

## **Build Your Dream (not just Big) Analytics Program**

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### **Abstract:**

This paper reports on a panel discussion held at AMCIS 2014 and subsequent panel member research and findings. We focus on curriculum design, program development, and sustainability in business analytics (BA) in higher education. We address some of the burning questions the IS community has asked concerning the various stages of BA program building, and we elaborate challenges that institutions face in constructing successful and competitive analytics programs. Furthermore, given that the panelists have achieved outstanding accomplishments in academic and industrial leadership, we share our experiences and vision of a “dream” analytics program. We hope that our community will continue a dialog that encourages and engages faculty members and administrators to reflect on challenges and opportunities to build dream programs that meet industry needs.

**Keywords:** Business Analytics | Data Analytics | Curriculum | Program Development | Industry Partnership

### **Article:**

#### **1. Introduction**

The term data scientist was created in 2008 by D. J. Patil (Chief Data Scientist for the White House Office of Science and Technology Policy) and Jeff Hammerbacher (Founder and Chief Scientist of Cloudera). In October 2012, Davenport and Patil (2012) published their famous article in the *Harvard Business Review* in which they name the data scientist as the sexiest job of the 21st century. Today, this “new breed” of talent is still the hottest in the market. Between 2012 and 2013, one-third of companies started aggressively using analytics across the entire enterprise and two-thirds appointed a senior leader of data analytics (such as a chief data officer) (Accenture, 2013). However, big data’s sky-high popularity is coupled with a considerable shortage of analytics expertise worldwide. Some predict that, by 2018, the United States alone may face a 50 to 60 percent gap in deep analytics talent (McKinsey Global Institute, 2014) and

that big data will need 4.4 million jobs globally by 2015, only one-third of which is expected to be filled (Gartner, 2012).

Reflecting the increasing demand for individuals with big data and analytics skills is the explosion of academic programs on business and data analytics in higher education. A keyword search at Petersons.com generates more than a hundred graduate and undergraduate programs related to business and data analytics. Academics across the globe have started to launch educational and training programs in various formats and lengths to educate professionals in analytics and big data, many of which integrate business intelligence and analytics in core business curriculum (Chiang, Goes, & Stohr, 2012; Gillon, Aral, Lin, Mithas, & Zozulia, 2014; Gorman & Klimberg, 2014; Gupta, Goul, & Dinter, 2015; Sircar, 2009; Wilder & Ozgur, 2015; Wixom et al., 2011, 2014). We recently documented 133 analytics programs in the US with 35 bachelor programs, 74 graduate programs, and 24 others offered in a concentration, minor, or certificate (Iyer & Schiller, 2014), most of which were established after 2010<sup>1</sup>.

Despite the blossoming of analytics programs, the journey of building a “dream” analytics program can be long, chock-full of political ramifications, and perilous. How can we, as a community, learn best practices from each other and together create more opportunities for success? This paper reports the discussions at a panel at the AMCIS 2014 and our following work and findings. We share experiences from several successful analytics programs and provide answers to the most important and challenging tasks and issues about designing, developing, and sustaining business and data analytics programs in higher education. Specifically, we comment on the dream model curriculum for analytics programs, the “unicorn” and “hydra corollary” strategies for building program competitiveness, integrating big data and related concepts into analytics curriculum, and establishing and maintaining a win-win relationship with industry partners.

## **2. Program Development**

In recent years, business analytics has been one of the fastest growing segments of information technology globally. Recent research by InformationWeek (Henschen, 2013) and Forbes (Columbus, 2014) has forecasted a significant shortage in analytical skills due to the emergence of big data and associated emerging technologies. In addition, 60 percent of 900 IT surveyed executives stated that they intended to increase yearly salaries for business intelligence and big data handling (Schwartz, 2013). Organizations around the world list business analytics as their number one concern in coming years and expect it to play a major role in daily business operations. When Gartner (2012) predicted the 4.4 million job shortage globally, about 1.9 million of those would be in the US alone. Thus, major companies are showing a serious interest in business analytics education. Companies such as Teradata, IBM, and SAS are partnering with academic institutions worldwide through various academic alliance programs to offer support and direction in educating the students that they hope to hire in the near future. Keeping in line with the demand and growth in business analytics, some academic institutions have been creating courses and programs at the undergraduate and graduate levels that focus on various aspects of business analytics (Chiang et al., 2012; Gupta et al., 2015; Iyer & Schiller, 2014; Wixom et al., 2014).

