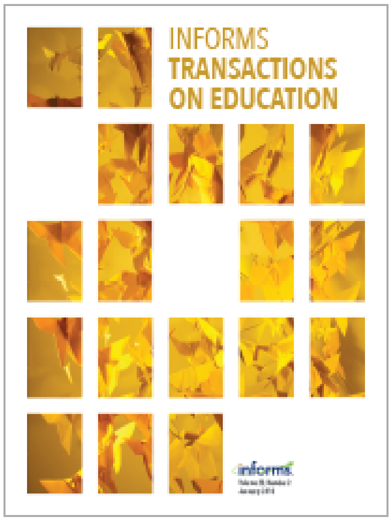

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Business Analytics Curriculum for Undergraduate Majors

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Analytics has become a new source of competitive advantage for many corporations. Today's work force therefore must be cognizant of its power and value to effectively perform their jobs. In this paper, we define the appropriate skill level and breadth of knowledge required for business school graduates to be successful. An undergraduate course of study in analytics is proposed for students with average to above-average analytical skills. Implementation guidelines are also addressed to ensure a successful program.

Keywords: business analytics; undergraduate curriculum; business analyst
History: Received: July, 20, 2014; accepted: September 9, 2014.

1. Introduction

Business analytics is something most people have heard about but fewer know or can agree on the definition. Some argue it is nothing new, simply another word for business intelligence. Others argue business intelligence and business analytics are two different disciplines, each with their own set of skills and software (Gnatovich 2006). The purpose of this paper is not to debate these issues. The focus herein is to position business analytics, by any name, in the undergraduate curriculum in a manner that best serves students. Business analytics, for our purposes, is the application of processes and techniques that transform raw data into meaningful information to improve decision making. Some of these techniques, such as regression and optimization, have traditionally been offered as part of the core business curriculum. Other tools, such as data mining, have not been included. These omissions along with increased demand for data-savvy professionals are valid arguments for a curriculum review.

A business justification begins the task of a curriculum review, for without it there is no reason to continue; designing a course of study for which there is no interest would be pointless. A review of trends in curriculum development for analytics is examined next. The ideas of this research are presented in the proposed business analytics curriculum section; a proposal that was recently submitted and approved at Valparaiso University. The proposal is tailored to the needs of undergraduate business students that are not technically oriented. A significant change to the traditional course offerings is suggested that may not be acceptable to everyone but there is room for compromise. The curriculum proposal is followed with implementation guidelines, which are essential to a successful program. Concluding remarks end the paper.

2. Business Justification

Transforming data into insights is not a new discovery. Analysis of the 1854 Cholera Epidemic in London is one of many early examples. John Snow used data to convince local authorities that the source of the epidemic was a water pump on Broad Street; an event that is celebrated to this day with a pub that marks the spot (Tufte 1997). Moreover, the practice of gathering intelligence is ancient. Therefore, why are many higher education institutions just now creating analytics majors, minors, and institutes? Because we have data—and lots of it.

In 1964, Gordon Moore observed that the amount of storable information doubled every year; the time frame has since been revised to every 18 months. As a result, we have produced "exponentially growing cellars and attics" in which to store all sorts of data (Claasen 1998, p. 184). These massive accumulations have been anointed with the moniker of big data; the distinguishing factors of which are volume, velocity, and variety (McAfee and Brynjolfsson 2012). Big data has opened the flood gates for data analysis to achieve heights not possible in the past.

Throughout history, businesses have adopted innovative management programsto remain competitive.

In the early 1800s, it was standardized parts. In the late 1800s, it was the era of scientific management followed by mass production. In the 1980s, businesses found their competitive advantage in lean production initiatives (Heizer and Render 2011). Analytics is projected to become the next source of competitive advantage for many industries and a key element in improving their performance (Barton and Court 2012).

According to the 2013 CIO survey conducted by Gartner, analytics and business intelligence (BI) was ranked as their number one technology priority; a position it has occupied in three of the last five years. Seventy percent of the CIOs rated mobile technologies as the most disruptive force with which they will be confronted in the next 10 years, followed by big data and analytics each at 55% (Gartner Inc. 2013). Business schools must be responsive to these new demands to ensure the success of their graduates.

