Systematically Generating Insights from Data

Who is this for?

This is a rigorous, data-driven process for generating high quality insights. Product strategists that already have clean and accessible data.

Consistent Insight Generation is a Loop

Always be willing to apply a **Bayesian Approach**: For every view that we hold, we should alway be willing to use new evidence to update that belief.

- Insights are rarely generated in a single step
- Data analysis =/= insight generation

What is an insight?

Insights are contextualized observations about user values, behaviors, circumstances, attitudes, or the overall market or environment, that have the potential to change how an organization acts and achieves success.

(shoutout to @Divya Kulkarni (Deactivated) for the baller definition)

What makes a good insight?

- **Actionable**: Provides a clear and justified next step
  - Who are the users we believe we have the greatest opportunity to impact?
  - What are actions that we want these users to take?
  - Why are these users and actions important? What is the resulting business impact?
- **Clear**: Easy to understand and relevant
- **High Quality**: Demonstrates thoughtful data analysis
- **Progressive**: Almost always leads to progressive analysis iterations

Defining Conjectures Correctly

- Ensures the resulting insight is actionable

📖 A **conjecture** is a debatable and testable statement that, when proved, has the potential to impact our product meaningfully

- Conjectures should not be phrased as questions since those aren't decision-forward. Instead, questions are stepping stones to conjectures.

- Conjectures should be collectively comprehensive to solve the problem we're facing
  - A common “sweet spot” is 3-4 distinct conjectures per problem, not necessarily exhaustive.
    - This helps manage bandwidth, which is important partly because more conjectures =/= more insights
- Brainstorming conjectures widely before prioritizing them allows us to triangulate and pivot (see: Bayesian approach above)

Establishing good conjectures (for insights):

1. Prioritize a metric to dig into based on current goals
   a. When possible, prioritize the one where we've consistently found success working on related user problems
   b. Absent a clear winner, prioritize the metric you have the least information about
2. Use a broad question to brainstorm potential conjectures for your prioritized metric. An example question might be: "What keeps us from reaching our goals?"
   a. Conjectures may be:
      i. Conventional: These are plausible answers to the question of "what keeps us from hitting our goals?"
         1. Example:
            a. Scenario: We’ve defined a target for sign ups that we’re not hitting.
            b. Conventional conjecture: We have too many steps in our onboarding process
      ii. Unconventional: These push boundaries of "what is" and "what could be"
         1. Scenario: We’ve defined a target for sign ups that we’re not hitting.
         2. Unconventional conjecture: We don't have a white-glove CS team like Superhuman that onboards users 1:1.
3. Narrow down your set of conjectures to the most compelling 3-4 by validating them:
   a. Is each conventional conjecture debatable?
   b. Is each conventional conjecture testable?
   c. Is each conventional conjecture meaningful?
   d. Using the unconventional conjectures, is the set of conjectures comprehensive?

Planning Effective Analysis

We do this to ensure the resulting insight is **Clear** and **High Quality**

- **Clear**: Easy to understand and relevant
- **High Quality**: Demonstrates thoughtful data analysis

> ⚠ If we don't plan: our analysis may be unclear, may be inefficient, and may miss important aspects

How to plan your analysis

1. Define your starting analysis type
   a. **Take into account time as a primary constraint.**
   b. Analysis types range from:
      i. quick data pulls (eg, “how many people used a coupon in the last 30 days?”) to
      ii. segmentation (how do two or more groups of users differ in their behavior?) or correlation analyses (is one or more metric correlated with another and how strongly?)
2. Define your analysis parameters
   a. Priority data sets to use: Start with the easiest-to-use data that tells us if we're going in the right direction or not
   b. Define the specific variables
      i. Who is the target audience?
      ii. What behaviors do we care about? These may also be characteristics of the audience
      iii. What time frame do we care about?

3. Define your expected output
    a. Having an expected analysis output in mind helps us recognize when we need to move on. When we can validate the *actual* analysis output with the *expected* output, we're able to identify our next steps more quickly. If the actual analysis confirms what we expected, then we know the conjecture is preliminarily true and we should continue to explore it. If it doesn't, then we know we likely need to pivot to a different conjecture.
    b. Visualize the type of chart and data points you'll use
    c. What do you expect to see if your conjecture is true?
4. Define how to control for confounding factors
    a. Confounding factors are extraneous variables in the same timeframe as our analysis that can incorrectly influence our results.
    b. Some common confounding factors that you should consider include holidays; marketing campaigns; promotional discounts or campaigns, for both your product and for major competitors; weekends, which may be more relevant for B2B companies; different length months, such as a 31-day month versus a 28-day one; geography; new feature releases; and product outages or downtime.
5. Start thinking about your next steps
    a. If your conjecture is true, how might you address it?
    b. If your conjecture is not true, what conjecture might you pivot to?

