Post01: Data Visualization with ggplot2

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Data Visualization with `ggplot2`

Introduction

Imagine this: You're presenting your extensive data analysis to your colleagues. You've never been more proud of a project. You load up your slideshow, tell your story, and conclude with a beautiful graph. It's basically artwork at this point. But then you see squints, head scratches, and confused looks. It's all gone downhill.

Sometimes, a clear visualization of even the most insignificant findings can make them stand out and seem more significant. On the other hand, a dull, obscure graph will make an analytical breakthrough seem mundane and unoriginal. That's why visualization methods are just as important as data wrangling, manipulation, and analysis.

Let's take a closer look at how `ggplot2` can enable you to tell impactful stories through your data analysis.

Motivation

When we discussed `ggplot2` in lecture and lab, we learned the basic functions, but somehow Professor Sanchez's graphs just always looked cleaner, easier to read, and more beautiful. I'm setting out to unlock these `ggplot2` hacks so that we Stat 133 students can all achieve new heights of data visualization and be more fluent in the once mysterious package.

Background

The package `ggplot2` was created by Hadley Wickham in 2005. It was designed to be based on the "grammar of graphics (gg)" approach, which takes care of the tedious tasks involved in creating graphs, like legends and labels. Since then, it's grown to be one of the Top 5 most popular R packages, with around 70,000 monthly direct downloads.

Clearly, there's something really significantly useful about this package. Not only does it have an easy-to-understand language, but it's flexible and allows for high levels of abstraction. It does all the hard work for you. Now that we have a solid grasp on the basic features of the package, let's take a closer look beyond the functions and parameters we've already used.

Some Features

`ggplot2` has an extensive documentation. From themes to layers to coordinate systems, the package allows for a lot of flexibility when it comes to visualizing data. Here are some interesting features you probably don't know about.

Customization

In `ggplot2`, graphs can be customized in an endless number of ways to work best for your purposes. The package has a lot to offer in terms of visuals, so it's no wonder why there's a separate feature called `aes`, where you can map data to aesthetics like color, fill, or shape.

Note: Setting vs. Mapping

The difference between setting and mapping aesthetics is whether you're looking to have `ggplot2` categorize your graph in terms of a certain variable, or whether you want to customize the entire output. For example, when we use **`geom_point(aes(color = some_variable))`**, `ggplot2` will colorize the points on your graph with as many different colors as there are unique values of that variable. But when we instead use **`geom_point(color = "red")`**, all of the points on the plot will be red.

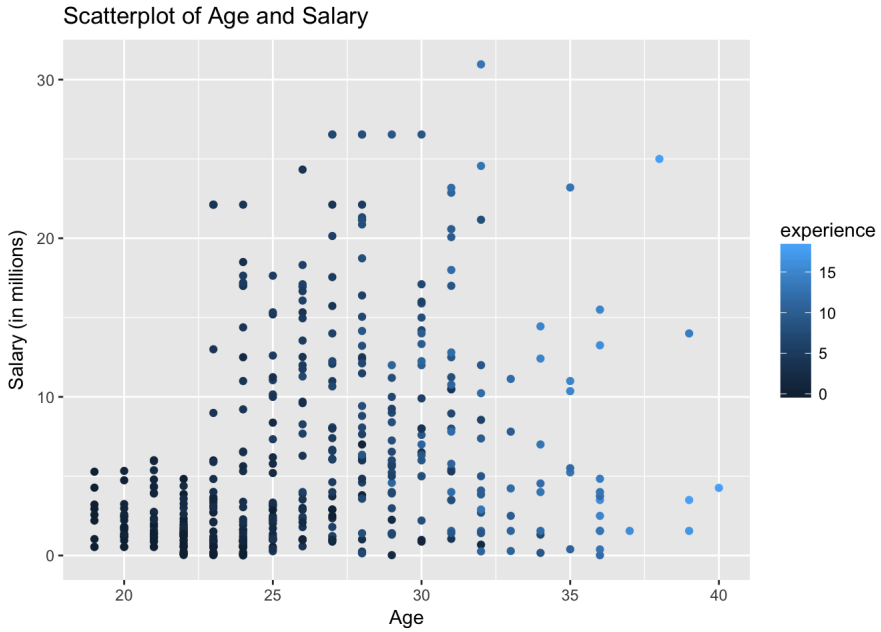
The following examples will be using some of the NBA data that we've seen in class.

```
# loading packages
library(ggplot2)
library(dplyr)

# reading input file
roster <- read.csv('../data/nba2017-roster.csv', stringsAsFactors = FALSE)
```

