Why data-informed beats data-driven.

Greg Reda
PyData Seattle
July 26, 2015

Alright - thanks everyone for sticking around and coming to this session. Hopefully some of you still have room left in your brains for more ideas. I’m not entirely sure I do, so I’ll forgive you if you don’t either.

So I’m going to be talking about the term data-driven. Based on this talk’s title, you can probably guess I’m not the biggest fan of it, but I’ll get into that more in a bit.

Hi. I’m Greg Reda.

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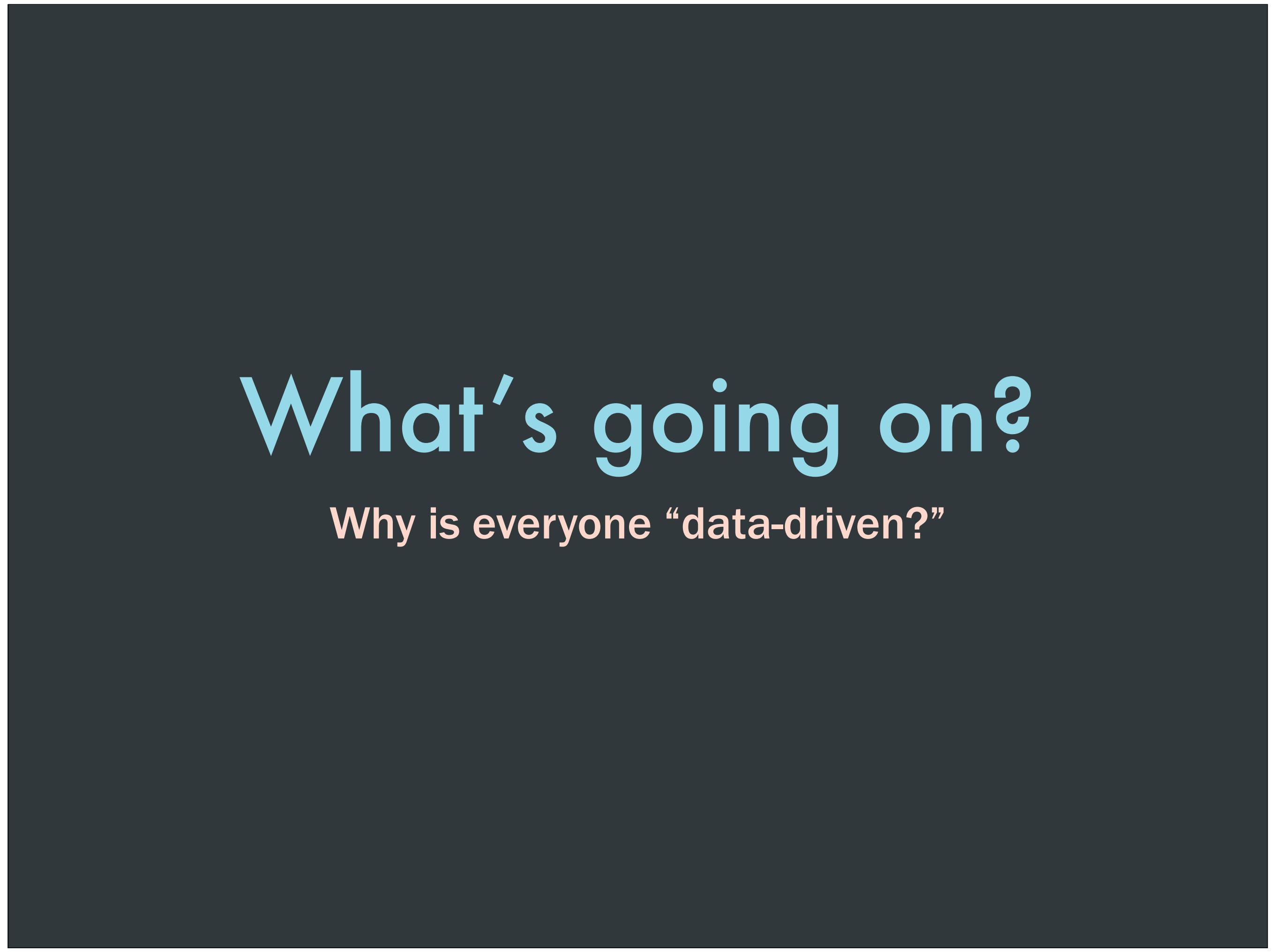
So, I’m Greg Reda and I’m a freelance data scientist based in Chicago. I’ve previously spent time at PwC, a small data science consulting firm called Datascope (influenced me), and GrubHub, which is why you might recognize that cartoonish style. Or, you’ve Googled something pandas-related and wound up on my blog. You can find me online at all the usual places - … posting the slides.

Who is data-driven?

Literally.

How many of you would say you’re data driven? In a literal sense, that data alone should drive your decisions.

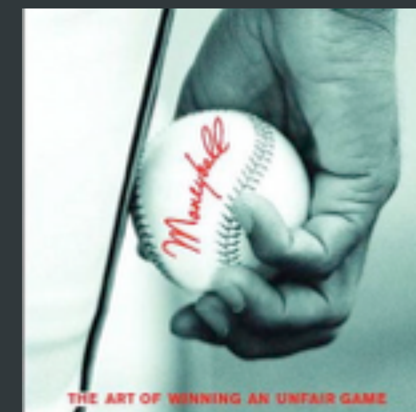
I’m not, or at least I don’t think I am … I love data, but I don’t love that term - I think being driven by data is a flawed approach. Hopefully by the end you’ll understand why I feel that way and maybe even be nodding along a bit. The nice thing about you nodding along is I won’t be able to tell whether you’d nodding off to sleep or actually nodding along with me, so either will feel like a compliment now that I’ve said that.



How did we everyone get here? Do we really think this is a good idea - to be driven by data?

