Emergence of Data Analytics in the Information Systems Curriculum

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Abstract

As a phenomenon of interest, impact, and import, there is little doubt that the pervasive expansion of data is upon us as Information Systems educators. Concerns and topics such as Data Science, Data Analytics, Machine Learning, Business Analytics, and Business Intelligence are now ubiquitous and often situated as being the "next big thing." Educators and practitioners who identify and resonate with information systems, as a discipline, are watching these developments with interest. With data being both input and output to so many concerns that intersect with the information systems discipline, several themes emerge when considering what curriculum and pedagogy are appropriate. The role, position, location, and shape of data science topics are considered. Curricular approaches are also discussed with an eye to breadth and depth. Fundamental and existential questions are raised concerning the nature of data science and what role the Information Systems discipline can play. We also discuss evidence from cases one involves a student business analytics competition and the other is researching a topic to offer insights as to how information systems knowledge areas can appropriate data science as an integral component of many competencies that are already considering solidly within the canon of IS topics.

Keywords: IS Curriculum, Data Science, Data Analytics, Machine Learning, Business Analytics.

1. INTRODUCTION

Big Data, Data Science, Data Analytics, Machine Learning, Business Analytics and Business Intelligence are becoming normal terms in the discussion of unfolding horizons that impact organizations, their use of information technology, and their expectations of it. These are elusive terms. They mean different things to different constituencies (O'Neil 2014).

We use the terms machine learning, and data science to highlight the Statistics-Math-algorithmic and the Computer Science aspect of the discipline where the theory is established and the algorithms are coded. We use the terms Data Analytics, Business Analytics or Business Intelligence to emphasize the applications side of the discipline where algorithms are understood, the underlying computing software is comprehended and utilized to solve business

problems, reveal patterns and extract insights from the data. This paper focuses on Curriculum issues as they relate to data (business) analytics. We will use Data Analytics to mean both data and Business Analytics

Simon (2013) describes data analytics as "…the combination of statistics, mathematics, programming, problem solving, capturing data in ingenious ways the ability to look at things differently and the activity of cleansing, preparing and aligning data.". Conway (2010) summarized it as the intersection of Hacking Skills, Math & Stats and Substantive Expertise. His Venn diagram elegantly and colorfully draws the boundaries between Machine learning, Traditional Research, Data Science and the danger zones. Figure-1 is a testimony of the many intersections of disciplines. For example, a self-driving car or a pattern recognition system is machine learning; however an Amazon recommender system or a system that is used to reveal patterns is data analytics. Figure 3 is an illustrative attempt to disambiguate the problem space.

Since 2000, data analytics have evolved from just having an elective course in an Information Systems (IS) Curriculum (Lenox 2002, Goharian 2004, Jafar 2008, Asamoah 2015) to offering a degree program. However, the content of the curriculum (or even the individual courses) has not been stream-lined as in the case with degrees in finance, accounting, marketing … Although we see the need for an extended minor, and/or an undergraduate degree in data analytics in the IS curriculum, in this paper we articulate the case and the requirements for a Master's degree in data analytics within an IS degree program.

As an inter-discipline, IS has commonly absorbed innovations over its history. It is quite normal for IS to develop existential conversation when new waves of innovation impact its shores. However, as a bridging discipline, between organizations, people, information and computing technology, data and quick and accurate insights into it is foundational to who and what IS is in an acute sense.

Neutering the Discipline
Data is in the very bloodstream of an organization, It cannot be pinned down to a single discipline. Every aspect of business, government, science, humanities, medicine, etc. has both a data and an analytics component. Further having emerged out of the various schools of business concerns, IS has always had a central focus on data and its processing.

Rhetorically, we can ponder "what do transaction processing and analytical processing have in common and where do they bifurcate?" Arguably, their intersection and union revolves around data. Transaction processing uses business models (rules) to manipulate the data, analytical processing relies on wider ranges of data including transaction processing and digital sensors (Social media, web, apps, government, commonly available). Analytical processing uses statistical models to sift through and extend the use of transactional data to produce insights and reveal patterns. We may even argue that analytical processing would not have existed if it was not for the maturity and openness of transaction processing systems. The Not Only SQL model (NoSQL), is nothing but the relational model extended.

Rush to Discipline
All of the business disciplines are exuberant over the prospects of data analytics. Further, this exuberance is leading to a rapid refashioning towards data analytics, up to and including the development of new programs. We could see a situation where no two Data Analytics degrees are the same as the tenets of the discipline are not focused, defined, or agreed upon. In many cases, this problem persists with IS discipline at large.

