

How to Analyze a Survey

Christopher Peters, June 25, 2015

Peters, C. (2015, June 25). *How to analyze a survey*. Zapier.

<https://zapier.com/learn/forms-surveys/design-analyze-survey>

6. How to Analyze Survey Results

It's easier than ever to [build an online survey](#) and send it out to customers, but analyzing the results is the tricky part.

As previously mentioned in the survey design section, there are four main ways to collect responses to each question and hence four main data types that you might confront when analyzing the results of a survey.

- Categorical data
- Ordinal data
- Interval data

Categorical Data

Calculate the total number of responses and then divide the number in each category by the total. These are called relative frequency statistics. Many just call them percentages or shares, but the important aspect is that the sum should be 100%. For example:

What do you like most about our product?

(Relative) Frequency Table

Answer	Responses	Share
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Fast customer service	30	$30 / 100 = 30\%$
Ease of use	40	$40 / 100 = 40\%$
Quality	16	$16 / 100 = 16\%$
Quantity	14	$14 / 100 = 14\%$
Total	100	100%

Categorical data can be made more useful by grouping results by customer segment. For example, you might want to know if new customers answered differently than long-time customers. Other popular categories include:

- Gender, age, or other demographic information
- Geographical segments like ZIP codes, county, or country
- New customer versus established customers

The important thing is to carefully think about which categories are likely to be most meaningful to your organization. The worst thing you can do is naively choose categories that aren't meaningful to your business. Age groups and differentiation by gender are commonly seen market segmentations, but make sure you know what you will actually do with that information.

After categorizing by groups, make a table or graph to report the data. For example, a contingency table (also called a cross-tabulation or crosstab)—which is a matrix of response counts or shares with one segment structured as rows and another as columns—can be very useful.

Contingency Table

This table summarizes a fictitious set of 100 responses. First, I split the surveys into two groups that become the rows of the contingency table: those who were new customers, and those who were established customers. The groups are mutually exclusive (not overlapping) and exhaustive (sum to 100%).

Next, I count the number of responses by answer to the question: *What do*

you like most about our product? Finally, I divide each count within each cell by the total number of responses to this question (including both groups).

(Total / share)	Fast Customer Response	Ease of Use	Quality	Quantity	Total
New customer	37% (28/75)	43% (32/75)	12% (9/75)	8% (6/75)	75% (75)
Est. customer	8% (2/25)	32% (8/25)	24% (6/25)	36% (9/25)	25% (25)
Total	30% (30)	40% (40)	16% (16)	14% (14)	100% (100)

Contingency tables show how responses differ by each category. What's interesting in this fictitious set of data is that new customers tend to like fast customer service the most, 4.6 times the rate that established customers do (37% / 8%). Also, established customers chose quality and quantity as most-liked characteristics 2- and 4.5-times more often than new customers chose those same characteristics, respectively.

Ordinal Data

Ordinal-type questions are very popular, but many people make a critical mistake when it comes to analyzing the data they produce. The worst thing you can do is convert the responses to numbers and then calculate the average of those numbers. The reason is that an arithmetic mean (the most common type of average, and there are many) like $(1 + 2 + 3 + 4 + 5) / 5 = 3$ implies that there is some measure of distance between values.

However, it doesn't make sense to say that feeling neutral is three times the feeling of strong disagreement, or that the feeling that something is important is twice the feeling that something is somewhat important. These are simple clues that converting ordinal labels to numbers can cause misleading results.

Instead, the best thing to do is to create a simple relative frequency table or contingency table like those shown above for categorical data.

How wrong can things really go? Well, consider a controversial question where most people are in either strong disagreement or strong agreement. In that case, an average would indicate that the data are centered in the neutral category. That's an extreme example, but the same thing can happen if the largest buckets are, say, "neutral" and "very important." Suppose responses were like:

Don't do this:

Not important (1)	Somewhat important (2)	Neutral (3)	Important (4)	Very Important (5)	Average
$1 \times 3 = 3$	$2 \times 60 = 120$	$3 \times 5 = 15$	$4 \times 2 = 8$	$5 \times 30 = 150$	2.96
3%	60%	5%	2%	30%	

The average of 2.96 would seem to imply that respondents felt neutral, when in reality a majority felt the subject was "somewhat important" (60%) and another large group (30%) felt the subject was "very important." In this context, even the label "neutral" feels out of place.

