Chapter 6: Communicating Visually

“The human visual system is a pattern seeker of enormous power and subtlety. The eye and the visual cortex of the brain form a massively parallel processor that provides the highest bandwidth channel into human cognitive centers.”

Colin Ware, “Information Visualization”

In chapter 1, we briefly mentioned how data analysis is like how we imagine archeology to be: spending hour after hour with small tools in the hope of uncovering even the tiniest of insights in the earth. That analogy can be extended into the shared desire to create a narrative. Archeologists attempt to recreate the stories of history by digging up parts of a story and it’s the same with data analysts. There are stories buried in the data and it’s up to the data analyst to uncover that narrative, piece it back together and communicate that story to others.

We have to do more with our data than just analyze it and present our numbers. Numbers are quite boring to most folks and more than just

stories are a part of our lives and they come naturally.

statistical narrative

At the basis of a good data story is truth. Remember, we are uncovering the truth in the data here and we are simply the messengers. Whatever we believe now, or before we looked at the data must be up for debate as we dig into the data. We want to be sure that the story we uncover is accurate and ensure the visual narrative is consistent with the accuracy of the data.

So What? Informative, actionable (or at least a personal connection),concerte

Contextual, meaning comparisons. If we say we have n vulnerabilities present, is that a lot? Did we expect that? Where should we be at? Compare to targets/forecasts, other similar things, to the whole (library of denominators).

Communicated in such a way the audience can understand

The data always should be communicated in its context and setting. We’ll want to identify the characters and walk through the relationships and events in the data. The reader should be able to follow the story as it unfolds right through until all questions and inconsistences are resolved. Thankfully as we dig around in the data, one or more narratives will naturally form and then we have the challenge: how can we best communicate the stories within our data to others? The answer is within the field of data visualization and is the focus of this chapter.

Our ability to visually process information is by far the most efficient path to human understanding. Like a good hacker, we want to learn about this system, understand how it functions (and how it doesn’t function) and then exploit this cognitive system to achieve our goal. In this case, our goal here is effectively and efficiently communicating the stories we find in our data.

Research into the science of perception has exploded in the past few decades. Psychologists, neuroscientists and others are chipping away at the mysteries of the human brain and slowly, the rules of how we visually process information have been emerging. Understanding the rules around how the human brain visually process information will be important in our reports, presentations and dashboards. But even more than that, we’ll want to also use visualizations in our analysis, and create a communication path from the data to us.

Why Visualize?

There are many advantages to using data visualization as a communication tool compared to other methods. To paraphrase Colin Ware (who we quoted to open this chapter), data visualization has the following advantages:

* **Data visualizations communicate complexity quickly.** Descriptive statistics (mean, median, variance, etc.) exist to describe and simplify data but tend to remove subtleties that may exist in the data. By visualizing the data, it’s possible to communicate millions of data points in seconds while minimizing the loss of detail and resolution.
* **Data visualizations enable recognition of dormant patterns.** Often times, visualizing data enables us to see patterns that would never be apparent using statistical methods or scanning the data. By visually representing the data, often times the patterns in a single variable or relationships across many variables may leap off the screen at us.
* **Data visualizations enable quality control on our data.** By visualizing the data, often times mistakes and errors with data collection or preparation become apparent. Data visualizations can serve as a good and quick sanity check on our work.
* **Data visualizations can serve as a muse**. It’s been said that most breakthroughs in science didn’t start with a “Eureka” but instead with a “Huh, that’s odd.” Laying out our data visually can give us new perspective and help facilitate our thinking and discovery process.

The fact that we’re focusing this chapter on visualization does not mean that visualizations are always the best way to communicate data. If the analysis can be summed up with a sentence in an email, or perhaps a simple table in a report, there’s no reason to force it into a visualization. Our focus is on the successful communication of the narrative; the method of communication is just a means to that end.

Unraveling Visual Perception

The system of we process of visual information is incredibly complex and much of our knowledge around it is still evolving. However, there are a few key (and hopefully easy) concepts that we should understand because how the brain visually processes information will help us create great visuals. Although equally as important, it will also help us understand a few ways not to create visuals.

We begin this journey with visual stimulus in the form of light that our eyes convert into electrical signals for our brain. This information will pass through stages of our **visual memory,** each with a specific set of strengths, limitations and functions. Before we are consciously aware of it, our brains rapidly scan the visual field, which is called **preattentive processing**. Finally the brain will instruct the eyes to focus elsewhere, and through a series of **saccadic movements** our eyes will focus on various features to help build up the image in our mind. With these three concepts within our visual processing system, we should be able create a solid foundation for good visuals and dashboards.

