doi:10.2498/iti.2013.0589

Business Analytics: Research and Teaching Perspectives

Ramesh Sharda, Daniel Adomako Asamoah, and Natraj Ponna
Institute for Research in Information Systems,
Spears School of Business, Oklahoma State University
Stillwater, OK 74078, USA
ramesh.sharda@okstate.edu asamoah@okstate.edu, natraj.ponna@okstate.edu

Abstract. *Business analytics and big data are being discussed everywhere right now. The objective of this paper is to provide a research and teaching introduction to business analytics. It begins by providing a quick overview of the three types of analytics. To assist the future analytics professionals, we identify various sectors of the analytics industry and provide a classification of different types of industry participants. Then it includes a brief description of some current research projects under way in our team. We also note some research opportunities in Big Data analytics. The paper also concludes with a discussion of teaching opportunities in analytics.*

Keywords. Analytics Big Data, Research, Athletic Injuries, Healthcare

Introduction

Although many authors and consultants have defined it slightly differently, one can view analytics as the process of developing actionable decisions or recommendation for actions based upon insights generated from historical data. The Institute for Operations Research and Management Science (INFORMS) has created a major initiative to organize and promote analytics. According to INFORMS, analytics represents the combination of computer technology, management science techniques, and statistics to solve real problems. Of course, many other organizations have proposed their own interpretations and motivation for analytics. For example, SAS Institute Inc. proposed eight levels of analytics that begin with standardized reports from a computer system. These reports essentially provide a sense of what is happening with an organization. Additional technologies have enabled us to create more customized reports that can be generated on an ad hoc basis. The next extension of reporting takes us to online analytical processing (OLAP) type queries that allow a user to dig deeper and determine specific source of concern or opportunities. Technologies available today can also automatically issues alerts for a decision maker when the performance issues warrant such alerts. At a consumer level we see such alerts for weather or other issues. But similar alerts can also be generated in specific settings when the sales fall above or below a certain level within a certain time period, or say when the inventory for a specific product is running low. All of the above applications are made possible through analysis and queries on data being collected by an organization. The next level of analysis might entail statistical analysis to better understand patterns. These can then be taken a step further to develop forecasts or models for predicting how customers might respond to a specific marketing campaign or ongoing service/product offerings. When an organization has a good view of what is happening and what is likely to happen, it can also employ other techniques to make the best decisions under the circumstances. These eight levels of analytics are described in more detail in a white paper by SAS. (http://www.sas.com/news/sascom/analytics_levels.pdf) [13].

This idea of looking at all the data to understand what is happening, what will happen, and how to make the best of it, has also been encapsulated by INFORMS in proposing three levels of analytics. These three levels are identified (http://www.informs.org/Community/Analytics) as: Descriptive, Predictive, and Prescriptive [5]. Figure 1 presents a graphical view of these three levels of analytics. The interconnected circles suggest that there is actually some overlap across these three types of analytics. We next introduce these three levels of analytics.

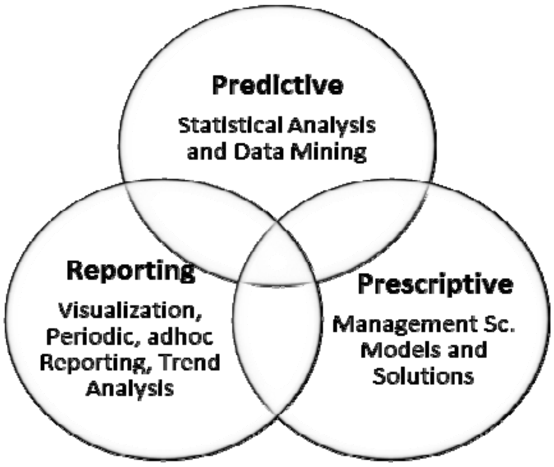

Figure 1. Three Types of Analytics

Descriptive or reporting analytics refers to knowing what is happening in the organization and understanding some underlying trends and causes of such occurrences. This involves consolidation of data sources and availability of all relevant data in a form that enables appropriate reporting and analysis. From this data infrastructure, we can develop appropriate reports, queries, alerts, and trends using various reporting tools and techniques. A significant technology that has become a key player in this area is visualization. Using the latest visualization tools in the marketplace, we can now develop powerful insights into the operations of our organization.