Instead, leave the data as a frequency table and allow the end-user to see the distribution of results directly. Avoid influencing stakeholders by showing the average. People love averages and tend to focus on them instead of the real story. Intentionally *avoid averages* and instead describe the data.

Do this instead:

Not important	Somewhat important	Neutral	Important	Very Important
3% (3)	60% (60)	5% (5)	2% (2)	30% (30)

Most respondents felt the subject was only somewhat important, but another large group felt the subject was very important. There are two main groups of customers here—we should try to figure out what those segments might be. This could let us focus resources on those who feel the subject is important and avoid wasting resources on those that feel the subject is only somewhat important.

How to Graph Ordinal Scale Data

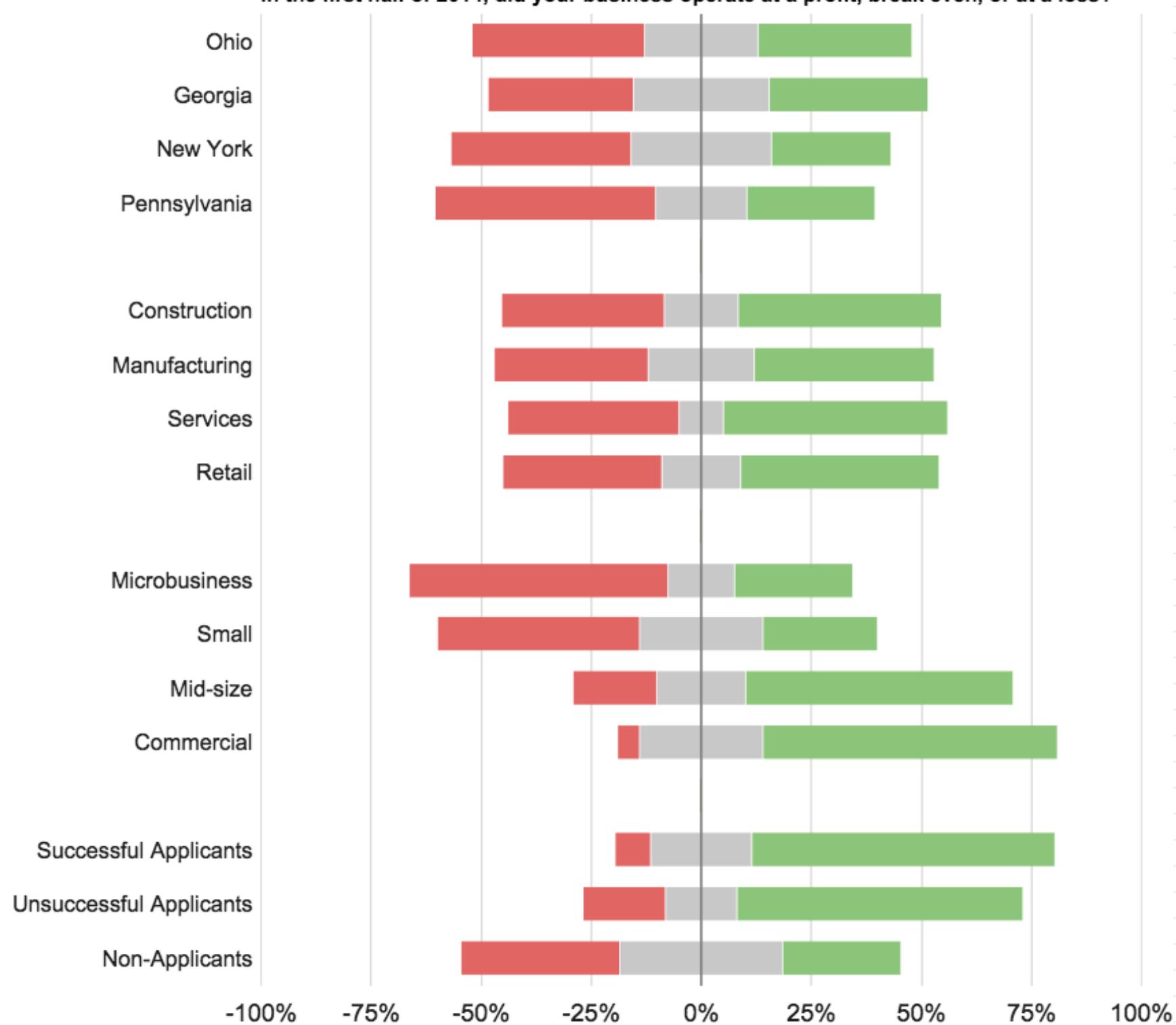
Diverging bar charts are a great way to visualize ordinal data. The distinctive element is a common baseline that allows the eye to measure the length of each bar very quickly. These charts are great for comparisons across segments. Let's take a look at a public data set for an example graph.