Visual Thinking

We will step through the various stages of memory within our visual perception. **Iconic memory** is the first stop for the visual information. It is a very brief stop, lasting around half a second or until it’s replaced with new information. But what happens in this tiny window is critical to creating good visualizations and dashboards. With the information stored in iconic memory, the brain preprocesses the image prior to giving it any conscious attention. From an evolutionary perspective this is quite helpful, this preattentive processing can help us quickly identify possible threats in our environment. For example, anyone who has been driving when an animal dashes in front of the car has probably felt that urgent message from the brain when it recognizes a possible threat. We begin to react immediately even before we can process the full extent of the threat. While we hope our visualizations aren’t treated like a threat, it’s that visual searching and preattentive processing that we can leverage to draw attention and even communicate some basic attributes of our data to make processing much easier when we begin to consciously process it.

**Working memory** is the next stop and things get a little more complicated here. First the brain will gather up and group visual aspects into meaningful objects and hold these individually in working memory. There is a lot of flexibility within working memory as we can rapidly replace or drop these objects as we take in more information, but the flexibility comes at a cost in capacity. We can only hold three to five objects in working memory depending on the task and objects. This limit is important when designing visualizations and dashboards. If we create a visualization with a legend that has ten different attributes, the reader will have to continually reference the legend in order to understand what they’re looking at. So as we communicate the stories in our data we want to limit each visual to no more than five objects (four to be safe).

**Long-term memory** is not directly important as we attempt to communicate our data other than both iconic and working memory are temporary stores. In order for something to move into long-term memory the reader needs to visually “rehearse” the information to transition that visual chunk from working memory into long-term memory. But indirectly, we will leverage long-term memory to detect meaningful patterns and relationships within the data. This type of deeper understanding and processing is only available with long-term memory.

Tracking Eye Movements

When we focus on something like a dashboard or visual on a computer screen, we do not simply fix our gaze on it and take in the image as a whole. Our eyes actually dash around the screen, focusing on very small portions for very short periods of time in order to build up the image in our mind. One of these rapid eye movements is called a saccade, overall they are called saccadic movements and they are anything but random. The brain has a set of rules (guidelines really) for how the next fixation point is prioritized. As an example, when another person greets us, our eyes perform scanning saccades over their entire face, bouncing from the distinct features of the face (eyes, nose and mouth) and establishing the edges. The scanning saccades help us with recognition not only of the person, but also of their emotions. The same applies to our visualizations and dashboards. The eyes will fixate on an obvious feature and bounce around and between to the points it considers important. We will build up the entire picture over a series of these movements and over time. Understanding these movements can help a visualization flow and feel natural (or at least not strained) to the viewer

The saccadic motion itself is largely unconscious and is thought to be a ballistic movement. Meaning once the brain initiates a saccadic movement, the muscles take over and handle the rapid acceleration and deceleration from beginning to end. This is important for two reasons: once it is initiated it cannot be changed or stopped and during the motion we suppress much of the visual input. We will want to limit the distance of these motions by creating compact dashboards and visualizations.

We can pull together a few important learning points from saccadic eye movements. Knowing that the eyes will bounce around from feature to feature and the ballistic nature of the movement, we should keep several points in mind as we create our dashboards and graphics:

* **Don’t overload the dashboard with visual features**. Keep the number of attention-grabbing features under control because if everything is important visually, than nothing will be important visually and the analyst will have to put more effort in to understand the visual.
* **Make the important messages obvious visual features.** Just as we will scan the important parts of a human face, we will look for the similar attention-grabbing features on the screen. Make sure that those features are clear and are important to the viewer.
* **Limit time wasted on saccadic movements.**  Saccadic movements that jump longer distances take longer to execute. Do not push the visual features into the corners or towards the edges. Forcing the viewer to bounce across large distances will decrease the amount of time they are actually seeing the features (and increase the time spent in saccadic movements).

The role of saccadic movements influence dashboards much more than static data visualizations. Typically in a static visualization we will have one, perhaps sometimes two visual features we want draw attention to and the eye movements are contained in a relatively compact space. But in a dashboard we may be trying to communicate several independent messages simultaneously with varying degrees of urgency. Good dashboard design, as we’ll cover in chapter 10, will want to limit the time spent in a saccadic movement and exploit the eye movement for efficiency in our communications.

