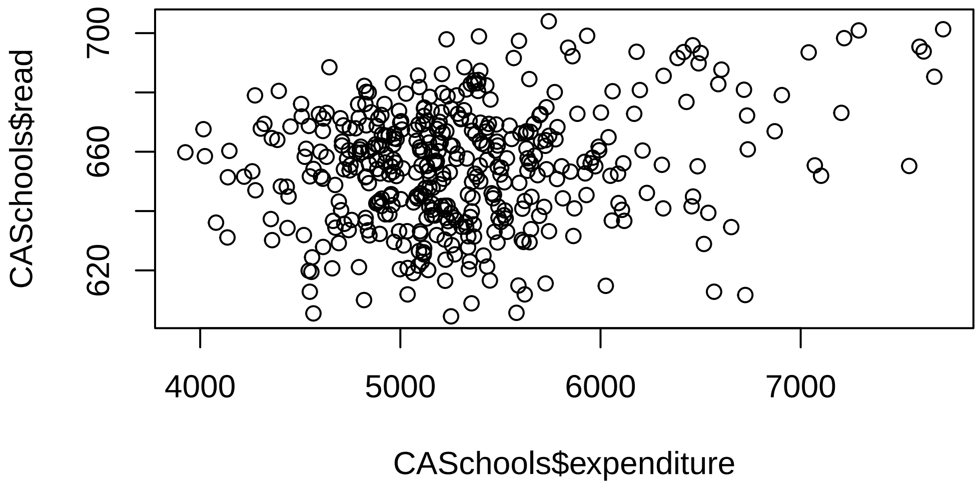
Scatterplots

A scatterplot displays bivariate (two variables) data. For each observation in the dataset, the value of one variable is plotted on the x-axis and the other on the y-axis.

To quickly create a scatterplot, use the base R function `plot()` with the x-axis variable as the first argument and the y-axis variable as the second argument.

The code plot displays the `expenditure` and `read` variables from the `CASchools` dataset as the x- and y-axis variables, respectively.

```
plot(CASchools$expenditure, CASchools$read)
```

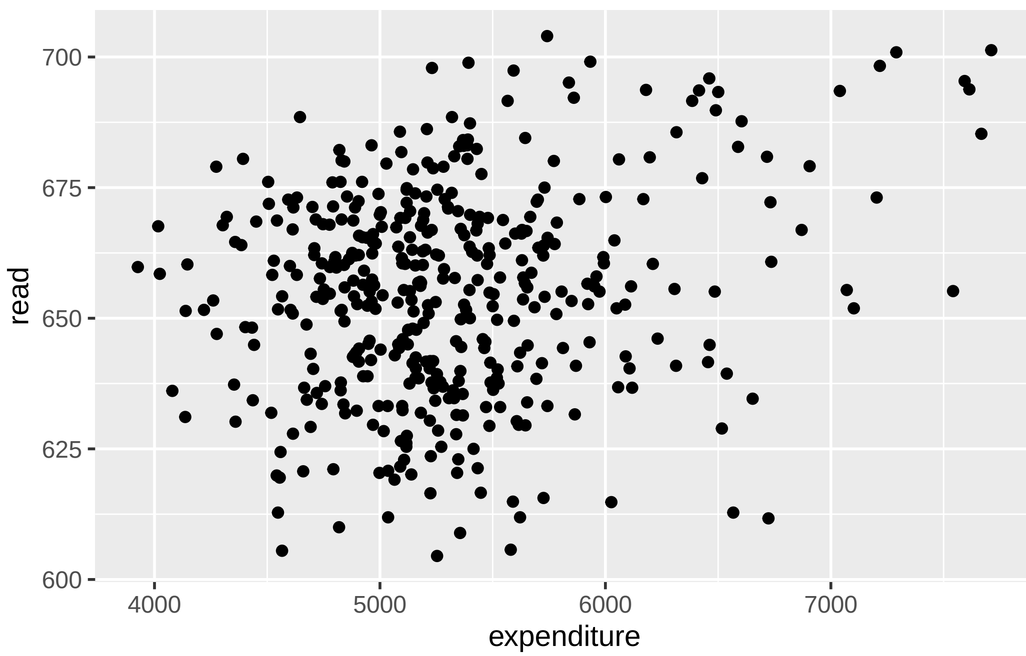


Using the `ggplot2` package, we can create a similar, slightly tidier plot using the `ggplot()` function.

The first line, `ggplot()`, tells it to create a plot object, and the second part, `geom_point()`, tells it to add a **layer** of points to the plot.