The skills necessary to pursue these opportunities are defined at three different levels, which lead to different career paths (Watson 2013, Manyika et al. 2011). The first skill level is appropriate for individuals with advanced degrees in a quantitative discipline. Although these professionals go by many titles, a common reference is data scientist. Their skill set must include a solid foundation in computer science and mathematics, which includes probability and statistics (Davenport and Patil 2012). Companies typically reserve data scientists to work on the more challenging problems, and for this reason, they are frequently used as consultants. These individuals may also be part of a specialized group such as operations research (OR), industrial engineering, management science, or other similar groups.

The next skill level is for data specialists. They need to understand how data is stored, how to access it, and how to analyze it. They need to use a company's resources to access data and produce reports. These individuals may be scattered throughout an organization in various functional areas or in a centralized IT support group.

The final skill level is a hybrid or dual specialization and the subject of this paper. These professionals are typically given titles such as business analyst or hold management positions. They need to be able to identify and exploit opportunities. They need sufficient functional expertise to frame business problems and interpret the results. Business analysts do not need to be experts in the various analytical tools but they need to have confidence in these tools. They simply need to ask the right questions and form the right hypotheses (Hopkins et al. 2010, p. 24). In a report published by the McKinsey Global Institute, this group is referred to as "data-savvy managers" (Manyika et al. 2011).

McKinsey estimates that by 2018, the talent shortage for those previously described as data scientists is estimated to be 140,000 to 190,000 and nearly 1.5 million for those described as business analysts (Manyika et al. 2011). All of North Carolina State's recent analytics' graduates were given competitive job offers; this was their seventh consecutive cohort to graduate fully employed (North Carolina State 2014).

A demand has been established and a shortage of supply identified in the field of analytics. Before proceeding to a review of current programs, it is important to ensure that the role and impact of a business analyst is fully understood; after all this paper is about developing a plan of study tailored toward their needs. One of the authors worked in an OR department for a large manufacturing company in a capacity, which today would be called a data scientist. On one occasion, a profitability model was developed using linear programming techniques. The model was a classic application of a typical optimization problem. What product mix should we produce, given our constraints (resources), to maximize profit? Management was suspicious of the production plan it produced because they were not familiar with the methodology; no manager is going to risk his career endorsing something he do not understand. The project was canceled and viewed as a bunch of geeks playing "SimCity" with company resources.

The rejection in the previous example was typical but not guaranteed. On another occasion, a new chemical lab was in the planning stage of construction. The chemical testing machines were seven-figure expenditures. The team leader did not want to purchase more machines than absolutely necessary to deliver a given service level. The team leader had an analytical background, and recognized the value of using data to drive decisions. He also realized the stakes involved and escalated the problem to the OR team. Opportunity was lost in the first example and while the second example was successful, it was not enough to create a culture of data-driven decision making. Eventually, the company eliminated the entire OR department and was later acquired by a company with a leader whose background was in OR!

The examples just cited are from personal experience, yet it is prevalent in business today with even greater consequences than those just stated. Davenport (2013) begins a recent article with a story about a mortgage business that lost billions of dollars in bad loans. A senior analyst in the story was confused about why this happened when his model indicated there was a problem. The analyst sent his model to the head of the mortgage department who later explained he did not use it because he could not understand it. It is, therefore, critical that business managers are data savvy; not experts, but skilled enough to understand the value and recognize the opportunities created with analytics.

3. Review of Analytics in the Curriculum

Current school offerings for business analytics are diverse. North Carolina State maintains a comprehensive list of graduate programs; as of this writing, there were 49 graduate analytics programs. The list is organized into three tiers depending on the targeted audience. The master of science in business analytics is described as appropriate for the "less technically oriented" and is typically administered by business schools (North Carolina State 2014). Many analytics programs, such as North Carolina State's, began at the graduate level. North Carolina State was the first institution, in 2007, to establish a program and many schools have since followed their lead. These graduate curriculums may be used as a compass to direct undergraduate studies.