This leads to questions regarding who "owns" the data analytics topic. In academia, we can posit that one common point of contention in academic institutions these days is the issue of ownership and where should the different courses be housed. What extents should be housed in computer science, mathematics, statistics or IS programs. We can even ask where interdisciplinary programs such as text analytics and social networks analysis should be housed. In the Kuhnian sense (2012) however; the ebb and flow, and evolution and emergence of disciplines is according to paradigmatic shifts. Disciplines flourish or famish according to need and environment, but also fad and fashion. Thus the ownership question remains. Whether computer science calls it machine learning or data science, math-statistics call is data science or data analytics, or IS programs call it data analytics or business; we acknowledge the fact that although the different disciplines have the same concerns, they have different focuses.

Fundamentals
In this paper we examine the nature of the plethora of concerns, trends, emerging disciplines, and other phenomena surrounding this rush to data. We consider data analytics in

terms of its first principles, and contrast and compare these first principles to those of IS.

Let us reflect on the circular relationship between transaction processing systems and analytic systems. To build transaction processing applications, data, business logic, and presentation are core concerns. To build analytical processing applications, data, algorithms, model validation, discovery, insights and presentation are core concerns. Further, we can characterize transaction and business processing algorithms as a transparent and open box, whereas analytic processing can be seen as a translucent black box. In both cases, core concerns remain data design, gathering, repurposing, conceptualizing, storing, retrieval, manipulation and presentation. Some common present day use cases come to mind and this use case belies the complexity and systems knowledge required to function effectively. Take the case of an association Rules (Recommender) System: Say

- Using R, prepare the data so it is a transaction.
- Clean up the data to establish non-duplicate items in a basket. Try to interpret the results.
- Grapple with incompatibilities between package versions and R-Versions as the project evolves.
- Often, the data is a mess and error-prone as given. Null values, type mismatches, and other data quality issues may take hours or even days to correct.
- Data consolidation and exploratory data analysis is challenging and may require a variety of tools (R, MySQL, Excel, Excel pivot tables and tableau).
- Multi-tasking and high task saturation commonly accompanies the above steps in an iterative nature where jumps among the steps are common.
- We may also think that a transaction processing system provided input data to the recommender system.

Thus, actionable results are not simply a matter of firing up a data analytics computing engine, connect to data, and display tidy results in a dashboard. Rather, it is a matter of integration. Classic problems related to software engineering and IS development are readily evident. Basically a data analytics project is just another software engineering project where different people with different skills work together to produce a software product.

This narrative gives way to the central theses of this paper:
- What is data analytics

- What does data analytics hold for IS, and vice versa?
- How have colleges and universities met the growing demand for data analytics skills?
- What is a good IS approach to incorporate data analytics into the curriculum?
- What have we learned from early experiences?

These questions come full circle to our context of IS education as we must decide how, and to what extent, will data analytics pervade the discipline? There are even questions related to the appropriate level for engaging data analytics. Should data analytics gravitate more towards a graduate-level concern? At the graduate level, given the demographics of the students, we may focus on skill building and expanding the boundaries of their technical skill knowledge, contrasted with their foundations in a given subject matter area of expertise (medical, financial, marketing, education, learning, etc.). At the undergraduate level, there may be the need of so many foundational systems development topics such that the data analytics path may not feasibly or fully explored. There is also a level of intuition, driven by tacit knowing and acumen in subject matter expertise that is wrought through long-term exposure to data. This is evident from the diversity of the degree programs in the area.

2. ARTICULATING A DATA ANALYTICS CURRICULUM FOR IS

As there are heterogeneous inputs to, and consumers of data analytics, it is natural for many disciplines to become involved with data analytics and otherwise appropriate its benefits to suit their ongoing core dialog. As such, given the nascence and emergence of the "field" it is difficult to know where data analytics should be at home, or, should we accept it as a new discipline, as was afforded to IS at one time.

As such, degrees in Data Analytics are elusive as they cross-cut multiple concerns (Figure 1). Upon early inspection, one would find that there is no uniformity in the course offering of such degrees across Universities (content, course descriptions, requirements, prerequisites and transferability). Whereas more established disciplines - Marketing, Finance, Computer Science, and Political Science - have established a reasonable degree of consistency in their curricula.

While data analytics is certainly consistent with most Universities' mission statements, there are no clear imperatives that compel data analytics to locate in one area or another. Furthermore,

even the modalities of delivery are neither suggestive nor limiting. Accordingly, digital learning, on-line programs, graduate programs and service to the local community – to attract professionals, continuing and life-long learners, or even alumni – are all also neither prohibitive nor suggestive. This paper's authors attempt to articulate a proposal of what a master's program in data analytics might look like. This section will proceed to share the broad strokes of the proposal to share our discoveries.