(when to use tables is few’s book)

The preattentive processing detects several attributes, such as color and the location of objects in a 2-d space. Because preattentive processing is tuned to these attributes they jump out at us and are therefor extremely powerful aspects of visual perception. If you want something to stand out in a table or graph, you should encode it using a preattentive attribute that contrasts with the surrounding information such as red text in the midst of black text. If you want things to be seen as a group, assign them the same preattentive attribute.

Preattentive Processing

The best way to describe preattentive processing is through pictures. Take a look at figure 6.1 and try to count how many capital X’s are in this completely random mix of letters and numbers.

Figure 6.1 Count the number of “X” characters [FILENAME 793725c06f001]

Because all of the letters are the same color and contained the same relative space, nothing about any of the characters really stands out. The brain simply sees a collection of shapes. In order to count the X’s we have to scan through each letter across the four rows. While we’re doing that we have to remember how many we’ve found as we scan so we don’t lose track. But now take a look at this completely random mix of letters and numbers with the X characters emphasized.

Figure 6.2 Count the number of “X” characters [FILENAME 793725c06f002]

Immediately we can see the X’s and count four of them. In our first look at this, the brain sees a background of gray symbols with four completely different objects that are similar to each other. Our preattentive processing will mentally create two groups, one group of all the gray symbols and a second group for the dark red X’s. A split-second later, we will consciously recognize the second group as what we’re interested in (the X’s), it becomes trivial to visually exclude the gray characters and now we can scan just through this group. Counting the X’s becomes a simple and quick task.

That mental grouping and ease of focus is what we are after. We want to enable our preattentive processing to effortlessly group similar objects and highlight where we want attention to be focused. But we have to keep in mind that the preattentive processing is not all that smart. There are only a handful of attributes that our preattentive processing will be able to pull out because the sole purpose of this processing is to recognize features in our visual environment. It will not be able to project meaning, interpret the objects or make meaningful associations (beyond simple visual grouping).

Through literally hundreds of studies, researchers have been able to differentiate visual attributes from what can be preattentively identified from those that can’t. Having looked through some of these studies they can get a little silly and abstract (how easy is *parallel* detected?), but looking at them as whole, we can create some high level categories of what can be preattentively processed. These categories are form (line, shape, size), color (hue and intensity), spatial position (two-dimensional, stereoscopic) and motion (blink, direction). And the list of specifics within those categories can get quite long, but thankfully we can experiment here and iterate through various visual features in our graphics. If one version doesn’t make highlight the data, try something different. Chances are good if it’s easy for you to pick out, it’ll be easy for others, and it’s a good idea to run things by others as a sanity check. Figure 6.3 gives a few visual examples of ways to differentiate based on preattentive attributes.

Figure 6.3 Examples of Preattentive Attributes [FILENAME 793725c06f003]

Not all preattentive attributes are created equal. Look at figure 6.3 again. While they all highlight the three data points, some make the three points slightly easier to see than others. For example in figure 6.3(e), if we would have chosen colors of pink and red, it would have been slightly more difficult to pick out the differences with the subtle difference in colors. The amount of “pop” for preattententive attributes depends on how different the attributes are. The shapes in example in 6.3(a) are more different from each other than the circles and squares in 6.3(b) and slightly easier to see. It’s still possible to see the difference in 6.3(b), but it’s just not as quick to “pop”.

This concept of preattentive processing should be treated as just that -- a concept. The line between our preattentive processing and conscious processing is gray and blurry. When looking at a visualization, we may slip between the two quickly and quietly. With repeated exposure too, we can actually train our preattentive processing. Meaning over time, no matter how poorly designed a dashboard is, analysts will eventually pick up skills to quickly identify important features depending on environment and culture. But the point remains for our visualizations and dashboards. If we want to direct the reader’s focus and attention we should leverage some basic elements like form and color to highlight the point we need to make in the data.

Finally, one last word of caution about preattentive processing: it’s possible to overload this process and negate any benefit. Take a look at Figure 6.4 below. In the first example 6.3(a), we separate three groups by color and it’s quite easy to pick them apart, not only are they spatially grouped, but the color highlights the difference. In 6.3(b), we attempt to communicate a difference with shapes and it’s a little harder to tell them apart, but we can still pick out the two groups. When we combine them in 6.3(c) things get a bit more complicated. Now to separate based on shape we have to actively inspect individual elements and separate them consciously. We have to be careful to keep the visuals as simple as possible to exploit the readers preattentive processing for their benefit.