Graduate programs within the same tier vary in their course requirements with some common core elements of various names. For example, a course in data management is common across programs but is offered in a variety of formats. At George Washington University, students are required to take a Data Warehousing course where they learn to work with data using Microsoft Access (George Washington University 2014). At Arizona State University, students are required to take an Introduction to Enterprise Analytics course where they learn how data flows across the organization and is managed (Arizona State University 2014). Many traditional quantitative courses such as regression, optimization, and simulation are also part of the course requirements. A nontraditional component, however, is a course (or two) in data mining and this course truly distinguishes analytics programs from earlier degrees such as management information systems (MIS) and decision upport (DS). Some schools such as New York University's Stern School of Business offerelectives such as Data Visualization, which emphasize the communication component (New York University 2014). A capstone course usually ends a plan of study in which students bring all they have learned together in one project. Current practices in curriculum design appear to be aligned with the findings of the BI Congress, a faculty group from various institutions working to close the gap between industry needs and academic offerings. This group recommends that students at a minimum understand data management, a business functional area, quantitative analysis, and communication (Wixom et al. 2011).

Gorman and Klimberg (2014) reviewed graduate and undergraduate analytics programs by conducting Web searches followed by personal interviews with selected representatives. They found graduate offerings were more innovative than their undergraduate counterparts. A key observation from their research was that more emphasis is placed on problem-solving skills and data visualization with a practitioner orientation. New topics are also emerging such as big data, unstructured data analysis, and network analysis (Gorman and Klimberg 2014).

Watson (2013) suggests that curricula cover all three types of analytics as they each require different skill sets. The first and most basic type of analytics is descriptive analytics, which examines what has already happened. The second type of analytics is predictive analytics, which examines what is expected to happen. The third and final type of analytics is prescriptive analytics, which explores what should happen. Traditional business curriculums have addressed these areas with beginning and advanced statistics courses. George Washington University has designed their entire business analytics program around these definitions along with a series of courses that are application specific such as, pricing and revenue analytics, sports analytics, and healthcare analytics (George Washington University 2014).

Undergraduate business students must be comfortable with quantitative thinking beyond the traditional business statistics and calculus courses; in fact, it may be time to redesign these very courses. McClure and Sircar (2008) advocate for the inclusion of modeling and risk management as essential components of a 21st century undergraduate program. In an ideal setting, modeling would be integrated into every course with the emphasis placed on the business problem but this line of attack is difficult for some institutions to implement (McClure and Sircar 2008). The University of Arizona approached this problem by restructuring their statistics and calculus courses. The mathematics department and the business school worked together to create two new courses: (1) Probability and Simulation and (2) Calculus and Optimization (Albers 2002). The courses are project oriented and students work in groups to present their work.

Industry demands on information systems' curricula have led to the addition of more managerial than technical courses; likewise more technical than managerial courses are being eliminated. One of the top 50 schools ranked by *U.S. News and World Report* actually dropped calculus as a required course; another added data mining as a required course (Benamati et al. 2010). It is clear that academic institutions are making incremental changes to appeal to a new audience and industry demands.

Changes are not limited to course additions/deletions; pedagogy is also on the list. Two of the top 50 business schools use inquiry-based learning in their statistics courses (Haskin and Krehbiel 2011). For example, the Goizueta Business School at Emory University uses data from the Atlanta Falcons in their business statistics course; students are asked at the beginning of the course to describe the typical season ticket holder, which then leads to students asking questions about statistical methods. Levine and Stephan (2011) advocate using a problem-solving framework, define, collect, organize, visualize, analyze (DCOVA), to teach statistics. This framework helps students connect the different statistical techniques and provides continuity.

The Institute for Operations Research and the Management Sciences (INFORMS) recently launched a Certified Analytics Professional (CAP®) exam (Nestler et al. 2012). Although undergraduate college students are not eligible for this certification without experience, it is an excellent guide for curriculum design. The exam is composed of seven domains: business problem framing, analytics problem framing, data, methodology selection, model building, deployment, and life-cycle management. A comprehensive program in analytics should expose students to each of these domains.

