**What I Learned in My First 6 Months as a Director of Data Science**

**On the challenges and rewards of transitioning to a new role in a different industry**

Prior to starting as the director of a data science team 6 months ago, I did what many other people do when faced with something new: I went searching on Medium for posts about what others had learned in the process. And I didn’t find that many posts on being a manager of data science (although I found [this post](https://medium.com/data-science-at-microsoft/onboarding-to-a-data-science-team-2b735dae464) to be very helpful!). There are plenty of posts on the technical aspects of data science and how to manage data science *projects*, but no so many on how to manage a *data science team*. So I figured I would share my learnings as I get used to this new role.

Tl;dr in this post I will first focus on my biggest challenges: (1) adapting to a company that is not a tech company, and (2) recruiting and hiring (which, in some cases, is tied to number 1). I have had other challenges so far, but I figured I would start with these two since they take up at least 75% of my day. Stay tuned for future posts about other challenges and observations!

**A bit about me…**

I am not new to management, but lately have been working as an IC in tech companies. Why? I missed coding and getting into the nitty gritty technical details.

And when I say that I am not new to management, my management experience has not been 100% in data science. I managed a team, both from the personnel side as well as the project side, several jobs ago. But they were having a lot of fun and, frankly, I was jealous that I didn’t get to have the hands-on-keyboard fun with them.

Also in a previous job I was a professor at an R1 university doing research at the forefront of applied data science and machine learning. Most people don’t think of that as a management job, but if you think about it, it really is. While there is the teaching component, at an R1 university research reigns supreme. But what does that mean for the day-to-day life of a professor? First and foremost it is about **securing funding** for the work through writing many lengthy proposals. And that means being able to demonstrate that you can **manage a budget**. Second, and just as important, it means **recruiting a team**. At its height, my team was 2 postdocs, 10 graduate students, and about 20 undergraduate students. The success of any professor’s research group is strongly a function on the quality of students they are able to recruit into their lab. They all needed to be **mentored**. They all had different skills and levels of experience. They all needed to regularly have their **performance reviewed** and feedback given. And they all had interpersonal issues that sometimes impacted the team. So yes, being a professor at an R1 is a management gig with a bit of teaching that has to be done on the side.

So why did I return to management if I love to code so much? I suppose it is because I realized that I also like to influence the direction of data science. As an IC data scientist, your day-to-day job is (ideally) solving problems, writing and reviewing code, and documenting your work. What I discovered in my time as an IC was that I was not given a lot of opportunity to be at the table discussing what the business needs were around a specific problem and whether data could actually solve that problem. I didn’t have the ability to drive the direction of the data science work. And I found that I missed that.

Based on that, I accepted what is a dream job for me: directing a data science team working in the ski industry — my passion industry.

**A bit about my company…**

The ski industry is not tech. Let’s face it. The industry may have existed for decades, but it was not founded by people who spend much time thinking about data. The people who founded the industry are very good at managing mountains. However, in general it was not initially structured in a way to be data-centric.

However, my most recent jobs have been in tech. What does that really mean for a data science manager? It means that we are building the infrastructure solutions as we go, typically along side the data science solutions. I spend a fair bit of time talking about and working on problems that data scientists at tech companies might take for granted. For example, what cloud platform should we be on and what are the correct tools (think version control, CI/CD, cluster management, etc.) we should use there? What is the correct storage solution for our *mountains of data*? (See what I did there? ;) ) What do we do when we have a ton of different data sources, even for the same type of data, each with their own schemas and sources of noise, that all have to play nicely together? In tech companies, these problems are largely solved or easy to deal with. If they aren’t yet solved, there is a small army of people to work on them. But in the non-tech world, data scientists have to be generalists, much more knowledgeable about things like full-stack solutions and less so about getting very technically deep on one subject. In addition to deciding on proper platforms and tooling, it is equally as important to be able to communicate those decisions to the business, both in terms of value as well as justifying the cost.

Sometimes I find this very challenging. Other times I find it a great opportunity to make positive impact. I very much believe that one’s happiness in a role like this is finding a way to look at things mostly like the later…and to help their team to do so as well.

**The most challenging problem I have faced so far: hiring**

Anyone reading this post knows that getting the right data science talent is very, very hard. Data scientists have been [likened to unicorns](https://pubsonline.informs.org/do/10.1287/LYTX.2019.04.02/full/). It is a unique skill set comprised of many complex, technical areas of expertise including coding, statistics, and business skills. What that means for me is that the competition is incredibly fierce to attract and compete for the best talent. Back when I was a professor I had a recruiter reach out to me about a data scientist job in Fintech that had a starting salary of $1,000,000/year plus bonuses. Yes, really. (I didn’t take it…I don’t think the strings attached to that kind of salary are worth it.)

The FAANG companies (Facebook-Apple-Amazon-Netflix-Google) can afford to pay amazing salaries. But most companies hiring data scientists are not like that. Don’t get me wrong! Data scientists still can make a very decent living! But in the world of actual practicing, non-tech data scientists, things are much more realistic. Unfortunately though, it means I am competing for talent against the FAANG companies.