Business analytics encompasses the knowledge, skills, and tools that enable one to collect, manage, use, and share information to support the delivery of all aspects of business operations (Watson, 2009). We provide an example to showcase how the following programs in business analytics were created at the University of North Carolina at Greensboro (UNCG) in 2014: a Graduate Certificate in Information Technology and a concentration in business analytics as part of its Master's in Information Technology and Management (MSITM) program. These programs are co-sponsored by SAS, one of the leading vendors in the analytics space whose Global Academic Program provides extensive teaching, learning, and research resources for higher education (<http://support.sas.com/learn/ap/prof/index.html>). Our process involved developing the curriculum internally (in the university) and working with SAS on the joint programs. While SAS has sponsored both programs, technologies used in the program do not only include SAS products. Various business analytics technologies in addition to SAS are used in the program including Tableau, R, Microstrategy, Microsoft products (SQL Server, Visio, Visual Studio, and Excel), and applications and software in the Teradata University Network ([www.teradatauniversitynetwork.com](http://www.teradatauniversitynetwork.com)).

Creating the concentration is well aligned with the missions of the university's Department of Information Systems and Supply Chain Management, the Bryan School of Business and Economics, and its partners at UNCG. We explain the details of each of the program and the development process in Section 2.1.

## **2.1 Business Analytics Program/Curriculum Development**

UNCG's Department of Information Systems and Supply Chain Management already had a full-fledged Master's in Information Technology and Management (MSITM) program. As part of the core requirements, students took one course in data management and another in business intelligence. With the growing need for business analytics talent, the department wanted to expand the course offerings to strengthen students' analytics skills. In doing so, the curriculum committees at the department and school level decided to offer a concentration in business analytics at the master's level for degree-seeking students. The department's advisory council that comprised area firm IT executives also whetted the ideas. We also consulted with SAS's Global Academic Program who offers a co-sponsored certificate option to schools with a minimum of 12 semester hours of course credit that:

- a) Cover topics in data management, such as collecting and preparing data for analysis
- b) Explore data
- c) Cover tools and techniques for mining data (including statistical techniques)
- d) Include hands-on projects that use BA tools and techniques, and
- e) Use SAS Enterprise Miner (with no restriction in use of other technology solutions).

The department formed a select task force of faculty to develop the curriculum to enable students to:

- 1) Demonstrate an ability to gather and manage transactional and informational data generated by businesses
- 2) Evaluate models, methods, and applications suitable for business analytics, and

- 3) Apply appropriate analytics tools, techniques, and strategies to analyze large amounts of business data for insightful decision making.

The above objectives ensure that students learn state-of-the-art methods, tools, and techniques to be a successful business analyst in any organizational setting. The following four courses (12 hours total) formed the core of the business analytics course work to meet those objectives:

### **2.1.1 Data Management**

The course covers fundamental concepts of database management systems, including designing and implementing databases and using the SQL query language. Specifically, students completing the course will be able to:

- 1) Model database requirements using the entity-relationship diagram
- 2) Apply the concepts of normalization in database design
- 3) Design and implement a relational database
- 4) Address issues related to concurrent data access
- 5) Apply methods to address various database security issues, and
- 6) Express queries using rational algebra.

### **2.1.2 Models and Methods in Business Analytics**

After completing this course, students will demonstrate a broad knowledge and clear understanding of models and methods in business analytics. This course extensively uses SAS Enterprise Guide and Enterprise Miner software. Specifically, students learn to:

- 1) Demonstrate an understanding of business analytics
- 2) Identify and assess different business analytics methodologies
- 3) Prepare and formulate data for analysis (collection, sampling, and preprocessing steps)
- 4) Describe data quality controls
- 5) Explore and develop descriptive and predictive analytic models
- 6) Apply and assess different predictive modeling techniques
- 7) Evaluate efficacy of different analytics model implementations, and
- 8) Demonstrate proficiency in using SAS Enterprise Guide and Enterprise Miner.

### **2.1.3 Business Analytics for Competitive Advantage**

Students completing this course will demonstrate a broad knowledge and clear understanding of critical concepts, practices, and issues in how one can use business analytics to achieve and sustain competitive advantage. The course extensively uses business analytics software including SAS Enterprise Guide, Enterprise Miner, and Visual Analytics. The course also discusses the managerial, privacy and organizational implications of business analytics. The course introduces students to several emerging topics in business analytics. Students learn to:

- 1) Describe the basic concepts of business analytics for competitive advantage
- 2) Evaluate methods for market basket analysis and rule discovery

- 3) Describe the challenges presented in analyzing and managing big data
- 4) Evaluate organizational, managerial, and privacy issues related to business analytics, and
- 5) Evaluate the emerging technologies in business analytics for competitive advantage.