The usual way to use `ggplot()` is to pass it a data frame (`CASchools`) and then tell it which columns to use for the x and y values as the **aesthetic** (`aes`) arguments.

```
ggplot(data = CASchools, aes(x = expenditure, y = read)) +
  geom_point()
```



Task 1

Take a look at the help documentation and descriptions of the variables available in this dataset. Select two other numerical variables from the CASchools dataset and create a scatterplot using the base R function

```
# Your code goes here...
```

and the `ggplot2` package.

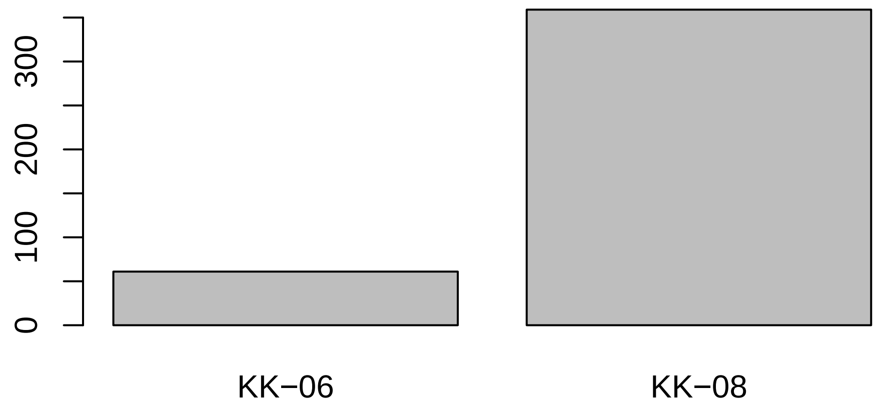
```
# Your code goes here...
```

Bar Graphs

Bar graphs are a handy visualization tool when we want to display the size of the categories of a categorical variable.

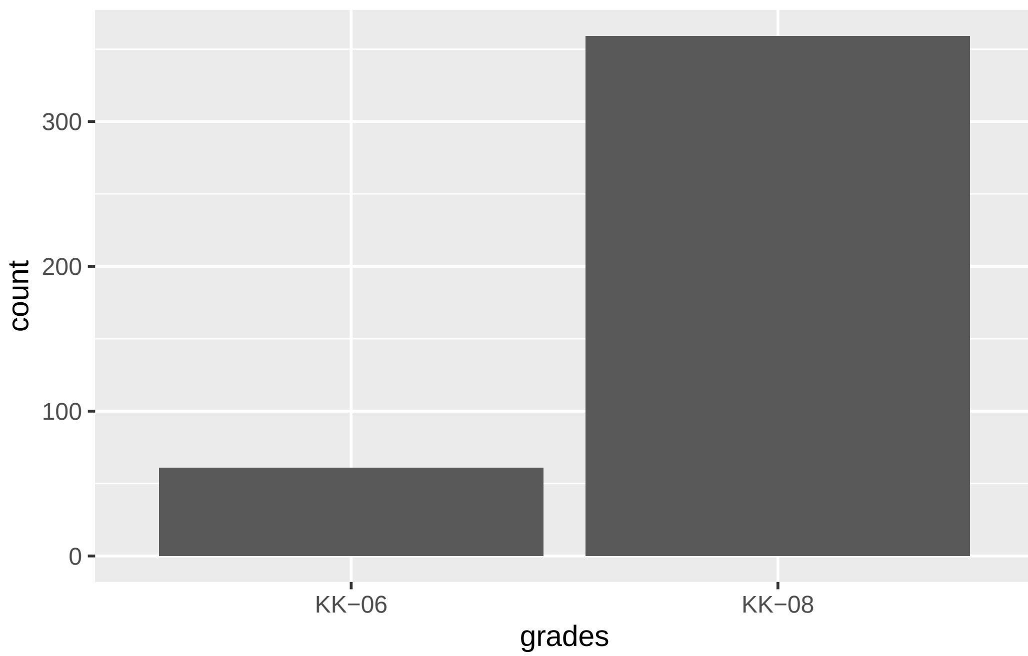
The base R code below uses the `barplot()` function to create a barplot for the `grades` variable. In the code chunk below, we have a function `table()` nested within `barplot()`. Try highlighting and running just the `table(CASchools$grades)` component of the code to see what information the `barplot()` function takes as input.

```r
barplot(table(CASchools$grades))
```



We can create a similar plot using the `ggplot()` function by setting `grades` as the `x` aesthetic and then adding the `geom_bar()` layer.

```r
ggplot(data = CASchools, aes(x = grades)) +
  geom_bar()
```



Task 2

The `county` variable is another categorical variable in this dataset that might lend itself nicely to a barplot. Using the same ggplot structure as we did above, create a barplot for the county variable.

```
# Your code goes here...
```

Because there are 45 different counties present in this dataset, it's probably pretty difficult to make any meaning out of the plot. There are a lot of different formatting options we can use in `ggplot2` to fix this issue. For now, we'll just opt for the quick fix of flipping the axes in the plot. Create a barplot using the `ggplot()` functions so that county is a `y` aesthetic instead of `x`.