Predictive analytics aims to determine what is likely to happen in the future. This analysis is based on statistical techniques as well as other more recently developed techniques that fall under the general category of data mining. The goal of these techniques is to be able to predict if the customer is likely to switch to a competitor ("churn"), what a customer is likely to buy next and in what quantity, what promotion a customer would respond to, whether this customer is a credit risk, etc. A number of techniques are used in developing predictive analytical applications including various classification algorithms. For example, we can use classification techniques such as decision tree models and neural networks to predict how well a motion picture would do at the box office. We can also use clustering algorithms for segmenting customers into different clusters to be able to target specific promotions to them. Finally, we can use association mining techniques to estimate relationships between different purchasing behaviors. That is, if a customer buys one product, we can predict other items the customer is likely to purchase. Such analysis can assist a retailer in recommending or promoting related products. For example, any product search on Amazon.com results in the retailer also suggesting other similar products that a customer may be interested in.

The third category of analytics is termed **Prescriptive analytics**. The goal of prescriptive analytics is to examine current trends and likely forecasts and use that information to make decisions. This group of techniques has historically been studied under the umbrella of operations research or management sciences and is generally aimed at optimizing the performance of a system. The goal here is to provide a decision or a recommendation for a specific action. These recommendations can be in the forms of a specific yes/no decision for a problem, a specific amount (say, price for a specific item or airfare to charge), or even a complete set of production plans. The decisions may be presented to a decision maker in a report, or may directly be used in an automated decision rules system (e.g., in airline pricing systems). Thus these types of analytics can also be termed **Decision or Normative Analytics**.

Analytics Industry Clusters

This section is aimed at identifying various analytics industry players by grouping them into various sectors. We note that the list of company names included is not exhaustive. These merely reflect our own awareness and mapping of companies' offerings in this space. Additionally, the mention of a company's name or its capability in one specific group does not mean that the specific activity is the only offering of that organization. We use these names simply to illustrate our descriptions of sectors. Many other organizations exist in this industry. Our goal is not to create a directory of players or their capabilities in each space, but to illustrate to the students that many different options exist for playing in the Analytics industry. One can start in one sector, and move to another role altogether. We will also see that many companies play in multiple sectors within the analytics industry and thus offer opportunities for movement within the field both horizontally and vertically.

Table 1 illustrates the nine clusters and examples of companies in those clusters. It includes nine key sectors or clusters in the analytics space. The first five clusters can be broadly termed technology providers. Their primary revenue comes from developing technology, solutions, and training to enable the user organizations employ these technologies in the most effective and efficient manner. The accelerators include academics and industry organizations whose goal is to assist both technology providers and users.

Research Perspectives

The last few years have witnessed significant growth in research in all types of analytics. Prescriptive analytics has been known historically as operations research/management science (ORMS). The typical emphasis in ORMS research was on algorithms. Now the emphasis is on innovative applications of these techniques. Journals such *Interfaces* and magazines such as *OR/MS Today* as well as the *Analytics Magazine* includes many interesting applications of such techniques. For example, Pekgün et al. (2013) created a revenue optimization model based on factors such as demand forecast, competitor rates, and availability of inventory and business rules [10]. The forecast model was built using the multiple linear regression technique. The project, termed Stay Night Automated Pricing (SNAP) has been deployed in the Americas, Middle East, Asia Pacific, Africa and Europe and has so far increased revenue by more than $16 million per year. In a similar project by Danaos Corporation, an innovated tool called the Operations Research In Ship Management (ORISMA) was created to optimize ship routing with the ultimate goal of maximizing revenue [16]. The optimization model was built based on such information as financial data, hydrodynamic models and weather conditions and makes a trade-off between least-cost voyage (less fuel cost but leads to loss of operational time) and faster voyage (gain in operational time but leads to more fuel cost). Eventual benefits of this model in 2011 include a $1.3 million revenue due to time saving and $3.2 million revenue due to fuel saving. Lee et al. (2013) describe use of similar techniques in healthcare [8]. They used Optimization and simulation techniques to build a decision support system that would help in deploying large-scale medical counter measures in the case of a public health emergency such as disease outbreak. Medical counter measures include medical supply distribution, medical staff staffing, resource allocation and location of dispensing units. These prescriptive analytics examples build on data analysis to help make better decisions.