Program Modalities
Increasingly, accommodating a wide variety of delivery modalities is necessary. Thus, any of the following modalities is recommended:
• An on the ground program
• An On-line program
• A hybrid of on-line and on the ground program

Proposed Degree Requirements
For the purpose of this paper, we surveyed more than 13 graduate programs that offer graduate degrees in Data Analytics, Data analytics, Business Intelligence or Business Analytics and more than and 8 undergraduate programs. We compared the content of their courses, pulled as many syllabi as we could, read and compared their course descriptions. We selected what we thought is a representative sample. We summarized and compared their course contents. Although all of these programs share a common theme, the structure of the curriculum, the course requirements, prerequisites, course descriptions, computing technologies, focus and depth of offering widely varied. We offer this as an indication of a discipline in flux and under formation. The findings of this analysis are shown in Figure 2. It is a summary spreadsheet of the 13 programs that we thought are most relevant.

From our review of these programs, the following curricular pattern emerges. Programs typically require a total of 30-36 credit hours as follows: 21-24 core credits + 6-9 Approved Elective credits + a 3 credits Capstone Course.

Students from a computing discipline such as Math, CIS, CS, Statistics may have 6 approved credits waived if they have completed the equivalent course work with a B grade or higher. Candidate courses are Programming, Data Management and Statistical Data Analysis. The courses for the degree are grouped into 5 separate categories as follows:
• Core Data Management: 3 Courses
• Core Statistical Data Analysis: 2 Courses
• Core Data Analytics: 2-3 Courses
• Core Capstone Course: One Course
• Electives from a List: 2-3 Courses

Pre-Requisite Knowledge
Fundamental prerequisite knowledge from an undergraduate (or graduate if 2nd masters) education would include knowledge: of programming, statistics, and calculus. For students who do not have the background knowledge, they would either take leveling courses or use identified bridging courses which may include approved MOOC courses where a certificate is offered to satisfy the prerequisites can be obtained.

The Graduate Education Component
1. Three Core Data Management Courses

1.1 Programming for Data Analytics
Prereq: Basic Programming Knowledge

Description: Reading data from different data sources & streams such as files, web-searching, etc. Organizing, manipulating and repurposing data. Parsing-in and storing-out data JSON formats, string manipulation using RegEx libraries, Sets, Arrays and dictionaries.

Technology: Python, RegEx, DOM, JSON.

1.2 Data Management for Data Analytics
Prereq: Programming

Description: Fundamentals of sound database design, storing, manipulating & retrieving data, Conceptual Data Modeling, SQL, Functional Dependencies, Data Normalization.

Technology: SQL, MySQL DBMS, MySQL Workbench, ER-Modeling tools.

1.3 Data Visualization for Data Analytics
Prereq: Programming & Stats-I

Description: Provide an understanding of the different data types and their encoding schemes. Learn data visualization principles and Mantra(s). Learn how to tell a story through data. Learn how to detect insight through data, learn and utilize current technologies to visualize large data sets for the purpose of providing insight.

Technology: Excel, Tableaux, Web-GL, D3.JS

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2. Two Core Statistical Data Analysis

2.1 Statistic-I for Data Analytics
Prereq: Business Calculus

Description: Probability distributions and their applications (geometric, binomial, Poisson, uniform, normal, exponential, t, F and Ki-Squared), Sampling Statistics, Confidence Intervals, Hypothesis Testing, Analysis of Variance and Linear Regression Modeling

Technology: Excel, R and R-Packages.

2.2 Statistic-II for Data Analytics
Prereq: Statistics-I

Description: The different types of Regression Models and Time Series forecasting. The course emphasizes statistical computing.

Technology: Excel, R and R-Packages.

3. Three Core Data Analytics

3.1 Principles of Data Analytic
Prereq: Stats-I, Data Management

Description: Exploratory Data Analysis, Statistical Models, Classification and Prediction, Clustering Analysis, Similarity Measures, Fitness of Models, learn how to use machine learning technologies to analyze data for the purpose of decision support.

Technology: Excel, R and R-Packages.

3.2 Advanced Data Analytics
Prereq: Data Analytics-I, Stats-II

Description: Optimization Models, Social Network Analysis, Text Mining, advanced Analytics Algorithms like SVM, Neural Networks, bootstrap models, Model Validation.

Technology: R, R-Packages, Gephi Gephi (Bastian 2009) & NodeXL.

3.3 Big Data Analytics
Prereq: Data Analytics-I

Description: Big Data Meets Data Science, Meets Data Analytics. Map-Reduce Model, Apache Spark, Mongo DB, NoSQL Model and Scale out Models.

Technology: Cloud Computing, Apache Spark, MongoDB.

4. Capstone Course

4.1 Capstone Course
Prereq: Data Analytics-II & Data Viz.

Description: Special Topics in Business Analytics with a comprehensive real world project, the project usually extends over 2-terms, a summer and the fall or the spring and the summer. Although the topics of the course are taught by one faculty and during one semester, a student might be working with another faculty from the program or from an approved discipline on their project. The project may be in collaboration with a partner organization or a business.