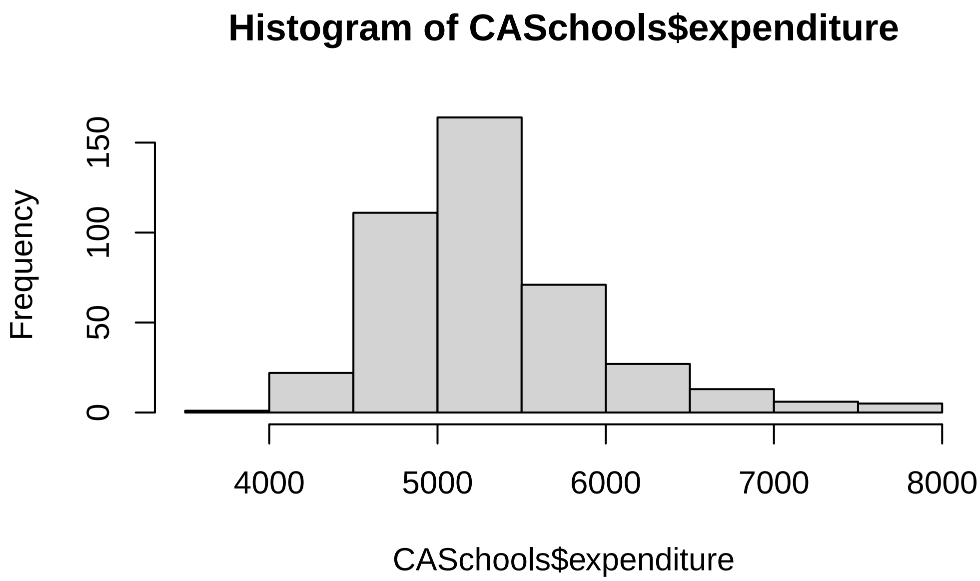
```
# Your code goes here...
```

Histograms

A histogram is useful for visualizing the distribution of a numerical variable. Each recorded value is placed in a **bin** and the bins are displayed as bars where the height of each bar corresponds to the number of observations within the bin.

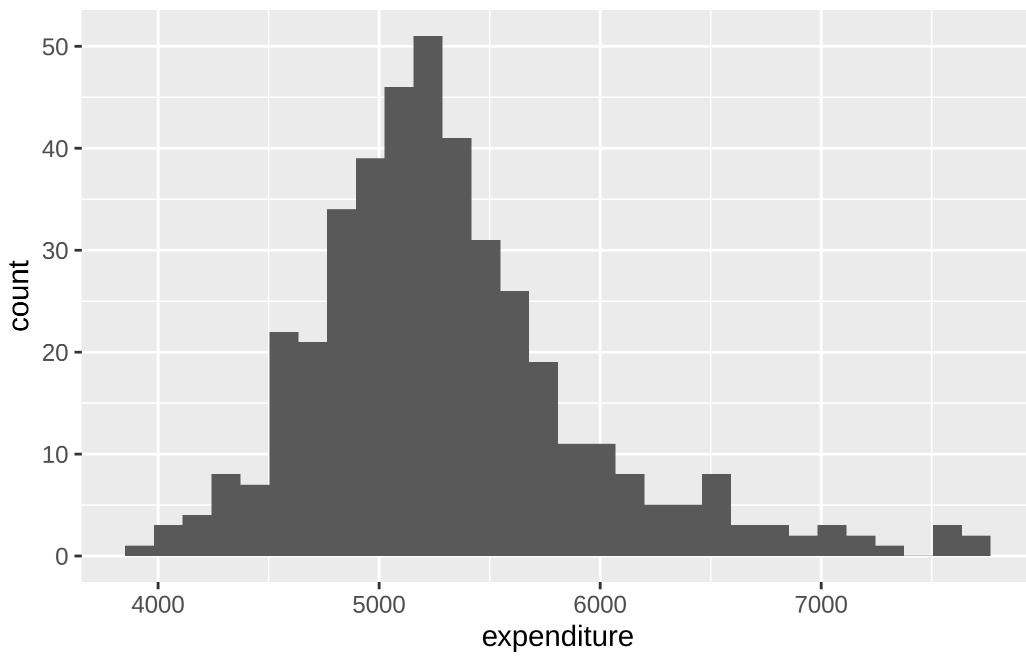
The base R function `hist()` takes a single numerical variable as its only required argument. The code below creates a histogram of the `expenditure` variable.

```
hist(CASchools$expenditure)
```