Predictive Analytics Research Examples

Research in applying predictive analytics has been growing exponentially over the last few years. The first wave of the research focused on developing algorithms in major categories of predictive analytics: classification, clustering, association mining, etc. These included decision trees, apriori algorithms, neural networks, and hundreds of other algorithms and variants. These algorithms have been applied in thousands of exploratory projects. A catalog of such research projects will fill a book. So we will only illustrate these opportunities by providing brief description of one recent project in applying predictive analytics in healthcare and sports.

Analyzing Athletic Injuries

Any Athletic activity is prone to injuries and if the injuries are not handled properly then the athletic team has adverse impacts. Using analytics to understand injuries can help in deriving valuable insights that would enable the coaches and the medical team to manage the team composition, understand the player profiles and ultimately aid in better decision making on which players might be available to play when.

In an exploratory study, American Football related sport injuries were analyzed using the reporting and predictive analytics by our research team. The project followed the CRISP-DM methodology to understand the business problem of making recommendations on managing injuries, understand the various data elements collected about injuries, cleaning the data, performing relevant imputations for the missing data, developing visualizations to draw various inferences, building predictive models to analyze the injury healing time period and drawing sequence rules to predict the relationship among the injuries and the various body part parts that were afflicted with injuries.

The Injury data set consisted of over 560 Football injury records that include injury-specific variables: body part / site / laterality, action taken, severity, injury type, injury start and healing date. It also includes player/ sport specific variables: Player ID, Position Played, Activity, Onset, and Game location. Based on

the injury start date and the healing date, healing time was calculated for each record which was classified into different sets of time periods: 0-1 month, 1-2 months, 2-4 months, 4-6 months and 6-24 months. The overall injury records with valid recovery time limited the final data available for modeling to 384 records.
We first began with descriptive analytics. Various visualizations were built to draw inferences, depicting the healing time period associated with player's positions, severity of injuries and the healing time period, treatment offered and the associated healing time period, major injuries afflicting body parts, type of field and game etc. Some of these are shown below. The first visualization in Figure 2 depicts the major injuries suffered by players at various positions and it can be inferred that the majority of injuries suffered are strains.

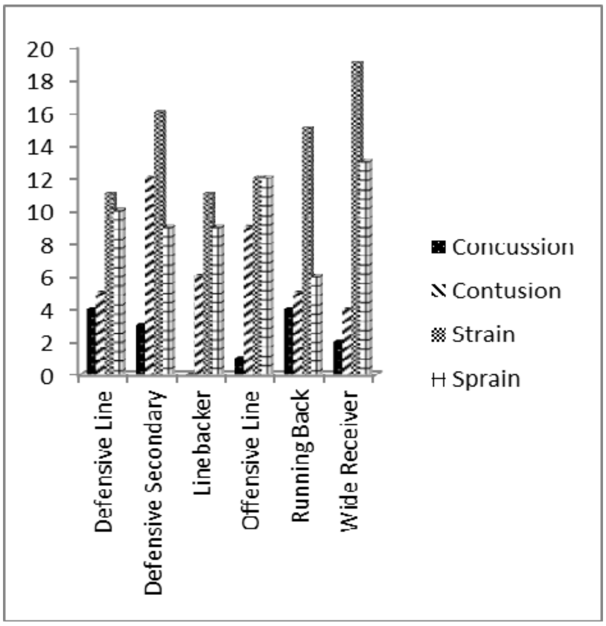

Figure 2. Injuries at Various Player Positions

Below visualization in Figure 3 indicates that the average recovery time for injuries to the Lumbar and Foot is higher than recovery time of other injuries.

