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Data Science Roles and the Types of Data Science Programs

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Abstract:

A growing field, data science (and, by extension, analytics) integrates concepts across a range of domains, such as computer science, information systems, and statistics. While the number of data science programs continues to increase, few discussions have examined how we should define this emerging educational field. With this in mind, during the 23rd Americas Conference on Information Systems (AMCIS'17), a panel discussion explored emerging questions regarding data science and analytics education. This paper reports on that panel discussion, which focused on questions such as what a data science degree is and what a data science program's learning objectives are. The panel also debated if there should be different types of data science-related programs (such as an applied data science program or a business analytics program) and, if so, should there be a common core across the different variations of programs. Information system educators who can gain a better understanding of current trends in data science/analytics education and other information system researchers who are interested in how data science/analytics might impact the broader field of information systems and management education should find interest in this report.

Keywords: AMCIS 2017, Data Science, Education, Analytics Education.

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1 Introduction

The data science field focuses on studying the computational principles, methods, and systems for extracting and structuring knowledge from data and applying and using those principles. Due to the increasing demand for data scientists and a data-literate workforce, colleges and universities have begun to develop and offer a growing number of data science programs (O'Neil, 2014). However, some researchers have noted that the education and training of data scientists currently lacks a commonly accepted set of learning objectives (Demchenko, Belloum, & Wiktorski, 2017). In other words, we lack commonly accepted norms about the learning outcomes for a data science program. In fact, many have expressed hope that we will soon more clearly understand what to expect in a data science program. For example, Majumder and Cheng (2017) note that "teaching courses in a data science program will face higher requirements as the definition of data science is refined". Hence, we need to discuss what constitutes a data science degree.

This paper reports on the results of a panel discussion on these emerging topics that took place during the 23rd Americas Conference on Information Systems (AMCIS'17) in Boston, Massachusetts. Specifically, it proceeds as follows: in Section 2, we provide some background information on the topic. In Section 3, we review the organization of the panel and, in Section 4, discuss the possible future demand for data science programs. In Section 5, we summarize the discussion with respect to the different types (or "flavors") of data science programs and, in Section 6, summarize the discussion with respect to the roles in a data science team and how they might relate to the different types of data science programs. Finally, in Section 7, we conclude the paper.

2 Background

While researchers have conducted some work on designing a data science curriculum (Ramamurthy, 2016; Asomoah, Doran & Schiller, 2016; Saltz & Heckman, 2016; Anderson, Bowring, McCauley, Pothering, & Starr, 2014), these previous efforts have not explored the difference between a data science degree, an applied data science degree, and an analytics degree, nor have they made any effort to take a holistic look about what should or should not be included in any of these programs. Others have studied data analytical programs, such as Strader and Bryant (2017), but not compared those programs to data science programs.

However, in the past year, researchers have started to at least broach the topic of what a data science program should include. For example, some have focused on the level of mathematics/statistics that a data science degree should require (Hardin & Norton, 2017) and argued that students who do not study math run the peril of black box thinking (e.g., with graduates who might use machine-learning algorithms but not understand the implications of doing so). In a similar fashion, Majumder and Cheng (2017) focus on the importance of information visualization in a data science program. Others still, such as Doan (2017), argue that we need to increase our focus on data wrangling.

Finally, the data science roles that a data science project requires and the skills that those roles require have also begun to gain increased attention (Lyon & Mattern, 2017; Saltz & Grady, 2017). These roles typically include statisticians, mathematicians, data engineers, data analysts, and data scientists. However, we do not know whether a data science program should address all of these roles or if each role requires a different academic program. We also do not know whether a single person might span multiple roles.

3 Organization of the Panel

The data science education panel focused on fostering a debate about the emerging field of data science/analytics education. The panel comprised experts who had extensive knowledge of both data science academic programs and and what organizations in practice desire and demand in their newly trained data scientists. Hence, the panelists could discuss the topic from both a practitioner and academic perspective.

The panel targeted information system educators who would benefit from better understanding current trends in data science/analytics education. Other individuals interested in data science or learning what it entails could also have found this panel of interest in that attendees could learn to appreciate how the trends in data science/analytics might impact the broader field of information systems and management education.

Specifically, the debate focused on questions such as what the key learning objectives for data science programs are and should data science/analytics education come in different “flavors” that lea to different degrees. Note that, for each of these questions, the panel did not make formal presentations; rather, each panelist took turns sharing their thoughts on each topic. In other words, the panel explored these questions via a debate, and, while the panelists provided the initial points of view, members in the audience also joined the discussion as equal participants.