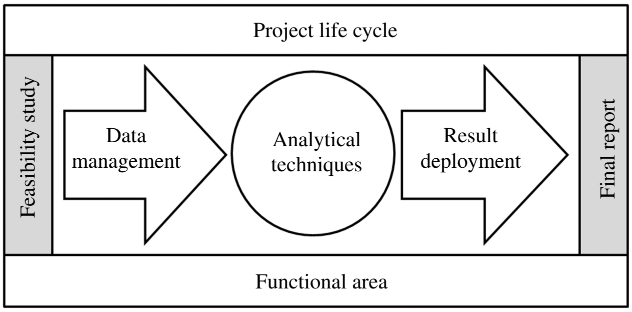
In an effort to provide students with real-world experiences, several schools have started accelerator programs. These schools obtain projects for students to work on from participating businesses. Vanderbilt University offers a summer internship program for undergraduate students and recent graduates (Vanderbilt University 2014). In their program, students are immersed in a month-long experience working in teams on a variety of projects for real businesses. The University of Connecticut, on the other hand, offers yearlong accelerator programs geared toward specific needs, such as the "Innovation Accelerator" (University of Connecticut 2014).

The next two sections, §§4 and 5, form the basis of this research. The ideas are appropriate for an undergraduate program and are targeted towards business students who possess average to above-average analytical skills. The mathematical aptitude for these students is less than that required of students in STEM (science, technology, engineering, mathematics) fields of study.

4. Proposed Business Analytics Curriculum

The proposed business analytics program is designed around five knowledge domains: project life cycle, data management, analytical techniques, deployment, and a functional area. These domains are diagramed in Figure 1. Business analytics is a multidisciplined education. It is different from a double major because the courses themselves are a combination of business

Figure 1 **Knowledge Domains**



and quantitative disciplines. It is important not to separate these skills into specialized courses but to keep the quantitative topics embedded in a business context.

Computer literacy is typically a core requirement for all students; it is not exclusive to business analytics majors. Therefore it is not included as part of this review since we are not advocating any changes to its placement; it is worth noting, however, that it is assumed that students will have achieved some minimum level of proficiency with Microsoft Office before they begin their major studies. On the other hand, data management skills and knowledge are not necessarily part of a business core at many schools. We have elected to cover it in one comprehensive course but advanced electives could easily be added. Analytical techniques such as statistical inference, regression, optimization, and simulation are dispersed among three separate courses categorized as descriptive, predictive, and prescriptive analytics. Decision trees and some of the nontraditional topics such as clustering, networks, and classification are grouped into a Data Mining course. We recommend that result deployment be covered in virtually every course. Students should be required to summarize their findings in a manner that is appropriate for a nontechnical audience; final reports should include (in addition to the results) the impact of their findings, the associated risks, and a description of any assumptions. One course, data visualization, is dedicated to the art and science of displaying data in a meaningful manner. Finally, a capstone course is included to provide students with challenging project work. This course is also an opportunity to include topics such as consulting, project management, and ethics.

Traditional quantitative core courses are reviewed to minimize redundancies. These courses are typically: finite mathematics, business calculus, and business statistics. The recommendation herein is to replace these courses to update offerings to match current business needs. This change should be viewed as an expansion and not an elimination of the core courses since the content will now be spread across six courses. More importantly, however, is that it is recommended that pedagogies are also revised, so that courses are project oriented and inquiry based using technology to perform high-level calculations. A mathematics course is typically a core requirement of most institutions. Eliminating the aforementioned courses creates a problem in satisfying these core requirements. An objective many business schools have for required mathematics courses is to build thinking skills; advanced algebra accomplishes this task and may be considered as an alternative.

Undergraduate majors at the author's institution are composed of approximately five to six (3-credit hour) courses in addition to qualified electives and core business courses. The proposed curriculum herein uses this standard; course descriptions follow.