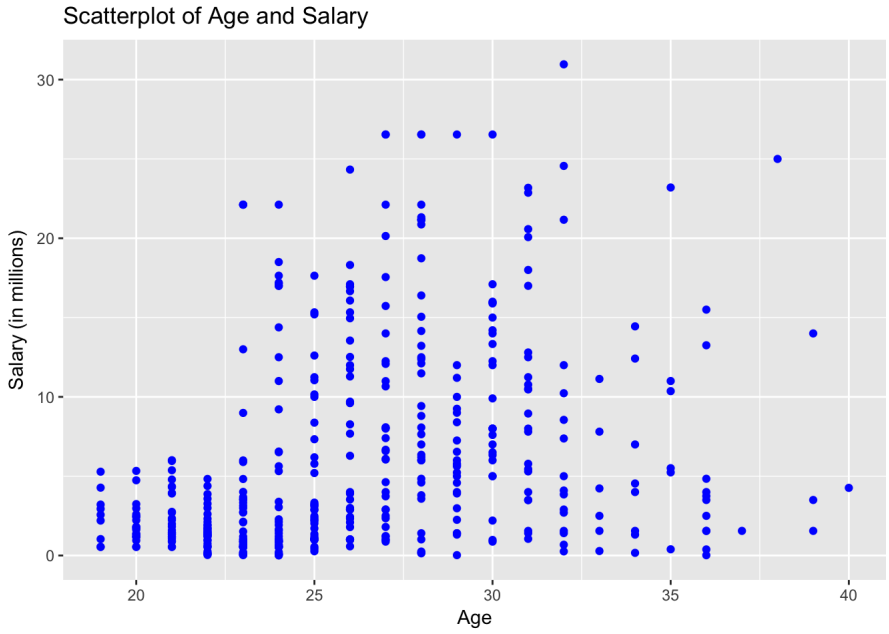
After loading the packages and reading the file 'nba2017-roster.csv', we can create plots.

```
ggplot(data = roster, aes(x = age, y = salary/1000000)) +
  geom_point(aes(color = experience)) +
    # mapping experience to color
  ggtitle("Scatterplot of Age and Salary") +
  xlab("Age") +
  ylab("Salary (in millions)")
```



Here we see that `ggplot2` creates a legend with the `experience` values in order to color the points on the scatterplot, and we see that the highest values are usually associated with age (which is self-evident) and salary. If instead, we want to color all of the points blue, here's how the code would change.

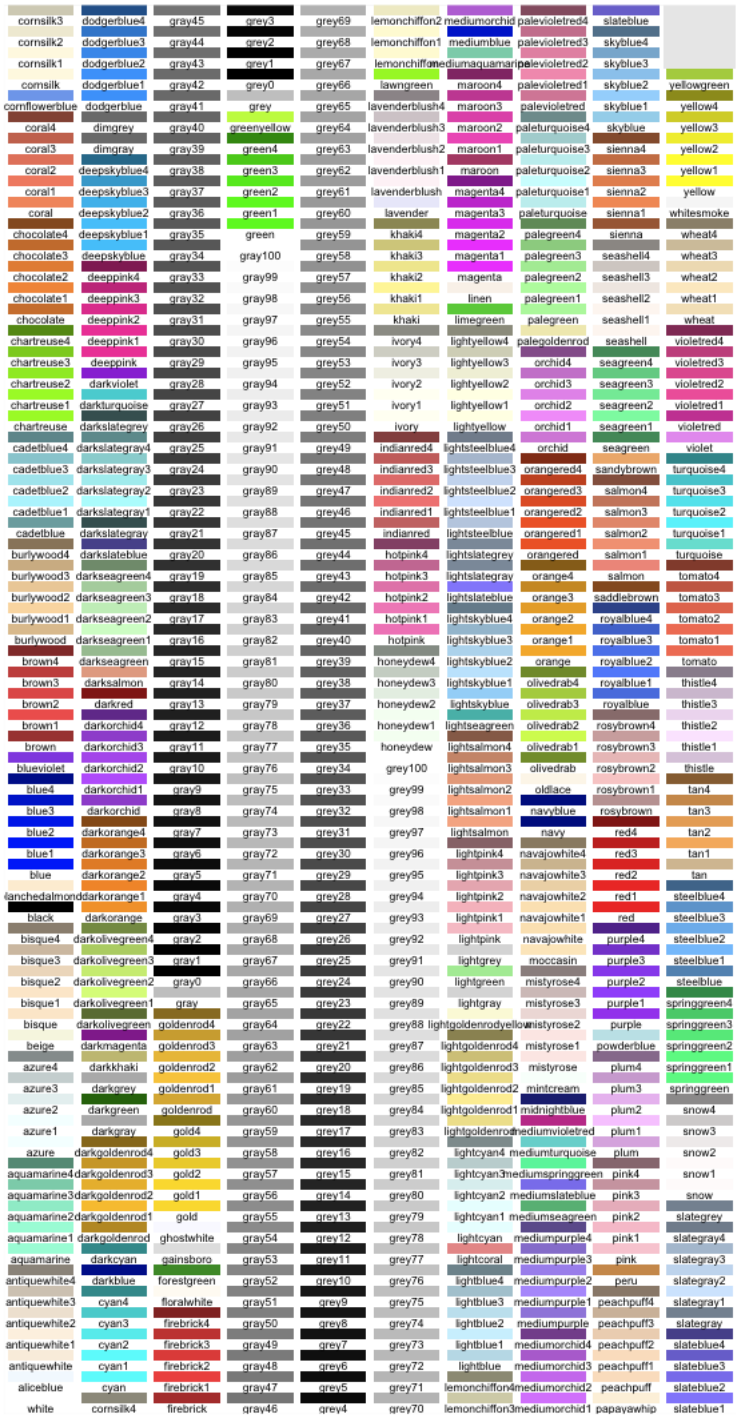
```
ggplot(data = roster, aes(x = age, y = salary/1000000)) +
  geom_point(color = "blue") +
    # setting color to blue
  ggtitle("Scatterplot of Age and Salary") +
  xlab("Age") +
  ylab("Salary (in millions)")
```