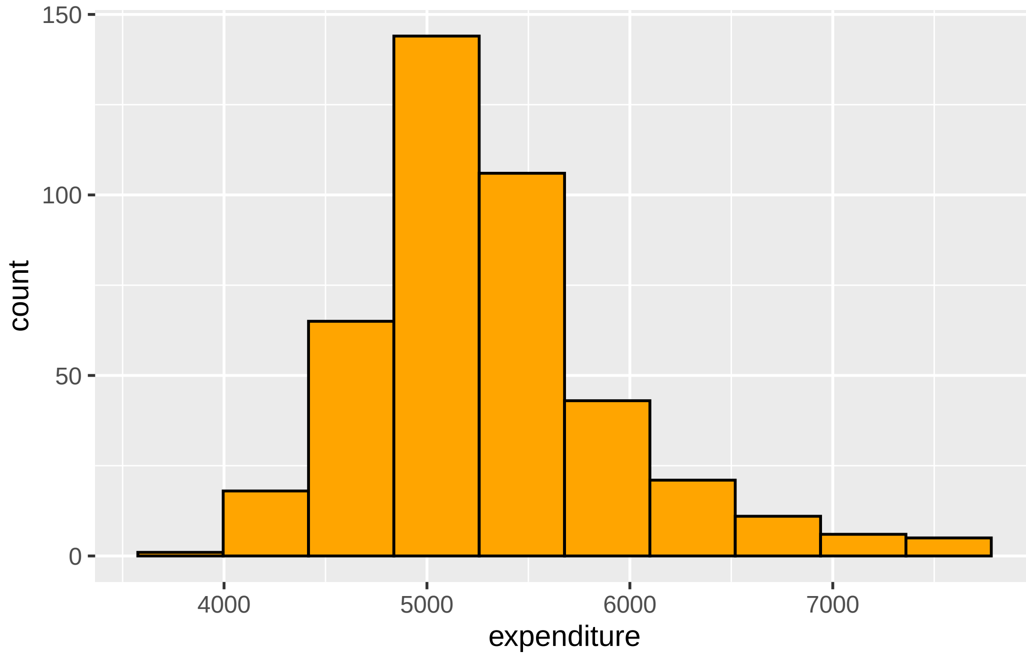
Again, we can create a similar, yet slightly more presentable version of the plot using the `ggplot()` function and the `geom_histogram()` layer.

```
ggplot(data = CASchools, aes(x = expenditure)) +
  geom_histogram()
```



Let's start to take advantage of the some of the nicer plotting features that the `ggplot2` package offers. We can specify some formatting options, such as outline color, fill color, and number of bins, specific to the `geom_histogram()` layer.

```
ggplot(data = CASchools, aes(x = expenditure)) +
  geom_histogram(bins = 10, color = "black", fill = "orange")
```



Task 3

Take a look at the help documentation and descriptions of the variables available in this dataset. Select a different numerical variable from the CASchools dataset and create a histogram of the data using the base R function

```
# Your code goes here...
```

and the `ggplot2` package. Customize your histogram by adjusting the number of bins and the outline and fill colors.