### **2.1.4 Projects in Business Analytics**

After completing this capstone project course, students will demonstrate a broad knowledge and clear understanding of critical concepts, practices, and issues in developing and completing business analytics projects. Specific course outcomes include being able to:

- 1) Accurately identify specific problems that organizations can solve using business analytics techniques
- 2) Integrate the learning experiences acquired in the program to effectively develop and recommend analytics-based solution(s) for business problems that organizations face
- 3) Synthesize the learning experiences acquired in the program to effectively develop and recommend analytics-based solution(s) for business problems that organizations face, and
- 4) Apply important business analytics concepts, principles, techniques, and practices needed to effectively leverage big data in support of organizational strategic goals.

The department-level committees approved the course syllabi before they were shared it with the SAS Global Academic liaison for approval. Once SAS approved the syllabi, we consulted the other departments in the school and university to avoid any conflict of interest. The school- and university-level committees subsequently approved the curriculum. The entire process from conception to approval took about seven months. Since we did not create a new master's degree program, we did not require system- wide approval. Programs aiming to create new degree programs rather than just a certificate or concentration must recognize the various approval processes in place and plan accordingly.

### **3. Unicorn and Hydra Corollary—Define the Program's Competitiveness**

Many of the nation's top business schools now offer business analytics programs. At this point in time, programs vary with respect to student recruiting targets, university departments or units involved, faculty members involved, jobs targeted, the skills, knowledge, and experiences baked into the curricula, and so on. Many programs have designed their curricula to adhere to what one might call "the unicorn hypothesis"; that is, they aim to graduate an entire cohort of that elusive, cross-functional, cross-discipline, all-knowing data scientist hero who can go to work for an organization and deliver valuable analytics insights from day one. Further, many educational programs promise to deliver this in 9-16 months with a set of courses taught by faculty from various disciplines who have never or hardly worked together before, and the courses offered are often structured as they were many years ago in the heyday of operations research and management science. We offer an alternative to the unicorn hypothesis, which we refer to as the "hydra corollary"—a much more realistic and pragmatic approach to viewing the design of business analytics programs.

The hydra corollary asserts that conducting data science in organizations is a team effort. We ascribe to the fact that different programs will likely have strengths and advantages over others in the spectrum of the complexities associated with providing value from analytics to organizations. In essence, we view data science projects as the important unit of analysis. A project may need specialized skills in, for example, architecture, and a dashboard or scorecard project would require leadership from an individual who understands how to embed new analytics into regular decision making workflows and teach the right people how to use the new system. The latter example would also require a winning personality to communicate and achieve change management. Other members of the team must be excellent at creating significant and relevant metrics, capturing requirements up-front, designing dashboard or scorecard user interfaces, designing master data management solutions, delivering ETL, and the list can go on. A data scientist leader may play a significant role in unifying the team’s efforts, but many other specialists educated in data science are needed as well to realize a robust solution.

While top-notch data scientists will remain the big dogs in the analytics area, we believe that our course will produce some unicorns no matter what our university curriculum might focus on. These individuals will be the naturals—much of what they bring to the table is likely part of their personalities and prior training; it is innate. The hydra corollary includes the reality that some of those who are trained in analytics programs will fill the unicorn bill. Our analytics curricula need to do no harm to these individuals; we just need to unleash what comes naturally to them. Some of those who are trained in university analytics programs and are placed on teams on graduation will ultimately emerge as a unicorn but only after gaining needed domain experience, mentoring, and industry/organizational understanding.

Many authors have described an emerging set of job titles for those working in the analytics discipline (see Table 1).

**Table 1. Sample Job Titles (Adapted from Accenture, 2013; SmartPlanet, 2012; Bertolucci, 2013)**

|   |  |
|---|--|
| Business analytics analyst                | Creates analytical solutions to business problems; conceptualizes and implements change to business processes by deploying analytics-based solutions.  |
| Data architect                            | Works with data that is messy, un-typed, missing values, and ambiguous.  |
| Data change agent                         | Drives change in business processes based on analytics.  |
| Data engineers and operators              | Designs, builds, and maintains big data infrastructures; ensures that big data systems are operating according to plan and that they are the ones one will need to, for example, add a MapReduce capability or a new appliance to an existing data architecture.   |
| Data virtualization and cloud specialists | Leverages complex on-site and off-site computing architectures to perform data-related tasks and to build visualization; understands provisioning of virtual systems with analytics software.  |
| Data visualization specialists            | Envisions how to best present data and evidence in a way that enables efficient management-level interpretation and reinforces follow-up action; understands the technical data and can translate that knowledge to a layman’s language and, thereby, enabling the exploration of different value propositions and alternate ways to assess business impact. |

At this point, we note that the hydra corollary has a limitation: one can view it as biased toward small and medium-sized organizations because they may not be able to afford hiring teams to serve in data science roles. However, there are now many alternatives such as Amazon’s analytics-as-a-service capability and other outsourcing firms that specialize in providing business

intelligence, predictive analytics, CRM, and other analytics services. These analytics utilities, however, will likely comprise teams much like what is seen in large organizations. To this point, our analytics curricula should consider the training needed to work with such outsourcing and service providers.