Figure 6.4 Too many attributes [FILENAME 793725c06f004]

Understanding The Components Of Visual Communications

We began by looking at how the brain visually processes information, how we can leverage our preattentive processing and saccadic movements to increase the reader’s perception of a visual. Now we’re going to focus on the visual building blocks and material that we have to work with. We need to begin with our data and encode the values through various attributes like position, shape, length and size. Perhaps we want to encode changes over time with slopes or angles and separate categories by color hue, saturation or lightness. If we combine elements and we can communicate relationships and groupings. Every choice we make in creating a visualization will affect how well others will decode the data.

Avoiding the third dimension

First and foremost we are almost always dealing in two dimensions. The screens we look at, the reports we print out and slides we project during presentations are all limited to width and height. Of course we can simulate the third dimension of depth, but this brings a challenge. Simulating a third dimension will always be just that, a simulation. In order to simulate depth, we change the very attributes we are using to convey the meaning of our data. Elements that are closer in the simulation will need to be bigger and those further away will be smaller. The effect from the simulated perspective will modify reader’s ability to compare and consume the data accurately. For this reason, we strongly recommend staying away from plotting in three dimensions. Two dimensions offer a tremendous amount of flexibility. Of course widely available desktop tools like MS Excel makes 3-d charts incredibly easy. However, we should fight the urge if our goal is communicating our data to others.

We shouldn’t think of working with 2 dimensions as a limiting factor any more than the 12 notes in a chromatic scale is limiting to western music. Even working with one dimension is good enough to convey the notion of passing time. By simply creating a line and projecting dates along the line, and placing points on the line, we can create a one-dimensional timeline of breaches.

Note: I wonder if we can include this as a demonstration of 1-d visual: <http://cdn.threatsim.com/wp-content/uploads/2011/12/RSA_Timeline_Large1.jpg>

Or this: <http://flowingdata.com/2011/06/13/largest-data-breaches-of-all-time/>

But we’re getting ahead of ourselves. We have to take a step back here and talk about two seminal papers published in the mid-1980’s by two statisticians William S. Cleveland and Robert McGill. They open the first paper, “Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods” with, “The subject of graphical methods for data analysis and for data presentation needs a scientific foundation.” And they did just that. They conducted experiments where subjects were shown various graphics and measured how accurately they were able to visually decode the quantitative information in them. In their second paper, “Graphical Perception and Graphical Methods for Analyzing Scientific Data”, they updated their results and offered an ordered list of visual encodings and the relative accuracy in their decoding.

Figure 6.5 Accuracy of Decoding [FILENAME]

These are not mutually exclusive and the lines between these get a little blurry. For example to decode a simple bar chart, we may use position on a common scale to determine the quantity, but then use length to compare two bars within the same chart. In a pie chart, we may primarily use angles, but the area of the slice and arc length may also factor in to our perception. The findings from this research should serve as a guideline, if our goal is communicating quantitative data accurately; a bar chart is always better than a pie chart and a grouped bar chart is better than a stacked bar chart. Let’s look at some examples.

However, with all guidelines, we can deviate from this advice. Sometimes our goal is not to convey specific quantitative data, and the lack of accuracy in decoding is desired. As an example, let’s look at figure 6.6. When looking at the pie chart on the left, it is relatively difficult to gauge the specific difference between the five slices. Looking at just the pie chart, we’d probably conclude that they are all about equal. However, if we look at the bar chart on the right, it’s relatively trivial to see the differences because we are using position on a common scale. Obviously, if we had confidence in the data its accuracy, the bar chart on the right is far easier to see the values and relationships. But, what if the data we have is from a small opinion survey? While we can calculate precise values, the differences in the values could easily be explained with sample error. In this case, we could justify using a less accurate method to communicate our data.

Figure 6.6 Comparing Pie and Bar Charts [FILENAME 793725c06f006]

type="note"

Save the Pies for Dessert

If you are new to data visualization, there are essentially two distinct (and sometimes very passionate) opinions when it comes to visualizations that use techniques lower on Cleveland’s accuracy list. Pie charts are often at the center of debate since they are used (and abused) more often than others. The core argument against pie charts is that the data can always be represented better and more accurately with other methods. As Stephen few said in his 2007 paper *Save the Pies for Dessert*, “Of all the graphs that play major roles in the lexicon of quantitative communication, however, the pie chart is by far the least effective. Its colorful voice is often heard, but rarely understood. It mumbles when it talks.” But on the other side is the point we made here, that the goal of communication may not be precision. There are other less convincing arguments in the defense of pie charts, but there is one piece of common ground: choose the visualization method deliberately and be sure it communicates the message you want to send.