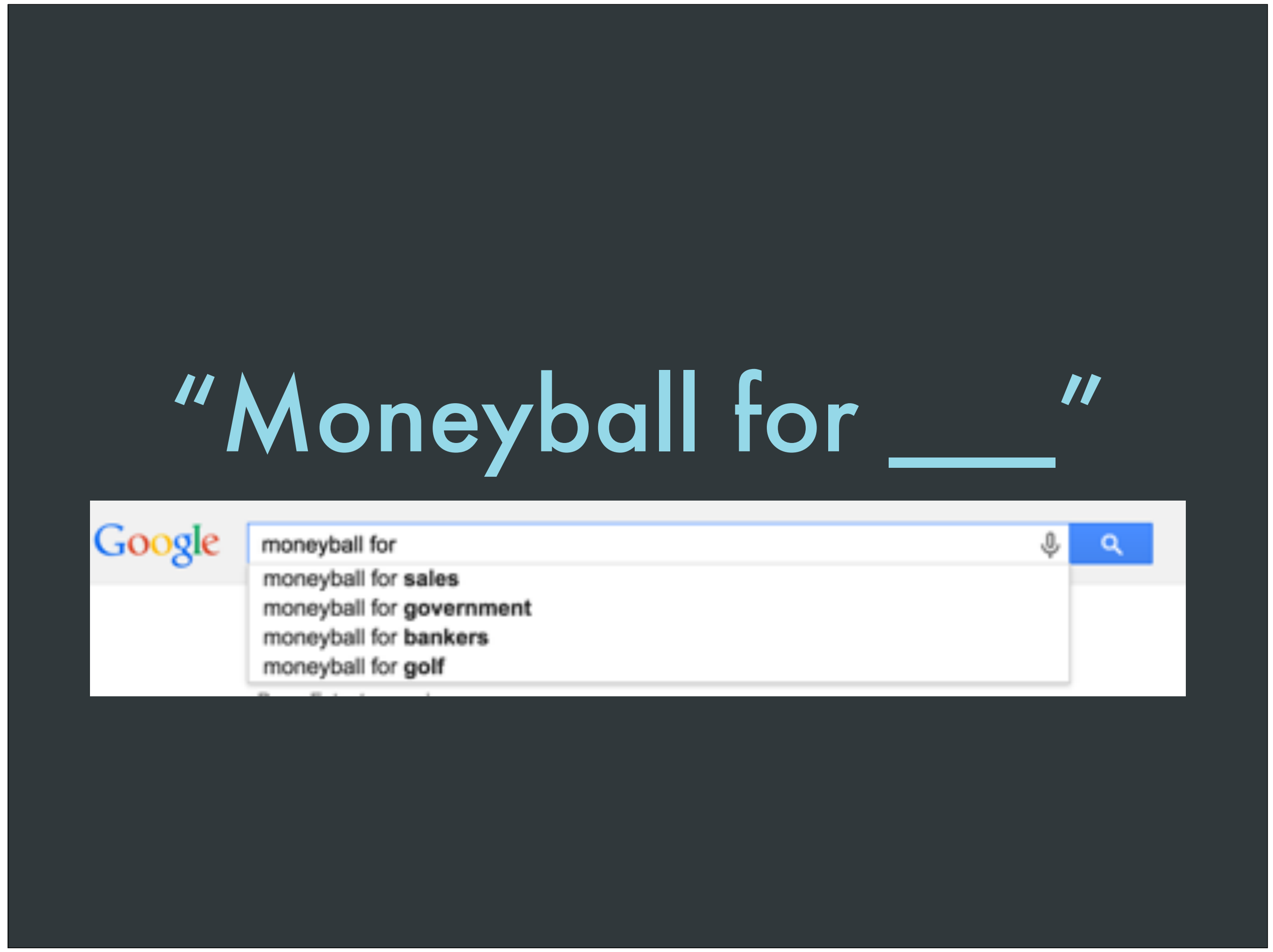
I've been known to go on my fair share of rants, and this is one of the topics that's been known to kick one up. It feels like everyone is trying to one up one another in terms of how "data-driven" they can be.

Moneyball



- How many of you have read or seen Moneyball?
- Please forgive me for the sports references I’m about to make. I’m a baseball fan.
- Story: Low low payroll; no salary cap; favors large markets; Dodgers 3x
- Partially to blame for all of this. Probably most well-known case of “data-driven-ness” in pop culture over the past decade.

<next> Moneyball for ___ </next>



You know how every startup is “Uber for X” - well Moneyball is kind of like that too.

<next> There’s even Moneyball for life </next>

SundayReview | LOOSE ENDS

Harvard Admissions Needs 'Moneyball for Life'

By MICHAEL LEWIS JUNE 20, 2015

Kyle Platts

http://www.nytimes.com/2015/06/21/opinion/sunday/harvard-admissions-needs-moneyball-for-life.html

[Pause]

