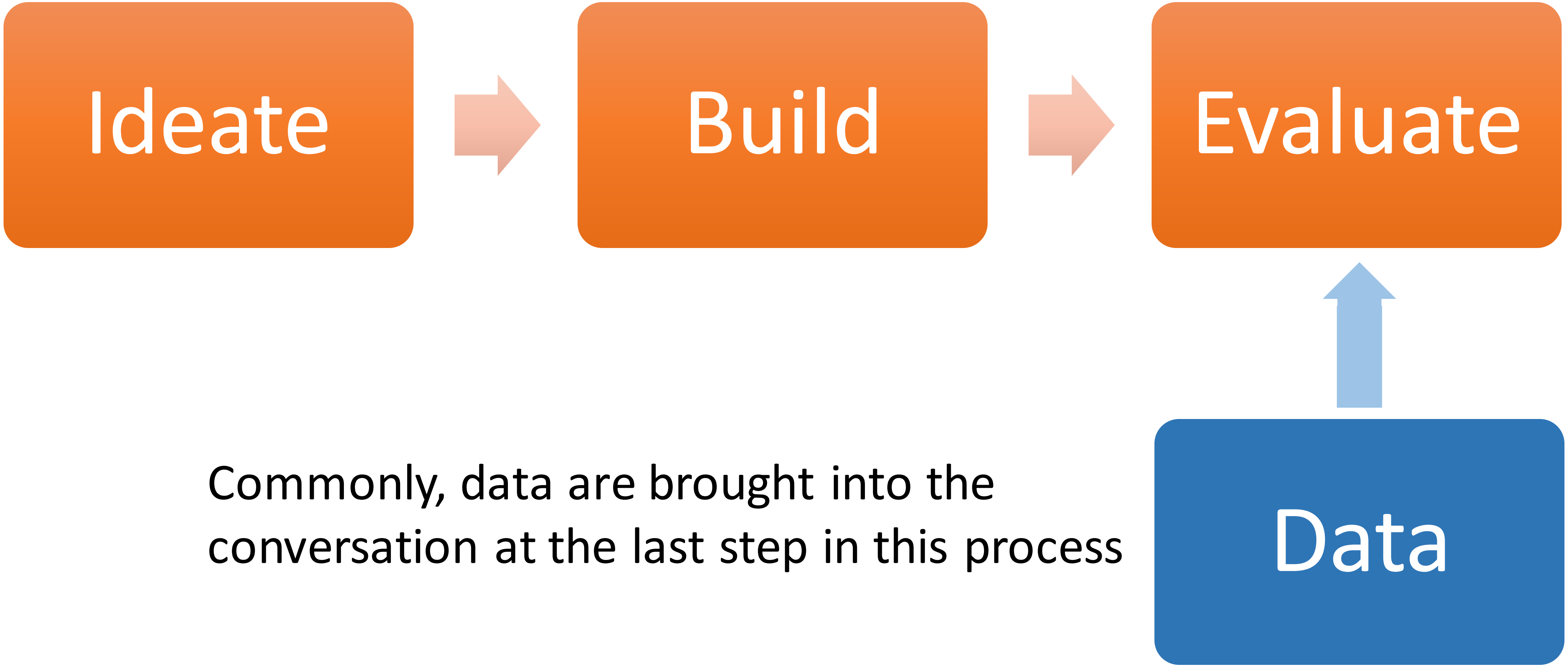
Creating a Healthy Data Culture

Jennifer Flashman, Ph.D.

Analytics Manager, Tinder

Typical Feature Journey



Commonly, data are brought into the conversation at the last step in this process