Technology: Whatever is needed for a successful project portfolio

5. Three Elective Courses (More electives can be added)

5.1 Legal and Ethical Issues of Data
Prereq: Data Management

Description: Provide an understanding of the legal and ethical issues as it relates to data storage, retrieval access and sharing as well as analytics models. copyright law, legal and ethical ramifications are at issue when recommending choices that have economic, social, environmental or legal impacts.

5.2 Project Management
Prereq: Data Analytics-I

Description: A data analytics project is just another software engineering project that will culminate in a software product. Deliverables, artifacts, timelines and resources need to be tracked and managed.
Technology: Project Management Software.

5.3 Decision Modeling
Prerg: Programming-1 and Stats-1

Description: Understand, formulate, solve and analyze optimization problems in the business domain and its operations. Utilize excel functions and macros to perform what-if analysis. Understand the geometric interpretation of linear optimization problems, Use solver family of packages to solve linear optimization problems. Formulate and solve Network graph types of problem especially in the social media domain.

Technology: Excel, Solver, Gephi.

In figure 4 a visual of the course sequences and their dependencies is presented.

3. TESTING THE ASSUMPTIONS – LESSONS LEARNED FROM TWO CASES

Student Data Analytics Competition Case

We continue our inquiry with a case description that illustrates some of the points made thus far about the nature of a data analytics curriculum and its relationship to the IS curriculum. The case is situated about a student data analytics competition held in New York City in the spring of 2016. The objective of the 2-day student competition was to provide insights into a data-set that was made available from an online discount retailer that aggregates luxury brands and offers them at discounted prices. The student team had 10 weeks to produce a poster that explains the nature of the data, the problems that surround it, and their insights into the data. The team's mentor (a coauthor of the paper) provided guidance and acted as a chief architect, coach, and project manager for the team. At the competition, the students presented their poster to a team of judges. Subsequently, after this initial round of judging, the students are given a new related data set that the team has not seen previously. Each team then had 12 hours in a reserved space to analyze the new data set to develop new insights, prepare and submit a presentation the next morning (No communication with the mentor was allowed). The team would then deliver a 10-minute presentation to a team of judges. Both the new analysis and preparation must have been completed within the 12-hour overnight period. There were 18 teams competing from various North American universities.

The crux of the competition is to use the given data, and the context of the company providing the data, to bring technical solutions to business problems. During the 10-weeks period, the students and mentor approached the problem as though it were an IS development, project which requires: planning; skills development; computing resources; produce artifacts and deliver a product. The team of interest consisted of juniors and seniors, 3-members total. Collectively, the team demonstrated sound business, analytical, technical skills and dedication. Salient to the competition, two students were enrolled in a data mining course during the semester of the competition. Relevant course topics included data mining applications, algorithms and technologies (using R, R packages, and Tableau). Further, at the start of the project, the team was already familiar with Python and its APIs, Data Modeling and SQL, SAS, R, Tableau, and everyone knew Excel very well. From an Analytical perspective, the team was familiar with data modeling concepts, business statistics, statistical modeling, Finance, Marketing, etc.

As the project progressed, the team's depth of knowledge matured as well as an increasing awareness that more concepts, knowledge, and technologies were yet to be learned. Concomitantly, as their semester in data mining wore on, the team acquired more in-depth knowledge of R's data mining packages, ggplot (a graphing and plotting package for R), and Tableau (for visualization and visual analytics) Furthermore, the students learned SQL-Server Analysis Services Business Intelligence platform and heavily utilized it into their analysis.

The poignant aspect of this case is the wonderful outcome whereupon this team won first prize in the competition. Thus, we present the case not only to characterize and celebrate the student accomplishment, but to highlight what can be learned from this experience on these main grounds:
• What can we generalize from the experience about a successful data analytics project?
• What are the implications of these generalizations on a data analytics curriculum?
• How can IS the discipline at large, incorporate data analytics into the curriculum?
• Lastly, what does IS have to offer to data analytics?

Upon reflection, the ingredients of the students' success can be attributed to the mix of student talent, mentoring, technology infrastructure, competency in underlying computing technology, and the utilization of data analytics skills with an eye for the foundational business problem. That is, the combination of these factors put these students in a good position to prevail.

As we generalize from the student's experience, it is important to note that the accomplishment and win was 100% their own work. Grappling with the new data set, the 12-hour overnight drill, the insights produced, and the quality of the presentation was accomplished with no input from the mentor. While orientation, training, coaching and mentoring all occurred in the lead up, the student team ran the relay race.

Lessons from the Case

While the lessons from the case are myriad, a standout lesson certainly lies in the blend of skills utilized, the quality of the individuals

involved, and the overarching perspective assumed throughout the competition.