Let's move on to new aesthetic features.

Aesthetics: *Color*

Colors in `ggplot2` can be specified with strings such as "red", RGB hexadecimal digits, or NA for a transparent color. Even without using RGB digits, the options when it comes to strings are endless. There's `"turquoise2"` and `"mediumorchid"` and even `"maroon4"`! (Sadly, no `"maroon5"` yet though.)

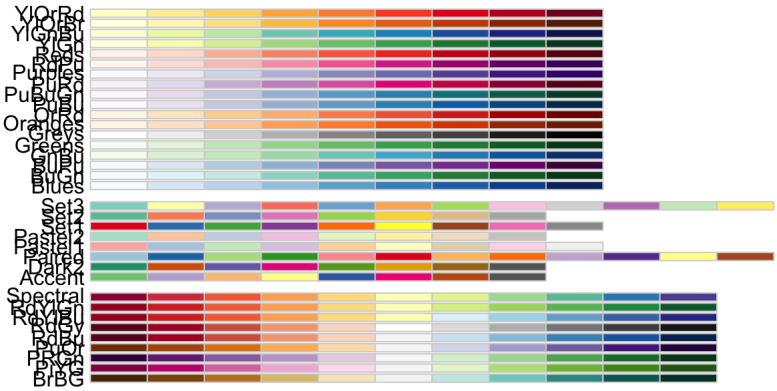


List of ggplot2 color names

There's also the option of using **Color Brewer**.

Color Brewer was briefly mentioned in lecture, but let's find out exactly how it can be used to take your graphs to the next level. The package `RColorBrewer` provides an extensive selection of "palettes" that can be used with `ggplot2` graphics. These can be accessed using the `display.brewer.all()` function.

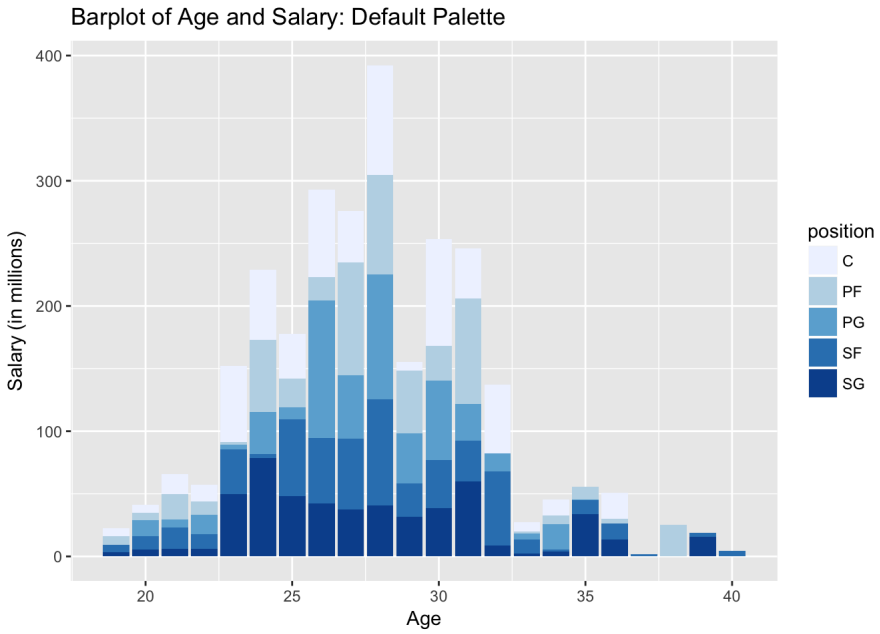
```
library(RColorBrewer) # loading RColorBrewer package
display.brewer.all() # all RColorBrewer palettes
```



These palettes can be applied to various plots when it comes to fill or color. Not only is there the option to use numbers, but the `palette` parameter can also be a string. The default palette is a blue gradient.