Every year (since 2010) the Federal Reserve Bank of New York publishes a [survey of small businesses](#) (as defined by a business with less than 500 employees) covered by the Reserve Banks of Cleveland, Atlanta, New York and Philadelphia. The main purpose of this study is to determine which small businesses are applying for and receiving loans—that's the context being referred to when you see the term "(credit) applicants" in this data.

By graphing the data with a common baseline, comparisons of losses, breaking-even, and profit are made clear across category.

In the first half of 2014, did your business operate at a profit, break even or at a loss?

In the first half of 2014, did your business operate at a profit, break even, or at a loss?



Retail businesses did poorly the first half of 2014. Successful applicants for credit were also much more likely to be profitable. Also, the larger the business the more likely it was profitable. This could be due to survivorship bias. That is, as insofar as a business is profitable does it become large. It could be that smaller businesses are more willing to operate at a loss. Or, it could be that larger U.S. businesses recovered faster from the financial crisis that began in late 2007.

If you find this graph style useful I've made [a template](#) that you can use.

7. How to Interpret Survey Results

Focus on the High-Points

Visualizing data is one of the most important activities I carry out at Zapier. It's a passion of mine because graphs can elicit a wide variety of emotional responses. People have very different reactions to data based on how it's graphed, so it's important to be thoughtful when creating visualizations.

Knowing the challenges with measurement, I guide my coworkers at Zapier to focus on trends and avoid reading too much into small differences in data. It's easy to lose the big picture when looking at statistics and graphs, so it's important to remember that some error exists with any method.

Don't miss the forest through the trees; when interpreting results, start with the largest differences first, not the most unusual. If you notice an unusual result, be skeptical and see if the result can be replicated in another survey.