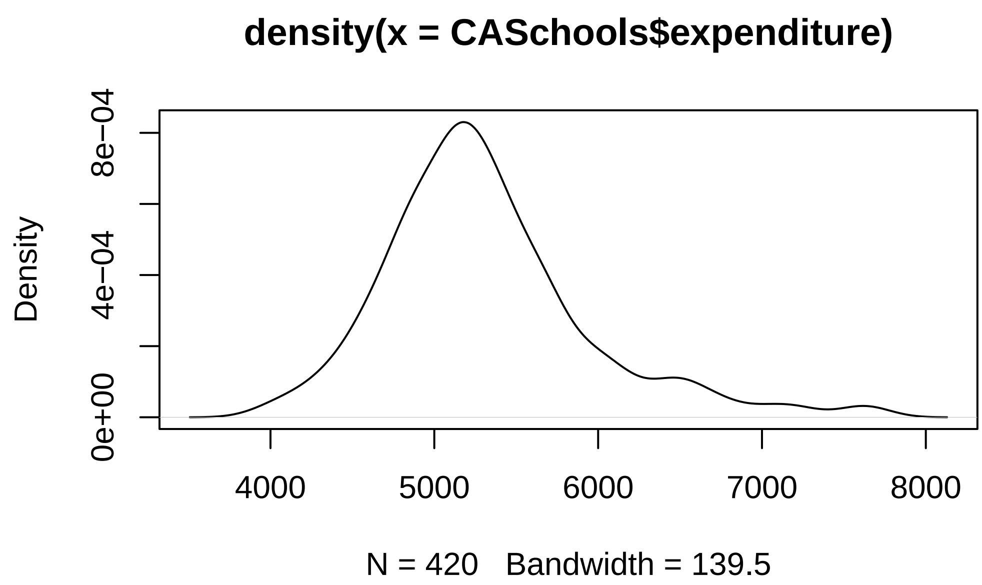
```
# Your code goes here...
```

Density Plots

A density plot is an alternative visualization to a histogram and can be particularly useful when the numerical variable we're interested in is continuous. It is a smooth version of the histogram that uses something called the *kernel density estimate* to create the curve. We won't get into get into how the kernel density estimate is determined in this class, but if you'd like to read more, you're welcome to.

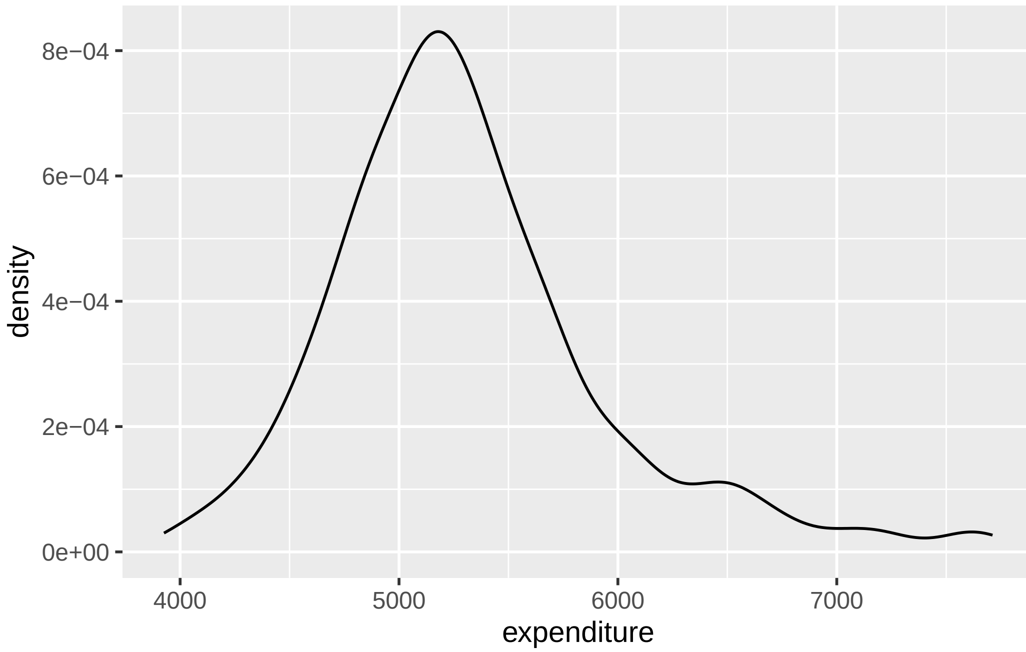
We can use the `density()` function nested within the `plot()` function to create a density plot of the `expenditure` variable.

```
plot(density(CASchools$expenditure))
```



Better yet, we can use the `ggplot()` and the `geom_density()` layer.

```
ggplot(data = CASchools, aes(x = expenditure)) +
  geom_density()
```



Task 4

Select a different numerical variable from the CASchools dataset and create a density plot using the base R function

```
# Your code goes here...
```