What they think it was about

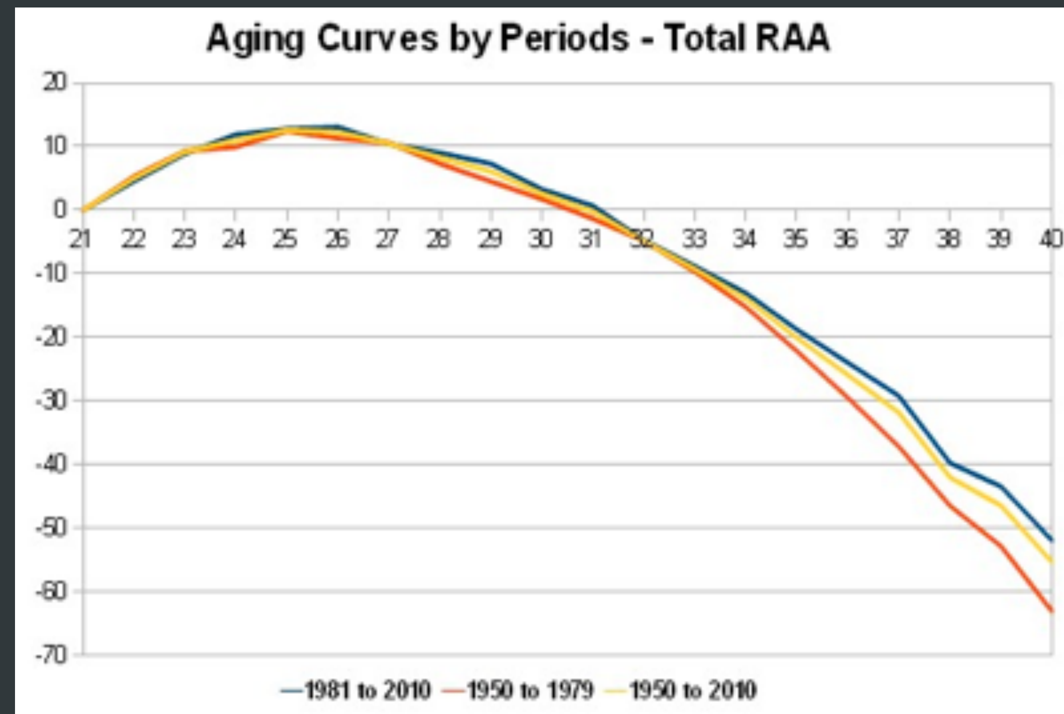
Statheads vs. Scouts

Despite their tight budget, the A's were perennial contenders in the early 2000s, reaching the playoffs five times for the years 2000 through 2006. They did this by making heavy use of stats and analytics to find market inefficiencies. For instance, they found that on-base percentage (hits + walks + hit by pitches) was a better indicator of offensive skill than the traditional focus on batting average. It's seems to be a very "duh" moment now, but no one cared about OBP in the late 90s and early 2000s, which is why the A's were able to produce wins so cheaply.

What everyone seems to take away from that story is that the stat nerds had found a way to exploit things the rest of the league had been undervaluing - that quantitative analytics had won.

However, in focusing solely on the quantitative aspects of the Athletics, many have lost sight of an important piece also covered in the book - specifically, that the A's couldn't have done it with analytics alone. Scouting - a traditional way of evaluating players - played an important role in their success. So much so that the A's have expanded their scouting department since the book's release.

Aging Curves



http://www.beyondtheboxscore.com/2011/5/31/2199146/hitter-aging-curves

This is what they aging curve looks like for a hitter in baseball. Describe.

You see, high-quality prospects - recently drafted players or talented minor league players - are extremely valuable to teams like the Athletics because they don't reach free agency until they've been a Major League player for six years, meaning you're paying them based on their rookie contract.

Mike Trout

To illustrate this point, consider the Anaheim Angels Mike Trout, who in just his fourth season has already won the MVP award once and finished runner-up twice. Oh, and his salary in each of those seasons was a million dollars or less. Compare that with Clayton Kershaw, who will make 33 million dollars this year (about 40% of the A's 2015 payroll), and you begin to understand the importance of drafting great players or acquiring them while they're still on rookie contracts. Scouting is crucial to this process.

What it was really about

Statheads + Scouts

It was through quantitative analysis AND qualitative analysis by their scouting department that the A's beat the odds that were stacked against them each year.

Following the success of the Athletics, we've seen most teams - across all sports - begin to adopt the use of advanced analytics , statistics, quantitative analysis - whatever you want to call it - in some form.

It was never the statheads vs. the scouts - it was the statheads AND the scouts, building on top of each other's work - whether they knew it or not - to build a better team.

Quants vs. Creatives

Sound familiar?

The interview

There was an assumption that there would be conflict, but in reality, our work would have been complementary. To create, we must first understand and empathize with our users. Data aids in that understanding. Additionally, it would allow them to gain a better understanding of what is an is not compelling content.

We have a lot in common with designers and other creative folk …

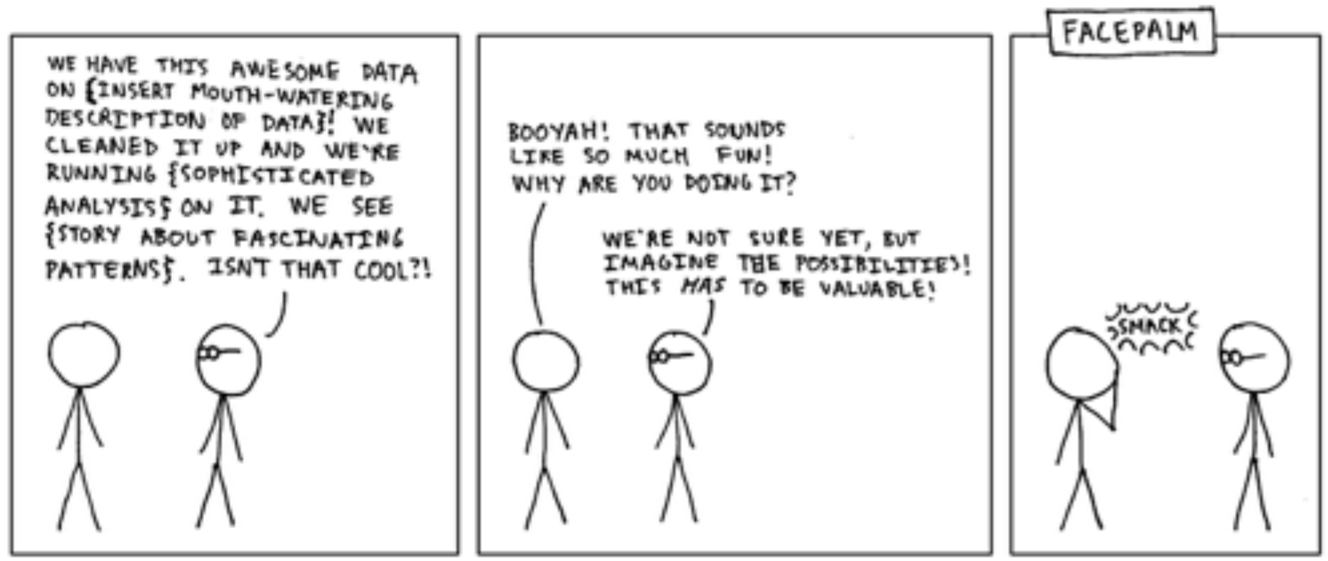
“Design is the process we undertake to solve a problem.”

- Mike Monteiro: *Why You Need Design*

Sounds familiar.

I’ve never had “designer” as a job title, nor do I think I ever will, but I really like this quote.

Why?



http://datascopeanalytics.com/blog/why-why-why/

[Pause - read comic]

I think sometimes we all do this - we become fascinated by the new shiny objects - the new tools, the new techniques - but we lose sight of the problem. What's it all for? What's the purpose we're serving?