4.1. Course: Data Management

The objective of this course is to ensure that students have the skills and knowledge to gather, store, and manipulate data to conduct an analytical study. The role of data in the project life cycle is introduced. The impact of big data on analytical studies is discussed. Topics may include but are not limited to: data architecture, storage, formats, ownership, privacy, metadata, data cubes, extract-transform-load (ETL) tools, structured querylanguage (SQL), data cleansing, and ethics. No prerequisite courses.

4.2. Course: Descriptive Analytics

The objective of this course is to ensure that students have the skills and knowledge to effectively describe events that have already occurred. Emphasis is placed on communicating results in a variety of formats. Topics may include but are not limited to: descriptive statistics, frequency distributions, discrete distributions, continuous distributions, sampling distributions, and statistical inference. Although this course may be taught without a prerequisite course, many institutions prefer to require a mathematics course as a prerequisite to ensure that students have stronger problem-solving skills.

The content covered in this course is typically covered in a traditional Business Statistics course as a core requirement of most business schools. It is not considered here as one of the courses that define the major but is included to show the comprehensive coverage of analytics. It is important that the focus of the course is on the interpretation and presentation of data and not on the calculations. It is useful for students to do manual calculations once or twice to aid in the understanding of what is being calculated, but software needs to be incorporated as well. Emphasis should center on getting students to be comfortable working with descriptive statistics while being exposed to their applications in business problems.

4.3. Course: Data Visualization

The objective of this course is to explore different techniques for presenting a wide variety of data for the purpose of making it meaningful to a targeted audience. Standard practices for the visual display of data are discussed. Technology is used extensively to produce visual interpretations of various data sets. Key performance indicators, scorecards, and dashboards are discussed and differentiated. Students will critique various displays from historical examples and recent news reports. Topics may include but are not limited to: creating various charts and graphs, use of color and formatting, and storytelling. No prerequisite courses required.

4.4. Course: Predictive Analytics

The objective of this course is to ensure that students have the skills and knowledge to recognize opportunities for predictive analytical approaches and exploit the results. Students will construct simple predictive models in an effort to enhance their understanding of the techniques. Emphasis is placed on framing the business problem and communicating the results, especially in a nontechnical language. Model implications, impact, and assumptions are discussed as they pertain to a variety of business problems. Topics may include but are not limited to: ANOVA, regression, correlation, Time series, and nonparametric methods. A prerequisite for this course is Descriptive Analytics.

The contents of this course are typically covered in an advanced Business Statistics course. A variety of applications should be used to illustrate the value and versatility of the methodologies.

4.5. Course: Prescriptive Analytics

The objective of this course is to ensure that students have the skills and knowledge to recognize opportunities for prescriptive analytical approaches and exploit the results. Students will construct simple models in an effort to enhance their understanding of the techniques. Emphasis is placed on framing the business problem and communicating the results, especially in a nontechnical language. The strengths and weaknesses of each technique are discussed using examples to elaborate. Model implications, impact, and assumptions are discussed as they pertain to a variety of business problems. Topics may include but are not limited to: calculus, optimization, and simulation. A prerequisite for this course is Descriptive Analytics.

Optimization is typically covered in a finite mathematics course, calculus in a course of its own, and simulation as an elective. It is important that the emphasis here is on problem recognition and interpretation and not the mechanics of the various techniques. For example, the simplex method of linear programming involves matrices. Row operations are used to arrive at an optimal solution; this is a tedious process for which software should be employed. A variety of applications should be used to illustrate the value and versatility of the methodologies.

4.6. Course: Data Mining

The objective of this course is to ensure that students have the skills and knowledge to recognize opportunities for data mining approaches and exploit the results. Data mining processes such as CRISP-DM (cross-industry standard process for data mining) and SEMMA (Sample, Explore, Modify, Model, and Assess) are compared. Students use large data sets to construct simple models in an effort to enhance their understanding of the techniques and challenges of working with big data. Emphasis is placed on framing the business problem and communicating the results, especially in nontechnical language. Model implications, impact, and assumptions are discussed as they pertain to a variety of business problems. Topics may include but are not limited to: classification, clustering, networks, geographical information systems (GIS), and decision trees (including Bayes' theorem). A prerequisite for this course is Descriptive Analytics.