Color

If you’re never had to select colors for a project this brief introduction may make color selection seem easy. We’ve got a few guidelines on what types of color palettes go with what types of variables and a deep well of knowledge from color research has brought us a handful of easy rules for palette creation. However, it won’t be until you’re trying yet another set of colors in your visualization that you will truly appreciate the words of Edward Tufte. “Avoiding catastrophe becomes the first principle in bringing color to information: Above all, do no harm.”

There are many websites and tools that leverage color theory to make palette selection relatively painless (see the appendix for resources, but Color Brewer and HCL Picker are our favorites). With some understanding of your data, picking colors that are good in [color] theory is the easy part. Colors also have to support and hopefully even highlight our message and be pleasing to the eye, which have a large element of subjectivity and are unique to each and every visual story. This creates the challenge with color: we have to balance function, aesthetics and theory across just a handful of colors.

Color is Relative

The first and perhaps most important aspect of color selection is that colors are always interpreted relative to the surrounding environment. For example, Figure 6.7 shows two rows of gray boxes on a gradient background. Even if we know each row has a consistent shade of gray, we will still see different shades on the same row as we scan from side to side. And to some, the upper left box looks the same color as the lower right. That’s because we see the shade in the boxes relative to the surrounding background. The boxes appear darker on a white background and lighter on a dark background. We can use this to our benefit as well. If we want to emphasize one variable above all else, we could choose a contrasting color from the rest. For example, a red shapes will stand out among shades of light blue shapes, but will blend in with pink and orange shapes.

Figure 6.7 Visual signal and noise detection illusion [FILENAME]

Palettes Depend on Data

We have not talked about it much before, but there are only a handful of high-level data types, and most of those fall into either categorical or quantitative values. **Categorical data** are represented as groups such as type of operating system or a programming language. **Quantitative data** are quantities (crazy, huh?) which are things we count or measure such as bytes, packets, sessions, number of servers and so on. Sometime categorical data may have a natural order to them. Rankings such as “first”, “second”, “third” or “high”, “medium”, “low” are treated like a categorical value but have an added sense of order to them. Sometimes the lines get blurry, TCP/UDP port numbers for example appear quantitative since they are sequential numbers going up to 65,535. But we have to treat them as categories: we would never add ECHO and two telnet ports to get DNS (yeah the math works out there). Another confusing data type is date/time. Most of the time we will treat this as an ordered categorical variable (such as the year, month, day of week, etc), but other times we’ll store it as a quantity (seconds since the epoch) to enable calculations on time, and *time series* data.

We have to be careful using colors to represent a quantity. We are relatively inaccurate when decoding quantity from color. But it may be used in circumstances where rough comparisons are enough. For example, back in Figure 5.7, it doesn’t matter if we can precisely see one in 724 people in Wyoming were infected with ZeroAccess. The color is simply communicating that Wyoming had more infections per person than any other state.

Figure 6.8 shows three types of color palettes from the Color Brewer website (colorbrewer2.org). We would select a palette of **sequential colors** to represent quantity or perhaps ordered categorical data. Sequential color palettes are built using a single hue (blue for example) and then adjust the lightness or saturation of that color to cover the range of the quantitative data. **Divergent colors** are also used on quantitative or ordered data, but help communicate above or below some middle value. Typically, the middle value is white and two divergent hues are used on either end. Divergent color scales may be used to convey two directions in the data such as above or below average (as it was used in figure 5.7). Finally we have **qualitative colors**, which are intended to not convey ordering and are used to represent categorical data.

Figure 6.8 Sample color palettes from Color Brewer [FILENAME]

Putting it all together

We’ve laid some good ground work here, now let’s look at how these things come together to help communicate our data. We’ll spend a little less time talking about how to create these and more on why we create these as we do. But all of the source data and code to create these visualizations in this chapter are on the book website.

Using Points

The easiest method to communicate and compare two quantitative variables is the basic scatter plot. Scatter plots position points along a common scale (both x and y scales) and allows the reader to very accurately determine the quantities of variables and compare between various points. creating it in R is insanely simple (plot(x, y))and we’ll often do this just to “see” the data we are working with. For example, figure 6.9 shows eight hours of firewall traffic. Each dot represents total number of packets on the x-axis and total number of bytes transferred on the y-axis this firewall saw in 5 minutes.