The hydra corollary has something to offer to every analytics degree program. For example, masters programs can admit students from a variety of disciplinary preparation areas so group projects can comprise a mix of individuals from different undergraduate degree backgrounds (e.g., computer science, business, math, statistics, etc.). This varied composition can lead to exciting and important inter- disciplinary learning. Further, undergraduate programs can be niched; they can be tailored to specific processes in an analytics lifecycle including phases such as extraction/transform/load, data warehouse administration, data mining of structured and/or unstructured data, visualization, storyboarding, performance management, and so on. From briefly analyzing a set of queries on Dice.com, the job titles “data engineer” and “data architects” most often appeared in analytics job postings. Schools can succeed by targeting undergraduate programs with essential skill sets that serve as part of a data science team. Further, these entry-level undergraduates can grow up with the analytics successes in an organization; and they can, over time, earn their way into more important and significant data science roles.

As with most university settings, there are politics associated with launching data science programs. Introducing new programs such as analytic programs can expose both the benefits and negatives of trans- disciplinary politics. For business schools, the best strategy may be to pursue collaboration with the strongest units or departments at the university, which are often seen as computer science, statistics, industrial engineering, and so on. Alternatively, or at the same time, the collaborations may require inter- departmental efforts in the business school (e.g., IS with marketing, supply chain management, accounting, etc). We suggest building one’s analytics initiatives around the strengths of one’s database and information management curricula. One should consider partnering with the strongest units/departments in their school/college/university to launch a new program, and one will likely have to work hard to pull faculty members from different disciplines if that would help to offer the best possible and most competitive analytics curriculum. In our experience, most business school deans are very supportive, and they can provide significant insights to the political realities of introducing new analytics programs.

It is a major decision to weigh the options of a go-it-alone program versus standalone elective course(s) in a larger program versus an MBA specialization versus certificate program alternatives, and so on. After all, we believe that the most important point to consider is to align the approach with the school or college’s strategy and mission. New program initiatives in universities should avoid the trap of focusing solely on professional society/industry certifications. These certifications are often set up to advance the mission of the association or of a particular non-profit organization. One of the best ways to protect against forging a low-value industry certification strategy is to engage the IS department’s industry advisory board. Even if an ad hoc advisory board is needed to be put together given how quickly the analytics discipline is moving, that effort will yield significant dividends. Members from certificate-granting entities can be included on the board, but the intent of this approach is to ensure an independent perspective.

The success factor for the new analytics program goes beyond just curriculum. One needs to also embrace student advertising and marketing teams and take time to train marketers, admission specialists, student services professionals, and career services leaders in what this new degree is all about. This oft-missed step will help the professional support staff to understand how to position the new program in view of competitor programs, guide recruiters to the pool of available talent, and deal with an exciting crop of students who will often be seen in the trenches discussing a way to analyze, view, or scrub a particular dataset.

Once launched, the new program will need continuous fine-tuning over time. At Arizona State University, fine-tuning has involved tweaking course durations, how to best manage student expectations given hydra corollary realities, seeding project teams with diversity in student domain expertise, and shoring up applied project/internship offerings and possibilities. We have also become vigilant at ensuring new vendor offerings are vetted and used in our courses, and we view hands-on activities as essential to student advancement.

The hydra corollary is most relevant for anyone considering an undergraduate program in business analytics. We advise those interested to consult with their university's advisory board with an eye out for "Scotty" versus "Spock" perspectives. These perspectives are, of course, in analogy to starring roles in Star Trek where the engineering types who keep the ship running and firing on all cylinders often have different views than those who view analytics from an exploratory, innovation-oriented vantage point. Neither is right or wrong: one may be more relevant to where an organization/industry might be in the state of its analytics maturity. But, if these organization types are the ones who will be recruiting the analytics undergraduate students, it just makes sense to take these perspectives into account in designing the curriculum.

There are tough questions associated with analytics programs that one must be prepared to answer. The most prominent one deals with information technology's history; for example, "will analytics be another e-commerce?". Will the degree become moot as the IT landscape matures and all disciplines launch analytics courses in their respective silos? In other words, will a finance analytics course model, a marketing one, and a supply chain one each emerge independently and, thereby, diffuse the need for a specialty program? We believe that at the center of the hydra corollary is data management, and that is clearly owned by information systems units. Without the data aspects being prominent in an analytics course, offerings in silos will miss the boat.

After all, what is unique about analytics for the information systems discipline is that analytics can lead organizations to change business strategy, which is a key to explaining the importance of new programs to all stakeholders. Discoveries enabled by analytics methods and data science can provide needed evidence to overturn folklore and even political pressures that exist in organizations. As they say, the facts can speak for themselves if a solid data science team has done its work well.