The reality is that …

Data science is about answering questions & solving problems

To me, this slide is what data science is at its core. Would anyone disagree with it?

It sounds a lot like Mike’s earlier quote about what design is.

Actually, we’re all probably designers …

Design thinking & data science

http://dschool.stanford.edu/wp-content/uploads/2012/02/steps-730x345.png

How many of you follow a process similar to this for your work? This goes by many different names - agile, scrum, the deming wheel - but the concepts are all similar. It's the design process.

Who remembers the Netflix Prize? This about how this would have impacted it …

The Netflix Prize

“Improve our recommendations algorithm by 10%.”

[Talk about Netflix prize - how people spent three years trying to reach this goal - a one million dollar prize]

Many years later, a team finally produced results that were 10% better …

The Netflix Prize

"Improve our recommendations algorithm by 10%."

"We can't use it."

But ultimately, they couldn't use it.

Instead, they created profiles within accounts, which improved recommendations. Everyone needed to step back from their solutions and really think about the problem - to define it. The reality was that many users were sharing accounts, which was muddying up the data waters (so to speak).

Part of the oversight here is that they didn't start with the problem they were trying to solve; instead, they started with a solution or an approach - what they wanted to accomplish, instead of what the issue was.

Mike Stringer: "set concrete goals, but define problems ambiguously"

Data Science vs. User Research

Another false dichotomy that I've seen play out is that of data scientists vs. user researchers. Or, quantitative analysis vs qualitative analysis.

But by this point in the talk, we should all know where this is going…

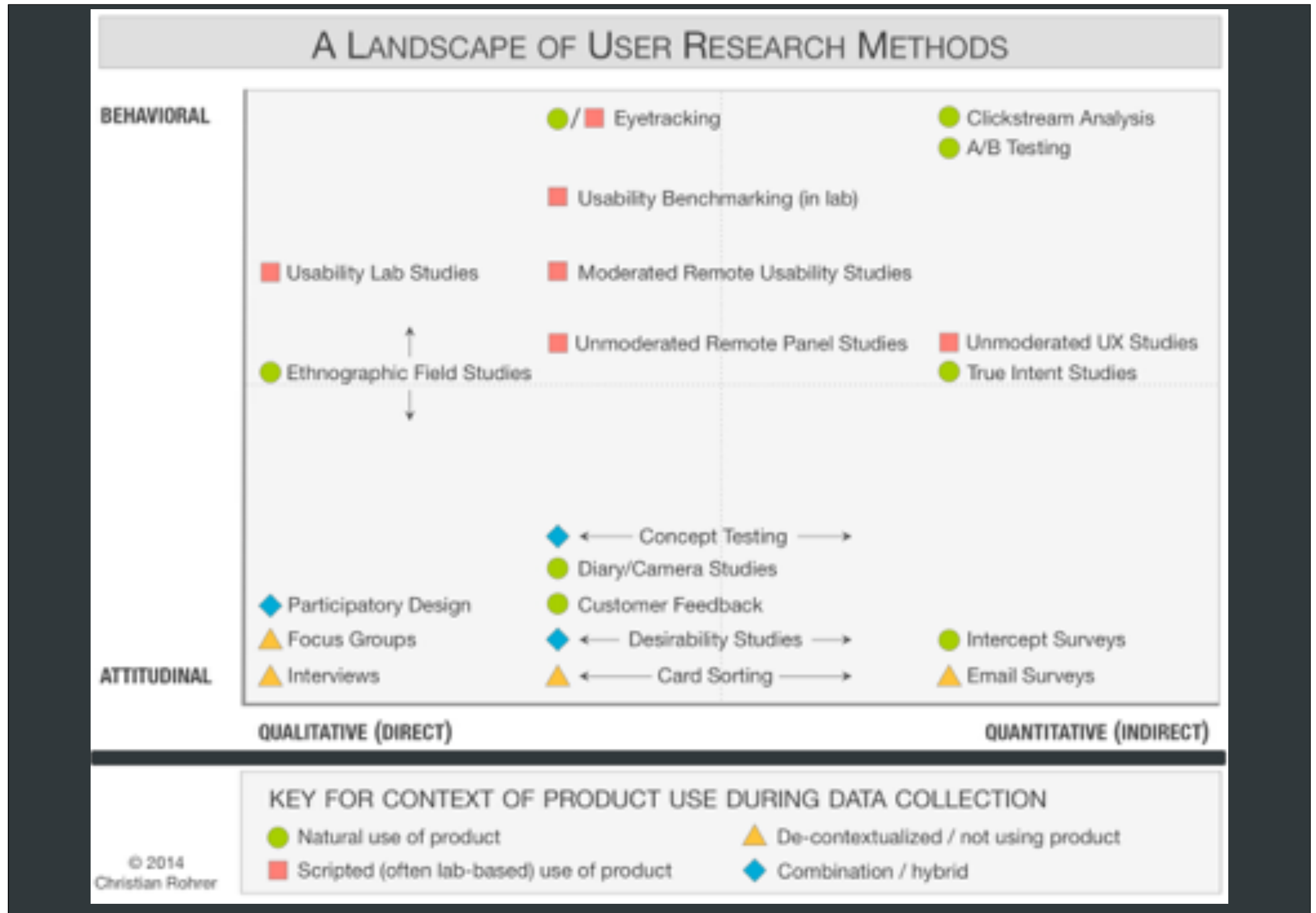
Data Science vs. User Research

It’s a trap!

Right, it’s a trap.

The reality is that we should be doing both. It’s extremely rare that we’re so constrained that we can only choose one or the other.