Example 1: scale_fill_brewer – default palette

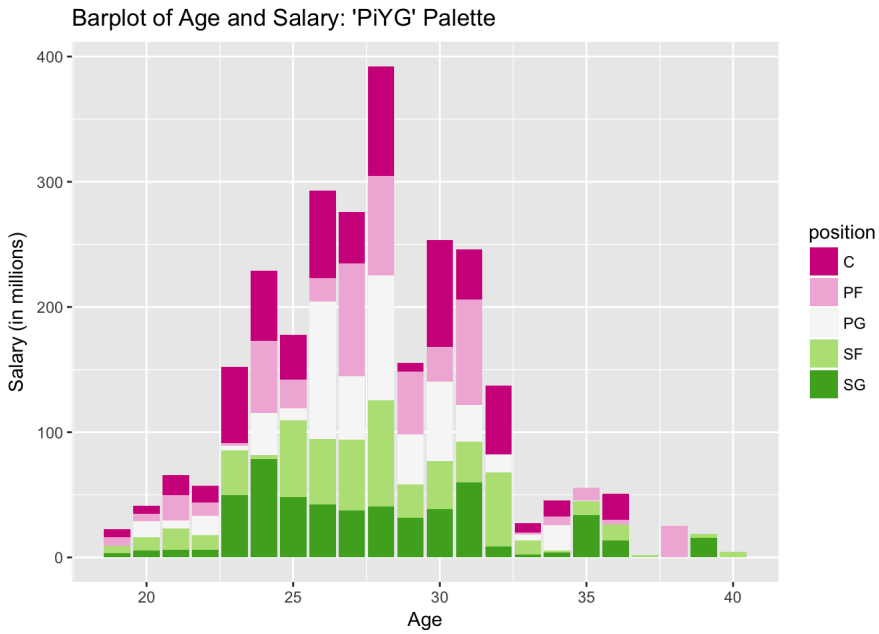
```
ggplot(data = roster, aes(x = age, y = salary/1000000,
                          fill = position)) +
  geom_bar(stat = "identity") +
  ggtitle("Barplot of Age and Salary: Default Palette") +
  xlab("Age") +
  ylab("Salary (in millions)") +
  scale_fill_brewer() # default palette
```



You can also choose one of the custom palettes from `RColorBrewer`, like “PiYG”.

Example 2: scale_fill_brewer – custom palette

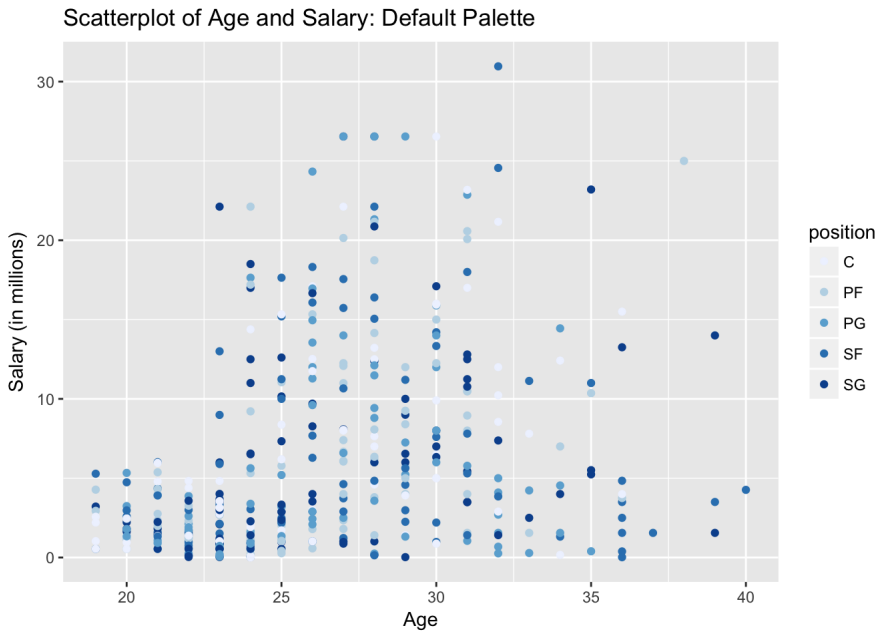
```
ggplot(data = roster, aes(x = age, y = salary/1000000,
                          fill = position)) +
  geom_bar(stat = "identity") +
  ggtitle("Barplot of Age and Salary: 'PiYG' Palette") +
  xlab("Age") +
  ylab("Salary (in millions)") +
  scale_fill_brewer(palette = "PiYG") # "PiYG" palette
```



Another option is to use `scale_color_brewer`, which is especially useful for scatterplots. Here is the default blue gradient palette.

