

Week 2 Recap

Preparing Data and Understanding Levels of Measurement

OPWL 508 · Data Visualization

Great work this week. Across both discussion activities, you showed real progress with preparing data, transforming it, classifying it correctly, and thinking about how those choices support visualizations.

This course is about data visualization, but I want to use this recap to highlight what else the work is doing for us. We are not just preparing data to make charts, but we are preparing data to support better questions and better decisions. How you transformed your data and how you classified your variables does not only decide what chart type you can use, but it actually decides what you see, interpret and act on (and whether that will be misinterpreted by others or not)

1. Transformations Help You Answer Questions, Not Just Clean Data

Everyone transformed their dataset in a way that made it more useful. The key idea is that a transformation is not about tidying the spreadsheet. It reshapes the data to fit the question you are trying to answer. Common transformations this week included filtering out noise, reducing granularity, aggregating to summarize, binning into ranges, and pivoting to compare.

Derived variables. These are variables that do not exist in the raw data until you built them. They are often what turns raw data into insight. Ben's DIFOT post is a great example. He built a single on-time-delivery flag out of a promised-delivery date and the latest receipt date. The following report would not be possible without this derived variable (also called composite variable or calculated variable).

Riley's post shows another version. She integrated two years of College Board score reports into one table, category by category, with a year-over-year difference column. This enabled her to then ask questions like "which content areas improved?"

Here is a quick recap/overview of the most common transformation types.

- **Filter** to remove irrelevant or noisy rows
- **Reduce granularity** (daily to weekly, raw events to counts)
- **Aggregate** to summarize patterns
- **Bin** variables such as tenure, score, or time into ranges
- **Derive** new variables that carry the insight

Keep in mind that we are not saying you need to perform these yourself. We want you to know what is possible and then if you cannot do it yourself, you can ask the owner of the data or the data team to help with it. In some cases, the visualization tool will do it for us as well.

2. Levels of Measurement Decide What You Can Do

Understanding levels of measurement matters because different types of data support different types of analysis and visualization. You all did well identifying nominal, ordinal, interval, and ratio. The reason we cover

this in a visualization course is because the level of measurement does not just describe your data, it determines what you can do with it (including what you can visualize). Here are the 4 levels of measurement:

- **Nominal** → grouping and comparison
- **Ordinal** → progression and ranking
- **Interval** → differences and trends
- **Ratio** → proportions, efficiency, and performance

Two things did not come up directly in the discussion forum but are important to share as it relates to 2 specific situations, I will share those in #3 and #4 below.

3. Dates Shift Levels Depending on the Question

Many of you worked with dates, and this is where it gets interesting. A date is unique because its level of measurement changes with how you use it. A raw date is interval. The day of the week is nominal. The month in sequence is ordinal. Days since a start point is ratio.

We often transform dates on purpose to match the question. The good news is that visualization tools usually do this for you. Understanding why still helps you make intentional choices instead of accepting the default.

- **Raw date (2025-02-15)** → interval → timelines and trends
- **Day of week (Friday)** → nominal → compare days
- **Month in sequence** → ordinal → ordered periods
- **Days since start** → ratio → duration and elapsed time

There are some examples of this in the 'Data Before You Visualize' Guide linked at the end of this.

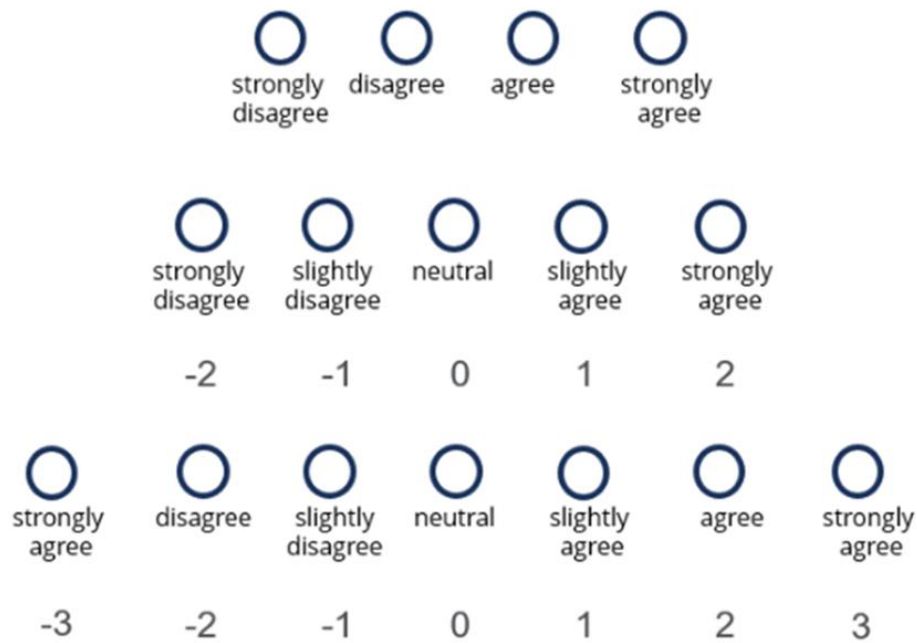
4. Likert Scales: Ordinal, With One Useful Exception