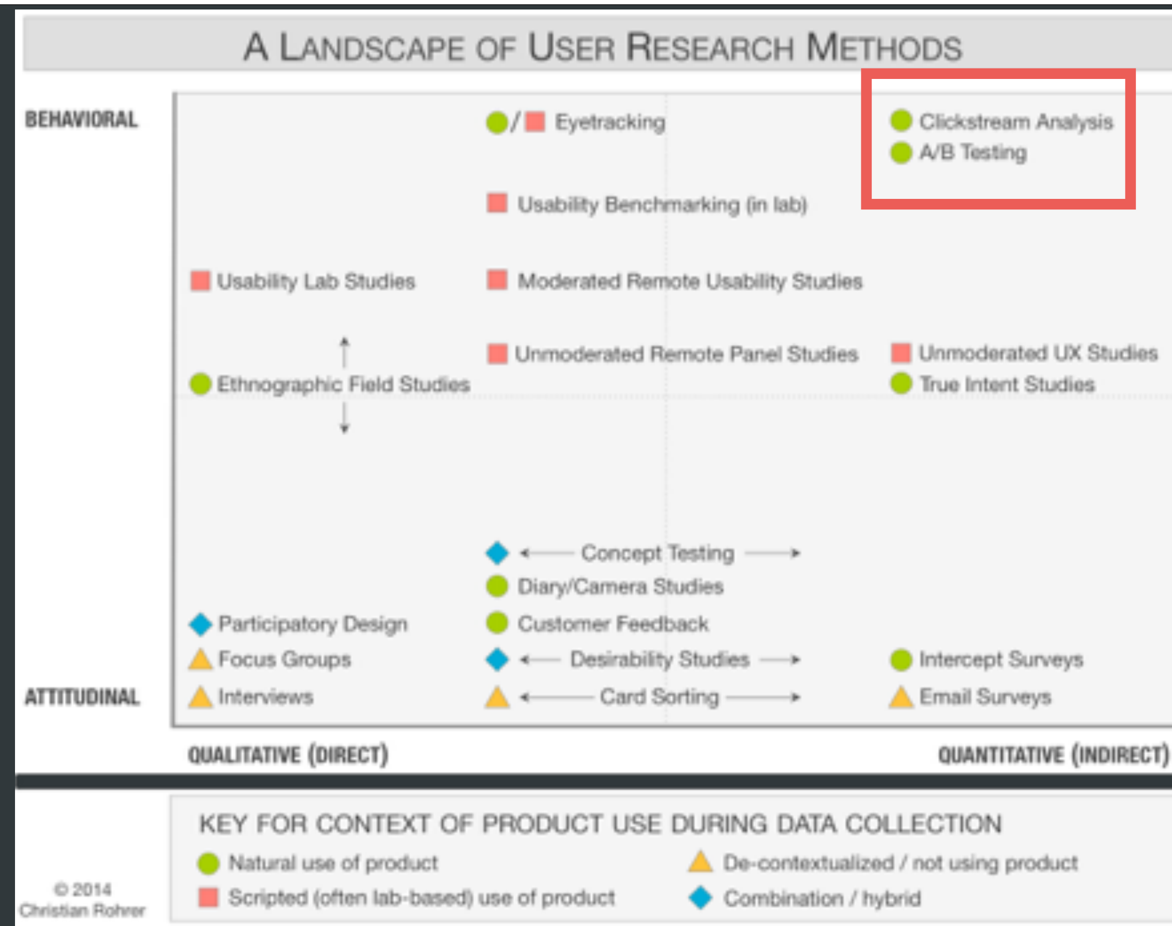
<next> user research landscape </next>



Christian Rohrer: http://www.nngroup.com/articles/which-ux-research-methods/

[Pause]
Similarly, we like to think of user research and data science as two separate things, but when Googling “user research techniques” last night, this image came up.

But look closely at that top right corner …



Christian Rohrer: http://www.nngroup.com/articles/which-ux-research-methods/

They are quantitative. A/B testing can even be considered a user research technique, but we'll come back to that a little bit later.

Most user researchers I've worked with tend to live in the left half of this chart. All of these techniques are great, but they suffer from a common problem …

They're narrow. User research is great at many things - particularly at giving us a deep understanding about our users, their environment, their behaviors, etc. How many users can we do a study with 10? 20? This won't give us an understanding of all of our users, but it will allow us to generalize about them - to potentially even create personas of our users.

Data Science & Analysis

~~“Why?”~~

Causality is hard.

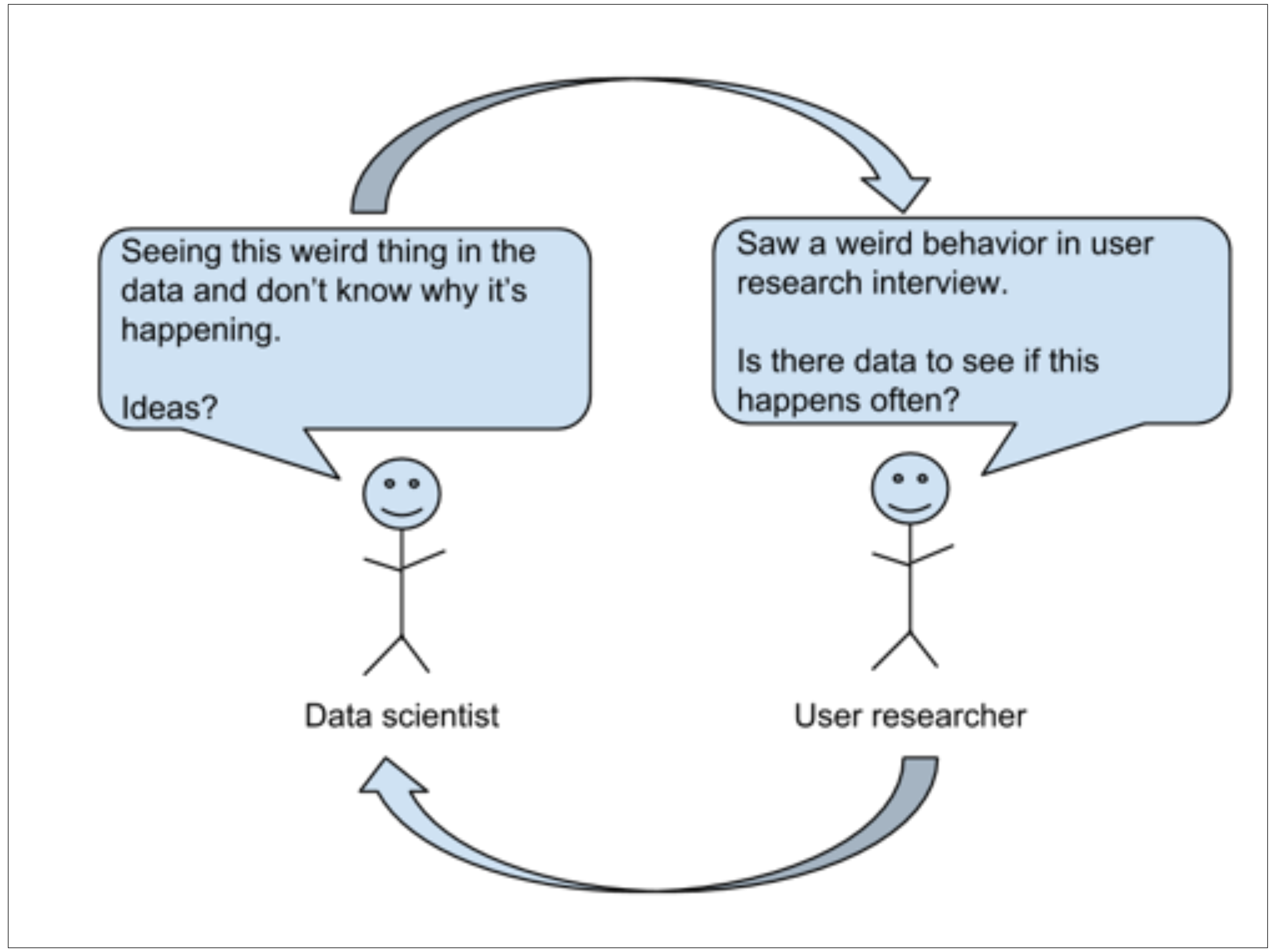
Shallow(ish) and wide.