Example 3: scale_color_brewer – default palette

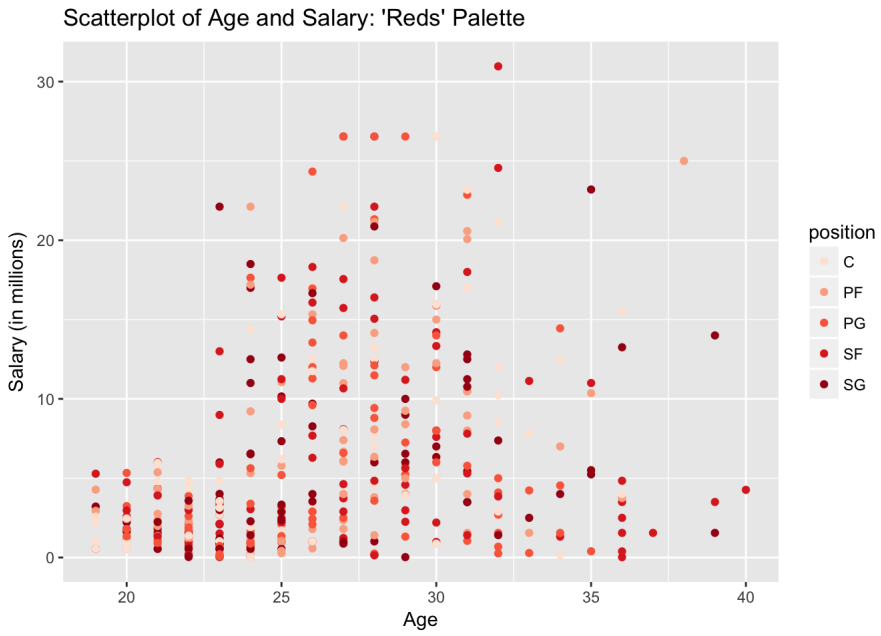
```
ggplot(data = roster, aes(x = age, y = salary/1000000,
                          color = position)) +
  geom_point() +
  ggtitle("Scatterplot of Age and Salary: Default Palette") +
  xlab("Age") +
  ylab("Salary (in millions)") +
  scale_color_brewer() # default palette
```



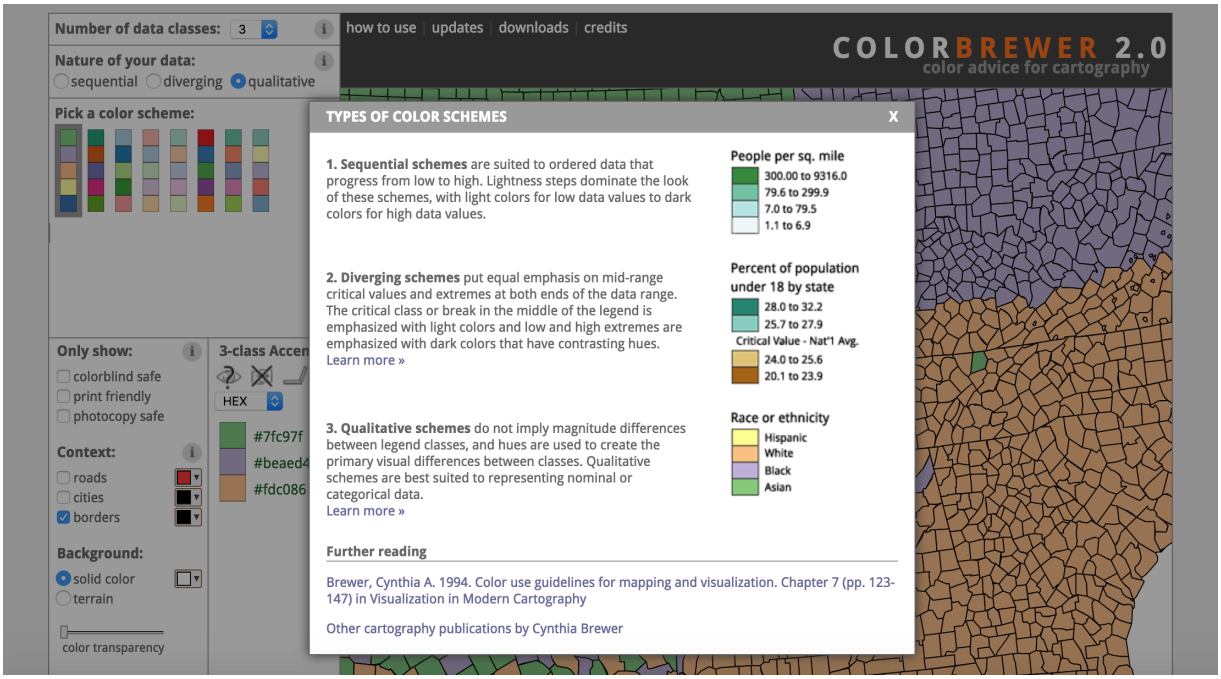
And here is a plot using the “Reds” palette.