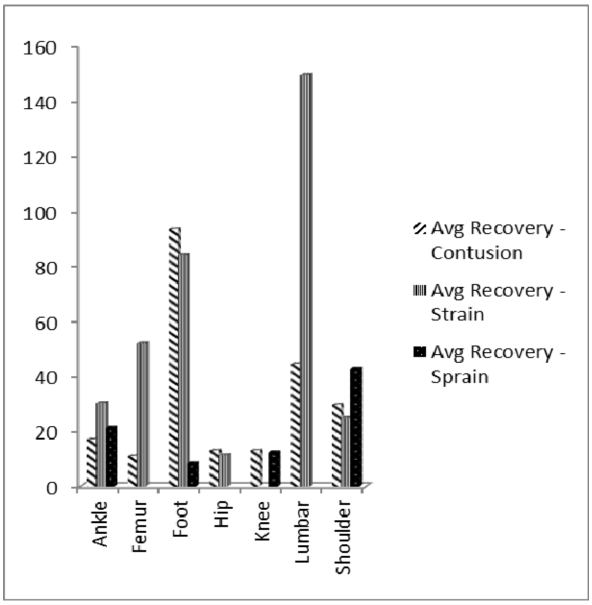

Figure 3. Average Injury Recovery Time in Days for Various Body Parts

Our analysis included many other visualizations that enabled better understanding the problem domain and the data. We then began to apply predictive modeling methods to be able to understand the recovery rates. IBM SPSS Modeler was used for predicting each of the healing time period categories. The data was divided into training and validation data sets and several predictive models using techniques like CHAID, CRT and Neural Networks were built. Of all the techniques, a neural network using multi-layer perceptron and a single hidden layer with 15 neurons yielded the best results.
Some of the predictor variables in the neural network model were: current status of injury, severity, body part, and body site, type of injury, activity, event location, action taken and position played. The success to classify the healing category was quite good with an accuracy of 79.6%. The overall percentage of the correct predictions of healing time period categories was 89.8%. The classification for healing category is shown in Figure 4.

Observed (months) \ Predicted (months)	0-1	1-2	2-4	4-6	6-24
0-1	97.3%	2.2%	0.5%	0.0%	0.0%
1-2	44.8%	55.2%	0.0%	0.0%	0.0%
2-4	18.8%	6.2%	75.0%	0.0%	3.9%
4-6	16.7%	0.0%	0.0%	83.3%	0.0%
6-24	0.0%	0.0%	25.0%	0.0%	75.0%

Figure 4. Classifications for Healing Category

We also performed a sequence analysis independently for injuries, body parts as well as both injuries and body parts taken together based on the time field of injury start date. The players are most likely to suffer the same injury again associated with same body part. But some other interesting patterns were found. These indicated possibility of injuries to the upper extremities when the player has already suffered lower extremity injuries. Some of these include possible injuries afflicting hand when the player has already had an injury to the ankle and injuries afflicting shoulder when the player has had an injury to the femur. This type of analysis has intrigued the training managers and coaches. Based on the analysis, many business recommendations were suggested which include: employ more specialist reviews right from the injury onset instead of letting the training room staff screen the injured players; training players at defensive positions to avoid getting injuries, and take precautionary measures for the future injuries that a player might suffer based on results of the sequence analysis.

This research project illustrates an interesting application of predictive modeling methods in athletic health issues. Of course, there is much talk about use of analytics in sports, especially popularized by the movie *Moneyball*, but there are many other opportunities to provide significant impact.

The next section describes an emerging area of research in analytics.

Big Data Research Opportunities

The bottleneck to knowledge generation and scientific progress is now an issue of effective data analysis rather than data availability. Contemporary lifestyles of individuals and technological advancements have resulted in generation of huge amounts of data in astounding proportions every hour in the form of emails, weblogs, tweets, sensor generated data, phone /GPS/traffic, video, and text. The data sources are mixture of both structured and unstructured data formats. Hitherto, large volumes of structured data have been mainly collected, stored and mined using traditional and relational data warehousing technologies. However, the fast growth of data has resulted in a new breed of analytics called Big Data Analytics to support large scale data analysis that focuses on large volumes of historical and near real-time data. At the core of big data research are business concepts, technologies and statistical techniques necessary to design highly scalable systems that can collect, process, store and analyze large volumes of both structured and unstructured data.

Just like other streams in the data analytics field, research in Big Data Analytics is applicable in almost all fields of practice and study. In areas like healthcare, logistics, marketing, retail and defense, it has become imperative to explore and analyze large amount of data in ways that supports effective decision making and strategic management. Such research and practice is growing rapidly. In the following, we describe one project that we are working on currently.

One of the nascent research streams in big data analytics is the role of electronic social media platforms in healthcare delivery. Early studies have established that factors such as evolving patient demographics, financial constraints and longer incidence of chronic diseases have enhanced the impact of social relationships in healthcare delivery [15]. Social relationships, which are associative bonds established between individuals with common aspirations and for the purpose of giving and receiving support, foster disease self-management programs that are vital to the management of chronic disease.