4 The Demand for Data Science Programs

The panelists and attendees agreed that the demand for these types of programs has been real, which the large turnout for the panel certainly validated. They also noted that the wide range of well-paying jobs that recent data science/analytics graduates find after graduation has triggered much demand from students to obtain degrees in the field.

However, the panel did not agree about how the field would evolve. For example, some thought that the demand for data science and analytical degrees will decrease but that the demand for a more data-literate workforce will become pervasive. In other words, as one panelist noted, how the need is satisfied might change, but the need itself will not go away. In addition, a different panel member cautioned that companies still struggle to get value from their data and so the field has room for growth, though the panel member noted the possibility that organizations could become disillusioned with data science and scale back their data-driven investments. In the end, the panel seemed to generally feel that demand for data science courses would continue to increase, but some thought that a plateau in the number of students who want to earn a degree in data science might emerge. In contrast, others felt that data science would emerge as a stable new domain with a steady stream of students who remain interested in data science programs.

5 The Different Flavors of Data Science Education

The panel spent much time discussing the different types of data science (or data analytics) programs. Panelists noted that multiple types of data science programs already exist. One panelist (Sharda) even joked that perhaps “50 shades of data science programs” (across statistics, math, business schools, computer science, operation research and many other departments) exist. Granville (2014) notes six to nine categories of data scientists. Hence, researchers have already answered the question as to whether multiple flavors of data science education should exist in the affirmative. However, the panel noted that the field lacks a consistent vocabulary to describe these different programs. Given the current situation, where we do not have a common vocabulary, each person (students, employers, faculty members) on their own needs to figure out how the different programs fit into their needs and desires, which leads to the potential of a mismatch between interests and sills. For example, a student might have been taught in one type of data science program but an organization might think it hired a person with a different set of skills.

5.1 Defining the Different Types Data Science Programs

As we note above in exploring the different types of programs, programs differ in terms of the level of programming proficiency and the amount of statistics knowledge expected from program graduates, which impacts a student’s ability to wrangle data or build new machine-learning algorithms. On the other hand, programs that focus less on programming typically have a higher focus on the ability to understand the client domain and how one might leverage data for actionable insight.

While an almost infinite set of variations with respect to the types of data science programs may exist, at a high level, a panelist suggested that the different data science programs might be analogous to the difference between MIS and CS programs in terms of technical depth and the focus on business analysis. In a similar vein, a different panelist agreed that one could trace much of the difference in programs to the department that sponsors the program. Many business schools, for example, offer a more business-focused degree, while computer science departments offer a more technical program. However, different universities do not consistently use the names of the programs, such as data science or data analytics.

During our discussion, we defined and described three different flavors of data science programs. These three types of programs varied from a technical focus at one end of the spectrum to a business analysis/client focus at the other end. These three programs, which we refer to as data analytics, applied data science, and foundational data science, all provide an understanding of data storage and access, data wrangling and data mining but at a different level of technical depth (see Figure 1 for a summary).

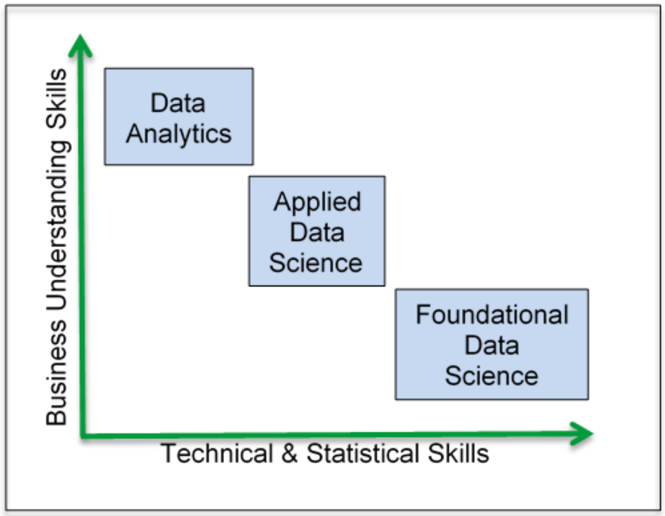

Figure 1. Exploring Three Data Science Programs

At a high level, all programs have similar objectives, such as ensuring that graduates can generate insight from data via visualization and machine learning, can obtain actionable insight that an organization will find useful, and can understand the potential bias that might impact an analysis and how to wrangle/clean the data. However, each of the programs has a different focus/depth. In this section, we briefly describe each program.