First, the success of the project was certain accorded to focus on the correct tools such that the true nature of a data analytics project is clear – it is still largely a software and systems problem. Tools to analyze, clean, prepare and repurpose the data were required in addition to knowledge about the nature of data – that the data requires review, cleaning and preparation.

Further, a business and subject-matter orientation was adopted, which is often characteristic of many contemporary software and systems approaches – early and iterative delivery of working artifacts in close cooperation and partnership with stakeholders.

Next, the team was aware of a blend of competencies that we can generalize away from the competition setting and to several emergent concerns. The team understood the importance of APIs – addressing them, consuming them, integrating their outputs into their analysis system, understanding how API inputs could emanate from their system, etc. Often, these APIs are consumed through calls to REST services where JSON is the carrier of the data. The team understood the general processes surrounding software and systems development as well as the concepts, tools and techniques of data analytics. For modeling, statistics were important as well as the modeling techniques inherent in data mining. Finally, business acumen – an awareness of the business context of the problem and the need to integrate business-oriented decision-making into and out of organizational management IS – was a significant success factor. Through the poster and the presentation, they were able to tell a story, reveal patterns and provide insights.

Some of the final lessons from this case pertain to curricular and disciplinary concerns. In a previous section, the outline for a graduate curriculum in data analytics was supported by the outcomes of the case. The curriculum for data analytics must blend data management, traditional system development, data and statistical modeling, and the business context. As is the case with computing, software, and systems, these elements span a spectrum where a universal curriculum of data analytics may not coalesce cleanly. Some of these concerns may lean considerably into traditional computer science and software engineering and yet others may lean towards the spaces occupied by IS. Additionally, some of the modeling may lean toward operations research. In the discussion,

we shall elaborate further on how the bridging and spanning nature of the IS discipline are well-suited to provide leadership as data analytics emerges as an ongoing concern.

Twitter Text Analytics Case
This case is an exposition on the requirements for a twitter text analytics project. This is shared to highlight typical challenges faced when undertaking a type of project typically used to characterize the power of data analytics. We highlight the challenges in what seems, on the surface, to be a simple and straightforward endeavor – using well-documented APIs to bring Twitter data into an application or data analysis context.

Twitter data are ready, as is, for text and social networks analytics is a widely held misconception. Some software package like *NodeXL (Hansen 2011)*, attempt to provide easy and straightforward access in the social network of a tweets dataset. However, in our experience, the matter is not simple unless the requirements for analysis are superficial. That is, repurposing Twitter data sets so it is ready for analytics, requires a wide variety of skills. Skills in programming languages like Python, in statistical packages like R and text analytics packages like R-tm. Occasionally web-development skills are required for DOM scrapping of web-pages. This does not even account for the set of skills required to build effective systems for reporting, integration, and other interactions required to make use of this knowledge. Commonly, Twitter allows access to their data in multiple modalities:

1. ***Through the web-interface***: Users search content based on screen-name, hashtags, mentions, body of text, etc. They can read content, take notes, print pages, type counts (favorite, retweet, etc.) into an excel spreadsheet. Content is not captured into structures in digital formats where it is easy to manipulate. This has disadvantages based on how cumbersome this process is when large datasets are desired.

2. ***Through the Twitter-API(s)***: These are well documented and afforded programmers with extensive real-time access to Twitter's data. For instance, a programmer may use Python to retrieve JSON data structures which can be passed on to R for analysis. Some of the challenges with this modality would be learning the protocols of the Twitter-API, communicate, request and store the content. It is important to note that these are

significant computing skills that need to be acquired in order to utilize this modality.

3. ***Subscription and purchase***: Based on usage agreements, users can purchase content from Twitter subsidiaries. Usually content is delivered in file fragments where each file may contain a bundle of tweets in JSON format plus some other trailing file meta-data that needs to be cleaned-up. These file bundles often need to be combined (and cleaned-up) in order to be useful.

The implication here is that the data will not move into and out of our data analytics systems without curation and coaxing.

Case Details

We continue with a discussion on how the Twitter data may be used in a typical data analytics context. In a recent project, we used Twitter data to analyze a crisis situation in a market-research study. We purchased 53,900 tweets from Gnip (a twitter subsidiary) that comprehensively covered 40 consecutive days of the hashtags "XXXXX" or "YYYYYY". During the analysis, we learned more about the Tweeters, their agendas, and their narratives. The primary Tweeter, and the creator of one of the hashtags that went viral is Mr. John Dow. In this study, we wanted to know what John Dow's social media interests on Twitter were the day before he brought these hashtags to life. The challenge lies in the fact that the Twitter timeline API allows access to a limited number of historical tweets from a user's timeline and Mr. DOW is an avid Tweeter, with a total of 24,866 tweets then. Thus the limited number of historical tweets was insufficient. Other than purchasing the content, it seemed that we could not answer that question. Initially, our only option was to scrape the data from twitter.com search. Using Google-Chrome with the advanced search option, we were able to display the tweets on the web-page. With Chrome Inspector, we pinned the content and saved it as html text document. Using Python, we wrote code that parsed the content of the file for the id(s) of the tweets, and then we used the Twitter API functions we iterated through the id(s), extracted the full content of the tweets. We were then able to perform the needed text analytics for the paper.