Data science suffers from the opposite problem - as we’ve learned from the talks on Spark, Dask, and Rob Story’s data bikeshed, sample size generally isn’t a problem for us. We can look at a TBs of data without too much difficulty.

But causality is hard. Data is great at telling us many things - who, what, where, when - but the one thing it often can’t tell us is _why_. Why is something happening?

The Feedback Loop

But if we align ourselves appropriately with our colleagues in user research, we're positioned to create a nice feedback loop, allowing each of us to build off of the other.



[Pause - Describe] So I'm terrible at illustration - this was the best I could do with Google Draw

They’re complements

Where data science falls short, user research excels.

And vice versa.

[Read slide]

Stephanie Kim gave a great talk yesterday about using NLP techniques to discover and measure points of friction for your users. Not only was it extremely practical, but I think it did a good job of subtly communicating the point that these things are not supplements - they are complements.

<next> Let’s go back to A/B testing though </next>

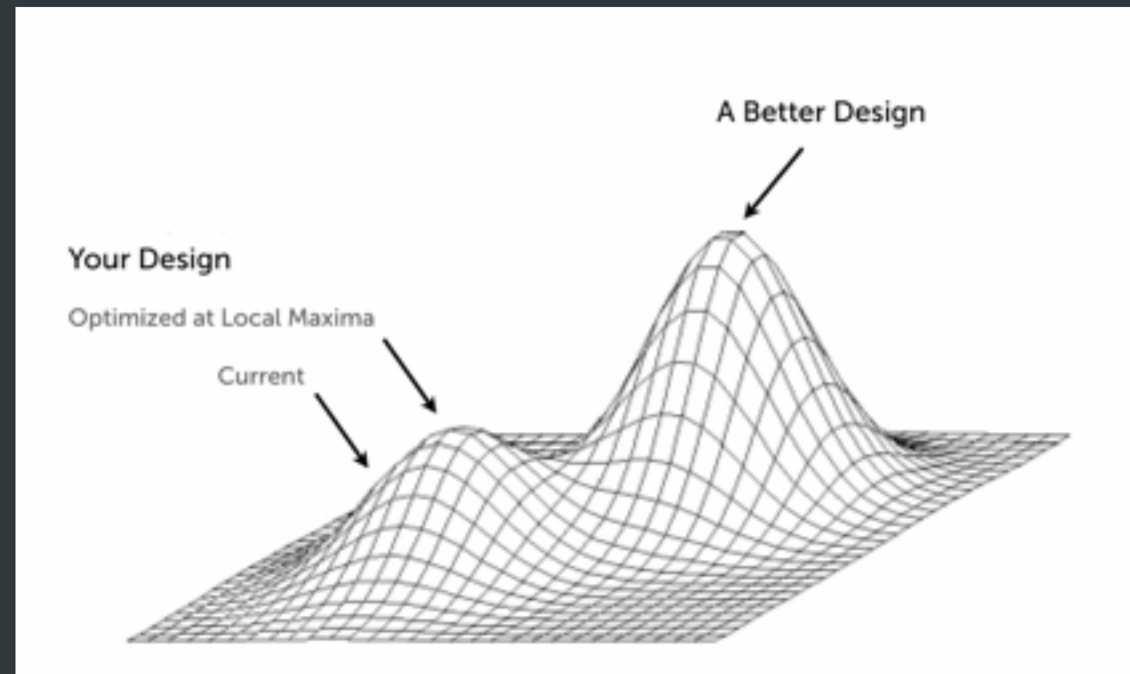
A/B Testing

The dreaded local optima.

Does everyone know what A/B testing is?

With A/B testing, we have even more opportunity for collaboration with our coworkers in design and engineering, but if we’re not careful, we find ourselves at the dreaded local optima.