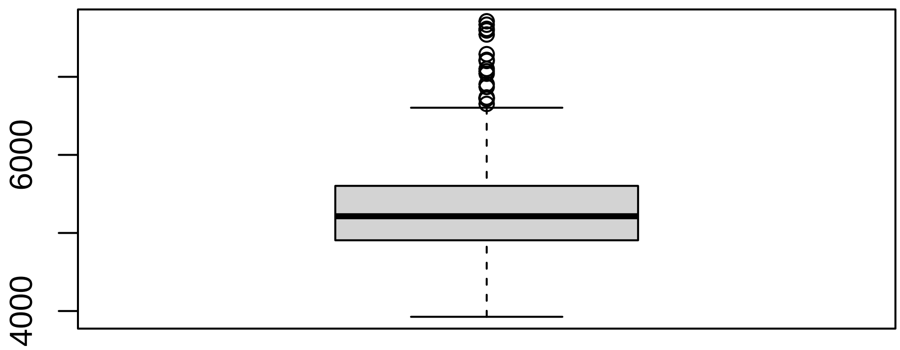
and the `ggplot2` package.

```
# Your code goes here...
```

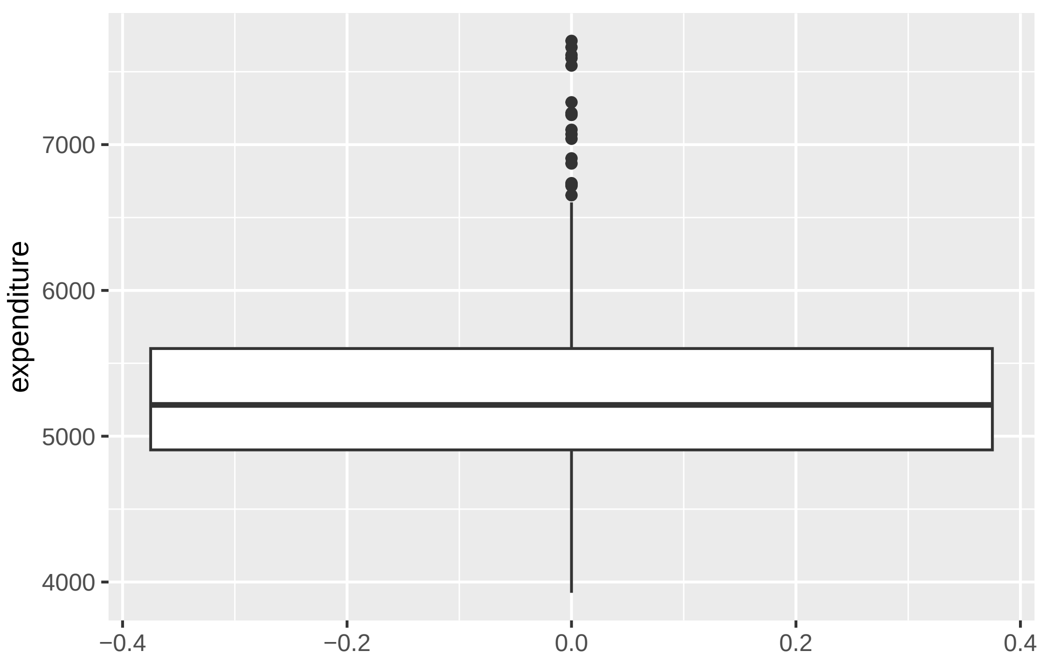
Boxplots

The last type of basic plot we'll look at in this lab is a boxplot. Boxplots, also used to displayed numerical data, can be useful for displaying a number of summary statistics. Read more about boxplots here.

```
boxplot(CASchools$expenditure)
```



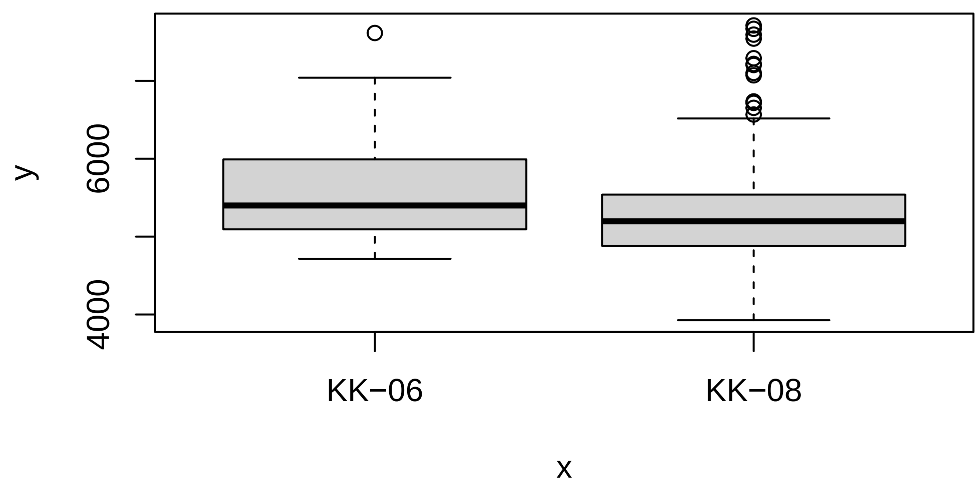

```r
ggplot(data = CASchools, aes(y = expenditure)) +
  geom_boxplot()
```