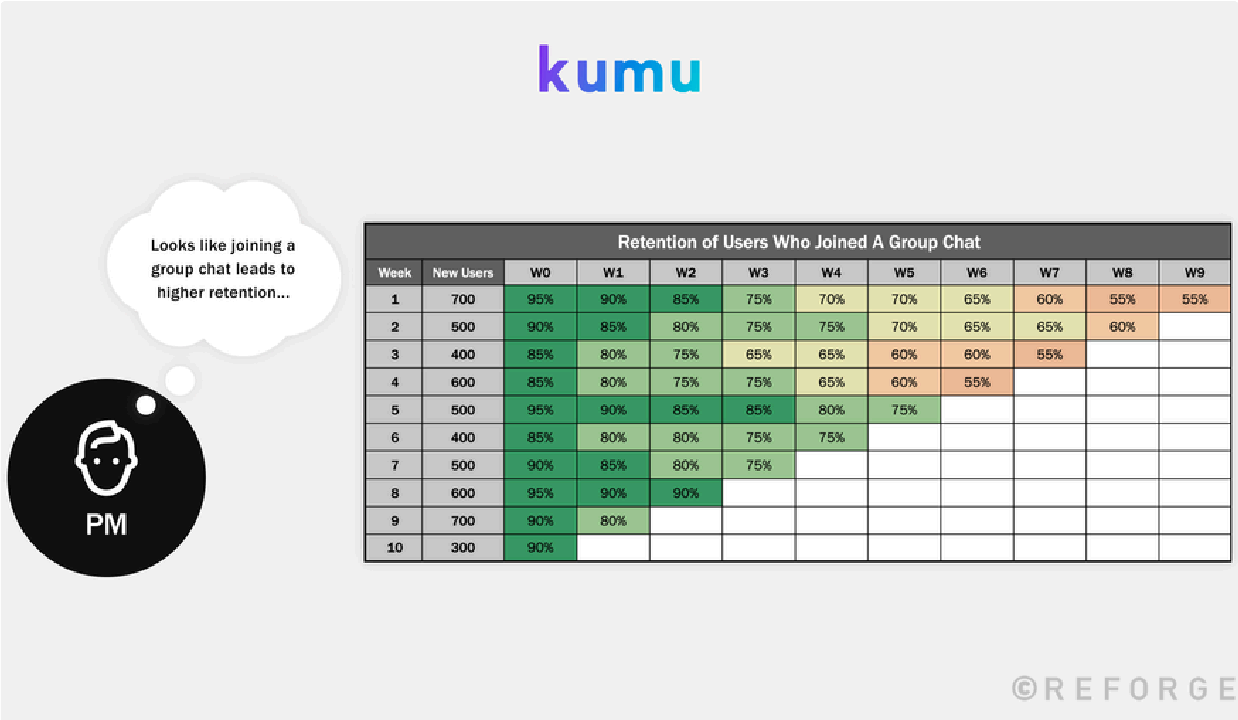
Pressure Testing Your Own Findings

> ⚠️ "Insights have to be demonstrably true across multiple analyses. If it's only true across one week or one slice, then it's not accurate."
> - Crystal Widjaja, CPO of Kumu

We need to always be vigilant to counteract **confirmation bias** and **selection bias.** We can avoid these, and the erosion of trust that comes with presenting faulty data by answering the following questions before presenting:

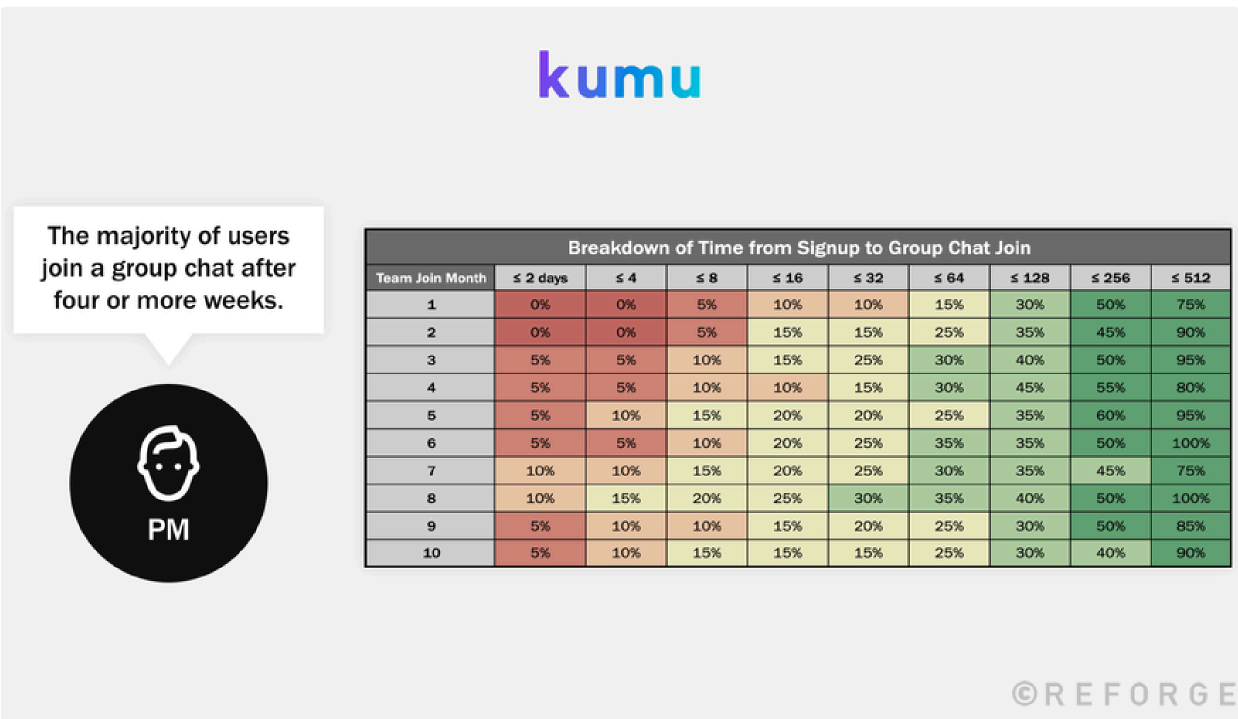
1. What additional analysis is needed to validate our findings?
    a. Triangulate with other data and consider other potential factors that might have introduced error. This usually involves testing against data beyond the initial, easiest-to-use data.
    b. Cross check:
        i. The data being used: until you've validated with more complex analyses like segmentation, correlation, and odds ratio, it's more likely that you've generated a guess or strong conjecture rather than an insight
        ii. The stability of trends: does the trend we observe hold true over a longer period of time? If not, why not?
        iii. The definition of key input variables: consider how potential alternative definitions might change the analysis. Would different segmentation affect the observed trend?
2. Are we addressing the intended target audiences?
    a. Compare target audiences from our conjectures against the user groups in your analysis to make sure they match.
3. What is the relative impact of my findings?
    a. **Relative impact** is proportional analysis that helps you understand the impact of your findings relative to the entire user population.
    b. Is our finding truly valuable relative to our overall product, and not just the segment of users we focused on in our analysis?
    c. "PMs should ask themselves: Could my findings be scaled up to meaningful value? How much of the target audience does this finding have the potential to significantly impact? This is very important to consider, because we've often whittled the audience down so much in our analysis that the finding turns out to be irrelevant, and yet we fail to notice because our judgment is clouded by confirmation bias." - Crystal Widjaja, CPO Kumu
4. Could my causality be backwards?
    a. Note that this is not typically an issue when it comes to monetization
    b. The gold standard test would be to run an A/B test, but these may be out of reach.
    c. In a pinch, you can invert your finding and run the analysis again

Reversing causality



Retention of Users Who Joined A Group Chat											
Week	New Users	W0	W1	W2	W3	W4	W5	W6	W7	W8	W9
1	700	95%	90%	85%	75%	70%	70%	65%	60%	55%	55%
2	500	90%	85%	80%	75%	75%	70%	65%	65%	60%	
3	400	85%	80%	75%	65%	65%	60%	60%	55%		
4	600	85%	80%	75%	75%	65%	60%	55%			
5	500	95%	90%	85%	85%	80%	75%				
6	400	85%	80%	80%	75%	75%					
7	500	90%	85%	80%	75%						
8	600	95%	90%	90%							
9	700	90%	80%								
10	300	90%									