Hill climbing

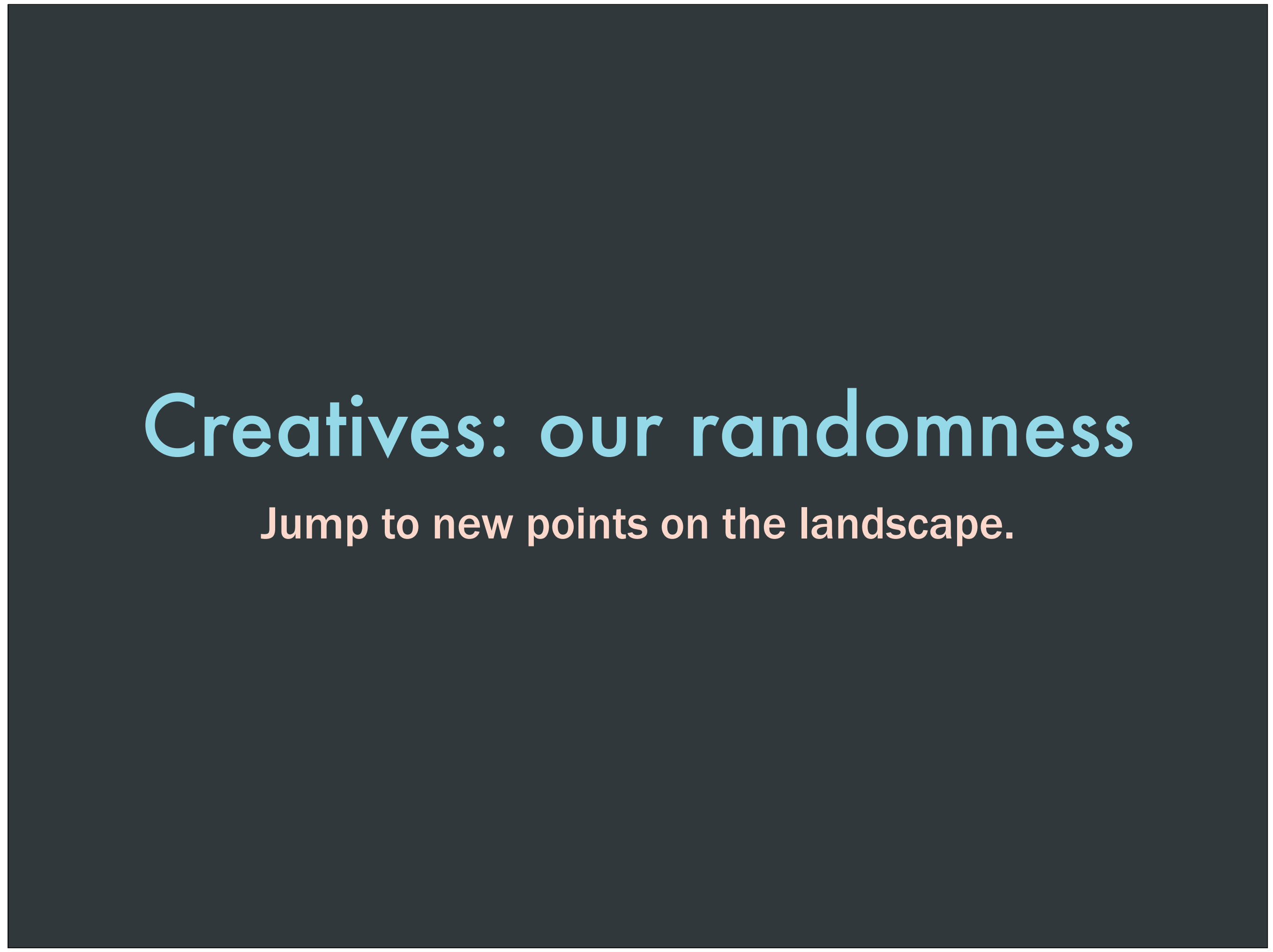


http://www.90percentofeverything.com/2011/01/06/local-maxima-and-the-perils-of-data-driven-design/

It's akin to hill climbing. If we are driven by data, we're at risk of hitting local maxima because we don't have a great understanding of where we are on the landscape.

How can we approximate that we're not at a local maxima though? How do we know?

We jump around with some randomness. Essentially, you randomly move to a new position on the map and if it's higher than your previous position … start climbing (and jumping around more).



Designers are our randomness - For our product to reach new heights, we need to take chances - and inject some randomness into it. If we continue to optimize the same thing, we'll run out of hill to climb. We need to evaluate new designs holistically; not just incremental changes - these new designs are akin to jumping around the landscape, and by jumping around, we learn more about the landscape and its topology.

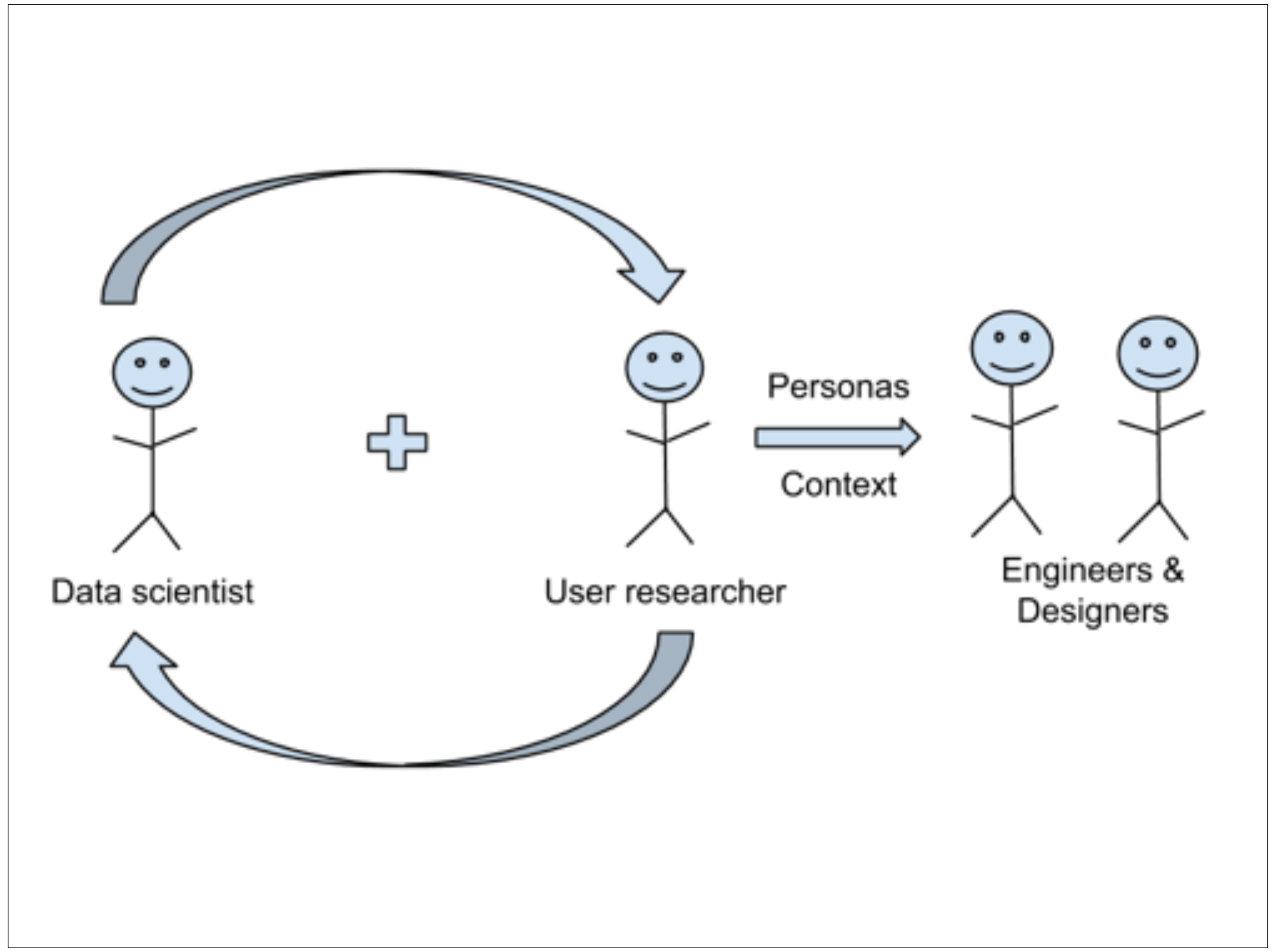
Team work makes the dream work.