5.1.1 Data/Business Analytics

Data (or business) analytics programs, which business schools often teach, focuses on ensuring that students know how to use data science and data analytics concepts to obtain a competitive advantage by enabling them to best understand the business context of how they might leverage data and present insights to key decision makers. These programs strongly emphasize “soft skills”. They should teach students to use high-level tools such as Tableau, SAS, and IBM SPSS Modeler to generate data insights. Essentially, a program in data analytics enables a student to use pre-existing tools and develop basic scripts (often in a language such as R and Python). Some panelists noted that the use of R for developing basic scripts represents a growing trend in business analytics programs, but others cautioned that programming does not represent a key aspect of this program type. However, most agreed that these programs would not develop students capable of filling programming positions. This program type has two key advantages: it is open to a broad range of non-technical students, and it teaches students how to apply data science concepts in a business context. Such programs are also likely to become specialized in particular domains such as health analytics, sports analytics, marketing analytics, location analytics, and so on. However, these programs’ ability to teach students to translate business problems into potential analytics projects and, conversely, the results of analytics projects into insights for decision making represent their most critical success factor. Thus, these programs need to teach visualization and communication skills more than the other types of data science programs.

5.1.2 Applied Data Science

Applied data science programs have a more technical focus as compared to a data analytics program and enable students to use advanced data science techniques to generate insights from data. Students in this type of program typically use programming languages such as R and Python to wrangle data and can create advanced scripts to do, for example, machine learning using the extensive set of available libraries in R and Python. An applied data science program provides students with the technical depth to develop proficiency in languages such as R and Python so that they can effectively perform tasks such as data wrangling and more advanced machine learning. This type of program also typically exposes students to big data techniques and technologies, such as Hadoop, but it does not produce big data developers. In the end, this type of program does not focus on teaching students to develop new machine-learning algorithms but focuses on applying the full range of data science concepts to deliver actionable data insights. These programs typically focus on data engineering such that students can bring data from multiple sources together through various APIs, optimize the data storage, and perhaps also focus on real-time applications of analytics through productizing the applications. Due to the growth of data science offerings through cloud-based platforms, individuals with skills from these programs also need to be conversant with cloud-based applications. In many applications, they also need to interact with domain experts, so they need soft skills as well, although less so than individuals who undertake data (or business) analytics programs.

5.1.3 Foundational Data Science

Foundational data science programs focus on teaching advanced programming, mathematical, and statistical knowledge so that graduates can develop new and enhanced machine-learning algorithms or models. Graduates from these programs should know how to use advanced programming, operations research, and/or statistics to generate new machine-learning algorithms. Graduates from these programs should also understand and use the technical stack required to analyze very large data sets and be able to enhance these big data technologies. While these students will typically have less exposure to the business context of data science, they should be able to provide tools that other data scientists and data analysts can leverage in their analysis.

5.2 Key Learning Objectives

As we note above, all the programs have similar high-level learning objectives. The panel generally agreed that all data science programs should prepare students to collect, organize, and manage data and to identify patterns in the data using a combination of visualization, statistical analysis, and data-mining techniques. In fact, even though the panelists discussed a broad range of programs, they agreed that, at a high level, all programs have similar objectives, which includes the ability to generate insight from data via visualization and machine learning, to produce actionable insight that organizations find useful, and to understand potential bias that might impact the analysis and how to wrangle/clean the data.

However, the question about the most important skills that students should acquire in a program saw much more debate mostly (again) due to due to the different flavors of data science. Some programs, for example, try to ensure a high level of technical competence in areas such as the establishing new statistical models, implementing new machine-learning algorithms, and optimizing existing machine-learning techniques. Other programs focus on teaching students to understand business processes and possible data sources and to effectively communicate with people working in other fields.

In any case, the panel clearly agreed that one program could not cover the full range of potential learning outcomes. In other words, one program cannot and should not cover all the skills that all possible roles in a data science team require. Since the programs have a different focus/depth across a range of skills, they will have different learning outcomes even though they may have similar high-level learning objectives. For example, while the panel agreed that all data science programs need some level of programming, the level varied from high-level scripting to significant programming capabilities. In the end, the panel agreed that the depth of the learning objectives for a data science program depended highly on the type of the data science program.

Table 1 shows the learning outcomes that one can typically find in the different data science/analytics programs and the level of depth/focus for each type of program’s learning outcomes. In the rest of this section, we briefly describe each of these learning outcomes.