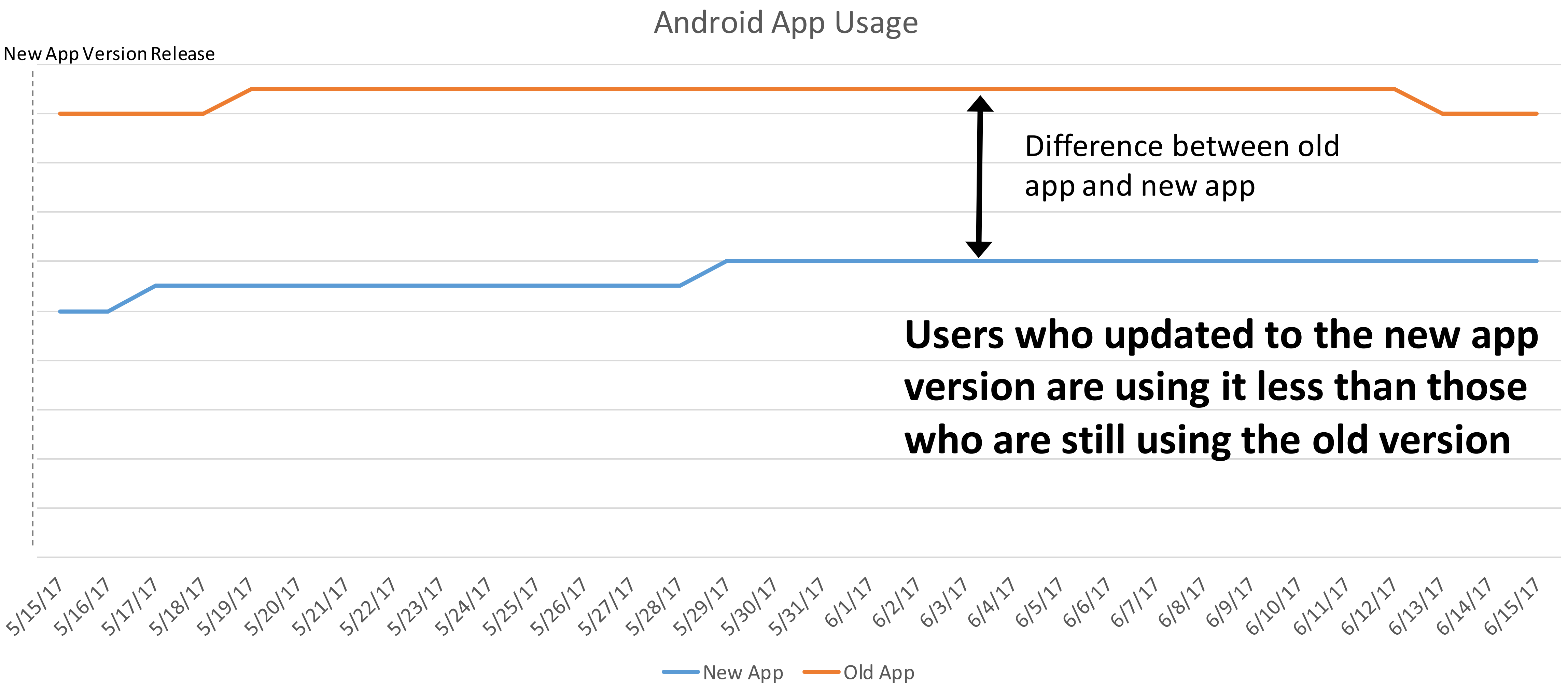
Example #1: What not to do

- Months spent redesigning and rebuilding the mobile app
- Released to Android users on May 15th
- A dashboard was built to track usage

