**How to Differentiate Yourself During Data Science Interviews**

*Note: At the bottom of this post are answers from some data scientists in industry about how best to land your first data science role.*

Landing a new data science position involves taking a series of steps to showcase your ability to work with data and whether you’ll be a good fit with the culture of a company. In this post, I’ll tackle one of the most important parts of the process (and often most dreaded): **the technical interview.**

Most people I’ve talked with spend a lot of time practicing for coding challenges and brushing up on skills like SQL queries. While these are important aspects of preparing for an interview, they place the emphasis solely on how well you can work with a keyboard.

During my own job search, I’ve instead spent a lot of time thinking about how I can instead use the technical interview as a means to differentiate myself from the other applications. Most of us can code a function to indicate whether a number is a prime number or not (hint: modulo is your friend). What is often overlooked is how each of your answers is an opportunity to provide context to your particular form of problem solving. The optimal context will depend on the particular question you’re posed, the interviewer, and the role that you’re applying for. However, from my experience there are three main types of context that work well during the interview process.

**Elaboration**

While coding questions often can be reduced to using native components of your preferred programming language, they indicate your problem solving capacity outside of knowing when to call a particular method. Whether answering verbally or on a whiteboard, each step of your solution should be articulated as to why you are choosing a particular approach. This allows you to discuss alternative solutions that may not perform as well as the one you selected, and shows that you are able to think about how your code may impact the scalability of a product.

A good tip here is to know [how to test the computational time of different approaches](https://jakevdp.github.io/PythonDataScienceHandbook/01.07-timing-and-profiling.html). So even if you are unfamiliar with which scales better, you can indicate that there are *n*number of solutions to the problem, and that it would be interesting to test the computational time of each. So even though you may not have a direct answer, you still demonstrate that you’re thinking about performance and that if you were sitting at a computer you would know how to test different approaches.

Another important aspect of elaboration is to discuss how a particular coding solution could be used in the context of a business problem someone in the company may be dealing with. While this won’t apply to every technical question, you should take any opportunity to discuss solutions in this context. An example is a data science role that deals with predicting customer churn, you may explain basic technical questions (e.g. how do deep neural networks work) in terms that problem. You can speak about what types of data would be input to a neural network, and how that network would optimize predictions using features relevant to churn.

**Storytelling**

Storytelling is similar to elaboration but involves using specific past events to highlight your skills. While working through a problem, you may indicate how you’ve implemented a similar solution in the past. It is important to emphasize relevant details of the project, the steps you took to solve the problem, and what the specific outcomes of that resulted from your efforts.

*I did action X during the feature engineering stage of project Y which resulted in Z increase in model accuracy and AUC scores.*

An important use of storytelling is also to demonstrate behaviors that communicate the values of the company. Many tech companies list their core values, sometimes called missions, on their webpage. Other companies such as banks and consultant agencies will be looking for leadership and resolution skills. As an example, Amazon interleaves questions assessing their leadership principles with data-oriented questions. A good framework for behavioral storytelling is the STAR format.

*The STAR format requires that you state your answer using four steps:*

*1. Situation*

*2. Task*

*3. Action*

*4. Response*

You can find out more about how to implement the STAR method [here](https://www.thebalancecareers.com/what-is-the-star-interview-response-technique-2061629).

**The Followup**

This strategy requires that you elicit specifics on certain problems that the company is currently facing. The idea here is twofold: to demonstrate that you’re approaching the role with a solution-oriented mindset and that you’re able to actually implement solutions to their problem.

The way this plays out is that when given the opportunity to ask the interviewer(s) questions, you ask about particular examples of problems you’ll face in the role, or important problems that the team is currently working on. After the interview is complete and you’re back home, you spend some time outlining the problem and a plan to implement a solution. This doesn’t need to be super technical, just an overview to show you understand the problem at hand and can come up with solutions to be implemented on your own. You then followup with the interviewer reiterating positive experiences from your interview and send them the document saying something along the lines of “By the way, I thought about the problem you’re currently facing and came up with three solutions that I could implement within the first month of starting at your company.” This effectively gives the interviewer a roadmap to starting you at the company and will likely become the first project you work on if hired.