As such I have had to get very creative in where I advertise my postings and do my recruiting. Data scientists will always look for jobs at the FAANG companies, but they don’t always think about non-tech companies as employing data scientists. So this means I have learned that I have to be much more proactive in marketing my open roles. LinkedIn is great and recruiters can be helpful. However, I have also found great success in recruiting in unusual online forums — places like Discord, Slack, and Twitter.

But make no mistake: recruiting data scientists is a full-contact sport! It is messy. You have to move quickly. It is vital to streamline the interview process to identify the talent very quickly. Think carefully about what you want your technical interview(s) to look like and how long they should last. Because within less than a week that ideal candidate can get hired out from under you!

**Roles and levels**

On my team we have both data scientists and machine learning engineers. There is a lot of discussion on what is the difference between the two, and this discussion does naturally happen on my team. Here is how it was structured before my arrival, and I have maintained this structure:

**Data scientists:** the people who create the models themselves.

**Machine learning engineers** (MLEs, also considered “data engineers” elsewhere): the MLOps folks who create the pipelines for the models the data scientists develop.

I can tell you that it is much easier to hire data scientists than MLEs. It is easy to teach basic data science skills and a lot of this can be done on your local machine or a small cloud instance. However, if you think about it, giving students access to complicated cloud pipelines with massive amounts of data is complicated and expensive. So expect it will take a while to find an experienced MLE!

As far as leveling goes, we have three levels on my team: data scientist/MLE, senior, and principal. I am working on updating our leveling guide right now. In general, I view the entry-level roles as being people who understand the basics of the subject and are able to do specific tasks assigned to them. The senior level to me is about owning a project whereby you are given a problem, break it into a series of tasks, and code it up to get it over the finish line. Finally, the principals are the ones who identify the problems themselves, mentor the team to solve those problems, and create high-level solutions to help the team in their solutions.

My job, on the other hand, is to make it possible for the team to get their jobs done while also working with other managers and stakeholders to scope the problems and communicate out the solutions. In many environments including both tech and non-tech, there can be the distinction between a role like “manager/senior manager” and “director.” The former manages down mostly, handling the day-to-day “care and feeding” of the team, whereas the later is a strange middle ground between managing down and managing up. I have found in my current role that I am doing about 50/50 of managing down and managing up.

**Advice to job seekers**

First off, really read the job ads. Look at what the desired skills are. For example roles above, in the job descriptions you might have been an MLE in your previous role building models. However, because these job titles are nebulous, you might be considered a data scientist elsewhere.

Second, the FAANG companies are going to expect you to answer really complicated questions, pair program, and/or white board in a high stress environment. There are plenty of blog posts on how to prepare for those types of interviews. These interviews are intense and require months of study. But for the rest of the world, this is not the norm (nor is it practical) and you really wouldn’t be expected to function in your job like that anyway. Be prepared with the basics. Keep it simple and easily communicated.

Finally, keep your resume clean and simple. Believe it or not, but on average a hiring manager looks at a resume for **6 to 7 seconds**. (If you don’t believe me, [read this](https://www.indeed.com/career-advice/resumes-cover-letters/how-long-do-employers-look-at-resumes#:~:text=How%20long%20do%20employers%20look,for%20only%20a%20few%20seconds.).) Don’t waste space on content that distracts from that 6–7 seconds like objective statements. Get to the meat quickly. If you don’t know what that is, the job ad will tell you.

**Conclusions and what I think I might expect in the next 6 months**

Most of my time in my first 6 months has been spent both learning the ways of working in data science for a non-tech entity as well as recruiting and hiring. I have learned new ways to look at how data science and infrastructure relate to the overall business and how to communicate that return on investment (ROI) to non-technical managers. I have also learned the importance of being both creative and proactive when it comes to recruiting. FAANG companies might not have to advertise that they hire data scientists, but I do. And most of my success in hiring has come from posting my job ads in unusual places.

While I don’t have a crystal ball to predict the future, there are some things I think I can say with reasonable confidence as to what the next 6 months will look like.

First, it is difficult to determine the impact the recent tech layoffs will have on my recruiting. However, some of those laid off have already reached out to me, so I cannot imagine that there will NOT be an impact. Second, I really should not have mentioned the words of “recruiting” and “hiring” without also including the word “retention.” But then, retention also needs to consider what is happening in the overall tech employment environment. Finally, working with humans of any type is complicated. Any manager has this consideration as part of their job. However, it is my opinion that there are some unique challenges to managing data scientists in this regard. For example, the field is evolving *very* quickly, perhaps more-so than other software development areas. Tools that were cutting edge when I started as an IC are now obsolete. New tooling and methods are constantly coming online. Keeping a team of data scientists fresh and current on all of these advancements is always on my mind. That could easily be its own blog post.

Stay tuned!