No data analysts/scientists were involved in any step of this process

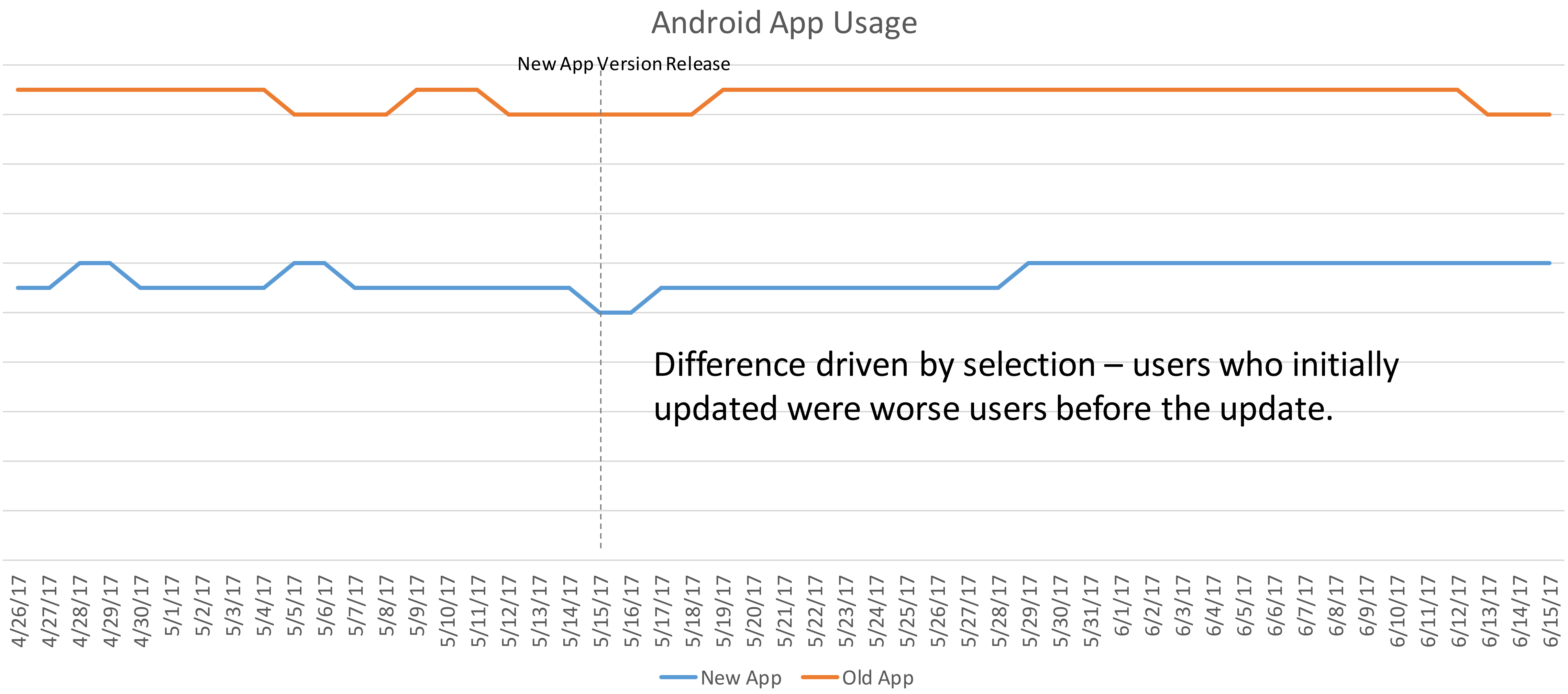
- Not in initial planning
- Not in an evaluation plan

1 Month After Release



Users who updated to the new app version are using it less than those who are still using the old version