Lessons from the Case

The most poignant lesson to emerge from the case described above is the issue of federation. Data will not always cleanly answer questions, and data analytics fundamentally exists to facilitate questioning the leads to information and decision-making. There are two important "gravities" here: the need to work with tools for data manipulation, and the need for discretion in subject-matter expertise that informs the extent to which we will strive for the needed data. These worked together in the case in that the subject-matter was not the social data, but the knowledge of how data can be obtained and maintained.

4. CONCLUSION

In summary, A Master's of Science in Data Analytics is a Multi-disciplinary degree; it requires knowledge areas from multiple disciplines. Data Analytics represents the intersection of Computing, Statistics, and other disciplines from Humanities, Business, Science, Bio-Informatics, Learning Analytics, Natural Language Processing, Social Networks Analysis, etc. At the same time, a data Analytics project is a software engineering project, it requires different people from different disciplines with different skills working together to build a data product that is useful, usable and maintainable. Although we do not expect everyone in the project to be as skillful, knowledge of analysis and design and project management principles is essential. Because of its nature, results should be reproducible and explainable. To build data products and to transfer data into insights that can be utilized, data engineers take large data sets from different sources that need to be repurposed, cross-referenced, analyzed and presented. The same project might require multiple computing machinery and machine learning algorithms to exploit the underlying structures of the data. Exploratory data analysis requires data visualization tools and dashboards, statistics and machine learning algorithms for the purpose of finding patterns that can be exploited within the underlying disciplines. Different data types require different types of repurposing techniques, analysis and discovery methods. Numeric data are statistical, social networks data are graphs, trees and associations' centric, textual data require natural language processing, named-entity recognitions and sentiment analysis. Being able to insure a reliable computing and hardware infrastructure is a challenge.

In conclusion, we hope that we made the case that a Master's degree in data analytics is the right place to start. It provides students with depth of coverage and competency. We also hope that we provided a template (based on our experience, research of the programs we

analyzed) that we provided a template and a road map of a model curriculum for a Master's degree in data analytics. However, at the undergraduate level an extended minor (Programming. Data Management, Advanced Statistics, Principles of Business Analytics plus another elective) gives undergraduate students reasonable amount of knowledge and awareness of the application of data analytics into their area of specialization.