Even though healthcare delivery and support has been traditionally made through channels such as physicians, nurses and other clinical experts, the advent of the Web 2.0 platform has ushered an era where patients are beginning to inculcate new healthcare delivery strategies in the self-management of chronic disease. In fact, some studies have suggested that traditional sources of health management information may no longer be enough in providing quality healthcare to patients [4]. Pharmaceutical companies and other healthcare-related businesses already market drugs and solicit consumer feedback from social networks about new drugs and disease management options.

Among a myriad of health related topics discussed on social media platforms for instance, is the management of chronic diseases such as Diabetes, Chronic Obstructive Pulmonary Disease (COPD), Major Depressive Disorder (MDD), Epilepsy and Cardiac Failure [2]. These social media platforms offer social support and information to patients and caregivers. Social support has been identified as a major factor for improving health outcomes in patients who suffer from various types of illness [3][6]. The concept of social support, also sometimes referred to as peer support has been shown to not only help disease prevention, but also fosters and promotes general well-being and health [15][14][7]. More research needs to be conducted to establish the role and effectiveness of social media platforms in healthcare delivery.

Previous studies have mostly investigated efforts made by healthcare institutions in using social media as a tool for healthcare management and information delivery [9]. Armstrong and Powell (2009) assert that patients value the additional support they receive from online communities and perceive online sources of information provided by lay people as a complement to information provided by professional healthcare providers [1]. In addition, studies have shown that peer-to-peer support creates an enabling environment for disease self-management. However, very few studies have investigated how disease management and healthcare support are initiated by patients in a social media domain. Patients like to be in contact with others with similar problems in order to draw both emotional support and obtain information on how to manage diseases [1].

It has been established that social media platforms are a viable avenue for disease self-management. The question, however, still remains whether self-management programs through social media platforms are an effective means of managing chronic diseases. Disease self-management, especially for chronic diseases, can be an important aspect of the healthcare delivery process. Self-management programs are designed as a complement to other treatment methods to put the patients in the driving seat and empower them to take control of them health care status. The aim of a self-help program includes teaching 1) appropriate use of medications, 2) evaluating methods and use of new treatment methods, 3) engaging in physical exercises that help decrease instance of fatigue, isolation and pain, 4) better ways of communicating with family, peers and clinical healthcare givers.

There is a need to investigate the effect of peer support and information exchange on social media in self-managing chronic disease conditions in an environment that is not directly mediated by a healthcare institution or any clinical stakeholder. Sarasohn-Kahn (2008) reported that expert information provided by a large collection of users on a social media platform is known to be at par in terms of quality with what would be provided by any single expert on a subject matter [12]. The same is true for clinical information provided by other users on a social networking platform. Hence, besides the healthcare advice from expert clinicians such as doctors, the advice and support provided on social media platforms by non-expert patients is vital to the achieving of the necessary health goals that needs to be attained by patients.

As the focus of traditional health informatics shifts from health professionals to consumers, Big data research assumes a vital role because it gives one the opportunity and flexibility to analyze extremely huge amounts of data rather than just a small sample and make inferences and decisions on the use and delivery of healthcare on social media platforms. Big Data research also delves into in-depth analysis and drawing of deeper conclusions on data generated from other domains of study. The highly scalable platform used for Big Data analytics is necessitated by three fundamental characteristics of data sources; volume, velocity and variety. Big Data research looks at how to analyze data in different domains with such characteristics and in a way that generate deeper knowledge and adds value to the decision making process in businesses.

Teaching Perspectives

In any knowledge intensive industry such as analytics, the fundamental strength comes from having students who are interested in the technology and choose that industry as their profession. Universities play a key role in making this possible. Academic programs that prepare professionals for the industry are being started virtually everywhere. These programs span various components of business schools such as information systems, marketing, management sciences, etc. Such programs are also emerging far beyond business schools to include computer science, statistics, mathematics, and industrial engineering departments across the world. These programs also include training of graphics developers who design new ways of visualizing information. Universities are offering undergraduate and graduate programs in Analytics in all of these disciplines, though they may be labeled differently. A major growth frontier has been certificate programs in analytics to enable current professionals to retrain and retool themselves for analytics careers. Certificate programs enable practicing analysts to gain basic proficiency in specific software by taking a few critical courses. Power (2012) published a partial list of the graduate programs in analytics, but there are likely many more such programs, with new ones being added daily [11]. Watson (2013) describes how he teaches his analytics courses and also argues for the growing popularity of such programs [17].