- **Assess an organization’s data analytics needs**: explain how to use data assets to develop a competitive advantage.
- **Collect, clean, organize and manage data**: how to collect, clean, and prepare data that one might leverage in a data science analytical technique or visualization (includes evaluating the data in terms of source quality and its volume, frequency, and flow).
- **Identify patterns in data**: identify and classify relevant variables for data science tasks using various machine-learning techniques. Be able to choose and apply the appropriate tools and methodologies to solve data science tasks and assess the models used to solve data science tasks.
- **Develop new machine-learning algorithms**: create new algorithms or improve existing algorithms such that other data scientists can leverage them.
- **Create actionable insight**: ensure that organizations find the analysis results useful and that they can lead to changes in organizational strategy and plans. More generally, integrate data science capabilities into the formation of a situation analysis. Identify and appraise the

leadership and management skills required to direct a team of data science professionals toward meeting organizational goals.

- **Communicate the findings**: write and orally communicate technical materials at an appropriate level of technical/mathematical level of detail. Specifically, help non-technical professionals visualize, explore, and act on data science findings.
- **Integrate ethics and privacy information**: identify and analyze social, legal, and ethical issues that might arise during a data science/analytics project. Specifically, be able to interpret the activities and choices of the team in an ethical framework and determine an appropriate action based on standards of professional conduct.

Table 1. Data Science/Analytics Learning Outcomes

	Data analytics	Applied data science	Foundational data science
Assess an organization’s data analytics needs	●	⭘	○
Collect, clean, organize and manage data	⭘	●	⭘
Identify patterns in data	⭘	●	●
Develop new machine-learning algorithms	○	○	●
Create actionable insights	●	●	⭘
Communicate the findings	●	●	⭘
Integrate ethics and privacy information	⭘	⭘	⭘
Key: ● deep focus, ⭘ some depth, ○ not a program focus.			

5.3 Comparing Technique and Tool Exposure

In addition to analyzing learning objectives, one can also explore the level of focus a program has on the various data science techniques and tools that one might leverage in a data science project. In this section, we briefly describe some of the key techniques and associated tools. Table 2 shows the level of focus for each of these key techniques for each type of program.

- **Business analytics**: iteratively exploring an organization's data with an emphasis on statistical analysis to enable data-driven decision making. Often done using Excel spreadsheets.
- **Data management**: the tasks and processes relating to acquiring, validating, storing, and protecting data so that it can be accessed in a reliable and timely manner for future analyses. Often involves using large databases and database languages such as SQL and noSQL.
- **Data integration**: combining data residing in different sources, such as multiple distributed databases, and providing a unified view of that data. Often done using tools such as Informatica PowerCenter or custom coding solutions.
- **Programming**: enable the creation of custom data cleaning and data analytics. The two most common programming languages for data science/analytics are R and Python.
- **Machine learning**: via creating analytical models, machine-learning algorithms focus on generalizing beyond the provided training data to predict the outcomes of additional data samples. Models used include supervised (e.g., support vector machines, neural networks, and logistic regression) and unsupervised (e.g., k-means clustering, association rules mining) learning algorithms.
- **Data mining**: using machine learning, statistics, and visualization to explore patterns in the investigated dataset.
- **Big data tools**: a collection of data sets so large and complex that one cannot easily process it using traditional applications/tools; hence, new tools and technologies, such as Hadoop (HDFS and MapReduce) and Spark, help one analyze these datasets.
- **Visual analytics**: analytical reasoning facilitated by interactive visual interfaces with which one can identify trends, patterns, and relationships in the data by using visual analytics software tools, such as Tableau, that make it easier for non-technical users to quickly gain insight via visually analyzing the data.

- **Client management**: understand the domain and be able to work with the client from inception to completion. Techniques include storytelling and analytical results presentation.

Table 2. Summary of Program Focus on Different Techniques and Tools

	Data analytics	Applied data science	Foundational data science
Business analytics	●	◉	○
Data management	◉	◉	◉
Data integration	○	◉	●
Programming (e.g., R and Python)	○	●	●
Machine learning	◉	●	●
Data mining	◉	●	●
Big data tools (e.g., Hadoop)	○	◉	●
Visual analytics (e.g., Tableau)	●	◉	○
Client management (soft skills)	●	◉	○
Key: ● deep focus, ◉ some depth, ○ not a program focus.			

6 Roles and Programs

Finally, a different thread of the discussion focused on describing these programs based on how they support the different types of data science roles, such as data engineer and data scientist. Hence, understanding the roles that a data science project requires and mapping them to the different flavors of data science programs can help one when discussing what a data science degree involves.

6.1 Roles on a Data Science Team

Researchers have described roles in a data science team across many contexts. For example, Saltz and Grady (2017) review roles as described by standards organizations such as the role descriptions from the EDISON project, an European Union-funded effort to increase the number of competent and qualified data scientists across Europe (Demchenko et al., 2016), and also how industry currently uses them, such as from Gartner (Linden et al, 2016), a consulting firm that specializes in strategic advice to business officers such as chief information officers.