An excellent example of this is Ramit Sethi’s [briefcase technique](https://www.youtube.com/watch?v=3p28MFt8RBA).

**Further Thoughts on Differentiating Yourself**

While preparing for interview, I queried friends who were working data science positions to hear about their experiences moving into the industry. Note that myself and these friends moved from PhD programs to data science roles, so if you’re coming from a different situation their responses should be interpreted from that standpoint.

The answers are in semi-anonymous format and come from data scientists at companies like Facebook, Uber, and Amazon. Hopefully they are useful as you think about how you might work on elaborations, storytelling, and followups during your interview process.

*Question 1: Aside from a good portfolio and technical skills, what would you say is important for a data/research/nlp science applicant at your company?*

**Response 1:**Product sense, with an emphasis on product metrics. This is specifically for the Data Science Product Analytics role (vast majority of roles at FB). In addition there is a small group of Core Data Science — they’re basically software engineers that also know stats and build the tools that the other DS use. There’s also Infrastructure Data Science and they are somewhat mysterious to me but work on our data warehouse. We also have Research Scientist roles, but these are very domain-specific.

**Response 2:** Business sense/insight — The ability to intuit what problems the company tries to address with data science, how they measure success, and how data science work can best meet those needs. Understanding how to take DS insights and translate them into actionable recommendations.Also, creativity, efficiency, independence, collaboration/altruism.

**Response 3:**It is definitely important that you can show the impact of your work and that you can highlight how this is a consideration in the work that you do. Part of that is being able to prioritize the most important work. At Facebook there is always a million things you could be working on and knowing which ones are the most important with the highest impact is key.

**Response 4:** Ability to make sense of data sets, ability to quickly learn things here, and ability to independently understand and learn concepts (there are a TON of wikis that you have to be able to read on your own and understand something).

*Question 2: When looking for your job, what area (e.g. portfolio, domain knowledge, specific skills, blog/outreach) did you focus on that didn’t have much of an effect on getting hired?*

**Response 1:**None really. I did the Insight Data Science fellowship and they provide very good preparation for passing DS interviews. (Note: if you can get into a data science bootcamp, you’re in a good position. Especially if it’s the [Insight Fellowship](https://www.insightdatascience.com/).)

**Response 2:** I didn’t have a blog, but did have a personal website and a github. I’m not sure if either were looked at when I was hired, but we would definitely look at them for a candidate now. Publication record of course wasn’t important (except to the extent that it demonstrates the ability to complete projects), but I expected that.

**Response 3:** That’s a really good question. I actually found throughout my path into tech that the most impactful were relationships. I actually did not get any job by just writing CVs. All of the jobs I got were through people knowing me or my work.

**Response 4:**My portfolio really didn’t matter I think haha.

*Question 3: If you were to redo your job search, what area would you spend more time focusing on?*

**Response 1:** I don’t have a great answer here, but that’s probably because my current role is fairly unique. If I was looking more broadly at DS openings today, I’d probably want to beef up on machine learning methods.

**Response 2:**Along similar lines as above. Networking, networking, networking. I had great success with giving talks. After one talk I basically had 3–4 companies interested in hiring me. This might be a bit harder coming out of academia though. I would definitely suggest to look for opportunities to volunteer at conferences. I would also prioritize to go to more meetups. Depending on where you are looking for a job it might also make sense to seek out people on linkedin that work there and ask them to meet (even it is via video conference). For those meeting make sure you have researched the person and have specific questions to ask.Another option might also be to find mentoring programs (I was a mentor for chic geek). Basically anything that builds real life relationships rather than just sending out CVs.