Another group of players assist in developing competency in the field of analytics. These are certification programs awarding a certificate of expertise in specific software. Virtually every major technology provider (IBM, Microsoft, Microstrategy, Oracle, SAS, Teradata, etc.) has their own certification programs. These certificates ensure that potential new hires have a certain level of tool skills. On the other hand, INFORMS has just introduced a Certified Analytics Professional (CAP) certificate program that is aimed at testing an individual's general analytics competency. Any of these certifications give a college student additional marketable skills.

Many of these industry leaders also have academic alliance programs to enable teaching their software etc. IBM, Microsoft, Oracle, SAP, and Teradata have major initiatives that allow faculty members to share software as well as other teaching materials. Watson (2013) provides a summary of several of these resources [17]. For example, Teradata University Network (www.teradatauniversitynetwork.com) also known as TUN is sponsored and supported by Teradata, a major provider of analytics hardware/software and applications consulting services. TUN is free to use and provides faculty members and students access to many case studies, white papers, teaching materials, and software for learning concepts, applications, and tools for analytics. Faculty members contribute such resources to TUN. Even teaching notes are available for many of the teaching materials. A recent addition is several videos that depict analytics applications in realistic settings. These videos have been developed by Dr David Schrader of Teradata. These are labeled Business Scenario Investigations (BSI), a takeoff on the popular TV show *CSI*. Not only these are entertaining but they also provide the class some questions for discussion. For example, go to http://www.teradatauniversitynetwork.com/teach-and-learn/library-item/?LibraryItemId=889. Watch the video that appears on YouTube. Essentially, you have to assume the role of a customer service center professional. An incoming flight is running late, and several passengers are likely to miss their connecting flights. There are seats on one outgoing flight that can accommodate two of the four passengers. Which two passengers should be given priority? You are given information about customers' profiles and relationship with the airline. Your decisions might change as you learn more about those customers' profiles. Watch the video, pause it as appropriate, and answer the questions on which passengers should be given priority. Then resume the video to get more information. After the video is complete, you can see the slides related to this video and how the analysis was prepared on a slide set at:
http://www.teradatauniversitynetwork.com/templates/Download.aspx?ContentItemId=891
This multimedia excursion provides an example of how additional information available through an enterprise data warehouse can assist in decision making. There are almost a dozen such videos available through TUN. There are also hundreds of other teaching resources available on TUN.

Conclusion

Overall, there is much to be excited about the analytics industry at this point. As illustrated in this paper, descriptive, predictive and prescriptive analytics applications and research opportunities are wide and growing. Research in Big Data is also growing. Support for teaching analytics is available from many major vendors. The industry clusters of analytics ecosystem show that there are many opportunities for students, academics and industry professionals.

References

[1] Armstrong N, Powel J. Patient perspectives on health advice posted on Internet discussion boards: a qualitative study. Health Expectations 2009; 12(13): 313-320.

[2] Bond G, Burr R, Wolf F, Price M, McCurry S, Teri L. The Effects of a Web-Based Intervention on the Physical Outcomes Associated with Diabetes among Adults Age 60 and Older: A Randomized Trial. Diabetes Technology and Therapeutics 2007; 9(1): 52–59.

[3] Dennis C-L. Peer support for postpartum depression: volunteers' perceptions, recruitment strategies and training from a randomized controlled trial. Health Promotion International 2013; 28(2):187-196.

[4] Evans M, Donelle L, Hume-Loveland L. Social support and online postpartum depression discussion groups: A content analysis. Patient Education and Counseling 2012; 87(3): 405-410.

[5] INFORMS. Analytics Section Overview. http://www.informs.org/Community/Analytics [02-01-2013].

[6] Lakey B, Cohen S, 2000. Social support theory and measurement. In: Cohen S, Underwood L G, Gottlieb B. (Eds.), Social Support Measurement and Intervention: A Guide for Health and Social Scientists. Oxford University Press, Toronto, 2000.

[7] Lara M E, Leader J, Klein D N. The association between social support and course of depression: Is it confounded with personality? Journal of Abnormal Psychology, 1997; 106: 478–482.

[8] Lee E K, Pietz F, Benecke B, Mason J, Burel G. Advancing Public Health and Medical Preparedness with Operations Research. Interfaces 2013; 43(1): 79–98.

[9] Martinasek M P, Panzera A D, Schneider T, Lindenberger J H, Bryant C A, McDermott R J, Couluris M. Benefits and Barriers of Pediatric Healthcare Providers toward Using Social Media in Asthma Care. American Journal for Health Education 2011; 42 (4).