User behavior before and after – W1 actives

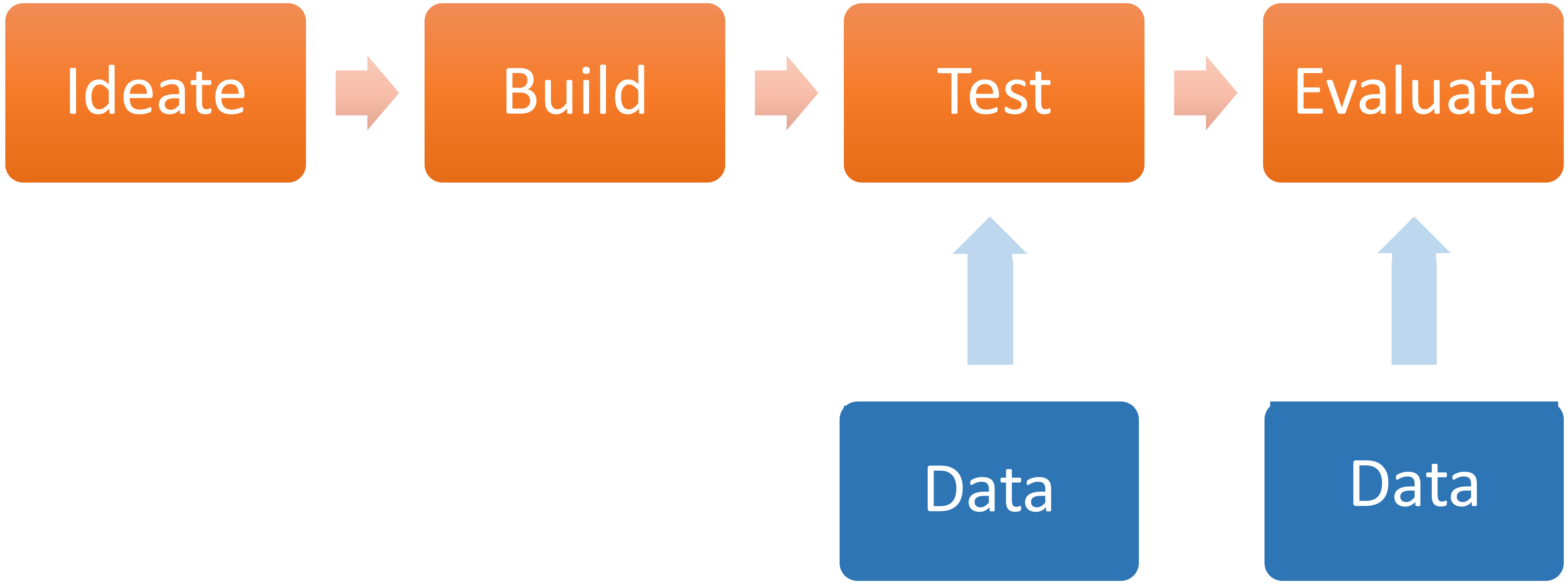


What went wrong?