#### **4. Big Data Curriculum**

Big data analytics has become an indispensable component of any analytics program. The era of big data has been ushered in by a plethora of data sources such as social media, RFID, medical

equipment, and GPS that produces data that has high volume, velocity, and variety (Watson, 2014). As more organizations jump onto the big data analytics band wagon, big data is poised to support extensive in- depth analyses of large volumes of data that cannot otherwise be effectively managed and analyzed with traditional data analytics tools. Gartner (2014) has predicted about 85 percent of Fortune 500 companies will be unable to effectively use their big data to gain a competitive advantage in 2015. One major concern is the lack of well-trained professionals who can manage and overcome the peculiar challenges that are associated with the managing big data, including a lack of technical knowledge on how to extract data and automatically read unstructured data. A key requirement for the well-trained analytics workforce is the requisite technical and methodological knowledge to perform and help enhance business processes hinged on a company's big data analytics capabilities.

The big data analytics platform employs several methods, processes, and frameworks that allows one to handle large volumes of data streamed at high speeds and characterized as multi-structured. Whereas there are multiple ways by which different businesses handle big data applications, one of the most common means is by using the Apache Hadoop platform from the Apache Software Foundation. The four basic components or sub-projects of the Hadoop ecosystem are the MapReduce sub-project, the Hadoop Distributed File System (HDFS), the Hadoop Common, and the Hadoop YARN (Apache Software Foundation, 2014). MapReduce is a programming model for parallel processing large amounts of data on a cluster of computers. HDFS is a fault-tolerant distributed file system that provide fast throughput to data. The Hadoop Common sub-project is a common set of utilities that support other modes on Hadoop. The Hadoop YARN is a framework for job scheduling and cluster management. Besides the above-mentioned sub-projects, there are other sub-projects that support various processes on the big data platform, such as Hive, Pig, Oozie, Cassandra, Mahout, and ZooKeeper.

In this section, we report our experiences on teaching a big data technologies course at Oklahoma State University. We explain how we achieved the learning outcomes of the course by focusing on two exercises that we introduced in the course. We taught our big data course as a management information systems (MIS) course with largely technical perspectives discussed throughout the course period. Furthermore, since the MIS program is situated in the business school, we focused significantly on the business use and implications of the big data analytics platform. Our students had already taken at least two other courses in analytics.

Our course had three main foci:

- 1) To help students to appreciate examples of use cases of Big data analytics
- 2) To expose students to several big data platforms during the entire course duration, and
- 3) To build expertise in at least one big data technology platform by working on a class project.

#### **4.1 Class Exercise 1**

We derived the first exercise from a telecommunications service provider company. The company noticed an increase in the number of customers cancelling its services over a period of time. This prompted it to enquire into its customers' behavior and their most common

communication patterns with the company prior to their cancelling the company's services—a central focus in churn analysis. The churn analysis is based on customer profiles and usage history. A key feature of the data sets used is the fact that they are from multiple sources and in multiple formats. Using big data analytics allows deeper level analysis using all sources and formats of data concurrently. This approach would, otherwise, present technical challenges to a regular data analytics system. The intent of the analysis was to develop a business strategy that would help identify a potential churn and resolve customer complaints before they decided to cancel services.

#### **4.1.1 Platform/Software Used**

The students used Teradata/Aster's unified data architecture (UDA) platform, which includes a Hadoop cluster, an Aster data management and analysis software program, and a Teradata enterprise data warehouse (EDW) (Teradata, 2014). The students used Aster nPath and Pathmap SQL-MapReduce functions to query the data. The students also used Tableau as an external tool to comprehensively visualize the results.

#### **4.1.2 Overview of Data and Analysis**

Students accessed a high volume of data from multiple sources: call center data on Hadoop, a weblog data on Aster, and an in-store data on Teradata EDW. The students also created a three-way join between all three data sources. The three types of data also had differing formats. For instance, the call center data was a non-traditional structured data.

This assignment emphasized the following concepts:

- 1) Time series analysis: prior to cancellation, students had to determine the specific order of customer activities.
- 2) Structured and unstructured data manipulation: the students used multiple sources of data with different cancellation formats. Students had to understand how unstructured data can be handled and combined with standardized data to further analyze it.
- 3) Visualization and professional communication: the students used Tableau to present results graphically and in a way that could be easily digested and used by non-experts in analytics.