A Likert item is the agree-to-disagree kind of survey question, like strongly disagree, disagree, agree, strongly agree

Technically those columns/variables are ordinal. The values have a real order, but you cannot assume the distance from a agree to strongly agree is the same as the distance from disagree to agree (as an example). That means, since it is ordinal, we are not supposed to average the responses. Plenty of analysts averaged them anyway, drew trend lines, and compared group means, treating the scale as interval without saying so.

Our own Dr. Yonnie Chyung, who wrote the book on survey design for Boise State, describes Likert data as ordinal but explains that it is fine to treat a 5-point or 7-point scale as approximate interval for practical purposes. That is a big deal for us, as it means we can calculate a mean, put a trend line on it, and interpret the differences between groups, none of which you are allowed to do with strictly ordinal data. Given how much survey work we do in OPWL, that flexibility is very valuable.

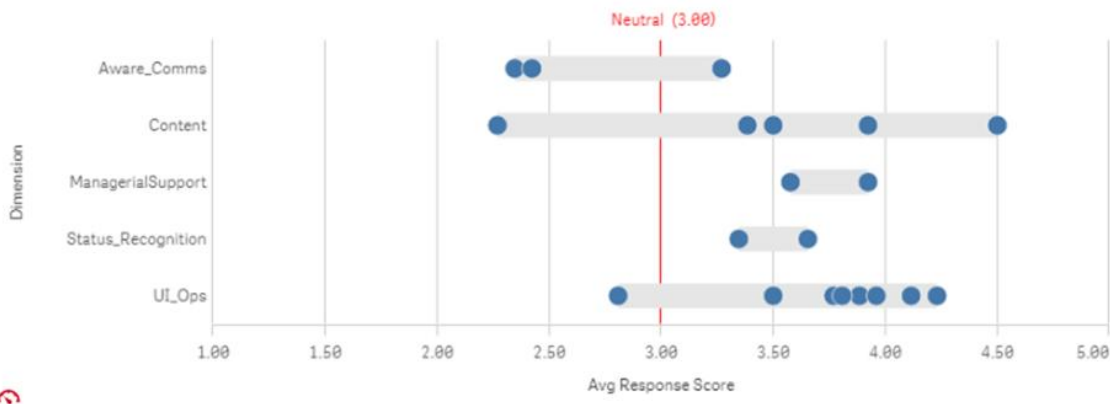
The catch is there needs to be a neutral value because the scale has to be symmetric, with a real midpoint and the same number of options on each side. Look at the three scales below.



The first scale has no neutral point, and the spacing is not even. The jump from disagree to agree is a bigger step than the jump from strongly disagree to disagree, because there is nothing in the middle. You cannot average that honestly. The 5-point and 7-point scales underneath are built around a neutral center, evenly spaced on both sides. Those are the ones you can average, and once you can average them, the interval-level visualizations become viable options.

This is exactly how I used it back in the day in my OPWL evaluation course project when I was a student in that course. We took the average response per question, grouped the questions into dimensions, and showed the average score per question within each dimension. We will get to this distribution chart next week, but you can already see what it gives you.

Question Averages by Dimension



Look at the Content row. It has the widest spread of any dimension, the highest average on one question and nearly the lowest on another. That spread is the signal. It tells me to drill into Content and ask why those two questions pulled so far apart. I could not see that at all if I had left the data as strictly ordinal, because I would never have computed the averages that make the spread visible.