Figure 6.9 Basic Scatter Plot [FILENAME 793725c06f009]

This is a good example of when a pattern quickly jumps out of a plot. We can see that the firewall traffic for the day ranges from around 7 gigabytes up to 19 gigabytes, and we range from 12 to 27 million packets. The linear relationship is very clear here: as we see more packets we see more bytes. Now this isn’t exactly a news flash or all that informative, but if we have data where we aren’t sure what’s in it, a simple scatter plot can do wonders. Figure 6.10 is an example of a scatter plot where we can quickly see something we didn’t know. This time we are putting the time of day along the x-axis against the number of sessions on the y-axis.

Figure Figure 6.10 Packets over Time [FILENAME 793725c06f010]

We did a couple of extra things here. We dropped some faint lines down from the points to give just a hint of a bar chart and visually tie the points (which are rather bunched up) back to the x-axis. We also wanted to highlight the repeating element of time so we darkened the line at the top of the hour and changed the points to be red every 30 minutes. It’s obvious to see why we did that. There is a noticeable dip at the top of the hour and not much significant change at the half-hour marks, but we wanted to emphasize those times for easier comparison (remember the preattiventive processing?). Perhaps it’s a meeting-heavy culture and people are walking to a new meeting around that time and not surfing. Who knows, but the pattern really jumps out with a simple scatter plot here.

Creating Directions with Lines

At some point, we heard someone say “lines are just points in motion” and that’s true, we see a lines having a sense of direction. Let’s take the same firewall traffic and separate out the types of devices on the network: desktops, servers, printers and networking equipment. Now let’s create two plots, the first the same type of scatter plot of the time series and then do the same thing with a line plot.

Figure 6.11 Points in Motion [FILENAME 793725c06f011]

It’s rather clear what’s going on with the line plot and it’s easy to follow the traffic over time for each of the four devices. The scatter plot on the left though is a little difficult to follow, though we can see trends and differences between the categories. Line plots are quite good at accurately communicating data since we are comparing points on the line along a common scale and we get the slope of the line as a sign of change. Steep slopes like on the printers. Line plots are most effective with at least one quantitative variable and some type of change within one or more categorical variables. In this case we are plotting number of packets (quantitative) on the y-axis against successive five-minute periods (ordered) with each line representing a category of device.

type="note"

Log Scales for Logs

Figure 6.11 has the y-axis plotted on a logarithmic scale. Notice how the values on the axis are increasing exponentially? If this plot was done on a normal linear scale, we’d see the workstation traffic at the top and then the other three lines would be reduced to visually zero. We changed to a linear scale because the tremendous skew in this data. By changing the scale to be logarithmic, we can see the patterns at the lower end of the spectrum. However we have to be careful when we change to a log scale. We are used to seeing linear scales and we mentally will do the comparison like that. For example, we may think that the networking equipment here is about half the traffic of the workstations because it’s visually about half of the workstations. But in reality workstations are generating about 10,000 times the traffic network devices are and if the logarithmic scale isn’t clear to the reader they could draw some incorrect conclusions.

Building Bar Charts

Bar charts are one of the most effective ways to communicate quantities of categories. There are a few variations on the basic bar chart. Figure 6.12 is showing three different ways of displaying vulnerability counts and severity classification per device. On the far left we have a typical bar chart with vertical bars. A simple modification of this is making the bars horizontal and the difference is largely for aesthetics and the context of where the chart will appear. The vertical bar chart is simple and shows the totals within each device type. This uses the common scale for comparison but we have the added feature of length. We can see easily see workstations have the most vulnerabilities and servers are close though with maybe 20% less or so. Then networking devices and printers are quite small in comparison.

Figure 6.12 Variations on Bar Charts [FILENAME 793725c06f012]

The other two bar charts have another categorical variable added to show severity of the vulnerability. The stacked and group bar chart applies a unique sequential color per severity and shows them slightly differently. With the stacked bar charts, we are still able to compare totals. It’s still clear that workstations have more vulnerabilities than all others. But comparing across severity is difficult as we lose the common scale. For example, attempt to visually compare the high vulnerabilities of workstations to servers. Since they are not aligned we purely judging by length on a non-aligned scale and we are less accurate. Now look at the grouped bar chart and we can easily see that servers have more high-severity vulnerabilities than workstations. The one draw back to the grouped bar chart is that we lose the overall count comparison. It is not as clear to look at the grouped bar chart and know that workstations have more vulnerabilities overall. The type of bar chart we choose is largely dependent on the message we are trying to send.

Using Slopes

Looking back at Cleveland and McGill’s chart, slopes are