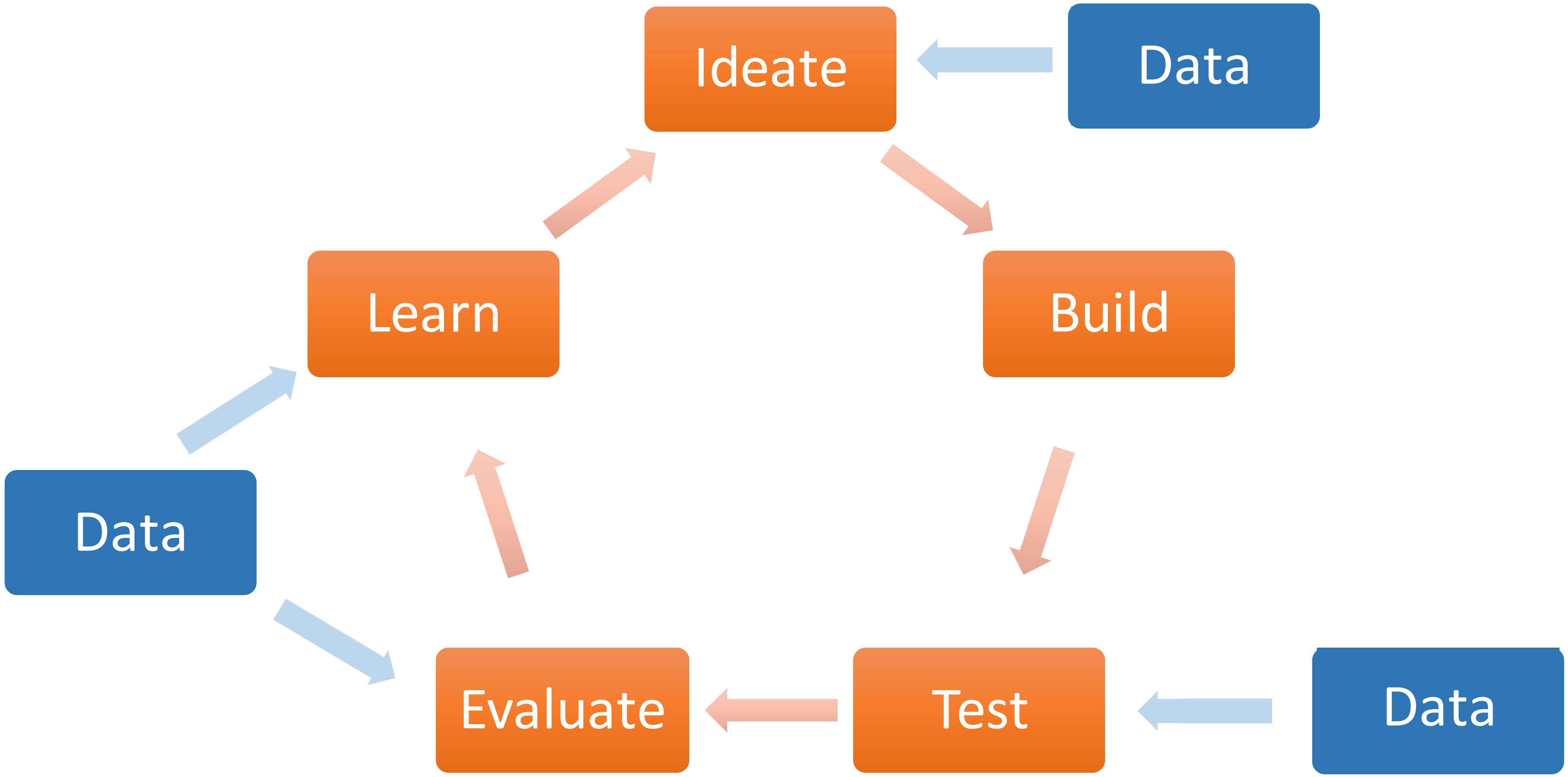
So many things…

1. No testing plan
2. No evaluation/analysis plan
3. Naïve interpretations of data led to incorrect conclusions
4. Assumption of success
5. No way to evaluate the impact of the change
6. No way to know what part of the redesign was successful and what was not - everything was changed at the same time
7. No learning to inform next steps

Better Feature Journey



Ideal Feature Journey



Example #2: Learning from Failure

Yet another app redesign (different app, different company).

Completely redesigned with several fundamental differences from the old app. Done strategically, against advice of data, but with open eyes.

Released under a 50/50 test. Half of Android users got the new app, half continued to use the old app.

Example #2: Testing

After a huge analysis looking at numerous user segments, nearly all metrics were down significantly for the treatment group relative to control.

The new app was not driving the behaviors originally intended and hurt all major KPIs

KPI	Treatment vs Control
Days Active	negative
Messages	negative
Views	negative

We had no clear indication of why the redesign performed so poorly. So much was changed all at once that it was impossible to isolate the culprit

Example #2: Regrouping

We put our heads together and came up with 2 hypotheses for why the feature performed so poorly.

Each hypothesis suggested a different direction to take the app.

The challenge: determine which hypothesis was correct

We sat down with the product managers and brainstormed simple tests to prove out each hypothesis.

Settled on a test that required minimal engineering effort. We believed it would be a **WORSE** experience but would distinguish between hypotheses and help us determine a path forward.