Based on how previous research has analyzed these roles, a set of typical roles in a data science team might include the following.

- **Data scientist**: finds and interprets rich data sources, merges data sources, creates visualizations, and uses machine learning to understand data. Knows about the end-to-end process and can present and communicate data insights and findings to a range of team members.
- **Data science researcher**: builds mathematical models and advanced machine-learning algorithms. Can apply the scientific discovery research/process, including hypothesis and hypothesis testing, to obtain actionable knowledge related to a scientific problem and/or business process or to reveal hidden relations between multiple processes.
- **Data science architect**: designs and maintains the architecture of data science applications and facilities. Creates relevant data models and processes workflows.
- **Data engineer:** makes the appropriate data accessible and available for data science efforts. Designs, develops, and codes data applications for capturing and analyzing data.
- **Data/business analyst**: analyzes a large variety of data, often using visual tools, to extract information about system, service, or organization performance and present the analysis in a usable/actionable form.

Table 3 summarizes how these roles could map to the different types of data science programs. While not all panelists agreed on the actual mapping of roles to the different programs, they agreed that a data science team involves different roles and that different programs focus, sometime implicitly, on these different roles.

Table 3. Roles and Types of Data Science Programs

	Data analytics	Applied data science	Foundational data science
Data scientist	↓	↑	↑
Data science researcher	↓	–	↑
Data science architect	↓	–	↑
Data engineer	↓	↑	↑
Data / business analyst	↑	↑	↓
Key: ↑ Strong match, – general match, ↓ weak match.			

7 Conclusion

In summary, in exploring the different variations of data science programs, the panel identified three types of programs: data analytics, applied data science, and foundational data science. Program leaders in domains related to data science may find this report useful in that it provides a framework to describe, and perhaps shape, their programs. Other information system educators and information system researchers could also leverage the discussion since it provides some context for data science education and the roles graduates of these programs can fill.

One can understand the different types of data science programs based on their learning outcomes. While the different types of programs have similar high-level learning objectives, they vary in how deeply they focus on them. In general, data analytic programs focus more on business understanding and less on technical skills. Foundational data science programs, on the other hand, focus much more on the technical skills required to develop new machine-learning algorithms. Applied data science programs try to balance these two alternatives and, thus, provide the technical skills to collect, clean, and wrangle data and to use advanced machine-learning techniques but not to develop new data science algorithms.

One can also understand the different types of programs based on which data science team roles the programs could support. For example, employers might focus on hiring data analysts from data analytics or applied data science programs and hiring data scientists from applied and foundational data science programs. However, universities currently do not typically leverage these roles in describing their programs, and many programs with similar program names target different roles.

Note that the panelists briefly discussed two other topics towards the end of the session. Panelists noted the first topic, ethics, to be very important. As the data science field becomes more mature, ethics becomes more important, and the range of ethical situations in data science is much broader than in computer science. However, the panelists generally felt that many programs do not adequately address this topic in their curriculum, which Table 1 reflects. The panelists also discussed the importance of introducing the concept of data science (or analytics) to the broader student population. For example, one panelist suggested that all business school students should have exposure to it (Excel spreadsheets, Tableau visual analysis). The discussion touched on the applicability of a university's introduction to data science course to the broader student community. One school of thought was that one course could support the needs of a data science program and the general student population. However, others noted that perhaps a difference course would be more appropriate (similar to the situation with many topics, such as computer science and mathematics). However, the panel did agree that the broader student population should have exposure to data science; some even went as far as to suggest that all students in a university should have to take a basic data science course. Also, for educational institutions with limited technical resources, cloud-based analytics platforms provide an attractive alternative to onsite hosting.

While the panel did not have time to discuss the topics that a more broad-based course should teach, the spirit of the discussion was that the course should cover basic data analytics and not require advanced programming.

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Jeffrey S. Saltz is an Associate Professor at Syracuse University and is the faculty lead for their Applied Data Science graduate program. He teaches data science to both graduate and undergraduate students and is the coauthor of *An Introduction to Data Science* (Sage), a new data science textbook. He led the development of the university's Applied Data Science graduate degree and has also been part of the team that defined their Data Science graduate program and a different team that defined their Business analytics graduate degree. His current research focuses on the socio-technical challenges of data science projects, such as how to coordinate and manage data science teams. Prior to joining Syracuse University in 2014, he spent 20+ years in industry leveraging emerging technologies and data analytics to deliver innovative business solutions.

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