#### **4.2 Class Exercise 2**

We based the second exercise on the IBM InfoSphere Streams Commodity Purchasing Case (IBM, 2013). As part of Company A's business operations, the company needed to make intermittent purchases of its main raw material called infoberry. The timely purchase of this commodity was paramount to the business's general performance. With the help of a stream processing application, we required students to support the company's acquiring infoberry by:

- 1) Keeping track of supply levels and automatically purchasing infoberries from the best supplier when necessary
- 2) Constantly seeking opportunities to buy high-quality infoberries, and

- 3) Out of a group of suppliers, determining what supplier to purchase infoberries from while taking into account the quality of product and other risk-management factors.

#### **4.2.1 Platform/Software Used**

In this exercise, the students used the IBM InfoSphere Streams platform. The platform is designed to allow one to extract and analyze large amounts of data from multiple sources in real time through developing streaming applications. In this exercise, students loaded infoberry-related data from multiple sources into multiple data sinks by using a browser-based stream processing application (IBM, 2013).

#### **4.2.2 Overview of Data and Analysis**

Infoberry purchases were to be made automatically based on a set of rules outlined in the processing application. For instance, if a weather warning developed for any particular location, then no purchase could be made from suppliers in that location to ensure irregular supply for raw commodity was avoided.

The application used weather data from the National Weather Service and geographic location information to generate weather scores for each location where a supplier was located. The application further calculated an average purchase score for each supplier. All suppliers were ranked based on weather score, weather warnings, recent temperature readings, and recent humidity. These factors ensured that the best infoberries in terms of quality were selected for automatic purchase. Information on weather warnings also ensured that situations affecting the delivery of the raw commodity after purchase were avoided.

We introduced students to stream mining, where data is continuously extracted and stored into storage units. The distinguishing feature identified in this exercise was the need to perform real-time analyses and make immediate decisions based on results. Key concepts discussed with this exercise were:

- 1) Stream mining: students experienced the process of generating instant and actionable insights from multiple sources of data from almost real-time data.
- 2) Structured and unstructured data manipulation: students sourced both structured and unstructured data from multiple locations. Students had to understand how to use unstructured data from different sources for real-time analysis.

#### **4.3 Concept Focused. Not Platform Focused**

To avoid making the class vendor specific, we did not stick to just one vendor but introduced students to multiple big data analytics platforms from different vendors. We required students to use several tools to complete their home works and projects, which added the extra benefit of exposing students to a wide array of software and platforms to enrich their technical knowledge. However, the vast amount of technical skills needed to manage each of the mostly nascent applications had the potential of focusing students' attention on knowing only how to use a particular software rather than learning the underlying concepts being discussed. Depending on

the background of the students and the primary aim and context in which such a course is taught, instructors need to be mindful about bogging down students with too many “cool” applications that would make them “application kingpins” rather than “big data professionals”.

Generally, students were receptive to the course’s structure and organization. Students particularly found the course to be challenging yet one that sustained their continual interest. They felt the course introduced them to a new discipline of analytics in an effective way. One student said of the course: “Very interesting and informative. Nice initiative to start the course”, and another said: “Clear and precise. Great class, learned a lot.”

## **5. Partnership with Industry**

Partnerships with industry are a key goal of most analytics programs, and many schools have corporate or industry advisory boards to capture industry inputs and foster strong relationships. For universities, collaborating with industry has countless benefits. When referring to analytics and big data, industry can provide valuable advice on evolving curriculum requirements (especially for big data), can possibly provide “real-world” problems that can spawn research and teaching activities, and, finally, can provide job opportunities for graduates.

Universities face some noticeable difficulties when building the “dream” analytics program including the question of turf (i.e., who “owns” analytics and where should it reside in the curriculum), the problem of making room to teach new topics in a typically already packed set of required courses, and the issue of hiring or retraining existing faculty to get up to speed on new analytics topics. A major dilemma is making sure that the curriculum has a mix of theory and hands-on practice without it becoming vocational training. Luckily, there are available resources today for faculty training and development on these topics (see the appendix).

Forging industry relationships is not easy, but there’s a big opportunity right now because of the hype around big data and the need for companies to hire more analytics-smart employees. Most companies realize that data is a key corporate asset. Most traditional processes are becoming more data-intensive because of the Internet of things (IoT) and growth in the number of customer channels. These will drive new requirements for graduates adept at data visualization, time series analytics, social network graph insights, and statistics acumen to pick out signals from noise.

Many schools are reacting by developing new analytics programs. Sometimes these new programs are minor modifications to existing programs. At typical schools, the program would include a few courses from each of the domains of business, stats, and IS and culminate with a capstone project involving a data set and the use of tools to illustrate comprehension of the class material. In the best case, students do the capstone by getting an internship with a company where they work on real data sets to solve real analytical problems. One example in this category is the Nationwide Center for Advanced Customer Insights (<http://fisher.osu.edu/centers/ncaci>), developed in conjunction with The Ohio State University, where MBA and undergraduate senior students intern at the center and analyze data to discover business insights.