[10] Pekgün P, Menich R P, Acharya S, Finch P G, Deschamps F, Mallery K, Sistine J V, Christianson K, Fuller J.Carlson Rezidor Hotel Group Maximizes Revenue Through Improved Demand Management and Price Optimization. Interfaces 2013; 43(1): 21–36.

[11] Power, D. P. What universities offer master's degrees in analytics and data science?2012. http://dssresources.com/faq/index.php?action=artikel&id=250 [02-01-2013].

[12] Sarasohn-Kahn J. The wisdom of patients: Health care meets online social media. Oakland, CA: California HealthCare Foundation. 2008. http://www.chcf.org/publications/2008/04/the-wisdom-of-patients-health-care-meets-online-social-media [10-01-2012].

[13]SAS.com. Eight Levels of Analytics http://www.sas.com/news/sascom/analytics_levels.pdf [02-01-2013].

[14] Skarsater I, Langius A, Agren H, Haggstrom L and Dencker K. Sense of coherence and social support in relation to recovery in first-episode patients with major depression: A one-year prospective study. International Journal of Mental Health Nursing 2005; 14: 258–264.

[15] Stewart M , Tilden V. The contributions of health care science to social support. International Journal of Nursing Studies 1995; 32: 535–544.

[16]Varelas T, Archontaki S, Dimotikalis J, Turan O, Lazakis I, Varelas O. Optimizing Ship Routing to Maximize Fleet Revenue at Danaos Interfaces 2013; 43(1): 37–47.

[17]Watson, H. The Business Case for Analytics. 2013. BizEd, May/June 2013: 49-54.

Table 1. Analytics Clusters and Examples

Analytics Cluster	Category	Examples
Data Infrastructure	Major Hardware and Storage Solutions	IBM, Dell, HP, Oracle, EMC, NetApp
	Indigenous Hardware and Software Platform	IBM, Oracle, Teradata
	Hardware independent Data solutions	Microsoft SQL Server
	Specialized Integrated Software	SAP
	Network Infrastructure/Cloud Computing	Amazon, Salesforce.com
	Big Data Infrastructure Services and Training	Cloudera, Hortonworks, Hadoop, Map Reduce, NoSQL
Data Warehouse	Data integration Services	EMC, IBM, Microsoft, Oracle, SAP, Teradata
Middleware	Reporting Analytics Solutions	IBM Cognos, Microstrategy, Oracle, Plum, SAP Business Objects
Data Aggregators / Distributors	Data Collection	Comscore, Experian, Google Nielson, Omniture
Analytics Software Developers	Reporting Analytics	Microsoft SQL Server BI, Tableau, SAS Visual Analytics
	Predictive Analytics	IBM, SAS, KXEN, Statsoft, Salford Systems, Alteryx,
	Open Source Platforms	R, RapidMiner
	Prescriptive Analytics	ILOG (IBM), SAS -OR / MS, FICO, AIIMS, AMPL, Frontline, GAMS, Gurobi, Lindo Systems
	Simulation Software	Rockwell (ARENA), Simio, Palisade
	Decision Analysis	Expert Choice, Exsys, XpertRule
	Big Data	Teradata Aster
Analytics Application Developers	Analytics Consulting	IBM, SAS, Teradata
	Specific Solutions/Industry Specific	Cerner, IBM Watson, Sabre
	Domain Specific Solutions	Axiom, FICO, Experian, Demandtec
	Web/Social media/Location Analytics	Sense Networks, X+1, Rapleaf, Bluecava, Simulmedia
	Specialized Analytical Solutions	Shazam, Siri (I phone), Google Now (Android)
Analytics User Organizations	Private Sector, Government, Education, Military etc.	Too numerous to classify
Analytic Industry Analysts and Influencers	Professional Organizations	Gartner group, Data Warehousing Institute, Forrester, McKinsey
	Professional Membership based societies	INFORMS, Special Interest Group on Decision Support Systems (SIGDSS), Teradata, SAS
	Analytics Ambassadors	Individual contributors of analytics through seminars, books and other publications
Academic Providers/Certification Agencies	Analytic Academic Programs	Business school courses on information systems, marketing, management sciences etc. Computer science, statistics, mathematics, and industrial engineering academic departments
	Analytics Certification programs	IBM, Microsoft, Microstrategy, Oracle, SAS, Teradata