5. Store at the highest level you can

You can always transform down the levels of measurement. Ratio collapses to ordinal, ordinal collapses to nominal, but you can never go back up. So it is best to try to capture and store your data at the highest level of measurement you can.

Say you are collecting ages on a survey. Right now all you care about is over 40 or under 40, so that is the question you ask, and that is what gets stored (over or under). That is nominal. But what happens when later the target moves and you now care about over 50 or under 50. Now you are stuck, because every row just says over 40 or under 40, and there is no way to recover an actual age from that. Someone marked "over 40" could be 41 or 71, and you will never know. The data cannot answer the new question, and you cannot re-ask a survey people already took.

If you are able to ask for the raw age instead, and you store the raw age, then you can transform down to whatever you want whenever you need to. Store 43, 58, 61, and you can split at 40 today, at 50 next year, and into decade bins the year after that.

6. Moving From Metrics to Systems

One thing I really liked this week was seeing several people stop thinking about individual variables and start thinking like systems instead. That is an important shift. Instead of asking "what does each variable show?" you begin asking "how do these variables work together?"

The best example came from Christy and Ben. Christy described a hotline where a volunteer fills out a Google Form on every call, which populates a spreadsheet, so she could bin by day, month, and time of day to find when demand peaks. Ben saw what that structure makes possible and took it a step further:

The beauty of using a Google Form is that the data is constantly updating the database, and tools like Power BI or Looker can connect to that data and automatically refresh. That could turn the data from a one-time report into a process control, or system feedback loop.

— Ben, responding to Christy

He then suggested pulling capacity into the same dataset and building a heatmap of utilization, days of the week as columns, times of day as rows, dark where the org is short-staffed and light where there is slack. That is the move from a report you read once to a system you monitor.

When you connect variables this way, a completion, a time, and a score become like a learning pipeline. An application, an interview, and a hire become a decision pipeline.

7. Observing Performance vs Shaping Performance

This follows directly from the previous section, one of the things I want to push everyone towards is moving away from just observing performance to using data and visuals to also shape performance.

- **Observing performance** = reporting what happened. Things like completion rates, averages, and totals.
- **Shaping performance** = identifying where to act. Things like where the process breaks, where the friction is, and where to intervene.

Structure the data to describe performance and you get a report. Structure it to locate friction and you get something you can act on.

Here is an example. Say you run an online certification with five required modules, and your data has one row per learner per module, with a status and a date.

If you store the fields like overall completion rate (68%), average time to finish (22 days), number of students certified this quarter (340), you have valuable information about your program, but does not give you any actionable insights about where or what to improve. 68% is a good number to look at and react to, but the data does not say where the other 32% went.

If we structure the data and rows in a different way, we can count how many learners pass each module, then we have more actionable insights. Let's say module 1 finishes at 96%, module 2 at 94%, module 3 at 91% and then module 4 drops to 62%. The loss is not spread across the course, it is more like a cliff at one module. The overall 68% average hid that cliff.

8. Week 2 References

Two references approach this material from different angles.

[The Week 2 Companion Guide](#) summarizes the key concepts in one place: transformations, levels of measurement, how dates shift, and how these connect to visualization choices. It covers the definitions, the distinctions, and the best practices we discussed.

[Data Before You Visualize](#) is interactive. Rather than summarizing the concepts, it shows why they matter through five worked examples with live charts. You can toggle between the right and wrong visualization and read the callouts that explain what goes wrong and why. It covers transformations, nominal versus ordinal, ordinal versus interval, interval versus ratio, and discrete versus continuous.

9. Looking Ahead to Week 3

Week 3 is where this comes together. You will learn to choose the right visualization based on the question you are answering, the level of measurement of your data, and the transformations you created.

Week 5 is dedicated to asking the right questions, but you will start practicing in Week 3. Rather than bringing a single question, think about several kinds at once:

- **Questions that add context** — which categories appear most often? who, what, when?
- **Questions that explain outcomes** — does performance vary by group? what drives it?
- **Questions that allow comparison** — which month is highest? which group performs better?
- **Questions that lead to action** — where should we intervene? what is slowing the process?

These are the questions that move a visualization from insight to decision. In the Week 3 discussions you can keep using the dataset from this week, or bring in a new one.