**Response 3:** Knowledge of ontological modeling (i still dont know what it is fully) and machine learning.

*Question 4: What would you say are a couple big differences between working in academia and industry?*

**Response 1:** Shipping something fast is far more important than shipping something perfect.

Project ownership — I was used to 100% owning whatever I worked on, but there are a lot more interdependencies in industry.

Communication is completely different because I’m almost never working with another data scientist. I’m talking to engineers / PMs / etc and have to adjust accordingly (e.g., no one cares or understands methods, they just want to know the outcome).

**Response 2:** Speed — In industry, there’s a bottom-line imperative to get actionable answers quickly, and perfect is the enemy of the good. In terms of speed/accuracy trade off, instinct (and your manager) should tell you when you’ve gotten the answer right \*enough\* and can move on.

Cross-functionality — Many data scientist work on xf teams and need to be able to communicate well with people from totally different backgrounds (like business, design, eng, etc).

**Response 3:** The biggest is definitely timelines and considerations of real life constraints. In academia the goal is usually to find the best and most sound answer with the most perfect method possible. The time it takes you often comes as a result or that consideration. In industry timelines rule everything. You have to be good at weighing, what is the best that you can do in the time you have with the resources you have while also balancing 3 other projects. Write-ups are also not very rigorous and there is very little efforts like literary review (if you have time to do it great but definitely not a requirement).

I actually love the fast pace of industry but it is something that people from academia struggle with sometimes.

Also, writing reporting. You have to be good at visualizing your findings and making it palatable for a wide range of people. That includes being able to write an executive summary that is easily digestible.

Also, you definitely need to be able to define actionable recommendations from the work that you do. It’s great to have an interesting finding but more importantly you have to show the “so what?”. What are steps to fix whatever you found or action it in a way that has impact for the business. So for that you also need to be really aware of what the business outcomes are that you are driving.

*Question 5: Any general advice on landing my first role at a tech company?*

**Response 1:** I wrote up a blog post on my transition from academia to DS [here](http://lindsayvass.com/2016/10/16/004-transitioning-from-academia-to-data-science/).

**Response 2:** Leverage referrals, that’ll get you at least a closer look by a recruiter or manager. Tailor your resume (no more than 1 page) to each role you apply to. Don’t say you know a skill if you can’t demonstrate that you know it in person. Research companies in advance of an interview, try their products if possible. Searching [HackerNews](https://news.ycombinator.com/" \t "_blank) was great for learning about Silicon Valley companies, may also be useful for you.

**Response 3:**Update your Linkedin. Make sure you have a summary and write up your experience with all the above in mind (illustrate the impact of your work, show that you can work under tight timelines, show that you can communicate your work to a wide range of audiences, etc.). Whoever considers you for hiring will likely look at your Linkedin. If you also have a website that is amazing.

Also don’t leave out the human component. Show what you are interested in, things that make you different, volunteering or work for social good you have done. Tech companies (at least Facebook) often look for people with a point of view as far as I can tell. Also make sure you review the values of the companies you apply to and reflect that you know them in your CV. (Facebook has values such as: be open, focus on impact, etc.)

*Bonus question: Do you have any insights to offer on the interview process at Amazon, or things you wish you’d prepped for more specifically in relation to the interviews?*

**Response 1:** In terms of interviewing, most of the questions will be behavioral questions. They assess you on how you did in a situation more than your actual skill set (although you might have one or two technical interviews — what position did you apply for again?) They prefer all your answers to be in the “STAR” format — situation, task, action, and result <- if you have some stories in this format prepared, great (you’ll do fine). And a lot of questions are silly and open ended such as “tell me about a time when you had to disagree with your supervisor (or advisor or research partner). What was it and how did you address it? What was the end result.” They also really like it if you can tie questions into these so called leadership principles (you dont have to explicitly say like, I wanted to demonstrate ownership or I wanted to dive deep into this issue, but your ability to demonstrate certain LPs in your answers will be discussed in a debrief.

I hope this helps everyone on their journey into and through data science. If you have any other tips or suggestions, please leave me a comment.

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**Responses**

Rishi Arora

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