Initial insight is that joining a group causes retention



Breakdown of Time from Signup to Group Chat Join									
Team Join Month	≤ 2 days	≤ 4	≤ 8	≤ 16	≤ 32	≤ 64	≤ 128	≤ 256	≤ 512
1	0%	0%	5%	10%	10%	15%	30%	50%	75%
2	0%	0%	5%	15%	15%	25%	35%	45%	90%
3	5%	5%	10%	15%	25%	30%	40%	50%	95%
4	5%	5%	10%	10%	15%	30%	45%	55%	80%
5	5%	10%	15%	20%	20%	25%	35%	60%	95%
6	5%	5%	10%	20%	25%	35%	35%	50%	100%
7	10%	10%	15%	20%	25%	30%	35%	45%	75%
8	10%	15%	20%	25%	30%	35%	40%	50%	100%
9	5%	10%	10%	15%	20%	25%	30%	50%	85%
10	5%	10%	15%	15%	15%	25%	30%	40%	90%

But by asking whether high-retention users are more likely to join a group chat, they see that the majority of users joined a group chat after meeting the criteria for high-retention.

Identifying Great Insights

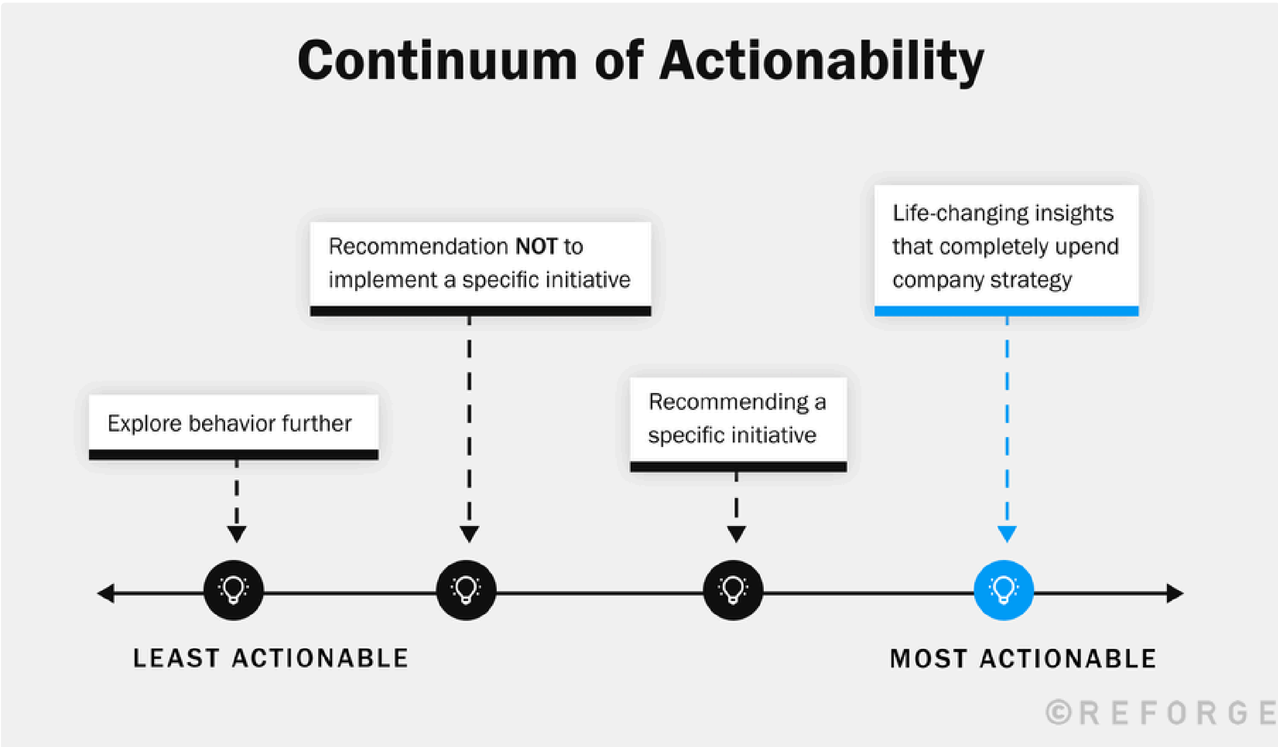
> **“Identifying good insights almost always involves multiple iterations. It’s rarely one analysis or one result.”** - Shaun Clowes, SVP Product MuleSoft

When to continue through the generation loop

1. We identify flaws in conjectures or issues in analysis when pressure testing
2. We see room to add depth to our insight

When should we stop looping?

One way to think about this tradeoff as Explore vs. Exploit: unless we can justify exploring something else, we should continue to exploit and improve an existing insight by adding meaningful depth of actionability to insights.



Two common signals to explore something else are:

1. Running out of time
2. Diminishing marginal utility
    a. Weigh whether the potential value we'd get out of another loop outweighs the added time we'd spend