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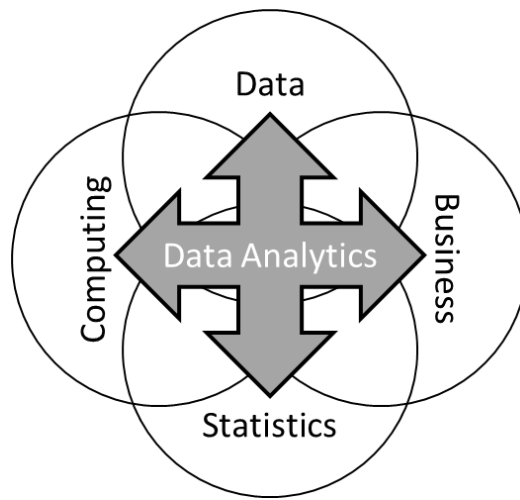
Appendix
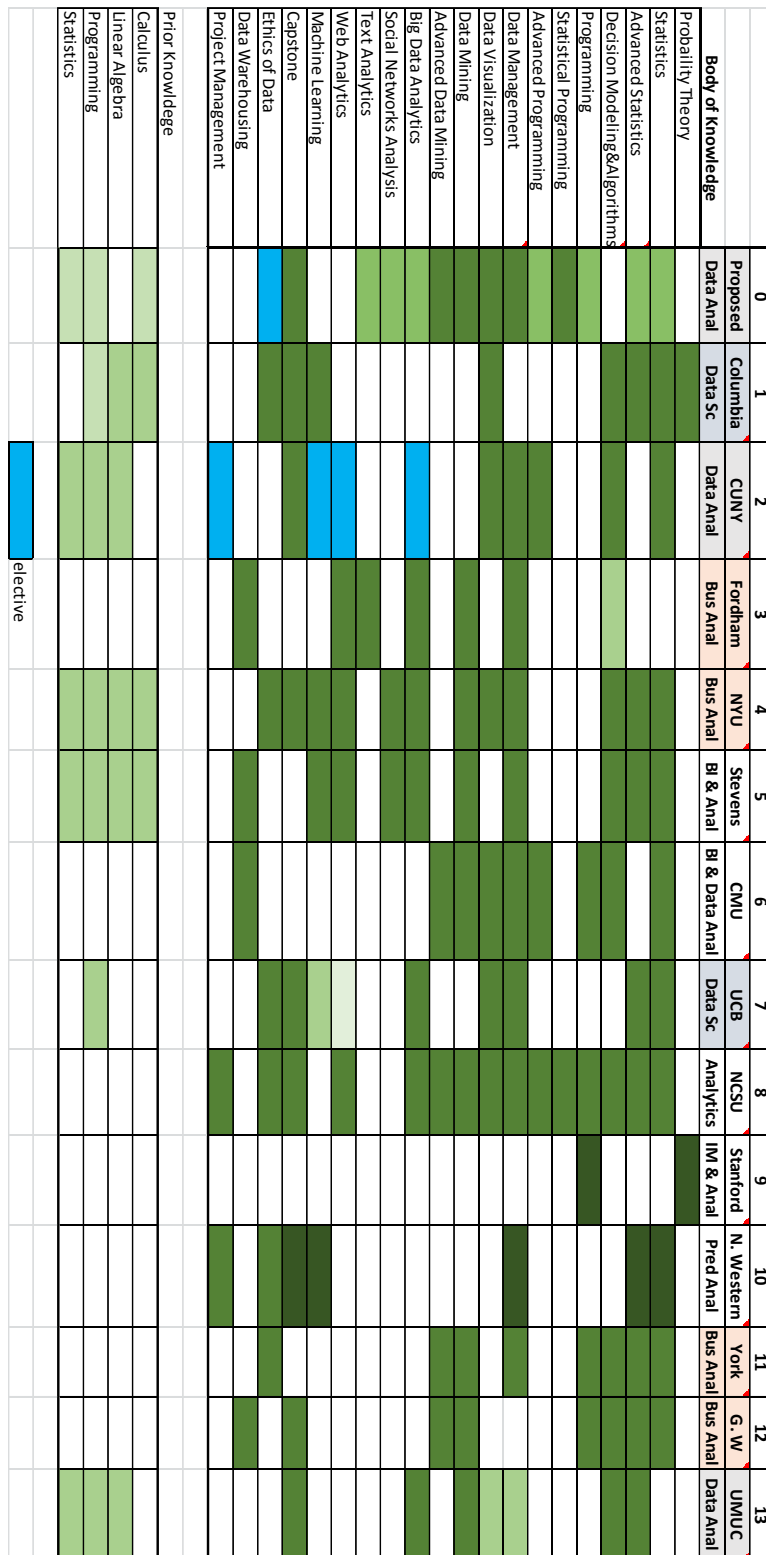

Figure 1: Data Analytics is Cross Cutting

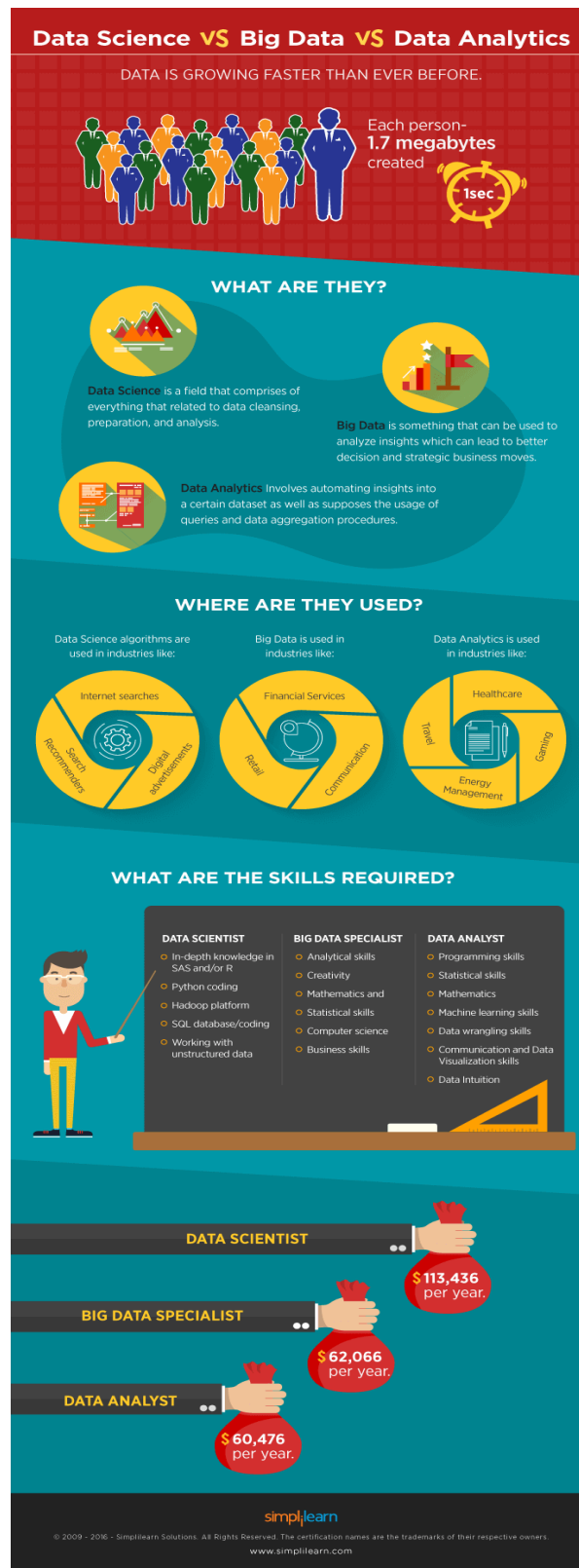Figure 2. Topic map against existing programs, the darker the color the heavier the emphasis