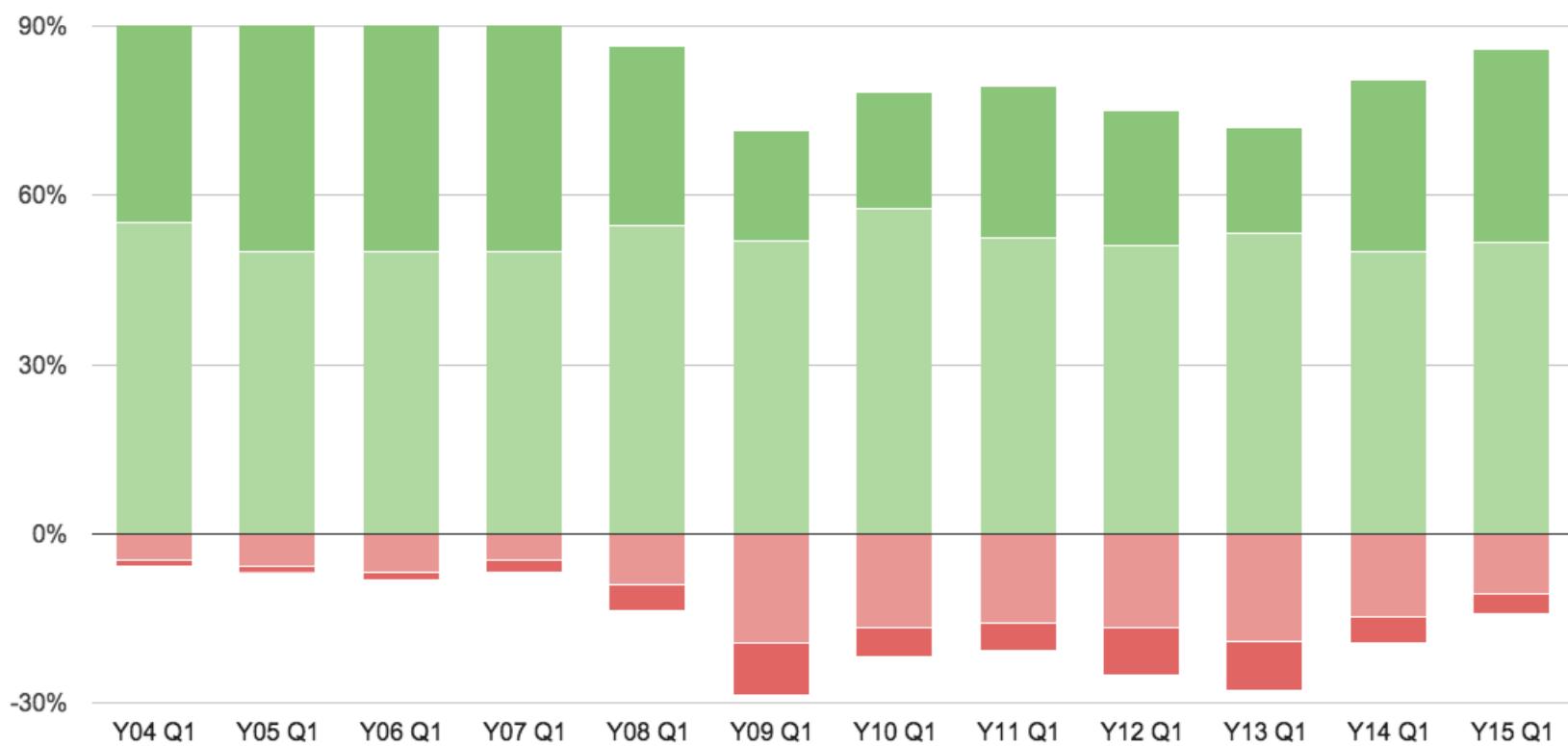
Table or Graph?

Tables are most useful when you're looking at precise numbers, or when there are few comparisons. But large tables make it hard to reason about the distribution of outcomes, and in these cases visualizations are preferable.

I'll use an interesting survey of small businesses as an example. The survey is carried out by Gallup, Inc. for Wells Fargo bank, and they present a raw table for you to use on the [Wells Fargo site](#).

In this case, the individual numbers are the important part. The table is useful, but it's very difficult to digest. Below is a visual representation of the table titled "Financial Situation 12 Months From Now":

How do you think your company's financial situation will be 12 months from now?



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The visualization (called a diverging bar chart) makes it clear that small businesses turned very pessimistic about their financial situations beginning in the first quarter of 2009. It's also clear that optimism hasn't yet returned to the levels seen when the survey data begins in 2004.

Conclusion

Surveys are a very effective tool for gathering feedback from customers and reducing the uncertainty around important decisions. By writing down the purpose of your survey and hypotheses up front, you'll be able to learn where your intuition is strong and find organizational blind spots.

Surveying is hard and biases can enter through poor survey delivery and poor question design. It's important to think about which data type will be most useful to answer the questions at hand. The process is as much about

finding the right questions as it is about finding their respective answers.

Keep in mind that the best designed survey in the world is useless if its results are not communicated effectively. Don't abuse categorical or ordinal data by taking averages, summarize by relative frequencies. Don't bombard readers with huge tables that are impossible to digest—take a bit of time and create a diverging bar chart. If you use interval data, keep in mind its utility for segmentation and don't fool readers by visualizing uneven intervals.

Finally, surveys are no place to get fancy. Keep it simple and you'll find that no matter the results you'll learn something of use!