Anyone building a dream model curriculum should consider the practical aspect of the program (i.e. where and how students can learn analytics best from the real business practices). From an

academic perspective, many educators have suggested the needed analytical skills and knowledge (Chiang et al., 2012; Gupta et al., 2015). In the ideal case, in addition to having coverage of these topics, the key is also to begin with data and data types and educate students about the various possibilities using plenty of industry examples. This first module could be a 6 credit hour survey course. This survey course could focus on explaining various data sets and data types/operators in the context of what various industries are doing. Depending on faculty and student interest, drill-down topics can include: marketing (Web click sequences, sentiment scoring of tweets, ad clicks, SEO, social media graphs), customer service (voice analytics, Web self-serve, agent behavior, service metrics), and operations (sensors in driverless cars and jet engines, Internet of things). A requirement of this first module would be that students need to find one or two data sets that they can use throughout their subsequent studies in the program

One should leverage the students' interests and the diversity of their previous academic backgrounds to encourage them to seek out data sets. Data could come from industry, other institutional departments (e.g., medical school, transportation operations research, sports science), or public sources such as: [www.GDELTproject.org](http://www.GDELTproject.org), [www.KDNuggets.com](http://www.KDNuggets.com), UCI Machine Learning data sets (<https://archive.ics.uci.edu/ml/datasets.html>), Eurostat and U.S. Government data sets ([www.google.com/publicdata/directory](http://www.google.com/publicdata/directory)), and so on. In addition, the contest site Kaggle ([www.kaggle.com](http://www.kaggle.com)) has a variety of data sets contributed by industries and non-profits that need analysis, often with prize money for the winners.

The survey class should be adapted so students learn and use various visualization techniques and tools. A requirement of completing this class is that the students does three or four visualizations on the two data sets they select. After completing this foundation, the remaining courses in statistics and IS should then drive students to use their datasets to address a specific analytical problems in a particular business domain such as healthcare or supply chain. Students learn to spot anomalies and glean insights from the data using SAS and R packages with SQL and, in some cases, especially when the curriculum includes computer science, even learn to write new algorithms on big data types. Most importantly, these flexible options allow (and require) students find their “niche of expertise” as an analytics program manager, deep analytics data scientist, or liaison between IT and business analytics.

A challenge of this approach will be that faculty must grow/adapt as they are exposed to the data sets the students find. As a starting point, there can be some “canned” data sets or the classes could use Kaggle knowledge contests (e.g., predict the survivors of the Titanic) to illustrate building and validating predictive models. Some faculty such as Professor Kai Larsen at the University of Colorado–Boulder requires his IT students participate in two Kaggle contests to pass his class.

There are a large and growing number of resources for building new curriculum modules that follow these ideas. Two books—“Taming the Big Data Tidal Wave” (Franks, 2012), and “The Analytics Revolution” (Franks, 2014), both by Teradata’s Chief Analytics Officer Bill Franks—provide a basic grounding of the industry needs and opportunities and technology/management fundamentals. In addition, there are also a growing number of assets free of charge to academics appearing on the Teradata University Network ([www.teradatauniversitynetwork.com](http://www.teradatauniversitynetwork.com)).

Building the curriculum to include big data topics should benefit relationships with industry. In the best case, the analytics program can obtain and leverage sample data sets from local companies. This model benefits both students and faculty because they become more fully aware of state-of-the-art technology and analytical needs. In some cases, collaborating with the industry may drive new research and funding opportunities and cross-department, inter-disciplinary contacts that otherwise might not happen. It also benefits industry because it presents industry needs to universities and provides graduates with skills that employers need. In all, the dream analytics program can start with the data and continue using data to drive and grow student exposure to advanced analytics throughout the ideal curriculum.

## 6. Conclusions

Building a dream analytics program is a journey. Many researchers are walking the same journey but are at different points and a varied pace. With this paper, we introduce a beginning to stimulate more conversations in our IS community and to help scholars, practitioners, and administrators further clarify and evaluate their positions regarding building their “dream” analytics programs. Our experiences, advice, guidance, and innovative ideas presented in this paper can be a reference point to other researchers’ journey. We hope that the paper will inspire researchers’ thinking and ongoing practices to continuously improve their dream analytics program versions and, ultimately, achieve significant program and student success.