Figure 3. Differentiating the Problem Space
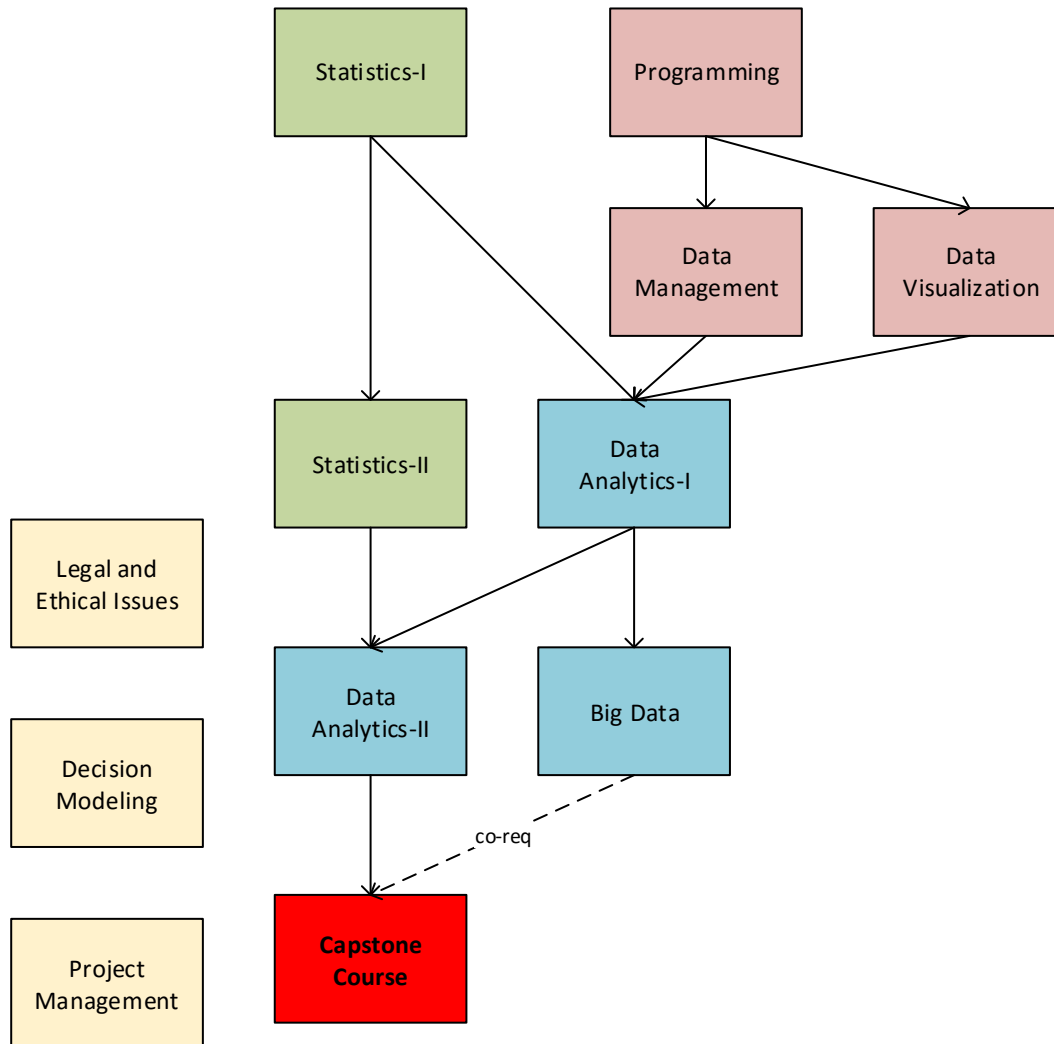(http://www.simplilearn.com/data-science-vs-big-data-vs-data-analytics-article)

Figure 4. Course Sequences and Dependencies