Data Science Diagram

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What does it mean to be a data scientist? What are the different skillsets one must have to be successful in a data science centric role?

The definition of a data scientist has notoriously always been broken down into two areas: someone who has knowledge in programming and statistics. While I believe that both of those areas are necessities, this can be expanded upon to include the below areas: data engineering, applied statistics, software engineering/computer science, and consulting. By no means is the below diagram all encompassing, but should serve as a quick overview of the different buckets of knowledge individuals should concentrate on when pursuing a career in data science. In some areas that seemed ambiguous, I tried to provide a few examples beneath the topic, but again this diagram is not all emcompassing. I also combined some sections for space's sake that I would probably break out separately if I wanted to make this more of an eye-sore.

Data Scientist Software Engineering/Computer Consulting **Data Engineering Applied Statistics** Science os Data Quality Data Statistics & Computer **Software** Specifics & **Programming** Hardware Infrastructure Management Learning **Networking** and Security **Visualization** Advanced Classification Neural **CPUs Containers** Code **Presentations** Time Speech Data flow. Data **Exploratory** inux/Unix/Linu EDA Networks Modeling & Efficiency & Management -Docker **Architecture** Data retreival. Simulation Structure Regression **GPUs Understanding** Respect **Analysis** scraping -Understanding Bash Measures of Computer - Discrete -Python, R -Linear vs. Multi Ability to the problem **Kubernetes** how the role (EDA) **Scripting** -API's, Data Central Vision (CV) Event Scope Work **OS Drivers** Appearance different tools pipelines, Tendency Simulation Code Supervised vs. **Understanding** and Cloud **Basics of** scheduling Data - Systems Natural Unsupervised Versioning Multi-tasking environments Customer Computing Parallel Computer Trust software, Cleaning Identifying Dynamic Language -Github play Data -AWS, Azure Networking **Processing** Exract, Simulation Bias Reinforcement **Processing** Accurate Threads vs Branding (NLP) Tranform. Learning Data Data Collaboration Communication **Estimations** processes Environmen^a **Distributed** Load (ETL) Optimization Principal **Enhancement** Coding Versioning variables Computing Audio Teamwork Component Common Knowing Leadership **Distributed** Analysis **Processing** Algorithims Risk **Databases** Virtual Your Creating Computing Security Data Reliability -Random forests. **Analysis** -Relational vs Environments Audience Representation **Organizational** Control & Mathematical support vector Non-relational Knowledge of Data High Access Concepts machines, logistic **Providing and Unit Testing** Converting **Performance** -Graphical regression, Receiving Understanding Requirements Computing clustering, etc Constructive from (HPC) Data Feedback **Business to** Feature Code -Structured Ensembling Tech **Engineering** Models Unstructured ML Agile **Engineering** Hyperparameter Development Tuning

- A great data scientist needs to have a general understanding of data engineering and be able to apply data engineering at least at an individual level
- Being able to communicate and, therefore, work more closely with data engineers is extremely important for project success
- Being able to understand how data is stored and having the ability to "self-serve" is crucial (a data engineer might not always be at your exposal) - have the ability to understand how to pull and manipulate data to suit the need of your analysis

- This is the meat of a data scientist's usefullness in an overall team. A data scientist should have the ability to summarize datasets via basic statistics and probability, as well as apply/understand the application of common machine learning algorithms
- Data scientists should know when to use which algorithms and the pros and cons of each, depending on the scenario

- A data scientist is useless unless they can apply their algorithms and experiments via a computer - this requires the ability to code.
- A data scientist does not need to be a full blown software engineer, but needs to understand basic software engineering processes and skills (althought the more the better)
- Having an understanding of computers operate, the different pieces of hardware, and how to communicate with them will ultimately make life easier, and is necessary for applying algorithms at large

- A data scientist who cannot communicate effectively to a customer, within a team, across teams, or to leadership will have an extremely hard time completing projects successfully
- Consulting is one of the most important skills to have to not only advance your career, but to grow as a professional and be someone other people want to work with/for
- This is the one piece of a data scientist that is considered an art and not a skill, and usually individuals who come from a strong techincal background struggle with this the most practice makes perfect
- Motivate yourself to take constructive feedback and improve yourself in this area - you represent your organization and yourself