## References

- Accenture. (2013). *The team solution to the data scientist shortage*. Retrieved from <http://www.accenture.com/sitecollectiondocuments/pdf/accenture-team-solution-data-scientist-shortage.pdf>
- Apache Software Foundation. (2014). *What is the ASF?* Retrieved from <http://apache.org/foundation/>
- Bertolucci, J. (2013). How to build an analytics A-team. *InformationWeek*. Retrieved from <http://www.informationweek.com/big-data/big-data-analytics/how-to-build-an-analytics-a-team/d/d-id/1112215?>
- Chiang, R. H. L., Goes, P., & Stohr, E. A. (2012). Business intelligence and analytics education, and program development: A unique opportunity for the information systems discipline. *ACM Transactions in Management Information Systems*, 3(3), 12:1-12:13.
- Columbus, L. (2014). Where big data jobs will be in 2015. *Forbes*. Retrieved from <http://www.forbes.com/sites/louiscolumbus/2014/12/29/where-big-data-jobs-will-be-in-2015/>
- Davenport, T. H., & Patil, D. J. (2012). Data scientist: The sexiest job in the 21st century. *Harvard Business Review*, 90, 70-76.

- Franks, B. (2012). *Taming the big data tidal wave: Finding opportunities in huge data streams with advanced analytics*. Hoboken, NJ: John Wiley & Sons.
- Franks, B. (2014). *The analytics revolution: How to improve your business by making analytics operational in the big data Era*. Hoboken, NJ: John Wiley & Sons.
- Gartner. (2012). *Big data creates big jobs: 4.4 million IT jobs globally to support big data by 2015*. Retrieved from <http://www.gartner.com/newsroom/id/2207915>.
- Gartner. (2014). *What information, if you had it, would change the way you run your business?* Retrieved from <http://www.gartner.com/technology/topics/big-data.jsp>
- Gillon, K., Aral, S., Lin, C.-Y., Mithas, S., & Zozulia, M. (2014). Business analytics: Radical shift or incremental change? *Communications of the Association for Information Systems*, 34(13), 287-296.
- Gorman, M. F., & Klimberg, R. K. (2014). Benchmarking academic programs in business analytics. *Interfaces*, 44(3), 329-341.
- Gupta, B., Goul, M., & Dinter, B. (2015). Business intelligence and big data in higher education: Status of a multi-year model curriculum development effort for business school undergraduates, MS graduates, and MBAs. *Communications of the Association for Information Systems*, 36, 449-476.
- Henschen, D. (2013). Big data analytics master's degrees: 20 top programs. *InformationWeek*. Retrieved from <http://www.informationweek.com/big-data/big-data-analytics/big-data-analytics-masters-degrees-20-top-programs/d/d-id/1108042?>
- IBM. (2013). *IBM InfoSphere Streams version 3.1 documentation*. Retrieved from [http://www-01.ibm.com/support/knowledgecenter/SSCRJU\\_3.1.0/com.ibm.swg.im.infosphere.streams.homepage.doc/doc/kc-homepage.html](http://www-01.ibm.com/support/knowledgecenter/SSCRJU_3.1.0/com.ibm.swg.im.infosphere.streams.homepage.doc/doc/kc-homepage.html)
- Iyer, L., & Schiller, S. (2014). List of analytics programs. *Teradata University Network*.
- McKinsey Global Institute. (2014). *Deep analytical talent: Where are they now?* Retrieved from [http://www.mckinsey.com/features/big\\_data](http://www.mckinsey.com/features/big_data)
- Schwartz, M. J. (2013). IT budgets, salaries to grow in 2014. *InformationWeek*. Retrieved from <http://www.networkcomputing.com/networking/it-budgets-salaries-to-grow-in-2014/d/d-id/1112190?>
- Sircar, S. (2009). Business intelligence in the business curriculum. *Communications of the Association for Information Systems*, 24, 289-302.
- SmartPlanet. (2012). 7 new types of jobs created by big data. *SmartPlanet*. Retrieved from <http://www.smartplanet.com/blog/bulletin/7-new-types-of-jobs-created-by-big-data/>

- Teradata. (2014). *Big data: Teradata unified data architecture in action*. Retrieved from <http://www.teradata.com/products-and-services/unified-data-architecture/?LangType=1033&LangSelect=true#tabbable=0&tab1=0&tab2=0&tab3=0&tab4=0>
- Watson, H. J. (2009). Tutorial: Business intelligence—past, present, and future. *Communications of the Association for Information Systems*, 25, 487-510.
- Wilder, C. R., & Ozgur, C. O. (2015). Business analytics curriculum for undergraduate majors. *INFORMS Transactions on Education*, 15(2), 180-187.
- Wixom, B., Ariyachandra, T., Douglas, D., Goul, M., Gupta, B., Iyer, L., Kulkarni, U., Mooney, B. J. G., Phillips-Wren, G., & Turetken, O. (2014). The current state of business intelligence in academia: The arrival of big data. *Communications of the Association for Information Systems*, 34, 1-13.
- Wixom, B., Ariyachandra, T., Goul, M., Gray, P., Kulkarni, U., & Phillips-Wren, G. (2011). The current state of business intelligence in academia. *Communications of the Association for Information Systems*, 29, 299-312.