Decision trees are typically covered in a finite mathematics course; the other techniques are not typically offered in a business curriculum. This course truly differentiates an analytics program from a previous course of study such as management information systems (MIS) or decision science (DS).

4.7. Course: Analytics Practicum

The objective of this course is to ensure that students have the skills and knowledge to manage and implement an analytics project; it serves as a capstone course. Project management basics are covered along with consulting practices, ethics, and standard practices. Students are required to choose an appropriate methodology for a given problem; this task varies from previous coursework where a technique is given along with the problem. Students complete their studies with an actual project for an operating business from which they will most likely have the experience of working with less-than-perfect data. Students should have completed all prior coursework before taking this course.

4.8. Course: Electives

A variety of electives complete the major. Some electives should be functional such as Marketing Research or Sports Analytics; others may cover specific techniques not covered in the core courses such as Web analytics, game theory, advanced visualization, or spreadsheet models. The number of electives, of course, will vary according to school requirements.

Our proposal consists of six courses: one core course and a variety of electives. It is understood that course names will vary across institutions. For example, at Valparaiso University, predictive analytics is covered in a course called Statistics for Decision Making (Valparaiso University 2014a). These inconsistencies in naming conventions will make it difficult to compare programs but it is a problem that is not likely to disappear any time soon. We used the descriptive, predictive, and prescriptive analytics course names used herein to show that the full spectrum of analytics was covered; it is not our intent to imply that they are required course names.

5. Implementation

The key to a successful analytics program for business students is in the implementation. Many of the topics covered in the proposed curriculum could also fit into a course of study for data scientists; it is the pedagogy and emphasis that differentiates them. The purpose of this section is to provide educators with a few guidelines on how to implement a successful program.

First, and foremost, *use a variety of specific examples instead of generalizations*. It is imperative that courses for business analysts are not combined with those for data scientists. It is tempting to teach general concepts to reach a larger audience but research has shown this method to be ineffective. "Mathematically trained teachers often imagine that they can gain efficiency by presenting general principles or structures first, followed by concrete 'special cases.' This doesn't work. Few people learn from basic principles down to special cases" (Moore 2001, p. 5). Business analysts are in positions that expose them to opportunities to use analytics but they must be able to recognize them first to employ the expertise of a data scientist. Instead of using general examples, educators must use specific examples from a variety of areas for students to fully appreciate the scope of their application.

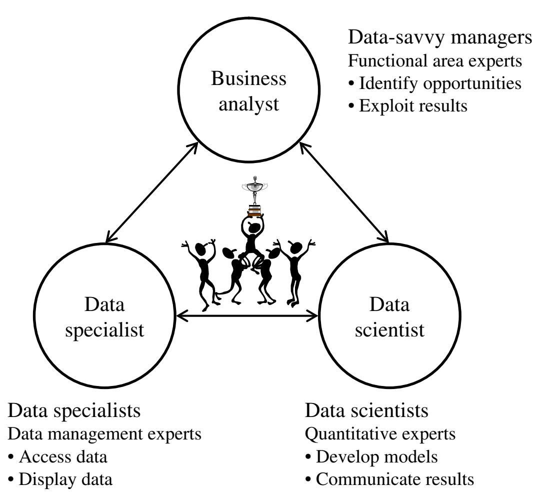
Do not stray from the objective, which is to *prepare data-savvy managers for success*. It is important to focus on problem solving, teamwork, and communication skills. Do not allow courses to become overtechnical. Students need to develop confidence in the techniques to recognize opportunities and exploit the results; not to become experts in optimization, for example.