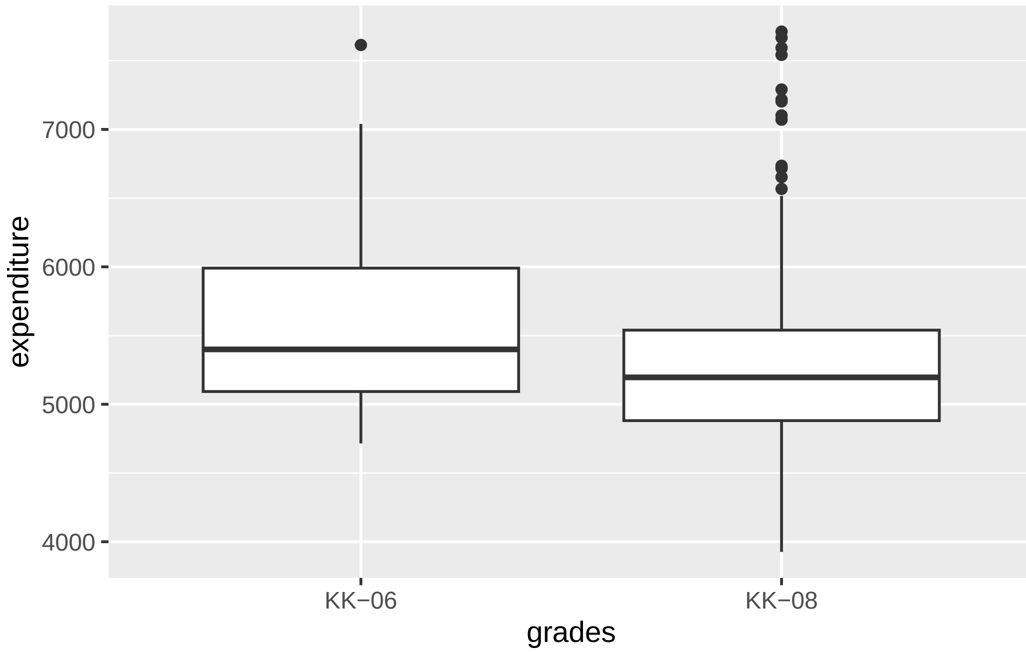
Boxplots can be especially useful when we want to compare the distributions of some numerical variable for multiple categorical variables.

The chunks of code below create side-by-side boxplots of the `expenditure` variable for each `grade` category, using the base R and `ggplot2` functions, respectively.

```
plot(CASchools$grades, CASchools$expenditure)
```

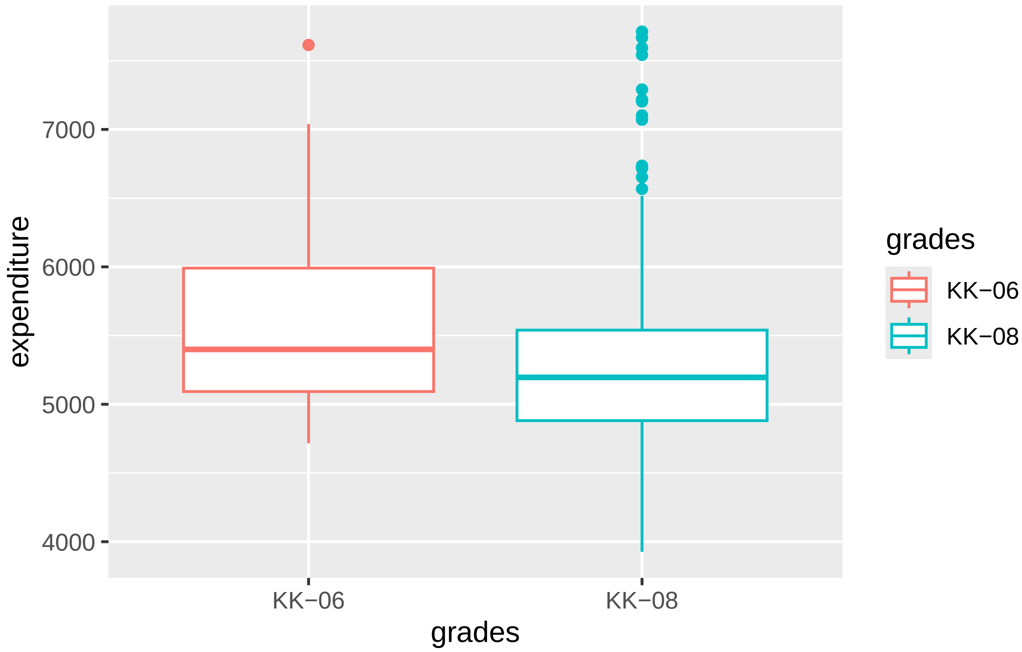



```
ggplot(data = CASchools, aes(x = grades, y = expenditure)) +
  geom_boxplot()
```