Example 4: scale_color_brewer – custom palette

```
ggplot(data = roster, aes(x = age, y = salary/1000000,
                          color = position)) +
  geom_point() +
  ggtitle("Scatterplot of Age and Salary: 'Reds' Palette") +
  xlab("Age") +
  ylab("Salary (in millions)") +
  scale_color_brewer(palette = "Reds") # "Reds" palette
```



`RColorBrewer` is a great tool for customizing your graphs. There are a variety of options you can use, including ones that are colorblind safe, print friendly, and photocopy safe. The color schemes can be used with **sequential** schemes (with ordered data from low to high), **diverging** schemes (with mid-range critical values emphasized in light colors and extremes in dark colors), or **qualitative** schemes (with categorical data). More info can be found on the website.

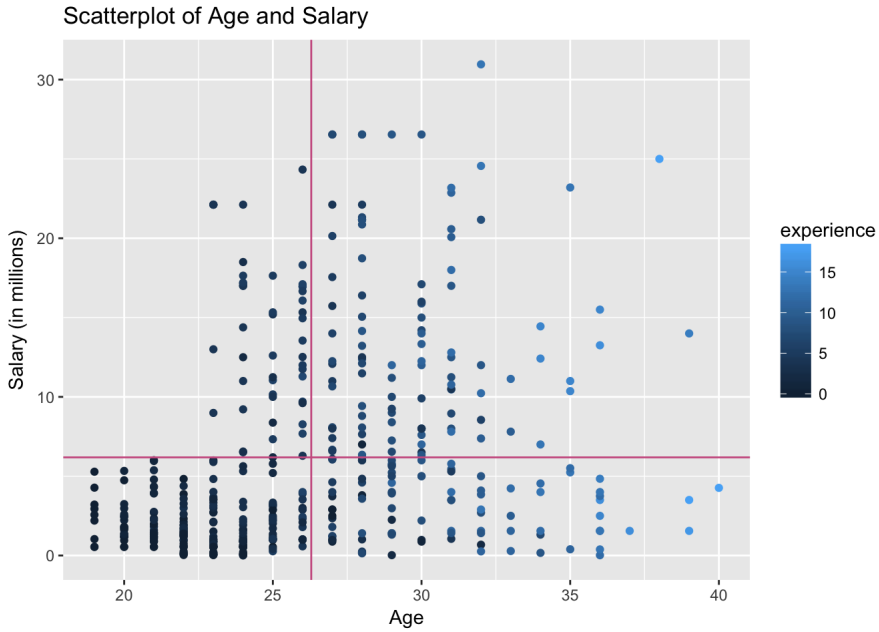


More Aesthetics: *Lines*

Lines in `ggplot2` are very useful for summarizing data and putting your findings into perspective. For example, just by adding the averages (in snazzy `"hotpink3"`) to the same scatterplot above, you can get an idea of how the points compare. The function `geom_vline` can be used to add vertical lines by specifying the `xintercept`, and `geom_hline` is used for adding horizontal lines by specifying the `yintercept`.

You can also choose to map the intercepts to variables or to set them to a specific value. For these plots, I'll be using `aes` to map the intercepts to either the `age` or `salary` value.

```
ggplot(data = roster, aes(x = age, y = salary/1000000)) +
  geom_point(aes(color = experience)) +
  ggtitle("Scatterplot of Age and Salary") +
  xlab("Age") +
  ylab("Salary (in millions)") +
  geom_vline(aes(xintercept = mean(age)),
             color = "hotpink3") +
  # vertical line
  geom_hline(aes(yintercept = mean(salary / 1000000)),
             color = "hotpink3") # horizontal line
```



Sometimes, highlighting the x and y axes is more useful. In that case, you'll want to set your `xintercept` and `yintercept` values to `0` rather than mapping to a variable. Or, you can also control the slope and intercept of your graph using `geom_abline`.