Determine the most appropriate home department to manage the major. Business analytics is an interdisciplinary major, which makes it difficult to find an appropriate home department. Many of the courses are applied quantitative courses; they apply quantitative skills to some functional area such as marketing. The question becomes, is such a course a marketing course or an applied mathematics course? Most institutions have elected to position these quantitative courses in a school of business. In a study of the top 50 U.S. undergraduate business schools, it was found that 68% of the schools taught the first statistics course in the business school and 81% did the same for the second course (Haskin and Krehbiel 2011). In a more recent survey of analytics programs, 89% (39/44) were administered by schools of business (Gorman and Klimberg 2014). Other schools, such as North Carolina State, have positioned these courses to an institution dedicated to the field of analytics (North Carolina State 2014); although this option is ideal, it is not one that most schools are able to pursue.

Confront the "I'm never going to use this stuff" syndrome with real-world experience. The primary assessment of an analytics' program is the completion of a team project in a capstone course. This real-world experience is measured from the perspective of the team composition and the nature of the project. Ideally, teams are interdisciplinary. Figure 2 illustrates the flow of information between the different specialists. Schools with analytics programs for data scientists and computer science programs for data specialists should require the same capstone course for their students; project teams then are comprised of representation from each area.

Schools with accelerator programs have a ready source for obtaining real-world projects. Schools without this advantage must satisfy this objective by other means. One option is for students to find their own projects with instructor approval. For example, Levine and Stephan used a local moving company for which students developed a model to predict the number of hours required to complete a moving job (Levine and Stephan 2011); different teams could approach different moving companies in the area to participate. A Special Issue of *INFORMS Transactions on Education*, was dedicated to the subject of student projects; it offers many insights and innovative ideas to apply to analytics course projects (Lowe and Armacost 2012).

Figure 2 **Communication Flows**



If necessary, *reduce the number of topics covered to allow students to gain confidence in their abilities*. For example, GIS may be dropped as one of the topics in the Data Mining course to allocate more time to decision trees; Valparaiso University, for example, has an entire course on the topic of GIS taught by its meteorology department. The course does not require any prerequisites and is open to students from other disciplines (Valparaiso University 2014b).

Challenge students with competitions, which will also serve to strengthen their resumes. Competitions may be schoolwide or international and may be used in conjunction with capstone projects. SAS sponsors a student poster competition at their annual analytics conference (SAS 2014); the top six winners receive a free trip to the conference. Bowling Green State University just launched its first schoolwide competition granting a $1,000 prize to the first-place team (Bowling Green State University 2014). The options are limited only by one's imagination.

Lastly, *obtain feedback from new graduates and employers to ensure that the intended objectives are met*. Success will be attained when stories of misunderstood models are diminished and data-savvy managers frequently solicit the expertise of data scientists.

6. Conclusion

The ideas presented herein target a new audience—students who are not technically oriented but are business savvy. Six major courses and one core course are proposed to fulfil the requirements of an undergraduate program in analytics. The proposed business analytics curriculum was recently developed for use at Valparaiso University. It has been reviewed and approved for the 2014–2015 academic school year. In effect, we added four new courses to our previous offerings: Data Visualization, Data Mining, Spreadsheet Models (Prescriptive Analytics equivalent), and Analytics Practicum.

Successful implementation is contingent on modifying pedagogies to emphasize problem solving, teamwork, and communication skills. It is recommended that current quantitative courses be revised; the result of which moves the content of two traditional mathematics courses (calculus, finite mathematics) to the business school. This move is sure to cause distress but these courses have not been revised in decades and do not prepare today's managers for the next competitive advantage. Data-savvy managers must be able to identify opportunities and exploit the results; not construct the models themselves. To communicate with model experts, they must have a high-level understanding of the techniques. Furthermore, if they are to exploit the results, they must have confidence in these same techniques. These skills require a different pedagogy and emphasis than those that experts require. It is acceptable but undesirable to include the traditional mathematics courses in a plan of study; they are redundant with much of the content now provided by analytics courses.

The focus of this paper was an undergraduate major but minors and certifications should also be considered. Some vendors such as SAS, offer certificates to students based on courses using their products and another option based on a standardized exam. This research also did not discuss the software, data, or other resources needed to implement the proposed program; these are topics for future research.

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