Our analysis can help pinpoint UX problems.

Our work informs design, UX, and engineering.

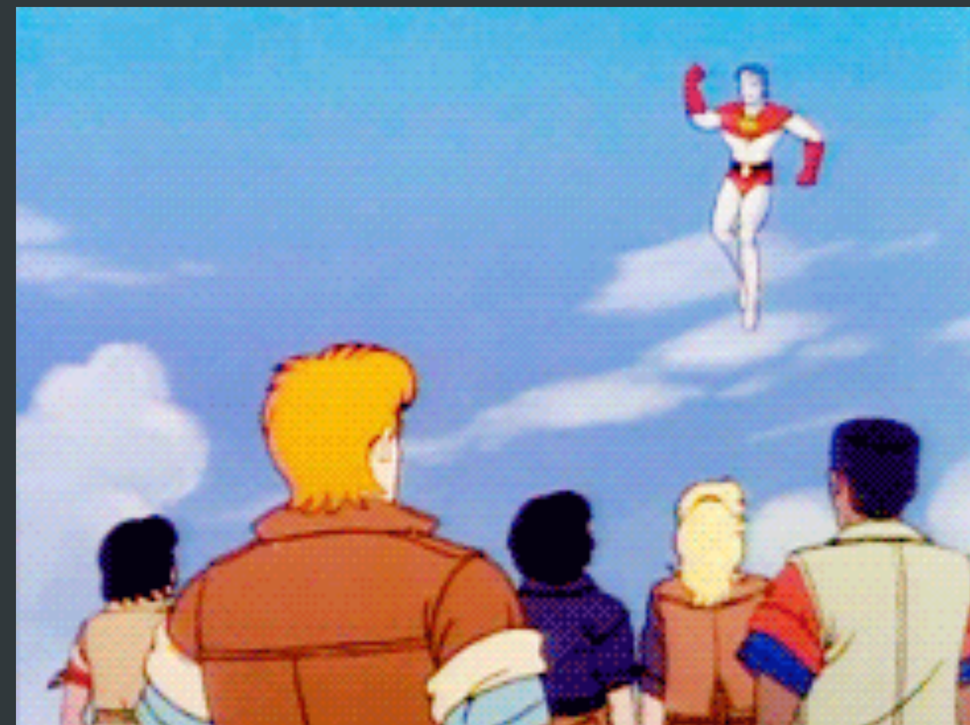
“Team work makes the dream work” - by creating multidisciplinary teams of data scientists, user researchers, designers, and engineers, we’re able to better inform everyone in the process, and create better experiences for our users.

It probably ends up looking something like this …



- Designers love this.
- See world through users' eyes - personas
- Data points about their users, coupled with behaviors, feelings, deep understanding from user research.
- Potential for tailored experiences; why "one-size-fits-all?"

“Superpowers”



Does anyone remember this cartoon?

I have a former colleague that likes to refer to each of us as having our own superpowers, and that by combining them, we elevate the abilities of those we’re working with. Kind of like Captain Planet and the Planeteers. This is what we should be striving for.

Make experiences

Not metrics.

- Even though we're answering questions and solving problems, the ultimate end is an experience to a user, not maximizing a metric
- Lorena talked a bit about that this morning - that we're optimizing for experiences, not metrics like grades and test scores. And that learning is a unique experience - we need to tailor our approaches to our audience - to use all available channels to communicate the concepts.

Data is powerful

But not something to be “driven” by.

Data is a powerful thing - extremely powerful - but we cannot let it be the only thing when consider when making decisions. If we do, we’re destined to lose sight of the big picture - why we’re doing these things, the problems we’re trying to solve, the goals we set out to achieve.

"The key to making a good forecast, ... is not in limiting yourself to quantitative information. Rather, it's having a good process for weighing the information appropriately."

- Nate Silver: *The Signal And The Noise*

In his book, Nate Silver said this about making a good forecast - I'm a big fan of this quote. I think it applies not only to forecasts, but really all decisions we make.

Good Reads

[How Not to Drown in Numbers](#) [NYT]
Creative Thinking And Data Science [Datascope]
Why? Why? Why? [Datascope]
How to Solve a Problem In 3 Steps … [Entrepreneur]
Recommendation Engines Aren't For Maximising Metrics, They Are For Designing Experiences [Mike Dewar]
The Signal and the Noise [Nate Silver]

If you've enjoyed this talk or are interested in some more in-depth pieces on the topic, here are some great reads - these people have written much on the topic and explained it in far better than I can.

Thank you.

Questions?

Thank you. I'd love to take questions and hear your thoughts.