To get different effects on your lines, you can change `linetype`, `size`, or `alpha` (transparency). Here are some of those features showcased on the previous plot. I'll set `linetype` to "dashed" on the vertical line and "twodash" on the horizontal line so that the two are more distinct.

```
ggplot(data = roster, aes(x = age, y = salary/1000000)) +
  geom_point(aes(color = experience), alpha = 0.5) +
  ggtitle("Scatterplot of Age and Salary") +
  xlab("Age") +
  ylab("Salary (in millions)") +
  geom_vline(aes(xintercept = mean(age)), color = "magenta2",
             linetype = "dashed", size = 1.5) +
  # vertical line
  geom_hline(aes(yintercept = mean(salary / 1000000)),
             color = "violetred2", linetype = "twodash",
             size = 1.5) # horizontal line
```

I've been using scatterplots and barplots to show off some of the different aesthetic elements, but now let's go beyond them to a few new types of visualization.

Plots

With `ggplot2`, a variety of different plots can be used to fit different types of data. The options go beyond the basics that we're familiar with and can even be used to make art (for advanced data scientists).

Violin Plot

We've used box plots as tools for visualizing the basic distributions of data, but they aren't as helpful for understanding the variation in the data. That limitation is taken care of with `geom_violin`. Let's look at an example using our NBA data.

Example: geom_violin

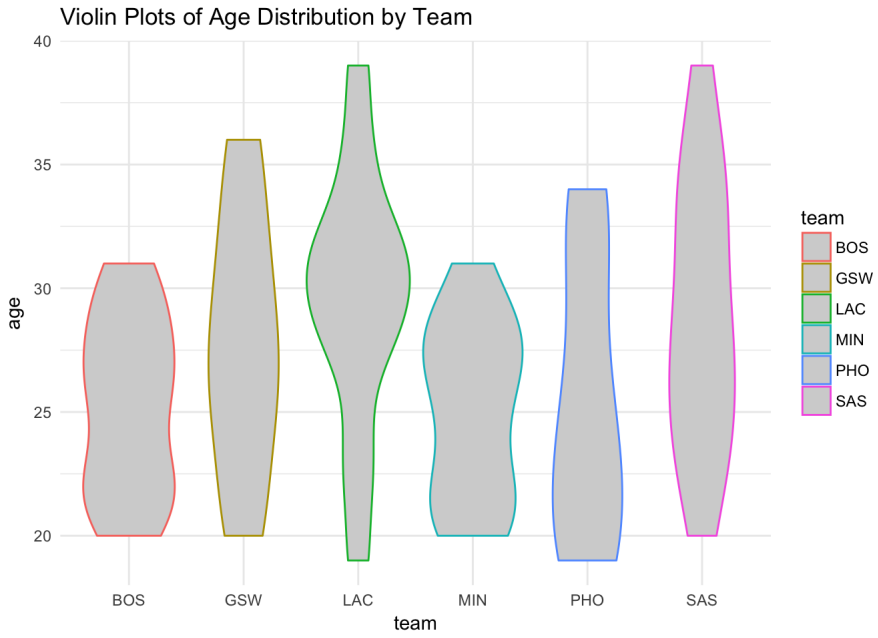
Suppose we're interested in analyzing the distribution and variation of player age by team. I've created a `mini_roster` of only 6 teams, just so that the graph is easier to read.

```
mini_roster <- roster %>%
  filter(team %in% c("GSW", "MIN", "SAS", "PHO", "LAC", "BOS"))
```

Violin plots are similar to boxplots, but also display the distribution of the data. Wider portions represent a higher probability, while narrower portions represent a lower probability. So, for example, an age of around 30 is most common on the LA Clippers (LAC) team.

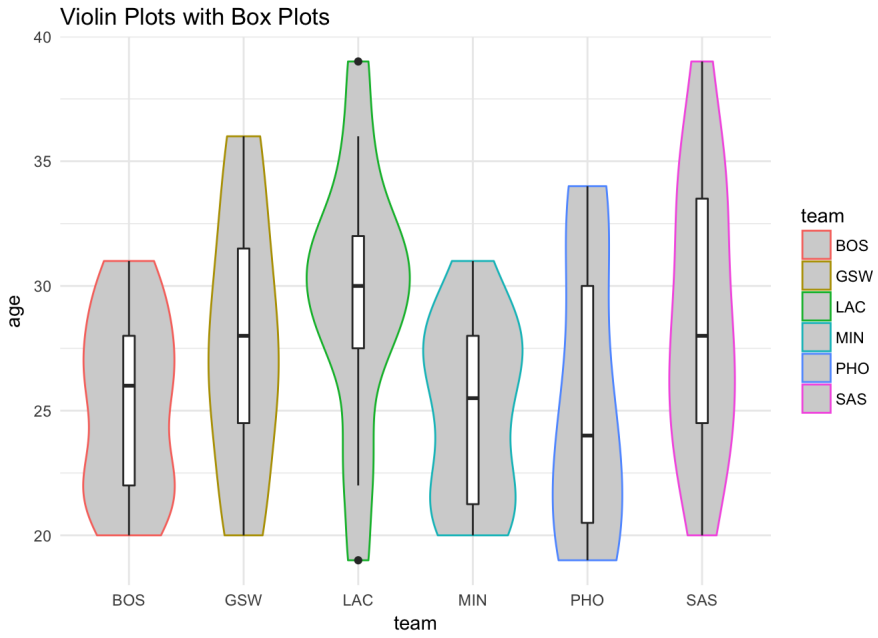
```
# manipulating the roster to get age by team
age_by_team <- mini_roster %>%
  select(team, age) %>%
  group_by(team)

# creating the violin plot
ggplot(data = age_by_team, aes(x = team, y = age)) +
  geom_violin(aes(color = team), fill = "lightgray") +
  theme_minimal() +
  ggtitle("Violin Plots of Age Distribution by Team")
```