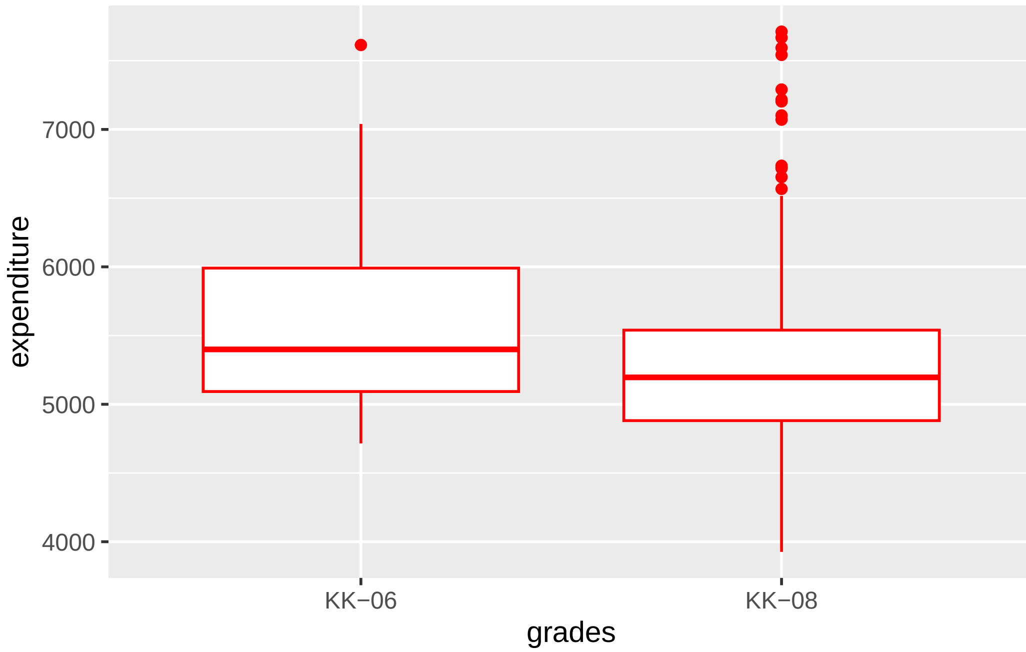
Earlier, we saw how to add customization arguments (e.g. `fill` and `color`) to change features of the entire plot. We may also want to customize our plot based on variables within our visualization. This is where aesthetic mappings comes into play. Let's **map** the `grades` variable to color. To do this, we must specify `color = grades` within the aesthetic function inside the `geom_boxplot` layer.

```
ggplot(data = CASchools, aes(x = grades, y = expenditure)) +
  geom_boxplot(aes(color = grades))
```



Compare how mapping `grades` to the color argument within the `aes()` function creates a different plot than specifying a specific color outside the `aes()` function.

```
ggplot(data = CASchools, aes(x = grades, y = expenditure)) +
  geom_boxplot(color = "red")
```



Task 5

Select a different numerical variable from the CASchools dataset and create side-by-side box-plots of the data grouped by the `grades` variable using the base R function

```
# Your code goes here...
```

and the `ggplot2` package.

```
# Your code goes here...
```

Wrap Up

We've now seen how to create a number of plot types using both base R functions and the `ggplot2` package. You may have noticed that there is quite a bit of inconsistency in the syntax used to create the base R plots. Base R plots are useful if you just want to look at your data quickly and you already have the code committed to memory. The `ggplot2` functions, on the other hand, all follow the same consistent structure. The layering technique we saw in each of the ggplot examples will allow us to easily customize and fine tune the visualizations we create throughout this course. All of the plots that you submit in this course will need to be created using the `ggplot2` package, unless specified otherwise, so if you're looking to commit one of these plotting techniques to memory, focus on the family of `ggplot()` functions.