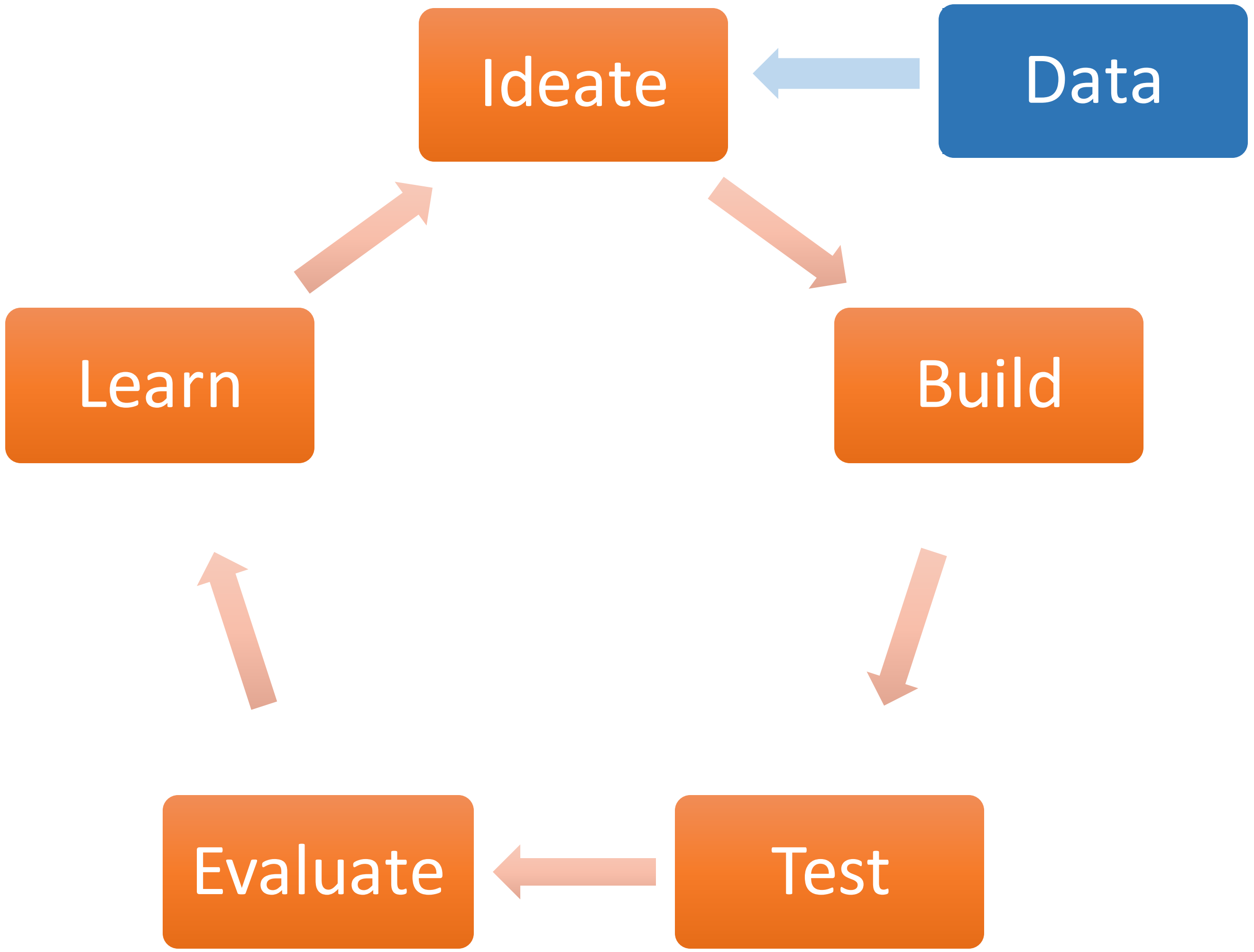
Example #2: Success!

Tested for 2 weeks on iOS
Significant gains on key metrics

Simple test provided key learnings to move forward with the mobile app and a new baseline to build from.

Why did this work?
1. Willing to roll back significant work, when it wasn’t working
2. Tested to learn, not to ship a feature
3. Trust between product and data

Using Data to Develop a Feature



Letting the Analyst Steer the Ship

Often overlooked benefit of a data team is their ability to drive insights outside of product development and evaluation.

Open ended questions driven by data scientists and analysts

- What drives users into the app?
- How are daily users different from weekly users from monthly users?
- What is the ideal number of push notifications to send?
- Should the new user experience differ from the experience of existing users?

Example #3: Identifying Network Effects

When a new user enters the product, how does the ecosystem impact their actions and ultimately whether they return?

Spurred by an initiative focused on new users, we dove into this question from a variety of angles.

Did a quick and dirty analysis to understand the relationship between the ecosystem activity and the likelihood that a new user is retained.

Creating a Culture of Sharing

Research is great but won't help anyone if the results are not made accessible and shared with a wider audience.

At Tinder, we are working on fostering this culture.

Yammer had a great model: Product Brain

- Monthly meeting with PMs, designers, UX researchers, and analysts
- Shared results of research, A/B tests, learnings
- Discussed learnings, applications, implications for future work

Recap: How to Use Data Effectively (more easily said than done)

1. Create strong partnerships between product, engineering, and data
2. Use data early and often
3. Let the analyst lead the data conversation
   Bad: I need to see active users by gender and age on Android
   Good: What do Android users look like?
4. Allow for failure
5. Incentivize learning
6. Share
7. Empower bottom up decision-making