If we add a `boxplot` to the above graph, we can also see the median, range, and quartiles. Here we see how the violin plot goes beyond the boxplot by displaying not just the average distribution, but the probability that a value will fall within the range as well.

```
ggplot(data = age_by_team, aes(x = team, y = age)) +
  geom_violin(aes(color = team), fill = "lightgray") +
  theme_minimal() +
  geom_boxplot(width = 0.1) +
  ggtitle("Violin Plots with Box Plots")
```

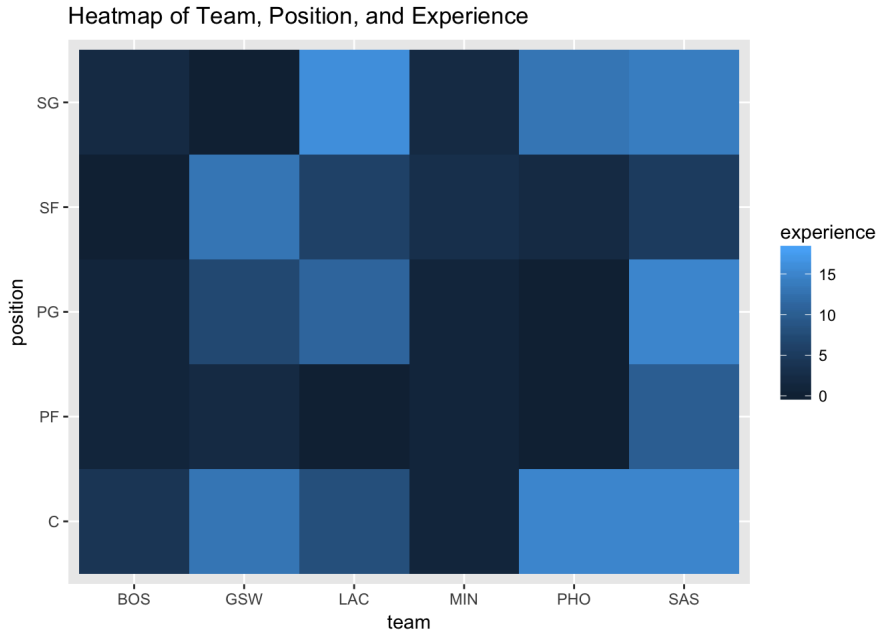


Heatmap

Using a heatmap, we can add another variable to our analysis of player age by team. In this case, we can create a heatmap using `geom_tile`.

```
# manipulating the roster to get position and experience
experience_by_position <- mini_roster %>%
  select(team, position, experience) %>%
  group_by(team)

# creating the heatmap
ggplot(data = experience_by_position, aes(x = team, y = position)) +
  geom_tile(aes(fill = experience)) +
  ggtitle("Heatmap of Team, Position, and Experience")
```



This is another way to visualize the data, where we can plot each team and each position, and see the squares with the lightest blue as an indicator of greatest years of experience in relation to each team's position.

Discussion

The package `ggplot2` is rich with all kinds of different features and parameters. While there is an infinite number of ways to visualize and interpret data, I hope this post will be a useful resource for understanding some of the basic and not-so-basic outputs you can achieve. Of course, this is only the beginning and there are numerous other ways to use `ggplot2` to its full potential.

Conclusions

Visualizing data is incredibly important. With clear and aesthetically pleasing graphics, the stories you tell will be far more compelling. It takes a lot of thought to determine the best way to represent your findings because the final product can make or break your presentation, no matter how much work you put in to the data manipulation. You'll learn more about your own data while coming up with the best way to display it. It's definitely worthwhile to explore `ggplot2` and other graphics packages so that you can take advantage of the tools they provide.

References

1. http://ggplot2.org/
2. http://ggplot2.tidyverse.org/reference/
3. http://ggplot2.tidyverse.org/articles/ggplot2-specs.html
4. https://www.datacamp.com/community/blog/the-5-most-downloaded-r-packages
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13. https://www.superdatascience.com/ggplot2-setting-vs-mapping-aesthetics/